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Advances in Scientific Possibilities Offered by Real-Time Monitoring Technology

Evan M. Kleiman and Matthew K. Nock

There has been a marked increase in research aimed at studying dynamic (e.g., day-to-day, moment-to-moment) changes in mental disorders and related behavior problems. Indeed, the number of scientific papers published that focus on real-time monitoring has been nearly doubling every five years for the past several decades. These methods allow for a more fine-grained description of phenomena of interest as well as for real-world tests of theoretical models of human behavior. Here we comment on the recent study by van Winkel and colleagues (this issue)as an excellent example of the use of real-time monitoring methods to better understand mental disorders. We also discuss the expanding universe of new technologies (e.g., smartphones, wearable biosensors) that can be used to make discoveries about psychopathology and related constructs and describe what we perceive to be some of the most exciting scientific possibilities that can be achieved in the near term by taking advantage of these new and rapidly developing tools.

The importance of directly observing psychological and behavioral phenomena of interest has been well understood for decades (Lorenz, 1981; Tinbergen, 1951, 1974). Despite this understanding, psychiatry and psychology have not historically devoted much effort to the direct observation of our phenomena of interest as they occur in nature, in part because the tools to do so were not readily available. Real-time monitoring (also called ecological momentary assessment, experience sampling methodology, and ambulatory monitoring; Shiffman, Stone, & Hufford, 2008) allows us to do this for the first time. Over the past several decades there has been a surge of interest in using real-time monitoring. A search for studies using the term “real-time monitoring” on Thomson Reuters Web of Science shows that the average number of studies published per year has nearly doubled every five years for the past 25 years (Figure 1).

In line with the increase in research using real-time monitoring, Van Winkel et al. (this issue) explored how daily behaviors and loneliness may contribute to the development of depression. There is a growing body of work studying the everyday lives of people with major depressive disorder (for reviews, see aan het Rot, Hogenelst, & Schoevers, 2012; Wenze & Miller, 2010). This research has focused mostly on describing the basic phenomenology of depression (e.g., variability in symptoms, relationship between life events and symptoms). There has been relatively little work, however, focused on the specific daily

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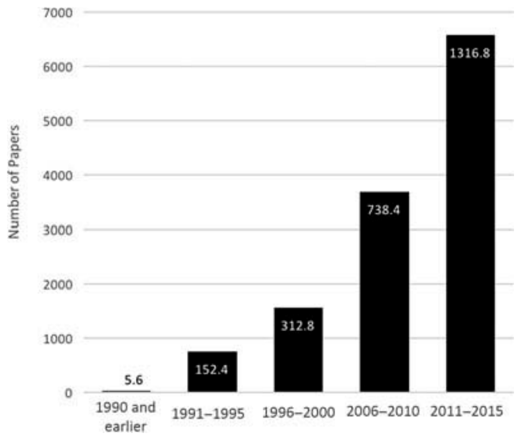

FIGURE 1. Total number of publications in Web of Science using real-time monitoring across five-year periods. *Note*. Search results in Web of Science were based on all English-language, peer-reviewed empirical articles using the terms (*real-time monitoring* OR *ecological momentary assessment* OR *experience sampling* OR *ambulatory assessment*). Inset number is average number of publications over the five-year period.

processes that might contribute to the development of major depressive disorder. Van Winkel et al. (this issue) reduced this knowledge gap by exploring daily processes hypothesized to lead to the development of major depressive disorder (MDD). They showed that for those who later developed MDD, negative appraisals of those around the respondents were followed by more frequent loneliness, and that loneliness predicted the later development of MDD. This study uses moment-by-moment assessments to highlight cognitive and behavioral factors that may be involved in the development of MDD. Van Winkel and colleagues should be commended for conducted such an important, rigorous, and valuable study.

A few aspects of the excellent study by van Winkel and colleagues will be important to address in future research. Their sample was composed entirely of White females, leaving open questions about the generality of the observed effects. The incidence rate of new cases of MDD during the follow-up period (10.0% of the sample) was unexpectedly high, especially in relative comparison to the lifetime prevalence rate at baseline (4.5% of the sample). There were significant group differences at baseline between the two groups (MDD versus no MDD) and a lag of 20 months between the real-time assessment and measurement of MDD diagnosis. Finally, although the use of paper-based monitoring procedures provides a significant improvement over less granular methods of assessment, it does not take advantage of the current state of the art in real-time monitoring methodology. Building on this last point, in the next section we discuss how newly available technologies can expand what is known about the occurrence of psychological processes of interest to psychological and psychiatric scientists.

INNOVATIONS IN REAL-TIME MONITORING METHODOLOGY

As noted, interest in real-time monitoring has increased considerably in recent years and, fortunately, so has the availability of new technologies to conduct such assessments. We focus here on three technologies that offer great potential to further expand the capabilities of real-time monitoring: (1) active smartphone-based assessment, (2) passive smartphone monitoring, and (3) data collection via wearable devices. We also comment briefly on new possibilities for (4) the development of real-time interventions.

Active Smartphone-Based Assessment

Smartphones have become nearly ubiquitous in many countries around the world. More than 80% of Americans aged 18 to 49 carry a smartphone with them throughout the day (Smith, 2015). The advantages to using such devices for data collection include better compliance than with using conventional paper-based or handheld electronic devices (e.g., PalmPilot) because participants do not have to remember to carry an extra device, better privacy because completing real-time monitoring on a smartphone looks no different than any other smartphone task, and better data fidelity because real-time monitoring software can time-stamp responses or limit survey availability to certain times, thus preventing participants from "back-filling" responses and guaranteeing that real-time data are actually collected in real time. As just one recent example, Torous, Staples, Shanahan, and colleagues (2015) used smartphone-based assessments to monitor daily depression symptoms in patients with MDD and found that patients report higher symptoms of depression and more incidents of suicidal ideation on smartphone assessments than they do on assessments completed in a clinician's office.

Despite the widespread availability of smartphones and the clear advantages for using them, adoption of this technology has been surprisingly slow. As shown in Figure 2, the proportion of studies published between 2011 and 2015 indexed by Thomson Reuters Web of Science that used "real-time monitoring" and also mentioned "phone" or "app" has been consistently low, reaching a high of only 14% in 2015. There are currently several EMA applications that run on both Android and iOS smartphones with which the interested reader should be familiar. Rather than suggest specific software, we suggest readers go to the Society for Ambulatory Assessment's overview of EMA software (http://www.saa2009.org/?page_id=57) because these technologies change so quickly.

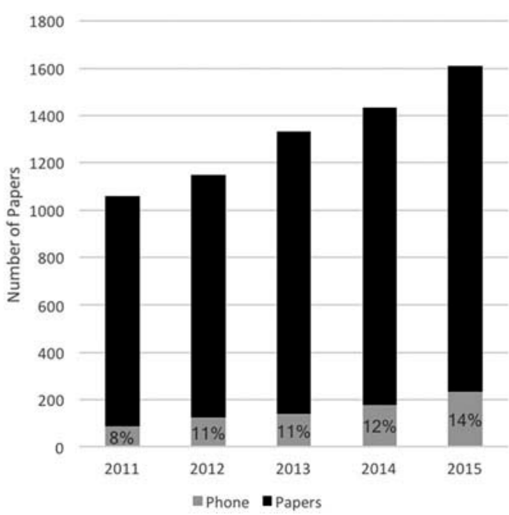

FIGURE 2. Total number of publications in Web of Science using real-time monitoring versus those that used advanced technology from 2011 to 2015. *Note*. Search results in Web of Science were based on all English-language, peer-reviewed empirical articles using the terms (*real-time monitoring* OR *ecological momentary assessment* OR *experience sampling* OR *ambulatory assessment*) AND (*phone* OR *app*). Inset number is percentage of publications that mentioned *phone* or *app*.

Passive Smartphone Monitoring

In addition to the ability for real-time monitoring apps to collect self-report data, smartphone applications are becoming increasingly sophisticated at passively collecting data from the smartphone's sensors without any participant interaction. For instance, passively collected global positioning system (GPS) and accelerometer data can provide objective information about people's movement and activity, whereas data about incoming and outgoing calls and text messages can provide data on actual patterns of social interaction. Such data can be used to create "digital phenotypes" of different conditions (Onnela & Rauch, 2016; Torous, Staples, & Onnela, 2015). These data can also be used to try to answer specific questions: Are episodes of depression characterized and predicted by periods of decreased activity and greater social isolation? Is the opposite true for mania? Such an approach is constrained by concerns about privacy, although many participants are comfortable providing access to this information for research use (Ben-Zeev et al., 2016).

Passive data also can provide richer information about an individual's social context than we could know from self-report alone. For example, mobile phones (assuming default settings) emit a consistent Bluetooth signal to detect the presence of Bluetooth peripherals (e.g., headphones).

Because Bluetooth has an effective range of around 30 feet, programs can collect the number of Bluetooth signals in an area, which can be used as an objective indictor of the presence of others (Nicolai, Yoneki, Behrens, & Kenn, 2006). These data can be integrated with call/SMS logs and social media usage data to create a full picture that shows with whom someone physically spends time and to whom the individual reaches out electronically. Such information would be useful in studies that assess the presence of others, such as van Winkel et al.'s, and for testing hypotheses regarding differences between physical and virtual social support.

Wearable Devices

Following the advent and popularity of wearable health trackers, such as Fitbit, has been a surge of interest in using these devices in real-time monitoring studies because they allow the self-report data to be supplemented with additional, objective behavioral and physiological measures. Several devices are currently on the market with different levels of features and sensors. Again, because this technology can change quite rapidly, rather than discuss individual devices, we discuss them in more general terms and refer readers to the Society for Ambulatory Assessment's list of wearable monitors (http://www.saa2009.org/?page_id=59). Many devices have sensors that can assess heartrate variability, electrodermal activity (also called galvanic skin response), movement, and various sleep parameters. Researchers can either use commercial (e.g., Fitbit, Jawbone UP) or research-grade (e.g., Empatica E4) wearable devices. The major advantages of using commercial devices are that they tend to be lower cost (many models are available for less than $150), are easily accepted by participants, and may even incentivize participants to participate in the study because they (at least for the time being) are novel technology. A disadvantage of these devices is that they tend to be less accurate than devices designed for research use. The major advantage of using devices designed for research is that they use higher-quality sensors that may provide cleaner and potentially more accurate data. However, their emphasis of function over form means that participants might be less likely to wear a less attractive device with fewer user-friendly features (e.g., a clock) for a long period of time.

Data from wearable physiological monitors can create an objective measure of emotional responding during everyday life that does not require participants to report on their emotions. This is important because people are not always skilled at recognizing and reporting their emotions or stress. Indeed, most population-based studies find that 10% or more people experience alexithymia (Mason, Tyson, Jones, & Potts, 2005). Research shows that physiological signals, especially heartrate metrics (e.g., interbeat interval) and electordermal activity, are strong objective indicators of stress (Healey & Picard, 2005). Data from wearable physical monitors can also create an objective measure of sleep length that does not rely on subjective recall. A body of literature demonstrates that people are less accurate on subjective reports of sleep relative to more objective methods (e.g., actigraphy) (Lauderdale, Knutson, Yan, Liu, & Rathouz, 2008). Many commercially available wearable devices have been able to assess sleep nearly as well as dedicated actigraphy devices (Cespedes et al., 2016). It should be noted, however, that both actigraphy devices and wearable monitors have demonstrated a tendency to inaccurately determine whether the wearer is awake or asleep.

Real-Time Interventions

A final novel application of real-time monitoring technology is its use as an intervention. Real-time interventions have the potential to allow access to care to individuals who would otherwise be unable or unwilling to attend therapy. This is important, because there is approximately one therapist for every 100 mentally ill individuals, with even fewer therapists in some rural areas (Kazdin & Blase, 2011). Moreover, many individuals cite as a barrier to care the stigma associated with treatment (Corrigan, Druss, & Perlick, 2014), and private smartphone-based interventions offer the ability to reduce this barrier. This is especially useful for populations, such as military service members or veterans, who may be at greater risk for some forms of psychopathology and suicide but are also more likely to report stigma as a barrier to receiving psychotherapy (Hoge et al., 2004). We do not propose that real-time interventions will replace in-person therapy, especially for high-risk individuals with complex psychopathology, but only that such approaches can provide access to therapeutic content to those who might otherwise not have access, and it may also serve as an entry point to in-person therapy for those who might otherwise be unwilling to try in-person therapy.

Real-time interventions can help bridge the gap between what is learned in the clinician's office and what one does in everyday life. For instance, it is often difficult to remember when to use therapy skills during everyday life and possibly even more difficult to actually use them during times of high stress. Smartphone-based interventions allow for the therapeutic content to be made available whenever it is needed, reducing barriers to remembering to use the intervention (because patients can be reminded to practice the intervention throughout the day) and barriers to actually using the intervention's skills (because it does not require the patient to need to recall all of the steps involved in using the skill). It is worthwhile to note that as the technology has become more available, it has also become more accepted by clinicians (Schueller, Washburn, & Price, 2016) and their patients (Torous et al., 2014). Moreover, the development of new technologies also has led to the development of novel interventions, such as those that use game-like apps to condition people to have an aversion to maladaptive behaviors (Franklin et al., 2016) or to use crowdsourcing to provide cognitive restructuring in real time when and where it is needed (Morris, Schueller, & Picard, 2015).

CONCLUSIONS

As evidenced by the exciting new study by van Winkel and colleagues (this issue), studies of daily life experiences can shed important new light on the characteristics, development, and treatment of psychopathology. New technologies, such as smartphone-based real-time monitoring, passive monitoring from such devices, and wearable monitors, can provide additional, objective, fine-grained information in each of these areas. Despite the clear advantages of using real-time monitoring to study phenomena of interest, clinical psychological and psychiatric scientists have—so far—been relatively slow to adopt new technology that maximizes the utility of such methods. We hope and expect that these new tools will provide not only advances in the quality and quantity of data collected in research and clinical settings but also significant improvements in our understanding of, and ability to predict and prevent, psychopathology and related conditions.

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