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No Time Like the Present: Discovering the Hidden Dynamics in Intensive Longitudinal Data

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Abstract
There has been a strong increase in the number of studies based on intensive longitudinal data, such as those obtained with experience sampling and daily diaries. These data contain a wealth of information regarding the dynamics of processes as they unfold within individuals over time. In this article, we discuss how combining intensive longitudinal data with either time-series analysis, which consists of modeling the temporal dependencies in the data for a single individual, or dynamic multilevel modeling, which consists of using a time-series model at Level 1 to describe the within-person process while allowing for individual differences in the parameters of these processes at Level 2, has led to new insights in clinical psychology. In addition, we discuss several methodological and statistical challenges that researchers face when they are interested in studying the dynamics of psychological processes using intensive longitudinal data.

Keywords
intensive longitudinal data, time series, dynamic multilevel modeling, within-person, intraindividual, experience sampling, diary study

Psychological processes unfold over time. Despite this obvious truth, the common ways of studying processes in psychology have been to (a) focus on the static outcomes of processes in experiments through comparing different conditions with each other; (b) use panel data consisting of a few snapshots, typically relatively far apart in time, by which only very crude changes are captured; or (c) use cross-sectional data and simply assume that individual differences somehow reflect within-person processes. However, as Figure 1 shows, there has been an exponential increase in the number of studies based on intensive longitudinal data obtained with ambulatory assessments, daily diaries, experience sampling, and ecological momentary assessments. The advantages of these kind of data—such as reduced recall bias and high ecological validity—have been discussed at length elsewhere (Mehl & Conner, 2012; Trull & Ebner-Priemer, 2014); here, we want to focus on an important but often neglected feature of these data: Intensive longitudinal data allow us to gain insights in the *dynamics of a process*—that is, the ways in which internal and external forces influence the course of the phenomenon under investigation.

In this article, we set out to highlight some of the exciting ways in which this arising methodology, combined with novel statistical techniques, has helped to gain new insights into psychological processes. Additionally, we discuss what we believe are the most important methodological and statistical challenges that characterize the current state of this emerging field.

Recent Results Using State-of-the-Art Techniques

Thanks to recent technological advances, such as smartphones and sensors, the possibilities for studying experiential, physiological, and behavioral processes in the social and medical sciences have been greatly facilitated. The steep increase in studies based on intensive longitudinal

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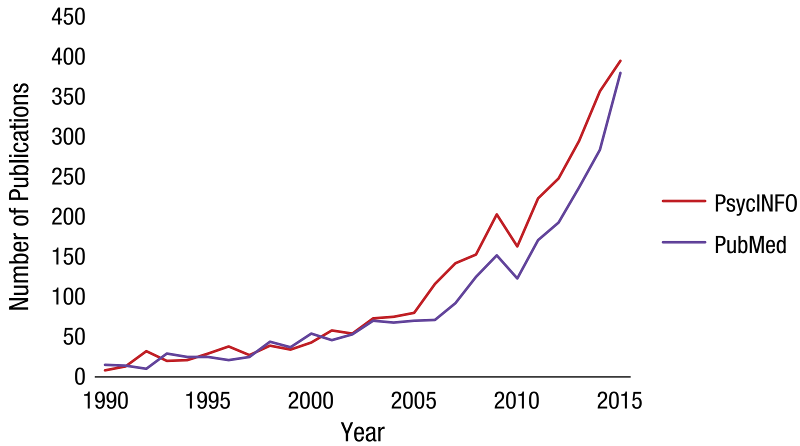

Fig. 1. Annual number of publications, based on searches using the PsycINFO and PubMed databases, with one or more of the following terms in the title, in the abstract, or as a keyword: *daily diary, experience sampling, ambulatory assessment, ecological momentary assessment*. Note that these are most likely underestimates of the actual numbers of studies based on intensive longitudinal data.

data reflects that researchers recognize the unique value these data have for studying a wide variety of phenomena. To analyze such data, researchers can choose from a range of different statistical techniques (Hamaker, Ceulemans, Grasman, & Tuerlinckx, 2015), but two approaches that seem particularly promising are *time-series analysis* and *dynamic multilevel modeling*.

Time-series analysis is a set of techniques that have been developed in the fields of econometrics, physics, and engineering and have been applied only occasionally in the social sciences (Hamaker & Dolan, 2009). In essence, it is a single-subject technique, in which a large number of repeated measures from a single system (e.g., a person or dyad) are analyzed, with a focus on how the current observation can be predicted from preceding observations of the same and/or other variables. One area in particular where this approach has been met with enthusiasm is clinical psychology. For instance, Stavrakakis et al. (2015) used a replicated time-series design to investigate the temporal dynamics between physical activity and affective states for 10 depressed and 10 nondepressed individuals. By investigating for each participant separately whether and how physical activity and affective states predicted each other over time, Stavrakakis et al. found large individual differences in both the strength and the direction of those relationships. Hamaker, Grasman, and Kamphuis (2016) also used a replicated time-series design when they compared the daily affective fluctuations of 3 rapid-cycling bipolar disorder patients and 11 healthy controls. The researchers specified a range of different time-series models intended to capture different forms of affective dysregulation, and they found both qualitative differences (i.e., different time-series models) and quantitative differences (i.e., different parameter values) between patients and controls. Wichers, Groot, and Psychosystems, ESM Group, EWS Group (2016) considered changes in dynamics using data from a depressed patient who reported on his affective state on almost 1,500 occasions. They found that the associations tended to grow stronger before a relapse in symptoms occurred, suggesting that the course of these associations over time could be used to predict the risk of relapse.

A more recently developed approach is dynamic multilevel modeling, based on a time-series model at Level 1 that describes the within-person process, while between-person differences in the dynamic features are modeled at Level 2. One line of research based on this approach has focused on inertia—that is, the tendency to remain in a particular state for a considerable amount of time. Inertia has been quantified as the autoregression of a variable, representing the carryover effect from one occasion to the next, which has been shown to be negatively related to psychological well-being and predictive of clinical depression 2.5 years later (Houben, Van den Noortgate, & Kuppens, 2015; Kuppens et al., 2012). Other research has focused on sensitivity to daily life events, such as rewarding situations. This research has shown that people who experience a larger increase in positive emotions in naturally rewarding contexts are better protected against developing depressive symptoms a year later (Geschwind et al., 2010). Also, in a randomized controlled trial with depressed patients, it was shown that increases in sensitivity to everyday rewards discriminated between patients who showed symptom reductions and those who did not, regardless of the intervention they received (Wichers et al., 2009).

Other studies have focused on *lagged relationships* between different variables—that is, relationships between variables measured on different occasions (Kramer et al., 2014; Ruby, Smallwood, Engen, & Singer, 2013; Wichers et al., 2012). A sophisticated approach in this context is the multilevel vector autoregressive (VAR) model, which can be used to examine the lagged associations between multiple variables (Schuurman, Ferrer, de Boer-Sonnenschein, & Hamaker, 2016). Bringmann and colleagues (2013) used this model to obtain individual networks of symptoms. Their empirical results showed that worrying is much more central in the networks of people high in neuroticism than in those of people low in neuroticism, implying that there are positive relationships between neuroticism and the ease with which the node "worry" is activated (through other experiential states; e.g., feeling down) and how easily this node (de)activates other experiential states (e.g., feeling anxious or cheerful).

These diverse lines of research show that the combination of intensive longitudinal data with time-series analysis or dynamic multilevel modeling facilitates a paradigm shift, away from trying to understand psychological processes using static outcomes, crude descriptions, and cross-sectional results toward an actual process-oriented psychological science that focuses on the within-person dynamics and between-person differences therein.

Challenges at the Dynamics Frontier

Although intensive longitudinal data bring great advances for studying psychological processes in innovative ways, this is also accompanied by diverse methodological and statistical challenges, which we outline below.

Methodologically, there are the challenges of setting up a measurement design that allows for a valid observation of the process of interest and supports causal conclusions. First, observing a process without changing it may be difficult. Designs with fixed measurement moments (e.g., every 2 hours on the dot) may lead participants to anticipate the next measurement moment and to change their behavior accordingly (Delespaul, 1995). Many researchers therefore use random-measurement designs, in which measurement moments vary randomly across and within individuals. Another concern is whether self-focus—which is encouraged when participating in an intensive longitudinal study—actually influences the course of the process under investigation. To determine whether the number of measurements affects the process that is measured, Stone et al. (2003) and Conner and Reid (2012) randomly assigned participants to conditions that differed with respect to the number of daily measurements. In both studies, there was no trend over time, nor were there differences in trends between the conditions, suggesting that the number of measurements per day did not alter the experience itself. However, Conner and Reid (2012) found significant interactions between the number of measurements per day and person characteristics (e.g., depression and neuroticism), showing that although there was no effect on average, the effect may differ across people.

A second methodological challenge is choosing the optimal time interval that suits the timescale of the process under investigation (Conner & Lehman, 2012; Dorman & Griffin, 2015). For instance, negative thoughts about the self and the future may change over weeks or months, whereas affective states change more rapidly, over periods of hours or even minutes. In the latter case frequent assessments are necessary to capture relevant fluctuations, whereas in the former case frequent measurements are unnecessary. Because this kind of research is still very new, researchers are facing this challenge without solid empirical knowledge to base their decision on. The issue is further complicated by the feasibility trade-off of the burden placed on participants: In designs that are based on very frequent measurements, the total time span that can be covered will be shorter than in designs with less frequent measurements. Although this is less of an issue for processes that can be measured with novel sensor measures (e.g., GPS-tracked location of participants, physical activity), most psychological processes cannot be captured validly using such technology at this point.

A third methodological challenge is in determining how intensive longitudinal designs can be combined with experimental manipulations at the individual level such that we can actually determine whether certain within-person relationships are truly causal. Currently, the bulk of intensive longitudinal studies have been based on purely correlational data. This means that the lagged relationships obtained are, at best, reflective of Granger causality—that is, a within-person predictive relationship that may or may not represent a causal mechanism. The concept of Granger causality is very popular in econometrics but has also been criticized harshly, as it is hampered by diverse problems, including the well-known omitted-variable problem (Eichler, 2012; Lütkepohl, 1982). Note that although there have been some combinations of experimental manipulations and intensive longitudinal data, these manipulations were either at the between-person level, with participants assigned to different conditions, or in a pretest/posttest design, with intensive longitudinal data gathered before and after an intervention. The latter is a within-person design that allows one to determine whether lagged relationships changed as a result of the intervention (or of time), but not whether the lagged relationships themselves are causal. In order to determine the latter, we need a within-person manipulation in which occasions are randomly assigned to different experimental conditions. Although this may be no easy task to accomplish in practice—especially outside the lab—it is probably an essential step in moving from prediction and description to a truly causal interpretation of the within-person relationships.

There are also several statistical challenges, some of which are relatively easy to tackle, whereas others are still in need of a solution. First, it is important to make sure we are separating the within-person dynamics from the between-person differences. There may be instances in which this is not an issue—for instance, when a single-subject approach is taken; however, when using dynamic multilevel modeling, a proper decomposition into within-person and between-person variance is crucial for the results to be informative about the within-person process (Bolger & Laurenceau, 2013). Failing to do so leads to results that have been described as an "uninterpretable blend" (Raudenbush & Bryk, 2002, p. 139) of within-person and between-person relationships.

Second, it is important to control for different forms of stability (Hamaker, Kuiper, & Grasman, 2015). From the multilevel literature, it is well known that we should control for stable, traitlike, between-person differences, and a commonly used approach to ensure this is through centering all Level 1 predictors per person (cf. Bolger & Laurenceau, 2013; Raudenbush & Bryk, 2002). Additionally, in the time-series literature concerning Granger causality, there is a strong emphasis on the need to account for moment-to-moment stability (e.g., through modeling autoregression) before considering the effect of an external predictor (Eichler, 2012). Failing to account for either of these forms of stability will most likely distort results, such that existing relationships between the predictor and the outcome variable may be obscured, or a spurious relationship may arise.

Third, it should be noted that when we are using a design that is based on randomly varying intervals as described above, these data do not seamlessly fit into time-series analysis and dynamic multilevel modeling, which are typically based on the assumption that the measurements are equidistant (i.e., obtained with equal intervals). In many of the existing studies that have combined such data with these statistical techniques, this issue has been ignored. A sophisticated method for handling non-equidistant measurements is continuous time modeling (Oravecz, Tuerlinckx, & Vandekerckhove, 2011; Voelkle, Oud, Davidov, & Schmidt, 2012), but current software implementations have certain limitations that are undesirable in the case of multilevel extensions. A pragmatic way of "handling" unequal intervals between measurements is adding missing observations in between the observed values, such that the measurements become "approximately" equidistant. Future research should determine the cost of ignoring unequal intervals, as well as the optimal time grid when attempting to make the observations approximately equally spaced.

Fourth, related to the previous point, some thought should be given to the actual nature of time—that is, should we think of the process as unfolding continuously over time, or is it something that occurs only at particular points in time? It is well known that the strength of lagged relationships depends on the interval between the observations (e.g., Gollob & Reichardt, 1987); as a result, two researchers who study, for instance, the lagged relationships between stress and anxiety may reach very different conclusions about the reciprocal nature and the "causal dominance" of these two variables, depending on the interval each uses. This phenomenon—known as the *lag problem*—confronts us with the unsettling reality that simply because we obtained measurements every 90 minutes (or every 3 hours, or once per day), this does not mean that the variables exert an influence on each other only at this interval. In fact, it may be argued that most variables vary continuously over time and that they affect each other continuously over time (Deboeck & Preacher, 2016; Dorman & Griffin, 2015; Oravecz et al., 2011; Voelkle et al., 2012). This leads to a radically different perspective that requires researchers to familiarize themselves somewhat with differential equations (which may be daunting), but this may prove essential for really understanding how psychological processes operate.

Fifth, a major challenge is how to relate developmental changes in two or more variables to each other. An increasingly popular model for studying reciprocal effects is the VAR model. Typically, when there are trends in the data, these are separated from additional fluctuations, such that the cross-lagged part of the model provides information about the detrended process. However, this approach may actually lead to ignoring the most important change process, simply because it forms a trend rather than stationary fluctuations. This has led some researchers to question the practice of uncritically detrending the data (e.g., Wang & Maxwell, 2015). Another way in which relating change can be complicated is through the presence of cycles in intensive longitudinal data (Liu & West, 2015): There may be monthly, weekly, and daily movements up and down, which can lead to spurious lagged relationships between variables. Detrending the data may seem like the easy solution, but again, this may result in throwing the baby out with the bathwater. Although methodologists and psychometricians are currently considering these issues, no consensus has been reached, and researchers need to carefully consider the pros and cons associated with different approaches.

Finally, a fundamental challenge that has received very little attention to date is how we can relate processes that operate at different timescales. For instance, many minor and seemingly insignificant negative interactions with a parent during one's childhood may accumulate into a sensitivity to stress as an adult, which could subsequently lead to a major depressive episode decades later. Although at this point the importance of such psychopathological cascades—which originate at the micro scale of moment-to-moment dynamics, and eventually spill over into the macro scale of lifetime development—is well recognized (Kramer et al., 2014; Wichers, 2014), how to measure and model such processes is still an open-ended question.

Conclusion

Intensive longitudinal data, combined with time-series analysis or dynamic multilevel modeling, form a powerful vehicle for an emerging paradigm that is concerned with the dynamics of processes and is characterized by a strong focus on where (i.e., within-person) and when (i.e., in real time) processes take place. This approach has the potential to change the way we think about, practice, and teach psychological science. What is needed at the present time is a careful investigation of the methodological and statistical challenges described above. If we prove successful at tackling these, psychological science will be awarded with a wealth of new insights that cannot be obtained otherwise.

Recommended Reading

Hamaker, E. L., Ceulemans, E., Grasman, R. P. P. P., & Tuerlinckx, F. (2015). (See References). A brief overview of the diverse statistical techniques available for modeling (affective) dynamics.

Houben, M., Van den Noortgate, W., & Kuppens, P. (2015). (See References). Provides a meta-analysis of the patterns of short-term emotion dynamics (including inertia and variability) in psychological well-being and psychopathology.

Mehl, M. R., & Conner, T. S. (2012). (See References). A true handbook for studying daily life as it unfolds.

Schuurman, N. K., Ferrer, E., de Boer-Sonnenschein, M., & Hamaker, E. L. (2016). (See References). A thorough discussion of how to standardize parameters in a multilevel VAR model in order to allow for meaningful comparisons between the cross-lagged relationships per individual.

Wichers, M. (2014). (See References). Presents the cascade model as a way to understand how micro-level processes may spill over into macro-level processes such as the onset and course of psychopathology.

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