Missed Beeps and Missing Data Dispositional and Situational Predictors of Nonresponse in Experience Sampling Research

By: Paul J. Silvia, Thomas R. Kwapil, Kari M. Eddington, Leslie H. Brown

Silvia, P.J., Kwapil, T.R., Eddington, K.M., & Brown, L.H. (2013). Missed beeps and missing data: Dispositional and situational predictors of non-response in experience sampling research. *Social Science Computer Review, 31(4),* 471-481. doi: 10.1177/0894439313479902

Made available courtesy of Sage Publications: http://dx.doi.org/10.1177/0894439313479902

Abstract:

Experience sampling research measures people's thoughts, feelings, and actions in their everyday lives by repeatedly administering brief questionnaires throughout the day. Nonresponse—failing to respond to these daily life questionnaires—has been a vexing source of missing data. The present research examined person-level, day-level, and signal-level predictors of nonresponse. We analyzed data from a sample of 450 young adults who were signaled 8 times a day for 7 days. At the person level, nonresponse was higher for men and for people high in positive schizotypy, depressive symptoms, and hypomania. At the day level, nonresponse increased over the first few days of the study and then declined toward the end. At the signal level, time of day strongly predicted nonresponse. Lagged signal-level analyses examined how emotions and experiences at a prior signal prospectively predicted the likelihood of ignoring the next signal. Only one variable—feelings of enthusiasm—had a significant lagged effect, which suggests that within-day experiences are not major sources of nonresponse. For the most part, the day of the study and the time of day had the most salient effects. Understanding the predictors of missing data allows researchers to implement methods to increase compliance and to handle missing data more effectively by including predictors of nonresponse.

Keywords: experience sampling method | ecological daily assessment | missing data | response rates | compliance

Article:

Missing data is one of the most vexing aspects of experience sampling research. Experience sampling studies seek to understand everyday experience by repeatedly sampling thoughts, feelings, and behaviors. It is a powerful assessment tool that allows investigators to examine psychological phenomena outside of the artificial constraints of the laboratory and the clinic. In modern computerized experience sampling designs, participants are first ''beeped'' by a device—a beeper, personal digital assistant (PDA), phone call, or text message sent to a smartphone—and then complete a brief questionnaire about what they are doing, thinking, and feeling at the moment (Conner, Tennen, Fleeson, & Barrett, 2009; Hektner, Schmidt, &

Csikszentmihalyi, 2007). But participants often ignore the beep—they are in their natural environments, not the constrained context of a research lab. Researchers have little direct influence in the moment over whether participants respond to a signal, although they can include procedures and contingencies in the study design to maximize response rates.

Experience sampling data have a distinctive pattern of missingness. At the within-person level—the questions asked many times per day—there is usually notable ‘‘beep-wise’’ missingness. The missingness is beep-wise because the data are rarely partial for a given beep: People typically either ignore the signal entirely (causing all items to be missing for that questionnaire) or they respond to all the items. Partial response occasionally happens—people may get interrupted, lose interest, or experience a technical problem—but the biggest source of missing data by far is not responding to a signal. At the between-person level—such as demographic characteristics and personality traits—there is usually little missing data: Such information is usually gained in a single session in the laboratory or the clinic at the start of the study (Conner & Lehman, 2012; Hektner et al., 2007).

When do people respond and when do people ignore a signal? Examining nonresponse is critical for experience sampling research. Understanding nonresponse is the first step in preventing and minimizing it. For example, if certain traits predict poorer compliance then reminders and follow-up messages can be targeted toward the people who are least likely to respond. Furthermore, understanding nonresponse enables researchers to evaluate the assumptions of statistical methods for handling missing scores. Maximum likelihood (ML) methods effectively estimate model parameters provided certain assumptions are met (Graham, 2009; McKnight, McKnight, Sidani, & Figueredo, 2007). If predictors of missingness are assessed, then they can be used to improve the performance of missing data analyses (Enders, 2010).

Because of the importance of understanding nonresponse, an emerging literature has begun to evaluate when people do not respond to experience sampling signals. In one project (Messiah, Grondin, & Encrenaz, 2011), 224 French college students were signaled on a palmtop computer 5 times a day for 7 days. At the between-person level, people missed more signals if they were male, a polydrug user, and higher in the novelty-seeking and persistence dimensions of temperament (Cloninger, Svrakic, & Przybeck, 1993). At the within-person level, people were more likely to skip a signal early in the day and in the middle of the weeklong study. In another project (Courvoisier, Eid, & Lischetzke, 2012), 305 Swiss adults received six cell phone calls a day for 7 days. At the between person level, people were more likely to respond if they had a college degree and if their daily mood was relatively calm and awake; none of the Big Five personality factors had a significant effect. At the within-person level, people were more likely to skip a signal early in the day and later in the week. Taken together, a few themes emerged from these studies. Some dispositional features—such as gender, educational level, and individual differences—predict compliance. The largest effects in both studies, however, were for within-person factors, particularly time of day and the day of the study.

The Present Research

The present research extends and expands the nascent literature on predictors of compliance in experience sampling designs. As in past research, we examined aspects of people, days, and signals that predicted whether participants responded to or ignored the beep. Our analysis extends past work in several ways. First, our research includes a wide range of person characteristics that have not yet been considered. Past work has examined the influence of dimensions of temperament (Messiah et al., 2011) and the Big Five factors (Courvoisier et al., 2012). In the present study, we included a broad range of individual differences related to psychological functioning, such as the variation in symptoms related to depression, anxiety, social anxiety, hypomania, schizotypy, and attention deficit/hyperactivity disorder (ADHD). Because of the wide interest in experience sampling methods with both clinical and nonclinical samples (aan het Rot, Hogenelst, & Schoevers, 2012; Oorschot, Kwapil, Delespaul, & Myin-Germeys, 2009; Trull & Ebner-Priemer, 2013), our research focused on understanding how symptom dimensions affect nonresponse.

Second, as in past work, we examined how aspects of days predict nonresponse, such as the time of day and the day of the study. In an important innovation, however, we used lagged predictors to gain some insight into experiential influences on compliance. For example, people's emotional states at one beep can be used to predict whether they responded to the next beep. It is hard to say if being happy, anxious, or tired makes people more likely to ignore a beep—if people do not respond, their scores are missing. But by using lagged scores—people's scores from the prior signal, if they responded to it—we can gain some information about how aspects of daily experience prospectively predict the likelihood of responding. We evaluated how a range of emotional states (feeling happy, relaxed, anxious, enthusiastic, and sad) and experiences (liking what one is doing, feeling tired, and being alone) at the prior beep predict the probability of ignoring the next beep.

Method

Participants

The participants were 450 students (334 women, 116 men) at the University of North Carolina at Greensboro who volunteered to take part and received credit toward a research option in a psychology class. The sample was primarily Caucasian (70%) and African American (26%) young adults (age M = 19.94, standard deviation [SD] = 3.76).

Procedure

The data were collected as part of a broader program of research on social and emotional behavior in daily life (Brown, Silvia, Myin-Germeys, & Kwapil, 2007; Brown, Strauman, Barrantes-Vidal, Silvia, & Kwapil, 2011; Burgin et al., 2012; Knouse et al., 2008; Kwapil, Brown, Silvia, Myin-Germeys, & Barrantes-Vidal, 2012; Kwapil et al., 2009). We pooled the data across the series of studies to gain a large sample with a diverse set of potential predictors of nonresponse.

In each study, people first took part in an hour-long laboratory session at which they provided informed consent, completed the measures of between-person variables, and learned how to operate the PDAs. People were then signaled 8 times a day for 7 days during the hours of 12 noon to 12 midnight, a period during which most American college students are awake and active. The 12-hr period was carved into eight 90-min blocks. People received one signal during each block, but the exact time of the signal within each block was determined randomly. The PDA—a Palm Pilot running iESP software (Intel Corporation, 2004)—signaled the participants, administered the questionnaires, and recorded and time stamped the responses. People had 5 min to respond to the signal and begin the questionnaire, which was roughly 30 items long, depending on item branching. The PDA deactivated after 5 min if people did not respond, which prevented them from going back to complete missed signals at later time points. As a result, there is no ambiguity about which signals were completed and which ones were missed. Participants met with the researchers twice during the 7 days to download their data from the PDA, which minimizes data loss and increases compliance (Barrett & Barrett, 2001). To further increase compliance, we created a drawing for a $100 gift card, and participants learned that they would be entered into the drawing if they responded to at least 70% of the signals.

Table 1. Effects of Between-Person Factors on Nonresponse.

Model and Predictors	b	SE	p	M (SD)	Level 2 n
1. Age	–.028	.021	.181	19.94 (3.76)	447
1. Gender	–.199	.098	.042	1.74 (.44)	450
2. Positive schizotypy	.112	.044	.011	0 (1)	414
2. Negative schizotypy	–.001	.044	.973	0 (1)	414
3. Anxiety (BAI)	.050	.078	.523	0 (1)	209
3. Depression (BDI)	.152	.074	.039	0 (1)	201
4. Social anxiety	–.025	.052	.633	0 (1)	271
5. Emotional expressivity	–.015	.041	.721	0 (1)	429
6. ADHD: inattentiveness	.055	.096	.568	0 (1)	207
6. ADHD: hyperactivity	.141	.089	.112	0 (1)	207
7. Hypomania	.249	.080	.002	0 (1)	130

Note. BAI ¼ Beck Anxiety Inventory; BDI ¼ Beck Depression Inventory; ADHD ¼ attention deficit/hyperactivity disorder;
SD ¼ standard deviation; SE ¼ standard error.
Predictors with the same model number appeared simultaneously in the regression model.

Within-Person Predictors. For each signal, a ‘‘missing’’ variable was created to indicate whether people responded to the beep (0 = response, 1 = missing). This binary variable was our central outcome. At the within-person level, we had several predictors of missingness. The same daily questionnaire was used in all the samples. For the present analyses, we focused on measures of emotional states and activities. At each beep, people described a range of emotional states: happiness (I feel happy right now), relaxation (I feel relaxed right now), enthusiasm (I feel enthusiastic right now), sadness (I feel sad right now), and anxiety (I feel anxious right now). We also asked items about whether people enjoyed their current activity (I like what I am doing right now) and their level of fatigue (I feel tired right now). Finally, we asked whether people were alone or with others (Are you alone at this time?). For most items, participants responded using a 7-point scale ranging from 1 (not at all) to 7 (very much). Being alone was scored 0 (with others) or 1 (alone).

Between-Person Variables. In addition to age and gender, we measured a wide range of individual differences relevant to mental health and psychological functioning. The person-level variables varied across the samples based on the emphasis of each subsample. As a result, the sample size for each between-person predictor varies. Table 1 lists the descriptive statistics and sample sizes for each between-person predictor. Schizotypy was assessed using the Wisconsin Schizotypy scales (Kwapil, Barrantes-Vidal, & Silvia, 2008). These scales can be combined to create scores for positive schizotypy (magical beliefs and perceptual aberrations) and negative schizotypy (anhedonic deficits for physical and social stimuli). Depressive symptoms were measured with the Beck Depression Inventory (Beck & Steer, 1987); anxiety symptoms were measured with the Beck Anxiety Inventory (Beck, Epstein, Brown, & Steer, 1988). Social anxiety was measured with two scales—the Social Phobia scale and Social Interaction Anxiety scale (Mattick & Clarke, 1998)—that were combined to create a global social anxiety score. ADHD symptoms were measured with the Attention Deficit/Hyperactivity Rating scale (DuPaul, Power, Anastopoulos, & Reid, 1998), which yields two subscores: inattentiveness and hyperactivity. Hypomania—a subclinical manifestation of manic symptoms such as grandiosity, high energy, and impulsivity—was measured with the Hypomanic Personality scale (Eckblad & Chapman, 1986). Finally, emotional expressivity—the tendency to express or inhibit overt displays of emotional states—was measured with the emotional expressivity scale (Kring, Smith, & Neale, 1994).

Results

Analytic Approach

The data were analyzed using multilevel models, which accommodate the nested data structures typical of experience sampling research (Heck & Thomas, 2009). We used ML estimation with robust standard errors (SEs), as implemented in Mplus 7. Our central outcome—whether or not people responded—is binary. For within-person predictors, the coefficients are thus logistic regression coefficients. For between-person predictors, the coefficients are linear: Mplus models the random intercepts as a continuous Level 2 latent variable with values that vary across people. All within-person predictors were group-mean centered (i.e., centered at each person's own mean); all between-person predictors were grand-mean centered (i.e., centered at the sample's overall mean), and all but age and gender were standardized.

Overall, people on average missed 30.1% of the beeps ($M=.301$, $SD=.168$). The variability around this average was wide: The percentage missed ranged from 0 to 84.7%, with a median of 27.0%.

Person-Level Predictors

What traits and demographic factors predicted compliance? We first conducted a series of models that estimated the effects of the between-person variables on nonresponse. Because the sample sizes for the between-person constructs varied, we ran separate models for each cluster of constructs. Table 1 displays the effects.

The demographic model examined age and gender as predictors. The effect of age was not significant—perhaps not surprising, given the narrow range of age in our sample—but the effect of gender was ($b = -.202$, $SE = .098$, $p = .039$). Men were significantly less likely to respond to a beep than women, a finding that has appeared in past research (Messiah et al., 2011).

Additional models examined individual differences. Table 1 displays the effects. To facilitate comparison across traits, we standardized their scores. The coefficients thus represent the change in the log odds per SD change in the predictor. Of the many traits we assessed, only a few—positive schizotypy, depression, and hypomania—significantly predicted nonresponse. As positive schizotypy, depression, and hypomania scores increased, people were less likely to respond to the signals. As an example, Figure 1 depicts the effect of positive schizotypy on the probability of responding to or missing to a beep. The remaining traits—negative schizotypy, anxiety, social anxiety, inattentiveness, hyperactivity, and emotional expressivity—did not predict nonresponse.

Day-Level Predictors

Were people less likely to respond on some days? We first examined how the day of the study predicted nonresponse. Days were a within-person predictor that ranged from 1 to 8, given that some participants were a day late in returning the PDA. We calculated both a linear and quadratic effect of day; the quadratic effect was computed by squaring the within-person centered linear effect. As Table 2 shows, both the linear and quadratic effects were significant (odds ratios [OR] = 1.095 and .970). Figure 2 depicts the proportion of missed beeps across the 7 primary days of the study. Nonresponse was lowest at the start of the study and then increased until the fifth day; the odds of nonresponse then declined as the study concluded.

Signal-Level Predictors

How did nonresponse vary within a day? Each person received eight signals during the 12-hr period of the study, so the time period (scored 1 through 8) was used to predict missingness. As before, both linear and quadratic effects were estimated. As Table 2 shows, both the linear and quadratic effects were significant (OR = 1.025 and .985). Figure 3 depicts the pattern of missed beeps. The odds of nonresponse followed an inverted-U function: People missed fewer beeps earlier in the day and later in the day. Nonresponse was greater than 30% for the three middle periods, which ranged from 4:30 p.m. to 9 p.m.

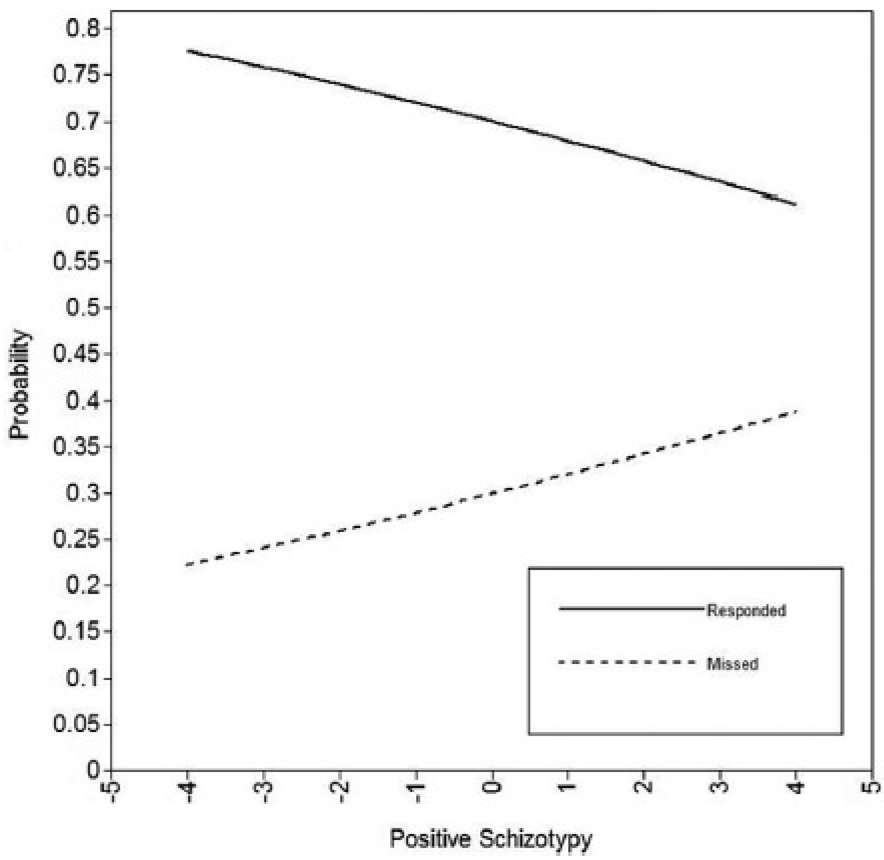

Figure 1. Effect of positive schizotypy on the predicted probability of responding to or missing a beep.

Table 2. Effects of Day and Time of Signal on Nonresponse.

	b	Standard Error (SE)	P	Odds Ratio
Day of study (Linear)	.091	.009	.001	1.095
Day of study (quadratic)	–.031	.004	.001	.970
Time of signal (linear)	.025	.008	.001	1.025
Time of signal (quadratic)	–.015	.003	.001	.985

Note. The coefficients are logistic regression coefficients.

Finally, was nonresponse predictable from people’s emotions and experiences at the prior beep? We included all eight emotions and experiences as lagged predictors of nonresponse. As Table 3 shows, only one predictor—feeling enthusiastic—was significant (OR = 1.050). As people reported higher feelings of enthusiasm at one signal, they were significantly less likely to respond to the following signal, perhaps because people were doing fun and engaging activities that interfered with responding to the following signal.

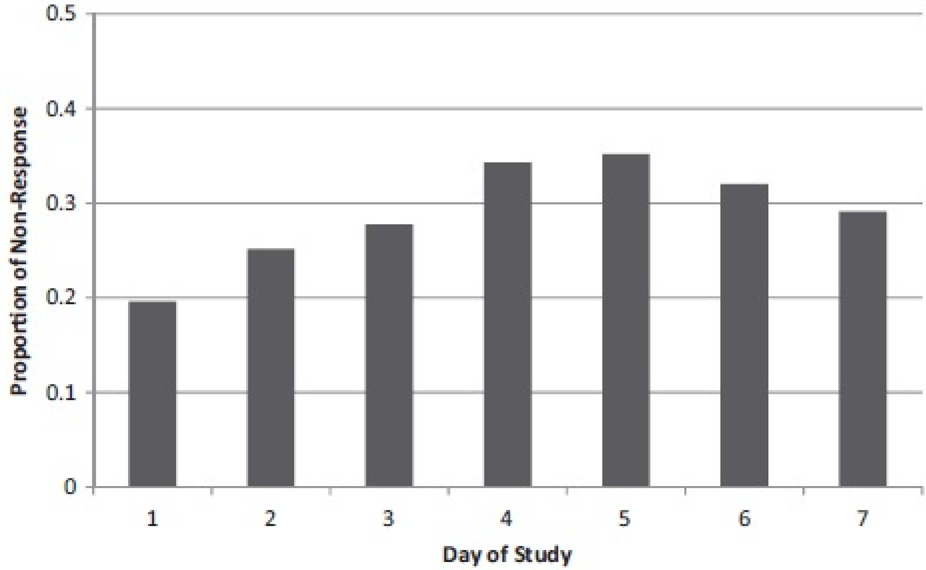

Figure 2. Proportion of missed signals across the 7 days of the study.

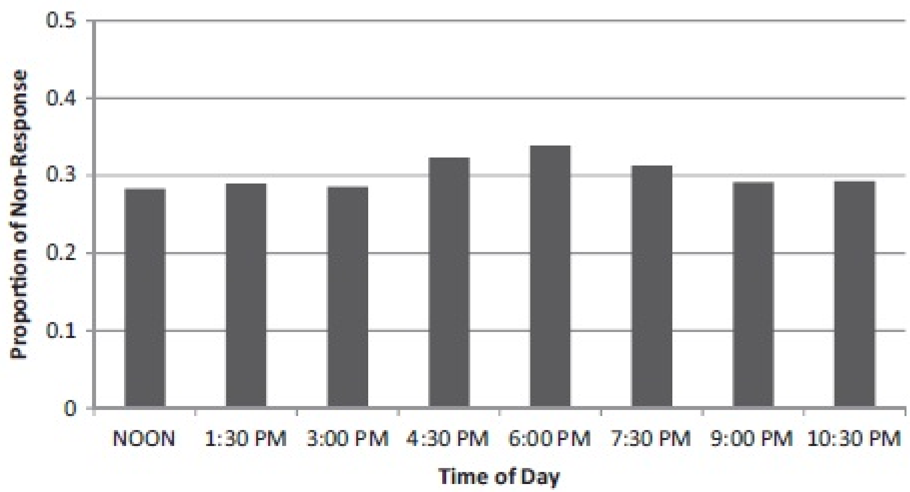

Figure 3. Proportion of missed signals across the eight daily signal periods.

Discussion

In experience sampling work, it is common to find beep-wise missing data rates of 15–35%. Why do people ignore the beeps? Understanding the causes of missing data allows researchers to try to prevent it (McKnight et al., 2007) and to handle it more effectively using modern missing-data methods (Enders, 2010). In the present work, we examined several classes of predictors of nonresponse: differences between people, between days of the study, and between time periods within a day.

Our findings replicated many of the findings from past work, which were conducted with samples from European countries. In particular, we found that most of the action was at the within-person level. The largest effects were for the day of the week and the time of day. Like past studies, we found that compliance drifted across the days of the study: It was high at first, declined across the days, and then increased somewhat as the study ended. In a prior study, compliance declined across the 7 days (Courvoisier et al., 2012). In that project, however, people received calls on their cell phones and did not have personal contact with a researcher at the study's end. In our project, the participants met the researcher at the end to return the PDA. Expecting to meet the researcher again should increase compliance (Barrett & Barrett, 2001; Burgin, Silvia, Eddington, & Kwapil, 2013; Hektner et al., 2007) and probably explains the uptick in responding at the end of our study.

We also found that time of day was a major predictor of nonresponse. In our study, nonresponse was an inverted U: people ignored more beeps during the middle periods. Past work found significant time-period effects as well: people were most likely to ignore the beeps early in the day (Courvoisier et al., 2012; Messiah et al., 2011). A notable difference of our project is that the beeps started at 12 noon, which was chosen as a realistic start time for American college students, a group known for staying up late and sleeping in. Past work started the signals earlier, such as after 8 a.m. (Messiah et al., 2011) and after 9 a.m. (Courvoisier et al., 2012). Nonresponse peaked in our sample at periods 4 (4:30 p.m. to 6 p.m.) and 5 (6 p.m. to 7:30 p.m.). We can only speculate, but we know that these are times when many students are driving home and working part-time jobs after classes, which are contexts that make it hard to respond to a PDA.

An innovative aspect of our analysis was examining within-day lagged predictors of nonresponse. We explored whether a range of emotions and experiences made people more or less likely to respond to an upcoming beep. Lagged effects are not ideal—in a perfect world, one would want to know people's emotional states at the time of the beep they ignored, not the prior period—but those scores are obviously missing. Moods and emotions can also be transient, which would reduce their effect on responses to an upcoming beep. But given the close proximity of the beeps in our study—one every 90-min period—lagged predictors offer some insight into how within-day experiences affect the likelihood of nonresponse. Only one variable—feelings of enthusiasm—prospectively predicted ignoring the next beep. This should be reassuring to researchers: For the most part, changes in people's daily experiences are not driving their inclination to respond to a signal.

Although the within-person factors had the biggest influences, some interesting effects were found for between-person factors. First, we found that men were less likely to respond, a finding that was significant in one prior study (Messiah et al., 2011) and in the same direction in another (Courvoisier et al., 2012). Second, we found that several individual differences—positive schizotypy, depression, and hypomania—predicted poorer compliance. Our study thus expands the set of factors known to affect nonresponse.

The effects found in our analyses were generally small. Most predictors did not significantly predict response rates, and among those that did, the effects were usually small in size. For the within-person predictors, the ORs were all close to 1. For the between-person predictors, the handful of significant predictors explained a modest percent of variance (the maximum estimated R^2 value, for hypomania, was 8.5%). This lends some useful perspective on the findings and should be reassuring to experience sampling researchers, who would prefer such effects to be small. Researchers should not casually brush off systematic predictors of missingness, but the degree of influence in the present sample was not severe.

When predictors of nonresponse are known, researchers can take action to reduce missing data. As McKnight, McKnight, Sidani, and Figueredo (2007) emphasize, the availability of statistical methods for handling missing data should not make researchers complacent about preventing and minimizing it. In experience sampling research, for example, researchers can increase compliance by building rapport with the participants, allowing people to call back within 5 min if they miss a signal, meeting with the participants mid-study to answer questions and provide feedback about compliance, choosing convenient devices, and reducing the number of items per signal (e.g., Burgin et al., 2013; Hektner et al., 2007; Silvia, Kwapil, Walsh, & Myin-Germeys, forthcoming). Some interesting options that have not been tried yet include asking people at the first completed beep after a missed one why the prior beep was missed, and having the device provide rewarding or encouraging feedback when people with relatively low compliance respond to a beep.

The present findings suggest that researchers should focus their prevention efforts on the time of day and the day of the study, which had the largest effects on nonresponse. Regarding time of day, researchers should thoughtfully choose times of day that are convenient for participants. For many young adults, for example, the early morning signals will always go unanswered, so starting signals at 7 a.m. will lead to higher nonresponse. In our recent and ongoing work that uses interactive voice response software to collect data via participants' cell phones, we have allowed participants to choose the 12-hr window in which they receive calls (Beaty et al., 2012). People choose widely variable windows (e.g., 7 a.m. to 7 p.m. for some, 1 p.m. to 1 a.m. for others), so providing this choice should reduce nonresponse by focusing the calls on each participant's window of activity.

Regarding days of the study, the decline in compliance observed in our research and past research (Broderick, Schwartz, Shiffman, Hufford, & Stone, 2003; Litcher-Kelly, Kellerman, Hanauer, & Stone, 2007) suggests the importance of contacting participants throughout the study, such as with brief e-mail contacts, short mid-week surveys, or face-to-face contacts with the researcher. If time and resources are tight, these methods can be targeted toward participants who are likely to respond less often (Messiah et al., 2011). For example, if researchers only have the time and personnel to contact half of the sample, they could focus their efforts on men, polydrug users, or other groups expected to show relatively poorer compliance.

Regarding statistical methods, ML methods for handling missing data assume that the data are missing completely at random or missing at random (MAR; missingness is related to a predictor variable). Meeting the MAR assumptions of ML methods requires researchers to measure the predictors and include them in the statistical model (Enders, 2010). Based on our findings and past work, researchers should consider including time of day, if nothing else, as a within-person predictor in their multilevel models. Time of day consistently emerges as a strong predictor of nonresponse, so including it in the statistical models should minimize some of the unwanted bias of missing observations.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article

References

aan het Rot, M., Hogenelst, K., & Schoevers, R. A. (2012). Mood disorders in everyday life: A systematic review of experience sampling and ecological momentary assessment studies. Clinical Psychology Review, 32, 510–523.

Barrett, L. F., & Barrett, D. J. (2001). An introduction to computerized experience sampling in psychology. Social Science Computer Review, 19, 175–185.

Beaty, R. E., Burgin, C. J., Nusbaum, E. C., Kwapil, T. R., Hodges, D. A., & Silvia, P. J. (2012). Music to the inner ears: The upside of involuntary musical imagery.

Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988). An inventory for measuring clinical anxiety: Psychometric properties. Journal of Consulting and Clinical Psychology, 56, 893–897.

Beck, A. T., & Steer, R. A. (1987). Manual for the revised Beck Depression Inventory. San Antonio, TX: The Psychological Corporation.

Broderick, J. E., Schwartz, J. E., Shiffman, S., Hufford, M. R., & Stone, A. A. (2003). Signaling does not adequately improve diary compliance. Annals of Behavioral Medicine, 26, 139–148.

Burgin, C. J., Brown, L. H., Royal, A., Silvia, P. J., Barrantes-Vidal, N., & Kwapil, T. R. (2012). Being with others and feeling happy: Emotional expressivity in everyday life. Personality and Individual Differences, 63, 185–190.

Burgin, C. J., Silvia, P. J., Eddington, K. M., & Kwapil, T. R. (2013). Palm or cell? Comparing personal digital assistants and cell phones for experience sampling research. Social Science Computer Review, 31, 244–251.

Brown, L. H., Silvia, P. J., Myin-Germeys, I., & Kwapil, T. R. (2007). When the need to belong goes wrong: The expression of social anhedonia and social anxiety in daily life. Psychological Science, 18, 778–782.

Brown, L. H., Strauman, T., Barrante-Vidal, N., Silvia, P. J., & Kwapil, T. R. (2011). An experience sampling study of depressive symptoms and their social context. Journal of Nervous and Mental Disease, 199, 403–409.

Cloninger, C. R., Svrakic, D. M., & Przybeck, T. R. (1993). A psychobiological model of temperament and character. Archives of General Psychiatry, 50, 975–990.

Conner, T. S., & Lehman, B. J. (2012). Getting started: Launching a study in daily life. In M. R. Mehl & T. S. Conner (Eds.), Handbook of research methods for studying daily life (pp. 285–301). New York, NY: Guilford.

Conner, T. S., Tennen, H., Fleeson, W., & Barrett, L. F. (2009). Experience sampling methods: A modern idiographic approach to personality research. Social and Personality Psychology Compass, 3, 292–313.

Courvoisier, D. S., Eid, M., & Lischetzke, T. (2012). Compliance to a cell phone-based ecological momentary assessment study: The effect of time and personality characteristics. Psychological Assessment, 24, 713–720.

DuPaul, G. J., Power, T. J., Anastopoulos, A. D., & Reid, R. (1998). ADHD rating scale-IV: Checklists, norms, and clinical interpretation. New York, NY: Guilford.

Eckblad, M., & Chapman, L. (1986). Development and validation of a scale for hypomanic personality. Journal of Abnormal Psychology, 95, 214–222.

Enders, C. K. (2010). Applied missing data analysis. New York, NY: Guilford.

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. Annual Review of Psychology, 60, 549–576.

Heck, R. H., & Thomas, S. L. (2009). An introduction to multilevel modeling techniques (2nd ed.). New York, NY: Routledge.

Hektner, J. M., Schmidt, J. A., & Csikszentmihalyi, M. (2007). Experience sampling method: Measuring the quality of everyday life. Thousand Oaks, CA: Sage.

Intel Corporation. (2004). iESP [Computer software]. Retrieved from http://seattleweb.intel research.net/projects/ESM/iESP.html

Knouse, L. E., Mitchell, J. T., Brown, L. H., Silvia, P. J., Kane, M. J., Myin-Germeys, I., & Kwapil, T. R. (2008). The expression of adult AD/HD symptoms in daily life: An application of experience sampling methodology. Journal of Attention Disorders, 11, 652–663.

Kring, A. M., Smith, D. A., & Neale, J. M. (1994). Individual differences in dispositional expressiveness: Development and validation of the emotional expressivity scale. Journal of Personality and Social Psychology, 66, 934–949.

Kwapil, T. R., Barrantes-Vidal, N., & Silvia, P. J. (2008). The dimensional structure of the Wisconsin schizotypy scales: Factor identification and construct validity. Schizophrenia Bulletin, 34, 444–457.

Kwapil, T. R., Brown, L. H., Silvia, P. J., Myin-Germeys, I., & Barrantes-Vidal, N. (2012). The expression of positive and negative schizotypy in daily life: An experience sampling study. Psychological Medicine, 42, 2555–2566.

Kwapil, T. R., Silvia, P. J.,Myin-Germeys, I., Anderson, A. J., Coates, S. A., & Brown, L. H. (2009). The social world of the socially anhedonic: Exploring the daily ecology of asociality. Journal of Research in Personality, 43, 103–106.

Litcher-Kelly, L., Kellerman, Q., Hanauer, S. B., & Stone, A. A. (2007). Feasibility and utility of an electronic diary to assess self-report symptoms in patients with inflammatory bowel disease. Annals of Behavioral Medicine, 33, 207–212.

Mattick, R. P., & Clarke, J. C. (1998). Development and validation of measures of social phobia scrutiny fear and social interaction anxiety. Behaviour Research and Therapy, 36, 455–470.

McKnight, P. E., McKnight, K. M., Sidani, S., & Figueredo, A. J. (2007). Missing data: A gentle introduction. New York, NY: Guilford.

Messiah, A., Grondin, O., & Encrenaz, G. (2011). Factors associated with missing data in an experience sampling investigation of substance use determinants. Drug and Alcohol Dependence, 114, 153–158.

Oorschot, M., Kwapil, T., Delespaul, P., & Myin-Germeys, I. (2009). Momentary assessment research in psychosis. Psychological Assessment, 21, 498–505.

Silvia, P. J., Kwapil, T. R., Walsh, M. A., & Myin-Germeys, I. (forthcoming). Planned missing data designs in experience sampling research: Monte Carlo simulations on efficient designs for assessing within-person constructs. Behavior Research Methods.

Trull, T. J., & Ebner-Priemer, U. (2013). Ambulatory assessment. Annual Review of Clinical Psychology, 9, 151–176.

Author Biographies

Paul J. Silvia is an associate professor of psychology at the University of North Carolina at Greensboro. He is interested in experience sampling methodology, the psychology of art and creativity, and the interface of cognition, motivation, and emotion. He is the author of five books, including How to Write A Lot: A Practical Guide to Productive Academic Writing. He can be contacted at p_silvia@uncg.edu.

Thomas R. Kwapil is a professor of psychology at the University of North Carolina at Greensboro. His research interests include risk for schizophrenia and bipolar disorders and the assessment of psychopathology in daily life. He can be contacted at t_kwapil@uncg.edu.

Kari M. Eddington is an assistant professor in the psychology department at the University of North Carolina at Greensboro. She studies cognitive and motivational factors in the development and treatment of depression. She can be contacted at kmedding@uncg.edu.

Leslie H. Brown is a postdoctoral scholar at the University of Pittsburgh Medical Center. Her research interests include the ambulatory assessment of psychosocial and psychophysiological indicators of risk for schizophrenia. She can be contacted at brownlh@upmc.edu.