The Emergence of Resilience: Recovery Trajectories in Sleep Functioning After a Major

Stressor

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Abstract

There is intuitive and practical appeal to the idea of emergent resilience, that is, sustaining healthy levels of functioning or recovering quickly after some degree of deterioration following exposure to heightened risk or vulnerability. Scholars typically utilise mean levels of functioning indices to identify qualitatively distinct latent subgroups of individuals who share similar patterns of change over time. We propose and showcase an alternative, yet complementary operationalisation of emergent resilience via temporal changes in within-person variability. Twenty-nine male personnel (26.25 $\pm$ 2.67 years) from the Australian Army who passed a 3-week Special Forces Selection Course provided device-based assessments of sleep functioning for seven nights immediately following course completion. Participants also provided a hair sample for cortisol analysis prior to and immediately after the selection course as an index of accumulated stress, and self-reported their adaptability prior to the seven day monitoring period. We combined latent growth modelling with an exponential variance function to capture fluctuations around latent means and their change over time. Consistent with our conceptualisation of 'bounce back' emergent resilience, within-person variability in sleep duration decreased each night by around 10%, which reflects a meaningful small mean decrease over time. We also revealed differential effects of the predictor variables; biological stress primarily influenced the total sleep duration on the first night of the 7-day monitoring period, whereas adaptability largely affected temporal changes in the within-person residual variances. These findings underscore the importance of synergising concept, operationalisation, and method for the science of human resilience.

Keywords: diary study; hair cortisol concentration; growth curve; military psychology; sleep variability.

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The dynamic and rapidly changing nature of modern workplaces means that individuals are required to navigate stressors regularly as part of their everyday occupational efforts. Stressors are events that pose heightened risk to optimal functioning because they tax people's resources in ways that may exceed their available reservoirs (Cohen et al., 2019). In occupational settings, stressors include events such as imposed organisational change, bullying, occupational health and safety issues, and co-worker conflicts, just to name a few (Cooper et al., 2001; Ganster & Rosen, 2013; Razinskas & Hoegl, 2020). It is well known that stress – an experiential state where the demands of the situation exceed our available resources to cope sufficiently with them (Lazarus & Folkman, 1984) – is often detrimental for psychological, physical, and social functioning (e.g., Bonde, 2008; Eddy et al., 2017; Starcke & Brand, 2016). Worldwide estimates indicate the economic costs of occupational stress are substantial (e.g., USD 221 million to 187 billion; Hassard et al., 2018). Thus, it is unsurprising that there exists substantial interest in occupational stressors and factors that enable people to demonstrate resilience to them.

Contemporary perspectives underscore the centrality of temporal dynamics for conceptualising and operationalising resilience (Bonanno et al., 2015; Gucciardi et al., 2018; Kalisch et al., 2017). For example, knowing which capacities individuals bring with them to a situation can shed light on protective factors that might maximise the likelihood of positive outcomes when confronted with heightened risk or vulnerability, yet the adaptive nature of these capacities and their mechanisms of action can be understood only when examined within a temporal process of responding to stressors or adversities. As an emergent concept, therefore, resilience reflects a system's trajectory of functioning following exposure to heightened risk or vulnerability (Bonanno & Diminich, 2013), which is the definition that underpins our work. Trajectories of functioning in response to stress and adversity show considerable variability between people (Bonanno & Mancini, 2012). Although there are several possibilities, 'bounce back' (i.e., initial

deterioration in functioning after adversity followed by relatively quick or gradual return to homeostasis) and 'withstand' (i.e., degree of healthy functioning is relatively stable) are the two most characteristic trajectories of functioning of emergent resilience (Galatzer-Levy et al., 2018)[1]. This conceptualisation and definition embraces emergent resilience as a higher-level manifestation of complex interactions among people and their environment; one that can be considered analogous to a puzzle, where individual pieces (i.e., resilience factors) are fit together in some way (i.e., resilience processes, such as starting with edge pieces and sorting by colour) to form an overall picture of their quality of functioning in response to heightened risk or disruption. Whereas existing definitions rely solely on mental health for inferences regarding emergent resilience (Kalisch et al., 2015), we propose that indices of functioning are best operationalised according to the nature of the situation and person (e.g., adversity type, developmental stage). For example, work productivity might be an appropriate indicator of functioning for employees during a period in which they are dealing with substantial work demands, whereas psychological health might be a salient indicator of functioning for children whose parents are undergoing a divorce. We focus on sleep as a broad category of resilient functioning in this study because of the wide-ranging effects of this behaviour on physical and mental health (Firth et al., 2020; Irwin, 2015; Yin et al., 2017). Irrespective of the nature of the context (e.g., type of stressor experienced by individuals), scholars consider sleep as a salient indicator of resilient functioning because it characterises an important element of mal/adaptive outcomes following exposure to extreme or chronic stress (Liu et al., 2017; Parrino & Vaudano, 2018).

The operationalisation of resilience as an emergent outcome is complex because it demands consideration of interactions between person, context, and time (Kozlowski et al., 2013). We

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[1] Our characterisation of 'bounce back' and 'withstand' trajectories of functioning resemble the 'recovery' and 'resilience' pathways, respectively, described by Galatzer-Levy et al. (2018; see also, Bonanno, 2004). However, we subscribe to the conceptualisation of 'bounce back' resilience with regard to homeostasis, rather a return to some pre-existing capacity or level (Bonanno, 2004), because it offers a comprehensive representation of the functioning of a system (e.g., one's pre-event level of functioning may actually be suboptimal) and provides commonality with the 'withstand' trajectory of resilience. By definition, homeostasis represents stability in a system's functioning while adjusting to dynamic conditions. The definition of complete stability depends on the indicator of functioning as well as personal and situational factors. Key here is the notion of stabilisation, which can be evidenced via decreases in the degree of fluctuation in markers of functioning over time, irrespective of knowledge of one's pre-event levels or the ideal zone of homeostasis.

showcase a new approach by examining within-person variability in a contextually salient indicator of functioning after a major stressor, utilising an innovative statistical approach to capture these temporal dynamics and their potential determinants. In so doing, our work contributes to the science of resilience in four ways. First, we provide a novel operationalisation that synergises concept and method whereby the emergent outcome of 'bounce back resilience' is inferred via temporal changes in within-person variability that support an interpretation of stabilisation in the markers of functioning. Within-person or intra-individual variability in longitudinal data is typically considered a nuisance factor, yet this variation provides rich information about the in/stability of a system that is absent from means alone (Kuppens & Yzerbyt, 2014; Lester et al., 2019; McNeish, 2020). Two people can be equivalent in terms of mean levels of sleep functioning over time, for example, yet differ meaningfully with regard to the magnitude of fluctuations around this average (e.g., low variability versus high variability; see Figure 1). People whose sleep varies substantially – just like many other cognitive, emotional, and biological factors (e.g., Houben et al., 2015; Segerstrom et al., 2017) – are at increased risk of a range of health and behavioural issues (Bei et al., 2016), including perceptions of stress (Veeramachaneni et al., 2019). Perhaps most salient for the current study, sleep variability is an important determinant of mental and physical functioning above habitual sleep patterns for duration, efficiency, and timing (Bei et al., 2016). Low within-person variability might be indicative of resistance to external (e.g., sleeping in an unusual environment) or internal (e.g., regulatory strategies) forces, whereas high variability might reflect maladaptive responses to them. In such cases, one might erroneously conclude that individuals displayed emergent resilience based on their average mean-level trajectory of total sleep duration over time alone.

Second, we explicitly consider the salience of context and time for the operationalisation of indicators of emergent resilience because within-person variability can characterise vulnerability or resilience, depending on situational factors. Take the case of emotions, for example, where high variability might reflect synchronicity of emotional and contextual dynamics – referred to as emotional flexibility – which is essential for psychological health and well-being (Kashdan &

Rottenberg, 2010). Indices of within-person variability offer complementary perspectives of emergent resilience and, therefore, potential for advancing theory and practice, yet it demands congruency between concept, operationalisation, and method. We focus on temporal changes in within-person variability in sleep functioning across a 7-day temporal frame as an indicator of emergent resilience among a healthy, non-clinical sample exposed to a major stressor. In this context, reductions in fluctuations of sleep functioning over time provide a means by which to make inferences regarding 'bounce back' emergent resilience because they characterise stabilisation of the system (see 'person 1' in Figure 1). Irrespective of the nature of the context (e.g., type of stressor experienced by individuals), scholars consider sleep broadly as a salient indicator of resilient functioning because it characterises an important element of mal/adaptive outcomes following exposure to extreme or chronic stress (Liu et al., 2017), particularly in military contexts (Nindl et al., 2018). Practically, sleep functioning is an important consideration for employee performance and health because sleep disturbances and problems are a risk factor for work injuries (Uehli et al., 2014), impairments to cognitive functioning (Fortier-Brochu et al., 2012; Lim & Dinges, 2010), poor health (e.g., anxiety, fatigue), affective outcomes (e.g., work engagement, job satisfaction), and job performance (e.g., task, safety) (Litwiller et al., 2017).

Sleep is considered an important marker of resilience within military contexts (Nindl et al., 2018). We focused on sleep variability as the primary metric of resilient functioning in this study because it maximises the congruence between the stressor experience and outcome. The stressor at the heart of this study was a 3-week military selection course designed to identify suitable candidates for Special Forces training, where candidates are exposed to numerous situations designed to simulate the harsh and unpredictable nature of combat environments (e.g., cognitive and physical exhaustion). Selection courses for entry into Special Operations of Military Forces worldwide are known for pushing candidates to the absolute limits of human endurance; sleep

disruption and deprivation are core to achieving this goal[2]. First, candidates are often woken up in the middle of the night to complete tedious cognitive (e.g., solve complex problems) and physical tasks (e.g., undertake lengthy physical training sessions). Second, there are several periods within the selection course where candidates are sleep deprived and expected to execute demanding mental (e.g., write essay, recall critical information) and physical challenges (e.g., traverse long distances over rugged terrain carrying heavy loads). The week after the selection course provides successful candidates with the opportunity to recover physically and psychologically in preparation for the start of specialist training that spans several months and which incorporates numerous stressor experiences. Accumulating sufficient sleep quantity and efficiency during this week is essential for subsequent training because it underpins cognitive performance of complex tasks (Lim & Dinges, 2010; Wickens et al., 2015). Equally, poor sleep prior to future stressor exposure – as was the case for our sample – can amplify the potential negative effects of such experiences (Parrino & Vaudano, 2018). Stress increases the likelihood of sleep disturbances (Bei et al., 2016; Kim & Dimsdale, 2007), including within-person variability in total sleep duration (Bustamante et al., 2020), making indices of sleep functioning ideal for analyses of emergent resilience in response to a major stressor where a return to typical functioning is required[3].

Third, we demonstrate the application of an innovative statistical model that permits a contemporaneous assessment of temporal changes in and predictors of means and variability. Among resilience researchers, the modal approach to studying heterogeneous trajectories of functioning following stressor or adversity experiences is via growth mixture models (Galatzer-Levy et al., 2018). In essence, this statistical framework facilitates the identification of qualitatively distinct latent subgroups of individuals who share similar patterns of growth or change over time, and tests the meaningfulness of hypothesised determinants of profile membership (Infurna &

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[2] Interested readers are referred elsewhere for detailed descriptions of such courses including documentaries (https://www.imdb.com/title/tt1786116/) and firsthand reflections (Couch, 2008).
[3] Scholars have examined the links between indices of sleep functioning and resilient outcomes (e.g., self-reported general health, health care utilisation) among military personnel (Seelig et al., 2016), which has supported calls for the inclusion of sleep hygiene strategies as part of resilience training programs (Germain & Dretsch, 2016). Our approach differs from this work in that we conceptualise resilience as an emergent outcome of dynamic person-situation interactions over time that can be operationalised via metrics of sleep functioning in response to a major stressor.

Grimm, 2018). This approach is appropriate when the objective is to discover the number and shape of growth patterns that distinguish latent subgroups within a sample and the proportion of people within each profile. However, scholars have questioned the interpretability of mixture profile trajectories (e.g., homogeneity of variance and slope variances are set to zero meaning all individual trajectories within a class are the same) and proposed growth curves as a complementary approach because they maximise insight into variations between people in the rate of temporal change (Infurna & Luthar, 2018). Briefly, growth curves capture the shape, rate, and magnitude of within-person change over time averaged among the sample in terms of a starting point (intercept) and trajectory (slope), and between-person variability around these fixed effects (for a review, see Grimm & Ram, 2018). As we demonstrate in this study, temporal changes in within-person residual variances over time is an underutilised feature of growth curve models that can shed new light on emergent resilience when considered alongside mean levels. In this context, therefore, reductions in one's sleep functioning variability over time can be considered reflective of stabilisation in markers of functioning and therefore an emergent resilience outcome.

Hypothesis 1 (H1): In the absence of prior work, we conservatively hypothesised a small-to-moderate 'bounce back' effect in the vicinity of 10-15% reductions in the residual variance at each assessment.

Our final contribution is that we examine the salience of a biological marker of stress and a psychological indicator of adaptive self-regulation capacity as predictors of temporal changes in mean levels and within-person variability in sleep functioning. Hair cortisol concentration is widely utilised for assessments of chronic activation of the hypothalamic-pituitary-adrenal (HPA) axis, as triggered by physical and cognitive stressors (Skoluda et al., 2012; Stalder et al., 2017). Stress represents a risk factor for optimal sleep functioning (Bei et al., 2016; Bustamante et al., 2020). Within the context of the current study, chronic activation of the HPA axis prior to and during the selection course may elicit carryover effects to the recovery week because of circadian misalignments, cognitive disruptions (e.g., rumination), and hyperarousal (Hirotsu et al., 2015; Kim

& Dimsdale, 2007; Sadeh & Gruber, 2002). In addition, adaptability is particularly salient in circumstances such as those in the current study where individuals are unable to disengage from their primary goal or change their path substantially because of external constraints, such as programming or sleeping in an unusual environment (Martin et al., 2012). We adopt the conceptualisation of adaptability as a capacity or potential for action, which is distinct from the process of adapting (i.e., behavioural enactment of adjustments or modifications) and associated adaptation outcomes (Maynard et al., 2015). Formally defined, adaptability captures the degree to which individuals can modify cognitive, emotional, and behavioural strategies in response to stimuli that are novel and/or uncertain in nature (Martin et al., 2012). Conceptually, individuals with higher levels of adaptability capacities may be better positioned to synchronise their self-regulatory processes with the nature of the situation and contextual temporal dynamics than people with lower levels of this potential for action.

Research Question 1: Owing to the exploratory nature of the interaction tests, we proposed a research question rather than hypothesis; that is, to what extent do (RQ1a) accumulated stress and (RQ1b) adaptability affect the degree of temporal changes in within-person variability in estimates of sleep functioning over the 7-day assessment period?

Methods

Participants

In total, 29 male personnel (26.25 $\pm$ 2.67 years) from the Australian Army who passed a 3-week Special Forces Selection Course took part in this study. The intake and number of successful candidates for one annual administration of the course determined our sample size for this study. Power simulations indicated that this sample size is sufficiently sensitive (> 80% power) to detect small-to-moderate effects (on average, 10% reduction in the residual variance at each assessment) for the primary hypothesis, and moderate-to-large effects for the interaction tests regarding the influence of accumulated stress and adaptability on temporal changes in sleep functioning (Lang et

al., 2019). The code and outputs of these power simulations are located on the Open Science Framework (OSF: https://osf.io/cg6ne/).

Measures

 Sleep duration and efficiency. We captured two indices of sleep functioning using a triaxial accelerometer (GENEActiv Original; Activinsights Ltd, Kimbolton, Cambs, UK) worn on the non-dominant wrist for 24 hours/day configured with a sampling frequency of 66.7Hz. Raw accelerometer data was processed using the R package GGIR version 3.3.3 (https://cran.r-project.org/web/packages/GGIR/) because it permits robust detection of sleep duration (van Hees et al., 2015) even in the absence of self-reported diary information (van Hees et al., 2018). The sleep time window represents the longest inactivity block; movement is distinguished from non-movement using the 10th percentile of an individual's threshold based on 5-min rolling median of the absolute change in the z-axis (dorsal-ventral direction when the wrist is positioned in the anatomical position) across a 24-hour period (van Hees et al., 2015). Sleep duration is calculated as the sum of all episodes within the sleep period time window with change in the z-axis of less than 5° lasting at least 5 minutes. Sleep efficiency is calculated as sleep duration divided by the total available time within a sleep period time window.

 Hair cortisol. To assess hair cortisol concentration (HCC), we sampled hair strands from the posterior vertex region of the head because this region has the least variation in the average growth of 1 centimetre per month (G. A. A. Cooper et al., 2012). Briefly, we used a small wooden peg to secure in place hair segments prior to cutting at root end using fine medical scissors. Hair samples were stored in aluminium foil at room temperature prior to analysis, where they were analysed in duplicate for cortisol using a validated, commercially available enzyme-linked immunosorbent assay (ELISA; Salimetrics, USA) by Stratech Scientific (pre-selection and recovery week intra-assay variability = 4.9% and 5.3%, inter-assay variability = 5.6% and 5.9%).

 Adaptability. Participants responded to 9 items to indicate the degree to which they modify cognitive, emotional, and behavioural strategies in response to stimuli that are novel and/or

uncertain in nature, using a 7-point scale anchored by *strongly disagree* (1) and *strongly agree* (7) (Martin et al., 2012). Originally developed within the context of education, the tool contains items that are 'context neutral' and therefore can generalise to other achievement contexts. Sample items include "I am able to think through a number of possible options to assist me in a new situation" (cognitive), "I am able to reduce negative emotions (e.g., fear) to help me deal with uncertain situations" (emotional), and "To assist me in a new situation, I am able to change the way I do things if necessary" (behavioural).

Procedure

[*name blinded for peer review*] human research ethics committee approved this study prior to execution. Participants who took part in this study were sampled from a pool of candidates panelled on a 3-week Special Forces Selection Course ($N = 143$[4]). Upon arrival at the military base, candidates were issued with relevant equipment and a unique identification number for the selection course. We subsequently briefed candidates about the nature of the study in groups of approximately 15-20 within a demountable office space. Consenting candidates first provided a hair sample (1.5 cm for 6 weeks of stress accumulation) and then moved to an adjacent demountable office space where they completed a survey package. Once candidates had completed the survey, they handed it back to the researchers and were thanked for their participation. Candidates who passed the selection course completed the 7-day recovery week in Barracks at an Australian Army military base. We met participants around 06:00 on the first morning of their recovery week, at which point they completed a survey, provided a hair sample (1 cm for 4 weeks of stress accumulation), and received their GENEActiv. Participants were instructed to wear their GENEActiv watch for 24 hours/day for the following 7 days. Our focus on a 7-day temporal period in this study is consistent with recommendations for assessing within-person variability in

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[4] Data collected with the total sample has been employed in a previous publication (Gucciardi et al., 2021), however, these outputs differ with regard to the (i) research questions, (ii) study variables, and (iii) theoretical frameworks. For comparison, we previously examined mental toughness as a determinant of behavioural perseverance in Special Forces selection whilst accounting for chronological age and a biological marker of approximately six weeks of accumulated stress, and couched this study within the context of conceptual work on goals, stress, and mental toughness. Here we focus on sleep variability as an indicator of trajectories of emergent resilience after a stressful event, and examine psycho-physiological determinants of this variability.

indicators of sleep functioning (Rowe et al., 2008). We downloaded sleep data using the

GENEActiv software (version 3.1), with raw .csv files converted into .bin files for data processing.

Statistical Analysis

We examined the primary hypothesis and research question within a mixed effects

modelling framework using an adaptation of the consensus emergence model to capture temporal

changes in within-person residual variances of sleep functioning (Lang et al., 2018). Briefly, this

statistical model combines fixed (intercept and slope means) and random (intercept and slope

variance, their covariance, and residual variance of outcome) effects of traditional latent growth

models with an exponential variance function (Pinheiro & Bates, 2006) to capture fluctuations

around these latent means and their change over time. Coding the temporal trend in one unit

intervals from a starting point of zero (e.g., 0, 1, 2, 3) provides a convenient interpretation of

changes in residual variance (δ_1); negative or positive values reflect a linear decrease or increase in

the magnitude of residual variance for each assessment, respectively, whereas values around zero

capture residual stability. The meaningfulness of change in residual variance can be tested using a

log-likelihood ratio test in which a null model is compared with a model that includes residual

variance change (Lang et al., 2018). We also examined hair cortisol concentration (HCC) prior to

the selection course and the start of recovery week alongside self-reported adaptability as predictors

of mean differences in sleep and residual variance change. These models included the main effect of

the predictor at baseline (δ_2) and its interaction with time (δ_3). The addition of these predictors to

the fixed and random effects components of the model can be tested using the log-likelihood ratio

test. For all models, we calculated R^2_{LR} to provide an indication of the overall variance explained

(Lang et al., 2019; Magee, 1990). We performed these statistical analyses in R (R Development

Core Team, 2018) using the nlme package (https://cran.r-

project.org/web/packages/nlme/index.html) and restricted maximum likelihood estimation (full

details of these analyses are provided on the OSF: https://osf.io/cg6ne/).

Results

Descriptive Statistics and Correlations

The means, standard deviations, and bivariate correlations among study variables are presented in Table 1. Briefly, these descriptive statistics indicate that participants, on average, accrued between 386 and 426 minutes of sleep per night, and that variation around this group mean decreased over the course of the recovery week. Sleep duration and efficiency were moderately correlated on each night indicating a positive association between these two indices of sleep functioning.

Emergent 'Bounce Back' Resilience

Visual depictions of individual level growth trends for total sleep duration and efficiency are provided in Figures 2 and 3, respectively. Model fit statistics and parameter estimates of within-person variability modelling with sleep duration are presented in Table 2. Briefly, the intercept represents the average total amount of sleep accrued on the first night (~412 minutes), whereas the slope characterises the average rate of change per night across the 7-day period (~ 3 minute decrease). For sleep duration, the likelihood test and increased explained variance ($\Delta R^2_{LR} = 5\%$) supported the superiority of the model including a variance function, when compared with one excluding it. Consistent with H1, within-person variability in sleep duration decreased each night by around 10%, on average, which coincides with a meaningful small mean decrease over time.

Biological Stress and Adaptability as Predictors of Emergent Resilience

HCC prior to the 3-week selection course and at recovery week both explained unique variance ($\Delta R^2_{LR} = 57\%$ and $\Delta R^2_{LR} = 55\%$), yet the likelihood test indicated the addition of the interaction term with time was statistically trivial. With regard to RQ1a, an examination of the parameter estimates indicated that HCC contributed mostly to the prediction of the intercept (e.g., $\Delta \upsilon_{00} \sim 350$). For RQ1b, self-reported adaptability added unique variance ($\Delta R^2_{LR} = 8\%$) and improved model fit; the time-by-predictor interaction term indicates that the within-person variability effect is stronger over time when adaptability is high. In other words, candidates with

self-reported adaptability one standard deviation above the mean evidenced the greatest decrease in sleep variability across the recovery week (see Figure 4)[5].

Discussion

Synergies between concept, operationalisation, and method are essential for advancing knowledge of emergent resilience. We showcased an underutilised feature of growth curve models that provides an alternative yet complementary perspective on the temporal dynamics of emergent resilience and, in so doing, offered three key contributions to theory and research. First, our findings demonstrated the importance of considering mean levels *and* within-person variability of indicators of functioning for inferences regarding emergent resilience over time and determinants of these temporal features. Second, we showcased the importance of explicit considerations of time and context for synergising elements of substance and method for the science of emergent resilience. Third, we demonstrated empirically that the phenomenon of emergent resilience can be observed in healthy samples exposed to a major stressor, specifically with regard to stabilisation in markers of functioning via decreases in the degree of fluctuations over time.

Conceptualised as an emergent outcome of dynamic person-situation interactions, resilience can be inferred only via indices of functioning after some experience or event that is characterised by heightened risk or vulnerability (Bonanno et al., 2015; Gucciardi et al., 2018; Kalisch et al., 2017). In contrast to past work that has focused on identifying qualitatively distinct latent subgroups of individuals who share similar temporal patterns in mean levels of functioning indicators over time (Galatzer-Levy et al., 2018; Infurna & Grimm, 2018), we proposed a new conceptualisation and operationalisation of emergent resilience via temporal changes in within-person variability in functioning that reflect stabilisation in system's functioning while adjusting to dynamic conditions. Our findings showed that participants, on average, experienced 10% reductions in residual variance estimates of total sleep duration each night across the 7-day period, which aligns with our conceptualisation of a bounce back emergent resilience trajectory. An inspection of individual

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[5] Owing to minimal variation in sleep efficiency, we experienced model convergence issues and were unable to execute this analysis (see Table 1).

trajectories reinforced the importance of modelling changes in both mean levels *and* within-person variability for inferences regarding emergent resilience, because there were several participants whose growth trend was relatively stable or flat, yet evidenced substantial nightly fluctuations around this line of best fit. For these reasons, modelling temporal means and within-person variability permits inferences of emergent resilience along a continuum that differs in degree and kind (e.g., stable mean trend, high variability) rather than an arbitrary dichotomy of resilient or not.

Time is an essential consideration for advancing knowledge of emergent resilience and identifying opportune points at which to intervene. By definition, inferences regarding emergent resilience can be made only within the context of one's trajectory of functioning over a temporal period during and/or following the experience of heightened risk or vulnerability. Scholars define time according to four key dimensions of a phenomenon, event, or process, namely the temporal length (duration), number of times (frequency), when something occurs (timing), and temporal ordering (sequence; Aguinis & Bakker, 2020, p. xx). Which of these four key elements of time is most essential to emergent resilience depends on the nature of the triggering stressor or adversity experience and indicators of functioning considered salient for this context. We focused on immediate, short-term emergent resilience in response to a 3-week long stressor because of the practical need for participants to recover quickly after a major stressor in preparation for subsequent training demands. Thus, we explicitly incorporated elements of duration (21 days) for the triggering stressor; duration (sleep minutes per night), frequency (7 nights of sleep), and timing (sleep time window where participants experienced the longest inactivity block) for the indicator of functioning; and sequence (temporal ordering) for the interaction between the stressor and indicators of functioning. Conceptually, therefore, our study design permits insight into short-term recovery dynamics in response to an extended stressor experience that might differ from long-term trajectories that span days, months, or even years (e.g., major surgery, geographical relocation).

In the current study, we focused on the objective elements of time to characterise the stressor experience and indicator of functioning for emergent resilience. Nevertheless, it is

important to acknowledge that people can differ with respect to their perceptions of time (Shipp et al., 2009). Time can be broadly distinguished as objective (i.e., passage of clock time in linear, homogenous, and absolute terms) or subjective (i.e., individualised experiences of the passage of time in dynamic, heterogeneous, and interpretive terms; e.g., "time flies" or "time is of the essence") in nature (Ancona et al., 2001; Shipp & Cole, 2015). Time pressure, for example, is one of the most studied individual temporal states in organisational research (Tang et al., 2020); perceiving one has insufficient time to complete a task (time pressure) is distinct from objective elements of time that are externally imposed (time constraint). The subjective view of time is largely absent from existing work on emergent resilience, despite the centrality of people's experiences and interpretations of time as causal factors in stress (Eldor et al., 2017). Temporal focus, which represents the degree to which people allocate attention to the past, present, or future and mentally navigate between these temporal periods (Shipp et al., 2009), is one important consideration for emergent resilience. Systematically reflecting on past stressor experiences to augment learning and development is one promising approach to optimising emergent resilience (Crane, Boga, et al., 2019; Crane, Searle, et al., 2019). In contrast, it is well established that ruminating about the past with respect to regrets, errors, or deficiencies is maladaptive for human functioning (e.g., Clancy et al., 2020; Ottaviani et al., 2016; Szabo et al., 2017). As such, explicitly integrating elements of objective and subjective time and their interaction in future work on emergent resilience represents an exciting opportunity for conceptual precision and optimised translation of empirical findings into practice.

The conceptualisation of resilience as an emergent outcome is agnostic to the capacities of the individual that underpin withstand or bounce back trajectories or the mechanisms by which they unfold in relation to heightened risk or vulnerability. Broadly speaking, resilience factors are resources that moderate or mediate the effect of stressor or adversity experiences on contextually salient indicators of functioning (Fritz et al., 2018). In the current study, we examined hair cortisol concentration to provide an assessment of accumulated environmental stress (Stalder et al., 2017),

and adaptability as a potential resource that maximises an individual's potential or readiness to mobilise self-regulatory strategies in ways that are synchronous with dynamic contextual factors (Martin et al., 2012). Keeping in mind that these interaction tests were sufficiently powered to detect moderate-to-large effects only, our findings provide insights that may inform future work rather than empirical evidence regarding their salience as resilience factors. Of particular relevance here is the differential effects of these factors on key parameters of the models; for instance, biological stress primarily influenced the total sleep duration on the first night of the 7-day monitoring period, whereas adaptability largely affected temporal changes in the within-person residual variances. These general trends have intuitive appeal because hair cortisol concentration is robust to acute variations in contextual (e.g., events) and psychological factors (e.g., moods) that are demonstrated in salivary cortisol (Stalder et al., 2017), whereas adaptability is sensitive to such person-situation interaction dynamics (Zacher, 2015, 2016). Thus, disentangling mean level trends from changes in within-person variability over time offers a new perspective from which to identify salient risk or resilience factors and the processes by which they unfold in relation to heightened risk or vulnerability. An important consideration for future research is to examine time-variant and time-invariant resilience factors because the degree to which a capacity or process is protective or adaptive may change over time.

Strengths and Limitations

Key strengths of this study include a synergy between concept, operationalisation, and method; a sample and design suitable to the examination of short-term temporal dynamics in response to a significant stressor; and an innovative statistical model that offers flexibility for disentangling temporal dynamics of mean levels and within-person variability of indicators of functioning for emergent resilience. Nevertheless, there are several key limitations to keep in mind when interpreting these data. First, although the sample size was adequately powered to examine temporal changes in within-person variability in sleep functioning, the design and test combination was insufficiently powered to detect small interaction effects that might reflect practically salient

antecedents of these temporal dynamics. We provide R scripts on the OSF project page for readers interested in conducting their own power simulations to determine a suitable combination of people (level 1) and assessments points (level 2). Second, we focused on one indicator of emergent resilience to synergise pragmatics and concept, yet acknowledge that resilient trajectories in one domain (e.g., sleep functioning) can co-exist with deficit patterns in other areas (e.g., social disconnection) (Infurna & Luthar, 2018). Third, we examined linear changes in mean levels and intra-individual variability only because this model aligned most closely with our conceptualisation of 'bounce back' resilience. Nevertheless, we acknowledge that non-linear trajectories might also offer interesting perspectives on the operationalisation of emergent resilience (e.g., variability reduces then subsequently increases, discontinuous). The analytical framework employed here is able to accommodate non-linear trajectories, yet their interpretation is challenging and their inclusion would increase the model complexity considerably. The statistical power for detecting such effects has not been systematically studied in field data so far (Lang et al., 2019). Finally, we examined only two time-invariant risk or resilience factors as predictors of key parameters in the model. Scholars have recently proposed a reconceptualisation of resilience factors as dynamic networks characterised by multiple factors interconnected via causal associations with each other (Kalisch et al., 2019). Consider the example of curiosity, stressor reflections, and self-regulation; a strong disposition to seek out new information and experiences (curiosity; Kashdan et al., 2020) may encourage one to engage systematically in reflections on their experiences with stressors (Crane, Boga, et al., 2019), which in turn may enable them to identify self-regulatory strategies that they have available to them to deal with similar stressors in the future (e.g., social support) or which they may need to learn (e.g., emotional flexibility). When combined with a temporal perspective, the network approach can shed light on the associations among resilience factors throughout different phases after experiencing an adversity. For example, resilience factors may be weakly interconnected with indicators of functioning during the initial phase after stressor or adversity exposure, yet the degree of interconnectedness may become stronger as time progresses.

Conclusion

The concept of resilience evokes substantial appeal across the human sciences where optimal functioning in the face of heightened risk or vulnerability is the goal. We proposed a conceptualisation of emergent resilience as one that reflects a system's trajectory of functioning following exposure to major stressors or adversities that can be operationalised via temporal changes in mean levels and within-person variability of indices of functioning. Using data collected with military personnel after a major stressor, we showcased the potential of this alternative conceptualisation and operationalisation for the study of emergent resilience and included analysis scripts for readers who may be interested in adapting this approach in their future work. The focus on sleep functioning offers important foundations for practical innovations for occupational health psychologists interested in minimising the deleterious effects of sleep disturbances on employee health, safety, and performance. Maximising synergies between concept, operationalisation, and method is essential for the development of pragmatic and scalable interventions for optimising resilience.

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Table 1. *Descriptive Statistics and Bivariate Correlations among Study Variables.*

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	HCC pre selection	-																
2	HCC recovery week	.87	-															
3	Adaptability	.11	.06	[.92]														
4	Sleep duration (1)	.03	.03	.17	-													
5	Sleep efficiency (1)	.21	.35	.04	.47	-												
6	Sleep duration (2)	-.26	-.10	-.04	-.01	.05	-											
7	Sleep efficiency (2)	-.10	.11	.22	-.09	.42	.48	-										
8	Sleep duration (3)	.40	.49	.07	-.05	.16	-.04	.44	-									
9	Sleep efficiency (3)	.08	.08	-.14	.12	.16	.10	.44	.49	-								
10	Sleep duration (4)	.02	-.06	-.21	.26	.42	.16	.21	-.02	.17	-							
11	Sleep efficiency (4)	.03	.02	.23	.17	.41	.37	.60	.17	.53	.40	-						
12	Sleep duration (5)	.11	.14	.53	.46	.06	.18	.25	.26	.32	.24	.17	-					
13	Sleep efficiency (5)	-.09	-.04	.42	.43	.21	.26	.56	.40	.35	.33	.39	.77	-				
14	Sleep duration (6)	-.12	.00	.11	.28	.10	.33	.14	-.22	-.09	.23	.26	.23	.01	-			
15	Sleep efficiency (6)	.06	.05	.38	.20	.30	.09	.51	.27	.50	.24	.50	.45	.34	.20	-		
16	Sleep duration (7)	-.21	-.04	.26	.55	.39	.41	.69	.43	.61	.35	.52	.71	.84	.17	.55	-	
17	Sleep efficiency (7)	-.05	.11	.30	.32	.45	.30	.51	.17	.56	.19	.60	.24	.22	.12	.35	.38	-
	Mean	7.40	6.05	5.97	405.90	.79	387.53	.79	428.48	.78	421.24	.78	386.93	.77	401.19	.77	386.85	.77
	Standard Deviation	11.76	6.97	.50	105.67	.09	82.40	.07	67.87	.07	55.99	.06	70.13	.10	61.17	.08	78.69	.09

Note: sleep duration = total number of minutes; sleep efficiency = sleep duration divided by the total available time within a sleep period time window; grey shading = $p < .05$; HCC = hair cortisol concentration; number in parentheses (1, 2…7) = night of assessment; composite reliability estimate for adaptability in brackets [] on the diagonal (see Hayes & Coutts, 2020).

Table 2. *Model Fit Statistics and Parameter Estimates of Consensus Emergence Modelling with Sleep Duration as the Outcome Variable.*

Parameters	Excluding Predictors		HCC at Selection		HCC at Recovery Week		Adaptability	
	Model 1	Model 2	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Fixed Effects								
Intercept (γ_{00})	411.00**	412.80**	418.27**	419.25**	418.06**	418.68**	414.35**	413.20**
Slope (γ_{10})	-2.61	-3.00	-2.93	-3.16	-3.43	-3.57	-3.38	-3.02
Predictor (γ_{01})	-	-	.81	1.02	1.49	1.89	-8.03	9.75
Time x Predictor (γ_{11})	-	-	-.27	-.30	-.27	-.37	6.99	2.94
Random Effects								
Intercept variance (υ_{00})	1322.83	580.44	269.50	232.72	329.16	325.24	505.78	524.12
Slope variance (υ_{11})	.72	11.38	24.11	28.40	28.52	29.02	15.36	15.22
Covariance (υ_{01})	-30.80	81.24	80.61	81.30	96.90	97.16	88.17	89.32
Residual variance (σ^2)	4607.07	7412.25	7609.29	7734.07	7371.54	7566.78	8429.31	8314.91
Time (δ_1)	-	-.10	-.12	-.13	-.12	-.13	-.13	-.14
Predictor (δ_2)	-	-	.01	.01	.005	.02	-.24	-.14
Time x Predictor (δ_3)	-	-	-	-.002	-	-.005	-	-.13
logLik	-1050.56	-1045.28	-955.37	-955.21	-960.59	-960.05	-1032.69	-1030.52
df	6	7	11	12	11	12	11	12
χ^2 vs previous model	-	10.57*	-	.32	-	1.09	-	4.33*
R^2_{LR}	.08	.13	.70	.70	.67	.68	.19	.21

Note: Model 1 = null mixed effects model (i.e., random intercept and slope and freely estimated covariance); Model 2 = consensus emergence model with no predictors; Model 3 = consensus emergence model with a predictor x time interaction and a variance function for the predictor only; Model 4 = consensus emergence model with a predictor x time interaction and variance function for the predictor and its interaction with time; HCC = hair cortisol concentration; logLik = Log-Likelihood; df = degrees of freedom; * $p < .05$; ** $p < .001$.
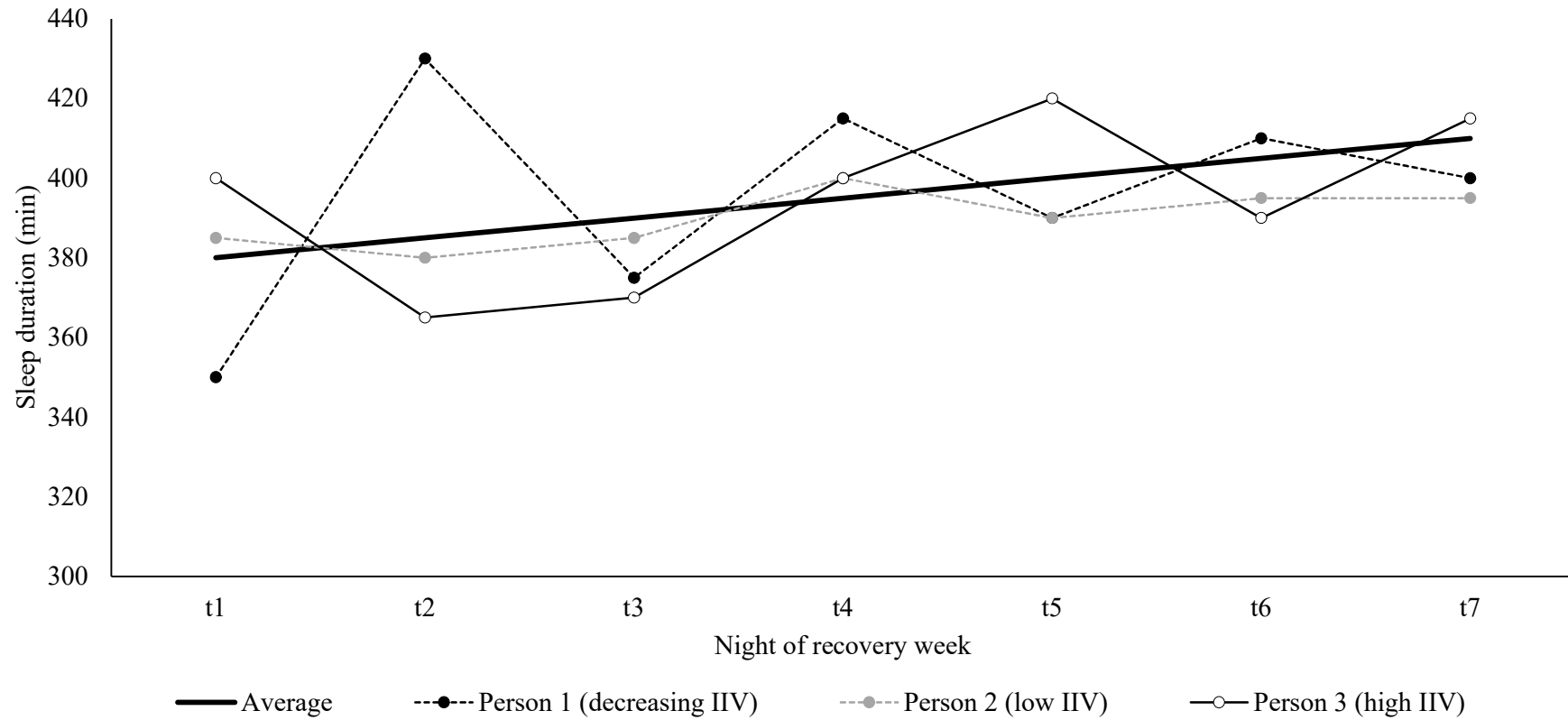
Figure 1. Example hypothetical scenarios in which individuals share approximately the same mean for sleep duration (y axis) though differ in their variability over time (x axis). Note: IIV = intra-individual variability.
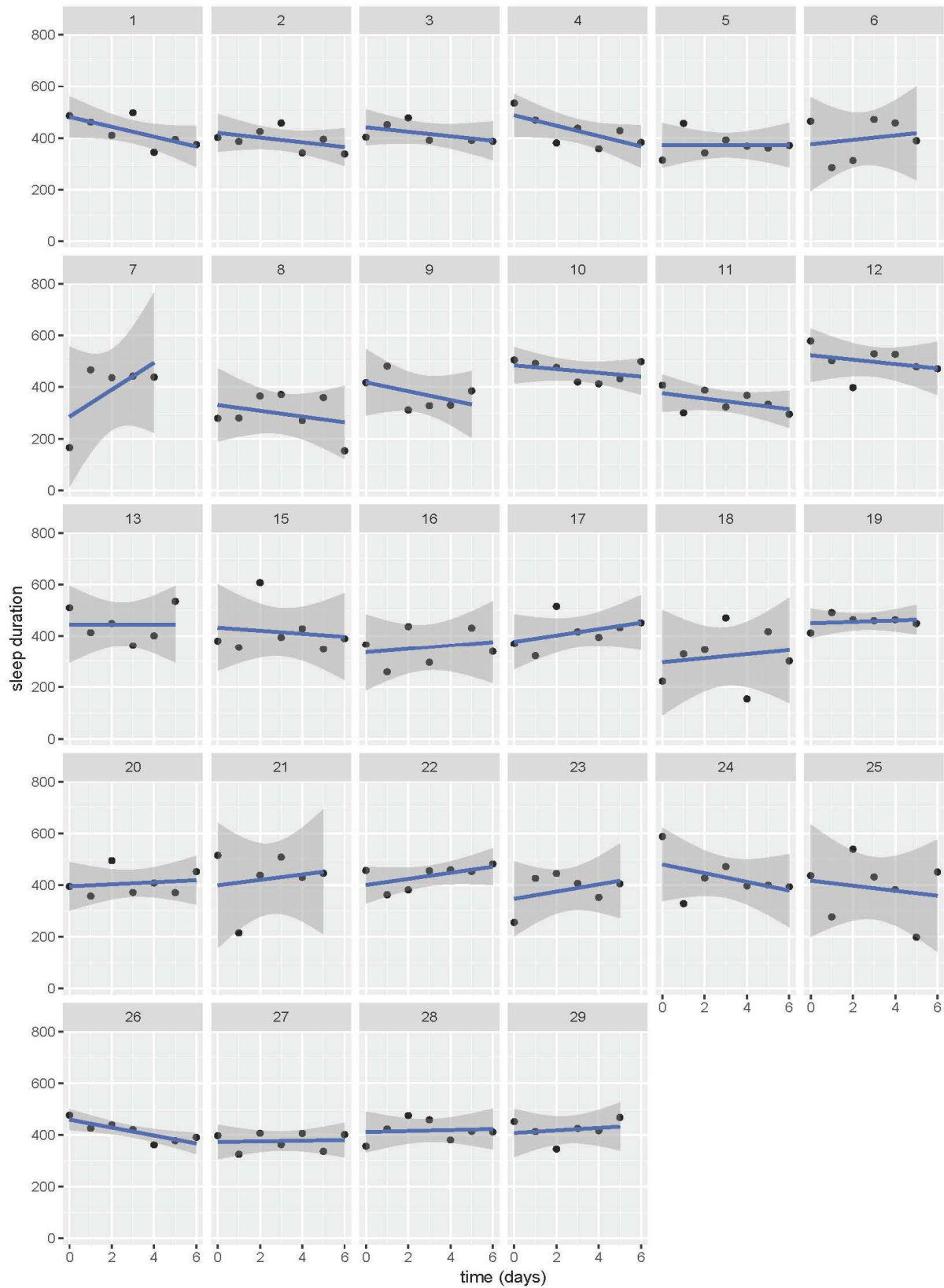
Figure 2. Individual temporal trajectories of sleep duration (minutes). Note: grey shade represents the 95% confidence intervals around the regression slope, given random sampling (see here: https://github.com/wilkelab/ungeviz/blob/master/README.md#bootstrapping).
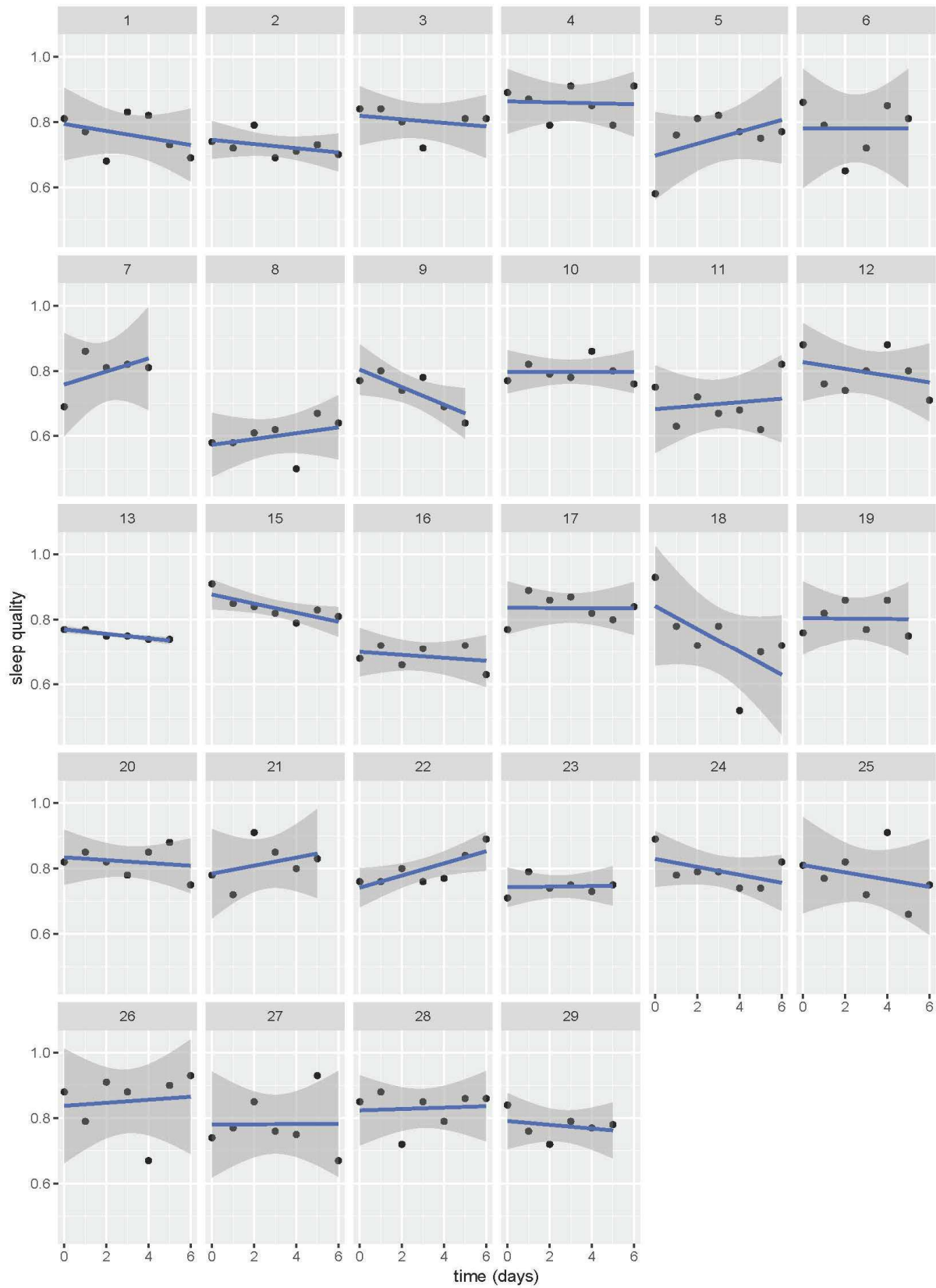
Figure 3. Individual temporal trajectories of sleep efficiency. Note: grey shade represents the 95% confidence intervals around the regression slope, given random sampling (see here: https://github.com/wilkelab/ungeviz/blob/master/README.md#bootstrapping).
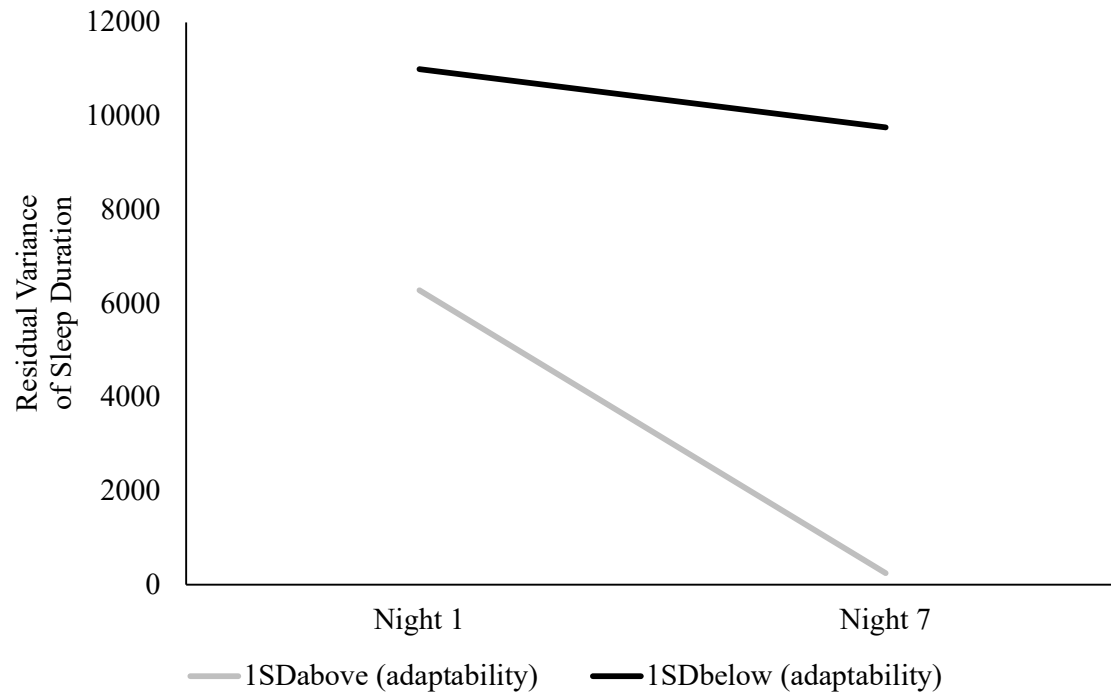
Figure 4. Visual depiction of the time x predictor interaction with self-reported adaptability.

Time x predictor formula for graphing interaction terms:
  (i)   1 SD above at start of study = σ^2 exp (2 x δ_1 x 0 + 2 x δ_2 x 1 + 2 x δ_3 x 0 x 1)
  (ii)   1 SD above at end of 7-days = σ^2 exp (2 x δ_1 x 6 + 2 x δ_2 x 1 + 2 x δ_3 x 6 x 1)
  (iii)   1 SD below at start of study = σ^2 exp (2 x δ_1 x 0 + 2 x δ_2 x -1 + 2 x δ_3 x 0 x -1)
  (iv)   1 SD below at end of 7-days = σ^2 exp (2 x δ_1 x 6 + 2 x δ_2 x -1 + 2 x δ_3 x 6 x -1)