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Computing Components of Everyday Stress Responses: Exploring Conceptual Challenges and New Opportunities

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Abstract

Repeated assessments in everyday life enables collecting ecologically valid data on dynamic, within-persons processes. These methods have widespread utility and application and have been extensively used for the study of stressors and stress responses. Enhanced conceptual sophistication of characterizing intraindividual stress responses in everyday life would help advance the field. This article provides a pragmatic overview of approaches, opportunities, and challenges when intensive ambulatory methods are applied to study everyday stress responses in "real time." We distinguish between three stress-response components (i.e., reactivity, recovery, and pileup) and focus on several fundamental questions: (a) What is the appropriate stress-free resting state (or "baseline") for an individual in everyday life? (b) How does one index the magnitude of the initial response to a stressor (reactivity)? (c) Following a stressor, how can recovery be identified (e.g., when the stress response has completed)? and (d) Because stressors may not occur in isolation, how can one capture the temporal clustering of stressors and/or stress responses (pileup)? We also present initial ideas on applying this approach to intervention research. Although we focus on stress responses, these issues may inform many other dynamic intraindividual constructs and behaviors (e.g., physical activity, physiological processes, other subjective states) captured in ambulatory assessment.

Keywords

stress, stressors, ecological momentary assessment, ambulatory assessment, experience-sampling methodology

Psychological stress occurs when environmental, physical, and/or psychological demands exceed perceived resources available to respond to a particular situation. This definition posits stress as a dynamic process consisting of multiple components (Lazarus & Folkman, 1984; Smyth et al., 2013), including initial reactivity and recovery. Despite being defined as a time-ordered process, stress has most often been measured and/or modeled as if it were static and used in a between-persons fashion. For example, large survey studies typically ask participants to recall details about a past exposure (Hardt & Rutter, 2004), report on recent exposures to potentially stressful events (Monroe, 2008), or provide a global estimate of perceived stress (Cohen et al., 1983). Such between-persons approaches yield an overall estimate of stress level at the time of the recall and have been shown to be quite valuable for distinguishing broad patterns between individuals or groups and predicting a variety of outcomes (e.g., Cohen, 2016;

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Cohen et al., 2007). Yet such measurement does not provide any information on within-persons processes, including different temporal elements of the stress response, such as how people initially react versus how quickly they recover. If personalized medicine aims to better predict and/or enhance health for an individual over time, researchers can benefit by expanding their thinking—in measures and statistical models—from solely the between-persons approach of who is stressed to the within-persons approach that examines when and how people respond to stress.

Studying stress as an individualized dynamic process is critical because research has identified within-persons variability in responding to stressors (e.g., Sliwinski et al., 2009). For example, individuals may engage in different activities to restore vigor and other positive states as a result of their workload for that day, and different activities and different levels of recovery are possible each day for that same person (e.g., Sonnentag et al., 2008; Sonnentag & Niessen, 2008). Yet aside from directly querying how much one is reacting or recovering as a result of a stressful experience, little guidance exists on how to best characterize the stress-response process in everyday life. Perhaps the closest model to understand the temporal components of stress responses are laboratory-based experiments that introduce (often standardized) exposures and carefully measure the magnitude of reactivity and the time course of recovery over predetermined periods of time (e.g., Miller et al., 2018). Note that this work acknowledges reactivity and recovery as different components that each need careful elucidation (e.g., Anderson et al., 2005; Linden et al., 1997; Lovallo, 2015). Laboratory studies, however, generally lack ecological validity in understanding stress responses as they would happen in everyday life. The context surrounding stress induced in laboratory studies is often unfamiliar, quiet, and relatively "sterile." In contrast, natural stress settings tend to be familiar everyday contexts; busy with many other sounds, people, and competing tasks; and messy in that they often overlap with prior histories and upcoming demands. In addition, experimental human studies rarely administer multiple stressors, particularly over periods exceeding a few hours, yet in people's everyday lives, there is the potential for stressors to occur simultaneously or in succession over many hours or days—a stress component we label "pileup." Thus, new approaches are needed to better understand everyday stress responses in natural settings.

In this article, we provide a conceptual overview of a selection of critical issues of using ambulatory assessment methods to study within-persons stress-response dynamics in everyday life and a preliminary treatment of how to implement such an approach. We start with a discussion of a vital conceptual issue that applies to everyday reactivity, recovery, and pileup (RRP) stress responses: how to establish a comparison baseline (i.e., stress-free resting state). We then follow with a discussion of the conceptual and operational challenges involved with constructing each of the stress-response components with ambulatory self-report data (although similar concepts can be applied to other forms of intensive longitudinal data). Finally, we discuss the implications and limitations of this approach to help inform future work.

We largely use examples and descriptors drawn from our work using ecological-momentary-assessment (EMA) methods. EMA and related ambulatory-assessment methodologies are used to repeatedly capture momentary experiences in everyday life and provide an opportunity to model intraindividual dynamic processes (see Smyth et al., 2017). EMA often focuses on self-reports of internal states, behavior, and context and is typically implemented on smartphones or other devices that are readily carried or worn in everyday life. In a typical EMA design, individuals are prompted, usually several times throughout the day, to complete self-reports on their momentary experiences. They may also be trained to provide reports at targeted times (e.g., in response to a particular event). Because EMA data are collected in the natural environment using momentary or very brief retrospective recall, the data are thought to have high ecological validity, minimize recall and reporting biases, and allow for the detection of fine-grained dynamic changes in behavioral process over time in real-life contexts (see Trull & Ebner-Priemer, 2013). In addition, an expanding array of wearable sensors allows for ambulatory monitoring of many other data streams, such as physiology, actigraphy (e.g., to measure movement), environmental parameters, and GPS-based location tracking.

Why Consider Temporal Dynamics of Stress Responses?

Although a robust literature on measuring stress responses in everyday life exists, it largely assumes that this experience is the same across all time points and within people. Commonly in ambulatory studies, individuals report whether a stressor event occurred. In analyses, these stressor moments are then averaged/aggregated and used to predict proximal (typically concurrent) "outcomes," such as one's mood or cognitive functioning, or more distal outcomes, such as subsequent sleep quality later that night. With this approach, each stressor moment is assumed to be interchangeable—being exposed to stress will produce the same level of emotional responding or affect sleep the same way. Yet stress responses are typically variable even in an individual. For example, people can habituate to being exposed to the same stimuli (Schommer et al., 2003), and the time of day of stressor exposure can change how people respond to stress (Dunn & Taylor, 2014). To measure variability in stress moments, some research measures aspects of the subjective response to a stressor, most typically an appraisal of the severity of that event. This work avoids the assumption that all stressors are the same and offers an initial approach to test, for example, effects associated with the perceived severity of a stressor. Yet there are still important limitations and considerations about how to use such information to characterize the stress response within individuals.

Our approach considers the extent to which a stressor elicits specific responses and, in turn, whether those stress-response components predict processes or outcomes in everyday life (e.g., health-behavior enactment, physiological processes). To this end, we approach stress moments ideographically, which allows the potential for each stress moment to vary according to how one responds to it over time. Responses to stress can thus be operationalized temporally (e.g., How long does the response last?), which allows a greater understanding of the stress response (e.g., identification of different components of the stress response, determining whether duration or timing matters). Evidence consistent with the promise of this approach has been found when using within-persons (daily) indicators of stress responding to characterize individuals. For example, more daily, stress-related, negative affect (used as a proxy for stress reactivity) predicts the development of chronic health conditions (Piazza et al., 2013), affective disorders (Charles et al., 2013), functional health (Leger et al., 2018), and mortality (Chiang et al., 2018). Note, however, that this past work largely did not consider temporal features of the stress response (i.e., it compares the mean of stress days to nonstress days without regard for when they occur).

What Are the Response Components One Might Want to Consider?

When considering how to temporally characterize everyday stress-response components from a within-persons perspective, we started with the well-established stimulus-reactivity-recovery model from experimental methods and then added the construct of pileup (for preliminary conceptualizations, see Smyth et al., 2018). *Reactivity* typically refers to capturing the highest degree of the stress response observed close in time to the eliciting stimulus. These dynamic responses can be estimated using a wide range of indicators of the stress response; in this work, we broadly construe these as affective and cognitive indicators (subjective stress, negative affect, or perseverative cognitions), although the logic could readily be extended to other types of indicators (e.g., physiological, behavioral). *Recovery* reflects the return to resting state following an initial stress reaction. To continue our example, this might reflect the change from a peak following a stressor moment to a subsequent nonstressor moment or moments following a stressor compared with an individual's resting state or baseline. We are also interested in the frequency and patterning of stress responses over intervals of time. We label the repeated elicitation of a stress response as pileup, defined as the accumulation of stressors and/or stress-reactivity-recovery cycles over time. Although this approach may seem quite simple, adapting it to everyday life also raises novel complicating features—such as the difficulty of defining a resting state, the possibility for multiple stressors experienced over relatively short time periods, or knowing when a discrete experience begins and ends.

Conceptual and Operational Issues With Stress Responses in Everyday Life

Defining a baseline in everyday life

In determining any stress response, it is vital to establish a comparison baseline. In the laboratory, determining the baseline from which to derive a stress response is relatively straightforward. For example, an individual arrives at the laboratory and rests for some predetermined period of time in a quiet and controlled space while various parameters are measured; this resting state is thus used as the baseline. Changes (i.e., reactivity) from that resting state in response to exposure to an experimental stressor and then how long it takes to return to the resting state after exposure is removed (i.e., recovery) are measured. This approach, although reasonable, creates in some sense an "optimal" baseline in that it typically creates a quiet and relaxed measurement context. Yet this baseline context may not actually be representative of a person's resting state in everyday life.

Researchers are thus faced with the challenge of how to construct the analogue of this resting state from naturalistic ambulatory data. They often do not see periods of quiescence and certainly not reliably so before each stressor experienced. People frequently encounter new stressors before resolving old ones and are sometimes able to leave the stressful location or avoid the situation. Unlike in the laboratory, the time and resources for resolving stressors in real life may be differentially available over time and contexts. What, then, is a resting baseline state in an EMA/daily diary study? Previous EMA/daily diary studies have in effect estimated a person-level resting state (i.e., referred to as *person mean*) from the person's average stress-response indicators on all nonstressor moments across the whole study period. Reactivity, then, is calculated by contrasting the mean value on negative affect, for example, during stressor moments to this person-mean "resting baseline state" (i.e., within-persons slope of stressor on negative affect). This post hoc approach to baseline, however, fails to preserve the time order between the resting state and subsequent reaction. In many situations, it may be necessary to preserve this time order when the change from a resting state to a stress-reactivity state as it happens is quantified. One notable example of this is the identification of moments of risk for potential intervention—often called "ecological-momentary intervention" or "just-in-time interventions" (Heron & Smyth, 2010; Nahum-Shani et al., 2018)—which post hoc approaches cannot achieve.

We now consider three alternative approaches for characterizing a resting state from ambulatory data, all of which preserve the time order of baseline stimuli, but each subtly alters the nature of the question being tested (Table 1). We do not argue that one approach is inherently superior to another but, rather, adopt the view that the choice of resting baseline state be informed by one's characterization and/or operationalization of stress: a change from (a) a previous state (what we call "proximal"), (b) an ongoing situation or context (what we call "local"), or (c) a set point (what we call "cumulative"). Thus, the selection of method or methods to characterize resting state should be thoughtfully determined according to the aims of the work being conducted. Below, we present representative examples of these approaches to explicate the logic underlying each. Drawing from work conducted in the laboratory, we believe one possibility is to look at the observations that occur immediately/closely before the stressor—to index what we call the "proximal baseline state" (Fig. 1a). Broadly, we view the proximal baseline state as reflecting the level of some stress-response indicator, such as negative affect, on nonstressor observations collected immediately before the stressor observation. Thus, by using this as a reference point, it allows one to measure the temporal changes from that recent proximal state to a subsequent stressor observation—which thus reflects reactivity. One advantage of this approach is that the relative closeness in time from the proximal baseline state to the reactivity measurement mitigates (but does not eliminate) the risk of intervening confounds. In addition, because this baseline relates a current stressor moment to a preceding nonstressor moment within a day, it is not influenced by between-days effects (e.g., weekend/weekday differences). This approach has limitations as well. For example, the desire to capture moments close in time results in using few data points for analysis, which may make this characterization of baseline state relatively unstable and potentially somewhat confounded with general variability in indicators, such as measurement error and/or interitem variability, or other non-stress-related influences, such as fatigue, time of day, and satiety. In addition, reactivity cannot be calculated until a nonstress moment occurs, which potentially eliminates observations that have stress reported at the beginning of each day. Finally, this characterization assumes that the prior moment to the stressor is a valid observation to compare. Yet people may anticipate—consciously or not—that a stressor is about to occur and begin responding even before labeling the event as a stressor (Neubauer et al., 2019), which results in estimates of reactivity that are smaller than if computed from a "true" resting state.

A second option for computing a baseline would be to expand the window for comparison points (e.g., selecting a moving window of 1–2 days prior) and perhaps specify rules for the windows (e.g., having no stressors occurred that day)—what we call the "local baseline state" (Fig. 1b). Unlike the proximal baseline state, which can consist of a single or very few scores, the local baseline state is an aggregate of multiple observations. This larger time window ensures that there is less likely to be a sudden increase or decrease to the baseline level and that there is a reasonable limit on the number of observations needed to quantify the baseline state that is consistent across all comparisons of stressor moments to baseline. This thus reflects a balance between enhancing estimation precision and stability of the individual's resting state with increased data/observation requirements. A limitation, however, is that the local baseline state can be confounded by intermittent events (e.g., poor sleep) because it is computed across multiple observations and could span more than 1 day. In addition, establishing the local baseline state requires an initial assessment period, which lengthens the total assessment time and precludes its use on the first set of observations or days when the local baseline is being established. Finally, comparisons using the local baseline may be comparing moments that are not occurring at the same time of day; if there are time-of-day/diurnal effects on the stress-response indicator or indicators, this may create nonequivalence in the comparison. Thus, it may be desirable to time match the local baseline to the stress response if possible (e.g., if time-matched stress-free moments exist). More generally, although diurnal effects on mood are often observed overall, they typically show considerable heterogeneity both across (e.g., the

Table 1. Overview of Resting-States Considerations

What type of baseline are you interested in using?	Name of resting state	Strengths	Limitations	Considerations for ecological-momentary interventions
Stress-response indicators on nonstressor moments immediately before the stressor	Proximal	Closest in time to the stressor Not confounded by day-level effects in ecological momentary assessment The closest analogy to an experimental approach Does not require longer study duration or run-in period	Includes few observations, which may reduce reliability, potentially confounding the effect of a stressor with general variability in the indicator Possibly biased stress-response indicators because of anticipation/buildup of a stressor (e.g., high stress before a stressful job interview elevates the baseline)	“High” reactivity could emerge from a lower baseline on the stress-response indicator (e.g., a mild stressor could falsely indicate a reactivity if it follows a nonstressor moment with unusually low values of the stress indicator, resulting in the identification of a moment that may not be ideal for intervention).
Stress-response indicators on nonstressor moments within a moving, local time window (e.g., the last 24 hr) before the stressor	Local	Moderately close in time to the stressor, thus local effects are likely to affect both the baseline and stressor (e.g., starting a new job vs. holidays). Flexible for changes because of an intervention; a successful intervention might reduce the local baseline and adjust the level required for the next intervention. Not confounded by diurnal patterns (e.g., higher stress indicators on certain hours of the day)	Can be confounded by intermittent events within the time window, such as poor sleep last night Possibly biased indictor scores because of anticipation/buildup of a stressor (e.g., minor interpersonal disagreements the last 24 hr building up to a major conflict)	“High” reactivity could be signaled because of a day-level drop in baseline stress-response indicator scores (e.g., a “mild” stressor could activate an intervention if it follows a day with unusually low levels of stress indicators).
Stress-response indicators on nonstressor moments on all study days before the stressor	Cumulative	Includes the most observations overall, which may increase reliability The closest to a robust person-level baseline after sufficient data accumulation but preserves the time order of measuring the baseline before the stressor	Can be confounded by distal and seasonal effects (e.g., holidays, starting a new job) In long-term studies, the baseline might be inflexible because recent observations have relatively little weight. Differential number of observations and reliability across the study	“High” reactivity because of low baseline in long-term studies may yield false intervention moments (e.g., a “mild” stressor could activate an intervention if it follows a low baseline level of stress indicators until the baseline adjusts slowly over time).

nature of the time-of-day effects) and within (e.g., across days, weekday vs. weekend) persons. Apparently, time-related associations may also be emergent from temporally entrained environmental factors (e.g., being at work vs. at home; spending time with other people has mood consequences, which are exhibited reliably at certain times of day).

A final approach we consider would be to take the average of all prior nonstressor moments to the stressor—what we call “cumulative baseline state” (Fig.

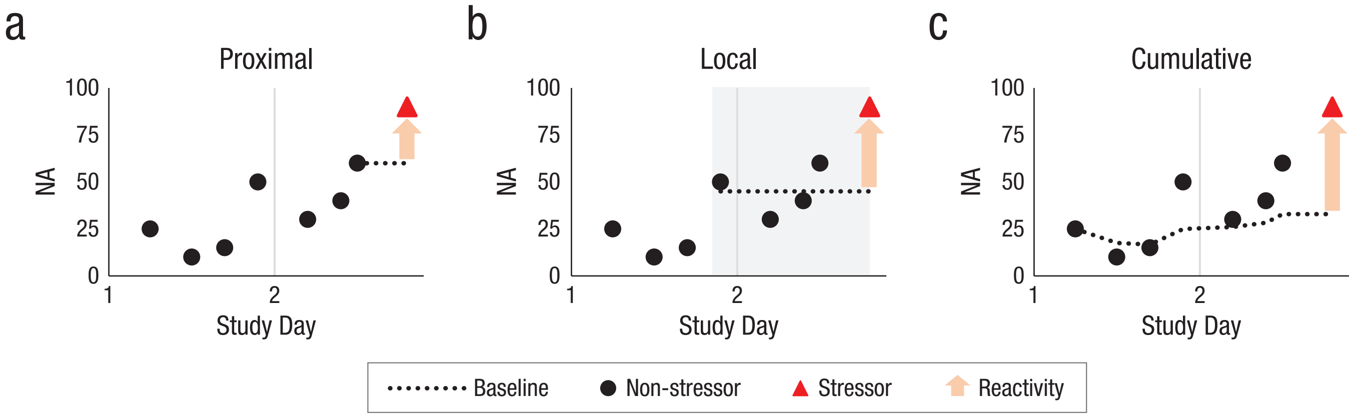

Fig. 1. Three ways to define a resting baseline using negative affect (NA) responses in ecological-momentary-assessment (EMA) designs. (a) Proximal: uses the score of the nonstressor observation preceding the stressor moment. (b) Local: computes the mean NA of nonstressors in a moving window. (c) Cumulative: measures since the onset of the study.

1c). The cumulative baseline state is meant to reflect the mean level of a stress-response indicator from the start of the study up to the current day/moment but include only all nonstressor observations that satisfy a certain rule for the windows (e.g., one could further specify that nonstressor moments must occur on days without stressors or before the first stressor of the day). This approach allows one to estimate the individual's usual resting level of stress-response indicators, comparable with the conventional approach of using the person mean while still preserving the time-order principle. The cumulative baseline state might be preferable when a researcher wishes to contrast the stressor responses to a set point, such as the starting point of an experiment, measurement burst, or at the end of an intervention. Because it uses all available information, it might be optimal for brief study periods in which no major shift in resting states is assumed to take place (e.g., several weeks with no major life events or other meaningful disruptions). As more data accumulates over time, however, these estimates become increasingly insensitive to local/short-term variations. As with local baseline, the cumulative baseline approach is limited by the need to collect sufficient within-persons data before a resting state can be established, potentially resulting in longer study durations.

Challenges for operationalizing reactivity

Choosing the right baseline. For baseline states, our position is that there is no "correct" answer as to which operationalization to use because each may give a different estimate depending on the specifics of the approach and associated assumptions. The proximal baseline state can be used in EMA studies that focus on the subtle differences of stress responses with transient changes over time in physiological measures (e.g., heart rate) and behavior patterns (e.g., physical activity or eating behaviors). The proximal baseline state is also well suited to studies that are conducted over a shorter period of time (e.g., 1 or 2 days). The local baseline state may be more suitable for detecting the changes in day-level variables, such as sleep or workday. However, the length of time windows used to calculate this resting state will depend on variables and research questions. The cumulative resting state can be used to examine trait-like individual differences or long-term changes (e.g., evaluation of long-term therapy or treatment processes).

Identifying when a response peaks. Identifying an appropriate baseline state provides only part of the story for understanding how much stress responding an individual is experiencing at any given exposure. Researchers also typically want to know the highest point of each experience. That is, if researchers know the trajectory of their stress-response indicators from the baseline state through the stressor moment up until the end of the response, they could examine this stress-response to locate the peak moment in which stress is maximum and subtract the baseline score from this maximum to index reactivity (i.e., the delta peak; see Yim et al., 2010). However, without continuous observation, researchers often do not know when a response to a stressor peaks and instead might capture moments too early or too late. Moreover, there is heterogeneity for peak both within and between persons, so this is not resolvable through coding observations or modeling alone. For example, even if researchers were to perfectly identify one stress-response peak for an individual, they do not know if that peak (timing, level, etc.) reflects the featural characteristics of other stress responses for that individual (and presumably it does not reflect other individuals' stress-response patterns). Finally, stress response may not peak at the same moment for different stress-response indicators. For example, an affective response to stress, such as negative affect, may reach an apex earlier than a cognitive indicator of stress response, such as rumination or worry, which can continue to increase as the stressor event is rehashed over time. In other words, different indicators of the stress response may operate on different timescales. To complicate matters even more, the response to a single stressor may have multiple response peaks over time. There is thus a need for more intensive ambulatory assessments (e.g., observations every 30 min) than are typically used to better model the time course of stress responses across indicators and stressors in everyday life. Yet this would increase participant burden and potentially reduce compliance. Thus, it might also be instructive to consider an adaptive signal-contingent scheduling in which an initial stressor report is followed by an intense burst of beeps inquiring about momentary stress-response indicators to obtain more specific peak (and other dynamic) estimates.

Conceptual challenges for operationalizing recovery

Establishing recovery in EMA and daily diary studies poses additional challenges. Not only do researchers likely need to determine a resting-state value, they must also characterize the shape of the response (e.g., determine the peak) and operationalize what signifies actual recovery.

When does return happen? The main challenge in determining recovery is knowing when the recovery process has completed, such as when a person returns to resting state after a stressor. To address this issue, researchers first need information regarding the initial timing and extent of reactivity. Likewise, it is important to have detailed timing information (e.g., when a stressor occurred, how far apart EMA observations are spaced) to be able to characterize the temporal trajectory of the recovery process from the peak to return to resting or near-resting state.

In Table 2, we highlight different potential ways to operationalize recovery. Again, appropriate choice depends on the question one is trying to answer. One approach to defining recovery is to statistically compute to what degree the indicator has returned to the resting state (e.g., the cumulative baseline), whether fully or incompletely (see Fig. 2a). In other words, recovery can be construed as an end state relative to a prestressor resting state in which "full recovery" would mean that the person has returned to the resting state and "incomplete recovery" would mean that within the time parameters, a resting state has not yet been reached and indicator levels are still elevated.

A second approach is to define recovery as a process independent of prestressor resting state but relative to the stressor itself (Fig. 2b). In other words, recovery can be used to refer to a magnitude in indicator decline from stressor to nonstressor moment (i.e., "immediate recovery") in which greater recovery means a "larger" reduction in indicator levels even though the person might still be above, at, or below the prestressor resting state. This characterization might be especially appropriate for examining predictors of the magnitude of the recovery process itself (i.e., the degree of recovery) regardless of whether a full return to resting state was achieved at the time of measurement.

A third approach to characterizing the amount of recovery is to combine the former two by accounting for both prestressor resting-state levels and the magnitude of the recovery drop itself (Fig. 2c). This could be construed as a proportional-recovery score in which the magnitude of the immediate recovery from a stressor to a nonstressor moment is compared with the magnitude of the initial stress reaction. Proportional recovery evaluates not only a persistent difference from resting states but also the amount of recovery from the initial reactivity response. Note, however, that by computing this as a proportion, it allows for different "amounts" of recovery to be estimated similarly. For example, both a 5-point decrease following an initial 10-point stress reaction and 50-point decrease following a 100-point reaction yield the same 50% recovery. This approach treats relative recovery as the important dimension (rather than the absolute amount, which would be quite different in this example); it thus becomes possible to estimate and contrast both approaches to determine under what circumstances each may be useful and important. Another way to evaluate both prestressor resting-state levels and the magnitude of the recovery is to compute the amount of recovery only when initial stress reaction from prestressor resting state is higher than a certain threshold (i.e., "meaningful reactivity"). This also helps guard against assuming an indicator is affected by a stressor, but then data are limited to recovery following only "meaningful" reactivity.

Conceptual challenges for operationalizing pileup

Do stressors happen (only) in isolation? The experience of one stressor earlier in a time period may make a person more vulnerable to subsequent stressors.

Table 2. Overview of Recovery Considerations

What type of recovery are you interested in using?	Name of recovery	Strengths	Limitations	Considerations for ecological-momentary interventions
Evaluating to what degree people have returned to their own resting state following a stressor	Return to resting state	Compute to what degree the stress-response indicator returns to resting states independently from reactivity to a stressor Different types of resting states can be used for computing (see Table 1 for details of resting states)	Cannot reveal the characteristics of the recovery process (e.g., whether an increase or decrease or slow or fast change has occurred from stressor to nonstressor moment)	Deliver an intervention for lack of recovery (i.e., unsuccessful return to resting state) but cannot deliver an intervention for slow reaction (e.g., no intervention when stress-response indicators are still elevated but are near resting state)
Evaluating to what degree a person has recovered from stressor to nonstressor moment	Immediate recovery	Compute recovery process independently from resting states	Recovery process highly dependent on how much the stress-response indicators react to a stressor and does not capture an end state (e.g., higher immediate recovery does not always mean successful return to resting state)	High immediate recovery following high stress reaction cannot deliver an intervention even if the stress-response indicators are still higher than resting states. Likewise, low immediate recovery following low stress reaction could activate an intervention.
Evaluating to what degree a person has recovered compared with the initial reactivity	Proportional recovery	Account for prestressor resting-state levels and the magnitude of the recovery at the same time	The different amount of recovery in stress-response indictor levels yields the same proportional recovery.	Small amount of recovery following a low reactivity could activate an intervention even if the stress-response indictors are near resting state.
	Recovery following meaningful reactivity	Account for prestressor resting-state levels and the magnitude of the recovery at the same time	Need to be computed with sufficient data because of data restriction for "meaningful reactivity"	A "mild" reactivity (i.e., nonmeaningful reactivity) could be excluded from intervention.

Alternatively, it is also possible that an earlier stressor may inoculate the impact of a later stressor. In both lab studies and most EMA/daily diary work, the potential for stressors to pileup has largely been ignored (cf. Bolger et al., 1989). At present, it is unknown whether a prior stressor makes a person more vulnerable or inoculated to a subsequent stressor, more vulnerable to a more severe (or blunted) response, or some combination (e.g., Schilling & Diehl, 2014). Yet pileup may be an essential aspect of understanding the risks associated with stress responding. Given that the psychological, affective, physiological, and/or behavioral sequelae of a single moment of stress-response reactivity or lack of recovery are likely relatively small, risks are likely to accumulate when such stress responses cumulate over time—this is what pileup is intended to measure.

How do we capture pileup? With respect to operationalizing pileup, one simple approach is to simply count the occurrence of stressors (Fig. 3a). This approach has some appeal in that it provides a relatively interpretable number and is relatively easy to collect. However, people respond differently to similar stressors, and a person often responds differently over time to even the same type of stressor (Schommer et al., 2003). Thus, counting all stressors as equivalent across people and over time may impose too many assumptions of equivalence. An alternative would be to count only moments when an

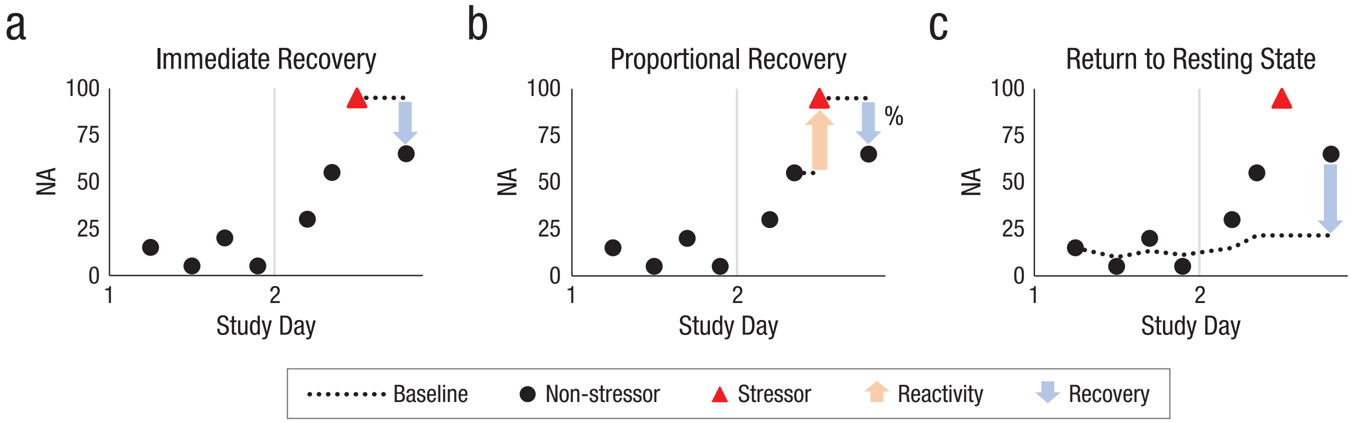

Fig. 2. Three ways to define recovery from a stressor using negative affect (NA) responses in ecological-momentary-assessment (EMA) designs. (a) Return to resting state: measuring to what extent the person has returned to the resting state on the following nonstressor observation. (b) Immediate recovery: the change from the stressor moment to the following nonstressor moment. (c) Proportional recovery: the immediate recovery in proportion to the reactivity.

individual exhibited a substantial and reliable stress response (Fig. 3b), for example, or the number of cycles of reactivity and recovery following the report of a stressor (Fig. 3c). This approach more directly ties deviations from resting state to responses to stressors and may thus reflect more meaningful stress experiences in everyday life relative to a simple count of stressors (that may not have all induced a stress response). This approach presumes that stressors that do not elicit a meaningful response, however, should be ignored—although reasonable, it is predicated on the indicators being used (i.e., researchers may miss a response on an unmeasured stress-response channel if there is not an indicator). An additional concern is that requiring the presence of a reported stressor also relies on the capacity of a participant to identify and accurately report stressor stimuli—any stimuli that are out of awareness or otherwise not labeled as stressors would therefore be missed using this approach (the first approach offered would similarly miss these; we return to this idea a bit later in the article).

How far should researchers look back? Another consideration is choosing a meaningful time window to explore. The premise behind pileup is that prior stressors may have a cumulative impact—that is, for example, a single stress-response cycle may be insufficient to disrupt health behavior, but when several occur in close temporal proximity (e.g., multiple events in a day or a series of stressful days), people's behaviors and/or other outcomes may suffer. Extending this rationale further, we argue that at some point, enough "linked" stressors become something qualitatively different than just another discrete-stressor event. Although it is often unclear what is meant by chronic stress conceptually, stressors that result in repeated and

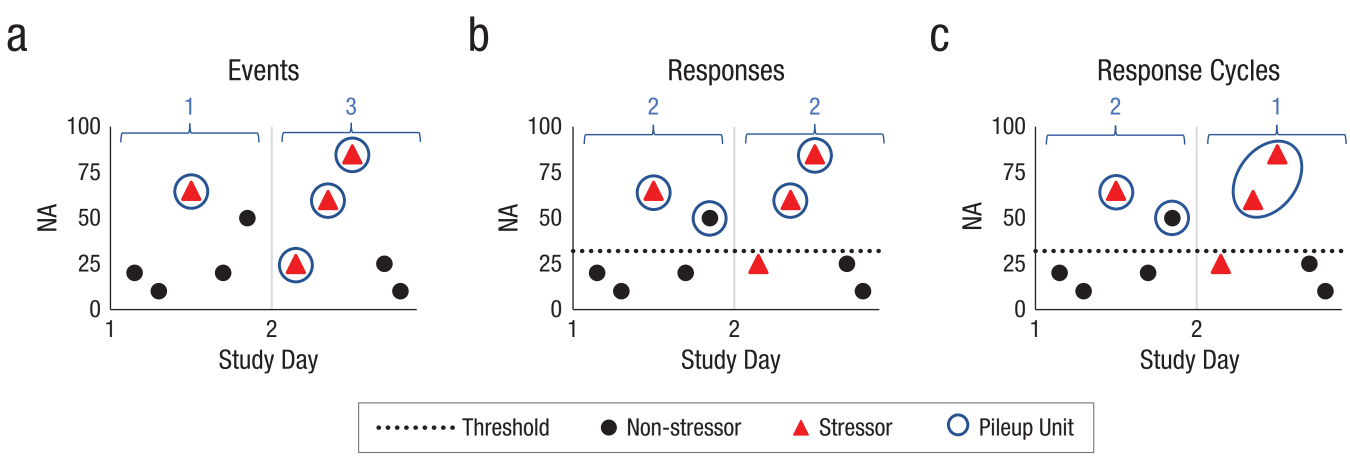

Fig. 3. Three ways to define pileup using stressor occurrences or negative affect (NA) responses in ecological-momentary-assessment (EMA) designs. (a) Events: counting the number of reported stressors. (b) Responses: counting stress responses above a certain threshold. (c) Response cycles: counting reactivity–recovery response cycles.

frequent activation of stress-response systems start to approximate a chronic stress environment (Smyth et al., 2013; Wheaton, 1994). A key issue is deciding what is a meaningful temporal window to explore how stressors link/pile up over time. For example, one might want to consider just those in a day (as we used in Fig. 1) and argue that sleep is a reset for each new day. However, one must then consider that a stressor may affect sleep at night, which in turn makes it more likely a person will experience stress the next day (and, to bring in other stress-response components, may influence the resting-state estimate for the following day, etc.). Alternatively, it may be useful to consider longer periods of times (e.g., 48-hr or 72-hr windows), but this approach then creates difficulty in determining what distal/earlier stress matters.

It is typically assumed that when people enter a study, they are "clean" or "fresh" in the sense of recent stress experiences (past stress is typically assessed over years, e.g., via life-event checklists, or the past month, e.g., with a perceived-stress scale). These are sensible approaches, but our view of pileup also suggests that people are entering a study with various degrees of pileup over the past few days. For example, if people have had a "bad week" or enroll in a study because of higher than typical stressors and/or stress responses in their lives, this would presumably reflect more pileup as the participants enter the study. If so, the implication would be that researchers need to adopt careful characterization of recent prior stressors at baseline and/or implement a run-in baseline period as standard practice at the start of the study to measure potential changes in pileup (e.g., measure 3 days of stress to get a working pileup score/baseline/etc. before doing the "real" study; although presented here in the context of pileup, we see this process as also being informative for reactivity and recovery as well).

Other Conceptual Considerations

What about stress that is not event- or stressor-based?

Thus far, we have assumed that for an RRP to occur, an external event should have happened that is identified by the participant. However, what if symbolic representations of past or future events can trigger the same type of responding? Much of the theoretical work on perseverative cognitions suggests this is a form of stress as well (Brosschot et al., 2006; Smyth et al., 2013). Some studies allow for and measure this possibility, but participants in research studies may still be inclined to focus on external events in their reporting. If one is concerned that people have events that they do not report or that there are nonevent elicitors that people do not think of, we propose that there might be other ways to look at RRPs.

Using this approach, it is possible to index a response even without a subjective report of an external event—although doing so requires additional assumptions. For example, extending what is shown in Figures 2a and 2b, we argue that a large/meaningful sudden increase in a stress-response indicator—even if no stressor was reported—might be considered a stress response. That is, one could look for meaningful changes in stress-response indicators even if no stressor was reported as an indicator of a stress response (and could compare these to stressor-triggered RRPs to assess differential predictive utility). One of the strengths of this approach is that it provides more information because the response may be due to a person missing a report of an external event or experiencing an internal stressor that is not reported as an (external) "event." In addition, if one had ongoing measures of heart rate or electrodermal activity assessed with a wearable device, for example, meaningful changes could be assessed passively (and could be used to trigger a self-report). However, a primary limitation of this approach is that one must presume negative disruptions in indicators are due to stress; it is certainly possible that the response could be due to something unrelated (or at least not recognized/appraised/attributed as a stressor), such as low-grade/prodromal illness, bad weather, and so on. This assumption may be more warranted under circumstances in which failure to account for the occurrence of non-event-based stressors would affect resting state (i.e., leading to a higher estimate of a resting state by including some of these "missed" stress-response moments) and could lead to underestimation of responses.

Positive events and experiences (measured or unmeasured) could also influence these processes. Although largely beyond the scope of the current work, we note that this possibility raises interesting potential extensions of this stress-response framework. For example, most simply, assessing and including positive events would be a ready extension. But interesting other options arise, such as characterizing positive RRPs in response to positive events (perhaps using positive affect as an indicator) and then integrating them with the negative/stress RRPs (e.g., in some dynamic affective offset manner that explores the relative changes of both positive and negative stress-response indicators in tandem and/or over time).

Any change or meaningful change?

Throughout our consideration of RRPs, we have assumed so far that all change is potentially important. Yet it is possible, perhaps likely, that small or incremental change is not (as) meaningful; rather, there are critical thresholds for the amount of change that is meaningful. If so, how does one choose those critical thresholds? One reasonable approach would be to standardize responses within a person and to select moments that are *X* standard deviations above a personal average. A related approach would be to first establish and then apply clinical cutoffs; at this time, given the novelty of this approach, we are unaware of any data to determine whether, let alone what, would constitute such a clinical cutoff. This is a potentially important line of future work. Another approach considers whether a person has a reliable change, meaning a difference in score that is greater than would be expected because of measurement error alone. Yet for both these approaches, and others, assumptions must be made as to what counts as meaningful: Should 1 *SD* or 2 *SD* be used? Should the cutoff be based on a *p* value of .05 or .01? Less stringent cutoffs would increase the number of moments that are explored, but perhaps only higher thresholds for stress responding would relate to clinically relevant processes and/or outcomes.

Other approaches

We, of course, recognize that there are other approaches to characterizing within-persons variability and that these other approaches have different strengths and weaknesses. Many other approaches generate indicators (e.g., person-specific variability) that are derived from rich within-persons data (e.g., EMA, physiology) but are used in a between-persons manner (i.e., to characterize individual differences). For example, the DynAffect model (e.g., Kuppens et al., 2010) uses sophisticated methodology to characterize individual differences in affect dynamics through three core processes: (a) an emotional home base (average level), (b) degree of variability, and (c) attractor strength—an index of the regulatory processes that try to return affect to the home-base level. Such approaches provide metrics and considerations that our model cannot achieve (e.g., we do not have person-level indicators of the self-regulatory process strength) but also cannot emulate aspects of our approach (e.g., integration of pileup, pragmatic computation in real time, and use in guiding intervention delivery to at-risk moments).

Data and Design Considerations

A critical element to this RRP approach is that every stressor has the chance to produce its own RRP profile, which allows variability both between and within persons. In addition, such RRP profiles may differ within individuals, for example, across different indicators. For instance, the trajectories of a person's subjective stress responses may look different than negative affect or rumination/worry responses. Although some existing approaches have attempted to identify temporal dynamics (e.g., How does a stressor at one time point influence negative affect at a later time point?; Scott et al., 2017, 2019), most work assumes that the dynamics are invariant for a person across time. For example, the typical within-persons multilevel model produces a person-level pattern that summarizes over all the person's events to describe why negative affect is sometimes higher and sometimes lower. Unless a temporal structure is explicitly considered (e.g., with lagged analyses, time-series model), these analyses are fundamentally correlational even when derived from intensive time-series data, such as EMA or daily diary. Although characterizing the stress-response components (RRPs) and allowing them to vary within persons over time may appear simple at first glance, it requires a great deal of information and requires important decisions be made about how to collect and treat data. Although we do not presume to have ultimate conclusions on these issues, we lay out herein the types of challenges faced in this approach and at least some strategies and approaches for managing them.

Design issues

When one is considering how best to assess the temporal profile of stress via RRPs, it is tempting to unilaterally suggest a more intensive assessment schedule. A more frequent assessment schedule allows for calculation of different resting states; a greater chance to capture peak and recovery, thus helping to distinguish between reactivity and recovery; and less likelihood that a stressor will be missed that would contribute to pileup. The push for more data must be weighed against the increasing burden that is placed on participants that can reduce quality of data and overall compliance (Eisele et al., 2022). EMA studies typically have employed dense measurements in a day for only a couple days or fewer measurements per day for more days to balance this burden; such shorter duration, however, may itself limit stressor and stress-response variability and the possibility to observe and characterize pileup across days. Alternatively, daily diary with one measurement per day typically has afforded lengthier periods of assessments and may be well suited for capturing pileup over extended periods of time. Another possibility would include "event-contingent" reporting in which participants provide a report following a specific target experience or context (e.g., in response to a stressor).

These approaches largely have assumed active responses on the part of participants (either in response to some reminder or target experience). Wearable sensors that measure physiological functioning (without requiring active responding) are being increasingly used in research, and physiology can be used to index affective and cognitive states (e.g., certain ranges of heart rate variability have been found to correlate with emotion regulation). Thus, it may be possible to passively assess one's state and use that to determine stress responding (or, alternatively, to frame an adaptive assessment protocol such that physiological indicators are triggers for self-reports to clarify atypical states). We do note that there are many difficulties in using physiology to index emotional and/or psychological states, particularly at the momentary level and in real time, rather than relying on analysis of data after the fact. Such challenges include but are not limited to issues related to precision and specificity (e.g., a particular affective state, e.g., stress vs. anger) and challenges inherent to capturing and interpreting physiology in messy ambulatory contexts.

Another issue is that it will be difficult to detect variability in RRPs for an individual who reports few stressors or has few total days when a stressor is reported. Instead, any relation to other variables/outcomes might be primarily driven by the mere presence or absence of (infrequent) stressors. Alternatively, someone who reports several stressors or days with many stressors will also pose problems. It will be difficult to estimate resting state because these individuals will exhibit a stress response for much of their available data. Accordingly, care should be taken in the consideration of sample-specific factors (e.g., presumptive stressor frequency) and how that may affect the capacity to characterize everyday stress responses (e.g., floor or ceiling effects). Related to a point above, in these situations, the thresholds for intervening may be better conceived as dynamic that shifts as needed to allow greater or fewer thresholds to be met.

To help illustrate the generation of RRPs in the broader context of the issues raised in this article, we provide a representative individual data stream (using EMA) and sample algorithm to generate RRPs (see the Supplemental Material available online). In addition, we include a file that details the outcomes of such an application (i.e., the consequent RRP outputs for each moment in the sample data) to help demonstrate how this approach can be readily applied to actual data in a comprehensive fashion.

Intervention considerations

RRP decomposition has the potential to help interventions be targeted more efficiently. If a person's health is influenced by reactivity to or even anticipation of stressors, then the intervention might need to be administered before the stressor occurs or almost immediately after the stressor. If the person has problems with recovery, the intervention might optimally be delivered in that process of recovery. For pileup, the intervention could be delivered early in a series of stressors. There are, of course, many variations of these tenets, but the core idea is that intervention timing and content can be carefully matched to the stress-response components. To this end, researchers and clinicians might benefit from examining targeted sets of indicators/components that are sensitive to that specific process instead of relying on global means. For example, imagine a person who is facing a deadline in a week and has a series of tasks to complete to meet the deadline. This person may have moderate levels of reactivity over the week when faced with each task. Yet no moment may be "severe" enough to trigger with a traditional intervention approach that does not consider pileup but, rather, absolute scores, overall means, or the greater the context in which reactivity is occurring. In contrast, identifying RRPs specific to an individual in any given moment may provide a highly ideographic and potentially effective approach to just-in-time interventions (Heron & Smyth, 2010; Smyth & Heron, 2016). In the example above, real-time calculations of stress-response indicators could be used to trigger an intervention relying on any indicator (e.g., if pileup reaches a certain amount) or based on additive or interactive combinations of RRPs (e.g., if moderate reactivity occurs while a person is experiencing pileup).

Conclusions

We posit that to characterize and understand fast-acting, within-persons stress responses in everyday life, information can be gleaned by modeling multiple elements (i.e., RRPs). The first is the onset of a stressor. In this article, we intentionally adopted a broad perspective of stressors, including reported external occurrences and perceived internal events. Although challenges are associated with this broad view (e.g., Are people aware of all stressors?), we feel it is contributory to the advancement of understanding stress. Second, we also provide several considerations for how to select and quantify a person-specific, nonstress baseline; this is essential as the within-persons comparator but has been largely neglected in ambulatory research to date. Third, some indicator is needed that captures the degree to which a person responded in a moment. We largely rely herein on considering subjective reports to characterize stress-response components; yet nearly any indicator (e.g., physiological changes, behaviors) could be used as long as it has the potential to vary within and across people in response to stressors and those changes can be measured. Fourth, an accounting for time is needed to be able to assess when responses happen in a manner that preserves temporal order and spacing. Within this framework, we drew on well-established traditions from experimental/laboratory work to propose pragmatic approaches to operationalizing three important elements of ambulatory and naturalistic stress responses: (a) reactivity—a measure of how big a response is immediately after the stressor; (b) recovery—a measure of the degree to which and/or how long a response persists; and (c) pileup—a measure of how frequently stress responses occur over relatively brief periods of time (e.g., hours, days).

It has long been recognized that the same stressor has the potential to elicit different responses from different people, and there have been numerous studies of individual differences in stress responses. However, research has been far less focused on the notion that stress responses vary within the same individual across time and situations. Extending existing between-persons approaches to studying stress to include characterization of stress as a within-persons process can improve the understanding of how stress affects health; in particular, such within-persons information can directly inform when and how interventions (e.g., just-in-time) can be delivered to reduce stress and its negative effects. Although a person may have a general range of stress responding (i.e., a more nuanced way of approaching between-persons processes), to effectively implement just-in-time and ecological-momentary interventions, it is critical to know how that person is responding at a particular moment (rather than that person's hypothetical range). Future research may look to incorporate between-persons and within-persons frameworks, such as using between-persons measurements to stratify individuals on risk and then implementing a within-persons measurement to identify those specific risk moments. Such an approach still requires studying core features of stress responses that are not easily studied in laboratory settings (e.g., pileup) or by reliance on cross-sectional retrospective reports (e.g., recovery).

Therefore, advancing the understanding of stress as a within-persons process and its downstream consequences on health and well-being requires augmenting laboratory and cross-sectional methods with ambulatory methodologies that permit repeated measurements over time in the context of a participant's everyday life. Such real-time and ecological data allow researchers to capture and model the time course of stress responses and decompose those response into their core components. This approach also challenges the notion that a stress response has an easily defined onset, reactivity, and recovery cycle in everyday life. Moreover, accounting for the accumulation and overall load of stress in everyday life, what we label pileup, reflects something quite different than a retrospective report of major life events over the past year. In this article, we provide an initial conceptual understanding of why RRPs are critical to examine, representative implementational strategies that can be used in real time to generate RRPs from ongoing data, and a discussion of many of the inherent difficulties when this approach is employed.

Going forward, we hope the framework provided here serves as an informative starting point to advance research design and methodology related to stress (and, perhaps, for other ambulatory-assessment topics as well). We present the possibility of considering not just whether one is experiencing stress and its potential impact on downstream health and well-being—the typical approach—but also the possibility to consider how much one responds to a stressor—an approach heretofore largely relegated to the laboratory. Adopting this stress-responding approach in EMA certainly has its challenges, many of which we outlined in this article. Yet the potential for such an approach to reveal unique associations with health and well-being and uniquely actionable targets for intervention makes resolving the challenges worth the effort.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/17456916221082108

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