

Usually, I don't ruminate, only from time to time: the
predictive value of trait and state measures of
rumination for the intensity of affective states

TUDOMÁNYOS DIÁKKÖRI DOLGOZAT

Hann Flóra

Pszichológia MA

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témavezetők:

Dr. Polner Bertalan

Rónai Levente



BUDAPESTI MŰSZAKI ÉS GAZDASÁGTUDOMÁNYI EGYETEM

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Abstract

Emotions and their regulation are essential in adapting to our environment. Individuals differ in their ability to regulate emotions, and this ability fluctuates over time. Repeated measures designs appear suitable to capture this variability within individual.

Rumination is the cognitive process of passively dwelling on negative feelings and their consequences. Recent results suggest only a weak correlation between state and trait rumination. Also, increased state (but not trait) rumination is associated with higher emotional reactivity, the emotional reactions experienced in response to a negative occurrence. However, the temporal, within-person examination of rumination may predict emotional reactivity even more accurately.

This study aims to confirm that state rumination is a stronger predictor of emotional reactivity than trait rumination. We also investigated the association between state and trait rumination.

247 individuals provided data for 28 days in an experience sampling method (ESM) study. They received 8 short questionnaires daily, assessing their momentary affective states, emotion regulation, and perceived stress. 14265 observations were obtained, then analyzed using mixed-effects models.

Results suggested that state, mean state, and trait rumination have independent predictive validity for emotional reactivity. However, the magnitude of effects overlapped, thus their importance could not be ranked. But when considering negative affect regardless of stress, mean state rumination was the strongest predictor. It can be considered an indicator ‘halfway between’ trait and state measures, possibly combining advantages of both, thereby holding the best predictive value.

We found only a moderate positive correlation between trait and state rumination. Psychometric and contextual differences could account for this result, and the different self-report techniques tapping different sources of information.

Our findings provide insight into the within-individual dynamics of emotion regulation and their relationship affectivity, overcoming some limitations of the common trait approach. They corroborate the need to re-evaluate the traditional measurement of psychological constructs. Our findings also have clinically relevant implications for the personalized prediction of emotional responses to stress through self-report tools applicable in everyday contexts.

1. Introduction

1.1. Emotion and Emotion Regulation

As crucial as emotions may be to human functioning, there remains a debate concerning their nature and mechanisms (J. J. Gross, 2015). There is consensus, however, that they play an essential role in adapting to our ever-changing environment and overcoming our challenges. Emotions may signal danger and trigger automatic responses to protect ourselves (LeDoux, 1995), or they may guide us in situations by helping us appraise others' attitudes toward us, thereby affecting our interactions with them (Frijda, 1986). A widely agreed-upon definition states that *emotion* (e.g., happiness) refers to certain states that are composed of subjective experience (e.g., experiencing happiness), expressive behavior (e.g., smiling), and peripheral physiological responses (e.g., lowered heart rate, Steptoe et al., 2005) (J. J. Gross & Feldman Barrett, 2011). Along these lines, emotions activate a coordinated set of response tendencies on behavioral, experiential, and physiological levels that influence how we act upon challenges and opportunities that arise (J. J. Gross, 2002). However, emotions do not force us to act in specific ways but only make us more likely to do so (J. J. Gross, 2002). This allows us to regulate them, which may be needed for healthy functioning in certain situations, while in others, experiencing a strong wave of emotions may be adaptive.

Emotion regulation has been the focus of research for over a century, dating back to Freud's work on psychological defenses (1937). Together with the study of stress and coping (Lazarus & Folkman, 1984), these efforts laid the groundwork for the modern research domain of emotion regulation emerging in the 1990s (Campos et al., 1989). Emotion regulation refers to the attempt to influence when, how and which emotions we experience and express (J. J. Gross, 1998). Regulating an emotion affects the response tendencies mentioned above: it may change the latency, magnitude, duration, or offset of the subjective experience, expressive behavior, and physiological response involved in that emotion (R. A. Thompson, 1990). For example, as a result of effective emotion regulation, one may be able to reduce their heart rate or their experience of distress, or exhibit fewer signs of fear when facing a terrifying situation.

1.1.1. *The process model of emotion regulation*

In an attempt to organize the variety of emotion regulation strategies in response to an endless combination of emotions, situations, and regulatory goals, J. J. Gross (1998) distinguished these strategies along the timeline of the unfolding emotion response in his

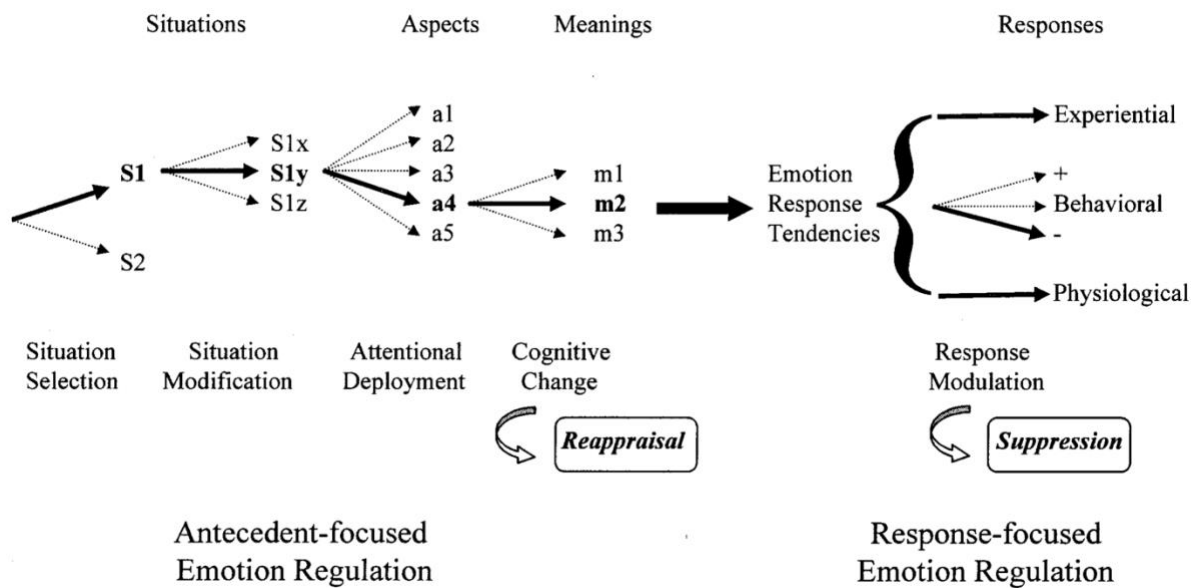
process model of emotion regulation. The model claims that the primary difference between emotion regulation strategies lies in *when* they impact the emotion generation process.

On the first level, the model differentiates between *antecedent-focused* and *response-focused* strategies. Antecedent-focused strategies include regulatory actions taken before the onset of emotion response tendencies, and before the changes they cause in behavior, experience, and physiology. An example of antecedent-focused regulation is declining a daunting job interview request, thereby avoiding the situation itself (McRae & Gross, 2020). On the other hand, response-focused strategies refer to things we do once the emotion response tendencies have been activated, and changes are underway (J. J. Gross, 1998). An example of this could be reinterpreting the interview as an opportunity or a challenge rather than a threatening and intimidating situation (McRae & Gross, 2020).

On the second level, strategies can be organized more specifically based on the point of the emotion-generative process at which they intervene, as illustrated by Figure 1 (J. J. Gross, 1998). The first stage is *situation selection* (e.g., avoidance; denoted in Figure 1 by the solid line toward S1 rather than S2), which entails regulating by approaching or avoiding certain places, people, or things – like declining the interview in the example above. *Situation modification* (e.g., direct request) occurs after selecting a situation that we later want to alter so as to modify its emotional impact (creating either S1x, S1y, or S1z in Figure 1). Continuing with the job interview example, this could mean requesting to arrange the interview online, so we can do it from the comfort of our home and thereby reduce anxiety. *Attentional deployment* (e.g., distraction or rumination) refers to consciously selecting a specific aspect (e.g., a4 in Figure 1) of the situation to focus on, for example, distracting ourselves by glimpsing at our notes instead of the interviewer's face (McRae & Gross, 2020). Next, we can employ *cognitive change* (e.g., reappraisal or acceptance) to choose which of the possible meanings (e.g., m1, m2, m3 in Figure 1) to attach to the selected aspect of the situation. For example, we can reappraise the situation by telling ourselves that the interviewer is not responsive enough because he was likely coached not to give overt positive feedback. Finally, by *response modulation* (e.g., expressive suppression), we can influence the emotion response tendencies (like decreasing expressive behavior in Figure 1) once they are underway. For example, we can suppress a disappointed facial expression after an unsuccessful interview.

Figure 1

A process model of emotion regulation.



Note. Based on this model, there are five points in the emotion generation process where emotion may be regulated: (1) selection of the situation, (2) modification of the situation, (3) deployment of attention, (4) change of cognitions, and (5) modulation of experiential, behavioral and physiological responses. The first four are antecedent-focused, and the fifth is response-focused. The heavy lines show an example of regulation at each point. Reprinted from “Emotion Regulation in Adulthood: Timing Is Everything,” by J. J. Gross, 2001, *Current Directions in Psychological Sciences*, 10, p. 215. Copyright 2001 by Blackwell Publishers.

1.1.2. Emotion regulation effectiveness and adaptivity

Besides the process model of emotion regulation, another approach to distinguish between strategies is based on their effectiveness and adaptivity. The effectiveness of a strategy is indicated by the success of achieving an emotion regulation goal, while adaptivity is defined in terms of links with better long-term health outcomes (McRae & Gross, 2020).

Research in the past century suggested that certain strategies are inherently more adaptive than others (Elkjær et al., 2022). Reappraisal and problem-solving were regarded as adaptive, for example, whereas rumination and suppression were considered maladaptive (Aldao & Nolen-Hoeksema, 2010; J. J. Gross & John, 2003; McRae & Gross, 2020). More recent theories, however, propose that the adaptivity of strategies may not be inherent but rather depend on contexts, like the person using them, the goal to be achieved, or the different aspects of stressors (Bonanno & Burton, 2013). Nevertheless, the literature still distinguishes between *putatively* adaptive and *putatively* maladaptive strategies to this day, as an individual’s habitual use of certain strategies is associated with different long-term functioning or even

psychopathology (Aldao & Nolen-Hoeksema, 2010, 2012). Such associations highlight emotion regulation's critical role in mental health (Berking & Wupperman, 2012; J. J. Gross & Muñoz, 1995).

One of the most extensively researched emotion regulation strategies is rumination, a cognitive process that involves repeatedly and passively dwelling on negative feelings and their consequences (Nolen-Hoeksema et al., 2008). Although generally considered a maladaptive strategy, it is debated whether rumination also has adaptive components (Joormann et al., 2006). In their recent article, Watkins and Roberts (2020) identified several adverse consequences of rumination. A negative effect of rumination is intensifying psychological stress responses and symptoms of psychopathology by extending and amplifying negative affective states and interfering with proactive cognition and behavior. The authors propose a model describing how rumination develops from dwelling on negative thoughts into cognitive biases. This model includes disturbed information processing and poor executive functioning, which then maintain rumination. All in all, there is evidence supporting that increased state (but not trait) rumination is associated with higher emotional reactivity (Hilt et al., 2015), that is, the emotional reactions experienced in response to an external occurrence, such as a specific event or stimulus (R. J. Thompson et al., 2012).

1.1.3. Emotional reactivity

As mentioned above, emotional reactivity captures the affective response elicited by an external occurrence, such as a negative stimulus or everyday stressors (R. J. Thompson et al., 2012; see Figure 2). Increased emotional reactivity is a robust correlate for poor mental health in general, and it is associated with conditions such as affective disorders and psychosis (Myin-Germeys et al., 2001, 2003), depression, and suicidality (Shapero et al., 2019).

Also, emotional reactivity can be regarded as an indicator of effective emotion regulation: in a series of experience-sampling (ESM) studies, Blanke et al. (2020a) investigated the adaptivity of emotion regulation variability in daily life. They assessed the downregulation of negative affect as a measure of the effectiveness of emotion regulation, and demonstrated the adaptiveness of the variability of emotion regulation. However, they did not account for changes in the context where emotion regulation occurs. They argue that future research should address this problem with more event-contingent designs to ensure that variability in emotion regulation reflects context-dependent flexible behavior. Here, we build on this recommendation and use emotional reactivity as an indicator of the effectiveness of emotion regulation by

including perceived stress in our measurements, which reflects an aspect of the environment and context.

Notably, Pe et al. (2015) employed an elegant way to measure emotional reactivity in their study examining the relationship between working memory updating and emotional reactivity and recovery. To assess emotional reactivity, they used unpleasant film clips to elicit negative emotions in their participants. According to their analyses, participants' negative emotions generally increased relative to their baseline levels after watching negative clips. These results demonstrate that negative affect is predicted by perceived unpleasantness, representing emotional reactivity. Moreover, the differences in the ability to update emotional information in working memory accounted for individual differences in emotional reactivity. This evidence of individual differences is also a relevant feature of the work of Pe et al. (2015) for the present study, where we use emotional reactivity as an indicator of how individuals vary in regulating their emotions.

As such, emotional reactivity seems an appropriate indicator to measure the effectiveness of emotion regulation. Besides the negative affect component – which people are generally motivated to reduce (Riediger et al., 2009) – it includes the unpleasantness of the last event experienced, thereby incorporating context as a factor. Based on Myin-Germeys et al. (2003), emotional reactivity can be operationalized as the statistical relationship between negative affect and perceived stress. The current study follows this approach.

Figure 2

An illustration of emotional reactivity.



Note. Emotional reactivity can be operationalized as the statistical relationship between negative affect and perceived stress.

1.2. Psychological differences between individuals vs. changes within them

The effectiveness of emotion regulation was considered a stable trait within individuals for most of the history of its research (Houben et al., 2015; Kashdan et al., 2015). Lately, however, it has been increasingly acknowledged as a dynamic characteristic that has variability not only between but also within individuals (Aldao et al., 2015). Generally speaking, the traditional investigation of psychological constructs has been based on analyzing data collected from large samples and generalizing results to the individuals of the population (Hamaker, 2012). This has been done by characterizing the sample using summary statistics such as means and variances. However, in order to be able to generalize processes observed in the sample to each individual of the population, we have to assume that those processes are *ergodic* (Molenaar, 2004). The ergodic theorem in mathematics is concerned with the generalizability of statistical phenomena across levels of analysis. It posits that generalization is appropriate only when the structures of variation in the population and within individuals are equivalent. Consequently, results observed in a sample can only be adequately generalized to individuals if the distribution of variables in the population reflects the distribution within an individual.

Ergodicity would imply that all individuals have the same average over time and are characterized by the same amount of within-person variance (Hamaker, 2012). Nonetheless, we can intuitively concede that these conditions of ergodicity will not hold in psychological phenomena, which typically have an individually variable nature. An example of an inferential error that violates the concept of ergodicity is Simpson's paradox (Simpson, 1951). Hamaker (2012) illustrates this with the example of the correlation between typing speed and the number of typos. If we analyze such data at the group level (i.e., cross-sectionally), we will likely find a negative relationship, whereby more experienced and skilled people will type faster and make fewer mistakes. However, this association will not hold at the individual level (i.e., longitudinally): when a given individual types faster compared to their average, they will likely make more mistakes relative to their performance when typing slower. This implies a positive within-individual relationship that is in stark contrast with the negative correlation between individuals, illustrating Simpson's paradox (Simpson, 1951). Therefore, an ecological fallacy (when statistical inferences derived from groups are inappropriately generalized to individuals) would be committed if assuming that the relationship observed at the group-level mirrors what happens within each individual (W. S. Robinson, 2009).

Beyond the intuitive example mentioned above, there is increasing empirical evidence underlining the importance of within-person variability and the problem of group-to-individual generalizability. In a comprehensive study, Fisher et al. (2018) analyzed data from six repeated-

measure design studies assessing several constructs (e.g., affective states, avoidance, and heart rate) to compare interindividual and intraindividual variation. Their results showed some consistency in mean estimates between groups and individuals across constructs and data collection paradigms. However, the intraindividual variance was two to four times larger than the interindividual variance in a given construct. For example, while someone may show high variability in their depressed mood over time, the overall variability of the sample would be much smaller.

Additionally, the variability of the correlations between affective states within individuals was also over two times larger than that of correlations between individuals. To illustrate this, we could imagine that in a certain individual, fear may relate positively to avoidance, while in others, fear could be unrelated to avoidance or may even show a negative association. At the between-person level, however, one may observe a positive correlation between fear and avoidance, meaning that those who tend to experience more fear are also more likely to demonstrate avoidance. Only taking into account this positive relationship at the group level may lead to falsely generalizing that fear leads to avoidance. To make accurate claims about individuals, however, we need to study within-individual associations. (For an illustration of the intraindividual and interindividual relationships between fear and avoidance, see the right panel of Figure 1 in Fisher et al., 2018.) These conclusions call attention to the fact that by aggregating across subjects, researchers in human sciences may overestimate the generalizability of their results. Therefore, the phenomena in question must always be explicitly tested for ergodicity to prevent inaccurate inferences.

An extensive study by Enkavi et al. (2019) adds to the literature which argues that certain psychological constructs, such as self-regulation, in this case, may not be conceptualized as traits. They assessed the test-retest reliability of different measures of self-regulation, including behavioral tasks, which are rarely tested for such psychometric properties. Their results indicated that behavioral tasks assessing self-regulation have low test-retest reliability in contrast with self-report measures (e.g., surveys). This implies high within-individual variability in the behavioral measures of self-regulation, thereby questioning their suitability for capturing trait constructs¹. Furthermore, this high within-subject variability suggests that self-regulation has a dynamic nature that fluctuates over time within individuals. All in all, this study by Enkavi et al. (2019) sheds light on the significance of the appropriate conceptualization

¹ We also note that poor test-retest reliability of behavioral tasks might be due to low between-person variability (Hedge et al., 2018).

and operationalization of psychological traits and states, thereby accurately distinguishing between them.

Correspondingly, some studies indicated that trait- and state-like measures of emotion regulation strategies show relatively little correspondence. For instance, Hilt et al. (2015) found no significant correlation between state and trait rumination in their laboratory study. Similarly, Brockman et al. (2017) found weak to non-existent correlations between daily and trait measures of emotion regulation. Although displaying a slight trend toward significance, trait-like measures of emotion regulation strategies (e.g., ‘I tend to keep my emotions to myself’) generally held little to no predictive value for the daily use of the same strategies (e.g., ‘In the past hour, I’ve been keeping my emotions to myself’). Even though this study measured daily emotion regulation use in addition to retrospective trait measures – thereby eliminating most problems associated with self-report measures – the fact that participants were only assessed at the end of each day could have introduced some recall bias. Furthermore, contextual factors outside of ‘the person’ were not studied, so as a result, the authors were unable to delineate specific contextual influences affecting the dynamics of emotion regulation. This would be a crucial aspect to investigate, considering that even though some strategies may appear more adaptive or maladaptive, their adaptiveness will ultimately depend on the context (J. J. Gross, 2015). Moreover, the generalizability of the findings of Brockman et al. (2017) is constrained by the use of a sample of university students. All in all, the results of this thought-provoking study by Brockman et al. (2017) can be interpreted as evidence of the differential predictive validity of trait and state measures in emotion regulation. However, a single study does not allow drawing firm conclusions, so we aimed to further corroborate these inferences in a different, more heterogeneous sample (recruited from the community), revising the methodology to minimize recall bias and allow for investigating contextual nuances.

In her rationale for taking research to the within-person level, Hamaker (2012) argues that psychological processes should be studied as they are occurring in daily life: within the individual, over time. This can be done using an intensive longitudinal sampling method that yields data from several measurement points for each participant. The experience sampling method (ESM; Csikszentmihalyi & Larson, 2014; Myin-Germeys et al., 2009, 2018) has proven to be a suitable tool for intensive time-series data collection, while the development of statistical tools such as mixed-effects models allows for the analysis of such nested-structure datasets (DiPrete & Forristal, 1994; Hamaker, 2012; Snijders, 2011). These tools provided the basis for the methodology of the present research.

1.3. The present research

Several aspects of the relationship between trait and state measures of emotion regulation remain unclear, such as the difference in their relationship with affective states and the influence of contextual factors on their variability. In the present study, we aim to contribute to delineating the nature of these measures by investigating how strongly different measures of rumination predict emotional reactivity in daily life.

Based on the evidence summarized above (e.g., Brockman et al., 2017; Hilt et al., 2015), we assume that trait indicators of rumination will not display a strong correlation with momentary rumination aggregates (Hypothesis 1). Following Pe et al. (2015), we assume that momentary negative affect will be predicted by momentary perceived stress, resulting in the measurement of emotional reactivity.

Since emotion regulation has proven to show significant variability within individuals (Aldao et al., 2015), we hypothesize that momentary rumination use will have a substantial predictive value for emotional reactivity within the same time window (Hypothesis 2a). We also expect that the aggregated mean of these momentary rumination measures will also be associated with emotional reactivity, although not as strongly (Hypothesis 2b). This is a composite indicator of the intensity of all of an individual's momentary rumination during the period of the study. Therefore, it can essentially be considered a trait measure to some degree, however, it incorporates the everyday variability of the process within an individual, thus differing from traditional, self-report trait measures that can be subject to recall bias and lower ecological validity. Accordingly, we expect trait rumination employment to have the lowest predictive value among the three measures for emotional reactivity in daily life (Hypothesis 2c).

Additionally, since rumination is generally regarded as a putatively maladaptive emotion regulation strategy (Aldao & Nolen-Hoeksema, 2010, 2012) we expect rumination measures to have independent predictive values for momentary negative affect, regardless of perceived stress. Based on the reasoning above, we anticipate that these measures will show the same pattern (momentary > average state-level > trait questionnaire) in the prediction of negative affect as in the prediction of emotional reactivity (Hypotheses 3a, 3b, 3c).

2. Methods

2.1. Participants and screening

Hungarian-speaking individuals were recruited from the general population through the press and social media. In the first phase of the study, a cross-sectional baseline assessment was completed by 304 participants (N[female] = 239, Mean[age] = 37.87 years, SD[age] = 12.96 years, Min[age] = 18 years, Max[age] = 82 years; see *Initial sample* in Table 1). To ensure the validity of our data, responses were screened based on completion speed: participants that were too fast (< 7 minutes; Median after screening = 12.83 minutes) were excluded, leaving a pool of 292 individuals. Of this initial pool, 247 individuals (N[female] = 198, Mean[age] = 38.38 years, SD[age] = 12.86 years, Min[age] = 19 years, Max[age] = 73 years; see *Final sample* in Table 1) proceeded to the second, longitudinal phase of the study, which comprised completing a short survey every two hours for up to four weeks (see ESM phase and Design sections for details).

The 247 individuals in the final sample completed a total of 14953 ESM surveys. After filtering surveys that were completed too quickly (< 30 seconds) or too slowly (> 10 minutes; Median after screening = 56 seconds), 14265 observations remained to be included in the statistical analyses (per capita: Median = 45, Obs. Range = 1-197, Theor. Range = 1-224). The demographic characteristics of the samples are reported in Table 1.

To evaluate any potential sampling bias introduced by the screening of participants, we compared observations included and not included in the final analyses. Observations included differed significantly from those not included in terms of education levels (with higher education levels in the former). No other significant differences were detected. The comparison of observations is reported in Table 1.

Participation was voluntary, and participants provided informed consent. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. The study was approved by the United Ethical Review Committee for Research in Psychology, Hungary (reference number: 2020-40).

Table 1*Demographic characteristics of study samples.*

	Initial sample	Observations not included	Final sample	Comparison (not included vs. final)
Size	304	57	247	
Age				$U = 6046.5$, $p = 0.097$
Mean	37.87	35.63	38.38	
Median	35	33	36	
SD	12.96	13.30	12.86	
Range	18 – 82	18 – 82	19 – 73	
Gender				$\chi^2 (2) = 2.271$, $p = 0.321$
Female % (N)	78.62 % (239)	71.93 % (41)	80.16 % (198)	
Male % (N)	21.05 % (64)	28.07 % (16)	19.43 % (48)	
Other % (N)	0.33 % (1)	0 % (0)	0.40 % (1)	
Education				$\chi^2 (5) = 12.628$, $p = 0.027^*$, $V = 0.20$
Primary school or lower % (N)	0.66 % (2)	1.75 % (1)	0.40 % (1)	
Vocational school without high school diploma % (N)	1.97 % (6)	5.26 % (3)	1.21 % (3)	
High school diploma or equivalent % (N)	21.05 % (64)	31.58 % (18)	18.62 % (46)	
Bachelor's or Master's degree % (N)	67.11 % (204)	57.89 % (33)	69.23 % (171)	
Doctorate (PhD) % (N)	6.25 % (19)	3.51 % (2)	6.88 % (17)	
Other % (N)	2.96 % (9)	0 % (0)	3.64 % (9)	
Trait rumination (CERQ rumination subscale)				$U = 7250.5$, $p = 0.724$
Mean	14.21	14.44	14.16	
Median	15	15	15	
SD	4.30	4.13	4.35	
Range	4 – 20	6 – 20	4 – 20	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

2.2. Measurements and design

2.2.1. Cross-sectional phase

The first, cross-sectional phase of the study contained questionnaires assessing trait-level constructs including the Hungarian translation of the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001; Miklósi et al., 2011). This questionnaire measures the tendency to use five adaptive (acceptance, refocusing on planning, positive refocusing, positive reappraisal, putting into perspective) and four less adaptive (self-blame, blaming others, rumination, catastrophizing) strategies. It includes 36 items that have to be evaluated on a 5-point Likert scale ranging from ‘almost never’ to ‘almost always’. Other constructs were measured as well, which are not analyzed in the present paper. Participants also provided demographic information and answered questions regarding their living arrangements and exercise habits.

2.2.2. ESM phase

In the two-hourly surveys, we asked participants to evaluate their momentary affective states on a 6-point Likert-scale ranging from ‘not at all’ to ‘completely’. As positive-valenced affective states, we included (not analyzed in the present analysis) *calm*, *enthusiastic*, *cheerful*, and *active*, whereas the negative states evaluated were *sad*, *afraid*, *unrested*, *angry*, and *irritated*. Items were selected based on the dimensional model of emotions (axes of arousal and valence; Russell, 2003) and previous studies (Brans et al., 2013; Bringmann et al., 2016; Rónai & Polner, in prep.; Wichers et al., 2016).

During each ESM session, participants were asked to evaluate the pleasantness of the most significant event they experienced in the past two hours on a 7-point Likert scale, 1 being ‘not at all pleasant’ and 7 indicating ‘entirely pleasant’. In order to facilitate interpretation, this item was reversed, resulting in ‘event unpleasantness’. In doing so, we aimed to capture perceived environmental stress, since, by the ‘event pleasantness’ item, we essentially measured the *positive valence* of a significant event that occurred recently.

The survey also included six 6-point (1 = ‘not at all’, 6 = ‘completely’) Likert-items evaluating distinct emotion regulation strategies (based on an ESM study by Brans et al., 2013). Items started with ‘In the past two hours...’ and continued with ‘...I calmly reflected on my feelings’ (reflection), ‘...I changed the way I think about what causes my feelings’ (reappraisal), ‘...I talked about my feelings with others’ (social sharing), ‘...I engaged in activities to distract myself from my feelings’ (distraction), ‘...I avoided expressing my emotions’ (expressive

suppression), and ‘...I couldn’t stop thinking about my feelings’ (rumination). In the present study, we only included rumination in our models.

2.2.3. Design

We used *formr.org* (Arslan et al., 2020), a browser-based application for collecting time-series data through an experience-sampling design. Individuals who decided to participate in the study received regular automatic emails from *formr.org* containing a link to the upcoming survey.

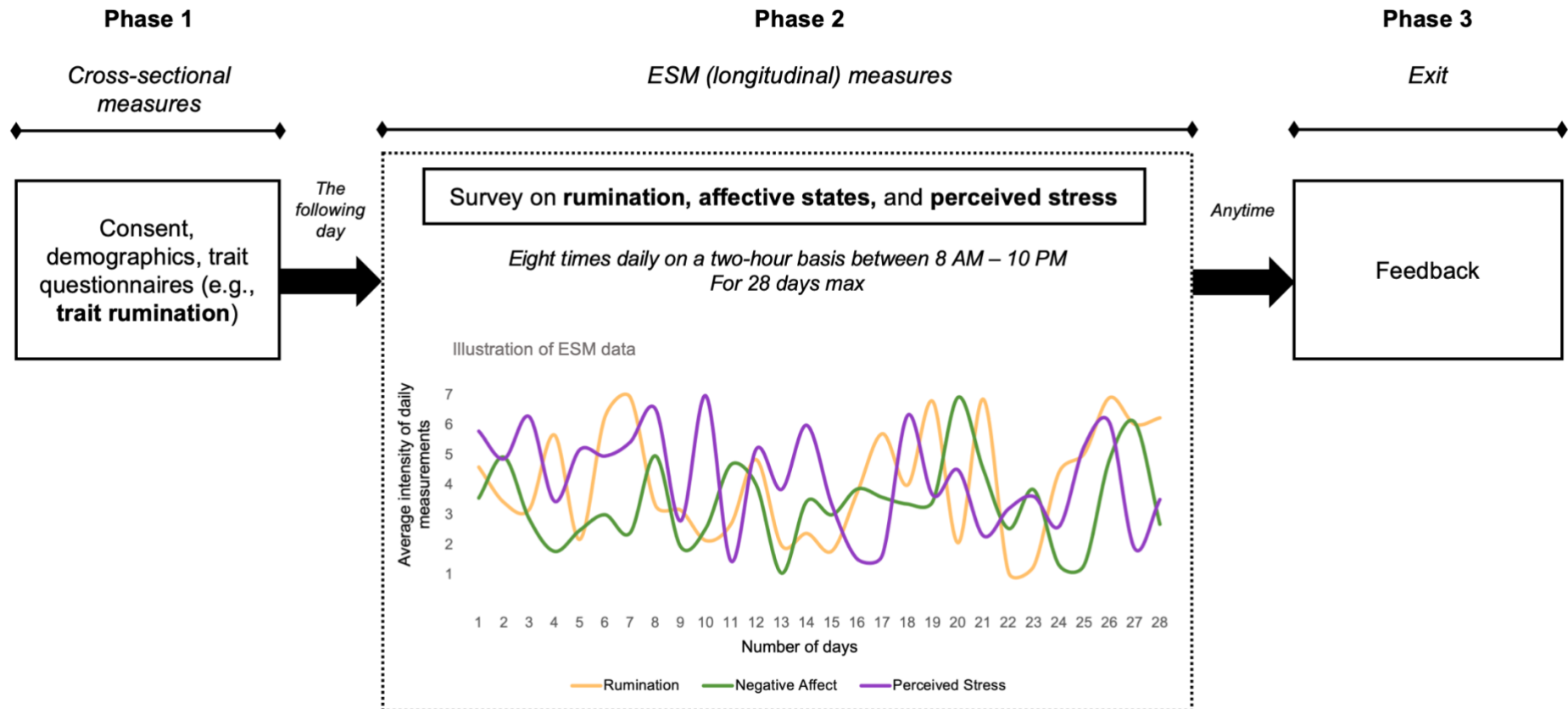
Upon entering the study, participants were asked to complete a survey containing trait-level questionnaires (such as the CERQ) and assessing demographic information. At the end of this section, participants could decide whether they wanted to take part in the ESM phase of the study, starting the following morning. Participants received 8 two-hourly prompts daily between 8:00 AM and 10:00 PM. These short, 5-minute sessions included the surveys mentioned above, related to momentary affective states, perceived stress, and emotion regulation, besides other items not analyzed in the present study.

Every third day, participants also received a 5-minute survey exploring depressive symptoms, stressful events, support, and environmental resources in the past 3 days. This was sent at 6:00 PM and could be completed by 10:00 PM. No other ESM prompt was sent later those days, with the next email arriving at 8:00 AM the following morning. These surveys are not included in the present analysis.

Participants could take part in the ESM phase for up to 28 days but had the option to quit at any point. After a minimum of 7 days of participation, they could choose to receive feedback containing figures about the daily fluctuation of their employed emotion regulation strategies, as well as their negative and positive affective states. The design of the study is depicted in Figure 3.

Figure 3

The design of the study.



Note. After finishing the first, cross-sectional part of the study (Phase I), participants could choose to enter the longitudinal section (Phase II), starting the next morning. This consisted of 8 two-hourly prompts every day including short surveys on momentary affective states, perceived stress, and emotion regulation. Participants could continue for up to 28 days, but could quit at any point (Phase III). Upon request, they received feedback containing figures that showed the daily fluctuation of their negative and positive affective states.

2.3. Statistical analyses

2.3.1. Computation of negative affect scores

To validate the factor structure of the affective states assessed, we used multilevel confirmatory factor analysis with the *lavaan* package (version 0.6-12; Rosseel, 2012) in R (version 4.2.0; R Core Team, 2022). Indices of a model of one within-person and between-person level improved after omitting the item ‘irritated’. Modification indices suggested a significant improvement of fit by including residual covariances between the items ‘angry’ and ‘afraid’ at the within-person level ($Est = -0.148, p < 0.001$). The final model had excellent fit indices ($\chi^2(3) = 38.22, p < 0.001$, CFI = 0.99, TLI = 0.99, RMSEA = 0.03, SRMR[within-person] = 0.01, SRMR[between-person] = 0.04) (see factor loadings in Appendix Table A1). For further analyses, the multilevel factor scores of negative affect were used as defined in this model. The reliability of these factor scores was adequate at the within-person level and excellent at the between-person level ($\omega[\text{within-person}] = 0.77, \omega[\text{between-person}] = 0.91$).

2.3.2. Factor structure of the CERQ rumination subscale

Confirmatory factor analysis was also used to analyze the structure of the CERQ rumination subscale. The one-factor model for rumination demonstrated an excellent fit ($\chi^2(2) = 4.192, p = 0.123$, CFI = 0.99, TLI = 0.99, RMSEA = 0.07, SRMR = 0.02) (see factor loadings in Appendix Table A2) and reliability ($\omega = 0.88$).

2.3.3. Correlation between trait and mean state rumination

Following Brockman et al. (2017), we calculated a correlation coefficient to investigate the association between the trait and state measures of rumination (Hypothesis 1). As our variables were ordinal and not normally distributed, we ran a Spearman correlation analysis in R using the *confintr* package (version 0.2.0; Mayer, 2022).

2.3.4. Mixed-effects modeling

We fitted linear mixed-effects models using the *lme4* in R (Bates et al., 2015) to test the relationship between different measures of rumination and emotional reactivity within and between individuals. As a baseline model (Model 0), we used factor scores of momentary negative affect as a dependent variable and event unpleasantness (perceived stress) as a predictor variable since their statistical relationship represents emotional reactivity (see, e.g., Myin-Germeys et al., 2003).

To test our second and third sets of hypotheses, we extended this baseline model with three measures of rumination and their interactions with event unpleasantness (Model 1). The three measures comprised 1) the CERQ factor score of the rumination subscale as a trait indicator, 2) the indicator of state rumination (within-person centered score on the rumination ESM item), and 3) the typical level of rumination during the study (person-specific mean of the rumination ESM item).

The second set of hypotheses (2a, 2b, and 2c) concerned the incremental validity of rumination measures in terms of predicting emotional reactivity. To test these expectations, we examined the standardized β coefficients, standardized confidence intervals, and p values of the interaction terms between each rumination measure and event unpleasantness in a model predicting negative affect. The third set of hypotheses (3a, 3b, and 3c) was about the incremental validity of each rumination measure in terms of predicting negative affect. Again, we examined the standardized β coefficients, standardized confidence intervals, and p values of the effect of each rumination measure for predicting negative affect.

Both models were detrended for the number of days that passed since enrolling in the study and the assessment session within days, and were adjusted for age and gender. Following past studies (e.g., Hamaker & Grasman, 2015), in order to capture the effects of within-person changes, momentary rumination and event unpleasantness were within-person centered. Furthermore, to improve the computation and interpretation of its main effect (Bauer & Curran, 2005), mean state rumination was grand-mean centered for all analyses.

The models were fitted with random intercepts for each participant and random slopes for event unpleasantness, state rumination, and their interaction. The Restricted Likelihood Method was used for fitting the models. As indicators of goodness of fit, we used the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), marginal (variance explained by fixed effects) and conditional R^2 (variance explained by both random and fixed effects). Based on these indicators, the fit of Model 1 (AIC = 30879.46, BIC = 31061.04, marginal R^2 = 0.424, conditional R^2 = 0.725) improved compared to Model 0 (AIC = 33556.42, BIC = 33639.64, marginal R^2 = 0.111, conditional R^2 = 0.665).

Assumptions of linearity, normal distribution of residuals and random effects, homogeneity of variance, and multicollinearity were tested (see Appendix Figure A1) using the *performance* (version 0.9.1; Lüdtke et al., 2021) and *nortest* (version 1.0-4; J. Gross & Ligges, 2015) packages in R: the leptokurtic distribution of residuals violated the assumption of normality ($D = 0.143$, $p < 0.001$), and log10-transforming the outcome variable (multilevel factor score for negative affect) did not significantly improve the distribution. Recent work

indicated that such models are robust to violations of this assumption (Knief & Forstmeier, 2021). Nevertheless, we used residual bootstrapping (using the *lmeresampler* package in R; Loy & Korobova, 2021) to corroborate the robustness of our findings (see results in Appendix Table A3 and Figure A2). The bootstrapped confidence intervals confirmed the significance of the parameters of Model 1. Furthermore, parametric bootstrapping yielded similar results. All other assumptions for Model 1 were met.

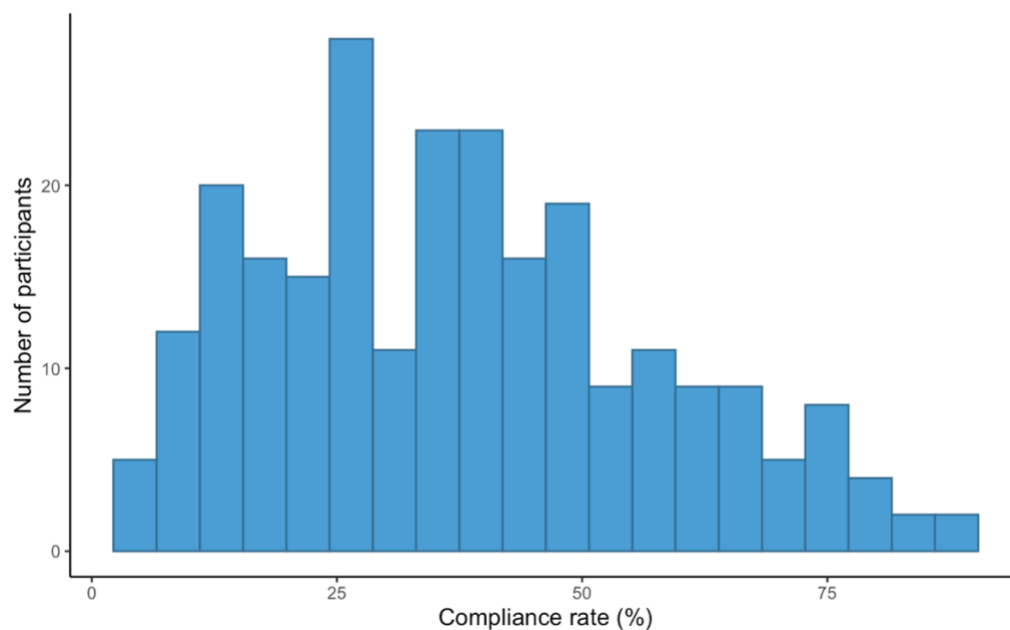
3. Results

3.1. Compliance and descriptive statistics

The ESM compliance rate in the final sample of 247 participants was acceptable (Median = 35.7%, Min = 4.2%, Max = 87.9%, SD = 19.7%, see Figure 4). Descriptive statistics of measures in the ESM phase can be found in Table 2.

Figure 4

The distribution of participants' compliance rates during the course of the study.



Note. Each participant's compliance rate was calculated against the number of days they spent in the study. For example, if a participant enrolled in the study for 10 days, they were sent 8 emails for 10 days, coming to a total of 80 surveys for the entire study. So in this case, the number of completed surveys is divided by 80.

Table 2

Descriptive statistics of emotion regulation, negative affect, and event unpleasantness measures in the ESM phase.

	Mean	Median	SD	Obs. Range	Theor. Range
Emotion regulation					
State rumination	1.63	1	1.21	1 – 6	1 – 6
Mean state rumination	1.63	1.35	0.70	1 – 6	1 – 6
Negative affect*	6.93	5	4.12	7 – 28	7 – 28
Event unpleasantness	3.28	3	1.57	1 – 7	1 – 7

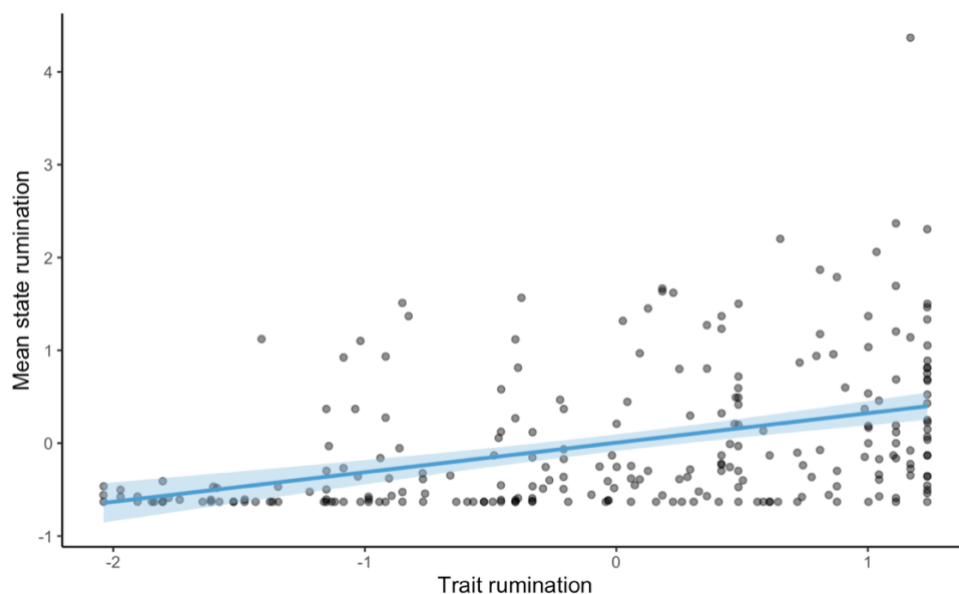
*Raw sum scores of negative affect are displayed. Note that for modeling, scores based on multilevel confirmatory factor analysis were used.

3.2. Correlation between trait and mean state rumination measures

First, we investigated whether a traditional questionnaire-based measure of rumination predicts the level of rumination as assessed in daily life with ESM (Hypothesis 1). The Spearman correlation analysis indicated a moderate positive monotonic relationship between trait and mean state rumination ($r_s(245) = 0.46$, 95% CI [0.36, 0.55], $p < 0.001$), indicating that the measures have some shared variance, although somewhat less than one might expect for self-report measures of the same construct. The association is depicted in Figure 5.

Figure 5

Correlation between mean state and trait rumination.



Note. We used the grand-mean centered aggregated mean of state rumination scores and factor scores of the CERQ rumination subscale.

3.3. Mixed-effects modeling

First, we established that participants demonstrated emotional reactivity in daily life. As shown in the baseline model (Model 0), perceived stress in the preceding two hours had a significant positive effect on momentary negative affect, representing emotional reactivity (see variables and model parameters in Table 3). Age, as well as the number of days spent in the study both significantly predicted negative affect. Specifically, older age and more days spent in the study were associated with lower momentary negative affect.

Additionally, the random intercept demonstrated variance ($\tau = 0.86$), indicating that participants varied in terms of their tendency to experience negative affect. The random slope for event pleasantness also varied ($\tau = 0.04$), showing that there were differences between individuals in emotional reactivity. These two random effects were correlated ($\rho = 0.63$), suggesting that the momentary affectivity of those who average higher in negative affect is more strongly predicted by fluctuations in perceived stress.

Table 3

Results of Model 0 as our baseline model confirming the adequate operationalization of emotional reactivity.

Prediction of negative affect			
Predictors	Standardized β coefficients	Standardized CI	p
Intercept	0.13	0.02 – 0.23	0.017*
Age	-0.09	-0.18 – -0.01	0.032*
Gender [male]	-0.21	-0.42 – 0.00	0.053
Gender [other]	-0.08	-1.25 – 1.09	0.888
Assessment session	0.01	-0.00 – 0.02	0.078
Day	-0.03	-0.04 – -0.02	<0.001***
Event unpleasantness	0.32	0.29 – 0.35	<0.001***

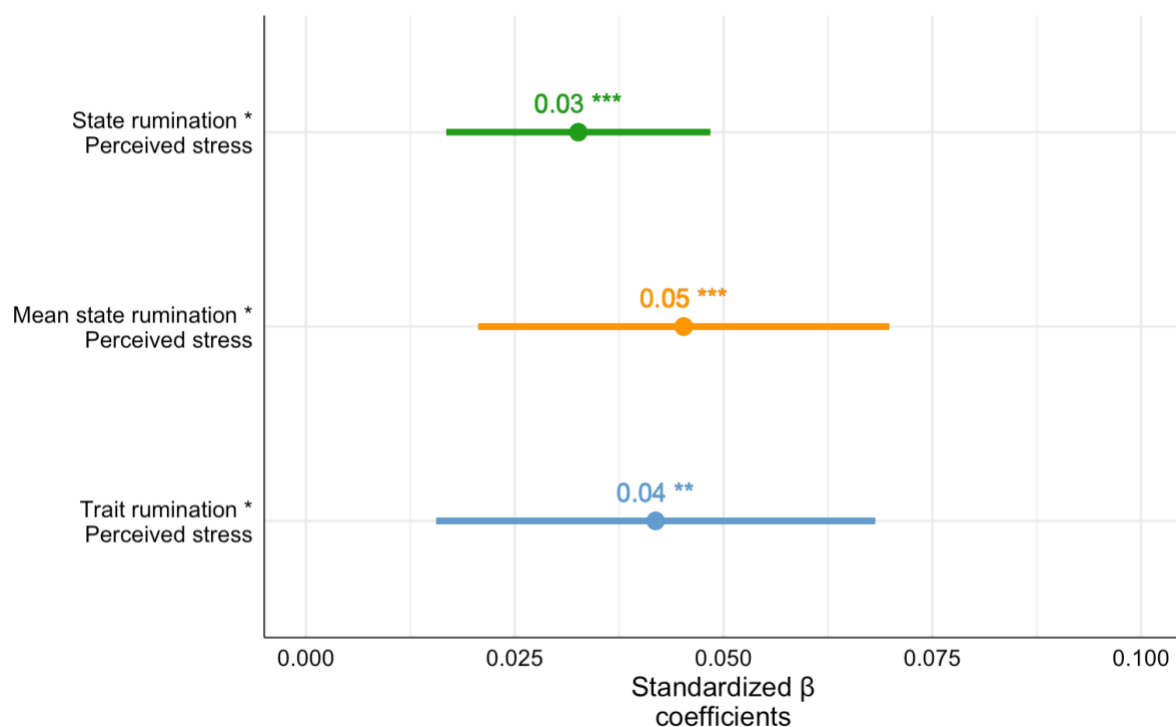
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Random effects	Estimates
σ^2	0.56
T00 id	0.86
T11 event unpleasantness	0.04
ρ_{01} id	0.63

Then, we examined whether some measures of rumination are better than others at predicting emotional reactivity in daily life. More specifically, we expected that the strongest predictor of emotional reactivity will be momentary rumination (Hypothesis 2a), followed by the aggregated mean of these momentary measures (Hypothesis 2b). Lastly, we assumed that trait rumination will be the weakest predictor of emotional reactivity (Hypothesis 2c). Therefore, these three measures of rumination were entered as predictor variables, together with their interactions with perceived stress. All three measures demonstrated significant positive associations with emotional reactivity (with rather small coefficients), however, their standardized confidence intervals highly overlapped (see results in Figure 6 and Table 4). Thus, all three measures have distinct incremental validities in terms of predicting emotional reactivity, but we cannot declare any one measure a better predictor than others.

Figure 6

Standardized β coefficients indicating the moderation of emotional reactivity by different measures of rumination.



Note. Error bars show 95% confidence intervals. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

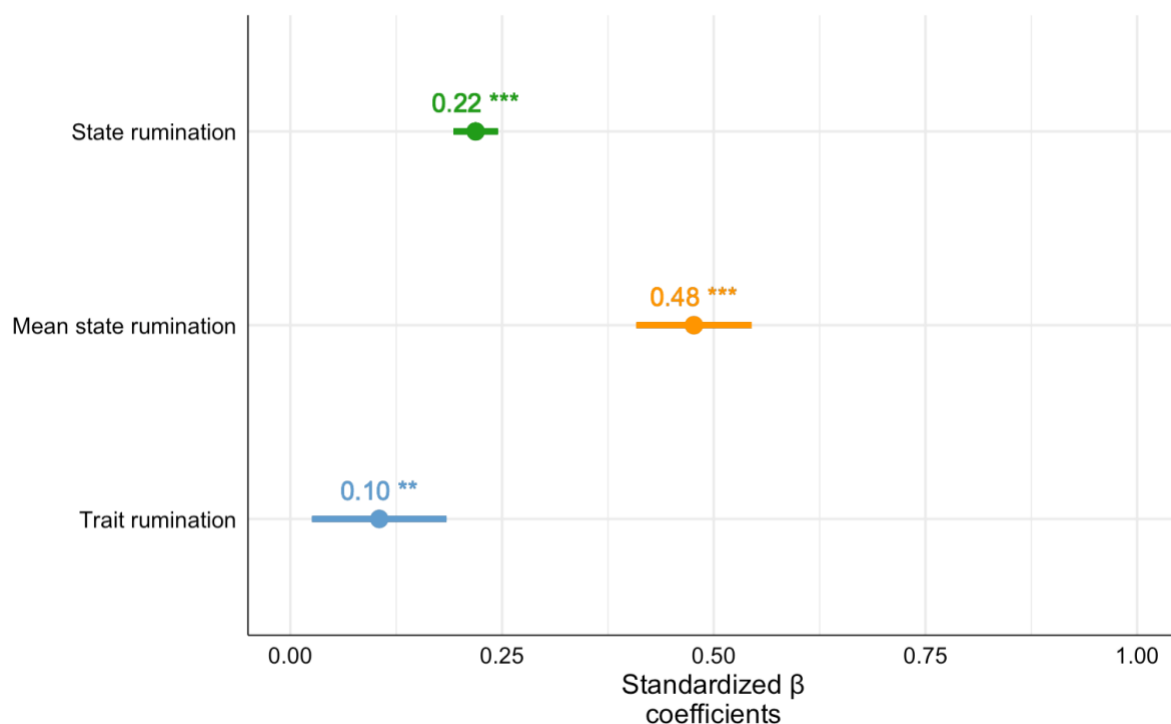
Our next point of interest was the association between the three rumination measures and momentary negative affect. Again, we expected that momentary rumination would be the strongest predictor (Hypothesis 3a), the aggregated mean of momentary measures would be the second strongest (Hypothesis 3b), and trait rumination would be the weakest predictor of

negative affect in daily life (Hypothesis 3c). The main effects of all three rumination measures were stronger than the effects of interaction terms and had distinct standardized confidence intervals, whereby mean state rumination emerged as the strongest predictor of momentary negative affect (see results in Figure 7 and Table 4). This indicates that the aggregated mean of state rumination measures is the most informative in terms of predicting momentary negative affect (disregarding the interaction with perceived stress). The second strongest predictor was within-person changes in rumination, followed by trait rumination. Associations of negative affect and rumination measures are illustrated in Figure 8.

Similarly to Model 0, the number of days spent in the study was negatively associated with negative affect, while emotional reactivity was once again represented by the positive relationship between perceived stress and momentary negative affect.

Figure 7

Standardized β coefficients indicating the prediction of negative affect by different measures of rumination.



Note. Error bars show 95% confidence intervals. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 4

Results of Model 1 as our main model testing the relationship between different rumination measures and emotional reactivity.

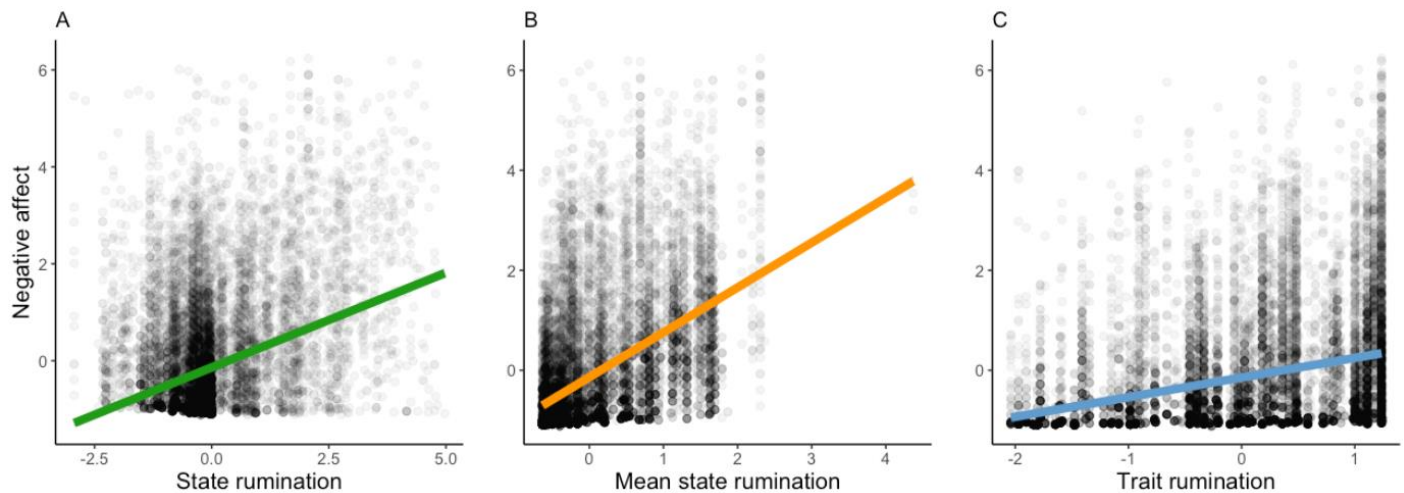
Prediction of negative affect			
<i>Predictors</i>	<i>Standardized β coefficients</i>	<i>Standardized CI</i>	<i>p</i>
Intercept	0.07	-0.00 – 0.15	0.057
Age	-0.02	-0.09 – 0.04	0.508
Gender [male]	0.02	-0.14 – 0.18	0.816
Gender [other]	0.15	-0.71 – 1.02	0.728
Assessment session	0.00	-0.01 – 0.01	0.799
Day	-0.03	-0.04 – -0.02	<0.001***
Event unpleasantness	0.26	0.24 – 0.28	<0.001***
State rumination	0.22	0.19 – 0.24	<0.001***
Mean state rumination	0.48	0.41 – 0.54	<0.001***
Trait rumination	0.10	0.03 – 0.18	0.009**
State rumination* Event unpleasantness	0.03	0.02 – 0.05	<0.001***
Mean state rumination* Event unpleasantness	0.05	0.02 – 0.07	<0.001***
Trait rumination* Event unpleasantness	0.04	0.02 – 0.07	0.002**

p<0.05 **p<0.01 *p<0.001*

<i>Random effects</i>	<i>Estimates</i>
σ^2	0.46
T00 id	0.43
T11 event unpleasantness	0.02
T11 state rumination	0.03
T11 event unpleasantness*state rumination	0.00
ρ_{01} event unpleasantness	0.58
ρ_{01} state rumination	0.37
ρ_{01} event unpleasantness*state rumination	-0.21

Figure 8

A comparison of the associations between negative affect and state (Panel A), mean state (Panel B), and trait rumination (Panel C).



Based on the correlations between random effects in Model 1, we can conclude that there is a rather strong positive association ($\rho = 0.58$) between the random slope of perceived stress and the random intercept of negative affect, meaning that the momentary negative affectivity of those who average higher in negative affect will be more strongly associated with fluctuations in perceived stress.

The same goes for the association between the random slope of rumination and the random intercept for negative affect (moderate positive correlation, $\rho = 0.37$), indicating that the larger the average negative affect, the stronger the relationship between momentary rumination and negative emotions.

The random slope of the interaction between perceived stress and rumination yielded a small negative correlation with the random intercept of negative affect ($\rho = -0.21$). This means that in individuals with a higher average level of negative affect, the association between changes in rumination and emotional reactivity (i.e., the effect of perceived stress on negative affect being a function of momentary rumination) will be smaller. In other words, if a person's general affectivity is more negative, when they ruminate more compared to themselves, the connection between stress and their momentary negative emotions will be weaker. However, if a person with lower average negative affect ruminates more than usual, that will increase the association between stress and momentary negative affect.

4. Discussion

Using data from an experiencing sample (ESM) study, we investigated the differences in the predictive validity of state and trait rumination measures. The outcome variable was emotional reactivity, a common ESM-based measure whose relevance for mental health is well-established (Myin-Germeys et al., 2001, 2003; Shapero et al., 2019). Psychological research has traditionally focused on how individuals differ in certain aspects, such as personality traits or cognitive ability; researchers analyzed data from large cross-sectional samples and generalized results to the within-individual level (Hamaker, 2012). Accordingly, emotion regulation effectiveness, too, has been seen as a stable attribute for the majority of its research (Houben et al., 2015; Kashdan et al., 2015). Recently, however, it has come to be recognized as a dynamic construct that varies not just across but also within individuals (Aldao et al., 2015). In general, evidence emerges that traditional laboratory measures and questionnaires capturing trait emotion regulation may not correspond to emotion regulation ability in real life as assessed by repeated measures designs. These processes appear to show different variability between and within individuals, implying that characteristics regarded as traits in psychology – e.g., emotion regulation strategies and effectiveness – may not reflect everyday functioning (Enkavi et al., 2019; Fisher et al., 2018).

We chose to examine rumination because it is among the most widely researched emotion regulation strategies, with results underlining its state-level, but not trait-level association with emotional reactivity (Hilt et al., 2015). The interesting lack of a strong correlation between state and trait rumination reported by Hilt et al. (2015), among others, also served as motivation for our analyses, where we examined the correlation between these two measures in a longitudinal design. In this regard, we found a moderate positive correlation between trait and state rumination indicators. Then, we moved on to establish that their non-shared variance is valid and informative. More specifically, we looked at the relationship between rumination and emotional reactivity by investigating the predictive value of three different indicators of rumination. We fitted mixed-effects models to time-series data that was collected in the context of daily life. Our main finding was that all three measures of rumination had independent predictive validity for emotional reactivity. However, the magnitude of these effects overlapped, and therefore, the importance of the measures could not be ranked. On the other hand, when the main effects on negative affect were considered, the mean of state measures of rumination emerged as the strongest predictor.

Regarding our first hypothesis, in line with the findings of Brockman et al. (2017) and Hilt et al. (2015), we found that mean state- and trait-level rumination were only moderately associated. This finding is especially curious as, until recently, psychology thought of the term *trait* as referring to the intraindividual mean (Hamaker et al., 2007). It is corroborated by our results, too, however, that “trait” scores measured by traditional questionnaires do not reflect too tightly the rumination measurements averaged across everyday situations. Certain differences in the methodological aspects of these measurements may partially underlie this lack of a strong correlation. As Conner and Barrett (2012) point out in their review, traditional self-report techniques, such as trait questionnaires, rely on a memory-based reporting format by asking participants to recall and summarize experiences over longer periods of time. This in itself may introduce bias whereby individuals’ generalized concepts about themselves are influenced by their current state or the fallibility of their memory due to its constructive nature. In their accessibility model of emotional self-report, Robinson and Clore (2002) argue that the divergence between traditional and momentary self-reports may be explained by more than the matter of bias. Since people tend to rely on different sources of knowledge when reporting their subjective experiences in these distinct ways, different means of self-report generally reflect different types of knowledge. According to the accessibility model of emotional self-report, trait questionnaires generally rely on semantic memory, that is, conceptual information about the self that has become detached from time and place. On the contrary, momentary self-reports were characterized by Robinson and Clore (2002) as measuring experiential knowledge, in other words, event-specific information about subjective experiences associated with a particular context. As a result, momentary assessments can directly reflect the experience as it is being generated.

Building on the perspective of Robinson and Clore (2002), Kahneman and Riis (2005) and Wilson (2009) suggest that the different means of emotional self-report tap different functional selves, or different types of consciousness about one’s experiences. These conscious selves serve various purposes in behavior and decision-making and are prompted under different conditions and task demands. While the *believing* and *remembering* selves are less linked to the present and rely more on memory, the *experiencing* self is tied more closely to the sensory phenomena of the present. The *believing* self essentially reflects a set of identities and self-concepts, whereas the *remembering* self maintains the continuity of the self and facilitates communication, planning, and decision-making. On the other hand, the *experiencing* self helps navigate physical and social environments and serves the maintenance of homeostasis. As a result, the *believing* and *remembering* selves generally become activated by

retrospective assessments, such as trait questionnaires, while momentary self-reports rely more on the *experiencing* self (Kahneman & Riis, 2005; Wilson, 2009). Such discrepancy in the information and processes participants rely on when responding to trait vs. state measures of rumination may explain their small shared variance and independent predictive validity.

While the effect of possible bias may suggest the definite advantage of momentary state measurements, one may argue that trait-based assessments are preferable from a psychometric and an assessment perspective. In the case of the present study, trait-level emotion regulation was assessed using the Cognitive Emotion Regulation Questionnaire (CERQ), which was completed by participants upon entering the study, after being informed that the entry survey battery takes around 20 minutes to complete. We expect that this likely prompted participants to find a time and place they can concentrate on the questions uninterrupted. In contrast, state measurements were, by nature, completed during a variety of situations where participants may not have been able to give their full attention. From a psychometric point of view, the CERQ is a validated questionnaire with an established and replicated factor structure (Garnefski et al., 2001; Miklósi et al., 2011) and well-phrased statements, whereas we used a single item to measure trait rumination, placing greater value on practicality and maximizing compliance. Nevertheless, in spite of these drawbacks, the ESM-based measures still outperformed the CERQ in terms of predicting negative affect.

The results of our mixed-effect models also underline the divergence between trait and state rumination as they indicate that the two measures have distinct incremental validities in terms of predicting emotion regulation. First, our baseline model (Model 0) confirmed the adequate operationalization of emotional reactivity, showing that if an individual experienced higher levels of stress in the preceding two hours, their negative emotions would be more intense at the time of the ESM assessment.

In our main model (Model 1), we found that state, mean state, and trait measures of rumination all independently predicted emotional reactivity. The confidence intervals of their coefficients overlapped, and therefore, we could not rank them based on their predictive validity, contrary to our second set of hypotheses (2a, 2b, and 2c). The effect of all three measures on emotional reactivity was rather small. However, the weak predictive value and lack of difference found between them could possibly be caused by low statistical power. Although we had an especially large number of observations ($N = 14265$), a mixed-effects model including an interaction term may sometimes be overly complex for certain effects to emerge. At any rate, results indicated that if an individual had higher state, mean state, or trait

levels of rumination, they had more intense negative affective reactions to perceived stress in the preceding two hours.

On the other hand, in the prediction of negative affect alone (and not emotional reactivity), a clear order emerged between the different measures of rumination. Trait rumination was the weakest predictor among all measures (in accordance with Hypothesis 3c), but it still had a positive association with negative affect. Interestingly, state-level rumination was the second in line, contradicting Hypothesis 3a, which assumed that it would be the strongest predictor. It also had a positive relationship with momentary negative emotions. By far the strongest predictor of negative affect was the aggregated mean of state-level rumination measures, which was also positively associated with negative affect. This finding was in contrast with our third set of hypotheses (specifically 3a and 3b), assuming that momentary rumination would have the best incremental validity regarding the prediction of negative affect, followed by the aggregated mean of momentary rumination measures and trait rumination. We made these assumptions based on evidence showing high within-individual variability in emotion regulation (Aldao et al., 2015) and results indicating that increased state rumination is associated with higher emotional reactivity (Hilt et al., 2015). Our finding indicates, however, that the strongest predictor of an individual's emotional reactivity in daily life is not their momentary rumination measured within the same time window, but the average of these momentary measures. Although this finding was in contrast with our hypotheses, it may just be an intriguing addition to the still ongoing trait vs. state debate and to understanding the within-person dynamics of psychological processes.

The aggregated mean of state rumination measures is a composite indicator of all of an individual's momentary rumination during the period of the study. As a result of this, it can essentially be considered a trait-level measurement that is based on repeated, temporally spaced everyday assessments of rumination within an individual. Thus, it could be regarded as a measurement 'halfway between' trait and state indicators that could possibly combine the advantages of both. Momentary measurements allow researchers to create their own aggregates of a process over time (Conner & Barrett, 2012), which includes the nuances of a dynamic phenomenon, thus maximizing ecological validity, while minimizing bias. These aspects could account for why the aggregate measure was the strongest predictor.

The results of our main model for predicting negative affect and emotional reactivity also fit in with the Density Distribution approach, originally conceptualized by Fleeson (2001) and applied to emotion regulation by Blanke et al. (2020b). The theory posits that an individual's behavior can vary from situation to situation, but also shows consistency within

the individual across time (Fleeson, 2001). For example, a person may usually ruminate when they feel as though they have no control over the situation, but not when they feel like they are in charge; whereas another person may ruminate in both kinds of situations. So in terms of traits, the first person is characterized by intermediate trait rumination and the second by high trait rumination. This illustrates that beyond the consistent differences in the between-person mean level of rumination (some people ruminate more than others), there are also consistent differences in within-person variability (some people are more variable in their ruminative behaviors). Thereby, based on multiple assessments of states under varying circumstances, density distributions of rumination, for example, would reflect between-person differences in both mean-level rumination and within-person variability in rumination across situations (Blanke et al., 2020b). Through this approach, Fleeson (2001) took a step toward integrating trait and state features and providing evidence for the influence of both the situation and the person when it comes to behavior.

Importantly, density distributions are based on within-person variability (standard deviations) as well as averages. In our analyses, we did not capture within-person variability *per se*, but intended to investigate the predictive value of intraindividual dynamics by adding deviation from one's typical level of momentary rumination as a predictor to our mixed-effects model, using random effects to account for within-person variation. In future analyses, it may be beneficial to include within-person variability explicitly to further investigate how the Density Distribution approach can be applied to emotion regulation. Examining within-person variability could, for example, give us an insight into individuals' ability to flexibly alter their use of an emotion regulation strategy across different contexts. As mentioned above, Blanke et al. (2020a) demonstrated the adaptiveness of the variability of emotion regulation in daily life. Given that rumination is generally considered a maladaptive emotion regulation strategy (Aldao & Nolen-Hoeksema, 2010; J. J. Gross & John, 2003; McRae & Gross, 2020; Watkins & Roberts, 2020), it could be assumed that more frequent and intensive use of rumination would be associated with less variability in state rumination and emotion regulation in general, both rumination and low variability being considered maladaptive.

Our analyses of the relationship between random intercepts and slopes yielded interesting implications for studying within-person differences in rumination and affectivity. Specifically, we can interpret the random intercept of negative affect as an indicator of neuroticism (typically defined as the tendency to experience negative emotions; Barlow et al., 2014), as it captures an individual's average negative affect across a period of time, aggregating

multiple measurement points. The associations of this between-person indicator with within-person dynamics suggest that the negative emotionality of individuals higher on neuroticism will be more strongly affected by perceived stress over time, making them more emotionally reactive. This is true for rumination as well: the momentary negative emotions of people higher on neuroticism will have a stronger relationship with rumination at the time. Rather interestingly, however, in individuals with high neuroticism, rumination does not amplify emotional reactivity much, since when these people ruminate more compared to themselves, the connection between momentary stress and negative affect becomes weaker. This only applies to those more prone to negative emotions (i.e., high neuroticism) and not individuals with relatively low average levels of negative affect. The reason for this could be that the emotional reactivity of people high on neuroticism is already much higher compared to people low on neuroticism – as illustrated by the positive correlations between the intercept and random slopes for perceived stress and rumination as well. These conclusions postulate a noteworthy approach to investigating individual differences in affectivity and their relationship to emotion regulation in a multilevel framework.

Limitations of this study include that over 80% of our final sample consisted of female individuals, and also 80% had at least one higher education degree, which limits the generalizability of our findings. Furthermore, after screening, we found a significant difference of moderate effect size in education levels between individuals included and not included in the final sample (with higher education levels in the former), which may introduce some bias to our results.

In addition, since we were unable to provide participants with financial compensation, we experienced lower compliance rates throughout the study than what would have been ideal. Although participant fatigue and reductions in compliance, unfortunately, are characteristic of study designs assessing experiences outside of the laboratory (Barrett & Barrett, 2001), there has recently been some controversy surrounding financial incentivization, questioning its legitimacy as the ultimate solution for low compliance (Howard & Lamb, 2022). In the future, similar studies should ideally aim to keep compliance as consistent across participants as possible, as unsteady compliance rates may introduce a bias when calculating aggregated mean state indicators. In the case of this work, we should take into account inconsistent compliance rates when looking at the mean of state rumination measures, as for certain participants, this aggregate may comprise very few observations, potentially distorting results. However, we expect this effect to be substantially counterbalanced by the large number of participants ($N = 247$).

Upon testing assumptions for our mixed-effects models, we found that the normality of the distribution of residuals was violated due to high kurtosis, with potential for outliers. Log10-transforming the outcome variable (multilevel factor score for negative affect) did not significantly improve the distribution, though it did reduce leptokurtosis somewhat. The leptokurtic distribution of residuals may distort the results of tests of significance, though according to recent analyses, linear models are robust to violations of normality (Knief & Forstmeier, 2021). Furthermore, the stability of model parameters was corroborated by bootstrapped confidence intervals.

Our design does not allow for drawing firm conclusions about the direction of causality between the constructs in question. Based on the literature (e.g., R. J. Thompson et al., 2012), we assume that, in general, perceived stress causes an increase in negative affect and that this relationship is moderated by rumination, whereby it increases the emotional response given to stress. However, since these processes were measured in the same time window, they could have influenced one another in different directions. For example, experiencing negative emotions can increase the probability of the perception of an event as more stressful (Levine & Safer, 2002; Thomas & Diener, 1990). In the future, we could enable more established conclusions to be drawn by analyzing lagged relationships, where we can ascertain that one event (e.g., stress) preceded (e.g., increase in negative affect) the other in time. This would, however, require much higher compliance rates with a large number of consecutive ESM surveys answered by each participant.

In conclusion, the present research examined the associations of trait and state measures of rumination as well as their predictive values for emotional reactivity, using intensive time-series data from an experience sampling design. Our results provide valuable insight for understanding the within-individual dynamics of emotion regulation and their relationship to stress and affectivity, nuancing the common trait approach and overcoming some of its limitations. Thereby, our results corroborate the need to re-evaluate the traditional measurement of psychological constructs. On a final note, these findings have clinically relevant, practical implications for the personalized prediction of emotional responses to stress through simple self-report tools applicable in everyday contexts (see Hitchcock et al., 2022 and Myin-Germeys et al., 2009).

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