The Current State of EMA and ESM Study Design in Mood Disorders Research: A Comprehensive Summary and Analysis

Meredith L. Wallace[1,2], Molly H. Carter[2,3] and Satish Iyengar[1]

[1]Department of Statistics, University of Pittsburgh, Pittsburgh, PA 15260, U.S.A.
[2]Western Psychiatric Institute and Clinic, University of Pittsburgh, Pittsburgh, PA 15213, U.S.A.
[3]Department of Psychology, Xavier University, Cincinati, OH 45207, U.S.A.

Abstract. Ecological momentary assessment (EMA) and experience sampling methods (ESM) are becoming increasingly prevalent in mood disorders research due to their potential for capturing underlying dynamic mood processes that cannot be observed through traditional clinical visits. There have also been recent statistical developments that allow for innovative EMA/ESM-related research questions to be answered. However, even the most sophisticated statistical methods cannot glean accurate representations of underlying mood processes when the data are sampled inappropriately. Unfortunately, there are few resources investigators can use to make informed decisions about EMA/ESM study design. Thus, we perform a comprehensive summary of current EMA/ESM study design methods used in mood disorders research, explore the rationale behind study design decisions, and investigate the relationship between compliance and various study design features. Results from these analyses are used to suggest improvements for designing and reporting future EMA/ESM studies.

1 Introduction

Clinical researchers and psychologists base their patient evaluations and diagnoses largely on retrospective self-report of experiences. However, this type of information can be biased by current mood state and day-to-day and even hour-to-hour variability in experiences and symptoms [1–3]. Because mood disorders such as unipolar depression (DEP), bipolar spectrum disorders (BD) and disorders of mood dysregulation such as borderline personality disorder (BPD) are defined by changes in mood state and mood variability [4], recall bias may be a particularly salient problem in this area. As a result, information conventionally collected in clinical settings can fail to capture the continuous, dynamic processes underlying mood disorders, thereby hindering researchers' abilities to characterize disease processes that may lead to specific and effective treatments. Furthermore, information collected in a clinical setting may not provide a sufficiently detailed understanding of a patient's course of illness, potentially contributing to the high rate of misdiagnosis across mood disorders [5–9].

Ecological momentary assessment (EMA) [1, 2] and experience sampling methodology (ESM) [10, 11] are data collection methods that allow clinical researchers and

L. Wallace M., H. Carter M. and Iyengar S..
The Current State of EMA and ESM Study Design in Mood Disorders Research: A Comprehensive Summary and Analysis.
DOI: 10.5220/0003878400030016
In *Proceedings of the 2nd International Workshop on Computing Paradigms for Mental Health* (MindCare-2012), pages 3-16
ISBN: 978-989-8425-92-8
Copyright © 2012 SCITEPRESS (Science and Technology Publications, Lda.)

psychologists to capture a patient's course of illness with greater frequency and sensitivity through the use of hand-held technological devices. When studying disorders of mood and mood dysregulation (henceforth, we will refer to them collectively as "mood disorders"), EMA and ESM are particularly useful for capturing both the mean and instability of mood [12]. EMA accomplishes this through the use of portable technological devices, such as hand-held computers and cellular phones, to capture self-reported measurements as they occur naturally in real time. In this way, EMA allows investigators to control timing precisely and track compliance [13]. EMA can also be used to capture behavioral and physiological data; however, the focus herein is on self-reported EMA. Like EMA, ESM also uses technological devices to capture data in real time; however, ESM typically uses a digital watch or pager to prompt participants to record their experiences in a paper-and-pencil diary [10, 11]. In this manuscript we focus on self-reported EMA and ESM, referring to them collectively as EMA.

As with any type of data collection method, EMA study design is of utmost importance. In general, there is consensus that random sampling should be employed and that the sampling frequency should match the temporal dynamics of the process of interest [11, 14, 15]. However, there is a paucity of formal empirical evidence regarding EMA study design methodology and rationale, particularly as it relates to the capture of underlying mood processes. One important breakthrough study in this area was performed by Ebner-Priemer and Sawitzki [14], who showed that a sampling interval of less than 30 minutes could optimally capture underlying dynamic processes in BPD, while intervals greater than 30 minutes could not. However, few research studies (especially those in clinical populations) are expected to support sampling intervals of less than 30 minutes due to concerns of participant burden [14].

The field of mental health, and mood disorders in particular, could benefit from the development of a more standardized set of EMA study design methods so that future researchers can make more informed decisions (e.g., consider the stringency with which clinical trials are designed and reported). As an initial step towards this end goal we present a comprehensive summary and analysis of study design features in mood disorders research, focusing on three specific aims:

1. Summarize the current state of EMA study design
2. Explore factors that researchers have considered when making EMA study design decisions
3. Investigate the relationships among study design features and compliance

Results from these three aims are used to suggest ways that EMA investigators could improve on the design and reporting of their studies.

2 Methods

To empirically describe and evaluate EMA study design in mood disorders research it is necessary to use the actual studies, rather than manuscripts generated from these studies, as the units of analysis. This presents a challenge because manuscripts and studies are not related on a one-to-one basis. That is, multiple manuscripts may stem

from one study or, alternatively, one manuscript may analyze data from multiple studies. We employed the following strategy to develop a data base with the study as the unit of analysis. First, we set inclusion and exclusion criteria for the types of studies that would be considered. Second, we used literature search engines to locate manuscripts that described studies meeting the inclusion and exclusion criteria. Third, we compared manuscripts to determine which stemmed from the same studies and which merged data from multiple studies. We contacted corresponding authors when questions or ambiguities arose. Fourth, we used the manuscripts and additional resources from authors (e.g., EMA study questionnaires and protocols) to enter the study-level data. We describe these steps in further detail below.

2.1 Study Inclusion and Exclusion Criteria

Study inclusion criteria were: 1) at least one subset of participants was clinically diagnosed with a mood disorder (BPD, DEP, or BD) and 2) an electronic ambulatory device, including but not limited to beepers, hand-held computers, cellular phones, and wristwatches, was used to capture self-report data at multiple time points. Self-report EMA may be either event-based (participant enters data before and/or after a prespecified event occurs), prompt-based (participant enters data when prompted by a technological device), or a combination of the two; however, the focus herein lies specifically in prompt-based EMA because it relies heavily on *a priori* decisions regarding sampling frequency. Thus, we excluded studies that did not include some type of prompt-based EMA. We also excluded EMA case studies because of our specific focus on the use of EMA to answer empirically-based research questions.

2.2 Search Strategy

We first aimed to identify all manuscripts arising from appropriate EMA studies by performing literature searches in PubMed, PsycINFO, and ProQuest (Dissertations and Theses) with the following keywords: *ambulatory assessment*, *ecological momentary assessment*, *experience sampling method*, *electronic diary*, *computer-assisted diary*, *electronic momentary assessment*, *ecological validity*, and *hand-held computer*. After removing duplicate references, we performed a computerized search of the resulting abstracts to narrow them down to those based on populations with mood disorders. Abstract search terms included *depression*, *depressive disorder*, *borderline*, *bipolar*, *mood disorder*, and *affective disorder*. All remaining abstracts were manually screened to further identify those which stemmed from studies that fit within our inclusion and exclusion criteria. The full text of each of the remaining manuscripts was then used to determine whether the study from which it arose would be considered appropriate for inclusion. Once the final subset of manuscripts was identified, the full text was again examined to determine which manuscripts stemmed from the same EMA study and which combined data from multiple EMA studies.

Figure 1 summarizes the search strategy and manuscript selection process. Table 1 lists the final 27 studies selected through this selection process. Because each of these 27 studies could generate multiple manuscripts, we refer to them in Table 1 by the by the

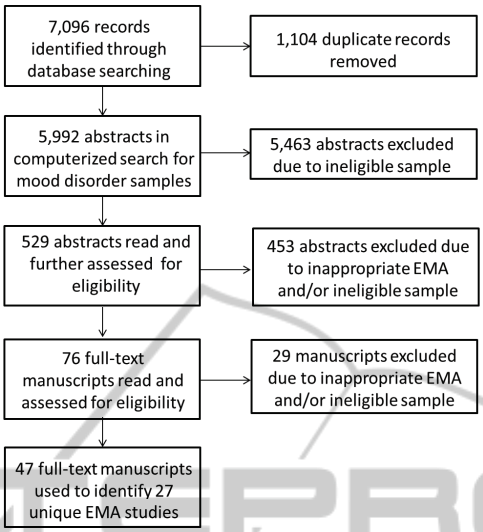


Fig. 1. Flow diagram for manuscript and study selection.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

first author and year of the earliest manuscript identified through the literature search. Other related manuscripts are displayed in the "References" column.

2.3 Data Collection

The manuscripts referenced in Table 1 and additional author resources (e.g, EMA questionnaires and study protocols) were used to develop a data base that included: 1) study design information, such as the sample size, duration of study, number prompts per day, number of questions per prompt, and the type of EMA device used, 2) demographic information for the samples used in each study, such as age and gender, 3) diagnostic groups studied, 4) justification of sampling design, and 5) compliance information, such as missing data and dropout percentages. When collecting the data from studies that also included a randomized trial component, we only included EMA data from the baseline weeks. This was done in an attempt to standardize the studies and also because treatment assignment may impact measures of compliance.

2.4 Data Analysis

We used descriptive statistics to summarize the 27 EMA studies with respect to sampling design and demographic and clinical characteristics of the participants (Aim 1). To explore investigators' rationale behind EMA study design selection (Aim 2) we first summarized the study design justifications provided in the associated manuscripts. Because only eight of the 27 studies actually provided this explicit justification (see Table 1), we used our observed data to further explore the rationale behind current EMA study design. This involved quantifying observed relationships among study design parameters (the number of days of EMA study, the number of prompts per day, and the number

Table 1. First author and year of the earliest manuscript identified with each study. All other related manuscripts are cited in the "References" column.

First Author (Year)	References	First Author (Year)	References
Armistead, M.S. (2010)	[16]	Husky, M.M. (2010)	[43]
Axelson, D.A. (2007)*	[17–21]	Links, P.S. (2007)*	[44–46]
Barge-Schaapveld (1995)	[22–25]	Mokros, H.B. (1993)	[47]
Ben-Zeev, D. (2009)	[26]	Myin-Germeys, I. (2003)	[48–50]
Ben-Zeev, D. (2010)	[27]	Peeters, F. (2003)	[51–54]
Biller, B.A. (2004)	[28]	Putnam, K.M. (2008)	[55]
Bower, B. (2010)*	[29, 30]	Stetler, C. (2004)*	[56]
Campbell, J.A. (1998)	[31]	Stetler, C. (2005)*	[57]
Conrad, A. (2008)	[32]	Stiglmayr, C.E. (2005)	[58]
Delespaul, P. (2002)	[33]	Stiglmayr, C.E. (2008)	[59]
Depp, C.A. (2010)*	[34]	Trull, T.J. (2008)	[60, 61]
Doyle, P.M. (2009)*	[35]	Wichers, M. (2010)	[62]
Ebner-Priemer, U.W. (2006)*	[14, 36–40]	Wolff, S. (2007)	[63]
Glaser, J.P. (2008)	[41, 42]		

*Reported rationale for study design

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

of questions per prompt) using scatter plots and Pearson product moment correlations. Because the distributions of these variables were highly skewed, we used the natural log transformation for all plots and calculations.

To investigate the relationships among study design features and compliance (Aim 3), we first needed to select a single compliance measure. After comparing various possibilities, we chose the percentage of unanswered prompts because it was frequently reported and also easily constructed from other types of reported compliance statistics. We calculated the percentage of unanswered prompts (P) as the number of unanswered prompts divided by the total number of possible prompts times 100. Some studies reported only P_1, the percentage of unanswered prompts based on a subset of $N_1 < N$ compliant participants with fewer than $X\%$ unanswered prompts. Hence, the percentage of unanswered prompts for the $N_2 = N - N_1$ participants, P_2, was unknown except for the fact that $X\% < P_2 \leq 100\%$. Because N_2 tended to be very small (e.g., one or two participants), we assumed that P_2 followed a uniform distribution and let $P_2 = .5 \times (100 - X)$. P was then calculated as a weighted average of the percentages of unanswered prompts prompts for the N_1 compliant and N_2 noncompliant participants, that is, $P = \frac{1}{N}(P_1 N_1 + P_2 N_2)$.

After calculating the percentage of unanswered prompts (P), we used scatter plots and Pearson product moment correlation coefficients to explore its relationships with various study design features. Specifically, we focused on the number of questions per prompt, the number of prompts per day, and the number of days of the EMA study. Because these study design features need to be carefully balanced to reduce participant burden, we also focused on their interactions: questions per day (questions per prompt $\times$ prompts per day), prompts per study (prompts per day $\times$ days of study), and questions per study (questions per prompt $\times$ prompts per day $\times$ days of study). Due to the highly skewed distributions of all variables involved, we used the natural logs of these variables in our plots and calculations.

3 Results

3.1 Aim 1: Summarize the Current State of EMA Research

Study design and demographic characteristics of the of the 27 EMA studies are summarized in Table 2. In general, study participants tended to be female and Caucasian, with a median age of 31. The study design characteristics selected by investigators (e.g., the number of questions per prompts, number of prompts per day, and number of days of EMA) varied widely across the 27 studies, as shown by the minimum and maximum scores in Table 2.

In addition to selecting the number of questions, prompts, and days of EMA, investigators must also choose a method for distributing these prompts throughout the study period. Within each day, the most common method for allocating prompts was random blocking (e.g., divide waking hours into 6 blocks and randomly sample once during each block); this method was used in 10 of the 27 studies (37%). Periodic sampling with random error (e.g., sample every hour plus or minus a ranodmly drawn number of minutes from a prespecified normal distribution) was the second most common method for allocating EMA prompts, seen in 8 studies (29.6%). Only five (18.5%) studies used random sampling (e.g., randomly select 10 times between the hours of 8:00 am to 10:00 pm) and only four (14.8%) studies used fixed time sampling (e.g., sample every hour on the hour).

The method for distributing prompts throughout the study period must also take into consideration the fact that participants are not able to answer prompts during sleep. Out of 26 studies for which this information was known, 70.1% (n=19) set a fixed daily interval during which prompts could occur (e.g., between the hours of 8:00 am to 10:00 pm for all participants). Other studies set *a priori* individualized sleep intervals tailed to each participant's needs (19.2%, n=5) or requested that the participant turn off the device during sleep (7.7%, n=2).

Investigators must also determine which technological device (e.g., hand-held computer, cellular phone, pager) to use to deliver each prompt. A hand-held computer, such as a "personal digital assistant" (PDA) was used in 59.3% of studies ($n = 16$). The next most frequently used technological device (37%, n=10) was a pager or wristwatch along with a paper-and-pencil diary. One study (3.7%) used a cellular phone.

Patients with depression (major depression, minor depression, or dysthymia) were included in eighteen studies (66.7%), patients with bipolar spectrum disorders were included in five studies (18.5%), and patients with borderline personality disorder were included in 9 (33.3%) studies. Other non-affective clinical groups (e.g., schizophrenia, panic disorder) were included in four (14.8%) studies. Healthy controls were used as a comparison group in 16 (59.3%) of the studies.

3.2 Aim 2: Explore Investigators' Rationale behind EMA Study Design Decisions

We first searched for explicit study design justifications in the manuscripts stemming from each study. Overall, we identified some type of sampling justification in eight of the 27 studies (29.64%). Two of these eight studies discussed rationale for the days on

Table 2. Demographic, clinical, and study design characteristics from 27 studies.

Characteristic	N Observed	Mean (SD)	Median	(Min, Max)
Demographic				
Average Age	26	31.69 (11.14)	31.04	(10.01, 62.45)
% Female	24	79.08 (16.54)	78.10	(50, 100)
% Caucasian	12	65.61 (23.72)	64.70	(33.33, 100)
% Higher Education	17*	56.81 (33.39)	64.50	(0, 100)
% Married or Cohabitating	15*	35.34 (32.00)	26.37	(0, 88.24)
% Employed (Full- or Part-Time)	12*	37.40 (17.77)	43.24	(0, 55.73)
Study Design				
Sample Size at Study Entry	27	78.67 (43.90)	73	(10, 164)
Days of EMA/ESM	27	9.33 (9.52)	6.79	(1, 42)
Prompts per Day	27	9.16 (9.63)	8	(1, 54)
Questions per Prompt	26	25.58 (16.91)	23	(1, 75)
Percentage of Missed Prompts	22	16.79 (10.40)	12.97	(3, 41.9)

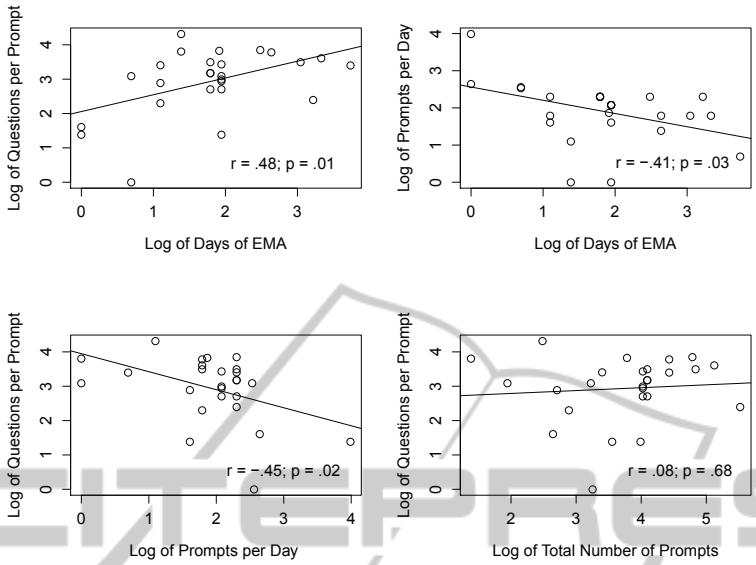
*Among 24 studies with an average participant age > 18

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

which EMA sampling occurred, citing that "the weekend was chosen because it is the time when adolescents have the greatest amount of free time and control over activities and companions" [21] and "the same weekdays (Tuesday-Thursday) were used to have a homogenous sample of days" [29].

The remaining six of the eight studies provided justification for the timing and/or frequency of prompts within each day. In two different studies, Stetler et al. [56, 57] sampled cortisol levels at the same time as the self-reported EMA. Specific sampling time intervals were chosen because they were previously found to "...adequately capture the diurnal pattern of cortisol secretion without placing undue burden on the participants" [56] and because they were able to "...capture the early morning peak that is part of the diurnal pattern of cortisol secretion" [57]. Ebner-Priemer and Sawitski [14] emphasized that "the temporal dynamics of emotional-cognitive processes are largely unknown", and thus, their study employed multiple sampling frequencies to investigate this question. Depp et al. [34] cited the "need to balance between 'coverage' of affective experiences and subject burden." Doyle [35] simultaneously employed three different types of recording procedures "to capture mood ratings in close proximity to the behaviors and events of interest...". Links [44] stated that "random times were used to approximate the daily range of a participant's affective intensity within the context and flow of the participant's daily experience."

Because there were only eight studies for which an explicit sampling design rationale was found, we also explored the observed relationships among the number of days of EMA, the number of prompts per day, and the number of questions per prompt. Because the study design variables were highly skewed, Figure 2 displays the associations among the log-transformed study design variables (henceforth, the reader may assume that all variables discussed are logged transformed). There was a strong negative association between the number of questions per prompt and the number of prompts per day ($r = -.45, p = .02$). Similarly, there was a strong negative association between the number of prompts per day and the number of days of EMA ($r = -.41, p = .03$). There



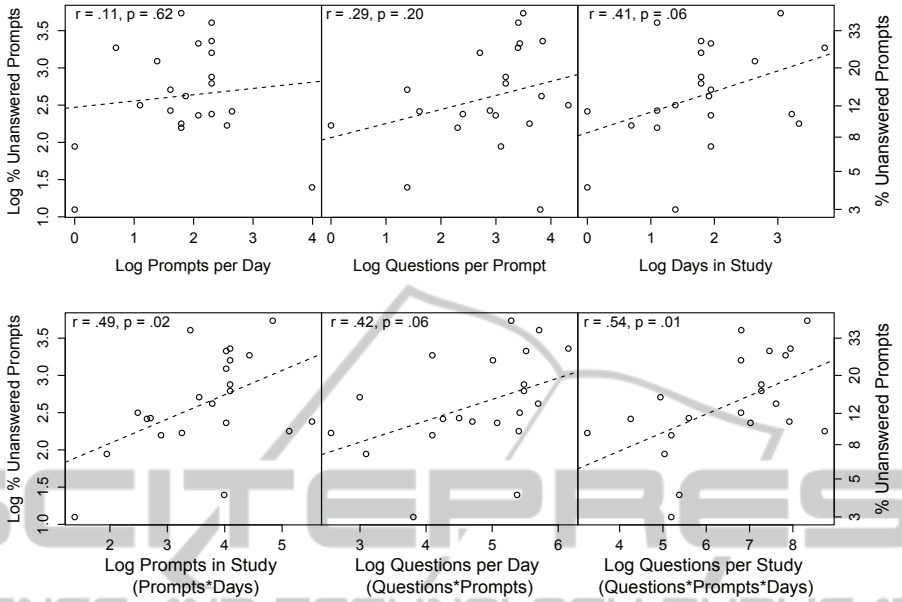
SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

Fig. 2. Scatter plots with least-squares regression lines displaying relationships among the log-transformed number of questions, number of prompts, and number of days of EMA. Pearson product moment correlation coefficients (r) and associated p-values are also displayed.

was a strong positive association between the number of questions per prompt and the number of days of EMA ($r = .48, p = .01$). The positive association may reflect the fact that more days of EMA leads to fewer prompts per day, which may in turn lead to more questions asked at each prompt. There was no significant association between the number of questions per prompt and the total number of prompts over the entire EMA study.

3.3 Aim 3: Investigate Relationships among Study Design Features and Compliance.

Figure 3 illustrates the relationships among the study design features and the percentage of unanswered prompts. The number of questions per prompt and the number of prompts per day were not significantly associated with the the percentage of unanswered prompts. After removing the high but valid outlier in the number of prompts per day (estimated 54 prompts per day [36]), there was a strong positive relationship between the percentage of unanswered prompts and the number of prompts per day (r = .44, p=0.05); however, the removal of this outlier only highlights the potential leverage of the low outliers (1 prompt per day [56, 57]). There were strong and borderline-significant positive relationships between the percentage of unanswered prompts and both the days of EMA and questions per day (questions $\times$ prompts). There were strong and significant positive relationships between the percentage of unanswered prompts and both the total number of prompts (prompts $\times$ days) and the total number of questions (questions $\times$ prompts $\times$ days).



SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

Fig. 3. Scatter plots with least-squares regression lines displaying relationships between the log-transformed study design features and the log percentage of unanswered prompts. Pearson product moment correlation coefficients (r) and associated p-values are also displayed.

4 Discussion

The overall goal of this manuscript is to provide researchers with a comprehensive summary and analysis of current EMA study design methods used in mood disorders research. To attain this goal, we summarized the current state of EMA study design used in mood disorders research, explored the rationale behind the selection of EMA study design features, and investigated the impact of study design on participant compliance.

The results of our comprehensive summary highlight the wide variety of EMA study design methods that are currently used in mood disorders research. This is particularly true regarding to the number of questions per prompt, the number of prompts per day, and the number of days of EMA. To a large degree, this variability may be explained by the fact that each study has its own unique goals, participants, and restrictions; thus, each study's design must be tailored to meet its specific needs. However, insight into this process was only provided to the reader in 8 of the 27 studies we investigated. This lack of detail may pose challenges for newer investigators who may want to enter into EMA research but do not have the experience to make these decisions on their own. It may also lead more experienced EMA researchers to use only one familiar study design, rather than tailoring each study design to match the temporal dynamics of the underlying process of interest.

The lack of explicit detail regarding study design rationale makes it difficult to explore which considerations are most important for EMA investigators. However, the observed negative associations between the number of prompts per day and both the

days of EMA and the questions per prompt suggests that investigators do indeed consider the need to balance these study design features, presumably to reduce participant burden.

Our investigation of the relationships among study design features and participant compliance showed that the number of study days may have a bigger impact compliance than either the number of prompts per day or the number of questions per prompt. Not surprisingly, the strongest observed relationship showed a positive association between the total number of questions asked during the study (questions $\times$ prompts $\times$ days) and the percentage of unanswered prompts. Although these relationships may not be unexpected, their quantification is an important first step towards developing a set of study design guidelines for future EMA research.

Although care was taken to avoid potential biases and when developing the data base, analyzing the data, and interpreting the results, there are limitations that must be considered. One such limitation stems from the fact that our primary unit of analysis was the study. As such, features of each study often had to be identified through manuscripts and by discussion with the actual study investigators. When investigators could not be reached, the full scope of the original EMA study was not always evident; this could lead to errors in the data base due to a lack of full study descriptions in these manuscripts. However, the fact that these study design features were not immediately evident from the manuscripts highlights the need for a more standardized approach to developing and reporting EMA studies.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

4.1 Future Directions

When designing EMA studies, two critical considerations are to obtain quality EMA data at the frequency necessary for modeling underlying dynamic processes and to use a sampling scheme that will not result in undue participant burden [14]. These considerations are often at odds with one another, and thus, pose challenges for EMA researchers. Furthermore, the "underlying temporal dynamics" of mood disorders are still largely unknown [14], making it difficult to select the appropriate sampling frequency even without participant constraints.

To overcome these challenges, it will be important to address three areas of EMA research: 1) monitor and standardize current sampling methods 2) evaluate whether current EMA sampling methods work actually work as intended (i.e., capture true underlying processes), and 3) develop new EMA sampling methods that can balance the need to effectively capture these processes while considering participant burden. The research presented herein is aimed at addressing the first area of research. We are currently working to address areas two and three so that future EMA investigators can have the tools they need to answer the critical EMA-related questions, both in the field of mood disorders specifically and in the broader fields of mental and physical health research.

References

1. Stone, A. A., Shiffman, S., Ecological Momentary Assessment in Behavioral Medicine. Annals of Behavioral Medicine 16 (1994) 199–202.

2. Shiffman, S., Stone, A. A., Hufford, M. R.: Ecological momentary assessment. Annual Review of Clinical Psychology 4 (2008) 1–32.
3. Solhan, M. B., Trull, T. J., Jahng, S., Wood, P. K.: Clinical assessment of affective instability: comparing EMA indices, questionnaire reports, and retrospective recall. Psychological Assessment. 21 (2006) 425-436
4. American Psychiatric Association, A. P., Diagnostic and Statistical Manual of Mental Disorders IV. 1994, Washington, D.C.: Author
5. Perlis, R. H.: Misdiagnosis of bipolar disorder. The American Journal of Managed Care 11 (2005) S271–S274
6. Zimmerman, M., Ruggero, C. J., Chelminski, I., Young, D.: Clinical characteristics of depression outpatients previously overdiagnosed with bipolar disorder. Comprehensive Psychiatry 51 (2010) 99–105
7. Zimmerman, M., Galione, J. N., Ruggero, C. J., Chelminski, I., Dalrymple, K., Young, D.: Overdiagnosis of bipolar disorder and disability payments. The Journal of Nervous and Mental Disease 198 (2010) 452–454
8. Hirschfeld, R. M. A., Lewis, L., Vorknik, L.A.: Perceptions and impact of bipolar disorder: How far have we really come? Results of the national depressive and manic-depressive association 2000 survey of individuals with bipolar disorder. Journal of Clinical Psychiatry 64 (2003) 161–174
9. Blacker, D., Tsuang, M. D., Contested boundaries of bipolar disorder and the limits of categorical diagnosis in psychiatry. American Journal of Psychiatry 149 (1992) 1473–1483
10. Csikszentmihalyi, M., Larson, R.: Validity and Reliability of the Experience-Sampling Method. Journal of Nervous and Mental Disease 175 (1987) 526–536
11. Bolger, N., Davis, A., Rafaeli, E.: Diary Methods: Capturing Life as it is Lived. Annual Review of Psychology 54 (2003) 579–616
12. Ebner-Priemer, U. W., Trull, T. J.: Ecological Momentary Assessment of Mood Disorders and Mood Dysregulation. Psychological Assessment 21 (2009) 463–475
13. Barrett L. S., Barrett, D. J.: An Introduction to Computerized Experience Sampling in Psychology. Social Science Computer Review 19 (2001) 175–185
14. Ebner-Priemer, U. W., Sawitzki, G.: Ambulatory Assessment of Affective Instability in Borderline Personality Disorder: The Effect of Sampling Frequency. European Journal of Psychological Assessment 23 (2007) 238–247.
15. Capturing Momentary, Self-Report Data: A proposal for reporting guidelines. Annals of Behavioral Medicine 24 (2002) 236–243
16. Armistead, M. S., Looking for Bipolar Spectrum Psychopathology: Identification and Expression in Daily Life. Unpublished thesis, University of North Carolina at Greensboro (2010)
17. Axelson D. A., Bertocci, M. A., Lewin, D. S., Trubnick, L. S., Birmaher, B., Williamson, D. E., Ryan, N. D., Dahl, R. E.: Measuring Mood and Complex Behavior in Natural Environments: Use of Ecological Momentary Assessment in Pediatric Affective Disorders. Journal of Child and Adolescent Psychopharmacology 13 (2003) 253–266
18. Silk, J. S., Dahl, R. E., Ryan, N. D., Forbes, F. E., Axelson, D. A., Birmaher, B., Siegle, G. J.: Pupillary Reactivity to Emotional Information in Child and Adolescent Depression: Links to Clinical and Ecological Measures. American Journal of Psychiatry. 164 (2007) 1873–1880
19. Whalen, D. J., Silk, J. S., Semel, M., Forbes, E. E., Ryan, N. D., Axelson, D. A., Birmaher, B., Dahl, R. E.: Caffeine Consumption, Sleep, and Affect in Natural Environments of Depressed Youth and Healthy Controls. Journal of Pediatric Psychology 33 (2008) 258–367
20. Forbes, E. E., Hariri, A. R., Martin, S. L., Silk, J. S., Moyles, D. L., Fisher, P. M., Brown, S. M., Ryan, N. D., Birmaher, B., Axelson, D. A., Dahl, R. E.: Altered Striatal Activation Predicting Real-World Positive Affect in Adolescent Major Depressive Disorder. American Journal of Psychiatry 166 (2009) 64–73

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

21. Bertocci, M. A.: Media Use by Children and Adolescents with and without Depression: Going it Alone? Unpublished thesis, University of Pittsburgh (2010)
22. Barge-Schaapveld D. Q. C. M., Nicolson, N. A., van der Hoop, R. G., deVries, M. W.: Changes in Daily Life Experience Associated with Clinical Improvement in Depression. Journal of Affective Disorders 34 (1995) 139–154
23. Barge-Schaapveld D. Q. C. M., Nicolson, N. A., Berkhof, J., deVries M. W.: Quality of Life in Depression: Daily Life Determinants and Variability. Psychiatry Research 88 (1999) 173–189
24. Barge-Schaapveld D. Q. C. M., Nicolson, N. A.: Effects of Antidepressant Treatment on the Quality of Life: An Experience Sampling Study. Journal of Clinical Psychiatry 63 (2002) 477–485
25. Geschwind, N., Nicolson, N. A., Peeters F., van Os, J., Barge-Schaapveld D., Wichers, M.: Early Improvement in Positive Rather than Negative Emotion Predicts Remission from Depression after Pharmacotherapy. European Neuropsychopharmacology 21 (2011) 241–247
26. Ben-Zeev, D., Young M. A., Madsen, J. W.: Retrospective Recall of Affect in Clinically Depressed Individuals and Controls. Cognition and Emotion 23 (2009) 1021–1040
27. Ben-Zeev, D., Young, M. A.: Accuracy of Depressed Patients' and Healthy Controls' Retrospective Symptom Reports: An Experience Sampling Study. The Journal of Nervous and Mental Disease 198 280–285
28. Biller, B. A.: Examining the Utility of Ecological Momentary Assessment with Individual Diagnosed with Depressive Disorder. Unpublished thesis, Pace University (2004)
29. Bower, B., Bylsma, L. M., Morris, B. H., Rottenberg, J.: Poor Reported Sleep Quality Predicts Low Positive Affect in Daily Life Among Healthy and Mood-Disordered Persons. Journal of Sleep Research 19 (2010) 323–332
30. Bylsma, L. M., Taylor-Clift, A., Rottenberg, J.: Emotional Reactivity to Daily Events in Major and Minor Depression. Journal of Abnormal Psychology 120 (2011) 155–167
31. Campbell, J. A.: Caregivers' Affective Attunement and Preadolescent Depression: An Ecological Approach. Unpublished thesis, Chicago School of Professional Psychology (1998)
32. Conrad, A., Wilhelm, F. H., Roth W. T., Spiegel, D., Taylor, C.B.: Circadian affective, cardiopulmonary, and cortisol variability in depressed and nondepressed individuals at risk for cardiovascular disease. Journal of Psychiatric Research 42 (2008) 769–777
33. Delespaul, P., deVries, M., van Os, J.: Determinants of Occurrence and Recovery from Hallucinations in Daily Life. Social Psychiatry and Psychiatric Epidemiology 37 (2002) 97–104.
34. Depp, C. A., Mausbach, B., Granholm, E., Cardenas, V., Ben-Zeev, D., Patterson, T.L., Lebowitz, B.D., Jeste, D.V.: Mobile Interventions for Severe Mental Illness: Design and Preliminary Data from Three Approaches. The Journal of Nervous and Mental Disease 198 (2010) 715–721
35. Doyle, P. M.: Mood Variability and Symptomatic Expression in Women with Bulimia Nervosa and Comorbid Borderline Personality Disorder. Unpublished thesis, Northwester University (2009)
36. Ebner-Priemer U. W., Kuo, J., Welch, S. S., Thielgen, T., Witte, S., Bohus, M., Linehan, M. M.: A Valence-Dependent Group-Specific Recall Bias of Retrospective Self-Reports: A Study of Borderline Personality Disorder in Everyday Life. The Journal of Nervous and Mental Disease 194 (2006) 774–779
37. Ebner-Priemer, U. W., Welch, S. S., Grossman, P., Reisch, T., Linehan, M. M., Bohus, M.: Psychophysiological Ambulatory Assessment of Affective Dysregulation in Borderline Personality Disorder. Psychiatry Research 150 (2007) 265–275
38. Ebner-Priemer, U. W., Juo, J., Kleindienst, N., Welch, S. S., Reisch, T., Reinhard, I., Lieb, K., Linehan, M. M., Bohus, M.: State Affective Instability in Borderline Personality Disorder Assessed by Ambulatory Monitoring. Psychological Medicine 37 (2007) 961–970

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

39. Reisch T., Ebner-Priemer U. W., Tschacher, W., Bohus, M., Linehan, M. M.: Sequences of Emotions in Patients with Borderline Personality Disorder. Acta Psychiatrica Scandinavica 118 (2008) 42–48.
40. Ebner-Priemer, U. W., Kuo, J., Schlotz, W., Kleindienst, N., Rosenthal, M. Z., Detterer, L., Linehan, M. M., Bohus, M.: Distress and Affective Dysregulation in Patients with Borderline Personality Disorder: A Psychophysiological Ambulatory Monitoring Study. The Journal of Nervous and Mental Disease 196 (2008) 314–320
41. Glaser, J.-P., van Os, J., Mengelers, R., Myin-Germeys, I.: A Momentary Assessment Study of the Reputed Emotional Phenotype Associated with Borderline Personality Disorder. Psychological Medicine 38 (2008) 1231–1239
42. Glaser, J.-P., van Os, J., Thewissen, V., Myin-Germeys, I.: Psychotic Reactivity in Borderline Personality Disorder. Acta Psychiatrica Scandinavica 121 (2010) 125–134
43. Husky, M. M., Gindre, C., Mazure, C. M., Brebant, C., Nolen-Hoeksema, S., Sanacora, G., Swendsen, J.: Computerized Ambulatory Monitoring in Mood Disorders: Feasibility, Compliance, and Reactivity. Psychiatry Research 178 (2010) 440–442
44. Links, P. S., Eynan, R., Heisel, M. J., Barr, A., Korzekwa, M., McMain, S., Ball, J. S.: Affective Instability and Suicidal Ideation and Behavior in Patients with Borderline Personality Disorder. Journal of Personality Disorders 21 (2007) 72–86
45. Links, P. S., Eynan, R., Heisel, M., Nisenbaum, R.: Elements of Affective Instability Associated with Suicidal Behavior in Patients with Borderline Personality Disorder. Canadian Journal of Psychiatry 53 (2008) 112–116
46. Nisenbaum, R., Links, P.S., Eynan, R., Heisel, M.J.: Variability and Predictors of Negative Mood Intensity in Patients with Borderline Personality Disorder and Recurrent Suicidal Behavior: Multilevel Analyses Applied to Experience Sampling Methodology. Journal of Abnormal Psychology 119 (2010) 433–439
47. Mokros, H. B.: Communication and Psychiatric Diagnosis: Tales of Depressive Moods from Two Contexts. Health Communication 5 (1993) 113–127
48. Myin-Germeys, I., Peeters, F., Havermans, R., Nicolson, N. A., deVries, M. W., Delespaul, P., van Os, J.: Emotional Reactivity to Daily Life Stress in Psychosis and Affective Disorder: An Experience Sampling Study. Acta Psychiatrica Scandinavica 107 (2003) 124–131
49. Havermans, R., Nicolson, N. A., deVries, M. W.: Daily Hassles, Uplifts, and Time Use in Individuals with Bipolar Disorder in Remission. The Journal of Nervous and Mental Disease 195 745–751
50. Havermans, R., Nicolson, N. A., Berkhof, J., deVries, M. W.: Mood Reactivity to Daily Events in Patients with Remitted Bipolar Disorder. Psychiatry Research 179 47–52
51. Peeters, F., Nicolson, N. A., Berkhof, J., Delespaul, P., deVries, M.: Effects of Daily Events on Mood States in Major Depressive Disorder. Journal of Abnormal Psychiatry 112 (2003) 203–211
52. Peeters, F., Nicolson, N. A., Berkhof, J.: Cortisol Responses to Daily Events in Major Depressive Disorder. Psychosomatic Medicine 65(2003) 836–841
53. Peeters, F., Berkhof, J., Delespaul, P., Rottenberg, J., Nicolson, N. A.: Diurnal Mood Variation in Major Depressive Disorder. Emotion 6 (2006) 383–391
54. Peeters, F., Berkhof, J., Rottenberg, J., Nicolson, N. A.: Ambulatory Emotional Reactivity to Negative Daily Life Events Predicts Remission from Major Depressive Disorder. Behavior Research and Therapy 48 (2010) 754–760
55. Putnam, K. M., McSweeney, L. B.: Depressive Symptoms and Baseline Prefrontal EEG Alpha Activity: A Study Utilizing Ecological Momentary Assessment. Biological Psychiatry 77 (2008) 237-240
56. Stetler, C., Dickerson, S. S., Miller, G. E.: Uncoupling of Social Zeitgebers and Diurnal Cortisol Secretion in Clinical Depression. Psychoneuroendocrinology 29 (2004) 1250–1259

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

57. Stetler, C., Miller, G. E.: Blunted Cortisol Response to Awakening in Mild to Moderate Depression: Regulatory Influences of Sleep Patterns and Social Contexts. Journal of Abnormal Psychology 114 (2005) 697–705
58. Stiglmayr, C. E., Grathwol, T., Linehan, M. M., Ihorst, G., Fahrenberg, J., Bohus, M.: Aversive Tension in Patients with Borderline Personality Disorder: A Computer-Based Controlled Field Study. Acta Psychiatrica Scandinavica 111 (2005) 372–379
59. Stiglmayr, C. E., Ebner-Priemer, U. W., Bretz, J., Behm, R., Mohse, M., Lammer, C.-H., Anghelescu, I.-G., Schmahl, C., Schlotz, W., Kleindienst, N., Bohus, M.,: Dissociative Symptoms are Positively Related to Stress in Borderline Personality Disorder. Acta Psychiatrica Scandinavica 117 (2008) 139–147
60. Trull, T. J., Watson, D., Tragessser, S. L., Jahng, S., Wood, P. K., Piasecki, T.M: Affective Instability: Measuring a Core Feature of Borderline Personality Disorder with Ecological Momentary Assessment. Journal of Abnormal Psychology 117 (2008) 647–661
61. Jahng, S., Wood, P. K., Trull, T. J.: Analysis of Affective Instability in Ecological Momentary Assessment: Indices Using Successive Difference and Group Comparison via Multilevel Modeling. Psychological Methods 13 (2008) 354–375
62. Wichers, M. H., Peeters, F., Geschwind, N., Jacobs, N., Simons, C. J. P., Derom, C., Thiery, E., Delespaul, P. H., van Os, J.: Unveiling Patterns of Affective Responses in Daily Life may Improve Outcome Prediction in Depression: A Momentary Assessment Study. Journal of Affective Disorders 124 (2010) 191–195
63. Wolff, S., Stiglmayr, C., Bretz, H. J., Lammers, C.-H., Auckenthaler, A.: Emotion Identification and Tension in Female Patients with Borderline Personality Disorder. British Journal of Clinical Psychology 46 (2007)347–360

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS