Emotion regulation dynamics in daily life: Adaptive strategy use may be variable without being unstable and predictable without being autoregressive

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Abstract

Recent research has demonstrated the adaptiveness of variability in emotion regulation (ER) by showing that variability between and, when controlled for depression, within ER strategies as assessed via the standard deviation was associated with less negative affect. We first replicated associations with negative affect by using the relative standard deviation which is less confounded with the mean. Second, following research on affect dynamics, we extended this line of research by examining five additional ER dynamic measures covering ER instability, inertia, predictability, differentiation, and diversity. Re-analyzing data from five ambulatory assessment datasets (*N* = 717), we found that (a) the eight ER dynamic measures loaded on five factors that explained unique variance, (b) most ER dynamic measures had good reliabilities, and (c) between-strategy mean endorsement was positively, whereas between-strategy variability and ER predictability were negatively associated with negative affect. These results suggest that the variable but predictable use of emotion regulation strategies in daily life is beneficial for individuals' affective well-being in daily life.

163 words

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Research on emotion regulation (ER) has traditionally focused on the effectiveness of ER strategies in changing affective experiences (Gross & Thompson, 2007). In this line of research, ER strategies that reduce negative affect and increase positive affect are viewed as adaptive, such as reappraisal or social sharing, whereas strategies that increase negative affect are deemed to be maladaptive, such as suppression or rumination. However, a large body of research has revealed only modest positive associations between adaptive strategies and indicators of affective well-being as well as only modest negative associations for maladaptive strategies (Webb et al., 2012). Thus, recent research efforts turned away from investigating the general adaptiveness of ER strategies but instead focused on the conditions under which circumstances a given strategy is adaptive and the flexible use of ER strategies (Aldao et al., 2015; Bonanno & Burton, 2013). As a consequence, ER is no longer seen as a relatively static process that is beneficial for an individual's affective well-being if it is only implemented successfully. Instead, adopting a dynamic process perspective, that takes the fit between situational demands, individuals' goal-, and ER strategy selection into account, seems to be more appropriate.

Given that evidence in this line of research is still relatively scarce and mostly limited to the assessment of ER variability, we re-analyzed five ambulatory assessment (AA) datasets to examine ER dynamics more elaborately. In particular, we replicated the beneficial associations between ER variability and negative affect found in prior research (Blanke et al., 2019), but we used an improved analytic approach to control for the confound with the mean. Moreover, given that ER variability does not contain any temporal information and is difficult to interpret in some cases, we extended this line of research by examining five additional ER dynamic measures covering ER instability, inertia, predictability, differentiation, and diversity. We used this wide range of ER dynamic measures to then examine the structure of these measures to detect potential patterns of redundancy and their associations with positive and negative affect.

Variability in emotion regulation

According to Aldao et al. (2015), flexibility in ER can be differentiated into variability and flexibility. Variability in ER is characterized as the variance with which several strategies are selected from a repertoire in a given situation (*between-strategy variability*) or at which one strategy is employed across several situations (*within-strategy variability*). ER strategy use can be considered flexible if it is in accordance with contextual variations and in line with an individual's regulatory goals (Aldao et al., 2015). Variability can thus be considered a necessary prerequisite for flexibility.

Evidence for the importance of between- and within-strategy variability has predominately been based on trait questionnaire data assessing coping flexibility (e.g., Cheng, 2001; Cheng, Lau, & Chan, 2014; Kato, 2012). However, evidence closer to the affective experiences of individuals is relatively scarce. For example, Bonanno, Papa, Lalande, Westphal, & Coifman (2004) found in a laboratory study that individuals who were able to variably switch between enhancing and suppressing emotions reported significantly lower levels of distress after two years. This association was replicated for a three-year period as well as using informant reports for the well-being measures (Westphal et al., 2010) and was moderated by the knowledge of which strategies work well (Southward & Cheavens, 2017). Another study investigated the associations of psychopathological symptoms with both the implementation and variability of several ER strategies (Aldao & Nolen-Hoeksema, 2012). Participants had to describe 24 distinct situations from the past two weeks that elicited four types of emotions (i.e., anxiety, anger, sadness, happiness) in three types of intensity (i.e., low, moderate, high) in two types of circumstances (i.e., social, achievement-related). They then rated the extent to which they implemented each of seven strategies. The authors found that the variability within acceptance and problem solving were significantly negatively associated with psychopathological symptoms but variability within other strategies such as reappraisal or suppression was not. With regard to between-strategy variability, research is even scarcer, with one study reporting that switching from a non-optimal to an optimal strategy was associated with less intense negative affect (Birk & Bonanno, 2016). Further evidence for the importance of the ER repertoire comes from research utilizing latent profile analysis of ER strategies, which found that the width and specific make-up of the ER repertoire was positively associated with individual’s wellbeing (Grommisch et al., 2019).

To provide more evidence and systematically examine associations between negative affect and between- and within-strategy variability, Blanke and colleagues (2019) recently re-analyzed four existing AA data sets. They found that only between- but not within-strategy variability was consistently negatively associated with negative affect (for within-strategy variability, a small negative association with negative affect only emerged when controlling for depressive symptoms). This research is so far the strongest evidence for the adaptiveness of between-strategy variability, which was associated with lower negative affect both at the between-person level and at the within-person level. However, there are a number of limitations that Blanke and colleagues (2019) acknowledged, indicating the need for further research: First, the authors assessed variability using the standard deviation (*SD*) which is known to be confounded with the mean due to the bounded nature of the used scales (bounded by the endpoints of the scale; Baird, Le, & Lucas, 2006). The authors controlled for mean levels of ER strategy endorsement to deal with the confound. However, this is not without problems, such as (a) increased likelihood of multicollinearity due to the high correlation between the *M* and *SD*, (b) possible non-linear dependencies between *M* and *SD*, as well as (c) a more difficult interpretation of the *SD* when the mean is controlled for (Mestdagh et al., 2018). Thus, it is unclear whether the reported associations of between-strategy variability are driven by the dynamic processes reflected in the variability or by the confound with the mean. Consequently, the first aim of the present research was to circumvent this confound by using the relative standard deviation (*RSD*), which reduces the problems of the *SD* and, thus, allows for better differentiating whether the association between ER variability and negative affect is driven by the actual variability or by the mean (see Figure 1a and 1b; Mestdagh et al., 2018). The *RSD* is computed by dividing the *SD* by the maximum *SD* of a given mean, with the underlying notion that variability is much more limited when an individual's mean is closer to the bounds of a scale.

Within-strategy dynamic measures

The second aim of the present research was to broaden the scope of the analysis of ER dynamics and their associations with affect in daily life and to introduce dynamic measures to ER that have been used in research on affect dynamics (e.g., Dejonckheere et al., 2019). Prior research has focused on the variability of ER (Blanke et al., 2019), with the underlying notion that variability within and between strategies could be beneficial in term of its impact on affect if it is synchronized with situational demands that are in line with an individual's goals. Variability was assessed via the SD, which is the second moment of a distribution and, thus, the most basic variability measure. Consequently, the *SD* only quantifies the magnitude of change in a given variable but does not offer information regarding the temporal processes or patterns underlying ER. Thus, we wanted to introduce several time-reliant ER dynamic measures that can capture temporal information in ER: ER instability, inertia, and predictability.

ER instability. An alternative to the *SD* that captures temporal aspects of variability is the root mean square of the successive differences (RMSSD; Ebner-Priemer & Trull, 2009), which summarizes the changes in a given variable from one time point to the next (Figure 1c). Although *SD* and *RMSSD* are often highly correlated, they are not the same: For example, time series A "0, 0, 6, 6" and B "6, 0, 6, 0" have the same $M = 3$ and $SD = 3.46$ but different *RMSSDs*: $RMSSD_A = 4.24$ vs. $RMSSD_B = 7.35$. Thus, the *RMSSD* is higher, the more pronounced consecutive changes are; hence it's used as a measure of emotional instability (Jahng et al., 2008; Trull et al., 2008). Research on emotional instability has demonstrated maladaptive associations with mental health, such that participants with borderline personality disorder reported significantly more emotional instability than healthy controls (Dick & Suvak, 2018; Ebner-Priemer et al., 2007). Furthermore, emotional instability strongly covaried with self-esteem variability in individuals with borderline personality disorder (Santangelo et al., 2017). Based on this evidence and based on the notion that ER is adaptive if synchronized with situational demands that are in line with an individual's goals, we hypothesized strongly fluctuating ER efforts could be seen as failed adjustments to situational demands, leading to a negative association between ER instability and affective well-being in daily life.

ER inertia. The second dynamic measure that captures associations between ERs from one time point to the next is the autoregression (AR) between them (Figure 1d). In affect dynamics research, it is used to assess emotional inertia, which has been shown, for example, to relate to lower life satisfaction (Kuppens et al., 2012) and higher depression (Koval et al., 2016). Translated to ER dynamic research, AR can be understood as the degree to which an ER effort using a particular strategy carries over from one timepoint to the following one. A strong autoregression may indicate that an individual highly relies on one strategy and does not readily disengage from this strategy, even when the situation may have changed. We would thus assume that a strong autoregression is negatively associated with affective well-being in daily life.

ER predictability. Both the RMSSD and AR are limited to changes between two time points only, which limit their ability to examine longer-term temporal ER processes. As an alternative, the recurrence quantification analysis (RQA) offers the opportunity to examine ER dynamics over more than two time points by searching for recurrent patterns of ER strategies over time (Wallot, 2017). Thus, RQA does not examine variability but quantifies how much of the daily fluctuations in ER follow recurrent patterns and are, thus, predictable (Figure 1e). Importantly, variability and predictability are theoretically independent from each other, as illustrated in Figure 1h.

The core concept of the RQA is the analysis of *recurrence*, that is, repetition of patterns in a sequence. The core tool of the RQA is the recurrence plot, which plots a time series on both the x- and y-axis to form a two-dimensional grid (Figure 2). In this grid, recurring states are denoted by a point, indicating that the same level of ER that a participant has previously reported has reoccurred. Of particular interest are recurrent points that form a diagonal line from the lower left to the upper right. These diagonal lines indicate that a sequence between at least two subsequent observations has reoccurred. In Figure 2, the sequence 6 – 3 – 4 occurs twice in the data (during observation 1-3 and 5-7), forming a diagonal line that is 3 observations long. The grey diagonal line in Figure 2 is the so-called line of identity, which reflects that each observation in a time series is recurrent with itself. Given that this does not convey any meaningful information, the points forming the line of identity are ignored when calculating our focal predictability measure, %DET. %DET is the number of recurrence points that form a diagonal line divided by the total number of points and can range from 0 to 1. In the example in Figure 2, the values 3, 4, and 0 each recur once and the value 6 recurs twice, amounting to a total of six recurrence points. However, only recurrence points that directly follow one another and, thereby, form a diagonal line, are counted as recurrent. Thus, out of the six recurrence points in Figure 2, three recurrence points form a diagonal line (under the line of identity), leading to %DET = 3/6 = 50%. Please note that there are several other measures that can be derived from the RQA, such as the number of recurrence points divided by the total number of spaces (recurrence rate or %REC), average diagonal length (ADL), maximum diagonal length (MDL), or repetitiveness. However, these measures are often highly intercorrelated. Moreover, these measures are not limited to predictability: For example, randomizing the order of the observations in the example in Figure 2 would not change %REC but would impact %DET (Jenkins et al., 2020). Thus, we opted for %DET as a measure of ER predictability given that it should be best suited as a measure of ER predictability.

RQA has been utilized to study emotion dynamics between mothers and adolescents during conflict discussions (Main et al., 2016) as well as the coordination of gaze patterns between cooperating individuals (Anderson et al., 2013). Recently, Jenkins et al. (2020) applied RQA to examine associations between affect variability / predictability and depressive / somatic symptoms. They found that affect predictability was significantly associated with lower depression scores beyond the mean and *SD* of affect. Overall, individuals who reported the lowest levels of depression also reported low levels of negative affect, high levels of positive affect, low levels of affect variability, as well as high levels of affect predictability.

In the present research, we wanted to extend this line of research to ER. With regard to ER, it is yet unclear to what extent the regularity and consistency of an individual's regulatory efforts in their everyday life can explain meaningful variance in positive and negative affect beyond the mean of and variability in ER. Furthermore, the direction of the association is not clear. On the one hand, high predictability could indicate a rigid ER strategy repertoire that is not well suited to meet situational demands, which would yield a negative association with affective well-being. On the other hand, higher predictability of ER could indicate a better adaptation to situational demands, as individuals repeat the regulatory efforts that they know to have worked best in the past. It is also possible that individuals live in environments that are better structured in ways that require less regulatory efforts. Following the latter reasoning, higher predictability should be associated with more positive and less negative affect.

Between-strategy dynamic measures

Blanke and colleagues (2019) showed that between-strategy variability was associated with lower levels of negative affect. One disadvantage of between-strategy variability is that it only demonstrates that there is variance between strategies but does not indicate how the ER strategies relate to each other. Higher between-strategy variability occurs when individuals prioritize few strategies over others. As higher between-strategy variability was shown to be associated with higher within-strategy variability (Blanke et al., 2019), it is likely that this prioritization does not always pertain to the same one or two strategies. However, it is unclear if a stronger differentiation between strategies (i.e., not only prioritizing few strategies, but ideally only one at a time) may be even more predictive of well-being than between-strategy variability. It is further unclear whether the distribution of strategies (selecting all strategies to a similar degree but at different times) might play a role for the adaptive nature of between-strategy variability. In the following, we thus present two additional non-time-reliant dynamic measures that provide additional information beyond ER variability: ER differentiation and ER diversity.

ER differentiation. One reason for the adaptive nature of between-strategy variability for affective well-being could be that it may facilitate the differentiation between strategies leading to a prioritization of the strategies that work best for given situational demands. Avoiding non-adaptive strategies could then decrease the strain of engaging in effortful regulation and reduce the chance of suffering the consequences of failed regulatory efforts. Thus, we hypothesized that individuals who differentiate better between ER strategies also report higher levels of positive and lower levels of negative affect. To capture ER strategy differentiation, we used the intraclass correlation that has been used to study emotion differentiation before (Barrett et al., 2001; Demiralp et al., 2012; Erbas et al., 2019), but that has not been used to examine ER dynamics. Thus, whereas *SD* or *RSD* quantifies the variance between strategies, the ICC quantifies the relatedness between one's own ER ratings over time (Figure 1f). The *SD* and ICC should be positively related but still convey different information: Table 1 illustrates the fictious time series data of two participants. The between-strategy mean on the individual level ($M = 4.00$) and between-strategy variability ($SD = 1.73$) are the same but the ER differentiation differs, with ICC = 0 for Participant 1 and ICC = .50 for Participant 2, indicating large ER differentiation in Participant 1 and medium differentiation in Participant 2.

ER diversity. Another way of quantifying the ER repertoire can be based on Shannon's entropy (ENT; Shannon, 1948), which has been used in affect dynamic research to investigate emodiversity, the variety and relative abundance of individuals' emotions (Quoidbach et al., 2014). Applied to ER research, ENT allows to quantify the equal distribution of ER strategies, with higher values indicating more equal distribution of different ER strategies (Figure 1g). Regarding affect dynamics, it was shown that high emodiversity was significantly related to lower levels of depression, even when controlled for mean positive and negative affect (Quoidbach et al., 2014). However, predictions regarding the direction of the association between ER diversity and affective wellbeing are difficult: On the one hand, high ER diversity could represent a wide ER strategy repertoire, which could be beneficial for individuals' wellbeing. However, previous research has also shown that a diverse profile with a preference for some particular strategies, such as situation modification and social sharing, was associated with the highest levels of well-being (Grommisch et al., 2019). An equal distribution of strategy use may therefore indicate no preference for particular ER strategies, which should be reflected in a negative association with individuals' wellbeing.

The present research

In the present research project, we re-analyzed five AA datasets to examine the association between a wide range of ER dynamic measures and affective wellbeing in daily life, thereby introducing several measures novel to research on ER dynamics. In particular, we connected to prior research that demonstrated that between-strategy variability was negatively related to negative affect in daily life (Blanke et al., 2019). We wanted to replicate these results by controlling for the confound with the mean more thoroughly, using the *RSD* instead of *SD*. Next, we introduced five additional dynamic measures that have not been examined in the context of research on ER dynamics: ER instability (RMSSD), inertia (AR), predictability (%DET), differentiation (1–ICC), and diversity (ENT). We then used these measures in addition to the *RSD* to examine the structure of ER dynamic measures and investigate their unique contributions to affective wellbeing in daily life.

AA is particularly well suited to study ER dynamics given that it allows for an assessment of the participants' emotional and regulatory trajectories that leads to rich ecologically valid data of high information density that concurrently captures a diverse set of situational characteristics and demands. This diverse range of situational demands is important with regard to ER dynamics given that they challenge individuals' affective well-being, making it necessary to flexibly engage in ER. Reanalyzing five datasets (the four datasets used in Blanke et al., 2019, three of which are obtainable here:

https://osf.io/MXJFH/, and one of Wenzel and Rowland (https://osf.io/dxpwm)) yields a total of N = 717 participants (n = 70 to n = 200 per dataset), which not only provides a better safeguard against the possibility of reporting false positives, but also allows to examine the homogeneity of the effect sizes across studies.

Method

Participants

The sample size of all datasets was not based on power simulations but instead was determined a priori by the respective principal investigators and their previous experiences with AA before any data was collected. All relevant information regarding the samples can be found in Table 2.

Procedure

General information regarding the procedure is summarized in Table 2. Participants in all studies except Study 4 took part in 1-2 laboratory sessions, in which they provided their informed consent to participate and received either smartphones or palmtops with the pre-installed AA application. In Study 4, which was a subsample of the innovation sample of the German Socio-Economic Panel (SOEP-IS; Richter & Schupp, 2015), a representative longitudinal survey in Germany, interviewers visited the participants at their homes (Everyday Experiences in the SOEP-IS study, EE-SOEP-IS; see Siebert et al., 2017). In Study 1 and 4, participants could prolong the AA phase by up to three (Study 1) or six days (Study 4) in total, for days on which they missed more than one signal. Ethical approval by the local institutional review boards was obtained for all studies.

Measures

All five studies assessed positive and negative affect as well as ER strategies at each AA signal, with the assessment of positive and negative affect referring to the actual moment (except in Study 1) and the assessment of ER strategies to the interval since the last signal. Positive and negative affect in Study 1 also referred to the interval since the last signal. The items and scales are reported in Table 3. Given that we conducted a secondary analysis utilizing different datasets, the choice and measurement of the variables in the datasets was not consistent or comprehensive across all datasets with regard to the range of possible items for affect and emotion regulation strategies. Affect items were based on the circumplex model of affect (Russell, 1980) to include emotions with low and high arousal as well as positive and negative valence. In Studies 1 and 4, some of these items were selected from the PANAS (Watson et al., 1988).

Mean positive and negative affect. First, the mean of all positive and all negative affect items was computed to obtain aggregate measures of positive and negative affect at the moment-level. Given that all following dynamic measures except for between-strategy variability could only be assessed on the person-level, we averaged the moment-level mean of positive and negative affect to obtain the person-level means.

Between-strategy mean endorsement. To assess the intensity with which participants implemented ER strategies, we computed the mean between the respective strategies within a given observation and averaged the results on the person-level.

Within-strategy variability. Following Blanke and colleagues (2019), we used the *SD* as an indicator of within-strategy variability. To that end, we computed the *SD* of between-strategy mean endorsement at the moment-level, which yields a person-level variable. Given that the *SD* confounds statistically with the mean due to the bounded nature of the assessment of affect and ER strategies, we computed the *RSD* (Mestdagh et al., 2018) by standardizing the *SD* by the maximum *SD* of a given mean. For example, given four items and a response scale from 0 to 6, the maximum *SD* given $M = 1$ would be $SD_{max} = 2$ (responses: 0, 0, 0, 4) and $SD_{max} = 3.46$ given $M = 3$ (responses: 0, 0, 6, 6). The *RSD* is bounded within 0 and 1, with higher values indicating that a person uses all ER strategies in a more variable manner across time. Finally, we computed the mean of the within-strategy variabilities (for each given strategy) across all strategies to obtain one indicator of within-strategy variability per person.

Between-strategy variability. Variability between the ER strategies was assessed again via the *RSD*. We first computed the *SD* of all ER strategies at each beep, standardized the *SD* by the maximum *SD* of a given mean and, finally, averaged the *RSD* to obtain a measure of between-strategy variability at the person-level.

RMSSD. As a measure of ER instability, we calculated the RMSSD by taking the square root of the sum of the squared differences between two successive ER scores (Ebner-Priemer & Trull, 2009). Thus, higher RMSSD scores indicate more ER instability. Again, the mean of all strategy-specific RMSSDs was computed for each individual, resulting in an overall indicator of ER instability.

AR. To assess ER inertia (autoregression), we computed multilevel models using Stata 16 (Stata Corporation, College Station, TX). Specifically, we computed a first-order autoregressive model where a particular ER strategy was predicted by the person-mean centered lagged ER strategy and where autoregressive slopes could vary randomly between individuals. The individuals' autoregressive slopes per strategy were averaged at the person-level, serving as the direct operationalization of ER inertia, with higher values indicating more ER inertia.

Emotion regulation predictability. ER predictability was assessed using the percent determinism (%DET) measure calculated with the crqa package (Wallot et al., 2016) in R 4.0.2 (R Core Team, 2020). We set the delay and embed parameter to 1 and the radius parameter to 0 for Datasets 1, 4, and 5. The latter parameter specifies the interval within which two successive values are assumed to be recurrent and was set to 0 given the discrete values of ER strategies. For Datasets 2 and 3 the radius was set to 0.2, as the original answering scales for ER strategies ranged from 1 to 100 (Dataset 2) or 0 to 100 (Dataset 3) and were rescaled to range between 0 and 6 to harmonize the scales across datasets. Thus, values that are closer than 0.2 (e.g., 2.68 and 2.84) or closer than 3.3 in terms of the unscaled variables (e.g., 44 and 47) were counted as being recurrent.

We used %DET as the operationalization of ER predictability, which is the number of recurrence points that form a diagonal line (repeated patterns of at least 2 successive values) divided by the total number of points and can range from 0 to 1. %DET is high if individuals have a recurrent pattern in their ER strategies, which could be due to usually not using a strategy (e.g., recurrence of 0 0 and 0 0) or due to usually using a strategy (e.g., 6 6 and 6 6), or also due to a repeating patterns of changes in ER (e.g., 4 2 and 4 2). Please note that %DET, *RSD*, and AR of a given strategy are not computed when there is no variation in strategy use (i.e., a person always uses a strategy to the same degree or not uses the strategy at all).

We used the term predictability instead of recurrence to connect more closely to prior research on affect predictability (Jenkins et al., 2020). Recurrent patterns are predictable in the sense that knowing the ER pattern of one individual's day or week makes it more likely to predict ER patterns on subsequent days or weeks if the ER patterns are recurrent.

Emotion regulation differentiation. In line with prior research on emotion differentiation (e.g., Erbas et al., 2018), the ER differentiation index was computed for each participant by calculating the ICC measuring consistency. The range of the ICC is between 0 and 1 and ICCs with a negative value were set to 0 given that they are impossible to interpret theoretically (Giraudeau, 1996). The ICC indicates how strongly ER strategies are correlated across time. Consequently, higher values indicate lower differentiation. To ease interpretation, the ICC scores were subtracted from 1, so that a high 1–ICC indicates better emotion differentiation.

ENT. ER diversity was computed following Quoidbach and colleagues (2014). First, we computed the proportion of the number of times a particular ER strategy has been endorsed (values > 0) and the total number of ER instances. These proportions were then multiplied by the natural log of these proportions. The products were summed up and multiplied by -1 to obtain ENT, with higher values indicating a more diverse set of endorsed ER strategies. Thus, an individual who endorsed only one specific strategy across all measurement occasions would have an ENT = 0.

Statistical Analyses

After computing the measures independently for each dataset, we analyzed the datasets separately to quantify the variability in the key results across the studies. To obtain averaged effect sizes, we did not meta-analyze the individual effect sizes but instead opted to perform a *mega-analysis* or *integrative data analysis* (Curran & Hussong, 2009), which is recommended when raw data are available due to lower standard error estimates compared to a meta-analysis or a linear regression with study as a categorical predictor (Boedhoe et al., 2019). Instead of meta-analyzing the individual effect sizes, mega-analysis is based on multilevel analyses where the different studies form the highest level. In our case, given that most measures were limited to the individual level, we, thus, computed a two-level model where the individual scores were nested within the datasets. Following Boedhoe et al. (2019), we tested whether the inclusion of random slopes in the two-level models by performing a likelihood-ratio test to statistically compare the random-intercept with the random-slope model. A significant likelihood-ratio then indicates a better fit of the random-slope model, in which case random slopes were included. Please note that this approach increases the standard error of the fixed effects in case large variance, i.e., heterogeneity, is present in the data between the datasets but is nevertheless preferred given that it yields a better model fit (as reflected in lower BIC).

In the first set of analyses, we computed zero-order correlations individually and mega-analytically to check the independent associations between the study variables.[1] To control for the dataset differences in the mega-analysis, we computed multilevel models with individuals at level-1 and dataset at level-2, where one ER dynamic measure was separately predicted by another one. Next, we predicted either positive or negative affect by each ER dynamic measure separately. In the second set of linear regression and two-level models, we predicted either positive or negative affect by each ER dynamic measure separately and controlled for between-strategy mean endorsement to estimate the added value of the respective ER dynamic measure beyond mean levels of ER. Finally, we computed linear and mixed regressions to estimate the unique contribution of each ER dynamic measure not only beyond between-strategy mean endorsement but also controlled for the associations of the other ER dynamic measures.

Given that most measures were limited to the individual level, all variables were z-standardized based on the individual dataset (individual analyses) or across all datasets (mega-analysis) to obtain standardized effect sizes. All analyses were performed in Stata 16. To control for the unreliability of the measures, we additionally reported the Spearman-

Brown corrected key associations by dividing the observed correlation by the square root of the product of the reliability of the two associated variables (Parsons et al., 2019; Spearman, 1904).

Results

Descriptive analyses

The descriptive statistics of all measures are shown in Tables 2 and 4. Given that the answering scale in Datasets 2 and 3 differed from the other three, we rescaled them to range between 0 and 6. Adherence to the protocol was good overall (Table 2), with 87.4% completed signals on average. At 88.9% (range: 71.3% to 95.1%) of the completed signals, participants indicated to have used at least one ER strategy since the last signal. Finally, given that negative affect was oftentimes relatively low in the five datasets and, thus, right-skewed, we computed the square root of negative affect before standardizing the variable.

For the reliability analyses, we report McDonald's Ω (Geldhof et al., 2014; McNeish, 2018), which is calculated by squaring the summed factor loadings and dividing it by itself and the sum of the error variances of the items. In case of within-strategy measures, we computed the ER dynamic measure for each ER strategy and then used them as indicators in the model to estimate their reliability. In case of between-strategy measures, we computed the ER dynamic measure for odd and even days (Mejía et al., 2014). Overall, reliability was good to very good, with the exception of ER inertia, which only showed acceptable levels of reliability (Table 4).

Main analyses

In the section on the main analyses, we focus on the key relationships. The data for Study 1-3 and 5 and the full models can be found at OSF (https://osf.io/9nd7r/). For Study 4, the data can be obtained upon request via the German Institute for Economic Reserach (https://www.diw.de/en/diw_01.c.792406.en/soep-is_innovative_modules.html).

Structure of ER dynamic measures. The results of the correlations between the ER dynamic measures are shown in Figure 3. Given the relatively large number of associations, we only present the associations derived from the mega-analysis and present the individual study results in the online supplementary materials (Supplementary Table S1 to S5). Figure 3 demonstrates small to large interdependencies between the ER dynamic measures. The largest correlation was between *RSD* within and between strategies, demonstrating the relatively large shared variance between the two measures. Importantly, the intercorrelations between the ER dynamic measures were not always positive: For example, ER predictability (%DET) was positively associated with ER variability within strategies (*RSD* within-strategy) but negatively with ER instability (RMSSD). Thus, in case of significant associations, this hints at the possibility of separate, sometimes possibly counteracting processes underlying ER dynamics.

To check for redundancy between the ER dynamic measures, we computed a principal factor analysis and used a Varimax rotation. The parallel analysis yielded five factors, which are illustrated in Table 5. Factor 1 captured variance related to variability, with very high factor loadings for ER variability within and between strategies (*RSD*). ER instability (RMSSD) loaded on the second factor and to a lesser extent on the first factor, with Factor 2 being best represented by between-strategy mean endorsement. Factor 3 covered ER differentiation (1–ICC) and Factor 4 captured ER predictability (%DET), whereas ER inertia (AR) loaded predominantly on Factor 5. The only ER dynamic measure that did not clearly load on only one factor was between-strategy diversity (ENT). To sum up, with the exception of ER instability (RMSSD) and diversity (ENT), all ER dynamic measures loaded strongly on only one factor.

Zero-order correlations between emotion regulation dynamic measures and negative affect. As illustrated in Figure 3, positive affect was not significantly associated with any of the ER dynamic measures, with a maximum correlation of an absolute value of .11. In turn, the ER dynamic measures were much more strongly associated with negative affect. Thus, we limit the following analyses to negative affect in order to streamline the results.

Figure 4 shows the results for negative affect from the individual analyses per dataset and the mega-analysis. Between-strategy mean endorsement (M), ER instability (RMSSD), and ER diversity (ENT) all showed medium to large positive associations (Funder & Ozer, 2019) with negative affect. In turn, variability within and between strategies (*RSD*) as well as predictability (%DET) were significantly associated with lower negative affect. That is, a variable but predictable repertoire of ER strategies was related with low levels of negative affect.

However, Figure 4 also shows that there was large heterogeneity, especially for between-strategy mean endorsement, ER variability, instability, and differentiation, with a mean $I^2 = 57.9\%$. Given the small to large interdependencies between the ER dynamic measures, we controlled for the overlap between between-strategy mean endorsement and the other ER dynamic measures in the next sections

Associations between emotion regulation dynamic measures and negative affect controlling for mean emotion regulation endorsement. To control for interdependencies between the ER dynamic measures, we computed linear and mixed regression models in which negative affect was predicted by one ER dynamic measure and between-strategy mean endorsement. The results for the individual datasets and the mega-analysis are illustrated in Figure 5, which also includes the tests of heterogeneity. Overall, all mean effect sizes were smaller when controlled for between-strategy mean endorsement, except for ER differentiation (1–ICC). However, the general pattern remained the same, with ER diversity (ENT) being associated with higher negative affect and ER variability (*RSD*) and predictability (%DET) being associated with lower negative affect. However, ER instability (RMSSD) was no longer significantly positively associated with negative affect, whereas ER differentiation (1–ICC) now emerged as a (barely) significant, negative predictor, such that higher differentiation between ER strategies was associated with lower negative affect. Finally, controlling for between-strategy mean endorsement reduced heterogeneity on average, with a mean $I^2 = 40.2\%$ compared to $I^2 = 57.9\%$ without the inclusion of between-strategy mean endorsement.

Unique contributions of emotion regulation dynamic measures in predicting negative affect beyond between-strategy mean endorsement. Finally, we examined the unique contributions of ER dynamic measures. However, given the medium-to-large interdependencies between the measures, entering all predictors simultaneously was not an option due to issues of multicollinearity and overfitting. For example, entering all predictors yielded a mean variance inflation factor (VIF) for the mega-analysis of VIF = 3.99, with individual values ranging from VIF = 1.45 to 9.68, thereby approaching or exceeding the common cut-offs of VIF = 10 (Kutner et al., 2004) and VIF = 5 (Sheather, 2009).

Thus, to combat these issues, we used cross-validation and regularization (de Rooij & Weeda, 2020). Cross-validation tests whether the inclusion of a predictor improves the explanatory power of the model. To that end, it uses one subset of the data to fit a specific model and then uses another subset of the data to evaluate the prediction error. We used adaptive LASSO given that LASSO is inconsistent when high correlations between the predictors exists (Zou, 2006). This model selected 6 out of 8 possible predictors, which were then entered in the models that are illustrated in Figure 6. *RSD* within-strategies and ER differentiation (1–ICC) were the measures that were not included as including them did not further improve the model fit (based on the cross-validation mean prediction error).

As can be seen in Figure 6, variability between ER strategies (*RSD* between) and ER predictability (%DET) remained significantly associated with lower negative affect. However, whereas the former was not affected by the inclusion of the other selected ER dynamic measures (β = -.37 compared to β = -.34), the coefficient of the latter was reduced from β = -.24 to β = -.13 once the shared variance of the other predictors was controlled for. Thus, variability between ER strategies represented the best predictor of lower negative affect, while ER predictability could explain a smaller unique share of variance in negative affect. The other ER dynamic measures remained positively associated with negative affect, demonstrating small-to-medium sized effects. Heterogeneity remained quite large for two measures but was reduced again on average to an acceptable level of a mean $I^2 = 30.1\%$.

Importantly, the mean VIF for the mega-analysis was 1.87, with the VIFs for the individual predictors ranging from 1.18 (ER inertia) to 2.63 (variability between ER strategies). Given that the VIF is the ratio of the variance in a model with multiple predictors divided by the variance of the model with only one predictor, we can take the square root of the VIF to illustrate how much the standard errors increased due to the inclusion of the other predictors. Thus, the standard errors increased by $\sqrt{VIF} = \sqrt{1.87} = 36.7\%$ on average when all selected predictors were entered simultaneously compared to individually.[2]

Discussion

Recent theoretical accounts on ER propose that using ER strategies flexibly, rather than merely using putatively adaptive strategies, is pivotal for well-being (Aldao et al., 2015; Bonanno & Burton, 2013). However, empirical evidence for this proposition is still sparse. In one of the first efforts to investigate ER variability, which is a prerequisite for flexibility, in daily life, Blanke et al. (2019) found that variability between strategies (operationalized as the *SD* between strategies) was related to lower negative affect across four AA studies above and beyond between-strategy mean endorsement and within-strategy variability (*SD* within strategies). However, using the *SD* as a measure of variability may not be ideal (Mestdagh et al., 2018), which is why we re-analyzed the data from Blanke et al. (2019), using the mean-corrected *RSD* and complementing it with another AA dataset. Furthermore, building on the affect dynamics literature (e.g., Dejonckheere et al., 2019; Jenkins et al., 2020), there are various other indicators which could be indicative of ER variability in daily life. Specifically, we introduced three time-reliant indicators of variability (RMSSD, AR) and predictability (%DET). Furthermore, as between-strategy variability is hard to interpret, we examined whether differentiation (measured with 1–ICC) rather than variability (*RSD*) was associated with lower levels of negative affect. We additionally measured ER diversity (using Shannon's entropy index), which may be seen as a counterpart to prioritization (i.e., using all strategies to a similar degree).

Using the data from five AA studies with several ER strategies, we replicated prior findings by Blanke et al. (2019) with a different indicator of variability (*RSD* instead of the *SD*), and showed that higher between-strategy variability was associated with lower negative affect. In fact, between-strategy variability remained the strongest predictor of lower negative affect above and beyond the other newly introduced ER measures. Additionally, we found our measure of ER predictability to be associated with lower negative affect, explaining unique variance above and beyond between-strategy variability. Together, our findings further refine our understanding of ER strategy variability and its potentially adaptive value in daily life. We interpret our findings as pointing towards the adaptive nature of variable ER strategy use that is characterized neither by high diversity nor by high differentiation. Instead, adaptive strategy use may be variable without being unstable, and predictable without being autoregressive.

Between-strategy variability remained the best predictor for lower negative affect

Using ER strategies in a variable way involves distinguishing strategies that are potentially adaptive in a given situation from strategies that are not. In line with Blanke et al. (2019), we found that individuals who reported higher variability between strategies on the individual level reported significantly less negative affect on average than individuals who reported lower between-strategy variability. This result was robust to controlling for mean strategy use as well as other indicators of ER variability and predictability, and between-strategy variability remained the best predictor for lower negative affect (of the researched indicators). As observed in Blanke et al. (2019), between-strategy variability was quite strongly associated with within-strategy variability, which we additionally corroborated using a factor-analytical approach. This may indicate that individuals who used strategies variably at each measurement occasion also exhibited variability within strategies over time. Although within-strategy variability was associated with lower negative affect (also when controlling for between-strategy mean endorsement), it was not predictive of negative affect above and beyond between-strategy variability and predictability, as including it did not improve the model fit when predicting negative affect.

As to be expected, ER differentiation was moderately associated with between-strategy variability. However, like within-strategy variability, it had no unique explanatory value above and beyond the other measures. This indicates that the relation of between-strategy variability and lower negative affect cannot simply be reduced to a strong differentiation between strategies. Overall, ER differentiation was rather high on average (as compared to emotion differentiation, see Erbas et al., 2019). This may indicate that most individuals do not use most strategies to a similar degree across time, and thus have the potential to be flexible. Also, as expected, ER diversity was negatively associated with between-strategy variability and ER differentiation. It did not predict negative affect above and beyond the other measures. Diversity was quite strongly positively associated with between-strategy mean endorsement, indicating that individuals with higher ER diversity generally endorsed all strategies to a stronger degree. If anything, diversity was associated with higher negative affect, also when controlling for mean endorsement, suggesting that using all strategies to a similar degree across time was not preferable. Instead, preferably using certain strategies more than others may be most adaptive (see also Grommisch et al., 2019).

Of the time-reliant measures, ER autoregression was not associated with negative affect in any of the analyses. We had expected a negative association, as problems with disengaging from a strategy may point towards inflexibility. However, this may vary across strategies: whereas not being able to disengage from rumination could be problematic (Blanke et al., in press), this may not be the case for other strategies.

ER instability (as measured with the RMSSD) was strongly associated with between-strategy mean endorsement (which is to be expected as the RMSSD is also based on the SD), and thus associated with higher negative affect at the zero-order level. However, when controlling for mean endorsement, the RMSSD no longer contributed to the prediction of negative affect.

In contrast to the other two time-reliant measures, ER predictability was associated with lower levels of negative affect above and beyond other ER measures as we discuss next. Of note, none of the ER measures were associated with positive affect. This may be the case as the strategies that were included in the present study were predominately strategies aimed at regulating negative experiences, such as distraction or suppression, and not strategies aimed at regulating positive experiences, such as savoring (Heiy & Cheavens, 2014).

Emotion regulation predictability as a novel predictor of lower negative affect

With regard to the new dynamic measures that have not been studied in ER research before, we found that ER predictability was significantly associated with lower levels of negative affect. This was the case above and beyond the other ER measures, notably also above the effect of between-strategy variability, with which predictability showed a moderate positive association. This suggests that using strategies in a predictable way over time may be adaptive for well-being. For example, an individual could strongly endorse distraction to calm down when something negative has happened recently. After a while, distraction may become less vital, because the issue is not perceived as negatively anymore (the resulting pattern would be in line with Figure 2). However, predictability may not be confused with autoregression, which showed only a small association with predictability. One drawback of the RQA used in the present research is that the %DET (as well as other RQA metrics) does not provide information about the respective patterns. This pertains to patterns within strategies, but also to patterns across strategies. It would be interesting to know which specific patterns are most adaptive: For example, constantly distracting from one's negative emotions may be less beneficial than distracting one's attention from an arousing situation before reappraising it.

Heterogeneity of the effect sizes

As Figure 4 shows, 5 out of 8 average effect sizes indicated significant heterogeneity. Although this is noteworthy, it is also important to consider the context of these heterogeneity measures. First, including the mean in the models reduced the heterogeneity between the ER dynamics effect sizes considerably, from 57.9% to 40.2% on average. Moreover, the heterogeneity was further reduced to 30.1% on average, when controlling for the other ER dynamic measures. This further highlights the importance of controlling for the mean and other dynamic measures when studying ER dynamics (Dejonckheere et al., 2019). Second, a high I^2 values does not necessarily mean that the individual effect sizes should not be averaged to answer a specific research question. For example, there was very large heterogeneity in the effect sizes of between-strategy mean endorsement for negative affect (Figure 4). However, even the lowest effect was positive and relatively large. Thus, it is also important to take into account the range of the individual effect sizes. With regard to our key results, it is evident that between-strategy variability showed robust and large negative effect sizes that were significant in all but one dataset when controlling for between-strategy mean endorsement and other ER dynamic measures, although there was considerable heterogeneity.

Limitations and future directions

Our research is inevitably bound by limitations. First, ER strategies were assessed with one item each in each dataset, which potentially limited their reliability. However, this tradeoff between space constraints and reliability and validity issues is typical for AA studies, which might explain why previous ER research also opted for single items (e.g., Brans et al., 2013; Koval et al., 2015). Furthermore, since we averaged across strategies and studies, our ER measures showed acceptable reliabilities. As noted above, we mostly included strategies that pertained to the regulation of negative affect, which may explain why associations with positive affect did not emerge at the aggregated level. Second, the samples mainly consisted of undergraduate students in their twenties (with the exception of Dataset 4) from Germany and Belgium, which limits the generalizability of our results to the general population. In a recent study, age differences between younger and older adults emerged in terms of their within-strategy variability (but not in terms of their repertoire; Eldesouky & English, 2018). This is in line with findings on lower affective variability in older than in younger adults, which may in part be explained by the fact that older adults experience a lower number of stressors and less diverse stressors in their daily lives as compared to younger adults (Brose et al., 2013). It may thus be the case that lower ER variability is not necessarily maladaptive in different populations.

Third, and related to the previous, it is important to note that we cannot draw causal inferences based on our findings. Our notion is that variability between strategies and ER predictability indicate that individuals with high levels of variability and predictability are better adapted to situational demands, selecting from a wider range of well-tested strategies to deal with the hassles and life events individuals encounter in their everyday lives. However, it is possible that individuals who lead more stressful lives and experience higher levels of negative affect, are in need of using strategies in less variable, more unstable and more diverse ways (e.g., engaging all strategies). Most likely, strategy use and affect often influence one another in a reciprocal way (Blanke et al., in press; Brans et al., 2013). Moreover, we cannot rule out the possibility that the retrospective evaluation of emotion regulation was impacted by the momentary affect (mood-state distortion; Naragon-Gainey et al., 2013). Given that an objective assessment of emotion regulation efforts at the very moment of the assessment is improbable in daily life, future research could counter this issue by combining the signal-based sampling schemes (as utilized in the five datasets to assess momentary affect) with an event-based sampling scheme to cover emotion regulation efforts closely to when the emotionally-relevant situation that has to be regulated occurs.

Fourth, both between-strategy variability and predictability, which emerged as most predictive for lower negative affect in our study, are difficult to interpret. Other approaches are necessary to answer the question of which specific strategies to use in combination or in sequence. Future research could explore emotion regulation sequences using cross RQA (Coco & Dale, 2014) to examine predictable pattern in two time series, such as switching from distraction to reappraisal, and using multidimensional RQA (Wallot et al., 2016) to examine predictable pattern in more than two time series. Importantly, we did not measure contextual variation in our studies, but assumed context to change during our participants' daily lives. Similarly, we assumed that the participants mostly pursued pro-hedonic goals (i.e., down-regulating negative affect, upregulating or maintaining positive affect; see Riediger et al., 2009). It is therefore not clear, whether our measures of ER variability are indicative of ER flexibility (Aldao et al., 2015).

Finally, not only the *SD* is significantly associated with between-strategy mean endorsement but also other dynamic measures as shown in Figure 3. While a relative index exists for the RMSSD (Mestdagh et al., 2018), future research could explore relative indices for the other measures such as %DET or ENT to control for the nonlinear association.

Conclusion

Most studies on ER rely on static measures of ER, although ER itself is characterized as a dynamic process that unfolds over time and that aims at adapting individual's emotion to situational, personal, and societal demands (Gross, 2015). We examined various indicators of ER dynamics across five datasets that captured ER strategy use in daily life. We replicated and extended previous findings by showing that between-strategy variability and ER predictability were associated with lower negative affect above and beyond between-strategy mean endorsement and other indicators of ER variability. We interpret our findings as evidence for the adaptive value of between-strategy variability and predictability, and conclude that prioritizing few strategies at each measurement occasion and employing them in a variable, yet predictable manner over time, was particularly adaptive in terms of lower negative affect in our study. Moreover, the present study also demonstrates how predictability can add to our understanding of ER as a process that requires both flexibility in reacting to a diverging range of situations, and reliability in the sense of knowing what works in a given situation and using it consistently to one's own affective advantage. Connecting ER variability and predictability to contextual factors and goals may be a next, major step in ER research.

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Footnotes

[1]Following Blanke et al. (2019), in Studies 1 and 4, we also included observations in the analyses that were only partially completed by the participants.

[2]We repeated the mega-analysis with the relative RMSSD instead of the RMSSD given that the RMSSD was also confounded with the mean (Figure 3) and given that a relative index of the RMSSD already exists (Mestdagh et al., 2018). Importantly, the inclusion of relative RMSSD did not change the results: Whereas the association between relative RMSSD and negative affect was still very small and not significant, $\beta = .01$, $SE = .04$, $p = .843$, 95% CI [-.07, .08], the coefficients of variability between ER strategies (*RSD* between), $\beta = -.30$, $SE = .09$, $p = .001$, 95% CI [-.49, -.12], and ER predictability (%DET), $\beta = -.16$, $SE = .03$, $p < .001$, 95% CI [-.22, -.09], were very similar and still significant.

Figures

Figure 1. Simulated data for each emotion regulation dynamic measure, showing how low and high values for each measure would manifest in an individual's emotion regulation time series. RSD, relative standard deviation; RMSSD, root mean square of the successive differences; AR, auto-regression; %DET, percent determinism; ICC, intra-class correlation; ENT, Shannon's entropy.

Figure 2. Recurrence plot of a simulated time-series. In the recurrence plot, the time-series data are placed on the *x*- and *y*-axis and recurrent states (i.e., predictable) are place where same values intersect. Black squares in a circle form a diagonal line, which are set in relation to the total number of squares, excluding the line of identity formed by the gray squares, to calculate the percent determinism (%DET).

Figure 3. Correlation plot illustrating zero-order correlations (above the diagonal), scatter plots including linear regression (below the diagonal), and histograms (diagonal). PA, positive affect; NA, negative affect; M, between-strategy mean endorsement; RSD (ws), relative standard deviation assessing within-strategy variability; RSD (bs), relative standard deviation assessing between-strategy variability; RMSSD, root mean square of the successive differences; AR, auto-regression; %DET, percent determinism; ICC, intra-class correlation; ENT, Shannon's entropy.

Figure 4. Coefficient plots show the regression coefficients (the dots) and their 95% CI (the whiskers) for the association between negative affect and one of the static and dynamic measures of emotion regulation. Stand., standardized; corr., Spearman-Brown corrected standardized coefficient; M, between-strategy mean endorsement; RSD (within-strat.), relative standard deviation assessing within-strategy variability; RSD (between-strat.), relative standard deviation assessing between-strategy variability; RMSSD, root mean square

of the successive differences; AR, auto-regression; %DET, percent determinism; ICC, intra-class correlation; ENT, Shannon's entropy.

Figure 5. Coefficient plots show the regression coefficients (the dots) and their 95% CI (the whiskers) for the association between negative affect and one of the dynamic measures of emotion regulation, controlling for mean emotion regulation. Stand., standardized; corr., Spearman-Brown corrected standardized coefficient; RSD (within-strat.), relative standard deviation assessing within-strategy variability; RSD (between-strat.), relative standard deviation assessing between-strategy variability; RMSSD, root mean square of the successive differences; AR, auto-regression; %DET, percent determinism; ICC, intra-class correlation; ENT, Shannon's entropy.

Figure 6. Coefficient plots show the regression coefficients (the dots) and their 95% CI (the whiskers) for the association between negative affect and all dynamic measures of emotion regulation that were selected by the adaptive LASSO procedure. Stand., standardized; corr., Spearman-Brown corrected standardized coefficient; M, between-strategy mean endorsement; RSD (between-strat.), relative standard deviation assessing between-strategy variability; RMSSD, root mean square of the successive differences; AR, auto-regression; %DET, percent determinism; ENT, Shannon's entropy.

Tables

Table 1

Fictitious data from two participants (ID) that rated four ER strategies (ERS) on a scale from 0 to 6 at three different time points (beep).

Identifier	Beep	ERS 1	ERS 2	ERS 3
1	1	6	4	4
1	2	4	6	4
1	3	1	1	6
2	1	6	4	4
2	2	6	4	4
2	3	6	1	1

Table 2

Overview of the datasets

Dataset	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5
Parent study	Blanke & Brose (2017)	Brans et al. (2013)	Koval et al. (2015)	Siebert, Blanke, & Brose (2017)	Wenzel & Rowland (https://osf.io/dxpwm)
Type	AA (self-report)	AA (self-report)	AA (self-report)	AA (self-report)	AA (self-report)
Country of data collection	Humboldt-Universität, Germany	KU Leuven, Belgium	KU Leuven, Belgium	Humboldt-Universität, Germany	Johannes Gutenberg University Mainz, Germany
Participants: *N*	70	95	200	179	173
Gender: % Female	50.0%	62.1%	55.0%	52.5%	51.5%
Age: *M* (*SD*)	25.55 (2.74)	19.06 (1.28)	18.32 (0.96)	50.93 (5.76)	24.98 (5.45)
AA design	Signal-contingent	Signal-contingent	Signal-contingent	Signal-contingent	Signal-contingent
Number of days	9-12	7	7	12 (3 times 4 days with 4 pause days in between)	7
Observations per day	6	10	10	6	12
Max. number of observations	max. 66 (goal: 54)	70	70	max. 96 (goal: 60)	84
Average number of observations per participant: *M* (*SD*)	54.4 (3.25)	60.3 (4.60)	61.5 (6.30)	69.33 (7.59)	57.71 (12.13)
Adherence	98.3%	86.1%	87.8%	98.7%	68.7%
AA application	Custom built	Custom built	Custom built	Custom built	movisensXS (movisens GmbH, Karlsruhe, Germany)
AA hardware ([a]smartphone, [b]palmtop)	Huawei Ascend G330[a]	Tungsten E2 PalmOne, Mankato, MN[b]	Motorola Defy Plus[a]	Huawei Ascend G330[a]	Motorola Moto G[a]
Compensation	65 € (on average)	70 €	60 €	80-90 €	50 €

Note. AA, ambulatory assessment.

Table 3

Overview of the measures

Dataset	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5
Positive affect items	• Content • Happy • Relaxed	• Happy • Relaxed	• Excited • Happy • Relaxed	• Inspired • Joyful • Interested • Relaxed • Content • Well	• Excited • Happy • Relaxed • Satisfied
Negative affect items	• Distressed • Downhearted • Nervous	• Angry • Anxious • Depressed • Sad	• Angry • Anxious • Depressed • Sad	• Angered • Downhearted • Jittery • Distressed • Nervous • Upset	• Angry • Anxious • Depressed • Sad
Answering scale	7-point scale from 0 (does not apply at all) to 6 (applies strongly	Slider scale from 1 (not at all) to 100 (very much)	Slider scale from 0 (not at all) to 100 (very much)	7-point scale from 0 (does not apply at all) to 6 (applies strongly	7-point scale from 0 (does not apply at all) to 6 (applies strongly
Emotion regulation strategy items	• Distraction from thoughts • Distraction from feelings • Reflection on thoughts • Reflection on feelings • Rumination on thoughts • Rumination on feelings	• Distraction • Reappraisal • Reflection • Rumination • Social sharing • Suppression	• Distraction • Reappraisal • Rumination (past) • Rumination (future) • Social sharing • Suppression	• Acceptance • Distraction • Positive reappraisal • Reflection • Rumination	• Distraction • Reappraisal • Rumination • Social sharing • Suppression
Answering scale	7-point scale from 0 (does not apply at all) to 6 (applies strongly	Slider scale from 1 (not at all) to 100 (very much)	Slider scale from 0 (not at all) to 100 (very much)	7-point scale from 0 (does not apply at all) to 6 (applies strongly	7-point scale from 0 (does not apply at all) to 6 (applies strongly

Note.

Table 4

Descriptive statistics (mean, standard deviation, and between-person reliability) of the (rescaled to range from 0 to 6) variables

Variable	Study 1 (*N* = 70)			Study 2 (*N* = 95)			Study 3 (*N* = 200)			Study 4 (*N* = 179)			Study 5 (*N* = 174)			Mean
	M	*SD*	Ω	*M*	*SD*	Ω	*M*	*SD*	Ω	*M*	*SD*	Ω	*M*	*SD*	Ω	Ω
1. Positive affect	3.26	0.77	.92	3.41	.80	.91	3.41	0.60	.90	3.19	0.76	.91	3.11	0.66	.87	.90
2. Negative affect (square-root transformed)	1.12	0.39	.92	0.88	0.34	.92	0.80	0.29	.95	0.94	0.41	.96	0.68	0.36	.94	.94
3. Between-strategy mean	1.87	0.70	.82	1.39	0.64	.84	1.28	0.68	.86	2.42	0.93	.81	1.11	0.77	.84	.83
4. Within-strategy variability of mean ERS (RSD)	0.51	0.12	.93	0.46	0.11	.90	0.46	0.12	.88	0.54	0.17	.95	0.61	0.12	.87	.91
5. Within-strategy instability (RMSSD)	1.53	0.41	.87	1.35	0.45	.89	1.28	0.46	.88	1.69	0.55	.87	1.34	0.49	.82	.87
6. Within-strategy inertia (AR)	0.21	0.06	.55	0.18	0.05	.64	0.19	0.05	.46	0.19	0.09	.75	0.25	0.08	.50	.58
7. Within-strategy predictability (%DET)	0.53	0.15	.87	0.44	0.12	.90	0.46	0.16	.93	0.55	0.017	.91	0.54	0.21	.94	.91
8. Between-strategy variability (RSD)	0.49	0.13	.82	0.40	0.14	.87	0.41	0.15	.88	0.52	0.20	.95	0.57	0.14	.85	.91
9. Between-strategy differentiation (1–ICC)	0.82	0.11	.77	0.84	0.11	.86	0.84	0.12	.64	0.82	0.16	.88	0.83	0.13	.69	.80
10. Between-strategy diversity (ENT x -1)	1.68	0.18	.94	1.70	0.17	.94	1.69	0.16	.81	1.55	0.10	.91	1.38	0.25	.84	.89

Note. Ω = between-person reliability (McNeish, 2018) using the measures for the single ER strategies (within-strategy) or the measures for odd and even days (between-strategy); ERS = emotion regulation strategies; *RSD* = relative standard deviation; AR = autoregression; %DET = determinism; ICC = intraclass correlation; ENT = Shannon’s entropy.

Table 5

Factors after varimax rotation

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Between-strategy mean	-.09	**.79**	.15	.03	.06	.34
Within-strategy variability of mean ERS (*RSD*)	**.96**	-.02	-.14	.01	-.01	.05
Within-strategy instability (RMSSD)	.47	**.69**	-.13	-.32	-.28	.10
Within-strategy inertia (AR)	.17	-.17	-.09	.09	**.50**	.67
Within-strategy predictability (%DET)	.30	-.24	.02	**.51**	.07	.59
Between-strategy variability (*RSD*)	**.87**	.11	.31	.16	.09	.11
Between-strategy differentiation (1–ICC)	.06	.07	**.62**	.05	-.05	.60
Between-strategy diversity (ENT x -1)	-.45	.41	-.26	-.38	-.08	.41
Eigenvalues	2.23	1.38	0.62	0.54	0.62	-
Variance explained	46.4%	28.8%	13.0%	11.3%	7.4%	-

Note. ERS = emotion regulation strategies; *RSD* = relative standard deviation; AR = autoregression; %DET = determinism; ICC = intraclass correlation; ENT = Shannon's entropy.

Factor loadings in bold are above .50.