The Night is Young: Urban Crowdsourcing of Nightlife Patterns

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ABSTRACT

We present a mobile crowdsourcing study to capture and examine the nightlife patterns of two youth populations in Switzerland. Our contributions are three fold. First, we developed a smartphone application to capture data on places, social context and nightlife activities, and to record mobile videos capturing the ambiance of places. Second, we conducted an "in-the-wild" study with more than 200 participants over a period of three months in two Swiss cities, resulting in a total of 1,394 unique place visits and 843 videos that spread across place categories (including personal homes and public parks), social and ambiance variables. Finally, we investigated the use of automatic ambiance features to estimate the loudness and brightness of places at scale, and found that while features are reliable with respect to video content, videos do not always reflect the place ambiance reported by people in-situ. We believe that the developed methodology provides an opportunity to understand the physical mobility, activities, and social context of youth as they experience different aspects of nightlife.

ACM Classification Keywords: H.4.m Information Systems Applications: Miscellaneous

Author Keywords: Mobile Crowdsensing; Youth; Nightlife

INTRODUCTION

Understanding nightlife, i.e., how party goers, nighttime entertainments, urban policies considering nightlife and inhabitants interact at night, is a relevant issue to multiple stakeholders including city officials, business associations, police departments, health and educational authorities. Among other conceptualizations, a vibrant nightlife scene can be simultaneously seen as an urban development strategy, an economic opportunity, a source of health and safety risks, and a way in which citizens co-create and appropriate the urban space [46]. Young people, including late teenagers and young adults, are key actors of nightlife, and as such become the focus of many of the above stakeholders, with respect to the design of strategies and policies that encourage the appropriation of the urban space while promoting healthy behaviors [23, 7].

We posit that Ubicomp research can contribute to the understanding of nightlife as experienced by young people, who happen to use mobile and social technologies day and night. This can provide social and health scientists with ecologically valid, in-situ contextual data about venues, mobility, activities, and social patterns, with high spatial and temporal resolution, and potentially at scale. Moreover, ubiquitous computing adds the possibility of collecting sensor data and media in addition to more traditional survey based data, e.g., via experience sampling done in a number of disciplines including social psychology, epidemiology, etc.

In cities, mobile crowdsourcing provides the possibility to study questions related to populations and their environments that have been elusive in the past. The engagement of mobile crowds to collect everyday life data using smartphones has followed two main directions in the literature. One approach relies on crowdsensing, i.e., the use of sensors in mobile devices to collect data (either at pre-defined regimes or opportunistically) without requiring human intervention [26, 5]. While many sensor data types (location, accelerometer, WiFi) can be reasonably processed using data coming from smartphones in pockets or bags, other sensors like camera and microphones suffer from it. The second trend in the literature involves requesting explicit actions from crowdworkers, including photo-taking and audio recording, where the sensors are unoccluded for data collection [25, 49, 37].

In this paper, we present the design and implementation of a mobile crowdsourcing study to capture, examine, and provide insights on nightlife patterns of youth (aged between 16–25 years) in Switzerland. We developed a smartphone application that captures data on where young people hang out, their social context, and their activities during night time. The field study was conducted in two Swiss cities (Zurich and Lausanne), which are recognized as the two national nightlife hubs among young people in the German and French-speaking regions of the country, according to city officials [29, 33]. In this paper, we address the three research questions:

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RQ1: How can mobile crowdsourcing be used to study nightlife patterns of urban young people? How can the collection of mobile videos be integrated as part of this crowdsourcing task?

RQ2: What are the places and social contexts in which young people hang out? How is the use of private and public places distributed among youth?

RQ3: To what extent do automatically extracted features from mobile videos represent the real-life level of loudness and brightness of nightlife places?

Novelty and Contributions: Our study has four novel aspects. First, we conducted a large-scale mobile crowdsourcing study to capture the nightlife behavior of over 200 young people for three months in two cities in Switzerland. The design of our mobile crowdsourcing methodology followed an interdisciplinary approach involving ubiquitous computing, alcohol epidemiology, and human geography. Second, our study involved in-situ collection of place videos to gain a detailed view into the physical and social experience of youth nightlife, which is difficult to assess with audio or still images. Third, the study resulted in documenting places that have been hard to study in the past at scale, namely private places (homes or friend's homes) [13], as well as public, non-commercial places where youth gather (e.g., public squares, parks, etc.) [8]. Our approach has clear connections to social media, where users publicly share images (and to lesser degree, videos) taken at popular places [36]. This content, while produced in large quantities, has some limitations in terms of representativeness, temporal resolution, and beautification [45]. Fourth, while characterizing ambiance of places (loudness and brightness) using videos, we conducted a systematic comparison between automatic feature extraction, in-situ self-reports and manual coding using Brunswik's lens model [3] to examine the reliability of different crowd-workers (in-situ and ex-situ) to inform various aspects of nightlife. Our contributions are:

1. We developed an Android smartphone application to capture the heterogeneity of youth nightlife patterns from self-reported data: the places where youth spend their weekend nights (physical mobility), the activities they perform (consumption of alcohol), and the people they meet (social context). For each place check-in, the application also requests users to capture a video providing a panoramic view of the checked in place.

2. We proposed a data-driven approach to define recruitment zones based on nightlife activity using Foursquare data, to increase the likelihood of finding potential study participants.

3. We conducted a study with more than 200 participants aged 16–25 years old in two Swiss cities. Switzerland has a tolerant attitude towards youth using public spaces and a non-criminalized attitude towards certain youth behavior.

4. The participants contributed a total of $1,394$ place visits and 843 videos capturing different place categories (including personal homes). Private places were reported to be brighter, and less crowded compared to public places. Bars and clubs were reported to be relatively more crowded, louder, and darker compared to the rest of public place categories. Overall, participants captured places along the full spectrum of place types, social context and ambiance.

5. We studied the use of automatic ambiance features to estimate the loudness and brightness of places. We found that these features are reliable with respect to the raw video content, but that the videos themselves do not always reflect the place ambiance reported in-situ.

6. We found that participants were compliant when it comes to recording videos in a variety of places, social settings or personal contexts, and privacy-related situations.

We believe that the developed methodology provides an attractive opportunity to improve our current understanding of patterns of physical mobility, activities, and social context of youth population, as they experience nightlife.

RELATED WORK

Given the multifaceted nature of our work, we review the related work along four domains: mobile sensing, mobile crowdsourcing, computational modeling of places, and the intersection of urban nightlife and youth studies.

Mobile Sensing for Data Collection

In mobile sensing, few groups worldwide have collected mobile sensor data that is at the same time rich, longitudinal, and that covers a large population. One of the earliest work was done as part of the MIT's Reality Mining initiative [11]. Another was the Nokia Mobile Data Challenge in Switzerland, which showed the feasibility of collecting continuous smartphone data from 200 users over one year [26, 27]. Most mobile sensing studies have focused on gathering sensor data including accelerometer, GPS, WiFi, Bluetooth. Other studies have also collected perceptual data including audio and still images for place characterization [6, 47, 28], life-logging [18], visual perception [37], etc. In contrast, fewer crowdsensing studies have collected visual data in the form of mobile videos. A recent study has proposed a crowdsourcing framework to acquire and transmit mobile videos under resource constraints for disaster response scenarios [43].

Mobile Crowdsourcing Platforms

The wide spread adoption of mobile devices has lead to the emergence of mobile marketplaces where mobile users are paid to perform tasks in the physical world. In these marketplaces, mobile users are asked to perform tasks which are characterized by users' physical mobility (location-based) or their real-time nature (e.g., surveys, performing household chores, etc). Mobile marketplaces are different from online crowdsourcing platforms like Mechanical Turk or CrowdFlower, which do not impose these physical constraints. Notable mobile marketplace platforms include GigWalk [15], TaskRabbit [21], and FieldAgent [1]. Following the rise of these platforms, recent research has examined the practices and dynamics of mobile marketplaces [32, 41, 42]. On one hand, these platforms provide relatively easy access to on-demand workforce (both online and mobile), however it is difficult to recruit crowdworkers using these platforms for a sustained period of time. Consequently, in some of the large-scale mobile sensing campaigns including in our current work, researchers themselves recruit participants to gain a more fine-grained control on demographics, location, study duration, etc. [6, 26, 11].

Place Characterization

Previous work has modeled places automatically using data obtained from mobile sensors [6, 47]. In [47], the authors used automatically extracted features from audio signals to infer the level of occupancy, human chatter, music, and noise of places. In [6], the authors addressed the task of place categorization based on the automatic processing of opportunistically captured audio signals and still images. In this regard, our work is closely related to work by Chon et al. [5], who carried out a two month deployment of a crowdsensing platform to collect 48,000 place visits from 85 participants in Seoul, to examine the coverage and scalability of place-focused crowdsensing.

Our research differs from prior works in three aspects. First, in addition to capturing similar mobile sensor modalities, we collected videos of places combined with location and time based surveys to gain additional context. As we show, videos provide a highly detailed window into the physical and social experience of the participants, closer to "being there" than what other sensors can provide. Second, all the data was collected with a participatory approach, where users intentionally captured videos (or answered a series of questions about the place) in-situ, as opposed to an automated sampling approach [6, 47]. As we explain later, the intentionality of our crowdsourcing task also allows to study issues related to the perception of social acceptability of video recording in everyday life. Finally, our study covers a much larger geographic area than [5, 48, 47], including two cities with linguistic and cultural differences, but also many areas around each city.

Urban Nightlife and Youth

In urban studies and human geography, researchers acknowledge that little attention has been given to understanding the dynamics surrounding youth experiences and urban nightlife [46]; this is certainly so in Ubicomp research [44, 17, 2]. Activities during daytime have often been the primary source of investigation to understand topics ranging from human mobility and experiences, to how spaces are used and regulated in urban areas [31, 4, 40, 19]. There is a significant body of work at the intersection of youth, drinking, and urban spaces, where researchers have examined drinking places including pubs and bars [10], house parties [22] and public spaces [8]. From the perspective of young people, research has also studied various aspects of alcohol consumption, ranging from "pre-loading" (a phenomenon where youth consume alcohol before going out for the night), to health risks associated with excessive drinking [46]. In contrast with these works, our paper captures the heterogeneity and complexity of the going out behavior of youth during night time using mobile crowdsourcing, which to the best of our knowledge has not been studied in urban studies and human geography.

STUDY DESIGN

We now describe the design of our study, including the development of the mobile application, the specific urban context, and the recruitment of participants.

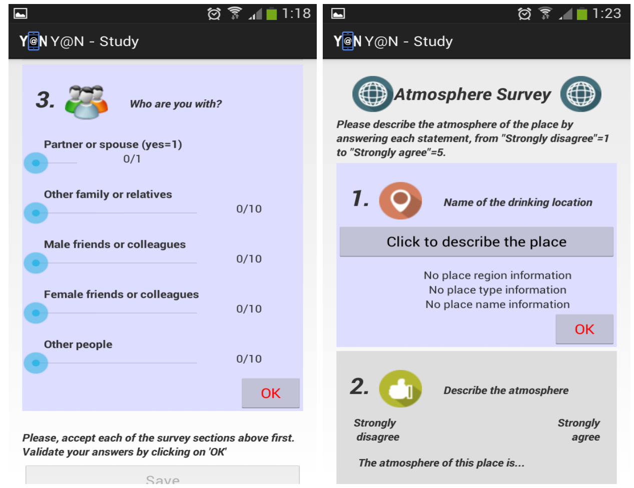


Figure 1: Screenshots of the survey logger mobile application

Mobile Application

We developed two custom Android-based smartphone applications: a survey logger and a sensor logger application. These applications allowed participants to respond to various surveys, while at the same collect sensor and log data in a non-intrusive and privacy-preserving manner. We used Android 4.0.3 version as it represents compatibility with over 95% of the total Android-based phones at the time of design [9]. During our recruitment campaign, we did not encounter any user having an Android phone below this version. Below, we describe these two applications in detail.

Survey Logger: The survey logger application let participants respond to various surveys in real-time on weekend nights (Friday and Saturday) from 8PM to 4AM (the next morning.) Surveys include place survey, video survey, and drink survey. We describe the questions asked in these three surveys in the next section. Figure 1 shows two screenshots of the application. Due to the multilingual Swiss population, the mobile interface was designed in three languages (English, German, and French), where users could choose their language of choice. Throughout the paper, "weekend nights" refer to Friday and Saturday nights between 8PM until 4AM.

Sensor Logger: We developed a second application to collect different types of sensor and log data. It was designed to run as a background process without any user interaction. The focus of this paper is to analyse and present results based on the data collected using the survey logger. The detailed analysis of sensor data will be reported as part of future work. Note that in this paper, we did not use the physical location (inferred via GPS) as we collected semantic location data (home postal codes, place categories, etc.) that enable us to estimate the spatial coverage of our experiments.

Study Context

Location: The study was conducted in two major cities in Switzerland, namely Zurich (German-speaking city with population of 400,000) and Lausanne (French-speaking city with population of 140,000). These cities were chosen in order to capture regional diversity and because both cities are the two major hubs for nightlife activities in Switzerland [29, 33]. Switzerland has a national population of 8 million people, i.e., about the same as New York City. Zurich and Lausanne are the first and fourth largest Swiss cities. The main nightlife areas in both cities are walkable, and many of them are in close physical proximity. Both cities provide excellent public transportation including during night time [38]. Due to these factors, both cities receive an influx of youth from neighbouring towns and even other cantons on weekend nights.

Nightlife and Youth: Nightlife for youth in Switzerland reflects patterns that are common in other western European countries. First, young people (especially those living on their own) often spend part or all of the night at home. This is partly related to the high cost of going out: the typical cost of a night out can easily reach 50 Swiss Francs (CHF), equivalent to 52 USD. Based on a pre-study survey conducted with 367 potential study participants (16–25 yo), we found that on average, young people spend 45 CHF per night when going out, with 17% of respondents reported to be spending more than 75 CHF per night. Note that unlike the US, the legal alcohol purchase age in Switzerland is 16 years for beer and wine and 18 years for spirits. Second, youth in Switzerland also spend part of the night in public spaces other than bars, restaurants, or clubs. This includes public squares, parks, train stations, but also streets and areas outside nightclubs [8]. It is important to note that drinking in public spaces (an activity associated with nightlife) is not criminalized in Switzerland. Third, young people (below 25 years old) are allowed subsidized travel from 7PM on all forms of public transportation, which encourages the use of public transportation and reduces the risks associated to driving cars.

In summary, this setting provides opportunities to examine the physical mobility, activities, and social patterns of young Europeans as they experience various aspects of nightlife.

Recruitment of Participants

For our field study, we recruited participants in Zurich and Lausanne, all between 16 and 25 years old. The field study was planned to run from September to December 2014, and participants were recruited in the month of September 2014. This period was chosen as it represents the time of the year after the summer holidays and before the Christmas break. For recruitment, young people on the streets were approached by our recruitment team on weekend nights between 8pm and midnight. Recruitment was done by a team of research assistants in groups of two to four people. Before the first recruitment session, the assistants got familiar with the smartphone application, practised their introduction speech, and were reminded of the recruitment process. An authorization from the city authorities was required to conduct recruitment on the streets. In order to identify the recruitment zones to help the assistants, we used a place dataset extracted from Foursquare [35]. Using the Foursquare data, recruitment areas were identified based on their nightlife activities (e.g., bars, clubs, public parks, streets, etc.) which were further discussed and validated with local experts (social workers and police.)

During the recruitment process, teams of research assistants carried a field diary to document their experiences. We manually coded these notes and found some common themes. First, our choice to wear a lime-green t-shirt having the study logo, worn by all recruiters, intrigued passers-by and assisted the team to engage in conversation. Furthermore, it legitimized the recruiters approaching people on the streets. Second, recruiters observed that the study payment of 100 CHF was a key factor for participants aged between 16 and 18 years old. Third, the recruitment team noted that young people were typically going out earlier than their older counterparts. Fourth, our team noted that many iPhone users appeared frustrated and even mentioned being "discriminated" as they appeared quite interested to participate in the study. Fifth, the weather played a role during the second week of recruitment: few people were going out as it was raining during that week, which reduced the pool of potential participants. We believe that these findings could be useful to Ubicomp researchers recruiting participants for similar crowdsensing campaigns.

Study Protocol

Before the study began, participants downloaded the two mobile applications (*survey* and *sensor* logger) and installed them on their own phones. During a weekend night, whenever participants were in a new location, they were asked to describe the place, its environment, and record a short 10-second video to capture their current environment using the survey logger application. While participants were at a given place, they were also asked to document their drinks (alcoholic and non-alcoholic), and describe the people they were with. In parallel, sensor data was continuously collected in the background using the sensor logger app. Note that we did not perform any real-time place detection on users' mobile devices, so we had no means to know if the participant had indeed moved to a new location during the night. It was left to the participants to self-report if they had moved to a new venue.

Participants were sent hourly prompts to remind them to report new locations. Participants could stop these prompts for a given evening (e.g. when going to bed) or snooze them (e.g. if they were in a theatre) at any time. At the end of the study, participants were given a monetary incentive of 100 CHF, if they completed at least 10 weekend nights of participation. Participants who volunteered for less than 10 evenings were compensated on a pro-rated basis, with a minimum of three nights. All participants were informed of the type of data collected as part of the study, as well as on all other aspects of the data collection. Our study was approved by the ethical review board of Vaud and Zurich cantons, respectively, for the cities of Lausanne and Zurich in Switzerland.

DATA COLLECTION FRAMEWORK

In this section, we describe our data collection framework including the various types of data collected, data transmission, and privacy.

Data Types

Study Long Questionnaire

After the recruitment phase and before the study, participants were asked to complete a questionnaire about their demographics, weekend nightlife habits, smartphone usage, and social media usage.

Survey Data

Place Survey: This survey was designed to document the functional attributes of the place and its in-situ atmosphere. Participants could answer the survey only when they reported to be in a new location during a night. If participants decided not to answer the survey when getting to a new place, they could have answered it any time while they were in that place. The place survey had two goals. First, to capture the place attributes including its city and place category (e.g., bar, restaurant, nightclub, public spaces, homes, etc.). We chose nine high-level categories adapted from Foursquare's place category hierarchy [14], as previously done in the literature [5]. Second, users were also asked to document the environment along three dimensions: occupancy, loudness, and brightness. These ratings were given on a five-point Likert scale, ranging from *very low* (1) to *very high* (5). For the place survey, we received a total of $1,394$ responses from 206 participants (Table 1). In our data, public places refer to all places that are not private, including bars, restaurants, cafes, clubs and other public spaces (e.g., parks, plazas, lakeside, etc.). To avoid confusion, we refer to this later category as *PBS* (PuBlic Space) in the rest of the paper.

Video Survey: In this survey, participants were asked to record a short 10-second video capturing the environment of their current place. Participants were instructed to capture a panorama by slowly recording a video turning from left to right with the phone in the landscape (horizontal) mode. Participants could take the video survey only after completing the place survey. If participants were unable or reluctant to take a video, we asked them to specify the reasons in form of a multiple-choice questionnaire. We gave participants the following five reasons to choose from: 1) Ethical ("It is not appropriate to record a video now"); 2) Legal ("Recording a video is not allowed in this place"), 3) Safety ("I don't feel safe recording a video now"), 4) Social ("I was asked by someone not to record a video"), and 5) Other. Participants were allowed to choose multiple reasons (and at least one) if they decided not to record a video. We obtained a total of $1,323$ responses to the video survey from 204 participants.

Drink Survey: This survey was designed to log participants' nightlife activities and social context of their place visits. Users were asked to describe their activities in form of drink consumption, both alcoholic and non-alcoholic beverages. Drink attributes include information on their current drink, including the type of drink, the size of the drink, and the alcohol quantity, which were selected based on existing literature on alcohol consumption [34]. To inform their social context, users also reported the people they were with, including friends, colleagues, or family members. For this survey, we received a total of $2,532$ responses from 218 participants.

Combined Dataset: During the study, we received a variable number of responses for each of the survey as reported in Table 1. For some place visits, participants responded to the place survey, but not to the video survey, while for other visits participants only responded to the drink survey, but did not provide answers to the place or video survey. This is inevitable given the "in-the-wild" nature of our study; similar trends have

Dataset	# Responses	# Users
Place Survey	1,394	206
Video Survey	1,323	204
Drink Survey	2,532	218
Combined Dataset	1,323	204

Table 1: Summary statistics of the collected dataset

been reported in previous mobile data campaigns [26]. Due to these missing records, we combined the survey responses to include only those check-ins for which all the three surveys have been answered, resulting in a total of $1,323$ check-ins from 204 participants. Consequently, for each check-in in the combined dataset, we have the complete information about the place functional attributes, activities (social and alcohol consumption), and the responses to the video survey. In the rest of the paper, a "check-in" refers to the act of recording place information (via the place survey) and responding to the video and drink survey.

Interviews

After the data collection study was concluded, we conducted semi-structured interviews with 40 participants. While conducting these interviews, participants' recorded videos were used as stimuli to talk about their going out practices during weekends. Participants were also asked about their video-taking experience. The purpose of these interviews was to gain personal insights about the way young people engage in urban nightlife as a complex way of enjoying themselves while negotiating the dangers of the city at night [20].

Data Transmission

To preserve users' cellular data and optimize battery life, data transmission from phones to the backend server was performed when the device was connected to a WiFi access point. Automatic data upload was scheduled for every Monday at a random time between midnight and 6AM. When the data was successfully transmitted it was deleted from the device. Participants were provided an option to force a manual upload, if automatic uploads did not succeed.

Data Privacy

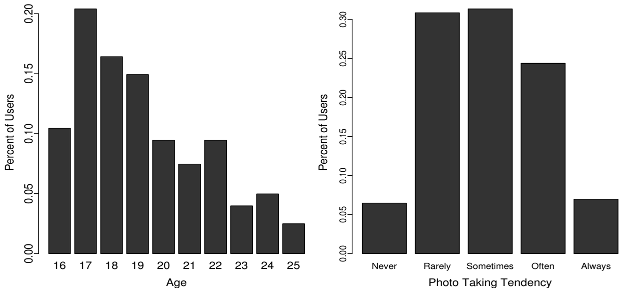
As stated before, the study was approved by the ethical review board of Vaud and Zurich cantons in Switzerland. Given the potentially sensitive nature of the collected dataset, we requested the consent of participants to share their data only within the research team. This restriction has implications on who can view and analyze the data, in addition to how the data can be manually coded.

RESULTS AND DISCUSSION

In this section, we first introduce the descriptive statistics of the survey questionnaires, then we describe the findings from the field study. We conclude with the results obtained by automatically analyzing the collected videos.

Analysis of Survey Data (RQ1)

Participants Demographics: Of the 204 participants who contributed data, 201 of them also responded to the study long questionnaire. Using the demographic information, we observe a fairly balanced gender ratio (52% male, 48% female).



(a) (b)

Figure 2: Plots showing the barplots for a) Age, and b) Photo taking tendency when going out at night for study participants.

We find that the majority of participants (62%) are below the age of 20, as depicted in Figure 2a. From an occupational point of view, 62% of participants reported being students, 24% reported apprenticeship as their occupation, while 4% declared to be working full-time. Over 83% of participants reported to be living with their parents, while only 10% reported to be living in either shared housing or a student residence. From these findings, it is clear that the demographics of participants are inclined towards teenage students and young adults living with their parents. During recruitment, our aim was to have a nightlife population as representative as possible. This population is significantly different than those reported in previous Ubicomp research, e.g., undergraduate and graduate students in Korea [5] or the US [48].

Smartphone Devices and Usage: Now we examine the diversity of mobile devices used by participants. The device information indicates eight mobile manufactures and 51 model versions, with Samsung being the dominant phone manufacturer (63%), followed by HTC (18%) and Sony (9%). Samsung Galaxy S4 and Galaxy S3 (released on April 2014 and 2013 respectively) are the two most popular model versions.

In terms of usage, more than 92% of participants reported to be using a smartphone for at least two years. 90% of them rated themselves as either a heavy or medium smartphone user. Over 81% of respondents send text messages more than half of the time when gone out during the night. When asked about the frequency of photo-taking when going out at night, 31% of respondents reported to be take photos often or always, as shown in Figure 2b. It is clear that the demographics of our participants align with their aggregated smartphone use.

Home Location and Going Out Behavior: 63% respondents reported going out at least once per weekend while spending an average of 42 CHF a night. Participants were asked to list the postal code of their residence as well. After geo-coding a total of 128 unique postal codes, we found that participants live in 11 different cantons (Switzerland has 26 cantons), with 52% of participants reported living in the canton of Vaud, 37% in the canton of Zurich, while the rest (11%) resides in the neighboring cantons. Interestingly, only 40% reported living within the city limits of either Lausanne or Zurich, while the rest of participants commute from neighboring towns for nightlife. As argued before, these findings confirm that both cities receive an influx of youth from neighboring cities and cantons on weekend nights. The spatial coverage of our data spans the main east-west corridor of Switzerland (distance between Lausanne and Zurich is 226 km), which differs from previous work (typically limited to one city.)

		Private $N = 626$	Public $N = 697$
Social	Alone	149	51
	At most 5 people	325	403
	More than 5 people	152	243
Ambiance	Crowdedness	1.88	3.0
	Loudness	2.14	3.19
	Brightness	3.14	2.84
Videos	# Videos Taken	416	478
	# Videos Not Taken	210	219

Table 2: Summary statistics across social, ambiance and collected videos across place types.

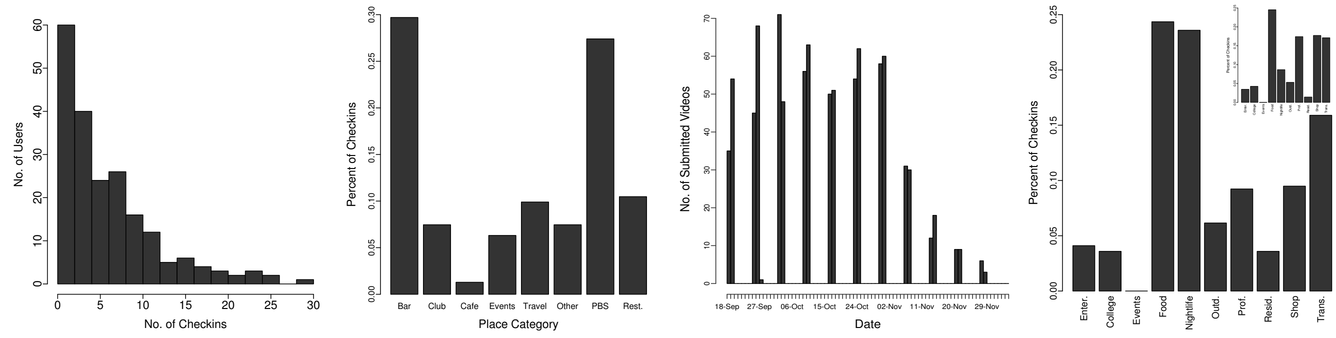
User Contributions: We received a total of 1,323 check-ins from 204 participants. On average, a participant contributed 6.5 place check-ins, with one participant submitting a maximum of 29 check-ins. Users' place check-ins follows a typical long tail distribution (Figure 3a). Similar heavy tail characteristics have been previously reported in the literature [5]. From 1,323 check-ins, participants submitted a total of 894 videos, while for the rest 429 check-ins participants did not to take a video. Figure 3c shows the distribution of submitted videos for every weekend night during the study duration. Note that the video dataset, discussed in the later sections, is different than [43] in that it is intentional, focused on nightlife patterns, and spans a variety of places.

Place Analysis (RQ2)

In this section, we examine the diversity and coverage of places in our collected data: (a) How well are different place types represented in our study? (b) How well the distribution of check-ins across place categories compare with the check-ins distribution from social media data?

Place Types: As reported earlier, participants recorded place information including the city of the check-in and place category using the place survey. We use the place category information to infer whether participants were at a public or a private place. When participants checked into a private place, we further asked them to specify whether the check-in was at their own homes, a friend's home, or other private venues.

Of all the 1,323 check-ins, 626 (47.3%) were at private places, and the rest (52.7%) at public places (Table 2). Of the 626 check-ins at private venues, 62% were reported from their own home, 30% from their friends' home, while the rest (8%) occurred at either their workplace or other private venues (e.g., student hostel, someone else's home while baby-sitting, etc.). A large number of check-ins at private venues might be due to two factors: a) the majority of participants (83%) reported living with their parents, and b) spending a night outside is relatively costly given the demographics and income earning status of participants. After manually browsing through some of the videos taken in private places, we found that some videos indeed show young people in large family homes (with a large living room and kitchen), but also studios and



(a) (b) (c) (d)

Figure 3: Plots showing the histograms for a) Number of contributed check-ins per user, b) Distribution of categories for public places, c) Number of submitted videos every weekend night, and d) Distribution of categories for Foursquare check-ins for night time. In inset, the overall distribution is shown.

small apartments that correspond to living alone and shared accommodation. Videos recorded at homes clearly have an intimate, unfiltered flavor. One can observe personal items, bedrooms, presence of friends, without the beautification often found in social media content. The video dataset offers an unprecedented way to conceptualize such places. The variety of private places captured on video is novel in and of itself, as previous studies have focused on college students (who in the US typically do not live with parents.)

For check-ins at public places, 30% were at bars, followed by 27% at PBS (including public parks, lakeside, etc.) as shown in Figure 3b. Restaurants and travel each contributed around 10% of all check-ins. We observe that a significant portion of check-ins happened at PBS, which suggests that youth spend a considerable amount of time hanging out in these spaces away from mainstream nightlife areas. This provides support for the qualitative work done with youth in the US context [2]. The PBS videos are specially interesting as they are unfiltered. Videos in dark parks or squares where people hang out, and video taken on streets outside commercial venues, are commonly found in our data. These places also provide support for qualitative work on the practices of Swiss youth in these venues [8]. Note that both Lausanne and Zurich have a scenic lakeside used often for recreational activities. Overall, these findings reflect that the study indeed captured different patterns of participants' nightlife behavior.

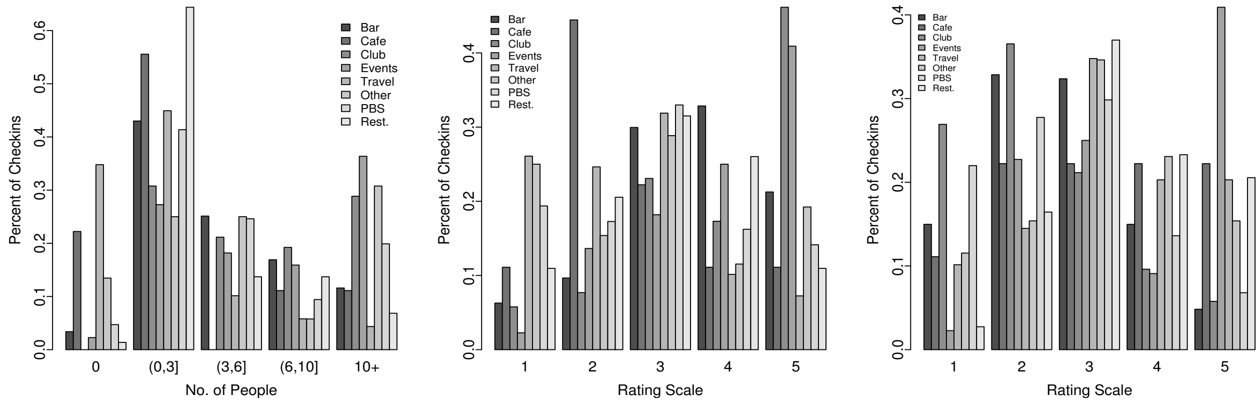
Comparison with Foursquare: Independent of this study, we have collected geo-localized check-ins within Switzerland using Foursquare (4SQ). We obtained a total of 54,184 publicly available check-ins for Zurich and Lausanne between Dec. 2011 and Feb. 2014. For all 4SQ check-ins for which place information was available, we plot the distribution across 10 Foursquare categories, temporally filtered between 8PM to 4AM in Figure 3d. In the inset of the same figure, we plot the overall 4SQ check-in distribution (i.e., without any temporal filtering). For both the temporally filtered and overall distribution, food places receive the most number of check-ins, which is in contrast with our study findings. Similar to previous work [5], we observe that places visited during night are more represented in our crowdsourcing study compared to Foursquare e.g., events category did not contain a single check-in for temporally filtered 4SQ data. For some of the categories, the check-in distribution of our study (Figure 3b) is similar to the temporally filtered 4SQ check-ins; however it is significantly different with respect to the overall 4SQ check-in distribution. These findings point towards limitations of social media in terms of representativeness and temporal resolution at least in the context of Switzerland [45].

Activities and Social Context: We now examine the activity and social context of participants at night, i.e., with whom and how many people participants were at the time of reporting their check-ins. For 24% (resp. 7%) of check-ins to private (resp. public) places, participants reported to be spending the night alone (see Table 2). We also observe that for 24% of private place check-ins, participants reported to be with more than five people. Digging further into these cases, we found that for 72% of these check-ins, alcohol was reported to be consumed, potentially suggesting social occasions or house parties [22, 13]. Looking at videos confirmed this point.

For check-ins to public places, we found that for most of the categories (except events and other), the majority of check-ins were reported to be with fewer than three people (Figure 4a). Digging further, we found that for bars and clubs participants reported to be with more than five people for 34% and 52% of check-ins respectively. Not surprisingly for event spaces, participants reported to be with more than 10 people for 36% of event check-ins; while for the travel category, 35% of check-ins were reported to be alone. The travel category corresponds to situations when people were walking, traveling in public transportation or using their personal vehicles.

Overall for 65% of place check-ins, participants reported consuming alcohol. We found that for check-ins at private venues, users reported drinking alcohol for 48% of cases, suggesting the trend of home drinking [13]. For check-ins at public venues, we found that users reported drinking alcohol for 80% of cases. Digging further into public place categories, we found that 84% of check-ins were reported with alcohol consumption in the PBS category. This finding provides support for qualitative work on the prevalence of "street square" drinking amongst Swiss youth [8]. Note that consuming alcohol in public places is not criminalized in Switzerland.

Ambiance Context: In the place survey, participants were asked to judge the environment in-situ along three dimensions:



(a) Social Context (b) Loudness (c) Brightness

Figure 4: Plots showing the histograms for a) Social Context, b) Loudness, c) Brightness across all public place category types.

place occupancy, loudness, and brightness. All ratings were given on a five-point Likert scale (1-*very low*, 5-*very high*). Using this data, we observe that public places are in general more crowded, louder, and darker relative to private places (see Table 2). These findings are not surprising. Figure 4b and 4c plots the distribution of loudness and brightness across all public place categories. On average, bars and clubs were reported to be relatively more crowded, louder and darker, compared to other categories.

Aside from this overall trend, we observe that irrespective of the place type, the study captured places along the full spectrum of ambiance variables, i.e., public places which were reported to be quiet, and private places which were reported to be very loud. This poses interesting challenges towards automatic analysis of videos (which is described in the next section), as the places covered are diverse in terms of overall physical ambiance dimensions.

Video Content Analysis (RQ3)

In this section, we explore the use of signal processing to measure two dimensions of place ambiance – loudness and brightness – automatically from videos. The automatic processing and characterization of place ambiance is a scalable alternative to manual data labeling. In contrast with prior work on computational modeling of places [6, 47], in this section we examine to what extent the automatically extracted features represent the in-situ levels of loudness and brightness of nightlife places, as perceived by both study participants and external observers of videos.

We conceptualize this problem in terms of Brunswik's lens model [3], a model often used in human perception research. The model involves computing cue utilization and cue validity of automatic features. In Brunswik's terms, *cue validity* refers to the correlation between automatically extracted ambiance and perceived in-situ ambiance (via self-reports), while *cue utilization* refers to the correlation between automatically extracted ambiance and manually coded perceived ambiance by external observers after watching the videos. On one hand, in-situ self-reports may be closer to the ground-truth, but they also include individual biases from participants, in part due to the explicit context of nightlife and potential alcohol use. On the other hand, manual coding may resemble automatically processed video content. Manual coding is also affected by individual biases, but these biases are smoothed by aggregating annotations by multiple coders. Our hypothesis is that cue utilization will be higher than cue validity in our data.

We believe it is important to examine the reliability of different crowd-workers (in-situ and ex-situ) in comparison with automatic feature extraction to better understand their strengths and biases to inform various aspects of nightlife. Are in-situ self-reports reliable when self-reporting itself might be affected by the situation being studied (e.g., nightlife and potential alcohol use)? In these situations, what can be considered the "ground-truth"? To the best of our knowledge, this kind of analysis has not been reported earlier in the Ubicomp community.

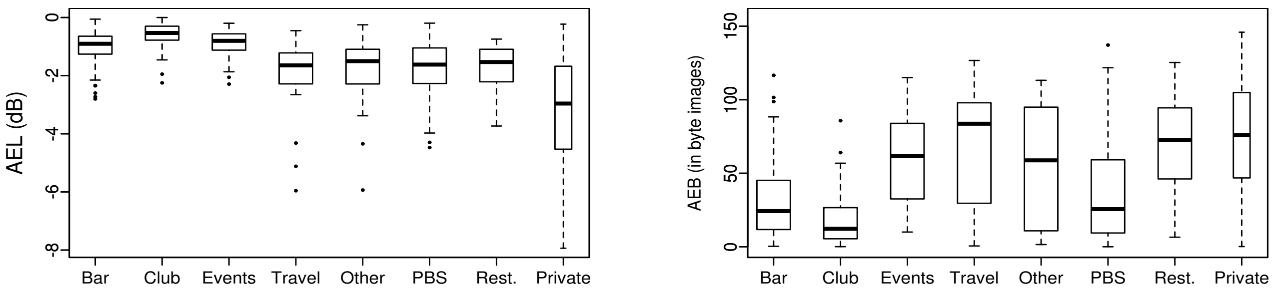
Crowdsourced Video Dataset

In our study, participants recorded a total of 894 videos, 51 of which were either corrupted or had null size. The remaining 843 (94%) videos had a mean duration of 9.4 seconds. 73% of the videos lasted exactly 10 seconds (the default setting while capturing videos via the app). In what concerns our analysis, the duration of videos limits the amount of information captured in videos, and thus, how accurate they may represent nightlife places and their ambiance. For the rest of the analysis we use the collection of 843 videos.

Manual Coding and Agreement

To annotate the video corpus, we asked two research assistants to rate the ambiance dimensions (i.e., occupancy, loudness, and brightness) after watching the videos. Annotators were also asked assign categories to places documented in the videos, as was done using the place survey. We measured the inter-annotator agreement and their agreement with in-situ self-reports using intraclass correlation coefficients ($ICC(1,k)$) [39] and Fleiss' Kappa coefficients (κ) [12], respectively for ordinal and categorical ratings.

While examining the external inter-annotator agreement, we observed fairly high agreement for all ambiance and place attributes including occupancy ($ICC = 0.90$), loudness ($ICC = 0.86$), brightness ($ICC = 0.75$), and place category ($\kappa = 0.75$).



(a) Loudness

(b) Brightness

Figure 5: Boxplots of AEL and AEB by place category. AEL values are normalized with respect to the loudest place and log-scaled. AEB is measured in byte images, a 8-bit integer ranging from 0 (dark) to 255 (bright). Note that the place category *PBS* refers to public spaces.

The aggregated external annotation scores achieved high agreement with self-reports for place category ($\kappa = 0.72$); moderate agreement for occupancy ($ICC = 0.50$) and loudness ($ICC = 0.55$); and, no agreement for brightness ($ICC = -0.07$). For brightness (resp. loudness), 50% (resp. 55%) of the videos had an ordinal scale difference of 1 or 2 points with respect to self-reports and 17% (resp. 8%) of them had a difference larger than 2 points, on a five-point scale. These findings suggest that assistants annotated some ambiance attributes differently from in-situ reports.

Feature Extraction and Analysis

We computed the loudness and brightness of videos using standard features from audio [24] and image processing [16], as described below:

Automatically Extracted Loudness (AEL): We extracted the loudness of places as the audio power (AP) using the audio channel of videos [24]. The AP coefficients are computed as the average square of digital audio signal $s(n)$ within successive non-overlapping frames. For each lth frame, AP is computed as: $AP(l) = \frac{1}{N_{hop}} \sum_{n=0}^{N_{hop}-1} |s(n + lN_{hop})|^2$, where L is the total number of time frames (each of time duration L_w) and N_{hop} is the number of time samples corresponding to the time interval between consecutive frames. For each video, AEL was the mean $AP(l)$ values across all frames, with L_w set to 128ms. The higher the value of AEL, the louder the video.

Automatically Extracted Brightness (AEB): We computed the average brightness of a video using a typical measure in image processing [16]. The brightness of a frame B is determined as the average intensity of the luminance channel $Y(x, y)$ computed across all N image pixels in the YUV color space, i.e. $B = \frac{1}{N} \sum_{(x,y)} Y(x, y)$. For each video, we computed B for every frame, and then take the mean to obtain AEB. The higher the value of AEB, the brighter the video.

Figure 5 shows the boxplots of AEL and AEB for each place type. Overall, we observe that private places are quieter compared to public places, which is consistent with the findings reported earlier using self-reported data (Table 2). When comparing the median values of AEL across public place categories, clubs, events, and bars are found to be the loudest places with low statistical dispersion (Figure 5a). In contrast, for the videos taken in private places, the distribution of AEL exhibits a wide spread with varying loudness profiles. The diversity in loudness of home environments may reflect different social settings e.g., private parties, family dinners, or being alone at home (see Table 2).

When comparing the median values of automatically extracted brightness, we find clubs and bars to be the darkest places together with PBS across all place types (Figure 5b). These findings are not surprising as clubs and bars at night are naturally expected to be darker than other public places such as restaurants (see Figure 4c). Among public places, restaurants have comparable distributional spread as private places. Finally, videos taken in the travel category have the highest median brightness, which mostly reflects on public transportation vehicles or stations that tend to be well-lit during night.

To validate these findings, we conducted a series of pairwise Kolmogorov-Smirnov test [30] across all place categories for AEL and AEB. For AEL, all the tests were significant at $p < 0.01$, except pair-wise tests between restaurant, travel and PBS, suggesting that these places have similar loudness profiles. For AEB, all the tests were statistically significant at $p < 0.01$ except tests between bar and PBS, and between restaurant, private and travel categories.

Feature Reliability

Now, we measure the cue validity (r_v) and cue utilization (r_u) of AEL and AEB by computing their pair-wise Pearson's correlations with self-reports and manual coding of loudness and brightness, respectively. Table 3 shows cue validity and utilization measures for each place type. Using these statistics, we observe the following trends. First, both AEL and AEB show significant cue utilization with moderate to high effect sizes ($0.48 \leq r_u \leq 0.83$) for all places types. Second, we obtain significant cue validity with moderate effect sizes ($0.25 \leq r_v \leq 0.48$) for both AEL and AEB for some of the categories. Third, cue utilization effect sizes are overall higher than for cue validity for both AEL and AEB, i.e., automatic ambiance features describe more accurately the perception of ex-situ annotators than that of participants in-situ. Fourth, the effect sizes of public and private places are comparable. Finally, AEB values are generally higher than AEL for cue utilization.

Apart from these findings, we observe that for place types with no significant cue validity, both AEL and AEB show statistically significant cue utilization (e.g., events, clubs). For these

Place Type	r_v	$p-$**value**	r_u	$p-$**value**
Loudness (AEL)				
Bar	0.34	2.26e-04	0.54	3.34e-08
Club	**0.31**	4.65e-02	0.62	1.89e-04
Restaurant	0.44	6.27e-03	0.53	8.05e-04
PBS	0.44	1.99e-07	0.48	1.68e-07
Events	**0.06**	7.33e-01	0.61	2.62e-04
Travel	**0.29**	4.24e-02	0.62	8.31e-06
Public	0.48	8.03e-26	0.67	7.83e-50
Private	0.45	5.77e-19	0.82	9.66e-82
Brightness (AEB)				
Bar	0.25	5.56e-03	0.71	2.03e-15
Club	**0.01**	5.35e-01	0.60	4.09e-04
Restaurant	**0.34**	3.7e-02	0.83	3.08e-10
PBS	0.38	8.08e-06	0.78	5.72e-23
Events	**0.25**	1.63e-01	0.83	8.38e-09
Travel	**0.31**	3.2e-02	0.72	3.94e-08
Public	0.43	1.00e-20	0.80	5.63e-82
Private	0.35	7.85e-12	0.73	2.78e-56

Table 3: Cue validity (r_v) and cue utilisation (r_u) for AEL and AEB ($N = 843$). Values marked in **bold** are **not** statistically significant at $p < 0.01$

place types, we watched a sample of videos where manually coded ratings were different from self-reports. While watching these videos, we did not find any obvious explanation for the difference in ratings, yet we found manual coding to be more reliable (i.e., correcting for biases and mistakes while self-reporting). For some other videos, we found that the presence of flashy lighting (common in clubs and events) may alter the perception of brightness between what is experienced in-situ and what is perceived manually. In general, we noted that videos tend to capture more diversity of content compared to audio content, which may explain higher cue utilization of AEB than AEL.

Overall, the current analysis confirms the diversity of our video dataset, and the value of understanding data quality using automatic and manual methods. We believe that the video dataset will open the door to additional research questions. As part of future work, we plan to automatically discriminate private vs. public places at night using video features.

EXPERIENCES OF VIDEO CROWDSOURCING

In this section, we first report results on participants' compliance with the video recording task, and then highlight a few observations from the qualitative interviews.

Compliance

We refer to compliance as the extent to which participants carried out the assigned task (video taking). In our study, we measure compliance on two aspects: 1) participants recording the video after check-in to a place, and 2) participants following the instructions given for video recording.

Recorded Videos: As stated before, participants recorded a total of 894 videos. Of all check-ins to public (resp. private) places, 68% (resp. 66%) resulted in a video (Table 2), suggesting that the video taking was not significantly different based on participants' location. When participants did not take a video, they had to specify one or more of the five predefined reasons. Of all the 429 check-ins with no video, safety, ethical, and social were the top three cited reasons (around 30% each). Only for 5% of cases, legal reasons were indicated for not recording a video, which in itself points towards ways in which participants perceived and conceptualized video taking in public and private places. When comparing the differences across place types, we found that social reason was specified more frequently in private places than in public ($\chi^2 = 16.56$; $p-value = 4.7e-05$); while safety reason was specified more in public places than in private ($\chi^2 = 5.69$; $p-value = 0.017$).

Video Attributes: Participants were instructed to take a 10-second video capturing a panorama with the phone in landscape (horizontal) mode. We used manual coding to annotate: 1) video orientation, and 2) if the video was captured with the camera panning. Based on the aggregated ratings, we found that 72% of the videos were recorded vertically, and 76% of videos captured a panoramic scene. Thus, we observe low to moderate compliance for these video attributes.

Qualitative Experience of Participants

To conclude this section, we report some key observations of participants' video-taking experience as shared on the qualitative interviews. One participant felt awkward taking videos in indoor and dark environments, but felt comfortable in outdoor places: "*It was somewhere indoor, and it was quite dark and it was pretty calm ... I can't just pull out my phone and film with a strong flash. I think people would have wondered what I was doing. But when I was simply outdoor, I didn't care*". Interestingly, some other participants did not differentiate between places to record, which could be interpreted as their indifference towards place type for video capturing. When asked about how recording a video made them feel unsafe, one participant noted: "*Because people don't like it. It could have led to conflicts. For example, people I don't know, they would have the feeling I film them, then they go nuts*" Apart from the stated reasons, few participants reported being too drunk, forgetful, or low battery for not taking a video.

CONCLUSIONS

In this paper, we presented a mobile crowdsourcing study to capture and examine the nightlife patterns of young people in Switzerland. The study resulted in a collection of 1,394 unique place visits and 843 videos that spread across different place categories (including personal homes), and across diverse social and ambiance settings. Private places were reported to be brighter, and less crowded compared to public places. Bars and clubs were reported to be relatively more crowded, louder, and darker compared to the rest of public place categories. Using automatically extracted ambiance features from videos, we found that while features are reliable with respect to video content, videos do not always reflect the place ambiance captured in-situ. Finally, we found that the study participants were compliant when it comes to recording videos in a variety of places, social settings or personal contexts, which shows the promise of collecting rich data for social science research in everyday life.

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