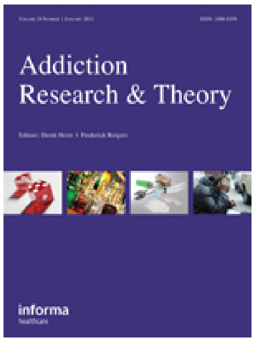

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Capturing drinking and nightlife behaviours and their social and physical context with a smartphone application – investigation of users' experience and reactivity

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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 16–25 (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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Ecological momentary assessment (EMA); smartphone application; drinking behaviours; assessment reactivity; response burden; long-tail data distribution

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 and 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 (Kuntsche and Labhart 2013; Clapp et al. 2017; Dulin et al. 2017; 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 (Monk and Heim 2013a, 2014; Freisthler et al. 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, Remmerswaal, 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.

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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).

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 (Rolstad et al. 2011; Carpenter et al. 2016). 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.

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 and Greenfield 2007) and the use and production of content in online media (Lerman 2007; Ochoa and Duval 2008; Poell and 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.

Methods

Youth@Night application

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).

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.

Questionnaires and media. Figures 1 and 2, and Table 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 preset 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 and 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 for an overview).

Finally, 40 qualitative interviews focussed 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.

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, 2540 photos, and 897 video clips.

Study procedure

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 maximise 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.

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 3–4 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 and 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

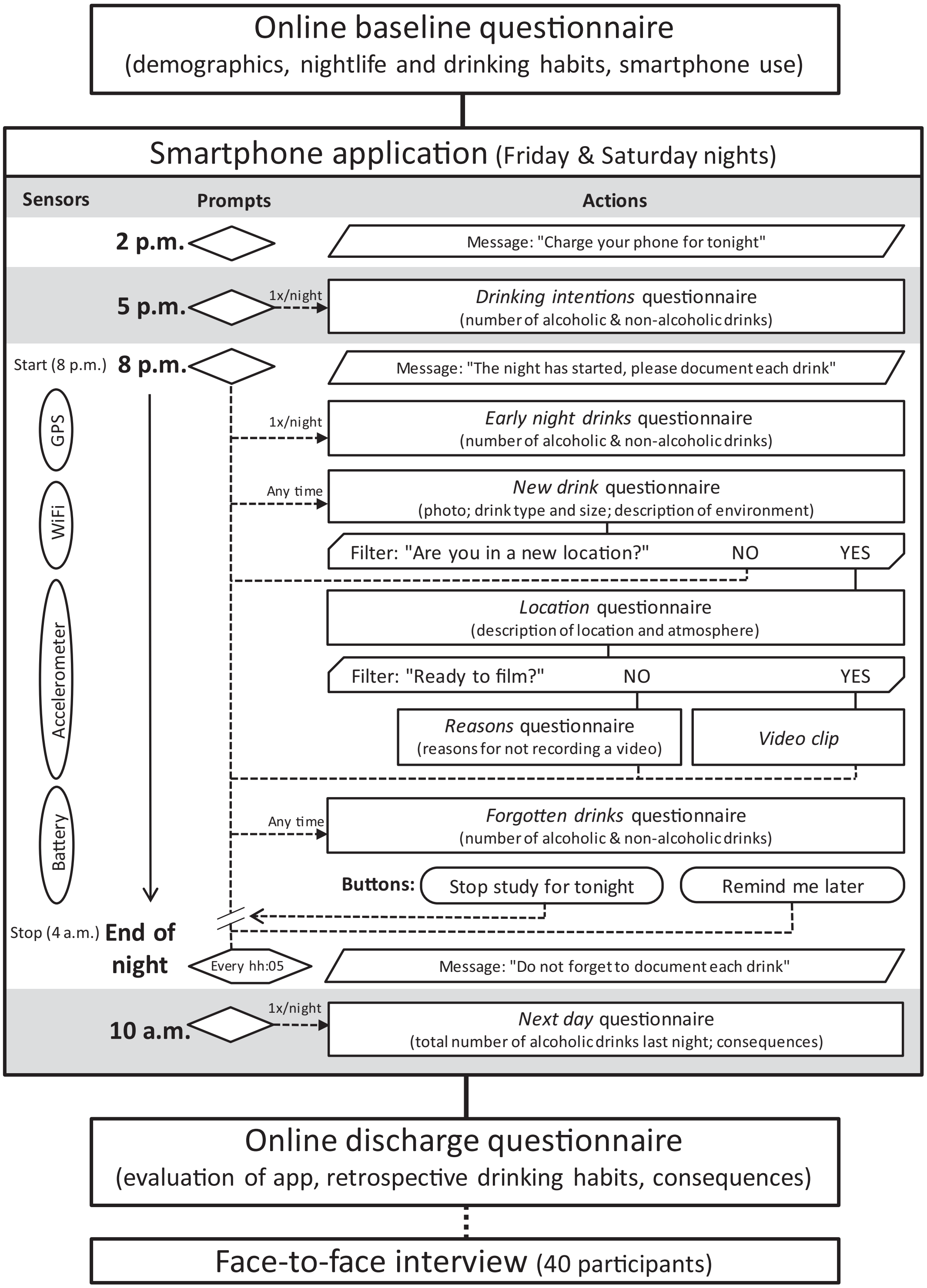

Figure 1. Structure of the data collection and schedule of application features (sensors, prompts, messages, questionnaires, filters, and buttons).

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).

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)

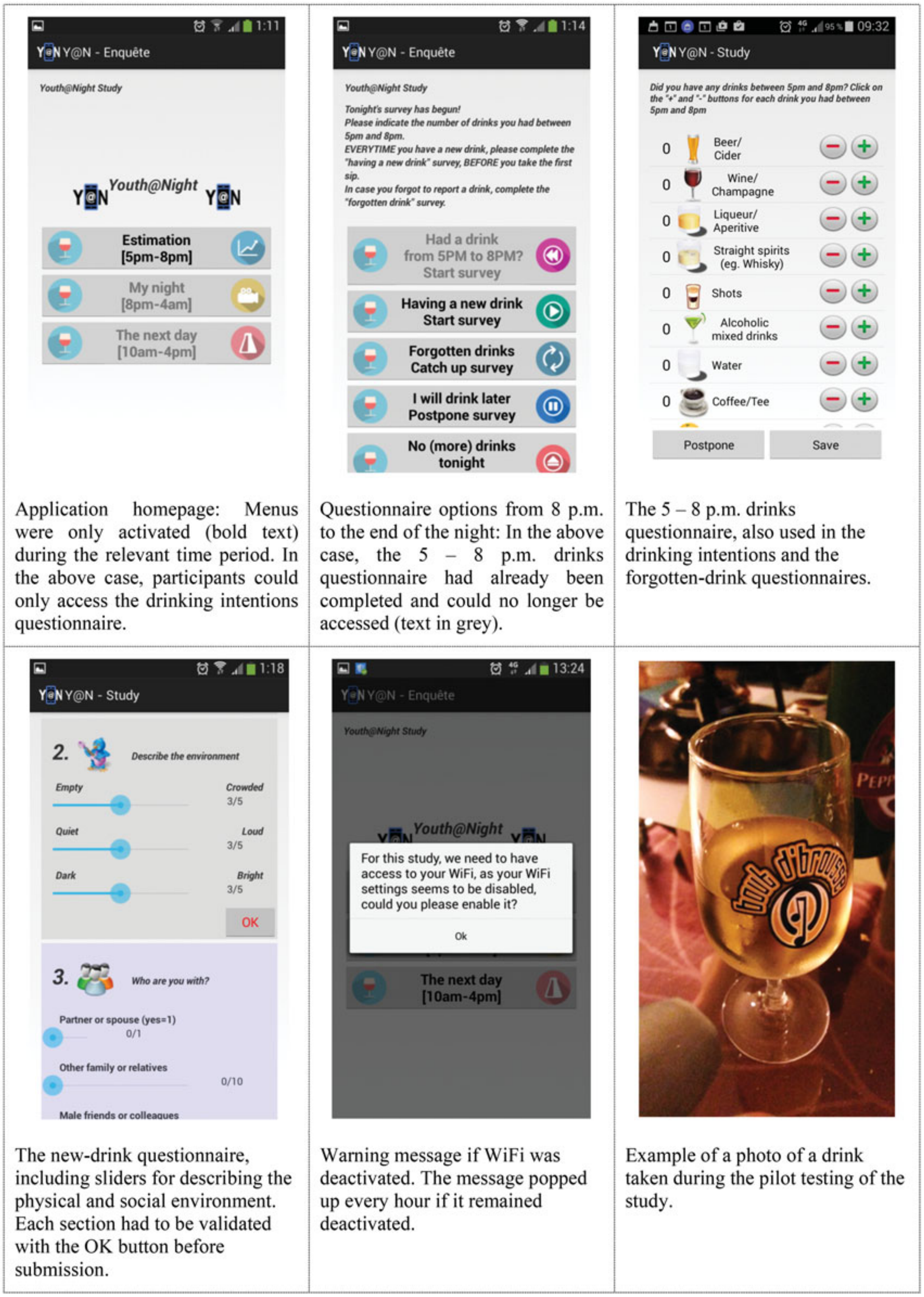

Figure 2. Screen captures of the application and example of a photo of a drink.

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).

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 contextualise and expand the findings from the quantitative data.

Table 1. Schedule and content of the questionnaires.

Questionnaire	Schedule	Type of data	Method of data collection
Drinking intentions	Prompt: 5 pm Close: 8 pm	Drinking intentions for the night	"+" and "−" buttons for each of the 12 drink types (Figure 2)
Early night drinks	Prompt: 8 pm 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 and Gatica-Perez2013) 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 and Gatica-Perez2015)
> Video	After *location* if participants were ready to film	10-s 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 participants 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.'

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 (67–103 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.

Results

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 min 40 s. The median of the five first completion times (i.e. when participants explored and familiarised themselves with the app features) was of 1 min 51 s 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 min 27 s and did not decrease further ($r_{[6+\text{ completions}]}(322) = -0.08$, $p = .110$).

As seen in Table 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).

When asked to record a 10-second video clip, participants recorded a video in about two-thirds of cases (68%; Table 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).

Most participants found the application intuitive and easy to use (item 1 in Table 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.

Table 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]						ANOVA[b]		
	Mean (SD)	*t*	*p*	d	Irregular Mean (SD)	Regular Mean (SD)	Assiduous Mean (SD)	F	*p*	η^2
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 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 (24.0%)	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.

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 3 and Table 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.

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 4). Figure 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), 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.

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 8-h 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), 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) 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), but another third reported that this was 'never' or 'rarely' the case. In qualitative interviews, several participants explained the situations in which

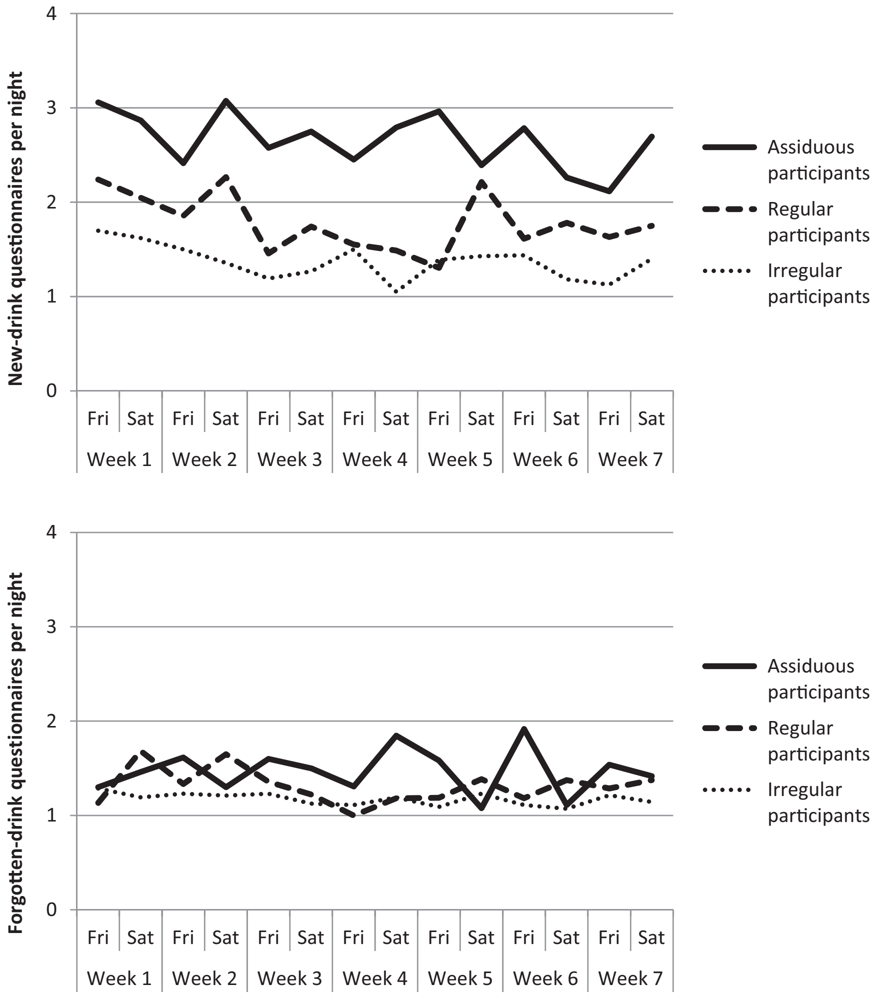

Figure 3. Numbers of new-drink and forgotten-drink questionnaires submitted per night of participation, per participant group.

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.

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).

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, Remmerswaal, 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, Remmerswaal, 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

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

Measure Compliance group	Average Mean (SD)	Trend Correlation[a]	Difference with Regular group Adjusted *t*-test[a]	Difference with Irregular group Adjusted *t*-test[a]
Numbers of new-drink questionnaires submitted per night of participation (Figure 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 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 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 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. [a]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.

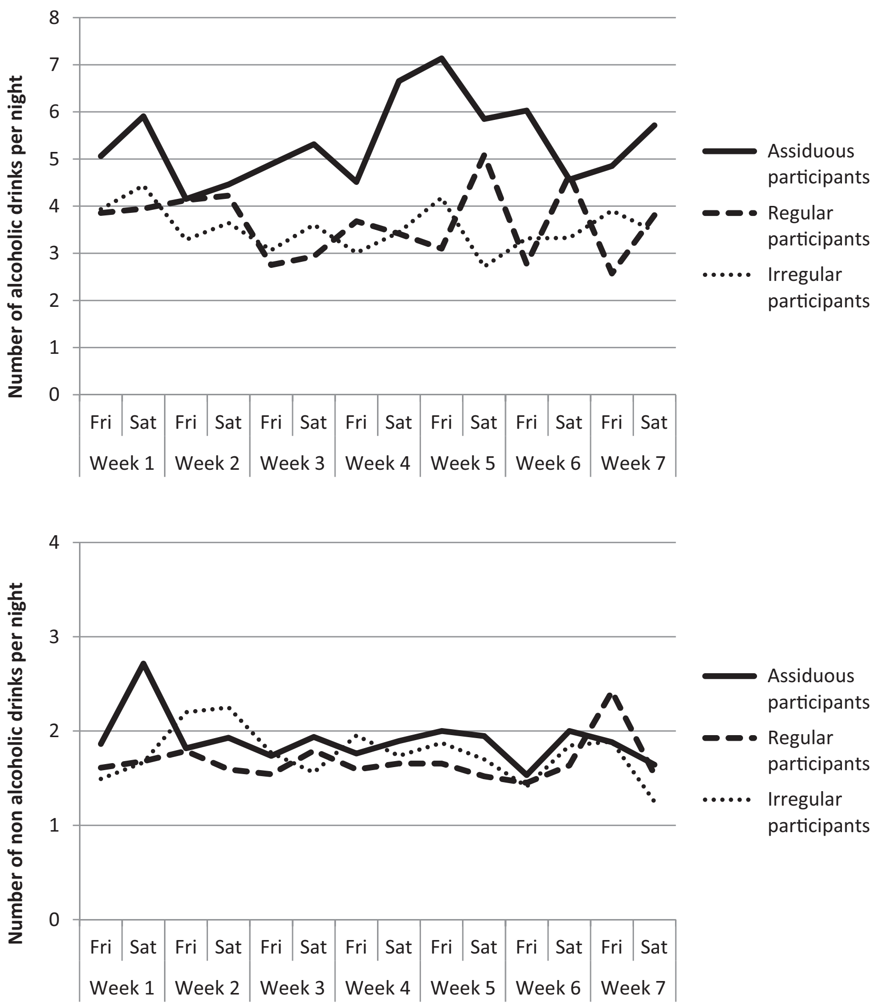

Figure 4. Numbers of alcoholic and non-alcoholic drinks reported per night of participation, per participant group.

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 and 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.

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.

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.

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 licenced venues (Landolt 2011; Labhart et al. 2013; Demant and Landolt 2014; Dietze et al. 2014). 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.

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.

Disclosure statement

The authors do not have any conflicts of interest.

Biographical notes

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