ORIGINAL INVESTIGATION

Modeling Complexity of EMA Data: Time-Varying Lagged Effects of Negative Affect on Smoking Urges for Subgroups of Nicotine Addiction

Mariya Shiyko PhD[1], **Pamela Naab** MA[1], **Saul Shiffman** PhD[2], **Runze Li** PhD[3]

[1]*Department of Counseling and Applied Educational Psychology, Bouvé College of Health Sciences, Northeastern University, Boston, MA;* [2]*Department of Psychology, University of Pittsburgh, Pittsburgh, PA;* [3]*Department of Statistics and the Methodology Center, Pennsylvania State University, University Park, PA*

Corresponding Author: Mariya Shiyko, PhD, Department of Counseling and Applied Educational Psychology, Bouvé College of Health Sciences, Northeastern University, 404 INV, 360 Huntington Avenue, Boston, MA 02115, USA. Telephone: 617-373-7527 Fax: 617-373-8892; E-mail: m.shiyko@neu.edu

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ABSTRACT

Introduction: Ecological momentary assessments (EMA) are increasingly used in studies of smoking behavior. Through EMA, examination of lagged relationships is particularly useful for establishing a temporal order of events and for identifying types and timing of risk factors. The time-varying effect model (TVEM) handles EMA data challenges and addresses unique questions about the time-varying effects.

Methods: Generalized TVEM was applied to EMA data from a smoking cessation study to investigate a "time-varying lagged" effect of negative affect on high smoking urges. Participants included 224 smokers with a smoking history of 23.1 years (SD = 9.8) smoking 27.3 cigarettes per day (SD = 10.7), which provided 11,394 EMAs following a quit attempt and prior to a smoking lapse.

Results: The effect of negative affect was found to vary as a function of a time lag, with stronger immediate effects: estimated odds ratio (OR) of 2.7 for the lower nicotine-dependence group (time to first morning cigarette > 5 min, 57.6%) and OR of 2.4 for the higher nicotine-dependence group (≤ 5 min). The magnitude of the effect persisted up to 7 hr while decreasing over time.

Conclusions: This analysis confirmed the importance of negative affect as a precursor of smoking urges while showing that the magnitude of the effect varies over time. An assumption of a constant lagged effect may bias estimates of the relationships and fail to provide a comprehensive outlook of the relational dynamics.

INTRODUCTION

Smoking is a unique addiction that manifests as discrete and repeatable behavior. Methods of real-life and real-time tracking such as ecological momentary assessments (EMA) are especially suitable for studying the development of this addiction, patterns of addiction, and processes related to cessation and relapse. Advantages of EMA methodology over recall methods include more accurate tracking of smoking frequency and patterns, a more detailed capturing of situational and personal factors preceding smoking urges and smoking events, and high ecological validity of data (Shiffman, 2009; Shiffman, Stone, & Hufford, 2008). The detailed real-life records of smoking behavior and related processes have contributed to the understanding of the etiology of smoking behavior and related processes (Piasecki, 2006; Piasecki, Fiore, McCarthy, & Baker, 2002; Shiffman, 2005) and stimulated development of more effective intervention and prevention programs (e.g., Berkman, Dickenson, Falk, & Lieberman, 2011). Although there has been notable progress, analyses of existing EMA datasets are still limited by analytical tools that do not address the unique aspects of such data (large volume, unbalanced sampling design, missing observations) and their dynamic and rich information properties. This may not only limit the nature of findings and research questions asked but also lead to biased inferences (e.g., when data are condensed or when assumptions being made are unrealistic).

The goal of this current study is to illustrate an application of a novel statistical technique, the generalized time-varying effect model (TVEM; with a theoretical introduction by Tan, Shiyko, Li, Li, & Dierker, 2012, and an application to normally distributed data by Shiyko, Lanza, Tan, Li, & Shiffman, 2012) to EMA data from a smoking-cessation study. In our illustration, we undertake an investigation of the time-varying

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"lagged" effects (effects of a covariate that precede an outcome in time) of affect on smoking urges—two extensively studied constructs in the theory of smoking and related EMA studies (McCarthy, Piasecki, Fiore, & Baker, 2006). Examination of the time-varying lagged relationship in groups of successful quitters and relapsers will contribute to the body of literature on the precursors of smoking urges and their effect on smoking cessation. In the presentation that follows, we set the stage for our empirical example and focus on the research question about the time-varying nature of covariates. Following a brief review of current modeling approaches for time-lagged relationships, we introduce the generalized TVEM for analysis of the time-varying relationships. Practical recommendations for EMA study design and implications for smoking research are discussed in Conclusion.

Triggers of Smoking and Prediction of Cessation Success

Quitting smoking is difficult, and attempts are often unsuccessful (Jarvis, 2003). Analyses of lapses and relapses have identified negative affect as an important contributing factor of lapses (Minami, McCarthy, Jorenby, & Baker, 2011; Piasecki, 2006; Shiffman et al., 2007; Shiffman & Waters, 2004) and a risk factor for failure in cessation (McCarthy et al., 2006). Baker, Piper, McCarthy, Majeskie, and Fiore (2004) have specifically suggested that craving is correlated with positive affect during ad libitum smoking but with negative affect during cessation. EMA research has generally found no relationship between smoking and affect during ad libitum smoking (Shiffman et al., 2002) but had a very strong association with negative affect during quit attempts (Shiffman, Paty, Gnys, Kassel, & Hickcox, 1996). These data specifically suggest a prospective relationship between craving, affect, and smoking.

Additional studies established a link between an elevated negative affect, smoking urges, and a relapse of 3 hr (Cooney et al., 2007), 2 hr (Berkman et al., 2011), and 15 min (Cooney et al., 2007) prior to smoking. Berkman et al. (2011) reported no effect of mood 4 hr prior to a relapse, whereas Shiffman and Waters (2004) reported rising negative affect some 6 hr before a subsequent lapse. Some of the above conflicting findings may be an artifact of differing EMA sampling schemes, differing tested models, and possible time-varying relationships among variables. This suggests the possibility that the effects of covariates across time may not be linear. These questions are the focus of the current investigation.

Of additional interest are the interindividual differences based on the level of smoking dependence. Piasecki, Jorenby, Smith, Fiore, and Baker (2003) demonstrated group differences in smoking withdrawal symptoms according to levels of dependence. Previous research has shown that time to first cigarette (TTFC) upon waking is one major indicator of addiction and is the most consistent predictor of a quit success (Baker et al., 2007; Donny & Dierker, 2007). Baker et al. (2007) compared individuals smoking within 5 min upon waking to those with TTFC of 6–30 min, 31–60 min, and > 60 min. The first group had the highest likelihood of and the shortest time to lapsing and relapsing after a quit attempt. Based on the importance of this indicator, we contrast highly dependent smokers (TTFC ≤ 5 min) and less-dependent smokers (TTFC > 5 min).

In this current study, we conducted an investigation (Donny & Dierker, 2007) of the relationship between affect and smoking urges for each subgroup of smoking dependence (lower and higher). We examine these relationships from the time-varying perspective, recognizing the fact that proximity of emotional experience may affect urges in a unique way that should be explicitly modeled and evaluated. The new method of TVEM is ideally suited for this empirical investigation given its fit to EMA data, flexible modeling of dynamics among variables, and capacity for subgroup analysis.

Existing Approaches to Modeling Lagged Relationships

This section contains an overview of current analytical methods for studying lagged relationships in EMA-based longitudinal studies. Investigation of lagged relationships is central for establishing temporal sequencing of events and a mechanism of plausible causation. Numerous smoking theories outline mechanisms of behavior (e.g., elevated negative affect → urge to smoke → smoking event → decrease in urge and negative affect), and EMA data provide opportunities for testing such mechanisms. However, analytical limitations pose a challenge.

Many smoking-related EMA studies utilize event- (e.g., cigarette smoking) and/or interval- (e.g., every 2-hr interval with random variability) contingent sampling (Shiffman, 2009). Such sampling approaches introduce a considerable amount of variation in timing between neighboring assessments. Because most current analytical approaches estimate a lagged relationship as a single numerical value, researchers select concurrent assessments (e.g., Shiffman et al., 2002; Shiffman & Waters, 2004), identify observations that fall within a window of interest (e.g., a 2-hr lag; Berkman et al., 2011), or make an assumption that effects of observations collected within a specified time frame (e.g., within 1 hr prior to an event of interest; Swendsen et al., 2000) are constant. These assumptions are rather stringent and may lead to loss of statistical power due to data reduction and a possible bias in the effect estimation due to mixing data collected at different time lags.

Multilevel modeling (MLM) has been the most widely used approach for analysis of EMA data (Schwartz & Stone, 2007; Walls, Jung, & Schwartz, 2006). It effectively handles different numbers of assessments across participants, missing data, and within-person observation dependency. This method is also easily accessible through high-quality software. An MLM approach can serve as a starting point for investigating a time-varying relationship. An interaction term between a lagged covariate and time would represent a simple linear time-varying effect. More complex and nonlinear patterns, however, are difficult to test and interpret within the MLM framework. TVEM introduced in this study simplifies this task and takes a semiparametric approach for modeling complex, time-varying relationships.

METHODS

Empirical Data

To facilitate introduction of TVEM for modeling lagged relationships in EMA data, first we will present empirical data that will guide research questions and model specification. As part of our empirical study, we will explore the time-varying lagged relationship between negative affect and smoking urges in two groups of smokers: those with higher and lower nicotine dependence. Details of the study design can be found in several publications (Shiffman, Paty et al., 1996; Shiffman et al., 1996, 2000, 2002). In this analysis, we use data from 224 participants who were monitored during their quit attempt. The analysis is restricted to individuals who achieved initial abstinence (24 hr) and to the period when abstinence was maintained (i.e., prior to any lapse). After a scheduled quit attempt, participants responded to random personal digital assistant (PDA) prompts up to five times a day and initiated assessments during episodes of high urges to smoke. On average, participants were aged 44.5 years (SD = 10.1), 58% female, 93% Caucasian, and well educated (71% completed at least some college). At baseline, participants reported smoking a mean of 27.3 cigarettes per day (SD = 10.7) over an average length of 23.1 years (SD = 9.8). Ninety-five participants (42.4% of the sample) reported smoking their first cigarette within 5 min of waking up. The sample was divided into two groups of higher (≤5 min) and lower (>5 min) nicotine dependence.

A total of 11,394 assessments were collected during the abstinence period, ranging from 1 to 207 assessments per person (median = 41, mean = 51.1, SD = 44.2). The group with higher nicotine dependence provided a total of 4,684 momentary assessments (41.1%), of which 862 (18.4%) were self-initiated. In comparison, the group with lower nicotine dependence provided 6,710 assessments, of which 1,038 (15.5%) were self-initiated. During each assessment, participants rated their smoking urges on a 0–10 scale (0 = *no urge*, 10 = *extremely strong urge*). The distribution of urges was severely positively skewed with an overpresentation of 0 (51.1% of observations). It was dichotomized to differentiate between high (≥5; 16.1%) and no-to-low (0–4) urges (of note, we have carried out analyses with a three-way split of no, low, and high urges, and results were similar to the current findings). Further, participants rated a set of 11 emotion adjectives. Based on factor analysis, an affective valence factor was identified (Shiffman, Paty et al., 1996). Low values corresponded to positive affect and high values to negative affect. TVEM was used to conduct a formal investigation of the time-varying lagged relationship between affect and smoking urges for two groups of smokers.

Time-Varying Effect Model

Research Question: Time-Varying Lagged Relationship

TVEM is a statistical approach that is uniquely suitable for analysis of temporal relationships in EMA or other types of intensively sampled data. TVEM originated in models designed for analysis of continuously sampled data (e.g., human physiology). This method was extended to handle nuances of data from social and behavioral sciences (such as EMA) that included missing observations and unbalanced observations across individuals and time points (i.e., differing number of observations per person and staggering of observations at unequal intervals). A technical introduction of the model can be found in Tan et al. (2012). TVEM is intended for studying dynamics in relationships between variables sampled on an intensive longitudinal time scale. As a semiparametric model, there is much flexibility in modeling the shape of dynamics: the model assesses how the relationship among two or more variables changes over time, without the need to prespecify the shape of that function over time.

For our empirical example, this implies that the effect of affect on smoking urges can be investigated over the full spectrum of lag times ranging from several minutes to several hours. Further, it determines whether the strength of the relationship changes over time, it describes the pattern of this change, it identifies critical periods where the effect is the strongest, and it compares relational dynamics across the two groups of smokers with lower and higher nicotine dependence. In our empirical illustration, the model assesses how affect at an initial time point is related to craving assessed at various lags from 0 to 7 hr later.

Model Specification

Guided by our research question, generalized TVEM for lagged effects is specified as follows:

$$\theta_{it_{i(j+1)}} = \beta_0 + \beta_1 \times \mathrm{TTFC}_i + \beta_2(\mathrm{lag}_{ij}) \times \mathrm{NA}_{it_{ij}} + \beta_3(\mathrm{lag}_{ij}) \times \mathrm{NA}_{it_{ij}} \times \mathrm{TTFC}_i, \quad (1)$$

where $\theta_{it_{i(j+1)}} = \log\left(\dfrac{p(\text{High urge})}{p(\text{Low urge})}\right)$.

In Equation 1, the outcome is measured on a binary scale (high vs. no-to-low urge). The logit-link function is used to account for the nature of the outcome. The urge is measured for every person i at a time $t_{(j+1)}$ that can be unique for each individual. The defining feature of the above model is the time-varying nature of the slopes β_2 and β_3 that represent the degree of relationships between lagged negative affect (NA) and smoking urges for two groups of smokers (TTFC = 0 for the lower dependence group and TTFC = 1 for the high-dependence group). Both parameters are summarized as population-level functions and take different values along the continuum of the time lag scale, lag_{ij} (for an extension of TVEM with random effects, see Li, Root, & Shiffman, 2006, which has more stringent data requirements). Thus, the strength of the association can vary depending on the time lag where the relationship is evaluated. Affect is assessed at a time point t_j that is unique to each person i.

Model Estimation and Model Fitting

Details of the model estimation and fitting procedure can be found in Tan et al. (2012) and Yang, Tan, Li, and Wagner (2012). The P-spline estimation method was used to determine shapes of parameter functions. This method achieves a balance between complexity of the parameter functions and data overfitting, making it suitable for most applications in social and behavioral sciences.

To evaluate the impact of affect preceding smoking urges, data pairs were created where assessments of negative affect at a time t_j were paired with urges measured at the next time point, $t_{(j+1)}$. We limited the analysis to assessments that occurred within the same day, excluding evening–morning pairs to avoid comparison of assessments of different nature. The length of the time lag (in minutes) separating two adjacent assessments was recorded. Values of lags varied from 3 to 973 min. Given there were only a few assessments with long time lags (>480 min) and a theoretical focus on momentary processes related to smoking urges, analysis was limited to the lag period of 7 hr and less. As expected, the lag distribution was positively skewed with higher frequencies of closely spaced assessments; the median time lag was 124 min (mean = 141.3; SD = 89.3; 1[st] quartile = 71 min, 3[rd] quartile = 190 min). Distributions were similar across the two groups of smokers.

Table 1. Summary of SAS Code for the Time-Varying Effect Model (TVEM)

%TVEM_logistic (	Call the macro for logistic TVEM
method = P-spline,	Specify estimation method
mydata = smoke,	Specify data set
id = SubjID,	Specify ID variable
time = Time_lag,	Specify indicator of a time lag
dep = UrgeMH,	Specify outcome
cov = x0 TTFC,	Specify time-invariant covariates: x0 is the intercept (a constant of 1 for everybody) TTFC tests for group differences in the intercept
tcov = NA_lag NA_lag_TTFC,	Specify time-variant covariates: lagged NA an interaction between lagged NA & TTFC
cov_knots = 10 10);	Specify number of knots for each time-varying covariate (10 is recommended in P-spline)

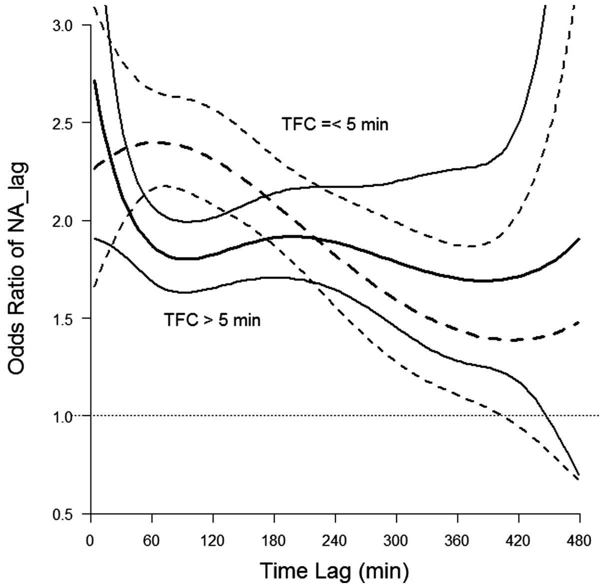

Figure 1. Results of generalized time-varying effect model: a graphical summary of the association (with confidence bands) between negative affect and experiences of high smoking urges along the continuum of a time lag for smokers with higher nicotine dependence (time to first cigarette, TTFC ≤ 5 min, dashed lines, N = 92) and lower nicotine dependence (TTFC > 5 min, solid lines, N = 132).

TVEM was fitted in SAS (TVEM SAS Macro Suite, 2012; Yang, Tan, Li, & Wagner, 2012), with the syntax summarized in Table 1. MLM analysis and graphical summaries of parameter functions were carried out in R (R Development Core Team, 2012).

RESULTS

MLM Results

Results of the multilevel model are presented first as a contrast to findings from TVEM. In MLM, linear and quadratic population-level lagged effects (to allow comparisons between the models) were evaluated for the two groups of smokers. The best-fitting model with random intercept and slope effects (selected based on deviance statistics, and Akaike's information criterion and Bayesian information criteria indices) yielded an effect of negative affect of the magnitude 1.536 (p < .001) on the odds ratio scale. Thus, a change of one point in negative affect (SD = 1, since affect score was standardized) translated into a 54% increase in odds of experiencing high urges, irrespective of timing of affect's assessment. This effect was not moderated by the nicotine-dependence group. However, controlling for affect, the high-dependence group was marginally more likely to experience high urges (OR = 2.04, p = .062).

TVEM Results

The TVEM results yielded overall group differences in urges (OR = 1.84, p < .001). Further, the model uncovered time-varying relationship between negative affect and smoking urges, summarized in Figure 1. For the lower dependence group, the effect varied from 1.7 to 2.7 on the odds ratio scale and for the high-dependence group from 1.4 to 2.4. As indicated by higher estimates for lower values of lags and overlapping CIs between the groups, the relationship was stronger for assessments taken closer apart and similar across the two groups. However, the magnitude and patterns of weakening in the relationships differed across the groups.

Specifically, for the lower dependence group, the effect substantially weakened over the course of the first hour, reducing from the odds of 2.7 to 1.8. This level of the effect persisted for several hours, although gradually weakening. For the high-dependence group, the effect of negative affect on urges remained strong (the odds of 2.3–2.4) in the first 3 hr, followed by a steeper decline and a disappearance at the lag of 7 hr. Based on the overlap in the estimated confidence bands between the two groups after the lag of 2 hr, the magnitude of the effect at those points was comparable. Similarly, for both groups, confidence bands widened for longer lags, an artifact of sparse data.

DISCUSSION

The complexity of smoking behavior and sophistication of data collected via EMA demands specialized and flexible analytical tools. To address this need, this study introduced the TVEM (Shiyko et al., 2012; Tan et al., 2012).

With the application of TVEM, our study investigated the role that affect plays as a precursor to smoking urges. We focused on assessments of affect that preceded later assessments of urges, thus evaluating the prospective, time-lagged relationship. This focus directly speaks to the theoretical conceptualization of smoking antecedents (Shiffman, 2009; Shiffman et al., 2002) rather than concurrent correlates. Further, we differentiated between assessments that occurred at different time lags, hypothesizing that more proximal experiences of negative affect would have a stronger effect on urges. The role of time proximity was explicitly modeled in TVEM, which allows the strength of relationships to vary as a function of a time lag in a flexible and nonlinear fashion. Finally, we differentiated between smokers with a higher degree of dependence and those with a lower degree as indicated by the time to first morning cigarette.

Based on the findings from this current study, there is clear evidence of a linkage between negative affect and the intensity of urges hours later. Based on Figure 1, more proximal experiences of negative affect have a stronger association with smoking urges. As hypothesized and predicted by the emotion-regulation theory of smoking (e.g., Baker et al., 2004; Carmody, Vieten, & Astin, 2007; Weinstein, Mermelstein, Shiffman, & Flay, 2008), urges arise in response to uncomfortable emotional states (e.g., negative affect), and thus, a stronger coupling of urges with more proximal affect is expected. Although not every urge translates into smoking behavior, experiences of high negative affect and high urges put one's inner coping resources to test. It has been posited that both regulation of emotions and resistance to temptation draw on limited resources of self-regulation (Muraven & Baumeister, 2000); thus, over time, these experiences may exhaust resources and lead to smoking.

Somewhat surprising is the finding that negative affect occurring a few hours prior to assessment of urges remains a strong predictor. It may be that both negative affect and urges are driven by a common underlying process, such as nicotine withdrawal, that may persist over hours. However, this does not account for the variation over time or the differences in variation over time between the higher and lower dependence groups. Most remarkable is the strong relationship between negative affect and urges among the highly dependent smokers over the 1- to 2-hr period after affect assessment. It is possible that more dependent smokers have been particularly accustomed to smoke soon after feeling stressed, and thus, during abstinence, experience an enhanced acute association between negative affect and urges. More dependent smokers might have acquired this tighter link between negative affect and smoking by repeatedly smoking to self-treat acute withdrawal during ad libitum smoking.

Implications for EMA Study Design and Data Analysis

The TVEM introduced in this study offers a number of advantages for modeling EMA data in smoking-related research. This method is a flexible tool that builds on the strengths of EMA data on dynamic processes. It also addresses challenges related to event-based or random sampling of smoking-related processes resulting in nonequidistant observations; an unbalanced number of assessments across days, weeks, and participants; missing data; and complex patterns of relationships among variables. The TVEM is well suited to answer research questions related to dynamics and changes in relationships across time. As a result, researchers can detect and describe complex patterns of change, evaluate periods of importance for clinical outcomes, and conduct a careful examination of between-group analysis.

An important feature of TVEM is its semiparametric approach to estimation of parameter functions. This leads to a flexible modeling of nonlinear patterns of change. Results of two analytical methods (TVEM and MLM) carried out in the current investigation highlight the implications of modeling time-varying relationships with more rigid approach. MLM failed to detect time-varying dynamics between lagged negative affect and urges to smoke, yielding a constant estimate of 1.43 on the odds ratio scale. This is a considerable underestimation compared with the results of TVEM. Such biases are hard to detect in MLM analyses.

With TVEM, model misspecification is easier to avoid since data are the driving force for estimating parameter functions. Although an advantage, the semiparametric nature of the model places higher demands on data quality and quantity. Thus, particular care should be taken in securing evidence-based sampling schemes of EMA that capture the complexity of dynamic processes. Researchers are advised to consult an increasing number of articles and volumes written on issues related to EMA study design (Mehl & Conner, 2012; Shiffman, 2009; Shiyko & Ram, 2011; Stone et al., 2007; Stone, Shiffman, Atienza, & Nebeling, 2007; Walls & Schafer, 2006). Important aspects to consider are theoretically hypothesized complexities of relationships between variables, speed of changes in measurable processes (fleeting or stable), subject burden, available technology, and cost, among others. To ensure sufficient statistical power, simulation studies are recommended, and future publications can demonstrate their utility and procedure. Finally, interindividual differences should be considered when fitting the model, as ignoring grouping of individuals may also lead to biases in parameter estimates.

Final Remarks

There is a need for improved understanding of the mechanism of smoking and more effective prevention and intervention practices. Statistical methods such as TVEM enable novel investigations that look into the depths of this complex and dynamic behavior. As EMA methods and technology are increasingly used for assessment and intervention (Heron & Smyth, 2010; Shiffman, 2009), new analytical tools are imperative to accommodate increased complexities of collected data. We hope that the introduction of the method combined with an empirical investigation will stimulate novel and high-impact research in the field.

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DECLARATION OF INTERESTS

None declared.

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REFERENCES

Baker, T. B., Piper, M. E., McCarthy, D. E., Bolt, D. M., Smith, S. S., Kim, S. Y., … Conti, D. (2007). Time to first cigarette in the morning as an index of ability to quit smoking: Implications for nicotine dependence. *Nicotine & Tobacco Research*, *9*, S555–S570. doi:10.1080/14622200701673480

Baker, T. B., Piper, M. E., McCarthy, D. E., Majeskie, M. R., & Fiore, M. C. (2004). Addiction motivation reformulated: An affective processing model of negative reinforcement. *Psychological Review*, *111*, 33–51. doi:10.1037/0033-295X.111.1.33

Berkman, E. T., Dickenson, J., Falk, E. B., & Lieberman, M. D. (2011). Using SMS text messaging to assess moderators of smoking reduction: Validating a new tool for ecological measurement of health behaviors. *Health Psychology*, *30*, 186–194. doi:10.1037/a0022201

Carmody, T. P., Vieten, C., & Astin, J. A. (2007). Negative affect, emotional acceptance, and smoking cessation. *Journal of Psychoactive Drugs*, *39*, 499–508. doi:10.1080/02791072.2007.10399889

Cooney, N. L., Litt, M. D., Cooney, J. L., Pilkey, D. T., Steinberg, H. R., & Oncken, C. A. (2007). Alcohol and tobacco cessation in alcohol-dependent smokers: Analysis of real-time reports. *Psychology of Addictive Behaviors*, *21*, 277–286. doi:10.1037/0893-164X.21.3.277

Donny, E. C., & Dierker, L. C. (2007). The absence of DSM-IV nicotine dependence in moderate-to-heavy daily smokers. *Drug and Alcohol Dependence*, *89*, 93–96. doi:10.1016/j.drugalcdep.2006.11.019

Heron, K. E., & Smyth, J. M. (2010). Ecological momentary interventions: Incorporating mobile technology into psychosocial and health behaviour treatments. *British Journal of Health Psychology*, *15*(Pt 1), 1–39. doi:10.1348/135910709X466063

Jarvis, M. J. (2003). Epidemiology of cigarette smoking and cessation. *Journal of Clinical Psychiatry Monograph, 18*, 6–11.

Li, R., Root, T. L., Shiffman, S. (2006). A local linear estimation procedure of functional multilevel modeling. In T. Walls & J. L. Schafer (Eds.), *Models for intensive longitudinal data* (pp. 63–83). New York, NY: Oxford University Press, Inc.

McCarthy, D. E., Piasecki, T. M., Fiore, M. C., & Baker, T. B. (2006). Life before and after quitting smoking: An electronic diary study. *Journal of Abnormal Psychology*, *115*, 454–466. doi:10.1037/0021-843X.115.3.454

Mehl, M. R., & Conner, T. S. (Eds.). (2012). *Handbook of research methods for studying daily LIfe*. New York, NY: Guilford Press.

Minami, H., McCarthy, D. E., Jorenby, D. E., & Baker, T. B. (2011). An Ecological Momentary Assessment analysis of relations among coping, affect and smoking during a quit attempt. *Addiction*, *106*, 641–650. doi:10.1111/j.1360-0443.2010.03243.x

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological Bulletin*, *126*, 247–259. doi:10.1037//0033-2909.126.2.247

Piasecki, T. M. (2006). Relapse to smoking. *Clinical Psychology Review*, *26*, 196–215. doi:10.1016/j.cpr.2005.11.007

Piasecki, T. M., Fiore, M. C., McCarthy, D. E., & Baker, T. B. (2002). Have we lost our way? The need for dynamic formulations of smoking relapse proneness. *Addiction*, *97*, 1093–1108. doi:10.1046/j.1360-0443.2002.00216.x

Piasecki, T. M., Jorenby, D. E., Smith, S. S., Fiore, M. C., & Baker, T. B. (2003). Smoking withdrawal dynamics: III. Correlates of withdrawal heterogeneity. *Experimental and Clinical Psychopharmacology*, *11*, 276–285. doi:10.1037/1064-1297.11.4.276

R Development Core Team. (2012). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Schwartz, J. E., & Stone, A. A. (2007). The analysis of real time momentary data: A practical guide. In A. A. Stone, S. Shiffman, A. A. Atienza, & L. Nebeling (Eds.), *The science of real-time data capture: Self-reports in health research* (pp. 76). New York, NY: Oxford University Press.

Shiffman, S. (2005). Dynamic influences on smoking relapse process. *Journal of Personality*, *73*, 1715–1748. doi:10.1111/j.0022-3506.2005.00364.x

Shiffman, S. (2009). How many cigarettes did you smoke? Assessing cigarette consumption by global report, Time-Line Follow-Back, and ecological momentary assessment. *Health Psychology*, *28*, 519–526. doi:10.1037/a0015197

Shiffman, S., Balabanis, M. H., Gwaltney, C. J., Paty, J. A., Gnys, M., Kassel, J. D., … Paton, S. M. (2007). Prediction of lapse from associations between smoking and situational antecedents assessed by ecological momentary assessment. *Drug and Alcohol Dependence*, *91*, 159–168. doi:10.1016/j.drugalcdep.2007.05.017

Shiffman, S., Balabanis, M. H., Paty, J. A., Engberg, J., Gwaltney, C. J., Liu, K. S., … Paton, S. M. (2000). Dynamic effects of self-efficacy on smoking lapse and relapse. *Health Psychology*, *19*, 315–323. doi:10.1037/0278-6133.19.4.315

Shiffman, S., Gwaltney, C. J., Balabanis, M. H., Liu, K. S., Paty, J. A., Kassel, J. D., … Gnys, M. (2002). Immediate antecedents of cigarette smoking: An analysis from ecological momentary assessment. *Journal of Abnormal Psychology*, *111*, 531–545. doi:10.1037/0021-843x.111.4.531

Shiffman, S., Hickcox, M., Paty, J. A., Gnys, M., Kassel, J. D., & Richards, T. J. (1996). Progression from a smoking lapse to relapse: prediction from abstinence violation effects, nicotine dependence, and lapse characteristics. *Journal of Consulting and Clinical Psychology*, *64*, 993–1002. doi:10.1037/0022-006X.64.5.993

Shiffman, S., Paty, J. A., Gnys, M., Kassel, J. A., & Hickcox, M. (1996). First lapses to smoking: Within-subjects analysis of real-time reports. *Journal of Consulting and Clinical Psychology*, *64*, 366–379. doi:10.1037/0022-006X.64.2.366

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, *4*, 1–32. doi:10.1146/annurev.clinpsy.3.022806.091415

Shiffman, S., & Waters, A. J. (2004). Negative affect and smoking lapses: A prospective analysis. *Journal of Consulting and Clinical Psychology*, *72*, 192–201. doi:10.1037/0022-006x.72.2.192

Shiyko, M. P., Lanza, S. T., Tan, X., Li, R., & Shiffman, S. (2012). Using the time-varying effect model (TVEM) to examine dynamic associations between negative affect and self confidence on smoking urges: Differences between successful quitters and relapsers. *Prevention Science*, *13*, 288–299. doi:10.1007/s11121-011-0264-z.

Shiyko, M. P., & Ram, N. (2011). Conceptualizing and estimating process speed in studies employing ecological momentary assessment designs: A multilevel variance decomposition approach. *Multivariate Behavioral Research*, *46*, 875–899. doi:10.1080/00273171.2011.625310

Stone, A. A., Shiffman, S., Atienza, A. A., & Nebeling, L. (Eds.). (2007). *The science of real-time data capture: Self-reports in health research*. New York, NY: Oxford University Press.

Swendsen, J. D., Tennen, H., Carney, M. A., Affleck, G., Willard, A., & Hromi, A. (2000). Mood and alcohol consumption: An experience sampling test of the self-medication hypothesis. *Journal of Abnormal Psychology*, *109*, 198–204. doi:10.1037/0021-843X.109.2.198

Tan, X., Shiyko, M. P., Li, R., Li, Y., & Dierker, L. (2012). A time-varying effect model for intensive longitudinal data. *Psychological Methods*, *17*, 61–77. doi:10.1037/a0025814.

TVEM SAS Macro Suite (Version 2.1.0) [Software]. (2012). University Park, PA: The Methodology Center, Penn State. Retrieved from http://methodology.psu.edu

Walls, T. A., Jung, H., & Schwartz, J. E. (2006). Multilevel models for intensive longitudinal data. In T. A. Walls, & J. L. Schafer (Eds.), *Models for intensive longitudinal data* [null] (pp. 3–37). New York, NY: Oxford University Press.

Walls, T. A., & Schafer, J. L. (2006). *Models for intensive longitudinal data*. Oxford University Press Inc. New York, NY

Weinstein, S. M., Mermelstein, R., Shiffman, S., & Flay, B. (2008). Mood variability and cigarette smoking escalation among adolescents. *Psychology of Addictive Behaviors*, *22*, 504–513. doi:10.1037/0893-164x.22.4.504

Yang, J., Tan, X., Li, R., & Wagner, A. (2012). *TVEM (time-varying effect model) SAS macro suite users' guide* (Version 2.1.0). University Park, PA: The Methodology Center, Penn State. Retrieved from http://methodology.psu.edu