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Smartphone Sensing Methods for Studying Behavior in Everyday Life

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Abstract

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.

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 (Furr, 2009): 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., Funder & Sneed, 1993; Gosling, John, Craik, & Robins, 1998; Letzring, Wells, & Funder, 2006). 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 (Reis, 2012).

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., Craik, 2000; Mehl, Gosling, & Pennebaker, 2006). 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 (Baumeister, Vohs, & Funder, 2007; Furr, 2009; Paulhus & Vazire, 2007; Vazire, 2006). 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, granular, and longitudinal real-world and real-time information (Campbell et al., 2008; Lane et al., 2010; Lathia, Rachuri, Mascolo, & Rentfrow, 2013; Miller, 2012). 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 (Harari et al., 2016; Pew Research Center, 2016). Moreover, mobile sensors operate imperceptibly, allowing for unobtrusive, naturalistic observational records that reduce the likelihood that participants will behave reactively (e.g., Craik, 2000; Mehl et al., 2006; Miller, 2012; Rachuri, Mascolo, Musolesi, & Rentfrow, 2011).

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 (Sandstrom, Lathia, Mascolo, &

Rentfrow, 2016), sleeping patterns and postures (Wrzus et al., 2012), and interpersonal behaviors in group settings (Mast, Gatica-Perez, Frauendorfer, Nguyen, & Choudhury, 2015). SSMs may also be used in studies focused on patterns of behavioral stability and change over time (Harari et al., 2017), towards the development of mobile interventions targeting mental health changes (Wang et al., 2016), and for the examination of social network systems (Kobayashi, Boase, Suzuki, & Suzuki, 2015).

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 Harari et al., 2016 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; Harari et al., 2016). Table 1 provides a summary of smartphone data sources and the behaviors they are used to measure.

Table 1

Overview of Smartphone Data Sources and the Behaviors They Measure

	Behaviors			
Data Source	*Physical Movement*	*Social Interactions*	*Daily Activities*	References
Accelerometer	✓	×	✓	Tseng et al. (2016); Abdullah, Matthews et al. (2016); Lu et al. (2010); Wang et al. (2014, 2015); Wang et al., (2016); Rabbi et al. (2011)
Bluetooth radio (BT)	×	✓	×	Chen et al., (2014); Yan et al. (2013)
Global-positioning system scans (GPS)	✓	×	✓	Tseng et al. (2016); Abdullah, Matthews et al. (2016); Canzian et al. (2015); Lu et al. (2010); Saeb et al. (2015); Wang et al. (2014, 2015); Wang et al., 2016)
Light sensor	×	×	✓	Tseng et al. (2016); Abdullah, Matthews et al. (2016); Wang et al. (2014, 2015); Wang et al., (2016)
Microphone	×	✓	✓	Tseng et al. (2016); Abdullah, Matthews et al. (2016); Lu et al. (2009, 2010, 2012); Wang et al. (2014, 2015); Wang et al., 2016); Rabbi et al. (2011)
WiFi scans	✓	×	×	Abdullah, Matthews et al. (2016)
Cameras	×	✓	✓	Werner et al. (2011)
Phone use logs	×	✓	✓	Tseng et al. (2016); Abdullah, Matthews et al. (2016); Murnane et al. (2015, 2016); Abdullah et al. (2014); Abdullah, Murnane et al. (2016); Saeb et al. (2015); Wang et al. (2014, 2015); Wang et al., (2016)
App use logs	×	✓	✓	Ferdous, Osmani, & Mayora (2015); Murnane et al. (2015, 2016); Jones, Ferreira, Hosio, Goncalves, & Kostakos (2015); Wang et al. (2014, 2015); Wang et al., (2016); Welke, Andone, Blaszkiewicz, & Markowetz (2016); Zhao et al. (2016)

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

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., Lane et al., 2010; Lu et al., 2009; Miluzzo et al., 2008). 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; Lu et al., 2010). 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 (Lu et al., 2010).

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 (Harari et al., 2017), and during weekends, weekdays, and academic breaks (Tseng et al., 2016). Studies have also examined relationships between sensed physical activity and well-being (Wang et al., 2014), happiness (Lathia et al., 2017), and academic performance outcomes (Wang et al., 2015).

Mobility patterns refer to behaviors that describe trajectories of human travel. Mobility patterns are typically measured using accelerometers, GPS, and WiFi network data. For example, accelerometers can assess modes of transportation (e.g., bus, train, metro; Hemminki, Nurmi, & Tarkoma, 2013), and have been combined with GPS and other smartphone data (e.g., microphone, orientation) to infer other transportation (e.g., cycling, driving in a car, taking a bus or the subway; Mun et al., 2009) and pedestrian behaviors (e.g., crossing roads, waiting for traffic lights; Wang et al., 2016) when traveling to different locations. GPS data assesses how far a person travels (i.e., distance travelled in kilometers or miles), the locations visited in a given day (e.g., café, shopping mall, work place), and the routes taken (e.g., Biagioni & Krumm, 2013; Eagle & Pentland, 2009; Saeb et al., 2015, 2016). These GPS-based mobility behaviors are inferred by processing latitude and longitude coordinates into broader location clusters that capture the locations a person has been. GPS data can also be combined with other types of data (e.g., Wi-Fi scans, digital compass data) to capture information about the routes people take when traveling to different outdoor and indoor locations, such as the amount of time in transit between locations and travel patterns that assess a person's location with room-level accuracy within a given building (Chon & Cha, 2011). Mobility patterns assessed using SSMs have been linked to mental health outcomes, such as depressive mood (Canzian & Musolesi, 2015; Chow et al., 2017; Saeb et al., 2015, 2016), positive and negative affect (Chow et al., 2017; Sandstrom et al., 2016), schizophrenic symptoms (Wang et al., 2016), and social rhythms in bipolar disorder (Abdullah et al., 2016).

Social Interactions: Face-to-Face Encounters and Computer-Mediated Communication

A second area of behavioral research using SSMs is focused on the assessment of social interactions. The social interactions measured are face-to-face encounters and computer-mediated communications (see Table 2 for a summary of these behavioral features).

Face-to-face encounters refer to social interactions carried out in-person without a mediating technology. Face-to-face encounters are typically measured using microphone sensors and Bluetooth data. Microphones assess whether a person is engaged in conversation, the frequency of conversations and their duration, the content of conversations, and turn-taking in conversations (e.g., Lu, Pan, Lane, Choudhury, & Campbell, 2009; Mehl et al., 2001; Miluzzo et al., 2008; Wang et al., 2014). In addition, microphones provide information about features of speech during in-person conversations such as a speaker's voice pitch, voice frequencies, and speaking rates (Lu et al., 2012; Rachuri et al., 2010). These face-to-face encounters are inferred by applying classifiers to microphone data to identify when an in-person conversation occurs (e.g., instances when a person is around silence, noise, or other voices; Lu et al., 2009). An example limitation of this approach is that conversation classifiers may have difficulty distinguishing in-person conversation from conversations occurring on a TV that is around the user. Bluetooth data assesses whether a person is physically isolated (or "co-present" with other people), the number of other co-present people, and the number of unique and repeated interaction partners (Chen et al. 2014; Wang et al., 2014). WiFi data has also been used to identify the size of co-present groups and the duration of such encounters (Vanderhulst et al., 2015). One limitation of this approach is the possibility of under or over estimating the number of people around the user. Specifically, it can be difficult to identify how many other people a person is around vs. how many other *devices* the person is around. This presents a problem because people may carry both a phone and laptop that transmit these signals, which could lead to over estimates. Longitudinal studies using SSMs to assess face-to-face encounters have examined change in students' conversation patterns before and after their midterm exam period (Harari et al., 2017), and examined relationships between face-to-face encounters and well-being (Wang et al., 2014), academic performance (Wang et al., 2015), and symptoms of bipolar disorder (Abdullah et al., 2016) and schizophrenia (Wang et al., 2016).

Computer-mediated communication refers to social interactions carried out through an electronic device. Computer-mediated communications are measured using data from smartphone application-use logs. Application use logs can assess the frequency and duration of incoming and outgoing calls, the frequency and content of text messages, and the number of unique and repeated interaction partners a person communicates with (e.g., Boase & Ling, 2013; Chittaranjan et al., 2011, 2013; Eagle & Pentland, 2006; Kobayashi et al., 2015). In addition, application use logs assess the frequency of using email and other communication applications (e.g., Facebook, Twitter) to interact with others (e.g., Mehrotra et al., 2017). Such communication measures have been used to understand people's social, family, and work networks (Min et al., 2013), identify different types of smartphone users (Welke, Andone, Blaszkiewicz, & Markowetz, 2016; Zhao et al., 2016), predict personality traits (Chittaranjan et al., 2011; 2013), stress levels (Ferdous, Osmani, & Mayora, 2015), and sleeping patterns (Murnane et al., 2015).

Other Daily Activities: Non-Mediated and Mediated Activities

A third area of behavioral research using SSMs is focused on the assessment of non-mediated activities and mediated daily activities (see Table 2 for a summary of these behavioral features). Non-mediated activities refer to behaviors that people engage in on a day-to-day basis that are not carried out through an electronic device (e.g., household chores, grooming behaviors). Non-mediated activities are typically measured using a combination of multiple types of sensor data, which are processed to infer an activity using classifiers or algorithms designed for the task. For example, accelerometers and microphone data can be combined to assess vacuuming, clapping, and taking out the trash (Lu et al., 2009) by training a classifier to recognize these activities based on characteristic patterns observed in example data obtained while performing the activity in question. Microphones can also assess health-related behaviors including respiratory symptoms (e.g., coughing, sneezing, throat clearing; Barata et al., 2016; Casaseca-de-la-Higuera et al., 2015; Sun et al., 2015), oral hygiene behaviors (e.g., brushing teeth; Korpela et al., 2015), and whether a person smokes (Jebara, 2014). Sleeping patterns can also be obtained from phone usage logs (Abdullah et al., 2014) and from combinations of several sensors (e.g., by integrating information from the phones to determine whether it is night time and the phone is charging, ambient light sensor to determine whether it is dark, accelerometer to determine if the phone is stationary, and microphone to determine if it quiet; Chen et al., 2013). Such sleeping pattern measures have been used to quantify circadian rhythms and disruptions (Abdullah et al., 2014), and predict next-day computer-mediated communication behaviors (Murnane et al., 2015). However, most of the research in this area to date has focused on the development of classifiers and algorithms needed to infer such behaviors, not on their relationship to other outcomes.

Mediated activities refer to daily behaviors that are carried out through an electronic device. Mediated activities are measured using smartphone application use logs. For example, application use logs assess whether a person is using their smartphone for entertainment or productivity (Abdullah et al., 2016; Murnane et al., 2016), or for listening to music, reading, or playing (Mehrotra, Hendley, & Musolesi, 2016; Mehrotra et al., 2017). Application use patterns have been used to predict people's moods (LiKamWa, Liu, Lane, & Zhong, 2013), depressive states (Mehrotra, Hendley, Musolesi, 2016), alertness (Abdullah et al., 2016), boredom (Pielot et al., 2015), and sleeping patterns (Abdullah et al., 2014).

Conclusions

Smartphones and their embedded mobile sensors hold much promise as assessment tools for measuring behavior in daily life. In particular, SSMs address limitations of survey-based approaches to behavioral measurement by permitting the naturalistic observation of daily behaviors (e.g., physical movement, social interactions, other activities). SSMs are promising for behavioral research because they can be used to obtain objective and automated measures of behavior, and allow researchers to recruit participants around the world. However, there are also some practical considerations to be kept in mind when designing a study that uses SSMs, such as decisions about the logistical setup and running of the study (e.g. duration, sampling rate, devices and application used, server setup, data management; see Harari et al., 2016 for a detailed discussion of such considerations).

Limitations of SSMs in practice also include technical constraints (e.g. device capacities regarding battery, memory, or sampling frequency), data security issues (e.g. anonymization of personally identifying data), and privacy concerns (e.g. respecting participants' privacy, institutional ethical standards, and laws). More generally, research is needed to identify the psychometric properties of sensor data (e.g., reliability, validity), develop additional automated behavioral classifiers (e.g., to predict complex behaviors like watching TV alone at home), and examine the relationships between sensed behaviors and consequential life outcomes (e.g., mental health, physical health, performance). As these methods become widespread in behavioral research, attention should also be directed to exploring the ethical implications of sensor-based behavioral observation for people's privacy and surveillance concerns. Finally, many of the existing SSM studies built proof-of-concept systems that are not designed to scale or be used by other researchers. In the coming years, we expect reliable SSM systems will be developed that alleviate the practical challenges facing researchers interested in SSMs for the study of behavior in daily life.

Table 2

Summary of Behavioral Features used to Measure Physical Movement, Social Interactions, and Daily Activities

Physical Movement		Social Interactions		Daily Activities	
Features	References	Features	References	Features	*References*
Physical Activity Sedentariness Movement Acceleration Standing Walking Running Step counts Climbing stairs	Lane et al., 2010; Miluzzo et al., 2008; Tseng et al., 2016; Wang et al., 2014	*Face-to-face Encounters* Number of conversations Duration of conversations Content of conversations Turn-taking in conversations Speaking rates Speaker's voice pitch Voice frequencies Co-presence with others Size of co-present groups Duration of co-presence Number of unique and repeated interaction partners	Chen et al. 2014; Lu, Pan, Lane, Choudhury, & Campbell, 2009; Lu et al., 2012; Mehl et al., 2001; Miluzzo et al., 2008; Rachuri et al., 2010; Wang et al., 2014	*Non-Mediated Activities* Vacuuming Taking out the trash Clapping Coughing Sneezing Throat clearing Brushing teeth Internal time (inferred chronotype using sleep tracking) Total sleep duration Wake times and bed times Sleep debt	Abdullah et al., 2016; Barata et al., 2016; Casaseca-de-la-Higuera et al., 2015; Korpela et al., 2015; Lu et al., 2009; Murnane et al., 2015; 2016; Sun et al., 2015;
Mobility Patterns Distance travelled Radius of gyration Maximum distance travelled between two tracked points Standard deviation of displacements Max distance from home Number of different places visited	Canzian et al., 2015; Hemminki, Nurmi, & Tarkoma, 2013; Saeb et al., 2015; Wang et al., 2016	*Computer-Mediated Communication* Number of mediated social interactions in a given day Maximum number of mediated social interactions in a given hour Number of hours between successive interactions Number of incoming and outgoing calls	Chittaranjan et al., 2011, 2013; Eagle & Pentland, 2006; Mehrotra et al., under review	*Mediated Activities* Frequency of locking and unlocking phone Duration of phone usage sessions Total number of phone use sessions in a given hour Average time between consecutive phone use sessions	Abdullah et al., 2016; Murnane et al., 2016; LiKamWa, Liu, Lane, & Zhong, 2013; Mehrotra, Hendley, Musolesi, 2016

Number of significant places visited Duration of time spent at primary and secondary locations Locational Routine index Normalized entropy (mobility between favorite locations) Location variance Mode of transportation (bus, cycling, driving, bus, subway)	Duration of calls Number of unique and repeated call interaction partners Number of incoming and outgoing text messages Length of text messages Number of unique and repeated text message interaction partners Frequency of using social media applications	Frequency of short phone use sessions (under 30 seconds) Number of unique applications used Switching between applications during use

Note. The columns labelled "Features" list the behavioral information extracted from smartphone data to infer physical movement, social interactions, and other daily activities. The columns labelled "References" list example publications that describe how to compute the behavioral features.

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Automated sensing of location, distance traveled, conversation frequency and non-stationary duration were used to infer stability and rhythmicity of daily schedules in individuals with bipolar disorder. Personalized models predicted stable and unstable states with high accuracy (precision of .85). [Seven participants used phones with a custom app for four weeks.]

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*Abdullah, S., Murnane, E.L., Matthews, M., Kay, M., Kientz, J.A., Gay, G., Choudhury, T. (2016). Cognitive rhythms: Unobtrusive and continuous sensing of alertness using a mobile phone. In: Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM

Phone usage (e.g. usage duration, average time between usage sessions, short session frequency) and sleep need/energy level (from time of day/sleep time) were used to predict alertness.[20 participants were followed over the course of 40 days.]

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*Lathia, N., Sandstrom, G. M., Mascolo, C., & Rentfrow, P. J. (2017). Happier People Live More Active Lives: Using Smartphones to Link Happiness and Physical Activity. PLoS One, 12(1), e0160589.

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*Mehrotra, A., Hendley, R., & Musolesi, M. (2016, September). Towards multi-modal anticipatory monitoring of depressive states through the analysis of human-smartphone interaction. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct* (pp. 1132-1138). ACM.

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The authors present a method to monitor depression using multi-modal smartphone sensing based on e.g. notification count, acceptance rate, phone usage time, click count. Current mood can be accurately predicted based on the data of the previous 14 days. [25 participants provided data for 30 days]

Miller, G. (2012). The smartphone psychology manifesto. *Perspectives on Psychological Science*, *7*(3), 221-237.

Miluzzo, E., Lane, N. D., Fodor, K., Peterson, R., Lu, H., Musolesi, M., Eisenman, S. B., Zheng, X., & Campbell, A. T. (2008). Sensing meets mobile social networks: the design, implementation and evaluation of the CenceMe application. In Proceedings of the 6th ACM conference on Embedded network sensor systems, 337-350. ACM. DOI: 10.1145/1460412.1460445

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Mobile Technology Fact Sheet. (2014). *Pew Research Internet Project.* Retrieved from: http://www.pewinternet.org/fact-sheets/mobile-technology-fact-sheet/

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Sleep sensing technology to predict sleep events and disruptions from daily usage patterns, which are related to cognitive performance, mood and attention. [9 participants participated for 3x ~3mths]

*Murnane, E.L., Abdullah, S., Matthews, M., Kay, M., , Kientz, J.A., Choudhury, T., Gay, G.,Cosley, D. (2016). Mobile manifestations of alertness: Connecting biological rhythms with patterns of smartphone app use. In: Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services. ACM

This paper shows how phone usage patterns vary as a function of individual body clock types, alertness and sleep characteristics, allowing the prediction of individual performance and design of technology that respects personal rhythms. [20 participants over 40 days]

Nave, C.S., Furr, R.M. & Feeney, M.G. (invited submission). Behavioral Observation. In V. Zeigler-Hill & T. K. Shackelford (Eds.) The SAGE Handbook of Personality and Individual Differences.

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Pentland, A. (2009). Reality mining of mobile communications: Toward a new deal on data. *The Global Information Technology Report 2008–2009*, 1981.

Pew Research Center. (2016).Smartphone Ownership and Internet Usage Continues to Climb in Emerging Economies: But advanced economies still have higher rates of technology use. Washington, DC: Jacob Poushter. Retrieved from http://www.pewglobal.org/2016/02/22/smartphone-ownership-and-internet-usage-continues-to-climb-in-emerging-economies/.

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Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes.*Perspectives on Psychological Science*, *2*(4), 313-345.

*Saeb S, Zhang M, Karr CJ, Schueller SM, Corden ME, Kording KP, Mohr DC. (2015). Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. Journal of Medical Internet Research, 17, e175, DOI: 10.2196/jmir.4273

Using smartphone usage and GPS data, the authors identified behavioral markers related to depression, such as regularity of circadian movement, mobility between favorite locations, location variance, phone usage duration and frequency. Preence of depressive symptoms could be accurately predicted with 86.5%. [28 participants for 2 weeks]

Sandstrom, G. M., Lathia, N., Mascolo, C., & Rentfrow, P. J. (2016). Putting mood in context: Using smartphones to examine how people feel in different locations. *Journal of Research in Personality*.

Smith, A. (2013, June 5). Smartphone ownership 2013. *Pew Research Internet Project.* Retrieved from: http://www.pewinternet.org/2013/06/05/smartphone-ownership-2013/

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*Tseng, V. W., Merrill, M., Wittleder, F., Abdullah, S., Aung, M. H., & Choudhury, T. (2016, September). Assessing mental health issues on college campuses: preliminary findings from a pilot study. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct* (pp. 1200-1208). ACM.

The paper shows how sleep, stress and activity routines can be captured using passively sensed smartphone data fluctuate and how they fluctuate across the week, term, exam, and break times. [22 students during an academic semester]

Vanderhulst, G., Mashhadi, A., Dashti, M., & Kawsar, F. (2015, November). Detecting human encounters from wifi radio signals. In *Proceedings of the 14th International Conference on Mobile and Ubiquitous Multimedia* (pp. 97-108). ACM.

Wang, R., Aung, M. S., Abdullah, S., Brian, R., Campbell, A. T., Choudhury, T., ... & Tseng, V. W. (2016, September). CrossCheck: toward passive sensing and detection of mental health changes in people with schizophrenia. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (pp. 886-897). ACM.

*Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., ... & Campbell, A. T. (2014). StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 3-14.

The paper presents relationships between passively collected smartphone sensor data (e.g. sleep, daily activity, conversation patterns) and mental health variables and educational outcomes of students during an academic term. The StudentLife dataset is publicly available. [48 students across a 10 week term]

*Wang, Q., Guo, B., Peng, G., Zhou, G., & Yu, Z. (2016, September). CrowdWatch: pedestrian safety assistance with mobile crowd sensing. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct* (pp. 217-220). ACM.

The authors present CrowdWatch, a system alerting pedestrians about dangers. Using acceleration, orientation, and GPS data on smartphones the system identifies overpasses, underpasses, traffic lights and dynamic barriers.

*Wang, R., Harari, G., Hao, P., Zhou, X., & Campbell, A. T. (2015, September). SmartGPA: how smartphones can assess and predict academic performance of college students. In

Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (pp. 295-306). ACM.

Automatically inferred behaviors from smartphones (e.g. activity, conversational interaction, mobility, class attendance, studying, and partying) can accurately predict GPA (within ±0.179 of the reported grade). [48 students across a 10 week term]

Welke, P., Andone, I., Blaszkiewicz, K. and Markowetz, A., 2016, September. Differentiating smartphone users by app usage. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (pp. 519-523). ACM

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