**Review – Cellphone tracking and Psychiatry**

((global positioning) OR (geolocation) OR (geospatial coordinates) OR (geospatial position) OR (geocoding) AND ((psychiatry) OR (mental health))

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| Author/Journal/Year | Title | Objectives | Sample | Main Findings | Observations |
| Sano et al.  *J Med Internet Res.*  2018  General psychopathology | Identifying Objective Physiological Markers and Modifiable Behaviors for Self-Reported Stress and Mental Health Status Using Wearable Sensors and Mobile Phones: Observational Study | They developed new tools that provide objective physiological and behavioral measures using wearable sensors and mobile phones, with methods that improve data integrity  The aim of the study was to examine, using machine learning, how accurately these measures could identify conditions of self-reported high stress and poor mental health and which of the underlying modalities and measures were most accurate in identifying those conditions | 201 college students at a single New England university, all socially connected  Age: 18-25 years old  Male:female=1.8:1  Follow-up: 1 month  **SNAPSHOT Study** – MIT/ Harvard | In general, wearable sensor features showed better classification performance than mobile phone or modifiable behavior features. Wearable sensor features, including skin conductance and temperature, reached 78.3% (148/189) accuracy for classifying students into high or low stress groups and 87% (41/47) accuracy for classifying high or low mental health groups. Modifiable behavior features, including number of naps, studying duration, calls, mobility patterns, and phone-screen-on time, reached 73.5% (139/189) accuracy for stress classification and 79% (37/47) accuracy for mental health classification  **Digital phenotyping:** moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices | Each student filled out standardized pre- and post-questionnaires (Morningness-Eveningness Questionnaire, Pittsburgh Sleep Quality Index, Myers Brigg Personality test, Big Five Inventory Personality Test, PSS,12-Item Short Form Health Survey for physical and mental component summary scores, and a set of social network surveys assessing with whom participants spent their time to help map their social networks) on stress and mental health  They also completed twice-daily electronic diaries (e-diaries), wore two wrist-based sensors (Q-sensor and Motion Logger) that recorded continuous physical activity and autonomic physiology, and installed an app on their mobile phone (Android) based on “funf” that recorded phone usage and geolocation patterns |
| Chow et al.  *J Med Internet Res.*  2017  Depression / Social anxiety | Using Mobile Sensing to Test Clinical Models of Depression, Social Anxiety, State Affect, and Social Isolation Among College Students | To test whether existing theoretical relationships between (trait and state) affect and social isolation could be found in a temporally rich dataset and to better understand how best to leverage time-rich data through different models (in terms of time windows and temporal links)  Hypothesis: more time spent at home would be associated with more negative and less positive  affect | 72 undergraduates recruited through email advertisements  Age: 18-23 years old (mean 19.8, SD 2.4)  37 females  Follow-up: 2 weeks | They obtained many of the expected main effects (although there were some null effects), in which higher social anxiety was associated with more time or greater likelihood of spending time at home, and more negative or less positive affect was linked to longer homestay  Interactions indicated that, among individuals higher in social anxiety, higher negative affect and lower positive affect within a day was associated with greater likelihood of spending time at home the following day. | They applied the Depression, Anxiety and Stress Scale (DASS-21) and the Social Interaction Anxiety Scale (SIAS) self-report. An app (Sensus) collected in situ daily self-reported state affect (using a visual analog scale) and GPS location data (time spent at home was a proxy for social isolation)  They conducted all analyses using generalized mixed-effects models and fitted them using the **lme4 package in R 3.3.2** (Bates, 2014) and computed effect sizes representing the amount of variance explained by the fixed effects in our generalized mixed-effects models using the **MuMIn package in R** (Williams, 2009)  Limitations: they did not use a diagnosed sample or administer structured clinical interviews; undergraduate students may have similar daily routines; they did not consider alcohol use; they did not obtain physiological correlates of affect such as heart rate and skin conductance; technical difficulties such as software bugs and compatibility issues |
| Ben-Zeev et al.  *Psychiatr Serv.*  2016  Schizophrenia | Mobile Behavioral Sensing in Outpatients and Inpatients with Schizophrenia | To examine the feasibility, acceptability, and utility  of behavioral sensing in individuals with schizophrenia | Clinically stable outpatients (N=9)  67% male  Average age: 39  Follow-up: 2 weeks  Acutely-ill inpatients (N=11)  Average age: 38  91% male  Follow-up: 1 week | Sensing successfully captured individuals’ activity, time spent proximal to human speech, and time spent in different locations  Outpatients / Inpatients (average - daily): active 2.5 / 2.1 hours; proximal to human speech 4.4 / 4/4 hours; distance covered 9 miles and spent 16.7 hours in the same location. Outpatients sent 4.5 text messages and made 7.2 calls, averaging 16.8 minutes each (these functions were disabled for inpatients)  Usability and acceptability ratings showed participants felt comfortable using the sensing system (95%), and that most would be interested in receiving feedback (65%) and suggestions (65%). Approximately 20% reported that sensing made them upset. A third of inpatients were concerned about their privacy, but no outpatients expressed this concern | Device-embedded sensors (i.e., accelerometers, microphone – for human speech, light-sensor, GPS, WiFi, Bluetooth) collected behavioral and contextual data. Participants completed usability/acceptability measures rating this approach  The software was developed by their research group (Darthmouth)  Obs.: 20 inpatients were approached for the study. 7 inpatients declined to participate; 3 stated that they were apprehensive about tracking technology; 2 were excluded because they failed the competency screener  Limitations: location ratings could not be provided for periods when outpatients were indoors (i.e., no GPS data) and out of WiFi or cellular network range, and when inpatients left the unit that was fitted with Bluetooth beacons |
| Ben-Zeev et al.  *Psychiatric Rehabilitation Journal*  2015  General psychopathology / Depression | Next-Generation Psychiatric Assessment: Using Smartphone Sensors to Monitor Behavior and Mental Health | To examine whether the information captured with multimodal smartphone sensors can serve as behavioral markers for one’s mental health  Hypothesis: unobtrusively collected smartphone sensor data would be associated with individuals’ daily levels of stress, and sensor data would be associated with changes in depression, stress, and subjective loneliness over time | 47 young adults – 64% undergraduate students and 36% graduate students from Dartmouth College) recruited through class announcements  Age: 19-30 years old (mean 22.5)  79% male  Follow-up: 10 weeks  Same group/ sample from the **Student Life Study** (Wang, 2014) - Darmouth | Sensor-derived geospatial activity (p <.05), sleep duration (p<.05), and variability in geospatial activity (p<.05) were associated with daily stress levels. Variability in the amount of time people spent proximal to human speech was marginally associated  Changes in depression were associated with sensor-derived speech duration (p<.05), geospatial activity (p<.05), and sleep duration (p<.05)  Changes in loneliness were associated with sensor derived kinesthetic activity (p<.01)  Of 37 participants who completed PHQ-9 (Spitzer et al., 1999) ratings at the end of the data-collection period, 11% endorsed no depressive symptoms, 38% reported minimal depression, 32% reported mild depression, 8% reported moderate depression, 6% moderately severe depression, and 5% reported severe depression  **Conclusion:** Integration of other digital sources of information (e.g., personal social media posts and crowd-sourced information about one’s immediate environment) into predictive models may also strengthen the role of assistive technology in quantified self-tracking | They used smartphones (Android 4.0 OS) with sensors and software that enabled continuous tracking of their geospatial activity (GPS and wifi fidelity), kinesthetic activity (multiaxial accelerometers), sleep duration (device-usage data, accelerometer inferences, ambient sound features, and ambient light levels), and time spent proximal to human speech (microphone and speech detection algorithms). Participants completed daily ratings of stress, as well as pre- and post-measures of depression (PHQ-9), stress (PSS) and loneliness (R-ULS)  Model fit and permutation tests were performed via the funreg (functional regression for irregularly timed data) **package in R** (Dziak & Shiyko, 2014), which makes the Goldsmith et al., 2011 technique available for intensively collected data  Limitations: speech-detection system may not be fully capable of differentiating live human speech from radio or TV- generated audio; modeling strategy assumed that sleep typically takes place in darkened environments, as indicated by the smartphone light sensor |
| Adams et al.  *J Psychiatr Res.*  2017 | Mobile Devices for the Remote Acquisition of Physiological and Behavioral Biomarkers in Psychiatric Clinical Research | **Review** on mobile Health (mHealth) tools that offer new opportunities to study relevant biomarkers in concert with other types of data (e.g., self-reports, global positioning system data)  They aim to provide an overview on the state of this emerging field and describe examples from the literature where mHealth tools have been used to measure a wide array of biomarkers in the context of psychiatric functioning | Search: mobile health, mhealth, psychiatry, psychology, stress, mental health, mental illness, psychiatric disorders, substance use disorders, addiction, alcohol, tobacco, technology, biomarkers, biochemical, sensors, biosensors, physiology, mobile phones, and smartphones  January 2016 | Table 1: Studies Involving Remote Biomarker Acquisition to Address Psychiatric Clinical Problems  Mobile biosensing of **stress and anxiety** (7 studies – 0 on non-adult population, n varies from 3-76)  Mobile biosensing in **cigarette smoking** (12 studies – 1 on non-adult population, n varies from 4-77)  Mobile biosensing in **alcohol use disorders** (2 studies – 0 on non-adult population, n varies from 13-30)  Mobile biosensing in **illicit substance use** (3 studies – 0 on non-adult population, n varies from 4-48)  Mobile biosensing in **autism** (2 studies – 2 on non-adult population, n varies from 12-121)  Mobile biosensing in **mood disorders** (3 studies – 0 on non-adult population, n varies from 9-40)  Mobile biosensing in **ADHD** (not cited in table)  Obs.: even though they are not in the table, the article cites other studyies | The advent of mobile phones and personal digital assistants brought new opportunities to gather psychosocial, contextual, and self-reported behavioral data in the field via electronic daily diaries and real-time experience sampling or ecological momentary assessment (EMA). These approaches automate several aspects of data collection and afford more rigorous tracking of timing and context than conventional paper-and-pencil techniques, which are vulnerable to recall bias and other errors  One potential avenue to build on this progress would be to integrate remote biomarker collection strategies into research on a broader range of disorders and constructs and in large samples. To illustrate, acute threat (a construct in the NIMH RDoC Negative Valence Systems domain) may be operationalized using physiological measures of startle, heart rate, skin conductance, blood pressure, eye tracking, and pupillometry (National Institute of Mental Health, 2011)—virtually all of these biomarkers of acute stress and fear have been or could plausibly be assessed using mobile technologies. Given that the majority of work in this area has involved adult samples, there may also be benefit in expanding mHealth biomarker research into youth populations to better characterize the development of psychiatric problems |
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| Boukhechba et al.  *JMIR Ment Health.*  2018 | Predicting Social Anxiety From Global Positioning System Traces of College Students: Feasibility Study | The objective of our study was to examine the feasibility of leveraging noninvasive mobile sensing technology to passively assess college students’ social anxiety levels. Specifically, we explored the different relationships between mobility and social anxiety to build a predictive model that assessed social anxiety from passively generated Global Positioning System (GPS) data | N = 228  Same group as Chow 2017 |  |  |
| Di Matteo et al.  *JMIR Ment Health.*  2018 | Patient Willingness to Consent to Mobile Phone Data Collection for Mental Health Apps: Structured Questionnaire | The aim of this study was to measure the ownership rates of mobile phones within the patient population, measure the patient population’s willingness to have their mobile phone used as an experimental assessment tool for their mental health disorder, and, finally, to determine how likely patients would be to provide consent for each individual source of mobile phone–collectible data across the variety of potential data sources | N = 82 |  |  |
| Saeb et al.  *JMIR Mhealth Uhealth*  2017 | Mobile Phone Detection of Semantic Location and Its Relationship to Depression and Anxiety | We aimed to examine the ability of mobile phone sensors to estimate semantic locations, and to evaluate  the relationship between semantic location visit patterns and depression and anxiety | N = 208 |  |  |
| Capon et al.  International Journal of Drug Policy  2016 | Realising the technological promise of smartphones in addiction research and treatment: An ethical review | This paper aims to identify ethical issues in the current uses of smartphones in addiction research and treatment. | 33 studies |  |  |
| Wahle et al.  *JMIR Mhealth Uhealth*  2016 | Mobile Sensing and Support for People With Depression: A Pilot Trial in the Wild | The objective of this study is 2-fold, first to explore the detection of daily-life behavior based on sensor information to identify subjects with a clinically meaningful depression level, second to explore the potential of context sensitive intervention delivery to provide in-situ support for people with depressive symptoms | N = 126 |  |  |
| Larsen et al.  *IEEE Journal of Biomedical and Health Informatics*  2015 | We Feel: Mapping emotion on Twitter | We describe the “We Feel” system architecture and data processing algorithms and, because of its potential to provide new and evolving information about the mental health of the community, our aim is to validate the data against known patterns of variation in mood. | 2.73×109 emotional tweets |  |  |
| Saeb et al.  *J Med Internet Res.*  2015 | Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study | The objective of this study was to explore the detection of daily-life behavioral markers using mobile phone global positioning systems (GPS) and usage sensors, and their use in identifying depressive symptom severity | N = 40 |  |  |
| Wang et al.  *ACM International Joint Conference on Pervasive and Ubiquitous Computing*  2014 | StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students using Smartphones | To shine a light on student life we develop the StudentLife smartphone app and sensing system to automatically infer hu- man behavior in an energy-efficient manner. | N = 48 |  |  |
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Other cited articles that didn’t show on the search:

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