Published in final edited form as:
Multivariate Behav Res. 2011 January 1; 46(6): 875–899. doi:10.1080/00273171.2011.625310.

Conceptualizing and Estimating Process Speed in Studies Employing Ecological Momentary Assessment Designs: A Multilevel Variance Decomposition Approach

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Abstract

Researchers have been making use of ecological momentary assessment (EMA) and other study designs that sample feelings and behaviors in real time and in naturalistic settings to study temporal dynamics and contextual factors of a wide variety of psychological, physiological, and behavioral processes. As EMA designs become more widespread, questions are arising about the frequency of data sampling, with direct implications for participants' burden and researchers' ability to capture and study dynamic processes. Traditionally, spectral analytic techniques are used for time series data to identify *process speed*. However, the nature of EMA data, often collected with fewer than 100 measurements per person, sampled at randomly spaced intervals, and replete with planned and unplanned missingness, precludes application of traditional spectral analytic techniques. Building on principles of variance partitioning used in the generalizability theory of measurement and spectral analysis, we illustrate the utility of multilevel variance decompositions for isolating process speed in EMA-type data. Simulation and empirical data from a smoking-cessation study are used to demonstrate the method and to evaluate the process speed of smoking urges and quitting self-efficacy. Results of the multilevel variance decomposition approach can inform process-oriented theory and future EMA study designs.

Recent technological innovations (e.g., web-based assessments, personal digital assistants, smart phones, global positioning systems, and automatic portable devices) allow for more frequent sampling of behavioral, psychological, and physiological processes in naturalistic settings. Real-time data collection methodology is bringing new advances in the design of ecological momentary assessment (EMA; i.e., Shiffman, Stone, & Hufford, 2008; Smyth & Stone, 2003; Trull & Ebner-Priemer, 2009), experience sampling (Larson & Csikszentmihalyi, 1983), ambulatory assessment (Ebner-Priemer, Kubiak, & Pawlik, 2009; Fahrenberg, Myrtek, Pawlik, & Perrez, 2007), and diary (Bolger, Davis, & Rafaeli, 2003) studies.

By design, the substantive phenomena being researched with EMA (used here as a general identifier for all the methods noted earlier) studies are dynamic. A main objective is to track the ongoing changes in a variety of contextual, social, psychological, and physiological

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factors. As EMA designs mature, more attention is being paid to the timing and frequency of experience sampling (Ram & Gerstorf, 2009). Questions such as "Are once-per-day assessments sufficient to capture the phenomena of interest?" or "Do random assessments, obtained within 2-hr blocks across the entire day, place an undue burden on participants?" are of primary importance for study design. As always, an explicit rationale for the timing and spacing of repeated observations helps formulate research hypotheses, develop an analytical strategy, direct study resources, and assure that the dynamic phenomena of interest are captured fully (Boker, Molenaar, & Nesselroade, 2009; Collins, 2006; Collins & Graham, 2002). In this article, we raise the issue of *process speed* and its implications for intensive repeated-measure study designs. Taking into account the methodological complexity of EMA data, we propose a novel application of multilevel modeling, aiming to identify and quantify the relative speed of change processes. The resulting information might then contribute (along with theory and intuitive impressions) to foundational knowledge that informs the design and choice of sampling intensity in future studies.

Temporal aspects of study design often rely on investigators' intuitive and theoretical understanding of the phenomenon of interest—how much and how often a variable changes over time (Adolph, Robinson, Young, & Gill-Alvarez, 2008; Boker & Nesselroade, 2002; Bolger et al., 2003; Burchinal & Appelbaum, 1991; Collins, 2006; Collins & Graham, 2002; Ebner-Priemer & Sawitzki, 2007; Nesselroade, 1991; Ram & Gerstorf, 2009; Stone & Shiffman, 2002; Warner, 1998). Despite the prevailing consensus that a sampling scheme should reflect the dynamics of the phenomenon under investigation and be discussed explicitly (Stone & Shiffman, 2000), very few EMA studies formally assess the appropriateness of their sampling protocol.

Psychological, physiological, and behavioral phenomena can be conceptualized in terms of *process speed*—or how frequently the attribute of interest (e.g., emotion, urge, activity level, pain) rises and falls over time. Knowledge of process dynamics is already used in many areas of science (e.g., medicine, physics) where spectral analytic and related techniques (Box & Jenkins, 1976; Jenkins & Watts, 1968; Koopmans, 1995) are applied to time series data (e.g., heart rate, sound, brain activation, commodity prices) to determine the speed at which change processes progress. For example, depending on the specific process being examined, an electrocardiogram may be set to sample cardiac activity at 200 Hz (200 assessments per second) for high-frequency waves, fast processes, or at 1 Hz for low-frequency waves, slow processes. The Nyquist-Shannon theorem (Nyquist, 1928/2002; Shannon, 1949/1998) states that the sampling rate should be at least twice as frequent as the shortest cycle of change. Knowledge of the cycle length of interest straightforwardly informs the study design. Unfortunately, the Nyquist-Shannon theorem, and the guidance it provides for collection and analysis of time series data, cannot be directly applied to EMA data. Many EMA designs obtain only a small number of assessments per person (< 100) at randomly spaced intervals throughout the day. The within-person series are relatively short and often replete with missingness. Such data do not really qualify as time series data and thus prohibit use of traditional time series and spectral analytic techniques for assessing process speed.

Fortunately, it appears that three principles fundamental to spectral analysis (Shumway & Stoffer, 2006; Warner, 1998) and other variance decomposition approaches can still be used to identify the approximate speed of processes embedded in EMA data. Specifically, the goal of this article is to illustrate how a multilevel variance decomposition approach can be used to isolate the likely time course on which particular change phenomena proceed. In the sections that follow, we provide a general overview of the fundamental principles underlying variance decomposition approaches such as the generalizability theory of measurement (Cronbach, Gleser, Nanda, & Rajaratnam, 1972; Cronbach, Nageswari, &

Gleser, 1963) and spectral analysis (Jenkins & Watts, 1968) and illustrate how those principles are used to conceptualize and quantify process speed using traditional spectral analytic techniques. We proceed to map these principles and procedures onto a multilevel variance decomposition approach that we believe can be used to extract information about process speed from EMA data. Then, using empirical data collected during a study of smoking cessation among newly diagnosed cancer patients awaiting surgery (Shiyko, Li, & Rindskopf, in press), we demonstrate how the model can be used to identify the relative speed of the processes underlying changes in smoking urges and quitting self-efficacy. In doing so, we hope to highlight some of the opportunities that exist for analysis or reanalysis of the plethora of EMA data already available. We conclude with discussion of how the approach and results might inform process-oriented theory and future study designs.

QUANTIFICATION OF RELIABILITY: GENERALIZABILITY THEORY OF MEASUREMENT

Generalizability theory (Cronbach, et al., 1972; Cronbach et al., 1963) provides a framework for identifying and designing dependable measures (Shavelson & Webb, 1991; Shavelson, Webb, & Rowly, 1989). In brief, observed variance is partitioned into multiple segments, each attributable to a particular source or facet of the measurement design (e.g., person, time, error).

Statistically, just as in factorial ANOVA, total variance is partitioned into several orthogonal components. For example, when multiple persons, p, are measured on an attribute Y on multiple occasions, o, the variance of observed scores, σ_Y^2, can be partitioned into three segments,

$$\sigma_Y^2=\sigma_p^2+\sigma_o^2+\sigma_e^2, \qquad (1)$$

where σ_p^2 is systematic variance due to between-person differences ("true-score" variance), σ_o^2 is systematic variance due to between-occasion differences, and σ_e^2 is residual/error variance. Of note, additional interaction components, for example, $p \times o$, can be added but are set aside for the moment. The relative magnitude of the variance components indicates how much each facet contributes to the observed measurements. From these estimated variance components, generalizability coefficients are calculated that can be used to optimize the design of the study (e.g., increase or decrease number of occasions) for obtaining dependable scores that generalize to a particular universe of interest. More broadly, generalizability theory emphasizes how aspects of a study's design can be used to explicitly isolate, quantify, and study specific sources' or facets' contribution to the observed data. As we demonstrate, the underlying principles of the theory—that sources of variance are indicative of and can be used to isolate and quantify the contributions of particular processes—can be used to study process speed. Focusing on multiple time-related facets of different lengths (e.g., hour, day, week), we illustrate how EMA designs can be utilized in determining process speed.

QUANTIFICATION OF PROCESS SPEED: SPECTRAL ANALYSIS

To illustrate phenomena with different process speeds, consider the three simulated time series shown in the left three panels of Figure 1. The slow process (Panel A) is characterized by ups and downs that occur relatively infrequently, with random noise throughout. In contrast, the medium (Panel B) and fast (Panel C) processes are characterized by relatively more frequent systematic ups and downs or moment-to-moment variability. Visually, the faster series appear much more jagged and sharp than do the slower series.

Spectral analysis is an analytic technique that provides a parsimonious framework for quantifying where embedded signals or processes fall on the slow-to-fast continuum (see Shumway & Stoffer, 2006; Warner, 1998). In brief, the data series is partitioned into a finite sum of cosine waves of different frequencies (where frequency or cycle length can be measured as the time between peaks). The general model can be written as

$$Y_t = \mu + \sum_{j=1}^{(N-1)/2} R_j \quad \cos\left(\omega_j t + \phi_j\right), \tag{2}$$

where Y_t, a univariate vector (or a multivariate vector, but we use a univariate case here) of repeated measures obtained from a single individual over time t, is modeled as a function of the mean μ and the sum of a collection of $j = 1$ to $(N - 1)/2$ (where N is the total length of a time series) cosine waves, each with a specific amplitude R, frequency ω (where $\omega = 2\pi = \tau$, and τ is the cycle length), and phase shift ϕ. Careful selection of the elements of the vector of frequencies, ω (e.g., the Fourier frequencies), allows for separation of the original time series into a set of orthogonal components. As in generalizability theory, each facet, here a cosine wave of specific frequency, accounts for a specific portion of the total variance of the time series. Examining the relative proportions of variance captured by these orthogonal components provides information about the predominant frequencies present in the data and, by inference, the speed of the underlying processes that produced the data.

Spectral variance decompositions can be succinctly summarized as a periodogram or power spectra—a graphical description of the relative magnitude of variance or power attributed to discrete frequency components. Making use of the fact that the variances of each frequency component sum to the total variance, statistical tests (e.g., Fisher, 1929) can be used to distinguish the most predominant cycles (those that account for more variance than would be expected by chance in a random time series) in the data. Periodograms with actual proportions of variance attributable to each cycle are often jagged, have wide confidence intervals, and are difficult to interpret. Thus, in practice, they are usually smoothed (i.e., neighboring frequencies are averaged using one of many algorithms that differ by window width and/or weighting) to obtain more reliable estimates of the contributions to total variance (*power*) across the full continuum of frequencies (*bands*).

Power spectra for our three simulated time series (after applying modified Daniell smoothing; Shumway & Stoffer, 2006) are shown in the corresponding panels on the right side of Figure 1. Each point on the curved line represents the amount of variance in the outcome attributed to a particular frequency band, with slower bands concentrated on the left side of the x-axis and faster bands on the right. As can be seen in the plot corresponding to the slow process (Panel D), the amount of variance captured by the low frequencies is substantially greater than the variance captured by the high frequencies. In contrast, for the fast process (Panel F), the amount of variance captured by the high frequencies is relatively greater than the variance captured by the low frequencies, and for the medium process (Panel E), the greatest power in the low-to-medium frequency band.

These spectral analysis procedures and tests, used widely in many areas of scientific inquiry, provide an analytical analogue and precise representation of the process-speed differences we can observe visually in the original time series plots. Paralleling the factorial ANOVA implementations of generalizability theory noted earlier, there are three central principles used in spectral analysis and the construction of power spectra. We describe each in turn here.

Partitioning of Variance

First, the variance in the data is split across multiple frequencies. Some of these frequencies represent fast timescales. Others represent slow timescales. For clarity, we write out a very simple case of the spectral analytic model. Consider a time series that can be modeled with only two cosine waves. The model given in Equation 2 reduces to

$$Y(t) = [\mu] + [R_0 \quad \cos(\omega_0 t + \phi_0)] + [R_1 \quad \cos(\omega_1 t + \phi_1)], \tag{3}$$

where μ is the overall mean of the series, ω_0 is a low frequency, and ω_1 is a high frequency. Replacing each of the bracketed components with $[\mu] = 0$, $[R_0 \cos(\omega_0 t + \phi_0)] = u(t)$, and $[R_1 \cos(\omega_1 t = \phi_1) = e(t)$, the model can be rewritten as

$$Y(t) = u(t) + e(t). \tag{4}$$

The model effectively splits the variance of the original series, σ_Y^2, into two pieces, σ_u^2 and σ_e^2.

Orthogonality of Variance Components

The specific frequencies used in the splitting can be selected purposefully so that they are orthogonal. Typically, this is done by using the Fourier frequencies, so that $\tau_j \in \left(\frac{1}{N}, \frac{2}{N}, \ldots, \frac{N-1}{N}\right)$. This assures that the variance accounted for by one frequency is independent of the variance accounted for by the other frequencies. As such, spectral analysis is an orthogonal variance decomposition method. In the simple two-component example, slow process variance, σ_u^2, is orthogonal to and separated from fast process variance, σ_e^2. That is, the $u(t)$ scores are uncorrelated with the $e(t)$ scores.

Quantification of Variance Components

The splitting of variance into orthogonal components of different frequencies allows for identification and separation of (cyclical) processes embedded in the data stream. Moreover, each variance component can be quantified as a proportion of the total variance to determine the strength of a particular signal. The specific frequencies of those signals can then be interpreted directly as an indicator of the process speed. Variance captured by relatively low frequencies is indicative of slow-moving processes. Variance captured by relatively high frequencies is indicative of fast-moving processes.

Making use of the fundamental principles of variance partitioning formulated in generalizability theory (i.e., that sources of variance are indicative of particularly relevant facets), spectral analysis uses orthogonal variance decompositions to isolate, identify, and quantify the particular signals that may be generating the data stream. As an exploratory technique, spectral analysis does not require a priori design specifications. Rather, the mathematical elegance of the Fourier transformations allows for post hoc evaluations of cycles of varying lengths, always partionionable, orthogonal, and quantifiable. Although flexible, this approach has limited applications to most types of EMA data. In particular, data streams collected at nonequidistant timepoints are not amenable to spectral analysis. In an attempt to overcome these hurdles, we forward the multilevel variance decomposition model (e.g., Raudenbush & Bryk, 2002) as an alternative approach that builds on the three principles of spectral analysis and generalizability theory and can be used to identify the approximate speed of processes in EMA type data.

QUANTIFICATION OF PROCESS SPEED: THE MULTILEVEL VARIANCE DECOMPOSITION APPROACH

Relative to traditional time series designs, where measurements are obtained at very regular intervals (e.g., every 100th of a second), EMA designs are often characterized by relatively irregular measurement protocols. Consider the following EMA study design, where individuals are asked to provide responses to a series of items every 2 hr or so throughout the waking daytime hours (e.g., between 8 a.m. and 10 p.m.) for 1 week. To alleviate rote responding, assessment prompts are programmed to arrive at random intervals within 2-hr blocks of time. By design, the number of occasions is relatively short by time series standards (e.g., < 100 occasions), and the amount of time between measurements is unequal (random timing of assessments) and has large but regular gaps during nighttime. If participants are unavailable (e.g., driving) when a prompt arrives, they are allowed to provide responses at a later time or skip the assessment altogether. EMA data are often fraught with missingness due to noncompliance, skipped assessments, technology malfunction, or other planned or unplanned factors—and thus quite different from traditional time series data.

Multilevel models (MLM) are widely used in the social sciences to accommodate hierarchical dependencies in the data, including organizational structures (e.g., students nested within classrooms within schools; Bryk & Raudenbush, 1988; Raudenbush & Bryk, 2002), social grouping (e.g., members of a family nested within family units; Nezlek & Zyzniewski, 1998; Snijders & Kenny, 1999), and repeated measurement of the same individuals (e.g., observations nested within individuals; Bryk & Raudenbush, 1987; Pinheiro & Bates, 2004; Singer & Willett, 2003). According to the specified nesting structure, the total variance in an outcome variable is partitioned into components. Generally, MLM is used to identify predictors that explain variation in the outcome (similar to other types of regression analysis). However, the building block of the model-fitting process (Raudenbush & Bryk, 2002, p. 230), the intercept-only model, can be specified in a manner that splits the variance into multiple levels (i.e., components). Specifically, we consider how the principles of variance decomposition used in generalizability theory and spectral analysis manifest in application of MLM to EMA data.

Partitioning of Variance

In the hypothetical EMA study design described earlier, momentary assessments are obtained during each 2-hr block of daytime for 1 week. It seems natural to investigate if and how variability at the hourly (momentary) level (e.g., Facet 1) can be separated from variability at a daily level (e.g., Facet 2). Data from a single participant (to parallel the spectral analysis approach) can be expressed as a multilevel model,

$$\begin{aligned}\text{Level} \quad 1{:}Y_{md} &= \beta_{0d} + e_{md}\\ \text{Level} \quad 2{:}\beta_{0d} &= \gamma_{00} + u_d,\end{aligned} \tag{5}$$

where, at Level 1, the individual's score on attribute Y assessed at moment m on day d is the sum of a daily score and a series of residual (error) scores that differ from moment to moment (the fast timescale). The daily scores are modeled at Level 2 as the sum of an overall mean and a series of residual (deviation) scores that differ from day to day (the slow timescale). Person centering the data, $\gamma_{00} = 0$, and substituting the Level 2 equation into the Level 1 equation, yields the model

$$Y_{md} = u_d + e_{md}. \tag{6}$$

In Equation 6, the total variance of the repeated measures of Y_{md}, σ^2_Y, is split into two components: daily variance σ^2_u and momentary variance σ^2_e. In principle, this is the same equation obtained in the generalizability theory example (Equation 1) and in the simple spectral analysis example presented in the previous section (Equation 4), where the variance of the original series, σ^2_Y, was also split into (at least) two components, σ^2_u and σ^2_e.

An important benefit of MLM is that data from multiple individuals can be analyzed simultaneously (as is demonstrated in an empirical example). In spectral analysis, signal waves are identified for each individual separately and then, if needed, summarized or compared across individuals. Almost all EMA studies, however, make use of multiple-participant designs. Although MLM can be carried out on an individual basis with a subsequent construction of distributions of σ^2_u and σ^2_e, it is more efficient to estimate variances from an entire sample, especially when EMA data strings are short, the sample of individuals is relatively homogenous (e.g., with no theoretical basis to assume different process speeds for subgroups of individuals; Ebner-Priemer et al., 2007; Ebner-Priemer & Sawitzki, 2007), and the main focus of analysis is identification of *prototypical* process speed.

Orthogonality of Variance Components

The components of variance are structured by the setup of the multilevel model such that variance accounted for at one level (e.g., Level 1 in Equation 5) is, by definition, independent of the variance accounted for at other levels (e.g., Level 2 in Equation 5). The u_d scores are uncorrelated with the e_{md} scores. Thus, the multilevel variance decomposition is orthogonal and can potentially be used and interpreted in a similar manner as the spectral analysis (Fourier) and simple generalizability theory decompositions.

Quantification of Variance Components

Following the same logic used in spectral analysis, variance in u_d is indicative of day-to-day changes and, by inference, the relatively slow-moving processes that accrue over a longer period of time. Variance in e_{md} is indicative of moment-to-moment changes and, by inference, the relatively fast-moving processes that accrue over relatively short periods of time. Thus, the relative magnitude of variance components present at either the “day” or “moment” spectra of the multilevel model would indicate the contributions of processes of different speed. It may be noted that in spectral analysis the specific structure of the orthogonal variance components depends on the arbitrary, but exact, length of the time series being analyzed (i.e., $1/N$, $2/N$, . . . , $N-1/N$). The structure is determined post hoc and in an “atheoretical” manner. As such, the frequency components being examined may or may not map directly to psychological or sociological meaningful units of time (although sometimes time series are purposively shortened to obtain specific frequencies and examine specific processes; e.g., Ram et al., 2005). In contrast, the multilevel variance decomposition approach makes use of the natural nesting of time that exists in most EMA studies (e.g., no reports during the nighttime hours). The structure of the orthogonal variance components is not dependent on the length of the time series and can be chosen a priori using substantive theory. That is, the levels (time frames) of nesting can be structured with respect to the meaningful units of time that individuals use to organize their lives. For example, moments may be nested within half-day periods (morning and afternoon) nested within days or moments nested within days within weeks. Theoretically, when the number of nesting levels is increased to the limit (each level containing only a single pair of observations), the multilevel decomposition would closely resemble the length-based ($1/N$, $2/N$, etc.) spectral analysis decomposition of time series (but would not be identified). Substantively, by making a priori decisions about and investigating meaningful levels of time (e.g., hours, days, weeks), we are still able to explicitly partition the overall variance into orthogonal components, compare the relative magnitude of those components, and evaluate process speed in relation to the cadences that most people use to organize their lives.

SIMULATION EXAMPLE

To illustrate the parallel between spectral analysis and the multilevel variance decomposition approach, we analyzed the three simulated time series of Figure 1 using both methods. The data were generated to resemble a typical EMA study design scenario of seven momentary assessments per day over the course of 2 weeks. However, in order that both spectral analysis and multilevel variance decomposition approaches could be applied to the data, we preserved the usual "artificial" time series structure (i.e., equal intervals of time between all measurements, data completeness, and a close-to-sufficient number of occasions: $N = 98$) and conceptualized the data as having a two-level nesting structure (momentary observations nested within days). Data were generated in three steps in R (R Development Core Team, 2010). First, depending on the process speed, either momentary or daily values were drawn from a random normal distribution. Second, either momentary or daily values were generated using the autoregressive integrated moving average (ARIMA) simulation function with autocorrelation parameters and the degree of autocorrelation varied to simulate slow, medium, and fast processes (Figure 1, Panels A, B, and C). Finally, daily and momentary data were combined and z-score standardized ($M = 0$, $SD = 1$)for ease of presentation.

As noted visually in the power spectra in Figure 1, results from the spectral analysis indicated that, for the first series, the largest proportion of variance was concentrated around .01, corresponding to a cycle length of 1/.01 or 98 observations, a slow process (2-week cycle). For the second series, power peaked around .07, a medium process (2-day cycle). And, for the third series, variance was concentrated at a high frequency, .46, equivalent to about 2 assessments or roughly a 7-hr cycle—a fast process.

In parallel, we applied the two-level multilevel variance decomposition model (Equation 5) to the same data. Estimates of standard deviations and proportions of daily and momentary variance components are summarized in Table 1. For the first series, almost all variance was concentrated on the daily level (99%) with little momentary variability (1%). For the second series, the variance was split almost evenly between the day (49%) and momentary (51%) levels. Finally, for the third series almost all variance was concentrated at the momentary level (about 100%). In sum, we were able to distinguish the relative speeds of the processes embedded in the generated data using both the spectral analysis and MLM approaches.

EMPIRICAL EXAMPLE

Clearly, the simulated data were meant to illustrate extreme situations, where process speed is easily identified as very slow, medium, or very fast. In this section, we present EMA data from a smoking-cessation intervention that made use of personal digital assistants (PDAs) to deliver a scheduled reduced smoking (SRS) intervention program (Cinciripini et al., 1997) and to capture momentary ratings of study participants' smoking urges and quitting self-efficacy. In doing so, we outline a step-by-step procedure that can be followed when using the multilevel variance decomposition approach to identify approximate process speed in EMA data.

Participants and Procedure

A detailed description of the clinical trial, designed to test the efficacy of delivering a smoking-cessation intervention to newly diagnosed cancer patients awaiting a cancer-related surgery, is provided in Shiyko et al. (in press). In this illustration, we focus on EMAs obtained from 74 patients who rated their momentary smoking urges and self-efficacy for presurgical smoking cessation. These individuals were followed, depending on the length of their SRS intervention, for a period of between 2 to 54 days (M = 14 days, SD = 10.5, median = 12 days). In brief, individuals followed an individualized smoking-tapering program where they were to smoke only when prompted by the PDA. Over the course of the presurgery intervention, the number of prompts was gradually reduced from individuals' baseline smoking rate (e.g., 18 cigarettes per day) to zero (at surgery). Fifty percent of smoking prompts were followed by a brief set of smoking-related questions, which were also answered at three additional occasions each day (randomly spaced and uncoupled from smoking prompts). A total of 2,670 momentary assessments were collected (average of 36 assessments per person; SD = 45.5, median = 21, min = 2, max = 267).

Measures

The intensity of *smoking urges* was measured with four items: "I want to smoke right now," "I need a cigarette right now," "Smoking would be pleasurable right now," and "Smoking would make me less distressed right now." Responses, obtained on a 5-point Likert-type scale, ranging from 0 = "not at all" to 4 = "very much so," were averaged across the four items to obtain a measure of the intensity of individuals' current/momentary urge to smoke. Data from 6 participants (selected at random from the sample) are plotted in Figure 2. From the graphical summary, smoking urges, characterized by rapid changes in magnitude from one assessment to the next, appear to be driven by a relatively fast process.

Quitting *self-efficacy*, individuals' confidence in their ability to quit smoking prior to surgery, was evaluated at each assessment with the item "Confidence to quit smoking before surgery right now" using a 0 = "not at all confident" to 4 = "completely confident" response scale. Figure 3 summarizes responses to this question for the same 6 participants. In comparison to smoking urges, self-efficacy appears to proceed more slowly. Responses were much more stable from one assessment to the next, with relatively few shifts in level over time.

Multilevel Variance Decomposition

To evaluate process speed more formally, we followed several analytic steps: data preparation, model construction, model estimation, and *interpretation.* First, responses on the two variables of interest (intensity of smoking urge and quitting self-efficacy) were person centered and standardized. We used the standardization to purposefully set aside individual differences in the magnitude of responses and keep the primary focus of our illustration on examination of intervariable differences in process speed. However, between-person differences can be examined either by applying the multilevel decomposition to each individual's data separately and summarizing results across individuals or by explicitly including an additional level of person-level variance into the aforementioned models.

Second, following the study's design, we specified a multilevel model with momentary assessments (Level 1) nested within days (Level 2) structure for the data. Specifically, the model was

$$Y_{mdi} = [\pi_{000} + v_{00i}] + u_{0di} + e_{mdi}, \tag{7}$$

where Y_{mdi}, the outcome variable (either smoking urges or quitting self efficacy) measured at moment m on day d for person i, was conceptualized as deviations from a grand mean π_{000} (or μ in previous Equations 1 and 3) for three study design facets (persons, days, moments) and residual error. Our person-centering and standardization during data preparation effectively removed variance related to the persons' facet of the design. Thus, our expectation was that the grand mean, π_{000}, and the between-person variance component, σ_v^2, would be near zero (and could in fact be removed from the model).

Third, model parameters were estimated using Restricted Maximum Likelihood as implemented with the *nlme* R package (although any multilevel program can be used). Results of the analysis are presented in Table 2. The bulk of variance in intensity of smoking urges (81%) was concentrated at the momentary assessment level, suggesting relatively fast process speed. For self-efficacy, 17 out of 74 individuals (about 23% of the sample) reported a constant level of the construct, meaning there was no variance to be partitioned. These "stable" individuals had a higher total number of EMAs than the "varying" individuals (t_{72} = 3.45, p < .001, M = 7.38, SD = 4.63, vs. M = 3.68, SD = 2.98; of note, there was no overall correlation between the number of EMAs and the amount of momentary variance, r = .12, p > .05 for self-efficacy and r = .02, p > .05 for smoking urges) and a slightly higher mean level of self-efficacy (t_{72} = −1.73, p = .088, M = 2.78, SD = 1.02, vs. M = 2.40, SD = .81). Logistic regression revealed that patients with thoracic cancers, which are often directly related to smoking, were 3.4 times more likely to be in the stable group (p = .049). It is possible that these individuals, seeing a direct causal connection between smoking and thoracic cancer, were more motivated to quit. For the rest of the sample, 46% of variance in self-efficacy was located at the daily level and 54% at the momentary level, suggesting relatively slower process speed. Of note, these decompositions were highly similar when excluding the assessments obtained at the scheduled smoking prompts, suggesting robustness of relative process speed across different portions of the data.

Although not the focus here, the multilevel variance decomposition approach can be used to examine interindividual differences in process speed. For instance, the person-level model, $Y_{md} + \pi_{000} + u_{0d} + e_{md}$, can be applied separately to each individual's data and the resulting person-specific estimates of σ_u^2 and σ_e^2 used to infer how slow or fast the underlying processes proceed for that individual. Such applications will require a longer time series than are typical in EMA studies. In our empirical example, we obtained person-specific variance estimates of smoking urges for 67 study participants (90.5% of the sample) and of self-efficacy for 52 individuals (70.3%; the remaining time series were too short). Putting all these results together we created a distribution of process speed scores (quantified as the proportion of variance located at the momentary level). For smoking urges the distribution was highly skewed, with a median of 80% and mean of 70.5% (SD = 33). For self-efficacy, the distribution was more normal, with a median of 43.1%, and mean of 42.5% (SD = 42.5).

Interpretation of the sample-level variance decompositions and the implications for timing and spacing of sampling are included in the discussion.

DISCUSSION

Psychological and/or behavioral phenomena proceed at inherently different speeds. Some manifest as changes over just a few seconds. Others take hours, months, or even years to produce notable changes in individuals' attitudes, abilities, and behaviors. Tracking and modeling fast processes requires frequent assessment, whereas slow processes can still be described well, and more efficiently, with infrequent assessment. The purpose of this article was to demonstrate feasibility of a multilevel variance decomposition procedure for describing and understanding the relative speed of various processes. With time series data, process speed can be conceptualized and quantified using traditional spectral analytic techniques. These methods partition variance in the observed data into orthogonal components that are indicative of different process speeds. Inferences about the speed of the process being studies are then made by evaluating proportions of variance accounted for by each component. Highlighting that the same underlying principles can be embedded in the multilevel modeling framework, we suggest that multilevel variance decomposition procedures be used with EMA data to build a knowledge base about process speed.

To summarize, based on the study design and the number of levels specified in the model, the extent of changes at different timescales can be quantified and compared with each other. Timescales that account for the most variance are interpreted as the most prominent, pointing to the temporality of processes underlying the observed changes. Study designs should examine the benefits of extended sampling at those timescales. In contrast, timescales that account for relatively little variability can be interpreted as stable or noncontributing and, for efficiency, removed from the study design.

Implications for Smoking-Cessation Studies

In our empirical example we used EMA data from a smoking-cessation study where individuals provided multiple reports each day about their feelings and behavior for, on average, 14 days, to examine process speed in smoking urges and quitting self-efficacy. Applying the multilevel decomposition, we found that 81% of the observed variance in smoking urges was located at the within-day (hour-to-hour or momentary) level and 19% at the between-day level. These results provide a set of evidence that relatively fast processes are driving changes in individuals' smoking urges. This inference aligns with Shiffman and colleagues' (2002) identification of situational and psychological antecedents of cigarette smoking, including food and alcohol intake, presence of other smokers, and feelings of restlessness—transient factors that change relatively quickly. In many EMA studies, smoking urges are typically sampled several times a day (e.g., 3–5 times) over the course of several weeks either right before or right after a smoked cigarette or at random timepoints (e.g., Dunbar, Scharf, Kirchner, & Shiffman, 2010; O'Connell et al., 1998; Shiffman et al., 2002). Our multilevel decomposition suggests that changes in smoking urges are primarily a within-day phenomena and less so a between-day phenomena. This implies that studies of the processes driving smoking urges should consider trading more frequent within-day assessments for fewer days. More frequent assessments obtained over just a few days may capture the process more fully.

Quitting self-efficacy is a central component of social learning theory (Bandura, 1997) in the context of smoking cessation (Condiotte & Lichtenstein, 1981). We found that for 23% of the sample there was no variance in self-efficacy (purely constant over time) and that for the reminder of the sample, the variance in self-efficacy was split almost evenly between the daily and momentary levels. Quitting self-efficacy, with both daily and momentary epochs contributing to observed changes, appears to be driven by relatively slower processes than smoking urges. Previous studies have demonstrated differences in self-efficacy across situations and smoking events—fast processes (e.g., Gwaltney, Shiffman, Balabanis, & Paty, 2005; Gwaltney et al., 2001; Gwaltney, Shiffman, & Sayette, 2005; Shiffman et al., 2000). Our multilevel variance decomposition provides some evidence that quitting self-efficacy should be examined in relation to both situational factors that likely change from hour to hour *and* more stable factors that may only change on a day-to-day timescale.

Advantages and Cautions

As the simulated and empirical examples illustrate, the multilevel variance decomposition procedure is a flexible tool that can locate important signals in EMA data streams that are indicative of the speed of an underlying process. The procedure is appropriate for and can be applied to data from commonly used EMA designs that are short (time series of less than 100 occasions), are not equally spaced in time, and may be not fully complete (i.e., have missingness). In our empirical example, for instance, individual time series consisted of, on average, 36 measurements, short by time series standards. Further, the intervals between occasions within an individual time series ranged from less than 10 min in some instances to over 12 hr (nighttime breaks) in others. Yet, despite these features of the data, which are very common in EMA type studies, we were still able to partition the data into orthogonal components, map the different portions of variance to specific timescales, and interpret the relative speed of underlying processes.

Clearly, the approach does not assess speed with the same level of precision that would be possible with spectral analysis given true time series data. However, as shown with the simulated data example, general indications of process speed can still be obtained. The correspondence of results suggests that EMA data can be used to obtain a picture, albeit somewhat grainy, of the likely time course on which changes in a variable proceed. Because of the fact that nesting levels in a multilevel model are predetermined, researchers can evaluate major epochs that are driving changes in the process. Although differences between 45% and 55% of the momentary variance components may not differentiate clearly between faster and slower processes, this approach nevertheless presents a useful guide that can inform where the bulk of assessments should take place.

The equal spacing of time series data facilitates numerous modeling opportunities, including the spectral variance decomposition. However, these methods, in some sense, split the data into "artificial" units. Each Fourier frequency, $\tau_j \in \left(\frac{1}{N}, \frac{2}{N}, \ldots, \frac{N-1}{N}\right)$, is superimposed on the data. The post hoc, exploratory nature of the approach provides mathematical convenience but may muddy substantive interpretation. For example, for the simulated fast process of Length 98 (Panel C of Figure 1), we identified the predominant frequency to manifest on a roughly 7-hr cycle, a timescale that does not easily translate into the regularity of daily life (which most people seem to be living on a 24-hr cycle). In contrast, EMA designs are often built around the "natural" structure of individuals' lives. Most prominently, data are typically not obtained during the hours that people are sleeping. Within the multilevel framework, the data, instead of being conceived and restructured as a collection of "artificial" frequencies, are conceptualized according to "natural" nesting of time units (e.g., waking hours within a day). The multilevel decomposition partitions variance among these a priori-determined time units. By design, the variance components are each likely to carry substantive meaning (e.g., circadian rhythms; Fushing, Chen, & Lee, 2010) and the variance can be attributed to and interpreted to reflect the "natural" (or socially imposed) timescales on which individuals' lives proceed.

Of course, it is very likely that many processes, proceeding at multiple timescales, contribute to the dynamics of an observed phenomenon (Brose, Schmiedek, Lövdén, & Lindenberger, 2011; Ram & Gerstorf, 2009; Schmiedek, Lövdén, & Lindenberger, 2009). In our example, we used a simple two-level nesting structure (moments within days) and partitioned variance among those two facets of the sampling design. Alternatively, the data could be structured as a three-level model, with moments nested within during-work and after-work periods within a day, in order to isolate an additional source of variation and process speed. The flexibility of the multilevel setup is in the opportunity to expand the model further by including several levels and evaluating multiple alternative nesting structures. Of note, the number of samples needed within a given unit or level (e.g., number of children sampled from each classroom) has been examined in a number of simulations studies for multilevel regression (e.g., Browne & Draper, 2000; Maas & Hox, 2005). However, it is not clear yet how this knowledge transfers into specific recommendations about the number of assessments needed within a day (or within a half-day, or within an hour) for application of the multilevel variance decomposition for assessing process speed. Simulations and focused power analyses are needed to obtain specific information about how to best sample a particular phenomena. In general, though, the data and model can be configured to accommodate many temporal structures in order to begin identifying the timescales at which major portions of variance are located.

It must be noted that at the lowest level of the multilevel decomposition, the variance, σ_e^2, is attributed to processes that proceed along the fastest timescale. Whether this variance should be attributed to the fleeting processes that produce measurement error or to fast, substantively interesting processes, is ambiguous. This is most prominent in the case where mostly fast processes are driving the data (Panel C of Figure 1). With almost all of the variance being attributed to σ_e^2, it is not possible to distinguish such a series from one that *only* contains random error or "white noise." This limitation might be addressed by including an additional "superfast" level, but this still requires assumptions about the relative quickness of error-related processes, the precision of the measurement instruments, and a sufficient number of occasions to accommodate an additional layer of nesting. More generally, considering that EMA-measured processes are dynamic, the response options and scale need to be sensitive to and able to capture meaningful changes in constructs being measured over time (e.g., Maydeu-Olivares, Kramp, García-Forero, Gallardo-Pujol, & Coffman, 2009). Establishing a theoretical level of "white noise" during questionnaire construction may inform how to distinguish between negligible and systematic fluctuations. As well, similar to other very fast processes, variance related to rare and/or very short-lived events (e.g., bulimic episodes, family conflicts) will also be indistinguishable from error. For such phenomena, one must consider not only the frequency of sampling during the events (fast process) but also the frequency of sampling during nonevent episodes (slow process) and what the relevant levels of time are (e.g., event episodes nested within time blocks nested within hours, etc.). Although it may be challenging to differentiate fast processes or rare events from white noise analytically, a combination of well-developed questionnaires, theory, and oversampling to obtain extra variance components can all help distinguish the substantively meaningful aspects of the data.

In applying the multilevel decomposition method, one needs to keep in mind that, as in generalizability-theory measurement studies, it is difficult to identify a timescale (facet) if a study was not designed to test for it. For example, a momentary level of fluctuation cannot be isolated if, by design, data were only collected on a daily basis or too few momentary observations were taken. In addition, as part of the Nyquist-Shannon theorem, assessment spacing that coincides perfectly with a specific oscillatory (sinusoidal) process may be erroneously mistaken for a much slower process. For example, a cyclical function measured repeatedly only at its peak may be mistakenly identified as a flat line (Collins & Graham, 2002). Thus, although multitudes of EMA data are available for further analysis and exploration of process speed, caution should be taken in interpreting results in cases when the sampling schemes do not capture particular timescales or are not frequent enough to capture and isolate fast-changing processes.

Finally, in our presentation and analysis we set aside interindividual differences. As a preliminary step, we standardized each individual's data ($\mu = \gamma_{00} = 0$, $\sigma_\gamma = 1$) to eliminate interindividual differences in mean levels and extent of within-person variability. Although we did report some interindividual differences, our intent and focus was on examining *intervariable,* rather than interindividual, differences in process speed and to highlight the parallels between spectral analysis of time series and the multilevel variance decomposition. However, it should be fully acknowledged that individuals likely differ in the extent to which fast and slow processes contribute or manifest in their data. With sufficient sampling, it is feasible to carry out the multilevel approach on a person-by-person basis and then construct and describe between-person distributions of the interesting variance components. With relatively homogenous samples and no theoretical basis for hypothesizing about interindividual differences in process speed, analyzing EMA data from multiple individuals can serve as a first step in establishing an empirical foundation for later examination of interindividual differences.

Design Notes

The frequency of sampling can be informed by prior knowledge of process speed or developed in accordance with specific hypotheses about the speed of underlying processes (see Adolph et al., 2008; Boker et al., 2009; Collins, 2006; Reis & Gable, 2000). Where prior knowledge or specific hypotheses are difficult to generate, one may be able to make use of the plethora of EMA data that is already available—applying the multivariate decomposition methods to explore process speed. Based on the findings, one could make an informed decision about the sampling frequency. We note, though, that due to the perceived high demand on participants from repeated self-reports (e.g., Napa Scollon, Kim-Prieto, & Diener, 2003), many EMA studies are likely to have undersampled phenomena that are driven by fast change processes. In the data sets we have examined, there are many variables where the majority of variance is located at the momentary level—an indication that even more frequent assessment may be needed. Thus, although analyzing existing data is a step forward toward understanding the dynamic nature of psychological and behavioral processes, we still advise using pilot studies that intentionally oversample with very frequent assessments. Such data will allow for separation of multiple fast timescales and provide valuable information about how fast the process actually is.

Phenomena with substantial variance at the momentary level might be sampled at very high frequency for just a few days at a time. Phenomena with substantial variance at a higher (longer) level of time might be sampled less frequently to preserve resources and reduce participant burden. When studying both slower and faster processes, measurement burst designs are recommended wherein individuals are measured at multiple timescales (Nesselroade, 1991). At the faster timescale, multiple observations are obtained at closely spaced intervals (e.g., hours)—a burst of measurement. At the slower timescale, these bursts are repeated more at widely spaced intervals (e.g., months). Such designs allow for coupling of shorter and longer term processes (Ram & Gerstorf, 2009; Sliwinski, 2008).

Synopsis

In conclusion, the multilevel variance decomposition approach is an intuitive and easily implementable method that can be used to explore the speed with which various time-dependent psychological, physiological, and behavioral processes proceed. As the number of EMA studies increases, questions about frequency and length of EMA series become central for design. On one hand, study participants' burden can be significantly reduced if slow processes are identified beforehand and sampled less frequently. On the other hand, adequate description of fast processes requires that their manifestations are captured with sufficient frequency to allow valid modeling and interpretation. We hope that the multilevel variance decomposition approach can be used to build a foundation of knowledge about process speed; design better studies; and help us extract, describe, and understand the processes that contribute to people's lives—in real time and in real context.

Acknowledgments

Mariya P. Shiyko's work was supported by the National Institute on Drug Abuse (Grant P50 DA010075); Nilam Ram's work was supported by the National Institute on Aging (RC1-AG035645, R21-AG032379, R21-AG033109) and the Penn State Social Science Research Institute. The content of this manuscript is solely the responsibility of the authors and does not necessarily represent the official views of the funding agencies.

We thank Stephanie T. Lanza, Xianming Tan, and John Dziak for comments on earlier drafts of this manuscript; Heather Wadlinger for early brainstorming sessions on the speed of emotions; and Jamie Ostroff, the principal investigator on the R01CA90514 study, for her generosity with the data from the smoking-cessation study.

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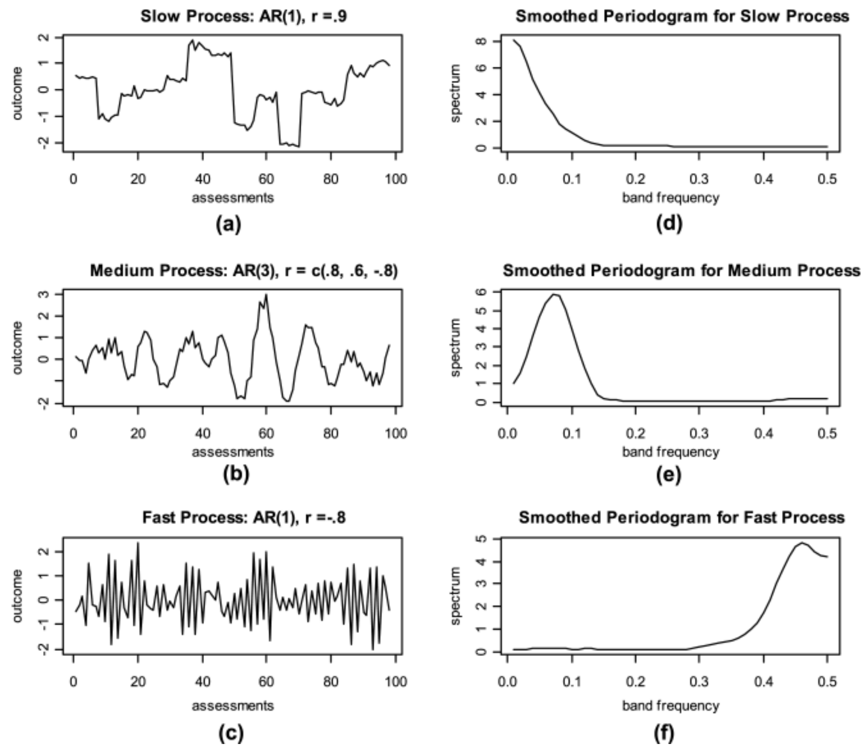

FIGURE 1.
Simulated time series for slow (A), medium (B), and fast (C) processes and corresponding power spectra (D–F).

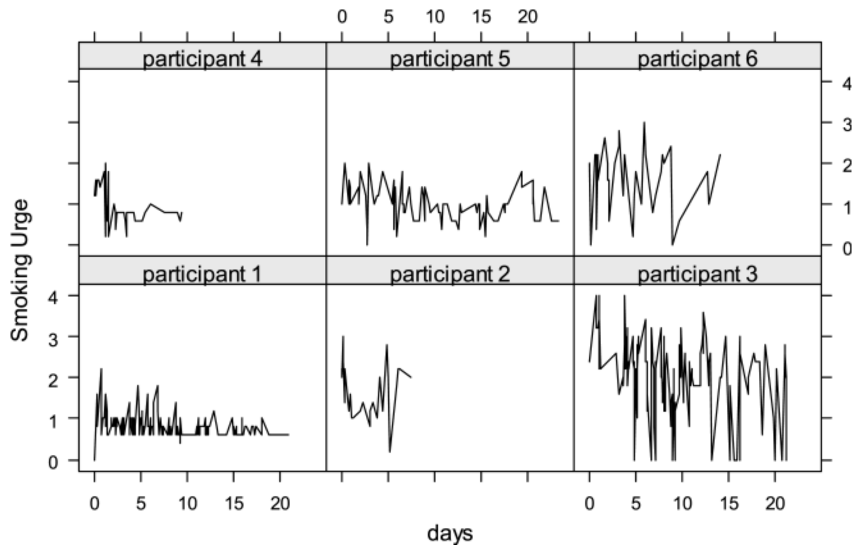

FIGURE 2.
EMAs of smoking urges in a random sample of 6 study participants. *Note.* EMA = ecological momentary assessments.

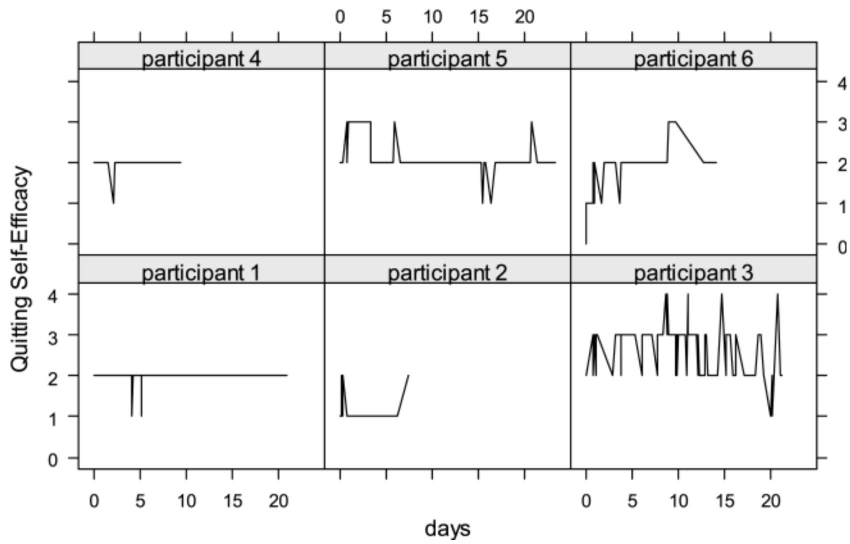

FIGURE 3.
EMAs of presurgical quitting self-efficacy in a random sample of 6 study participants. Note. EMA = ecological momentary assessments.

TABLE 1

Results of the Multilevel Variance Decomposition Model for Three Simulated Time Series

Processes	Day-Level SD, σ_u, (95% CI)	Proportion of Total Variance (%)	Momentary-Level SD, σ_e (95% CI)	Proportion of Total Variance (%)
Slow	1.027 (0.696, 1.515)	99	.102 (.088, .119)	1
Medium	.709 (.456, 1.104)	49	.727 (.625, .845)	51
Fast	~0(~0; ~0)	~0	1.0 (.869, 1.151)	~100

Note. CI = confidence interval.

TABLE 2

Results of the Multilevel Variance Decomposition Model for Smoking Urges and Quitting Self-Efficacy EMAs From the Smoking-Cessation Trial

Processes	Day-Level SD, σ_u, (95% CI)	Proportion of Total Variance (%)	Momentary-Level SD, σ_e (95% CI)	Proportion of Total Variance (%)
Smoking urges	.430 (.376, .491)	19.0	.894 (.866, .922)	81.0
Quitting self-efficacy	.709 (.650, .774)	46.3	.765 (.740, .792)	53.7

Note. CI = confidence interval.