Ambulatory Assessment: Methods for Studying Everyday Life

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Abstract

Ambulatory assessment is a class of methods that use mobile technology to understand people's biopsychosocial processes in natural settings, in real time, and on repeated occasions. In this essay, we discuss the rationale for ambulatory assessment including the benefits of measuring people in the real world (greater ecological validity, better understanding of people in contexts), in real time (avoidance of memory bias, greater sensitivity for capturing change), and over time (capturing within-person patterns and temporal trends). Then, we review the latest ambulatory assessment techniques for measuring experiences, behaviors, and physiology in daily life. Experiences such as emotions, physical pain, and daily stressors can be tracked using daily diaries and smartphone-based experience sampling. Behaviors such as activity, movement, location, and natural language use can be tracked using accelerometers, portable actigraphs, global positioning system (GPS) coordinates, and the electronically activated recorder (EAR). Physiological processes such as heart rate, blood pressure, and electrodermal activity can be measured using an array of ambulatory biosensors. Ambulatory assessment will continue to be revolutionized by smartphones, which are becoming integrated seamlessly into people's lives. Emerging trends include social sensing applications that make inferences about users' psychological processes based on multi-channel information collected from smartphones, emergence of "big data collection" whereby ambulatory assessment data is gathered *en masse* from large populations, and the growing field of mobile health. These trends raise questions around the protection of participants' privacy and the synthesis of immense amounts of digital data. Ultimately, these developments will narrow the separation between science and everyday life as ambulatory assessment becomes an integrated part of people's mobile lives.

INTRODUCTION: DEFINITION OF AND RATIONALE FOR AMBULATORY ASSESSMENT

Laboratory-based methods have historically been the strength and pride of the social and behavioral sciences. Most research method textbooks emphasize how laboratory research helps control confounding variables and thereby allows for the isolation of a causal factor of interest. Laboratory

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research has contributed enormously to our understanding of human social behavior. Ultimately, though, laboratory research can exclusively accumulate knowledge on what *can* happen—under isolated and controlled circumstances—and it cannot speak to what *does* happen under the circumstances that people normally encounter in their everyday lives. Therefore, a comprehensive science of human behavior also requires "thinking outside the experimental box" and necessitates the study of humans in their natural habitat—that is, the collection of data from individuals as they live their lives in their daily environments.

This essay reviews existing methodologies for studying experiences, behavior, and physiology in daily life (for a comprehensive review, see Mehl & Conner, 2012). We here refer to these methodologies collectively as ambulatory assessment methods. According to the Society for Ambulatory Assessment, *Ambulatory Assessment* "comprises the use of field methods to assess the ongoing behavior, physiology, experience and environmental aspects of humans or nonhuman primates in naturalistic or unconstrained settings. [It] designates an ecologically relevant assessment perspective that aims at understanding biopsychosocial processes as they naturally unfold in time and in context" (www.ambulatory-assessment.org). Other common names to denote these methodologies include experience sampling methods, diary methods, and ecological momentary assessment. At their core, these methods allow researchers to study individuals (i) in their *natural settings*, (ii) in *real time* (or close to real time), and (iii) on *repeated occasions*. Ambulatory assessment derives its scientific rationale directly from these three measurement characteristics (i.e., "real-world," "real-time," "within-person").

The "real-world" quality allows unprecedented access to what actually happens in a person's everyday life and the contexts that surround such events (Mehl & Conner, 2012, Ch. 1). For example, ambulatory assessment is a great way to track how much people are exercising every day and the conditions that make exercise more or less likely. This real-world quality also enables researchers to capitalize on the power of evocative daily events that are difficult, if not unethical, to mimic in controlled laboratory settings such as positive or negative daily interactions, disagreements with a friend, issues with children, commuting, excessive smoking, or drinking. Moreover, how people respond to a standardized laboratory stressor such as giving a speech may differ from how they respond to stressful experiences in their lives. Wilhelm and Grossman (2010) describe a participant who showed rather minimal heart rate increases in response to a laboratory stress protocol but quite dramatic heart rate increases later in the afternoon while watching a soccer game at home. In addition, in a reverse pattern, patients often have high blood pressure readings in the physician's office but not in their home environment—a phenomenon called the *white coat hypertension*. By testing behavior in real-world settings, researchers have greater confidence about the *ecological validity* of findings—that is, whether an effect is representative of how it operates in reality.

The "real-time" quality of ambulatory assessment enables researchers to understand experiences as they occur, not how people represent them later from memory. This quality is especially important for experiences that are fleeting and often misremembered (e.g., emotions, and pain). A person's memory for how they "felt over the past week" or "the past month" is influenced by a host of factors including salient experiences, mood at the time of recall, personality traits, beliefs about the acceptability of certain emotions, gender stereotypes, and cultural norms (Mehl & Conner, 2012, Ch. 2). In fact, there is strong evidence that as the time delay between experience and reporting lengthens, self-reports become more stable, reflective, belief-driven, and culturally homogenized rather than malleable, reflexive, experience-driven, and individualized (Robinson & Clore, 2002). This distinction between real-time and recalled reporting can make a big difference in understanding psychological processes. For one, ambulatory approaches may be more sensitive for capturing change in emotional states in response to interventions. In a trial of antidepressant medication treatment, changes in depressive symptomology were detected earlier among patients randomly assigned to track their symptoms each day for 30 days compared to patients who reported their symptoms using standard one-week recall measures (Lenderking *et al.*, 2008). Other studies find stronger links between real-time reports of emotion and atherosclerosis risk, immune system function, and genetic vulnerability [reviewed by Conner and Barrett (2012)]. These examples illustrate how-real time measurement may be more sensitive than traditional memory-based measures under certain circumstances.

The "within-person" element of *ambulatory assessment* refers to the capacity to identify patterns of behavior within the person across time (i.e., idiographic assessment) (Mehl & Conner, 2012, Ch. 3). This approach differs from traditional cross-sectional research, that aims to identify patterns of behavior between people (i.e., nomothetic assessment). Unlike cross sectional research which observes people at a single time point, ambulatory assessment tracks individuals' experiences, behaviors, or physiology intensively over time, yielding "intensive longitudinal data" (Walls & Schafer, 2006). That data can be analyzed to uncover the temporal patterns and trends in each person's data, as well as commonalities and differences in these trends across people. For example, in a classic study, Bolger and Schilling (1991) examined the within-person relationships between daily stressors and anxiety for 339 people and found stronger within-person relationships for people higher in Neuroticism. Ambulatory assessment has been used to uncover a wide variety of within-person relationships, including the antecedents of heavy drinking, triggers of smoking cravings, relationships between stress and coping, and links between food consumption and mood.

FOUNDATIONAL RESEARCH: AMBULATORY ASSESSMENT METHODS

AMBULATORY ASSESSMENT OF EXPERIENCE

One of the most common uses of ambulatory assessment is for studying self-reported experiences in naturalistic settings. Experiences include current mood states, levels of perceived stress, feelings of bodily pain or discomfort, and other aspects of daily life that can be self-reported. Thus, ambulatory assessment of experience inherently involves asking people to respond to questions about their experiences as they go about their daily lives. The Internet and, especially smartphones have revolutionized this methodology (Miller, 2012) and now represent the main interface for ambulatory self-report techniques. In general, there are two main ways of measuring experience through ambulatory assessment—through Internet daily diaries and mobile phone-based experience sampling.

Daily diary methods are probably the most common form of ambulatory assessment. Daily diary methods are now done mainly through Internet surveys in which participants access the survey each day (or night) for a week to three weeks to answer questions about their experiences that day. Diaries are often used to assess experiences and events that occur on a daily basis and can be easily recalled at the end of each day such as daily hassles, social activities, emotions felt that day, and health behaviors such as alcohol use, smoking, and food consumption. Although this approach is neither "real time" nor necessarily ambulatory, it is considered "near to real time" and an improvement upon asking people to recall their experiences across the entire week or longer. Although daily diary studies are widely applied, they have probably had the most impact on the psychology of romantic relationships, the role daily stressors in mental and physical health, and the correlates and consequences of daily health behaviors such as alcohol use (Mehl & Conner, 2012, Ch. 8). In addition, daily diary techniques are fairly easy to implement. Researchers can design a simple Internet survey through any number of companies such as SurveyMonkey, Qualtrics, or SurveyGizmo. Participants then access that survey during a specified time period, and the data can be downloaded at the end of the study.

A second approach to measuring experience is through mobile-phone-based experience sampling. Experience sampling is the process of randomly signaling a person (typically 4–8 times per day) to report on their experiences at that moment [see suggested reading by Hektner, Schmidt, and Csikszentmihalyi (2007)]. This approach is used to study fleeting and ongoing subjective experiences such as mood, pain, and stress because these experiences are quick to decay in memory and are best assessed in true real time. Experience sampling has probably had the most impact on the psychology of emotion. Emotions are highly variable—they ebb and flow throughout the day in response to changing internal and external events (Mehl & Conner, 2012, Ch. 27). Experience sampling is ideally suited to capturing this changing profile—an emotional "signature" that can reveal dynamic aspects of functioning obscured by standard one-time surveys. Experience sampling has revealed diurnal and weekly patterns in emotion, individual differences in affective instability as a marker of psychopathology, differences in the structure of emotional experience, divergences between experienced versus remembered emotions, and covariation between emotions and health-related factors. Experience sampling has also been used to identify the emotional correlates of psychopathology including heightened affective instability, anhedonia, and the emotional precursors to self-harm (Mehl & Conner, 2012, Ch. 23).

Currently, there are three main approaches to experience sampling with mobile phones. In each of these approaches, the trend is towards using people's own phones to allow for seamless participation without the need for an extra specialized device. One very simple approach is to send questions via SMS text messaging. Texts can be scheduled and sent automatically through most commercial SMS companies (e.g., www.message-media.com). Participants reply to the questions contained in the text using numbers on their keypad and the data can be downloaded from the SMS company server at the end of the study. Although this approach is simple and does not require a smartphone (mobile phone with Internet capability), it is also the least flexible because of limited timing controls, lack of branching, and restricted space for questions. A second approach is to send a hyperlink to an online survey via SMS text messaging to participants with Internet enabled smartphones. Here, participants receive a text message with a hyperlink that directs them to a mobile-ready Internet survey. The survey can be developed through any number of companies such as SurveyMonkey, and the hyperlink to the online survey can be sent through a commercial SMS company or a specialized service designed for experience sampling (e.g., www.surveysignal.com). A third approach is to use application-based smartphone tools. Here, participants download a smartphone app that delivers a specialized survey to their smartphones. Although these apps and surveys can be designed from the ground up, there are a growing number of companies that provide assistance with survey development at a reasonable charge (mEMA, iHabit, iForm, ISurvey, MovisensXS, and Qualtrics). There are also a growing number of open-source development tools (Paco and Funf). One issue with app-based experience sampling is that apps and surveys are often designed for only one operating system (e.g., Apple's iOS or Google's Android) that places limits on recruitment and participation. However, increasingly, tools are being developed for both platforms.

Ambulatory Assessment of Behavior

Although self-reports are important to social science, oftentimes people cannot or sometimes might not want to accurately report what they do. In these circumstances, the direct—and ideally nonreactive—assessment of real-world behavior is of high importance. For example, Mehl and colleagues have developed the electronically activated recorder or EAR methodology that allows for the relatively unobtrusive naturalistic observation of participants' acoustic behavior in daily life (Mehl, Pennebaker, Crow, Dabbs, & Price, 2001). The current EAR system, the "iEAR," consists of a free iOS app that runs on iPod touch and iPhone devices. Participants carry an iEAR device on them as they go about their normal lives. The app periodically records snippets of ambient sounds (e.g., 30 s every 12 min) thereby creating a series of sound bites that, together, amount to acoustic logs of participants' days as they naturally unfold. The ambient sound recordings are later securely downloaded, reviewed by participants, and then coded for aspects of participants' momentary locations (e.g., in a public or private place), activities (e.g., watching TV, and eating), interactions (e.g., along, in a group, and on the phone), and emotional expressions (e.g., laughing and sighing).

Initial EAR research focused on the psychometric properties of naturalistically observed daily social behavior. This research showed (i) that a broad spectrum of behaviors can be assessed reliably and with low levels of reactivity from the sampled ambient sounds, (ii) that these behaviors show large between-person variability and good temporal stability, and (iii) that they have good convergent validity with theoretically related measures (e.g., Big Five personality dimensions) (Mehl & Conner, 2012, Ch. 10). The second generation studies, then, focused on the EAR's potential to address questions that are difficult to answer with other methods. For example, in a cross-cultural study, Ramirez-Esparza and her colleagues used the EAR method to study self-reported sociability in relation to observed sociability in the United States and Mexico. They found that although American participants rated themselves significantly *higher* than Mexicans on the question "I see myself as a person who is talkative," they actually spent almost 10% *less* time talking (Ramírez-Esparza, Mehl, Álvarez-Bermúdez, & Pennebaker, 2009). In a similar way, Mehl and his colleagues used the EAR method to debunk the long-standing myth that women are by a factor more talkative than men (Mehl, Vazire, Ramirez-Esparza, Slatcher, & Pennebaker, 2007). Using data from six studies, they showed that both sexes use on average about 16,000 words per day. Together, these studies showed how the EAR method can be used to study objective aspects of daily behavior and how it can yield results that diverge from findings obtained with other methods.

A series of other creative ways for assessing behavior directly and unobtrusively in the real world have been developed. For example, time-lapse photography has been used to study the flow of people and the use of space in urban public places (Whyte, 1980). In modern studies, participants' movement and location are tracked via actigraphy and GPS information. To determine sleep patterns and circadian rhythms, studies have participants wear small, rugged wrist watches that log body movements along with day-night (i.e., light) patterns (Van de Water, Holmes, & Hurley, 2011). Multi-channel activity monitoring devices provide more detailed information on posture and motion through the placement of small accelerometer sensors on different body locations (e.g., arm, leg, or waist). Classification algorithms then convert the raw sensor input into discrete posture (e.g., lying, and sitting, and standing) and motion (e.g., walking, cycling, and driving) patterns. Importantly, validation studies have consistently found critical discrepancies between self-reported and objective activity records (Mehl & Conner, 2012, Ch. 13). Finally, location-tracking via either dedicated GPS devices or smartphones with GPS and Wi-Fi sensors are on the way of becoming mainstream in the social sciences (Montoliu, Blom, & Gatica-Perez, 2013; Wolf & Jacobs, 2010). Although these tools currently exist as stand-alone assessment devices, in the future, they will be integrated into mobile devices that people naturally carry with them which will allow more seamless integrated assessment (Miller, 2012).

Ambulatory Assessment of Physiology

Finally, ambulatory assessment methods also exist for the sampling of physiological activity in everyday life. An array of biosignals can now be measured reliably via portable signal recording devices (e.g., electrocardiogram, blood pressure, electrodermal activity, and body temperature) (Wilhelm & Grossman, 2010). Recently researchers have added ambulatory assessment of hormones and other biomarkers to the list (Mehl & Conner, 2012, Ch. 11). As an example of research that implemented traditional ambulatory physiological monitoring, Lane, Zareba, Reis, Peterson, and Moss (2011b) used experience sampling combined with ambulatory electrocardiography (a so-called Holter monitor) to show that daily emotions—even at low intensities—triggered abnormal cardiac activity among patients with a congenital heart abnormality. In a classic study on hormonal responses in daily life, Smyth *et al*. (1998) combined experience sampling with momentary assessment of cortisol. They found that momentary reports of current or anticipated stress predicted increased cortisol secretion 20 min later.

Taken together, these two examples illustrate how ambulatory physiological monitoring has been used to link mundane and seemingly inconsequential experiences in our daily lives to objective physiological responses. The development of novel ways to track what goes on underneath our skins as we go about our lives is a rapidly advancing field and important advances can be expected in the future (Kim *et al*., 2011).

CUTTING-EDGE RESEARCH AND FUTURE DIRECTIONS

As the mobile device revolution is unfolding around us, it is clear that ambulatory assessment will, over time, be revolutionized by it. Smartphones will not just be devices for everyday communication but will also become devices for large-scale scientific data collection and intervention (Kaplan & Stone, 2013; Yarkoni, 2012). They automatically store vast amounts of real-world user interaction data and are equipped with an array of high quality sensors to track the physical (e.g., location and position) and social (e.g., blue tooth connections) context of these interactions. Finally, with add-on sensors, they will be able monitor physiological parameters. In a visionary article, Miller (2012) states, "the question is not whether smartphones will revolutionize psychology but how, when, and where the revolution will happen" (p. 234).

SMARTPHONE SENSING

One flourishing research area at the intersection of the social and computer sciences is the development of "smartphone sensing" applications. The idea behind these applications is to make inferences about users' emotions, behavior, environments, and life patterns through computational integration of the data produced by (i) interactions with the user interface (e.g., timing and duration of phone calls number text messages) and (ii) the multiple sensors embedded in smartphones (e.g., Bluetooth, GPS, and accelerometer). For example, de Montjoye, Quoidbach, Robic, and Pentland (2013) recently showed that the personality of smartphone users (e.g., extraversion and neuroticism) can be predicted with high levels of accuracy from information that is routinely part of the data logs of mobile phone carriers (e.g., number of interactions, number and diversity of contacts, response latency to events, and distance traveled).

Lu *et al*. (2012) have applied this idea to automatic voice-based stress detection via smartphones. Drawing on prior stress research, the so-called StressSense app monitors ambient sounds for voices, performs speaker separation, and extracts stress-relevant voice parameters (e.g., speech rate, pitch variability, and jitter). These parameters are then integrated into stress-level estimates using machine learning algorithms that are trained with the user's galvanic skin response as the "ground truth" of how stressed the user really is. The authors report high classification accuracy for both outdoor and indoor environments. In a similar way, Rachuri *et al*. (2010) have been developing a mobile phone application for the automatic recognition of discrete emotions. Their "EmotionSense" app operates by extracting voice parameters and comparing them against an internal "emotion prosody library" that is derived from voice feature analysis of enacted target emotions (happy sad, fearful, angry, neutral).

Finally, in an intriguing study, Lane *et al*. (2011a) report the development of "BeWell" as a smartphone application to promote healthy lifestyles. The app continuously monitors users' physical activity (via the embedded accelerometer), sleep activity (via the accelerometer and recharging information), and social activity (via ambient sounds containing voice). In a second step, it compares the estimated levels against established health recommendations (e.g., ideal value of 7 h of sleep). In a third step, the app feeds the results back to the user intuitively on the display where it visualizes a person's wellness through an aquarium with swimming fish—the vitality of which reflects the state of wellness. Because all computations are run directly on the phone, the app is self-sufficient but currently absorbs a high amount of processing time and battery life. As a proof-of-concept study, though, it shows a powerful application of mobile-phone based social or "life-style" sensing.

"Big Data" Collection

Future progress in this area is also tied into a rapidly decreasing per-person cost thereby allowing data collection at large-scale levels. Already we are beginning to see studies with "big data" from thousands of people. For example, one group of researchers analyzed Geographical Positional System signals from 100,000 mobile phone users over a 6-month period to show reproducible regularities in their within-person movement patterns (Gonzalez, Hidalgo, & Barabasi, 2008). Other research uses experience sampling tools made available to a wide audience in exchange for scientific use of their anonymized data (e.g., Mappiness, Trackyourhappiness, EmotionSense, and Happathon). For example, data from 2250 users of TrackYourHappiness was used to show the conditions and contexts in which people report being happier, such as when they are social and not "mind-wandering" (Killingsworth & Gilbert, 2010). Likewise, Mappiness data from nearly 22,000 users in the United Kingdom found that people reported greater happiness when they were located near natural environments as determined by GPS location (MacKerron & Mourato, 2013). Other big data projects include the Gallup-Healthways Well-Being Index, an American-based population-based phone survey of over 1,000,000 people that includes a daily mood measure, the World Well-Being Project, which analyzes language in Facebook and Twitters posts to index differences in psychological states, and large-scale mining of Twitter data (e.g., Golder & Macy, 2011)

Mobile Health: Large Scale Sampling of Electronic Health Information

Large scale ambulatory assessment will also transform health research. The E-Heart Study at the University of California San Francisco is a creative new project that aims to collect ambulatory heart health data from one million people. Tools in the study include mobile phone surveys, mobile apps, and special sensors integrate with participants' smartphones to provide real-time health recordings (heart rate, blood pressure, activity, sleep quality, etc.). Their goal is to capitalize on big data to "develop strategies to prevent and treat all aspects of heart disease" (https://www.health-eheart-study.org/study). Other large mobile health projects include the National Experience Sampling Project, which aims to collect ambulatory health data at the population level. Future progress in this area will also benefit from disposable wireless biometric patches that can be worn continuously.

Key Issues Going Forward in Ambulatory Assessment

Two of the most pressing issues going forward concern (i) the protection of participants' privacy and (ii) the synthesis of the immense amount of digital data. There is little doubt that the Internet and, most importantly, online social networking has already dramatically changed notions of privacy in people's personal lives. About a decade ago, it was ethically questionable to "Google" someone before a date. Now, Facebook users readily post private pictures of and intimate comments about their lives to hundreds of online friends. For maximizing the capabilities of their mobile phones, people also accept the complete, centralized tracking of their locations, browsing and search history, and entertainment choices (e.g., iTunes, Netflix, YouTube, and Kindle). These changes in how private information is shared are bound to affect perceptions of what data is acceptable to collect for scientific purposes. At the same time, though, these changes have profound implications for the confidentiality of scientific data and the protection of participants' privacy. King (2011) pointed out that it is *de facto* impossible to guarantee anonymity by combining the three demographic variables date of birth, gender, and zip code. In a similar way—and directly in the context of mobile data collection—Kosinski, Stillwell, and Graepel (2013) recently showed that highly private and often stigmatizing characteristics such as sexual orientation, ethnicity, and religious and political affiliation can be readily predicted from only one type of digital data, "Likes" in users' Facebook profiles. The same was true for important health behaviors such as smoking, drinking, and drug use. Combined with the scientifically desirable trend towards data sharing and making (taxpayer-funded) data bases publically available and advances in large-scale "big data" mining, it is clear that the ambulatory assessment researchers, and the scientific community more generally, have to develop new guidelines and methods of protecting the privacy of human subjects.

Researchers will also need to develop better strategies for handling large amounts of data. Ambulatory assessment data is already quite large and requires specialized tools for treating the nested data structure such as multilevel modeling. However, big data will increase the size and complexity of these data structures exponentially. Such data will require different analytic approaches that likely draw on techniques from bioinformatics and computer science. Yarkoni (2012) calls this new approach "psychoinformatics," which can include tools such as network analysis, large-scale exploratory data analysis, and a greater reliance on more flexible open-source statistical software such as *R*. This requirement for greater statistical sophistication will require new forms of training and greater collaboration among statisticians, computer scientists, and psychological scientists.

CONCLUSION

The separation between science and everyday life will become narrower with each decade as ambulatory assessment becomes integrated seamlessly into people's lives. Although ambulatory assessment will continue to complement rather than replace controlled laboratory science, it will begin to play a larger role in science than it has in the past especially as findings from population-based data-sets begin to bear fruit. Issues of privacy and data management notwithstanding, the future of ambulatory assessment future will be a dynamic, collective, and collaborative process.

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