A multi-site study on walkability, data sharing and privacy perception using mobile sensing data gathered from the m^k-sense platform

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Abstract. Walking is a fundamental part of a physically active lifestyle, it is one of everyday activities that positively impacts health and wellbeing. In this paper we describe the challenges and experiences of conducting a sensing campaign in the wild. We make use of m^k-sense; a software platform to facilitate the deployment of collaborative sensing campaigns. We elaborate on two cross-cultural studies conducted in four different countries (Mexico, Turkey, Spain, and Switzerland) with a total of 77 participants. We present a detailed description of the data collected from one of the studies aimed at measuring walkability around three different university campuses. The analysis of the data shows that walkability can be assessed using information from the sensors in the smartphones and results from surveys answered by participants. In addition, we analyze issues about data sharing and privacy awareness.

Keywords. Smartphone, sensing campaign, data sharing, privacy concern, completeness data.

1 Introduction

In the last decade, the use of mobile devices has grown considerably. These devices have become the fastest-selling gadgets, outselling computers four to one (Berkeley 2015). Smartphones include a variety of sensors from which data about the user's activities and environment can be collected. Cameras, accelerometers, microphones, GPS and NFC chips are some of them. These capabilities enable gathering information from many perspectives in a pervasive and ubiquitous way (Satyanarayanan 2001), giving rise to the field known as mobile sensing (Macias *et al*. 2013). Mobile sensing is giving researchers the opportunity to create new knowledge in various fields such as epidemiology, sociology, and transportation. Today, mass usage of Smartphones provides efficient mechanisms to conduct crowdsourcing campaigns through participatory sensing applications (Kanhere 2013). The concept of crowdsourcing has emerged as a new paradigm of citizen science, enabling collaboration to gather users' data in large urban areas. Some authors have created models to guide in participatory sensing and data collection, focused on specific crowdsourcing environments (Moraes *et al.* 2014).

On the other hand, several studies have shown the potential of collecting and analyzing user's information from mobile devices in multiple domains. Silva, T.H. *et al.*, explored the use of participatory sensing derived from location sharing systems (*e.g.,* Foursquare) to understand human dynamics of cities (Silva *et al.* 2014). Eagle, N. *et al.*, used smartphones' Bluetooth antenna as a proximity sensor, frequency of application use, and call records to recognize social patterns in daily life in order to infer relationships, and to identify socially significant locations (Eagle and Pentland 2006). Also, Corno, F. *et al.* proposed a low-energy method to predict user presence in a meaningful place by collecting data from user activity, received notifications and device status (*i.e.,* battery level and ringtone mode). The collected data were analyzed using a variety of machine learning algorithms (Corno *et al.* 2017). Wearable devices are also used to gather information from users and their environment. For instance, Berke, E.M. *et al.* performed a study to measure sociability and physical activity in older adults by using a bracelet with sensors that continuously capture data from an accelerometer, a microphone, a barometer, and sensors for measuring temperature, humidity, and light. After a period of data collection and analysis, they compared the results with those of traditional questionnaires. They showed that the amount of collected information influences the quality of the study: the more information we have, the more reliable are the results and conclusions obtained if the analysis of the data is appropriate (Berke *et al.* 2011). In this direction, Chen, P. *et al.* introduced the concept of crowdsourcing methods for mobile sensing to promote the massive participation of users in specific experiments (Chen *et al.* 2015).

Extracting collective information holds the potential to help us understand the dynamics of society, and consequently to study its impact on fields such as healthcare. Prominent examples include the observation of spatiotemporal movements of millions of people during disease outbreaks (Bengtsson *et al.* 2011), and the rapid detection of an unusual respiratory illness in a remote village (Brownstein *et al.* 2009). In addition, behavioral data regarding social interactions, daily activities, and mobility patterns are valuable for psychological purposes (Harari *et al.* 2016).

Involving large numbers of volunteers in this data-driven approach to discovery, in what has been also referred as citizen science or crowd-sourced research, is providing a new lens for understanding human behavior. As smartphones are providing an extension of user habits and lifestyle, analyzing the information collected by them allows discovering people behaviors, and / or needs (Campbell *et al.* 2008).

In this paper, we present a comparison among similar mobile sensing platforms to address our earliest contribution in m^k-sense. We describe two studies conducted in naturalistic conditions in which we used our earliest version of the m^k-sense. We elaborate on the multi-site study on walkability: A 21-day sensing campaign, by summarizing collected data and presenting early results on walkability and privacy awareness. We conclude with lessons learned and future work.

2 Platforms for mobile sensing

In recent years several software platforms for mobile sensing have been developed, including a few meant to be used by researchers with limited or no programming skills (Kim *et al.* 2013). In this paper, we review some of these platforms and highlight the opportunity for the new system being proposed. Table 1 shows a comparison of those platforms that have similar features as our introduced platform m^k-sense (further discussed on Section 3).

The Bubble-Sensing platform enables the creation of sensing tasks for collecting sample of sensor data at specified periods of time. Moreover, it provides a mechanism for sharing resources between participants (Lu *et al.* 2010). AnonySense implements a privacy-aware architecture for conducting opportunistically applications based on collaboration (Cornelius *et al.* 2008). The PRISM (Platform for Remote Sensing using Smartphones) allows tailoring a sensing application by using predefined modules (Das *et al.* 2010). Mobiscopes hybrid system is designed to achieve high-density sampling coverage over a wide area of mobility entities, for instance: mobile devices such as smartphones and vehicles (Abdelzaher *et al.* 2007). The PHONELAB provides a manageable interface to initiate a sensing campaign with no coding involved (Nandugudi *et al.* 2013). The MyExperience platform combines sensor and questionnaire collection of data among other functions (Froehlich *et al.* 2007). The FUNF system consists of an open source framework to collect sensor data remotely and it provides services to define technical configuration at a low level[1].

PLATFORMS	**GENERAL**				**FEATURES**			
	G1	**G2**	**G3**	**G4**	**F1**	**F2**	**F3**	**F4**
Bubble-Sensing	NO	+	YES	NO	NO	YES	NO	NO
AnonySense	YES	+	YES	NO	NO	YES	NO	NO
PRISM	YES	+	YES	NO	NO	YES	NO	NO
Mobiscopes	YES	++	YES	NO	NO	YES	NO	NO
PHONELAB	YES	++	YES	YES	NO	YES	NO	NO
MyExperience	YES	++	YES	YES	NO	YES	NO	NO
FUNF	YES	++	YES	YES	NO	NO	NO	NO
m^k-sense	**YES**	**++**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**

Table 1. Comparison among sensing platforms. There are two categories of evaluation. General characteristics (labeled with prefix G) and Features (labeled with prefix F), where + represents that the platform is limited to physical sensors (*e.g.*, accelerometer, gyroscope), ++ stands for flexibility to handle both: physical and soft sensors such as app used, messages sent / receive, and so on. Please refer to section below for more information about each evaluation.

[1] Funf: Open Sensing Framework. http:// funf.media.mit.edu.

From the analysis of the literature and our own experience conducting sensing campaigns we have identified two main types of desirable aspects to enhance multi-site sensing campaign platforms: General characteristics (label G as presented in Table 1) that refers to the general functionality of the platform as a sensing device, and Multi-site campaign features (label F, as presented in Table 1):

- **Reconfigurable (G1).** It allows the researcher to implant a new sensing campaign, by defining issues such as the sensors to be used, and the frequency of sensing.
- **Support for multiple sensors (G2).** While all platforms support at least a few sensors (*e.g.*, accelerometer and GPS), some others support a few dozens different sensors including soft sensors.
- **Security and privacy (G3).** Enable at least an automatic mechanism for data encrypting and / or keep user information anonymous. This also includes preventing the applications from misusing sensitive sensors data, and providing users with awareness of the data being shared.
- **Support for participatory sensing (G4).** It supports mechanisms to request information from the user including filling questionnaires to provide voluntary qualitative information (*a.k.a.*, self-reported information) through the platform.
- **Mechanism for monitoring participants (F1).** Informative mechanism to keep track of participation during a study and to monitor possible problems gathering data during the sensing campaign.
- **Study-package campaign design (F2).** Provide mechanisms to facilitate the creation of a new sensing campaign.
- **Communication with participants (F3).** Provide mechanisms to directly inform participants about any concern that might emerge during the study, for example to inform them about a software update.
- **Support to assess data quality (F4).** It provides the person in charge of a sensing site and/or the individual being monitored the means to provide an assessment of the conditions in which the data is being gathered.

As illustrated with the previous examples, while most platforms address to a large degree the general requirements (G1-G4), they lack some of the features we find desirable for conducting multi-site sensing campaigns. Current platforms have already tackled several of these issues (*i.e.,* scalability, no technical knowledge required, and a variety on features such as sensor collection and surveys). Few efforts however, have focused on providing monitoring services to supervise data completeness during sensing campaigns, which is important in terms of the quality and quantity of samples being collected, moreover, they also lack communication mechanisms to directly inform participants of any maintenance needs. These features are associated to the assessment of the data quality being gathered, a topic of increasing importance in mobile sensing. The m^k-sense platform, described in this paper, puts special emphasis on this topic. It incorporates services aimed at monitoring and assessing the quality of the date gathered during a sensing campaign (see Table 1).

3 m^k-sense as a platform

m^k-sense is a platform which aims to reduce the effort of researchers when conducting sensing campaigns. It consists of a client and a server side implementation to design campaigns and monitor data completeness. m^k-sense helps researchers to conduct multiple sensing campaigns, requiring minimal technical knowledge to effectively operate the platform.

3.1 Architecture

The design of m^k-sense is based on a three-layer client-server architecture. User and device data, questionnaires and responses, and sensor data are sheltered within a relational database on the data-layer. The web interface that enables the creation of study campaigns and facilitates the monitoring of data completeness, is stored within the presentation-layer. Collected data is kept in raw format, due the motivation of this project, which lies on research purposes. Moreover, sensor data on the client-side is temporarily stored within the client device and managed on the business-layer.

As illustrated in Fig. 1, the architecture design involves two main categories: data collection and data completeness, on the client and server side; respectively. Sensor and questionnaire data are temporarily sheltered on the smartphone, for further opportunistic transmission to the server. Once the server receives the data, it is backed-up and parsed in a dedicated repository, allowing researchers to have a real-time overview of the running studies by providing a set of completeness views.

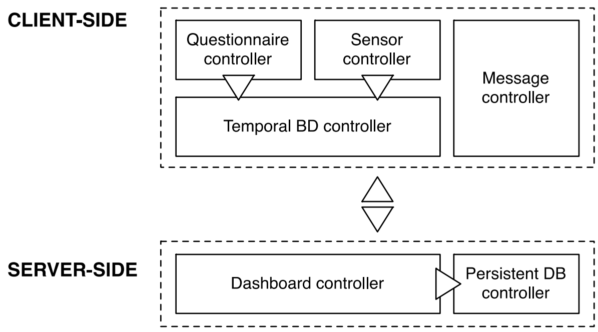


Fig. 1. m^k-sense data collection architecture.

Client-side: It consists of an Android application supported by an extensible framework designed to collect sensor probes. It allows devices to be remotely setup from 3 different categories. (1) Sensor elements: accelerometer, Bluetooth devices, gyroscope, location, proximity and light sensor, and WiFi scan. (2) Mobile device: applications used, battery information, browser search history, cell towers, contact list, hardware information, on / off screen-event, OS information, phone-call logs, running applications, and SMS history. (3) Voluntary input: questionnaire answers in multiple formats, such as text and audio recording, and photo images.

Server-side: It consists of a web interface built over the Laravel framework[2] as a web service using REST and JSON-schema format calls, using a MVC (Model View Controller) architecture. Both sensor and survey data are temporarily stored in the Client-side by the Temporal BD controller (Figure 1) waiting to be sent opportunistically by a wireless connection to the server. Thus, batches of data are sent periodically to the server-side. When the data is successfully received by the server, files are deleted from the data collecting smartphone. Then, the data received are parsed and stored into a dedicated database.

3.2 Features

m^k-sense consists of five distinctive features that distinguishes it from other sensing platforms:

- **Questionnaires.** They consist of a series of question and other prompts with the purpose of gathering specific information using a participatory sensing paradigm. m^k-sense supports two questionnaire mechanisms: (1) experience sampling; which gathers responses based on random periods of time, and (2) daily reconstruction survey; which collects responses with a pre-defined schedule. Both types of questionnaire can include a combination of input types, for example: audio message, check boxes, sliders, and text entry.
- **Audio recording.** Audio data are a rich source of information, which helps to better understand the context of a specific event, for example, to detect whether someone is having a conversation. In this context, most people reject audio recordings due to privacy issues. Hence, in order to overcome this tradeoff, a privacy preserving mechanism was implemented, in a way that the user can manage whether a specific audio recording should be uploaded for further processing.
- **Photo collection.** Photographs are another rich source of information, which helps on providing a better understanding context through a graphic presentation.
- **Study package.** It follows the concept of enclosing resources in a single virtual location to keep information organized. A package can be created by defining a list of sensors, a set of rules to define duty cycles, and triggering conditions.
- **Dashboard.** It is implemented to facilitate the supervision of the mobile devices participating in the sensing campaign. Sensor data are monitored using a set of different view components, for example to monitor accelerometer and location functionality, as shown in Fig. 2.

[2] https://laravel.com/

Fig. 2. Acceleration sample (left side) that consists of acceleration from the last 6 hours of data collected, and geolocation component (right side) that take into account all locations data available for each participant.

The dashboard provides a manageable mechanism available for researchers, so they can monitor participant's data, for example, Fig. 3 shows accelerometer data collected for 9 days in sensing campaign. The graphical representation illustrates that during the afternoon of March 15th, an atypical behavior happened for 3 hours; similarly, on March 13rd and 14th. In previous cases, the data location problem was solved and data collection was resumed.

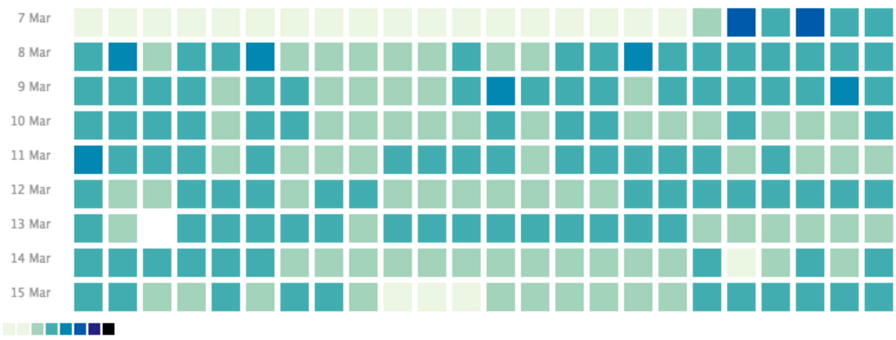


Fig. 3. Data completeness visualization of accelerometer data. Each line corresponds to one day and each square corresponds to one hour of data being sensed. Color-coding indicates the amount of data collected: bright color indicates no / less data; dark color stands for a higher percentage of data being collected.

In this context, if the researcher observes a gap of data during a sensing campaign period, he or she can inform the participant(s) by sending a notification message. Messages are sent directly to the participants' mobile device. Alternatively, the system can be configured to automatically notify once a condition is detected.

3.3 Using m^k-sense: The Tholilo campaign

To illustrate the use and advantages of m^k-sense, we next present a multi-site sensing campaign that was deployed in two countries using the m^k-sense platform. It is a collaborative research study that involves computer engineers and psychologists. Thought and Life Logging (Tholilo) is a project focused on mental time travel in which we retrieved both: self-reported and mobile sensor data.

Mental time travel is the ability to project ourselves into the future to simulate possible future events, as well as reliving our past experiences (Suddendorf and Corballis 2007). Mental time travel research relies mostly on self-reports (non-momentary, retrospective questionnaires that may include memory inaccuracies / biases) and experiments that may not generalize to real life. A novel and functional / ecological approach to mental time travel necessitates the investigation of the phenomenon in the real world. Thus, we used the "experience-sampling methodology", which involves repeated sampling of the same individuals' thoughts / feelings / behaviors over time in natural contexts. The Tholilo package of m^k-sense allowed us to use this experience-sampling method: It signaled participants at random times a day and sent them a very short survey. In addition, we used audio recording as a way of collecting objective (non-self-report) sensory data from the participants' environments.

We examined how and why people think and talk about their personal past/future in everyday life. Using the Tholilo package of m^k-sense, we signaled participants seven random times a day for 10 days and asked them what they were thinking or talking about at that moment. Participants rated how much their thoughts / utterances were focused on their personal past and future, and rated the emotional valence and functions of their thoughts / utterances. They also reported their current context (*e.g.*, location, activity) and mood. Some of the questions are depicted in Fig. 4. All questions are based on previous published work and on pilot studies conducted at the Psychology Department at the University of Zurich (Pasupathi and Carstensen 2003).

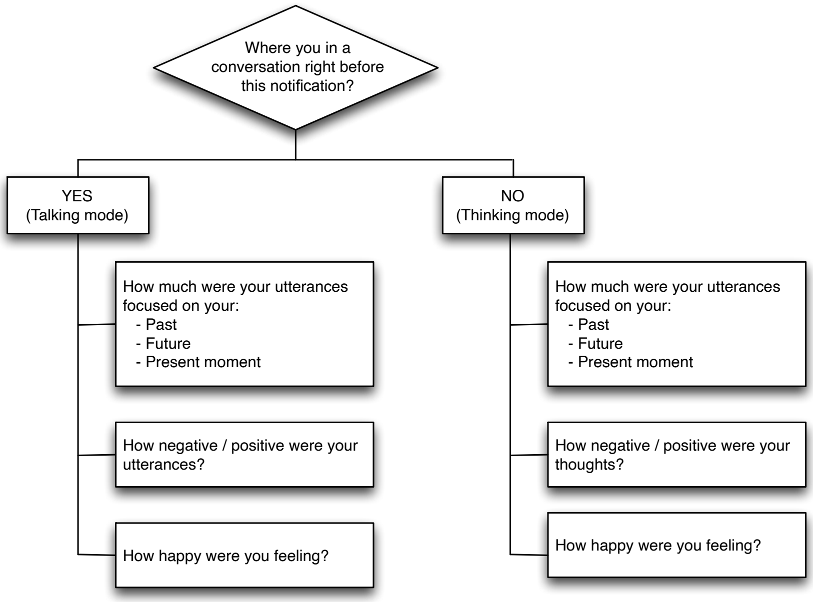


Fig. 4. Workflow of some of the questions on each survey notification. The flow depends on the context the participant is involved right before the notification; thus the participant might answer questions related to the "talking "or "thinking" activity.

Data were collected in two different locations: Istanbul, Turkey and Zurich, Switzerland. In order to keep the battery consumption low, sensor data were not collected continuously, but in periodic time intervals. Data was gathered from the Bluetooth sensor every 5 minutes to detect people physically close to the participant, location information was recorded every 30 minutes; 10 second sample of accelerometer data is recorded every 5 minutes; the applications running on the device and the state of the screen (on / off) are registered as well.

Participants consisted on 6 students / worker from each institution (*i.e.,* 1 male and 5 females) with an average age of 33 and 23 years old; respectively. In the beginning of the study, participants were invited to the laboratory for an introduction session, in which they were given instructions on study procedures and various psychological questionnaires to fill out. They downloaded and installed the Tholilo app in their personal smartphones according to instructions given by the researchers. After having installed the app, participants were trained to appropriately fill out the experience-sampling surveys.

After this introductory session, the Tholilo app was active for 13 hours per day for 10 days. Participants could select the starting time of this 13-hour period each day (*e.g.*, from 8 a.m. to 9 p.m.). From the starting time, the app sent seven surveys at random times with at least 30 minutes between each signal. If the participant did not answer the survey right after being signaled, a reminder signal was sent five minutes after the initial signal. If the survey remained unanswered for ten minutes after the reminder signal (15 minutes after the initial signal), the survey disappeared. Right before each signal, a one-minute audio sample was recorded, resulting in seven recorded sound files per day.

After having completed ten days of experience-sampling, participants were asked to come to the laboratory for a feedback session. It took participants approximately 20 minutes to complete questionnaires and to give feedback about the study app and procedures. At the end of the session, they were thanked and given CHF 60 for their participation. Please refer to our previous publication in which we elaborate on a more detailed description of data analysis (Hernández *et al.* 2015).

4 Multi-site study on walkability: A 21-day sensing campaign

Walking is part of a physical active lifestyle, it is one of the daily life activities that positively impacts health and wellbeing. It is commonly recommended by physicians since it does not require neither specialized equipment nor controlled conditions. The built environment in our surrounding has a significant influence in behaviors that influence our health, such as walking and socializing. Everyday chores we can conduct by walking versus using a car or public transportation, have a direct impact on the prevalence of public health concerns such as obesity, cardiovascular diseases and depression (Perdue *et al.* 2003). Studies on the effects of the built environment and health often rely on self-report, such as walking, and then compared to characteristics of the neighborhood, such as the presence of greenness, population density, and walkability (Villanueva *et al.* 2013).

Several projects have proposed mechanisms to define and compute a walkability score[3]. Evaluations might be based on different aspects. For example, user's feedback, social media inputs, concurrency, among others (Quercia *et al.* 2015). An additional approach estimates a walkability index with land use mix (Christian *et al.* 2011). While the results are preliminary, this approach has the advantage of being relatively easy to estimate.

The walking sensing campaign aims at exploring mechanisms to automatically evaluate how friendly a road / path is for walking, and eventually estimating a walkability index from the user behavior. The walkability of an area is influenced by the diversity of aspects such as infrastructure and physical access (*e.g.*, street layout, sidewalks, lighting), the existence of places of interest to visit (*e.g.*, market, parks, schools, transit stops), and proximity to home. In addition, we were interested in learning about their users perceived privacy and their willingness to share data.

While most walkability studies focus on the neighborhood where people live, we decided to focus on the vicinity of university campuses where our participants studied or worked. Thus facilitating obtaining sufficient data from a relatively small number of subjects. The study was replicated with strict supervision (*i.e.,* same directions and training procedures were provided) in three cities of three different countries: Ensenada, Mexico, Istanbul, Turkey, and Ciudad Real, Spain.

[3] Walkscore: https://www.walkscore.com

In order to keep the battery consumption low, sensor data were collected in periodic time intervals. We were interested in knowing the location of the subject while around the university campus and measure when and where they walked. To gather this data, we configured m^k-sense to record location data using the GPS every 30 minutes and 20 seconds of accelerometer data every 5 minutes.

Each participant received a questionnaire under two conditions: automatically triggered by detecting that the participant had walked continuously for 5 minutes, or on demand; by participants' request when they wanted to contribute data. Surveys focused on evaluating walkable areas and pedestrian experience.

Participants received a technical training session to operate the applications, and were asked to sign-up a consent letter to participate in the study; providing respective right to analyze collected data respecting their identity.

Inclusion criteria was restricted to participants who owned a smartphone with Android O.S., carried their phone regularly, and frequently visited the surrounding areas in their scholar campus.

4.1 Description of collected data

For the participants to appropriately collaborate on the study, they installed m^k-sense (*i.e.,* client-side). Once the application was installed, they individually selected a privacy option for setting up the study-package. The data consisted of four categories:

- **Demographic data:** due privacy aspects, it is restricted to participant's age, gender, city and country.
- **Sensor data:** include acceleration[4] under two configurations (*i.e.,* with and without gravity force included); sample rate with a frequency according to user's device configuration, and geolocation[5] data either from network or GPS connection.
- **Questionnaires:** They include pedestrian experience inputs, and walkability evaluation based on the user perception. They are based on four questions / statements, as enlisted below.
    1. Take a photo of a street / road you often walk along, and answer the following questions related to his road.
    2. Answer 9 statements such as "This road is free of obstacles" or "This road has an enjoyable landscape", using a 7-item Likert scale.
    3. What did you try to convey about this road by taking this picture?
    4. How would you rate your experience walking this road considering that 0 means Poorly, and 6 means Excellent?

Questions were translated to three different languages (*i.e.,* Spanish, English, and Turkish). They were validated for 3 native speakers from each country involved in the study.

[4] http://developer.android.com/guide/topics/sensors/sensors_motion.html
[5] http://developer.android.com/reference/android/location/Location.html

— **Privacy option-data:** consisted of two package-configuration options (*i.e.,* basic and advanced mode). Participants were presented with a description of the data that would be collected from their smartphone; as showed in Fig. 5, and the privacy considerations that were taken to hide their identity. The information was made sufficiently detailed so that the users had to scroll at least once in order to read all the data. With this we wanted to know how many participants were sufficiently concerned about the data they were going to share, to at least read the whole description. In addition, they were given the opportunity to modify the amount of data they could share, by selecting between two conditions. The first condition (Basic) included accelerometer and GPS in the vicinity of the University campus exclusively on weekday (*i.e.,* from Monday to Friday). In the Advanced condition, the data is recorded regardless of the location of the data and at a higher frequency all days of the week. Users were able to change the data sharing configuration at anytime during the study. Two weeks into the study, the participants were informed that a third option was being added, in which they could have access to a webpage were they could visualize the data that was being collected from them, but this option included the Advanced configuration. That is, they would obtain an additional service if they would agree to share more data. With this we aimed at finding: a) if they were concerned about the data they were sharing and were at least curious to revisit the condition they had selected, and b) if having access to their data would motivate them to change the configuration to share more information or would make them more aware to return to the Basic condition. Several studies have shown that privacy becomes a concern once the user is made aware of the data being shared and the inferences that can be made from them (Tentori *et al.* 2006).

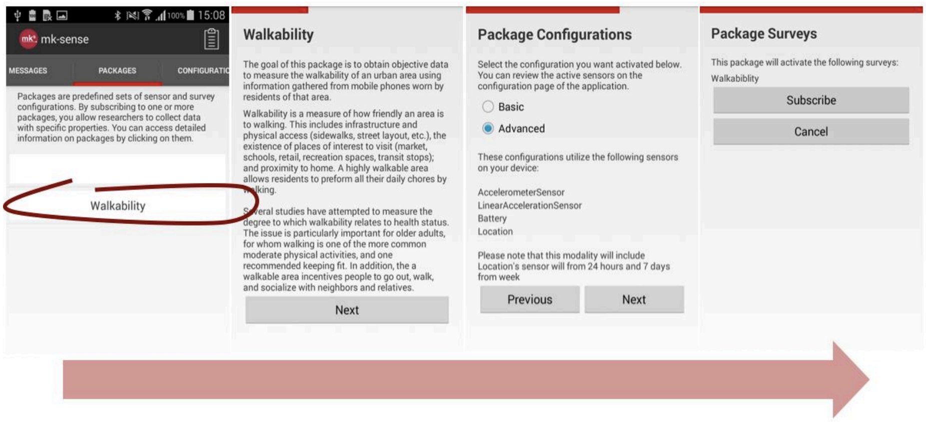


Fig. 5. Illustration of the phases for the participant to appropriately subscribe and setup the m^k-sense application, and participate on the walkability study.

4.1.1 Dataset

A total of 65 participants collaborated in the study, as presented in Table 2.

No. of participants	Group A	Group B	Group C
	29	21	13
City, Country	Ensenada, Mexico	Istanbul, Turkey	Toledo & Ciudad Real, Spain
Size of the city	Medium (500k)	Large (14M)	Small (84k) & Large (75k)
Density of population	9/km^2	2.6k/km^2	362/km^2 & 260/km^2
Gender	(15 male; 14 female)	(17 male; 4 female)	(4 male; 9 female)
Average age (S.D.[6])	28.48 (5.79)	23.24 (3.62)	28.42 (9.08)

Table 2. Information of participants in the Walkability Study.

We anticipated that some participants would drop from the study based on conditions such as concerns about the performance of their smartphones (*e.g.*, memory space or battery consumption of the m^k-sense application), technical issues (*e.g.*, sensors weren't working as expected), or other reasons (*e.g.*, unexpected renewal of smartphone). A total of 5, 0, and 2 participants from Mexico, Turkey, and Spain were excluded *at-posterior*, according to one of these criteria. Thus, 58 subjects participated in the walkability study.

The amount of data collected during the study included 528 questionnaires, with 110 audio recordings, and 528 photographs, as presented in Table 3.

Weekday	Ensenada, Mexico				Istanbul, Turkey				Ciudad Real, Spain			
	Q	**P**	**A**	**D**	**Q**	**P**	**A**	**D**	**Q**	**P**	**A**	**D**
Sunday	12	12	0	5	5	5	3	2	2	2	1	2
Monday	36	36	2	13	28	28	6	12	15	15	8	8
Tuesday	61	61	12	15	43	43	6	13	17	17	9	5
Wednesday	71	71	5	19	26	26	4	13	19	19	9	9
Thursday	63	63	7	18	17	17	4	10	25	25	13	8
Friday	46	46	10	18	3	3	1	2	8	4	3	4
Saturday	23	23	0	5	0	0	0	0	8	8	7	2
Total:	**312**	**312**	**36**	**93**	**122**	**122**	**24**	**52**	**94**	**90**	**50**	**38**

Table 3. Summary of data gathered from the surveys at each location, where Q represents the total amount of questionnaires replied, P is the number of roads / spots photographed, A represents the number of audio messages voluntary recorder, and D the number of days in which the surveys where delivered.

Geo-locational sensor data, consisted of 1,897,102 data points, representing approximately 2,212 different roads / spots walked by the participants.

[6] Standard Deviation

To illustrate the amount of data collected within and at surrounding areas of the campuses, Table 4 presents the amount of different roads / spots walked by the participants.

Country	Within 1 km from campus (%)	Within 2 km from campus (%)	Further that 2 km from campus (%)
Mexico	176,415 (7.08)	181,824 (7.3)	722,631 (29.01)
Turkey	287,418 (11.54)	292,810 (11.76)	279,761 (11.23)
Spain	120,389 (4.83)	206,805 (8.3)	222,552 (8.94)
Total	463,833 (23.46)	506,534 (27.36)	1,390,568 (49.18)

Table 4. Number of roads / spots of walked by participants, considering three variants on distance from a center data-point settled at the center of the scholar area from each campus.

On the other hand, accelerometer data was recorded for a total of 641 hours (with a sample rate of 100 hz).

4.1.2 Walkability results

As mentioned before, walkability is a measure of how friendly an area is to walk. A highly walkable area allows residents to preform all their daily chores by walking. Moreover, walkable area motivates people to go out, walk, and socialize with peers and neighbors.

A first evaluation of the collected data, measure the walkability of scholar campuses and surrounding areas (*i.e.*, up to 1 km from campus). Figure 6 illustrate the University Campus from Istanbul, Turkey (*i.e.*, Boğaziçi University) using the data gathered from all participants. Color-coding is based on heat-range, which indicates the amount of data collected: bright green color indicates less data; yellow color stands for a median level of data, and red color represents the higher percentage of data being collected. On this map we can observe that places of interest included classrooms / laboratories, coffee places / restaurants, and dormitories; as marked on the map.

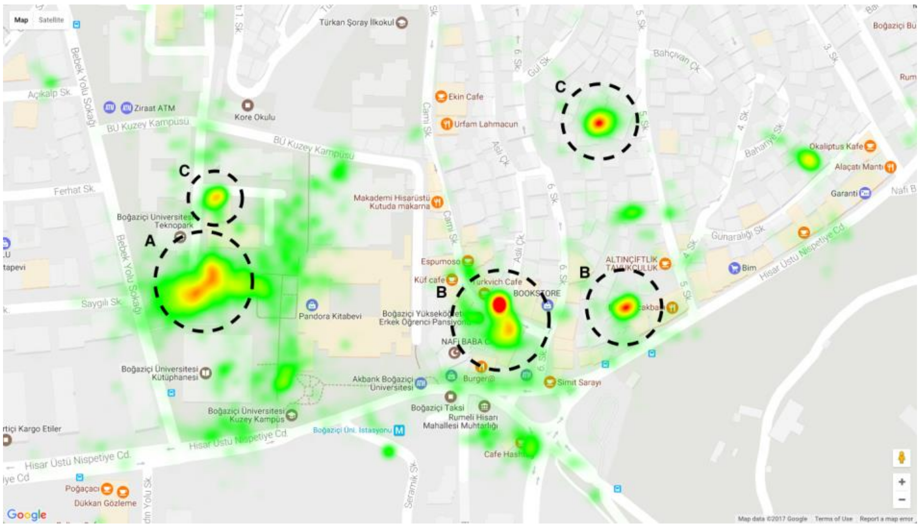


Fig. 6. Campus area from the institution that participated on the study: Boğaziçi University at Istanbul, Turkey. Color-coding represent paths / roads and spots frequently visited by the participants.

Fig. 7 is a visualization of the reports created by the participants. Each spot represents either a comfortable road / spot to walk or a poor or dangerous zone for walking. Color-coding is based on a range from 0 to 6; where 0 represents the best level of walkability, and 6 represent the worst walkability conditions reported by participants. Thus: bright blue color represents an adequate area to walk, while darker blue color indicates the presence of significant inconvenience that negatively affected the pedestrian experience of participants; and red zones represents locations that were highly inconvenient for walking. On this map we can observe the concern or participants to report un-walkable areas. Darker blue and red spots included areas with steep slopes, or roads that were blocked (see Figure 8a). On the other hand, participants also shared photographs or audio clips to mark areas when they were motivated to walk (Figure 8b; and section C in Figure 7).

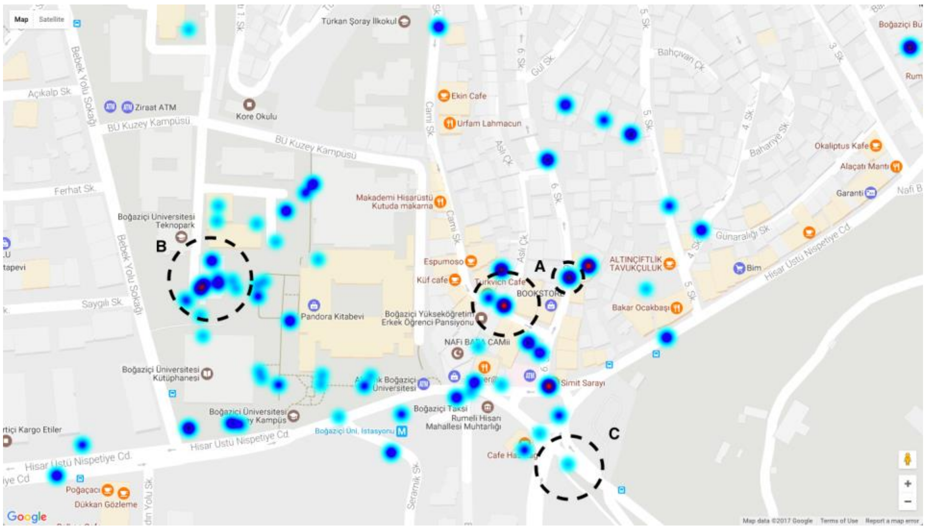
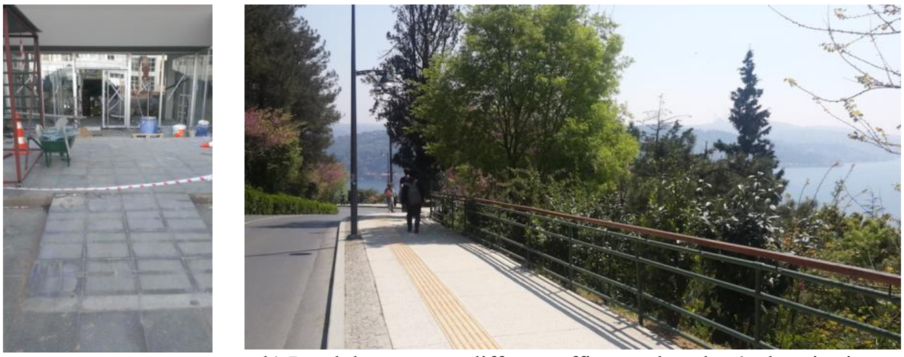


Fig. 7. Campus area from the institution that participated on the study: Boğaziçi University at Istanbul, Turkey. Color-coding, represents the paths / roads, and spots reported by the participants as poor / dangerous to walk.



a) Blocked access to classrooms building.

b) Road that connect different offices and student's dormitories.

Fig. 8. Sample photographs shared as part of the walkable report. Left image shows restricted access to a facility, while the image on the right was used by the participant to explain why he preferred to walk rather than using the intra-campus transportation.

When comparing the three participating university campuses, data shows that the highest overall score was given by users walking around the campus of Ciudad Real, Spain (*i.e.,* 3.92 in a 1-7 scale with 1 being the lowest possible score), with the lowest score being the campus in Ensenada, Mexico (*i.e.,* 3.42); which is uneven and includes steep slopes. However, the Ensenada campus had the highest score in cleanness and enjoyable landscape.

Although walkability is indeed a multifactorial construct and a single score oversimplifies its complexity, these results indicate that by using either opportunistic sensing (location and accelerometer data), or participatory sensing (questionnaires, photos and audio recordings), we can obtain a good measure of the walkability of an area. Furthermore, by monitoring changes in the data being collected we can identify trouble spots and areas of opportunity for urban development.

4.2 Data sharing and privacy issues

Of the 58 participants, 23 (42%) did not scroll on the configuration screen that described the data that was going to be gathered during the study. 31% scrolled once, and 33% scrolled that screen more than once along the duration of the study. Thus, almost half of the participants did not bother to learn about the data being collected beyond the explanation that was given to them.

Most participants (38/58) initially selected de Advanced configuration for data sharing, while less than 40% (20/58) selected the Basic configuration. A majority of the participants (38/58) made just one selection in the initial configuration, that is, they did not select the alternate option to read about the data to be gathered with that condition. Of these, 25 selected the Advanced condition. That is, more than half of the participants just selected the advanced condition without even considering the other alternative. These participants did not seem particularly concerned about the data they were sharing.

Of those who explored different configurations before deciding among the initial setup, there are 3 who changed the configuration in average 6 times, which seems to indicate that they were carefully considering between the two alternatives. Two of these participants opted for the Basic condition, while the other one selected the Advanced configuration.

Only five participants (9%) changed the privacy configuration during the duration of the study. Two of them did it to opt for the Advanced configuration that gave them the opportunity of visualizing their own data. Both of them had originally opted for the Advanced condition. The other three participants changed from the Advanced to the Basic configuration after they were informed of the option to visualize their data. This seems to indicate that this raised their awareness about privacy concerns and made them decide to share less information. Nonetheless, it is interesting to note that most participants did not seem to be particularly concerned about the data they were sharing, nor on visualizing the information that was collected from them.

5 Conclusion and Future work

In this paper, we introduced m^k-sense, a research initiative to facilitate the deployment and supervision of multi-institutional sensing campaigns. Principles of the platform were based on a user-centered design and modulation by study-package. The main features of m^k-sense are (1) the package-study feature; (2) real-time data quality monitoring; and (3) a graphical interface to manage sensing campaigns. Altogether, the tool reduces the barrier for non-technical researchers to design and deploy a sensing platform, allowing them to focus on data analysis.

We conducted two multicultural sensing campaigns in four different countries (*i.e.*, Turkey, Mexico, Switzerland, and Spain): (1) Tholilo campaign, and (2) Multi-site study on walkability: A 21-day sensing campaign. A total of 12 and 65 participants; respectively, collaborated in the studies. Over the course of these campaigns we faced four relevant aspects:

- **User-experience:** Users tend to rely on mobile phones for critical communication functions, like emergency calls, thus, a mechanism to guarantee uninterrupted support during sensing campaigns was included in the protocol, nevertheless, we would like to guarantee it programmatically into the m^k-sense application.
- **Platform issues for deployment:** Heterogeneous software, and functionalities available, model / brand devices' specifications should be taken into account *a priori* a sensing campaign. Thus, we will address a new mechanism when collecting data to guarantee high quality in heterogeneous datasets.
- **Data monitoring:** To improve coordination among multiple collaborators involved in a sensing campaign, we consider it important to include a multilevel privilege section in further versions.
- **Replication of study:** To ensure that a campaign's protocol is appropriately attended, it is important to extend the current version with a module to keep control of times and sequence of tasks, in which collaborators are able to create a personal schedule of activities, as well as provide / get feedback in real-time from the experience from collaborators in different locations.

With respect to the multi-site study on walkability, we were able to identify areas that promote or discourage walking. In addition, by monitoring changes on smartphones' sensor data, we can identify opportunities for improving pedestrian paths. Thus, future work will include the design and a proof of concept mechanism to estimate a walkability index, we will take into account both: qualitative feedback that participants provided along the study and the collected sensor data from mobile devices.

Moreover, we plan to integrate mechanisms that would facilitate the management of heterogeneous datasets obtained from sensing campaigns and include metadata related to data quality. In addition, we will improve the database storage mechanism that has been implemented to enhance performance.

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References

Abdelzaher T, Anokwa Y, Boda P, *et al* (2007) Mobiscopes for human spaces. IEEE Pervasive Comput 6:20–29 . doi: 10.1109/MPRV.2007.38

Bengtsson L, Lu X, Thorson A, *et al* (2011) Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: A post-earthquake geospatial study in haiti. PLoS Med 8: . doi: 10.1371/journal.pmed.1001083

Berke EM, Choudhury T, Ali S, Rabbi M (2011) Objective measurement of sociability and activity: Mobile sensing in the community. Ann Fam Med 9:344–350 . doi: 10.1370/afm.1266

Berkeley J (2015) Planet of the phones. Econ 12–17 . doi: 10.1001/archopht.122.4.666

Brownstein JS, Freifeld CC, Madoff LC (2009) Digital disease detection-harnessing the Web for public health surveillance. N Engl J Med 360:2153–2157 . doi: 10.1056/NEJMp1002530

Campbell AT, Eisenman SB, Lane ND, *et al* (2008) The rise of people-centric sensing. IEEE Internet Comput 12:12–21 . doi: 10.1109/MIC.2008.90

Chen PY, Cheng SM, Ting PS, *et al* (2015) When crowdsourcing meets mobile sensing: A social network perspective. IEEE Commun Mag 53:157–163 . doi: 10.1109/MCOM.2015.7295478

Christian HE, Bull FC, Middleton NJ, *et al* (2011) How important is the land use mix measure in understanding walking behaviour? Results from the RESIDE study. Int J Behav Nutr Phys Act 8:55 . doi: 10.1186/1479-5868-8-55

Cornelius C, Kapadia A, Kotz D, *et al* (2008) Anonysense: privacy-aware people-centric sensing. Mobisys08 Proc Sixth Int Conf Mob Syst Appl Serv 211–224 . doi: 10.1145/1378600.1378624

Corno F, De Russis L, Montanaro T (2017) Estimate user meaningful places through low-energy mobile sensing. In: 2016 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2016 - Conference Proceedings. pp 3039–3044

Das T, Mohan P, Padmanabhan VN, *et al* (2010) PRISM: Platform for Remote Sensing using Smartphones. Proc 8th Int Conf Mob Syst Appl Serv MobiSys' 10 63–76 . doi: 10.1145/1814433.1814442

Eagle N, Pentland A (2006) Reality mining: Sensing complex social systems. Pers Ubiquitous Comput 10:255–268 . doi: 10.1007/s00779-005-0046-3

Froehlich J, Chen MY, Consolvo S, *et al* (2007) MyExperience: a system for in situ tracing and capturing of user feedback on mobile phones. Proc 5th Int Conf Mob Syst Appl Serv San Juan,:57–70 . doi: 10.1145/1247660.1247670

Harari GM, Lane ND, Wang R, *et al* (2016) Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges. Perspect Psychol Sci 11:838–854 . doi: 10.1177/1745691616650285

Hernández N, Yavuz G, Eşrefoğlu R, *et al* (2015) Thought and life logging: A pilot study. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp 26–36

Kanhere SS (2013) Participatory sensing: Crowdsourcing data from mobile smartphones in urban spaces. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp 19–26

Kim S, Mankoff J, Paulos E (2013) Sensr: Evaluating a flexible framework for authoring mobile data-collection tools for citizen science. In: Proceedings of the 2013 conference on. pp 1453–1462

Lu H, Lane ND, Eisenman SB, Campbell AT (2010) Bubble-sensing: Binding sensing tasks to the physical world. Pervasive Mob Comput 6:58–71 . doi: 10.1016/j.pmcj.2009.10.005

Macias E, Suarez A, Lloret J (2013) Mobile Sensing Systems. Sensors 13:17292–17321 . doi: 10.3390/s131217292

Moraes ALD, Fonseca F, Esteves MGP, *et al* (2014) A meta-model for crowdsourcing platforms in Data Collection and Participatory Sensing. In: Proceedings of the 2014 IEEE 18th International Conference on Computer Supported Cooperative Work in Design, CSCWD 2014. pp 429–434

Nandugudi A, Maiti A, Ki T, *et al* (2013) {PhoneLab}: A large programmable smartphone testbed. Proc First Int Work Sens Big Data Min 1–6 . doi: 10.1145/2536714.2536718

Pasupathi M, Carstensen LL (2003) Age and emotional experience during mutual reminiscing. Psychol Aging 18:430–442 . doi: 10.1037/0882-7974.18.3.430

Perdue WC, Stone LA, Gostin LO (2003) The Built Environment and Its Relationship to the Public's Health: The Legal Framework. Am. J. Public Health 93:1390–1394

Quercia D, Aiello LM, Schifanella R, Davies A (2015) The Digital Life of Walkable Streets. doi: 10.1145/2736277.2741631

Satyanarayanan M (2001) Pervasive computing: Vision and challenges. IEEE Pers. Commun. 8:10–17

Silva TH, Vaz de Melo POS, Almeida JM, *et al* (2014) Revealing the City That We Cannot See. ACM Trans Internet Technol 14:1–23 . doi: 10.1145/2677208

Suddendorf T, Corballis MC (2007) The evolution of foresight: What is mental time travel, and is it unique to humans? Behav Brain Sci 30: . doi: 10.1017/S0140525X07001975

Tentori M, Favela J, González V (2006) Quality of Privacy (QoP) for the design of ubiquitous healthcare applications. J Univers Comput Sci 12:252–269

Villanueva K, Pereira G, Knuiman M, *et al* (2013) The impact of the built environment on health across the life course: design of a cross-sectional data linkage study. BMJ Open 3:e002482 . doi: 10.1136/bmjopen-2012-002482