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# Examining everyday emotion regulation as an ability: Emotion regulation monitoring, but not general strategy implementation ability, is significantly associated with affective well-being in daily life

**Mario Wenzel, Paula Philippi* and Aleksandra Kaurin***


## Abstract

Research on everyday emotion regulation (ER) has primarily examined how the habitual use of ER strategies relates to affective well-being, categorizing ER strategies as generally adaptive or maladaptive. However, it remains unclear whether individuals have a general ability to regulate their emotions or whether distinctive ER strategies are differentially effective across individuals. We hypothesized that the prioritized use of those ER strategies that are individually most effective (*ER monitoring ability*) is key to an individual's affective well-being and introduce a novel measure aimed at inferring ER monitoring ability from participants' self-reported ER behavior. Analyzing 13 ambulatory assessment datasets (1,798 participants, 162,061 observations), we found no evidence for a general ER strategy implementation skill. Instead, ER monitoring ability emerged as an important predictor of affective well-being, explaining on average an additional 3.8% of the variance in affective well-being beyond ER strategy use. Importantly, a random-intercept cross-lagged panel model revealed that better ER monitoring ability was significantly associated with better overall affective well-being about half a year later, but not vice versa, suggesting a directional relationship. Taken together, the adaptiveness of ER for well-being depends on an individual's inclination to use those ER strategies that are individually most effective for them.

## Plain language summary

Research has primarily focused on how people manage their emotions, specifically using different emotion regulation strategies. These strategies are often categorized as either helpful or harmful for one's emotions. However, it remains unclear whether people possess a general skill for managing their emotions or if certain strategies are more effective for certain individuals. We think that an important aspect is whether someone uses the strategies that work best for them in their everyday life, which is a form of monitoring one's emotions. We developed a new way to measure this monitoring by inferring emotion regulation monitoring from participants' ER behavior. Our analysis of data from 13 studies, where participants reported their emotions multiple times a day, included a large sample of 1,798 people and 162,061 observations. There was no evidence to suggest that people possess a general skill for successfully managing their emotions using multiple strategies. Rather, using strategies that one can successfully implement was linked to an overall improvement in affective well-being. In summary, the key to one's affective well-being is utilizing the strategies that work best for the individual.



## Keywords

Emotion regulation, effectiveness, monitoring, ambulatory assessment

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## Introduction

Emotion regulation (ER) refers to the processes by which individuals influence the experience, intensity, and expression of their emotions (Gross, 2015). ER can be understood as a sequential and temporal process that involves several key steps (Figure 1). First, individuals must identify the situation and the emotions that arise, to then select appropriate ER strategies to finally implement them (Koval et al., 2023). Throughout this process, individuals monitor their progress, make necessary adjustments, and learn which strategies are effective in different circumstances.

In the study of ER, previous research has primarily focused on the ER strategy that individuals select and implement by demonstrating the associations of these ER

Department of Psychology, Bergische Universität Wuppertal, Wuppertal, Germany

*Shared senior authors.

**Corresponding author:**
Mario Wenzel, Institut für Psychologie, Bergische Universität Wuppertal, Gaußstr. 20, 42119 Wuppertal, Germany.
Email: mwenzel@uni-wuppertal.de

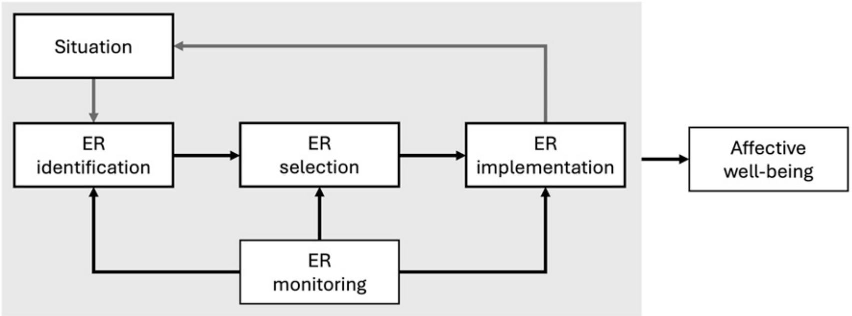


**Figure 1.** Conceptual framework.

strategies with indicators of well-being and mental health (e.g., Aldao et al., 2010; Hu et al., 2014). The goal of this line of research is to identify those ER strategies that are generally adaptive or maladaptive for individuals' affective well-being,[1] using trait self-reports (Aldao et al., 2010), daily measures (Boemo et al., 2022; Wenzel et al., 2025), or experimental tasks of ER use (Webb et al., 2012). This line of research is ultimately interested in finding the ER strategy that are most suited to be targeted in prevention and intervention programs to improve affective well-being on average (e.g., Wang et al., 2021). In the present study, we sought to complement this line of research on ER strategies with a focus on individual differences in ER ability. As shown in Figure 1, participants may differ in their ability to perform each step, with ER ability being defined as having a positive impact on individuals' affective well-being. Specifically, if there are universally effective strategies, selecting more effective strategies should be associated with increased affective well-being (i.e., ER selection ability). In addition, participants may differ in how well they can generally implement the various ER strategies (i.e., ER implementation ability) and how well they can monitor the ER process (i.e., ER monitoring ability).[2] To provide this complementary perspective on ER, we re-analyzed 13 ambulatory assessment (AA) datasets and synthesized their results.

## Strategy-focused research perspective on ER

Research using trait self-report measures of ER asks participants to indicate the extent to which they typically use various ER strategies in their daily lives. A comprehensive meta-analysis of 241 effect sizes from 114 studies found significant associations between mental health indicators—such as anxiety and depression—and ER strategy selection. Specifically, the study found that more frequent use of acceptance and reappraisal was associated with better mental health, while more frequent use of distraction (referred to in the study as avoidance), rumination, and suppression was associated with poorer mental health outcomes (Aldao et al., 2010). Thus, this line of research suggests that habitual selection of acceptance and reappraisal can be considered adaptive, whereas habitual selection of distraction, rumination, and suppression can be considered maladaptive. These findings are reflected in research that meta-analyzed current evidence in daily life (Wenzel et al., 2025). Specifically, this research found that acceptance, reappraisal and social sharing were generally effective in upregulating positive affect, whereas rumination, suppression and, to a lesser extent, distraction were generally ineffective. The results for downregulating negative affect were similar, but reappraisal and social sharing were less effective.[3] In addition to this research using self-reports of ER selection, laboratory-based experimental research has focused on the effectiveness of ER strategies, that is, how implementation of an ER strategy leads to decreases in negative affect and increases in positive affect. Here, participants do not report how often they use each ER strategy but are presented with emotionally relevant stimuli that they are instructed to regulate with specific ER strategies. A comprehensive meta-analysis that included 306 experimental comparisons from 190 laboratory studies (Webb et al., 2012) found that the instructed use of acceptance (termed "Reappraise: response" in the study), reappraisal, and distraction were significantly more effective in downregulating negative affect compared to control conditions (e.g., no instructions or specific instructions to increase or not regulate emotion). In contrast, rumination (referred to as "concentration" in the study) significantly increased negative affect, while suppression did not significantly affect negative affect on average compared to the control instructions.

Taken together, research using several types of data, that is, Q-, L-, and T-data (Cattell, 1983), found relatively consistent evidence that some ER strategies, namely acceptance and reappraisal, are generally more adaptive than other strategies, mainly distraction, rumination, and suppression. However, overall, effect sizes are only small to moderate. In Webb et al.'s (2012) meta-analysis including laboratory experiments, the most effective ER strategy, reappraisal, showed a moderate (according to Funder & Ozer, 2019) mean effect size of $\overline{d} = 0.45$ for reducing self-reported negative emotions, while the least effective strategy, rumination, showed a small mean effect size of $\overline{d} = -0.28$ in the opposite direction. We found similar effect sizes for the spontaneous use of ER in daily life, with $\overline{\beta} = .07$ for reappraisal and $\overline{\beta} = -.16$ in upregulating positive affect. In addition, these fixed effects do not contain any information about the between-person variability in this relationship (Hox et al., 2017). This is critical because previous studies have shown significant between-person variability in the effectiveness of implementing ER strategies (Brans et al., 2013; Brockman et al., 2016; Zetsche et al., 2024). More specifically, we found significant between-person variability for six different ER strategies across twelve ambulatory assessment datasets, with some ER strategies showing a wide range of person-specific effectiveness (Wenzel et al., 2025). For example, the person-specific effectiveness of reappraisal ranged from $\beta = -.41$ to $\beta = .64$, indicating that within-person effects did not only vary in magnitude but also in direction (Brockman et al., 2016), for example, higher daily reappraisal use relates to higher positive affect in some but lower positive affect in others. This indicates that although there are significant differences in the fixed effects, that is, mean differences in the effectiveness of implementing the various ER strategies, people vary widely in how effectively they can implement these ER strategies. Thus, it is important to complement the strategy-focused research perspective on ER with an ability-focused perspective on ER to better understand why some people are better at ER than others.

## *Ability-focused research perspective on ER*

In an ability-focused view of ER, we are interested not only in which ER strategy is more effective than other strategies but also in the extent to which and how individuals differ in their ability to use ER adaptively (i.e., ER ability), where adaptive is operationalized as a positive association with long-term affective well-being. As illustrated in Figure 1, long-term affective well-being could be influenced by ER identification, ER selection, ER implementation, and ER monitoring. The strategy-focused research perspective on ER is represented by ER selection, that is, which strategies are more positively associated with long-term affective well-being than other strategies (Table 1). However, individuals may differ not only in which ER strategy they use but also in how effectively they can use it and how well they can monitor the ER process and learn from the situations they encounter in everyday life.[2]

*ER implementation ability.* The effectiveness with which an individual can implement a particular ER strategy can be inferred from a multilevel analysis of intensive longitudinal data collected through AA. ER implementation (or effectiveness) is operationalized by predicting current affect at measurement occasion t by an ER strategy, controlling for prior affect at measurement occasion t-1 (Table 1). The fixed effect is then used as an estimate of the general effectiveness of each ER strategy, while the random effect (i.e., random variance) reflects between-person differences in the effect of an ER strategy on change in affect. Thus, a person-specific ER strategy effectiveness can be estimated by computing the best linear unbiased predictions (White & Hodge, 1989) of the random effects and adding them to the fixed effect for each person. By doing this for each person, we can assess the extent to which a person can effectively implement a particular ER strategy in their daily life in terms of changing affect from moment to moment. To obtain a measure of the general effectiveness of ER implementation, one can then calculate the mean of the person-specific effectiveness of implementing the respective ER strategy.

Importantly, research on the extent and adaptiveness of general ER implementation effectiveness is scarce because studies have only focused on the strategies themselves, that is, the extent to which a strategy leads to a change in affect across participants, both in laboratory settings (e.g., Webb et al., 2012) and in daily life (e.g., Boemo et al., 2022; Brans et al., 2013), or on trait self-reports of specific strategies (e.g., Garnefski & Kraaij, 2007). Thus, ER research has not yet developed a questionnaire that assesses an ER ability in a manner similar to trait self-control (e.g., Tangney et al., 2004) but rather one that assesses a relatively broad range of both adaptive and maladaptive ER strategies (Garnefski & Kraaij, 2007). However, as these questionnaires mainly capture the tendency to use the respective ER strategies (Koval et al., 2023), the use of a total score would only reflect ER selection, but not an ER implementation ability.

Consequently, research on between-person differences in ER implementation as a general ER ability is lacking, and

**Table 1.** Operationalization of emotion regulation components using self-reports from AA datasets.

| ER component | Operationalization | Interpretation | Predicted association with affective well-being |
|---|---|---|---|
| Adaptive ER strategy selection | Mean of acceptance, reappraisal, and social sharing use[a] | Higher scores reflect greater use of commonly effective ER strategies in daily life | Positive association |
| Maladaptive ER strategy selection | Mean of distraction, rumination, and suppression use[a] | Higher scores reflect greater use of commonly ineffective ER strategies in daily life | Negative association |
| ER implementation ability | Mean of person-specific ER strategy implementation effectiveness derived from best linear unbiased predictions from a multilevel model in which affect balance was predicted by all ER strategies and by prior affect balance | Higher scores reflect a greater ability to implement ER strategies more effectively | Positive association |
| ER monitoring ability | Within-person correlation between ER strategy use and ER strategy implementation effectiveness | Higher scores reflect a greater ability to implement ER strategies more frequently that one can implement more effectively | Positive association |

Note. ER, emotion regulation.
[a]Classification based on Wenzel et al. (2025).

it is unclear whether some individuals are better at implementing ER strategies in general than others. To address this research gap in the present study, we first computed the person-specific effectiveness of implementing each ER strategy and then took the mean to obtain a measure of ER implementation ability for each participant. This measure was then correlated with affective well-being to test whether being good at regulating one's affect from moment to moment is associated with better affective well-being over the course of the study. In addition, we correlated the person-specific effectiveness values of implementing each ER strategy for each participant. If the effectiveness values of different ER strategies within an individual are highly correlated (i.e., coefficients close to 1), this suggests that effective implementation of one ER strategy may also indicate effective implementation of another ER strategy. This would suggest that there is a general ER implementation ability, such that some individuals are simply better at ER than others. This would require a shift from examining individual ER strategies that are more effective than other ER strategies to an individual difference perspective on ER by identifying individuals who are more effective at implementing all kinds of ER strategies.

*ER monitoring ability.* However, if the ER strategy effectiveness values correlate close to 0, this argues against a general ER implementation ability. Instead, it rather indicates that individuals are good at implementing, for example, reappraisal but not good at implementing distraction. Thus, it may be important to recognize individually effective ER strategies and to prioritize them over less effective alternatives in everyday life, as it is conceivable that the possession of this competence could have a significant impact on a person's affective well-being. This is closely related to the concept of ER monitoring (Figure 1), which describes the process of monitoring the ER process to adjust it to changing circumstances. ER monitoring is similar to the idea of metacognitive knowledge (Flavell, 1979), which originally referred to people's understanding of cognitive tasks and their effective problem-solving approaches (Donker et al., 2014). This understanding of the ER process and one's ability to effectively implement specific strategies also builds on the sequential regulatory flexibility framework proposed by Bonanno and Burton (2013), particularly the responsiveness to feedback component. Just as they recognize that incorporating feedback on the effectiveness of past regulatory efforts and strategies is essential for ER in general and improving regulatory flexibility in particular, our understanding of ER monitoring reflects this. However, ER monitoring is difficult to assess and examine because it involves the entire ER process that unfolds in the short and long term. In the present research, we propose an indirect measure of ER monitoring ability that we define as the propensity to implement ER strategies that one can implement more effectively, with more positive values indicating better ER monitoring ability. Specifically, we propose to use the correlation between an individual's use of ER strategies and their idiosyncratic effectiveness (Table 1). This correlation is expected to be positive when individuals use ER strategies that are more personally effective more frequently, indicating a greater understanding of which ER strategies they can use to enhance their affective well-being. This measure has the advantage of limiting self-report bias by inferring ER monitoring ability from actual (self-reported) behavior, that is, correlating how strongly individuals choose ER strategies and how effective their implementation is.

Evidence regarding the role of ER monitoring for individuals' affective well-being is very limited. So far, research has focused on the relationship between ER selection and implementation effectiveness but produced mixed results that were based on laboratory research using instructed ER use. In one study, habitual reappraisal use was positively linked to reappraisal effectiveness, but only via self-reports, not behavioral measures (Troy et al., 2017). Studies that combine experimental assessments of ER strategy effectiveness (i.e., ER implementation) with self-reported ER strategy use (i.e., ER selection) generally find nonsignificant correlations (Gärtner et al., 2023; Troy et al., 2010). However, in a recent experiment, participants who were better at using reappraisal than distraction in one task showed a clear preference for reappraisal over distraction in another laboratory task (Rammensee et al., 2023). Only one study examined the role of metacognitive knowledge via AA and found that self-regulatory success depended not only on mastery of individual self-control strategies but also on an individual's ability to flexibly adapt to different challenges (Bürgler et al., 2021). However, in contrast to the laboratory studies, metacognitive knowledge in this study was assessed by a short questionnaire.

## The present research

Taken together, little is known about the differential impact of ER selection, ER implementation ability, and ER monitoring ability on individuals' daily affective well-being. In the present study, we aimed to address this gap in the research literature by reanalyzing 13 AA datasets. We first tested whether a general ER implementation ability exists and therefore computed the person-specific effectiveness of implementing each ER strategy and computed the internal consistency of cross-strategy effectiveness (Hypothesis 1). Second, we examined how ER selection in terms of the use of generally effective (i.e., acceptance, reappraisal, and social sharing) versus generally ineffective ER strategies in daily life (i.e., distraction, rumination, and suppression), ER implementation ability, and ER monitoring ability are related to long-term affective well-being, that is, over the course of the study. Specifically, we hypothesized that the use of generally effective ER strategies (Hypothesis 2a), but not generally rather ineffective ER strategies (Hypothesis 2b), as well as ER implementation (Hypothesis 3) and ER monitoring ability (Hypothesis 4) would be associated with better affective well-being. To that end, we introduce a novel measure of ER monitoring ability which emerges from the individual interaction of ER strategy use and the corresponding ER strategy effectiveness. However, these concurrent associations cannot show that ER implementation and monitoring ability cause changes in affective well-being. To provide causal evidence in the sense of Granger causality (Granger, 1969), that is, to show that one time series is useful in predicting another time series, we examined the one-year prospective relationships between ER implementation and monitoring ability and affective well-being using a random-intercept cross-lagged panel model (Hypothesis 5).

## Methods

### Transparency and openness

We included all datasets we had access to that used an ambulatory assessment design with multiple measurement occasions per day and that included measures of affective well-being and ER strategies. Comprehensive reporting of data manipulation and exclusion procedures is provided for all key variables in the present research. Importantly, sample sizes in each dataset were not predetermined according to the objectives of this study, because the data were originally collected for a different purpose and thus the present research should be viewed as exploratory. Other work has previously reported data from some of these samples (see Table 2 for a reference for each dataset), but none of the publications using these datasets focused on ER implementation ability and ER monitoring ability as predictors of affective well-being. A detailed summary of the analyzed datasets can be found in Table 2. Data and code for datasets 1 and 2 is available via https://osf.io/ke6qc. Dataset 3 was derived from the first wave of the "Everyday Experiences" study (Siebert et al., 2017), and access can be requested via the DIW Berlin at https://www.diw.de/en/diw_01.c.601584.en/data_access.html. Dataset 4 was collected in the project "STECCO – Starting Tertiary Education during the Corona Crisis: A Challenge and an Opportunity" (Sosin et al., 2024) and can be accessed via https://osf.io/bhq3p/. Datasets 5–13 are part of the EMOTE database (Kalokerinos et al., in preparation). The EMOTE datasets are available upon request to the EMOTE database, using our data request number (2MV32BT4RW). Analysis scripts and the data used for the synthesis are available at the OSF (https://osf.io/ke6qc). Finally, the data were not transformed to change the distribution of the measures and we did not include any covariates in the models.

### Participants and procedure

Table 2 presents an overview of the sample characteristics. To ensure consistency with previous procedures, we excluded participants with less than one-third of completed observations, resulting in a total of $N = 1798$ participants and $N = 162{,}061$ observations. Across datasets, the average age was 27.1 years, with an average female representation of 67.3% and mean compliance rates of 79.1% (see Wrzus & Neubauer, 2023, for comparison).

### Measures

The descriptive statistics, between-person reliability, and the zero-order correlations are shown in Table 3.

*Affective well-being.* To bring differently assessed positive and negative emotions (see Table 2) to the same metric, we harmonized them by computing the Percent of Maximum Possible Score (POMP; Cohen et al., 1999). The POMP is a linear transformation that does not alter the distribution and ranges between 0 and 100. The resulting POMP scores can be interpreted as percentages of the possible maximum score. To calculate affect balance as a measure of affective well-being (Diener et al., 2010), we subtracted positive from negative affect, with more positive values indicating better affective well-being ($M = 69.0$, $SD = 12.0$). Akin to bipolar affect scales such as Short Mood Scale (Wilhelm & Schoebi, 2007), this measure reflects the preponderance of positive over negative affect. We used affect balance rather than examining positive and negative affect separately because it allows us to estimate person-specific ER strategy effectiveness that incorporates both upregulation of positive affect and downregulation of negative affect. To gauge the measure's reliability, we computed split-half reliability by correlating the affect balance between the first and second halves of the AA and applying the Spearman–Brown formula (Eisinga et al., 2013), resulting in $r_{SB} = .89$ for affect balance for between-person differences (Table 3).

*Emotion regulation.* In all thirteen datasets, ER was assessed by asking participants how strongly they used the following ER strategies since the last beep: acceptance, distraction, reappraisal, rumination, social sharing, and suppression.[4] Because the response scales differed between the datasets, that is, some datasets used 5- or 7-point scales and other datasets used sliders ranging from 0 to 100, all ER strategies were POMP-transformed. Based on a recent meta-analysis using these datasets (Wenzel et al., 2025), we computed the mean of acceptance, reappraisal, and social sharing to obtain a measure of *adaptive ER selection* and the mean of distraction, rumination, and suppression to obtain a measure of *maladaptive ER selection*.

### Analytic approach

*Data preparation.* Data were prepared and analyzed in Stata 17 (College Station, TX, USA: StataCorp LP). Assessing affect and ER strategies repeatedly over hours results in a hierarchical data structure wherein momentary self-reports of affect and ER strategies (within-person level) are nested within individuals (between-person level). Individual differences in momentary affective well-being, that is, the difference between positive and negative affect, and ER strategies were modeled using multilevel modeling using the average level of endorsement of each of these variables across momentary assessments. Figure 2 provides a schematic overview of our data analytic approach.

Next, we created variables to capture the ER components (see Table 1). *Adaptive ER strategy selection* was assessed by taking the mean of acceptance, reappraisal, and social sharing use, which were found to be mostly effective (Wenzel et al., 2025). In turn, *maladaptive ER strategy selection* was assessed by taking the mean of distraction, rumination, and suppression, with evidence suggesting a general ineffectiveness of these strategies on average across individuals (Wenzel et al., 2025). To assess ER implementation and monitoring ability, we first obtained the mean person-specific ER implementation effectiveness for each ER strategy. To that end, we computed a multilevel

**Table 2.** Dataset characteristics.

| Data-set | *N* | Age in years: *M* (*SD*) | % Female | Obs. | Days | S./day | Adher. | Affective states | ER strategies | Reference |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 125 | 22.9 (5.1) | 77.6% | 22,844 | 40 | 6 | 76.2% | PA: Excited, happy, relaxed, satisfied<br>NA: Afraid, angry, anxious, depressed, sad | dis, rea, rum, soc, sup | Rowland et al. (2016) |
| 2 | 175 | 25.0 (5.4) | 52.0% | 10,095 | 7 | 12 | 68.7% | PA: Excited, happy, relaxed, satisfied<br>NA: Afraid, angry, anxious, depressed, sad | dis, rea, rum, soc, sup | Wenzel et al. (2022) |
| 3 | 179 | 50.9 (5.8) | 52.5% | 12,608 | 6 | 12 | 97.8% | PA: Content, inspired, interested, joyful, relaxed, well<br>NA: Angered, distressed, downhearted, jittery, nervous, upset | acc, dis, rea, rum | Siebert et al. (2017) |
| 4 | 297 | 19.8 (2.1) | 76.8% | 11,198 | 14 | 5 | 52.3% | PA: Balanced, cheerful, happy, lively, relaxed<br>NA: Afraid, angry, exhausted, sad, worried | rea, rum, sup | Sosin et al. (2024) |
| 5 | 200 | 18.3 (1.0) | 55.0% | 34,840 | 7 | 10 | 87.3% | PA: Excited, happy, relaxed<br>NA: Angry, anxious, depressed, sad, stressed | dis, rea, rum, soc, sup | Erbas et al. (2018) |
| 6 | 178 | 27.0 (9.0) | 65.2% | 28,344 | 21 | 9 | 83.8% | PA: Happy, relaxed, stressed<br>NA: Angry, sad, stressed | acc, dis, rea, rum, sup | Grommisch et al. (2020) |
| 7 | 122 | 21.1 (3.5) | 66.4% | 5519 | 7 | 8 | 80.7% | 22 items from the PANAS-X | dis, rea, rum, soc, sup | Medland et al. (2020) |
| 8 | 101 | 18.6 (1.5) | 86.1% | 8260 | 9 | 10 | 90.9% | PA: Content, happy, proud, relieved<br>NA: Angry, ashamed, anxious, disappointed, sad, stressed | acc, dis, rea, rum, soc, sup | Kalokerinos et al. (2019) |
| 9 | 95 | 19.1 (1.3) | 62.1% | 4303 | 7 | 10 | 84.1% | PA: Happy, relaxed<br>NA: Angry, anxious, depressed, sad | dis, rea, rum, soc, sup | Koval et al. (2013) |
| 10 | 101 | 20.8 (2.1) | 72.9% | 7122 | 9 | 10 | 78.3% | PA: Connected, contempt, elated, happy, proud, relaxed<br>NA: Angry, ashamed, disappointed, sad, stressed | dis, rea, rum, soc, sup | Pasyugina et al. (2015) |
| 11 | 47 | 21.5 (3.9) | 53.2% | 2332 | 7 | 10 | 70.9% | PA: Happy, relaxed<br>NA: Angry, anxious, depressed, stressed | dis, rea, rum, soc, sup | Brans et al. (2013) |
| 12 | 102 | 24.1 (6.9) | 86.1% | 8795 | 14 | 7 | 88.0% | PA: Happy, relaxed<br>NA: Angry, sad, stressed | dis, rea, rum, soc, sup | Dejonckheere et al. (2019) |
| 13 | 73 | 23.3 (3.6) | 61.6% | 4303 | 7 | 10 | 84.2% | PA: Calm, confident, happy, proud<br>NA: Angry, anxious, embarrassed, guilty, sad | acc, dis, rea, sup | Haines et al. (2016) |

Note. *N*, number of participants; % female, percentage of participants who identified themselves as females (compared to as males); Obs., total number of observations (this is based on affect balance values and may thus differ from previously reported adherence rates); S./day, ambulatory signals per day; Adher., adherence; PA, positive affect; NA, negative affect; ER, emotion regulation; acc, acceptance, dis, distraction; rea, reappraisal; rum, rumination; sup, suppression.

model, in which momentary affective well-being at $t$ was predicted by all within-person centered ER strategies at $t$ (referring to the interval since the last measurement occasion) in one model, controlling for prior affective well-being at $t$-1 (see Figure 2 *within-person level*) and allowing for random effects for all predictors. Specifically, we estimated the best linear unbiased prediction of the random effects, also known as empirical Bayes estimates (Karunamuni, 2002), for each participant and ER strategy. The best linear unbiased prediction has a mean of zero and captures the person-specific deviation from the fixed effect. We then took the sum of it and the fixed effect of the respective ER strategy to the obtain person-specific implementation effectiveness of the respective ER strategy for each participant. Consequently, a higher person-specific strategy implementation score reflects greater effectiveness in the short-term implementation of that particular strategy in daily life, that is, a more positive change in affective well-being. *ER implementation ability* was then assessed by taking the mean of the person-specific ER implementation effectiveness scores across all ER strategies, with higher scores reflecting better overall ER

**Table 3.** Mean, standard deviation, between-person reliability, and zero-order correlations of the study variables.

| Measure | *M* | *SD* | *Min* | *Max* | Rel. | 1. | 2. | 3. | 4. |
|---|---|---|---|---|---|---|---|---|---|
| 1. Affective well-being | 68.8 | 12.2 | 5.8 | 99.7 | .89[a] | – | | | |
| 2. Adaptive ER selection | 32.9 | 21.1 | 0 | 100 | .89[a] | .10* | – | | |
| 3. Maladaptive ER selection | 28.7 | 19.3 | 0 | 100 | .89[a] | −.29* | .57* | – | |
| 4. ER implementation ability | −4.2 | 7.4 | −47.5 | 28.8 | .20[b] | −.13* | .26* | .22* | – |
| 5. ER monitoring ability | 20.0 | 55.7 | −100 | 100 | .67[a] | .32* | .44* | −.12* | .17* |

Note. SD, standard deviation; Rel., between-person reliability; ER, emotion regulation.
Estimates in bold do not include zero in their 95% CIs.
[a]Between-person reliability was estimated using the Spearman-Brown-corrected split-half reliability based on the first and second halves of the AA (e.g., Wendt et al., 2020).
[b]Between-person reliability was estimated by computing McDonald's $\omega$ as a measure of internal consistency (McNeish, 2018).
*$p$ < .05.

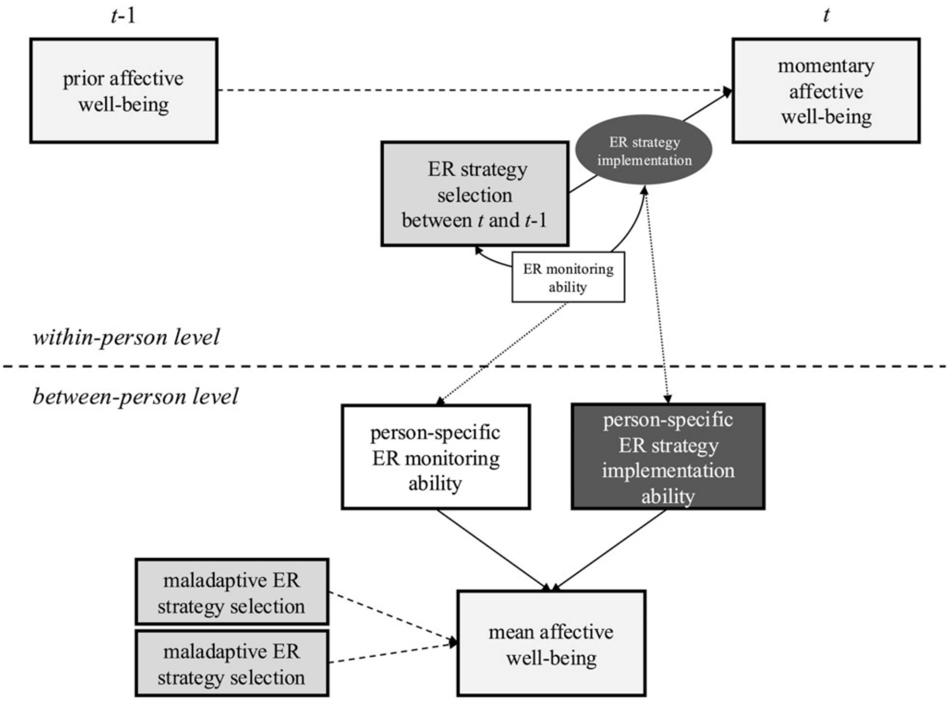


**Figure 2.** Conceptual overview of the study variables and the analytic approach.

implementation ability. Because this approach is novel, we cannot cite existing research. However, we build on typical research on ER in everyday life, in which the effectiveness of an ER strategy is assessed by predicting an affect measure by strategy use and controlling for prior affect to model the change in affect due to strategy use (e.g., Brans et al., 2013). We then derived person-specific effectiveness (rather than focusing on "average" effectiveness across participants, i.e., fixed effects) for each ER strategy. This reflects how effective an individual is at implementing a particular ER strategy. To obtain a measure of overall ER implementation ability, that is, how effectively a participant can implement all ER strategies, we took the mean of the person-specific ER strategy effectiveness scores.

*ER monitoring ability* was assessed by correlating the person-specific ER implementation effectiveness score for each ER strategy with the average extent to which they used that strategy and then taking the mean of all strategy correlations (see Figure 2 *within-person level* and Dejonckheere et al., 2018, for a similar approach). Thus, positive scores reflect that a participant used ER strategies more often that they can implement effectively, while negative scores reflect that they used personally effective strategies less often.

*Main analyses.* To test Hypothesis 1, we computed the zero-order correlations between the person-specific ER strategy effectiveness measures and computed McDonald's $\omega$ as a measure of internal consistency (McNeish, 2018).

To test Hypotheses 2 to 4, we computed a linear regression model for each of the thirteen datasets, in which we predicted mean affect balance by adaptive and maladaptive ER strategy selection, ER implementation ability, and ER monitoring ability, aggregating the data at the between-person level. We then synthesized the estimates using a random-effects meta-analysis with a restricted maximum likelihood estimator. We chose a random-effects meta-analysis to better capture uncertainty due to heterogeneity between datasets (Dettori et al., 2022). We considered the meta-analytically derived mean associations to be heterogeneous if Cochran's $Q$ indicated significance ($p$ < .05) and, given that Cochran's Q depends on the number of

Q depends on the number of associations included in the analysis, if the $I^2$ statistic was at least 50% or greater. We used a statistical significance threshold of $p < .05$ and a recent guideline to judge the size of associations (Funder & Ozer, 2019).

Finally, we computed a random-intercept cross-lagged panel model (Hamaker et al., 2015) to test Hypothesis 5. Specifically, we used Dataset 5, which contains three waves that were approximately half a year apart each, and conducted models in Mplus 8.10, using a maximum likelihood estimator with robust standard errors. The three-wave random-intercept cross-lagged panel model (RICLPM) is shown in Figure 3. We chose a RICLPM because it can control for, that is, remove, stable between-person differences that could be due to unmeasured covariates (Hamaker et al., 2015). Specifically, the model separates the variance of each variable in the model into a stable, trait-like part that is time-invariant and captured by random intercepts, and a variable, state-like part that is time-variant and captured by a latent factor per wave. Thus, the expected value is based on these two parts: For example, if a participant has a mean affective well-being of 4, the mean deviation can be used to estimate the expected value for that individual at each wave. In the case of a grand mean of 2 at wave 1, this individual would have an expected value of 4 – 2 = 2 at wave 1. However, if the actual value is 3, there is a difference of 1, which is captured by the within-person latent factor at each wave. These within-person latent factors are then used to estimate within-person prospective relations, which do not indicate rank-order stability, but whether, for example, mean affective well-being changes if participants report better ER monitoring than they typically report. Since the autoregressive effects do not contain both within-person and between-person effects, they reflect within-person carryover, that is, whether differences from the expected value at one wave carry over to the next wave. Cross-lagged effects thus reflect whether, for example, changes in the variability of affective well-being at wave 1 (i.e., a difference from the expected value at wave 1) lead to changes in affective well-being at wave 2. For more technical information, we refer to Hamaker et al. (2015).

## Results

### Hypothesis 1: General ER implementation ability

To test whether a general ER implementation ability exists, (Hypothesis 1), we first examined the zero-order correlations among the ER strategy effectiveness estimates. As detailed in Table 4, only half of these correlations reached

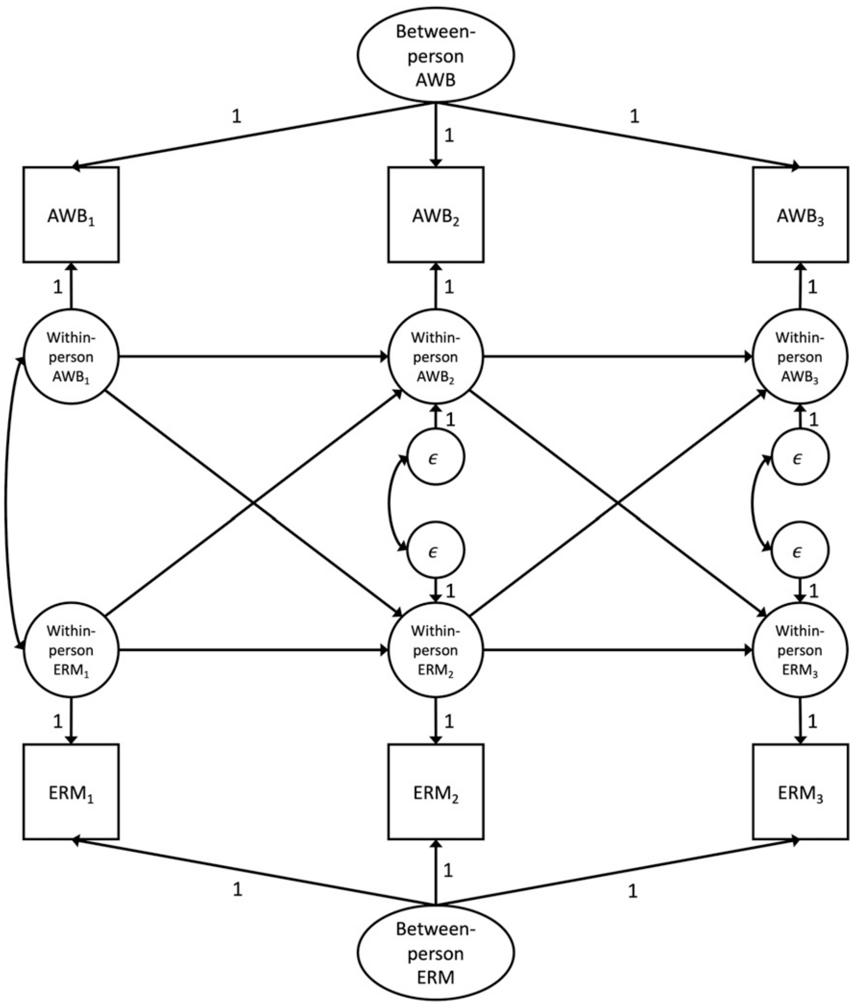


**Figure 3.** The three-wave random intercept cross-lagged panel model. Note. AWB, affective well-being; ERM, emotion regulation monitoring. The correlation between the random intercepts is not shown.

statistical significance, and all were characterized by very small or small effect sizes. The strongest correlation observed was $\bar{r}$ = .14, which represented the association between acceptance effectiveness and social sharing effectiveness. Thus, being proficient in one ER strategy, such as distraction, does not necessarily imply proficiency in another, like suppression.

To provide a direct test for Hypothesis 1, we computed the internal consistency of general ER ability by computing McDonald's $\omega$. Meta-analyzing the individual datasets with the metafor package in R using the "ARAW" option for raw alpha values, we found a mean internal consistency of general ER ability of $\bar{\varpi}$ = .20, suggesting very weak evidence for a general ER implementation ability.

### *Hypothesis 2–4: Concurrent relationships between affective well-being and ER strategy selection, ER implementation ability, and ER monitoring ability*

In terms of ER selection, we found that individuals who used more ER strategies that are generally effective in regulating affect in the short term in everyday life, such as reappraisal, reported *better* affective well-being in everyday life than individuals who used them less, $\bar{\beta}$ = .21 (Figure 4(a)). In turn, individuals who used more ER strategies than others that are generally ineffective in regulating affect in the short term in everyday life, such as suppression, reported *worse* affective well-being in everyday life than individuals who used them less, $\bar{\beta} = -.50$ (Figure 4(b)). Thus, we found support for both Hypothesis 2A and 2B.

Although there was little evidence for a general ER implementation ability (Hypothesis 1), we nevertheless tested Hypothesis 3 to determine whether an internally inconsistent ER implementation ability was yet significantly related to better affective well-being at the between-person level as well as to control for this proportion of variance.

As illustrated in Figure 4(c), ER implementation ability was not significantly associated with mean affective well-being, $\bar{\beta}$ = .02, yielding an effect size that was very close to zero, even when accounting for measurement error, $\bar{\beta}_{SB}$ = .03. Thus, implementing ER strategies more effectively than other individuals could not explain between-person differences in affective well-being in daily life, which did not support Hypothesis 3. Instead, tests of Hypothesis 1 revealed significant variability among participants in their effectiveness of ER strategy. Therefore, testing Hypothesis 4, we examined whether the more frequent use of individually effective strategies (i.e., ER monitoring ability) may be more strongly linked to improved affective well-being at the between-person level. Figure 4(d) shows that we found a medium-sized mean association between ER monitoring ability and mean affect balance of $\bar{\beta}$ = .21, that amounted to $\bar{\beta}_{SB}$ = .27 when accounting for measurement error. Thus, participants who were more likely to select ER strategies that supported an effective regulation of their affective state, reported higher overall affective well-being. Although we found evidence for significant heterogeneity (see Figure 4(d)), only 2 out of the 13 associations were below .10, demonstrating a relatively robust positive association. Moreover, ER monitoring ability could explain an additional variance of 3.8% in affective well-being on average above and beyond adaptive and maladaptive ER selection and ER implementation ability.[5]

However, Figure 4 shows that there was significant heterogeneity in the mean association between ER monitoring ability and affect balance. To explain this heterogeneity, we conducted a moderator analysis using the dataset characteristics in Table 2. First, we computed a meta-regression including one of the ten dataset characteristics (i.e., number of participants, mean age, percentage of participants who identified as female, total number of observations, number of days, number of signals per day, adherence rate, number of positive affect items, number of negative affect items, and number of ER items). Only five characteristics reduced the $\Delta I^2$ heterogeneity statistic by at least 2%, namely number of participants, number of days, number of signals per day, adherence rate, and number of ER items. We included these five characteristics in a full meta-regression model, which showed a reduction in $\Delta I^2$ = 7.1%, but which still showed substantial heterogeneity overall, $I^2$ = 53.6%, suggesting the presence of other moderators. In addition, none of the individual moderators reached significance.

Finally, it could be argued that the integration of positive and negative affect in affect balance as a single measure of affective well-being may obscure possible unique associations of positive and negative affect with ER implementation ability and ER monitoring ability. For example, some ER strategies may be more effective for regulating positive than negative affect and some individuals may have better knowledge of which ER strategies are effective for regulating negative than positive affect. Thus, we repeated the analyses using positive and negative affect instead of affect balance. The results, which can be

**Table 4.** Zero-order correlation of ER strategy effectiveness.

| Emotion regulation strategy | 1. | 2. | 3. | 4. | 5. |
|---|---|---|---|---|---|
| 1. Acceptance | – | | | | |
| 2. Distraction | .03 [−.05, .11] | – | | | |
| 3. Reappraisal | **.10** [.02, .19] | **.10** [.04, .15] | – | | |
| 4. Rumination | .06 [−.03, .16] | −.04 [−.09, .02] | .00 [−.05, .05] | – | |
| 5. Social sharing | −.02 [−.14, .09] | −.03 [−.08, .03] | **.08** [.02, .13] | **.07** [.01, .12] | – |
| 6. Suppression | −.01 [−.12, .09] | **.14** [.08, .19] | **.06** [.01, .11] | **.10** [.05, .15] | .00 [−.05, .06] |

Note. Estimates in bold do not include zero in their 95% CIs.

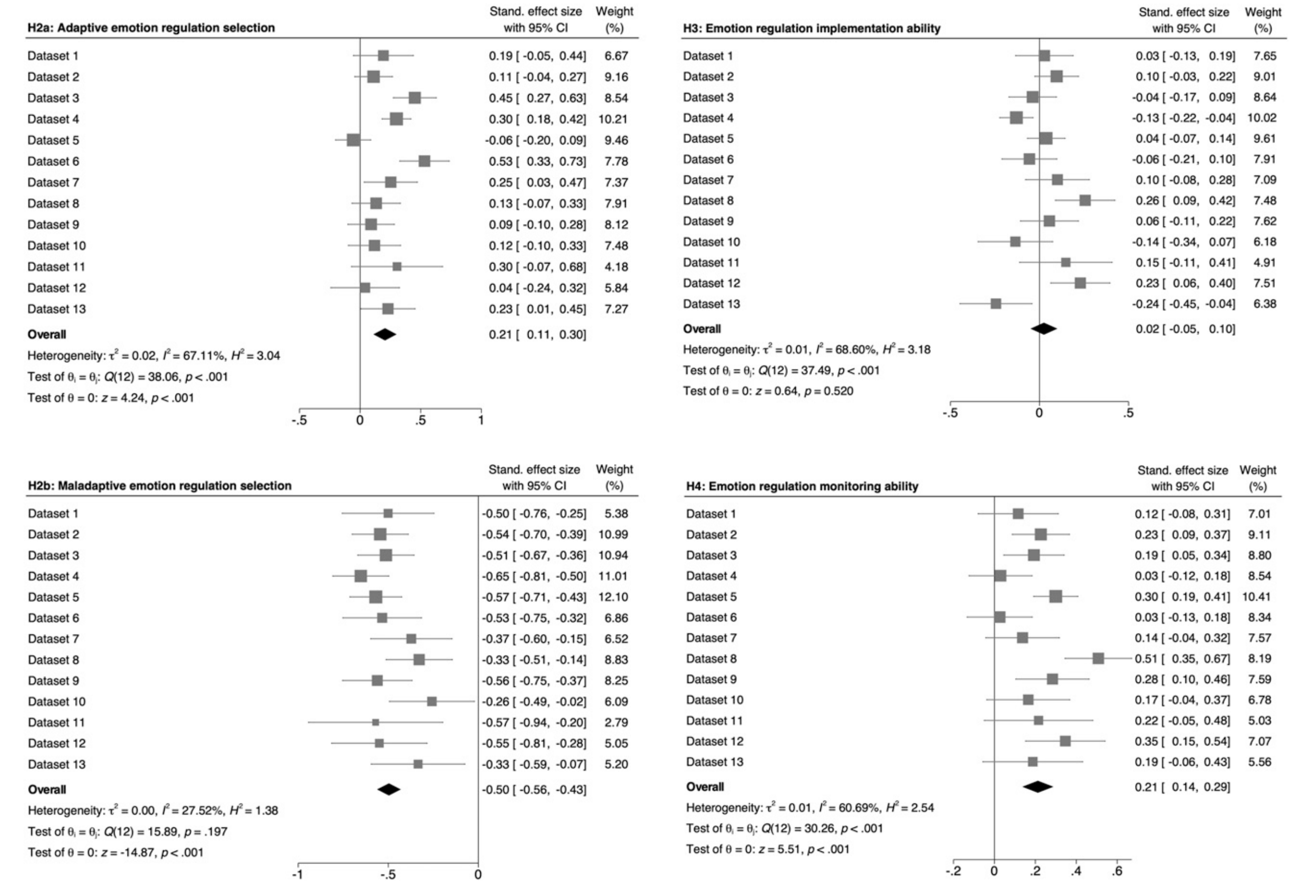


**Figure 4.** Forest plots of the association between affective well-being and adaptive ER selection (H2a), maladaptive ER selection (H2b), ER implementation ability (H3), and ER monitoring ability (H4).

found in full in the online supplement (https://osf.io/4r2b9), demonstrate that ER implementation ability was not significantly associated with positive affect, $\overline{\beta} = -.04$, 95% CI [−.12, .05], $I^2 = 70.0\%$, $p_Q < .001$, but with negative affect, $\overline{\beta} = -.08$, 95% CI [−.15, −.01], $I^2 = 67.4\%$, $p_Q < .001$, indicating that better ER implementation ability was linked to less negative affect. However, the mean association was very small and heterogeneous. For ER monitoring ability, we found a significant association with both increased positive affect, $\overline{\beta} = .18$, 95% CI [.10, .26], $I^2 = 59.2\%$, $p_Q = .005$, as well as decreased negative affect, $\overline{\beta} = -.19$, 95% CI [−.26, −.12], $I^2 = 63.6\%$, $p_Q = .004$. Thus, better ER monitoring ability was linked to more positive affect as well as less negative affect, as evidenced by the small-to-medium-sized effect sizes.

### *Hypothesis 5: Prospective relationship between ER monitoring ability and affective well-being*

Given that only ER monitoring ability, but not ER implementation ability, showed a significant concurrent relationship with overall affective well-being, we focused on ER monitoring ability in Hypothesis 5. Testing Hypothesis 4, we found a medium-sized positive association between ER monitoring ability and overall affective well-being. However, it is difficult to draw causal inferences from such a concurrent relationship because it is unclear whether ER monitoring ability might lead to better overall affective well-being or whether participants with higher levels of affective well-being have better ER monitoring ability. Therefore, we wanted to provide provisional evidence of causality by testing for Granger causality using a random intercept cross-lagged panel model and examine whether change in ER precedes change in affective well-being (see Figure 5). This model showed a very good fit to the data, $\chi^2(2) = 9.73$, $p = .465$, $RMSEA = .00$, $CFI = 1.00$, $SRMR = .04$. Specifically, Figure 5 shows that while affective well-being did not significantly predict subsequent ER monitoring ability approximately half a year later, the other direction was significant, with higher ER monitoring ability predicting better affective well-being in the form of a more positive affect balance approximately half a year later. Thus, we found evidence that changes in monitoring ability precede changes in affective well-being, but not vice versa.[6]

### *Additional analyses testing hypothesis 3 and 4*

We used a two-step approach in the present research, in which we first obtained slope coefficients, that is, ER implementation ability and ER monitoring ability, in a first step, which we then used as predictors of affective well-being at the between-person level in a second step. This two-step approach is associated with several problems because the measure from the first step is treated as a variable that was assessed with perfect reliability when it is used as a predictor in the second step, which underestimates standard errors and can inflate Type I errors (Liu et al., 2021). In addition, because participants in AA studies differ

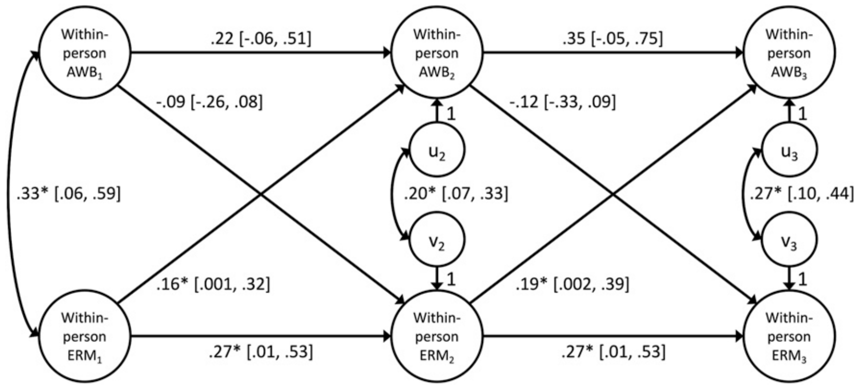


**Figure 5.** Results of the three-wave random intercept cross-lagged panel model, simplified for the purpose of illustration. Note. AWB, affective well-being; ERM, emotion regulation monitoring ability. Note that we show only the estimates that are relevant to the present research (see Figure 3 for the full model tested).

in the number of completed measurement occasions, estimates of person-specific ER strategy effectiveness are based on different numbers of sampled measurement occasions per participant and thus differ in their reliability, which may further bias estimates of person-level constructs (Lüdtke et al., 2008). To address these issues, we repeated the analyses using dynamic structural equation modeling in Mplus (Asparouhov et al., 2018). Specifically, we first estimated the effectiveness of using ER strategies by predicting momentary affect balance by each ER strategy in a model, controlling for prior affect balance and allowing for random slopes of all predictors. We then extracted the person-specific effectiveness estimates for each strategy as factor scores and transformed the data into the long format so that each observation indicated how strongly an ER strategy was used and how effectively it was used by each individual. Next, we loaded the data into Mplus to estimate a model in which the within-person association between ER strategy use and ER strategy effectiveness predicted between-person affect balance, that is, a cross-level interaction. To take advantage of latent mean centering in Mplus to avoid both Nickell's and Lüdtke's biases (McNeish & Hamaker, 2020), we followed the approach introduced by Speyer et al. (2023) and extracted the within-person components as factor scores in a first step and then used the level-one residuals, that is, the remaining variance in the measures that cannot be explained by the person mean, in a second step to test the between-person interaction. Thus, in this model, we first computed the within-person association between ER strategy use and ER strategy effectiveness by multiplying their level-one residuals, and then used this product to predict between-person affect balance along with mean ER strategy use and mean ER strategy effectiveness. Finally, we synthesized the individual results.

All dynamic structural equation models used a Bayesian estimator with two MCMC chains, the default Gibbs sampler, default priors so that the results were driven by the data, a thinning of 20, and a convergence cutoff of a potential scale reduction = 1.005 (Zitzmann & Hecht, 2019). A thinning value of 20 means that out of 20 iterations of the MCMC chains, only 1 is saved. Thus, instead of running at least 2000 iterations per chain, Mplus ran 20 × 2000 = 40,000 and saved every 20th iteration, which reduces issues with possible autocorrelations. Moreover, we required a minimum of 2000 saved iteration before model estimation was terminated in case the convergence cutoff was met to ensure and check for a stable potential scale reduction. After model termination, we visually inspected the models for signs of misspecification, that is, unstable potential scale reduction values, large ($r > .20$) autocorrelations, and trace plots that did not resemble a large, hairy caterpillar, which we did not find.

The results supported the findings of the main analyses (full results: https://osf.io/4r2b9), with a mean association between ER monitoring ability and mean affect balance of $\overline{\beta} = .39$, 95% CI [.27, .51], $I^2 = 63.3\%$, $p_Q = .002$. However, datasets containing fewer than five ER strategies (datasets 3, 4, and 13) had very large effect sizes and standard errors. When these datasets were removed, the mean effect size was still large and significant, $\overline{\beta} = .34$, 95% CI [.23, .44], $I^2 = 49.4\%$, $p_Q = .043$, with the individual results ranging from $\beta = .07$ to .56. This indicates that participants who used the ER strategies more strongly that they could use more effectively reported better affective well-being than participants who did not, further supporting Hypothesis 4. In turn, mean ER strategy effectiveness was again not significantly associated with better affective well-being, $\overline{\beta} = .04$, 95% CI [-.08, .16], $I^2 = 6.8\%$, $p_Q = .407$.

## Discussion

Research has predominantly adopted a strategy-focused perspective on ER, aiming to identify ER strategies that are generally effective across individuals (Boemo et al., 2022; Webb et al., 2012; Wenzel et al., 2025) and the conditions under which they are most effective (e.g., Aldao et al., 2015; Bonanno & Burton, 2013). This approach has been valuable in categorizing ER strategies as generally adaptive or maladaptive (Garnefski & Kraaij, 2007; Koval et al., 2023). However, it fails to account for individual differences in ER (strategy selection and implementation) abilities and the potential variability in strategy implementation effectiveness across individuals.

In the present research, we expanded on this perspective by adopting an ability-focused approach to ER, examining individual differences in ER implementation and ER monitoring, in addition to ER selection in everyday life. This approach aligns with recent calls for a more nuanced understanding of ER processes that considers both between-person differences and within-person variability (Brans et al., 2013; Brockman et al., 2016; Zetsche et al., 2024). By re-analyzing thirteen AA datasets and synthesizing the individual results, we sought to test (a) whether some individuals are generally more effective at implementing ER strategies and, thus, whether a general ER implementation ability exists, and (b) whether ER implementation ability and ER monitoring ability can explain additional variance in affective well-being beyond ER selection.

Regarding the first aim, our findings suggest that being good at one ER strategy was only very weakly related to being good at another ER strategy and thus we did not find evidence for a general ER implementation ability (Hypothesis 1). This result challenges the notion of a unified ER ability and aligns with previous research showing significant between-person variability in the effectiveness of implementing ER strategies (Brans et al., 2013; Brockman et al., 2016; Wenzel et al., 2025). In addition, ER implementation ability was not significantly associated with better affective well-being (Hypothesis 3), as evidenced by a mean effect size that was close to zero and not significant. Thus, there was no evidence for general implementation ER ability, and being good at implementing many different ER strategies effectively was not significantly adaptive for one's affective well-being, complementing the results from studies combining experimental assessments of ER strategy effectiveness with self-reported ER strategy use (Gärtner et al., 2023; Troy et al., 2010).

Instead, ER monitoring ability emerged as a significant predictor of affective well-being above and beyond ER strategy selection (Hypothesis 2): Participants who were more likely to use individually more effective ER strategies in their daily lives also reported higher affective well-being compared to those who did not (Hypothesis 4). This was not only the case for the concurrent relationship across all thirteen datasets, but also prospectively using Dataset 5, where we found that better initial ER monitoring ability was significantly associated with better affective well-being approximately half a year later, but not vice versa (Hypothesis 5).

Taken together, these findings provide preliminary evidence for the causal role of ER monitoring ability in shaping long-term affective well-being and demonstrate that ER research benefits from both a nomothetic and an idiographic approach. Although some strategies are generally effective and thus form suitable intervention targets, exclusively targeting universally adaptive strategies may not constitute the sole solution. Instead, a focus could also be on identifying and promoting the frequent use of individually effective strategies in daily life and on the ER monitoring process in general. In this context, our results also provide important implications for the development of ER-interventions such as, for instance, just-in-time adaptive interventions (JITAIs), which have already yielded promising results for promoting behavior change in other domains (Nahum-Shani et al., 2018) and would be a viable possibility: By establishing individual affect levels and identifying individually effective ER strategies, JITAIs enable prompting of these specific ER strategies precisely when a person deviates from their typical affect. This temporal and contextual alignment between affect (deviation) and ER strategy use could in turn help improve ER monitoring in the long term, akin to the responsiveness to feedback component of regulatory flexibility (Bonanno & Burton, 2013).

A further potentially significant contextual factor influencing momentary ER is the emotional intensity of the situation, as evidenced by laboratory studies where participants tend to favor distraction over reappraisal when facing high negative affect situations (Sheppes et al., 2011, 2014). However, testing the translatability of these findings to everyday life has yielded inconsistent results (e.g., Blanke et al., 2022; Lennarz et al., 2019; Mehta et al., 2020; Wilms et al., 2020), with recent research failing to provide supportive evidence for the adaptiveness of favoring distraction over reappraisal in intense situations (Wenzel & Rowland, 2024). Thus, in addition to exploring contextual factors that influence ER tendency and effectiveness, research should also acknowledge personal factors that moderate the impact of contextual factors, adopting a person-by-situation interaction perspective on ER. One such personal factor could be that some ER strategies were implemented ineffectively because participants were not skilled in implementing them or did not fully understand what was meant by each ER strategy. The possibility of an interaction of such factors with a high situational intensity is apparent and again emphasizes the importance of continuing to adopt a person-by-situation interaction perspective on ER and the need for future research to consider potential deficits in ER strategy implementation when designing ER trainings.

Despite notable strengths of our study design, such as the inclusion of 13 AA studies whose protocols were fairly similar and whose temporal assessment schedule of ER closely matched its conceptual definition, which allowed the compilation of a large AA dataset, it is important to discuss potential limitations of the present study. First, most of the datasets we analyzed in this study did not assess ER goals. In the present research, we assume that individuals are inclined to upregulate their affective well-being by endorsing ER strategies (Tamir, 2016). However, it is important to recognize that individuals may not always be motivated solely to reduce their negative affect. For example, in situations where negative affect serves as an instrumental motive and immobilizes an individual from taking action (e.g., as illustrated by Ford et al., 2019), the goal may not be to reduce negative affect, but to achieve some other goal. Thus, future research should take a broader view of ER success by considering not only the upregulation of affective well-being but also other dimensions by addressing the achievement of specific ER goals (Springstein & English, 2024).

Second, all the AA datasets we included in the present study assessed ER only with respect to an unspecified event since the last measurement occasion, and thus it is unclear how the subsequent measurement occasion relates to the previous one, if at all. Furthermore, the time interval between two measurement occasions was approximately 2 hours, which is typical in personality and social psychology (Wrzus & Neubauer, 2023) but might be too long to capture short-term ER processes (e.g., Verduyn et al., 2009, 2012). At the same time, it might also be too short because ER monitoring is an ongoing process that spans many ER episodes that individuals monitor, adapt to, and learn from (Gross, 2015). Thus, future research could employ high-frequency signal-based or event-based sampling schemes combined with measurement burst designs (Sliwinski, 2008) to capture the entire ER processes in general and ER monitoring in particular. Also, the AA datasets still rely on self-reports, which are susceptible to biases such as imperfect self-awareness or social desirability (Bettis et al., 2022). Although these biases are weaker in AA methods (Conner & Barrett, 2012), future research could include passive sensing to further reduce these biases.

Related, thirdly, we investigated ER monitoring ability as a measure of interindividual difference based on the within-person correlation between the use and effectiveness of ER strategies. This has the advantage of capturing self-reported ER strategy behavior, but we do not know the extent to which participants were aware of the relationship between ER strategy choice and idiosyncratic ER strategy effectiveness. Thus, our measure is more limited than ER monitoring, which would include measures of conscious processes as well as other ER abilities such as emotional clarity and context sensitivity. However, we view our measure as an important step in advancing the study of ER monitoring because it captures relations between self-reported ER behavior and effectiveness. Future research could build on this measure and develop and test more elaborate measures that fully capture ER monitoring.

Fourth, we used first-order lags with semi-random intervals, where the maximum interval length differed between datasets. Thus, future research could better capture these dynamics, for example, by treating time as continuous (Driver & Voelkle, 2018).

Fifth, it could be that individuals consistently use only a single ER strategy and do so effectively, which would result in a high overall ER implementation ability even though an individual limits their repertoire to one strategy. However, this was not an issue in the present research because 92.5% of all participants used each ER strategy presented to them in the respective dataset at least once, while only a total of 15 participants (fourteen participants in Dataset 4 and one participant in Dataset 10) used only a single strategy (and only a total of 29 participants used only two strategies).

Despite these limitations, our study provides important insights into the nature of ER implementation and monitoring abilities and their relationship with affective well-being. To conclude, we did not find evidence for a general ER implementation ability, as being good at implementing one ER strategy did not mean being good at implementing another strategy. This finding challenges the notion of a unified ER skill and highlights the importance of considering individual differences in ER abilities (Brans et al., 2013; Brockman et al., 2016). Instead, the adaptiveness of ER for affective well-being appeared to hinge on the inclination to endorse and employ strategies that are individually useful, a component of ER monitoring ability. This aligns with the concept of regulatory flexibility (Bonanno & Burton, 2013) and emphasizes the importance of considering both person-specific strategy selection and implementation effectiveness processes in understanding effective ER. Thus, future research should embrace this complexity and further explore individual characteristics and their interplay with broader contextual and narrower situational factors in the daily life to gain a deeper understanding of individually adaptive ER. This approach will contribute to the development of more personalized and effective interventions for improving ER and, ultimately, affective well-being.

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## Declaration of conflicting interests

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## Open science statement

Data and code for datasets 1 and 2 is available via https://osf.io/ke6qc. Dataset 3 was derived from the first wave of the “Everyday Experiences” study (Siebert et al., 2017), and access can be requested via the DIW Berlin at https://www.diw.de/en/diw_01.c.601584.en/data_access.html. Dataset 4 was collected in the project “STECCO – Starting Tertiary Education during the Corona Crisis: A Challenge and an Opportunity” (Sosin et al., 2024) and can be accessed via https://osf.io/bhq3p/. Datasets 5–13 are part of the EMOTE database (Kalokerinos et al., in preparation). The EMOTE datasets are available upon request to the EMOTE database, using our data request number (2MV32BT4RW). Analysis scripts and the data used for the synthesis are available at the OSF (https://osf.io/ke6qc). Finally, the data were not transformed to change the distribution of the measures and we did not include any covariates in the models.

## ORCID iDs

Mario Wenzel https://orcid.org/0000-0003-2839-9482
Paula Philippi https://orcid.org/0000-0003-2331-9527

## Notes

1. Affective well-being is one of the two components of subjective well-being (Schimmack et al., 2008). Affective well-being depends on the balance between positive and negative emotions, in contrast to cognitive well-being, which is based on a reflexive evaluation of subjective well-being (Diener et al., 2010).
2. We did not mention ER identification ability here because we did not examine it in the present research.

3. It is important to note that individuals engage in ER not only for prohedonic motives but also for instrumental motives, for example, maintaining anger to gain a competitive advantage in an athletic contest. While we acknowledge these other ER motives, they were not assessed in the datasets that form the basis of the present research. Thus, we consider the use of the ER strategy to be effective when positive affect is up- and negative affect downregulated, even though the participants might have had other ER motives activated that were not assessed.
4. Some datasets included additional ERSs. To be consistent with our previous research, we did not include any other ERSs that were included in the datasets (for an overview of ERSs, see https://osf.io/w6xc9). However, none of the additional ERSs were included in more than three datasets.
5. Although an additional explained variance of nearly 4% might seem small at first, the effect size of the association between ER monitoring ability and mean affect balance of $\overline{\beta} = .21$ can be interpreted as medium and is in line with the median association of $r = .19$ found in social and personality psychology (Gignac & Szodorai, 2016).
6. The autoregressive effects of affective well-being were not significant, which may be surprising (see Figure 4). It is important to note, however, that these estimates cannot be interpreted in terms of rank-order stability, since the (possibly stable) between-person variance is removed. Instead, they represent within-person carryover, that is how much of the wave-to-wave variation in affective well-being can be explained by knowledge of affective well-being in the previous wave. Thus, a nonsignificant result could indicate that affective well-being in the previous wave did not affect affective well-being in the subsequent wave, for example, due to different circumstances in the respective week of the ambulatory assessment. In addition, the autoregressive effect sizes were moderate to large, but the uncertainty was relatively large, as indicated by the wide 95% CIs. Thus, it is important to replicate our findings in future research efforts to provide more robust evidence regarding the temporal relationship between ER components and affective well-being.

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