Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in Behavioral Sciences

Smartphone sensing methods for studying behavior in everyday life

Gabriella M Harari[1], Sandrine R Müller[2], Min SH Aung[3] and Peter J Rentfrow[2]

Human behavior is the focus of many studies in the social, health, and behavioral sciences. Yet, few studies use behavioral observation methods to collect objective measures of behavior as it occurs in daily life, out in the real world — presumably the context of ultimate interest. Here, we provide a review of recent studies focused on measuring human behavior using smartphones and their embedded mobile sensors. To draw attention to current advances in the field of smartphone sensing, we describe the daily behaviors captured using these methods, which include movement behaviors (physical activity, mobility patterns), social behaviors (face-to-face encounters, computer-mediated communications), and other daily activities (non-mediated and mediated activities). We conclude by pointing to promising areas of future research for studies using Smartphone Sensing Methods (SSMs) in the behavioral sciences.

Addresses
[1] Stanford University, USA
[2] University of Cambridge, UK
[3] Cornell University, USA

Corresponding author: Harari, Gabriella M (gharari@stanford.edu)

Current Opinion in Behavioral Sciences 2017, **18**:83–90

This review comes from a themed issue on **Big data in the behavioural sciences**

Edited by **Michal Kosinski** and **Tara Behrend**

http://dx.doi.org/10.1016/j.cobeha.2017.07.018

Human behavior is the focus of many studies in the social, health, and behavioral sciences. Behavior is important because it can serve four main roles in research [1]: Behavior can serve as a primary phenomenon to be explained (*e.g.*, *What causes or predicts a behavior?*), the foundation of theoretical phenomena (*e.g.*, *How do observations of behavior inform theoretical investigations?*), a mechanism in psychological processes (*e.g.*, *How does behavior affect psychological outcomes?*), and a consequential outcome (*e.g.*, *What are the behavioral implications of a construct or measure?*). As such, behaviors constitute the independent or dependent variables in many research studies. When studies of behavior are done in the laboratory they are often designed to recreate real-world conditions (*e.g.*, [2–4]). However, few studies use behavioral observation methods to measure behavior as it occurs in daily life, out in the real world — presumably the context of ultimate interest [5].

The lack of research using behavioral observation in daily life is driven by the fact that collecting data on behaviors as they unfold has been almost impossible to do, especially if it must be done without affecting the behavior one is trying to record. The rare studies that have collected objective measures of behavior in everyday life tend to have sampled behaviors just once or on only a few occasions (*e.g.*, [6,7]). Moreover, past approaches have been enormously time consuming such that they cannot be deployed at scale and they capture only a small percentage of the behaviors emitted and the contexts in which they occur. Consequently, most studies have relied almost entirely on subjective self-report measures of past or typical behavior [1,8,9,10]. This is a problem because self-report data have significant drawbacks (*e.g.*, being disruptive, time consuming, leading to expectancy effects, being subject to recall biases, memory limitations, and socially desirable responding).

One relatively underused big data approach for behavioral observation is the use of mobile sensors, such as those embedded in smartphones and wearable devices (*e.g.*, smartwatches, fitness bands), as data collection tools for inferring everyday behavior. Smartphones provide an especially useful tool because they enable researchers to measure individuals' thoughts and feelings (via notifications to respond to self-report surveys or by collecting language-based data), and behaviors (via phone logs and mobile sensor data) as they naturally occur in daily life. Furthermore, with their powerful sensing and computational capabilities, smartphones have the potential to passively collect social and behavioral data nearly continuously, providing valuable objective, longitudinal, real-world, and real-time information [11–14]. Thus, Smartphone Sensing Methods (SSMs) hold much promise for behavioral science because smartphones have become the central communication and computing device used in the daily lives of people around the world [15•,16]. Moreover, mobile sensors operate imperceptibly, allowing for unobtrusive, naturalistic observational records that reduce the likelihood that participants will behave reactively (*e.g.*, [6,7,14,17]).

SSMs can be applied in several research domains (*e.g.*, clinical psychology, health sciences, organizational psychology) and are particularly useful for studying topics that are not easily assessed using retrospective surveys. For example, past research has used SSMs to investigate day-to-day variations in emotional experience [18], sleeping patterns and postures [19], and interpersonal behaviors in group settings [20]. SSMs may also be used in studies focused on patterns of behavioral stability and change over time [21], towards the development of mobile interventions targeting mental health changes [22,23•], and for the examination of social network systems [24].

To draw attention to current advances in the field of smartphone sensing, here we provide a review of recent studies focused on measuring human behavior using smartphones. Our aim is to provide a common framework for describing the behaviors captured using SSMs, and point to promising areas of future research for studies using SSMs in the behavioral sciences. A discussion of the practical considerations and key methodological features of SSM studies is out of scope for the present article, however we point interested readers to [15•] for a summary of key issues to consider when setting up an SSM study.

Which behaviors can be measured using smartphone sensing methods?

Smartphones can be used to measure several different types of behavior. In particular, SSMs are well-suited to objective assessment of people's daily behaviors, such as physical movement behaviors (activity, mobility patterns), social interactions (face-to-face encounters, computer-mediated communications), and other activities (*e.g.*, household chores, using smartphone applications to play games; [15•]). Table 1 provides a summary of smartphone data sources and the behaviors they are used to measure.

Physical movement: activity and mobility patterns

Many studies using SSMs focus on the assessment and prediction of human movement. The movement behaviors typically measured are *physical activity* and *mobility patterns* (see Table 2 for a summary of these behavioral features).

Physical activity refers to behaviors that describe movement of the human body. Physical activity is primarily measured using accelerometer sensors. Accelerometers assess varying degrees of physical activity, from being sedentary to walking or running (*e.g.*, [12,25,26]). Such physical activity behaviors are inferred by applying classifiers to the data. The classifiers are developed based on a 'training' dataset, which consists of accelerometer data that has been labeled to indicate when different activities occurred (*e.g.*, stationary, walking, running). For example, a classifier would be trained to recognize the characteristic magnitude patterns in accelerometer data that are associated with being stationary (very low to no amplitude), walking (low amplitude), and running (high amplitude; [27]). Training classifiers that robustly infer user behavior is challenging. For example, a classifier trained to identify cycling may have been trained on data collected while a phone was carried in a person's pants pocket. However, if a person were to take a call while cycling and then transferred the phone to their backpack, the accuracy of detecting the cycling activity would decrease [27].

Frequently, the physical activity inferences are aggregated to obtain the duration of time spent engaged in sedentary or moving behaviors in a given day. Longitudinal studies using SSMs to assess physical activity have examined patterns of change in activity among students during an academic semester [21], and during weekends, weekdays, and academic breaks [28•]. Studies have also examined relationships between sensed physical activity and well-being [29•], happiness [30•], and academic performance outcomes [31•].

Table 1

Overview of smartphone data sources and the behaviors they measure.

Data source	Behaviors			References
	Physical movement	Social interactions	Daily activities	
Accelerometer	✓	×	✓	[22,23•,27,28•,29•,31•,40•,70]
Bluetooth radio (BT)	×	✓	×	[46,71]
Global-positioning system scans (GPS)	✓	×	✓	[22,23•,27,28•,29•,31•,36•,38•,40•]
Light sensor	×	×	✓	[22,23•,28•,29•,31•,40•]
Microphone	×	✓	✓	[22,23•,25,27,28•,29•,31•,40,44,70]
WiFi scans	✓	×	×	[40•]
Cameras	×	✓	✓	[72]
Phone use logs	×	✓	✓	[22,23•,28•,29•,31•,36•,41•,57•,63,65•]
App use logs	×	✓	✓	[22,23•,29•,31•,54–56,57•,65•,73]

Note. ✓ = data source can be used to collect the behavior, × = data source is not typically used to collect the behavior.