The Shape of Emotion Regulation:

Trait Emotion Regulation as Density Distributions of States

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Tables

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Other findings from this study are reported in Blanke et al. (2019). We report how we determined our sample size, all data exclusions, and all measures as relevant for the research questions. There were no manipulations.

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Abstract

The Density Distribution approach to personality characterizes traits using both mean levels and within-person variability of behaviors. Recent theory highlights that emotion regulation (ER) is inherently variable, and this Density Distribution approach seems particularly suitable to understand both average tendencies and dynamics of ER as person-specific characteristics. However, there is not yet empirical evidence for this suggestion. To fill this gap, we investigated the reliability of density distribution information gathered from repeated assessments of state ER (within-person mean levels and standard deviations). Specifically, we studied the reliability of ER strategy use in terms of internal consistency and short- and long-term stability within and across two waves of experience sampling (N = 153, M = 70 measurement occasions). Across both average tendencies and within-person variation, we found that individuals used different ER strategies relatively consistently. Overall, within-person ER mean levels and standard deviations were stable within and across the waves. Taken together, this suggests that the person-specific overall pattern of ER use in daily life is captured reliably using ESM.

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Research on emotion regulation (ER) is increasingly acknowledging the importance of going beyond trait reports of average ER strategy use to consider state ER and the dynamics of ER in daily life. Specifically, increasing attention is being given to differences in how flexibly individuals use ER strategies in daily life (e.g., Aldao, Sheppes, & Gross, 2015). However, a prerequisite to flexible ER – that is, goal-oriented and context-specific ER strategy use – is *variability* in ER strategy use, which can be captured using the experience-sampling methodology (ESM), also referred to as ambulatory assessment (AA). However, it is an open question whether such patterns of ER dynamics, which are characterized not only by person-specific average tendencies, but also by variability across time, are reliably measured with the ESM approach. Reliable, and thus systematic, differences in how much people vary in ER strategy use would provide support for the idea that some individuals are more flexible in their use than others. Such support is a necessary foundation for the movement towards flexibility in the field.

Person-specific aspects of behavior that go beyond trait reports, including the distributional characteristics of behaviors (i.e., variability), have also been considered in personality psychology. Specifically, this topic is central to the person-situation debate, which centers around the relative importance of aspects of the individual (i.e., their personality) and aspects of the situation in guiding behavior. This debate has led to an increase in the conceptualization and measurement of personality constructs as *states,* in addition to traditional *trait* approaches. An influential conceptualization is the *Density Distribution approach* (Fleeson, 2001) which is based on the idea that individuals' behavior can differ from one situation to another, but is still consistent within individuals across time. For example, one person may usually behave in a talkative, extraverted way when surrounded by friends, but not when surrounded by strangers, whereas another person may be talkative in both situations. Thus, there are not only consistent differences in the mean level of extraversion (some people are more extraverted), but also consistent differences in *within*-person variability (some people are more variable in their extraverted behaviors). Based on multiple assessments of states in different situations, density distributions reflect between-person differences in both *mean level* and *within-person variability* across situations.

Given the rising interest in distributional characteristics of ER dynamics, and based on the theoretical foundation provided by the density distribution approach to personality, this study examines the reliability of between-person indicators derived from state ER (means and within-person variability). Such demonstration is a necessary first step in establishing that density distributions are a meaningful approach to comprehensively capture between-person differences in ER (Eid & Diener, 1999; Fleeson, 2001). In the present research, we establish this foundation by investigating the reliability of ER density distributions using an intensive longitudinal design.

The Density Distribution Approach

One of the fundamental disagreements in the person-situation debate in personality psychology has revolved around the question of whether behavior is consistent enough across situations to justify the concept of personality traits (Fleeson & Noftle, 2009). Traditional trait measures such as the Five Factor Model reflect the conceptualization of traits as “relatively enduring patterns of thoughts, feelings, and actions” (McCrae & Costa, 2008) and thus favor the “person” side of this debate. However, such conceptualizations do not consider the degree to which trait expression varies within a given individual, or whether there are individual differences in this degree of variability.

Fleeson (2001) considered this variability, and in doing so, provided evidence for the power of both the situation *and* the person. By observing trait-relevant behavior in multiple situations, he found that individuals’ behavior differed across situations, exhibiting high within-person variability, highlighting the power of the situation. However, individuals still differed reliably in their average levels of trait-relevant behaviors, and they also differed reliably from each other in the amount of variability of their behavior across situations, highlighting the power of the person. That is, individuals' behavior formed density distributions, described by two stable parameters: First, the *location* of the distribution, which is the aggregated individual mean (i*M*). Second, the *size* of the distribution, which is the individual standard deviation (i*SD*), here also referred to as within-person variability. A person who acts moderately extraverted most of the time displays a moderate i*M* and a small i*SD*. A person who only acts extraverted in some situations, but not in others, may display a similar i*M,* but a higher i*SD.* Fleeson (2001) showed that both i*M*s and i*SD*s of Big Five-relevant behaviors were stable across two weeks in two studies (correlations for i*M*s between .87 and .97, for i*SD*s between .55 and .85). This suggests that stable individual differences encompass both average behavioral tendencies and the amount of behavioral variation. Hence, for an adequate understanding of personality and individual differences, we need to consider both.

Furthermore, average behavioral tendencies as observed with the Density Distribution approach have a different meaning to traditional trait measures. Traditional trait measures commonly assess trait behavior via global evaluations of one's typical thoughts and behaviors. Such measures are likely shaped by memories and beliefs about the self that are no longer tied to a specific time and place when providing answers (i.e., by semantic knowledge; Robinson & Clore, 2002). In comparison, aggregated means and indicators of variability are based on multiple reports of states. Such state reports are directly linked to experiential knowledge (Robinson & Clore, 2002). Consequently, an aggregated mean reflects a different type of a global behavioral tendency than a score derived from traditional trait measures. In line with this, a meta-analysis reported medium-sized associations between traditional Big Five trait measures and aggregated states of density distributions (Fleeson & Gallagher, 2009). Moreover, indicators from both approaches may have differential predictive value

(Conner & Barrett, 2012), as some outcomes can be more influenced by semantic knowledge (e.g., decisions that are guided by memories) and others by experiential knowledge.

Extending the Density Distribution Approach to Emotion Regulation

While this trait-as-density distribution perspective has so far mostly been limited to the Big Five personality traits, its logic also applies to other personality characteristics (Fleeson, 2001). For example, research has already investigated the role of within-person variability, above and beyond mean levels, in affective experiences (Eid & Diener, 1999). Similarly, recent theoretical perspectives imply that within-person variability in ER is a between-person characteristic (Aldao et al., 2015). However, systematic evidence for this view is missing. To provide this evidence, we used the trait-as-density distribution perspective as a framework to investigate ER.

ER describes the variety of processes through which individuals influence their emotions (Gross, 1998). Traditionally, ER has been approached and measured as a trait, reflecting the idea of habitual ER strategy use. However, ER targets emotions relatively immediately and modulates how affect unfolds over time. Therefore, ER is increasingly being investigated using *state* questionnaires and intensive longitudinal designs such as the experience-sampling method (ESM; e.g., Brans, Koval, Verduyn, Lim, & Kuppens, 2013; Brockman, Ciarrochi, Parker, & Kashdan, 2017; Haines et al., 2016; Kashdan & Steger, 2006). These studies showed that a large portion of variance in ER is within person, highlighting the importance of considering both between- and within-person variation in ER.

Moreover, current ER theories increasingly emphasize the role of context, which calls for the examination of within-person variation in ER (e.g., Bonanno & Burton, 2013). To capture such within-person variability in ER in response to contextual changes and between-person differences in these changes, one must repeatedly measure which ER strategies an individual employs across situations (Aldao et al., 2015). In line with this suggestion, ER research is emerging that considers variability—and thus is in accordance with the traits-as-density distribution perspective on traits. First, researchers have started to investigate associations between the amount of ER variability and other person-level characteristics, such as age (Eldesouky & English, 2018). Second, researchers have started to investigate whether ER variability is associated with well-being outcomes. In our own research, using data from four ESM studies, we examined the predictive validity of within-person variability in ER strategy use (Blanke et al., 2019). We found a small negative association between the amount of variability and negative affect. In a different approach, Haines et al. (2016) showed that the covariation of the use of cognitive reappraisal with contextual factors was associated with higher well-being. Together, these results suggest systematic and meaningful differences in how much people vary in ER strategy use across occasions.

The Present Study

Contemporary research acknowledges the partly variable nature of ER. Yet, a systematic test of the idea that the *distribution* of ER (i.e., density distributions characterized by means and variability) as a between-person characteristic is missing from the literature. We therefore investigated distributional characteristics of repeatedly measured state ER in daily life. We used data from two waves of a study that combined ESM of ER strategies with traditional trait assessment of ER. The two waves of ESM were three weeks long and approximately one year apart.

We expected the within-person aggregated means (i*M*s) and the within-person variability estimates (i*SD*s) to be relatively stable across the three weeks of ESM within each wave. This would provide evidence for the claim that the amount of within-person variability, in addition to average behavioral tendencies, characterizes individuals' behaviors. It is important to note that given a high number of random measurement occasions, i*M*s and i*SD*s will naturally become stable within a given time period (Du & Wang, 2018). We therefore compared i*M*s and i*SD*s within each week of assessment with each other, to investigate short-term re-test stability. We furthermore expected long-term stability (across annual waves) in i*M*s and i*SD*s of the ER density distributions. This would provide evidence for the claim that ER density distributions are stable traits across a longer period.

We assessed five specific ER strategies. To examine whether individuals use of ER is systematic across these specific strategies, we also investigated reliability in terms of internal consistency of strategy-specific within-person aggregated means and variability indices within both waves (see also Blanke et al., 2019). A high internal consistency in aggregated strategy means would suggest the existence of some underlying, higher order construct (i.e., the tendency to engage in ER). A high internal consistency in variability indices across different strategies would suggest that the amount of variation is also systematic beyond a single strategy and thus, that some individuals are generally more variable in ER strategy use than others. Regarding the association between aggregated means and trait reports of ER, we tentatively expected to find moderate correlations, given the results of previous research (e.g., Kashdan & Steger, 2006), indicating both some convergence, but also distinctiveness of aggregated means and trait reports.

Methods

Participants and Procedure

This study included middle-aged participants from the Innovation Sample of the German Socio-Economic Panel study (SOEP-IS), a longitudinal survey of individuals from all over Germany (SOEP-IS; Richter & Schupp, 2015). Interviewers from the Humboldt-Universität zu Berlin visited the participants at two occasions, approximately one year apart (for details, see Siebert, Blanke, & Brose, 2017). At these home sessions, participants worked on computerized questionnaires and tasks. Afterwards, participants received smartphones (Huawei Ascend G330) programmed with a custom-made ESM program (see Blanke et al., 2019, Study 4). The ESM phase started the day after the visit and consisted of three assessment phases of four sampling days, each followed by four pause days. At each sampling day, participants received six ESM prompts (beeps) in a semi-random fashion in a 12-hour period. The assessment phases were prolonged by up to two days if participants missed more than one assessment a day. In total, participants received 170 to 190 Euros for participation in the two waves, depending on whether they completed 60 beeps or more in the ESM phases.

The present study was part of a larger multi-purpose project. Design decisions regarding sample size ($N = 180$ Wave 1) and number of assessment occasions ($t = 70$) were made by the principal investigator based on statistical analyses with available datasets and previous experiences with longitudinal sample dropout in ESM research, targeting study purposes unrelated to the present paper. Regarding the specific analyses reported in this paper, no a priori power analyses were conducted. For the present work, we excluded three participants who completed less than 50% of the aimed-for 60 beeps (10-20 beeps) in Wave 2, because for those participants the aggregated data is likely not as reliable as for the individuals with more data points.

The final sample thus consisted of 153 participants (53.59% female), aged between 38 and 61 ($M = 50.88$, $SD = 5.79$) at Wave 1. Participants reported receiving between seven and 18 years of education ($M = 12.78$, $SD = 2.44$, $Mdn = 11.50$). Our final sample ($N = 153$) did not differ from the subsample of the individuals who did not participate in Wave 2 or who provided no or only little data during the ESM phase ($n = 26$) in terms of age and gender. However, individuals in the final sample completed more years of education ($Mdn = 11.50$) than the subsample who did not participate in Wave 2 ($Mdn = 10.50$; $U = 1{,}251$, $z = -3.06$, $p < .01$). All measurement occasions at which participants completed all relevant questions were used (Wave 1: $M = 70.90$, $SD = 5.53$, range = 31–85 occasions; Wave 2: $M = 69.83$, $SD = 7.05$, range = 41–86 occasions). The study was approved by the ethics committee of the Humboldt-Universität zu Berlin.

Measures

State emotion regulation. At each ESM prompt, participants were asked *"Think about the most unpleasant or stressful things / feelings you have had since the last beep* (at the first beep of the day: since you woke up). *How did you handle them?".* Then, participants were presented with five ER strategies that they rated on a 7-point scale from *0 – does not apply at all* to *6 – applies strongly*. These strategies were: rumination (*"I could not stop thinking about it"*), distraction ("*I distracted myself from the distressing things and feelings"*), reflection ("*I thought about it in a calm and relaxed fashion."*), positive reappraisal *("I searched for positive aspects of this matter."*), and acceptance (*"I accepted the things / feelings."*). If participants did not experience any unpleasant or stressful things or feelings, they were instructed to choose 0 – *does not apply*.

Trait emotion regulation. Trait ER was assessed with the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski & Kraaij, 2007; German version by Loch, Hiller, & Witthöft, 2011). For three of the five strategies assessed in the ESM (rumination, positive reappraisal, and acceptance), there were trait equivalents in the CERQ (response scale ranging from *1 – [almost] never* to *5 – [almost] always*). The internal consistencies for three subscales in each wave were α = .74/.74 for rumination, .84/.83 for positive reappraisal, and .60/.63 for acceptance. The latter was rather low, which was in accordance with the German validation study (i.e., α = .60; Loch et al., 2011). In our study, the re-test stability across waves was r = .53 for rumination, .59 for positive reappraisal, and .36 for acceptance (all *p*s <.01). These correlations were overall lower than in the German validation study; however this validation study tested stability over the course of only seven months.

Data analysis

We used SPSS version 25 to prepare and analyze the data (input and output data can be find in the Electronic Supplementary Materials). Overall, 13 univariate outliers were adjusted to three *SD*s below and above the sample mean. To examine whether the density distributions (i*M*s and i*SD*s) of state ER reflect traits, we first examined their short-term stability within the waves by computing correlations between the i*M*s for each of the three assessment weeks within the waves for each strategy. We did the same for the i*SD*s. Next, we examined the internal consistency (Cronbach's alpha) across the strategies to determine whether individuals tended to use all strategies and vary within their strategy use to a similar degree (i.e., alpha was calculated for the i*M*s and i*SD*s of the five strategies). For long-term stability (across one year), we calculated correlations between scores at Wave 1 and Wave 2 for i*M*s and i*SD*s. To ensure the discriminant validity of the i*SD*s from the i*M*s, we also provided information on correlations between i*SD*s and i*M*s, and between residualized i*SD*s (partialing out the i*M*s in both a linear and a quadratic fashion) at the level of the waves. Finally, we calculated within-wave correlations between the i*M*s and the trait mean scores to examine the overlap between the different sources of information.

Results

Descriptive information and intercorrelations between the strategies are reported in Tables 1 and 2. As some variables were not normally distributed, we also calculated Spearman correlations. However, these correlations were similar to the Pearson correlations so that we only report the Pearson correlations. As can be inferred from the intra-class-correlations (ICCs), half or less than half of the variance in ER strategy use was between-person variance. The correlations between the i*M*s and the i*SD*s at the level of the waves were small to medium-sized.

Short-term Stability (Re-test Correlations Across Three Weeks Within Waves)

The stability of the i*M*s and i*SD*s within the waves is depicted in Table 3. For both i*M*s and i*SD*s, all correlations were high (i.e., above .50, except for the Week 1-3 correlations for the i*SD*s of rumination [.48] and positive reappraisal [.42] in Wave 1). This generally indicated a high stability of both aggregated means and variability indices across weeks. That is, individuals were stable in their ER strategy use across the three weeks within each wave, including both average use and amount of variation. Descriptively, stabilities were stronger for i*M*s than i*SD*s, and stronger for successive weeks.

Within-wave Internal Consistency

The internal consistency of the i*M*s was α = .80 in Wave 1, and .82 in Wave 2. This indicates that individuals used all five strategies to a relatively similar degree within the two waves (e.g., individuals who engaged strongly in reappraisal also engaged strongly in the other ER strategies). The internal consistencies of the i*SD*s were .88 at both waves. Thus, individuals varied in their strategy use to a relatively similar degree within the two waves (e.g., individuals varied strongly from occasion to occasion in their use of reappraisal also varied strongly in their use of the other ER strategies). This may indicate an underlying ER factor that drives how individuals use ER strategies in daily life.

Long-term Stability (Re-Test Correlations Between Waves)

The stability of the i*M*s and the i*SD*s across the two waves is depicted in Table 4. The stability of the i*M*s was high (ranging from .68 for acceptance to .78 to rumination). Similarly, the stability of the i*SD*s was high (ranging from to .64 for acceptance to .71 for rumination and reappraisal). These results show that individuals used the ER strategies in a similar fashion in Wave 1 as in Wave 2, indicating stable density distributions across one year. These results remained unchanged when partialing the i*M*s out of the i*SD*s (linear and quadratic, see Table 4). That is, stabilities of the i*SD*s were independent from the stabilities of the means. In comparison, the stabilities of trait reports of ER were somewhat lower. However, especially in the case of acceptance, this may be the result of less reliable measurement (internal consistency) within each wave.

Within-wave Correlations between i*M*s and Trait Means

The correlations between the i*M*s and the traditional trait measures of ER were small to medium sized in both waves. In Wave 1, correlations were $r = .40$ for rumination, .39 for positive reappraisal (both *p*s < .01), and .18 for acceptance ($p < .05$). In Wave 2, correlations were $r = .33$ for rumination, and .23 for positive reappraisal, and .27 for acceptance (all ps < .01). This indicates that aggregated states and traditional trait scores measure partly overlapping and partly independent aspects of ER.

Discussion

Using data from a longitudinal study, we investigated the reliability (internal consistency and stability) of emotion regulation (ER) density distributions within as well as across two waves of experience sampling spanning a time interval of approximately one year. For each of the five ER strategies, aggregated means (i*M*s) and within-person variability indices (i*SD*s) showed high within-wave stability and high between-wave stability (re-test correlations). These results indicate that ER strategy use, including the average tendency as well as the amount of variation, are trait-like characteristics that can reliably be captured using intensive longitudinal research and parameters of density distributions. Descriptively, i*SD*s tended to be less stable than i*M*s. This is in line with previous research and likely due to a smaller amount of relative true variance (Schmiedek, Lövdén, & Lindenberger, 2009).

The two parameters of the density distributions, i*M*s and i*SD*s, were internally consistent across the five strategies within the waves. This shows that individuals tend to be rather consistent in their use of ER strategies in terms of intensity and variability, regardless of the specific strategy. Some individuals used strategies generally more intensely than others, and some were generally more variable in their strategy use. This could indicate that the five strategies reflect individuals' overarching tendency to engage in ER (although rumination descriptively was not as strongly associated with the other strategies).

Given the recent interest in using aggregated states of ER and within-person ER variability indices as between-person differences characteristics (Blanke et al., 2019; Eldesouky & English, 2018), it is reassuring that these indices are indeed reliable. More generally, our findings represent an important step in establishing ER density distributions as reliable between-person characteristics. As in research on personality traits, the focus of ER research has so far been on the average behavioral tendencies, that is, whether individuals use strategies more or less. However, current research underlines that the adaptive use of ER strategies depends on the situation (Haines et al., 2016). As Aldao et al. (2015) highlighted, variability can be an indicator of an adaptive form of flexibility, if this variability is a reaction to shifting contextual demands and shifting goals. Together, our results encourage the use of ER density distributions in future research.

The associations between the aggregated state means and trait means were significant, but small to medium in size. That is, although both aggregated states and traditional trait measures captured average behavioral tendencies, the information that both measures contain seems to be partly distinctive. This may be due to the different sources of information that one relies upon when responding to these two types of measures (Robinson & Clore, 2002). Additionally, these associations depend on the conceptual overlap of the state and trait measures and their internal consistencies. For example, for the strategy acceptance, the low correlation between trait and state may in part be due to the low reliability of the trait measure. Also, the trait measure captures acceptance of situations, whereas the state measure captures acceptance of both situations and feelings. In previous research, associations between aggregated state ER and trait ER ranged from non-significant small correlations (e.g., Brockman et al., 2017) to medium or high positive correlations (e.g., Kashdan & Steger, 2006). Future research examining the reasons for convergence or discrimination between traditional ER trait and state measures is thus necessary.

We also need a better understanding of the differential predictive value of traditional trait and aggregated state measures in the case of ER. In this way, we might identify occasions at which traditional trait assessment (which is generally more economical) may suffice, and occasions at which it is important to use information obtained from density distributions. In trying to explain variability and using variability indices to predict other outcomes, it is further important to keep in mind that i*M*s and i*SD*s are statistically dependent. Theoretical models of their dependence, and methods that control for such dependencies are thus needed (see, e.g., Mestdagh et al., 2018; Schmiedek et al., 2009).

A limitation to current ESM research in general is the lack of validated measures to assess constructs at the state level (Brose, Schmiedek, Gerstorf, & Voelkle, 2019). With regard to ER, this means that the selection of strategies within a given study is often somewhat arbitrary. This was also the case in our study. At both the trait and state level, we selected frequently studied strategies, which are strategies that regulate negative emotions, and did not include strategies that deal with positive events (e.g., savoring). Furthermore, we focused on cognitive (attention- and appraisal-focused) strategies, which may have led to a relatively high internal consistency of the strategy use. In future studies, sampling more diverse strategies would be desirable.

In addition, we assessed each ER strategy with one item each, as is usual in research on state ER (e.g., Brans et al., 2013). However, this approach does not allow for the estimation of within-person reliability and, relatedly, the adjustment for measurement error. In the future, we would thus ideally measure each strategy with multiple items. Researchers, however, must strike a balance between optimal measurement and participant burden. A related concern is sample selectivity. In the present study, longitudinal sample dropout was in the expected range, and participants who completed both waves were comparable to dropouts on characteristics such as age and gender. However, a lower level of education was related to a higher likelihood to quit participation after T1, which could be a consequence of participant burden of our ESM procedure.

In line with previous work in the field of personality psychology (Fleeson, 2001) and in the field of emotion regulation (e.g., Brans et al., 2013), our ESM measures of emotion regulation do not refer to states in a narrow sense, but to behavior during time frames. We chose this approach to capture emotion regulatory efforts, which can be fleeting, potentially meaning they are unlikely to be present at the exact random sampling moments given they are not based around emotional triggers. Possible downsides of this approach may be short-term retrospective biases, and demand characteristics (i.e., participants may feel that they should have regulated their emotions in certain ways throughout the last hours).

Moving forward, we as researchers should provide a rationale for the selection of state ER strategies in our research, while considering the psychometric properties of the measurement instruments that we use. Our present results suggest that ER density distributions (means and variability) can represent reliable between-person characteristics. Such ER density distributions may be useful in fostering an understanding for ER flexibility, as current theory points to the importance of ER variability as prerequisite for flexibility (Aldao et al., 2015). Our own research provides initial evidence that variability in the use of certain strategies (within-person variability) alone is not highly predictive of well-being, indicating that variability may not equal flexibility (Blanke et al., 2019). We thus believe that important next steps are to investigate why some individuals are more variable than others in their ER strategy use, and what reliable individual differences in ER variability represent, to then use this information in the prediction of future behavior and well-being.

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Table 1
Descriptive Information

	State					Trait	
	i*M* (*SD*)	Min–Max i*M* Percentiles	i*SD* (*SD*)	Min–Max i*SD* Percentiles	ICC	*M* (*SD*)	Min–Max *M* Percentiles
Wave 1							
1. Rumination	1.47 (0.95)	0.00–4.17 0.74/1.41/2.16	1.29 (0.47)	0.00–2.34 0.95/1.30/1.60	0.32	2.52 (0.80)	1.00–5.00 2.00/2.50/3.00
2. Reappraisal	2.42 (1.46)	0.00–5.98 1.19/2.49/3.38	1.27 (0.54)	0.00–2.74 0.89/1.19/1.64	0.53	3.13 (0.90)	1.50–5.00 2.50/3.00/3.75
3. Acceptance	3.11 (1.25)	0.27–6.00 2.43/2.96/4.00	1.41 (0.52)	0.00–2.63 1.04/1.33/1.79	0.41	2.77 (0.70)	1.25–5.00 2.25/2.75/3.25
4. Reflection	2.88 (1.31)	0.36–6.00 1.98/2.93/3.62	1.30 (0.51)	0.00–2.62 0.89/1.25/1.71	0.46		
5. Distraction	2.22 (1.28)	0.03–5.95 1.25/2.20/2.99	1.33 (0.51)	0.16–2.73 0.98/1.26/1.65	0.44		
Wave 2							
1. Rumination	1.52 (1.08)	0.00–5.17 0.65/1.35/2.20	1.22 (0.50)	0.00–2.56 0.88/1.22/1.55	0.39	2.52 (0.76)	1.00–4.75 2.00/2.50/3.00
2. Reappraisal	2.17 (1.47)	0.01–6.00 1.01/2.00/3.21	1.18 (0.54)	0.00–2.81 0.80/1.10/1.50	0.56	3.11 (0.87)	1.00–5.00 2.50/3.25/3.75
3. Acceptance	2.99 (1.39)	0.07–5.98 2.29/2.97/3.92	1.36 (0.57)	0.12–2.82 0.97/1.30/1.75	0.47	2.79 (0.72)	1.25–4.50 2.25/2.75/3.25
4. Reflection	2.71 (1.46)	0.07–6.00 1.56/2.73/3.81	1.25 (0.54)	0.00–2.54 0.82/1.21/1.56	0.53		
5. Distraction	2.10 (1.38)	0.00–5.83 0.91/2.09/3.02	1.21 (0.53)	0.00–2.64 0.87/1.13/1.54	0.52		

Note. There were no trait measures for reflection and distraction.
M = mean*, SD* = standard deviation, i*M* = within-person mean*,* i*SD* = within-person *SD*, ICC = intra-class-correlation.

Table 2

Correlations Between Strategies

	State i*M* and i*SD*					Trait *M*	
	1.	2.	3.	4.	5.	2.	3.
Wave 1							
1. Rumination	*.34***	.10	<.01	.01	.39**	-.18*	.14
2. Reappraisal	.42**	*.03*	.46**	.81**	.73**		.30**
3. Acceptance	.49**	.72**	*-.05*	.63**	.47**		
4. Reflection	.40**	.73**	.76**	*-.31***	.60**		
5. Distraction	.54**	.67**	.64**	.53**	*.13*		
Wave 2							
1. Rumination	*.33***	.26**	.14	.21**	.50**	-.06	.23**
2. Reappraisal	.43**	*.02*	.35**	.81**	.71**		.26**
3. Acceptance	.50**	.59**	*.06*	.59**	.41**		
4. Reflection	.45**	.76**	.79**	*-.14*	.67**		
5. Distraction	.59**	.69**	.57**	.53**	*.23***		

Note. There were no trait measures for reflection and distraction. *M* = mean, *SD* = standard deviation, i*M* = within-person mean, i*SD* = within-person *SD*. State correlations: i*M* correlations above diagonal; *iM-iSD* correlations in the diagonal, i*SD* correlations below diagonal.
** $p < .01$, * $p < .05$.

Table 3
Within-Wave Stability Estimates: Pearson Correlation Coefficients

	i*M*			i*SD*		
	Week 1-2	Week 2-3	Week 1-3	Week 1-2	Week 2-3	Week 1-3
Wave 1						
Rumination	.78	.81	.67	.54	.66	.48
Reappraisal	.88	.92	.81	.60	.75	.42
Acceptance	.77	.90	.73	.57	.80	.51
Reflection	.85	.91	.80	.64	.73	.55
Distraction	.86	.91	.79	.61	.72	.52
Wave 2						
Rumination	.83	.88	.81	.58	.76	.58
Reappraisal	.90	.95	.88	.68	.80	.64
Acceptance	.88	.92	.83	.63	.65	.62
Reflection	.92	.93	.88	.56	.75	.61
Distraction	.91	.94	.88	.65	.75	.61

Note. i*M* = within-person mean, i*SD* = within-person SD. In Wave 2, within-wave stability for Week 2-3 and Week 1-3 only rely on 152 instead of 153 persons, as one person only provided answers in the first two weeks.
All *p*s < .01.

Table 4

Between-wave Stability Wave 1 to Wave 2 Across Weeks: Pearson Correlation Coefficients

	i*M*	i*SD*	Residualized i*SD* (linear)	Residualized i*SD* (linear+quadratic)
Rumination	.78	.71	.72	.77
Reappraisal	.71	.71	.71	.73
Acceptance	.68	.64	.64	.68
Reflection	.69	.67	.69	.72
Distraction	.72	.68	.68	.72

Note. i*M* = within-person mean, i*SD* = within-person SD. Residualized i*SD* = i*M*s partialed out of iSDs (linear / quadratic).

All *p*s < .01.