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Bouncing back from emotional ups and downs: insights in emotional recovery using survival analyses of burst ESM data

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ABSTRACT

Many experience sampling (ESM) studies suggested that high resilience is reflected by quickly recovering one's emotional baseline. However, former studies relied on coarse data and did not look into differential recovery from emotional ups and downs. This preregistered proof-of-concept study therefore used high-resolution data collected in 2022 to compute emotional recovery after high levels of positive versus negative emotions. Adults ($N = 68$) participated in a three-week ESM study with eight assessments per day, complemented by short-spaced burst assessments. Resilience was assessed at baseline (trait-level; TR) and daily (day-level; DR). Multilevel survival analyses showed that high DR predicted faster returns from negative emotions, but also delayed returns following positive emotions ($\exp(\beta) = 1.32$, $p = 0.006$). Instead, TR did not relate to emotional recovery ($\exp(\beta) = 0.85$, $p = 0.067$). These findings were generally robust across different sensitivity analyses. This illustrates how innovative ESM designs combined with time-to-event analyses may further our insight in emotional recovery and the timescale at which it unfolds.

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Emotions are responses to daily events (Ryan et al., 2023). To illustrate, accidentally breaking a wineglass may trigger frustration and a lack of happiness. After such events, both positive and negative emotions may return to their respective baselines (i.e. mean levels), which is termed emotional recovery. Of interest, distinct scientific domains have proposed that quick emotional recovery may signal resilience (Kalisch et al., 2017; Ong & Leger, 2022; Scheffer et al., 2018, 2024), and hence, accelerating emotional recovery may be pivotal to the prevention of mental disorders (Kalisch et al., 2017) while delayed emotional recovery could signal heightened vulnerability to mental disorders (Scheffer et al., 2024).

Emotional recovery can be studied using the experience sampling method (ESM), in which people monitor their emotions several times a day for multiple consecutive days, weeks, or even months. The speed with which emotions (whether positive or negative) return to their baseline can then be approximated by computing the autocorrelation in ESM data[1] (Kuppens, Oravecz et al., 2010; Scheffer et al., 2024). Specifically, high autocorrelations have been considered a sign of emotional inertia or rigidity, indicating a slow return to baseline (and thus, slow emotional recovery)upon emotional ups and downs (Kuppens, Allen et al., 2010; Suls et al., 1998; van de Leemput et al., 2014). In agreement, higher autocorrelations have consistently been related to lower resilience – and, by extension, lower well-being and higher psychopathology (Brose et al., 2015; Dejonckheere et al., 2019; Houben & Kuppens, 2020; Kuppens, Allen et al., 2010). Recently, a similar association has been proposed on a within-person level, implying that rising autocorrelations may be a person-specific warning sign of declining resilience (Bos et al., 2022; Curtiss et al., 2021; Ludwig et al., 2024; Schreuder et al., 2023; Smit et al., 2023; Wichers et al., 2015). Yet, despite their popularity in psychology as well as other fields studying resilience

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(Scheffer et al., 2018), whether autocorrelations in ESM data accurately reflect people's resilience can be questioned. This is because autocorrelations come with several conceptual limitations that are often overlooked. First, autocorrelations do not take into account the direction in which emotions depart from their baseline. In other words, high autocorrelations indicate a delayed recovery from *both* emotional ups and downs. Yet, quick returns to baseline during negative episodes may be adaptive (as negative feelings do not linger), while quick returns to baseline during positive episodes may be maladaptive (as positive feelings do not last) (De Haan-Rietdijk et al., 2016; Wirth et al., 2022). Second, autocorrelations assume that emotions exponentially decay, thus disregarding other possible trajectories. In conclusion, reliance on a single estimate, which cannot distinguish between recovering from emotional ups versus downs and presumes exponential decay, does not optimally serve our understanding of emotional recovery.

The above issues may be in part addressed by measuring emotional recovery directly from ESM data, which can be done by modelling the effect of prior stressful events on current emotion levels (Ader et al., 2022; Drake et al., 2022; Kuranova et al., 2020; Vaessen et al., 2019) or by using survival analysis (De Calheiros Velozo et al., 2023; Lachowicz et al., 2023; Li et al., 2024; Verduyn et al., 2009), which concerns the focus of the current manuscript. Earlier studies that applied survival analysis confirmed that upon reporting stressful events, individuals with depressive symptoms (De Calheiros Velozo et al., 2023) and higher levels of anxiety (Lachowicz et al., 2023) show a delayed return to their emotional baseline compared to healthy individuals. Similar associations have been reported on the within-person level, where worsening emotion regulation coincides with delayed emotional recovery in individuals with psychosis (Li et al., 2024). While these studies tentatively support the link between resilience and emotional recovery, several limitations should be acknowledged. First, former studies had on average 90 min between assessments, which could be too sparse for assessing emotional recovery (Verduyn et al., 2009). Second, earlier studies selectively focused on recovering from stressful events, thereby ignoring the distinction between recovery from ups and downs. This is unfortunate, as it is precisely this distinction that could not be captured by studies that measured emotional recovery indirectly (i.e. using autocorrelations), and therefore deserves attention. In sum, investigating emotional recovery through the lens of survival analysis may address some of the limitations of studies that approximated emotional recovery through autocorrelations. To focus this lens, however, it is necessary to apply survival analysis to high-resolution ESM data, and to examine within- and between-person differences in recovery from both emotional ups *and* downs.

This preregistered study (link to preregistration: www.osf.io/afhkp) applied multilevel survival analysis to burst ESM data to investigate how resilience relates to emotional recovery from emotional ups and downs (hereafter, positive and negative episodes). In the burst ESM study, participants received short-spaced "burst assessments" whenever they reported a high levels of positive or negative emotions, allowing us to zoom in on subsequent returns to their emotional baseline. Resilience was assessed on a between-person level (i.e. trait-level) as well as on a within-person level (i.e. day-level) – thus allowing for extending recent between-person findings on emotional recovery (De Calheiros Velozo et al., 2023; Lachowicz et al., 2023) to the within-person level. We hypothesised that there would be an interaction effect between type of episode (positive vs. negative) and resilience on return times, such that *lower trait- and day-level resilience* would predict *delayed returns to baseline* during negative but not positive episodes. We further hypothesised that this interaction would remain when controlling for previous negative episodes and episode intensity.

Materials & methods

Participants and procedure

Adult, Dutch-speaking individuals were recruited via university channels. After providing written informed consent, participants first completed several baseline assessments and then took part in the experience sampling study (see below). Thereafter, participants received financial compensation that was contingent on their compliance as well as a descriptive report of their own data. Of the 69 individuals who completed the study, 1 was excluded because of having too little variation in the final two weeks of the study.[2] This left 68 individuals who were included in analyses. This study's procedures were approved by the local Ethical Committee of the KU Leuven (G-2021-2990-AMD).

Baseline assessments

Trait resilience (TR) was assessed using the Dutch version of the Connor Davidson Resilience Scale (CDRS) (Connor & Davidson, 2003). The CDRS consists of 25 items that are measured on a 5-point scale ranging from 0 (not at all true) to 4 (true nearly all of the time), and has good psychometric properties (Crohnbach's $\alpha = 0.89–0.96$).

Experience sampling study

The experience sampling period lasted for three consecutive weeks. Participants received a smartphone notification eight times a day at equidistant, fixed intervals. These notifications ("beeps") prompted them to complete a brief questionnaire consisting of three questions. For the current study, only the emotion-related question will be used ("How do you feel right now?"). This question was rated on a visual analogue scale ranging from 0 ("very negative") to 100 ("very positive"). At the final beep of each day, participants were additionally asked to rate their resilience on that day, which was assessed through eight questions that were all rated on a scale from 0 to 100. These latter questions were derived from the CDRS and slightly rephrased in order to cover the past day. Daily total scores on these questions reflected people's day-level resilience (DR), which had good within-person reliability ($\omega = 0.88$) (Geldhof et al., 2014). A list of questions that were assessed in the experience sampling study can be found online (www.osf.io/afhkp).

Based on the emotion ratings collected during the first week, person-specific upper limits (85th percentiles) and lower limits (15th percentiles) were computed. From the second week onwards, on top of the eight scheduled beeps that were also sent in the first week, participants could receive bursts that were triggered whenever participants reported a score below their own lower limit (i.e. feeling very bad) or a score above their own upper limit (i.e. feeling very good). These bursts consisted of four beeps delivered at 10-minute intervals. To prevent overburdening participants, bursts were not sent after the final beep of each day.

Analysis

Analyses were preregistered on the Open Science Framework (www.osf.io/afhkp). We inspected the time it takes to return to baseline using multilevel Cox proportional hazard models, which required careful preprocessing. First, to account for response shifts, we re-computed participants' upper and lower limits based on the final two weeks of ESM data, rather than the first week of ESM data (which we preregistered).[3] Participants' baselines (mean levels) were also computed based on the final two weeks of ESM data. Next, using the ESM data from the final two weeks, we determined whether participants had experienced positive emotional episodes, which started with a score above their upper limit, or negative emotional episodes, which started with a score below their lower limit. Subsequent returns to baseline were defined as the earliest moment at which participants reported a score above baseline (negative episode) or below baseline (positive episode; Supplement Fig. S2). In case returns did not occur before the next missing observation or before the end of the day, they were considered right censored. As a consequence, missing observations – which we anticipated to be frequent in bursts assessments – could potentially lead to a high number of right censored (incomplete) returns. Therefore, we filled in missing observations within bursts, meaning that the last non-missing observation within the burst carried forward (i.e. was copied). This led to imputing a single value in 261 cases, two values in 180 cases, and three or more values in 280 cases, amounting to 1607 imputed values in total (i.e. 13% of all emotion ratings). We inspected the influence of this imputation by re-running all analyses on the original data. Here, missing observations were dealt with by considering episodes as right-censored. Finally, we computed characteristics of emotional episodes that were considered as covariates, namely the occurrence of earlier positive or negative episodes on the same day, episode intensity (i.e. the absolute difference between the participant's emotions and their upper limit (positive episodes) or lower limit (negative episodes)), and the occurrence of cumulative episodes prior to reaching recovery (or prior to the next missing assessment or reaching the end of the day). Specifically, for the latter covariate, it was noted whether or not *during* each emotional episode (i.e. after the start and before the end), scheduled emotion ratings exceeded the limits again. The occurrence of cumulative episodes was not preregistered as a covariate, nor was the occurrence of earlier positive episodes, but both were later considered important for improving insight in emotional recovery.

Model fitting

Return times were predicted by trait resilience (hereafter TR; assessed at the start of the study), day-resilience (hereafter DR; assessed with experience sampling), type of episode (positive vs. negative, with positive as the reference category), the interaction between TR and type of episode, and the interaction between DR and type of episode. A random intercept was included to allow for individual differences in the probability to return to one's emotional baseline.[4]

As a second step, we fitted a model with four additional predictors, namely the occurrence of earlier negative or positive episodes (i.e. two dummy variables with the levels reflecting no previous negative or positive episodes, or one or more earlier negative or positive episodes), episode intensity, and the occurrence of cumulative episodes (i.e. a dummy variable with the levels reflecting no successive episodes, or one or more successive episodes).

Third, and finally, we conducted sensitivity analyses, in which we defined people's emotional baseline as the mode and median (instead of the mean). Additionally, we re-ran all models without imputed data. Models were fitted in R (version 4.3.2), using the coxme and survival packages (for details, see Supplement 1. Analysis details) (R Core Team, 2020; Therneau, 2022, 2023).

Results

Most participants (51, or 75%) were female and were aged between 21 and 25 years (Table 1). On average, participants completed 76.19% (SD 21.79) of the scheduled assessments and 60.43% (SD 22.00) of the burst assessments, yielding an overall average compliance of 70.16% (SD 20.10). In total, there were 1228 emotional episodes (M = 18.06 episodes per person; Supplement Table S4, Fig. S3), 506 (41.21%) of which would have undetected if we would have used outdated limits (i.e. those obtained in the first week, as opposed to the final two weeks). In main analysis, 50% of episodes were right-censored (as opposed to 68% of episodes in sensitivity analysis, in which missing values within burst assessments where not imputed).

Table 1. Model estimates.

		β	HR	95% CI	P
1	Episode type[negative]	0.59	1.80	1.49–2.19	<0.001
	Trait resilience	0.15	1.16	0.94–1.42	0.170
	Day resilience	−0.14	0.87	0.74–1.01	0.069
	Type * trait resilience	−0.17	0.85	0.71–1.01	0.067
	Type * day resilience	0.28	1.32	1.08–1.60	0.006
2	Episode type[negative]	0.53	1.70	1.35–2.14	<0.001
	Trait resilience	0.08	1.09	0.89–1.33	0.420
	Day resilience	−0.09	0.92	0.78–1.07	0.270
	Intensity	0.09	1.10	0.99–1.21	0.071
	Previous neg. episodes	0.26	1.30	0.97–1.73	0.074
	Previous pos. episodes	−0.03	0.97	0.69–1.36	0.850
	Cumulative episodes	−1.24	0.29	0.20–0.42	<0.001
	Type * trait resilience	−0.14	0.87	0.72–1.04	0.130
	Type * day resilience	0.19	1.21	0.99–1.48	0.067

Note: Type of episode could be either positive (reference) or negative.

For individuals with an average DR and TR, emotional recovery lasted longer for positive episodes compared to negative episodes ($\exp(\beta) = 1.80$, $z = 6.00$, $p < 0.001$; Table 1). This is also reflected in median survival times, which indicate the time after which 50% of emotional episodes have ended (more than 3 h for positive episodes; 1 h and 40 min for negative episodes). We hypothesised that these differential durations of positive versus negative episodes would depend on DR and TR, such that higher resilience would be associated with prolonged positive episodes and shortened negative episodes, but this interaction effect was only significant when considering DR (Table 1 and Figure 1). Specifically, on days with high resilience, positive episodes tend to last longer than negative episodes, while on days with low resilience, the opposite is true ($\exp(\beta) = 1.32$, $z = 2.75$, $p = 0.006$). This means that, assuming average TR, a one standard-deviation increase in DR would make a return at the next moment in time 4 times *less* likely for positive episodes (HR = 0.26) while returns within negative episodes would be more than 6 times *more* likely (HR = 6.27). For TR, a significant interaction effect with type of episode was not found ($\exp(\beta) = 0.85$, $z = 1.83$, $p = 0.067$). When baselines were based on the median or mode instead of the mean, findings remained similar, although main effects of episode type and DR sometimes changed in significance (for details, see Supplement 3).

After accounting for earlier episodes, episode intensity, and cumulative episodes, all above-mentioned effects except episode type (positive vs. negative) were no longer statistically significant (Table 1). Instead, there emerged a significant effect of cumulative episodes, indicating that episodes during which an additional episode occurred lasted longer compared to episodes without cumulative effects ($\exp(\beta) = 0.29$, $z = 6.38$, $p < 0.001$; Table 1, Figure 1, Fig. S4). By contrast, when using the median or mode as baselines, the interaction between DR and episode type remained statistically significant even after accounting for covariates (for details see Supplement 3).

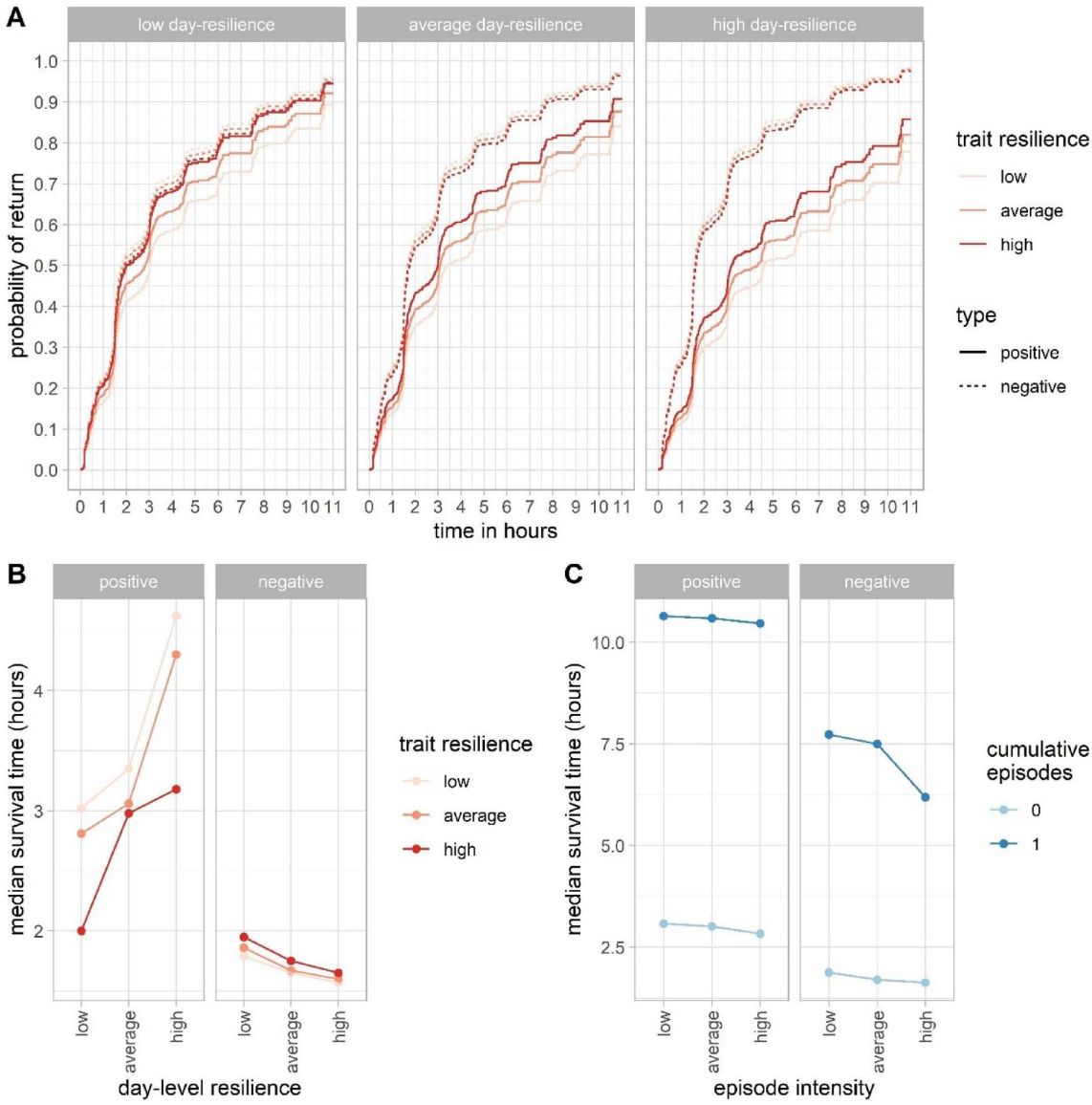

Figure 1. Survival curves (A) and median survival times (B,C), quantifying the return to the emotional baseline after positive vs. negative emotional episodes for different levels of trait- and day-resilience. (A) Survival curves indicate the probability of returning to baseline after increasing amounts of time. (B and C) Median survival times indicate the time after which 50% of emotional episodes have ended, i.e. when return to baseline has occurred. Low, average, and high trait- and day-resilience refer to the 15th, 50th, and 85th percentiles (e.g. low day-resilience means that an individual scored substantially lower than their average day-resilience, and that equally low or lower scores would be expected on around 15% of the days).

Finally, it is worth noting that all of the above findings remained unchanged when missing observations were not imputed (see Supplement 4).

Discussion

Different research fields have proposed that quick emotional recovery may signal resilience. Despite a long-standing interest in emotional recovery, differences in recovery during positive versus negative episodes have so far remained ambiguous. This preregistered study addressed this by measuring return times directly in burst ESM data, not just for negative episodes but also for positive ones. We found that days on which people reported high resilience coincided with a somewhat quicker recovery

during negative episodes and a delayed return during positive episodes. Vice versa, days with low resilience were characterised by relatively brief positive episodes and prolonged negative episodes. Contrary to our hypotheses, trait resilience was unrelated to emotional recovery. Further, after accounting for episode intensity, previous episodes, and cumulative episodes, day resilience was no longer related to recovery, although the association remained present with different baseline operationalisations. Of the aforementioned covariates, cumulative episodes were particularly strongly related to recovery, which could mean that additional episodes prolong recovery from a prior emotional episode – or vice versa, that the probability of experiencing an additional episode becomes more likely as the original episode prolongs. In other words, the direction of the association between cumulative episodes and emotional recovery remains unclear. Altogether, this study illustrates how combining high-resolution ESM data with survival analysis – which have a long history in epidemiological and medical research but are only beginning to be discovered in psychology – allows for uncovering meaningful (intra-)individual differences in emotional recovery.

One of the interesting properties of survival analysis is that it yields an approximation of the amount of time that passes between experiencing a peak in emotions and returning to one's emotional baseline. Previous research has looked into this by explicitly asking people how their emotions last, and found that half of emotional experiences dissipate within 11 to 30 min (Verduyn et al., 2009). However, such short durations may in part be due to the fact that all episodes longer than one or two hours were considered right-censored. When the duration of emotional episodes is derived from self-reported emotional experiences, as in more recent work (De Calheiros Velozo et al., 2023; Lachowicz et al., 2023; Li et al., 2024), higher median survival times are found (range: 1–2 h). Interestingly, even though the current study included bursts with highly frequent assessments and could theoretically capture much faster emotional recoveries compared to earlier studies, we found similar median survival times (1.7 h for negative episodes[5]). On the one hand, this implies that highly frequent assessments may not be necessary for capturing emotional recovery. On the other, it can be concluded that ESM studies with more than around 1.7 h between assessments may fail to capture around 50% of recoveries from high levels of negative emotions. Thus, to assess the full range of recovery trajectories, faster sampling frequencies may still be favourable, which calls for innovative designs (Delecroix et al., 2023; Revol et al., 2024).

The short duration of emotional episodes is particularly apparent when considering negative episodes. These episodes lasted shorter than positive episodes, especially on days at which people reported higher resilience. Speculatively, this interaction effect could explain why studies that could not distinguish between positive versus negative emotional episodes found inconclusive support for the within-person relation between emotional recovery and resilience. In youth, for instance, rising vulnerability to mental ill-health did not consistently coincide with slowing emotional recovery (Schreuder et al., 2023). Likewise, individuals with remitted depression and bipolar disorder did not always show increasing inertia as their resilience declined (Bos et al., 2022; Ludwig et al., 2024; Smit et al., 2023). According to the current study, the ambiguous association between inertia and resilience could be due to the possibility that this association may vary depending on the type of episode that people experience (and thus, is cancelled out when not distinguishing between episodes). A tentative conclusion that follows is that attempts to monitor slowing recovery *within* individuals should selectively focus on increasingly delayed recovery from *negative,* or stressful, episodes.

In contrast to within-person differences in resilience, trait resilience was unrelated to emotional recovery. This contrasts with earlier literature, which consistently reported higher emotional inertia (Brose et al., 2015; Houben & Kuppens, 2020; Koval et al., 2012; Kuppens, Allen, et al., 2010) and delayed emotional recovery (De Calheiros Velozo et al., 2023; Kuranova et al., 2020; Vaessen et al., 2019) in individuals with mental health problems. As a notable exception, a recent study that used survival analysis to investigate emotional recovery found that worse emotion regulation relates to delayed emotional recovery on the within-, but not the between-person level (Li et al., 2024). Further, there are many examples in the broader field of psychology that illustrate that associations may be different on the within- versus between-person level, thus stressing the importance of distinguishing between both levels (Kievit et al., 2013). Besides statistical reasons for differing within- versus between-person associations (Neubauer et al., 2024), more substantive reasons could also play a role. For instance, it could be that

trait- and day-level resilience cover different aspects of resilience, with trait-resilience covering stable characteristics (e.g. trust in self, self-efficacy), while day-level resilience may cover aspects of resilience that vary across contexts (e.g. perseverance, adaptation to change) (Child & Medvedev, 2023). It has been suggested that precisely these context-related responses are informative of resilience (Kalisch et al., 2017), which could explain why day-level resilience showed a stronger connection to emotional recovery than trait resilience in the current study.

Strengths, limitations and considerations for further research

A major strength of this study is that we directly estimated how long it takes people to recover their emotional baseline – analogous to how medical researchers estimate the time it takes before people are recovered (after initiating treatment) or die (after a diagnosis). The resulting findings may improve our understanding of emotional recovery, as well as inform future ESM studies with respect to the timescale at which emotional recovery evolves.

A drawback of applying survival analysis to ESM data is that demarcating emotional episodes is not straightforward (De Calheiros Velozo et al., 2023; Smyth et al., 2022). Firstly, the start of emotional episodes could be defined as reporting a stressful event (e.g. De Calheiros Velozo et al., 2023) or alternatively, reporting a relatively high or low score (current study). Secondly, deciding when episodes end is challenging, as baselines need not be defined as mean levels but could also be defined as the emotion levels prior to the start of emotional episodes (Ader et al., 2022; De Calheiros Velozo et al., 2023; Lachowicz et al., 2023; Li et al., 2024; Vaessen et al., 2019). Thirdly, regardless of how returns to baseline are defined, returns are never observed directly, and may have occurred before individuals were prompted. In survival analysis literature, this is called interval censoring. The presence of interval censoring generally necessitates either parametric models or imputation of exact return times. However, both methods come with reduced flexibility (e.g. in terms of random effects estimation), and we therefore ignored possible interval censoring. Finally, it should be noted that semi-parametric Cox proportional hazards models yield effects that can only be interpreted in a relative sense (e.g. negative episodes have a 1.8 times higher chance of recovery compared to positive episodes), precluding more absolute (and perhaps, more intuitive) statements about these effects.

While the high-resolution data provided by the burst ESM design provided an excellent opportunity to zoom in on emotional recovery, further research is needed to address some challenges pertaining to this design. First, mean levels and variance may shift in reaction to the experience sampling procedure (Nesselroade et al., 1991), and the threshold for triggering burst assessments should ideally account for such response shifts (Revol et al., 2024). The challenge here will be to separate shifts that are potentially meaningful (e.g. an individual's baseline may shift due to adaptation to new circumstances, which in itself can be considered a sign of resilience; Kalisch et al., 2017) and shifts that – for present purposes – create noise (e.g. an individual's baseline may shift due to initial elevation bias; Shrout et al., 2018). Further, there remain several more practical questions, for instance pertaining to the optimal number and scheduling of burst assessments and the feasibility of the design in terms of burden and compliance (Ji et al., n.d.).

Conclusions

Resilience is defined as people's ability to bounce back from adversity and may be reflected in a delayed recovery during momentary negative episodes. Yet, many earlier studies investigated emotional recovery without distinguishing between types of episodes. This study investigated recovery during both positive and negative episodes, and found that resilience does not relate to recovery on the between-person level. Yet, on days when individuals feel relatively resilient, positive episodes prolong while negative episodes shorten. In conclusion, when investigating within-person fluctuations in emotional recovery, it is crucial to consider *what* people are recovering from.

Notes

1. Autocorrelations are commonly estimated in a lag-1 autoregressive model, which can be written as follows: $Y_t = c + \varphi Y_{t-1} + \varepsilon$. Here, Y reflects repeated emotion assessments from a single individual, and φ reflects the autocorrelation.
2. This lack of variation was due to almost always reporting the same mood rating, which may be considered a form of careless responding. In this case, the 15th and 85th percentiles were equal, which made it impossible to define positive vs. negative emotional episodes and emotional recovery.

3. Response shifts mean that distributions change throughout the ESM period, implying that the percentiles obtained in the first week are not equal to those of the second and third week (Revol et al., 2024). In our preregistration, we stated that we would exclude individuals with such response shifts, but as this would have led to the exclusion of many individuals (leaving a final sample of 37 individuals), we decided to instead recompute limits based on the final two weeks. This allowed us to preserve our initial sample. Re-running our analyses in a smaller sample (as preregistered) did not change our inferences and conclusions.
4. We used likelihood ratio tests to compare the random intercept model to an empty model (without random effects) and a more complex model (which included a random effect for DR, as preregistered) (Moore, 2016). The first comparison showed that including a random intercept substantially improved model fit ($\chi^2(2) = 102.27$, $p < 0.001$). The second comparison showed that additionally including a random slope for DR did not improve model fit (log likelihood 2858.0 vs. 2858.8; $\chi^2(2) = 1.47$, $p = 0.480$). We therefore proceeded with the random intercept model, and report the findings from the random slope model in Supplement 1, Table S3.
5. For positive episodes, this study found a median survival time of >3 h. This duration cannot be compared to earlier studies, as those only looked into recovery from stressful events (i.e. negative episodes).

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