# OSF Preregistration Update: Oct 2023

The pre-registration was updated in October 2023. The pre-registered questions remained the same but differed from the original version (see https://osf.io/9vx7t) in four areas:

1. Inclusion of 4 extra datasets for a total of 5 datasets.
2. The methodology used to calculate emotion regulation variability.
3. An updated power analysis reflecting the new methodology.
4. Updated analysis plan to accommodate the inclusion of more datasets, forming a mega-analysis to address the same research questions.

## Section 1: Updated list of datasets

| **Dataset** | G(v)oed voor elkaar | Emotions in daily life 2011 | 3-wave longitudinal study | Emotions in daily life | Outside-in |
|---|---|---|---|---|---|
| **Institute** | Radboud University | KU Leuven | KU Leuven | Tilburg University | Ghent University |
| **Project contact person** | Nina van den Broek | Peter Koval | Peter Kuppens | Eeske van Roekel | Matteo Giletta |
| **N** | 87 | 100 | 202 | 175 | 244 |
| **Age *M* (*SD*)** | 16.42 (0.61) | 19.05 (1.28) | 18.32 (0.96) | 20.84 (1.67) | 13.47 (0.41) |
| **Observations per day** | 10 | 10 | 10 | 5 | 5 |
| **Number of days** | 7 | 7 | 7 | 14 | 14 |
| **Interval scheme** | Semi-random | Stratified-random | Stratified-random | Quasi-random | Fixed |
| **Negative emotions** | Irritated<br>Worried<br>Depressed<br>Insecure<br>Loneliness | Anger<br>Sadness<br>Anxiety<br>Depression | Loneliness<br>Anger<br>Anxiety<br>Sadness<br>Depression<br>Stress | Irritated<br>Bored<br>Nervous<br>Sad<br>Angry<br>Depressed | Sad<br>Angry<br>Afraid<br>Insecure<br>Bored<br>Stressed |
| **Emotion regulation strategies** | Acceptance<br>Reappraisal<br>Suppression | Rumination<br>Reflection<br>Reappraisal | Rumination<br>Worry<br>Distraction | Distraction<br>Avoidance<br>Rumination | Reappraisal<br>Distraction<br>Social Sharing |

| | | | | | |
|---|---|---|---|---|---|
| | Rumination<br>Social Sharing | Suppression<br>Social Sharing<br>Distraction | Reappraisal<br>Suppression<br>Social Sharing | Problem Solving<br>Acceptance<br>Social Sharing<br>Co-Brooding | Suppression<br>Rumination<br>Self-Compassion<br>Expression |
| **Positive emotions** | Content<br>Relaxed<br>Joyful<br>Energetic | Relaxed<br>Happy | Happy<br>Relaxed<br>Cheerful | Enthusiastic<br>Content<br>Energetic<br>Calm<br>Powerful<br>Cheerful<br>Grateful | Happy<br>Calm<br>Enthusiastic |

Note that the final N might be smaller as we plan to exclude participants above 25 years old and participants with questionable data quality (see section 27 in the initial pre-registration).

All ESM items (negative emotions, emotion regulation strategies, and positive emotions) will be harmonized to a scale from 0 to 10 prior to index calculation and main analyses. Positive emotions are also included for the exploratory analyses registered in the original version of pre-registration.

## Section 2: Updated methodology to calculate emotion regulation variability

In the initial pre-registration, we were still working on the exact calculation strategy for calculating emotion regulation variability. In a recent paper, we demonstrated that Bray-Curtis dissimilarity, an index commonly used in ecology, is adequate in detecting moment-level emotion regulation variability and outperforms other multivariate variability indices (Lo et al., 2023). Bray-Curtis dissimilarity is bounded between 0 and 1. It is low when the same strategies tend to be used to the same extent across moments – for example, suppressing the expression of emotions for hours without employing other strategies. It is high when one changes the extent to which they use strategies or switches between different ER strategies – for example, when one increases their effort in suppression or switches from suppression to social sharing. To facilitate the interpretation of coefficients in our multilevel models, we multiply Bray-Curtis dissimilarity by 10 so that it is bounded between 0 and 10, on the same scale as other ESM items.

## Section 3: Updated power analysis

We made use of a comparable pilot dataset with 46 participants collected from a separate project in Radboud University for power analysis. This dataset has 4 negative emotion items and 6 emotion regulation strategies. We ran the planned analyses (model 1 and model 2) and obtained the following parameters.

*Model 1: emotion differentiation predicts subsequent emotion regulation variability (controlling for negative emotion intensity and emotion regulation strategy use)*

*Model 2: emotion regulation variability predicts subsequent emotion differentiation (controlling for lagged emotion differentiation, negative emotion intensity and emotion regulation strategy use)*

| **Power analysis input** | **Model 1 Value** | **Model 2 Value** |
|---|---|---|
| Fixed Intercept | 3.207712 | -1.7496 |
| Fixed Slope | -0.01573 | -0.18653 |
| SD of residual | 0.63557 | 2.5827 |
| Phi (autocorrelation of residual) | 0.20953 | 0.117546 |
| SD random intercept | 0.737566 | 0.51444 |
| SD random slope | 0.02664 | 0.41687 |
| Correlation between random intercept and random slope | -0.174 | 0.124 |
| Mean of X | 3.221006 | -2.88262 |
| SD of X | 1.175158 | 6.078867 |

We estimated the power of these models under different numbers of participants using PoweranalysisIL on Github, using “Power Analysis Model 3: Effect of a level-1 continuous predictor (random slope)” (Lafit et al., 2021). In addition to the model parameters, we also needed to provide the number of observations available per participant. We conservatively assumed 13 observations per participant, based on the least number of observations participants can report on their emotion regulation strategy use among all datasets, and the previously reported compliance rate and likelihood of rating having encountered an event that was at least moderately unpleasant (Rintala et al., 2019; Schneiders et al., 2006). By specifying 1000 simulation repetitions, we obtained the following power analysis estimates.

| | N=50 | N=100 | N=300 | N=500 | N=700 |
|---|---|---|---|---|---|
| Model 1 | 0.08 | 0.19 | 0.46 | 0.68 | 0.80 |
| Model 2 | 0.86 | 0.99 | 1.00 | 1.00 | 1.00 |

The sample size requirement of Model 1 and 2 differed vastly. This is because the fixed slope in Model 1 is smaller relative to other parameters than that in Model 2 (e.g., the fixed slope to SD of residual ratio is 2% in Model 1 but 7% in Model 2). Smaller ratios indicated a smaller effect size, which required a larger sample to detect so. We can see that with fewer than 100 participants, we lack the statistical power to test model 1 adequately. We anticipate having at least 700 participants in total across 5 datasets, after excluding participants with problematic data quality (e.g., zero variance in negative emotion items). With this sample size, we achieve over 80% power for testing model 1. As for model 2, we have sufficient power even when tested with just the original dataset from Radboud.

## Section 4: Updated analysis plan

In the original analysis plan, we planned to run two multilevel models. Model 1, corresponding to Hypothesis 1, had negative emotion differentiation as the predictor and emotion regulation variability as the outcome. Model 2, corresponding to Hypothesis 2, had emotion regulation variability as the predictor and emotion differentiation as the outcome. In both multilevel models, observations (Level 1) were nested within participants (Level 2). The outcome variable at each moment was predicted by both the time-varying (Level 1) within-person component and the time-invariant (Level 2) between-person components of predictor variables.

With the inclusion of new datasets, participants have age range from 11 to 25, which is wider than the range in the Radboud dataset. Therefore, we will add age as a time-invariant (Level 2) control variable. To further account for other between-dataset differences, we will conduct a one-stage mega-analysis with data from all datasets. First, we will pool data from multiple datasets into an overall dataset. Then, we will analyze Models 1 and 2 as multilevel modeling with 3 levels, where observations (Level 1) are nested within participants (Level 2) and further nested within datasets (Level 3). Specifically, we will include random intercepts and random slopes for datasets and participants nested in datasets. However, with only 5 datasets at Level 3, the two multilevel models may not converge (e.g., one-stage mega-analysis with random slope did not converge in a recent study that included 7 datasets, Maciejewski et al., in press). If that happens, we will simplify the model by removing the random slopes so that only random intercepts are retained. If the models still do not converge, we will account for differences in datasets by conducting 2-level modeling but adding time-invariant dummy variables (fixed-effects approach, Boedhoe et al. 2019). This will be done in two steps: first, create 4 dummy variables for the 5 datasets that we have and include these dummy code variables; second, add these dummy variables to the originally specified 2-level models as time-invariant (Level 2) variables. By doing so, coefficients and residual variances are constrained to be the same across all datasets. The fixed-effects approach performs well when there are few datasets (McNeish & Stapleton, 2016). The one-stage mega-analysis, in any of the approaches described above, is expected to have narrower confidence intervals and smaller standard errors than a two-stage meta-analysis (i.e., separately analyze each dataset, then synthesize the results to estimate the overall effect) (Boedhoe et al., 2019).

## Reference


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