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Exploring the Utility of a Real-Time Approach to Characterising Within-Person Fluctuations in Everyday Stress Responses

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ABSTRACT

Few studies have measured components of stress responses in real time—an essential step in designing just-in-time interventions targeting moments of risk. Using ecological momentary assessment (EMA), we characterised stress response components to everyday stressors, including reactivity (the response following a stressor), recovery (the return towards baseline), and pile-up (the accumulation of stressors) (RRPs) by quantifying the dynamics of response indicators (i.e., subjective stress, negative affect, and perseverative cognition). To determine the utility of these novel measures in capturing and characterising acute moments of the stress response, this study evaluated the proportion of variance in RRPs attributed to (1) between-person, (2) between-days, and (3) within-day (momentary) levels. Healthy adults (n = 123; aged 35–65, 79% women, 91% non-Hispanic White) participated in a 14-day study assessing stress response via EMA 6 times a day. RRPs were constructed from 10,065 EMA reports. Multilevel models with moments nested within days nested within persons were used to partition variance in the RRPs. Reactivity and recovery indicators captured the most variation within-days (i.e., across moments; range 76%–80% and 87%–89%, respectively), with small amounts of variance between-person. For pile-up, variation was mostly observed between-days (range 60%–63%) and between-persons (range 27%–31%). In contrast, raw measures of stress response reflected substantial between-person (range 32%–54%) and within-day (range 34%–53%) variance. These results demonstrated that a person-specific approach to measuring stress response components (i.e., RRPs) can capture the dynamic within-person variation in stress response, as it occurs in real time, making it well-suited for use in novel just-in-time interventions targeting moments of risk.

1 | Introduction

Stress, broadly defined as a phenomenon where environmental, physical, and/or psychological demands exceed perceived resources available to respond to the situation (Lazarus and Folkman 1984; J. M. Smyth et al. 2013), is an important risk factor. Classical studies showed that those experiencing higher levels of stress (compared to individuals with lower stress levels) had higher risk of developing a variety of health issues such as clinical depression, cardiovascular disease, HIV/AIDS, and cancer (Cohen, Janicki-Deverts, and Miller 2007, 20). Indeed, this between-person examination of stress (i.e., evaluating how stress levels and related metrics covary with outcomes across individuals) have greatly contributed to our current understanding of the link between stress and health. We posit, however, that this does not capture the essential within-person process aspect of stress. That is, a person's experience of stress differs not just from person to person, but also from one moment to another, for a given person. Thus, within individuals, moments of stress may also convey risk (relative to moments of less stress) and such moments may be appropriate to target with just-in-time intervention (Nahum-Shani, Hekler, and Spruijt-Metz 2015). To effectively characterise and potentially intervene on the within-person stress response processes, our conceptualisation and measurement of stress should be sensitive to the dynamics of the stress response occurring across time and context within the same individual.

The emergence of ambulatory assessment methodologies combined with novel statistical approaches in analysing repeated measurement data have opened opportunities to study these dynamic processes in everyday life. In particular, ecological momentary assessment (EMA) uses brief self-reports to allow individuals to repeatedly report their experience (e.g., affective state, behaviour, and/or contextual information) in real-time and in real-world setting (Shiffman, Stone, and Hufford 2008; J. M. Smyth et al. 2018), a method well suited to study the within-person stress response process. Studies that explore how acute stress affects a person's engagement in health-related behaviours usually utilise EMA reports to measure indicators of stress response, including a self-report of negative affect (NA), perseverative cognitions (PC; e.g., rumination, worry), or simple subjective stress (SS), and relate them to outcome variables (often co-occurring at that particular moment). Typically, this approach to within-person associations utilises a person-specific mean centred predictor (Curran and Bauer 2011; Stephen W. Raudenbush & Anthony S. Bryk 2023), thus largely removing between person differences and capturing the predictive utility of moments being above or below the individual's own mean (i.e., if higher or lower than is typical for the person). This approach has proven fruitful in identifying within-person associations and processes in naturalistic settings and has contributed to the field tremendously [and continues to do so; for example (Aldridge-Gerry et al. 2011; Bernstein et al. 2019; Braun et al. 2020; Kim, Conroy, and Smyth 2020)].

Furthermore, the study of dynamical within-person processes is also gaining momentum. Emotion dynamic research often employs EMA methods to characterise the trajectories, patterns, and regularities in changes/fluctuations of affect and emotions within-person across time (Kuppens 2015). These studies utilised metrics that describe the patterns of variation in mood/emotions in terms of the range or amplitude of someone's emotional states across time (*variability*), the magnitude of emotional changes from one moment to the next (*instability*), and the degree to which an emotional state can be predicted from the emotional state at a previous moment (*inertia)*. However, despite their usefulness in predicting health outcomes such as wellbeing (Houben, Van Den Noortgate, and Kuppens 2015; Schulz et al. 2021; Xia et al. 2021), these metrics are often person-level characteristics that describe a within-person process. Therefore, their usefulness is in identifying who are at risk, but are limited in identifying when (and related questions, such as where, to what degree) a person is exhibiting a high stress response moment and thus may benefit from micro-intervention (Heron and Smyth 2010). Recent advances in statistical methodologies also employed more sophisticated modeling techniques to elucidate the interaction between variables and how these interaction changes and evolve over time (Hamaker, Kuiper, and Grasman 2015; Reitzle and Dietrich 2019). Similarly, this post-hoc examination of the data has limited utility for the real time detection of moments of risk and/or opportunities (varying over time within an individual) to deliver novel adaptive interventions.

A within-person approach to capturing stress response processes as they unfold in real time can yield information more useful in elucidating the different within-person processes that affects an individual's risks and/or opportunities for engaging in healthy/unhealthy behaviour on a particular moment—an important element in developing personalised and adaptive health interventions. Yet little guidance exists on how to best characterise the stress response process in everyday life. Perhaps the closest model to understand the temporal components of stress responses are lab-based experiments that introduce (often standardized laboratory) exposures and carefully measuring the magnitude of reactivity and the time course to recovery (Miller 2019)—and attention to the need to distinguish between reactivity and recovery has long been noted (Linden et al. 1997; Suls and Martin 2005). In our approach, we argue that to develop effective and efficient just-in-time interventions, we need a within-person measure of stress response that can (1) quantify and detect natural variations in stress response from one stress moment to another, within-person, (2) disentangle influence from between-person processes (to facilitate development of intervention algorithms), and (3) compute these dynamic processes in real-time. These characteristics are essential in developing novel interventions that can detect and adapt to the ever-changing need of an individual.

In previous papers, we proposed (J. Smyth et al., 2023; J. M. Smyth et al., 2018) and operationalised a novel measure of ambulatory stress response that embodies the three key characteristics mentioned previously. These papers advocated for the measurement of unique components of stress response—that is, initial reactivity, degree of recovery, and the repetition or 'pile-up' of stressors (RRP)—by situating each stress event and characterising how a wide range of response indicators, including a self-report of subjective stress (SS), negative affect (NA), and perseverative cognitions (PC; e.g., rumination, worry) respond to this specific stressor. *Reactivity* generally refers to the initial peak of the stress response observed shortly after the eliciting stressor. *Recovery* is broadly defined as the return to resting state following an initial stress reaction. Lastly, *pile-up* is defined as the frequency and patterning of stress responses across time or the accumulation of stressors and/or stress response cycles over time. A detailed description of how these stress response components can be operationalised is beyond the scope of this paper but is documented elsewhere (J. Smyth et al. 2023, 20). Briefly, to capture the temporal dynamics of this process, the RRP approach necessitates having repeated measures of the experience of stressors (i.e., stress exposure), an outcome i.e. an indicator of how one responds to the stressor (e.g., subjective stress), and an understanding of the temporal order of these measures to generate real-time, person-specific, stress response indicators.

In this paper, we aimed to provide a preliminary evaluation of the utility of the RRP assay in capturing within-person stress response dynamics. Specifically, we first provided descriptive characteristics (i.e., frequency, mean, SD) of RRPs occurring at the person level. Then, we examined the proportion of variance in RRPs attributed to (1) differences between people (*between-person*), (2) variations within a person across days (*between-days*), and (3) variations within a person within a day from moment to moment (*within-day*). We hypothesise that by design, these RRP components will be highly variable within-person. Finally, we evaluated level-specific reliability of these measures. Ultimately, this will highlight the potential for use in developing just-in-time interventions that target stressful moments.

2 | Methods

2.1 | Participants

Participants were recruited via study flyer and online advertisements from November 2017 to June 2018. Due to our interest in the association between stress responses and the enactment of health behaviours (i.e., physical activity and sleep, not reported on herein), we had broad inclusion and exclusion criteria. Interested participants were screened for eligibility which included (a) age 35–65 years, (b) able to read, understand, and speak English, (c) free of visual or motor impairments that may prevent the use of a smartphone screen or computer, and (d) in good general health, ambulatory, and free of functional activity limitations. In addition, participants were excluded from the study if: (a) reporting a mental health condition diagnosed and/or required treatment change or hospitalisation over the last 3 months, (b) primary caretaker of severely disabled family member, (c) employment that required work between the hours of 10 p.m. and 6 a.m., and (d) self-reported or medical diagnosis of sleep apnoea, use of C-PAP machine, or a score of 5 or more on an obstructive sleep apnoea (Nagappa et al. 2015) screening questionnaire, (e) self-report of physical exercise of 200 min or more per week. All study procedures were approved by the university institutional review board.

2.2 | Procedures

Eligible participants were invited for an initial two-hour laboratory visit to provide informed consent and complete a series of baseline demographic, health, and psychological measures. All study participants were provided with an android LG Rebel 3 smartphone. The smartphones were be preloaded with the MovisensXS (Karlsruhe, Germany) application, a secure assessment application that delivers, collects, and uploads the study smartphone surveys to a secure server. Participants received instructions and detailed training on how to use the study devices and on how to respond to the EMA items. Participants were asked to continue with their usual daily activities while completing EMA surveys approximately every 2.5 h (with a minimum one-hour interval between EMA prompts) from 8:00 a.m. to 9:00 p.m. (maximum of 6 EMA per day) for 2 weeks. Participants were given up to 15 min from the initial beep to complete the EMA prompt. If they fail to respond to the initial beep, they are reminded to take the EMA prompt every 5 min. At the end of the 2-week assessment period, participants returned their study devices and received compensation.

2.3 | Raw Stress Response Indicators

Participants reported their responses to everyday stressors in the EMA surveys which include questions regarding the occurrence of stressors and stress responses in the form of SS, NA, and PC. Stress response indicators of SS (*How stressed do you feel right now?*), NA (six items: anxious, annoyed, upset, sluggish, bored, and sad), and PC (three items: stressful thoughts, intrusive thoughts, and difficulty focussing) were rated using a seven-point Likert scale (i.e., 1 = *not at all* to 7 = *extremely*) and calculated as the average of available subitems to serve as reference values. These indicators had been shown to provide valid and reliable measures of stress response and are empirically linked to stress-related outcomes and processes (Moberly and Watkins 2008; Scott et al. 2020; J. Smyth et al. 1998; J. M. Smyth et al. 2018; Watson, Clark, and Tellegen 1988). Evaluating RRPs derived from these common measures of stress response permit us to examine potential temporal variations in response between these indicators and to further distinguish one stress moment from another.

2.4 | Stress Response Components

RRP. We utilised the stress indicator scores described above to calculate the stress response components. Although the process of adapting RRP seems straightforward, operationalising these variables in a free-living EMA study can be done multiple ways depending on how certain parameters are defined (i.e., baseline, peak, and return to baseline response (J. M. Smyth et al. 2018)). Obviously, these differences in characterisation can represent conceptually different variants of RRP (e.g., reactivity relative to how one was feeling a few hours ago vs. relative to how one has typically felt over the last few days). To provide proof of concept, in this study we examined one variant of each RRP component that closely reflects our overall aim—to capture and characterise nuanced stress responses within the individual. Thus, for this study, we defined reactivity as the proximal change in SS, NA, or PC score from a non-stressor (resting state) moment to a subsequent stressor moment (i.e., Proximal Reactivity). A stressor moment was defined as any EMA moment where participants reported experiencing a stressor (common examples of potential stressor events such as argument, disagreement, or conflicts, difficulties involving job/work/school, difficulties at home, health issue or accident, or some negative event involving another person that have been identified, developed, and refined (for training purposes) in prior work) since the last prompt. Recovery was operationalised as the difference between the indicator score from a stressor moment to the following non-stressor moment (i.e., Proximal Recovery). Lastly, pile-up was operationalised as the count of all moments with significant responses to stressors over the last 48-h moving window. In this case, we defined a 'significant response' as a moment with the indicator score one standard deviation above that specific indicator's person-mean from all non-stressor moments prior to that moment. An RRP component was calculated separately from each indicator. Lastly, moments between days were treated separately; as such, reactivity or recovery scores were not calculated using moments from the previous day.

2.5 | Statistical Analysis

Descriptive statistics (i.e., $M \pm SD$) were used to summarise demographic information and reports of overall NA, PC, and SS. Reflecting the assessment design, we examine how RRP components vary at three levels: between-person (i.e., variations due to differences between individuals), within-person between-days (i.e., variations due to day-to-day fluctuations within an individual) and within-person within-days (i.e., the moment-to-moment fluctuations within individuals and days; this level by definition also includes measurement error). To partition the variance, we examined the variance estimates from the unconditional null models, using the RRPs as outcomes, in a three-level multilevel model. Variance components for each model were examined and the proportion of variance attributed to each level were calculated. To compare results with conventional methods of assessing stress responses, the same variance analyses were conducted using the raw NA, PC, and SS scores. Furthermore, because this approach combined any meaningful variation at the lowest level with error variance, it is important to evaluate the within-person reliability of each component. As such, we calculated a composite reliability score according to methods used in a previous study (Geldhof, Preacher, and Zyphur 2014). We calculated the ω coefficients to estimate the level-specific reliability for each RRP component using the indicators of stress response (i.e., NA, PC, SS). That is, in this model of reliability, the variances between indicators from which each RRP component was calculated offers another source of variation at the within-person level. The ω coefficient is then calculated as the ratio between the true moment-to-moment variability of a specific RRP component and the total (observed) within-person variability of that RRP component (i.e., as the sum of the true moment-to-moment variability of the RRP component and the within-moment variability across the indicators) using this formula:

$$\omega = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k} \theta_{ii}}$$

where λ_i represents the factor loading of item i onto a single common factors and θ_{ii} is the unique variance of item i. This model only assumes congeneric items (i.e., that the component scores calculated from each indicator are measurement of the same latent construct—in this case, of that stress response component) and allows for the possibility of heterogeneous item-construct relations (i.e., factors loadings items onto the latent construct differs), which is consistent with our conceptualisation of the relationship between these indicators and the stress response components.

3 | Results

A total of 123 participants completed EMA reports for 14 days. Participants were primarily women (78.7%), self-identified as non-Hispanic white (91%; the rest self-identified as Black (2%), Asian (2%), Native Hawaiian or Pacific islander (2%), and mixed race (3%)), and ranged in age from 35 to 65 (M ± SD = 46.8 ± 8.8) years. More than half (53%) of the sample reports having an annual household income of at least $80,000. Generally, there was high compliance with the EMA protocol, with participants responding to 89% (SD = 10.0) of the EMA queries. Overall, participants contributed 10,065 EMA responses, and reported low-medium average levels of SS, NA, and PC ($M \pm SD$ of 2.6 ± 1.6, 2.0 ± 0.8, and 2.4 ± 1.3, respectively).

Participants reported a mean of 16 (SD = 11; ~20% of all EMA moments) stressors across the study period, which is consistent with frequencies observed in prior work (Zawadzki et al. 2019). Given the conditions required to calculate an RRP score (see methods section), not all moments have an RRP score. The number of observations with calculable RRPs scores are presented in Table 1. As expected, because of the conditions that each moment must meet for calculating reactivity (i.e., non-stress moment followed by a stressor moment) and recovery (i.e., non-stress moment preceded by a stress moment) scores, these scores occur in about 10% of the total moments. As pile-up can be more readily calculated (due to using a pre-specified time window, 48 h in this case), we were able to derive pile-up scores for approximately 90% of our moments. The mean reactivity was 0.95 ± 1.69 for SS, 0.42 ± 0.88 for NA, and 0.73 ± 1.27 for PC. Similar degrees of recovery were observed with 0.98 ± 1.49 for SS, 0.42 ± 0.80 for NA, and 0.74 ± 1.21 for PC. Finally, the daily mean number of significant pile-up responses were 2.77 ± 2.39 for SS, 2.53 ± 2.22 for NA, and 2.56 ± 2.33 for PC. On average, participants had a total of 90.6 ± 13 RRP scores across the 14-day study period, averaging 6.5 ± 1 RRP scores per day.

3.1 | Variance Partitioning of RRPs

Table 1 and Figure 1 summarises the results for the variance partitioning analyses of each RRP component. The reactivity scores exhibited relatively minimal between-person (*range* 3%–8%) or between-days (*range* 11%–19%) variance, with most variance attributed to the within-day level (*range* 76%–80%). Likewise, the majority of the variances in recovery scores were at the within-day level (*range* 87%–89%), with minimal contribution from the between-person (*range* 6%–11%) and between-days (*range* 0%–6%) levels. For pile-up, computed from a 48-h window, most of the variance was due to differences between

TABLE 1 | Variance partitioning analysis of RRPs (N = 123).

	Number of observations	$M \pm SD$	Proportion of variance (%)		
			Between-person	Between-days	Within-day
Reactivity					
SS	908	0.95 ± 1.69	5.56*	18.91*	75.53**
NA	902	0.42 ± 0.88	2.56	17.52*	79.92**
PC	896	0.73 ± 1.27	8.48**	11.04	80.48**
Recovery					
SS	978	0.98 ± 1.49	6.44*	5.52	88.04**
NA	976	0.42 ± 0.8	7.72**	5.30	86.98**
PC	968	0.74 ± 1.21	10.72**	0.00	89.28**
Pile-up					
SS	8439	2.77 ± 2.39	29.48**	61.14**	9.39**
NA	8439	2.53 ± 2.22	27.28**	63.39**	9.32**
PC	8439	2.56 ± 2.33	30.56**	60.33**	9.11**

Note: Asterisk represents that the proportion of variance is significantly different from zero at $^{*}p < 0.05$ or $^{**}p < 0.001$.
Abbreviations: NA = Negative affect; PC = Perseverative cognition; SS = Subjective stress.

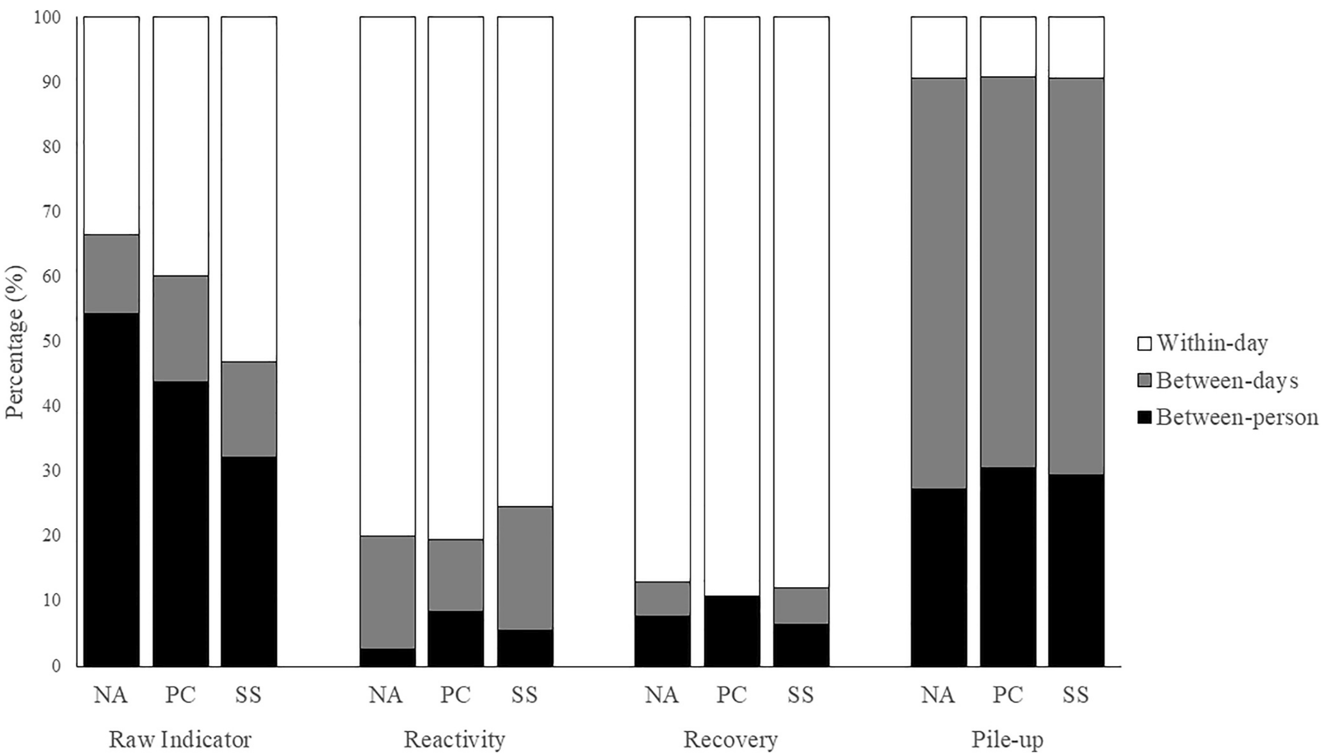

FIGURE 1 | Variance Partitioning Analysis of Raw Indicators and RRPs (N = 123). NA = Negative affect; PC = Perseverative cognition; SS = Subjective stress.

days (*range* 61%–63%), with the remainder between-person (*range* 27%–31%) and within-day (about 9%).

When examining differences in proportion of variance between RRP indicators (see Table 1), reactivity scores from SS and NA showed similar pattern of partitioning (largely from within-day variation). In contrast, reactivity scores from PC revealed roughly equal proportion of variance attributed to between-days and between-person variations. The pattern of partitioning of variance was also similar in recovery scores from SS and NA. For the recovery scores from PC, variance was largely observed at the between-person and within-day levels. The proportion of variance attributed to each level for pile-up scores were similar across all indicators.

3.2 | Variance Partitioning of Raw Indicators

The results of the variance partitioning analyses based on all observed raw indicators (i.e., SS, NA, and PC) are presented in Table 2. Consistent with prior work (Scott et al. 2020), momentary SS, NA, and PC reflected substantial between-person differences (*range* 32%–54%), some between-days (*range* 12%–16%), and substantial within-days (*range* 34%–53%) variance. The results in Table 2 reflect the proportion of variance attributed to each level from all EMA responses; that is, the result reflected the variance of the raw indicators for both stressor and non-stressor moments. To allow a more direct comparison to Table 1, we also conducted a variance partitioning analysis of SS, NA, and PC using only those moments on which we were able to calculate a RRP score (matched for each indicator). Although we matched observations for each RRP, results were similar across the RRP components so only the variance partitioning results of observations with reactivity scores were presented (see Table 3). Results showed higher proportions of variance attributed to the between-days (*range* 19%–24%) and within-day (*range* 40%–48%) and a lower proportion from between-person variations (*range* 28%–39%).

3.3 | Reliability of RRPs

For this analysis, we emulated Geldhof and colleagues' equation for estimating within-person reliability in detecting systematic moment-to-moment changes in the RRPs. The results are summarised in Table 4. All stress response components exhibited good between-person reliability of 0.76 (0.48, 1.04), 0.86 (0.72, 0.99), and 0.77 (0.70, 0.84) for reactivity, recovery, and pile-up components. Similarly, the reliability at the within-person level for the reactivity [0.70 (0.66, 0.74)], recovery [0.68 (0.64, 0.72)], and pile-up [0.803 (0.796, 0.810)] indicated moderate to good reliability in detecting systematic moment-to-moment changes in these scores.

4 | Discussion

Conceptualising the stress response using the RRP approach allows an advancement to how researchers understand stress by ideographically situating each stress experience. That is, this proposed approach provides a way to characterise and compare/contrast one moment of stress response to another within the same person; this approach is notably advantageous when studying within-person processes. This is because the RRP approach were designed to separably characterise different dynamical features (components) of the stress response process, namely: reactivity, (lack of) recovery, and pile-up. Capturing separable elements of the stress response can thus be used to identify moments of high risks for mal-adaptive stress responding and as (potential) markers of opportune moments to deliver just-in-time interventions (i.e., triggering variable) but in a manner i.e. sensitive to the component (e.g., is the person at a risk moment due to heightened reactivity or delayed recovery). Further making this approach distinct from more standard stress measurement approaches, these RRP markers have two additional innovative features. First, they are a pure measure of the within-person process; that is, by capturing momentary deviations from each individual's typical experience, they are free from differences in overall/average stress response levels or characteristics between individuals (although this approach can also generate between-person indicators as well, and use such information—e.g., as a moderator). Second, the RRP scores can be calculated in real time using minimal computing resources making it highly efficient and effective for use in just-in-time interventions. The objective of this study was to provide preliminary, "proof of concept" evidence supporting the utility of the RRP in the development of just-in-time interventions. Our results indicated that our constructions of RRPs are capable of characterising person-specific everyday stress responses across multiple indicators within an individual. The variance partitioning analysis revealed that minimal amounts of variability in the reactivity and recovery component were attributed to the between-person level, confirming our hypothesis and consistent with our goal of generating a personalised stress response indicator. Furthermore, the level-specific

TABLE 2 | Variance partitioning analysis of raw indicators for all moments ($N = 123$, $n = 10{,}065$).

Indicators	Number of observations	Proportion of variance (%)		
		Between-person	Between-days	Within-day
SS	9225	32.18**	14.76**	53.05**
NA	9204	54.37**	12.09**	33.54**
PC	9186	43.88**	16.21**	39.91**

Note: Asterisk represents that the proportion of variance is significantly different from zero at *$p < 0.05$ or **$p < 0.001$.
Abbreviations: NA = Negative affect; PC = Perseverative cognition; SS = Subjective stress.

TABLE 3 | Variance partitioning analysis of raw indicators only for moments with a reactivity score ($N = 123$).

Indicators	Number of observations	Proportion of variance (%)		
		Between-person	Between-days	Within-day
SS	908	27.56**	23.99**	48.45**
NA	902	38.90**	21.21**	39.89**
PC	896	36.28**	18.75**	44.97**

Note: Asterisk represents that the proportion of variance is significantly different from zero at *$p < 0.05$ or **$p < 0.001$.
Abbreviations: NA = Negative affect; PC = Perseverative cognition; SS = Subjective stress.

TABLE 4 | Between and within-person reliability estimates of RRPs ($N = 123$).

	$\omega_{between}$	95% CI	ω_{within}	95% CI
Reactivity	0.759	(0.478, 1.039)	0.696	(0.655, 0.737)
Recovery	0.856	(0.723, 0.989)	0.679	(0.636, 0.723)
Pile-up	0.773	(0.702, 0.844)	0.803	(0.796, 0.810)

reliability analysis provided evidence that these measures are reliable at both the between- and within-person levels. Overall, these results broadly support the use of the RRP to provide a person-specific quantification of the extent to which an individual responds to a stressor. This may help inform future studies evaluating how the dynamics of stress responses relate to health behaviours in 'real-time'.

The RRP approach appears largely successful in capturing the dynamic within-person components of the stress response indicated by the high proportion of variance attributed to the within-day level—a desirable feature for just-in-time interventions targeting moments of risk. Furthermore, the RRP method was able to disentangle, to some degree, the within-person dynamics from the between-person differences in stress response. For comparison, we also conducted similar analyses on raw indicators of stress response (i.e., SS, NA, and PC). Our results showed that when looking at all moments, approximately half of the variance in the raw indicators could be attributed to between-person differences and the other half to within-person differences (both between-days and within-day variations), which were very similar to that of previous studies (Podsakoff et al. 2019; Scott et al. 2020). For additional comparability, when analyses were limited to moments where we were able to calculate the reactivity component, the proportion of variance attributed to between-person differences was slightly lower and within-person variability slightly higher. These changes, however, were minor relative to the proportion of variance observed in the variance partitioning analyses of the RRP components. This demonstrates that in the RRP approach, the variance from the within-person level makes up most of the total variance compared to the raw scores, suggesting that this novel method may be more sensitive to the fluctuations in moment-to-moment variations in how an individual responds to stress. To be clear, in this study we are simply describing the proportion of variance attributed to each level; the differences in the proportion of variance attributed to a certain level does not indicate that the RRP method has more total variance than that of the raw indicators.

Furthermore, we recognise that variability at the within-person, within-day level reflects variation due to reliable moment-to-moment differences and measurement error. Our examination of the within-person reliability of each RRP component revealed moderate to good reliability scores reducing concerns that the observed variability is simply due to poor measurement. Another method to disentangle this true variance from random error would be to determine how this within-day variation covaries with another outcome at the same level—something beyond the scope but a logical next step for this research.

As previously alluded to, a researcher can also use other approaches such as the person-centring approach or more sophisticated modeling techniques (e.g., latent change score models) on raw stress response indicators to disentangle within-person effects from between-person effects and examine how this covaries with other time-varying factors. This approach may have utility for some research questions, but there are some limitations. Most notably in our view, the calculated centred score represents the participant's reactivity score relative to the mean of *all gathered responses* from that participant—i.e., this approach usually includes responses that come after the moment of interest (i.e., from the future). Conceptually, this would be problematic when implemented in adaptive just-in-time interventions where such future responses may not yet be available (and should not inform the risk calculation for the current moment). Moreover, this approach also ignores the other dynamic aspects of stress response (i.e., rate of return to baseline and pile-up of multiple stressors). In contrast, the RRP approach captures the proximal stress response within individuals and days, using only data available up to that moment in time, to better characterise this dynamic process. Specifically, this approach may help in identifying moments of vulnerability characterised by specific aspects (i.e., reactivity, recovery, or pile-up) of maladaptive stress responding and to precisely deliver just-in-time interventions at moments characterised by stress responses to ameliorate the negative effects of stress.

Despite these advantages, there are conceptual and practical issues that need to be considered when using this approach (J. Smyth et al. 2023). As these processes are highly sensitive to the timing of assessments and the timing of the underlying processes, choosing the appropriate timescale or interval for assessment is crucial to properly characterise these processes. e.g., in this study we assessed recovery about 2.5 h after a reported stressor. If recovery happens earlier than this interval, our method could miss this timing; i.e., the EMA reporting time scale (e.g., right now vs. since the last beep) and frequency (e.g., every hour or every 4 h) needs to be selected to match the timescale of the processes, and this selection feeds forward into the construction of momentary RRP indicators. The RRP methods are also heavily reliant on participants being compliant with the EMA protocol and a significant proportion of missed prompts may severely diminish the effectiveness of the RRP to capture the stress response process. To mitigate this issue, we have utilised extensive training and have incentivise participants to maximise compliance rates.

In addition, there is an inherent imbalance in observations between raw indicators versus the RRP components for reactivity and recovery. Because these components can only be calculated on moments where there is a reported stressor, the variance partitioning analyses of these components were essentially describing moment-to-moment variations in potential stress response moments and does not represent the full expression of these indicators across all measurement moments. Broadly consistent with past work (Zawadzki et al. 2019), a stressor was reported on about 20% of moments. Reactivity and recovery scores were able to be calculated for about half of these stressor moments, reflecting the restrictive operationalizations of reactivity and recovery we applied (e.g., only calculating a reactivity score if the moment prior to the stressor was a non-stressor moment). Although we believe this is consistent with the goals of characterising moments of stress responding, future work will want to test different formulations of RRPs, acknowledging the different assumptions that accompany each version.

Relatedly, we acknowledge that particular operationalizations of RRPs may result in potential challenges under certain circumstances. For example, when computing reactivity as a proximal indicator, which calculates the difference between the current and prior moment's score, this may introduce potential bias in reactivity estimates when applied to individuals who experience frequent or consecutive stressors. These frequent stressor events may create an artificially high proximal "baseline" which may result in lower calculated reactivity scores across consecutive assessments (although this persistently high response should be characterised by persistent non-recovery and/or higher pile-up scores over time, which we see as a strength of our approach—the capacity to separate different aspects of stress responses). A separate paper (J. Smyth et al. 2023) presents a more comprehensive conceptual framework for how to address these issues, including different variations on how to operationalise the RRP components. Following the example above, although we might argue that non-recovery and pile-up are characterising the response correctly, there are alternative approaches to estimating "baseline" from which we can calculate the reactivity component that may better capture responses in the context of frequent stressors. These approaches, rather than rely on proximal/acute changes use estimates from how the individual "typically" is when not experiencing stressors. For example, one can calculate changes from a current stressor response to that individual's states from stress-free observations (and this can be calculated over different time-scales from days to weeks), providing alternative methods to capture repeated/frequent stress reactivity. We readily acknowledge that the specific approaches to calculating RRPs should vary depending on the specific situation and sample being studied and we encourage future research to further investigate these nuances.

Another potential issue is that the frequency of stressor moments coupled with the conditions we imposed to be able to calculate RRP scores, particularly in the recovery scores, results in relatively few RRP observations. A longer period of assessment and/or more frequent EMA prompts may provide better coverage. Finally, the current sample is highly selective and may raise questions about the generalisability of our results. However, it should be noted that our within-person approach helps here, as each person has moments serving as their own control (for RRPs, and thus potential JITAI) which should inherently provide for tailoring an intervention to the person (and person characteristics).

Again, we want to highlight that the primary endeavour of this manuscript is to provide a "proof of concept" of the utility of the RRP approach for identifying periods of risks (of maladaptive stress responding) that may be targeted by JITAI. Although we believe that our proposed methodology shows promise for such endeavour, we do not claim that our approach is the only correct approach. Certainly, there is room for more sophisticated methodology (e.g., combining wearable and EMA methodologies and AI and/or machine learning approaches) for passive detection of these at-risk moments, and we are open (and look forward to) advances in this field and extension to the specific approaches taken to characterise and apply person-specific stress responses in real-time and real-place.

5 | Conclusion

These results support our premise that our novel person-specific approach to measuring stress response components (i.e., RRPs) can effectively identify within-person stress-related risk as it occurs. In particular, reactivity and recovery scores are ideographically sensitive to the moment-to-moment differences in stress response within an individual and avoids some of the problems inherent in some other approaches. The RRP approach was also able to capture slightly different patterns of variance partitioning between RRP scores of different indicators (i.e., NA, SS, PC) suggesting potential sensitivity to differences in response between these indicators. As such, implementing this approach may better characterise moment-to-moment change in indicators in a way that preserves proximal temporality and better lends itself to identifying moments of elevated risk. Although promising, further investigation on the predictive power of this approach is warranted. We see the promise of this method in helping to identify moments of risk or vulnerability characterised by specific stress response components (i.e., Reactivity, Recovery, or Pile-up) of stress responding and to precisely deliver just-in-time interventions to reduce the negative effects of stress.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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