# Chapter 5
# A Close Look at the Role of Time in Affect Dynamics Research

**Gal Lazarus, Jiyoung Song, Christopher M. Crawford, and Aaron J. Fisher**

**Abstract** Affective experiences and related cognitive and motivational processes unfold within individuals over time. Vital information is inherently embedded in the time scale, shape, and context of affective processes' temporal dynamics. Thus, time itself may serve as a useful proxy for various underlying causal processes that researchers can identify and model. Considering the role(s) of time in theoretical conceptualizations and including time-derived variables in statistical models is likely to significantly improve the understanding of affect dynamics and their place among other dynamic processes. In this chapter, we delineate three sets of factors to be addressed in the study of affect-related temporal dynamics: The first set concerns the time scale in which the target system's core processes unfold. The second set concerns the shape of temporal (co)variation within the target system—that is, the trends, cycles, and discrete phenomena involved. The third set concerns the sources of within-individual variation in the target system across time and context. Although many of these themes have already been spelled out in the affect dynamics literature, their incorporation into research remains limited. Facing recent concerns regarding the robustness of affect dynamics findings and renewed interest in psychological theory development, thorough consideration of temporal dynamics becomes crucial.

**Keywords** Affect dynamics · Time scales · Cycles · Idiographic methods

## 5.1 Introduction

Psycho-behavioral phenomena unfold within individuals over time (e.g., Fisher et al., 2018; Hamaker & Wichers, 2017). Accordingly, a basic (implicit or explicit) tenet in the theoretical definitions of many psychological constructs and processes

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is their presence and development within individuals and along time (e.g., Fisher, 2015; Wright & Zimmermann, 2019). Only in recent years, various strands of research have adapted their designs to correspond to this fundamental truth by collecting intensive longitudinal data and modeling them while considering (to various degrees) the role of time (for a recent review, see Trull & Ebner-Priemer, 2020). Such approaches offer the opportunity to examine psychological processes as they unfold in individuals' daily lives and assess their *dynamics*.

Dynamic indices quantify the time-dependent (co)variation present within repeated measurements of one or more variables. Ideally, specific indices would function as operationalizations of well-defined affect-related processes. In the present chapter, we first point out that the time-dependency of affect dynamics indices creates ambiguity in their interpretation that is often unrecognized. Then, we argue that to address this ambiguity, researchers should attend to the distinct time-related effects present in their data by considering and modeling the rich information the passage of time represents. Subsequently, we specify three sets of time-related factors that can guide such consideration—the time scale in which the core processes of the target system unfold, the shape of temporal (co)variation within the target system (e.g., trends, cycles), and the sources of within-individual variation in the target system across time or context. We conclude by offering an integrated perspective of the different sets and emphasizing some practical recommendations vis-à-vis the field's current state.

## 5.2 The Role(s) of Time in Affect Dynamics

One field that has benefited significantly from the recent methodological advances in data collection and modeling is affective science, in which the study of affect dynamics has flourished (e.g., Kuppens, 2015; Kuppens et al., 2010a, b). Various indices quantifying the patterns with which emotions or moods (co)vary across time have been suggested (e.g., mean square successive differences [MSSD], autoregression) and found to be associated with indices of psychological well-being (e.g., Houben et al., 2015), personality (Erbas et al., 2014), and psychopathology (e.g., Trull et al., 2015). Despite the growing interest in affect dynamics and the accumulating findings regarding their correlates, recent work utilizing large and diverse samples has shown that specific affect dynamics indices may have little incremental validity beyond affect mean and variability in predicting indices of psychological well-being (e.g., Dejonckheere et al., 2019), psychopathology (Bos et al., 2019), and personality (Wendt et al., 2020).

How can findings demonstrating poor incremental validity of affect dynamics indices be reconciled with the strong intuition and sound reasoning that the patterns with which individuals' affect change over time hold unique and important information regarding their psychological characteristics? In this chapter, we contend that some of the observed limitations in current affect dynamics research stem from theoretical ambiguity regarding the underlying data generating processes that give rise to specific affect dynamics. It is often the case that the processes involved in the dynamics themselves, including the identity of their components, the relations between them, their putative effects, and the ways all these unfold in time, are only vaguely defined. Theoretical statements with greater specificity (e.g., regarding the emotions involved), quantifiable features, (e.g., the size and the shape of expected associations, e.g., Haslbeck et al., 2019), delineation of circumstances in which effects are expected (Fried, 2020; Yarkoni, 2020), and an emphasis on causal inference may each contribute to the generation of stronger affect dynamics theory. Importantly, as we endeavor to uncover *causal* explanations for individual behavior, delineating underlying—likely neurobiologically-derived—sources of variation from more reflexive, cognitive-affective responses to external stimuli will help to refine and sharpen our theoretical argumentation.

The MSSD, for example, summarizes the average within-person (squared) differences between consecutive observations. As applied to the dynamic unfolding of negative affect (NA) in daily life, higher levels of these differences are thought to be generated by emotion regulation difficulties. Indeed, MSSD in NA has been found to be associated with indices of psychological maladjustment (for a meta-analysis, see Houben et al., 2015) and is often referred to as emotional or affective instability (Trull et al., 2015). However, at least some of these within-person NA successive differences are likely generated by flexible adjustments to environmental demands and adaptive internal processes.

Identifying the actual data generating processes underlying specific affect dynamics indices is likely to require both theoretical deliberation and methodological innovation. In the above example, theory-driven contextual factors (e.g., some situational features) that may be relevant to the specific population may be introduced to the measurement scheme. Whereas the temptation to measure many contextual factors is understandable, researchers are limited in their ability to expand the breadth of data collected in each survey to avoid overburdening participants. This constraint is especially pressing in the high-measurement-frequency designs that are often employed in affect dynamic studies. Hence, thoughtful consideration of the most informative and temporally pressing contextual features is essential for maximizing the predictive validity of ambulatory data sources.

The temporal unfolding of the data contains rich and essential information, waiting to be examined (e.g., Jebb et al., 2015; van de Maat et al., 2020)—and potentially mined for causal explanations. For instance, although some affective fluctuations cannot be predicted by any measured variable and may only be categorized as unexplained instability, other fluctuations may follow a fixed time-related pattern (e.g., diurnal), allowing researchers to generate specific time-dependent hypotheses about underlying causal processes (such as diurnal variation in cortisol). Thus, rather than reflecting volatility in underlying processes, some sources of variability may represent stable fluctuations that follow consistent daily (approximately 24-h), ultradian (less than 24-h), or infradian (more than 24-h) patterns. One study, which examined fluctuations in daily anxiety, proposed that diurnal variation in distress was likely the result of unresponsiveness to environmental contingencies, a pattern which improved during successful cognitive-behavioral therapy (e.g., Fisher

& Newman, 2016). Though largely semantic, one takeaway from these findings is that the variability in these data seemed to reflect emotional rigidity, rather than instability.

In general, greater consideration of the role(s) played by time might clarify the underlying mechanisms that affect dynamic indices attempt to capture. In analyses of human emotion and behavior, time is likely to be an ever-present hidden third variable. Because all processes—whether causal, reflexive, or epiphenomenal—unfold over time, vital information will be inherently embedded in the scale and structure of the temporal dynamics of those processes. Thus, time itself may be a useful proxy for uncovering and understanding underlying causal processes that are yet to be identified or otherwise unmeasured. It follows that including time in our theoretical conceptualizations may shed light on the understanding of dynamic processes and including it in our statistical models is likely to significantly alter the findings and their interpretation. For instance, failure to account for linear trends in longitudinal data can artificially inflate correlations between two longitudinally measured variables (e.g., Falkenström et al., 2017).

Thorough consideration of the role(s) of time necessitates careful estimation of the particular affect-related processes that comprise the target phenomena for a particular population under particular conditions. Specifically, relying on relevant existing theories and prior findings, researchers should consider three sets of determinants. The first set concerns the time scale. How quickly does a given process occur? How should measurement paradigms and analyses be calibrated to accommodate and accurately reflect the temporal scaling? These decisions are paramount for determining the magnitude of (co)variation at varying intervals between consecutive measurements within a target system (e.g., Adolf et al., 2021; Dormann & Griffin, 2015), informing interpretations of vital phenomena such as autocorrelations and cross-lagged predictions. The second set relates to the *shape* of temporal (co)variation within the target system—that is, the trends, cycles, and discrete phenomena (i.e., dichotomous, present or absent events) that make up the patterns of variation in the data. These features can be thought of as the system's temporal *structure*, the building blocks of (co)variation at various time scales and measurement intervals. Finally, the third set concerns sources of within-individual variation in affect dynamics (e.g., Bringmann et al., 2018; Koval & Kuppens, 2012) across time or context that may be relevant for the target system. Moreover, these within-individual processes are likely to result in between-individual variation (i.e., individual differences) in affect dynamics. Thus, care should be taken to assess and possibly categorize within-individual heterogeneity in affect dynamics.

Importantly, such theoretical clarity, in our view, may benefit both measurement and modeling practices in the study of affect dynamics. Measurement practices, for example, can be improved by considering the appropriate time scales and frequency (e.g., lag length, signal/event trigger), questionnaire instructions (e.g., adjusting the frame of reference of the affect item), and/or contextual variables that most accurately represent underlying data generating process. Modeling practices can be improved by selecting appropriate statistical frameworks (e.g., regression, network, non-linear models), including relevant temporal variables representing trends (e.g., linear) or cycles (e.g., diurnal), and/or estimating time-varying effects. In the following sections, we expand the discussion of the three sets of determinants as applied to theory, measurement, and modeling.

## 5.3 Time-Related Considerations in Affect Dynamics Research

### *5.3.1 Choosing the Appropriate Time Scale*

Numerous leading affect dynamics researchers have recognized the importance of the time scale at which affect is being measured and modeled (e.g., Butler, 2015; Hollenstein, 2015; Kuppens, 2015), and similar recognitions have been made for other psychological processes studied using intensive longitudinal methods (e.g., Boker et al., 2009; Hamaker & Wichers, 2017; Neubauer & Schmiedek, 2020). Indeed, assessing affect hourly, as opposed to daily, for example, would not only produce different profiles of change, but also most likely reflect different affective processes altogether (Koval et al., 2013).

Surprisingly, extensive meta-analytic work conducted thus far indicates that the time scale at which affect dynamics are assessed does not appear to significantly moderate observed relationships with psychological well-being indices (Houben et al., 2015). As the authors noted, however, the reviewed literature has mostly consisted of studies measuring changes in affect across hours or days, as opposed to minutes or seconds. We also must ask ourselves whether the same affect dynamic, measured at different time scales, represents the same underlying construct or data generating process. For instance, much is made of the contrast between emotion and mood, where the former is thought to operate on a faster, contextualized time scale, and the latter is thought to be a slower-moving, possibly characterological phenomenon. Thus, while similarity in correlations between affect dynamics and other variables of interest across multiple time scales may indicate some degree of consistency, such correlations cannot comment on the nature of the relationship between the affect dynamic and the other variable. Assessing the magnitude of the similarity between specific affect dynamic indices derived from different time scales may constitute a preliminary step before assessing causal relationships with other constructs.

Clarifying the role of different time scales in the study of affect dynamics (not only in relation to other constructs but also within the affective dynamic indices themselves) requires empirical investigation and careful theoretical reasoning. In an important contribution, Ebner-Priemer and Sawitzki (2007) measured subjective distress every 15 min for 24 h and then compared the observed time series to those randomly shuffled within each person (i.e., without the sequentially-dependent structure) across different time scales. They found that only time series based on time scales equal to or shorter than one hour could be distinguished from randomly shuffled ones. This pattern was present both for individuals with borderline personality disorder (BPD) and healthy controls. The authors concluded that distress dynamics derived from time series with intervals longer than one hour are likely to altogether ignore the target system's temporal structure.

The common use of longer than one-hour time scales in affect dynamics research may shed light on some recent findings. First, the lack of incremental predictive validity of the *time-dependent* instability indices (Bos et al., 2019; Dejonckheere et al., 2019; Wendt et al., 2020) over the *time-independent* variability indices may be explained if the time scale used cannot reflect true temporal unfolding of affect. Second, the presence of specificity of affective variability in individuals with BPD, but not of affective instability (e.g., Houben et al., 2020; Mneimne et al., 2018; Santangelo et al., 2016), may similarly reflect the limited ability of the design to capture valid time-dependency.

By and large, assessing target processes at time scales larger than those at which processes unfold may result in misleading or inaccurate inferences. In the example study below, we demonstrate the impact of varying time scales on commonly used operationalizations of affective instability and inertia (i.e., autoregression).

#### 5.3.1.1 Example Study 1

Data for this example study come from Fisher et al. (2017). Participants ($N = 80$) were a mixture of individuals with primary diagnoses of generalized anxiety disorder ($n = 23$), major depressive disorder ($n = 11$), or both ($n = 11$), and healthy controls ($n = 35$). Those with diagnoses were enrolled in an open trial of a personalized cognitive-behavioral intervention for mood and anxiety disorders. Before engaging in any intervention, all 80 individuals completed 30 days of self-reported EMA surveys four times per day. In each survey, participants rated their experience of each item over the preceding hours using a 0-100 visual analog slider with the anchors "not at all" and "as much as possible" for the 0 and 100 positions, respectively. In the present study, positive affect (PA) was assessed with a single-item measure (Song et al., 2021), and NA was calculated by averaging the angry, irritable, guilty, afraid, down, worried, and hopeless items at each time point.

In the present investigation, we examined seven different time scales: all four surveys (4-h intervals), first and third surveys of each day (8-h interval), second and fourth surveys of each day (8-h interval), and once a day for each of the four surveys (e.g., first survey of each day, second survey of each day, etc.; 24-h interval). We calculated affect dynamics intra-daily for the 4-h and 8-h time scales and inter-daily for the 24-h time scales. Of the affect dynamics, we chose to examine instability (the magnitude of moment-to-moment emotional changes) and inertia (the magnitude of moment-to-moment emotional carry-over) because they are time dependent and thus most likely to vary across time scales.

Table 5.1 presents the correlations between the instability indices, and Table 5.2 presents the correlations between the inertia indices. Across the seven time scales, instability (mean $r$: 0.77; range: 0.64–0.91) was generally more well correlated than inertia (mean $r$: 0.31; range: −0.03–0.65) for both PA and NA. Still, instability was nevertheless dependent on the time scale in which it was measured, with

**Table 5.1** Correlations of affect instability indices across seven time scales

| Time scale | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Four times a day | | .83 | .86 | .77 | .68 | .76 | .76 |
| 2. First and third surveys each day | .91 | | .78 | .76 | .73 | .68 | .80 |
| 3. Second and fourth surveys each day | .90 | .80 | | .76 | .77 | .72 | .79 |
| 4. First survey each day | .80 | .83 | .74 | | .68 | .64 | .77 |
| 5. Second survey each day | .81 | .79 | .82 | .74 | | .72 | .70 |
| 6. Third survey each day | .83 | .87 | .78 | .69 | .75 | | .71 |
| 7. Fourth survey each day | .82 | .70 | .83 | .76 | .73 | .69 | |

*Note*. Positive affect correlations are below the diagonal, and negative affect correlations are above the diagonal

**Table 5.2** Correlations of affect inertia indices across seven time scales

| Time scale | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Four times a day | | .53 | .54 | .34 | .43 | .36 | .34 |
| 2. First and third surveys each day | .57 | | .36 | .32 | .31 | .17 | .22 |
| 3. Second and fourth surveys each day | .65 | .32 | | .23 | .42 | .31 | .35 |
| 4. First survey each day | .17 | .35 | .20 | | .37 | .39 | .31 |
| 5. Second survey each day | .26 | .21 | .20 | −.03 | | .26 | .18 |
| 6. Third survey each day | .38 | .34 | .34 | .07 | .33 | | .36 |
| 7. Fourth survey each day | .37 | .24 | .29 | .17 | .15 | .30 | |

*Note*. Positive affect correlations are below the diagonal, and negative affect correlations are above the diagonal

overlapping variance ranging from 41 to 83%, leaving anywhere from 17 to 59% of the variance unexplained. Thus, changes in emotional experience that unfold over a span of an hour versus 4, or 24 h are not likely to reflect the same psychological phenomena, and future studies should look to uncover the sources of unexplained variance in different constructs across differing time scales.

The inconsistency in inertia values across time scales was salient—on average, there was less than 10% of shared variance between two inertia values derived from two different time scales. This finding may indicate that the autocorrelation metric may reflect different psychological processes as a function of the time scale from which it derived (or that it fails to capture any single process reliably). The sensitivity of the inertia index to the lag-length may explain some of the mixed findings regarding inertia's associations with psychopathology indices, and specifically with depression.

Indeed, using second-by-second time-series data collected in the lab, Kuppens et al. (2010a, b) found that depressed participants exhibited a higher level of negative affect inertia than nondepressed participants. Conversely, Thompson et al. (2012) and Bos et al. (2019) used EMA consisting of 8 and 3 surveys per day, respectively, and found no significant association between inertia and depression indices. Contrasting these findings further, Brose et al. (2015) did find a significant association between inertia derived from daily affect reports and depression symptoms, yet their sample eschewed clinical participants. Supporting the notion that time scale matters, Koval et al. (2013) showed in a single sample that higher inertia of NA in the lab (based on less than a minute intervals), but not in daily life (based on hours intervals), is predictive of depressive symptoms.

There might exist a threshold at which substantive similarity in psychological process is preserved across time scales (e.g., Houben et al., 2015). Identifying such a threshold is an important scientific endeavor, and until it is established researchers may be wise to either oversample—as Ebner-Priemer and Sawitzki (2007) did to identify the time scale at which the target psychological process operates—or choose a time scale based on a sound, concrete theory or empirical findings that offer temporal information about the phenomenon of interest. An important source of such information are studies assessing emotion duration (e.g., Kalokerinos et al., 2017). One such study has shown that 80% of reported emotions return to baseline in less than an hour (Verduyn et al., 2009).

#### 5.3.1.2 Special Consideration for Lag Lengths

The lag lengths used in the analyses of (and indices calculated from) time-series data can differ, that is, be longer, than the measurement interval used for data collection. Indeed, different processes measured in an EMA study may unfold in different time scales and require adjusting the lag length accordingly (see Jacobson et al. [2019], who recently developed a tool to automate the process of detecting optimal lag lengths). Different lag lengths are likely to influence the magnitude (and shape) of lagged associations and time-dependent affect dynamics (e.g., Adolf et al., 2021; Dormann & Griffin, 2015).

Only a few affect dynamics studies to date, however, have empirically examined the role of lag length, and most researchers default to a lag-1 structure. Such practices may be problematic not only because a lag-1 structure may represent different time intervals across different studies but also because it disregards individual differences in psychological and affective trajectories (Boker et al., 2009). To demonstrate the presence of such individual differences, in our second example study, we examined which lag length produced the maximal inertia values for each individual in our PA and NA data.

#### 5.3.1.3 Example Study 2

The data employed for Example Study 2 were again the 80 participants from Fisher et al. (2017). Here we examined seven different lag lengths: 4 h, 8 h, 12 h, and 24 h. For the daily (i.e., 24-h interval) lag length, we once again separated the four daily surveys to create four separate lag conditions. For each of the 80 participants, we computed PA and NA inertia values derived from the seven different lag lengths and determined which of them resulted in the maximum autocorrelation. Figures 5.1 and 5.2 present the distribution of the optimal lag lengths (i.e., the lag with the highest autocorrelation) for PA and NA, respectively.

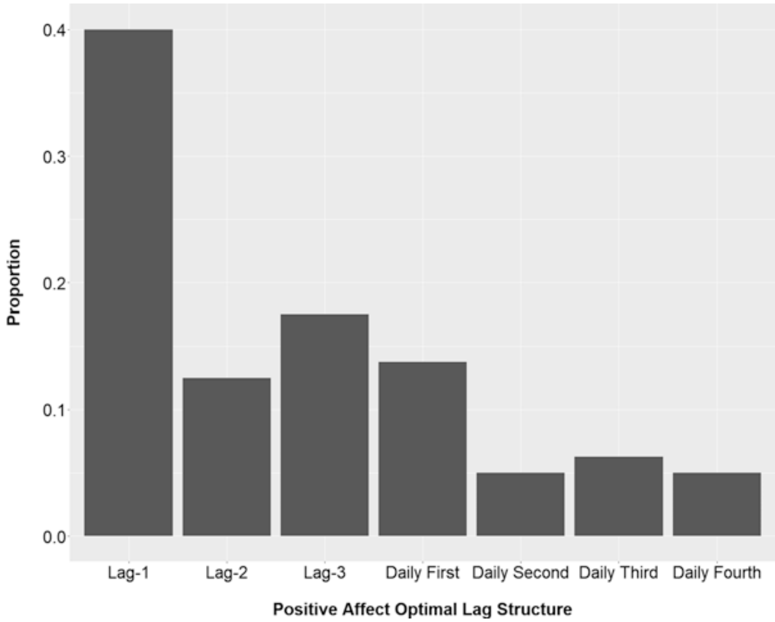


**Fig. 5.1** Optimal Lag Structure for Positive Affect

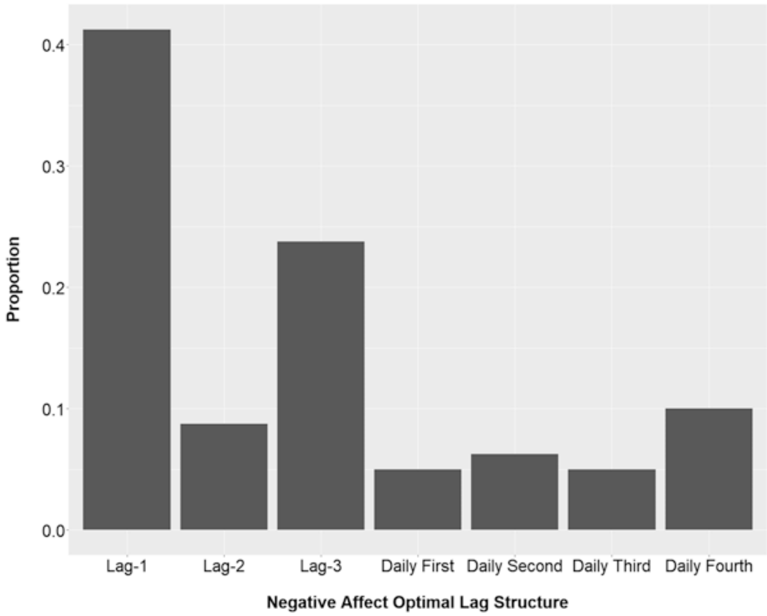


**Fig. 5.2** Optimal Lag Structure for Negative Affect

As can be seen in Figs. 5.1 and 5.2, for both PA and NA, about 40% of the participants' highest autocorrelation resided within the shortest lag length available in our study (i.e., 4 h). This was expected, as the shortest time interval offers the least number of opportunities for participants to have experiences that may shift their affective states. However, the optimal lag length for the remaining 60% of the participants ranged from 8 to 24 h. The observed heterogeneity in optimal lag length also included time of day. That is, for the participants whose optimal time lag was 24 h, there was heterogeneity in which of the four daily surveys produced the largest inertia value (morning, midday, evening or nighttime).

For affect dynamics to adequately capture a psychological process of interest, we suggest careful, theoretically grounded consideration of the time intervals at which such processes operate. Conversely, identifying optimal lag lengths for each individual might require more data-driven approaches to adequately describe the temporal pattern unique to each person. Thus, effective utilization of affect dynamics as tools to understand psychological processes and mechanisms requires both sound theory and data analytic strategies.

### *5.3.2 Considering Linear and/or Cyclical Time Effects*

The dynamic change of repeatedly measured variables is subject to the influence of various factors associated with the passage of time. They often render the time series of these variables non-stationary, that is, one with distributional characteristics (e.g., mean, variance, autocorrelations) that change across time and/or context (e.g., Molenaar & Campbell, 2009). The manifestations of these factors can be divided into two general groups: trends and cycles. Trends reflect relatively macroscopic shifts in a variable's mean over the measurement period. Conversely, cycles reflect more granular temporal processes that rise and fall in likelihood at 12-h, 24-h, weekly, monthly, and/or seasonal frequencies. Researchers can model these patterns and assess their impact by creating variables that reflect the wide range of temporal dynamics, including trends, cycles, and regular intervals (e.g., time of day). In this section, we discuss the relevance of different types of trends and cycles for affect dynamics research. Specifically, we posit that ignoring such patterns may result in misinterpreting the meaning (i.e., the underlying data generating processes) of affect dynamics indices.

Trends are familiar among researchers employing intensive longitudinal methods. The most commonly examined trend is linear, capturing stable directional changes in a time series. There are occasions when a time series exhibits higher-degree polynomial trends indicating that its values tend to rise or fall at a rate that is not constant. For example, a quadratic trend suggests that the rate of change decreases or increases over the measured time period and may also account for changes in the slope's direction (e.g., initial increase followed by a decrease). Higher-level polynomials (e.g., cubic) allow for more complex patterns of change (Jebb et al., 2015).

EMA-based affect dynamics studies typically involve a week to month-long time series, which are likely to contain time trends. Such trends may be caused by external events that are emotionally significant to participants. For example, an impending exam—a common event among undergraduate samples used in affect dynamics research—will likely induce an increase in anxiety levels until the test, which may then gradually dissipate following the test. Depending on the specific place the exam takes along the time series, different trends may emerge. Notably, also lab-based affect time series may contain trends which are often caused by situational demands (e.g., high arousal at the beginning of a videotaped interaction that wears off with the passage of time).

The presence of time trends may increase correlation-based intrapersonal affect dynamics indices such as inertia, possibly confounding two data generating processes: the extent to which an emotion is resistant to a change (i.e., "true" inertia), and the increasing or decreasing effect of an external event. Similarly, in the case of interpersonal affect dynamics, synchrony measures will be strongly affected when both persons' data series share a similar time trend (e.g., due to shared event or context). Here, too, an association between the two time series will not be solely the product of affective processes often considered to underlie such associations (e.g., transmission or similar affective reactions to immediate contextual factors).

Whereas linear time trends are often considered in affect dynamics studies (e.g., Butler, 2011; Trull et al., 2015), cyclical effects are typically ignored (despite high quality work stressing their importance, c.f. Larsen, 1987; Hamaker & Wichers, 2017; Ram et al., 2005; van de Maat et al., 2020). These effects may stem from various sources and manifest across a wide range of time scales. Diurnal patterns have received the most attention, and research examining the temporal patterning of affect in daily life has observed robust daily periodicities. PA, for example, has been found to follow a diurnal pattern, increasing from morning to early afternoon and falling in the evening (Golder & Macy, 2011; Clark et al., 1989). Conversely, NA was found to decrease during the morning hours and increase throughout the remainder of the day (Golder & Macy, 2011). Furthermore, work assessing relations between affect dynamics and circadian rhythms has demonstrated that a significant amount of within-day variance in PA can be explained by a 24-h sinusoid, with greater effect sizes observed in conditions characterized by constant and controlled sleep cycles (Murray et al., 2009). These diurnal patterns may be driven by both exogenous contextual factors (e.g., Beal & Ghandour, 2011) and endogenous psychophysiological ones (e.g., Adam et al., 2017). Notably, the ability to identify cycles depends on the duration of the data collection period and should be a part of the factors considered in the study design.

Importantly, cyclic affective patterns are not limited to the daily time scale. Indeed, there is evidence for weekly affective cycles (e.g., Beal & Ghandour, 2011; Liu & West, 2016), which may stem from factors such as the structure of the work week (e.g., with greater stress during the weekdays). Additionally, monthly affective patterns have been observed and were found to be associated with menstrual cycles (Farage et al., 2008; though see Hengartner et al., 2017) and lunar tidal cycles (Wehr, 2018). This corpus of work suggests that despite the conceptualization of affect as being constantly modulated by relatively stochastic internal and external events, stable patterns of variation are common.

Figure 5.3 provides a visual illustration of simulated time-related effects on a single participant's time series data. As can be seen in the figure, despite their strength (vs. the random deviations from the mean), these effects are not easily

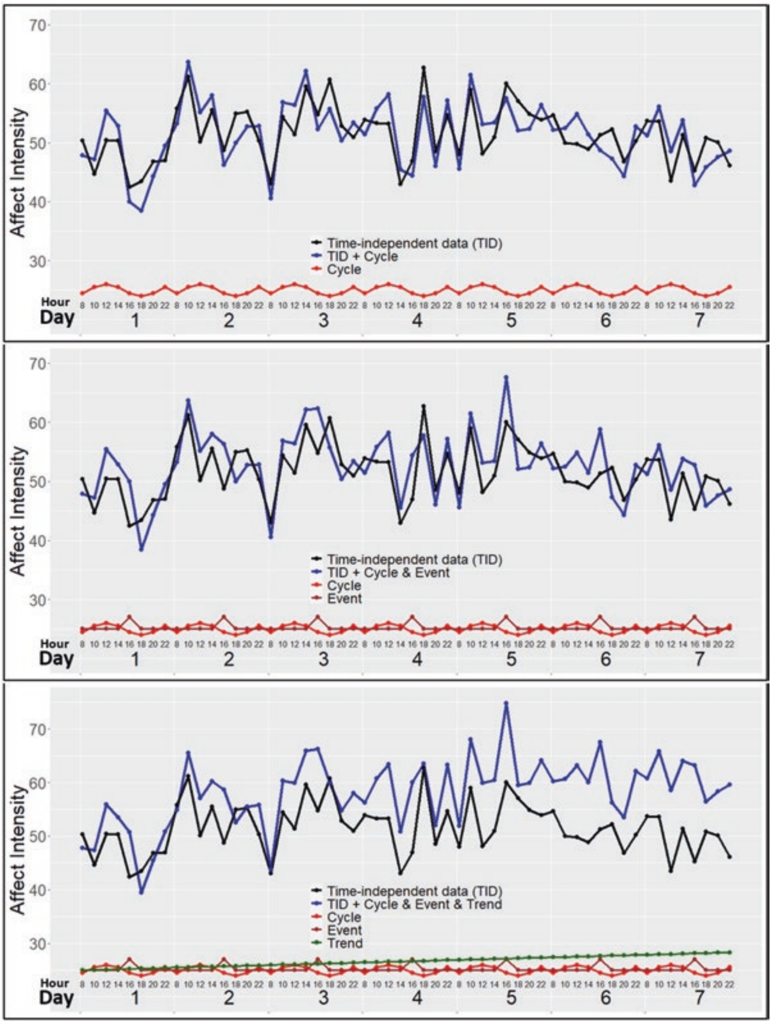


**Fig. 5.3** A visual illustration of time-related effects on a single participant's time series data. The original time series (black) was derived from random normally distributed data [Mean = 50, Standard deviation (SD) = 5] and is time-independent. Each of the panels shows the original time series, an additional time series modified by time-related effects (cycle, event, and trend), and a representation of the modifiers (red, brown, and green). The upper panel's time series was modified by a 12 h cycle with an effect size equal to one SD. The central panel's time series was modified by the same cyclic effect and a single daily event effect (at 16:00 each day) with an effect size equal to two SDs. The lower panel's time series was modified by the same cyclic and event-related effects, as well as by a linear trend with an effect size equal to approximately two SDs

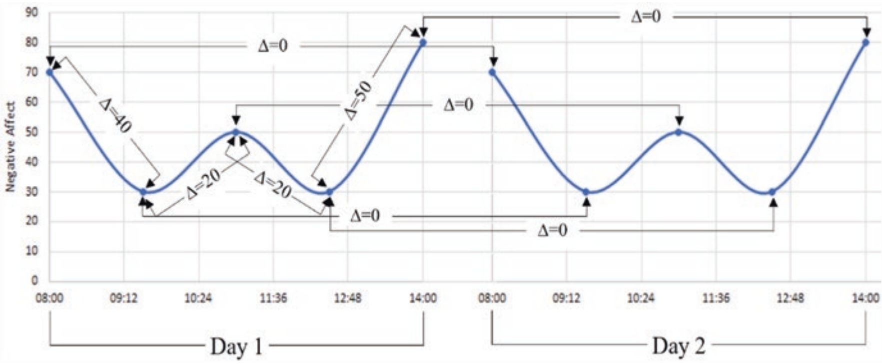


**Fig. 5.4** Demonstration of negative affect levels fluctuating along the first part of two consecutive days and the corresponding absolute differences in negative affect at lags of 1 observation (lower Δ's) and 5 observations (uppermost Δ)

recognizable by the naked eye. This visualization demonstrates the importance of making the modeling of time-related effects an integral part of any affect dynamics exploration.

Cyclical patterns may play a similar confounding role to the trends described above when examining correlation-based indices. Importantly, they may have an additional substantive impact on understanding differences-based indices (e.g., MSSD) that are used as operationalizations for affective instability. These indices ignore the broader temporal structure of the construct that they purport to describe. Specifically, the MSSD—representing the average magnitude in observation-to-observation fluctuations over time—does not assess the degree to which variations in affect represent stable, repeating patterns.

Consider the following example: a high school student experiences an increase in NA while waiting in the cold for the bus. This NA quickly subsides, however, as the student reunites with their friends before class. Their NA levels continue to rise and fall over the course of the day as they engage with unpleasant (e.g., speaking in front of the class) and pleasant (e.g., eating lunch with friends) stimuli, and these fluctuations persist from day-to-day and week-to-week. A visual representation of these fluctuations in NA can be seen in Fig. 5.4. As operationalized by the MSSD, this time series would be characterized as unstable, but this quantification obscures the fact that these fluctuations are stable at the between-day level.

Research by Fisher and Newman (2016) has demonstrated the importance of considering such cyclical patterning in the context of a therapeutic intervention for individuals diagnosed with generalized anxiety disorder (GAD). The authors hypothesized that since for individuals with GAD, the feared outcomes in worry episodes may be invoked regardless of external context, they may become entrained to fixed patterns of anxiety on a day-to-day basis. Indeed, using spectral analysis (Scargle, 1982) and spectral power to determine the degree to which variation in daily anxiety symptoms was related to the presence of sinusoids in the data, Fisher and Newman found that the observed diurnal rigidity—the degree to which anxious distress was dictated by 24-h periodic patterns—decreased throughout the therapeutic intervention, and the degree to which rigidity was reduced was associated with reliable change post-treatment. Moreover, this reduction in periodicity predicted reliable change post-treatment even when controlling for change in MSSD (which did not significantly predict the treatment outcome). The implication of these findings is straightforward: when variability in a construct of interest over time is best characterized by stable, cyclical patterns (e.g., a sinusoid), the use of the MSSD as an operationalization of instability may provide misleading results.

This example illustrates a crucial point—the reason for modeling the effects of time is not necessarily only to statistically adjust for them (using methods such as detrending). In cases where the dynamics of interest do not form stationary fluctuations but a trend or a cycle, detrending will result in throwing out the baby with the bathwater (e.g., Wang & Maxwell, 2015). For instance, Butler and Randall (2013) describe interpersonal morphogenic processes (e.g., mutual arousal modulation towards optimal bounds), which are trend-driven interpersonal affect dynamics. Hence, researchers should consider the meaning of trends and cycles on a case-by-case basis.

### *5.3.3 Modeling Within-Individual Variability in Affect Dynamics*

As noted above, affect and affect-related processes are often non-stationary. Hence, affect dynamics themselves can, and often do, vary not only between but also within individuals (e.g., Albers & Bringmann, 2020; Bringmann et al., 2017). For example, both affect polarity (Dejonckheere et al., 2021) and affect differentiation (Erbas et al., 2018) were found to change as a function of stress. Importantly, on some occasions, such changes may be a central outcome variable. For example, Van der Gucht et al. (2019) showed that affect differentiation increased following a mindfulness-based intervention.

Exploring changes in affect dynamics is possible with or without pre-existing expectation or knowledge regarding the nature of change and/or its timing. In cases where the timing of changes is expected, such as following an intervention (Van der Gucht et al., 2019), separate affect dynamics indices can be calculated for different sections of the individual's data. Additionally, contextual variability in an individuals' time-series (e.g., daily stress) can be tested as a predictor of local affect dynamics indices (e.g., Dejonckheere et al., 2021; Erbas et al., 2018). In cases where the timing of changes or their predictors are unknown, data-driven statistical methods can be used to detect both gradual (e.g., Bringmann et al., 2017, 2018) and abrupt (e.g., Albers & Bringmann, 2020; Cabrieto et al., 2018) changes in the time series.

The presence of within-individual variation in affect dynamics brings about interesting research directions. First, modeling affect dynamics indices as within-individual predictors or outcomes corresponds more closely to the psychological theories that conceptualize psychological processes as unfolding within individuals over time (c.f. Molenaar & Campbell, 2009). This approach can add an explanatory process-focus layer to a field that has been largely focused on descriptive individual differences. For example, lower differentiation between negative emotions is thought to lead to greater psychological distress (Pascual-Leone & Greenberg, 2007). Considering emotion differentiation (ED) as a trait or stable ability and measuring its association with distress indices is informative and useful but tells us very little about the way ED works in the within-individual level (Fisher et al., 2018). Examining the effects of within-individual ED (Erbas et al., 2021) allows for a better assessment of the dynamic processes involved and hence for a more direct theory testing and development (e.g., Haslbeck et al., 2019).

Relatedly, the recognition that affect dynamics themselves change across time as a function of contextual factors invites examining them under different conditions. In light of recent findings regarding the limited incremental predictive validity of affect dynamics, the field may likely benefit from identifying the exact conditions under which they may exert more robust effects (Dejonckheere et al., 2020; Lapate & Heller, 2020). Notably, when the focus is on specific conditions, researchers may want to trade the goal of obtaining a representative yet sparse assessment of the entire day for a focused and more frequent assessment in the time of interest. Furthermore, researchers can estimate dynamics that are derived from affect data collected in specific contexts in which affect plays a particularly central role (e.g., psychotherapy sessions—Galili-Weinstock et al., 2020; Lazarus et al., 2019). Altogether, a contextualized, systems-related perspective on affect dynamics places these metrics within their intended domain of dynamic, time-dependent emotional functions.

Lastly, the presence of within-individual variation in affect dynamics calls for employing an idiographic approach (e.g., Fisher et al., 2017; Molenaar & Campbell, 2009; Wright & Zimmermann, 2019) and invokes the question regarding the extent to which the associations between these dynamic indices and other constructs generalize from the between-individual level to the within-individuals level (i.e., the extent to which the associations are ergodic; Fisher et al., 2018; Molenaar, 2004). Importantly, the inferences drawn at one level may differ from an inference drawn at another level. For example, at the between-individual level, individuals who demonstrate greater fluctuations in affect are thought to have poorer regulation skills and lower psychological well-being (e.g., Houben et al., 2015). However, at the within-individual level, are greater periodic emotional fluctuations indicative of lower or less effective regulation? It is entirely possible that momentary increases in emotion fluctuation could represent spikes in negative affect followed by subsequent successful down-regulation—a sequence which could look like instability without appropriate contextualization. The answers to such questions are likely to be quite complex. We may expect a considerable variation in the magnitude (e.g., Fisher et al., 2018) and the shape of the intraindividual associations which may warrant within-person data analysis and render generalizations hard to attain.

Despite the major challenges posed by idiographic modeling of affect dynamics, it likely holds great promise. Clinicians have expressed interest in the potential of employing an idiographic approach in assessment and intervention planning (Fisher, 2015; Piccirillo & Rodebaugh, 2019; Wright & Woods, 2020). Affect and affect-related constructs play a central role in such clinical efforts, though these efforts often employ novel modeling techniques at the expense of the traditional affect dynamics indices (Fisher et al., 2019; Fisher & Bosley, 2020). Indeed, the shift from assessing between-individual differences in a set of fixed indices to identifying person-specific clinically significant affective patterns calls for the creation of personalized indices that comprise personalized arrangements of items.

## 5.4 Concluding Thoughts

Time is the medium through which affective experiences and related processes unfold. It encapsulates the effects of myriad unmeasured variables. In this chapter, we illustrated how a thoughtful consideration of time-related patterns could enrich the conceptualization, measurement, and modeling of affect dynamics. To do so, we delineated three sets of determinants to be addressed: the first pertains to the temporal scaling of the studied phenomena, that is, the time scales suitable to capture and model the phenomena; the second pertains to the *structure*, the shapes of the (co) variation in the data source. These relate to the trends, cycles, autoregression, and cross-predictions embedded in the data. The third pertains to the within-individual *variation* across time in the studied phenomena. We simply expect people to differ in any and all ways, including those pertaining to the temporal scale and structure of their affective experience.

Notably, these different sets should be considered in tandem. For example, different trends and cycles may be more prominent at different time scales. Furthermore, there is likely to be not only between-individual variability in the optimal time lag (as we show in Example Study 2) but also within-individual variability. Similarly, the strength of specific trends or cycles is also likely to vary within individuals. For example, affective diurnal cycles were shown to change as a function of psychological interventions (Fisher & Newman, 2016).

Including a thorough evaluation of the role of time in our array of considerations when studying dynamic processes may seem to bring with it an unwieldy range of measurement and modeling options. Ideally, decisions in these matters would be guided by fine-grained theories relevant to the phenomena of interest. Unfortunately, current psychological theories are often not specific or accurate enough to provide such guidance. Typically, such theories remain silent about the magnitude, shape, and direction of associations, or the time scales and contextual conditions under which they are likely to appear (Fried, 2020).

In a series of recently published papers, leading theorists and methodologists have identified a “theory crisis” in psychological science (e.g., Borsboom et al., 2021; Eronen & Bringmann, 2021; Fried, 2020). These authors contend that the field suffers from a lack of proper theory construction and testing procedures and that most psychological theories are weak in their accuracy and testability. We believe that a rigorous exploration of time-related processes of the sort we describe here can contribute to constructing stronger and more cumulative theories in psychological science.

Notably, an essential part of constructing a stronger affect dynamics theory is contextualizing them in a manner that allows drawing causal inferences. We must ask whether affect dynamics are themselves derived from underlying causal systems, or whether they are reflective of adaptive or maladaptive responses to environmental demands. For instance, current theory regarding the MSSD statistic posits that the absolute value of changes in affect from moment to moment represents the stability versus volatility in the selected affect measure. What remains to be understood is whether this volatility is reflective of lability in neurobiological emotion-generating processes, whether it reflects anxiogenic, depressogenic, or generally dysphoric schemata that amplify innocuous or ambiguous stimuli, or whether it reflects relatively adaptive responses to shifting environmental demands. Delineating these influences moves the MSSD beyond descriptive or statistical utility into a potentially causal role.

To increase our chances of constructing strong affect dynamics theories that involve causal explanations and accurate prediction, we may need to revise some of our methods. Though this chapter did not focus on describing specific methods, it does have some broad methodological implications. First and foremost, modeling trends and cycles in affect dynamics research is crucial for accurate interpretation of their meaning. Importantly, adjusting for such trends or cycles (for example, by using detrending) should not be done automatically since in some cases their presence is at the core of the phenomena of interest (e.g., Butler & Randall, 2013; Fisher & Newman, 2016). Additionally, the value in considering cycles is not limited to covariance-based dynamic indices (e.g., inertia, synchrony) but extends to difference-based indices (e.g., MSSD).

Second, adjusting the measurement frequency to the putative data generating processes of the target system may improve researchers' ability to accurately model them (e.g., Ebner-Priemer et al., 2007; Haslbeck et al., 2019). In the case of affect dynamics, that would usually mean using relatively high-frequency measurements (e.g., Verduyn et al., 2009). Recent findings support the feasibility of such designs as they indicate that increased sampling frequency is not tied with greater participant burden (but surveys' length does—Eisele et al., 2020). Third, measuring contextual variables is essential to improve our understanding of how and why affect changes across time, and particularly to make possible the examination of within-individual variation in affect dynamics.

Many of the themes described in this chapter have been pointed out before. The importance of time scale (e.g., Dormann & Griffin, 2015; Ebner-Priemer et al., 2007), linear or cyclical effects (Hamaker & Wichers, 2017; van de Maat et al., 2020), and within-individual variation (Dejonckheere et al., 2021; Erbas et al., 2018) has been acknowledged. To date, however, their incorporation into actual research efforts, whether in theory or study design, has remained rather limited. The current timing provides a unique opportunity for change—recent indications regarding the limited incremental predictive validity of affect dynamics indices (Bos et al., 2019; Dejonckheere et al., 2019; Wendt et al., 2020) and the growing attention to psychological theory development (e.g., Borsboom et al., 2021; Eronen & Bringmann, 2021; Fried, 2020), may be seen as an invitation to finally taking temporal dynamics seriously.

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