Context is Everything:

Using a Smartphone App to Capture Young People's Drinking Behaviours, Cognitions, Environments, and Consequences

Submitted by

Florian Labhart, MA

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School of Psychology and Public Health
College of Science, Health and Engineering
La Trobe University
Victoria, Australia

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Abstract

Each alcoholic drink consumed is a distinct event, taking place in a specific socio-ecological context, at a defined moment in time. In recent years, the development of event-level data collection methods has enabled initial investigations of the interplay between alcohol use and context. Yet, these evidence have been largely dependent on participant self-reports and considered only a few contextual characteristics concurrently. This thesis was leveraged from a multi-disciplinary project (Youth@Night) and presents the development and results of a custom-developed smartphone application designed to record multiple physical and social contextual characteristics of drinking events by means of questionnaires, sensors, pictures and videos.

The thesis is divided into seven empirical chapters. Following from the introduction (Chapter 1), chapters 2 and 3 present the development and evaluation of the smartphone application and of the recruitment method. The next chapters investigate various aspects of the event-level associations between alcohol use, cognitions, context and consequences, namely the influence of the context on drinking intentions (Chapters 4 and 5), the impact of ambient loudness, brightness and attendance on drinking (Chapter 6), the motivations to pre-drink (drinking in private settings before going out; Chapter 7), and the thresholds at which adverse consequences occur (Chapter 8).

The discussion (Chapter 9) focuses on the technical and analytical implications of this versatile data collection tool. In contrast to the ease of collecting data from questionnaires and sensors, participants found it more difficult to integrate the provision of pictures and videos into their weekend routines. The method of combining questionnaire, sensor and media data allowed the identification of several contextual risk factors for increased alcohol use, such as intentions to drink more than usual, large social gatherings, attending multiple locations, and louder venues. These risk factors can serve as important foundations for the development of dedicated individual and structural prevention measures.

Statement of Authorship

This thesis includes work by the author that has been published or accepted for publication as described in the text. Except where reference is made in the text of the thesis, this thesis contains no other material published elsewhere or extracted in whole or in part from a thesis accepted for the award of any other degree or diploma. No other person's work has been used without due acknowledgement in the main text of the thesis. This thesis has not been submitted for the award of any degree or diploma in any other tertiary institution.

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Bio

Florian Labhart has started working in alcohol research in 2008, after the completion of his Master's degree in social sciences at the University of Lausanne in Switzerland. Over the past 12 years of employment at the Research Department of Addiction Switzerland, he has contributed to 26 research projects. He has notably worked on survey-based studies, such as the "Global Status Report on Alcohol" for the World Health Organisation and the "European School-Survey Project on Alcohol and Drugs (ESPAD)". Additionally, he is currently responsible for the collection and analyses of the opioid substitution treatment national statistics, on mandate from the Swiss Federal Office of Public Health.

However, his main research focus and interest remains the development and evaluation of event-level data collection methods to capture young people's drinking behaviour and context in real life. In particular, he has investigated the prevalence, circumstances and motivations of young people who pre-drink (i.e. drink in private settings before going out), findings of which are published in ten peer-reviewed publications. In 2017, he joined, on a part time basis, the Social Computing Research Group at the Idiap Research Institute, where he collaborates with researchers in machine learning and computer science.

He started his doctoral studies as an external PhD candidate at the Utrecht University, the Netherlands, in 2016, and transferred to La Trobe University in Melbourne, Australia, in 2018. He has published more than 60 peer-reviewed articles, book chapters, and research reports (Google Scholar h-index$_{\text{(July 2020)}}$: 17) , and has contributed to more than 40 conferences and scientific meetings. He is an editorial board member of the International Journal of Alcohol and Drug Research (IJADR, since 2016), the secretary of the Swiss Foundation for Alcohol Research (SFAR, since 2017), and a member of the Coordinating Committee of the Kettil Bruun Society for Social and Epidemiological Research on Alcohol (KBS, since 2019).

Chapter 1: General Introduction

The act of drinking alcohol is a context-dependant behaviour, in the sense that each drink consumed is a singular event related to a larger ecological context at a specific moment in time. Each drinking event is unique, with regard to the type and size of the drink consumed, the social and physical context (e.g. type of location, people present, ambiance), as well as the drinker's intentions or motivations to drink at that time (Cahalan et al., 1969; McCarty, 1985). Although scholars have conceptualised the consumption of alcohol as being closely linked to its context for several decades, the methods used to collect data, typically retrospective questionnaires or location-based observations, remain limited in terms of recall bias or external validity. The recent development of smartphones, however, has enabled the collection of data and investigation of the interplay between alcohol use behaviours and characteristics of the immediate context in real time.

The research in this thesis is located at the intersection of several research disciplines and aims to investigate how alcohol consumption relates to its immediate context at the event-level, using data collected with a custom-build smartphone app. Firstly, the work falls within the development of ecological momentary assessment (EMA) methods in the alcohol research field, and aims to capture information on drinking behaviours at the time of consumption to minimise recall bias and maximize ecological validity (Bolger et al., 2003; Kuntsche & Labhart, 2012; Monk et al., 2015). Secondly, it proposes to investigate the relationship between alcohol use and its immediate drinking context literally at the 'event' level, by considering each drink consumed as a singular event, which essentially takes place in a unique moment in time and space, and therefore in a unique social and physical environment (Freisthler et al., 2014). Thirdly, it uses some of the most advanced technologies in smartphone applications development and ubiquitous computing to collect, within a single device, multiple and complementary types of data –questionnaires, pictures, videos, sensors– in real-life and in real-time (Biel et al., 2018; Kuntsche & Labhart, 2014; Santani et al., 2018). Taken together, this thesis presents an applied example of how smartphone technology can contribute to a greater understanding of where, when, how much and with whom people drink alcohol, shedding new light on well-established concepts, methods and limitations of traditional survey-based alcohol research.

1.1 The drinking context: a multifaceted research object

“The concept of a 'drinking setting' is beguilingly simple until examined more closely.”

(Stockwell et al., 1993)

“The point […] is to emphasize that the environment is problematic. Not only is it not "there" as […] something obvious and immediately apparent, but it also persists in being a concept of disturbing complexity. The properties of the environment, rather than being ready-to-hand, need instead to be constituted by the investigator.”

(Jessor, 1979)

For decades, the context, in which the act of drinking takes places, has been known to be an important influencing factor of alcohol use behaviours (Cahalan et al., 1969; Jessor, 1979). In particular, it is important to distinguish between the influence of the larger context (also called ‘macrosetting’) which relates to the legal, cultural and economic context, and the influence of the immediate context (also called ‘microsetting’) which relates to the social and physical characteristics of any drinking occasion (Connors & Tarbox, 1985; McCarty, 1985; Stevely et al., 2019).

Research on the ‘macrosetting’ typically focuses on societal characteristics, which tends to affect the behaviours of all drinkers from a given area or population through norms and regulations. Evidence has for example shown that increased alcohol use and harms in the general population are associated with a higher density of alcohol outlet, extended opening hours, lower prices of alcoholic drinks, and with higher social acceptability of drinking and drunkenness (Ahern et al., 2008; Gmel et al., 2016; Gruenewald et al., 2014; Holmes et al., 2014; Labhart, Ferris, et al., 2017; Livingston, 2011; Popova et al., 2009; Sudhinaraset et al., 2016).

Research on the ‘microsetting’, in contrast, focuses on characteristics of the immediate drinking context, which vary across drinking occasions. These characteristics include notably the type of setting (e.g., type of location), the setting’s physical attributes (e.g., light, temperature, furniture), the setting’s social attributes (e.g., type and gender-composition of the drinking group, on-going activities), and the user’s attitudes and cognitions (McCarty, 1985). Different methodological approaches have been used to explore the links between the immediate context and drinking behaviours. Results from cross-sectional retrospective surveys have for example shown that increased drinking among young people was associated with attending private parties, bars, or nightclubs, and being with large groups of friends (Demers et al., 2002), drinking beer and being surrounded by intoxicated people (Clapp & Shillington, 2001; Demers et al., 2002). Results from observations in bars have shown that, for example, crowding or louder music were associated with increased patron drinking (Carlini et al., 2014; Guéguen et al., 2008; Hughes et al., 2012). Finally, results from EMA studies have shown that greater levels of alcohol consumption happened on nights when: drinking occurred across multiple locations (Labhart et al., 2013), with mixed gender friend groups (Thrul et al., 2017), and with easier perceived access to alcohol (Lipperman-Kreda et al., 2018).

While the combination of the above-mentioned findings gives an impression of coherence and completeness, each study taken separately seems to have only focused on some narrow characteristics of the entire context. However, real-life drinking contexts combine several characteristics that have prevented previous studies from gaining a comprehensive understanding of the interactions between the numerous contextual factors in shaping alcohol use. Firstly, there are virtually an infinity of drinking contexts with their own particularities. For instance, observational studies have documented contextual characteristics of environments that are easily accessible to researchers, namely pubs and nightclubs (Hughes, Quigg, Eckley, et al., 2011), but little is known on the social and physical characteristics of locations, such as homes and public parks. To make a landmark step towards a comprehensive understanding of contextual influences on alcohol use, research methods need to be able to capture data on the context and people's behaviours in all kind of locations and types of social and physical attributes. Secondly, the drinking context is perpetually changing. Even in the same location over the course of a night, the context might never be replicated. A comprehensive understanding of the interplay between context and drinking requires the collection of data at the *event level*, namely at the same time of each drink consumed (Shiffman, 2009). Thirdly, the same context might be perceived differently by different people or at different state of inebriation, and is subject to interpretations (Jessor, 1979). However, previous evidence reflected either the perception of the actors of the drinking event (e.g., questionnaire or diary-based studies) or the perception of external observers (e.g., observational or laboratory studies), which might significantly differ from each other (Jones & Nisbett, 1987; Letherby et al., 2012). A comprehensive understanding of the influence of the context on individuals' drinking behaviours might therefore require the collection of data reflecting the actors' impression of their own environment, as well as the impression of external observers.

Unsurprisingly, to date, no study has managed to take into account all features and perceptions of the context. Instead, researchers have focused their attention on some particular aspects of the context, such as the type of location, the type or volume of background music, or the type and number of people present (Stevely et al., 2019), and from a single point of view (either the actors or the observers). Thus, the existing body of evidence partly reflects methodological choices and limitations related to the designs and methods used, echoing Jessor's observation that "the properties of the environment, rather than being ready-to-hand, need instead to be constituted by the investigator" (Jessor, 1979, p. 230). Yet, Jessor also envisioned an alternate way to overcome this fragmentation of evidence, characterised by the consideration of only few contextual characteristics at once, and advocated in particular for the development of cross-disciplinary methods and collaborations.

The present work is one example of Jessor's invitation for cross-disciplinary collaborations. Aiming to capture a comprehensive representation of the nightlife of young people and their drinking behaviours on weekend (Friday and Saturday) nights, the Youth@Night project (presented in details in Chapter 1.4) gathered the expertise of three research teams interested in drinking contexts, from a qualitative perspective (human geography), a quantitative perspective (social epidemiology), and a computer science perspective (ubiquitous computing). Although we could not take into account all features and perceptions of the context, the tools developed for this study allowed us to collect not only in-depth data on participants' usual alcohol-related behaviours and cognitions, but also in-depth data on multiple drinking events, including the social and physical features of immediate drinking contexts as perceived by both actors and observers.

1.2 'Event-level' research: because drinking is an event

"It is no accident that EMA methods have seen particularly wide adoption in studies of drug use, because EMA methods are particularly well-suited to studying drug use. Drug use itself is a discrete, episodic behavior that lends itself to event-oriented recording, making EMA a useful method for tracking its frequency and distribution over time."

(Shiffman, 2009)

Independent of quantity and duration of the occasion, the consumption of alcohol relates to a specific moment in time and in space. For more than half a century y (e.g., Bruun, 1967), the concept of 'drinking occasions' has been used to refer to the consumption of some alcohol in a given social and physical context (e.g. in a pub with friends, at home having a party) or over a given period of time (e.g. in a day, in an evening, in two hours, before an event; Cahalan et al., 1969).

The notion of a 'drinking occasion' or 'drinking session' is commonly used in retrospective questionnaires to capture respondents' typical drinking behaviours. This approach is for example used in the third item of the Alcohol Use Disorder Identification Test (AUDIT: Babor et al., 2001) asking "how often do you have six or more drinks *on one occasion*?" or the sixth item asking "how often during the last year have you needed a first drink in the morning to get yourself going after *a heavy drinking session*?". Given that the circumstances of these drinking occasions, in terms of time and space, are not precisely defined, this offers a significant margin of interpretation to those interviewed to adapt the notion to their own typical or usual drinking habits. This approach is certainly convenient for quickly assessing someone's drinking pattern in clinical practice or for estimating drinking habits (e.g. typical quantity or frequency of drinking) of the general population.

However, to more closely investigate the dynamics at play around the consumption of each drink (e.g. influence of the gender and number of people present), the use of retrospective questionnaires which refer to generic drinking occasions is problematic. Firstly, the indeterminacy of the circumstances, in terms of time and space, of each occasion provides each participant with the possibility to understand the question differently, which threatens the validity of the data. Secondly, retrospective assessment methods are particularly subject to recall bias, since people are known to forget or misreport details of their behaviours after a couple of days (Coughlin, 1990; Ekholm, 2004). Thirdly, by requesting people to aggregate their consumption over multiple occasions (e.g. item 2 of the AUDIT: "How many drinks containing alcohol do you have on a typical day when you are drinking?"), the very format of the question eliminates the intra-individual variance which might be linked to changes of contextual characteristics across drinking occasions. Lastly, even when focusing specifically on particular drinking occasions (Thrul et al., 2018) or drinking days (Sobell & Sobell, 1992), respondents are unlikely to accurately report characteristics of the context that they did not pay attention to while drinking.

Since the 1980s, researchers have developed diary-based study designs in order to obtain more reliable measures of people's alcohol consumption (O'Hare, 1991; Poikolainen & Kärkkäinen, 1983). By requesting respondents to repetitively report details of their alcohol use behaviour in their natural environments and within a short recall period (at least once a day), diary-based methods –also called ecological momentary assessment (EMA), ambulatory assessment, or experience sampling methods– minimise recall bias and maximise ecological validity (Bolger et al., 2003; Moskowitz & Young, 2006; Shiffman et al., 2008). Compared to retrospective surveys, EMA allows investigation of each drinking occasion as a specific and unique event occurring within a setting of particular locational, social and physical characteristics (Freisthler et al., 2014).

1.2.1 The search of technical solutions

At the millennium, EMA researchers transitioned from using paper-pencil diaries to exploring electronic diaries to increase the reliability of the collected data and reduce participant burden (Hufford & Shields, 2002; Kuntsche & Labhart, 2013a). Examples include interactive voice autoresponders (IVR), short message service (SMS) and handheld computers (Kuntsche & Robert, 2009; McKay, 1999; Perrine et al., 1995). Compared to paper-pencil diaries, these methods provided better control over the timing of the collected data by allowing only one assessment to be completed at a time. However, these methods remain limited, in terms of the quantity of information collected per assessment and, to our knowledge, have not been used to collect information on the drinking context.

The development of mobile internet, which allowed access to online questionnaires via smartphone browsers, opened the opportunity for increasing the quantity of data collected per assessment compared to IVR or SMS. In 2010, the pilot study of the

Internet-based Cellphone Assessment Technique (ICAT; Kuntsche & Labhart, 2013b) was launched. The study aimed to investigate the technological feasibility and related burden of collecting detailed information on the quantity of alcohol consumed in the past hour for different drink types, the locations attended and the characteristics of social environment using questionnaires prompted at random. The evaluation of the method showed a good retention rate, even among participants who received three questionnaires per night (Kuntsche & Labhart, 2013b). The pilot study provided the first event-level evidence, to our knowledge, that the consumption of alcohol on weekend nights was as prevalent in homes and parks as it was in licenced venues. The amounts consumed per hour were higher in licenced venues compared to other venues and drinking amounts increased in the presence of larger groups of friends (Labhart & Kuntsche, 2011).

The follow-up ICAT study, conducted in 2012, used a fixed prompts schedule with 6 assessments per night (at 8, 9, 10, 11, 12pm and 11am the next morning) to exploit the full potential of this method to capture event-level data on alcohol use and its immediate context at multiple times over the course of a night. Results of this study revealed that participants reported twice as many drinks consumed per night using ICAT than when asked retrospectively at baseline (Kuntsche & Labhart, 2012). These findings reflected previous observations that retrospective surveys only capture about half of people’s real alcohol consumption (Livingston & Callinan, 2015; Monk et al., 2015). This study also allowed to overcome participants’ subjectivity in the assessment of pre-drinking behaviours, namely the consumption of alcohol in private setting prior to going out. While previous studies relied on the participants’ subjective identification of their pre-drinking occasions (Borsari et al., 2007; Hughes et al., 2008; Pedersen & LaBrie, 2007), this study allowed identification of pre-drinking patterns uniquely based on the sequence of locations attended (Labhart et al., 2013). Finally, while previous evidence has shown that the number of people in a drinking group is associated with the quantity of alcohol consumed, this study added further evidence that amounts consumed also depend on the gender composition of the drinking group (Thrul et al., 2017; Thrul & Kuntsche, 2015).

In relation to the ultimate goal of capturing contextual characteristics of drinking events at the exact time of the drinking, the ICAT’s fixed hourly assessment schedule appeared inappropriate because real-life drinking behaviours do not follow a fixed prompt schedule. While increasing the frequency of the assessments is technically feasible, too frequent prompting could negatively affect the quality of the data by increasing response burden and inducing fatigue and reactivity. In addition, the aggregation of contextual characteristics over a 1-hour timeframe (e.g. the number of female friends present) prevent the identification of the exact contextual characteristics for each of the drinks consumed during this period of time. Finally, ICAT entirely relied on self-reported data, which only accounted for the participants' subjective perception of their context. Thus, we transitioned towards the development of a smartphone application that would capture simultaneously: self-reported information on drinks consumed, characteristics of the environment using sensors and a large numbers of contextual characteristics (e.g. loudness level, luminosity, type of location, number of people present) by means of short panoramic video clips.

1.3 The smartphone: an all-around data collection tool

"The smartphone can be used as a measurement instrument as it has the hardware capabilities, such as sensors and wired or wireless interfaces, in order to measure physical quantities and the operating system to manage the whole hardware platform, for processing the measured values and for interacting with the user."

(Daponte et al., 2013)

In the last 20 years, mobile technologies have had exponential growth due to the development of network capabilities, the integration of sensors on mobile phones and the introduction of elaborate user interfaces. The era of smartphones started in 2005 (Daponte et al., 2013), with the integration of Bluetooth interface, GPS receiver and memory card slot within a single device, in addition to more traditional functions of mobile phones such as calls, SMS, 2G internet (WAP) and a camera. Two years later, the first iPhone added a new set of sensors, namely accelerometer, proximity sensors, and WiFi. Then, the creation of the Apple App store and Android Play store in 2008 democratized the possibility for any smartphone user to customize their phone by installing personalized applications for leisure and professional purposes.

At the beginning of this PhD project in 2014, a special issue of Drug and Alcohol Review was dedicated to studies on 'Alcohol and drug use patterns in the event' (Kuntsche et al., 2014). The 16 papers outlined a global overview on the latest methodological and technological developments in data collection for alcohol and other substance use at (or close to) the time of the consumption. None of the 14 research teams worldwide represented in the special issue, had collected data using a smartphone application. Several reasons might explain why event-level research on substance use did not utilise smartphone applications earlier. Firstly, EMA research in this domain had traditionally been conducted using self-reported questionnaires, which could be implemented using more simple mobile phones technologies, such as SMS or internet-based questionnaires (Kuntsche & Labhart, 2013b). Secondly, a sufficient penetration rate of smartphones (i.e. at least 50 per 100 inhabitants) in the population of developed countries only occurred in 2011 (International Telecommunication Union, 2019), which changed the belief that smartphones were a niche product for tech-savvy people only. Thirdly, the scientific community (at least in the alcohol research field) showed clear hesitations in the adoption of innovative ideas and data collection tool methods (Kuntsche & Labhart, 2014).

However, in 2014, hundreds of alcohol-related smartphones apps were available, essentially for recreational purposes but also as self-monitoring and health promotion tools (Weaver et al., 2013). It was therefore clearly time for alcohol researchers to start exploring how smartphone applications could overcome the limitations of self-reported questionnaires and of in-situ observation methods for capturing contextual characteristics of drinking occasions. Moreover, despite being a relatively new technology, smartphones had a large penetration rate in the general population in 2014, with e.g. 81.1 active mobile-broadband subscriptions for 100 inhabitants in the developed world (Table 1-1). This rate has increased and expanded in the last years, with an estimation of 121.7 active mobile-broadband subscriptions for 100 inhabitants in developed countries in 2019, and of 75.2 in the developing countries (International Telecommunication Union, 2019).

Smartphones provide all of the necessary built-in functions to actively and passively collect data on young people’s drinking behaviours and their contexts in real life and in real time. For self-reported information in questionnaires, smartphones support display of complex questionnaires structures on multiple pages, with response options widgets (e.g. sliders) and alternative questions based on previous answers, participant prompts and date stamping to record time of questionnaires submission.

Table 1-1: Number of mobile-cellular telephone subscriptions and of active mobile-broadband subscriptions in the World, in 2014 and 2019

	2014		2019*	
	N (millions)	Per 100 inhabitants	N (millions)	Per 100 inhabitants
Mobile-cellular telephone subscriptions				
Developed	1'527	122.0	1'649	128.9
Developing	5'468	91.4	6'656	103.8
World	6'996	96.7	8'304	108.0
Active mobile-broadband subscriptions				
Developed	1'015	81.1	1'556	121.7
Developing	1'645	27.5	4'823	75.2
World	2'660	36.8	6'380	83.0

Note: * estimates
Source: International Telecommunication Union (2019)

To passively sense contextual features, smartphones also provided a large range of built-in sensors (e.g., GPS, accelerometer, WiFi), the connectivity systems to external sensors (e.g. Bluetooth) and the ability to collection audio/video media data. In contrast to self-report, sensor data capture is independent from participants' actions or subjectivity and therefore does not suffer from recall bias and can be repeated multiple times without inducing response burden, reactivity or fatigue. For example, several studies have used GPS to investigate people's movement patterns without any action from participants (Clapp et al., 2017; Mennis et al., 2017). With regard to alcohol use behaviours, evidence from different research groups indicates that drinking occasions can be detected with an accuracy of about 80% using only the sensors of the smartphone and that the most useful sensor for this task is the accelerometer (Bae et al., 2018; Killian, 2018; Phan et al., 2020; Santani et al., 2016). In addition, using wired or wireless connection interfaces (e.g. Bluetooth, NFC), smartphones can sense biological functions by means of third-party dermal sensors, such as alcohol intake excreted through perspiration, electrocardiography, blood pressure or sugar blood level (Bertz et al., 2018; Kumpusch et al., 2010; Luczak et al., 2018).

Finally, another asset of smartphones is the possibility to capture high-quality photos and videos (Phan et al., 2019). In contrast to sensors, smartphone cameras cannot record data without an action from the participant, but the content of photos and videos share the similarity of being free of recall bias and have the potential to capture many contextual characteristics, including those that the participant may not pay attention to but may still influence their behaviour.

1.4 The Youth@Night project: a multi-disciplinary multi-method study

“Awareness of the relative advantages and disadvantages of particular methods argues strongly for a research strategy that relies upon multiple methods. […] I want to urge that research on drinking contexts become more cosmopolitan, more comprehensive, and thus more compelling by incorporating wherever possible a strategy that relies on multiple methods.”

(Jessor, 1979, p. 232)

The Youth@Night project originated in the understanding that, based on the positive experience and outcomes with ICAT (see “Event-level research” section above), research methods on contextual determinants of alcohol use at the event level should be improved in two directions, namely by collecting more data on the context without increasing response burden using automated sensors, and by complementing the collection of event-level data with qualitative interviews. The Youth@Night project was developed as a joint venture between three research groups from different research backgrounds, namely alcohol epidemiology, human geography and computer science, utilising different research methods, namely quantitative analysis, qualitative analysis and machine learning, but with the same interest of understanding how people interact with their immediate physical and social context in situations that most likely involves alcohol consumption (Figure 1-1).

The project was funded by the Swiss National Science Foundation, initially for the period 2014 to 2016 but, because the data collected were so rich and innovative, a second research proposal was granted to allow continuing analyses for almost four years. The Youth@Night project had three primary objectives that required the expertise of all three institutes involved, namely to a) to develop and evaluate the performance of a custom-developed smartphone app to collect data by means of questionnaires, sensors and media, b) to examine the role of drinking environments and situational and environmental factors in influencing young people’s drinking on Friday and Saturday nights, and c) to investigate urban structure, mobility patterns, the number of drinking locations and young people's experiences and views on drinking in the nighttime economy.

Figure 1-1: Illustration of the joint venture of the three partners of the Youth@Night project

This thesis presents the outcomes from the alcohol epidemiology perspective of the project. Three additional PhD theses were conducted, two in computer science and one in human geography, using the mobile sensor data (Santani et al., 2016, 2018) and the media data (Phan et al., 2019, 2020), and the qualitative interviews content (Truong, 2018a, 2018b; Truong et al., 2019).

1.4.1 The study setting

The setting of young people's nightlife and drinking behaviours on weekend night was chosen for multiple reasons. Firstly, all research partners were familiar with this setting and research in both alcohol epidemiology (Kuntsche & Labhart, 2012; Labhart et al., 2013) and human geography (Landolt & Backhaus, 2009; Landolt & Demant, 2011) had provided initial evidence and insights into young people's going out and drinking behaviours on Friday and Saturday evenings in an urban context in Switzerland. Secondly, young people's alcohol use and experiences of negative consequences peak on weekend nights (Kuntsche & Labhart, 2012) and scholars had described this phenomenon as a deliberate 'culture of intoxication' (Measham & Brain, 2005). Seeking to understand the personal and contextual determinants for individual and normative excessive alcohol use is therefore a public health priority. Thirdly, to collect data in real-time is challenging due to: the diversity of environments (e.g. home, parks, bars, restaurants, night clubs; Dietze et al., 2014; Purcell & Graham, 2005), the dynamic aspects of a 'night out' (e.g. attendance in multiple successive locations; Labhart et al., 2013) and the diversity of competing activities that might distract the participants from participating conscientiously (Jones et al., 2018). Finally, the smartphone ownership rate among young people was particularly high, compared to other segments of the population, which made young people an ideal target group for a smartphone-based study (Kuntsche & Labhart, 2013a). For example, they could use their own smartphone to take part in the study and were already familiar with its functionalities (installation of the app, use of camera, activation of sensors, etc.).

1.5 Thesis outline

The overall aim of the thesis is to investigate the associations between specific characteristics of drinking and alcohol use behaviours, in terms of quantities and cognitions at the event-level, using data collected with a custom-build smartphone app. Additionally, given the lack of perspective on the use of smartphone apps in alcohol research, this work also explores different aspects of the development and implementation of smartphone-based data collection methods, in order to contribute to a greater understanding of where, when, why, how much and with whom people drink in the event. This work comprises (1) the development of our 'Youth@Night' app and the evaluation of users' experience with this data collection tool, (2) the implementation of a representative street-intercept recruitment technique using geo-located data generated on social networks' apps to quantify the popularity of nightlife regions over an entire city (3) the exploration of the associations between alcohol use behaviours, cognitions and their immediate physical and social contexts, at the event level and prospectively, using questionnaire data, and (4) the investigation of the opportunity to replace participants' self-reports of their behaviour and context by collecting media data, in the form of short video clips of the immediate environment.

Chapter 2 presents the development and evaluation of the Youth@Night app. The app was designed to document young people's nightlife and drinking behaviours in real-time with event-level questionnaire, photos of the drinks consumed, 10-second video clips of the environment and all available built-in sensors (GPS, Bluetooth, Accelerometer, etc.). Due to the repetition of assessments, the requirement to self-monitor, and the request to take pictures and video clips throughout the night could induce some response burden, Chapter 2 investigates participants' experience and compliance to the research protocol, with regards to (1) retention and drop-out rates, (2) assessment reactivity, and (3) disruption of participants' normal lives.

Chapter 3 presents the development and implementation of the recruitment of participants in two cities for the Youth@Night study. It shows how publicly available social network data, namely geo-localised check-ins collected with the Foursquare app, can be used to identify and quantify the most popular nightlife spaces over an entire city in order to recruit a sample of nightlife-goers that is quasi-representative of the diversity of spaces, patrons and locations at the city level.

Chapter 4 explores associations between drinking cognitions (i.e., short-term drinking intentions over the course of a weekend night), amounts of alcohol consumed in the event and characteristics of the drinking contexts, using data collected prior to starting drinking, during the night and the next morning. By comparing night-level assessments of drinking intentions with total night consumption, this chapter proposes a simple method, free of participants' subjectivity, to identify the nights participants have exceeded their drinking intentions and investigates what contextual factors contribute to drinking more than intended. To the best of our knowledge, this is the first study to explore the dynamics of short-term intentions and demonstrate the influence of the immediate drinking context on such cognitions. In terms of advanced statistical methods, this chapter demonstrates the benefits of applying person-mean-centering to the night-level observations to account for night- and person-level effects in multilevel regression models (Enders & Tofighi, 2007; Hoffman & Stawski, 2009).

Chapter 5 expands on findings from Chapter 4 and investigates under which circumstances young people acknowledged having drunk more than they intended the previous night. People's ability to correctly identify over-consumption occasions is essential in order to prevent future over-consumption (Martens et al., 2005) or to serve as a diagnosis criterion of alcohol dependence and alcohol abuse in the DSM-

IV and DSM-V (National Institutes of Health, 2014). However, this feedback-loop process might be altered or facilitated by the circumstances of the drinking occasion. By comparing participants' statement of having, or not, drank more than planned the previous night (assessed the next morning) with the level and circumstances of the actual consumption, this chapter investigates the extent to which contextual characteristics contribute to people's recognition that they have deviated from their drinking intentions.

Chapter 6 explores the similarities and differences between participants' 'subjective' perception and app-based 'objective' sensor-based measurements of the social and physical characteristics of the drinking context. The chapter elaborates on the premise that participants and external observers might perceive contextual characteristics (namely brightness, loudness and number of people present) differently, because the external observers are not influenced by the specificities of the drinking event. Observer-like insights were collected by means of 10-second video clips recorded by the participants and contextual characteristics were extracted using manual annotations and computerized algorithms. After assessing the extent to which extent participants' and video-based impressions of the context are complementary or overlapping, this chapter investigates how brightness, loudness and attendance, measured by either participants, annotators computerized algorithms, relate to participants' choice of drinking alcohol or not.

Chapter 7 uses person-level data to explore the motivations of young people to engage in a very context-specific drinking pattern called 'pre-drinking'. Pre-drinking is event-specific and occurs on particular nights and in particular contexts, typically with small-to-large groups of friends in private places or public spaces, prior to going out to licensed venues. Pre-drinking is often described as a functional way of maximising drunkenness and reducing monetary spending on alcohol before a night out. Yet, other contextual characteristics relating to the physical environment (e.g., room and furniture), the social environment (e.g., chatting, meet new people) or the ambiance (e.g., music, nibble) might also act as motivators to engage in pre-drinking. This chapter aims to explore the different motivational dimensions of pre-drinking and develop a state-of-the-art scale using exploratory and confirmatory factor analyses.

Chapter 8 focuses on the ability of EMA methods to capture prospective association of amounts of alcohol consumed with short-term consequences. Although the notions of heavy episodic drinking, risky single occasion drinking, or binge drinking have been used for decades, no evaluation of the appropriateness of the 4+/5+ threshold for women/men has been undertaken at the event or night level (Pearson et al., 2016). This chapter uses questionnaire data from two event-level studies (the app-based Youth@Night study and its predecessor, the ICAT-based study presented in Chapter 1.2) collected the next morning on the number of drinks consumed and related consequences experienced, and aims to determine the optimal thresholds for the detection of five acute alcohol-related consequences (hangover, blackout, risky sex, fights and injury) using the Receiver Operating Characteristic curve and Youden Index methods.

The last chapter summarises and discusses the main findings that emerged from Chapters 2 to 8. Reflecting on the definition of the 'microsetting' elaborated in Chapter 1.1, particular attention is given to the individual and combined contributions of the different types of contextual characteristics (location, physical, social and individual characteristics) to alcohol use behaviours and cognitions. In addition, given the novelty of several aspects of the Youth@Night app, this chapter critically reviews the advantages and limitations of the key components of this data collection tool. Finally, it addresses the implications of the findings for public health and prevention as well as the limitations of this thesis, and offers directions for future research.

Chapter 2

Capturing drinking and nightlife behaviours and their social and physical context with a smartphone application – investigation of users' experience and reactivity [1]

Abstract

Background: Many addictive behaviours are influenced by the context in which they occur, but methods for simultaneously capturing the characteristics of a behaviour and its context are scarce. This study describes a smartphone application developed to document young adults' nightlife and drinking behaviours and investigates its impact on participants' lives.

Methods: 241 participants, aged 16 to 25 (46.5% women), were asked to document 10 Friday and Saturday nights over seven weekends. Using their own smartphones, they documented the beverages consumed and the social and physical context by means of questionnaires, photos, and video clips, while phone sensors (e.g., GPS, Bluetooth, accelerometer) were running in the background. Quantitative and additional qualitative data (40 in-depth interviews) were used to investigate response burden, assessment reactivity, and disruption of usual activities among three participant groups, arranged according to the number of reports submitted during the study.

Results: 69% of participants documented 10 or more nights. Compared with the most frequent contributors, regular and irregular participants reported similar numbers of non-alcoholic drinks per night, but lower numbers of alcoholic drinks. Within each group, the number of drinks consumed did not change over the course of the study. Taking pictures and video clips was sometimes perceived as inappropriate and potentially disruptive to the ongoing social activities.

Conclusion: The application required a high but sustainable degree of commitment and did not induce reactivity. The method might be adapted to study other context-dependent addictive behaviours. Measures to decrease response burden and disruption of usual activities are proposed.

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2.1 Introduction

The purpose of Ecological Momentary Assessment (EMA) is to capture "life as it is lived" (Bolger et al., 2003), which means to record individuals' behaviours in their environments and over time (Trull & Ebner-Priemer, 2014). In recent decades, reliable methods and devices have been developed to monitor specific addictive behaviours, such as smoking (Thrul et al., 2015), alcohol use (Clapp et al., 2017; Dulin et al., 2017; Kuntsche & Labhart, 2013b; Merrill et al., 2017) and illegal drugs (Kennedy et al., 2013). However, even though these behaviours and related cognitions are known to be influenced by immediate contextual features (Freisthler et al., 2014; Monk & Heim, 2013, 2014), capturing rich contextual features at the same time as a behaviour of interest in real-life environments remains challenging due to the diversity of real-life environments and competing participants' activities (Jones et al., 2018).

Regarding volumes of alcohol consumed, for example, in-situ experiments demonstrated the impact of ambient music volume on drinking (Guéguen et al., 2008), bar-laboratory experiments explored the influence of pastime activities on drinking (Bot et al., 2007), and hourly diary studies showed that increased drinking on nights out was related to drinking in multiple locations (Labhart et al., 2013) and with larger groups of friends (Thrul et al., 2017). However, none of these methods appear elaborate enough to capture highly detailed aspects of the drinking and of the immediate environment in real-time (e.g., for each single drink) and in varied everyday environments.

Taking advantage of the versatility of smartphones (Carpenter et al., 2016), this paper presents how reporting and sensing functions were combined within a single smartphone application to capture young adults' drinking behaviours on weekend nights and investigates possible side effects of this method in terms of response burden, assessment reactivity, and disruption of normal smartphone usage.

A team of researchers in the fields of ubiquitous computing, alcohol epidemiology, and human geography developed the Youth@Night application (app) as a way of documenting young adults' nightlife behaviours using both user-generated content and sensor-generated content. Weekend nights were chosen for their public health relevance –alcohol use and related risks peak on those nights– and the challenging variety of contexts in which they occur (e.g., homes, pubs, nightclubs, streets, parks, on public transport). After recruitment in the streets of two Swiss cities, participants used their own phone to document at least 10 Friday and Saturday nights over seven consecutive weekends. The app collected detailed information on participants' alcohol use, activities, mobility, as well as a large spectrum of characteristics of the physical (e.g., types of locations, loudness, luminosity, ambience) and social environments (e.g., number and types of people present, place occupancy) using context-specific questionnaires, pictures, videos and built-in sensors. In addition to being free of cognitive distortion and subjective evaluation (Kiukkonen et al., 2010), sensor data (GPS, accelerometer, Bluetooth, battery status, etc.) were expected to record detailed environmental features while limiting disruption of the ongoing social dynamics and activities (Bae et al., 2018).

A couple of papers have described various aspects of the data collected with the Youth@Night app. For example, using only sensor data (accelerometer, GPS, etc.), machine learning algorithms were able to predict whether participants drank alcohol or not on each participant-night with an accuracy of 77% (Santani et al., 2018). It was also demonstrated that levels of occupancy and loudness of the environment could be reliably extracted from short in-situ videos clips recorded by participants, and that these measures corresponded to participants' and external annotators' evaluation of the same environment (Santani et al., 2016). Finally prospective analyses demonstrate the influence of social and environmental factors on exceeding the participants' own drinking intentions for a given evening (Labhart, Anderson, et al., 2017) and the number of drinks per drinking occasion associated with experiencing consequences (Labhart et al., 2018).

2.1.1 Study aims

Participation in the Youth@Night study required a high degree of commitment from participants; they had to rigorously complete self-reported questionnaires, agree that sensors continuously collected data, and take pictures and videos in varied situations. Consequently, a key question for future developments of such a research method is whether and how it affected participants' nightlives and drinking behaviours. This paper aims to investigate participants' experience with the application according to the following sources of assessment bias.

Firstly, the repetition of assessments, the requirement to self-monitor, and the request to perform unusual tasks can carry a significant *response burden*, consequently reducing compliance and increasing drop-out (Carpenter et al., 2016; Rolstad et al., 2011). We will therefore investigate the extent to which participants completed the requested 10 nights of the study, the time required to fully document a drink and its context, and the level of compliance with the request to record video clips.

Secondly, participants' behaviour might also be affected by the way their behaviour is assessed (Goodwin et al., 2008). By repetitively drawing participants' attention to a particular behaviour (e.g., alcohol use, physical exercise), the study protocol might raise their awareness of this behaviour and initiate a decision to change it. This phenomenon, called *assessment reactivity*, may be particularly likely to occur when participants can exert control over the behaviour of interest and when the study protocol requires them to self-monitor (Hufford et al., 2002; Shiffman et al., 2008). We will therefore investigate whether the number of alcoholic and non-alcoholic drinks reported per night and the types of questionnaires used for it changed over the course of the study, and explore participants' feelings about reactivity.

Thirdly, the application could *disrupt participants' normal lives* if, for example, they felt uncomfortable documenting nights in private settings, ongoing activities were interrupted by prompts, or the phone battery ran down. We will therefore compare participants' perceptions of prompts prior to and during the night, and investigate situations in which their phones ran out of battery charge.

2.1.2 Comparisons across compliance groups

Large variations in compliance levels across participants are commonly observed in EMA studies (Newcomb et al., 2018). Yet, in contrast to most EMA studies using scheduled assessments, the Youth@Night app required participants to document aspects of their nights (drinks consumed, locations, etc.) as often as these occurred or changed. As a result, the number of reports ranged from zero to a high number for any participant-night. Such an unequal distribution of data per participant, commonly named 'long-tailed' or 'Pareto' distribution, with most of the data being produced by a small number of actors (Newman, 2005), is in fact inherent to real-life behaviours similar to those assessed in the present study, such as amounts of alcohol consumed (Kerr & Greenfield, 2007) and the use and production of content in online media (Lerman, 2007; Ochoa & Duval, 2008; Poell & Borra, 2012).

We could not find any previous examples of how to group participants into distinct compliance groups in the presence of a long-tailed data distribution. Participants were thus allocated to three same-size groups based on the total number of reports submitted per participant during the whole study. A secondary aim of the study is thus to investigate how the three sources of assessment bias described above differ across compliance groups.

2.2 Methods

2.2.1 Youth@Night application

2.2.1.1 Operating system

The application was developed in early 2014 for the Android operating system (4.0.3+) for the following reasons: it enabled connections to all built-in sensors and interactions with other apps; unlike iOS apps, it supported a large variety of smartphone manufacturers; and it was the most prevalent operating system in the world, with a market share of 55.7% at the time of the study (StatsCounter, 2015).

2.2.1.2 Measures

Sensors. From 8 p.m. to 4 a.m., data was automatically acquired from the smartphone sensors to document participants' activity (accelerometer, running applications), phone state (battery status, mobile signal strength, WiFi), location (GPS, passive location), and proximal and distal social contacts (Bluetooth, logs of text message and phone call). If GPS and WiFi were not activated, participants were reminded to do so manually. The app captured sensor data at regular intervals to be economical in terms of battery use. However, it had no control over the use of GPS by other applications, which could potentially exhaust the battery within hours. Participants were therefore reminded to charge their phones in the afternoon.

Figure 2-1: Structure of the data collection and schedule of application features (sensors, prompts, messages, questionnaires, filters, and buttons).

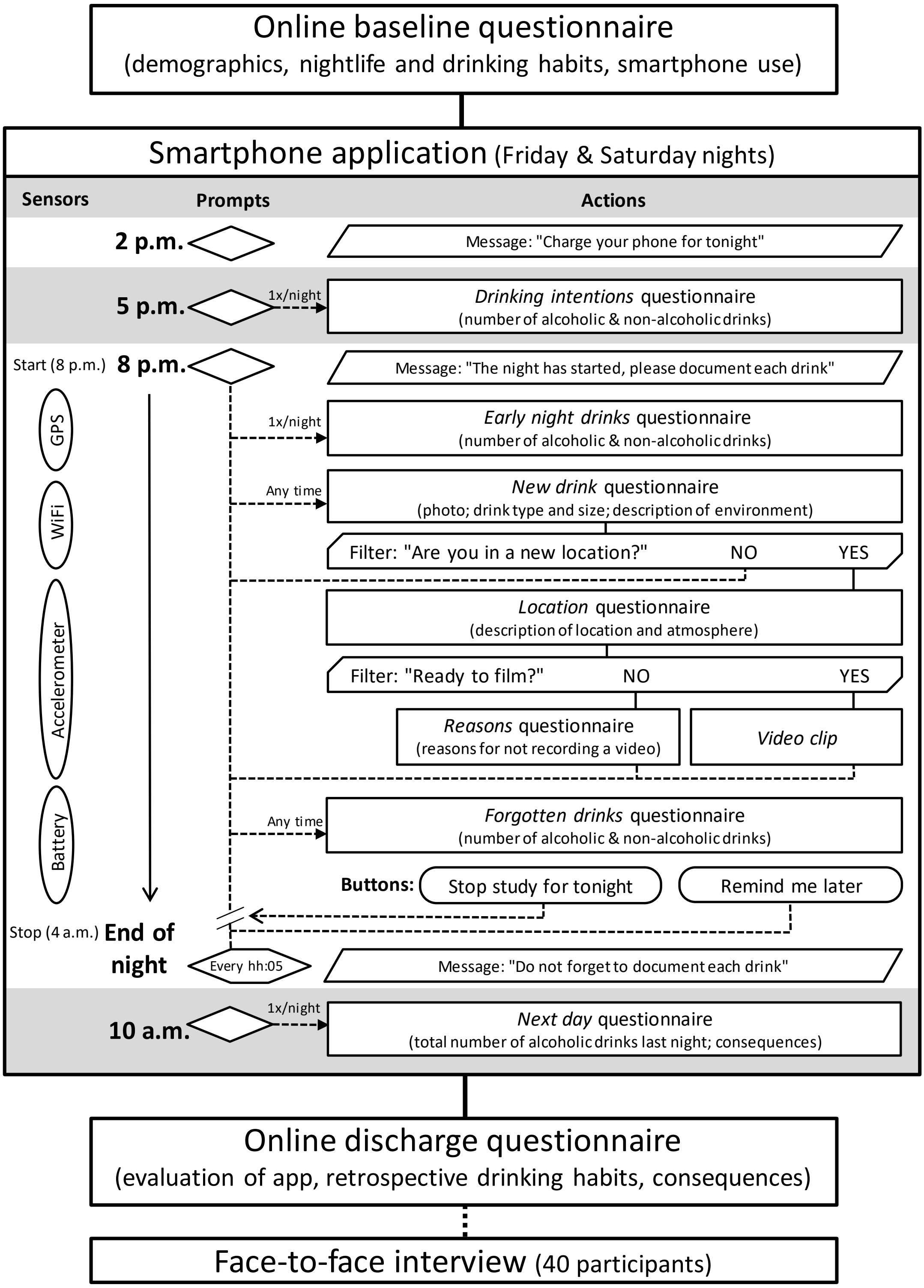
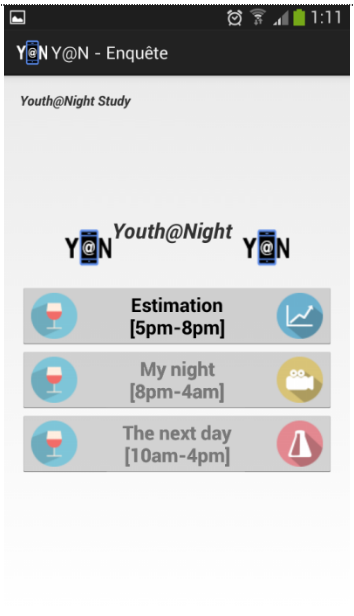


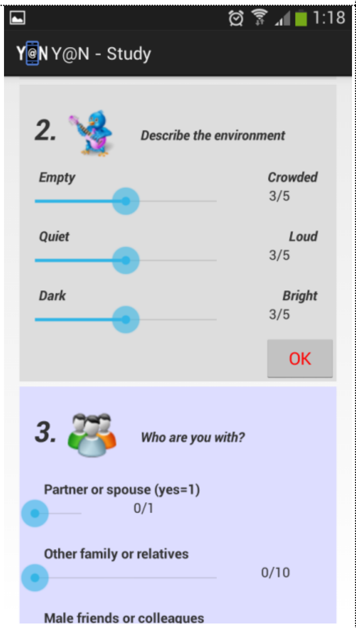
Figure 2-2: Screen captures of the application and example of a photo of a drink



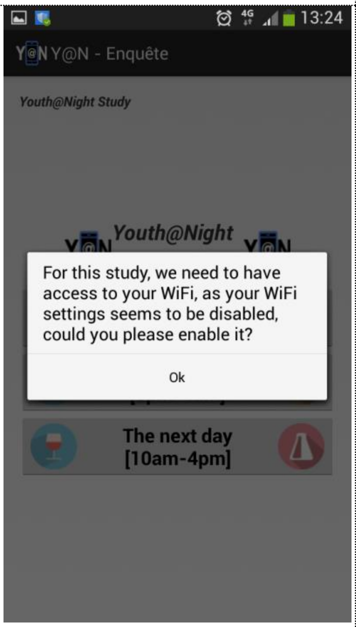
Application homepage: Menus were only activated (bold text) during the relevant time period. In the above case, participants could only access the drinking intentions questionnaire.

Questionnaire options from 8 p.m. to the end of the night: In the above case, the 5 – 8 p.m. drinks questionnaire had already been completed and could no longer be accessed (text in grey).

The 5 – 8 p.m. drinks questionnaire, also used in the drinking intentions and the forgotten-drink questionnaires.



The new-drink questionnaire, including sliders for describing the physical and social environment.
Each section had to be validated with the OK button before submission.



Warning message if WiFi was deactivated. The message popped up every hour if it remained deactivated.

Example of a photo of a drink taken during the pilot testing of the study.

Table 2-1: Schedule and content of the questionnaires

Questionnaire	Schedule	Type of data	Method of data collection
Drinking intentions	Prompt: 5pm Close: 8pm	Drinking intentions for the night	"+" and "-" buttons for each of the 12 drink types (Figure 2-2)
Early night drinks	Prompt: 8pm Close: end of night	Drinks consumed between 5 and 8 pm	"+" and "-" buttons for each of the 12 drink types
New-drink + picture	Prompt: every hour Self-initiated: any time Close: end of night	Picture of the drink	Camera in portrait mode to provide an alternative source of information on the drink vessel (glass, bottle, etc.), size and content
		Description of the drink	Predefined lists for the 12 drink types: e.g., for beer: size: 'small (25 cl),' 'medium (33 cl),' or 'large (50 cl)'; content: 'alcohol–free,' 'light (2-4%),' 'medium (4-6%),' and 'strong (6% or more)'
		Description of the physical environment	Five-point sliders ranging from 'empty' to 'crowded' (place occupancy), 'quiet' to 'loud' (loudness), and 'dark' to 'bright' (brightness)
		Number of people	Sliders ranging from '0' to '10+' for family members or relatives, male friends, female friends, and 0/1 for partner
› Location	After new-drink + picture if participants were in a new location	Type and name of the location	Predefined lists of semantic locations: 'bar/pub,' 'club,' 'coffee shop/bakery,' 'event space (sport, concert, art),' 'restaurant,' 'public place/space,' 'private place' 'travelling,' and 'other.' Then, for each option, predefined lists of popular locations identified on FourSquare (Santani & Gatica-Perez, 2013) and manually curated.
		Ambiance of the place	Seven-point sliders to indicate the degree of agreement with adjectives describing the place's ambience, such as 'arty,' 'formal,' 'romantic,' 'trendy' (Santani & Gatica-Perez, 2015)
› Video	After location if the participants were ready to film	10-seconds panorama of the drinking setting	Camera in landscape mode to provide objective data on the noise and luminosity levels, as well as an insight into the participants' lives used in the qualitative interviews.
› No video	After location if participant were not ready to film	Reasons for not making a video	Multiple choices: 'It is not appropriate to record a video now', 'I don't feel safe recording a video now', 'I was asked by someone not to record a video', 'Recording a video is not allowed in this place', and 'other'.
Forgotten drink	Alternative to new-drink + picture	Number and type of drinks consumed	"+" and "-" buttons for each of the 12 drink types to indicate the types and numbers of drinks that were forgotten to be reported
Next-day	Prompt: 10 am Close: 4 pm	Last night total alcohol consumption	Slider ranging from '0' to '30+'
		Alcohol-related negative consequences	Multiple choices including 'hangover (headache, upset stomach, etc.),' 'inability to remember what happened (even for a short period of time),' 'injury to themselves or someone else,' and 'drinking more alcohol than was originally intended.'

Questionnaires and media. Figures 2-1 and 2-2, and Table 2-1 provide a detailed overview of the sequences and content of questionnaires. In all questionnaires, drink options were separated into six types of alcoholic drinks (beer/cider, wine/champagne, liqueur/aperitif, straight spirits, shots, and alcoholic mixed drinks) and six types of non-alcoholic drinks (water, coffee/tea, fruit juice, soft drinks, energy drinks, and dairy drinks). Questionnaires and media files were stamped with the time of submission. If the questionnaire had already been completed during the night, slider positions were pre-set to the values entered in the previous questionnaire. To prevent submission of incomplete answers, each section of the questionnaire had to be validated with an OK button before submission.

Other measures. The baseline questionnaire at the start of the study (Figure 1) included questions on demographics, past and usual nightlife behaviour (e.g., frequency, locations, social company, usual drinking patterns), pre-drinking and drinking motives (Labhart & Kuntsche, 2017), personality factors (Gosling et al., 2003), and smartphone usage habits.

The discharge questionnaire contained questions on participants' feedback and experiences with the application (see Table 2-3 for an overview).

Finally, 40 qualitative interviews focused on experiences of nights out, drinking narratives of the participants, and the ways in which mobile internet technologies shape contemporary nightlife (Truong, 2018a, 2018b). Furthermore, the interviews engage with the experiences with the study application (Truong et al., 2019). The purpose of the latter part of the interview was to reconstruct participants' subjective experiences of both the self-initiated and automated sensor data collection during the study.

2.2.1.3 Data storage and security

During the study, questionnaires, photos, video clips, and sensor data were stored in the smartphone memory before being automatically uploaded to the study server. Data was uploaded via WiFi to minimise drainage of participants' personal phone data. A NoSQL database was used on the server with documents stored in JavaScript Object Notation (JSON) format. Each piece of data uploaded from the users was anonymized and encrypted. From the 241 participants who uploaded data, 54 different types of smartphones from eight manufacturers (e.g., Samsung, Sony, HTC) were identified. By the end of December 2014 (when all participants had completed the seven-week study), several million data points had been uploaded, including 10,843 questionnaires, 1,810,912 battery logs, 638,647 location points, 770,346 accelerometer points, 2,540 photos, and 897 video clips.

2.2.2 Study procedure

2.2.2.1 Recruitment and study protocol

Participants were recruited on Friday and Saturday nights in the nightlife districts of the two major nightlife hubs in Switzerland, Lausanne and Zurich, in September 2014. The Geographical Proportional-to-size Street-Intercept Sampling method was used to maximize the diversity of the nightlife populations approached (Labhart, Santani, et al., 2017). Eligibility criteria were: being aged between 16 and 25 years, having consumed alcohol at least once in the past month, having been out in the city at least twice in the past month, and owning an Android smartphone. Having given their e-mail address to the recruiters, volunteers received an email containing links to the study website (www.youth-night.ch) and the online consent form. After signing the consent form and completing the baseline questionnaire, participants were asked to download, install, and activate the app by entering their credentials and selecting one of the three languages offered (English, French, and German) and start using it the following Friday. Participants had to document at least 10 Friday or Saturday nights over seven consecutive weekends to receive the full incentive payment of CHF 100. Lower incentives were given for fewer nights of participation (CHF 70 for seven to nine, CHF 50 for five to six, and CHF 30 for three to four nights). We instructed participants to document any Friday and Saturday night, including those when they do not go out or do not drink alcohol, in order to acquire a broad overview of Friday and Saturday nights.

2.2.2.2 Contact with participants

Throughout the study, participants could ask for support by email, text message, and phone. The research team also used these communication channels to guide them through the registration and installation procedures. After three to four weeks, reminders were sent by email and phone calls to motivate infrequent participants. After seven weeks, participants were instructed to uninstall the application and complete the discharge questionnaire. At any time during the study, participants could uninstall the application and stop participating. To gain participants' trust and support their understanding of the importance of study (Csikszentmihalyi & Larson, 2014), participants were directed to a frequently-asked questions page on the study website which provided extended information about the conditions of participation and the data collection, and examples of photos and video clips. An online 'remove content' form was also provided in case participants wished to delete any data. The study protocol was approved by the Lausanne and Zurich cantonal ethics committees for research on human beings (protocol 145/14).

2.2.2.3 Sample

In total, 3,092 people were approached in both cities (mean age = 19.6 [SD = 3.3]; 46.9% women). Of those, 881 (28.5%) agreed to pre-register, 859 (27.8%) did not want to participate, 1,119 (36.2%) had an incompatible phone type, and 233 (7.5%) were not in the required age range. Of the 881 people who pre-registered, 629 (71.4%) signed the online consent form. Of those, 367 (58.3%) completed the baseline questionnaire, 263 (41.8%) installed the application, 241 (38.3%) uploaded data, and 201 (32.0%) completed the discharge questionnaire. The sample of 241 participants who uploaded data (mean age = 19.0 [SD = 2.4]; 46.5% women) was slightly younger than the rest of the eligible pool of passers-by approached on the streets ($t_{(1372)} = 2.22$, $p = .026$) but similar in terms of gender ($\chi^2_{(N = 2141;\ df = 1)} = 0.01$, $p = .926$).

2.2.2.4 Analytic strategy

Participants' use of the application and responses to the discharge questionnaire were used to provide different perspectives on the three sources of assessment bias investigated in this study. All analyses were computed using the software STATA SE 14.1. Whenever needed, test-power values of Pearson's correlations, independent sample *t*-tests and chi-squared tests were adjusted to account for the nested structure of the data, with nights being clustered within individuals. Whenever possible, qualitative data from participant interviews was used to contextualize and expand the findings from the quantitative data.

Regarding *response burden*, we investigated a) the proportion of participants who completed the minimum of 10 nights, b) the time required to document a drink and its context, c) the proportion of video clips being recorded rather than being skipped, and d) participants' agreement with the statement that the use of the application became a routine.

Regarding *assessment reactivity,* we investigated a) the evolution of the number of 'new drink' and 'forgotten drink' questionnaires submitted per night over time via its correlation with number of study days already completed, b) the evolution of the number of alcoholic and non-alcoholic drinks reported per night over time via its correlation with number of study days already completed, and c) participants' agreement with the statement that taking part in the study did not incite them to drink more or less on any particular night.

Regarding *disruption of usual activities*, we investigated a) the type of documented locations, b) the circumstances when participants ran out of battery, c) participants' perception of the app's impact on battery consumption, and d) feedback about the impact of using the app on ongoing social dynamics.

Exploratory analyses of the long-tailed distribution of the app data showed that the number of reports submitted per participant over the course of the study weakly correlated with age (r = 0.20, p = .002) and monthly quantity of alcohol consumed (r = 0.27, p < .001), but not with any other characteristic assessed at baseline, including gender, personality, frequency of going out or smartphone usage habits. To further investigate how differences in participants' commitment levels related to the three sources of assessment bias, participants were allocated to three same-size groups based on the total number of reports submitted during the whole study which represented low, mid and high compliance to EMA protocols. The group of a*ssiduous* reporters comprised the 35 most frequent contributors (104 or more reports per person) and accounted for the upper third (4758 reports) of all reports submitted; the group of *regular reporters* comprised 58 average contributors (67 to 103 reports per person) and accounted for the middle third (4691) of all reports; and the group of *irregular reporters* comprised the 148 most infrequent contributors (66 or fewer reports per person) and accounted for the lower third (4822) of all reports.

2.3 Results

2.3.1 Response burden

Almost two-thirds (165 of 241; 69%) of participants submitted questionnaires on at least 10 nights (mean = 11.3; SD = 5.2; median = 13). Irregular participants submitted reports on 9.4 nights on average (SD = 5.6; median = 10), regular participants on 13.8 nights (SD = 2.6; median = 14), and assiduous participants on 15.1 nights (SD = 2.0; median = 14). The number of nights of participation was uncorrelated with participants' age ($r(239) = 0.03$, $p = .636$), gender ($r(239) = 0.05$, p = .489), alcohol use quantity-frequency ($r(239) = 0.02$, $p = .765$), frequency of going out ($r(239) = -0.04$, $p = .591$), and smartphone usage frequency ($r(239) = 0.05$, $p = .494$). Despite being reminded to uninstall the application at the end of the seventh study weekend, 60 participants (25%) continued to use the app on more than 14 nights.

The median completion time for documenting a drink and its context (i.e. photo, new-drink, ambiance and location questionnaires, video clip) was 1 minute 40 seconds. The median of the five first completion times (i.e. when participants explored and familiarised themselves with the app features) was of 1 minute 51 seconds but showed a decreasing trend ($r_{[1\text{ to }5\text{ completions}]}(559) = -0.23$, $p < .001$). For successive completions, the median time dropped to 1 minute 27 seconds and did not decrease further ($r_{[6+\text{ completions}]}(322)= -0.08$, $p = .110$).

As seen in Table 2-3, documenting drinks with photos and new drink questionnaires was mostly done by assiduous and regular participants, while irregular participants tended to opt for questionnaires with less burden (i.e., intention, early night, forgotten-drink and next-day questionnaires) which could be completed within a couple of seconds. Conversely, the number of sensors data collected per participant-group reflected the number of nights of participation in each group, although assiduous participants seemed slightly more likely to activate their GPS.

Table 2-2: Participants' experience with the app, means (standard deviations in brackets) and difference from scale midpoint across participant groups

	Total sample				Participant group					
		One-sample t-test[a]			Irregular	Regular	Assiduous	ANOVA[b]		
	Mean (SD)	t	p	d	Mean (SD)	Mean (SD)	Mean (SD)	F	p	η²
Degree of agreement (1 = 'strongly disagree'; 4 = 'strongly agree')										
1. The application was intuitive and easy to use	2.9 (0.6)	9.8	<.001	0.81	2.9 (0.7)	3.1 (0.6)	3.0 (0.5)	2.56	.080	0.025
2. After a while, the use of the application became a routine that I did automatically without having to think about it too much	2.5 (0.9)	0.3	.736	0.05	2.4 (1.0)	2.7 (0.9)	2.4 (0.8)	2.25	.108	0.022
Frequency of observations (1 = 'never'; 5 = 'always')										
3. It was easy for me to document my drinks because the choice of drinks in the application corresponded well to what was available	3.9 (0.9)	14.1	<.001	1.18	3.7 (1.0)	4.0 (0.6)	4.1 (0.7)	3.21	.043	0.031
4. My phone battery ran down faster than usual	3.1 (1.4)	0.6	.556	0.10	2.9 (1.4)	3.2 (1.4)	3.4 (1.5)	2.08	.128	0.021
5. The application reminders (GPS, battery, WiFi) were disruptive	3.9 (1.1)	11.9	<.001	0.75	3.9 (1.0)	3.8 (1.1)	3.8 (1.1)	0.24	.791	0.002
6. The application reminders (GPS, battery, WiFi) were useful to me	2.6 (1.1)	-4.9	<.001	0.31	2.5 (1.1)	2.8 (1.2)	2.6 (1.0)	1.04	.357	0.010
7. I liked using the application	3.1 (0.9)	2.1	.041	0.14	3.1 (1.0)	3.2 (0.9)	3.0 (0.8)	0.48	.618	0.005
8. It was hard for me to document my drinks (photo, questionnaire, video) because it disrupted my evening/bothered my friends	2.9 (1.1)	-0.9	.381	0.07	3.0 (1.2)	2.8 (1.0)	2.9 (0.9)	0.40	.672	0.004
9. I received comments from people who were unhappy that I was making a video with my smartphone	1.8 (1.0)	-16.8	<.001	1.16	1.7 (1.0)	1.8 (1.0)	1.9 (1.1)	0.54	.581	0.004
10. Taking part in the study incited me to drink less on a particular evening	1.8 (1.1)	-15.9	<.001	1.12	1.8 (1.0)	1.8 (1.1)	1.8 (1.1)	0.00	.997	0.000
11. Taking part in the study incited me to drink more on a particular evening	1.5 (0.9)	-22.0	<.001	1.52	1.5 (0.9)	1.6 (0.9)	1.7 (1.1)	0.52	.597	0.005

Note: N = 201; a) df = 200; mean different from 2.5 (items 1-2) and from 3.0 (items 3-11); b) $df_{[between,within]}$ = 2, 198.

Table 2-3: Number of participants, nights and contributions, per participant groups

	Contributions per participant groups				Goodness of Fit[a]	
	N	Assiduous	Regular	Irregular	χ^2 (df = 2)	p
Participants	241	35 (14.5%)	58 (24.1%)	148 (61.4%)		
Nights	2867	529 (18.5%)	828 (28.9%)	1510 (52.7%)		
Total Questionnaires + Media[b]	14,271	4758 (33.3%)	4691 (32.9%)	4822 (33.8%)		
Questionnaires						
Intention	1908	436 (22.9%)	586 (30.7%)	886 (46.4%)	155.5	<.001
Early night drinks	1037	255 (24.6%)	339 (32.7%)	443 (42.7%)	48.1	<.001
New drink	2540	1104 (43.5%)	849 (33.4%)	587 (23.1%)	164.9	<.001
Location	1394	551 (39.5%)	509 (36.5%)	334 (24%)	61.7	<.001
No video	429	143 (33.3%)	147 (34.3%)	139 (32.4%)	0.5	.783
Forgotten drink	932	271 (29.1%)	312 (33.5%)	349 (37.4%)	8.8	.013
Next-day	2594	495 (19.1%)	780 (30.1%)	1319 (50.8%)	386.8	<.001
Media						
Pictures	2540	1104 (43.5%)	849 (33.4%)	587 (23.1%)	164.9	<.001
Videos	897	399 (44.5%)	320 (35.7%)	178 (19.8%)	87.5	<.001
Sensors						
Accelerometer	770,346	158,714 (20.6%)	252,246 (32.7%)	359,386 (46.7%)	11,317.4	<.001
Locations (GPS)	638,647	142,291 (22.3%)	231,182 (36.2%)	265,174 (41.5%)	32,141.5	<.001
Bluetooth	176,827	32,538 (18.4%)	55,105 (31.2%)	89,184 (50.4%)	487.2	<.001

Note: a) test of equivalence with the distribution of ‘Questionnaires + Media’ for questionnaires and media, and to ‘Nights’ for sensors; b) Criteria used to allocate the participants to the three groups of commitment

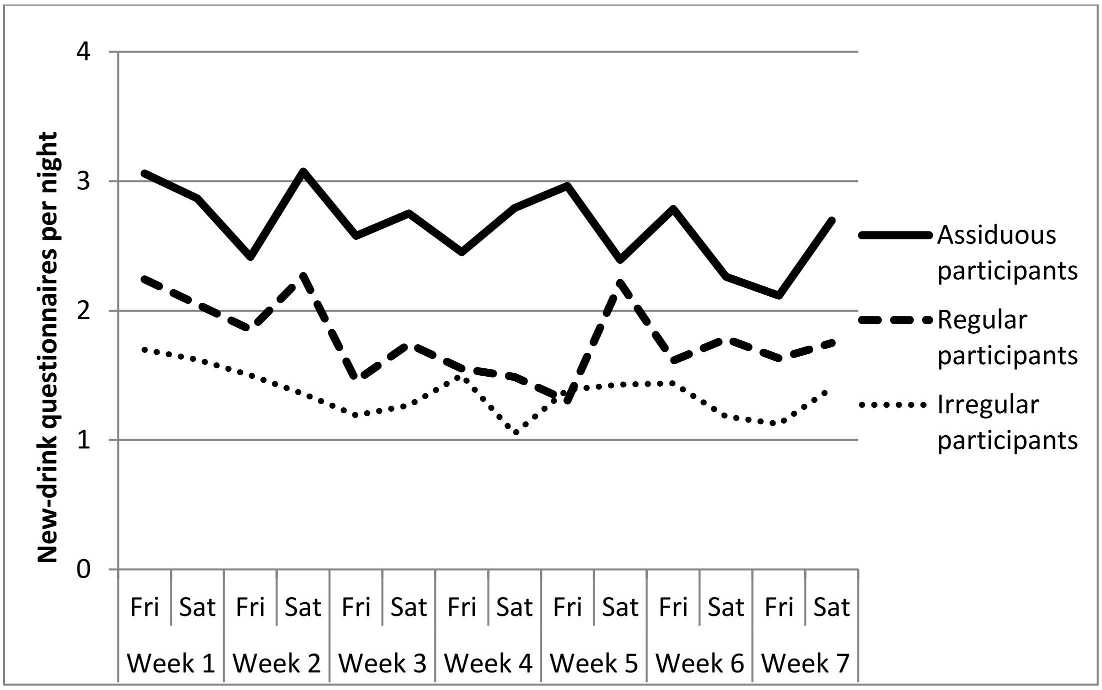
When asked to record a 10-second video clip, participants recorded a video in about two-thirds of cases (68%; Table 2-3). Reasons for not recording a video were: 'It is not appropriate to record a video now' (29%), 'I don't feel safe recording a video now' (29%), 'I was asked by someone not to record a video' (27%), 'Recording a video is not allowed in this place' (5%), and 'other' (17%), independently of the participant group. Irregular participants skipped this task more often (44%) than assiduous participants (26%; $F_{(1.8,\ 373.9)} = 2.78$, $p = .027$). Although, in the discharge questionnaire, participants from all groups mostly indicated that they 'never' or 'rarely' received comments from people who were unhappy that they were making a video (item 9 in Table 2-2).

Most participants found the application intuitive and easy to use (item 1 in Table 2-2) and liked using it (item 7). Documenting drinks appeared easy because the choice of drink categories corresponded well to what was available (item 3); although, this was less pronounced among irregular participants. However, no significant agreement or disagreement among the compliance groups was found for the statement that "after a while the use of the application became a routine" (item 2). During the qualitative interviews, a couple of participants elaborated on the point that, when drinking with friends on nights out, taking photos interrupted the social dynamics and was perceived as inappropriate in certain situations.

2.3.2 Assessment reactivity

Per night of participation, assiduous participants documented their drinking using an average of 2.7 new-drink questionnaires (SD = 1.8) and 1.5 (SD = 0.8) forgotten-drink questionnaires (which could be an alternative without taking a picture and documenting the location). As shown in Figure 2-3 and Table 2-4, regular and irregular participants submitted significantly less new-drink questionnaires and slightly less forgotten-drink questionnaires. Over the course of the study, the number of new-drink and forgotten-drink questionnaires submitted per night of participation by assiduous participants did not change, while the number of new-drink questionnaires decreased slightly among regular and irregular participants.

Figure 2-3: Numbers of new-drink and forgotten-drink questionnaires submitted per night of participation, per participant group



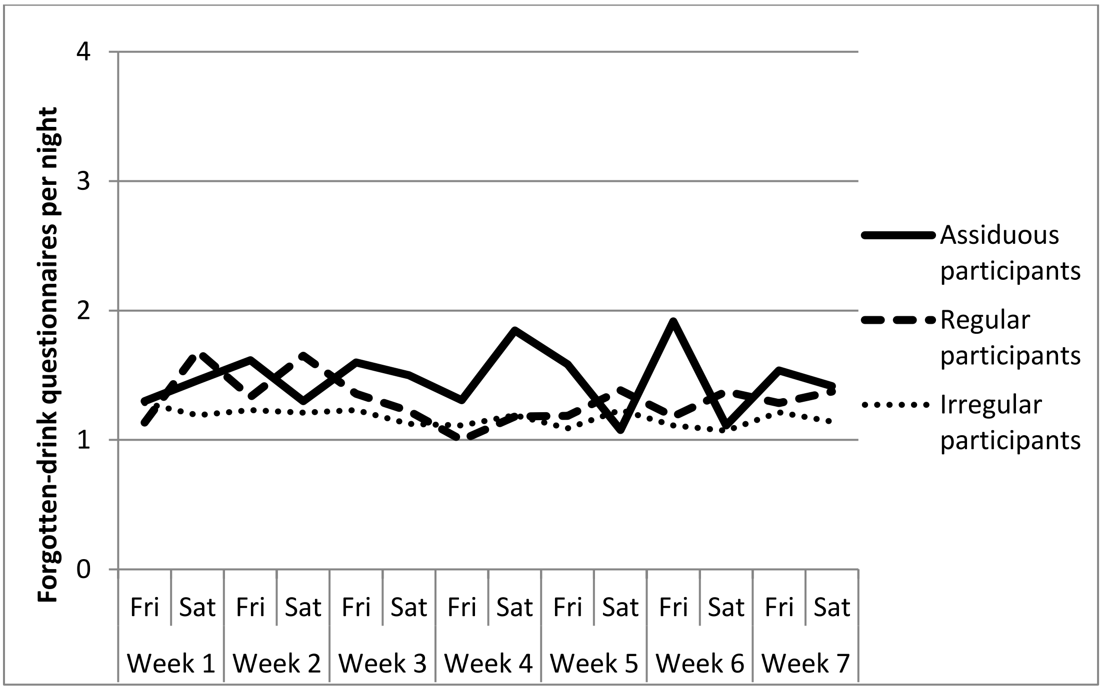


Table 2-4: Mean number of questionnaires submitted and drinks reported per night of participation and trends over the study

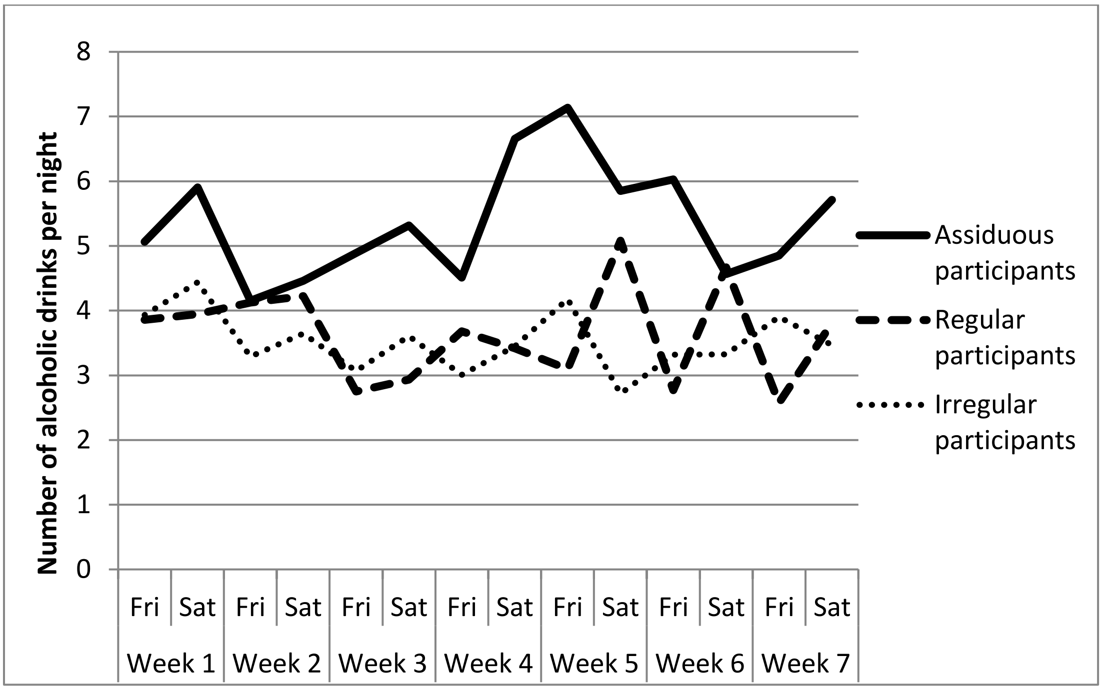
Measure	Average	Trend	Difference with Regular group	Difference with Irregular group
Compliance group	Mean (SD)	Correlation[1]	Adjusted t-test[1]	Adjusted t-test[1]
Numbers of new-drink questionnaires submitted per night of participation (Figure 2-3A)				
Assiduous	2.7 (1.8)	*r*(391) = -0.08, *p* = .103	F(1, 216) = 19.0, *p* < .001	F(1, 216) = 39.4, *p* < .001
Regular	1.8 (1.3)	*r*(465) = -0.12, *p* = .010		F(1, 216) = 12.2, *p* < .001
Irregular	1.5 (0.9)	*r*(384) = -0.16, *p* = .002		
Numbers of forgotten-drink questionnaires submitted per night of participation (Figure 2-3B)				
Assiduous	1.5 (0.8)	*r*(165) = 0.01, *p* = .946	F(1, 162) = 4.4, *p* = .037	F(1, 162) = 15.2, *p* < .001
Regular	1.3 (0.6)	*r*(225) = -0.08, *p* = .240		F(1, 162) = 4.1, *p* = .045
Irregular	1.2 (0.5)	*r*(276) =-0.08, *p* = .187		
Numbers of alcoholic drinks reported per night of participation (Figure 2-4A)				
Assiduous	5.3 (1.3)	*r*(295) = 0.05, *p* = .396	F(1, 201) = 11.4, *p* < .001	F(1, 201) = 12.9, *p* < .001
Regular	3.7 (3.8)	*r*(341) = -0.02, *p* = .766		F(1, 201) = 0.0, *p* = .868
Irregular	3.6 (3.9)	*r*(385) = -0.06, *p* = .268		
Numbers of non-alcoholic drinks reported per night of participation (Figure 2-4B)				
Assiduous	1.9 (1.2)	*r*(255) = -0.08, *p* = .183	F(1, 191) = 1.7, *p* = .190	F(1, 191) = 0.9, *p* = .335
Regular	1.7 (1.2)	*r*(351) = 0.03, *p* = .608		F(1, 191) = 0.2, *p* = .665
Irregular	1.7 (1.2)	*r*(312) = 0.02, *p* = .745		

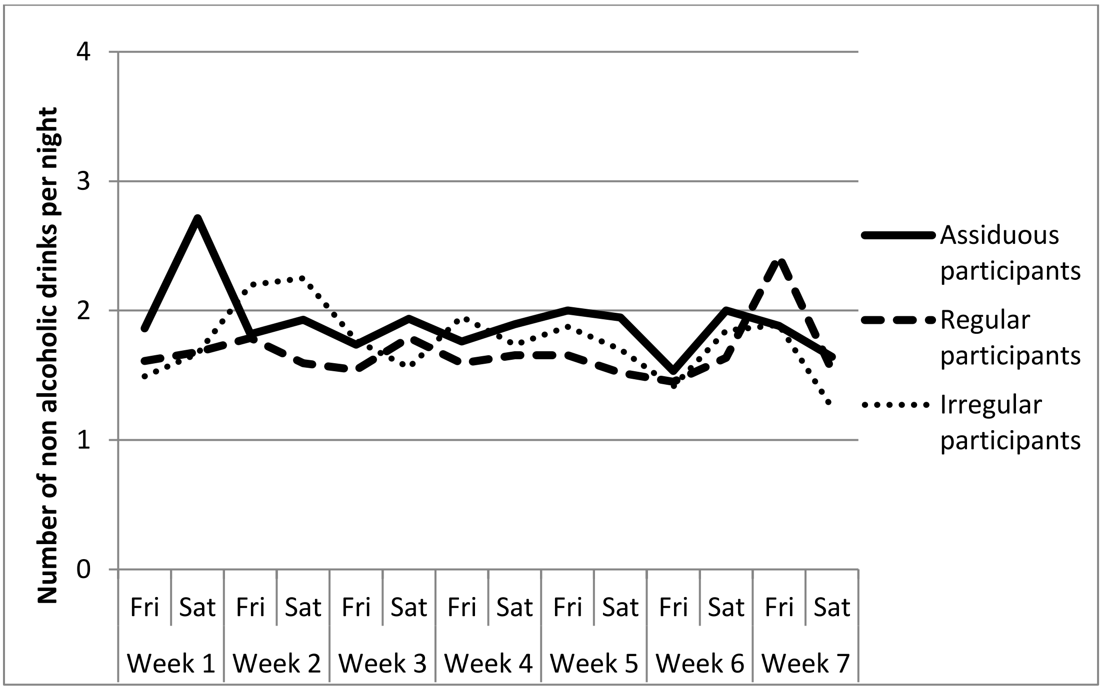
Note: 1) Test-power values of Pearson's correlations and independent sample *t*-tests were adjusted to account for the nested structure of the data, with nights being clustered within individuals.

With regard to drink types, assiduous participants reported an average of 5.3 (SD = 4.1) alcoholic drinks and 1.9 (SD = 1.2) non-alcoholic drinks per night of participation (Table 2-4). Figure 2-4 shows that regular and irregular participants reported fewer alcoholic drinks than assiduous participants but all three groups reported a similar number of non-alcoholic drinks. Further, the number of alcoholic and non-alcoholic drinks completed per night did not change over the course of the study among each of the three participant groups. Notably, the increase in the number of alcoholic drinks reported around week 5 occurred during the autumn holiday period.

In the discharge questionnaire, most participants indicated that taking part in the study never or rarely incited them to drink more or less on any particular night (items 10 and 11 in Table 2-2), with no significant differences between the three participant groups. In the qualitative interviews, some participants reported that they experienced their participation in the study as an opportunity to be or become more aware of their drinking practices. Some also mentioned that it was interesting to estimate how much they intended to drink before the night and then to record it during the night.

Figure 2-4: Numbers of alcoholic and non-alcoholic drinks reported per night of participation, per participant group





2.3.3 Disruption of usual activities

Participants documented spending their night mostly in homes (55%), bars (15%) and in public parks or streets (14%). Drinking while travelling (5%), in restaurants (5%) and in clubs (4%) were less frequent. All participant groups provided the same distribution of locations (adjusted Chi-squared test: $F_{(9.7,\ 2063.1)} = 0.91$, $p = .523$).

The average hourly battery use was of 8.2% of total charge (SD = 4.9%), independently of the participant groups, corresponding to 66% for the eight-hour study duration per participant-night. However, batteries were above 66% at 8 p.m. in less than half (46%) of participant-nights, dropped below 20% (i.e., level at which automatic sensor data capture self-deactivated) during 48% of participant-nights, and reached 0% (i.e., phone and app shutdown) on 12% of participant-nights. Participants' feedback relating to battery use was mixed. Around one-fifth of participants stated that their battery 'always' ran down faster than usual, whereas another fifth stated that this 'never' occurred (item 4 in Table 2-2), with no significant difference between the compliance groups.

Reminders sent at midday and 4 p.m. that participants should charge their phones were mostly perceived as disruptive (item 5 in Table 2-2) and not particularly useful (item 6). In qualitative interviews, participants explained that daytime reminders were perceived as disruptive and inappropriate because they were busy with other activities (e.g., studying or working). Hourly prompts during the night were mainly well-tolerated, however.

Participants' feedback regarding the disruptiveness of the application's use on ongoing social dynamics was mixed. Across all compliance groups, around a third of participants stated that it was 'often' or 'always' hard to document their drinks because it disrupted their night or bothered their friends (item 8 in Table 2-2), but another third reported that this was 'never' or 'rarely' the case. In qualitative interviews, several participants explained the situations in which documenting a drink was inappropriate or impractical. For example, this can interrupt social rituals at parties, such as toasting, so that participants had to explain the study requirements to friends. Also, after having ordered a drink in a crowded bar, they sometimes felt it too difficult to take out their smartphones and take a photo without spilling the drink.

2.4 Discussion

This study aimed to investigate participants' experience, compliance and reactivity with a smartphone application that was designed to document various aspects of young adults' weekend nightlife and drinking behaviours and their context with minimal burden and biases. The method was implemented in a challenging environment given the diversity of real-life contexts that the application was supposed to capture and that it had to be used during activities dominated by the pursuit of pleasure (Measham, 2004).

2.4.1 Response burden

With 69% of participants documenting their drinking on at least 10 nights, the retention rate is slightly lower than the pooled compliance rate of 71% found in a recent meta-analysis of prompt-based EMA studies among substances users who used their own smartphone for data collection (Jones et al., 2018). Yet, our study is not entirely comparable to those included in this meta-analysis since we used mostly event-contingent reports and collected media and sensors data in addition to questionnaires. The fact that about one quarter of participants continued participating even after 14 nights suggests that the high degree of commitment required was sustainable for most participants. In particular, the use of event-contingent reports might have increased participant engagement (Jones et al., 2018) and various features of the app, such as predefined lists of locations and drinks, auto-completion of unchanged characteristics (e.g., number of friends present), and synergies with sensor-based data collection, received positive feedback and certainly helped to reduce the overall burden. Nevertheless, results also indicate that the present method imposed a significant burden on many participants, particularly regarding the provision of media data. Several lessons can thus be learned from this study for future studies.

Firstly, with about one third of the video clips being skipped, recording videos in-situ appeared to be the most burdensome aspect of the study. Assiduous participants were more compliant than others, but still skipped one quarter of requests to record a video. Interestingly, recording video clips was rarely described as disruptive to others and participants provided mainly internally-motivated reasons for not recording videos. This suggests that participants generally understood whether making a video was possible or not, and that providing the option to skip this task was essential.

Secondly, the discipline of taking pictures of ordinary drinks could be perceived as burdensome. This was surprising considering that taking photos to post on social media is a common occurrence on young peoples' nights out (Lyons et al., 2017; Phan & Gatica-Perez, 2017). However, as explained in the interviews, young people normally take pictures with a motive (e.g., if the drink looks very special) but taking pictures of ordinary drinks is no normal practice. Therefore, participants may have had to explain to friends that they were participating in a study, which was more disruptive than the act of taking the picture itself.

Thirdly, providing alternatives to the most burdensome parts of the data collection might be beneficial to prevent drop out and increase the quantity of data collected, but also reduces the quality of the data. For example, the time required to document a drink and its environment (i.e., with a picture and several questionnaires) was substantial. While the time required decreased after a few completions, it may have encouraged irregular participants to opt for the shorter forgotten-drink questionnaires. While using the alternative 'forgotten drink' questionnaire resulted in a loss of information on the drink and its context, it nevertheless allowed participants to provide reliable information on the core topic of the study (i.e., quantity and type of alcohol beverages).

Fourthly, the burden was unequally distributed among participants, with heavier drinkers being the more frequent contributors. For ethical reasons, we chose to remunerate participants pro-rata for the nights of participation, rather than for the number of reports submitted, as this could have promoted heavier drinking and induced reactivity. However, future research might consider a fairer reward system, not necessary monetary, which could motivate irregular participants to increase compliance and reward assiduous participants for their efforts.

2.4.2 Compliance groups

At first sight, the division of participants into the three compliance groups appear tautological since 'assiduous' participants were labelled as such because they had submitted more questionnaires than others. Yet, while assiduous participants provided more contextually-rich data than the other groups, regular and irregular participants documented as many non-alcoholic drinks per night of participation, and provided almost as much sensor data and as many intention and next-day questionnaires over the study. Thus, all participants significantly contributed to the overall data collection process. This understanding of the benefits of retaining less-assiduous participants is important to ensure the external validity of the findings, as only a sample with all compliance groups can be assumed to be representative of the larger general population.

2.4.3 Assessment reactivity

The results of this study are consistent with the general observation that the magnitude of reactivity is limited in EMA (Shiffman et al., 2008). The number of alcoholic and non-alcoholic drinks reported per night among the three participant groups did not change significantly over the course of the study and their self-evaluation of reactivity was comparable to those observed by Luczak and colleagues (2015) and Hufford and colleagues (2002) in other alcohol-based EMA studies using mobile phones or handheld computers. Yet, the use of new-drink questionnaires tended to decrease among irregular and regular participants over time. This finding echoes the observation that some participants might have noticed part-way through the study that they could also document their drinks (and more than one at once) using the forgotten-drink questionnaires. A deeper understanding of this issue is recommended for future studies.

2.4.4 Disruption of usual activities

Even though, as discussed above, the need to take pictures and videos sometimes disrupted ongoing social activities, the use of the application appeared to have a limited overall impact on participants' usual nightlife and smartphone usage. The fact that half of the documented locations were homes reflects previous observations that large parts of young adults' weekend nights happen outside of licensed venues (Demant & Landolt, 2014; Dietze et al., 2014; Labhart et al., 2013; Landolt, 2011). Importantly, participants documented all locations (including homes) with pictures and videos, which allows researchers to virtually enter these usually hidden places, and offers new possibilities of, for example, investigating the influence of ambient loudness and brightness (Santani et al., 2016) on drinking in homes and other places.

The body of findings suggest that participants generally succeeded at integrating the study into their nightlife activities, but were not willing to be disturbed by prompts or reminders during daytime hours. The app conveyed daytime reminders to participants to charge their phone because running out of battery was shown to be common in large-scale mobile sensing of everyday activities (Kiukkonen et al., 2010). However, the results showed that participants were marginally concerned about running out of battery, as their smartphones were rarely fully charged at the beginning of the night, and daytime reminders were often perceived as disruptive. These findings are particularly problematic in terms of missing data, since battery failures induce a selection bias towards events that occurred either early at night or in locations where it was possible to charge phones. To partly counteract this, future research might integrate 'catch-up' questionnaires that record, in a summary form, events that were not reported while the phone was switched off. Enabling participants to select the time and types of reminders they receive provides another promising counter-action.

2.5 Limitations and conclusion

An important limitation of the data collection method is that only 241 of the 3092 people approached participated in the study. Having access to all sensors was only possible on Android phones at the time of the study, resulting in the loss of many potential participants owning smartphones with other operation systems including iPhones. This is now also possible on Apple smartphones (Bae et al., 2018), which should maximise inclusion in future studies. Although the gender ratio and the age of the sample of participants were similar to the rest of the eligible pool of passers-by, selective drop-out on other criteria cannot be excluded as a source of bias and might limit the generalisability of the present findings. Another limitation is that we mostly rely on participants' event-contingent reports to allocate them to the different compliance groups and to conduct correlation analyses on reactivity. It is thus possible that parts of the participants' behaviours were not self-reported and that the results are biased by missing data, particularly among regular and irregular participants groups.

To conclude, this paper showed that collecting a wealth of information on alcohol consumption and contextual factors simultaneously is technically possible and scientifically promising. Based on a close collaboration between social, behavioural and computer scientists, the simultaneous collection of sensor, media and questionnaire data offers interesting cross-disciplinary perspectives for research (e.g., Santani et al., 2016, 2018) and interventions (e.g., Bae et al., 2018). During the entire development process of such a tool, researchers should always consider the participants' experience as the highest priority, as such an intensive data collection method may be relatively burdensome in terms of time, attention (e.g. need to self-monitor), active disruption (e.g., interference with social life) and passive disruption (e.g., battery drain). Finally, this study demonstrated that all participants, even those having participated irregularly, are important to retain as they contribute to the overall understanding of the phenomenon of interest. For this purpose, implementing measures to skip the most burdensome (e.g., lengthy or momentarily inappropriate) tasks is important to maximise both the quality and the quantity of the collected data.

Chapter 3

Development of the Geographical Proportional-to-size Street-Intercept Sampling (GPSIS) method for recruiting urban nightlife-goers in an entire city [2]

Abstract

We developed the Geographical Proportional-to-size Street-Intercept Sampling (GPSIS) method in order to obtain a sample of nightlife-goers which accounted for the diversity of spaces, patrons and locations within two Swiss cities. Popular nightlife zones were identified and quantified using social media data and local experts' knowledge. Young people were recruited in the streets on Friday and Saturday nights on three consecutive weekends using the 'fixed-line method, pro-rated for the zone's estimated popularity. Of the 3092 young adults approached, 896 agreed to pre-register. The importance of recruitment in multiple zones and over multiple weekend-days was evidenced by significant variations in participant demographics and registration rates between recruitment zones, times and weather conditions. To conclude, by combining a geographical approach with in-situ recruitment, GPSIS has considerable potential as a tool for recruiting samples that represent the diversity of the nightlife population and spaces.

[2] Published as: Labhart, F., Tarsetti, F., Bornet, O., Santani, D., Truong, J., Landolt, S., Gatica-Perez, D. & Kuntsche, E. (2017). Development of the Geographical Proportional-to-size Street-Intercept Sampling (GPSIS) method for recruiting urban nightlife-goers in an entire city. *International Journal of Social Research Methodology*, 20(6), 721-736. https://doi.org/10.1080/13645579.2017.1293928

3.1 Introduction

Urban nightlife is characterised by a broad diversity of cultures, entertainment offerings, venues and patrons, and is often spread over large geographical areas within a city. According to Chatterton and Hollands' (2002) ethnographic work in large UK cities, the urban playscape in nightlife areas is divided into different spaces (labelled as 'mainstream', 'residual' and 'alternative'), which relate to different production, regulation and consumption cultures and are located in different parts of the city. Such cultural and spatial divisions of recreational nightlife scenes were also found, for example, for juvenile substance use in Zurich (Demant & Landolt, 2014) and in different cities in the UK (Chatterton & Hollands, 2003; Measham & Moore, 2009; Roberts, 2015). Ethnographic studies in San Francisco (Cavan, 1966) and Toronto (Purcell & Graham, 2005) further revealed several distinct categories of bars and nightclubs. The latter study identified obvious differences in the patrons' characteristics (e.g. age, gender and dress code) and activities between different nightclubs, as well as a distinct geographical distribution of nightclubs across the city (e.g. techno in the entertainment district, salsa and alternative scenes downtown, and live music in the suburbs).

While numerous public health studies have documented elements of individual practices in urban nightlife, quantitative research has generally failed to account for the diversity of spaces, patrons and locations. One of the main reasons for this is related to the recruitment strategies traditionally used. In epidemiology, sampling is usually based on a *randomised selection, e.g. of households* (Dietze et al., 2014), to obtain a representative sub-sample of a given population, with the advantage that the information obtained can be transferred to or held true for an entire population. However, since many participants may be unfamiliar with the nightlife in a given city, such a recruitment strategy necessitates contacting a very large random population in order to eventually achieve a large enough sample of nightlife-goers. In smaller-scale studies, *convenience sampling* (Northcote & Livingston, 2011)*, snowball sampling* (i.e. recruitment using seed-participants' social networks to access specific populations), *respondent-driven sampling* (i.e. weighted snowball sampling: Bellis et al., 2008; Bryant, 2014) and *online network sampling*, such as adverts on Facebook (Lea et al., 2013; Rife et al., 2016) or using Amazon Mechanical Turk (Boynton & Richman, 2014), proved to be efficient and cost-effective recruitment methods for reaching specific groups of nightlife-goers. However, since participants might know each other or share similar behavioural traits, such recruitment strategies could suffer from selection bias and data contamination and may represent only a fraction of nightlife spaces and patrons (Miller & Sønderlund, 2010). By recruiting people directly in a nightlife setting, *portal sampling* (i.e. at venues entrance or exit: Miller et al., 2013; Thombs et al., 2010) and *street-intercept sampling* (i.e. on the way to and from the entertainment district: Graham et al., 2014; Johnson et al., 2006) strive to obtain ecologically valid data while minimising recall bias. However, such methods are susceptible to sample selection bias since participants are clustered within a selection of recruitment locations, which might not be representative of all nightlife spaces in the city. Finally, *time-space sampling* (i.e. a probability-based portal sampling with randomization of venues, time and patrons: Muhib et al., 2001; Parsons et al., 2008)has the highest potential for generating a representative sample of nightlife-goers. The drawback is that this recruitment method is time-consuming and expensive (Kendall et al., 2008) and cannot include hundreds of nightlife venues simultaneously. It has therefore usually been used to recruit samples of specific, hard-to-reach populations within particular venues rather than across an entire city.

Using a geographical parameter such as the density of alcohol outlets (Ahern et al., 2013; Groff & Lockwood, 2014; Rowland et al., 2016) appears to be a more successful way of encompassing a city in its entirety by starting from an exhaustive list of registered locations. This enables quantification of people's activities within defined zones such as census boundaries, postcode areas or buffers surrounding locations of interest. The official registry of alcohol outlets, however, is not the best estimator of the geographical distribution of young nightlife-goers since it excludes alternative drinking locations such as homes, streets and parks. With their almost full registry of locations and all-year-long real-life check-ins, online location-based social networks (LBSNs, i.e. social networks allowing people to share their physical location in real-time with friends by means of their smartphone: Bentley et al., 2015) offer promising opportunities for capturing geographical activity over an entire city from the perspective of nightlife-goers themselves. Although LBSN users' primary objective when sharing their location (known as a 'check-in') is to meet friends or keep a record of the places they have been to and who was with them (Frith, 2014; Lindqvist et al., 2011), the collection of check-ins from thousands of real-life nightlife-goers provides a unique estimator for identifying and quantifying attendance of popular nightlife venues or areas.

We developed the *Geographical Proportional-to-size Street-Intercept Sampling (GPSIS)* method with the aim of recruiting as representative a sample as possible of young people on nights out. Its three-step procedure consists of a) identification and delimitation of popular nightlife zones accounting for different types of venues and patrons, b) quantification of the popularity of nightlife zones and definition of recruitment quotas per zone in proportion to its attendance, and c) application of a systematic method for approaching and recruiting participants on the street in each zone over multiple nights. Since the procedure combines systematic in-situ sampling within proportional-to-size clusters, nightlife-goers theoretically have the same probability of being recruited whichever zone they are in. In contrast to portal and time-space sampling, GPSIS has the advantage of sampling all young people participating in urban nightlife, even those who are not at a bar or nightclub. Furthermore, nightlife activities are subject to constant change, depending notably on the events taking place, the time and weekday, but also on the weather conditions. This dynamic feature of nightlife-going populations (i.e. different individuals may go to different places at different times on different weekends) makes the recruitment of a representative sample of nightlife-goers unrealistic in absolute terms. However, as a multi-site systematic method, GPSIS has the advantage of maximising the diversity of the people approached and, consequently, the potential representativeness of the final sample.

This aim of this paper is to describe the development and implementation of GPSIS in two major nightlife hubs in Switzerland and to evaluate its potential for recruiting representative samples of young people on nights out. Specifically, we will (a) investigate the extent to which the selection of recruitment zones based on LBSN data represented a diversity of drinking location types, (b) compare participant recruitment quotas based on LBSN data with local experts' estimations and with the samples actually recruited for each recruitment zone, (c) compare the demographic characteristics of the people approached and the registration rates across zones, (d) investigate the impact of external conditions (time of day and weather) on registration rates, and (e) explore participants' and recruiters' feedback on the recruitment process.

3.2 Methods

3.2.1 Procedure

The development of GPSIS was part of a larger study (Labhart & Kuntsche, 2017; Santani et al., 2016) which used a smartphone application to collect event-level data on young people's nightlife behaviour in the cities of Lausanne and Zurich (approximately 20,000 to 30,000 nightlife-goers per night in Lausanne and 100,000 in Zurich: Frutiger, 2012; Zürich City, 2014) located respectively in French-speaking and German-speaking Switzerland. On Friday and Saturday nights over seven consecutive weekends, participants aged 16 to 25 were requested to document their evenings using an Android smartphone application developed for the study. From 8 pm to the end of the night, series of event-level questionnaires were used to document the drinks consumed, the locations attended, and the characteristics of the environment. Participants had to take a picture of each drink and make a 10-second video clip of the environment when attending a new location. Additionally, the participants' activities and displacements were automatically recorded by the smartphone sensors (e.g. GPS, accelerometer). Participants were given a monetary incentive of CHF 100 (approximately GBP 70) if they completed at least 10 nights of participation. They were instructed to document any night, including when they did not go out or did not drink, in order to provide an overview of the different kinds of situations young people experience on Friday and Saturday nights. Finally, 20 qualitative interviews were conducted in each city. The study protocol was approved by the Lausanne and Zurich Cantonal Ethics Commissions for Research on Human Beings (protocol 145/14).

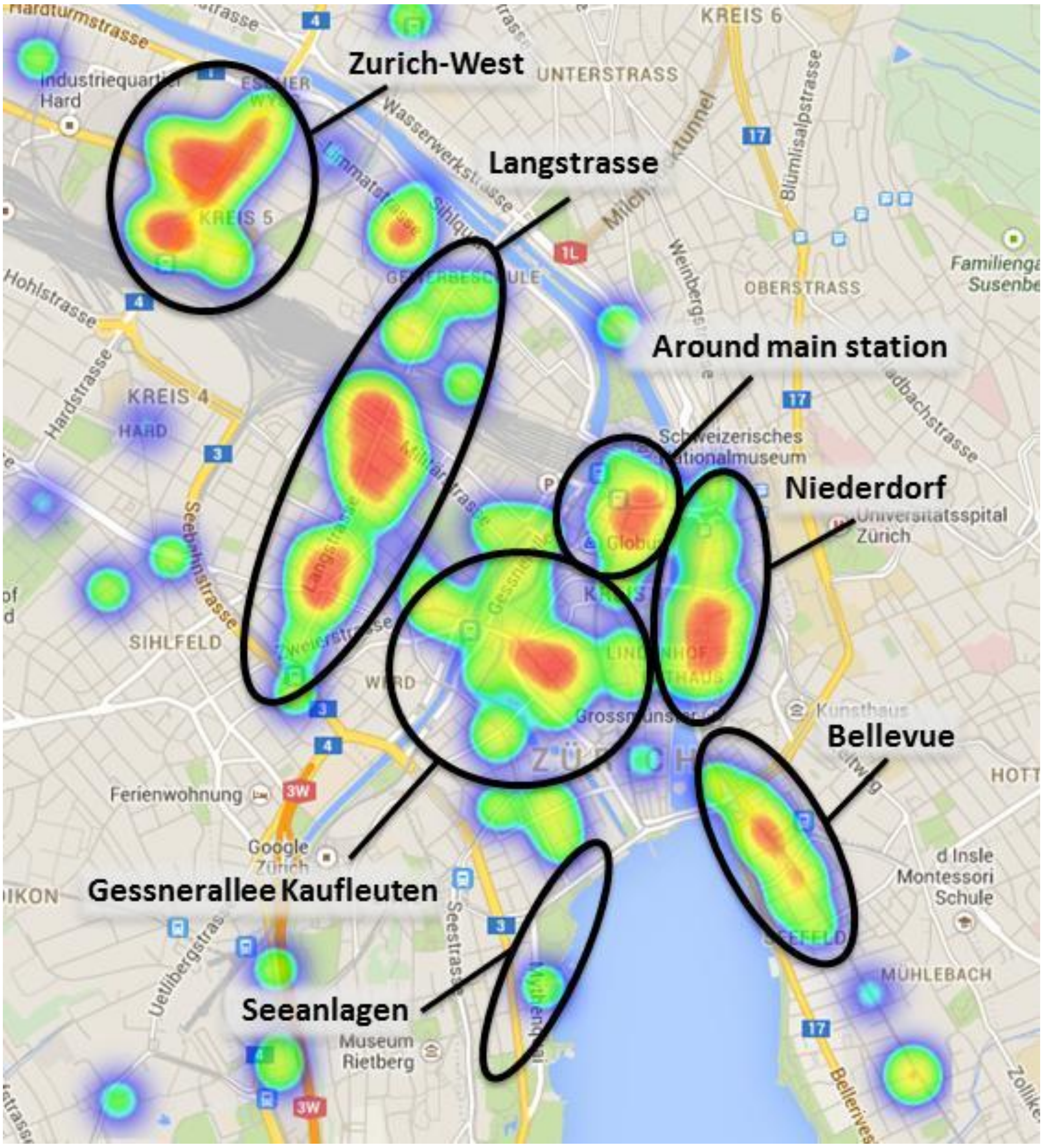
3.2.1.1 Mapping popular nightlife zones using social networks

The implementation of GPSIS started with the identification of the most-frequented nightlife zones in Lausanne and Zurich. For this, we used geolocalised check-ins from Foursquare, the most popular LBSN. More than 50 million people use Foursquare every month and 65 million places are indexed worldwide (Foursquare HQ, 2016). This data source was chosen since it provided an almost exhaustive catalogue of nightlife locations such as pubs, clubs and parks in most cities (Bentley et al., 2015; Hecht & Stephens, 2014) and had users similar to the targeted age groups for the study (Frith, 2014; Lindqvist et al., 2011). For each registered location, Foursquare provided full information on the type of location, the number of check-ins and the geographic coordinates. Locations were filtered by city and type to retain only check-ins related to nightlife activities (i.e. location types: bars, nightclubs, cinemas, theatres, public parks and streets) in Lausanne and Zurich. This data-set, accounting for all-year-long check-ins until August 2014, comprised 36,590 check-ins from 148 different locations in Lausanne and 116,099 check-ins from 506 locations in Zurich. Finally, to gain an overview of popular nightlife zones, heat maps of Foursquare check-ins were generated for each city (Figure 3-1). Locations with fewer than 50 check-ins were omitted in the maps in order to enhance the visual impression of geographically confined nightlife zones within the entire city.

3.2.1.2 Selection of recruitment zones

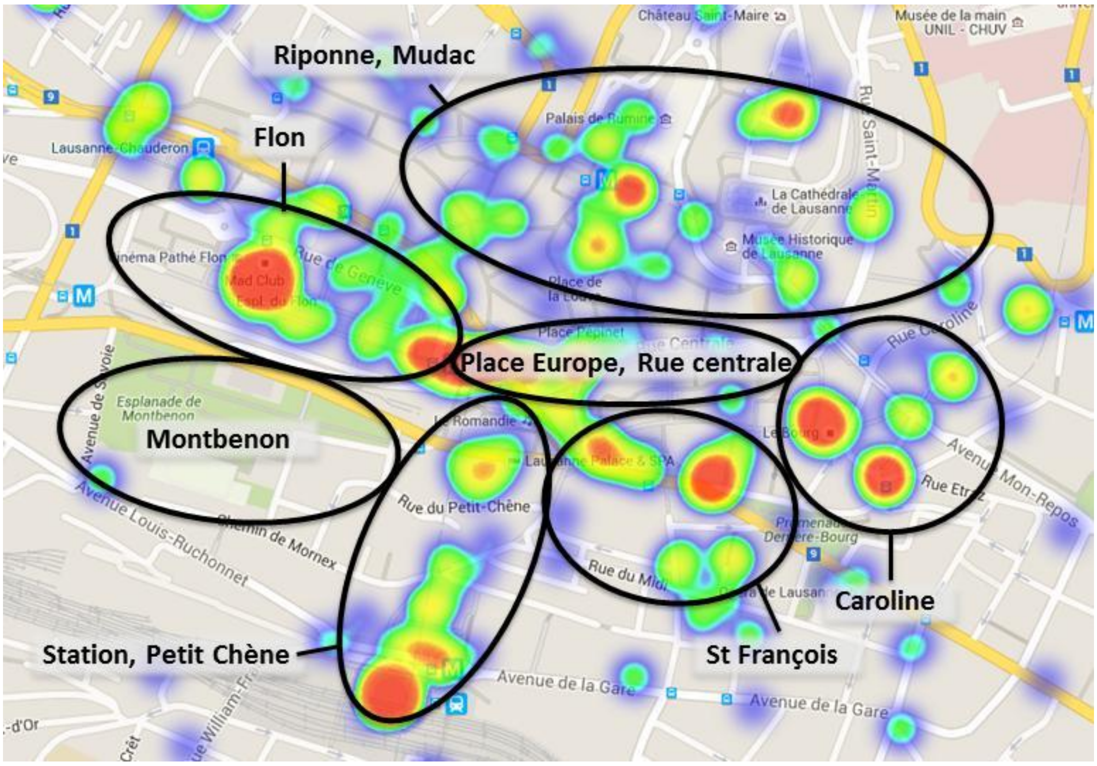
The selection of recruitment zones was discussed with various local nightlife experts. To obtain different perspectives on nightlife activities, we held separate meetings with street social workers, who were in charge of managing daytime and evening activities for young people, and with community-based police officers in charge of nightlife security. After introducing the study and the recruitment strategy, the experts were provided with the heat maps of Foursquare check-ins and were first asked whether the popular zones shown on the maps corresponded to their experience of the city’s nightlife. Since the heat maps represented nightlife activity over almost the past three years, the experts were then asked to indicate the most adequate recruitment zones in order to encompass current trends, such as the emergence of popular new venues and seasonal effects, and to ensure a broad diversity of venue types (e.g. mostly bars vs. mostly nightclubs vs. mostly parks) and populations across recruitment zones. On the basis of these criteria, we proposed seven zones in each city. The experts agreed with the choice of zones in Lausanne. In Zurich, they suggested that we add a new recruitment zone next to the lake (see ‘Seeanlagen’ in Figure 3-2) as many frequent nightlife-goers would spend part of their evenings and nights in lakeside parks (i.e. because the recruitment was taking place in September) and that we drop a zone in which the two major drinking venues had closed in the previous months. During these meetings, we also asked for advice and safety precautions to integrate into the guidelines for the recruiters.

Figure 3-1: Heat map showing the density of Foursquare check-ins and the seven selected recruitment zones in Zurich



Note: Locations with fewer than 50 check-ins were omitted to enhance the visual impression of geographically confined zones.

Figure 3-2: Heat map showing the density of Foursquare check-ins and the seven selected recruitment zones in Lausanne



Note: Locations with fewer than 50 check-ins were omitted to enhance the visual impression of geographically confined zones.

3.2.1.3 Definition of recruitment quotas

Recruitment quotas per recruitment zone were defined using both the filtered Foursquare check-ins, which were considered to be the most objective source of data available, and estimations from the local experts, which were regarded as the most accurate experience-based data. While estimates were provided in Lausanne, the experts in Zurich only provided relative indications rather than specific estimates (e.g. ‘much more’, ‘more’ or ‘less’ than the quotas from Foursquare) as no official statistics were available (Table 3-1). The ‘ideal’ recruitment quotas were defined by averaging the two estimates in Lausanne, while in Zurich, we aimed to follow both indications (e.g. ‘much more’ than the 1.4% estimated by Foursquare in Seeanlagen) but without using pre-set quotas. Overall, the experts recommended that we increase the recruitment quotas in zones dominated by parks and at the lakesides (e.g. Montbenon, Seeanlagen and Bellevue) to account for seasonal effects (i.e. because young people spend time in parks during warm evenings in September). They also advised us to decrease the quotas in zones with a high density of pubs and clubs due to a possible over-representation of check-ins (e.g. Flon) and in zones patronised by older nightlife-goers (e.g. Langstrasse).

3.2.1.4 Systematic recruitment approach

Recruitment took place with the approval of the local authorities on Friday and Saturday nights on the first three weekends of September 2014. Most recruiters were local university students who were close to the upper age range of the target population (Lausanne: 8 women, 2 men, mean age = 25.2 [SD = 2.8]; Zurich: 10 women, 3 men, mean age = 23.8 [SD = 3.8]). About a week before the recruitment took place, they were provided with a recruitment guide including a description of the study, the recruitment procedure and a number of safety recommendations, such as remaining with the team of recruiters at all times and leaving the area if they felt unsafe. Before the first recruitment session, a kick-off meeting was organised to familiarise recruiters with the online recruitment form, remind them of and discuss the recruitment procedure, practise what they would say when they approached potential participants and form teams of two to four recruiters in a relaxed atmosphere. Recruiters were also provided with bright lime-green t-shirts displaying the study logo, which were designed to attract attention and ease contact with potential participants. So that they could demonstrate how the Youth@Night application worked, recruiters were provided with an open version for installation on their own smartphone and a leaflet containing screen captures of most features.

Recruitment sessions took place between 9 pm and midnight with approximately 10 recruiters in each city simultaneously. This timeframe was chosen in order to reach young people on their way to the nightlife districts while minimising the risk of encountering people who were inebriated (Pennay et al., 2015). Following a strict time schedule, the recruiters approached young people in the target age group as they passed by on the street, introduced the study and pre-registered volunteers. The ‘fixed-line method’ (i.e. approaching every n^{th} person crossing a virtual line on the street) was used to ensure a random selection of passers-by (Graham et al., 2014; Johnson et al., 2006). To be eligible, participants had to be between 16 and 25 years of age, have consumed alcohol at least once in the past month, have gone out in the city of recruitment at least once in the past month and own a smartphone with Android OS 4.0.3 or higher. After describing the study’s goal, methods and incentives, recruiters pre-registered volunteers by recording their phone number, email address, age and gender. To prevent data contamination, a maximum of two persons could pre-register within the same group of friends. When people declined to take part, recruiters also recorded their age, gender and reason for declining whenever possible.

After pre-registration, participants were automatically sent an email containing hyperlinks to the study homepage and the consent form. After signing the online consent form, participants were instructed to complete a baseline questionnaire, download and install the study application on their smartphone and start using it the following Friday night. Emails, text messages and phone calls were used to support participants and give them reminders throughout this procedure. An online FAQ page also provided additional information on the study. Participants could unsubscribe and withdraw from the study at any time.

After each weekend, the samples of people approached and of pre-registered participants were compared with the ideal quotas. The schedule for the following weekend was then designed in such a way as to compensate for any deviation. Assuming that two-thirds of those approached would not be interested in participating or would refuse to provide personal information (Kuntsche et al., 2008), two-thirds of the interested persons would not be eligible (i.e. out of age range or no Android phone: Casais & Casais, 2016; Clapp et al., 2009; Graham et al., 2014), and one-third would not register or would drop out over the course of the study (Kuntsche & Labhart, 2013b), we estimated that 2700 people had to be approached to obtain the final sample of 100 participants per city.

3.2.2 Measures

Geolocalised Foursquare check-ins were used to plot the density of nightlife activities for local experts and determine pro-rata attendance per zone prior to recruitment. Numbers of check-ins were aggregated per recruitment zone and venue type.

For each person approached in the street, recruiters recorded their age, sex, recruitment zone and intention to participate or not. Reasons for not participating included (a) not interested, (b) outside the target age range, (c) not in possession of an Android phone and (d) refusing to give personal information.

For each recruitment day, hourly weather conditions (temperature and wind speed) were documented using readings from the Federal Office of Meteorology and Climatology.

Participant feedback on the recruitment was recorded in the closing questionnaire after the smartphone study. Participants had to indicate on a four-point scale the extent to which they agreed or disagreed with statements such as ‘the recruiters approached me in a friendly and non-intrusive manner’ (items and answer categories are provided in Table 3-3).

Recruiters’ feedback and observations were taken from the field diary completed after each recruitment session.

3.2.3 Statistical analyses

In addition to descriptive analyses provided in the Tables, bi- and multivariate tests (χ^2-tests, t-tests and analysis of variance) were used to test differences in pre-registration rates, participants’ age and gender across recruitment zones, and differences in pre-registration rates across times and days of recruitment. Additionally, for each city, a two-step logistic regression model was used to estimate pre-registration rates based initially on times of recruitment and weather conditions only. In a second step, the age and gender of the people approached were entered into the model in order to assess whether the former set of predictors remained significant over and above the latter. Finally, one-sample t-tests were used to assess whether participants’ ratings differed from the midpoint of the four-point assessment scale. All analyses were conducted using SPSS 21 (IBM Corp, 2012). In the Results section, we only reported statistically significant test results in order to improve the flow of the text. Unreported test results can be obtained from the authors upon request.

3.3 Results

3.4 Diversity of locations and recruitment zones

As seen in Table 3-1, almost half of all Foursquare check-ins occurred in pubs (48.6% in Lausanne and 42.5% in Zurich), followed by streets and plazas (27.7 and 30.1%, respectively). Most recruitment zones were characterised by a high proportion of check-ins in only one type of location (e.g. 84.9% pubs in Riponne, Mudac, 92.6% parks in Montbenon, and 73.4% plazas in St-François) but, at the city level, at least one zone was characterised by either a high proportion of pubs, parks or streets and plazas, highlighting both the uniformity (within zones) and diversity (across zones) of nightlife locations. Additionally, a couple of recruitment zones showed a high proportion of check-ins at several location types (e.g. Flon and Zurich-West), illustrating that a large diversity of nightlife locations might also be found within specific zones.

3.4.1 Demographics and registration rate per city and per zone

In total, 3092 people were approached in the street in Lausanne and Zurich. Mean age was around 19.3 years in both cities and slightly more men were approached in Zurich ($\chi^2_{(1)}$ = 5.5, p = .019). Across recruitment zones, populations approached were globally homogeneous in Lausanne (i.e. no significant differences for age and gender ratio) but not in Zurich, where the people approached on Langstrasse were about 2.5 years older than in the rest of the city and mostly male.

The pre-registration rate varied greatly between cities (it was almost eight percentage points higher in Lausanne than in Zurich), across recruitment zones in each city ($\chi^2_{(6)\text{Lausanne}}$ = 17.8, p = .007; $\chi^2_{(6)\text{Zurich}}$ = 26.8, p < .001) and across participant demographics, with men being more likely to pre-register than women ($\chi^2_{(1)\text{Lausanne}}$ = 7.3, p = .004, $\chi^2_{(1)\text{Zurich}}$ = 17.4, p < .001) and pre-registered participants being younger than those who declined to participate ($t_{(510)\text{Lausanne}}$ = 5.5, p < .001; $t_{(983)\text{Zurich}}$ = 5.1, p < .001).

Overall, the major reason for declining participation was not having an Android-compatible smartphone. This proportion was almost 13 percentage points higher in Zurich than in Lausanne, which appears to be the main reason for the above-mentioned eight percentage-point difference in pre-registration rates between the two cities. More importantly, the proportion of people not interested in participation was about a quarter in both cities.

Table 3-1: Recruitment quotas, diversity of nightlife venues, recruitment outcomes (number of people approached, pre-registration rate, age and gender of participants) and stay-points per recruitment zone and city

	Lausanne								Zurich							
Recruitment zones:	Caroline	Flon	Station, Petit Chêne	Montbenon	Place Europe, Rue centrale	Riponne, Mudac	St François	Total	Bellevue	Gessnerallee, Kaufleuten	Langstrasse	Niederdorf	Seeanlagen	Around main station	Zurich-West	Total
Foursquare check-ins																
Proportion of check-ins per zone (%)	9.8	28.8	10.4	5.7	14.3	19.9	11.0		17.3	27.3	23.2	10.5	1.4	6.2	14.2	
Check-ins in pubs (%)	54.0	39.6	52.5		52.8	84.9	17.7	48.6	26.5	49.7	48.1	47.5	33.7	56.8	31.1	42.7
Check-ins in clubs (%)	26.3	16.1	7.1		11.3		9.0	10.6	8.5	7.9	19.3	0.4		12.6	23.9	12.3
Check-ins at cinemas, theatres and music venues (%)	4.5	21.7	40.3	7.5	0.9			11.4	10.4	3.5	6.9	2.6	1.2	3.5	16.3	7.2
Check-ins on streets and plazas (%)	15.3	22.6	0.1		35.0	15.1	73.3	27.3	49.1	30.7	8.8	47.4		26.5	28.7	29.6
Check-ins in parks (%)				92.5				2.1	5.4	8.3	17.0	2.1	65.1	0.6		8.3
Local experts																
Proportion of people per zone (%)[a]	10	20	10	10	25	20	5		++	-	-	+	++	+	o	
People approached in the street																
N	129	347	111	97	295	220	135	1,334	412	95	157	343	219	407	125	1,758
Proportion of people per zone (%)	9.7	26.0	8.3	7.3	22.1	16.5	10.1		23.4	5.4	8.9	19.5	12.5	23.2	7.1	
Mean age [b]	20.1	19.9	20.3	19.4	19.4	19.9	19.0	19.7	19.1	19.7	22.1	19.5	19.0	19.8	21.4	19.6
Proportion of men (%) [c]	63.2	50.6	58.6	50.6	43.5	50.6	44.1	50.2	46.1	48.0	37.5	60.2	51.0	63.6	64.2	55.1
Pre-registration status																
Agreed to pre-register (%)	31.8	31.1	24.3	34.0	35.3	44.5	31.1	34.0	28.6	27.4	16.6	24.8	32.9	18.7	20.0	24.3
Not interested (%)	27.9	29.4	39.6	21.6	28.5	17.3	34.1	27.9	16.0	29.5	26.1	22.2	11.4	42.0	40.0	26.2
No compatible phone (%)	31.0	29.7	25.2	29.9	26.1	29.5	30.4	28.7	48.3	43.2	47.8	49.6	35.6	32.2	33.6	41.9
Not in age range (%)	9.3	7.5	10.8	14.4	9.8	7.7	3.0	8.5	7.0	0.0	9.6	2.6	20.1	6.1	6.4	7.2
Pre-registered participants																
Proportion of people per zone (%)	9.1	23.8	6.0	7.3	23.0	21.6	9.3		27.6	6.1	6.1	19.9	16.8	17.8	5.8	
Mean age [d]	20.0	19.3	20.0	19.2	19.4	19.7	18.9	19.5	18.8	17.9	20.2	19.3	18.6	19.0	19.5	19.0
Proportion of men (%) [e]	70.7	49.0	74.1	60.6	48.1	57.7	50.0	55.2	58.1	44.0	52.0	65.5	73.2	64.4	84.0	63.6

Note: Recruitment zone names and locations are shown on the maps in Figure 7-1.
a) Local experts provided specific quotas in Lausanne and relative indications (i.e. "++" = much more, "+" = more, "o" = no change, "-" = less, "--" = much less) in Zurich; b) information available for 1,497 persons; c) information available for 2,320 persons; d) information available for 881 persons; e) information available for 896 persons.

Of the 881 pre-registered participants (454 in Lausanne and 427 in Zurich, not tabulated), 629 (71%) signed the online consent form, 367 (58%) completed the baseline questionnaire, 241 (27%) installed the app and documented at least one night and 168 (19%; 94 in Lausanne and 74 in Zurich) documented at least 10 nights with the smartphone application. Participants using the app were slightly younger than the rest of the pool of people approached in Zurich (mean age = 18.5; $t_{(983)} = 3.47$; $p < .001$) but not in Lausanne (mean age = 19.4), and the gender ratios were similar in both cities (53% men in Lausanne and 54% men in Zurich).

3.4.2 Influence of weather and time on registration rate

As seen in Table 3-2, weather conditions were good on the first weekend (temperature between 18.0° to 19.5° and almost no wind), but colder on the second weekend and slightly more windy on the third. The pre-registration rates were higher on Fridays than on Saturdays as well as between 10 and 11 pm than one hour earlier or later.

Results of the multivariate logistic regression models estimating the registration rate based on time and weather conditions (Model 1 in Table 3-3) showed that a higher a pre-registration rate was achieved on Fridays and between 10 and 11 pm in both cities, as well as in more pleasant temperatures in Lausanne and in calm wind conditions in Zurich. Most predictors remained significant when the age and gender of passers-by were taken into account (Model 2), except for temperature which became non-significant in both cities.

3.4.3 Feedback from participants and recruiters

Table 3-4 summarises participants' experience and their feedback on the recruitment. Almost all participants judged that the recruiters' approach was friendly and non-intrusive (98% agreed or strongly agreed) and that they provided clear and complete information about the study (93% agreed or strongly agreed). Additionally, 94% thought that the recruitment happened early enough in the evening so that they were still sober enough to concentrate on what the recruiters told them, and 96% did not feel forced to register. All feedback differed significantly from the midpoint between agreement and disagreement.

Table 3-2: Number of people approached, pre-registration rate and weather conditions per recruitment weekday, time and city

	Lausanne							Zurich						
	Weekend #1		Weekend #2		Weekend #3			Weekend #1		Weekend #2		Weekend #3		
	Fri.	Sat.	Fri.	Sat.	Fri.	Sat.	Total	Fri.	Sat.	Fri.	Sat.	Fri.	Sat.	Total
Recruitment time														
9-10 p.m.														
People approached	67	108	98	68	85	117	543	67	92	100	113	168	102	642
% pre-registered	31.3	31.5	31.6	29.4	28.2	36.8	31.9	56.7	27.2	20.0	25.7	15.5	15.7	24.0
10-11 p.m.														
People approached	98	86	110	66	71	78	509	84	74	107	120	117	79	581
% pre-registered	53.1	44.2	30.9	31.8	46.5	29.5	39.5	35.7	41.9	24.3	16.7	26.5	24.1	27.0
11-12 p.m.														
People approached	83	92	26	5	48	28	282	63	93	106	100	91	82	535
% pre-registered	34.9	31.5	19.2	20.0	25.0	10.7	28.0	39.7	23.7	23.6	15.0	19.8	14.6	21.9
Total														
People approached	248	286	234	139	204	223	1334	214	259	313	333	376	263	1758
% pre-registered	41.1	35.3	29.9	30.2	33.8	30.9	34.0	43.5	30.1	22.7	19.2	19.9	17.9	24.3
Weather conditions														
Temperature at 10 p.m. (°C)	18.3	19.5	14.6	16.2	17.3	18.2		18.0	18.4	10.8	12.8	17.8	18.5	
Wind speed at 10 p.m. (m/s)	1	1	3	5	2	2		0	1	2	2	1	2	

Table 3-3: Logistic regression models for registration rate on time and weather conditions of recruitment and passer-by demographics, per city

	Registration rate in Lausanne				Registration rate in Zurich			
	Model 1		Model 2		Model 1		Model 2	
	OR	95%-CI	OR	95%-CI	OR	95%-CI	OR	95%-CI
Weekday (reference = Friday)	0.70*	(0.52-0.95)	3.51**	(1.64-7.53)	0.78*	(0.63-0.97)	0.65**	(0.49-.085)
Time (reference = 10-11 p.m.)								
9-10 p.m.	0.67**	(0.51-0.86)	0.30**	(0.14-0.62)	0.93	(0.71-1.22)	0.92	(0.65-1.28)
11 p.m. – midnight	0.57**	(0.41-0.80)	0.34*	(0.14-0.85)	0.74*	(0.56-0.78)	0.60**	(0.41-0.86)
Temperature (°C)	1.15*	(1.03-1.29)	0.84	(0.65-1.09)	1.01	(0.96-1.06)	0.96	(0.91-1.03)
Wind (m/s)	1.01	(0.86-1.18)	0.75	(0.49-1.14)	0.71**	(0.55-0.91)	0.48***	(0.34-0.66)
Age			0.80***	(0.73-0.87)			0.91***	(0.87-0.95)
Gender (reference = women)			0.98	(0.55-1.83)			2.19***	(1.66-2.89)

Note: * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 3-4: Participant feedback on the recruitment process

Coding:	Strongly disagree (1)	Disagree (2)	Agree (3)	Strongly agree (4)	Mean (SD)	t(df=200)[a]
1. The recruiters approached me in a friendly and non-intrusive manner	1.0%	1.5%	19.9%	77.6%	3.7 (0.5)	33.1***
2. It was already late in the evening and I was unable to concentrate on what the recruiters were saying	55.2%	38.3%	6.5%	0.0%	1.5 (0.6)	-22.7***
3. The recruiters were available to answer my questions	1.0%	3.0%	31.8%	64.2%	3.6 (0.6)	25.7***
4. The information given by the recruiters was clear and complete	1.0%	6.5%	40.3%	52.2%	3.4 (0.7)	20.1***
5. I felt forced to register	79.6%	16.4%	3.0%	1.0%	1.3 (0.6)	-31.7***

Note: a) Mean different from 2.5 (= neither agree nor disagree); *** $p < .001$

The recruiters documented their experiences and the reactions of the people they approached in a recruitment field diary. Firstly, the bright lime-green t-shirts with the study logo worn by all recruiters were perceived as a factor that fostered group cohesion among the recruiters and gave them the legitimacy to approach potential participants. The t-shirts' unusual colour caught the attention of passers-by (some started talking to the recruiters out of curiosity) and helped the recruiters to make contact. The recruiters enjoyed being in teams of two to four as this enabled them to support each other. Secondly, when the weather was bad, relatively few people spent time outside, which reduced the pool of potential participants. Thirdly, it was difficult to apply the fixed-line method on quiet streets or in bad weather. In such cases, the recruiters approached all eligible passers-by. Fourthly, it seemed easier to recruit younger participants because the monetary incentive appeared more attractive to them. Finally, participants were generally surprised that they would have to register on their own later rather than completing a questionnaire at the time of recruitment. Many were nevertheless attracted by the innovation of using a smartphone application for a study on nightlife.

3.5 Discussion

The aim of this article was to evaluate the feasibility and implementation of the *Geographical Proportional-to-size Street-Intercept Sampling* (GPSIS) method developed to recruit representative samples of nightlife-goers in the cities of Zurich and Lausanne. The first premise of this recruitment method was to use Foursquare to identify the most-frequented zones by adopting a geographical perspective encompassing all nightlife areas. Heat maps of Foursquare check-ins provided a convenient tool for identifying the nightlife ‘hotspots’ and could be easily reviewed by local experts. As expected, the selection process resulted in varied configurations of different indoor and outdoor locations across zones, echoing the overall diversity of nightlife venues and locations.

The second premise was to quantify attendance of nightlife zones using different sources of information. Due to the dynamics of nightlife activities from one night to the next, considerable attention had to be paid to the issue of how to obtain recruitment quotas that would be representative of the population under investigation. The combination of different sources to quantify attendance of nightlife zones therefore appeared to be a key component of GPSIS’s success. As a quantitative data source, the Foursquare check-ins could easily be filtered and aggregated for each zone and venue type to calculate users’ attendance in proportion to the size of each zone. However, all-year-long check-ins from users that might not be fully representative for nightlife-goers and locations (Hecht & Stephens, 2014) only constituted long-term tendencies and needed refinement. Qualitative experienced-based knowledge from local experts was therefore an indispensable addition to our study to account for temporary circumstances, such as seasonal effects, even though these experts’ opinions may have been distorted by personal perceptions and preferences. In the present study, we triangulated information from two types of sources in order to attenuate their specific limitations. Future research could nevertheless extend the procedure to include more data sources. For example, subjective recruitment quotas might also be requested from club and pubs owners. Additionally, more precise estimations might be obtained by combining Foursquare check-ins with other LBSN sources (e.g. geolocalised tweets) and by filtering LBSN sources by user demographics, season or weekday.

The third premise was the application of a systematic street-intercept method in multiple zones simultaneously and in proportion to the size of each zone. We did not expect problems with this part of GPSIS as the fixed-line method had already been successfully implemented elsewhere. While previous studies (Graham et al., 2014) did not report any time- and weather-related variations, our recruiters' experience showed that the sampling rate (every n^{th} person) needed to be adapted to weather conditions and variations in the flows of passers-by and that pre-registration rates varied according to weekday, time and weather conditions. Since all recruitment teams faced similar weather conditions simultaneously and, consequently, similar flows of passers-by, variations in these factors had little impact on the proportional-to-size principle of GPSIS. However, these results highlight the importance of conducting recruitment over multiple time periods and weekends to account for changing recruitment conditions. Notably, higher pre-registration rates were found between 10 and 11 pm than one hour earlier or later. A likely explanation for this is that, in the middle of the evening, when dinner time is usually over and most nightclubs are beginning to open, young people might be more relaxed and have more time to talk to recruiters than at any other period of the evening. Since hourly variations in recruitment rates have not been published in previous studies, more research is needed to determine the most suitable timeframes for recruitment in line with local cultural practices, such as customary dinner time, nightclub opening hours or the existence of happy hours.

The results of the recruitment process also highlight the importance of conducting recruitment in different zones of a given city. This appeared particularly relevant in Zurich, the larger of the two investigated cities, where systematic differences were found across zones in terms of the age and gender of the people approached and in pre-registration rates. In smaller cities, such as Lausanne, the close proximity of the nightlife zones might increase the mixing of populations, whereas nightlife populations might be more segmented in a larger city with more widely scattered nightlife.

As highlighted by the reluctance of the experts to provide numbered recruitment quotas in Zurich, it was almost impossible to achieve a sample that was representative of all nightlife-goers across an entire city given the constantly changing nature of nightlife in general. What can, however, be achieved is to maximise the diversity of the people approached in order to account for the diversity of the population of nightlife-goers. In this respect, in comparison with the previously existing recruitment techniques, the present study confirmed the considerable potential of GPSIS as a tool for maximising the likelihood of approaching a large diversity of nightlife-goers while taking into account the proportional distribution of this diversity across places and times.

The recruitment method was developed independently from the content of the study to be subsequently conducted using the participants' smartphones. However, we observed that the particular type and length of the present study (a 10-night-long diary study) and the type of device used (Android smartphones) introduced a small selection effect in the sample of registered participants, since men and younger people were more likely to pre-register than women and those aged 20 and above. One explanation for the gender effect could be the higher proportion of Android smartphone ownership among men than among women (Benenson et al., 2013). Also, since a majority of the recruiters were young women, this may have encouraged some male participants to pre-register. The age effect may be linked to the size of the incentive, which was fairly small relative to the requirements for participation in the smartphone study. This also concurs with the recruiters' observation that the incentive was more attractive for young people, whose nightlife budget is usually smaller. In addition, while the overall pre-registration rate was lower in Zurich than in Lausanne, the results show that this was largely due to a higher proportion of people not being eligible to participate because they owned an iPhone. All in all, it appears that the lower numbers of registrations among older and wealthier people were probably due to the study constraints and the expected inconvenience of what was an intensive, long-lasting nightlife study for Android smartphone owners only, rather than being a feature of the GPSIS method per se.

Finally, several limitations of the present study might be considered in future developments of the GPSIS method. Firstly, we implemented GPSIS in cities with medium-sized nightlife scenes. As a result, the number of recruitment zones used in the present study might be not be sufficient to account for the diversity of locations and patrons in larger cities. A higher number of recruitment zones might consequently require more teams of recruiters. Secondly, by focusing on the most-frequented zones, the present selection of zones might have favoured mainstream nightlife locations over alternative scenes. The number of recruitment zones could be increased in future research to account for more varied types of nightlife locations and scenes. Additionally, the present study conceived the diversity of nightlife essentially in terms of locations (geographical zones and venue types).

Future research might try to find quantitative data sources which allow researchers to account for the diversity of musical preferences and of alcohol and drug consumption patterns among nightlife-goers, for example. Thirdly, the present application of GPSIS relied on freely accessible LBSN data to identify zones and set recruitment quotas. LBSNs have now been recording check-ins around the world for many years, so the GPSIS method should be replicable and implementable in most cities. However, since such data might depend on the smartphone ownership rates and media literacy of the population of interest, alternative sources of information on pro-rata attendance per place might be considered, such as statistics from pubs or clubs or counts of people appearing on safety cameras. Finally, only participants who took part in the smartphone study provided feedback on the recruitment process in the closing questionnaire. Despite this potentially positive selection, the very positive feedback from the participants suggests that street recruitment was generally well-tolerated.

3.6 Acknowledgements

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Chapter 4

The spirit is willing, but the flesh is weak: why young people drink more than intended on weekend nights – an event-level study [3]

Abstract

Background: Heavy alcohol use is common among young adults on weekend nights and is assumed to be intentional. However, little is known about the extent to which heavy consumption is planned prior to the onset of drinking and what factors contribute to drinking more than intended. This study investigates drinking intentions at the beginning of an evening and individual and situational factors associated with a subsequent consumption over the course of multiple nights.

Methods: Using a smartphone application, 176 young people aged 16 to 25 (mean age = 19.1; 49% women) completed questionnaires on drinking intentions, consumption, and drinking environments before, during, and after multiple Friday and Saturday nights (n = 757). Multilevel regressions were used to investigate individual-level and night-level factors associated with previous drinking intentions and subsequent deviations from intentions.

Results: Participants intended to consume 2.5 drinks (SD = 2.8) per night yet consumed 3.8 drinks (SD = 3.9) on average. Drinking intentions were higher among those who frequently went out at night and engaged in more frequent predrinking. Participants drank more than intended on 361 nights (47.7%). For both genders, the number of drinks consumed before 8 p.m., attending multiple locations, and being with larger groups of friends contributed to higher consumption than intended at the individual and the night levels. Heavier consumption than intended also occurred when drinking away from home for men and when going to nightclubs for women.

Conclusions: Making young adults aware of the tendency to drink more than intended, particularly when drinking begins early in the evening, moves from location to location, and includes large groups of friends, may be a fruitful prevention target. Structural measures, including responsible beverage service, may also help in preventing excessive drinking at multiple locations.

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4.1 Introduction

Friday and Saturday nights are peak times for heavy alcohol use among young adults, with the number of drinks consumed often exceeding the thresholds for heavy episodic drinking (HED, i.e. consumption of 5 or more drinks per occasion among men, 4 or more among women: Heeb et al., 2008; Labhart & Kuntsche, 2014). Based on the observation that getting drunk is an important motivation for drinking among many young people, drinking heavily on weekend nights is generally assumed to be intended rather than accidental (Room & Livingston, 2009). While event-level evidence partly support this assumption (e.g., 39.0% of US bar patrons intended to get ‘a little’ and 17.2% ‘very’ drunk when interviewed in drinking venues; Clapp et al., 2009), it remains unclear whether drinking heavily was intended prior to the onset of drinking or whether it developed over the course of the night. This study examines drinking intentions for a given evening, set prior to the onset of consumption, among young adults and explores the individual and situational factors that contribute to shifts from initial intentions.

According to the theory of planned behavior (TPB: Ajzen, 1991; Ajzen & Madden, 1986), behavioral intentions play a central role in the prediction of future behavior. In a recent review, Cooke and colleagues (2016) reported consistent medium- to large-scale associations between intentions, measured in the framework of the TPB, and different alcohol use indicators, including ‘drinking to get drunk’ ($r+ = .54$) and ‘heavy episodic drinking,’ defined as consuming more than 56 g of pure ethanol per occasion ($r+ = .52$). The TPB instruments view intentions as traits (Boldero et al., 1992); as such, studies included in this review assessed the predictive value of drinking intentions over extended periods of time (two weeks: Johnston & White, 2003; one week: Norman & Conner, 2006). Over shorter time periods, both trait-like personal characteristics (French & Cooke, 2012; Litt et al., 2014; Patrick & Lee, 2012) and state-like occasion-level influences might affect drinking intentions and behaviors (Mushquash et al., 2014; Northcote, 2011). Night-level drinking intentions may also be a function of usual drinking behaviors (i.e. heavier drinkers are likely to encompass heavier drinking intentions) as well as the previous night’s consumption (Labhart & Kuntsche, 2014), the types and size of social events attended (Thrul et al., 2017), and the intended sequence of drinking events, such as predrinking before going out (Labhart et al., 2013). The first aim of the present article is to explore the variability of night-level drinking intentions and the extent to which these reflect participants' usual drinking-related behaviors.

With regard to the subsequent consumption, findings suggest that young people are likely to deviate from their declared intentions over the course of the night. First, intentions are partly a function of self-perception of past behaviors (Conner et al., 1999). Young people are known to underestimate their past drinking behaviors due to recall bias (Kuntsche & Labhart, 2012; Monk et al., 2015); as a result, they may set their intentions based on erroneous estimates of how much alcohol is needed to achieve the desired effect. Second, according to the TPB, a strong intention-behavior association requires full volitional control, where the person can decide at will to carry out or not carry out the behavior, and high self-efficacy, namely the belief that the individual can successfully carry out the behavior required to fulfill the intention (Ajzen, 1991; Ajzen & Madden, 1986; Bandura, 1977). Situational factors, however, may alter both volitional control and self-efficacy over the course of an evening. For example, weekend drinking commonly occurs at social gatherings where the situational dynamics (e.g., peers' drunkenness, crowding) and the social activities (e.g., flirting, participation in drinking games) might lead to higher or lower consumption than intended (Trim et al., 2011). Finally, young people might intend to reach a certain degree of inebriation (e.g., feeling a little drunk) rather than consuming a fixed number of drinks (Giraldo et al., 2017), impacting a priori estimates of consumption. In addition, the delay between alcohol intake and the perception of the effects (Tapert et al., 2004) makes it likely that youth will consume one or more additional drinks before fully experiencing the effects of earlier consumption. The second aim of the study was to explore, over and above initial drinking intentions, the contribution of individual- and night-level characteristics to heavier or lower consumption than intended. Person-mean centering will be used to distinguish the effect of the participants' trait-like, usual intentions and behaviors and the state-like event-specific intentions and behaviors.

At the individual level, past drinking habits have been shown to predict future drinking in excess of intentions (Conner et al., 1999; Cooke et al., 2006). As more frequent and experienced drinkers tend to deviate less from their usual consumption on weekend nights than infrequent drinkers (Labhart & Kuntsche, 2014), we expect that heavier drinking in the past will be associated with higher drinking intentions at the beginning of an evening and less deviation from that intention over the course of the night. Similarly, since being a regular nightlife-goer might help young adults better anticipate the course of their nights out and have more accurate reported intentions, the average frequency of going out will also be included as a potential individual-level predictor.

At the night level, several situational and environmental factors, known to be associated with heavier consumption on specific drinking occasions, might contribute to deviations from a priori drinking intentions. First, predrinking (i.e. drinking in private settings prior to going out) has been found to increase the level of intoxication among bar patrons (Clapp et al., 2009; Hughes et al., 2008) and almost double the amount of alcohol consumed over the course of a night as compared to non-predrinking nights (Labhart et al., 2013). Second, drinking at multiple locations also appears to be an important component of nights when heavy drinking occurs (Dietze et al., 2014) and intentions to continue drinking (Clapp et al., 2009). Third, converging evidence shows that alcohol consumption is typically higher and HED more frequent in certain types of locations, such as bars, nightclubs, and parties at someone else’s home, than at other locations (Callinan et al., 2014). Finally, the social environment could also contribute to drinking more than intended. Event-level studies have shown, for example, that the size of the drinking group is positively associated with the number of drinks consumed (Thrul & Kuntsche, 2015) and intensifies the effect of intoxication on plans to continue drinking (Reed et al., 2013). Further, converging evidence suggests that heavy drinking occurs when men and women drink in mixed-gender groups of friends and when men drink exclusively with other men (Labhart & Kuntsche, 2014; Thrul et al., 2017; Trim et al., 2011). Considering the above, we expect that starting drinking early in the night, drinking at bars, nightclubs, and outdoors, and drinking in larger mixed-gender groups or groups of only men will be associated with drinking more than intended on a given weekend night.

4.2 Materials and Methods

4.2.1 Study design

Participants were recruited from two major nightlife hubs in Switzerland, Lausanne and Zurich, in September 2014. Applying the Geographical Proportional-to-size Street-Intercept Sampling method (Labhart, Santani, et al., 2017), groups of recruiters approached passers-by on Friday and Saturday nights between 9 pm and

12 midnight in popular nightlife areas. Eligibility criteria were being between the ages of 16 and 25 (i.e. legal purchase and drinking age is 16 for beer and wine in Switzerland), owning an Android smartphone, having consumed alcohol at least once in the past month, and having been out in the city at least twice in the past month. After introducing the aim and design of the study, recruiters either preregistered volunteers by recording their email address or noted their reason for refusing to take part. Volunteers were automatically sent an email containing links to the study website and the online consent form. After signing the consent form and completing the baseline questionnaire, participants had to install the Youth@Night smartphone application and begin using it on the following Friday night.

The Youth@Night app was specifically developed for documenting young adults' nightlife behaviors using event-level questionnaires, pictures, videos, and sensors such as GPS, accelerometers, and Bluetooth (Santani et al., 2016). From 5 pm to the end of the night, participants were requested to report various components of their nights, including the types of drinks consumed and characteristics of the locations attended (see 'Night-level measures' below). Participants were required to document at least 10 Friday or Saturday nights over seven consecutive weekends to receive the full incentive of CHF 100 (approximately USD 103). Lower incentives were given on a pro-rata basis in the event of fewer nights of participation (CHF 70 for 7 to 9, CHF 50 for 5 to 6, and CHF 30 for 3 to 4 nights). Participants were instructed to document any night, including when they did not go out or did not drink, to get an overview of the different kinds of situations young people experience on Friday and Saturday nights. At any time during the study, participants could uninstall the application and stop participating. The study protocol was approved by the Lausanne and Zurich Cantonal Ethics Committees for Research on Human Beings (protocol 145/14).

4.2.2 Individual-level measures (baseline questionnaire)

The *monthly frequency of going out* was assessed using a summary score of participants' answers to the following questions: "How often do you go out in [the city of recruitment] on weekend nights (bars/pubs, nightclubs, restaurants, cinemas, etc.)?" and "How often do you go out in other cities on weekend nights?" For both questions, response options were 'never' (coded as 0), 'one night per month or less' (0.5), 'one night every two weekends' (2.1), 'one night per weekend' (4.3) and 'two nights per weekend' (8.6), and were coded to represent a 30-day frequency measure (e.g., 'two nights per weekend' = 2/7*30 = 8.6).

To calculate the *monthly frequency of predrinking*, the frequency of going out per month was multiplied by the relative frequency of predrinking. The latter was assessed with the question, "When you go out at weekends, how frequently do you drink alcohol prior to going out ('predrinking', 'pregaming', 'prepartying,' or 'preloading')?" Response options were 'never' (coded as 0%), 'some of the time' (25%), 'half of the time' (50%), 'most of the time' (75%) and 'always' (100%).

Monthly alcohol consumption was calculated by multiplying the daily frequency of alcohol use with the usual quantity consumed per drinking day. The former was measured using the question, "How often do you usually have an alcoholic drink?" Response options were coded to represent a 30-day frequency measure, using the midpoint of categories if applicable: 'never' (coded as 0), 'less than once a month' (0.5), 'one to three times a month' (2), 'one to three times a week' (8.6), 'almost every day' (21.4), and 'every day' (30). Usual quantity was measured using the question, "How many drinks containing alcohol do you have on a typical day when you are drinking?" Response options were '1 or 2' (coded as 1.5), '3 or 4' (3.5), '5 or 6' (5.5), '7, 8, or 9' (8) and '10 or more' (11). Examples of beverage-specific glasses containing about 10 grams of pure ethanol were provided to illustrate standard drink sizes.

4.2.3 Night-level measures (smartphone application)

At 5 pm, participants were prompted to indicate how many *drinks they intended to consume* on that night, providing separate figures for alcoholic and nonalcoholic beverages. This questionnaire could be completed only once per night and only before 8 pm

At 8 pm, participants were asked to indicate the number of *drinks they had consumed between 5 and 8 pm*, using separate figures for alcoholic and nonalcoholic beverages. If no drink had been consumed during that period of time, they could either submit an empty questionnaire (i.e. with only zero values) or leave it unanswered.

From 8 pm until the end of the night, participants were asked to report the *number of men and women friends present* every time they had a new drink. Answer options were one-unit increments from ‘0’ to ‘9’, plus ‘10 or more’ (coded as 15 friends present). Summary scores were created by averaging the number of friends per report over the entire night for three mutually exclusive categories: men only, women only, and mixed-gender groups of friends.

Additionally, at the beginning of the night and whenever they changed locations, participants had to indicate the *type of location* they were attending. Response options were ‘Bar/pub,’ ‘Club,’ ‘Coffee shop/bakery,’ ‘Event space (sport, concert, art, etc.),’ ‘Restaurant,’ ‘Public place/space,’ ‘Private place,’ ‘Traveling’ and ‘Other’. An overall summary score was created by adding up the *number of different locations* attended over the entire night. Additionally, dichotomous variables were used to represent whether or not the participant attended each location type during the night. Reports of the social and physical environments were self-initiated by the participants any time during the night and took less half a minute to complete. Hourly reminders were automatically displayed on their smartphone to prompt reporting of any changes in the environment. Unless the participant indicated that their night was over, the application remained active until 5 a.m.

At 10 a.m. the next morning, participants were prompted to indicate the total *number of alcoholic drinks they had consumed the previous evening* using a sliding scale ranging from 0 to 30 drinks. This questionnaire could be completed only once and, if no data were entered, was deactivated automatically at 4 pm

Deviation from intentions was calculated by subtracting the number of drinks a person intended to consume from the total number of drinks he or she consumed over the night. A positive value indicated a heavier consumption and a negative value a lower consumption than intended.

4.2.4 Sample

In total, 3,092 people were approached in the streets of Lausanne and Zurich. Of those, 1,119 (36%) did not have an Android smartphone, 859 (28%) were not interested in the study, and 233 (8%) were outside the required age range. Of the 881 who were eligible and interested in participating, 629 (71%) signed the online consent form, 367 (58%) completed the baseline questionnaire, and 241 installed the app and documented at least one night (27%; mean age=19.0, SD = 2.4; 47% women). Participants using the app were slightly younger than the rest of the pool of people approached (mean age = 19.8, SD = 3.5; $t_{(1,495)} = 3.21$; $p < .001$) but their gender ratio was similar (47% women, $\chi^2_{(1,\ N = 2,320)} = 0.02$, $p = .88$).

Overall, the 241 app users submitted 1,905 drinking intentions assessments, 2,542 social contexts, 1,393 locations, and 2,588 assessments of the total night consumption. Because participants were allowed to not complete all of these assessments each night, we restrained the analysis to a selection of 757 nights during which 176 participants provided full information on events throughout the night. This sample (mean age = 19.1, SD = 2.4; 49% women) did not differ significantly in terms of age and gender from the total sample of participants. The resulting data included 757 drinking intention and total consumption questionnaires (one per night), 1,648 social contexts, 1,050 location questionnaires (one or more per night), and 356 consumption before 8 pm questionnaires (completed if more one or more drinks were consumed). On average, 4.3 fully documented nights (SD = 3.1) were included for each participant with 6.0 questionnaires per night (SD = 2.2).

4.2.5 Analytic strategy

Prior to analysis, extreme outliers in the number of drinks which people intended to consume and the total number of drinks were winsorized at 3 standard deviations (Tabachnick & Fidell, 2007) in order to better approximate a normal distribution. This impacted 12 reports (1.6%) above 11 drinks for drinking intentions and 9 reports (1.2%) above 15 drinks for the total night's consumption.

Besides descriptive statistics, gender differences in participants' nightlife and drinking habits (individual level) and drinking intentions, deviation from intentions, and physical and social environment characteristics (night level) were assessed using mean- and proportion-tests. Intraclass correlation coefficients (ICCs) were estimated to evaluate the clustering of drinking intentions, total consumption, and deviation from intentions across study days within individuals. Finally, Pearson's correlation coefficients were computed to assess the link between drinking intentions, total consumption, and deviation from intentions. Descriptive statistics and bivariate analyses were conducted using STATA SE 14 (StataCorp, 2015). Standard errors of correlations and night-level mean- and proportion-tests were adjusted to account for the effect of nights being nested within individuals (Goodwin et al., 2008).

Series of multilevel regression models were estimated to investigate individual- and night-level predictors of drinking intentions and deviation from intentions, respectively. Individual-level predictors comprised age, city of recruitment, nightlife habits, and past drinking habits. Night-level variables were day of the week, consumption of alcohol before 8 pm, number of men or women friends present, total number of locations attended, and attendance (yes/no) at bars, nightclubs, public places/spaces, and private settings. Person-mean-centering was applied to all night-level variables by subtracting the participant's average across the study from each night-level observation (Enders & Tofighi, 2007; Hoffman & Stawski, 2009). The participant's averages were entered at the individual level in the model to represent the participants' trait-like typical behaviors (e.g. an average of two drinks before 8 pm across ten nights) and the person-mean-centered scores were entered at the night level to represent state-like specific behaviors on each night (e.g. two drinks more than average before 8 pm on the first night, one drink less than average before 8 pm on the second night, etc.). Additionally, as deviation from intention is dependent on the initial level of intention, the deviation-from-intention model also controlled for initial intention levels. This model thus estimates the contribution of night-level variables to the deviation from intention, over and above initial intention levels.

The intention model was first estimated with gender as an individual-level predictor. As the effect of gender was significant (unstandardized b = 0.96, SE = 0.28, $p < .001$) and due to known gender differences in alcohol use in general (Graham et al., 1998) and on weekend nights (Kuntsche & Labhart, 2012; Thrul & Kuntsche, 2015), we decided to conduct the analyses separately for men and women. The multilevel regression models were estimated in Mplus 7.3 (Muthén & Muthén, 2015) using the maximum likelihood robust estimator and the full information maximum likelihood option to handle missing assessments of the number of alcoholic drinks consumed before 8 pm Reported effect sizes were unstandardized regression coefficients (b), standard errors (SE) and explained variance (R-squared).

4.3 Results

On average, participants went out on weekend nights 6 times per month and engaged in predrinking approximately 3 times per month (Table 4-1). Men consumed significantly higher amounts of alcohol per month than women (32.3 and

21.1 drinks, respectively). All other individual-level comparisons were not statistically significant.

Table 4-1: Number of participants and questionnaires, usual nightlife and drinking habits, and characteristics of the environment on Friday and Saturday nights for men and women

		Men	Women	Test value[a]
Individual-level				
N		89	87	
Age, mean (SD)		19.3 (2.5)	19.0 (2.3)	-1.04
Monthly frequency of going out, mean (SD)		6.1 (3.1)	5.7 (2.8)	-0.85
Monthly frequency of predrinking, mean (SD)		3.6 (2.8)	3.4 (2.8)	-0.61
Monthly alcohol consumption, mean (SD)		32.3 (28.3)	21.1 (26.6)	-2.69**
Night-level				
N		392	365	
With alcohol use, %		82.7	75.1	2.32
Saturday nights, %		52.1	47.7	2.14
Alcohol use before 8 pm:	% nights[b]	52.4	37.4	3.59
	mean (SD)[b]	2.3 (2.1)	1.6 (1.0)	-6.99**
Only women present:	% nights	5.9	18.4	15.36***
	mean (SD)[c]	2.6 (3.2)	2.0 (1.3)	-0.61
Only men present:	% nights	29.3	9.9	28.00***
	mean (SD)[c]	3.9 (3.5)	2.5 (2.3)	-6.13*
Men and women present:	% nights	32.9	35.9	0.37
	mean (SD)[c]	7.8 (6.4)	8.7 (7.8)	0.54
Number of locations visited, mean (SD)		1.4 (0.7)	1.3 (0.7)	1.93
Attendance in bar/s (%)		19.4	20.8	0.12
Attendance in club/s (%)		4.8	6.0	0.31
Attendance in public place/s and space/s (%)		17.9	13.2	1.74
Attendance in private place/s (home) (%)		57.4	60.0	0.24

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; (a) T-tests were used to test for differences between continuous data; χ^2-tests were used to test for differences between proportions. For night-level measures, standard errors of t- and χ^2-tests were adjusted to account for the effect of nights being nested within individuals; (b) Calculated for nights when reports of consumption before 8 pm, respectively 185 among men and 171 among women, were submitted (c) Calculated for nights on which the category of friends referred to were present.

At the night level, consumption of alcohol occurred on 79% of all nights. It began before 8 pm on 45.2% of the reported nights, with about 2 drinks consumed when such occasions occurred. Participants mostly attended 1 or 2 different locations, with homes being the most prevalent (58.7%), followed by bars (20.1%), and public places and spaces (15.6%). Participants most commonly reported being with either mixed-gender groups of friends (both men and women present) or same-gender friends (Table 4-1).

On average, men intended to drink 3.1 alcoholic drinks (with HED intended on 27.6% of nights) and women 1.8 (HED: 18.6%; Table 4-2). The next morning, men reported having drunk 4.6 drinks on average the previous night (HED: 43.6%) and women 2.9 (HED: 31.2%). Thus, men drank more than planned on 51.0% (+1.4 drinks on average) and women on 44.1% (+1.1 drinks) of all nights. While men intended to drink more and eventually did drink more than women, the deviation from intentions was similar. For both genders, drinking intentions were correlated with total consumption and total consumption was correlated with deviation from intentions. However, no significant correlation was found between intentions and deviation from intentions. For all 3 measures, but particularly for deviation from intentions, high standard deviation of means and intraclass correlations (ICC) lower than .5 revealed relatively large variations from one night to the next, both between- and within-individuals.

Table 4-2: Drinking intentions, total consumption, and deviation from intentions, and correlations between the three measures for men and women

		Men	Women	Test value[a]
Intention: Number of drinks participants intended to consume at start of night				
Mean (SD)		3.1 (3.2)	1.8 (2.0)	15.82***
Intraclass correlation (ICC)		.506	.389	
HED[b] (%)		27.6	18.6	3.61
Total: Number of drinks consumed over the entire night				
Mean (SD)		4.6 (4.4)	2.9 (3.2)	14.08***
Intraclass correlation (ICC)		.452	.371	
HED[b] (%)		43.6	31.2	5.57*
Deviation from intentions: *Total* minus *intention*				
Mean (SD)		+1.4 (3.1)	+1.1 (2.6)	+1.01
Intraclass correlation (ICC)		.324	.373	
% lower than 0		16.8%	14.0%	
% equal to 0		32.1%	41.9%	1.87
% greater than 0		51.0%	44.1%	
Correlations				
Intention	↔ Total consumption	.702***	.539***	
Total consumption	↔ Deviation	.660***	.774***	
Intention	↔ Deviation	-.069	-.113	

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; (a) Standard errors of t-tests (continuous data) and $\chi 2$-tests (proportions) were adjusted to account for the effect of nights being nested within individuals; (b) Heavy episodic drinking = 4 or more drinks for women / 5 or more for men.

Significant individual-level predictors of high drinking intentions were the monthly frequency of predrinking for both genders and monthly alcohol consumption for men (Table 4-3). Additionally, women intended to consume 0.6 drinks more on Saturdays than on Fridays; this effect was not found for men. Age and frequency of going out were not related to drinking intentions, however.

Table 4-3: Multilevel models predicting drinking intentions and deviation from intentions for men and women (unstandardized coefficients and standard error reported)

	Men		Women	
	Intention	Deviation from intention	Intention	Deviation from intention
	b (SE)	b (SE)	b (SE)	b (SE)
Individual-level (baseline)				
Age	0.08 (0.09)	-0.04 (0.08)	-0.09 (0.07)	0.08 (0.09)
Monthly frequency of going out	0.05 (0.08)	-0.11 (0.07)	-0.10 (0.07)	-0.17* (0.07)
Monthly frequency of predrinking	0.37** (0.13)	0.22* (0.09)	0.32*** (0.08)	0.27** (0.09)
Monthly alcohol consumption	0.04** (0.01)	0.02 (0.01)	0.01* (0.00)	0.00 (0.01)
Individual-level (person mean of night-level observations)				
Intention		-0.35* (0.15)		-0.75*** (0.01)
Number of drinks before 8 pm		0.42*** (0.10)		1.37*** (0.27)
Number of friends:				
Only women present		-0.13 (0.27)		0.29 (0.19)
Only men present		0.21* (0.10)		0.31 (0.24)
Mixed-gender groups		0.11 (0.06)		0.09* (0.05)
Number of locations visited		1.50** (0.55)		0.45 (0.35)
Attendance in bars		-1.14 (1.22)		0.36 (0.68)
Attendance in clubs		-1.55 (2.57)		1.25 (1.08)
Attendance in public places/spaces		-1.40 (0.90)		1.55 (0.96)
Attendance in private places (home)		-1.91* (0.77)		-0.75 (0.90)
Night-level (deviation from person-mean)				
Weekend-day[a]	0.00 (0.26)	0.03 (0.27)	0.60*** (0.18)	0.39* (0.18)
Intention		-0.29** (0.10)		-0.49*** (0.10)
Number of drinks before 8 pm		0.60** (0.19)		1.44*** (0.31)
Number of friends:				
Only women present		-0.08 (0.04)		0.03 (0.09)
Only men present		0.14* (0.06)		0.51** (0.18)
Mixed-gender groups		0.11** (0.04)		0.07* (0.03)
Number of locations visited		1.04*** (0.22)		0.85** (0.24)
Attendance in bar/s		-0.63 (0.42)		-0.27 (0.42)
Attendance in club/s		-0.67 (0.87)		1.61** (0.58)
Attendance in public places/spaces		-0.04 (0.52)		0.52 (0.52)
Attendance in private places (home)		-1.13** (0.39)		-0.19 (0.36)
R-squared				
Individual-level	0.57***	0.73***	0.46**	0.83***
Night-level	0.00	0.17**	0.04	0.37***

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; Models adjusted for the city of recruitment; (a) Reference category = Friday

For both genders, lower drinking intentions were associated with higher deviation from intention, and inversely, at the individual and the night levels (Table 4-3). Drinking early in the night also impacted the deviation from intention at the individual and the night levels; the deviation from the intention increased by +0.42 drinks for men and +1.37 for women for each additional drink *usually* consumed before 8 pm, and increased by another +0.60 drink for men and +1.44 for women for each drink consumed *over and above* the person's usual consumption before 8 pm

With regard to the other predictors, differential effects were found at the individual and the night levels as well as for women or men. At the individual level, being with larger groups of men for men and mixed gender friends for women was associated with greater deviation from intention. On the event level, however, both men-only and mixed gender groups had an increasing effect; for example, drinking with the usual number of mixed gender friends does not make men drink more than intended, but drinking with a larger number of friends than usual does. This effect was also shown in the inverse; drinking with fewer men-only and mixed gender friends than normal had a protective effect. Regarding drinking locations, similar effects were found for men at the individual and the night levels; visiting a greater number of venues increased the deviation from intention while being at home decreased the deviation. Among women, the only night-level effects were found for locations, namely that visiting a greater number of venues than usual and attending nightclubs on specific nights increased deviation from intention. Finally, being a less frequent nightlife-goer contributed to higher consumption levels than intended for women.

4.4 Discussion

The aim of the present study was to investigate individual-level factors associated with the number of drinks young adults intended to consume on weekend nights as well as individual- and night-level factors contributing to deviating from initial drinking intentions. With regard to drinking intentions, results of the present study not only confirmed previously reported associations between usual drinking habits and trait-like intentions (Cooke et al., 2016) for both long-term (monthly alcohol use) and night-oriented (frequency of predrinking) drinking patterns, but also revealed considerable within-person variability in state-like intentions from one night to the next, as shown by most ICCs being lower than .5. Unfortunately, except for drinking intentions, no other information on the plans for the night was collected at the beginning of each night, preventing further investigations of the within-person variability of state-like intentions across nights. Future research in this respect is clearly recommended.

Overall, participants drank more than intended on almost half of all nights, and they exceeded the thresholds for HED twice more often than planned. The significant positive correlation between drinking intentions and total consumption suggested that participants generally had a broad idea of the amount of alcohol they would consume on most nights. However, when accounting for the other night-level covariates, results of the multilevel models revealed significant negative associations between drinking intentions and deviation from intentions, suggesting a prominent tendency for young people to either underestimate the number of drinks they would eventually consume or to change their intention over the course of the night. This phenomenon appears more important when drinking intentions were low at both the individual (i.e., participants with low intentions in general tended to deviate more than those who usually intend to drink more heavily) and the night levels (i.e., on nights with lower intentions than usual, participants tended to deviate more than on nights with higher intentions). The underestimation of drinking intentions might partly be due to by biased recall of past drinking occasions (Kuntsche & Labhart, 2012; Monk et al., 2015) as well as attempts to avoid alcohol-related harms (e.g., they may plan to drink but not explicitly plan to get drunk, or they may intend to get drunk but not enough to pass out; Litt et al., 2014).

Additionally, adhering to the intended amount throughout an entire night of drinking is not a single action but a long sequence of choices and actions (Gollwitzer, 1999). In this respect, the present results suggest that many individual and contextual factors are likely to contribute to deviating from one's original intentions. At both individual- and night-levels and for both genders, the frequency of predrinking and the number of drinks before 8 pm were significantly associated with heavier drinking than intended. Although we do not have any information on drinking contexts before 8 pm, we can assume that participants generally predrank on these evenings. These findings are not surprising considering that engagement in predrinking has been shown to almost double alcohol intake over the course of a night out compared to non-predrinking nights (Labhart et al., 2013) and that duration of the drinking event increases the number of drinks consumed (Clapp et al., 2009; Labhart et al., 2014; Yurasek et al., 2016). It is surprising, however, that drinking intentions were also formulated at the beginning of the night but seemed to only partly take predrinking into account. A likely explanation is that when formulating their intentions, young people expect to drink less later that night if they predrink (Wells et al., 2009b), but forget their initial intentions and lose control over consumption as the night progresses. In this respect, the ignition effect of predrinking on subsequent drinking appears particularly marked for women. For men, each additional drink more than usual before 8 pm results in only half a drink more than intended over the course of the night (effect size = 0.6), suggesting that each drink consumed before 8 pm is partly compensated for by a reduction in the subsequent drinks planned. However, the effect size of 1.44 among women suggests that each unintended drink before 8 pm is followed by an additional unintended 0.44 drink later in the night.

Additionally, the findings show that each additional drinking location attended directly increased participants' deviation from intention by about 1 drink for both genders. This result appears particularly robust as it was found over and above the usual number of locations visited, the usual frequency of predrinking, and the drinks consumed before 8 pm, all of which likely imply at least 1 change of location. One explanation for this effect may be that entering a new drinking location places pressure on people to have a new drink because it is offered or available (e.g., at private or outdoor parties), because it is the norm (e.g., at bars), or because a voucher is provided (e.g., at some nightclubs), for example. However, as young people could also opt for a non-alcoholic beverage when entering a new location, more research is needed to better understand the link between the number of locations visited and drinking more than intended.

Over and above the number of locations attended, going to nightclubs was found to contribute to drinking 1.6 more drinks than intended for women. As one possible explanation for this effect, women might be offered drinks by others more often in nightclubs than in bars as flirtation strategy. This finding also fits with the observation that, for women, less frequent nightlife-goers were also more likely to drink more than intended. Lack of experience and knowledge about ways to regulate drinking (e.g., refusing drinks offered, alternating with nonalcoholic drinks) may further increase the loss of control in such settings. By contrast, being in private locations (e.g., homes) was found to decrease the deviation from intentions among men by 1.13 drinks compared to the other locations. Given that homes are common drinking locations, it is possible that young men regulate their drinking more effectively in such situations due to past experience and cues for not drinking. It may also be easier to keep track of consumption at home where, for example, empty bottles may be left in the open or may have to be disposed of. Additionally, reasons for reduced drinking at home may include having a more limited supply of alcohol

(Kuntsche & Gmel, 2013) and a higher degree of social control from parents, partners, or roommates. Unfortunately, evidence on the respective influence of both the type and the number of locations visited on a single night is still very limited. More research is clearly needed to extend the present findings.

Regarding the social environment, drinking with larger groups of friends than normal contributed to drinking more than intended in mixed-gender settings or when being with men for both men and women. This might be due to a combination of different factors, including that the number of drinking partners and alcohol providers (in the case of private parties) increases with the number of people present, the influence of drunken peers (Reed et al., 2013), and the role alcohol plays in flirting and hooking up in mixed compared to same-gender groups (Garcia et al., 2012). In this respect, women appeared to be particularly influenced by the presence of one or two men (i.e., 0.51 additional drinks for each additional man present), while in other configurations, much larger groups of friends were required to deviate from intention (i.e. effect sizes ranging between 0.07 and 0.14 per additional person present). Interestingly, no significant effect was found when men were drinking with one or more women. This finding might indicate that men were norming on women's use patterns in such contexts. In the case of dates or romantic nights, young men might also desire to show a favorable impression of themselves and therefore tend to drink less than with solely other men (Thrul et al., 2017).

4.4.1 Limitations and recommendations for future research

A number of limitations should be acknowledged. First, drinking intentions and total night consumption were assessed in terms of number of drinks, but not size of those drinks. Although participants were provided with pictograms corresponding to approximatively 10 grams of pure alcohol, it is possible that the drinks consumed were actually larger than 'standard drinks'. However, as both drinking intentions and total night consumption were assessed the same way, the related constructs (e.g., night-level deviation from intentions, person-mean-centered intentions) were also adjusted to the participants' usual drink size, ensuring within-individuals consistency over the course of the study. Second, no defined time frame was provided when assessing consumption the previous evening. Whereas intentions were asked at 5 pm, we cannot be sure that participants systematically reported or recalled all the drinks consumed from 5 pm onward. As such, the total night consumption might be underestimated, resulting in conservative estimates in the deviation from intention model. Third, in case no drinking occurred between 5 and 8 pm, participants could leave the related questionnaire unanswered, making it possible that participants missed reporting some drinking. However, we believe this was unlikely to make a major impact on the results as missing assessments were entered as such in the multilevel models, avoiding the inappropriate coding of missing assessments as zeros. Finally, it is possible that participants missed reporting changes in the social context or the locations attended. Although a conservative selection process was applied to retain only thoroughly documented nights, it is possible that the number of locations attended was underestimated, for example.

In the present study, drinking intentions were assessed on a night-level basis with respect to alcohol consumption happening within the next few hours. Although this short-term conception of drinking intentions was much shorter than in previous research using weeks or months as the time reference (Cooke et al., 2016), drinking intentions might even change across the night. Many factors may either instigate (e.g. unexpected encounters, enjoyable music, bar-hopping, flirting) or inhibit (e.g. blackout, injury) alcohol consumption and therefore reshape initial drinking intentions. In this respect, future research is needed to investigate the impact of ongoing activities and contextual features, such as engagement in drinking games, drink specials (Thombs et al., 2008), or the attitude of service staff (Stockwell et al., 1993) in bars and nightclubs, on the evolution of drinking intentions over the course of the night. Dynamics within social groups (Dumas et al., 2014) and the presence of drunken peers (Reed et al., 2013) are also promising factors to study to understand the short-term evolution of drinking intentions. Such additional in-the-event assessments should balance response burden and quantity of collected data; strategies such as using hourly assessments of past-hour drinking behaviors and environmental characteristics (Kuntsche & Labhart, 2012), as well as drinking intentions for the next hour or hours might be applicable.

4.5 Conclusion and recommendations for prevention

According to the TPB model (Ajzen, 1991; Ajzen & Madden, 1986), high volitional control and high self-efficacy are required for people to keep their drinking within intended limits. However, in the case of weekend nights, the present study suggests that many individual and contextual factors are likely to reduce volitional control. Given the general tendency to underestimate the amount of alcohol consumed at both person and night levels, prevention measures that target both individual and situational risk factors (Demers et al., 2002) may help young adults set realistic drinking intentions and not exceed them.

At the individual level, the adoption of protective behavioral strategies (Martens et al., 2005; Pearson, 2013) – such as deciding in advance not to exceed a set number of drinks, keeping track of the number of drinks consumed, and leaving the bar or party or stopping drinking at a predetermined time – showed promising effects on reducing young peoples' alcohol use (Lewis et al., 2012; Pearson et al., 2013), especially among those with high drinking intentions (Grazioli et al., 2015). As the present findings showed that exceeding HED thresholds was much less often intended than actually occurred, prevention and brief intervention messages should make young people aware of the widespread tendency to underestimate total consumption when planning to drink. Particular unanticipated events occurring over the course of a night might also contribute to drinking more than intended (e.g., spontaneous invitations to go out, being bought drinks, and meeting people by chance). As such, simulation training could be used to help youth identify potentially critical situations, such as entering new locations or refusing drinks, and to increase volitional control and drink refusal self-efficacy (Anderson et al., 2014; Young et al., 1991), even in people with little previous experience of alcohol use or nightlife.

At the situational level, structural measures may be needed to reduce high total consumption accumulated through drinking at multiple locations. These could include restricting late-night opening hours, drinking in public places, and access to drinking establishments for people who are already intoxicated. Training staff to detect inebriated customers before they enter the premises and to ensure responsible beverage service (Stockwell, 2001; Toomey et al., 2007) might also prevent intoxication among those who started drinking early or changed locations over the course of the night.

Chapter 5

What reminds young people that they drank more than intended on weekend nights – an event-level study [4]

Abstract

Objective: Young people often drink more alcohol than intended over the course of a night. This study investigates individual- and night-specific factors predicting young people's acknowledgment of having drunk more than intended.

Method: Using the Youth@Night smartphone application, 176 people aged 16 to 25 documented 757 Friday and Saturday nights. Participants recorded their drinking intentions at the beginning of the night, the composition of the social and physical environment over the course of the night, and, the next morning, the previous night's total consumption and whether they had drunk more than intended or experienced other alcohol-related consequences. Bivariate statistics and multilevel logistic regressions were used based on the 361 nights during which 139 participants (53.2% men, mean age = 19.3) exceeded their drinking intentions.

Results: Participants acknowledged higher consumption than intended on 36.7% of nights. At the night level, higher drinking intentions than usual (odds ratio [OR] = 1.36, 95% CI [1.13, 1.65]), attending a larger number of locations than usual (OR = 1.84, 95% CI [1.11, 3.04]), having a hangover the next morning (OR = 3.23, 95% CI [1.50, 6.95]), or spending more money than planned (OR = 3.12, 95% CI [1.56, 6.26]) were associated with acknowledgment of drinking more than intended. No individual characteristics were associated with acknowledgment of exceeding drinking intentions.

Conclusions: Young people not only tend to drink more than intended on weekend nights but also often fail to acknowledge this the next morning. Event-based prevention measures aimed at narrowing the gap between drinking intentions and quantities of alcohol consumed are recommended.

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5.1 Introduction

To reduce heavy drinking and its related harms, person-centered prevention approaches presuppose people's ability to set and respect drinking intentions (Webb et al., 2010). Several protective behavioral strategies, such as deciding in advance not to exceed a set number of drinks and keeping track of the number of drinks consumed (Martens et al., 2005; Pearson, 2013), directly depend on young people's monitoring ability and self-control over the course of the drinking occasion. However, exceeding one's drinking intentions over the course of a night appears quite common, as suggested by a recent study of young adult nightlife-goers showing that more alcohol was consumed than intended on 47.7% of all weekend nights (Labhart, Anderson, et al., 2017). Similar figures were found in a study of young adult students, with 93% of respondents scoring positively on the *Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition* (DSM-IV; American Psychiatric Association, 1994) "Longer/Larger" criterion of alcohol use disorder (Slade et al., 2013), assessed with the question: 'In the past year, have you had times when you ended up drinking more, or longer, than you intended?' (National Institutes of Health, 2014).

Although, exceeding one's drinking intentions on a given occasion might be part of a conscious process when people are, for example, "enjoying the moment" or "feeling their peers' influence" (Slade et al., 2013), evidence suggests that drinking-related activities and the characteristics of the drinking event contribute to people exceeding their drinking intentions also without noticing. Laboratory experiments showed, for example, that even with moderate alcohol doses (0.65 g/kg) contextual alcohol cues (such as images of alcoholic drinks) are likely to compromise an individual's control over the amounts consumed during a given drinking occasion (Weafer & Fillmore, 2008, 2015). In addition, specific social and contextual characteristics, such as the size of the drinking group, starting drinking early in the night, or attending multiple locations, were found to contribute to drinking more than intended (Labhart, Anderson, et al., 2017). Thus, drinking intentions might often be overridden by external influences without an individual's awareness, consequently limiting the effectiveness of protective behavioral strategies, since the unnoticed additional drinks consumed cannot be taken into account to adjust plans for on-going and future drinking occasions, and increasing the probability of false negatives in the detection of impaired control over a person's drinking using the "Longer/Larger"

DSM-IV and DSM-5 (American Psychiatric Association, 2013) criterion (Caetano & Babor, 2006; Martin et al., 2008). It is therefore crucial to understand under which circumstances people are able to acknowledge having exceeded their drinking intentions.

Using an event-level longitudinal design, this study aims first to investigate the extent to which young people acknowledge having drunk more than intended and second to identify event- and individual-specific predictors of that acknowledgment. At the event level, the most obvious indicator of having drunk more than intended should be the number of additional drinks consumed in excess of intentions. Yet, one or two additional drinks might easily go unnoticed, meaning that the deviation from their intentions might have to be larger for them to notice. In addition, particular circumstances—such as predrinking (Labhart et al., 2013), drinking within large groups of people (Thrul & Kuntsche, 2015), or attending multiple locations (e.g., pub crawls), and the occurrence of adverse consequences—might also constitute salient signs of higher consumption than intended. The link between individual characteristics and acknowledgment of drinking in excess of intentions is less clear and we could not find any literature on this topic. We will therefore explore whether age, gender, usual drinking and nightlife habits are associated with acknowledging a heavier consumption than intended.

5.2 Methods

5.2.1 Study design

Participants were recruited on the streets of the entertainment districts in Lausanne and Zurich in September 2014. Applying the Geographical Proportional-to-size Street-Intercept Sampling method (Labhart, Santani, et al., 2017), recruiters approached passers-by on Friday and Saturday nights between 9 p.m. and midnight in popular nightlife areas. Eligibility criteria were being aged between 16 to 25 years old, owning an Android smartphone, having consumed alcohol at least once in the past month, and having been out in the city at least twice in the past month. Volunteers automatically received an invitation email containing links to the study website and the online consent form. After signing the consent form and completing a baseline questionnaire, they were requested to document their Friday or Saturday nights, including the drinks consumed, the locations visited, and the social and physical contexts, over seven consecutive weekends using the specifically developed Youth@Night smartphone application (Santani et al., 2016, 2018). The study was approved by the Lausanne and Zurich Cantonal Ethics Committees for Research on Human Beings (protocol 145/14).

5.2.2 Sample

Of the 3,902 young people approached, 629 signed the online consent form, 241 installed the smartphone application, and 176 provided full information on events over 757 entire nights (Labhart, Anderson, et al., 2017). For this study, we retained only the 361 nights (47.7%) during which 139 participants (79.0%) drank more than intended. No selection effect was found between the 139 participants who drank more intended and those who did not in terms of gender (male: 53.2% vs. 40.5%; $\chi^2_{(1)} = 1.89$, $p = .170$) and age (mean = 19.3 (SD = 2.5) vs. 18.7 (SD = 1.8); $t_{(174)} = -1.38$, $p = .169$), while drinking intentions were slightly higher among the former (mean = 2.8 (SD = 2.8) vs. 2.2 (SD = 2.8); $F_{(1, 175)} = -4.31$, $p = .039$).

5.2.3 Measures

5.2.3.1 Night-level independent variables.

On Friday and Saturday nights, the smartphone application prompted participants at 5 p.m. to indicate the number of alcoholic drinks they *intended to consume* that night and, at 8 p.m., to indicate the number of *drinks they had consumed between 5 and 8 p.m*.

From 8 p.m. until the end of the night, participants were asked to report the number of friends present – separately for male and female friends (range: ‘0’ to ‘10 or more’ [coded as 15] for each category) and intimate partners – every time they had a new drink. A summary score was created by averaging the total *number of friends* per report over the entire night. Additionally, at 8 p.m. and whenever they changed location, participants were asked to report the type of location they were at. Response options were: ‘Bar/pub,’ ‘Club,’ ‘Coffee shop/bakery,’ ‘Event space (sports, concert, art, etc.),’ ‘Restaurant,’ ‘Public place/space,’ ‘Private place,’ ‘Traveling,’ and ‘other.’ A summary score was created by adding up the *number of different locations* attended over the entire night.

At 10 a.m. the next morning, participants indicated the total number of alcoholic drinks they had consumed the previous night. The number of *additional drinks* was calculated by subtracting the number of drinks participants intended to consume from the total number of drinks consumed. In addition, they reported whether the following *consequences* occurred as a result of the previous night's events: 'Hangover (headache, upset stomach, etc.),' 'spending more money than originally intended,' or 'doing impulsive things that you later regretted.' These consequences were selected because they represent salient signs that unusual or unplanned events might have happened the previous night.

Person-mean centering (also called 'group-mean centering', if considering that each participant documented a group of nights) was applied to all continuous night-level variables. This procedure consists of subtracting the mean of the night-level observations per participant (Enders & Tofighi, 2007; Hoffman & Stawski, 2009) to distinguish participants' night-specific behaviors (e.g., consuming four drinks more than usual) from each participant's usual behavior across the study (e.g., usually consuming two drinks; see individual-level independent variables below). Person-mean centering was based on the full sample of 757 nights in order to reflect participants' habits and deviations from these habits in general, rather than only on nights with higher consumption than intended.

5.2.3.2 Individual-level independent variables.

Age and *sex* were recorded in the baseline questionnaire.

Typical drinking and nightlife habits – namely average levels of drinking intentions, usual deviation from intentions, usual number of drinks before 8 p.m., usual size of drinking group, and usual number of locations visited – were computed by taking the mean of the night-level variables described above.

5.2.3.3 Dependent variable.

Alongside the previous night's consumption and the alcohol-related consequences assessed the next morning (see above), participants were asked whether or not (yes/no) they 'drank more alcohol than originally intended' the previous night. Because the analyses were conducted for the subset of nights with higher consumption than intended, a positive answer was considered to be an *acknowledgment of higher alcohol consumption than intended*.

5.2.4 Analytic strategy

Before the analyses, extreme outliers in drinking intentions and total number of drinks consumed were winsorized at 3 standard deviations to better approximate a normal distribution (Tabachnick & Fidell, 2007).

Besides descriptive statistics, bivariate associations between acknowledgment of higher consumption than intended and drinking intentions, number of additional drinks, drinks before 8 p.m., average number of people present, number of locations attended, and occurrence of alcohol-related consequences were tested using mean and proportion tests. Standard errors were adjusted to account for the effect of nights being nested within individuals using the software STATA 14 (StataCorp, 2015).

Subsequently, a multilevel logistic regression model was estimated to determine the contribution of age, gender, the individual-level independent variables, and the night-level independent variables to the acknowledgment of higher consumption than intended. Because continuous night-level variables were person-mean-centered (i.e. representing participants' habits), the night-level scores represented the contribution of the deviation from these habits to the independent variable. The model was estimated in Mplus 7.3 (Muthén & Muthén, 2015) using the maximum likelihood robust estimator. Reported effect sizes were odds ratios, 95%-confidence intervals, and explained variance (R^2).

5.3 Results

Participants acknowledged having drunk more than intended on slightly more than one-third of nights (36.7%; Table 5-1). Bivariate analyses showed that acknowledgment of a higher consumption than intended was independent of levels of drinking intentions, starting drinking early in the evening, and impulsive actions that were later regretted, but was associated with a higher number of additional drinks consumed above intentions (4.3 additional drinks vs. 2.8), a higher number of locations attended, drinking in larger groups, having a hangover and having spent more money than intended.

Table 5-1: Night and individual characteristics, bivariate comparisons, and multilevel logistic regression predicting the acknowledgment of higher alcohol consumption than intended

	Acknowledgment of higher alcohol consumption than intended		Bivariate test	Multilevel logistic regression	
	NO	YES	F(1, 138) [a]	OR (95%-CI)	
Night characteristics (N = 361)					
Number of nights	235 (63.3%)	136 (36.7%)			
Drinking intentions	2.5 (SD = 2.6)	3.2 (SD = 3.0)	3.62	1.10	(0.90-1.35)
Additional drinks [b]	2.8 (SD = 2.3)	4.3 (SD = 3.0)	22.82***	1.36**	(1.13-1.65)
Number of drinks before 8 p.m.	1.5 (SD = 2.1)	1.4 (SD = 1.5)	0.09	0.76	(0.52-1.12)
Number of locations attended	1.4 (SD = 0.8)	1.7 (SD = 0.9)	9.14**	1.84*	(1.11-3.04)
Number of friends present	4.4 (SD = 5.8)	6.0 (SD = 6.4)	6.03*	0.99	(0.94-1.04)
Hangover	18.3%	46.8%	27.97***	3.23**	(1.50-6.95)
Spending more money than intended	8.9%	30.2%	27.99***	3.12**	(1.56-6.26)
Impulsive actions that were later regretted	4.3%	7.1%	1.24	1.02	(0.22-4.68)
Individual characteristics (N = 139)					
Sex				0.63	(0.27-1.49)
Age				0.98	(0.87-1.10)
Drinking intentions [c]				1.13	(0.95-1.36)
Additional drinks [c]				1.21	(0.97-1.51)
Number of drinks before 8 p.m. [c]				0.81	(0.65-1.02)
Number of locations attended [c]				0.95	(0.48-1.90)
Number of friends present [c]				1.09	(0.98-1.20)
R-squared					
Night level				0.320***	
Individual level				0.271	

Note: * $p < .05$; ** $p < .01$; *** $p < .001$;
a) Standard errors of *t*-tests (continuous data) and χ^2-tests (proportions) were adjusted to account for the effect of nights being nested within individuals;
b) Total night consumption (i.e. the sum of 'drinking intentions' and 'additional drinks') was 5.4 (SD = 3.7) on nights without acknowledgment of drinking in excess of intentions and 7.6 (SD = 4.0) on nights with such acknowledgment;
c) Person-mean centered value.

Results of the multilevel logistic regression showed that, at the night level, the likelihood of acknowledging higher consumption than intended was significantly associated with a higher number of locations visited than usual, and a higher number of additional drinks than usual, as well as having a hangover and spending more money than intended. However, the number of friends present was not significantly associated when taking the other predictors into account. Last, no individual-level characteristics were associated with the likelihood of acknowledging higher consumption than intended.

5.4 Discussion

The first aim of this study was to investigate the extent to which participants acknowledged, the next morning, having drunk more than intended on the previous night, and the results showed that they did so on only one-third of the nights, despite an average additional consumption of 2.8 drinks. One possible explanation for this widespread tendency not to acknowledge a heavier consumption than intended is that, in the absence of a strong commitment to keep to the intended amount, participants have changed their drinking intentions over the course of the night. Also, given that they were asked about the previous night’s consumption and whether it exceeded their intentions in the same questionnaire, participants may also have been attempting to avoid cognitive dissonance (Festinger, 1962; Mäkelä, 1997) by revising their original intentions to more closely match the amounts actually consumed.

The second aim of this study was to investigate the circumstances in which young people would acknowledge having drunk more than intended. It appears that only particularly salient (i.e. difficult-to-ignore) signs of heavier drinking than usual, namely consuming an additional amount that almost qualifies as binge drinking (+4.3 drinks on average), having a hangover, and exceeding one’s monetary budget, were likely to make participants aware that the previous night had not gone as intended. In contrast, other contextual aspects that relate to consumption in excess of intentions but do not affect well-being the next morning might easily be ignored or forgotten.

In terms of clinical practice, these results add new evidence to the discussion on the operationalization of exceeding one’s intentions as a symptom of an alcohol use disorder in the DSM-IV and DSM-5. This criterion has been criticized as difficult to measure using retrospective questionnaires and as often misunderstood by young people among whom drinking more than intended is common (Caetano & Babor, 2006; Martin et al., 2008; Slade et al., 2013). Our results show that event-level data collection methods are more sensitive for detecting occasions with heavier consumption than intended than self-reports, since people tend to acknowledge only occasions with much larger intake than intended or with the co-occurrence of salient consequences. However, given that participants acknowledged heavier drinking than intended mainly after such ‘at risk’ occasions, self-acknowledgment appears as a more accurate sign of an alcohol use disorder among young adults, as conceptualized in the DSM-IV and DSM-5, than automatic detection using event-level questionnaires.

From a prevention perspective, combined with the observation that acknowledging heavier consumption than intended was completely independent of any of the individual characteristics investigated, the present findings suggest that the implementation of event-specific prevention programs (Neighbors et al., 2007) that reach young people when the ‘deviation from intention’ process is in progress, namely during a drinking occasion either in situ or using with smartphone-based interventions (Wright et al., 2017), may be beneficial. With the aim of narrowing the gap between drinking intentions and amounts consumed as well as raising peoples’ awareness when they are deviating from their intentions, prevention programs might include a comparison of the current state of intoxication with initial drinking intentions, and a comparison of actual spending with intentions. They might also raise attention to the influence of particular circumstances, such as predrinking and large drinking group size, that are apparently not recognized as risk factors by young people.

Among the strengths of the present study is the collection of rich data in real-life settings, on multiple nights, from a substantial sample of individuals, and its event-level longitudinal design which enabled us to investigate within- and between-individual variations in drinking intentions and behaviors. A couple of shortcomings and limitations of the present study should also be mentioned. First, drinking intentions were measured before the night started, but no information was collected on whether participants changed their intentions over the course of the night. Given the general tendency to exceed drinking intentions, we might assume that some participants may have changed their intentions toward higher levels and, consequently, the rate of nights with heavier consumption than intentions (47.7%) would be lower and the acknowledgment rate (36.7%) would be higher. Implications on the model results are less clear. Therefore future research is needed to refine the present findings by investigating to what degree drinking intentions change during a drinking occasion and what factors or circumstances may be responsible for such a change. Second, the present study focused on contextual factors of drinking occasions associated with acknowledging heavier consumption than intended and did not investigate cognitive processes underlying such an acknowledgment. In line, with the previous limitation, future research on the cognitive processes underlying potential changes in drinking intentions, willingness to commit to the intended amounts and awareness of deviating from one's intentions is recommended.

Chapter 6

Ten seconds of my nights: using short video clips to investigate how brightness, loudness and attendance vary with alcohol use from the perspective of participants, annotators, and computer algorithms [5]

Abstract

Introduction: Alcohol use occurs in different contexts and is influenced by the characteristics of these environments. Event-level studies have provided initial insights on the influence of social and physical contexts, but these only accounted for participants' 'subjective' impressions. This study explores the feasibility of collecting more 'objective' contextual information using 10-second video clips recorded in real-life situations, and examines how contextual features, assessed by either participants, annotators or computer algorithms, relate to alcohol use.

Methods: Using a custom-built smartphone application, 215 16-25-year-olds documented characteristics of 2,380 weekend night drinking events using questionnaires and videos. Data on loudness, brightness, and attendance (number of people) were obtained from three sources: in-situ participants' ratings, videos-based annotator ratings, and videos-based computerized algorithm ratings. Bivariate statistics and correspondence matrices explored differences in contextual features rated by each source. Multilevel logistic regressions assessed the influence of contextual features on alcohol use, controlling for age, gender and drinks consumed earlier that night.

Results: Raw ratings of brightness, loudness and attendance differed slightly across sources, but were all significantly correlated (r = .38 to .60 between participants and annotators or algorithms; r = .62 to .82 between annotators or algorithms). Participants rated bars/pubs as being louder, and annotators rated private places as darker when alcohol was consumed than when alcohol was not consumed. Multilevel logistic regressions showed that in private places, drinking was more likely in louder (according to all sources), more attended (participants and algorithm) and darker (algorithm) environments. In commercial venues, drinking was more likely in louder (participants and annotators) and darker (participants) places.

Conclusions: Several contextual features are associated with increased odds of drinking in private and commercial settings. Despite differences in raw ratings, annotators and algorithms might serve as rough substitutes of participants' in-situ impressions for correlational and regression analyses.

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[5] Submitted as: Labhart, F., Muralidhar, S., Massé, B., Kuntsche, E. & Gatica-Perez, D. (submitted). Ten seconds of my nights: using short video clips to investigate how brightness, loudness and attendance influence alcohol use from the perspective of participants, annotators, and computer algorithms. *Submitted for publication.*

6.1 Introduction

Every drinking occasion takes place in a given context and is largely influenced by the physical and social characteristics of this context (Burke et al., 2009; McCarty, 1985; Stanesby et al., 2019). Yet, collecting objective and ecologically valid information on contextual correlates of alcohol use is a methodological challenge, because actors of a given situation may have problems recalling or even noticing influential contextual features. Therefore, it is difficult to rely exclusively on participants' subjective perception, which makes capturing contextual characteristics from an external observer-like viewpoint important. Using a unique dataset of real-life 10-second video clips, the purpose of this paper is to understand how human participants, human annotators, and computer algorithms rate brightness, loudness, and attendance in various contexts, and to examine how contextual characteristics assessed by these three data sources are associated with the consumption of alcohol.

6.1.1 The complementary perspectives of actors and observers

Understanding the behaviors of people in their immediate environment largely depends on the source of the collected data. In sociology, a distinction is made between the people involved in a situation (the insiders) and those who observe the former (the outsiders). Insiders are actors –or 'subjects'– in the situation and they provide knowledge permeated by the history and symbolic meaning of their current situation and actions (Letherby et al., 2012). In contrast, outsiders –or observers– are blinded to such specificities and rather consider the situation as an 'object' of observation (Letherby et al., 2012). Therefore, collecting information from both perspectives –subjective experience and objective facts– is necessary to gain a comprehensive picture of any given situation (Merton, 1972; Olson, 1977).

The discrepancy between the actors' and the observers' perspectives is also the foundation of the actor-observer asymmetry theory in psychology (Jones & Nisbett, 1987). This theory, developed to explain the errors that one makes when forming an attribution about the behavior of others, states that actors are more likely to attribute their actions to the particular circumstances of a given situation, whereas observers tend to attribute the actions of others to more general personality traits, independently of the momentary circumstances (Jones & Nisbett, 1987). If we transpose these distinct attribution processes to the way people perceive their surrounding context, we might then expect actors to pay more attention to the momentary state-like characteristics of the situation (e.g. it is darker than the last time; this place is very crowded tonight), and observers to pay more attention to trait-like characteristics of similar places (e.g., music is loud like in any nightclub). Thus, actors' impressions may contribute to an understanding of the unusual contextual characteristics associated with alcohol use, while observers' impressions might explain the impact of typical venue characteristics on people's alcohol use.

6.1.2 Existing evidence on contextual correlates of alcohol use

In the past decades, social and physical contextual correlates of alcohol consumption have been investigated using various data collection methods. A first group of methods aimed at capturing contextual features from the perspective of the participants. For example, cross-sectional surveys have asked respondents to describe, retrospectively, the context of a typical or the last occasion in which they drank alcohol (e.g., Bertholet et al., 2013; Demers et al., 2002; Thrul et al., 2018). For example, Canadian students reported consuming more alcohol per occasion when they were at a party (as opposed to other drinking occasions), in bars or at home rather than in a restaurant, and with larger groups than with a small groups of friends (Demers et al., 2002). However, retrospective surveys are particularly subject to omissions and recall errors, since respondents are known to forget or misreport details of their behaviors after a couple of days (Coughlin, 1990; Ekholm, 2004). This method also suffers from limited ecological validity because 'typical' or 'last' occasions are likely not representative of the diversity of all real-life occasions one could experience.

Diary-based methods, such as ecological momentary assessment (EMA), aim to overcome the aforementioned limitations by requiring participants to describe characteristics of the immediate context while participating drinking events reported in almost real time (Kuntsche & Labhart, 2013b; Witkiewitz et al., 2012). For example, young Swiss adults who completed six consecutive hourly assessments on weekend nights were found to drink twice as much alcohol per night, compared to their retrospective reports at baseline (Kuntsche & Labhart, 2012). They were also found to drink higher amounts of alcohol when drinking occasions started in private places before going out (Labhart et al., 2013), and in the presence of a higher number of friends (Smit et al., 2015; Thrul & Kuntsche, 2015). However, an important limitation of EMA research is that increasing response burden limits the number of contextual features that can be captured.

Contextual characteristics of real-life settings can, for example, be measured from an external viewpoint using dedicated devices such as decibel meters for sounds levels (Guéguen et al., 2008). For example, in-bar loudness measurements revealed that patrons' drinking pace and amounts increased in louder environments (Guéguen et al., 2004, 2008). To explain this phenomenon, authors argue that high sound levels create a high level of arousal among patrons, who enhance their behavioral response toward the stimulus (Guéguen et al., 2008; Welch & Fremaux, 2017). Additionally, while music at moderate sound levels plays an important role in the socialization process in pubs and nightclubs (Forsyth & Cloonan, 2008), loud music impedes conversation and likely increases patrons' drinking pace.

In-situ observations are also often used to document characteristics of nightlife settings such as bars and nightclubs from an external viewpoint (Graham et al., 2006; Hughes, Quigg, Eckley, et al., 2011; Miller et al., 2013). For instance, observational studies have shown that intoxication levels of bar patrons are associated with promotion of soft or energy drinks, poor washroom facilities or presence of a dance floor, but not with brightness of the place or music sound level (Hughes et al., 2012). A major advantage of in-situ sensors and observations is that they provide standardized measures that can be compared across locations and times. However, such methods cannot easily be used outside of publicly accessible locations and cannot follow individuals when they change locations.

Over and above differences in the methods used, this body of findings provides concurring evidence that particular features of the social (e.g., the size of the drinking group) and physical context (e.g., the type of location and the noise level) influence peoples' in-situ drinking behaviors, both when documented by participants and by observers. However, an important limitation of the existing literature is that each study only accounts for the perception of either the participants or the observers. Additionally, the existing literature remains limited in terms of types of location investigated, especially with in-situ observations. For instance, almost all evidence has been collected in commercial venues, namely bars and nightclubs, but little is known about other public settings, such as parks, streets, and means of transportation, as well as in private settings.

6.1.3 Capturing contextual features with 10-second video clips

To address these gaps, in the Youth@Night project, a multidisciplinary team developed a method for documenting physical and social characteristics of different drinking settings from both actors' and observers' perspectives. The overall aim of the project was to document young adults' nightlife and drinking behaviors by means of a custom-made smartphone application, collecting data via questionnaires, sensors, pictures, and short video clips (Labhart et al., 2020). In order to capture characteristics of the immediate drinking context, participants had to report the type of attended location and to indicate the levels of brightness, loudness, and the number of people present every time they had an alcoholic or a non-alcoholic drink. Additionally, each time they had a drink in a new location, participants were requested to record a 10-second panoramic video clip of the surrounding context to be later annotated by research assistants and analyzed via computer algorithms.

Exploratory analyses of the participants' reports and the video content revealed that typical levels of brightness varied across location types, with bars and nightclubs being darker and louder than other public spaces and private places (Santani et al., 2016). Furthermore, participants' ratings of brightness and loudness correlated poorly to moderately with observers' annotations in the videos, echoing the actor-observer asymmetry assumption, i.e. participants' impressions of their own context differed from observers' impressions of the same situation. Finally, the high consistency found between annotators' ratings and computerized extraction of audio/video channels for brightness and loudness suggested that computer algorithms are able to provide very similar measures to annotators when it comes to assessing contextual characteristics from real-life short video clips (Santani et al., 2016). However, inconsistencies in the annotation procedure (i.e., several annotators worked on separated subsets of videos) limited internal consistency and issues in the loudness extraction algorithm prevented firmer conclusions. For the present study, the entire collection of 843 video clips was re-annotated by five independent annotators, brightness and loudness extracted algorithms were adjusted to match human perception characteristics of light and sound, and a new algorithm was used to count the number of people appearing in the videos.

6.1.4 Study aims

The overall aim of this paper is to understand how human participants, human annotators and computer algorithms assess brightness, loudness, and attendance (number of people present) in various contexts, and to examine how contextual characteristics assessed by these three data sources are associated with alcohol consumption. Given that computer algorithms are not as capable as humans to identify social bounds or process cognitions, we limited the analyses to factual characteristics of the physical and social context. Compared to the study of Santani and colleagues (2016), this analysis will also include characteristics of the social context (namely the number of people present around the participants) as this element was frequently described in previous literature (Demers et al., 2002; Smit et al., 2015; Thrul & Kuntsche, 2015). Furthermore, following assumptions of the actor-observer asymmetry (Jones & Nisbett, 1987), the analysis will provide an applied example of how the same contextual characteristics assessed by three different sources might reveal different associations with alcohol consumption.

The first part of the analysis explores the convergence of participants', annotators' and computer algorithms' ratings at the bivariate level and investigates levels of brightness, loudness, and attendance across seven different types of locations (including bars, nightclubs, restaurants, public parks, and homes) depending on whether the participants were drinking an alcoholic or a non-alcoholic drink.

The second part will investigate how levels of brightness, loudness, and attendance perceived by either participants, annotators or computer algorithms are associated with the consumption of alcoholic versus non-alcoholic drinks. Because the actors' perception of their context might be altered by the consumption of alcohol earlier in the night, the analysis will account for this confounder, in addition to gender and age effects.

6.2 Materials and Methods

6.2.1 Study design

Participants were recruited in the streets of the two major nightlife hubs in Switzerland (Lausanne and Zurich) between 9pm and midnight on Friday and Saturday nights in the first three weekends of September 2014. In defined nightlife areas, research assistants approached every nth person crossing a 'virtual line' on the street (Labhart, Santani, et al., 2017). Eligibility criteria were being aged between 16 and 25, owning an Android smartphone on which the Youth@Night app could be installed, having consumed alcohol at least once in the past month (legal drinking age is 16 for beer and wine in Switzerland), and having been out in the city at least twice in the past month. After explaining the aim and procedure of the study, recruiters recorded volunteers' email address, and volunteers then automatically received an email containing a link to the study website and the online consent form. After signing the consent form and completing the baseline questionnaire, participants installed the Youth@Night application on their smartphone. This app was specifically developed to record various aspects of the participants' Friday or Saturday nights, including the types of drinks consumed and the social and physical characteristics of locations attended over seven consecutive weekends, using questionnaires, pictures, video clips, and sensors (Labhart et al., 2020). The study was approved by the Lausanne and Zurich Cantonal Ethics Committees for Research on Human Beings (protocol 145/14).

6.2.2 Samples

In total, 3,092 people were approached in the two cities. Of those, 1,119 (36.2%) did not have an Android smartphone, 859 (27.8%) were not interested in participating in the study and 233 (7.5%) were outside the required age range of 16 to 25. Of the 881 who agreed to participate, 629 (71.4%) signed the online consent form, 367 completed the baseline questionnaire (41.7%) and 241 documented their nights using the smartphone app (27.4%; mean age = 19.1, SD = 2.4; 46.5% women) (Labhart, Santani, et al., 2017).

Participants documented their drinks and contexts via various questionnaires (see measures section below). To reduce response burden, participants were required to document each attended location only once per night, namely when they had their first drink there, by taking a video if the situation allowed it (e.g. not forbidden or not disturbing other patrons: Labhart et al., 2020). In total, 2,420 drinking situations were documented through 2,420 drink pictures including a brief description of the context, 1,394 labels of the location, and 843 video clips of the context. From these, we excluded 18 videos (and related pictures) that annotators reported as being entirely dark and silent (i.e., not containing any relevant information for the present analysis). Using the sequence of events during the night, location coordinates and the observable context in the background of drink pictures, we were able to assign the type of location to 987 additional drinking situations. Analyses were thus conducted on a sample of 2,358 situations documented with data on the drink and the location and a subset of 825 situations documented with a video. The situations were reported by 210 participants who were slightly older than the rest of the participants (mean age = 19.2, SD = 2.4, t = -2.1; p = .037) but similar in terms of gender ratio (47.1% women; χ^2 = 0.07, p = .791).

6.2.3 Extraction of audio and visual cues from the videos

After the fieldwork, we developed an online annotation task to extract visual and audio cues from the videos taken by the participants (Phan et al., 2019). Five independent annotators watched in a random order the entire set of videos and annotated the type of location, the loudness and brightness, the number of people visible, and other situational cues (e.g. ongoing activities, people's reaction to being filmed). After a training session, annotators completed the annotation task at their own pace over two months using their computer.

6.2.4 Measures

6.2.4.1 Participants

Age and *sex* (women = 0, men = 1) were recorded in the baseline questionnaire.

Alcoholic versus *non-alcoholic drinks.* From 8 p.m. until the end of the night, every time they had a new drink, participants were asked to take a picture of their drink and label it as one of six types of alcoholic drinks (e.g., beer, wine, spirits, cocktails; coded as 1) or six types of non-alcoholic drinks (e.g., water, soda, energy drink, tea/coffee; coded as 0).

Brightness and *loudness.* Each time they documented a drink, participants were also asked to describe the current context in terms of brightness, loudness, and attendance. All ratings were given on a five-point Likert scale ranging from 0 (very low) to 4 (very high).

Attendance: In the same questionnaire, participants were asked to report the type and number of people present around them by indicating how many of the following people were present: ‘partner or spouse’ (0 or 1), ‘family or relatives’ (answer options: increasing integers from 0 to 10, plus ‘more than 10’ [coded as 15]), ‘male friends or colleagues’ (same options), ‘female friends or colleagues’ (same options), and ‘other people’ (same options). All categories were summed up to represent the total number of people present.

Locations. At 8 p.m. and each time they changed location, participants were asked to report *the type of location* they were at. Responses were recoded into the following categories: ‘bars/pubs,’ ‘nightclubs,’ ‘restaurants,’ ‘events and leisure’ (e.g. sport arenas, concerts, bowling), ‘public parks and streets’, ‘travelling’ (e.g. on trains, cars) and ‘private places’. Locations indicated by the participants were compared with those identified by the annotators (see below) from the videos and, in case of disagreement, latitudinal and longitudinal coordinates were checked to ensure the correct categorization of the location. To distinguish between types of nightlife venues, locations were also categorized at the coarser level into commercial venues (bars/pubs, nightclubs, restaurants, and events/leisure), non-commercial public spaces (parks, streets, and travelling), and private places.

When having their first drink in a new location each night, participants were requested to take a 10-second *video clip* of the location using their smartphone’s camera. The following instructions were shown in the app before each video recording in order to accurately document the loudness, brightness, and ongoing activities in their immediate environment: use landscape format (horizontal), generate a full view (360°) of the environment by slowly turning from left to right, take a video even if the scene was dark, and do not cover the microphone with your hand. Participants could skip the video if they did not feel comfortable or ready (i.e., not an appropriate moment, not feeling safe, forbidden in the location, someone objected to it). The rates of recording a video after having taken a picture were 30.6% of the cases in private places, 39.4% in commercial venues (32.3% in restaurants, 35.9% in bars, 50.0% in nightclubs) and 44.0% in public spaces (39.6% on streets and parks, 56.5% while traveling).

The number of *prior drinks consumed* that night were obtained by summing up the total number of alcoholic drinks already reported by the participants using the new drink questionnaire (described above) or the forgotten drink questionnaire (i.e. drinks reported without pictures) (Labhart et al., 2020). Drink content was converted into standard drinks containing 10 grams of pure alcohol (World Health Organization, 2000).

6.2.4.2 Annotators

Brightness and *loudness.* Using the same five-point Likert scale (0-very low, 4-very high) used by participants, external annotators rated the context along three dimensions: brightness, music loudness, and chatter loudness. The maximum score of music loudness and chatter loudness was used to represent the overall loudness. Intraclass correlation coefficients (ICC) showed an excellent level of agreement between the five annotators for both dimensions, namely $ICC(2,k)_{brightness} = 0.948$, and $ICC(2,k)_{loudness} = 0.955$ (Cicchetti, 1994; Shrout & Fleiss, 1979). To obtain a 5-point scale as for participants, annotators' ratings were aggregated as follows: if the majority of annotators (3 or more) agreed on one value, this value was selected, otherwise the mean of the 5 ratings was rounded to the closest integer. Compared to systematically selecting the mean of the 5 annotations, this method has the advantage of giving more importance to concordant answers and being less sensitive to outliers.

Attendance. Annotators were asked to indicate how many people appeared in the video (in addition to the phone holder) using the following answer options: '0', '1', '2-4' (coded as 3), '5-10' (7.5) and 'more than 10' (15). An excellent level of agreement was found between the five annotators ($ICC(2,k)_{attendance} = 0.915$). Given the linear nature of the measure, recoded scores were averaged across all five annotators.

6.2.4.3 Computer algorithms

Brightness. For each frame of the video, brightness (B_{avg}) was computed by averaging the intensity of each pixel ($I(x,y)$) in the YUV color space using the formula: $B_{avg} = \frac{1}{N}\sum_{(x,y)} I(x,y)$. Total average brightness, expressed on a 0 (all black) to 255 (all white) 8-bit scale, was obtained by averaging B_{avg} values across all frames in the video (Bezryadin et al., 2007). This value was then transformed into human perceived brightness (L; also called relative luminance (Kingdom, 2011)) on a 0 to 100 scale using Glasser's formula (Glasser et al., 1958): $L = 25.29Y^{1/3} - 18.38$; where $Y = \frac{100}{255}B_{avg}$. Finally, to allow comparison with the participants' and annotators' ratings, perceived brightness was rescaled to a 0 to 4 scale using 20-point increment cut-offs (e.g., 0 to 19.9 = 0; 20 to 39.9 = 1, etc.).

Loudness. We first computed the temporally-smoothed instantaneous audio power (*AP*) using the formula: $AP(l) = \frac{1}{N_{hop}} \sum_{n=0}^{N_{hop}-1} |s(n + lN_{hop})|^2 \quad (0 \leq l \leq L-1)$; where L is the total number of time frames (each of duration L_w), and N_{hop} is the number of time samples corresponded to the time interval between consecutive frames. Then, the total average loudness was obtained by averaging *AP(l)* across all frames in the video, with L_w set to 100ms. Finally, total average loudness was log-transformed to account for the exponential nature of sound measurements (Gonzalez & Woods, 2002; Kim et al., 2006; Santani et al., 2016). The total average loudness was converted into decibels (dB) using the formula: $dB = 10 \times log_{10} \frac{Intensity}{10^{-12}\ W/m^2}$. and adjusted to standard human hearing ability (e.g. whisper = 30dB; maximum recommended exposure for 15 minutes = 100dB) (Berger et al., 2016; Krug et al., 2015). To allow comparisons with the participants' and annotators' ratings, loudness was rescaled to a 0 to 4 scale using the following ranges: less than 40, 40-49, 50-69, 70-84, and 85 or more.

Attendance: On each video frame, we used the YOLOv3 object detector (Redmon & Farhadi, 2018). YOLOv3 uses a 53-layer fully convolutional neural network trained on the 80 categories from the MS-COCO dataset (Lin et al., 2014) to find bounding boxes containing the category "person". Counting boxes allows the algorithm to count the number of people in each video frame. To avoid counting each person multiple times and to identify which boxes correspond to the same person in successive frames, we used the Deep-SORT tracker (Wojke et al., 2017) that combines a geometric approach (Bewley et al., 2016) (position, size, and speed of a bounding box sequence) with an appearance model (Wojke & Bewley, 2018) (whether the content of bounding boxes look similar or not). Finally, we report the number of identity clusters according to the tracker as the number of people shown in the video.

6.2.5 Analytic strategy

Prior to analysis, extreme outliers in the number of prior drinks consumed and in attendance levels were winsorized at three standard deviations in order to better approximate a normal distribution (Tabachnick & Fidell, 2007). This impacted 46 reports (2.0%) above 12.1 prior drinks, 52 reports (2.2%) above 32 people reported by participants, and 12 reports (1.2%) above 35 people identified by the algorithm.

On the full sample of observations, descriptive statistics were used to describe the average levels of brightness, loudness and attendance from the participants', annotators' and algorithms' perspective. Level of agreement between participants', annotators' and algorithms' ratings of brightness, loudness, and attendance were illustrated using correspondence matrices and measured using Pearson's correlations and paired-sample *t*-tests. Correlation coefficients under .40 were considered as 'poor', between .40 and .59 as 'fair', between .60 and .74 as 'good' and above .75 as 'excellent' (Cicchetti, 1994).

For each type of location, descriptive statistics and correspondence matrices were used to describe the average levels of brightness, loudness and attendance from participants', annotators' and algorithms' perspectives. Additionally, differences in levels of brightness, loudness, and attendance between situations with and without alcohol use were assessed using Cohen's *d* and independent sample *t*-tests.

Multilevel logistic regression models were estimated to investigate the mutually-adjusted associations of brightness, loudness, and attendance with the likelihood of drinking an alcoholic drink (dependent variable) (Sommet & Morselli, 2017). Nine models were estimated separately for participants', annotators', and algorithms' ratings, and for the three locations categories. Due to the small number of observations in some types of locations, the models were estimated only at the coarser level, i.e. for commercial venues, public spaces, and private places. Situational-level predictors were brightness, loudness, attendance, and number of alcoholic drinks already consumed, and individual-level predictors were age and gender. The models controlled for the number of alcoholic drinks consumed earlier in the night because the actors' perception of their context might be altered by the level of inebriation. The models were estimated with Mplus 7.3 (Muthén & Muthén, 2015) using the maximum likelihood robust (MLR) estimator to account for deviation from normal distribution. Reported effect sizes were odds ratios (OR) and 95%-confidence intervals.

6.3 Results

As seen in Table 6-1, annotators provided the lowest ratings for all three features. Participants rated their environment generally brighter than the two external sources, while algorithms rated the environment as louder than the two human sources. Both participants and algorithms reported the presence of six people on average, while annotators reported an average of five. As seen in Figure 6-1, annotators rarely rated brightness and loudness levels using the maximum level of '4', resulting in narrower and significantly lower average ratings than those of the participants. Similarly, algorithms never attributed the maximum score for brightness levels. While all correlation coefficients between sources were positive and significant (Figure 6-1), the level of agreement between participants and both annotators and algorithms was lower ($r = .38$ to $.60$) than between annotators and algorithms ($r = .62$ to $.82$).

In all three sources, loudness was positively correlated with attendance (i.e. louder environments tended to also be better attended, and vice versa). In addition, based on annotators' and algorithms' ratings, brightness and loudness were negatively correlated. In all sources, prior and concurrent alcohol use was positively correlated with loudness and attendance, and negatively correlated with brightness. Furthermore, while inconsistent results were found for age, participants' gender was correlated with brightness (women rated environments brighter than men) in all sources. Overall, patterns of ratings appear very similar across all three sources, and especially between annotators and algorithms.

Table 6-1: Average ratings of brightness, loudness and number of people per data source, and bivariate correlations with drinking behaviors and participants' demographics

	Brightness	Loudness	Attendance
Scale	0-4	0-4	Linear
Participants' ratings in situ, mean (SD)	2.0 (1.2) [c]	1.7 (1.4) [b]	6.3 (8.6) [b]
Annotators' ratings from videos, mean (SD)	1.5 (0.9) [a]	1.6 (1.1) [a]	5.0 (5.2) [a]
Algorithms, mean (SD)	1.9 (1.0) [b]	2.3 (1.1) [c]	6.1 (9.8) [b]
Pearson's correlations			
Participants' ratings:			
Brightness	-	-.01	.04*
Loudness	-	-	.35***
Current alcoholic drink (yes = 1)	-.06**	.33***	.21***
Number of earlier alcoholic drinks	-.04	.24***	.15***
Participant age	-.04*	.00	.04
Participant gender	-.03	.03	.03
Annotators' ratings:			
Brightness	-	-.27***	-.06
Loudness	-	-	.63***
Current alcoholic drink (yes = 1)	-.23***	.47***	.30***
Number of earlier alcoholic drinks	-.15***	.23***	.20***
Participant age	-.05	.05	.10**
Participant gender	-.12**	.07	.03
Computer analysis ratings:			
Brightness	-	-.31***	.14***
Loudness	-	-	.34***
Current alcoholic drink (yes = 1)	-.27***	.44***	.16***
Number of earlier alcoholic drinks	-.14***	.23***	.07
Participant age	.00	.05	-.02
Participant gender	-.13***	.04	.03

Note: N = 825; * $p < .05$, ** $p < .01$, *** $p < .001$;
paired-sample *t*-tests in columns with a < b < c at $p < .05$ significance level.

Figure 6-1: Correspondence matrix, Pearson's correlations and mean difference tests of participants', annotators' and computer algorithms' ratings of brightness, loudness and attendance in the 825 drinking situations

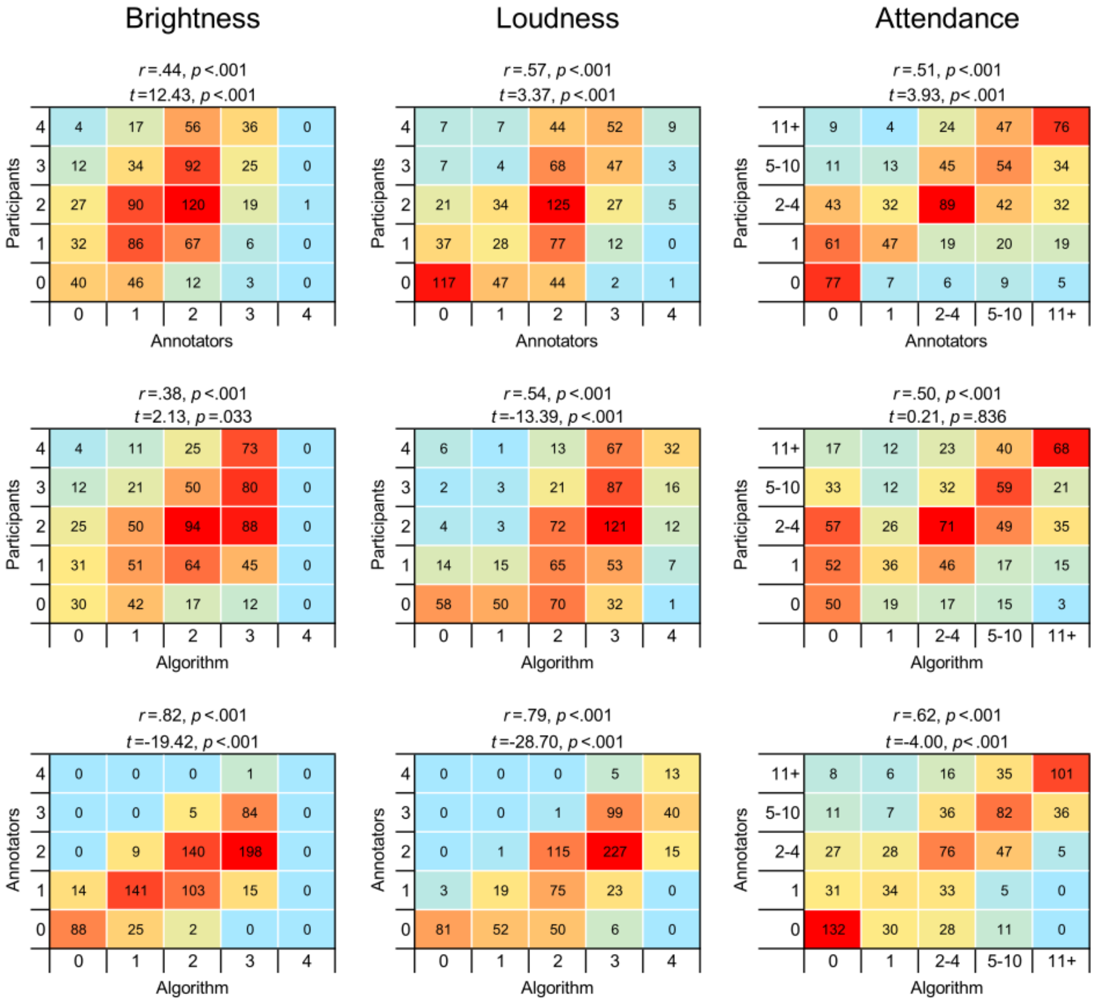
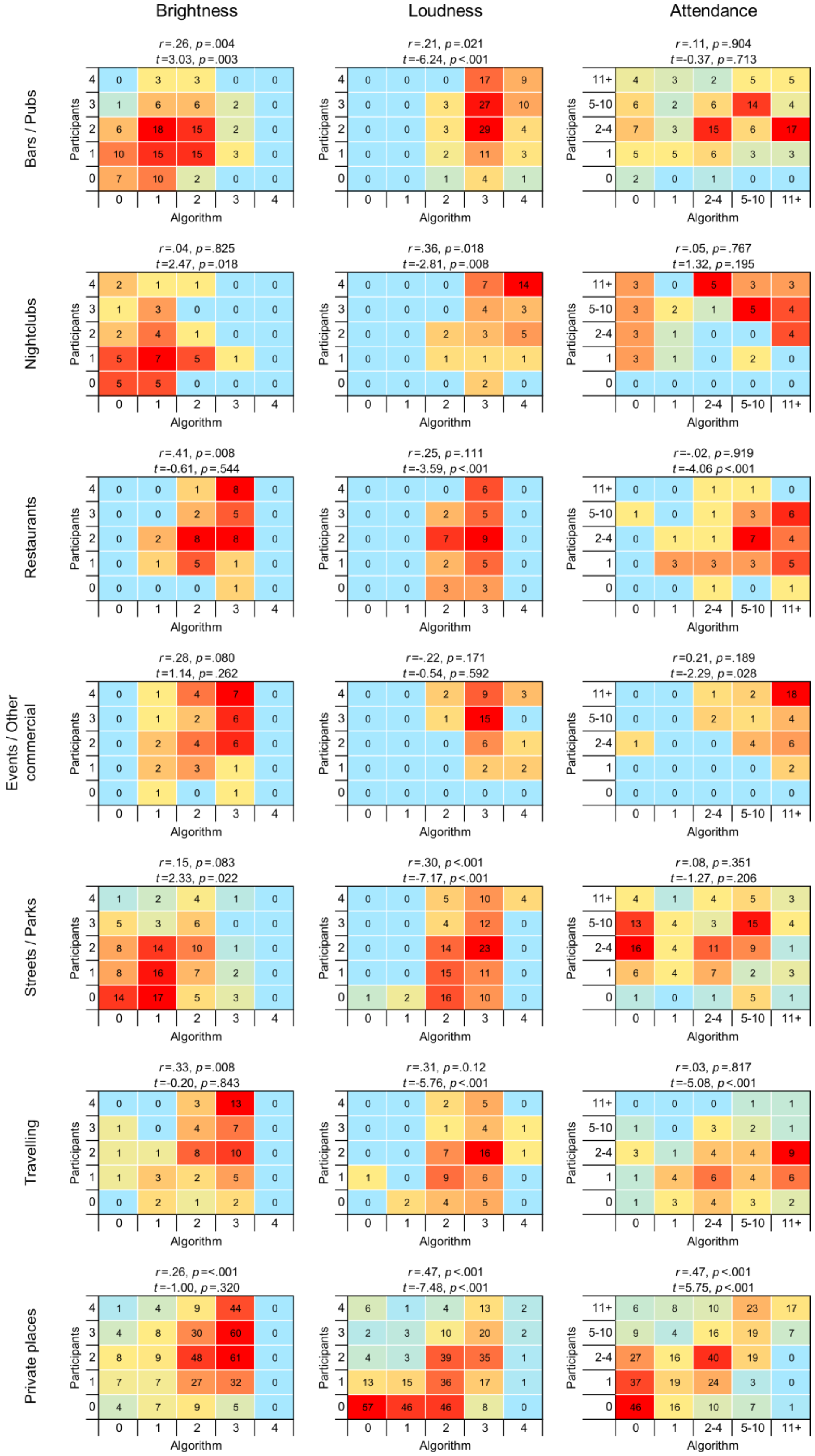


Figure 6-2 extends the results of Figure 6-1 by splitting the correspondence matrices per location type and shows that convergence in participants' and algorithms raw ratings largely varied across locations. In fact, participants and algorithms provided dissimilar raw ratings in many situations, as indicated by significant *t*-tests and non-significant correlation coefficients. In particular, participants tended to perceive dark environments (pubs, nightclubs, and parks) as brighter than the algorithms. In these environments, the algorithm occasionally failed to detect the presence of people, resulting in evident discrepancies between the two sources. Regarding loudness, only private places were measured as being mostly silent by the algorithm, although participants often rated streets/parks, means of transport, and restaurants as such.

Figure 6-2: Correspondence matrix, Pearson's correlations and difference tests of participants', computer algorithms' ratings of brightness, loudness and attendance per location type



As shown in Table 6-2, the average scores of brightness, loudness, and attendance also varied significantly across types of locations (see superscript letters indicating mean differences in each column). For example, all three sources rated restaurants, modes of transport, and events among the brightest environments, while public parks and nightclubs were rated among the darkest. Nightclubs, events, and bars were rated among the loudest environments, and private places as the most quiet. Nightclubs, events, bars, and restaurants were rated as the most attended places, whereas private places were the least attended.

Table 6-2 also shows the average scores of brightness, loudness, and attendance per type of location, depending on whether participants were documenting an alcoholic or a non-alcoholic drink. Nearly all drinks reported in nightclubs (94.2%), pubs (93.3%), and public streets and parks (86.9%) contained alcohol. Inversely, only half of the drinks reported in private places (52.9%) and restaurants (50%) contained alcohol. Differences in average scores between situation with and without alcohol use were assessed using Cohen's D and *t*-tests. Overall, most variations were consistent across sources, but of small to medium magnitude (e.g., all sources rated nightclubs as being darker, louder, and less attended when alcohol was consumed, but below significance level). Nevertheless, a couple of noteworthy effects can be observed across sources. Regarding brightness, all three sources rated pubs as brighter when alcohol was consumed, but the difference was significant only for external observers (annotators and algorithms). Also, while private places were rated as darker by annotators and algorithms when alcohol was consumed, this effect was not found among participants. Regarding loudness, participants reported bars/pubs as being louder when alcohol was consumed, while the algorithm found the opposite, yet not significantly. Regarding attendance, annotators and algorithms identified a larger number of people present when alcohol was consumed at events. Interestingly, the high attendance at festivals, concerts, or sporting events resulted in a particularly high number of people identified by the algorithm. Finally, all sources rated private places as much louder (+1 on the 5-point scale) and much more crowded (about 3 times more people) when alcohol was consumed.

Table 6-2: Number and proportion of observations, average scores, Cohen's d and t-tests for brightness, loudness and number of people per drinking location and types of drinks (alcoholic vs. non-alcoholic) in the three data sources

	Number of observations		Brightness		
	Participants N (%)	Annotators N (%)	Participants Mean (SD)	Annotators Mean (SD)	Algorithms Mean (SD)
Bars / Pubs					
Total	345	124	1.7 (1.1) [a]	1.0 (0.7) [b]	1.3 (0.8) [b]
Non-alc. drinks	23 (6.7%)	10 (8.1%)	1.5 (1.3)	0.6 (0.8)	0.6 (0.8)
Alcoholic drinks	322 (93.3%)	114 (91.9%)	1.7 (1.0)	1.1 (0.6)	1.3 (0.8)
Cohen's *d*			0.19	0.71	0.88
t-test			0.88	2.12*	2.64**
Nightclubs					
Total	86	43	1.5 (1.2) [a]	0.6 (0.7) [a]	0.9 (0.8) [a]
Non-alc. drinks	5 (5.8%)	4 (9.3%)	2.4 (1.5)	1.0 (0.8)	1.3 (0.5)
Alcoholic drinks	81 (94.2%)	39 (90.7%)	1.4 (1.2)	0.6 (0.7)	0.8 (0.8)
Cohen's *d*			0.85	0.66	0.56
t-test			-1.81	-1.20	-1.06
Restaurants					
Total	129	42	2.4 (1.0) [b]	2.2 (0.7) [d]	2.5 (0.6) [c]
Non-alc. drinks	64 (49.6%)	22 (52.4%)	2.3 (1.1)	2.3 (0.8)	2.6 (0.6)
Alcoholic drinks	65 (50.4%)	20 (47.6%)	2.4 (1.0)	2.0 (0.6)	2.3 (0.7)
Cohen's *d*			0.03	0.32	0.36
t-test			0.22	-1.43	-1.76
Events / Other commercial					
Total	74	41	2.3 (1.2) [b]	2.1 (0.8) [d]	2.3 (0.8) [c]
Non-alc. drinks	20 (27.0%)	9 (22.0%)	2.1 (1.1)	1.9 (1.1)	2.0 (0.9)
Alcoholic drinks	54 (73.0%)	32 (78.0%)	2.4 (1.2)	2.1 (0.8)	2.4 (0.7)
Cohen's *d*			0.28	0.25	0.49
t-test			1.21	0.73	0.78
Streets / Parks					
Total	324	127	1.6 (1.2) [a]	0.8 (0.6) [a]	1.1 (0.9) [a,b]
Non-alc. drinks	41 (12.7%)	16 (12.6%)	1.8 (1.1)	0.9 (0.7)	1.1 (0.8)
Alcoholic drinks	283 (87.3%)	111 (87.4%)	1.5 (1.2)	0.7 (0.6)	1.1 (0.9)
Cohen's *d*			0.21	0.33	0.02
t-test			-1.31	-1.23	0.08
Travelling					
Total	114	64	2.4 (1.3) [b]	2.1 (0.8) [d]	2.4 (0.8) [c]
Non-alc. drinks	32 (28.1%)	19 (29.7%)	2.2 (1.0)	1.9 (0.9)	2.3 (1.0)
Alcoholic drinks	82 (71.9%)	45 (70.3%)	2.5 (1.4)	2.2 (0.8)	2.4 (0.8)
Cohen's *d*			0.20	0.29	0.17
t-test			1.05	1.28	0.78
Private places					
Total	1286	384	2.2 (1.2) [b]	1.8 (0.7) [c]	2.3 (0.9) [c]
Non-alc. drinks	601 (46.7%)	189 (49.2%)	2.1 (1.1)	1.9 (0.6)	2.5 (0.7)
Alcoholic drinks	685 (53.3%)	195 (50.8%)	2.3 (1.2)	1.7 (0.8)	2.1 (1.0)
Cohen's *d*			0.08	0.23	0.31
t-test			1.64	-2.83**	-3.95***

Note: * p < .05; ** p < .01; *** p < .001; a-e) *t*-tests in columns with *a* < *b* < *c* < *d* < *e* at p < .05 significance level.

Table 6-2 (continued):

	Loudness			Attendance		
	Participants Mean (SD)	Annotators Mean (SD)	Algorithm Mean (SD)	Participants Mean (SD)	Annotators Mean (SD)	Algorithm Mean (SD)
Bars / Pubs						
Total	2.5 (1.2) [c]	2.5 (0.6) [d]	3.1 (0.5) [c]	6.7 (7.1) [c]	8.5 (5.0) [c]	7.0 (8.2) [c]
Non-alc. drinks	2.0 (1.0)	2.4 (0.5)	3.3 (0.5)	8.5 (9.7)	9.1 (5.3)	5.9 (8.9)
Alcoholic drinks	2.5 (1.2)	2.5 (0.6)	3.1 (0.5)	6.6 (6.8)	8.4 (5.0)	7.1 (8.2)
Cohen's *d*	0.50	0.10	0.33	0.27	0.14	0.15
t-test	2.30*	0.30	-0.98	-1.24	-0.41	0.45
Nightclubs						
Total	2.7 (1.5) [c,d]	3.0 (0.8) [e]	3.5 (0.6) [d]	10.2 (9.3) [d]	10.5 (5.9) [d]	7.3 (8.8) [c,d]
Non-alc. drinks	3.4 (0.9)	3.3 (0.5)	3.5 (0.6)	14.0 (10.7)	12.9 (4.2)	12.5 (12.0)
Alcoholic drinks	2.6 (1.5)	2.9 (0.8)	3.5 (0.6)	10.0 (9.3)	10.3 (6.0)	6.8 (8.4)
Cohen's *d*	0.53	0.36	0.05	0.44	0.44	0.69
t-test	-1.15	-0.71	-0.12	-0.94	-0.93	-1.25
Restaurants						
Total	1.9 (1.2) [b]	1.9 (0.7) [c]	2.7 (0.5) [b]	5.2 (6.6) [a,b]	8.1 (4.4) [c]	10.4 (8.1) [d]
Non-alc. drinks	1.7 (1.2)	1.8 (0.8)	2.7 (0.5)	5.8 (7.4)	8.0 (4.7)	9.6 (8.0)
Alcoholic drinks	2.1 (1.2)	2.0 (0.5)	2.7 (0.5)	4.6 (5.7)	8.1 (4.1)	11.3 (8.4)
Cohen's *d*	0.27	0.19	0.04	0.20	0.02	0.19
t-test	1.80	-0.90	-0.21	-1.00	0.09	0.66
Events / Other commercial						
Total	2.9 (1.0) [d]	2.6 (0.8) [d]	3.1 (0.5) [c]	13.5 (10.6) [e]	12.3 (3.9) [d]	19.7 (11.3) [e]
Non-alc. drinks	2.8 (1.1)	2.1 (0.8)	2.9 (0.6)	9.6 (9.1)	9.3 (4.7)	11.4 (8.8)
Alcoholic drinks	2.9 (0.9)	2.8 (0.7)	3.1 (0.4)	14.9 (10.9)	13.1 (3.2)	22.0 (10.9)
Cohen's *d*	0.16	0.71	0.33	0.49	0.85	0.93
t-test	0.77	2.31*	1.35	1.97	2.83**	2.66*
Streets / Parks						
Total	1.8 (1.4) [b]	1.7 (0.8) [c]	2.6 (0.6) [b]	5.8 (6.0) [b,c]	4.5 (4.1) [b]	4.7 (6.7) [b]
Non-alc. drinks	1.7 (1.3)	1.4 (1.0)	2.4 (0.5)	5.1 (7.1)	4.5 (4.4)	5.4 (8.7)
Alcoholic drinks	1.8 (1.4)	1.8 (0.7)	2.6 (0.6)	5.8 (5.9)	4.5 (4.1)	4.6 (6.4)
Cohen's *d*	0.07	0.42	0.18	0.12	0.02	0.12
t-test	-0.34	1.69	0.78	0.70	0.06	-0.43
Travelling						
Total	1.7 (1.3) [b]	1.4 (0.8) [b]	2.6 (0.7) [b]	3.1 (4.6) [a]	5.6 (4.7) [b]	8.1 (8.7) [c,d]
Non-alc. drinks	1.8 (1.2)	1.2 (0.9)	2.5 (0.7)	2.0 (3.5)	5.9 (5.9)	8.8 (11.5)
Alcoholic drinks	1.6 (1.3)	1.5 (0.8)	2.6 (0.7)	3.5 (5.0)	5.5 (4.2)	7.9 (7.4)
Cohen's *d*	0.20	0.37	0.06	0.33	0.10	0.11
t-test	0.41	1.50	0.28	1.57	-0.34	-0.38
Private places						
Total	1.3 (1.3) [a]	1.0 (1.0) [a]	1.7 (1.1) [a]	5.6 (7.6) [b]	2.3 (3.4) [a]	3.2 (4.3) [a]
Non-alc. drinks	0.8 (1.1)	0.5 (0.8)	1.1 (1.0)	2.9 (5.1)	0.9 (2.4)	1.7 (2.9)
Alcoholic drinks	1.7 (1.2)	1.6 (1.0)	2.2 (1.0)	8.0 (8.6)	3.6 (3.7)	4.6 (4.9)
Cohen's *d*	0.73	1.03	0.83	0.68	0.81	0.67
t-test	14.32***	11.85***	10.22***	12.89***	8.50***	7.03***

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; a-e) *t*-tests in columns with $a < b < c < d < e$ at $p < .05$ significance level.

Table 6-3 presents the extent to which variations in brightness, loudness, and attendance, perceived by either participants, annotators, or computer algorithms are associated with the consumption of an alcoholic drink (versus a non-alcoholic drink as reference) in the three major types of nightlife settings. In commercial venues, results show that participants were more likely to drink alcohol when the context was reported as being less bright (OR = 0.70) and louder (OR = 1.49) by the participants, and louder (OR = 2.70) as assessed by the annotators. In public spaces, no clear association with brightness, loudness and attendance levels was found. Yet, in line with the previous observation that women tended to assess the context as being brighter than men, results from participants' ratings show that alcohol use was more likely in darker public spaces (OR = 0.73) and among men (OR = 3.99). Finally, the likelihood of drinking alcohol in private places was associated with all three investigated contextual characteristics. In private, alcohol use was more likely with increased loudness (effect found in all three sources), with higher attendance (participants and algorithm), and reduced brightness (algorithm). Additionally, drinking in private was found to be more likely among men (participants) and older participants (all three sources). Interestingly, no effect of the number of prior drinks consumed was found.

6.4 Discussion

The overall purpose of this paper was to investigate how a select set of contextual characteristics assessed by the in-situ actors, external human observers (annotators), and computer algorithms are associated with the consumption of alcohol in different nightlife settings. Data were collected by means of a custom-built smartphone application recording in-the-event reports of alcohol use, location attended, brightness, loudness and attendance level from study participants, as well as 10-second panoramic video clip of the drinking environment. Videos were recorded at the same time as drinks were consumed, meaning the video clips provided researchers with drinking context data of a high ecological validity, that could later be extracted by external annotators and computer algorithms. Using a ubiquitous data collection method also enabled documentation of a large diversity of locations, including private places that are normally inaccessible to researchers for conducting in-situ observation.

Table 6-3: Multilevel logistic regressions estimating the contribution of contextual features and person-level characteristics to the likelihood of consuming alcoholic drinks in different settings, separately per data source

	Commercial venues (e.g., pubs, nightclubs)			Public spaces (e.g., streets, parks, travelling)			Private places (e.g., homes)		
	Participants	Annotators	Algorithms	Participants	Annotators	Algorithms	Participants	Annotators	Algorithms
	OR (95%-CI)	OR (95%-CI)	OR (95%-CI)	OR (95%-CI)	OR (95%-CI)	OR (95%-CI)	OR (95%-CI)	OR (95%-CI)	OR (95%-CI)
Situation level									
Brightness	0.70* (0.52-0.94)	0.59 (0.33-1.06)	0.62 (0.37-1.03)	0.73** (0.58-0.92)	0.59 (0.29-1.22)	0.66 (0.36-1.22)	1.09 (0.91-1.31)	0.83 (0.55-1.24)	0.64* (0.42-0.98)
Loudness	1.49** (1.14-1.94)	2.70* (1.23-5.92)	1.43 (0.70-2.92)	0.85 (0.60-1.20)	2.39* (1.20-4.78)	1.30 (0.56-3.04)	1.86*** (1.53-2.26)	2.97*** (1.83-4.84)	2.50*** (1.60-3.92)
Attendance	0.99 (0.94-1.04)	0.96 (0.89-1.03)	1.02 (0.98-1.07)	1.13* (1.03-1.24)	0.90 (0.77-1.05)	0.96 (0.89-1.03)	1.09** (1.03-1.15)	1.15 (0.92-1.42)	1.18** (1.05-1.33)
Prior drinks	1.11 (0.95-1.30)	1.09 (0.86-1.37)	1.14 (0.92-1.41)	1.11 (0.87-1.43)	1.08 (0.78-1.50)	1.09 (0.82-1.44)	1.08 (0.96-1.22)	1.05 (0.89-1.23)	1.07 (0.89-1.29)
Participant level									
Sex	0.87 (0.42-1.80)	1.75 (0.74-4.15)	1.35 (0.63-2.88)	3.99* (1.24-12.85)	1.69 (0.34-8.48)	1.61 (0.34-7.71)	2.25* (1.14-4.46)	1.86 (0.85-4.04)	2.07 (0.93-4.60)
Age	1.17 (0.99-1.38)	1.16 (0.93-1.45)	1.13 (0.92-1.38)	1.05 (0.81-1.37)	1.46* (1.03-2.08)	1.36 (0.98-1.90)	1.19* (1.03-1.37)	1.21* (1.03-1.42)	1.26** (1.07-1.50)
R-square									
Situation level (SE)	0.17* (0.08)	0.24* (0.11)	0.13 (0.08)	0.20 (0.10)	0.23* (0.11)	0.12 (0.09)	0.35 (0.08)***	0.40 (0.08)***	0.44*** (0.09)
Participant level (SE)	0.08 (0.07)	0.24 (0.27)	0.34 (0.79)	0.10 (0.08)	0.16 (0.12)	0.12 (0.11)	0.11* (0.05)	0.29 (0.12)	0.26* (0.13)

Note: * p < .05; ** p < .01; *** p < .001; CI = confidence interval; SE = standard error

6.4.1 Convergence of data sources

The first part of the analysis aimed at comparing the ratings of brightness, loudness, and attendance from participants, annotators, and computer algorithms in general, and in different types of locations (e.g., bars, nightclubs, restaurants, public parks, and homes). Differences in raw ratings (e.g., algorithm attributed higher loudness levels than the other sources) suggest that neither algorithms, despite correcting brightness and loudness levels to human perception abilities, nor external annotators can substitute for the actors' in-situ experience of any given situation in absolute terms. In relative terms however, the patterns of bivariate associations across contextual features and the ratings order per location type (e.g., loudness: nightclubs > pubs > travelling > private places) were very similar across all three sources. These results suggest that videos, generally, adequately captured relevant contextual features (as these were experienced by the participants) and that all three sources are partly interchangeable for correlational and regression analyses. Results therefore rebut an adaptation of the actor-observer asymmetry theory (Jones & Nisbett, 1987) to the relative perception of the context, over and above the fact that absolute (raw) levels might differ across sources of observations. This has important implications for future research on context-dependent behaviors. Unless researchers are primarily interested in absolute ratings of contextual characteristics (e.g. loudness level under a defined threshold in decibels), future studies might collect contextual data via sensors to reduce participant burden (Carpenter et al., 2016) and limit participants' self-reports either for subjective data or for contextual characteristics that cannot be documented in another way. Additionally, the high correlations between annotators' and algorithms' ratings suggest that part of the research cost, burden, and privacy issues may be alleviated by using algorithmic analyses for extracting basic information from videos rather than annotators. In order to strictly preserve participants' privacy and ensure data protection, future studies might, for example, embed the extraction algorithms directly in the data collection application, so that only processed results, rather than raw content, will be accessible to the research team.

Because of the innovative and exploratory nature of this study, we did not anticipate such contrasting associations between absolute and relative ratings. The present results highlight the complexity of collecting meaningful data on the association between context and drinking behaviors depending on the specific advantages and limitations of each data sources. In this respect, several noteworthy differences of ratings across sources shall be considered by future studies. Systematic differences may relate to technical and measurement impediments. For example, unlike participants, results showed that annotators and algorithms almost never selected the highest score for brightness. The algorithm almost exclusively rated nightclubs as dark or very dark, while participants reported the opposite in about 40 percent of the cases. This discrepancy can be explained by the different ways smartphone cameras and human eyes function. With increasing brightness, camera sensors adapt by increasing contrast. Consequently, very bright environments might appear moderately bright in videos (Wanat & Mantiuk, 2014). Conversely, the human eye adapts to dark conditions (Winn et al., 1994), which might explain why the algorithms rated nightclubs, streets, and parks as mostly dark very or dark, while several participants reported them as being relatively bright. As another example, the algorithm tended to rate the context as louder than humans (participants and annotators). This might be explained by the fact that the audio sensors capture very high energy sounds that are not accounted for by the human reporters, but were accounted for by algorithms.

Differences between participants' and observers' ratings may also result from the conditions in which participants recorded the videos. Participants may have provided biased representations of the situation by, for example, standing close to loudspeakers, talking while recording in a silent place, or recording videos in another place than the one described in the in-situ questionnaire (e.g. chill-out room of a nightclub). They might also have not complied with the instructions on how to record the video, e.g., by failing to record a 360-degree panorama or focusing more on bright or dark zones. Occasional unintended intervention or lack of compliance to instructions appears likely given the high consistency between annotators' and algorithms' ratings. To ensure that participants provide material that is representative of their environment, future research might analyze the brightness and loudness levels of the videos as soon as they are recorded and warn the user whenever these levels do not correspond to their description.

6.4.2 Contextual correlates of alcohol use

The second aim of the study was to investigate how variations in brightness, loudness, and attendance identified by the participants, annotators, and algorithms relate to whether alcohol is consumed. The results notably corroborate previous evidence showing that increased odds of drinking alcohol are associated with larger numbers of people present based on participants' reports (Labhart, Anderson, et al., 2017; Labhart et al., 2014; Thrul & Kuntsche, 2015), as well as with higher levels of loudness in pubs and nightclubs from an external observer's perspective (Guéguen et al., 2008; Hughes, Quigg, Eckley, et al., 2011). Although the study design does not allow to determine whether participants choose to attend darker venues for drinking or whether changes in the venues context influenced the choice to order an alcoholic drink, the consistent associations between characteristics physical context and alcohol use have implications for public health. In the same way that alcohol use was experimentally proven to increase with music loudness levels (Guéguen et al., 2004, 2008), this study suggests that manipulating brightness level might influence alcohol use. Therefore, similarly to policies regulating maximum loudness levels in nightclubs and events to prevent hearing loss (World Health Organization, 2015), minimum brightness levels might be implemented and evaluated to determine if those could constitute an effective structural prevention measure to reduce alcohol intoxication and related harms.

The present study also extends the existing literature by providing detailed and systematic results on contextual characteristics outside of commercial venues. Among all location types investigated, the interplay between contextual characteristics and drinking was particularly evident in private places. The findings that private places were louder -and darker according to algorithms- when alcohol was consumed, suggest that people prepare their homes when drinking on a weekend night e.g., by moving furniture, manipulating lighting, and changing the music type and volume. In fact, unlike commercial venues and public spaces, private settings can be configured by their users (Lincoln, 2012) by manipulating the attributes of the place depending on the number of attendees and the planned activities. This echoes previous evidence that young adults intentionally choose locations where they can play the music they like and host enough people to socialize when drinking off-premise before going out (Labhart & Kuntsche, 2017).

6.4.3 Limitations and challenges of assessing event-level contextual characteristics

Over and above the impediments of the data collection procedure previously mentioned, some limitations of the current analyses should be acknowledged. First, although the study is based on multiple reports per participant and per type of location, results do not provide evidence on whether the investigated contextual characteristics increase the likelihood of drinking or are the consequence of it, and thus should not be interpreted as causal relations. Second, annotators worked in uncontrolled conditions, probably with self-set screen brightness settings and audio rendering devices. This may have caused some variations in conditions between annotation sessions within and between annotators. Third, the study focused on basic contextual features that could easily be annotated by external observers and identified by computer algorithms from a short video clip. This approach de facto excluded many aspects that have also been shown to influence drinking behaviors at the event level, such as cognitions of the drinker, alcohol consumption and characteristics of those around the drinker including friends, colleagues and the gender composition of the drinking group. Unfortunately, these aspects could not easily and reliably be identified by computer vision algorithms.

While questionnaire-based ecological momentary assessment studies generally request participants document their behavior within several minutes or hours (Kuntsche & Labhart, 2013b; Stevely et al., 2019; Witkiewitz et al., 2012), a major asset of recording contexts in videos is to force participants to provide an instant snapshot of the momentary circumstances. Thus, this study has the advantage of collecting behavioral and contextual data at the very *event* level, namely, the exact same time and space as the event of interest, enhancing, therefore, the ecological and internal validity of the findings. Yet, qualitative feedback after the seventh week of the app-fieldwork revealed that recording panoramic videos clips was not an ordinary action for young adults on weekend nights (Truong et al., 2019). While recording selfies might be common on nights out, intentionally filming the location and the people present could be perceived as intrusive and burdensome by some participants (Labhart et al., 2020). To keep response burden as low as possible, we, for example, requested participants take videos only when they changed location rather than for every drink consumed, and future research should also consider the balance between data quantity and participant burden (Labhart et al., 2020).

6.5 Conclusions

This study explored the feasibility of collecting diverse data on the physical and social characteristics of drinking occasions at the event level, and examined how contextual features, assessed by either participants, annotators or computer algorithms, relate to alcohol use. The results showed that this could reliably be achieved by requesting participants record a 10-second video clip of their context whenever they had a drink, and annotate those using either human annotators or algorithms. In terms of methods, this study showed that, despite differences in raw ratings, annotators' or algorithms' ratings might serve as substitute to participants' in-situ impressions for correlational and regression analyses. In terms of public health, findings that the consumption of alcohol in private places and in commercial venues is associated with reduced brightness and increased loudness might serve as a foundation for structural prevention measures to reduce alcohol intoxication and related harms.

6.6 Acknowledgements

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Chapter 7

Development and Validation of the Predrinking Motive Questionnaire (PMQ) [6]

Abstract

Elaborating on instruments for U.S. university students, we developed and validated the predrinking (drinking before going out) motives questionnaire (PMQ) for general populations of young adults. In popular nightlife areas in Switzerland, 316 predrinkers aged 16-25 (48% women) were recruited. Focus group interviews and exploratory and confirmatory factor analyses yielded a three-factor measure, with a structure that was invariant across linguistic regions, gender, age and student status. 'Fun/intoxication' motives were associated with predrinking but 'conviviality' and 'facilitation' motives were not. Men scored higher on 'facilitation' than women and those from the French-speaking region scored higher on 'conviviality' than German-speaking participants. Although yet to be replicated in other countries, the PMQ appears to be an appropriate general measure of predrinking motives.

[6] Labhart, F. & Kuntsche, E. (2016). Development and Validation of the Pre-drinking Motive Questionnaire. *Journal of Applied Social Psychology*, 47(3), 136-147. https://doi.org/10.1111/jasp.12419

7.1 Introduction

Drinking in private settings before going to a public drinking establishment such as a bar or nightclub or to a social engagement such as a sporting event or a music concert, known as “predrinking”, “preloading”, “prepartying” or “pregaming” (Pedersen & LaBrie, 2007; Wells et al., 2009a), is a widespread phenomenon among young people in most regions of the world including North America (Merrill et al., 2013; Wells et al., 2015; Zamboanga et al., 2011), South America (Santos et al., 2015), Europe (Hughes, Quigg, Bellis, et al., 2011; Labhart et al., 2013; Østergaard & Skov, 2014; Wahl et al., 2013) and Oceania (MacLean & Callinan, 2013; McCreanor et al., 2016; Peacock et al., 2016). Different aspects of this particular drinking behaviour have been documented in each region but the practice of predrinking appears to be universally associated with increased alcohol consumption during the evening and a higher risk of experiencing negative consequences, including alcohol poisoning, drunk driving and blackouts (see Foster & Ferguson, 2014 for a review).

Young people were found to have particular motives for engaging in predrinking. Some of these are associated with the act of drinking and its inebriation and disinhibition effects in relation to what will happen after predrinking. For example, US university students most frequently endorsed ‘to save money’, ‘to get a buzz before going out’, and ‘because it makes going out more fun’ as reasons for predrinking (Pedersen et al., 2009; Read et al., 2010). To a lesser extent, predrinking was also found to be motivated by a desire to ‘reduce social anxiety’ when arriving at a later event, as well as serving as a ‘social lubricant’ at a later event and making it easier to ‘hook up’ with a sexual partner (DeJong et al., 2010; Pedersen et al., 2009). In addition, engagement in predrinking was shown to be motivated by contextual factors that are not primarily related to the consumption of alcohol, among which socialisation appears central. For example, 19% of Australian nightlife-goers were motivated by the ‘chance to catch up with friends’ (Miller et al., 2016), while 31% of Canadian college students reported a desire to spend time with close friends before going somewhere where encounters would be more superficial (O’Neil et al., 2016).

Two comprehensive instruments have been developed to measure predrinking motives among U.S. college students. The Pregaming Motives Measure (PGMM) developed by Bachrach and colleagues (2012) includes three dimensions:

“inebriation/fun” (e.g. ‘to get drunk at a more accelerated pace’), “social ease” (e.g. ‘to feel less anxious at the event) and “instrumentality” (e.g. ‘fraternities do not supply enough alcohol at parties’). The inebriation/fun and instrumentality subscales were associated with predrinking in the past 30 days, while social ease was associated with alcohol-related consequences. The Prepartying Motivations Inventory (PMI) developed by Labrie and colleagues (2012) includes four dimensions: “interpersonal enhancement” (e.g. to ‘pump myself up to go out’), “situational control” (e.g. ‘to enjoy my favourite drink in case the place I’m going does not serve that drink’), “intimate pursuit” (e.g. ‘to increase the likelihood of hooking up’) and “barriers to consumption” (e.g. ‘because I am underage and cannot purchase alcohol at the destination venue’). All four PMI subscales were positively correlated with predrinking frequency and typical number of drinks consumed during predrinking.

Despite the important contribution of these two instruments, several cultural and contextual issues make the direct use of the PGMM and the PMI outside North America difficult. First, both instruments were developed in the US where the legal drinking age is 21, whereas in Europe, Australia, New Zealand and Canada, the legal drinking age is at most 19 for all alcoholic beverages and as low as 16 for beer and wine (World Health Organization, 2014). Consequently, engagement in predrinking in these countries is unlikely to be motivated by a fear of legal sanctions or the anticipation of not being able to obtain alcoholic beverages when they go out. While confirming the PMI structure among young Canadian college students (mean age = 20.3), O’Neil and colleagues (2016) noted that the item related to underage drinking was irrelevant for these students, and also that three of the four dimensions were hardly mentioned at all in open-ended questionnaires (4% mentioned motives that could be categorised as “barriers to consumption”, 2% “situational control” and 0% “intimate pursuit”). Instead, 54% reported motives related to “monetary concerns”, 31% “socialisation”, 22% “intoxication”, 11% “peer influence” and 10% “boredom relief”. Secondly, unlike research on predrinking outside North America which largely focuses on general populations of nightlife-goers (Foster & Ferguson, 2014), the two instruments were developed using samples of university students only. Predrinking motives identified were therefore likely to be influenced by specific features of the North American university system and drinking cultures such as being a member of sororities, fraternities or sports clubs (Turrisi et al., 2006).

However, such features are uncommon in Europe (Wicki et al., 2010) and are irrelevant for the majority of young adults not attending university.

The purpose of this study was to develop and validate a predrinking motives questionnaire (PMQ) designed for the general population of young adult nightlife-goers. In countries where drinking is legal for young people and can happen in many other contexts than private settings, it is important to understand why young people choose to drink specifically at home or in a park prior to going out. Over and above the effects of alcohol, predrinking might be motivated by context-specific characteristics of private settings that differ from those of licensed venues.

To account for differences in drinking cultures, the study was conducted in both the French and German-speaking regions of Switzerland. Located at the centre of Europe, Switzerland is distinguished by the fact that it represents different facets of European drinking cultures (Mäkela, 1983; Room & Mäkelä, 2000) within one country (Fahrenkrug & Gmel, 1998; Mäkelä et al., 2006). The French-speaking region, traditionally a wine-producing area, used to be influenced by the 'Mediterranean' drinking culture (i.e. consumption of alcohol being part of a larger culinary culture including frequent but moderate consumption with food), whereas drinking habits in the German-speaking region, traditionally a beer-brewing area, were characterised by less frequent but more excessive consumption of beer. Nowadays, alcohol consumption remains more frequent in the French-speaking region and the proportion of wine consumed is higher than in the German-speaking part (Gmel et al., 2012).

Finally, motives for predrinking might share some common features with motives for drinking in general. The Motivational Model of Alcohol Use (MMAU: Cox & Klinger, 1988, 1990)categorises general drinking motives by valence (positive or negative reinforcement) and source (internal or external). Crossing these two dimensions, the Drinking Motive Questionnaire Revised (Cooper, 1994) measures four distinct motive categories: social (positive, external; e.g. 'to make social gatherings more fun'), enhancement (positive, internal; e.g. 'to get high'), coping (negative, internal; e.g. 'to forget about problems') and conformity (negative, external; e.g. 'to fit in with a group'). However, previous studies provided conflicting evidence. Whereas all subscales of the PGMM were positively correlated with all DMQ-R dimensions, none of the PMI subscales were significantly correlated.

The first aim of the present study was to derive a culturally appropriate list of reasons for predrinking and to investigate their underlying factor structure by means of focus group interviews. The second aim was to confirm the factor structure in general and across linguistic regions, genders and age groups using confirmatory factor analysis (CFA). The third was to test the links between the emerging predrinking dimensions and those of the general drinking motives.

7.2 Methods

7.2.1 Selection of culturally appropriate items

A convenience sample of Lausanne university students was recruited using snowball sampling for participation in a focus group interview on predrinking behaviour. The participants – three men and five women aged between 21 and 32 – had all been regular nightlife-goers for many years (age of nightlife onset: mean = 16.0; SD = 1.3) and had ample experience of predrinking (age of predrinking onset: mean = 18.5; SD = 2.4). At the time of the focus group interview, they were engaging in predrinking about 2.6 times per month (SD = 2.5) and 58% of their nights out started with predrinking. The aims were (a) to discuss the relevance and cultural appropriateness of each item used in the PGMM and PMI (Bachrach et al., 2012; LaBrie et al., 2012), (b) to select the items which match the participants' personal predrinking experiences and (c) to develop an additional list of culturally appropriate motive items.

7.2.2 Development and validation of the PMQ

The 24 items selected at Stage 1 (Table 8-1) were included in the baseline questionnaire of a larger study which used an Android smartphone application to collect event-level data on young people's nightlife behaviour by means of questionnaires, pictures, videos and sensors such as GPS, accelerometers and Bluetooth (Santani et al., 2016). Participants were required to document their behaviour on at least 10 Friday or Saturday nights over seven consecutive weekends to receive an incentive of CHF 100 (approximately GBP 70).

Participants were recruited in the cities of Lausanne and Zurich, the two major nightlife hubs in the French-speaking and German-speaking regions of Switzerland, respectively. The recruitment strategy combined a proportional-to-size selection of popular nightlife areas in both cities, based on social network data and local experts' recommendations, with the 'fixed line' street intercept method (Graham et al., 2014). Over the first three weekends of September 2014, on Friday and Saturday nights from 9 to 12 p.m., groups of two to four recruiters were positioned in the defined nightlife areas and approached small groups or individuals in accordance with a systematic criterion (every n^{th} person crossing a virtual line on the street). Eligibility criteria were being aged between 16 and 25, having consumed alcohol at least once in the past month, having been out in the city at least twice in the past month and owning a smartphone with the Android operating system. A maximum of two individuals were recruited within the same group to avoid representativeness sampling biases. Having given their email address to the recruiters, the participants were automatically sent an email containing a link to the online consent form which had to be approved before accessing the baseline questionnaire. The study protocol was approved by the Lausanne and Zurich cantonal ethics committees for research on human beings (protocol 145/14).

7.2.3 Sample

In total, 3,092 people were approached in both cities. Of those, 1,119 (36%) did not have an Android smartphone, 859 (28%) were not interested in the study and 233 (8%) were outside the required age range. Of the 881 who agreed to participate, 629 (71%) signed the online consent form and 367 completed the baseline questionnaire (58%; mean age=19.1, SD=2.4; 48% women; 55% in Lausanne). Whenever possible, the age and gender of the people approached were recorded. Participants in the baseline questionnaires were slightly younger than the rest of the pool of people approached (mean age = 19.8, SD = 3.6; $t_{(1372)} = 3.90$; $p < .001$) but their gender ratio was similar (47% women, $\chi^2_{(1,\, N = 2320)} = 0.10$, $p = .76$). The present analysis uses data from the 316 participants (86%) who reported predrinking at least 'some of the time' (see Measures section below) and therefore completed the items on predrinking motives. Of those, 123 (39%) were working full or part-time, 81 (26%) were secondary school students and 96 (30%) were university students. The sample of predrinkers was slightly older in Lausanne than in Zurich (mean age: 19.6 (SD = 2.6) vs. 18.9 (SD = 2.2); $t_{(314)} = 2.46$, $p = .01$) whereas the proportion of women was similar (52% vs. 43%; $\chi^2_{(1,\, N = 316)} = 2.71$, $p = .10$).

7.2.4 Measures

Gender, *age,* and the following measures were recorded in the baseline questionnaire. Several steps of back-and-forth translation ensured that the French, German and English versions were equivalent.

University student status was assessed on the basis of the highest level of education attained (e.g. compulsory education, high school, bachelor's or master's degree) and current occupation (e.g. working full-time, student, apprentice). For the present analysis, university students (i.e. educational level attained: high school or higher; occupation: student) were compared with the rest of the sample.

Frequency of going out was assessed using a summary score of participants' answers to the following questions: "How often do you go out in [the city of recruitment] on weekend nights (pubs, night clubs, restaurants, cinemas, etc.)?" and "How often do you go out in other cities on weekend nights?" For both questions, response options were coded to represent a 30-day frequency measure: 'never' (coded as 0), 'one night per month or less' (0.5), 'one night every two weekends' (2.1), 'one night per weekend' (4.3) and 'two nights per weekend' (8.6).

Relative frequency of predrinking was assessed with the question: "When you go out at the weekend, how frequently do you drink alcohol prior to going out ('predrinking', 'pregaming', 'prepartying' or 'preloading')?" Response options were 'never' (coded as 0%), 'some of the time' (25%), 'half of the time' (50%), 'most of the time' (75%) and 'always' (100%).

The 24 *predrinking motive items* generated at stage 1 were shown to the 316 participants who reported predrinking at least 'some of the time'. Participants were asked: "Thinking back to the times over the last 12 months when you 'pre-drank' or 'pre-gamed' on a weekend evening before going out, please state how often you did this for the following reasons...". Each item had to be rated on the following relative frequency scale: 'never' (coded as 1), 'rarely' (2), 'sometimes' (3), 'often' (4) and 'always' (5).

General *drinking motives* were assessed with the DMQ-R SF (Kuntsche & Kuntsche, 2009), which is a 12-item self-report measure of the relative frequency of drinking for enhancement, social, conformity and coping motives in the last 12 months. Each item had to be rated on a relative frequency scale, ranging from 'never' (coded as 1) to 'always' (5). For each dimension, the 3 items were added up to form a summary score (total sample: Cronbach's $\alpha_{enhancement}$ = .78, α_{social} = .80, $\alpha_{conformity}$ = .76, α_{coping} = .85).

7.2.5 Analytic strategy

Two random subsamples were created, one for selecting items generated at Stage 1 and attributing them to factors by means of exploratory factor analysis (EFA) and one for validating this factor solution by means of confirmatory factor analysis (CFA) and structural equation modelling (SEM). To prevent selection bias during the random-split, participants were first allocated to eight subgroups based on three dichotomous criteria: linguistic region (French-speaking vs. German-speaking), gender (men vs. women) and age (median split: 16-18 vs. 19-25). Then, in each subgroup, about one-third of participants was randomly assigned to the EFA sample (N = 95, 30%) and two-thirds were assigned to the CFA sample (N = 221, 70%). Both subsamples were similar in terms of linguistic region (57% vs. 53% from the French-speaking area, $\chi^2_{(1,\, N = 316)}$ = 0.41, p =.52), gender ratio (45% vs. 49% women; $\chi^2_{(1,\, N = 316)}$ = 0.35, p =.56), age (45% vs. 45% aged 16 to 18; $\chi^2_{(1,\, N = 316)}$ = 0.01, p = .94), proportion of university students (30% vs. 31%; $\chi^2_{(3,\, N = 316)}$ = 0.44, p = .44) and relative frequency of predrinking (0.63 vs. 0.67, $t_{(314)}$ = -0.59, p = .56).

7.2.5.1 Exploratory factor analysis

Bartlett's test of sphericity and the Kaiser-Meyer-Olkin measure of sampling adequacy were used to assess the factorability of the correlation matrix (Worthington & Whittaker, 2006). A significant value from the Bartlett's test and a Kaiser-Meyer-Olkin value of .6 or higher were required to conduct the analysis (.6 or higher required: Tabachnick & Fidell, 2007). Subsequently, EFA was used to select items from the item pool created at Stage 1 and to group them according to factors based on their shared variance. Due to the ordinal nature of the variables, weighted least squares means and variance-adjusted (WLSMV) estimation was used in the analysis (Schmitt, 2011). The oblique Geomin rotation was chosen since it is more appropriate for correlated factors and offers a good compromise between factor complexity and interpretability (Sass & Schmitt, 2010).

To select the most relevant factor structure, the χ^2-value of the model fit was used in two ways – to ensure a sufficient fit of the specified x-factor model in comparison with (a) the empirical data and (b) the next more complex (x+1)-factor model. A *p*-value larger than .05 indicated (a) an insufficient fit of the model in general compared with the empirical data and (b) that a more complex model would not provide a better representation of the data (parsimony principle).

The following criteria were used to reduce the number of items: (a) items not loading sufficiently on any factor (i.e. .4 or higher: Jöreskog & Sörbom, 1993) were removed, (b) cross-loading items were removed in order to prevent factor inter-correlations and improve the simplicity of the factor structure (Worthington & Whittaker, 2006), and (c) factors with fewer than three items were removed (Tabachnick & Fidell, 2007).

7.2.5.2 Confirmatory factor analysis

CFA, conducted in the second subsample using WLSMV estimation, was applied in order to validate the factor structure resulting from the EFA. To evaluate model fit, a root mean square error of approximation (RMSEA) of lower than .05 was indicative of excellent fit, between .05 and .08 of adequate fit and higher than .08 of poor fit. Similarly, comparative fit index (CFI) and Tucker-Lewis index (TLI) values of higher than .95 were indicative of excellent fit, between .95 and .90 of adequate fit and lower than .90 of poor fit (Hooper et al., 2008; Hu & Bentler, 1999). Internal consistency of the items included in each predrinking motive factor was assessed using Cronbach's α, where values greater than or equal to .7 were considered to be acceptable (Nunnally & Bernstein, 1994).

Comparisons of nested CFA models were used to ascertain (a) that less complex models (i.e. items of any two factors constrained to load on the same factor) do not represent the empirical data as well as or better than the final three-factor model and (b), by means of multiple-group CFA, that the final three-factor model fits the data equally well in subgroups characterised by linguistic region, gender, age and university student status. The comparisons of model fit in nested models were conducted with the Mplus DIFFTEST option for WLSMV estimation using scaling correction to better approximate chi-square under non-normality (Muthén & Muthén, 2015). A significant χ^2 difference signifies that the fit of the constrained model (i.e. with less freely estimated parameters and more degrees of freedom) is significantly worse than the unconstrained model.

7.2.5.3 Mean differences

Adjusted for region, gender and age differences, intra-individual differences in the hierarchy of motives endorsement were tested using 2 (region) × 2 (gender) × 2 (age [16-18 vs. 19-25]) × 3 (motive dimensions) mixed model analysis of variance (ANOVA). Inter-individual differences in the mean scores of each motive factor across linguistic region, gender, age and university student status were tested using independent sample t-tests.

7.2.5.4 Links to predrinking behaviour and general drinking motives

Multiple linear regressions were used to regress PMQ subscales on general drinking motives (DMQ-R SF). This procedure was preferred to pairwise correlations due to the known collinearity between general drinking motives (Gmel et al., 2012). Finally, a region, gender and age-adjusted SEM was estimated to test the association of the PMQ dimensions (latent factors as independent variables) with the frequency of going out and the relative frequency of predrinking (as dependent observed variables).

Bivariate analyses and ANOVA were performed using SPSS 21 (IBM Corp, 2012). EFA, CFA and SEM were carried out with Mplus 7.4 (Muthén & Muthén, 2015).

7.3 Results

7.3.1 Selecting culturally appropriate items

In the focus group interviews, 16 items from the two previous instruments were retained or rephrased and eight new items were added (Table 7-1). Some items from the previous instruments were dropped because of: (a) the difference in the legal drinking age (the legal age for purchasing beer and wine in Switzerland is 16; e.g. PMI item 14: “because I am underage and cannot purchase alcohol at the destination venue”), (b) the irrelevance of student associations (e.g. sororities or fraternities) in the general population of young people (e.g. PGMM item 12: “fraternities do not supply enough alcohol at parties”), and (c) the irrelevance of items focusing only on events occurring after predrinking (e.g. PMI item 3: “to meet new friends once I go out”), because the focus group participants considered predrinking as a drinking occasion in its own right, independently of the kind of event or circumstances that might happen later that night.

The new items related to the context and atmosphere of predrinking (items 5, 9, 13 and 17) and to the possibility of combining predrinking with eating (items 3 and 4). Moreover, the item “to go out while already being a little bit drunk” (item 20) was added to the item “to go out while already being properly drunk” (item 21) because the focus group participants mentioned that intoxication was not necessarily their goal.

Table 7-1: Source of items selected at Stage 1 and factor loadings of the initial four-factor model

Item no.	Source	F1	F2	F3	F4
1. To have a good time with friends	c	**.626***	**.481***	.013	-.321*
2. To start the night earlier	b	**.520***	**.401***	-.016	-.060
3. Because you can eat snacks (e.g. crisps, peanuts) while you are drinking	a	-.206	**.658***	.089	-.065
4. I usually have a drink or two (wine, beer) when I'm eating before going out	a	-.073	.347*	.090	.185
5. Because we can chat in a quiet environment, while nightlife venues are usually noisy	a	-.013	.360*	.345*	.046
6. It is the normal way to start an evening	c	**.604***	.097	.318*	-.027
7. To get drunk quickly	b	**.744***	-.192	.048	.288*
8. Because it makes the rest of the evening more fun	c,e	**.695***	.329*	-.022	.019
9. To have enough space to all be together	a	-.018	**.596***	.313*	.013
10. To spend less money on alcoholic drinks	b	**.566***	-.111	.325*	-.053
11. To get into a party mood	c	**.759***	.140	.063	.059
12. Because I got invited	a	.040	.101	**.437***	-.028
13. Because the location is pleasant, enjoyable	a	.018	.018	**.918***	.002
14. To take part in drinking games	c	.334*	.373*	.063	-.010
15. To meet new people	e	.079	**.664***	-.088	.324*
16. Because I cannot drink alcohol during the rest of the evening	c,e	-.107	-.030	.204	**.662***
17. Because we can listen to the music we like	a	-.068	**.637***	.227*	.021
18. Because we can drink alcoholic drinks/self-mixes/cocktails that are not served in the bars	c,e	.086	.287*	.280*	.085
19. To relax before going out	b,d	.076	**.677***	.037	.080
20. To go out while already being a little bit drunk	a	**.786***	-.012	-.052	.208*
21. To go out while already being properly drunk	b	**.793***	-.016	-.073	.257*
22. To increase self-confidence before going out	d	.043	.168	-.030	**.648***
23. Because it helps for hitting on someone, flirting or being charming	b,d	-.002	.317	.001	**.712***
24. To be able to cope with the downsides of nights out more easily (queuing, etc.)	c	.127	.035	.322*	**.537***

Notes: N = 95;
a) new item from the focus groups; b) identical item from the Pregaming Motives Measure (PGMM: Bachrach et al., 2012); c) rephrased item from the PGMM;
d) identical item from the Prepartying Motivations Inventory (PMI: Labrie et al., 2012); e) rephrased item from the PMI;
* significant at 5%-error level;
bold: loading > .4

7.3.2 Exploratory factor analysis

Both Bartlett's test of sphericity ($\chi^2_{(276)} = 1041.0$, $p < .001$) and the Kaiser-Meyer-Olkin index value (.801) supported performance of the analysis. Examination of the model fit indicated that both the four and the five-factor solutions were satisfactory (Table 7-2). However, the χ^2-difference test between the four and the five-factor solutions was not significant, indicating no further improvement in model fit. Following the parsimony principle, the four-factor solution was chosen to start the process of examining the dimensions and deleting potentially irrelevant items.

Table 7-2: Results of the exploratory factor analysis (EFA) models

	Model fit			Comparison with previous model		
	χ^2	df	p	$\Delta\chi^2$	df	p
1 factor	557.5	252	<.001			
2 factors	348.3	229	<.001	140.5	23	<.001
3 factors	254.9	207	.013	78.0	22	<.001
4 factors	216.7	186	.061	38.1	21	.012
5 factors	192.8	166	.076	26.9	20	.138

Note: N = 95; df = degrees of freedom

Examination of the factor loadings of the four-factor solution revealed that the number of items and the number of factors could be reduced since (a) four items (items 4, 5, 14 and 18) had factor loadings below .4 on all four factors, (b) two items (1 and 2) had prominent cross-loadings on the first and second factors and (c) only two items (12 and 13) loaded on the third factor. Item 20 was also removed since it loaded on the same factor as item 21 and therefore did not provide additional information as regards a potential difference between being 'a little bit' vs. being 'properly' drunk. Consequently, a three-factor solution with 15 items was retained for further consideration using CFA. After examination of the items' loading, the three factors were labelled as: '*fun/intoxication*', '*conviviality*' and '*facilitation*' (Table 7-4). Items in the fun/intoxication dimension describe predrinking as a low-cost way of maximising drunkenness at the beginning of the evening, with the effects of the alcohol consumed being expected to foster a positive mood over the entire night. Items in the conviviality dimension describe predrinking as an occasion for socialising in an appropriate atmosphere, and those in the facilitation dimension describe predrinking as a preparatory step which helps those concerned overcome shyness and alleviates adverse circumstances later in the evening.

7.3.3 Confirmatory factor analysis

Results from the CFA conducted on the second subsample showed that the three-factor model provided an adequate fit for the data (Table 7-3), which was significantly better than any of the two-factor models. Tests of equivalence of the PMQ model structure revealed that the three-factor structure fit the data equally well in both linguistic regions, for both genders, across age groups and among university students and other participants.

Table 7-3: Results of the confirmatory factor analysis (CFA) models, goodness-of-fit indices and comparison of the final three-factor model with one-factor-less models and grouped models

Type	Model fit						Comparison[a]		
	χ^2	*df*	*p*	CFI	TLI	RMSEA	$\Delta\chi^2$	*df*	*p*
Final three-factor model	174.1	87	<.001	.926	.911	.067	-	-	-
Two-factor models									
Factors 1&2 together	340.8	89	<.001	.787	.749	.113	52.3	2	<.001
Factors 2&3 together	297.4	89	<.001	.824	.792	.103	45.0	2	<.001
Factors 1&3 together	270.9	89	<.001	.846	.819	.096	39.6	2	<.001
Grouped by region									
Unconstrained	306.3	203	<.001	.918	.915	.068			
Factor loadings equal	298.2	215	<.001	.934	.936	.059	11.7	12	.470
Grouped by gender									
Unconstrained	295.4	203	<.001	.921	.918	.064			
Factor loadings equal	285.7	215	<.001	.940	.941	.055	7.6	12	.814
Grouped by age									
Unconstrained	290.3	203	<.001	.928	.925	.062			
Factor loadings equal	274.5	215	.004	.951	.952	.050	7.1	12	.850
Grouped by student status									
Unconstrained	295.4	203	<.001	.934	.932	.064			
Factor loadings equal	296.7	215	<.001	.942	.943	.058	15.4	12	.220

Note: N = 211;
[a] the differences between the absolute χ^2 difference of the constrained vs. the unconstrained model shown in the table and the value of the comparison $\Delta\chi^2$ are due to the scaling correction applied in the Mplus DIFFTEST option (see Methods section);
df = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation

All factor loadings were significant at $p < .001$ (Table 7-4). Items related to fun/intoxication were globally the most highly endorsed (subscale mean = 3.0), while items in the facilitation dimension received the lowest endorsement (mean = 1.7). Inter-factor correlations revealed significant associations, suggesting that the constructs were referring to conceptually different although related motivational dimensions. The internal consistencies were all above .7.

Table 7-4: Standardised factor loadings and means, correlations, reliabilities and means of the PMQ subscales

		Fun/intoxication	Conviviality	Facilitation	*M* (SD)
Items					
11.	To get into a party mood	.836			3.2 (1.1)
8.	Because it makes the rest of the evening more fun	.824			2.7 (1.2)
21.	To go out while already being properly drunk	.679			2.5 (1.3)
7.	To get drunk quickly	.602			2.1 (1.1)
6.	It is the normal way to start an evening	.595			3.0 (1.3)
10.	To spend less money on alcoholic drinks	.399			4.1 (1.0)
17.	Because we can listen to the music we like		.754		2.9 (1.3)
9.	To have enough space to all be together		.681		2.6 (1.3)
19.	To relax before going out		.652		2.4 (1.2)
15.	To meet new people		.651		2.6 (1.2)
3.	Because you can eat snacks (e.g. crisps, peanuts) while you are drinking		.426		2.3 (1.3)
23.	Because it helps for hitting on someone, flirting or being charming			.895	1.8 (1.1)
22.	To increase self-confidence before going out			.865	1.8 (1.0)
24.	To be able to cope with the downsides of nights out more easily (queuing, etc.)			.717	1.8 (1.1)
16.	Because I cannot drink alcohol during the rest of the evening			.369	1.6 (0.8)
Subscales					
Correlations:					
Fun/intoxication					
Conviviality		.276	-	-	
Facilitation		.404	.388	-	
Internal consistency (Cronbach's α)		.828	.733	.715	
Mean (SD)		3.0 (0.9)	2.6 (0.9)	1.7 (0.8)	

Note: N = 211; all factor loadings and correlations are significant at $p < .001$

7.3.4 Mean score comparisons

The 2×2×2×3 mixed model ANOVA revealed an intra-individual main effect for the predrinking motive dimensions ($F_{(2,434)} = 206.1$, $p < .001$), namely that participants scored highest for the fun/intoxication dimension followed by conviviality and facilitation. Inter-individual comparisons showed that conviviality motives were more strongly endorsed in the French-speaking part than in the German-speaking part of

Switzerland (Table 7-5). Additionally, endorsement of both fun/intoxication and facilitation predrinking motives was found to be higher among men than among women.

Table 7-5: Endorsement of the three PMQ subscales (means with standard deviation in brackets) by linguistic region, gender, age group and student status

	Fun/intoxication	Conviviality	Facilitation
Region			
French-speaking	2.93 (0.91)	2.81 (0.84)	1.66 (0.76)
German-speaking	3.00 (0.83)	2.25 (0.79)	1.81 (0.74)
	t = -.57, p = .57	t = 5.12, p < .001	t = -1.42, p = .16
Gender			
Male	3.12 (0.84)	2.63 (0.82)	1.87 (0.79)
Female	2.81 (0.88)	2.46 (0.90)	1.58 (0.68)
	t = 2.69, p = .01	t = 1.41, p = .16	t = 2.92, p < .01
Age group			
16-18	3.01 (0.94)	2.43 (0.87)	1.81 (0.75)
19-25	2.94 (0.82)	2.64 (0.85)	1.67 (0.75)
	t = .55, p = .58	t = -1.78, p = .08	t = 1.32, p = .19
Student status			
University student	2.87 (0.77)	2.66 (0.87)	1.69 (0.83)
Other	3.01 (0.91)	2.50 (0.85)	1.75 (0.71)
	t = 1.10, p = .27	t = -1.27, p = .21	t = .59, p = .56

Note: N = 211; degrees of freedom for all t-tests = 219

7.3.5 Associations with general drinking motives

Regression of the PMQ dimensions on the general drinking motives revealed different results for each dimension (Table 7-6). Social motives were associated with both fun/intoxication and facilitation predrinking motives. Additionally, enhancement motives were associated with fun/intoxication and conformity with facilitation. There was, however, no association between conviviality and general drinking motives.

Table 7-6: Predrinking motives (PMQ; in the columns) regressed on general drinking motives (DMQ-R SF; in the rows)

	Fun/intoxication	Conviviality	Facilitation
Social	.41***	.13	.44***
Enhancement	.28***	-.01	-.04
Coping	.09	-.00	.00
Conformity	.00	.06	.31***

Note: *** p < .001; standardised regression coefficients (ß) are shown

7.3.6 Associations with nightlife behaviours

Bivariate correlations revealed that all PMQ subscales were significantly correlated with the frequency of predrinking but only the fun/intoxication subscale was correlated with the frequency of going out (Table 7-7). Region, gender and age-adjusted regressions showed that the higher participants scored on the fun/intoxication motives, the more often they went out and the more frequently they engaged in predrinking. There was, however, no significant association for conviviality and facilitation-related motives.

Table 7-7: Correlations and multiple regressions of nightlife and predrinking frequency with the three PMQ subscales, controlled for region, gender and age

	Frequency of going out	Relative frequency of predrinking
Pairwise correlations		
Fun/intoxication (*r*)	.22 **	.57 ***
Conviviality (*r*)	.06	.24 ***
Facilitation (*r*)	.12	.20 **
Multiple regression		
Fun/intoxication (ß)	.24 **	.62 ***
Conviviality (ß)	-.02	.14
Facilitation (ß)	.00	-.17
Region	-.07	.03
Gender	-.02	-.11
Age group	-.07	.08

Note: N = 221; standardised regression coefficients (ß) are shown for multiple regressions; ** $p < .01$; *** $p < .001$

7.4 Discussion

The first aim of the present study was to develop and provide an initial validation of the Predrinking Motives Questionnaire (PMQ). While similar instruments have been developed among underage US university students (Bachrach et al., 2012; LaBrie et al., 2012), the PMQ was devised for the general population of young adult nightlife-goers. The three-step analytical approach included focus group interviews to draw up a list of reasons for predrinking, exploratory factor analysis to investigate the underlying factor structure of the PMQ and to remove inappropriate reasons, and confirmatory factor analysis to confirm the factor structure in general and across linguistic regions, genders and age groups.

The results revealed a three-factor solution related to aspects of the fun/intoxication, conviviality and facilitation dimensions. Seeking to have fun and to get drunk was the most commonly endorsed motivational factor for predrinking. The positive associations of fun/intoxication motives with the frequencies of predrinking and of going out suggest further that ‘fun/intoxication predrinkers’ see predrinking as a common way of getting drunk before or during a night out. The higher endorsement found among men concurs with the assumption that some young men like and actively seek the feeling of drunkenness when predrinking (Peacock et al., 2016) as well as other extreme sensations due to their extraverted, risk-seeking personality (Kuntsche et al., 2006) and that they apparently use predrinking as a way of attaining that goal. Since by definition it precedes another drinking event but does not replace the drinking at the later event (Hughes et al., 2008; Labhart et al., 2013; Miller et al., 2016; Wahl et al., 2010), predrinking for fun/intoxication-related reasons appears to be a particularly risky way of starting a night out in terms of the total amount of alcohol consumed and the related consequences.

Of the eight new items included in this study which were intended to represent more culturally appropriate reasons for predrinking, three remained in the PMQ and all three loaded onto the conviviality factor. In line with findings outside the US (McCreanor et al., 2016; Miller et al., 2016; O’Neil et al., 2016) and suggestions from focus group participants, the operationalisation of young adults’ motivations for socialising during predrinking and in a convivial environment appear to be among the PMQ’s main innovations in comparison with the PMI and the PGMM. Although it might appear trivial, item 17 “because we can listen to the music we like” had the highest factor loading and was the most endorsed item in the conviviality dimension. This appears important to the participants because, over the course of a night out, predrinking is the only time when they can create or choose their own drinking environment (e.g. the size of the place, the music played, the food available), which is later determined by the venues they go to. However, the mere fact that predrinking appears to be a particularly convivial drinking occasion does not mean that the ‘conviviality predrinkers’ in our sample pre-drank more frequently. One explanation is that predrinking is only one of various types of social drinking occasion. ‘Conviviality predrinkers’ might therefore occasionally meet directly at a nightlife venue (e.g. at a concert, in a pub or a nightclub) without predrinking. Conversely, they may also change their plan and, rather than going out, continue with the event in private at home or in a park, for example.

As with the instrumentality dimension of the PGMM and most items of the PMI, items in the facilitation motives dimension describe predrinking as a preparatory and facilitating stage for what will happen later in the evening. Like conviviality, facilitation motives were not associated with frequency of going out or predrinking, but may rather be linked to individual characteristics, such as introversion or a general lack of self-confidence, or to situational characteristics, such as attending events at which problems are expected or being a designated driver, which usually impedes alcohol consumption later in the evening. Scoring higher than women for this motive factor, men appear to be more attracted by the facilitation potential of predrinking, perhaps because they rely more often on alcohol for flirting or ‘hooking up’ (Abrahamson, 2004; Garcia et al., 2012; Pedersen et al., 2009). However, more research is clearly needed in order to come to firmer conclusions in this respect.

With regard to the second aim of the study, results revealed that the three-factor structure of the PMQ appropriately represented the empirical data and it was even found to be invariant across linguistic regions, gender, age groups and university student status. These results underline the PMQ’s stability in different settings and make us confident that it could be replicated in other countries and cultures in which alcohol consumption is legal for young people. Furthermore, a higher level of endorsement of conviviality motives was found in the French-speaking region of Switzerland. As a social drinking practice, conviviality-related predrinking should therefore be considered in the light of the larger cultural framework linking the act of drinking with social practices and traditions.

In relation to the third aim, we found a positive link between general enhancement motives and predrinking for fun/intoxication purposes, which involves aspects of fun or getting drunk quickly. Since this often occurs in a social context (e.g. to ‘get into a party mood’), the link with general social motives also is not surprising. Interestingly, predrinking for facilitation purposes was related to both general social and conformity motives. Given that these two motive categories refer to the instrumental use of alcohol in social contexts, facilitation predrinking appears to be used by young people to stand downsides of nights out, such as crowding, being chatted up or having to queue. Finally, the finding that conviviality predrinking was not associated with any drinking motives might be explained by the fact that these predrinking motives are mainly related to situational characteristics and thus not to the personality of the drinkers, which is closely linked to general drinking motives (Kuntsche et al., 2006).

Several limitations have to be kept in mind when interpreting these results. First, only one focus group of young adults was used to add culturally appropriate items to the initial pool of reasons for predrinking that was based on previous research. While the participants all had several years of experience with predrinking, we may have failed to include some potentially important items, particularly those relevant for adolescents. Secondly, the quantity of alcohol consumed per predrinking occasion was not assessed in the baseline questionnaire. Future research should try to obtain further validation of the PMQ by investigating the associations of the three dimensions with the amounts of alcohol consumed both during predrinking and over the entire night. Thirdly, although the recruitment procedure was designed for recruiting a representative sample of nightlife-goers by means of the proportional-to-size street intercept method, the dropout rate was rather high. This was however probably due to the requirements and the expected inconvenience of the subsequent event-level smartphone study for which the participants were being recruited (an intensive nightlife study for Android smartphone users only). Fourthly, both EFA and CFA were conducted on rather small subsamples. However, both subsamples did not appear to be biased by outliers since no differences were found between the two samples in terms of linguistic region, gender ratio, age group, average frequency of predrinking and student status. Finally, the study was conducted in only one country. Despite the advantage that the different linguistic regions represent different (drinking) cultures within one country, our sample is not representative of drinking cultures in other parts of the world. In particular, item 3 on eating snacks (“snacking on crisps/peanuts, etc.”) may be less appropriate in Nordic countries or in the UK, where young adults consume particularly large amounts of alcohol in a very short time in comparison with other European countries (Hughes, Quigg, Bellis, et al., 2011; Kuntsche et al., 2011) and where conviviality might play a minor role in relation to drinking.

7.5 Conclusion

The PMQ was shown to be a reliable, valid and culturally appropriate instrument for assessing predrinking motives in the general population of young adult nightlife-goers (i.e. not only among university students). With three new items highlighting the importance of the social gathering during predrinking irrespective of what happens later in the evening, the development of the PMQ adds important new aspects to the understanding of predrinking motives. Given that its three-factor structure was found to be invariant across linguistic regions, gender, age groups and university student status, we are optimistic that it can be replicated and usefully applied in other countries and drinking cultures.

Chapter 8

After how many drinks does someone experience acute consequences? Determining thresholds for binge drinking based on two event-level studies [7]

Abstract

Background and Aims: The threshold of 4+/5+ drinks per occasion has been used for decades in alcohol research to distinguish between non-risky versus risky episodic drinking. However, no study has assessed the validity of this threshold using event-level data. This study aimed to determine the optimal thresholds for the detection of five acute alcohol-related consequences (hangover, blackout, risky sex, fights and injury) using data from two event-level studies.

Design: An event-level study to assess the ability to use the number of drinks consumed to discriminate between nights with and without consequences using the area under the receiver operating characteristic (AUROC) curve. Optimal thresholds were determined using the Youden Index based on sensitivity and specificity. Separate thresholds were estimated for gender and age groups (16–17 versus 18–25).

Setting: Lausanne and Zurich, Switzerland.

Participants: Three hundred and sixty-nine participants aged 16–25 years.

Measurements: On 3554 weekend nights, participants reported total number of alcoholic drinks consumed the previous night and acute consequences (hangover, blackout, risky sex, fights and injury)

Findings: Hangover was the most frequently reported consequence and injury the least for both genders. Throughout age groups and studies, optimal thresholds for any consequence, and for hangover only, were equal to 4+/5+ (40+/50+ g alcohol) while those for blackouts, risky sex, fights and injuries were up to three drinks higher. Adolescents tended to experience consequences more often and at slightly lower drinking levels than did adults. For all consequences but injuries, the optimal thresholds were one to two drinks lower for women than for men.

Conclusions: Event-level data collection techniques appear particularly suitable to estimate thresholds at which acute alcohol-related consequences occur. Binge drinking thresholds of 4+/5+ (women/men) drinks, equivalent to 40+/50+ g pure alcohol, predict the occurrence of consequences accurately in general but are too low to predict severe acute alcohol-related consequences.

[7] Labhart, F., Engels, R., Livingston, M., & Kuntsche, E. (2018). After how many drinks does someone experience acute consequences? Determining thresholds for binge drinking based on two event-level studies. *Addiction*, 113(12), 2235-2244. https://doi.org/10.1111/add.14370

8.1 Introduction

Binge drinking is one of the most important and widely employed concepts in alcohol epidemiology to discriminate non-risky drinking from risky drinking and to determine the burden resulting from alcohol use (World Health Organization, 2014). The measurement of binge drinking dates back to the late sixties (historical overview: Courtney & Polich, 2009; Jackson, 2008; Kuntsche et al., 2017) and focuses upon the high-risk aspect of heavy consumption in a short time-frame (Gmel et al., 2011; Wechsler et al., 1994; Wechsler & Nelson, 2001) which results in high blood alcohol concentration and increases psychomotor and cognitive impairment (Dawson, 2011; Gmel et al., 2011; Pearson et al., 2016). This behaviour has been linked to a wide range of acute (short-term; e.g. hangovers, blackouts, injuries) and chronic (long-term; e.g. liver and cardiovascular diseases) consequences (Gmel et al., 2003). Nowadays, the most widely used definition of binge drinking is the consumption of four or more drinks among women, and five or more among men, within two hours or at a given drinking occasion, corresponding to approximatively 40 g of pure alcohol for women and 50 g for men (Kuntsche et al., 2017; Wechsler & Nelson, 2001).

Nevertheless, despite its widespread use, the operationalization of 4+/5+ drinks as the most appropriate threshold to predict the experience of alcohol-related consequences appears challenging. First, given the close relation between alcohol use and alcohol-related consequences (i.e. the higher the number of drinks, the more likely the consequence), any threshold might discriminate a lower from a higher risk of consequence (Gruenewald et al., 2003; Pearson et al., 2016). For example, despite variations of thresholds across countries, in terms of number of drinks (e.g. Australia: 5+ for both genders) and of alcohol content per drink (e.g. Australia, Switzerland: 10 g of pure alcohol; the United Kingdom: 8 g; the United States: 12-14 g; Canada: 13.5 g: Butt et al., 2011; National Health and Medical Research Council, 2009; World Health Organization, 2000), studies still find consistently that binge drinking is associated with increased risks of consequences. Secondly, thresholds might vary by the types of acute consequences (e.g. a lower intake is usually required for a hangover than for blacking-out) and any given threshold might predict only partially the experience of different types of adverse consequences. Thirdly, the dose-response effect of alcohol varies by peoples’ age and is more pronounced among adolescents than older drinkers (Huntley et al.,

2015) suggesting that, for the same risk level, lower thresholds might apply for the former than the latter. Finally, only a few studies have attempted to assess the optimal threshold for predicting the experience/occurrence of different types of alcohol-related consequences; those that have used a range of different analytical approaches and produced mixed findings.

Using retrospective self-reports of alcohol use and consequences during the past year, three studies aimed at finding the optimal threshold that maximizes the sensitivity (i.e. the correct classification of the occurrence of a consequence at or above a certain number of drinks) and the specificity (i.e. the correct classification of the absence of a consequence at or below a certain number of drinks) of the drinking-consequence relationship (Kumar & Indrayan, 2011; Metz, 1978). For Dawson and colleagues (2012), thresholds that discriminated most clearly between US adults with and without severe concurrent alcohol-related harms (past-year alcohol dependence, alcohol abuse, injury, job loss, and hypertension) consisted of 3+ drinks (36 g alcohol) for men and 4+ drinks (48 g) for women. Among the general Australian population, Livingston (2013) reported that optimal thresholds varied by the kind of outcome (past-year injury, hazardous behaviours and delinquent behaviours), while noting that optimal thresholds for all outcomes were seven drinks (70 g) or fewer. Finally, among adults from two US clinical trials, Pearson and colleagues (Pearson et al., 2017) found no clear threshold and concluded that any binary classification of alcohol consumption levels performs poorly in predicting past-year occurrence of 45 different consequences from the Drinker Inventory of Consequences (Miller et al., 1995). Unfortunately, although balancing sensitivity and specificity is state-of-the-art for such a research question, these studies provided limited evidence on the short-term binge drinking-consequence relationship. By using past-year self-reported cross-sectional surveys, individuals, instead of drinking events, were compared in terms of frequency and intensity of drinking and of consequences but no temporal association can be established at the drinking occasion level. Additionally, retrospective self-reported alcohol use is subject to recall bias due to memory deficits after even a few days (Ekholm, 2004; Gmel & Daeppen, 2007), which make such assessments particularly at risk of underestimation, both in terms of frequency of drinking occasions and of drinking levels per occasion (Kuntsche & Labhart, 2012).

Event level research has also produced mixed findings. On the one hand, a large body of emergency-department studies show that the odds of injury are increased at even low volumes of consumption, such as one or two drinks (Dawson, 2011; Taylor et al., 2010). On the other hand, two studies based on diaries completed by young adults reported that, compared to lower levels, thresholds of 10+ drinks are the most predictive of hangovers (Epler et al., 2014; Jackson, 2008). While such studies assessed the drinking-consequence relationship at the event level and without recall bias, emergency-department studies tend to favour high sensitivity (i.e. lower thresholds) in order to include all positive cases even at low drinking levels. In contrast, the diary studies considered the average consumption levels only on events with negative consequences, biasing their results toward high specificity (i.e. higher thresholds) due to the exclusion of negative cases.

To overcome these limitations, this study aims to determine the optimal thresholds for the detection of several acute adverse alcohol-related consequences based on event-level data and giving equal weight to sensitivity and specificity. For five acute consequences that might be experienced at different drinking levels and have more or less serious implications for health and wellbeing (hangover, blackout, risky sex, involvement in fights, and injury: Brown et al., 2016; Huntley et al., 2015; Quinn et al., 2013; Taylor et al., 2010; Wetherill & Fromme, 2016), separately and together, we will determine thresholds for adolescents and young adults separately, and women and men separately. Additionally, because the assessment method might alter the way the drinking-consequence relationship is captured, we will use the data from two event-level studies using different assessment schedules of alcohol use (six night-level questionnaires versus one questionnaire the next morning) and different assessment modes of consequences (with and without explicit attribution to alcohol as the cause: Gmel et al., 2010).

8.2 Method

The analyses were conducted on similar data sets from two studies. An overview is presented in Table 8-1.

Table 8-1: Characteristics of the ICAT and Youth@Night (Y@N) studies

	ICAT study	**Y@N study**
Recruitment		
Recruitment period:	April 2010	September 2014
Target population:	Students from three higher education institutions in French-speaking Switzerland	Nightlife goers, aged 16 to 25, from the two major nightlife hubs in Switzerland
Method:	Mass mail sent to all students	Street intercept using the Geographical Proportionate-to-size Street intercept sampling
Adolescent samples		
N:	-	67
Gender ratio (% men):	-	47.8
Age (range; mean [SD]):	-	16-17; 16.6 (0.5)
Month frequency of alcohol use (mean [SD]) [a]	-	4.7 (3.9)
Usual number of drinks per occasion (mean [SD]) [a]	-	3.9 (1.9)
Adult samples		
N:	152	150
Gender ratio (% men):	46.7	54.7 [ns]
Age (range; mean [SD]):	18-25; 22.6 (1.9)	18-25; 20.2 (2.0) ***
Month frequency of alcohol use (mean [SD]) [a]	9.5 (7.1)	6.6 (6.0) ***
Usual number of drinks per occasion (mean [SD]) [a]	3.4 (1.8)	3.8 (2.1) *
Event-level data collection		
Period:	5 consecutive weekends in May-June 2010	7 consecutive weekends September-November 2014
Nights of interest:	Thursday, Friday and Saturday	Friday and Saturday
Method:	Online questionnaires prompted by SMS	Smartphone application
Languages supported:	French and English	French, German and English
Nights (N, [mean per person]):	1,209 (8.0)	2,345 (10.8)
Measures		
Age, gender and drinking behaviour in past 30 days:	Baseline questionnaire before event-level data collection	Baseline questionnaire before event-level data collection
Number of drinks consumed per night:	Beverage-specific assessments submitted six times over the course of the night	Total night consumption assessed the next morning
Occurrence of acute consequences:	Assessment the next morning; with attribution to alcohol as the cause	Assessment the next morning; without attribution to alcohol as the cause
Ethics Review Board	Ethics commission of canton de Vaud (protocol 223/08)	Lausanne and Zurich cantonal ethics commissions for the Research on Human Beings (protocol 145/14)

Notes: (a) Frequency and quantity in the past 30 days;
(ns) non-significant difference between study samples;
(*, ***) significant differences between study samples at $p < .05$ and $p < .001$

8.2.1 The Youth@Night study

8.2.1.1 Design and participants

The Youth@Night (Y@N) study aimed to document young people's behaviours on Friday and Saturday nights using a specifically developed smartphone application collecting event-level data (e.g. questionnaires, pictures, videos, GPS coordinates) repeatedly over the course of the night (see for full details of the study: Labhart & Kuntsche, 2017; Santani et al., 2016).

Participants were recruited in two major nightlife hubs in Switzerland, Lausanne and Zurich on Friday and Saturday nights in September 2014 from 9 to 12 p.m. (Labhart, Santani, et al., 2017). Eligible volunteers (i.e. aged 16 to 25 years and owning an Android smartphone) had to confirm their participation by entering their mobile phone number in the online consent form. After completion of a baseline questionnaire, participants were asked to document up to 10 Friday and Saturday nights over seven consecutive weekends.

Of the 241 participants who used the application (Labhart, Santani, et al., 2017), 234 (97.1%) documented their previous nights' drinking and related consequences at least once. To ensure consistency with the selection procedure of the Internet-based Cellphone-optimized Assessment Technique (ICAT) sample (described below), 17 participants (7.3%) who never reported any alcohol use during the study were excluded. The final data set thus comprises 2345 nights from 217 participants.

8.2.1.2 Measures

Gender and *age* were recorded in the baseline questionnaire. Participants aged 16 to 17 years were categorized as *adolescents* (in Switzerland, they can purchase beer and wine legally, but not distilled alcoholic beverages, and cannot usually enter nightclubs) and those aged 18-25 as *adults*.

On Saturdays and Sundays, the application prompted participants to indicate the *total number of alcoholic drinks* they had consumed the previous night using a slider ranging from 0 to 30 drinks. The questionnaire could be completed between 10 a.m. and 4 p.m. Each drink corresponded to approximately 10 grams of pure ethanol (Labhart, Anderson, et al., 2017).

Acute consequences. Participants were also requested to report whether or not each of “the following situations occurred during or since last night” (answer categories: ‘yes’ or ‘no’): ‘hangover (headache, upset stomach, etc.)’, ‘inability to remember what happened (even for a short period of time)’, ‘unintended or unprotected sex’, ‘involvement in a fight or a quarrel’, and ‘injury to yourself or someone else’.

8.2.2 The ICAT study

8.2.2.1 Design and participants

The ICAT study aimed at documenting young adults' behaviours on Thursday, Friday and Saturday nights with hourly questionnaires completed on the smartphone browser using the Internet-based Cellphone-optimized Assessment Technique (ICAT: Kuntsche & Labhart, 2013b).

Participants were recruited from three higher education institutions in French-speaking Switzerland in April 2010. An invitation e-mail was sent to all students, including detailed information about the study and a link to the registration webpage. Volunteers had to confirm a unique code sent by the short message service (SMS) to validate the online consent form and access the baseline internet questionnaire (Kuntsche & Labhart, 2012). On Thursday, Friday and Saturday nights for 5 consecutive weeks, participants were prompted by SMS to complete six assessments (at 8, 9, 10 and 11 p.m., and 12 and 11 a.m.) about their alcohol use covering the time-frame from 5 p.m. to the end of the night.

Of the 183 participants who fully documented their nights and reported the consumption of at least one alcoholic drink over the study (Kuntsche & Labhart, 2012), 31 participants aged above 25 were excluded to obtain a sample of the same age range than the Y@N adult sample. The final data set comprises 1209 nights from 152 participants. In terms of baseline characteristics, ICAT adults were older and more frequent drinkers, but drank slightly less per occasion than the Y@N adults (Table 7-1).

8.2.2.2 Measures

Gender and age were recorded in the baseline questionnaire.

*Number of drinks***.** Each assessment throughout the night asked: 'how many of the following alcoholic drinks did you have between…?' with the time-frames of '5–8 p.m.', '8–9 p.m.', '9–10 p.m.', '10–11 p.m.', '11 p.m.–midnight' and 'midnight–end of the night'. For each drink type—'beer', 'wine or champagne', 'aperitifs or liqueurs', 'spirits', 'self-mixed drinks (e.g. whiskey and cola) or cocktails' and 'pre-mixed drinks)'—six answer categories were provided, ranging from '0' to 'five or more' (coded as 5.5). A standard drink was defined as 10 g of pure ethanol (Labhart et al., 2013). The total number of drinks consumed was obtained by summing up the drinks reported per type and assessment over the entire night.

Acute consequences. The next day, participants were asked whether 'any of the following occurred last night as a result of your drinking' (i.e. explicitly mentioning alcohol as being the cause; answer categories: 'yes' or 'no'): 'hangover (headache, upset stomach, etc.)', 'unable to remember what has happened (even for a short period of time)', 'unintended or unprotected sex', 'involved in fight or quarrel', and 'injured yourself or someone else'. The questionnaire could be completed between 11 a.m. and 10 p.m.

8.2.3 Analytic strategy

The following analyses were conducted separately for each gender, study, age group and consequence, as well as for all consequences together.

First, in order to assess whether the consequences had a significant dose-response relationship to drinking levels (Gruenewald et al., 2003), the number of drinks consumed was compared between nights without and with each consequence. Given the over-dispersed number of drinks consumed in some cases, differences were tested using negative binomial regression models, adjusted for the night-level observations being nested within individuals using the linearized variance estimator (also known as sandwich estimator) in Stata version 14 (StataCorp, 2015), with the occurrence of the consequence (yes/no) as independent variable.

Secondly, the area under the receiver operating characteristic (AUROC) curve (Hanley & McNeil, 1982; Metz, 1978) was calculated to measure the ability of an increasing number of drinks consumed to discriminate nights with a given consequence correctly from nights without this consequence. AUROC values range from 0 to 1, with 0.5 indicating no better discrimination than random chance and 1 indicating perfect discrimination (Hanley & McNeil, 1982). Empirical 95% confidence intervals of AUROCs were estimated using 1000 bootstrap replications, with Stata version 14 accounting for the night-level observations being nested within individuals when replicating the samples.

Thirdly, to determine the optimal threshold, we chose to give an equal weight to sensitivity and specificity as the purpose of the binge threshold is to distinguish the presence from the absence of alcohol related risks equally. For this purpose, we used the Youden Index (Youden, 1950), which determines the point on the receiver operating characteristic (ROC) curve furthest from chance by identifying the threshold with the highest sum of sensitivity and specificity. This method has been shown to be the most appropriate when equal weight is given to sensitivity and specificity (Perkins & Schisterman, 2006).

8.3 Results

Hangover was the most commonly reported consequence both at the person level (e.g. at least one hangover was reported by 38% to 60% of women; Table 8-2) and the night level (e.g. 5.9% to 14.0% of all women’s nights) and injury was the least common for both genders. Except for risky sex among women, consequences tended to be more common for adolescents than older participants, both at the individual and the night levels.

Overall, an average of two to three drinks were consumed by women (Table 8-3) and three to four by men (Table 8-4) on nights without consequences. Approximately three to four times more drinks were consumed on nights with hangovers and blackouts for both genders and all age groups, as well as for all consequences in the ICAT samples. Numbers of drinks consumed were also much higher (approximately two to three times higher) on nights with risky sex, fights and injuries in the Y@N samples, although in a few cases the difference failed to reach 5%-significance level.

Table 8-2: Number of participants, nights and prevalence of consequences, per age group, study and gender

	Men		Women	
Study	Persons[1]	Nights	Persons[1]	Nights
Participants				
Adolescents [Y@N] (n)	32	347	35	391
Adults [Y@N] (n)	82	857	68	750
Adults [ICAT] (n)	71	528	81	681
Consequences				
Hangover				
Adolescents [Y@N] (%)	81	18.7	57	12.3
Adults [Y@N] (%)	61	16.6	60	14.0
Adults [ICAT] (%)	35	8.0	38	5.9
Blackout				
Adolescents [Y@N] (%)	31	4.6	17	2.8
Adults [Y@N] (%)	13	2.2	16	2.3
Adults [ICAT] (%)	13	2.7	9	1.0
Risky sex				
Adolescents [Y@N] (%)	22	4.6	9	1.5
Adults [Y@N] (%)	11	2.3	10	1.5
Adults [ICAT] (%)	9	1.1	6	0.9
Fight				
Adolescents [Y@N] (%)	25	3.6	17	2.0
Adults [Y@N] (%)	13	4.6	6	0.7
Adults [ICAT] (%)	6	0.5	4	0.4
Injury				
Adolescents [Y@N] (%)	25	2.9	9	1.3
Adults [Y@N] (%)	9	0.8	4	0.4
Adults [ICAT] (%)	7	0.9	3	0.3
At least one consequence				
Adolescents [Y@N] (%)	88	25.6	66	14.3
Adults [Y@N] (%)	65	19.4	65	15.6
Adults [ICAT] (%)	45	10.2	42	7.2

Note: (1) For consequences: at least once during the study

Table 8-3: Levels of alcohol use without and with consequences, AUROC and optimal thresholds, per age group and study (Women)

	Drinks per night			AUROC (95%-CI)		Optimal threshold		
	Without conseq. mean (SD)	With conseq. mean (SD)	Diff. *p*-value[1]				Sensitivity/ Specificity	Youden Index[2]
Hangover								
Adol. [Y@N]	1.6 (2.2)	6.0 (4.6)	<.001	0.85	(0.80-0.90)	3	93.8/74.9	168.7
Adults [Y@N]	2.1 (3.1)	7.9 (5.5)	<.001	0.85	(0.80-0.90)	4	81.9/79.1	161.0
Adults [ICAT]	2.6 (4.0)	10.5 (5.1)	<.001	0.90	(0.86-0.95)	6	85.0/85.3	170.3
Blackout								
Adol. [Y@N]	2.0 (2.6)	7.4 (8.4)	<.001	0.74	(0.58-0.90)	3	72.7/67.6	140.4
Adults [Y@N]	2.8 (4.0)	7.9 (3.0)	<.001	0.87	(0.78-0.95)	5	94.1/77.9	172.0
Adults [ICAT]	2.9 (4.4)	11.6 (4.0)	<.001	0.92	(0.87-0.98)	6	100.0/82.1	182.1
Risky sex								
Adol. [Y@N]	2.0 (2.7)	7.3 (11.3)	.007	0.63	(0.49-0.76)	4	66.7/75.3	142.0
Adults [Y@N]	2.9 (4.0)	8.7 (6.4)	<.001	0.77	(0.63-0.92)	5	72.7/77.0	149.7
Adults [ICAT]	3.0 (4.5)	8.7 (6.0)	<.001	0.80	(0.62-0.93)	4	83.3/71.1	154.4
Fight								
Adol. [Y@N]	2.0 (2.6)	7.5 (10.4)	.002	0.58	(0.34-0.81)	12	37.5/99.2	136.7
Adults [Y@N]	2.9 (4.1)	5.6 (4.5)	.102	0.64	(0.22-1.06)	7	60.0/87.0	147.0
Adults [ICAT]	3.0 (4.5)	10.0 (6.1)	<.001	0.88	(0.78-0.98)	6	100.0/81.6	181.6
Injury								
Adol. [Y@N]	2.0 (2.6)	10.6 (12.1)	<.001	0.68	(0.44-0.92)	10	60.0/98.7	158.7
Adults [Y@N]	2.9 (4.1)	6.3 (7.1)	.146	0.58	(0.07-1.09)	5	66.7/76.4	143.1
Adults [ICAT]	3.0 (4.4)	17.0 (12.7)	<.001	0.94	(0.85-1.03)	8	100.0/87.8	187.8
At least one consequence								
Adol. [Y@N]	1.5 (2.2)	5.7 (4.5)	<.001	0.83	(0.76-0.90)	3	89.3/75.8	165.1
Adults [Y@N]	2.1 (3.1)	7.6 (5.4)	<.001	0.83	(0.78-0.88)	4	79.5/79.8	159.3
Adults [ICAT]	2.5 (3.9)	10.3 (5.6)	<.001	0.90	(0.85-0.94)	5	87.8/81.2	168.9

Notes: 1) Negative binomial regression, adjusted for the design effect of cluster on individuals;
2) Youden Index = max{*sensitivity(c)* + *specificity(c)* – 1}, for *c* = all possible cut-points.

Table 8-4: Levels of alcohol use without and with consequences, AUROC and optimal thresholds, per age group and study (Men)

	Drinks per night			AUROC (95%-CI)		Optimal threshold		
	Without conseq. mean (SD)	With conseq. mean (SD)	Diff. *p*-value[1]				Sensitivity/ Specificity	Youden Index[2]
Hangover								
Adol. [Y@N]	2.3 (3.5)	9.2 (6.5)	<.001	0.87	(0.80-0.93)	5	86.2/81.2	167.4
Adults [Y@N]	3.2 (4.1)	9.1 (5.6)	<.001	0.81	(0.76-0.86)	5	80.3/73.3	153.6
Adults [ICAT]	3.6 (4.7)	14.2 (8.3)	<.001	0.89	(0.85-0.93)	5	97.6/71.8	169.4
Blackout								
Adol. [Y@N]	3.3 (4.5)	9.6 (9.3)	<.001	0.72	(0.54-0.89)	4	81.3/63.4	144.7
Adults [Y@N]	4.0 (4.8)	10.5 (4.3)	<.001	0.85	(0.78-0.91)	7	84.2/76.6	160.8
Adults [ICAT]	4.0 (5.1)	19.9 (8.5)	<.001	0.96	(0.93-0.99)	11	100.0/89.3	189.3
Risky sex								
Adol. [Y@N]	3.4 (4.6)	7.9 (9.5)	.022	0.59	(0.37-0.80)	6	50.0/79.2	129.2
Adults [Y@N]	4.1 (4.9)	7.4 (6.6)	.015	0.63	(0.45-0.81)	8	50.0/79.0	129.0
Adults [ICAT]	4.3 (5.7)	12.3 (7.8)	<.001	0.84	(0.74-0.95)	5	100.0/67.1	167.1
Fight								
Adol. [Y@N]	3.4 (4.7)	7.7 (9.0)	.072	0.56	(0.24-0.87)	8	46.2/87.1	133.3
Adults [Y@N]	4.0 (4.8)	10.9 (5.5)	<.001	0.83	(0.74-0.91)	6	87.5/71.0	158.5
Adults [ICAT]	4.3 (5.6)	20.0 (13.4)	<.001	0.89	(0.75-1.04)	14	75.0/92.2	167.2
Injury								
Adol. [Y@N]	3.4 (4.7)	10.3 (9.0)	.003	0.75	(0.54-0.96)	4	90.0/62.9	152.9
Adults [Y@N]	4.1 (4.8)	15.7 (4.3)	<.001	0.95	(0.90-0.99)	10	100.0/86.5	186.5
Adults [ICAT]	4.3 (5.6)	17.4 (13.0)	<.001	0.87	(0.75-0.98)	5	100.0/66.9	166.9
At least one consequence								
Adol. [Y@N]	2.2 (3.4)	7.7 (6.5)	<.001	0.77	(0.69-0.84)	5	70.8/82.2	153.0
Adults [Y@N]	3.0 (4.0)	8.9 (5,7)	<.001	0.80	(0.75-0.85)	5	76.5/74.2	150.8
Adults [ICAT]	3.3 (4.4)	13.9 (7.7)	<.001	0.91	(0.87-0.94)	5	98.2/73.6	171.8

Notes: 1) Negative binomial regression, adjusted for the design effect of cluster on individuals;
2) Youden Index = max{*sensitivity(c)* + *specificity(c)* – 1}, for *c* = all possible cut-points.

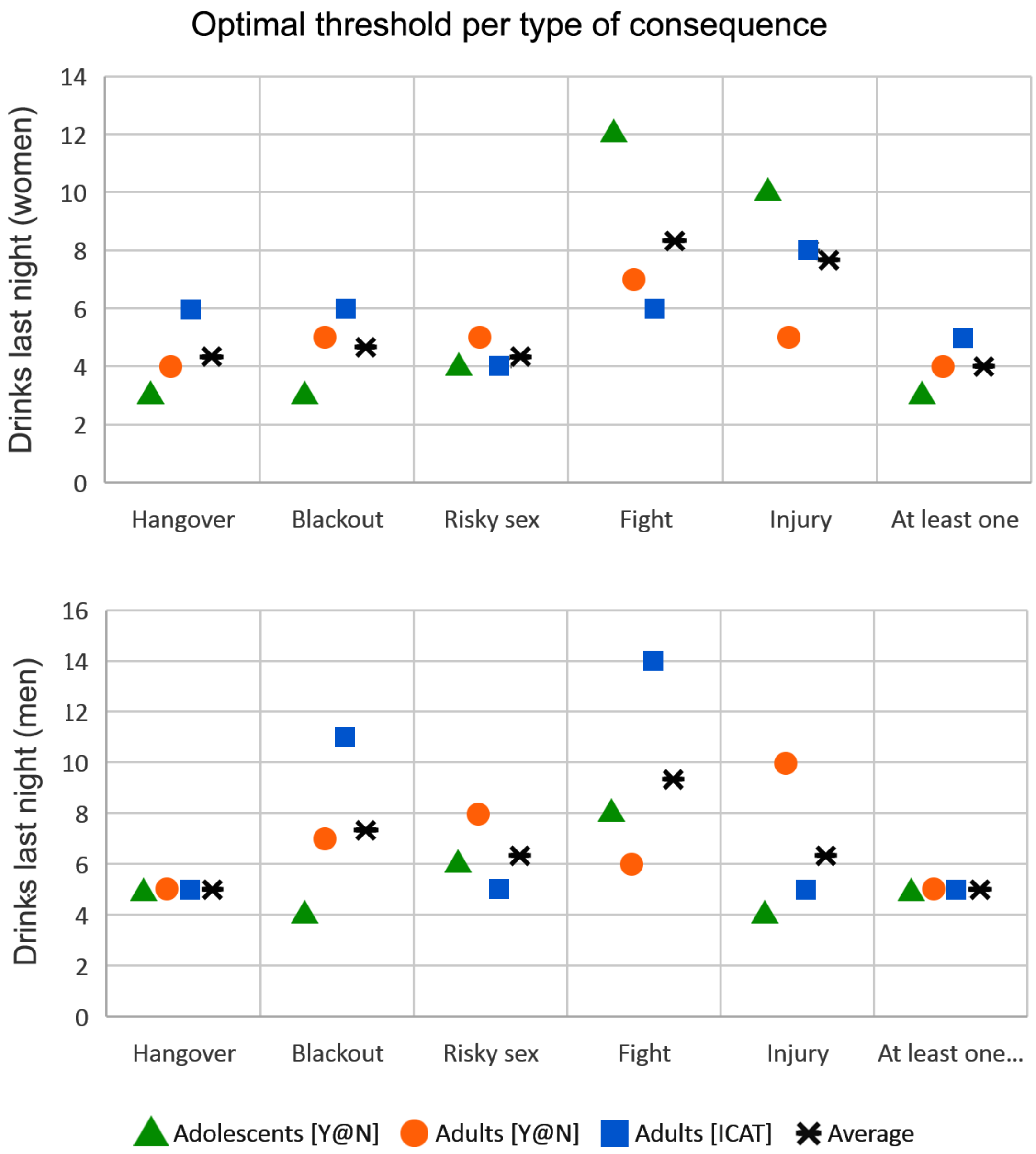
Throughout age groups and studies, the highest AUROC values (indicating higher accuracy in the discrimination of nights with from nights without consequences) were generally found for hangovers, injuries and blackouts among men and for hangovers and blackouts among women, while the lowest were found for fights and risky sex for both genders. Regarding age groups and studies, AUROC values were the lowest among Y@N adolescents and the highest among adults in the ICAT sample.

As shown in Figure 8-1, almost no thresholds were below the commonly used binge threshold, namely four drinks for women and five drinks for men, and these concerned only adolescents (see also Tables 8-3 and 8-4). Overall, the highest thresholds were found for fights among both genders, followed by injuries among women and blackouts among men, and the lowest for hangovers. For all consequences but injuries, the thresholds were on average 1.0 to 2.6 drinks lower for women than for men. Regarding the detection of at least one consequence, thresholds for all age groups were 5+ drinks for men and approximately 4+ for women. Lower thresholds tended to be found for adolescents compared to adults among all consequences. Finally, regarding study differences among adults, optimal thresholds in the ICAT sample were generally higher than in Y@N sample, although not systematically.

8.4 Discussion

Using data from two event-level studies, the aim of this study was to determine the optimal number of alcoholic drinks consumed to discriminate nights with from those without acute adverse consequences. For all investigated consequences, there was a clear association between heavier drinking levels and increased risk. Hangovers and blackouts were related strongly and consistently to drinking levels in all age groups, genders and studies, whereas the dose-response effect appeared slightly less consistent for risky sex, fights and injuries. This difference might be explained by the differential contribution of alcohol to these consequences. In contrast to risky sex, fights and injuries, hangovers and blackouts are unlikely to occur without alcohol use, which, to a large extent, explains the generally lower AUROCs of the former than the latter.

Figure 8-1: Optimal thresholds for each consequence and altogether, per gender and age group and study



While caution is needed in comparing our findings with previous studies due to differences in data collection methods and analytical strategies, our findings appeared broadly similar in several aspects. For example, Epler and colleagues (2014), using a similar design (21-day diary) and sample (young adults aged 23 years on average) reported that approximately 60% of their participants experienced a hangover at least once during the study, that approximately 20% of drinking episodes were followed by hangovers and that the participants drank on average nine drinks on episodes followed by hangovers. Similar to Huntley and colleagues (2015)our results also showed that adolescents tended to experience consequences related directly to drinking levels at lower levels that adults. With regard to gender, higher thresholds were found for men than for women with few exceptions. These results concur with the general use of different thresholds to account for differences in body constitution and alcohol metabolism of men and women (Lange & Voas, 2001; Wechsler et al., 1995).

The 4+/5+ thresholds for binge drinking, representing consumption of 40 g of alcohol for women and 50 g for men, appeared optimal for predicting the experience of any consequence (i.e. at least one per night). This finding is consistent with the current conceptualisation of binge drinking. However, given that higher thresholds were found for blackouts, risky sex, fights and injuries when considered separately, these present findings recommend the use of higher thresholds to specifically measure the risk of more serious consequences than hangovers.

Between adult samples, higher drinking levels were found consistently on nights with consequences in the ICAT sample, compared to those in the Y@N sample. As baseline characteristics showed that the Y@N adults used to drinking more per occasion than the ICAT adults, this finding might rather be explained by the type of assessment method, with alcohol use being assessed six times per night in the ICAT study but only once in the Y@N study. Thus, as shown in previous studies (Monk et al., 2015), higher numbers of assessments and shorter recall periods, as was the case in the ICAT study, probably resulted in higher reported drinking levels. Additionally, consequences were assessed using explicit attribution to alcohol use as the cause in the ICAT study and without attribution in the Y@N study. Thus, it is not surprising to observe closer associations (i.e. higher AUROCs) between the number of drinks consumed and the occurrence of consequences in the ICAT study, as only consequences with an obvious relationship to previous alcohol use for the participants were reported. These findings should be interpreted with caution as the use of alcohol-attributed items in questionnaires is prone to underestimate the effective number of experienced consequences and bias the measurement of the drinking-consequence relationship (Gmel et al., 2010).

Several limitations need to be acknowledged. First, with the exception of hangover, the investigated consequences did not occur frequently, despite having sampled thousands of nights. Considering the relatively low prevalence of risky sex and injuries, related results might be affected by reporting errors of participants and levels of sensitivity and specificity might be slightly overestimated (Leeflang et al., 2008). Secondly, only five acute alcohol-related consequences were investigated. Different thresholds might apply to other consequences, especially those relating to multiple drinking events (e.g. dependence, job loss). Thirdly, the present findings were obtained among two samples of young people in Switzerland. Different dose-response relationships between drinking levels and the occurrence of adverse consequences might be expected in other drinking cultures and among older populations. Fourthly, no information was available on the actual size of the drinks consumed, making the results dependent upon the participants' self-estimation of standard drinks. Nevertheless, this approach has the advantage that participants reported their drinks in the same way that they would understand drinking guidelines, making these findings a reliable basis for communication to the general public. Fifthly, no information was collected on participants' height and weight and on the time and size of each drink consumed. It was therefore not possible to adjust the analyses for the participants' body mass index (Courtney & Polich, 2009) or estimated blood alcohol concentration. Finally, the present findings relate to standard drinks containing approximately 10 g of pure alcohol. The thresholds might need to be adapted in countries with different standard drink sizes.

The main strength of the present paper is the use of event-level data to determine the most appropriate thresholds for risky drinking. In contrast to previous studies based on yearly retrospective assessments, the present thresholds were supported by higher levels of sensitivity and specificity. Hence, a large majority of Youden Indices in this study were higher than the highest Indices (134 and 152) found in Pearson and colleagues (2017) and Livingston (2013) respectively. These comparisons confirm the higher accuracy of event-level studies to determine relevant thresholds with regard to acute alcohol-related consequences (Pearson et al., 2016). Another strength is the assessment of five acute consequences on approximately 8–10 nights among the same participants in their natural environment. Each participant thus serves as its own control, across nights and consequences. The present findings are therefore characterized by a high ecological validity and minimized recall bias.

8.5 Conclusions

Relying upon event-level evidence, results of this study confirmed that the 4+/5+ threshold for binge drinking (Kuntsche et al., 2017; Wechsler et al., 1994), corresponding to 40+/50+ g of pure alcohol in this study, appear appropriate to predict the experience of acute consequences in general, as well as hangovers, in both genders. Thresholds to predict more severe consequences were higher and those for adolescents slightly lower. These findings suggest the use of different thresholds to measure the real health-related burden resulting from different kinds of acute consequences among different populations. With the aim of preventing the occurrence of negative consequences, it is recommended to keep communicating thresholds corresponding to 40+/50+ g per occasion, especially for adolescent drinkers.

Chapter 9: General Discussion

The overall aim of this thesis was to investigate the associations between specific characteristics of the environment and the individual on alcohol-related outcomes in drinking events, using data collected with a custom-build smartphone app. Additionally, given the novelty of using smartphone apps for alcohol research, this work also aimed to evaluate the advantages and challenges of collecting questionnaires, sensor and media data at the drinking event level. The key findings that emerged from Chapters 2 to 8 are summarised in Table 9-1 and their implications are discussed in the sections below.

9.1 Contextual influences on alcohol-related outcomes

As a multifaceted research object, the drinking context is comprised of several dimensions, including the type of setting, physical attributes, social attributes and user's attitudes and cognitions (see McCarty's (1985) definition of the "microsetting" in Chapter 1). Yet, in scientific studies, the complexity of the drinking context is often reduced to a list of distinct characteristics, among which the researcher selects some disparate elements when designing the data collection protocol or a publication (Jessor, 1979). A major criticism of the existing evidence on drinking context is the fragmentation of knowledge, because researchers have examined only one or two contextual characteristics at the same time (Stevely et al., 2019). Building on an interdisciplinary collaboration to develop a comprehensive and complex data collection tool, this work explored multiple innovative aspects of the impact of contextual characteristics and individual cognitions on alcohol use.

9.1.1 Types of location

Prior event-level research has mostly focused on the impact of attending commercial venues, such as pubs and nightclubs (Hughes, Quigg, Eckley, et al., 2011; Stevely et al., 2019), or the sequence of attending different locations, e.g. at home prior to attending commercial venues (Forsyth, 2010; Hughes et al., 2008; Labhart et al., 2013) on heavier consumption over the course of a night. The present findings corroborate such evidence by showing, for example, that attending nightclubs is associated with drinking more than intended among women (Chapter 4).

Table 9-1: Overview of the key findings of Chapters 2 to 8

Chapter, Findings
2. The smartphone application developed for this study successfully collected numerous data types, including manual inputs, media (video and pictures), and sensors simultaneously. Context-specific sequences of questionnaires (e.g., skips) and widgets (pre-defined lists of options and pre-filling of fields) contributed to reduce participation burden. The use of event-contingent self-initiated assessments resulted in the provision of more reports by some participants than others. This imbalance in the numbers of reports per participants reflected to a large extent participants drinking habits (i.e. heavier drinkers submitted more reports of drinking events) as well as the adoption of strategies to reduce burden by less assiduous participants (i.e., preference for “forgotten drink” questionnaires). The collection of media data (pictures and video clips) created the most burden for the participants.
3. To recruit a diverse sample of nightlife-goers, data from social networks provided valuable information to measure the respective popularity of multiple nightlife zones over an entire city. Local experts (police and social street workers) recommended minor adaptations of quotas of people to recruit per zone to account for seasonal preferences (e.g., increase quota in parks and waterside in summer and autumn). The recruitment procedure (groups of 2 to 3 recruiters with easily recognisable (‘branded’) clothing recruiting from the early evening until midnight) was felt appropriate by the recruiters and the participants. Almost half of the potential participants for the project had an iPhone, which was incompatible with the study app, resulting in a significant loss of potential participants.
4. Short-term drinking intentions and related contextual factors can be assessed, reliably, using assessments of pre-night drinking intentions, of contextual characteristics during the night and of total alcohol consumption retrospectively the next morning. Participants consumed more drinks than initially intended on 47.7% of all weekend nights. Several contextual and night-level factors contributed to higher consumption than intended: starting drinking early in the night, attending multiple locations, and being with larger groups of friends (both genders), being away from home (men only), and attending night-clubs (women only). Individuals with usually low intentions and lighter drinkers were more likely to exceed their drinking intentions.
5. Despite exceeding their drinking intentions on almost half of all nights, participants acknowledged having drunk more than intended on only 36.7% of those nights. Few contextual and night-level factors contributed to participants’ acknowledgement of having drunk more than intended, namely having higher drinking intentions than usual, having attended more locations than usual, having a hangover the next day, and having spent more money than planned. Beyond these event-level effects, no individual characteristic was found to have any effect on the acknowledgement of having drunk more than intended.

Table 9-1 (continued)

Chapter, Findings
6. Physical and social contextual characteristics of drinking events (loudness, luminosity and number of people present) can be captured by means of 10-second video clips and measured using manual annotations and a computerized algorithm, independent of the participants' subjective perception of the context. Ratings from all three sources were significantly correlated, suggesting that sensor-based measures might to some extent replace participants' self-reports of these characteristics. Participants were more likely to drink an alcoholic drink, compared to a non-alcoholic drink, in louder and darker commercial venues, and in louder, more crowded and darker private places. Measurement issues in very loud or very dark environments, combined with the feedback from participants, that the act of recording videos was sometimes perceived as inappropriate, suggested that video clips are not the panacea for reliable and unobtrusive assessment of drinking contexts.
7. Pre-drinking motives can be classified into three motivational dimensions: 'fun/intoxication', 'conviviality' and 'facilitation' dimensions. The conviviality dimension mostly relates to particular characteristics of the drinking context, including the size of the location, the presence of people to meet, the music played, and the availability of food. Participants from the French-speaking Switzerland scored higher the 'conviviality' dimension compared to German-speaking participants, reflecting cultural variations in the endorsement of this dimension. The absence of a similar dimension in other instruments from the US might reflect cultural variations in pre-drinking motives and expectancies among young people, as well as differences in scholars' attention to influences from the drinking context when designing their instrument.
8. EMA methods enable micro-longitudinal designs and the collection of multiple assessments within the same individuals. These designs are particularly suitable for estimating the drinking thresholds at which acute alcohol-related consequences are more likely to occur. Results confirmed that the commonly used 4+/5+ threshold (for women/men) for 'heavy' or 'binge' drinking is appropriate for predicting the occurrence of the lesser harmful acute alcohol-related consequences (e.g. hangover) overall. However, this threshold is too high for adolescent drinkers and too low to predict more severe consequences (e.g. blackout, injury). Different thresholds are required to precisely measure the health-related burden of heavy drinking.

One unique characteristic of this thesis is all weekend nights (Friday and Saturday) were documented, even when participants did not go out or did not drinking. As such, we were able to conduct one-to-one comparisons across different types of location as well as to focus on private homes specifically. In this respect, results showed that almost every second alcoholic drink was consumed in private places on weekend-nights (Chapter 6), highlighting the importance of homes as place to spend the night on weekends or to start alcohol consumption (Dietze et al., 2014).

Additionally, collection of data across multiple nights, on the same person, allowed the studies to examine differences in participants' behaviour across locations at the within-person level. In this respect, the findings that male participants were less likely to exceed their drinking intentions when staying in homes (Chapter 4), and only half of all drinks documented in homes contained alcohol (Chapter 6), revealed that homes remain generally places of low alcohol consumption compared to commercial nightlife venues. It should yet be acknowledged that this work did not distinguish between different types of private places, such as one's own home versus someone else's home. The present findings therefore call for replication and development taking into account the specificities of the nature of the private place.

9.1.2 Physical characteristics

Compared to other contextual characteristics, the physical environment (e.g., loudness, brightness) has rarely been investigated as a potential source of influence on drinking behaviours (Stevely et al., 2019). Among the few notable studies, in-situ observational studies showed that higher levels of loudness (Guéguen et al., 2004, 2008) and lower levels of lighting (Hughes, Quigg, Eckley, et al., 2011) are associated with heavier alcohol use in commercial venues. The present findings not only confirm this association, using a different approach (i.e., measures provided by the drinkers themselves), but also show that the same phenomenon occurs in private homes (Chapter 6). With the demonstration that darker and louder environments are associated with higher likelihood of drinking in commercial venues, private places and public spaces, this thesis calls for more systematic investigations of the physical contextual characteristics, given this characteristic of the context can be manipulated to prevent excessive alcohol use.

Regarding alcohol-related cognitions, this thesis contributes to the literature showing that, as part of the development and validation of the pre-drinking motives scales

(Chapter 7), several physical characteristics of the context, including the available space, the ambient music, and the availability of food (e.g. snacks, crisps, peanuts), are important factors in young people's propensity to pre-drink for 'conviviality' motives.

9.1.3 Social characteristics

In recent years, a significant number of studies have investigated the impact of friends (the number of and gender) on the participants' drinking consumption level (Monk & Heim, 2014; Smit et al., 2015; Thrul & Kuntsche, 2015). The findings of Chapter 6 contribute to this body of evidence by showing that the number of friends present impacts alcohol consumption only in outdoor public spaces and in private places. Locations where the drinking group size can be freely chosen by the drinkers appears critical to this effect, given that this effect was not observed in commercial venues, where the number of available seats might be restricted by external constraints (e.g. the venue size or the overall attendance).

Regarding alcohol-related cognitions, the findings of Chapter 4 and 5 show that the number of friends, particularly male only or mixed gender groups of friends, are significantly associated with drinking more than intended. However, the size of the drinking group does not influence people's ability to remember and acknowledge having drunk more than intended the previous night. This suggests that not only that the social context is particularly influential at the event-level but also that drinkers are mostly unaware of this source of influence.

Finally, besides the quantitative evaluations of the social context above, findings from Chapter 7 also highlight the importance of the social context for its primary function, namely as a space for social interaction. In this respect, several characteristics of the context, including enough space to comfortably host all attendees, and the opportunity to meet new people, are important factors in young people's propensity to pre-drink for 'conviviality' motives.

9.1.4 Individual characteristics

A critical component of the drinking context is the drinker, through their own behaviour and cognitions. For each drinking occasion, both the individual (trait-like) and the event-specific (state-like) characteristics of the drinker might influence the alcohol-related outcomes (Labhart & Kuntsche, 2014). At the individual level, the person's own alcohol consumption likely impacts subsequent drinks consumed over the course of a night (Kuntsche et al., 2015). Reflecting previous evidence, that even moderate alcohol doses are likely to compromise an individual's control over the amounts consumed during a given drinking occasion (Weafer & Fillmore, 2008, 2015), results from Chapter 4 showed that less experienced drinkers and less frequent nightlife-goers were more likely to exceed their drinking intentions, and consequently experience adverse consequences the next morning (Chapter 8).

The results presented in Chapter 4 also revealed that drinking intentions that participants form for any given night are influenced by both individual and night-specific characteristics of participants simultaneously. At the individual level, more frequent pre-drinkers, less frequent nightlife goers (among women only) and those who frequently start drinking before 8 p.m. were found to be more likely to drink more than intended, on any given night. In addition, at the night level, having lower drinking intentions, than usual, and starting drinking before 8 p.m. were also associated with drinking more than intended (Chapter 4). In addition to providing the first pieces of evidence on short-term drinking intentions, this work contributes to the literature by highlighting the importance of considering both trait-like and state-like characteristics of the drinker. In this respect, the application of person-mean centring (Enders & Tofighi, 2007; Hoffman & Stawski, 2009) is recommended, given its ability to distinguish between the individual-specific influences (e.g., average level of drinking intentions across study nights) and the night-specific influences (e.g., drinking intentions at a given evening) using only EMA data.

Interestingly however, while few night-level characteristics were associated with the acknowledgement of having consumed more than intended the previous night (Chapter 5), such as having consumed larger amounts than usual and experiencing negative consequences, this trend was not evident for any of the individual-level characteristics investigated. Therefore, these findings show that the process of recalling and comparing the previous night's drinking intentions and consumption is in fact independent from the drinker's usual characteristics, and is only linked to the night-specific behaviour and cognitions, in line with other night-level circumstances.

Finally, regarding pre-drinking motives, findings from Chapter 7 revealed the existence of several internally-driven motivations for engaging in pre-drinking, such as the intention to 'get drunk quickly' and to 'go out while already being properly drunk' (belonging to the 'fun/intoxication' motive), or because alcohol is not available later at night (belonging to the 'facilitation' motive), which might likely drive people's drinking behaviours on such occasions.

9.1.5 Sequence of events

In addition to the four categories above, the timing and sequence of events are also core characteristics of the drinking context (Stanesby et al., 2019; Stevely et al., 2019). In this respect, the number of different locations visited over the course a night are known to be associated with heavier drinking (Labhart et al., 2013, 2014). The present work contributes to this topic by showing that the number of locations is also associated with heavier drinking than intended (Chapter 4) and with acknowledgement of having drunk more than intended the previous night (Chapter 5).

The present work also highlighted that starting drinking early, therefore extending the available time for drinking over the course of the night, is not only associated with heavier consumption on a given night, as shown by previous research (Groefsema et al., 2019; Labhart et al., 2014), but also significantly contributes to drinking more than intended (Chapter 4) without making people aware of having done so (Chapter 5).

9.1.6 The whole is greater than the sum of its parts

To effectively reduce the fragmentation of knowledge outlined above, it is important to conceive contextual characteristics as a network of interdependent elements, rather than as a list of stand-alone features, in order to account for the relationships between features of the same context. For example, as demonstrated in Chapter 6, loudness and attendance levels in general are positively correlated, which is not surprising given that large groups of people are often more noisy than smaller groups. However, only one or the other feature was associated with drinking in certain types of locations (e.g. loudness, but not attendance, in commercial venues). On the one hand, this suggests that in places where attendance is independent from the drinking group size, such as commercial venues, where music is played and multiple groups are present, only the ambient loudness level impacts alcohol use. However, when the drinking group is the main source of noise, such as in homes or outdoors, the results of the regression model suggest that both loudness and attendance are associated with alcohol use over and above their reciprocal association. An important contribution of the present work to the existing literature is therefore the reminder of the importance of multivariate modelling approaches to identify the unique contribution of each characteristic individually when analysing the impact of multiple characteristics simultaneously.

Drawing on an interdisciplinary collaboration is an ideal opportunity to reduce the fragmentation of knowledge on drinking context and alcohol-related outcomes, as demonstrated by the work in this thesis, and also reported by other research groups (Olabisi et al., 2020). The Youth@Night project assembled the expertise of three research groups from different scientific disciplines, namely alcohol epidemiology, human geography and computer science, sharing the same interest for understanding how peoples' behaviours interact with their immediate physical and social context (see Figure 1-1 in the Chapter 1). Because the research required the development of a data collection tool that would satisfy the different conceptualisations of the drinking context for each discipline, this collaboration gave birth to a comprehensive and complex data collection scheme, including in-the-event questionnaires, mobile sensing, and qualitative interviews (Chapter 2). As a result, a large array of contextual characteristics of young people's nightlife activities were collected, some of which were presented in this thesis and in publications from study partners (Pelzelmayer et al., 2020; Phan et al., 2019, 2020).

9.2 Capturing the context with a smartphone application

When we launched the Youth@Night project in 2014, little research had been conducted with smartphone apps in the alcohol research field (Kuntsche et al., 2014). The aim of this section is to provide an overview of the advantages and limitations of the key components of this data collection tool.

9.2.1 Collection of questionnaire data

The collection of data using questionnaires remains a 'safe bet' to ensure the comparability of the data collected with previous and historical studies. As seen in Chapter 8, questionnaire data from the Youth@Night app on the number of drinks consumed per night and related consequences could easily be combined and compared with data collected with online mobile questionnaires (Kuntsche & Labhart, 2013c; Labhart et al., 2013).

In comparison to other EMA studies, one particularity of the Youth@Night app was to use event-contingent self-initiated assessments (i.e., participants should answer a short questionnaire whenever they had a drink) rather than fixed-scheduled prompted assessments. The main advantage of this design was to collect data on the drink and its context at the exact moment of consumption. This method was reinforced by the requirement to provide a picture of the glass almost full, therefore maximizing the ecological validity of the collected data. However, this design produced an unequal number of assessments per participant-night, which is atypical even in EMA studies (Jones et al., 2018). The implications of this are a reduced comparability of the findings with other EMA studies using fixed-scheduled assessments. For example, the calculation of the response and retention rates (Chapter 2) cannot be based on a standard number of assessments submitted a priori because participants could legitimately submit no assessment on nights when they did not drink. Furthermore, the volume of questionnaire data collected per participants followed a typical ‘long-tail’ or ‘Pareto’ distribution, due to the fact that heavier drinkers and more assiduous participants provided more assessments than the others (Kerr & Greenfield, 2007; Newman, 2005). Nevertheless, despite these specificities, event-contingent assessments still appear the most appropriate approach to assess the interplay between drinking and context at the very event-level, given its very limited recall bias and high ecological validity (Shiffman, 2009; Shiffman et al., 2008).

9.2.2 Collection of sensor data

In contrast to questionnaire data, that require a participant action for each assessment, sensors can passively and unobtrusively collect data for long periods of time without any user intervention. In addition to the absence of assessment reactivity, high volumes of data can be collected from all participants, independently of their drinking frequency or level of commitment to the study (Chapter 2). For this research thesis, sensor data were used parsimoniously, notably the GPS to identify the location where each picture of a drink was taken (Chapter 6). However, publications from study partners demonstrated the possibility to infer participants’ drinking behaviours based on the sensors only, including the consumption of at least one alcoholic drink over an entire night with an accuracy of 76% (Santani et al., 2018) and the detection of heavy drinking nights with an accuracy of 71% (Phan et al., 2020).

Another advantage of sensors is the invariability of the protocol and frequency at which data are collected. This provides truly standardised measures that can easily be combined across locations or drinking situations. However, this may not be the optimal way of capturing contextual characteristics that could influence drinking behaviours. At the start of this project, based on previous knowledge on how the quality of questionnaire data can be affected by recall bias and assessment reactivity, we envisioned the collection of sensor and media data (see Chapter 9.2.3) as a way to overcome participants’ subjectivity and, eventually, better capture contexts ‘as they were lived’ (Bolger et al., 2003). However, the results of Chapter 6 revealed that: a) rather than being incompatible, questionnaire and sensor data are complementary because they cover slightly different perceptions of the same situation, and b) depending on the situation, one or the other approach can better explain the link between contextual characteristics and drinking behaviours (e.g. is the exact number of people counted by a sensor or the perceived human density of the participant more closely associated with alcohol use?). All things considered, pending study replication, these findings raise questions regarding the degree to which ‘objective’ measurement of contextual characteristics using sensors are useful for understanding ‘subjectively-driven’ behaviours, such as alcohol use, given that each drink consumed is initiated, in the moment, by the user’s subjective experience.

The impact of the battery life is among the shortcomings of sensor data collection using smartphones. The most obvious risk for data collection is that, when the battery dies (or drops below 20% for the present study), data is not collected. In this project, we collected battery-intensive sensor data, e.g. GPS, at regular intervals rather than continuously to limit the drain on the battery. Yet, as seen in Chapter 2, participants often failed to recharge their phone before a night out (Chapter 2).The fact that participants’ smartphones ran out of battery in 12% of all participant-nights appeared thus to be mostly related to a lack of users’ anticipation to recharge their phones, rather than a flaw in the app design.

Lastly, due to the large volume and complexity, sensor data cannot be analysed in the same manner as questionnaire data or similar social science data. Inter-disciplinary collaborations with computer scientists is essential to either extract or rescale raw sensor data (as seen in Chapter 6, loudness or brightness perception are perceived differently by humans and devices) or mutually discuss the results of machine learning models (Phan et al., 2020; Santani et al., 2018).

9.2.3 *Collection of media data*

Pictures and video clips were the third type of event-level source of information collected using the Youth@Night app. Given their audio and visual content, one asset of media data is their ability to record many contextual characteristics within seconds. These features can be consistently and reliably identified by human annotators, as demonstrated by the high interrater reliability among the five annotators of the video (ICC = 0.95; see Chapter 6). While this work only investigated the impact of loudness, brightness and human attendance on drinking (Chapter 6), many other contextual characteristics were annotated from the drink pictures and the video clips, such as the activities in progress, the number and gender of people present, and the type of room in a house. These additional contextual characteristics are documented elsewhere (Phan et al., 2019).

Another advantage of collecting media data as part of a research project is the possibility to capture snippets of real-life behaviours and contexts in a participant observation-like approach, in the absence of a physical observer. In this respect, the collection of video clips made it possible to regularly capture insights into the participants' context over multiple drinking occasions and in multiple types of settings. As noticed by study partners working on social media data (Phan et al., 2019, 2020), the content of the video clips was exceptionally genuine compared to the millions of pictures and video clips of drinks and nightlife locations found on social media. Because the videos were not intended to be shared with others, they were not staged or retouched. It should also be noted, since the enforcement of the European Union general data protection regulation in 2018, that researchers cannot have access to or use social media for research without the informed consent of the users (Hoofnagle et al., 2019). The collection of media data in a dedicated study appears therefore a more reliable and ethical option to capture authentic snippets of real-life behaviours and contexts.

As mentioned, at the start of the project, we envisioned media data as a way to overcome participants' subjectivity, in the same way as sensor data. Yet, unlike sensors that are passively collected, the provision of the media data resulted from the deliberate actions of the participants. The extraction of data from the video clips could be realised unobtrusively using algorithms or annotators, without participant actions. However, participant subjectivity was still apparent in the study, as participants chose to record, or not, a video clip at a given moment, and chose what to record. In addition, as shown in Chapter 2 and reported in the qualitative feedback after the app fieldwork (Truong, 2018a), the provision of media data, especially video clips, was described as the most burdensome component of the study. While recording pictures and videos might be common practice for young people during a night out, the purpose is typically to record a special moment or share content with others (Truong, 2018a). Recording systematically each drink in each new place could be perceived as awkward or intrusive by the participants and the surrounding people. Due to our inexperience with such data, we certainly overlooked this issue and recommend future research to consider the suggestions provided in Chapter 2 to alleviate this burden.

Lastly, built-in smartphone camera apps do not exactly provide raw representations of the recorded scenes. In 2014, and even more so in 2020, embedded artificial intelligence technologies in these apps are programmed to optimise the end result and compensate for extreme conditions, such as high brightness by reducing the luminosity level. In terms of software, the custom-development of camera apps might resolve this issue partly. Yet, as seen in Chapter 6, smartphone cameras also have hardware limitations, especially in dark environments, which resulted in the majority of the video clips recorded in parks being mostly black footage. As a consequence, the features extracted from the videos did not correspond to the participants' in-situ perception in absolute terms (i.e., significant differences in raw levels of brightness and loudness) but did in relative terms (i.e., high correlations coefficient). Physical characteristics of the context assessed though video clips should be considered as reliable proxies of participants' perception in correlational or regression analyses.

9.3 Implications for public health and prevention

This work identified several contextual risk factors for heavier drinking and related consequences that might serve as basis for the development of prevention and harm reduction measures. With regard to structural prevention measures, the findings that louder and darker environments tend to favour the consumption of alcohol (Chapter 6) shall interest policy makers seeking to reduce alcohol use in commercial venues by defining maximum loudness as well as minimum lighting levels. Maximum loudness policies are already implemented in many countries to prevent hearing damage (Krug et al., 2015). These guidelines might also serve to prevent heavy alcohol use. It is acknowledged that the present work does not provide causal evidence on the impact of loudness and darkness on alcohol intoxication, more research is needed for stronger conclusions. Additionally, based on our findings, that attending multiple locations per night is associated with drinking more than intended (Chapter 4), we recommend the implementation of policies to reduce opportunities to attended multiple venues per night or, at the very least, to prohibit drinking in new locations for those who have already consumed significant amounts elsewhere. This may include, for example, restriction of access to commercial venues once intoxicated, staff training to detect inebriated patrons before they enter commercial venues and responsible beverage service (Stockwell, 2001; Toomey et al., 2007).

This work also highlighted people's homes as common weekend night drinking places. Findings from Chapters 6 and 7 suggest that young people appreciate the possibility to arrange the physical space to turn their home into a party space, for example by dimming the lighting, playing their preferred music, or arranging the furniture. In terms of structural harm reduction and prevention measures, in the absence of the opportunity to enforce measures through venue owners (as in the case for commercial venues), the role of parental and peer supervision is emphasised, notably to limit the supply of alcohol to adolescents and temper the drinking pace of adult offspring (Ryan et al., 2010; Wood et al., 2004). In addition, the reduction of late night selling hours for retail shops may also contribute to reduce the availability of alcohol, and consequently consumption, over the course a night (Popova et al., 2009).

With regard to individual prevention measures, the present work provided the first in-depth investigation of short-term drinking intentions (Chapter 4 and 5). A vast literature has investigated the effect of intentions on drinking behaviours on long term drinking intentions (i.e., several weeks or months) as part of the theory of planned behaviour (Cooke et al., 2016), but such investigations have never been conducted over much shorter timeframes, such as single drinking occasions. Interestingly however, the preventive effect of short-term intentions on occasion-level drinking outcomes is presupposed in several items of the widely used Protective Behavioral Strategies (PBS) scale (Martens et al., 2007). This scale assesses the strategies respondents use to keep control over their drinking by, for example, 'determining not to exceed a set number of drinks', 'leaving the bar/party at a predetermined time', and 'stopping drinking at a predetermined time'. Yet, although total night consumption was effectively found to be associated with pre-night intentions, the present findings showed that young people drink more than planned almost every second night and that they fail to acknowledge it almost two thirds of the time. Exceeding one's intentions appears to be more the norm rather than accidental, and does not serve as a basis to recalibrate drinking intentions towards lower levels for the next drinking occasion. In addition, results of Chapter 5 highlight that only very salient signs of a heavy drinking night, such as a hangover, having spent more money than planned, or exceeding initial drinking intentions by four or more drinks, might raise peoples' awareness that they have drunk more than intended. The anticipation or occurrence of negative consequences does therefore not appear to be a reliable lever to prevent overconsumption of alcohol, especially given that negative outcome expectancies are known to decline in saliency as consumption increases (Monk & Heim, 2014). Prevention interventions using the PBS to reduce heavy drinking, should therefore not only rely on participants' cognitive ability to stick to their intentions, but provide them with tools or strategies to effectively monitor their intentions and consumption. One example of this is recording pre-night intentions to provide feedback the next morning, allowing people an awareness of the large tendency to drink more than intended. Additionally, young people should be educated to identify typical contextual characteristics that contribute to drinking more than planned, such as large gatherings and attending multiple locations.

Finally, this work provided clear evidence on the direct link between amounts of alcohol consumed and the occurrence of negative consequences during or closely after the drinking occasion (Chapter 8). This implies that each avoided drink effectively delays or prevents the occurrence of one or several consequences. The Youth@Night application was designed to collect data in real-time without interfering with the participants' behaviour in order to avoid assessment reactivity. However, this design could be translated to provide context-specific just-in-time interventions aimed at reducing amounts of alcohol consumed. While the most recent trial of just-in-time interventions in alcohol research are still mainly based on participants self-reports (Haug et al., 2020; Wright et al., 2017), sensor data and media data capture have the potential to play a more central role in the detection of risky contextual characteristics and behavioural patterns (e.g. walking drunk) (Bae et al., 2018; Mariakakis et al., 2018; Phan et al., 2020).

9.4 Limitations and future directions

The present work collected data on contextual characteristics that were common across most weekend night drinking occasions. This selection of characteristics was determined by the study aim, which was to document various types of weekend nights that young people experience in real life, even when they do not drink alcohol and do not go out. A limitation of this design is that it provided an overview of common characteristics (e.g. type of location, social context) in most settings but it did not capture characteristics known to influence drinking behaviours in specific settings, such as happy hours or staff permissiveness in commercial venues (Hughes, Quigg, Eckley, et al., 2011), or alcohol supply by peers and presence of parents in private places (Ryan et al., 2010). While some information could be further drawn from the video clips, such as engagement in drinking games or overall cleanliness, future studies focused on particular settings should adapt the data collection scheme to also capture these aspects.

Another limitation of the present work was the high dropout rate, which can be explained by several factors. Firstly, the study application was only developed for smartphones running on the Android operating system (OS) because, at the time of the development of the app, iOS did not allow access to most of the required sensors. Consequently, iPhone owners, which accounted for more than 40 percent of the people approached in the streets, were unable to participate (Chapter 3). To our knowledge, access to sensors on iOS is now easier (Bae et al., 2018) which might remove the above-mentioned barrier if researchers can develop apps for both iOS and Android. Secondly, participation in the study required a high degree of commitment throughout several weekends, and the provision of media data could be perceived as particularly burdensome. Less committed participants tended to opt for documenting their drinks using the “forgotten drink“ questionnaire (Figure 2-2) which only recorded the type and number of drinks consumed rather than providing full information on the context and the drink characteristics (Chapter 2). While this strategy probably made it possible to keep these participants in the study, it resulted in a significant loss of data on the context. It is recommended that future studies also record key information on the context in similar ‘retake’ questionnaires to keep track of contextual changes over the course of the night. Additionally, measures should be taken to decrease participant burden and better integrate the provision of media data as part of the participants’ on-going activities.

The Youth@Night study was designed to document weekend nights of young adults, recruited in the nightlife districts of two cities of Switzerland, by means of a custom-built smartphone application. While several measures were taken to maximize the diversity of participants in terms of age, gender and nightlife habits with the development of a new recruitment technique (Chapter 3), their cultural diversity with the conduction of the study in two linguistic regions (Chapter 3), and the diversity of nights by documenting multiple participant-nights with their own smartphone (Chapter 2), the present results may not be representative of the nightlife and drinking behaviours of young people everywhere in Switzerland or in other countries or in other age groups.

A further shortcoming of the present work is the limited inclusion of multi-method findings, which might be surprising for a multi-disciplinary project aimed at reducing the fragmentation of knowledge. In fact, the development and evaluation of the app (Chapter 2), the development and evaluation of the recruitment (Chapter 3), and the influence of loudness, brightness and attendance on alcohol use (Chapter 6) are the only chapters requiring the analysis of multiple data types (qualitative, questionnaire-based or sensor-based) and the involvement of project partners from different domains. This can be explained by the fact that the remaining chapters address research questions specific to alcohol research domains, namely short-term drinking intentions (Chapters 4 and 5), pre-drinking motives (Chapter 7) and night-level threshold of risky drinking (Chapter 8) which did not require multi-disciplinary inputs.

This project utilised the smartphone built-in sensors and software to collect information on the participants' nightlife behaviour and context, but not on their alcohol use. All alcohol use measures were therefore dependent on participants' recall ability (memory) and desire to respond honestly. The evaluation of participants' experience with the app in Chapter 2 suggest that self-reported data on alcohol were reliable given that the number of drinks consumed by participants per night was relatively stable over the course of the study. For future studies, it is important to also test the reliability of self-reports of consumed amounts. In particular, wearable mobile technologies, through the connection of smartphone apps to external sensors, offer significant potential for also monitoring alcohol consumption in unobtrusive ways in EMA studies. Among the readily-available solutions are the alcohol transdermal sensors allowing alcohol consumption measurement through perspiration (Barnett et al., 2014; Caluzzi et al., 2019). Additionally, specific apps can be developed to measure alcohol intoxication level in real time using for example the velocity and accuracy of the fingers on the smartphone screen when the user is writing or surfing, the person's motion and balance, the heart rate, as well as performance and reaction tasks (Mariakakis et al., 2018).

By collecting data on multiple contextual characteristics within the same study framework, the present work extends existing evidence on the influence of the social context (Demers et al., 2002; Smit et al., 2015; Thrul et al., 2017; Thrul & Kuntsche, 2015) and the physical context (Guéguen et al., 2008; Hughes, Quigg, Eckley, et al., 2011; Stevely et al., 2019) by showing that contextual characteristics are likely to influence each other. Future research should not only consider multiple characteristics at once in multivariate analyses, as undertaken in Chapter 4, 5 and 6, but should go one step further to find typical constellations of factors (e.g. at home + absence of supervision + 10 or more friends present) that increase the risk of heavy drinking and adverse consequences.

Finally, data on people's drinking behaviour and the associated drinking context are highly sensitive in terms of confidentiality and privacy (Capon et al., 2016; Carter et al., 2015). Given the large array of personal data that can be collected via smartphone technologies, both passively and actively, on the participants themselves and on the people around them (e.g. people appearing in their video clips or pictures), strict data safeguards should be implemented during the data collection and analyses phases to ensure the full privacy and security of the collected data. These include specific measures to ensure data security during the data collection period (e.g., data encryption, unidentified usernames), secure data storage (e.g., institutionally owned servers) and ethical use of the data (e.g., ensuring informed consent, possibility for participants to remove compromising content, data access restricted to the research group).

9.5 Conclusion

This work aimed to investigate the influence of several contextual characteristics on drinking behaviour by means of a custom-built smartphone application collecting questionnaire, media and sensor data. The combination of these three data sources captured multiple contextual characteristics for almost every drink consumed, which allowed the identification of several contextual risk factors for increased alcohol intake. These factors can serve as a basis for the development of dedicated structural and individual prevention measures. The collection of questionnaires and sensor data was uncomplicated for the participants, but the provision of pictures and videos was more difficult to integrate into their weekend routines. Alcohol researchers and computer scientists are encouraged to further explore the interplay between drinking and the context with apps, and should pay attention to the ethical, technical and practical implications of such a versatile data collection tool.

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