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State of the Art and Future Challenges

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Modeling Affect Dynamics: State of the Art and Future Challenges

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Abstract

The current article aims to provide an up-to-date synopsis of available techniques to study affect dynamics using intensive longitudinal data (ILD). We do so by introducing the following eight dichotomies that help elucidate what kind of data one has, what process aspects are of interest, and what research questions are being considered: (1) single- versus multiple-person data; (2) univariate versus multivariate models; (3) stationary versus nonstationary models; (4) linear versus nonlinear models; (5) discrete time versus continuous time models; (6) discrete versus continuous variables; (7) time versus frequency domain; and (8) modeling the process versus computing descriptives. In addition, we discuss what we believe to be the most urging future challenges regarding the modeling of affect dynamics.

Keywords
affective dynamics, intensive longitudinal data, within-person

Introduction

The famous phrase *Panta rhei* ("everything flows") from the ancient Greek philosopher Heraclitus indicates that everything changes all the time. This is certainly true for affect: It tends to fluctuate throughout the day, changing from moment to moment as it is being perturbed by external events and our appraisal of these (e.g., Butler, 2015; Montpetit, Bergeman, Deboeck, Tiberio, & Boker, 2010; Wichers et al., 2009). In addition, affect steers our motivation and behavior, and thus contributes to shaping our subsequent experiences. Hence, understanding the dynamics of affective processes is crucial for understanding human experience.

To study affective processes, we need intensive longitudinal data (ILD) that are dense enough to capture the relevant dynamics. This implies that—depending on the process we are interested in—we may need day-to-day, moment-to-moment, or even second-to-second measurements, which can be obtained using a daily diary, ambulatory assessment, experience sampling, observations, or laboratory measurements (Bolger, Davis, & Rafaeli, 2003; Trull & Ebner- Priemer, 2013). Recent technological developments such as smartphones, accelerometers, and smart shirts have made gathering ILD relatively easy, and as a result intensive longitudinal studies have become a reasonable

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alternative to our more traditional research methods, such as cross-sectional and panel research.

However, many of the key ILD publications focus rather strongly on why and *how* we should gather ILD, but say very little about the *analysis* of ILD (for exceptions, see Bolger & Laurenceau, 2013; Mehl & Conner, 2012; Walls & Schafer, 2006). As a consequence, researchers are likely to revert to techniques they are familiar with, but that are suboptimal—if not simply inappropriate—for ILD, especially when the true interest is in the underlying dynamics.

With the current article, we opt to provide the novice with a bird's-eye view of the diverse techniques that are available for the analysis of ILD. We emphasize here that it is not our intention to present a detailed road map, covering each and every existing technique and discussing all their particularities—this would require multiple books, at least. Instead we will focus on eight dichotomies regarding data features and research questions relevant to ILD, and review associated techniques. In doing so we hope to give the reader a flavor of the many possibilities, while simultaneously raise awareness about the most important issues that are involved. Through the included references, the interested reader will be able to follow up on specific approaches. We end by indicating what we consider the biggest challenges in the years ahead for the study of affect dynamics.

State of the Art in Modeling ILD

We present eight dichotomies that researchers can use to evaluate the kind of data they have and to determine what sort of process features they are interested in. These are: (1) single- versus multiple-person data; (2) univariate versus multivariate models; (3) stationary versus nonstationary models; (4) linear versus nonlinear models; (5) discrete time versus continuous time processes; (6) discrete variables versus continuous variables; (7) time domain versus frequency domain; and (8) modeling the process versus computing descriptives. A brief overview of these dichotomies is given in Table 1.

Dichotomy 1: Single- Versus Multiple-Person Data

ILD techniques adopted from other disciplines, such as econometrics, were often designed for the analysis of single-subject data. The most prominent class of single-subject techniques is time series analysis, which includes autoregressive moving average (ARMA) modeling and multivariate extensions such as the vector autoregressive (VAR) modeling as special cases (Hamilton, 1994). However, ILD in affect research is often obtained from multiple persons. This implies that the researcher has to decide whether only general, nomothetic effects—describing some average across individuals—are of interest, or that also between-person, idiographic differences are important. We can distinguish between three approaches here.

First, one may concatenate the data of all persons and obtain estimates of the general effects. Some approaches that disregard possible interindividual differences are pooled time series analysis (Sayrs, 1989), and multilevel regression with only a general effect. Second, one may ignore general effects and separately analyze the data of each person using a replicated single-subject design (Madhyastha, Hamaker, & Gottman, 2011; Nesselroade & Ford, 1985). While this leaves ample room for revealing interindividual differences in the underlying affective processes (Hamaker, Dolan, & Molenaar, 2005), this approach has clear drawbacks in that comparing the estimates becomes cumbersome when there are many individuals, while the estimates are not very reliable when the number of time points per person is relatively small.

A third approach consists of trying to have the best of both worlds by using a hierarchical extension of a single-person method, which can be applied to the data of all persons simultaneously, while allowing for between-person differences. The latter can be modeled as random deviations from the general effects using a multilevel approach (Bringmann et al., 2013; Song & Ferrer, 2012; Wang, Hamaker, & Bergeman, 2012; Wichers et al., 2009), or alternatively, the population can be assumed to represent K different subpopulations that are characterized by different processes (e.g., de Roover et al., 2012).

In addition, ILD in affect research may come from dyads or families, such that "single-subject" should be replaced by "single-system." These studies allow us to focus on the interplay between two (or more) individuals (see Butler, 2015). Again, researchers may choose to analyze the data for each system separately (Madhyastha et al., 2011; Sadler, Ethier, Gunn, Duong, & Woody, 2009), or to combine the data in one analysis that either does or does not allow for differences between the individual systems (de Haan-Rietdijk, Gottman, Bergeman, & Hamaker, 2014; Song & Ferrer, 2012).

Dichotomy 2: Univariate Versus Multivariate Models

ILD can consist of univariate or multivariate measurements over time. In the latter case, both univariate as well as multivariate processes can be of interest. Univariate processes may pertain to general development over time (e.g., growth and decline, circadian or weekly rhythms; Moberly & Watkins, 2008; Ram et al., 2005), and sudden changes in such trends at known or unknown occasions. Another important feature of a univariate process in affect research is inertia, which is quantified by the autoregressive coefficient or simply the autocorrelation and represents the carryover effect of affect from one occasion to the next (Kuppens, Allen, & Sheeber, 2010; Trull, Lane, Koval, & Ebner-Priemer, 2015; Wang et al., 2012; Wichers, Wigman, & Myin-Germeys, 2015).

A multivariate process perspective focusses on how variables influence each other *over time* (i.e., cross-lagged relations), or on how they are related to each other *within the same occasion*. Recent applications of network analysis are based on multivariate time series techniques and consist of visualizing the autoregressive and cross-lagged relations between multiple variables (Bringmann et al., 2013; Schmittmann et al., 2011).

Table 1. Brief overview of the eight dichotomies.

Dichotomy		
1	*Single-subject data* • Study dynamics of single individual • Time series analysis	*Multiple-subject data* • Study the average pattern of dynamics • Study individual differences in dynamics using random effects models or clustering approaches
2	*Univariate process* • Inertia • MSSD • Trends and cycles	*Multivariate process* • Factor structure (including DFA) • Cross-lagged influences and network analysis • Concurrent influences
3	*Stationary process* • ARMA-based modeling (including VAR and TAR)	*Nonstationary processes* • Trends • Change-point analysis
4	*Linear process* • ARMA model • VAR model • Factor models (including DFA)	*Nonlinear process* • TAR model and change point analysis • Catastrophe theory • Chaos
5	*Discrete time* • ARMA-based modeling	*Continuous time* • Differential equations • MSSD
6	*Discrete variables* • Link function • (Hidden) Markov model	*Continuous variables* • ARMA-based modeling
7	*Time domain* • Most approaches	*Frequency domain* • Spectral analysis
8	*Modeling the process* • Mathematical models	*Obtaining descriptives* • MSSD • State-space grid

Alternatively, one can study whether a time-varying covariate, such as the occurrence of negative or positive events, predicts concurrent affect (Wichers et al., 2009), or whether the experience of one emotion augments or blunts the experience of another (Pe & Kuppens, 2012).

Multivariate ILD can also be used for latent variable modeling, if it is assumed that the observed variables are indicators of one or more underlying constructs. As discussed by Schmittmann et al. (2011), within this category of techniques a further distinction can be made between reflective, factor-analysis-based approaches on the one hand (e.g., Molenaar, 1985), and formative, component-analysis-based approaches on the other (e.g., de Roover, Timmerman, van Diest, Onghena, & Ceulemans, 2014).

Dichotomy 3: Stationary Versus Nonstationary Models

An important question when studying affective dynamics is whether the intraindividual processes under study are assumed to be stationary or nonstationary. Stationary processes are characterized by fluctuation over time while the distributional characteristics (such as the mean, the variance, and the autocorrelations) do not change over time (Hamilton, 1994). Currently, whether an affective process is considered stationary or not depends largely on its theoretical status, although formal statistical tests of nonstationarity exist (e.g., Hamilton, 1994; Weber, Molenaar, & van der Molen, 1992). Some phenomena, such as emotional inertia and blunting (Pe & Kuppens, 2012), are typically treated as stable traits of people and thus as characteristics of stationary processes. Others, like emotional response concordance (Mauss, Levenson, McCarter, Wilhelm, & Gross, 2005; Sander, Grandjean, & Scherer, 2005), are inherently time-varying and hence nonstationary.

Well-known techniques to model stationary processes are vector autoregressive models (Hamilton, 1994) and dynamic factor analysis (DFA; Molenaar, 1985), as well as multilevel extensions of these (Bringmann et al., 2013; Oravecz, Tuerlinckx, & Vandekerckhove, 2011; Song & Ferer, 2012). In some cases, these techniques can be modified in order to account for nonstationarity, for instance, by including time as a predictor. To model nonstationary processes one can also choose a model in which the parameters that describe the dynamics vary slowly over time (Chow, Zu, Shifren, & Zhang, 2011; Molenaar, 1987; Shiyko, Lanza, Tan, Li, & Shiffman, 2012). Furthermore, under some conditions (e.g., sufficiently dense time grid) the measurements across time can be considered as curves (i.e., functions), such that they can be modeled with methods from functional data analysis (Verduyn, van Mechelen, & Frederickx, 2012).

Affective ILD may also be generated by multiple linear, stationary processes, between which the individual switches. If it is known when these switches occur, a covariate can be included that indicates to which process each time point belongs (Bringmann et al., 2013), whereas if the change points are unknown, the analysis becomes more challenging because they also have to be retrieved from the data (Wang & McArdle, 2008). Such models may be stationary or nonstationary, depending on whether the switches are recurrent, or only happen once. A few recently developed techniques for detecting change points in affective time series are DeCon (Bulteel et al., 2014), and switching component analysis (de Roover et al., 2014). Other options that have been considered in affect research are regime switching state-space models (Hamaker & Grasman, 2011), and threshold autoregressive models (de Haan-Rietdijk et al., 2014; Madhyastha et al., 2011), both of which tend to be stationary.

Dichotomy 4: Linear Versus Nonlinear Models

In a linear model, changes that occur in an outcome variable are proportional to the changes in the predictors or input variables. Note that the latter may include nonlinear transformations of original predictors, such as the square or exponent of a predictor, or even the product between two predictors. In contrast, when changes in the outcome variable are not proportional to changes in the input, this is referred to as a nonlinear model (Deboeck, 2013). Nonlinearity may give rise to more complex behavior than linear models, and has gained particular interest in some areas of psychology because of its relationship to chaotic behavior, catastrophe theory, and attractors (van der Maas & Molenaar, 1992). However, this interest has been largely of a theoretical nature, in that chaos and catastrophe have been used to describe psychological phenomena, while modeling has been largely based on linear approximations.

In affective research, van de Leemput et al. (2014) considered the idea of critical slowing down before a stage transition (which is considered one of the flags of catastrophe; see van der Maas & Molenaar, 1992), and showed that autocorrelations and cross-correlations indeed increase before individuals switch to a state of depression (see also Wichers et al., 2015). Heiby, Pagano, Blaine, Nelson, and Heath (2003) used several methods—since there is no single method to detect chaos—to determine whether there was evidence for chaos in the affective measurements of a depressed person and compared this to the pattern in a healthy control. To allow for a more explicit investigation of nonlinear processes, Chow, Ferrer, and Nesselroade (2007) considered an extension of the Kalman filter, which they applied to affective interactions between husbands and wives.

Dichotomy 5: Discrete Time Versus Continuous Time Models

It could be argued that—even though our observations are necessarily made at discrete points in time—affective processes evolve continuously over time (Hu, Boker, Neale, & Klump, 2014). To adequately capture the dynamics of the process under investigation, researchers have to decide on important issues like the sampling frequency (i.e., the number of measurements per time interval), the length of the measurement period, and whether the intervals between measurement occasions should be of equal length or that they should be varied randomly (Bolger et al., 2003).

Regarding the latter, the main concern is whether or not anticipating a measurement can affect the measured process: if this is the case, it is better to use a measurement design based on random intervals (such as in experience sampling methods), which captures the individual in the moment; if it is not the case, using fixed intervals is preferable, as most data analysis methods are implemented on the assumption of equal time intervals. However, in practice data with unequal intervals are often analyzed using models that are based on the assumption of equal time intervals (Kuppens et al., 2010), which may be particularly problematic when the focus is on lagged effects between variables (see Oravecz & Tuerlinckx, 2011, for some preliminary results). Some researchers have tried to account for varying intervals by adding the length of the time interval as a covariate, but this does not solve the problem in (vector) autoregressive processes. More elegant alternatives are based on treating time as continuous in differential equations (Bisconti, Bergeman, & Boker, 2004; Deboeck, 2013; Deboeck & Bergeman, 2013; Oravecz et al. 2011; Voelkle & Oud, 2013).

While the continuous time approach has many advantages—especially for dealing with unequal intervals between the observations and missing data—there are two side notes that need to be made. First, the multilevel approaches based on differential equations still have some limitations and are not as fully developed as their discrete time counterparts. That is, currently there is no approach available that allows for random cross-lagged coefficients that are allowed to differ from each other within a person or dyad. Second, affective daily diary data may not be appropriate for continuous time modeling, because participants are asked to provide ratings that pertain to the entire day: As a result, the measurement procedure results in a discrete dynamic process—even though the underlying process may evolve continuously over time—that can be handled well with models based on discrete time.

Dichotomy 6: Discrete Variables Versus Continuous Variables

The observed variables can be continuous, counts, ordinal (e.g., Likert scale data) or nominal (e.g., coded category). In contrast, most existing techniques for handling ILD were developed for continuous data that are assumed to be normally distributed. To use such techniques in case of noncontinuous data, researchers may consider the framework of generalized linear models (Fahrmeir & Tutz, 2001), in which a link function transforms the observed variable into a continuous variable. For instance, Kuppens et al. (2010) analyzed binary behavioral observations using a logistic extension of the autoregressive multilevel model in order to investigate inertia in diverse second-to-second affective behaviors.

Another option, which is used regularly, is to sum a number of the original variables per time point in order to obtain variables that are approximately continuous and normally distributed. For example, Wang et al. (2012) used a sum score of negative affect items that were scored on a 5-point Likert scale. However, summing is not sensible when the observed variables represent distinct elements of a process or when the variables are nominal rather than ordinal.

When the chosen approach includes latent variables, these can also be either discrete or continuous. For instance, in multilevel models, factor analysis, and principal component analysis (PCA)-based methods, it is often assumed that latent variables are continuous. Alternatively, the latent variable can also be a discrete classification, such that persons are grouped into a few latent classes or clusters (Vermunt, 2008). Closely related to this are (hidden or latent) Markov models (Rijmen, Ip, Rapp, & Shaw, 2008; Rovine, Sinclair, & Stifter, 2010; Visser, 2011), and switching component models (de Roover et al., 2014), which allow individuals to switch between a number of categorical latent states. An advantage of Markov models is that they are flexible in combining categorical and continuous observed variables, making it a valuable alternative when more common approaches are not appropriate. Note that Markov models can also be used to model switching in an observed categorical variable.

Dichotomy 7: Time Domain Versus Frequency Domain

At a very general level, all the approaches towards time series data and ILD can be divided into two main domains: the time domain, in which the goal is to describe how the data are a function of time (e.g., there may be a linear or quadratic trend, or a week cycle in the data), and/or how the observations can be predicted from previous observations (e.g., through the inclusion of autoregressive and cross-lagged relationships); and the frequency domain, in which the data are considered as a function of many different sine waves, with different frequencies (Hamilton, 1994). Most of the techniques that are described in this article and applied in affective research based on ILD, fall in the time domain category. In the frequency domain, the typical approach is to use spectral or spectrum analysis, also referred to as frequency analysis.

Spectral analysis is often used for psychophysiological measures such as interbeat intervals of heart rate, magneto-/electro-encephalogram, and respiratory rate. Ram et al. (2005) used frequency analysis as an exploratory approach to determine the length of the most dominant cycle per person in daily affect measurements. Heiby et al. (2003) used the log-log transformed power spectrum to find evidence for chaotic behavior in the data, but this particular use of frequency analysis has been heavily criticized (Wagenmakers, Farrell, & Ratcliff, 2004). Sadler et al. (2009) used the cross-spectral density of the bivariate data from spouses to determine how attuned the partners are at different frequencies as well as overall.

Dichotomy 8: Modeling the Process Versus Computing Descriptives

If one has ILD from multiple persons, one could decide to use a statistical technique in which the individual trajectories over time are modeled, separately or simultaneously, as described extensively above. Alternatively though, researchers can choose to use a summary measure of each individual's dynamics, which is then used in more conventional analyses. Some examples of this have already been discussed before (e.g., Sadler et al., 2009). Two other descriptive approaches we like to emphasize here, are the mean squared successive difference (MSSD; Jahng, Wood, & Trull, 2008), and the use of state-space grids (SSG; Granic & Hollenstein, 2003).

The MSSD is based on taking the difference between two consecutive measurements, squaring it and taking the mean of all of the squared differences per person. It is a way to capture measurement-to-measurement variability, regardless of whether or not there is a trend in the data. In affect research the measure has been referred to as *affect instability* (Trull et al., 2015; Wichers et al., 2015). SSG is a tool that was developed to study dyads, although it can be used for other bivariate systems as well. In essence it is simply a way to visualize the behavior of a bivariate system, where the two variables—which are either nominal or ordinal—form a grid and each cell represents the combination of two categories of the two variables. Measures that have been derived are: the number of switches between cells, or the time it takes to return to a cell or quadrant in the SSG once it is left. As with the MSSD, once a summary measure has been obtained for each individual or dyad, it can be used subsequently in group comparisons or regression analyses. A major advantage of such descriptives is that they do not require the researcher to define an underlying process.

Most Urgent Challenges for the Years Ahead

Although studies based on ILD have been part of psychological research since the beginning, it was not until recently that it has become a more feasible approach in mainstream research. We wholeheartedly welcome this development, as we strongly believe that the shift from studying static outcomes of processes to focusing on the actual processes as they evolve over time, is a crucial step in the progress of psychology: Only through the careful study of patterns of fluctuations over time—how these patterns differ across individuals and how these patterns then change over time—can we begin to understand the essence of human beings.

From the current article it has become clear that there are many options for analyzing ILD, and that the choice between these options requires careful consideration from the researcher. In addition, we want to draw attention to two general considerations, which we believe are fundamental to this kind of research. First, as already mentioned, it is important that the measurement frequency is dense enough to capture the actual process one is interested in. This is not a matter of one-size-fits-all, but rather requires careful consideration, theory and empirical studies to determine for any particular psychological phenomenon whether one needs second-to-second, moment-to-moment, or day-to-day measurements. Choosing a measurement schedule with a frequency that is too low results in finding no meaningful relationships over time (cf. Trull et al., 2015). On the other hand, a too high frequency will form an unnecessary burden for the participants, leading to unnecessary dropout. Moreover, it probably limits the time span that can be covered in the study, such that one may not be able to detect the actual fluctuations of interest. Thus, it is crucial that researchers find ways to determine at which time scale the process of interest actually operates.

Second, a related question is at what time lag variables influence each other. For instance, if a negative event occurs, does this immediately lead to an increase in negative affect, or does it require some time before it impacts our mood? Gollob and Reichardt (1987) already pointed out that the results one obtains, depend on the length of the time lag between measurements. Continuous time modeling has been suggested as a way to overcome this "lag-problem," as it allows one to see how the effect of one variable on the other changes as a function of the interval between cause and effect (Voelkle & Oud, 2013). However, the issue of influence is probably more complicated, as variables may influence each other differently at different time scales. For instance, Butler (2015) discusses the "coconstruction" of emotional meaning, which implies that an individual's stance towards an event may change after discussing it with other people. Wichers et al. (2015) also suggest that there may be different time scales involved in psychopathology, and that the cumulative effect of many small—seemingly meaningless—effects may result in large, meaningful effects in the long run. Suppose for instance that a parent yells at a child: In the short run this may lead to a change in behavior on part of the child (e.g., the child yells back, or stops the annoying behavior), but many incidents such as this are also likely to have a formative effect that is more than simply the sum of all the small effects. How to relate moment-to-moment and day-to-day processes to developmental processes spanning years or even a lifetime, is one of the fundamental questions that will be begging an answer over the following decade.

To conclude, we pose that using ILD to tap into the dynamics of processes—rather than focusing on their static outcomes—is an important first step; seeing how the dynamics themselves change, is the logical next step. That is, *Panta rhei* not only pertains to affective phenomena, but also to their dynamics.

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References

Bisconti, T. L., Bergeman, C. S., & Boker, S. M. (2004). Emotion regulation in recently bereaved widows: A dynamical systems approach. *Journal of Gerontology: Psychological Sciences*, *59*, 158–167.

Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology*, *54*, 579–616.

Bolger, N., & Laurenceau, J.-P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*. New York, NY: Guilford Press.

Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., … Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PLoS ONE*, *8*(4), e60188.

Bulteel, K., Ceulemans, E., Thompson, R. J., Waugh, C. E., Gotlib, I. H., Tuerlinckx, F., & Kuppens, P. (2014). DeCon: A tool to detect emotional concordance in multivariate time-series data of emotional responding. *Biological Psychology*, *98*, 29–42.

Butler, E. A. (2015). Interpersonal affect dynamics: It takes two (and time) to tango. *Emotion Review*, *7*, 336–341.

Chow, S.-M., Ferrer, E., & Nesselroade, J. R. (2007). An unscented Kalman filter approach to the estimation of nonlinear dynamical systems models. *Multivariate Behavioral Research*, *42*, 283–321.

Chow, S.-M., Zu, J., Shifren, K., & Zhang, G. (2011). Dynamic factor analysis models with time-varying parameters. *Multivariate Behavioral Research*, *46*, 303–339.

Deboeck, P. R. (2013). Dynamical systems and models of continuous time. In T. D. Little (Ed.), *The Oxford handbook of quantitative methods* (Vol. II, pp. 411–431). New York, NY: Oxford University Press.

Deboeck, P. R., & Bergeman, C. S. (2013). The reservoir model: A differential equation model of psychological capacity. *Psychological Methods*, *18*, 237–256.

De Haan-Rietdijk, S., Gottman, J. M., Bergeman, C. S., & Hamaker, E. L. (2014). Get over it! A multilevel threshold autoregressive model for state-dependent affect regulation. *Psychometrika*. Advance online publication. doi:10.1007/s11336–014–9417-x

De Roover, K., Ceulemans, E., Timmerman, M., Vansteelandt, K., Stouten, J., & Onghena, P. (2012). Clusterwise simultaneous component analysis for analyzing structural differences in multivariate multiblock data. *Psychological Methods*, *17*, 100–119.

De Roover, K., Timmerman, M. E., van Diest, I., Onghena, P., & Ceulemans, E. (2014). Switching principal component analysis for modeling changes in means and covariance structure over time. *Psychological Methods*, *19*, 113–132.

Fahrmeir, L., & Tutz, G. (2001). *Multivariate statistical modelling based on generalized linear models*. New York, NY: Springer-Verlag.

Gollob, H. F., & Reichardt, C. S. (1987). Taking account of time lags in causal models. *Child Development*, *58*, 80–92.

Granic, I., & Hollenstein, T. (2003). Dynamic system methods for models of developmental psychopathology. *Development and Psychopathology*, *15*, 641–669.

Hamaker, E. L., Dolan, C. V., & Molenaar, P. M. C. (2005). Statistical modeling of the individual: Rationale and application of multivariate stationary time series analysis. *Multivariate Behavioral Research*, *40*, 404–418.

Hamaker, E. L., & Grasman, R. P. P. P. (2011). Regime switching state-space models applied to psychological processes: Handling missing data and making inferences. *Psychometrika*, *77*, 400–422.

Hamilton, J. D. (1994). *Time series analysis*. Princeton, NJ: Princeton University Press.

Heiby, E. M., Pagano, I. S., Blaine, D. D., Nelson, K., & Heath, R. A. (2003). Modeling unipolar depression as a chaotic process. *Psychological Assessment*, *15*, 426–434.

Hu, Y., Boker, S. M., Neale, M. C., & Klump, K. (2014). Coupled latent difference equations with moderators: Simulation and application. *Psychological Methods*, *19*, 56–71.

Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in EMA: Indices using successive difference and group comparison via multilevel modeling. *Psychological Methods*, *13*, 345–375.

Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychological Science*, *21*, 984–991.

Madhyastha, T., Hamaker, E. L., & Gottman, J. (2011). Investigating spousal influence using moment-to-moment affect data from marital conflict. *Journal of Family Psychology*, *25*, 292–300.

Mauss, I., Levenson, R., McCarter, L., Wilhelm, F., & Gross, J. (2005). The tie that binds? Coherence among emotion experience, behavior, and physiology. *Emotion*, *5*, 175–190.

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

Moberly, N. J., & Watkins, E. R. (2008). Ruminative self-focus and negative affect: An experience sampling study. *Journal of Abnormal Psychology*, *117*, 314–323.

Molenaar, P. C. M. (1985). A dynamic factor model for the analysis of multivariate time series. *Psychometrika*, *50*, 181–202.

Molenaar, P. C. M. (1987). Dynamic assessment and adaptive optimization of the psychotherapeutic process. *Behavioral Assessment*, *9*, 389–416.

Montpetit, M. A., Bergeman, C. S., Deboeck, P. R., Tiberio, S. S., & Boker, S. M. (2010). Resilience-as-process: Negative affect, stress, and coupled dynamical systems. *Psychology and Aging*, *25*, 631–640.

Nesselroade, J. R., & Ford, D. H. (1985). P-technique comes of age: Multivariate, replicated, single-subject designs for research on older adults. *Research on Aging*, *7*, 46–80.

Oravecz, Z., & Tuerlinckx, F. (2011). The linear mixed model and the hierarchical Ornstein– Uhlenbeck model: Some equivalences and differences. *British Journal of Mathematical and Statistical Psychology*, *64*, 134–160.

Oravecz, Z., Tuerlinckx, F., & Vandekerckhove, J. (2011). A hierarchical latent stochastic differential equation model for affective dynamics. *Psychological Methods*, *16*, 468–490.

Pe, M. L., & Kuppens, P. (2012). The dynamic interplay between emotions in daily life: Augmentation, blunting, and the role of appraisal overlap. *Emotion*, *12*, 1320–1328.

Ram, N., Chow, S.-M., Bowles, R. P., Wang, L., Grimm, K., Fujita, F., & Nesselroade, J. R. (2005). Examining interindividual differences in cyclicity of pleasant and unpleasant affects using spectral analysis and item response modeling. *Psychometrika*, *70*, 773–790.

Rijmen, F., Ip, E. H., Rapp, S., & Shaw, E. G. (2008). Qualitative longitudinal analysis of symptoms in patients with primary and metastatic brain tumours. *Journal of the Royal Statistical Association, Series A*, *171*, 739–753.

Rovine, M. J., Sinclair, K. O., & Stifter, C. A. (2010). Modeling mother–infant interactions using hidden Markov models. In P. C. M. Molenaar & K. M. Newell (Eds.), *Individual pathways of change* (pp. 51–67). Washington, DC: APA Press.

Sadler, P., Ethier, N., Gunn, G. R., Duong, D., & Woody, E. (2009). Are we on the same wavelength? Interpersonal complementarity as shared cyclical patterns during interactions. *Journal of Personality and Social Psychology*, *97*, 1005–1020.

Sander, D., Grandjean, D., & Scherer, K. (2005). A systems approach to appraisal mechanisms in emotion. *Neural Networks*, *18*, 317–352.

Sayrs, L. W. (1989). *Pooled time series analysis* (Series: Quantitative applications in the social sciences, Issue 70). Newbury Park, CA: Sage.

Schmittmann, S. D., Cramer, A. O. J., Waldorp, L. J., Epskamp, S., Kievit, R. A., & Borsboom, D. (2011). Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas in Psychology*, *31*, 43–53.

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: Difference between successful quitters and relapsers. *Prevention Science*, *13*, 288–299.

Song, H., & Ferrer, E. (2012). Bayesian estimation of random coefficient dynamic factor models. *Multivariate Behavioral Research*, *47*, 26–60.

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

Trull, T. J., Lane, S. P., Koval, P., & Ebner-Priemer, U. W. (2015). Affect dynamics in psychopathology. *Emotion Review*, *7*, 355–361.

Van de Leemput, I. A., Wichers, M., Cramer, A. O. J., Borsboom, D., Tuerlinckx, F., Kuppens, P., … Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences*, 111, 87–92.

Van der Maas, H. L. J., & Molenaar, P. C. M. (1992). Stagewise cognitive development: An application of catastrophe theory. *Psychological Review*, *99*, 395–417.

Verduyn, P., van Mechelen, I., & Frederickx, E. (2012). Determinants of the shape of emotion intensity profiles. *Cognition and Emotion*, *26*, 1486–1495.

Vermunt, J. K. (2008). Latent class and finite mixture models for multilevel datasets. *Statistical Methods in Medical Research*, *17*, 33–51.

Visser, I. (2011). Seven things to remember about hidden Markov models: A tutorial on Markovian models for time series. *Journal of Mathematical Psychology*, *55*, 403–415.

Voelkle, M. C., & Oud, J. H. L. (2013). Continuous time modelling with individually varying time intervals for oscillating and nonoscillating processes. *British Journal of Mathematical and Statistical Psychology*, *66*, 103–126.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2004). Estimation and interpretation of $1/f^{a}$ noise in human cognition. *Psychonomic Bulletin & Review*, *11*, 579–615.

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

Wang, L., Hamaker, E. L., & Bergeman, C. S. (2012). Investigating inter-individual differences in short-term intra-individual variability. *Psychological Methods*, *17*, 567–581.

Wang, L., & McArdle, J. J. (2008). A simulation study comparison of Bayesian estimate with conventional methods for estimating unknown change points. *Structural Equation Modeling*, *15*, 52–74.

Weber, E. J. M., Molenaar, P. C. M., & van der Molen, M. W. (1992). A nonstationarity test for the spectral analysis of physiological time series with an application to respiratory sinus arrhythmia. *Psychophysiology*, *29*, 55–62.

Wichers, M., Barge-Schaapman, D. Q. C. M., Nicolson, N. A., Peeters, F., de Vries, M., Mengelers, R., & van Os, J. (2009). Reduced stress-sensitivity or increased reward experience: The psychological mechanism of response to antidepressant medication. *Neuropsychopharmacology*, *34*, 923–931.

Wichers, M., Wigman, J. T. W. (Hanneke), & Myin-Germeys, I. (2015). Micro-level affect dynamics in psychopathology viewed from complex dynamical system theory. *Emotion Review*, *7*, 362–367.