Bites'n'Bits: Inferring Eating Behavior from Contextual Mobile Data

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We collect and analyze mobile data about everyday eating occasions to study eating behavior in relation to its context (time, location, social context, related activities and physical activity). Our contributions are three-fold. First, we deployed a data collection campaign with 122 Swiss university students, resulting in 1208 days of food data, 3414 meal occasions, 1034 snacking occasions, 5097 photos, and 998 days of physical activity. Second, we analyzed the collected data and report findings associated to the compliance, snacks vs. meals patterns, physical activity, and contextual differences between snacks and meals. Third, we addressed a novel ubicomp task, namely the classification of eating occasions (meals vs. snacks) in everyday life. We show that a machine learning method using time of day, time since last intake, and location is able to discriminate eating occasions with 84% accuracy, which significantly outperforms a baseline method based only on time.

Additional Key Words and Phrases: Mobile Crowdsensing, Eating Behavior, Snack and Meal, Physical Activity, Machine Learning

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1 INTRODUCTION

Understanding patterns of perception and consumption of food and beverages in everyday life is fundamental to promote and support healthier eating practices [2, 8, 33, 53, 60, 69]. As with much of human activity, eating is structured around routines and is affected by a number of contextual factors such as time, location, social factors, physiological states and psychological traits, as well as personal and professional constraints [10, 19, 23, 64, 96]. Research on eating routines has made significant progress towards understanding what these factors are and how they affect eating behaviors, based mainly on

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small sample studies and qualitative methodologies to document eating practices, e.g. using 24h dietary recall interviews [43].

With the emergence of mobile technologies, which are shifting the practices of data collection and analysis in behavioral sciences, researchers have developed mobile apps to keep food diaries mainly for dietary management and intervention studies [3, 14, 49, 59]. Mobile phones facilitate the collection of data on multiple aspects: potentially reducing the burden to participants, enabling the collection of ecological data outside the lab, improving data quality, and providing new sources of data for rich reporting, including photos and sensors. Following this interest, numerous research works on eating behaviors have studied the reliability and acceptability of photo-based methods to document food and beverage intake [20, 21, 59, 88], while fewer works have focused on dietary patterns using location and physical activity sensors [55, 85].

Much work remains to be done to exploit the full potential of mobile technologies to enhance our understanding of people's eating behavior. For example, little research has used mobile applications to characterize broader behavioral insights around eating and drinking [33, 84], including the influence of situational context (e.g. where, when, with whom) on the eating and drinking behavior of healthy populations [55, 85], collecting data longitudinally, and with large samples [55]. Moreover, past research in machine learning and ubicomp applied to food studies has focused on analyzing food images to identify foods and estimate their calories [63, 92, 105], and on using wearable devices to develop reliable dietary logging methods [1, 93, 102].

In this article, we collect and analyze mobile data about everyday eating behaviors and their context. Furthermore, we examine the feasibility of using mobile surveys, wearable sensor data, and machine learning methods to classify real-life eating occasions, specifically meals vs. snacks. This task is important if we want to be able to predict the nature of the different meal occasions and best advise people at the right moment about healthier food choices.

The contributions of this article are the following:

(1) We carried out a data collection campaign for 10 weekdays with 122 participants aged 18-26 years to capture food and beverage consumption in their natural environment in relation to its context (time, location, social context, related activities and physical activity). The resulting dataset is rich in terms of the data types and the captured real-life behavior.. We collected 1208 days of food data, including 3414 meals, 1034 snacking events, and 5097 food photos, and 998 days of Fitbit data.
(2) We analyzed the collected data and report findings associated to three main areas: compliance, snacks vs. meals patterns, physical activity, and contextual differences between snacks and meals.
(3) We show that a machine learning model using time, time since last intake, and location is able to classify eating occasions with 84% accuracy, compared to a baseline based on time that achieves 69%. To our knowledge, this represents a novel task in ubiquitous computing. Our results showcase that a combination of machine learning and mobile data can be used to predict meal patterns and open the door to new predictive behavioral tasks such as estimating the time of the next eating occasion or the type of food that is expected to be consumed.

The article is organized as follows. We start by reviewing related work in Section 2. In Section 3, we present the design of the mobile application. Next, we describe the data collection campaign in Section 4. Section 5 reports the main data analysis. In Section 6, we address the classification of eating events and analyze in more depth the performance of the features. Finally, we discuss and conclude with a summary of findings and possible research directions for future work in Section 7.

2 RELATED WORK

2.1 Mobile studies and food consumption

In the last years, the use of mobile devices has grown in interest in the field of dietary research, notably for dietary management and intervention studies [14, 37, 47, 49, 59] and recently in a behavioral intervention among young participants to reduce alcohol consumption using smartphone sensors to detect drinking events [5]. Following this interest, numerous research works have focused on assessing the reliability and acceptability of mobile-based methods to report individual food and beverage intake. Methods to collect food intake include the selection of food items and portions sizes from a database [13, 14], the use of food photographs to aid dietary recall at the end of the day [4], and the collection of food photographs in real-time [20, 21, 48, 58, 59, 88] in conjunction with textual, audio and video descriptions [48, 49, 81]. The reliability of these methods has been measured in comparison with reference estimates of energy, micro and macro-nutrients (i.e. food categories), and portion sizes obtained using traditional methods such as the 24h-recall [13, 14] in in-home weighted diet record [48] or food intake measurements in laboratory [58]. To extract this information from photos, three main approaches have been developed: using trained dietitians [58], crowdsourcing with non-experts annotators [71, 95] and automatic methods based on computer vision [11, 32, 91]. The reader can refer to [86] for a detailed review of these methods. While all these methods have shown similar but not superior reliability compared to conventional methods, the use of mobile devices has a higher acceptability among participants, has the potential to reduce participant burden, and may help reduce missing data from forgotten food reports [86]. In our work, we adopt the collection of mobile food photos as a method to document food and beverage intake, and text descriptions as backup method for forgotten reports.

To our knowledge, less research has used mobile applications to characterize broader behavioral insights around eating, including the influence of situational context in healthy populations. In a recent study [33], researchers developed a phone app to monitor healthy American adults for three weeks and collected food and beverage pictures and time of the day. Their focus on diurnal patterns of caloric intake revealed frequent and very variable daily eating patterns, in contrast to the three meals a day self-reported by participants. Implications of these behaviors were discussed in the frame of weight management. In our view, this work illustrates the type of rich contextual insights that can be gathered from large populations using mobile methods. In [55], researchers used a Personal Device Assistant (PDA) application to collect dietary behaviors of adults in five U.S. cities to study whether places of consumption are associated to different types of eating occasions: meal, snacks, beverages and non-fruit desserts. Among other results, their analysis showed that snacking on low-nutrient foods was more likely to occur in non-designated eating places (i.e. places not originally designed for eating); that snacking was more likely at work than at home; and that sugar sweetened beverage consumption was more likely at food service outlets than at home. Finally, in [85], researchers used a mobile application to collect data from participants during three weeks using multiple sensor and self-reported data: including time, location obtained from GPS, physical activity from accelerometer, and emotional states. They examined to what extent a set of context-based individual-specific linear regression models (i.e. applied to each user individually) were able to explain the portion sizes eaten by participants.

Our work contributes to the existing literature by using mobile and wearable technologies to capture food and beverage consumption in everyday life, with specific focus on collecting data about the eating context of a healthy population in a European university.

2.2 Location, social context and related activities

Eating location has been associated to factors such as the physical atmosphere of the place, food accessibility, social context, and distractions that can influence eating behavior [57, 100]. As discussed in [10], research studying location has mostly viewed location in general terms (i.e. home, restaurant, and work) [50, 57, 69, 70], or has focused on eating behaviors in front of the TV [46, 90], to show that meals and snack choices can be restricted by location. Most of these studies concur that eating outside home has a negative impact on the nutritional quality of the diet compared to eating at home or at work for both meals and snacks [50, 57, 69, 70]. Similarly, eating in front of the TV was associated to higher energy intake and frequent eating [90], and higher between-meal snacking [46]. Beyond these general results obtained with traditional methods, the way location influences food choice may unveil more subtle processes and links. In [70, 72], researchers found that eating-at-home vs. outside-home behavior was different only for individuals that occasionally eat out compared to frequent outside-home eaters. In [23], overweight participants reported to consume larger meals than normal participants when eating away but not at home. The authors speculate that this association might be explained by high responsiveness of overweight individuals to food-related cues combined with widespread availability of food outside the home as also suggested in [61]. In [55], researchers proposed a framework to study eating location based on the designation of the place as primary intended for eating or not, showing that snacking on low-nutrient dense foods was more likely to occur in non-designated eating places. In documenting locations, all these works have categorized locations based on the population under study [50, 57, 69, 70]. Our data collection combines an exhaustive list of locations in the life of students with places not originally designated for eating (i.e. classroom, working area, couch, bedroom, etc) as done in [55], thus providing finer-grain location information than most previous studies.

One basic fact of eating occasions is that they often are social events [62]. Literature has documented three main effects related to these factors: social facilitation, social modeling, and impression management [80]. Social facilitation refers to increases in food intake when people eat together as compared to when eating alone [39]. This effect is regulated by the level of acquaintance between people: compared to eating with friends and family, eating with strangers is rather inhibitory [22]. Social modeling refers to people using others as a guide to decide what and how much to eat, an effect that is attenuated for healthy-snack foods and meals such as breakfast and lunch, and that is partially mediated by behavioral mimicry [19]. Finally, impression management consists in modifying one's eating behavior in order to create a particular impression, which is regulated by social stereotypes, and can be specially relevant in healthy vs. unhealthy eating behaviors [97, 103]. The current literature provides a framework to define the attributes that better characterize social context: group size, gender, and the level of acquaintance [83], which we capture in our data collection, thus giving the possibility of studying social context in parallel to other factors.

Eating routines are embedded in daily schedules of work, family, and recreation activities that dictate where people eat, with whom, and what activities occur during, before, and after eating [43]. Previous research has studied the associations between activities and eating behavior in qualitative studies and found that work demands, family demands, and time scarcity are associated with less time for eating, multi-tasking [26], and the consumption of convenience, prepared, or ready to eat foods [42]. Understanding the links between food consumption and concurrent activities is an open field of research [10]. Our work contributes to this literature capturing concurrent activities as part of the eating context using mobile surveys.

Our approach to collect information on the eating context is inspired by the work in [10], which to our knowledge, is one of the few studies reporting on the multi-dimensional aspect of eating occasions. In this work, a data-driven approach was used to build a conceptual framework that characterizes eating and drinking episodes according to eight interconnected dimensions: food and drink, time, location, activities, social setting, mental processes (motivations, emotional states, etc), physical condition, and recurrence (i.e. how much behaviors repeat). All of these features have been operationalized in our work.

2.3 Physical activity and food consumption

Recent research in mobile health has used wearable devices to study associations between weight fluctuation and physical activity [76], and to measure the efficacy of self-monitoring in weight loss interventions, both in a randomized controlled pilot study [82] and comparing the success of independent programs [34]. These studies show that users of self-monitoring technology might sustain their desired health outcome. More broadly, past research in ubicomp studied the use of activity monitoring devices to achieve health-related personal goals [18, 30], and also investigated practical issues of physical activity device usage by large university student populations [78], as we address in this paper.

In contrast, fewer works have focused on the connections between physical activity and food choice. Before the emergence of commercial self-monitoring devices, researchers had already identified the need for reliable, physical activity data to understand eating habits of young people [67]. In [55], participants wore an accelerometer to estimate physical activity. Physical activity was computed as time spent in moderate-to-vigorous physical activity (MVPA), and was used to explain the frequency of four different eating occasions (healthy snack, unhealthy snack, sugar sweetened beverage, and non-fruit dessert). The average daily MVPA of participants was not significantly associated with the eating occasions. In [85], a small sample of twelve Chinese students used a phone app that recorded accelerometer data from the phone during six days of diet monitoring, in which meals were video recorded. This data was turned into an energy expenditure variable used in individual specific models to explain the portion sizes of consumed food, with R-squared values ranging from 0.7% to 88%. Finally, in [15], physical activity was measured from GPS data as the percentage of time spent in non-stationary location states, and was incorporated to a CART model that predicts food purchases using smartphone data from 25 students from the StudentLife Dartmouth project [99]. The activity feature had a significant contribution to the performance of the model, but was less important than other features such as location and time of the day. Adding to this emerging literature, our work integrates data from Fitbit in addition to location, survey and image data for 122 Swiss students; we analyze basic physical activity patterns and assess their power to classify meals vs. snacks.

2.4 Meal and snack eating behaviors

The increase of daily eating occasions reported in US in the last decades (from 3.8 in 1977-78 to 4.9 in 2003-06) is suspected to be a major contributor of the rise of obesity in developed countries [28]. More specifically, snacking occasions (i.e. eating occasions defined by respondents as "snacking" or "food break") increased among US adults [28], while a large increase in salty snacks and candy consumption was reported among children [74]. Understanding internal and external cues guiding snacking behaviors is therefore crucial to promote healthier eating habits.

Nutrition and behavioral sciences have studied what constitutes a meal vs. a snack, and how meal and snacking patterns affect diet quality and weight control [7, 40, 52, 75, 87]. Findings of research investigating the association between snacking and BMI are contradictory [73]. In [27], snack foods and snacking were often associated to poor diet and weight gain, whereas in [51] no relationship was observed between snacking behavior and BMI. There is also evidence that snacking may facilitate weight management and lower BMI [7, 40] and could be part of a healthy diet pattern [106]. The nature of the consumed snack, i.e. healthy (e.g. a fruit) or unhealthy (e.g. a pastry) may partly explain the divergence on the direction of the relationship between snacking and weight status [38]. As discussed in [7, 40, 45, 104], some of these discrepancies may also be explained by a lack of agreement among researchers on the definition of what is a snack or a snacking occasion.

Independently of the existence of a common definition of snack, how people label an eating occasion influences what and how much people eat on that occasion and over the remainder of the day, and may even affect their satiety after eating [41, 75, 87]. In this context, some works have relied on study participants to label their eating occasions with and without explanatory information [57, 98, 101]. In [101], participants associated meals to factors like eating quality food in larger portions, with family for 30min while sitting, using ceramic plates, and cloth napkins. In contrast, snacking was associated to eating inexpensive, low quality food, eating alone for 10min while standing, and using paper plates and napkins. In [57], participants associated certain times of the day and location to meals or snacks. In [98], some foods were consistently categorized as snacks, others as meals, and some as both equally.

To our knowledge, inferring the eating habits of people in everyday life using mobile data is still an open problem. Previous work in machine learning and ubicomp applied to food studies has focused on analyzing food images to identify foods and estimate their calories [63, 92, 105], and to use wearable devices to develop reliable dietary logging methods [1, 93, 102]. Other recent work aims at identifying food types from multiple (head and hand mounted) wearable sensors [65]. The closest work to ours is [15]. This paper addressed the task of predicting near-future food purchase or not (as a binary task) using inferred behavioral (physical activity and sociability) and location and time data from smartphones. They achieved 68.6% accuracy using a generic model and 74% using a user-adapted model. Our work is the first attempt to classify meals vs. snacks based on contextual data collected form participants using mobile surveys. While previous works have used context-based linear regression models to explain *the frequency* of eating occasions [55, 85], they did not address the task as a prediction or classification task at the *eating occasion level* as we do here.

2.5 Commercial applications and food research

Many commercial applications exist such as myFitnessPal and LoseIt! to track food intake. Compared to our application and other applications used in academic research, these applications tend to be superior in terms of user experience, by providing sophisticated data entry means like food product barcode scanning and leveraging very large food databases including food ingredients and calorie estimation from popular food manufacturers and restaurants (for a review of functionalities you can refer to [31]). The implementation of these features (e.g. a large scale food database) is possible within the economies of scale of commercial applications. However the commercial focus of these applications leaves little opportunities for academic research. These applications are focused on food and calorie tracking for weight management purposes, and, with the exception of physical activity, they do not enable the collection of other types of data (such as contextual data about users eating occasions), which was the focus of our work. In addition, data is not readily accessible to researchers. As an example, researchers in [24] analysed myFitnessPal data, but this was data explicitly made public by users on their Twitter channels.

3 STUDY DESIGN

3.1 Mobile application

We designed a mobile application to enable the collection of food intake data, including surveys, photos, time of the day, GPS location and physical activity. The mobile application was developed using Ionic

Framework[1], an open source mobile SDK for cross-platform development, and IonicResearchKit[2], an open source library equivalent of Apple's ResearchKit Framework to implement mobile surveys. To enable participants to take photos of their food, we extended IonicResearchKit with a photo capture feature. To avoid issues with mobile data plans, participants could configure the upload of the surveys to be restricted to WIFI access. The server was developed using Flask and data was cached using SQLite databases and HTML5 storage. The minimum requirements for our application were Android version 5.0 and iOS version 8.0.

Figure 1 shows the mobile application interface, with all the surveys explained in the next subsections. All the questionnaires were translated to French, as this was the language of the participants. The full description of the mobile survey can be found in [9].

3.2 Food and beverage data collection

We designed a set of surveys to collect food intake and contextual data. Two different surveys were designed for meals and snacks. Since our research was to focus on snacking events, the survey for meals contained less questions compared to the one for snacks in order to reduce the overall burden of the task. In the instructions given to participants, we explicitly defined *meals* as breakfasts, lunch, and dinner (including food and beverage except water), and *snacks* as all the food and beverages (except water) consumed outside meals, without giving examples of what foods constituted a meal or snack. Thus, participants were free to decide whether to document an eating occasion as a meal or a snack based on their perception.

3.3 Reporting a meal

Participants were asked to report all their main meals using three steps. Before starting the meal, participants responded to the *New meal* survey (NM), took a photo of their meal (one single photo of all food and drinks together), report their location (among 10 main semantic location categories, and 59 sublocations); with whom they were eating (including number of people, gender and relationship); and what other activities were being done while eating. During the meal, participants could use the *Add a meal item* survey (MI) or the *Add a meal serving* survey (MS) to take a photo of any extra food/drinks or servings they may have. At the end of the meal, participants used the *Finish meal* survey (FM) to report leftovers (including a picture, if they were any), and any shared food or drinks. All these surveys were combined to provide a seamless data entry flow to report meals, as shown in Figure 1.

When taking the photo, we asked participants to use their student ID card upside down as a fiducial marker, as done in other works [37, 58]. This was an appropriate choice because students use their card very often in campus to make payments, but potentially introduced the possibility that students would take photos with the card upside, thus revealing their personal identity in the photos. We investigated this issue in our analysis.

3.4 Reporting a snack

Participants were asked to report all their snacking events (food and beverages) using three steps, as in meals. Before starting a snack, participants used the *New snack* survey (NS) with the same contextual information as for meals (i.e. location, social context, and activities). Second, participants used the *Add a snack item* survey (SI) to take a photo of the snack itself or the snack barcode for packaged snacks. As for

[1]https://ionicframework.com/
[2]https://github.com/ninoguba/ionic-researchKit

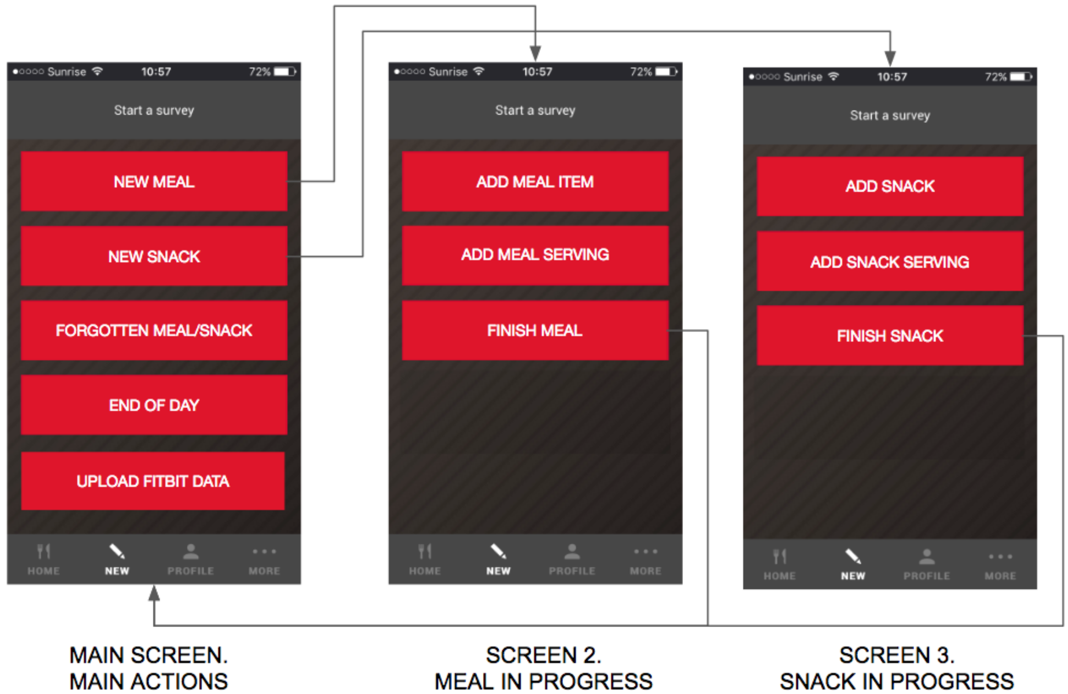


Fig. 1. The mobile application interface with short surveys to document meals throughout the day: *New meal*, *New snack*, and *Forgotten Meal/Snack*, *End of day* survey, and *Upload fitbit* data. Participants were expected to spend a total of 30 minutes a day to complete the mobile surveys.

meals, students used their student ID card as fiducial marker whenever the snack was not packaged. The SI survey was designed to provide detailed information for snacks. In snacking occasions with multiple snack items (e.g. a coffee and a chocolate), each snack item was to be reported individually. Participants reported where and when the snack was bought, when they planned to eat it, and the motivations for eating it. Motivations for eating snacks were reported with a modified version of the brief TEMS including 49 reasons for eating [79]. Finally, participants could use the *Add a snack serving* (SS) to take a photo of any extra serving. At the end of the snacking event, participants used the *Finish snack* survey (FS) to report food leftovers (including a picture, if they were any), and any shared food or drinks.

Note that while the content of the meal and snack reports is analyzed in Section 5, the detailed analysis of the motivations for snacking is out to the scope of the present paper.

3.5 Reporting a forgotten meal or a snack

Participants were given the chance to use the *Forgotten Meal/Snack survey* (FMS) whenever they realized they had forgotten to report a meal or snack. In this survey, participants reported the time of the eating event, the context (i.e. location, social context, and activities), and the type of meal (breakfast, lunch, dinner, or snack). For snacks, participants provided a short text description of the snack and reported the motivations for eating, as in the SI survey. Finally, participants indicated why they had forgotten to report the eating event.

3.6 End of day survey

Participants were asked to respond this survey at the end of each day (before going to bed) and to report: their physical activity (time seated, time walking, time of moderate physical activity, time of intense physical activity, and whether they had worn the Fitbit during these activities); the time to bed for the previous day and the wake up time on the current day; any missing meal or snacking events, and the reason why they were missed.

3.7 Time and GPS location data

Every time participants filled up the surveys, the mobile app collected the time and the GPS location. This data was uploaded to the server as part of the survey data. Note, that using the timestamps of the surveys completed at the start and end of eating occasion surveys we are able to compute the duration of both meal and sacking occasions.

3.8 Fitbit data

Participants could opt-in to use a Fitbit Flex to collect physical activity data. We integrated the collection of Fitbit data using the Fitbit API (https://dev.fitbit.com/) to import data directly from Fitbit servers after participants granted authorization to access their data. To upload data, participants synchronized their wearable device with the mobile Fitbit phone app, and our server imported the data automatically once a day. An *Upload Fitbit data* survey reminded participants to upload their data and verify that the data was made available to the Fitbit app. Participants were asked to wear the Fitbit during their waking hours and were free to take it out in bed. Thus, no Fitbit data was to be collected during sleeping.

3.9 Notifications

Our app integrated notifications to remind participants to complete their surveys. We integrated notifications three times a day at 06:45, 12:00, and 18.30 to remind participants to document their meals or snacks (these notifications were opt-in for users); one notification at 21:30 to remind about the end of day survey; and one notification at the beginning of each week (Monday, 06:30) to remind participants about the data collection. In addition, a reminder to complete the *Finish Meal* and the *Finish Snack* survey was prompted after 15min of the start of the meals and snacks respectively.

3.10 Entry and exit questionnaires

Previously to start the mobile data collection, participants were asked to complete three short entry questionnaires administered with the app. This included basic demographic questions (age, gender, self-reported weight and height), a personality trait questionnaire (TIPI) [35], and a food involvement survey (FIS) [6].

At the end of the study, participants were administered seven exit surveys using our online website (https://www.bitesnbits.org). Six of the questionnaires were handpicked from nutrition and eating behavior science literature to measure several aspects of people's eating behavior: motivations for eating (Brief TEMS) [79], emotional eating (DEBQ) [56], taste preference (PrefQuest) [25], mouth behavior (JBMB) [44], Swiss Food Frequency Questionnaire [66], and Intuitive eating (IES) [12]. The seventh questionnaire was divided in two: a questionnaire about eating habits and a questionnaire about user experience. The eating habits questionnaire asked participants to report how frequently they incurred into five different behaviors: having 3 meals a day, skipping breakfast, skipping lunch, skipping dinner, and snacking. The user experience questionnaire asked about several aspects regarding the use of the mobile application: intrusiveness, easiness of use, workload, etc.

In this article, we report results related to the demographics, the eating habits and the user experience questionnaires. The rest of entry and exit questionnaires are out of scope of the present paper.

3.11 Expected completion of data collection

The final mobile application presented here resulted from an interactive process involving 2 pilot studies of 5 days with 10 colleagues whose experience was used to assess the workload imposed to participants. Based on the final design, we estimated that participants would spend a total of 30 min/day using the mobile app and 1h to complete the exit questionnaires.

4 DATA COLLECTION FRAMEWORK

The research protocol was approved by the Human Research Ethics Committee at the Ecole Polytechnique Fédérale de Lausanne (EPFL) in August 2016.

4.1 Study design

The protocol was designed to collect data for 10 consecutive weekdays and took place in the EPFL campus between November 28 and December 22 2016. This period corresponded to the end of the school semester, previous to the Christmas break and before the university exams in mid-January. Note that we did not consider weekends because they are known to be non-representative of people's eating routines [33].

Participants were asked to meet the following criteria: between 18 and 34 years old; EPFL students with a valid student ID card; living in Switzerland for at least 5 years; French speaking; having an iPhone (iOS 8.0 or more) or Android (v5.0 or more); being able to report at least three eating occasions per day (meals or snacks); not having diabetes; not being pregnant nor breastfeeding and not having an eating disorder (anorexia, bulimia, etc); not following any restrictive diet (paleo, vegan, food allergy-free); and not taking a medication known to affect appetite.

Participants received a compensation of 150 CHF for the collection of 10 days of mobile data, the entry, and the exit surveys. In addition, participants that opted-in to contribute physical activity data using a Fitbit Flex, could keep the device at the end of the study. To compensate users, we considered a valid day of data, if they reported at least three different eating occasions (including meals, snacks and forgotten meal/snacks). For participants using Fitbit, a day of data was considered valid only if they provided the three food reports and physical data for the same day. In addition, although the data collection was planned for two weeks, we gave participants one extra week to compensate for missing days and reach the 10 days. Participants who contributed less than 10 days at the end of the third week were compensated pro-rata.

Our student population, drawn from a public university, was expected to be relatively homogeneous in socio-demographics and thus in terms of their general eating behaviors (frequency of eating occasions, eating times, food types). Nevertheless, we were aware that the data collection period was a very busy period for students and that could potentially influence their regular behavior. We also expected students to have a variety of food consumption patterns, including eating in campus facilities or elsewhere, purchasing prepared foods at supermarkets/cafeterias, or preparing their own food at home.

4.2 Data collection setup

The study was announced via an online information page and a video (https://www.bitesnbits.org) that were distributed to the student population by email. Interested students were invited to assist to a personal information session run by one researcher and three research assistants. First, participants were

	Users	Food user-days	Meals	Snacks	Photos	Fitbit user-days
# items	122	1208	3414	1034	5097	998

Table 1. A summary of the data collection.

informed about the study before signing a participation consent form. Second, participants installed the mobile app, and completed the three entry questionnaires. Third, participants watched two videos explaining how to use the mobile app to report meals and snacks, and how to take photos of their food and drinks, and then completed all the questionnaires at once (including taking pictures of food) to get familiar with the functioning of the app. Participants choosing to use Fitbit were instructed to set up the wearable, synchronize it with their smartphone, and authorize access to our application. Overall, the session lasted 20-30 minutes and was used to make sure that participants understood the protocol as well as to verify the functioning of the app in the multiple mobile devices and operative system versions used by participants. A handful of students were not able to participate in the study because the mobile surveys did not work properly on their phones. In total, 128 participants registered to the study, and 108 opted-in to use a Fitbit device. 90% of the participants opted-in to receive the optional mobile app notifications. This number of participants is 3-4 times larger than previous crowdsensing ubicomp research studying young populations (e.g. 48 students in [99], 30 in [5], 36 in [17]), comparable to the 85 participants in [16], and about half of [84].

5 DESCRIPTIVE DATA ANALYSIS

5.1 Population description

Demographics: Based on the demographic survey data, students in our study were between 18 and 26 y/o, with a mean of 20.57 years old (SD=1.69). BMI ($BMI = \frac{weight}{height^2}$), computed using the self-reported height and weight, was between 16.92 and 31.17 with a mean of 21.58 (SD=2.45). Only 10 students were overweight with a BMI over 25 (which is the threshold set up by WHO to indicate overweight[3]). Regarding gender, our sample was unbalanced, with 65% males and 35% females, which is representative of the male-dominated student population of EPFL (official figures report that 27% of the 10536 students at EPFL are female[4]).

Smartphone devices: The device information obtained from the mobile app indicated 12 different manufacturers and 39 model versions, out of which 65% run iOS from Apple and 35% run Android, with Samsung (13%), Sony (10%) and Huawei (2%) amongst the most popular brands. These numbers reflect the importance of developing a mobile application that is available to both iPhone and Android users.

5.2 Summary of the dataset

We preprocessed the survey data to consider only user-days with at least 3 eating reports (including meals, snacks and forgotten meals/snacks) for users without Fitbit, and at least 3 reports and 1,000 steps per day for users with Fitbit. For the 2 users that lost their Fitbit during the campaign we only considered their food reports.

Table 1 summarizes our dataset. Based on the above criteria, our final dataset resulted in 1208 days of food data from 122 users, and 998 days of both food and Fitbit data from 101 participants. For both food and Fitbit data, this includes 10 days of data for all users, except for 7 users with 9 days, 1 user with 8

[3]"BMI Classification". Global Database on Body Mass Index. World Health Organization. 2006. Retrieved August 2007.
[4]EPFL, Official statistics, http://information.epfl.ch/cms/site/accueil/lang/fr/chiffres-detailles

Question	Never	Rarely	Sometimes	Often	Always
Has 3 meals a day	2	5	13	33	47
Skips breakfast	41	18	19	17	5
Skips lunch	76	11	8	4	1
Skips dinner	69	14	11	6	1
Has snacks	7	28	25	30	11

Table 2. Summary of self-reported habits collected from participants using the self-reported eating habits in the exit questionnaire (% of participants reporting each response).

days, and 1 user with 7 days. The food dataset consists of data from 3414 meals (2.8 meals per user/day), 1034 snack events (0.85 snacks per user/day) and 5097 photos (including photos before and after eating).

5.3 Self-reported eating habits

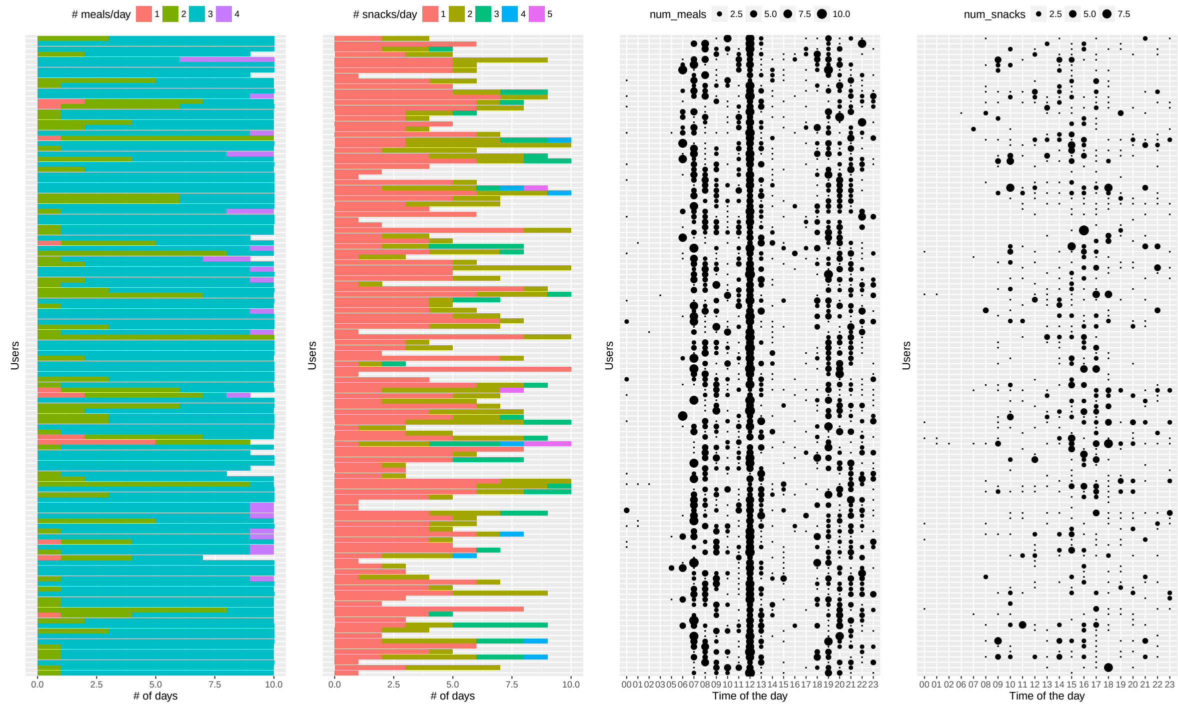
Table 2 summarizes the participants responses for the eating habits exit questionnaire. These questions provide a global view of the self-reported habits of our sample. Our population typically has 3 meals, sometimes skips breakfast, and snacks often. 80% of the participants reported eating 3 meals per day often or always. Breakfast was reported as the most frequently skipped meal: 22% of the participants reported skipping breakfast often or always, while only 5% and 7% of participants reported the same for lunch and dinner respectively. Finally, 41% of the people reported to snack often or always, while 7% of the participants reported never having a snack. This data will be compared with the mobile data in the next subsection.

5.4 Eating reports: Meals vs. Snacks

Participants reported a total of 3166 meal reports using the *New Meal* survey (i.e. an average of 2.8 meals per day per user) and 990 snacking events using the *New Snack* surveys (i.e. 0.85 snacks per day per user). They also used the *Forgotten meal or snack* survey to report 248 forgotten meals and 44 forgotten snacks Finally, participants used the *End of day* survey, to report forgetting 51 meals (5 breakfasts, 18 lunches, and 28 dinners) and 34 snacks, which corresponds to a small percentage (1.4% and 3.1% respectively) of all the reported data. Figure 2a shows the participant contributions in terms of number of meals and snacks reported per day. In total, 80% of the user-days in our dataset correspond to days with 3 meals, 19.6% with 2 meals, and only 1.4% with 1 meal. At the individual level, 103 participants (84%) reported 3 or more meals for more than half their days.

We compared the collected meal and snack reports to the self-reported eating habits discussed in Section 5.3, as a common method used in traditional research. Figure 3a shows a positive relationship between the participants' self-reported frequency of eating 3 meals a day and the percentage of days they contributed with 3 or more meals. Figures 3b-d were obtained by clustering meals into three different time slots that correspond to standard eating Swiss times: 06:30-08:30 for breakfast, 11:30-13:30 for lunch, and 18:30-20:30 for dinner (in total 61% of the meals fall into these slots). Figure 3b and Figure 3c show a clear association between the participants' self-reported frequency of skipping breakfast and lunch and the average number of these meals collected. Figure 3d shows no clear relationship between these same measures for dinners.

Figure 2b shows the participant contributions in terms of number of snacks reported per day. In total, 59% of the user-days in our dataset contained at least one snacking event. At the individual level, 84 participants (68%) contributed five or more days with snacks, 29 (23%) between one and 4 days, and 9 users (7%) reported only one day with snacks. As with meals, Figure 3e shows similar trends between the



(a) meals/day for each user (b) snacks/day for each user (c) meal times for each user (d) snack times for each user

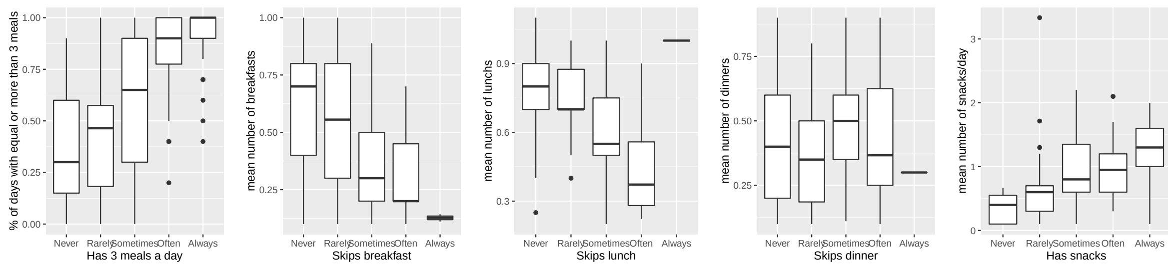
Fig. 2. Summary of participant contributions in terms of reported meals and snacks. Each row corresponds to one participant. (a) and (b) show the number of meals and snacks reported for each user per day of data collection. Note that the days of each user have been ordered on a timeline of 10 days, but this does not reflect the actual time span (in days) in which the data was collected, as some participants needed a third week to complete the data collection (in total 6% of days were collected in the third week). (c) and (d) show the meal and snack reported by each user aggregated by time of the day (the size of dots is proportional to the number of reports: the larger the dot, the larger the number of reports).

exit questionnaire self-reported frequency of snacking and the average number of snacks collected using the mobile application.

To sum up, our analysis shows consistency between the self-reports of participants concerning the number and type of eating occasions and the surveys using the mobile application.

5.5 Temporal statistics

Using the timestamps of the eating events, we inspect several temporal aspects of food intake following a similar analysis to the one presented in [33]. Figure 2c shows the user meals aggregated by time of the day. The figure shows a clear breakfast-lunch-dinner pattern for many of the participants but with varying hours. Taking into account all user-days with 3 meals, we computed the average time and the day-to-day standard deviation of each meal at the participant level. On average, the first meal of the day is at 08:29 (SD = 56min), the second meal is at 12:42 (SD = 48minutes), and the third meal is at 20:30 (SD=1h



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

Fig. 3. Benchmark summary of meal and snack mobile data vs recall-based self-reported meal and snacking habits.

11min) indicating that people are more regular on their breakfast and lunch time, compared to dinner. As shown in Figure 2c, snacks are concentrated in the afternoon (the average time is 16:00 and 50% of the reports decreases between 13:30 and 18:30), but a second snacking peak appears between 09:00 and 10:00. We argue that the class schedule at EPFL may be shaping the eating times of participants specially for lunch and snacking while in campus. Undergraduate students (most of our sample), spend most of their time in classes between 08:00 and 17:00, with a one-hour break between 12:00 and 14:00, which conditions the time for lunch and limits the options for snacking.

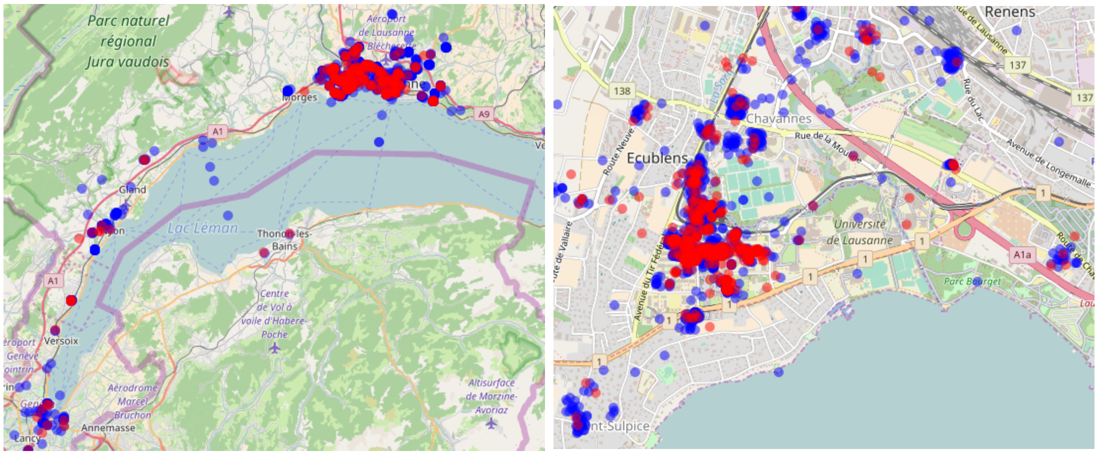
We computed the duration of meals and snacks based on the timestamps of the *New meal* and *Finish meal* surveys and the *New snack* and *Finish snack* surveys, respectively. Unexpectedly, we found that 42% of the meal questionnaires had time differences of 1 min or less, indicating that participants were responding to the after eating survey before having finished their meals (in contrast, this only happens with 7% of snacks). We discuss this issue in Section 5.11. Considering only eating events that lasted longer than 1min, the median eating duration was 19min for meals and 4min for snacks. For meals, this duration varied depending of the type of meal (breakfast, lunch or dinner). Taking all user-days with 3 meals, the duration was 17min for the first meal, 21min for the second meal, and 22min for the third meal. These numbers are similar to the ones reported in [33]. Including meals and snacks, the median inter-intake interval was 4h 42min (quantile 25th = 3h 36min, quantile 75th = 6h 12min).

Defining eating duration as the time interval between the first and the last intake, we found that the median eating time interval was 12h, and that 15 (12%) participants had a duration of less than 10h. This is shorter than the 15h reported in [33]. Eating time interval correlated negatively with first intake ($r = -.58$, $p < 2.2\text{x}10^{-6}$) and positively with last intake ($r = .77$, $p < 2.2\text{x}10^{-6}$), i.e. long eating time intervals is determined both by early intakes and late intakes, but contrary to what was found in [33], early intake time correlated only mildly with last intake ($r = .14$, $p < 2.2\text{x}10^{-6}$), i.e. having an earlier intake did not imply having an earlier last intake.

To conclude, this temporal analysis evidences that our student sample follows a traditional three meals/day structure.

5.6 Eating places

As shown in Figure 4, eating occasions occurred at the university campus (40% of all eating events) as well as outside campus (54% outside campus private places, and 6% outside campus public places). This differs



(a) Lake-view of data-collection

(b) Campus view of data collection

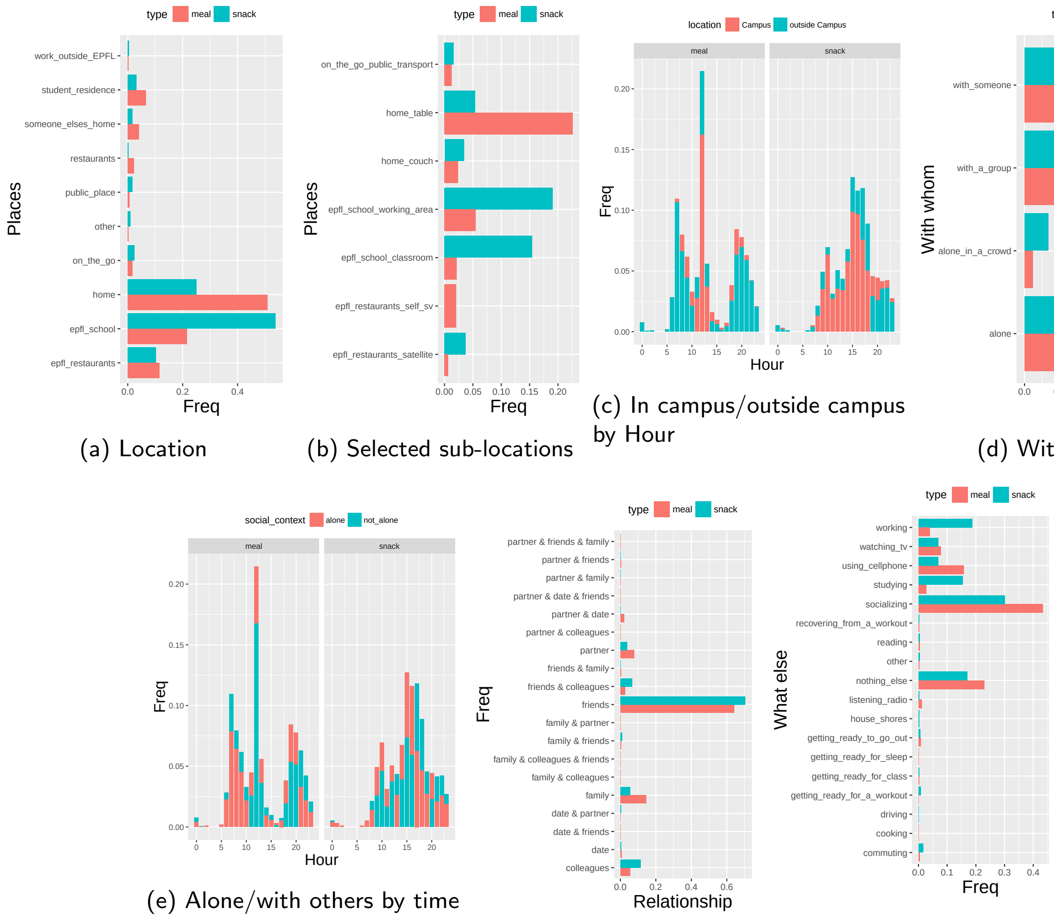
Fig. 4. Summary of contextual data (meals are shown in blue and snacks in red).

from data collected in other ubicomp studies [15], where students live in university housing facilities and spent most of their time in campus. Figure 5a shows a breakdown of place categories reported for meals and snacks. Meals were more often consumed at private places (50% home, 7% student residence, and 4% at someone else's home), compared to snacks, which were eaten more frequently in campus facilities (64%). As shown in Figure 5c, these patterns vary depending on the time of the day. Students typically had lunch in campus, and had breakfast and dinner somewhere else (typically at home), while many of the snacks were taken during school hours (typically from 08:00 to 17:00).

Concurring with related literature [55] snacks were more likely eaten in places not originally designated for eating. For example, with the exception of one self-service facility and a very popular bar, all the restaurants in campus concentrated mostly meals, while working areas concentrated mostly snacks (working areas: 18% snacks vs. 5% meals, classrooms: 15% snacks vs, 2% meals). Similarly, at a more detailed level, eating around a dining table was more associated to meals than snacks (22% meals vs. 5% snacks), while the amount of meals and snacks eaten in the couch was similar (3.5% snacks vs. 2.5% meals). These results suggest that location should be a good cue for recognition of meals vs. snacks. Unfortunately, due to a technical problem, reports in the kitchen (designated for eating) and in the bedroom (non-designated for eating) were saved in our database as being in the kitchen, and no distinction can be made between the reports of these two places in terms of their location.

5.7 Social context

We now inspect the social context in terms of the number, the gender, and the level of acquaintance of people with whom participants ate. Figure 5d shows that meals and snacks have similar patterns in terms of food eaten alone (alone or alone in a crowd, 51% in total) or with others (with one person or a group of people, 49% in total). This contrasts with related literature reporting that eating episodes are more likely to be considered as meals if the person eats with other persons [101]. Moreover, this social eating pattern was very different if the analysis considers context by time of the day, as shown in Figure 5e. Meals eaten alone correspond mostly to breakfast and late dinners, while most lunches and early dinners



(a) Location (b) Selected sub-locations (c) In campus/outside campus by Hour (d) With whom

(e) Alone/with others by time of the day (f) People by relationship (g) Activities done while eating

Fig. 5. Summary of contextual data (see in color).

are eaten with other people. In terms of snacks, morning and early afternoon snacks were eaten with other people, while late afternoon and early evening snacks were equally eaten alone or with people, and very early morning and late night snacks were eaten alone.

Figure 5f shows as well similar patterns for meals and snacks on the relationship with the people with whom participants eat. Only a small number of eating events occurs with family (14% for meals and 5% for snacks), which concurs with the fact that most of the students live in share flats and residences, and only a small portion of them live with family.

Both meals and snacks were eaten more frequently with male people (37%) compared to female (22%), and 40% of the meals were eaten with mixed groups. This may be a consequence of the gender bias in our population.

Survey name	# Photos uploaded	# Photos missing
New Meal	3166	39
Add meal item	362	7
Add meal portion	264	8
Finish meal	144	0
Add snack	1047	9
Add snack portion	50	1
Finish snack	64	0
Total	5097	64

Table 3. Summary of photo collection using different mobile surveys.

5.8 Activities while eating

Six activities were most frequently reported, with different patterns for meals and snacks: socializing, doing nothing else, working, studying, using cellphone, and watching TV. Compared to snacks, meals were more often consumed in a social setting (socializing: 43% meals vs. 28% snacks) or are consumed while using the smartphone (15% meals vs. 7% snacks). In contrast, snacks were more often eaten while working and studying than meals: (working: 18% snacks vs. 4% meals, studying: 15% snacks vs. 3% meals). This suggests that concurrent activities might be useful to discriminate between meals vs. snacks.

As expected, socializing was associated to being with a group of people. Other activities such as working and studying were both associated to being alone and in a group (though being alone was more frequent), and using cellphone and watching TV were mostly associated to being alone.

5.9 Photos

Table 3 summarizes the collection of photos taken by participants using the different surveys. 1.2% of the photos taken were missing due to technical problems during the upload.

The collection includes one photo for each of the 3166 meal events collected, 362 extra food items taken with the *Add a meal item* survey, and 264 photos taken with the *Add an extra portion* survey. For snacks, participants contributed 1047 photos. Note that 32 out of the 990 snacking events were reported using text (i.e. without a photo), and 85 included more than one photo (i.e. they consisted of more than one snack item). The low number of additional photos taken after meals and snacks suggests that people finished most of their food, or that they found this part of reporting difficult to comply with.

A manual annotation task performed by research assistants was applied to check whether the students complied with the instructions of using the student card for reference, and to ensure that photos did not contain any sensitive privacy information. Only 1.4% of photos included personal information (mostly because the student card photo was visible). The detailed analysis of the content of food images will be the focus of future work.

5.10 Physical activity

Our data collection contains 998 days of Fitbit data from 101 users. Participants walked an average of 8676 steps/day (min= 1375 steps, max= 25000 steps). The range of 6000-7000 steps is indicative of an active day in the life of a healthy adult *without* moderate or intense physical activity [94]. In our data, 71% of the user-days were above 7000 steps and 10% between 6000 and 7000 steps, which suggests that most of the days of our participants could be representative of a normal active day of an adult, and hence, less likely to be missing some data. In [78], the heart rate (HR) sensor integrated in the Fitbit device was used to identify whether participants wore the Fitbit or not. Unfortunately, Fitbit Flex does not integrate such HR sensor. This means that low estimates of Fitbit activity in our data can be due to sedentarism of participants as well as participants not wearing the device or having battery problems. Only 8% of the user-days were below 5000 steps, what can be considered as a sedentary day or a day missing data [94]. 48% of the users reported at least one day with less than 5000 steps, 3% of the users had more than 3 days, and 1% had 6 days below this activity level.

We also inspected the physical activity reports in the *End of the day* survey (time seated, time walking, time of moderate physical activity, and time of intense physical activity). To start with, we found that 17% of the responses were unreliable due incorrect data reporting. In addition, participants reported not wearing the Fitbit during part of the day: 1.5% during their time walking, 4.6% during moderate activities, and 7.4% during their intense physical activity. Focusing on the reliable data, participants reported a mean of 8.4h seated (1st quartile= 6.5h, 3rd quartile=10h), 50min walking (1st quartile= 30min, 3rd quartile=60min); 25min of moderate activity (1st quartile= 0min, 3rd quartile=30min); and 20min of intense physical activity (1st quartile= 0min, 3rd quartile=25min) per day. 54% of participants reported to walk more than 30min a day for more than half their days. These numbers concurs with other reports of physical activity of Swiss people for the age group of 18-34 y/o, as we discuss in Section 7 [68].

Fitbit also categorizes the step activity data of every minute into four different activity levels: sedentary, lightly active, fairly active, and very active. As a first analysis, we analyzed to what extent this data correlates with the physical activity reports in the *End of the day* survey (time seated, time walking, time of moderate physical activity, and time of intense physical activity). Based on the Fitbit data, the time spent in each activity levels is: 20.16h sedentary (1st quartile=19.3h, 3rd quartile=21h), 3.2h lightly active (1st quartile=2.5h, 3rd quartile=3.9h), 15.3min fairly active (1st quartile=4min, 3rd quartile=20min) and 17.39min very active (1st quartile=4.2min, 3rd quartile=24.7min). Using the reliable data from physical activity reports, we found low yet significant correlations between the reported activity durations for each one of the physical activity questions in the survey and the four levels of activity reported by Fitbit: time seated as reported by participants and "minutes sedentary" from Fitbit were correlated with $r = .20, p < 10^{-8}$; time walking and "minutes lightly" active were correlated with $r = .30, p < 10^{-16}$; time of moderate activity were correlated with "minutes fairly" active with $r = .17, p < 10^{-7}$; and time of intense physical activity was correlated with "minutes active" with $r = .35, p < 10^{-16}$. The Fitbit data may not necessarily represent the same type of data as the one collected using questionnaires. To start with, Fitbit Flex counts any time sleeping/not wearing the device as a sedentary activity, hence distorting the day aggregates of this level of physical activity (which explains the average of 20.16h); for walking, participants were asked to report only the times in which they walked more than 10min non-stop; while for moderate and intense physical activity, to our knowledge it is not known how Fitbit measures different sport activities. Related works comparing direct versus self-report measures for assessing physical activity in adults show a lack of a clear trend amongst the differences between the self-report methods for assessing physical activity and the more robust direct methods [29, 77].

Overall, the relatively low physical activity self-reported at the end of the day (long seated hours and low moderate and vigorous activity) are consistent with the idea that the estimates of Fitbit activity are associated with low moderate and intense physical activity and not missing data, and concur with participants comments during participation that this was a very busy period at school with little time for leisure.

5.11 Compliance

We refer to compliance as the extent to which participants contributed to the data collection documenting all their meals and following the instructions given to them.

Food reports and physical activity: To help people comply with the data collection, we tracked the amount of data generated by participants on a daily basis during the collection process. Participants with less than 3 food reports per day were contacted by email by the research team to have an on-the-spot understanding of the reasons behind this. Participants missing the *End of day* survey were contacted by email the morning after and asked to complete the survey. Finally, participants with missing Fitbit data were asked to synchronize their devices. Out of the 128 participants who started the data collection, 5 participants were invited to stop their participation after the first week because they had completed less than 2 days of data, and one dropped voluntarily for personal reasons. In addition, 2 people lost their Fitbit and continued without it. At the end of the two weeks, participants missing between 1 and 4 days of data collection (including at least 3 meals and 1,000 steps of Fitbit data) were invited to extend their participation for an extra week. Out of the 122 participants that finished the study, 110 (90%) of the participants finished the data collection in 12 days: 65 (53%) people finished the data collection in 10 days, 27 (22%) people in 11 days and 18 (14%) in 12 days. 3 additional participants took up to 5 extra days to complete the data collection, and 9 (7%) participants using Fitbit did not manage to provide the full 10 days with both Fitbit and food data despite having contributed more than 10 days of food and Fitbit data.

In our communication with participants during the campaign, participants informally reported that the reasons for the cases of low number of food reports included skipping meals due to lack of appetite or time, having technical issues with the phone, and forgetting to report meals. In some cases, users said they did not eat more than what was reported in the app. This was confirmed in both the forgotten meal/snack survey and the end-of-day survey, where the aggregate reasons for missing food reports included: forgetting (43%), being in a hurry (15%), having no battery (11%), and due to the social context (10%). We asked the subset of participants who did not report any snacks after the first few days of participation about the reasons for this. Most of them replied that they were usually not snacking. This is consistent with our analysis of self-reported food habits from the exit reports presented in Section 5.4. Finally, in the few cases of very low amount of Fitbit data, participants did not realize that the Fitbit had run out of battery.

Completion of end-of-day surveys: Up to 43 (35%) participants needed to be reminded at least once by email to complete the *End of day* survey the day after. In total, 11% of the *End of day* reports were completed the day after, and 4% reports are missing.

Completion of end of eating occasion surveys: As mentioned in Section 5.5, we found that 42% of the meal reports had time between the new meal and finish meal surveys of less than 1 min, indicating that participants responded to the *finish meal* survey before finishing their meals (i.e not following the instructions). For snacks, this percentage was only 7%. This problem was frequent among many participants: 49 (40%) participants had more than half of their end of meal reports less than 1 min apart from their meal survey, and 12 (9%) participants had time differences larger than 1 minute for all their reports. We did not find any correlation between this behavior and meal type or the day of the data collection. We also found that 4% meals and 6% snack reports were finished after 2h of being started. This is most likely because participants forgot to complete the survey. Overall, these results indicate that using end of eating occasion surveys may not be an appropriate strategy to collect meal duration information.

Feature	Description	Type
Where (W)	Place category reported in the mobile survey	categorical (10)
Where in detail (WID)	Place subcategory reported in the mobile survey	categorical (59)
With whom (WW)	Number of people with whom eating	categorical (4)
With whom relationship (WR)	Relationship with people with whom eating	categorical (19)
What else (WE)	Activity done while eating	categorical (17)
Time (T)	Time of the day (in minutes) extracted at the start of each food intake report	numeric
Time since last intake (TSLI)	Time since last food intake computed from the participant reports. We set a maximum of 12h to account for missing data	numeric
Physical activity before eating (PB)	Steps and activity level from Fitbit for the two hours previous to start eating (total steps, max steps, median steps, mean steps, SD steps, minutes sedentary, minutes moderate activity, minutes fairly active, minutes very active)	numeric
Physical activity after eating (PA)	Steps and activity level from Fitbit for the two hours after eating (total steps, max steps, median steps, mean steps, SD steps, minutes sedentary, minutes moderate activity, minutes fairly active, minutes very active)	numeric

Table 4. Contextual and physical activity features for the classification of eating events. For categorical features, numbers in parenthesis indicate number of levels of the feature.

Photos: Based on the manual annotation of snack and meal images, we found that 82% of the images contained the EPFL reference card, which shows a high level of compliance. Furthermore, 1.4% of photos contained sensitive information from the card used as reference. We also asked the annotators to assess whether photos of food seemed to have been taken after the eating had started. As participants were asked to take pictures before eating, this gives another idea of the level of compliance with the study instructions. Annotators reported evidence of eating previous to photo taking in 7% of the images.

To conclude, our analysis shows that, with the exception of the end of eating occasion surveys, participants were compliant with the instructions of the study:

6 CLASSIFICATION OF EATING EVENTS

This section reports results of the classification of meals vs snacks based on contextual data.

6.1 Classification method

We choose Random Forests as a state-of-the-art method for classification because they are naturally able to deal with both numerical and categorical. In addition, Random Forests are robust to overfitting and not very sensitive to the model parameters (the number of trees *ntree* and the number of candidate predictors chosen at every node m_{try} [54]. In our experiments, we used $ntree = 500$ and evaluated different numbers of m_{try} as recommended in [54], but the classification accuracy remained fairly stable for the different values.

6.2 Feature description

Table 4 summarizes the features representing each eating event. All the categorical features were obtained from the responses to the *New meal* and *New snack* surveys. These include the eating location (where, where in detail), the social context (number of people with whom eating, relationship with these companions) and the concurrent activities while eating (what else). In addition to the survey responses, we included the time of the day (as directly extracted at the start of completing the survey) and the time since last intake. This feature was computed for each participant-event based on the full sequence of participant reported events. To deal with missing data or with events at the beginning of the week or the extra days of data collection without a previous day, we set up a 12h maximum value for this feature. We originally considered the duration of the meals as a potential feature, however, as discussed in Sec 5.5, 25% of the meals had durations of less than 1min, which made this feature very unreliable, and hence it was discarded.

Finally we computed physical activity features before and after eating based on the step and the physical activity levels from Fitbit. For steps, we aggregated the time-series obtained in slots of 10min, and then computed statistical features (sum, max, median, mean, sd) of these slots in 2h window before and after each eating event. The 2h window was chosen to limit this feature to activity surrounding the eating occasion. For physical activity levels, we summed all the minutes spent on each of the four activity levels during the 2h: minutes sedentary, lightly active, fairly active, and very active. Because the end time of meals was unreliable, we set the start of the 2h window after eating 15min after the start of the meal.

Categorical variables with too many levels relative to the size of the data may be problematic as most of the levels will be rare and hence difficult to learn [107]. We proposed two ways to use each categorical feature: (1) as a single feature of k levels, and (2) using one-hot-encoding to create a binary variable for each level of our categorical variable. We found that only where in detail (WID) benefited form using one-hot-encoding, and hence it was applied for this feature in all the experiments reported in this section.

6.3 Performance evaluation

We used a 10-fold cross validation approach to train and test a series of Random Forest models (at each resample iteration, one fold was used for testing and the rest of 9 folds for training). Since our dataset is imbalanced, we randomly sub-sampled the majority class to train our models using a balanced dataset. In addition, because we only have Fitbit data for a sample of the users, we replicated the experiments using two different datasets, one with all users, and a second one using only Fitbit users. Results between the two experiments were similar, and hence we report only experiments with Fitbit users ($N = 1610$).

We report the classification accuracy of the models on the test data and compare the performance of our models to three baseline models: random guess (Model accuracy = .50), a model using participant personal information (gender, age, BMI or a combination), and a time rule-based model (TRB) deciding that any event between 06:30-08:30, 11:30-13:30, and 18:30-20:30 is a meal, and anything else is a snack. These times were chosen based on our own assumptions of most common swiss eating hours (as no commonly agreed reference was found for it).

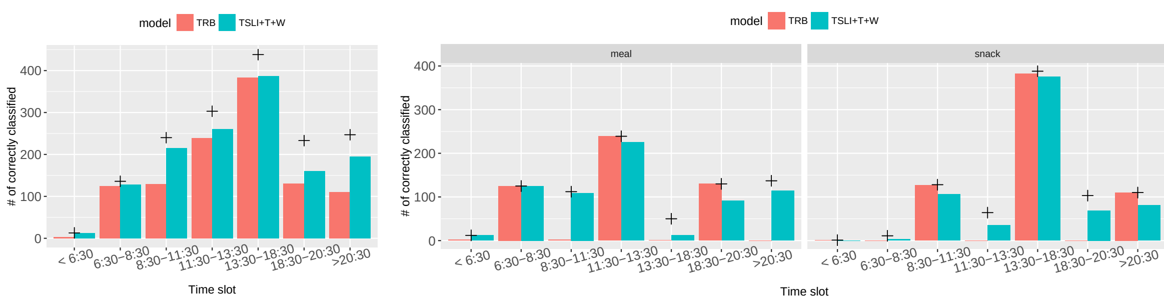
6.4 Results of meal vs. snack classification

We report the results for the task of snack vs. meal classification in Table 5. To understand the contribution of each feature, we report the results using each feature separately and in combination. As a notable result, we found that the time-rule-based baseline (TRB) achieved an accuracy of 69%.

In terms of individual features, we found that Where in detail (WID, 72%), Time since last intake (TSLI, 68%) and Time (69%), where the highest performing features. First, WID (72%) outperformed Where (67%) as a single feature. Second, the time-rule-based baseline (TRB) and the time model performed the same. Among the rest of the features, what else (WE, 66%) performed slightly worse than the time-rule-based baseline (TRB), while with whom (WWR, 54%) and physical activity before eating (PAB, 56%) only performed slightly better than the random baseline. $\mathcal{X}$-squared proportion tests indicate that all differences of 4.5 points in accuracy are statistically significant with $p < 0.01$. Finally, we found

Baseline	Acc(%)		Acc(%)
Random Guess	50		
Time rule-based (TRB)	69		
Single feature		Feature combination	
Age (A)	51		
Gender (G)	46		
BMI	45	A+G+BMI	48
Where in detail (WID)	72	WID+T	78
Time since last intake (TSLI)	68	T+TSLI	82
Where (W)	67	W+T	77
Time (T)	69	TSLI+T+W	84
What else (WE)	66	TSLI+T+W+WE	85
Physical activity before (PB)	56	TSLI+T+W+WE+PB	85
With whom relation (WWR)	54	TSLI+T+W+WE+PB+WR	85
With whom (WW)	51	TSLI+T+W+WE+PB+WR+WW	85
Physical activity after (PA)	50	TSLI+T+W+WE+PB+WR+WW+PA	85

Table 5. Classification results for meals vs snacks ($N = 1610$). Accuracy (Acc) differences of 4.5 points are significant with $p < 0.01$.



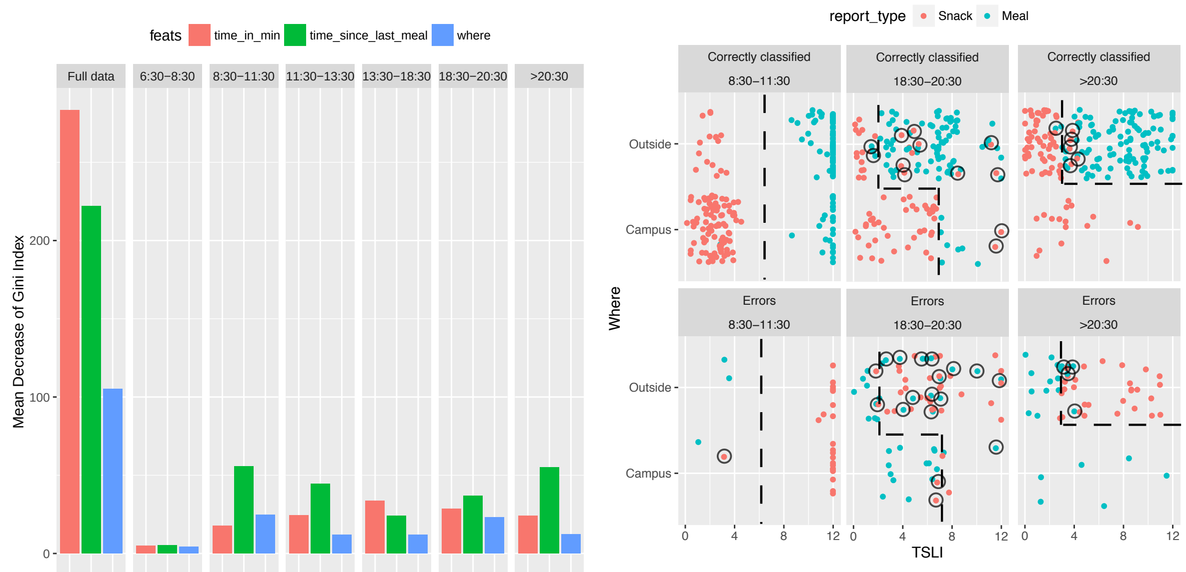
(a) All data

(b) Meals vs. snacks

Fig. 6. Performance comparison between TRB model and TSLI+T+W model across different time-slots. The (+) symbol indicates the number of eating occasions N_t to be classified at each time-slot t and corresponds to the maximum performance achievable by any model at this time slot.

that BMI was not a good predictor of snacking behavior. However, because only ten participants were overweight no conclusion can be drawn from this observation.

In terms of feature combinations, we obtained the largest improvement when combining Time and Time since last intake (T+TSLI, 82%). Interestingly, while the performance of WID alone (72%) was superior to Where (W, 67%) combining Where and Time (W+T, 77%) led to similar performance than combining Where in detail and Time (WID+T, 78%). This suggests that Where in detail may encode temporal information that becomes redundant when Where with Time are combined, not adding any predictive value. This is an important result in the design of surveys because it suggests that collecting some data may be unnecessary when combining several data sources (e.g. WID in addition to Where). Similarly, despite the improvement combining Where and Time (W+T, 77%), adding Where to the



(a) Gini importance

(b) Where vs. TSLI feature scatterplots for selected time slots

Fig. 7. Summary of the importance of features in the TLSI+T+W model. (a) shows the mean decrease of the Gini index for each of the features of the model for the full data and different time slots. (b) shows Where vs. TSLI feature scatterplots for selected time slots. In all scattered plots, red points represent snacks, and turquoise points represent meals. Each subplot shows correctly classified instances (top) and missclassifed instances (bottom) for each time slot. For visualization purposes, values of Where are categorized between Campus and Outside campus, but the actual model uses all the categorical values. TSLI is measured in hours. Dashed lines draw data partitions based on these three features using naked-eye inspection. We use circles (○) to mark points from to mark points of mismatch between the visual partition and the one found by the Random Forest. The presence of these points indicates that the actual partition learned by the model is more complex.

combination of Time and TSLI (T+TSLI, 82%), only improved results marginally (TSLI+T+W, 84%). Further feature combinations result in minimal improvements, up to 85%.

Overall, our results have implications in the development of context-aware application, highlighting a the need to tradeoff between complexity of the solution and performance. For instance, TRB shows fairly good performance and is easy to implement, as it essentially requires no training data, compared to the machine learning-based approaches.

On the other hand, the 15% performance gain of TSLI+T+W compared to TRB, requires the use of machine learning and the implementation of automatic estimates of the TSLI metric and location (W) in the mobile app. A more performing algorithm can be justified in general, or in particular cases of interest. One can imagine an app that only focuses on eating events at night, for which method TSLI+T+W shows higher performance (as shown in Figure 6 for >20:30).

6.5 Detailed analysis of results

To further understand the better performance of the TSLI+T+W model with respect to the TRB model, we compared the performance of the two models at different times of the day. Figure 6 aggregates the classification results using the same temporal slots that were used to define the time rule-based model, for all the data, and for meal and snacks samples separately. As shown in Figure 6a, the TSLI+T+W model outperforms the TRB model in all time slots, with the higher improvements for the time slots 8:30-11:30, >20:30, and 18:30-20:30. $\mathcal{X}$-squared tests indicate that all the performance differences between the two models are significant with p-values $\leq 1.3 \times 10^{-4}$, with the exception of time slots 13:30-18:30 and 6:30-8:30. Moreover, Figure 6b shows that the performance of the model TSLI+T+W varies depending on the time slot and type of eating occasion. For the slots of 8:30-11:30 and >20:30, the TSLI+T+W model outperforms TRB on predicting meals (i.e., late breakfasts and late dinners) at the expense of a lower performance on predicting snacks. For the time slots 18:30-20:30 and 11:30-13:30, the TSLI+T+W model outperforms TRB on predicting snacks at the expense of a lower accuracy on predicting meals (i.e., dinners and lunches).

While the Random Forest classification ability comes with a trade-off on interpretability, we found that the analysis of feature importance and feature scatter plots across time slots is able to provide further insights on the classification decisions made by the model.

Figure 7a shows the Gini importance of each feature for the TSLI+T+W model trained in all the data, and for different time slots. The mean decrease in Gini coefficient is a measure of how much a feature contributes to the homogeneity across the outputs of all the nodes in the random forest (the higher the decrease, the more useful the predictor). The figure (see bar plots for full data) shows that Time is the most important feature of the model, followed by TSLI and Where. The importance of the Time feature may explain the comparable performance of TSLI+T+W and TRB for some of the time slots (e.g. 06:30-08:30 and 13:30-18:30), as shown in Figure 6a. For the rest of the bar plots in Figure 7a, the Gini importance values for each time slot were obtained by training models using the data of each time slot separately (with the exception of time slot <06:30, that had $N_t \leq 100$ data points). First, note that these values can be interpreted as the residual importance of the features in nodes deep in a tree that creates a partition of the data using Time in the most shallow nodes. This explains why the importance of the Time feature appears lower than TSLI (i.e. it can be interpreted as a residual importance). Second, note that the importance values computed for individual time slots are lower as they are computed in partitions of the full data. The figure shows that given an initial partition based on Time, TSLI is the most important feature on classifying meals vs. snacks for all the time slots except 06:30-8:30. This slot had very few snacks and the model is biased towards predicting meals, which may explain the rather low importance of all the features. The importance of TSLI is higher for the time slot 08:30-11:30 and >20:30, i.e. for breakfasts vs. morning snacks and for late dinner vs. night snacks, and it's lower for the rest of slots. The slot 11:30-13:30 is the one for which the contribution of the Where feature is lower. This may happen because most of the eating occasions in this time slot correspond to one class (i.e. meals). For the rest of time slots, the importance of this feature is comparable.

Figure 7b shows scatterplots of Where vs. Time since last intake (TSLI) features for the time slots 08:30-11:30, 13:30-18:30 and >20:30. Note that for visualization purposes, Where was categorized between Campus and Outside campus. We show that using naked-eye inspection, we can draw data partitions that classify meals vs snacks that roughly follow the correctly classified eating occasions and the residual errors made by the model. In the figure, we use dash lines to draw these partitions and circles ($\circ$) to mark points of mismatch between the visual partition and the one found by the Random Forest. The existence of these points indicates that the actual partition learned by the Random Forest is more complex than the ones we draw as an example. For the slot 08:30-11:30, meals can be differentiated from snacks using time since last intake (TSLI): low TLSI is associated to snacks and high TLSI is associated to meals. Note that High TLSI in this time slot indicates that an eating occasion is the first intake of the day, and in our data this is typically associated to a meal (i.e. breakfast) as opposed to a snack. For the time slot of >20:30, the model classifies Outside campus meals with TSLI higher than 3.5h as meals, thus benefiting from both Where and TSLI data. Finally, for the time slot of 18:30-20:30, the visual partition and the one found by the Random Forest differ more than for the other slots (as shown by the higher number of points of mismatch between the two partitions), but nevertheless illustrates that we can separate meals vs. snacks using different thresholds of TSLI for different locations (Where).

7 DISCUSSION AND CONCLUSIONS

In this article, we collect and analyze mobile data about everyday eating behaviors and their context (time, location, social context, related activities and physical activity). The resulting dataset is rich in terms of the data types and the captured real-life behavior, including mobile surveys, food images, location and physical activity from a population of 122 Swiss university students. Our analysis resulted in the main following findings.

1. Study participants were compliant: Participants in our data collection were compliant as shown by several indicators: the amount of meal and snack reports generated, the low number of drop outs, the total number of days required to contribute 10 days of data collection, the completion of end-of-day surveys, and the use of reference card when taking photos. These indicators were used to measure compliance because we do not have any ground truth for the expected number of meals and snacks of participants. Previous research in ubicomp shows that participant compliance depends on the duration of the data collection and the workload associated to participation [78, 89, 99]. Thus, comparing compliance to other works is not straightforward. In [78], compliance of participants wearing a Fitbit was measured thanks to the device's HR sensor that could be used to assess whether participants wore the device or not. In [89, 99], compliance was measured in terms of days without data. Taking into account the number of days required to complete the 10 days of data in our collection, we counted 7% of person-days of participation without data, which is lower than the values range of 13% and 19% reported in [99]. However, their data collection lasted for 6 weeks and required participants to carry an extra phone specifically for the data collection.

2. Meals and snack reports were consistent with end-of-study self-reports and previous literature studying similar target populations: Data showed that participants were quite consistent in their number and type of eating occasions reported when asked in an exit questionnaire after the test period and when answering surveys in-situ during their eating occasions using the mobile application. In addition, we compared our data to two large scale studies about food eating behaviors in Switzerland [38, 68]. In [38], more than 6,000 participants from the Swiss Food Panel filled a Food Frequency Questionnaire. In [68], the eating practices of 2000 participants were recorded through one dietary face-to-face interview and one phone interview. In terms of meals, our data concurs with these two studies in that breakfast is the meal most often skipped. For snacks, however, the results are difficult to compare. In [38], the authors reported 0.80 snacks/day for the whole Swiss population (similar to our study). In [68], authors reported that 28% of the population between 18 and 34 y/o snacks at least 3 snacks per day, but did not mention anything about the 72% of the population that snacked less. Our data collection also concurs with [68] in that the most popular snacking times are around 09:00 and 16:00.

Regarding physical activity, our Fitbit data showed low estimates of physical activity that are consistent with a relatively low physical activity self-reported using end of the day surveys (including long periods seating and low moderate to vigorous activity). This concurs with participants comments that the data collection was a very busy period at school with little time for leisure. The self-reported values including walking time and sitting hours of our population are also close to those in [68], which show that only 45% of people in the age group of 18-34 y/o walk more than 30min a day/more than five days a week, and that 42% in the same age group spent more than 8h30min sitting (the highest sedentary adult age group) [68].

3. Meals and snack show contextual differences that are backed-up by existing literature: Regarding the eating context, our results concur with existing literature that associates snacking to areas non-designated for eating [55, 104]: working areas and classrooms (in campus), couch (at home) or public transport, and bars where no meals are served.

A relatively small number of activities occurred when eating: socializing, doing nothing else, working, studying, using cellphone, and watching TV. While socializing was related more often to meals than snacks, both meals and snacks took place equally eating alone or with people and with a very clear temporal pattern: early breakfasts and late meals are eaten alone, while lunch was mostly social; in contrast, snacks during class hours were more social than evening snacks. Using cellphone appeared among the most frequent activities while eating (more than watching TV), and was higher for meals (15%) than for snacks (7%). We do not know of any work investigating eating behaviors related to cellphone usage, but research investigating the influence of screen use (TV, computer) on eating [46, 72, 90], shows that it distracts people and promotes mindless eating. The use of smartphones may lead to similar outcomes, but this would have to be investigated in future work.

4. Meals and snacks can be classified up to 84% accuracy using Time, Location and Time since last intake: We showed that it is possible to classify eating occasions into snacks and meals categories with 84% accuracy using contextual features, compared to a baseline based on time that achieves 69% accuracy. In particular, time since last intake (TSLI) and location (where) were the most informative features alone. In combination, Time (T) and TSLI achieve 82% accuracy, while location (Where) provides a marginal improvement. The best combination (T+TSLI+Where) is better than a time-rule-based model in all time slots. These results partly support literature using traditional methods that has defined eating occasions on the basis of time and location[7, 40, 45], and suggest that other factors like TSLI are as well determinants for an eating occasion to be a snack or a meal. We also found that models using physical activity data did not perform better than random. The literature reports contradictory results on the topic: the work in [55] found that average daily moderately-to-vigorous activity measured from accelerometer was not significantly associated to the number of healthy snacks, unhealthy snacks, sugar sweetened beverages, or non-fruit desserts. The work in [51] reported that snacking events and hours of moderate-to-vigorous physical activity were positively associated. In [15], physical activity measured from GPS data contributed to predicting near-future food purchases. We also found that BMI was not a good predictor of snacking behavior. This may be due to the uniformity of our student sample in terms of weight.

To our knowledge, this is the first attempt to classify meal vs. snack eating occasions using everyday contextual cues like time and location that are readily available from phones, in contrast to multiple or more specialized wearable sensors [65] or image-based analysis [63]. The current accuracy of 84% in the classification of meals vs snacks clearly leaves room for improvement. One future research issue is to understand whether similar performance could be obtained with (1) a more general population, and (2) with more data, meaning more days for a given user and more users. A second aspect for future work would be to identify applications for which this level of inference performance is already useful. One example is a system to recommend healthy food options depending on the eating occasion type inferred by our contextual classifier. Furthermore, this work is a starting point to motivate other predictive behavioral tasks that could be used in future applications to encourage and support healthy eating in context. This includes (but is not limited to) tasks such as predicting the time of the next meal, the food type or the food amount to be consumed (as in [65]); or predicting unhealthy behaviors such as meal-skipping and having late snacks. Answering some of these questions may require larger-scale and more longitudinal data, as well as collecting fine-grain sensor data to develop models that can unobtrusively estimate the eating context from mobile sensors: e.g. location, social setting, and related activities. Several related works in ubicomp are already going in this direction [15, 84].

The collected data also offers numerous opportunities to study other aspects of eating behavior not addressed in this article. Regarding food images, our collection provides very challenging data for automatic analysis. Based on initial manual inspection of the images, we found that many of the students prepared their own food, which resulted in a large percentage of pictures including food containers where food components are hidden or mixed, and hence difficult to identify. Knowing that there is no straight forward and accurate approach for estimating quantities, we plan to describe the food pictures with respect to main categories adapted from the Swiss Food Frequency Questionnaire. This may allow to predict the type of snacks to be consumed in a snacking occasion (fruits vs sweets, solid vs fluid snacks) and consequently support healthy eating in context. As part of future work, we also plan to analyze the rest of entry and exit questionnaires, including the motivations for eating snacks. In addition to the new research directions discussed above, extensions to the task of classification of meals vs. snacks include evaluating additional features such as the label of the previous eating occasion, and other personal features extracted from the exit questionnaires (like the personality traits). We also plan to investigate unsupervised machine learning methods to discover eating routines that emerge from the data.

Limitations of our work: One of the limitations of our work was the entry of manual data by participants and the burden that this generates. Despite the high motivation expressed by participants previously to the study (which is supported by the participant compliance showed in our analysis), some participants reported, during the data collection, that they were concerned about forgetting to report eating occasions; that the data collection was repetitive and boring; and that it was intrusive because surveys had to be responded in a social context that required their attention, or when they just wanted to eat. Limited user experience and time-consuming manual data entry are a common problem in mobile food studies, which calls for alternative approaches to data collection that are less intrusive. From the perspective of ubiquitous computing, some of the data entries could be semi-automatically feed into the system instead of asking participants to do so. In our work, we explicitly made the decision of collecting manual input for contextual variables. We acknowledge (and this is confirmed by the analysis of the results) that an automatic or semi-automatic approach could have been used for some of the the contextual cues. For instance, current state of tech could e.g. allow for automatic inference of location, which would reduce the burden to enter this data for every meal. However, our study was designed such that the manually inputted data could be compared to previous nutrition science literature. Furthermore, for other contextual cues, the performance of a fully automatic extraction is not sufficiently high. Furthermore, the development of any context-aware systems requires the collection of reliable groundtruth. The collection of participant self-reported groundtruth shows a trade-off between reliability and scalability. While works like ours show the feasibility of collecting this type of data around eating occasions using mobile surveys, we believe that there is a need for manual approaches to data collection that are more entertaining. In this line, initial work suggests that conversational interfaces (i.e., chatbots) could be more engaging than mobile applications to document eating occasions, but further research is needed to demonstrate that chatbots can boost participation in long-term studies [36].. Another limitation was the use of passive notifications based on time instead of personalized notifications based on context. Our originally idea was to minimize the use of notifications to be as less intrusive as possible to participants in their daily routine. However, after two pilot data collections with a small sample of volunteers, we realized that notifications were necessary to increase compliance, as using the mobile app interfered with participants habits during eating times, specially when this involved a social setting. Implementing automatic notifications (e.g. based on location or location change) would have required additional time devoted to the development of these features previously to actual data collection.

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