ORIGINAL ARTICLE

Using the Methods of Ecological Momentary Assessment in Substance Dependence Research—Smoking Cessation as a Case Study

Stuart G. Ferguson¹ and Saul Shiffman²,³

¹University of Tasmania, Hobart, Australia; ²University of Pittsburgh, Pittsburgh, Pennsylvania; ³Pinney Associates, Pittsburgh, Pennsylvania, USA

Ecological momentary assessment (EMA) is the name applied to any of a range of research methodologies that aim to assess participants in near real time as they go about their regular day-to-day activities. Such methods have particular utility for studying drug use and drug dependence. Using the area of nicotine dependence as a case study, this review highlights how EMA can be used to build upon the findings from more traditional research methods to enhance our understanding of drug use. Particular attention is given to the role that advances in technology have played in the adoption of EMA in drug dependence research.

Keywords ecological momentary assessment (EMA), smoking cessation, review

INTRODUCTION

Fundamental to any approach to understanding or treating drug abuse¹ is to be able to accurately assess it and the variables that influence it. Drug dependence has traditionally been investigated using either highly focused laboratory studies (e.g., cue reactivity studies; Carter & Tiffany, 1999) or observational or epidemiological study designs. However, while these study designs can provide important information about drug use, they are ill suited to exploring the interplay of social and situational factors that are believed to drive and maintain drug dependence or to studying processes that are believed to vary with the passage of time, such as drug withdrawal and drug relapse. Unlike many other phenomena of interest to social scientists, drug use consists of discrete events (that is, drug administration) that have antecedents and consequences. As such, drug use researchers must turn to other methodological approaches to fully explore and understand drug dependence: One class of study design that is particularly well suited to exploring such relationships is ecological momentary assessment—or EMA.

The last decade has seen a rapid expansion in the use of EMA for the study of a wide range of both psychological and physical phenomena. The array of phenomena studied so far includes drug use (e.g., alcohol: Collins et al., 1998; ecstasy: Hopper et al., 2006; tobacco: McCarthy, Piasecki, Fiore, & Baker, 2006), pain (e.g., Broderick et al., 2008; Raselli & Broderick, 2007), eating disorders (e.g., Vansteelandt et al., 2004), cognitive processes (e.g., Waters & Li, 2008), and nausea (Badr, Basen-Engquist, Carmack Taylor, & de Moor, 2006) to name but a few. There have been a number of EMA review articles published to date (e.g., Shiffman, Stone, & Hufford, 2008; Stone & Broderick, 2007). These reviews have tended to focus on the definition of EMA research and the scope of methods that can be thought of as falling under the umbrella of real-time data capture methodologies. This current review does not aim to replicate this literature. Instead, the primary purpose of this review is to demonstrate how EMA research designs are specifically applicable to the study of drug dependence and how EMA designs can be used to probe questions of interest to drug dependence researchers, particularly research questions that are problematic to explore, using more traditional research methodologies. Using the area of nicotine dependence as a case study, we aim to highlight how EMA has been used to help extend the findings obtained from observational, epidemiological, and laboratory-based procedures traditionally used to study nicotine dependence. Using examples, we address the types of questions that lend themselves to being addressed with EMA and discuss the advantages of using EMA methodologies for exploring them. We end with a discussion of technological challenges—and possible solutions—involving with real-time data capture. Technological advances—particularly

¹The journal’s style utilizes the category substance abuse as a diagnostic category. Substances are used or misused; living organisms are and can be abused. Editor’s note.

Address correspondence to Dr. Stuart G. Ferguson, School of Pharmacy, University of Tasmania, Private Bag 26, Hobart, Tasmania 7001, Australia; E-mail: stuart.ferguson@utas.edu.au

87
in the last decade—have increased the feasibility of the use of EMA in research environments. As we will discuss, while EMA studies do not necessarily need to involve advanced technology, the use of electronic devices—particularly handheld computers—allows for more complicated EMA study protocols to be utilized. Before we do so, however, we start by providing a brief description of EMA.

**WHAT IS EMA?**

EMA is the name given to any of a number of research methods that aim to collect data from participants in their natural environment in as close to real time as possible. EMA study designs aim to collect information, repeatedly, from participants (usually, but not always, via a questionnaire) while they are going about their daily lives. Typically, the information being sought concerns current (or very recent) activities, situations, thoughts, feelings, or behaviors.

The drive to collect information within a participant’s natural environment is born out of the knowledge that behaviors and experiences can be affected by social setting. As such, for observations to be ecologically valid they need to be gathered in the environment in which the target behavior or experience occurs. This can be seen as the primary goal of EMA techniques—to collect data on phenomena within the natural setting in which they occur. As succinctly put by Shiffman and colleagues (2008), if you want to know about how a participant feels at work, there is no point asking them how they feel in a laboratory.

In addition to context, the way a participant reports on an experience can also be shaped by the process of time. Asking a participant to report how they felt at some previous point in time involves the process of recall, which is not just fallible but also potentially biased (Bradburn, Rips, & Shevell, 1987; Hammersely, 1994; Ross, 1989). Such biases can affect data collected after even short periods of delays. The fact that EMA attempts to collect data in real time, with as little delay as possible between the occurrence of the target event and its assessment, is perhaps its most prominent feature; indeed, in some discussions the phrase “real-time data capture techniques” is used in place of EMA (e.g., Stone & Broderick, 2007). Arguably, the primary advantage of using EMA techniques is that it gathers data from a participant while minimizing the amount of recall (and hence bias and/or “noise”) that is involved.

The final defining characteristic of EMA techniques is that they involve multiple assessments of variables of interest over time. The fact that variables are repeatedly sampled allows a researcher to build up a picture of how experiences and behavior vary both over time (for example, to look for cyclical patterns) and across situations. Additionally, taking multiple assessments can provide a more accurate measurement of a variable, when aggregated, than a single assessment if the variable of interest fluctuates over time and/or across situations (e.g., drug craving, which is both temporal dynamic, e.g., Shiffman & Ferguson, 2008, and fluctuates in response to environmental stimuli, e.g., Ferguson & Shiffman, 2009). The timing of the repeated assessments can be scheduled on the basis of either time (e.g., sampling at fixed or random time points during the day) or the occurrence of a certain event of interest (also called participants initiated assessment, as researchers rely on the participant to indicate when an assessment is required, e.g., sampling occasions when participant drinks alcohol), or some mixture of the two. The study of drug dependence lends itself primarily to episode-based sampling. Drug use consists of discrete, easily definable acts (or “events”), and researchers are often interested in what is occurring at the time of drug administration, what led up to it, and what its effects are. The fact that the behavior of interest—drug administration—is so easily definable, and salient, means that participants can readily be trained to administer an assessment at these moments. However, as will be discussed in detail later in this review, overlaying additional time-based assessments can be beneficial, as they allow the researcher to build a picture of how variables of interest might be varying in the absence of drug administration. In either case, following data collection, researchers may then choose to combine multiple assessments (e.g., average assessments over a day) or examine each of the assessments individually.

**Summary**

As discussed, the core features of the EMA data are that they contain repeated, ecologically valid real-time assessments of a target variable or variables. Such characteristics make EMA data particularly useful in the study of certain types of research questions. The next section of this review will discuss the types of drug use research questions that lend themselves to EMA research and, in doing so, demonstrate how EMA can be used to extend findings from alternate research methodologies.

**EMA IN RESEARCH—SMOKING CESSATION AS A CASE STUDY**

Because of the prevalence of studies in the area that have utilized EMA, nicotine dependence research is an excellent case study for demonstrating the utility and the power of EMA as a means of data collection. The development of EMA methods has allowed researchers of substance dependence to explore many questions that had hitherto been very difficult to study in a controlled fashion. It is worth noting here that it is not our position that EMA obviates the need for research using more traditional methodologies; indeed, there are many questions that are better suited to exploration using non-EMA procedures (for example, using controlled laboratory procedures where extraneous variables can be monitored and/or controlled so as to isolate the effects of discrete factors of interest). Nevertheless, as will be discussed below, EMA study designs can be used to collect data that other study designs cannot generate. In doing so, EMA studies can contribute to our knowledge about the causes and treatment of drug dependence.
Shiffman and colleagues (2008; see also Bolger, Davis, & Rafaeli, 2003) identified four broad classes of research problems that are particularly suited to the investigation using EMA methodologies, namely, (1) characterizing individual differences, (2) describing the natural history of a variable of interest, (3) assessing contextual associations, and (4) documenting temporal sequences. Each of these classes of research questions is relevant in the study of drug dependence. The remainder of this review will be devoted to demonstrating—using examples from the area of nicotine dependence—how EMA techniques can be used to probe such types of questions and hence extend the findings from other research methodologies. Where relevant, a brief background on the non-EMA literature pertaining to the question of interest will be provided—this is done not as a comprehensive summary of the available literature but, rather, to demonstrate how data from EMA studies can build upon that from more traditional research models.

**Individual Differences**

Individual differences—be it in behavior or responses to treatment or in any other relevant variable—can be explored using many research methodologies. Laboratory studies, case–control studies, and epidemiological survey research studies can all be used to gather data that can be used to examine individual differences on a given variable/s. However, EMA techniques have the advantage of obtaining multiple assessments. When EMA data are used to characterize individual differences, it tends to be done by aggregating multiple assessments across a given time period (e.g., days, treatment period, baseline; Shiffman et al., 2008). The advantage of using EMA data to explore individual differences is that if the variable of interest fluctuates over time or in response to environmental factors, then the aggregate of multiple assessments is more likely to be more accurate than a single measure taken at a particular point in time.

For example, Shiffman, Ferguson, Gwaltney, Balabanis, and Shadel (2006) took advantage of the multiple observations generated by using an EMA design to examine the effect of nicotine patch treatment time on withdrawal symptoms experienced during an attempt to quit smoking. Such close examination of the effect of treatment on withdrawal can also be informative for our understanding of treatment efficacy. The investigators used electronic diaries to monitor withdrawal symptoms during both ad-lib smoking and the first weeks of a quit attempt. Over the course of the study, participants—some of whom were treated with nicotine patches and others were treated with placebo—were assessed at randomly selected moments four to five times per day (during waking hours). During these assessments, participants reported the levels of withdrawal they were currently experiencing (that is, they were not asked to use recall, just to report their current momentary state). In this way, the researchers compared the severity of nicotine withdrawal between participants treated with active nicotine patches and those treated with placebo patches. Such analyses are crucial to understanding the effectiveness of treatments—the one in question, for example, showed that treatment with active patch eliminated abstinence-related changes in effect (both positive and negative) and attention, returning these symptoms to levels seen during baseline ad-lib smoking. Such findings are important for understanding the process of relapse, not just for nicotine dependence but for all drug use.

**Natural History**

With many variables, we are often not just interested in how they are experienced “on average” but also interested in how they vary over time. Such natural history studies are often very difficult to conduct using laboratory-based experiments (logistically, it is very difficult to keep participants housed in a laboratory for extended periods of time; and even if you can, there is not much that is “natural” about laboratory settings!), and retrospective timeline follow-back (Brown et al., 1998) procedures are prone to biases involved with recall (discussed earlier). EMA techniques, however, are well suited to answer these types of questions because the longitudinal data are gathered in the participant’s natural environment (hence no need to house the participant for extended periods) and in real time (obviating issues with recall).

In the nicotine dependence literature—and also true for research into other “drugs of abuse”—an example of a topic where natural history information is crucial is in the study of drug withdrawal. Dependent users often report withdrawal symptoms during periods of abstinence, and most theories of dependence have posited that continued drug use is, at least in part, driven by withdrawal symptom avoidance. To understand the role that withdrawal plays in dependence, it is necessary to examine how it changes over the course of a cessation attempt. A number of EMA studies that have examined withdrawal symptom severity have been conducted (McCarthy et al., 2006; Shiffman, Ferguson, Gwaltney, Balabanis, et al., 2006; Shiffman, Patten, et al., 2006). The study conducted by Shiffman, Patten, and colleagues (2006) is illustrative. Using a procedure very similar to that described above (Shiffman, Ferguson, Gwaltney, Balabanis, et al., 2006), the investigators used electronic diaries to monitor withdrawal symptoms—using random prompts—during both ad-lib smoking and the first weeks of a quit attempt. In this way, the researchers could build up a picture of how withdrawal changed over time. Using such focused, fine-scale examination, researchers have been able to accurately describe the time course of nicotine withdrawal (McCarthy et al., 2006; Shiffman, Ferguson, Gwaltney, Balabanis, et al., 2006; Shiffman, Patten, et al., 2006) and to relate fluctuations in withdrawal severity to the outcome of a quit attempt (Ferguson, Shiffman, & Gwaltney, 2006; Shiffman et al., 1997). Such studies have generated surprising findings regarding the time course of nicotine withdrawal, findings contrary to those found in studies that have evaluated the time course retrospectively. For example, the finding that many withdrawal symptoms return to baseline levels sooner
than expected affects theoretical models of the role that these symptoms could play in relapse.

The closer examination of the time course of withdrawal afforded by using EMA methods has allowed researchers to examine mechanisms of treatment efficacy. The efficacy of both bupropion (McCarthy et al., 2008; Piper et al., 2008) and nicotine patch (Ferguson et al., 2006) has been explored by examining whether reduction in withdrawal severity brought about by active treatment mediates the efficacy of these treatments. Such analyses help researchers to understand how treatments work, which has clinical implication both for the application of currently available cessation medications and for the development of new approaches to helping smokers quit.

As a final example, EMA data can also be used to help explore patterns of drug use, which may help to identify phenotypes of users who are in greater need of assistance with cessation. For example, Chandra, Shiffman, Scharf, Dang, and Shadel (2007) took advantage of the multiple observations generated by using an EMA design to examine differences in the daily temporal patterns of smoking. In this study of ad-lib smoking, participants were required to record each cigarette that they smoked in real time, using an electronic diary. Because these assessments were time and date stamped, Chandra and colleagues could generate an average distribution of cigarettes over the course of a day for each participant (because each participant had multiple days of observation, which could be collapsed). Using this procedure along with cluster analysis techniques, Chandra and his colleagues identified four unique patterns of daily smoking (based on the rate of smoking that occurred at different times of the day). Importantly, Chandra and his colleagues went on to demonstrate that the different patterns of smokers were related to differential outcomes during a later cessation attempt, underscoring the importance of examining the natural history of drug use.

In conclusion, because they gather real-time longitudinal data in the participant’s natural environment, EMA studies are well suited to exploring questions that involve any element of time. Such questions are common in the field of drug dependence in general; they are not just specific to nicotine dependence. The chosen examples of natural-history-type research questions—the study of withdrawal severity over time and of how users relapse following a period of cessation—a long with other similar questions have obvious parallels in other fields of drug use research.

**Contextual Associations**

Many physiological and psychological variables of interest—including drug use—are believed to be driven by the interplay of a number of situational factors or processes. Such phenomena are difficult to investigate in the laboratory, as the factors necessary to generate them often cannot be replicated in a meaningful way: Either these events will not occur in artificial laboratory environments, or, if they do occur, they may do so in an unrealistic fashion. In short, laboratory experiments lack ecological validity and, as such, are unsuitable for the study of phenomena that are driven by environmental factors.

Take, for example, drug use relapse following a period of cessation. The behavior of cigarette smoking is notoriously difficult to disrupt. Since the watershed publication of the 1964 *Surgeon General’s Report* on the health effects of tobacco smoking—in which smoking was linked to numerous negative health outcomes such as lung cancer, bronchitis, emphysema, and coronary heart disease—researchers have been interested in developing methods to aid smokers who want to stop smoking to successfully quit. Despite the attention of countless researchers, smoking cessation rates, even among smokers highly motivated to quit, have remained low.

In order to develop successful cessation programs and methods—not just for nicotine but for any drug that is used—researchers and theorists need to understand the drug use on a fundamental level; they need to understand what processes were underpinning the behavior. In the case of nicotine, findings from laboratory animal studies demonstrated that nicotine itself was an addictive drug, but it was clear that more was behind smoking than a simple physical dependence—nicotine dependence is also maintained, in part, by learned relationships (see Niutta et al., 1988).

Using EMA methods, nicotine researchers have been able to assess participants in real time when they lapse during a cessation attempt, monitoring such factors as withdrawal symptoms and social situations. Such investigations have shed light on situational and social factors that increase a smoker’s risk of lapsing. In one study, Shiffman, Paty, Gnys, Kassel, and Hickcox (1996) randomly assessed participants who were taking part in a quit attempt at multiple times during the waking hours of the day. These random assessments helped to build up a general picture of what participants were doing and how they were feeling, on average, during their quit attempt. Additionally, participants were also asked to complete an assessment whenever they lapsed back to smoking. These participant-initiated assessments were largely identical to those conducted during random nonsmoking time points, which allowed the investigators to directly compare nonsmoking assessments to lapse assessments in a case-controlled fashion.

The ability to compare lapse episodes to randomly scheduled nonsmoking episodes was crucial in helping to understand lapses. The reason why understanding nonsmoking situations is important is that they give us a situation against which to contrast our events of interest (in this case, smoking lapses). For example, let us say a researcher was interested in the relationship between stress and alcohol consumption. This researcher asked participants to report what their level of stress was each time they consumed alcohol and found that 80% of the time a participant reported drinking, they also reported that they were stressed. On the basis of this finding, one might be tempted to conclude that being stressed increases a participant’s “risk” of alcohol consumption. However, unless one knows the proportion of time that a participant...
was stressed when they were not drinking, this would be an erroneous conclusion. It might just happen that these participants are stressed 80% of the time in general; in such a situation, the associate between stress and alcohol consumption is spurious. Thus, by knowing what their participants were doing and how they were feeling during randomly selected nonsmoking times, Shiffman and colleagues (1996) were able to determine the factors and situations that were more likely to be related to lapsing. Doing so allowed them to shed light on the complicated interplay of a number of social and/or situational factors associated with smoking lapses and highlights the benefit of using EMA methodologies to explore such research questions.

Temporal Sequences

The final category of research questions that EMA can be used to explore is of ones that involve a temporal sequence. In order to understand temporal sequences, researchers need longitudinal data, that is, multiple assessments over time. Longitudinal data are crucial so that the antecedents and/or consequences of a target event can be determined.

An apt example of analysis of temporal sequences is Shiffman and Waters’s (2004) analysis of the role of negative affect in smoking lapses. As with many drugs, negative affect (or mood) is believed to promote smoking lapses; however, much of the support from this premise was generated from retrospective—and hence bias-prone—studies of smoking lapses. Taking a different approach, Shiffman and Waters first isolated participants who lapsed during the course of an EMA smoking cessation study and then examined their self-reported negative affect during the days leading up to the lapse episode and the hours leading up to the episode on the lapse day itself. In this way, the researchers could examine prospectively whether changes in negative affect in the days and hours before a lapse predicted a participant’s risk of lapsing. Surprisingly—and contrary to findings from prior non-EMA research—the affect on preceding days did not predict lapse risk. However, when they examined affect ratings more proximal to the lapse, they found that negative affect started increasing some 5–6 hours prior to the lapse. This example again demonstrates the importance of obtaining detailed real-time, longitudinal, prospective data over time to understand the dynamics of drug use.

Another example comes from Shiffman, Ferguson, and Gwaltney’s (2006) analysis of how the initial lapse affects subsequent risk. Relapsing following a period of abstinence involves a series of lapses. Previous retrospective research on smoking lapses concluded that participants treated with nicotine patches during a quit attempt obtain less satisfaction from a smoking lapse than untreated participants (presumably because the active patch participants already have nicotine in their blood from the active treatment, and hence the cigarette is not providing as much of a “hit”; Levin et al., 1994). Levin and his colleagues posited that this reduced satisfaction might explain how patch treatment reduces a single smoking lapse from becoming a full-blown smoking relapse (see Shiffman, Scharf, et al., 2006). Shiffman and colleagues collected real-time assessments of smoking satisfaction at the time of a participant’s first lapse and used survival analyses to assess whether higher satisfaction ratings increased a participant’s risk of progressing to relapse. Participants who expressed more satisfaction with the first lapse indeed were at a greater risk of progression to relapse (as predicted by Levin and colleagues, 1994). Interestingly, the study found that, contrary to the earlier findings, when lapse satisfaction was assessed in real time—without the bias introduced by recall—satisfaction with lapses did not differ by treatment group.

Together these examples highlight both how the longitudinal nature of EMA data can allow researchers to explore the antecedents and consequences of events and how the use of retrospective methods can introduce bias and reduce the validity of data. Such data are important for the understanding of drug dependence.

Summary

Using examples from our own work on cigarette smoking, the above discussion demonstrates how EMA study designs can be used to investigate drug-dependence-relevant research questions that are problematic to explore using alternate study designs and, in doing so, shows how EMA studies can contribute to our knowledge about the causes and treatment of drug dependence. While all the examples used were drawn from the nicotine literature, the natures of the questions themselves pertain to issues that transcend any particular substance, being common to dependence in general: withdrawal symptoms, relapse, and drug maintenance.

Devices for EMA Data Collection

The collection of data in a participant’s environment presents a number of unique technological challenges that are not seen when experiments are conducted within the confines of a laboratory. To name but a few, consider the following: How will participants be notified that an assessment is required of them? How will the participant then complete the required assessment? How will the data be conveyed to the researcher? How will the researcher know that the assessment was completed when it was supposed to be?

Over the years, numerous different tools, or devices, have been used to collect real-time data from participants, ranging from low-tech (e.g., pencil-and-paper diaries) to high-tech (e.g., electronic diaries, mobile phone), and each has inherent advantages and disadvantages. Multiple factors need to be considered when determining the best data collection device for a particular research study. Such considerations include sampling requirements (e.g., time-based or event-based sampling schemes, use of random assessments), length of assessment, available funding for the study, participant characteristics, and the duration of the planned study. When considering data collection, it is beneficial to break the process into two
tasks: prompting and assessment. Using this distinction, prompting refers to the process of actually indicating to a participant that an assessment is required, while assessment refers to the task of actually administering, or conducting, the assessment itself. While is it possible—and, we will argue, preferable—to accomplish both of these tasks through a single device, some studies (e.g., Litt, Cooney, & Morse, 1998) choose to use separate devices for the tasks of prompting and assessment. Below, we introduce some of the more commonly used data collection devices and the advantages and disadvantages of each.

Diaries
Perhaps the most straightforward—or at least the most low-tech—method of collecting data from participants in the field is to supply them with paper copies of the assessments that are required and simply ask them to complete these assessments on whatever schedule the study requires (e.g., fill out an assessment at bedtime each night; fill out an assessment after each meal). While technically such a data collection strategy can fall under the umbrella of an EMA sampling procedure (as it, nominally at least, is real-time data collected within a participant’s environment), it has several key limitations. First, and foremost, we have good reason to doubt whether data gathered using pencil-and-paper diaries are indeed “momentary” and hence are actually being collected within the environment of interest. Research on participant’s use of pencil-and-paper diaries suggests that the majority of entries are made in “batches” after-the-fact, rather than being complete over time as requested (Stone, Shiffman, Schwartz, Broderick, & Hufford, 2003; cf. Green, Rafaeli, Bolger, Shrout, & Reis, 2006). More troubling, it is not just the case that participant’s backfill missed assessments—there is also evidence that participants forward-fill assessments; that is, they complete assessments in advance, in essence reporting how they think they will feel at some stage in the future (Stone et al., 2003). The inability to obtain an accurate, reliable time stamp for when an assessment is completed is a major limitation with pencil-and-paper diaries.

Furthermore, without involving a separate device for prompting participants, pencil-and-paper diaries are also limited in the scheduling of assessments that can be used: Participants can only feasibly be asked to complete an assessment at set time points (e.g., every 2 waking hours and immediately before bedtime) or in relation to milestones or events of interest (e.g., after dinner and when taking a medication). One cannot, however, ask participants to complete an assessment at random, which, as discussed earlier, can provide “background” data against which to contrast the data gathered during events of interest. Some studies get around this prompting limitation of pencil-and-paper diaries by supplying a separate device that can serve to prompt participants to complete assessment. For example, Litt and colleagues (1998) asked participants to complete a pencil-and-paper diary assessment when prompted to do so by a programmable wristwatch. While this creative solution overcomes the problem of prompting assessments, it does not solve the problem of time stamping: We cannot be sure that the individual assessments are actually completed in a momentary, real-time fashion. Indeed, when Litt and his colleagues debriefed a subset of the participants used in the aforementioned study, a substantial proportion (70%) admitted that they had lied about what time they had actually completed the assessments.

In summary, pencil-and-paper diaries, while having the advantage of being relatively inexpensive, have severe limitations when it comes to their use in EMA studies. The two primary limitations discussed—particularly the inability to obtain an objective time stamp for assessments—make it difficult to recommend pencil-and-paper diary methods for the collection of EMA data. The addition of a second device to prompt assessment, while allowing for more complicated sampling procedures, does not appear to solve the problem of ensuring that participants complete assessments in real time.

The limitation of pencil-and-paper diaries noted above can largely be overcome using electronic diaries. Handheld electronic diaries are perhaps the most commonly used assessment tool for EMA studies; indeed, they have become almost synonymous with EMA research itself (Hufford & Shields, 2002; Shiffman et al., 2008); the prominence of such devices in EMA studies is well justified. In addition to allowing researchers to time and date stamp each assessment—which means that researchers can be confident that they know exactly when each assessment was completed—electronic diaries allow for the administration of complicated surveys, including those that branch depending on participant answers, complicated sampling schedules (including time-based random sampling, and sampling of only a randomly selection portion of target events); and the data are automatically recorded and stored in a database which can then be downloaded, saving time and removing the opportunity for transcription errors.

However, the use of electronic diaries is not without limitations. First, while the unit cost of electronic diaries has decreased over recent years, these devices still require a relatively large upfront cost to the researcher, and researchers also need to consider that over the course of the study a certain percentage of these devices will need to be replaced because of theft, damage, or general wear and tear. While damage and loss can be reduced by implementing appropriate safeguards, the experience from our lab suggests that up to 20% of devices will need to be replaced each year, a nontrivial study expense. In addition to the cost of the units themselves, electronic diaries can be difficult to program, often requiring researchers to engage the services of a specialized computer programmer. Finally, the use of electronic diaries requires the implementation of comprehensive training and support programs to ensure that participants understand how they are used and can obtain help when trouble strikes (which invariably will).

Non-diary Assessment Tools
Diaries—electronic or otherwise—are not the only devices that can be used to collect EMA data. Time-stamped
data can be obtained using mobile phone by having participants call an interactive voice recognition (IVR) system to complete assessments; or using more modern mobile phones, data can be collected by having participants complete a Web-based survey over their phone. Additionally, a growing number of phones can be programmed and hence can be used to administer assessments on flexible schedules (e.g., assessments at random time points); such devices have the potential to offer all of the advantages of handheld personal electronic diaries (discussed earlier) and, in doing so, may come to represent the most state-of-the-art data collection devices for EMA procedures in the near future.

Mobile phones have the additional advantage that they can be used to gather qualitative data. For example, we recently conducted an exploratory study of nondaily smoking patterns in which we had participants call a study answering machine whenever they smoked a cigarette (Shiffman, Kirchner, Ferguson, & Scharf, 2009). Participants were instructed to leave a voice message describing—in their own words—what they were doing and what caused them to smoke. These content-rich, time-stamped, qualitative data were then coded and key themes extracted. Finally, other, less common, tools for EMA data collection include handheld dictation machines (e.g., O’Connell, Gerkovich, Bott, Cook, & Shiffman, 2002) and non-self-report data collection devices such as blood pressure monitors and blood-alcohol monitors. These less commonly used data collection devices may require a separate prompting device (e.g., a programmable wristwatch) if researchers plan to collect data on a complicated schedule and cannot provide time-stamped data, both of which are limitations that need to be considered by researchers prior to their use.

SPECIAL ISSUES FOR REAL-TIME DATA COLLECTION IN DRUG DEPENDENCE RESEARCH

This review has used nicotine dependence as a case study for how EMA can be used to study drug use and dependence in general. However, while different forms of drug use share many similarities, nicotine dependence is not a perfect parallel in all cases; the study of other drugs of dependence will probably require special challenges. Unlike cigarette smoking, the use of illicit drugs, for example, carries the possibility of criminal prosecution, which may make participants reticent to disclose instances of this behavior to researchers. (It is worth noting that this, however, is not unique to EMA; it is a challenge for any researcher wanting to study illicit drug use, regardless of the study methodologies utilized. Nevertheless, EMA researchers need to be aware of this consideration.) Additionally, cigarette smoking is a relatively frequent activity—researchers have the opportunity to assess tens of occurrences of drug administration each day. Other drugs, however, may be administered on a leaner schedule, which means that researchers hoping to use EMA will need to monitor participants in the field for longer periods of time in order to record sufficient instances of drug use.

Additionally, the collection of real-time data in the context of drug use presents some unique challenges not seen when using EMA for the study of other phenomena. Perhaps the most obvious of these concerns is that assessments may be completed under the influence of drugs, which may limit the accuracy of the data obtained. Alternatively, instead of supplying inaccurate data, in some cases participants may be too intoxicated to comply with the study procedures and hence fail to complete the necessary assessments, leaving the researcher without any data (useable or otherwise). In addition to data quality concerns, when high-tech data collection tools are used, researchers need to consider the very real possibility that some participants will steal these devices. It is worth noting, however, that EMA has successfully been used to study such extreme populations as homeless cocaine addicts (Freedman, Lester, McNamara, Milby, & Schumacher, 2006), suggesting that with careful planning such concerns can be mitigated.

As noted earlier, the study of drug use probably necessitates an episode-based assessment procedure. Such procedures carry special issues, most notably that they, by definition, rely on participants to initiate assessments. The success of episode-based assessment strategies depends on the ability and willingness of participants to actually initiate and complete an assessment. Establishing clear guidelines for participants and, if possible, developing objective compliance measures are crucial.

A final, particularly relevant concern is that of data privacy in the case of lost data collection devices or from “snooping” by a participant’s friends, relatives, or colleagues. Researchers need to consider strategies to help alleviate these issues; careful piloting of procedures can be helpful in this respect.

SUMMARY

The purpose of the discussion above was to demonstrate how the EMA methodology can be used to build upon, and compliment, the findings from more traditional research approaches. The examples from the nicotine dependence literature demonstrate how EMA data can be used to (1) characterize individual differences, (2) describe the natural history of a variable of interest, (3) assess contextual associations, and/or (4) document and test temporal sequences.

EMA techniques offer researchers a unique opportunity to investigate phenomena that do not occur in artificial environments or, if they do occur, may do so in an unrealistic fashion; processes that are believed to be driven by the interplay of a number of social and/or situational factors; and/or processes—physiological or psychological—that are believed to systematically, and meaningfully vary with the passage of time. A number of devices can be and have been used to collect EMA data. EMA techniques compliment, and build on, findings from epidemiological and laboratory studies.
Declaring of Interest

Dr. Shiffman is a cofounder of invivodata, Inc., which provides electronic diaries for clinical research. Dr. Ferguson has no conflicts to disclose.

THE AUTHORS

Stuart G. Ferguson, Ph.D., currently works as a senior research fellow at the University of Tasmania, Hobart, Australia. He previously completed a post-doctoral fellowship at the University of Pittsburgh working in the Smoking Research Group. He completed his undergraduate degree in Australia before receiving his Ph.D. in psychology from the University of Otago, Dunedin, New Zealand. His primary research interest is the process of drug relapse.

Saul Shiffman has a Ph.D., in clinical psychology from the University of California at Los Angeles. He is currently Research Professor of psychology (in the programs in clinical and health psychology), psychiatry, and pharmaceutical sciences at the University of Pittsburgh. He also serves as Senior Scientific Advisor to Pinney Associates, a science and policy consultancy, and is a cofounder of invivodata, Inc., a company that provides electronic diary services for research. Dr. Shiffman’s scientific interests include drug dependence and relapse (particularly in tobacco use) and methods for real-time data collection.

GLOSSARY

Ecological momentary assessment (EMA): Any of a number of research methodologies that aim to collect data from participants in their natural environment in as close to real-time as possible.

Lapse: In the smoking cessation literature, a lapse is defined as an isolated, individual instance of smoking during a quit attempt.

Relapse: In the smoking cessation literature, a relapse is defined as the resumption of regular smoking after a period of cessation.

REFERENCES

Badr, H., Basen-Engquist, K., Carmack Taylor, C. L., & de Moor, C. (2006). Mood states associated with transitory physical symp-


