Revision of the Mindfulness Manuscript

Dimensionality Test

To examine the dimensionality of state self-compassion, we fitted a series of multilevel CFA models to account for the hierarchical structure of the data, where repeated measurements were nested within days, and days were nested within individuals. Three models were specified: a One-Factor Model, a Two-Factor Model, and a Bifactor Model.

- In the **One-Factor Model**, we hypothesized that state self-compassion could be represented by a single latent factor, capturing variance both within and between individuals.

- The **Two-Factor Model** allowed for a conceptualization where state self-compassion is represented by two distinct latent factors—Compassionate Self (CS) and Uncompassionate Self (UCS)—operating at both the within-person and between-person levels.

- The **Bifactor Model** tested whether state self-compassion is best represented by a general self-compassion factor alongside orthogonal specific factors (CS and UCS), separating variance attributable to the general factor from variance explained by the specific factors.

The goodness-of-fit indices for each model are presented in Table 1.

Table 1. Goodness-of-Fit Indices for the One-Factor, Two-Factor, and Bifactor Models

Model	CFI	TLI	RMSEA	SRMR (Within)	SRMR (Between)	AIC	BIC
One-Factor	0.935	0.910	0.050	0.033	0.058	475881.5	476195.3
Two-Factor	0.972	0.959	0.034	0.024	0.050	474810.2	475139.6
Bifactor	0.987	0.971	0.029	0.016	0.031	474376.7	474816.0

As shown in Table 1, the goodness-of-fit indices progressively improve from the One-Factor Model to the Two-Factor Model, with the Bifactor Model demonstrating the best overall fit.

The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) both exceed the commonly accepted threshold of 0.95 for the Two-Factor and Bifactor Models, indicating strong model fit. Additionally, the Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) values decrease across models, further supporting improved fit with more complex structures.

We conducted a series of Likelihood Ratio Tests (LRTs) to formally assess improvements in model fit:

- Comparing the One-Factor Model with the Two-Factor Model yielded an LRT statistic of 1068.792 with 5 degrees of freedom ($p < 0.001$), indicating that the Two-Factor Model significantly improves fit. This suggests that conceptualizing state self-compassion as two distinct components (CS and UCS) better represents the data.

- The comparison between the Two-Factor Model and the Bifactor Model resulted in an LRT statistic of 506.656 with 17 degrees of freedom ($p < 0.001$), demonstrating that the Bifactor Model offers further improvement in fit. This suggests that, beyond distinct compassionate and uncompassionate components, a general self-compassion factor provides additional explanatory power.

In summary, from a psychometric standpoint, both the Two-Factor and Bifactor Models provide better fit than the One-Factor Model, with the Bifactor Model yielding the best statistical fit. These results suggest that self-compassion is best conceptualized as comprising both a general factor and specific components (CS and UCS). However, while the Bifactor Model offers superior statistical fit, its added complexity raises questions about the practical significance of modeling both general and specific factors.

Practical Importance

Dimensionality assessments should not rely exclusively on statistical fit indices but should also consider the substantive contributions of each factor (Rodriguez, Reise, and Haviland 2016; Pere J. Ferrando and Lorenzo-Seva 2018). While more complex models typically achieve better fit, they may overfit the data, particularly when too many factors are specified (Pere Joan Ferrando and Lorenzo-Seva 2019). A balance between model complexity and interpretability is essential for drawing meaningful conclusions.

To evaluate whether the data supports a unidimensional or multifactorial structure, we applied the following criteria:

1. **Factor Correlation**:
   In the Bifactor Model, correlations between the general factor and specific factors are constrained to zero, theoretically separating them. The lack of correlation between general and specific factors implies a distinct role for each factor, negating the need to interpret correlations in this case.

2. **Explained Common Variance (ECV)**:
   ECV estimates how much common variance is explained by the general versus specific factors. The general factor in the Bifactor Model (Gen_w) has high standardized loadings on items (e.g., SCP1 = 0.614, SCN2 = 0.579 at the within-level), suggesting it accounts for most of the variance. Specific factors (POS_w and NEG_w) show weaker loadings, indicating that the general factor dominates the variance explanation.

3. **Omega Hierarchical (H)**:
   H measures how much variance in the total score is due to the general factor. In the Bifactor Model, the general factor explains a large proportion of the variance (e.g., SCP1 = 0.614, SCN2 = 0.579), while specific factors contribute much less, supporting the predominance of the general factor.

4. **Bifactor Model Analysis**:
   The Bifactor Model confirms the dominance of the general factor, as specific factor loadings are consistently lower (e.g., POS_w on SCP3 = -0.313, NEG_b on SCN8 = 0.288), indicating that the specific factors add limited explanatory value beyond the general factor.

5. **Change in R-squared**:
   The general factor in the Bifactor Model explains a substantial portion of variance (e.g., R-squared for SCP1 = 0.425 within-level, 0.786 between-level). In contrast, the specific factors provide only marginal additional explanation, suggesting that a unidimensional solution may be more parsimonious without significant loss of explanatory power.

In summary, the results from the multilevel CFA analysis support Neff's hypothesis that CS and UCS are related at the trait or global level, as indicated by the superior fit of the Two-Factor and Bifactor Models. The strong correlation between CS and UCS at the latent level suggests that, across participants, individuals with high levels of CS tend to have lower levels of UCS, and vice versa.

However, it is important to emphasize that multilevel CFA examines *latent, person-level relationships*, which capture general trends over time and context. The present analysis demonstrates that CS and UCS are correlated at a global level. In contrast, other analyses focused on *momentary dynamics* may suggest that CS and UCS operate more independently within individuals over short time periods. This distinction clarifies that Neff's hypothesis may hold at a trait level but requires further exploration at the momentary level.

External Criteria

While the preceding statistical analyses rely solely on internal item data, a comprehensive assessment of the bipolar continuum hypothesis should also incorporate external criteria (Pere Joan Ferrando and Lorenzo-Seva 2019). This involves examining the validity of relationships between scale scores and relevant external variables.

Modeling the Dynamic Relationship Between Compassionate and Uncompassionate Self: An Idiographic Approach

In our earlier analyses, we found evidence supporting the "essential unidimensionality" (Reise, Bonifay, and Haviland 2013) of the augmented State Self-Compassion scale, employing a multilevel framework that accounted for repeated measurements within individuals over several days across a three-month period. These analyses provided compelling support for the idea that compassionate and uncompassionate self-responding (CS and UCS) are inversely related at the *nomothetic level* – that is, when examined across the entire sample.

In our psychometric evaluation using *internal criteria* (fit indices), we observed that more complex models, while improving statistical fit, did not fundamentally challenge the consistency of the results with Neff's hypothesis of a bipolar continuum. Minor deviations, such as differences in the variances for CS and UCS, were present, but the overall pattern of findings still aligned with the notion of CS and UCS as opposing dimensions. This conclusion was further validated when considering *external criteria*, including covariates like momentary negative affect and context evaluation, indicating that these situational factors did not significantly alter the core relationship between CS and UCS.

However, *nomothetic analyses* – focused on group-level patterns – may obscure important individual differences in how self-compassion operates in everyday life. The variability in how individuals experience and express self-compassion across different contexts might not be fully captured in these broad, averaged analyses. To delve deeper into these person-specific dynamics, we conducted an *idiographic analysis* to explore how CS and UCS interact at the individual level (Ferrari et al. 2022).

Bayesian Hierarchical Model

To investigate the momentary relationship between CS and UCS more precisely, we combined data from both experiments and applied a Bayesian hierarchical model. This approach allows us to account for moment-to-moment, daily, and individual differences in self-compassion, providing a detailed view of how CS and UCS interact dynamically over time. The model specifically examines whether the relationship between CS and UCS varies across individuals depending on momentary negative affect and context evaluation, offering a nuanced exploration of these constructs in real-world contexts. [^1]

The model assumes a linear relationship between CS and UCS to maintain consistency with Neff's hypothesis, which posits that CS and UCS are opposing ends of a continuum. By doing so, we avoid overfitting (which could occur if we assumed complete independence between CS and UCS) while testing the robustness of the hypothesized inverse relationship at the momentary level.

For each participant, the model estimates a random regression slope, reflecting how changes in CS influence UCS at the individual level. This slope is central to determining whether Neff's hypothesis holds across participants:

- If the *slope is negative*, it suggests that for that individual, higher momentary levels of CS are associated with lower levels of UCS, in line with Neff's hypothesis.
- If the *slope is flat*, it indicates that momentary changes in CS and UCS are unrelated for that participant, challenging the bipolar continuum hypothesis.
- If the *slope is positive*, it implies that CS and UCS may increase or decrease together, which directly contradicts Neff's hypothesis that these dimensions should be inversely related.

By incorporating individual-specific slopes, the model not only tests the hypothesis at the group level but also accommodates the possibility of individual-level deviations from the expected pattern. This provides a more comprehensive understanding of how CS and UCS operate in real-time across varying emotional and contextual states. The model's structure enables the inclusion of individual-specific slopes while accounting for momentary and day-level predictors, as well as random effects associated with participants, days, and measurements.

$$
\begin{aligned}
\mathrm{UCS}_n \sim {}& \text{Student-t}(\nu, \mu_n, \sigma_{\mathrm{UCS}}) \\
\mu_n = {}& \alpha_{\mathrm{UCS}} + \sigma_{\mathrm{participant}} z_{\mathrm{participant},n} + \sigma_{\mathrm{day}} z_{\mathrm{day},n} + \sigma_{\mathrm{measurement}} z_{\mathrm{measurement},n} \\
& + (\beta_{\mathrm{CS}} + \sigma_{\mathrm{participant,\ slope\_cs}} z_{\mathrm{participant,\ slope\_cs},n}) \mathrm{CS}_n \\
& + (\beta_{\mathrm{neg\_aff,\ Moment}} + \sigma_{\mathrm{participant,\ slope\_na}} z_{\mathrm{participant,\ slope\_na},n}) \mathrm{neg\_aff\_Moment}_n \\
& + \beta_{\mathrm{neg\_aff,\ Day}} \mathrm{neg\_aff\_Day}_n + \beta_{\mathrm{neg\_aff,\ Person}} \mathrm{neg\_aff\_Person}_n \\
& + \beta_{\mathrm{interaction}} \mathrm{CS}_n \times \mathrm{neg\_aff\_Moment}_n \\
& + \beta_{\mathrm{context\_eval,\ Moment}} \mathrm{context\_eval\_Moment}_n \\
& + \beta_{\mathrm{context\_eval,\ Day}} \mathrm{context\_eval\_Day}_n + \beta_{\mathrm{context\_eval,\ Person}} \mathrm{context\_eval\_Person}_n
\end{aligned}
$$

This model allows for a flexible investigation of how CS and UCS interact dynamically at the *momentary level*, accounting for random effects and external influences. The Student-t distribution accounts for potential outliers or non-normality in the data, while weakly informative priors are employed to avoid overfitting (see Supplementary Information for the full model specification).

Results

Key parameters of interest in this Bayesian hierarchical model include the random slopes of CS on UCS (β_{CS} and $\sigma_{\mathrm{participant\_slope\_cs}}$) and the interaction between CS and momentary negative affect ($\beta_{\mathrm{interaction}}$).

The posterior mean of the fixed effect of CS on UCS (β_{CS}) was -0.380 (89% CI: [-0.406, -0.352]), indicating a general negative association between CS and UCS at the group level, consistent with Neff's hypothesis. However, the random slope ($\sigma_{\text{participant\_slope\_cs}} = 0.324$, 89% CI: [0.304, 0.345]) suggests substantial individual variability in this relationship. Specifically, only 67% of participants demonstrated the expected negative association, while a significant minority showed weaker or even *positive associations* between CS and UCS (see Figure XX).

This variability challenges the assumption that CS and UCS are universally inversely related for all individuals at the momentary level. Furthermore, the interaction term ($\beta_{\text{interaction}} = -0.0304$, 89% CI: [-0.0380, -0.0230]) suggests that higher negative affect amplifies the inverse relationship between CS and UCS. That is, during moments of emotional distress, the opposition between CS and UCS becomes more pronounced.

Discussion

The results of this idiographic analysis reveal that, while Neff's hypothesis generally holds at the group level, there is considerable individual variation in the relationship between CS and UCS at the momentary level. For a subset of participants, CS and UCS are not inversely related, and in some cases, they even fluctuate together—an observation incompatible with the bipolar continuum hypothesis (Ferrari et al. 2023; Ullrich-French and Cox 2020).

Moreover, the interaction between momentary negative affect and the CS-UCS relationship highlights the contextual sensitivity of these constructs. When individuals experience higher negative affects, the inverse relationship between CS and UCS intensifies, suggesting that emotional states can moderate this dynamic (Dejonckheere et al. 2021).

In summary, this idiographic analysis offers a nuanced view of the relationship between CS and UCS. While the nomothetic analyses support Neff's hypothesis at the global level, the idiographic findings emphasize the importance of individual differences. For most individuals, increases in CS lead to reductions in UCS, but for some, the relationship may be more complex or even contradictory. This highlights the need to consider both nomothetic and idiographic perspectives when investigating the dynamic nature of self-compassion.

Supplementary Material Description

Dimensionality Test

Mplus script for the One-Factor Model

```
TITLE: Multilevel One-Factor Model with covariates at moment, day, and person level;

DATA:
  FILE = "/Users/corrado/Documents/bipolar_continuum/data/mplus_data/neff_2.dat";

VARIABLE:
  NAMES = user_id day time_window scs_pos_1 scs_neg_2 scs_pos_3 scs_neg_4
    scs_neg_5 scs_pos_6 scs_pos_7 scs_neg_8 neg_aff_Moment neg_aff_Day neg_aff_Person;
  USEVARIABLES = scs_pos_1 scs_neg_2 scs_pos_3 scs_neg_4 scs_neg_5 scs_pos_6
    scs_pos_7 scs_neg_8 neg_aff_Moment neg_aff_Day neg_aff_Person;
  CLUSTER = user_id;   ! Clustering at the subject level
  WITHIN = neg_aff_Moment neg_aff_Day;   ! Covariates at the moment and day level
  BETWEEN = neg_aff_Person;   ! Covariate at the person level

MISSING = .;

ANALYSIS:
  TYPE = TWOLEVEL;   ! Multilevel model with user_id as the cluster
  ESTIMATOR = ML;   ! Maximum likelihood estimation

MODEL:
  %WITHIN%   ! Level 1: Within-subject and within-day variation
    SelfCompassion_w BY scs_pos_1 scs_neg_2 scs_pos_3 scs_neg_4 scs_neg_5
      scs_pos_6 scs_pos_7 scs_neg_8;
    SelfCompassion_w ON neg_aff_Moment neg_aff_Day;
    ! Regress self-compassion factor on momentary and daily negative affect

  %BETWEEN%   ! Level 2: Between-subject variation
    SelfCompassion_b BY scs_pos_1 scs_neg_2 scs_pos_3 scs_neg_4 scs_neg_5
      scs_pos_6 scs_pos_7 scs_neg_8;
    SelfCompassion_b ON neg_aff_Person;
    ! Regress between-level self-compassion factor on person-level negative affect

OUTPUT:
  TECH1 TECH8 STANDARDIZED MODINDICES;
```

Mplus script for the Two-Factor Model

```
TITLE: Multilevel Two-Factor Model with covariates at moment, day, and person level;

DATA:
  FILE = "/Users/corrado/Documents/bipolar_continuum/data/mplus_data/neff_2.dat";

VARIABLE:
  NAMES = user_id day time_window scs_pos_1 scs_neg_2 scs_pos_3 scs_neg_4
    scs_neg_5 scs_pos_6 scs_pos_7 scs_neg_8 neg_aff_Moment neg_aff_Day neg_aff_Person;
  USEVARIABLES = scs_pos_1 scs_neg_2 scs_pos_3 scs_neg_4 scs_neg_5 scs_pos_6
    scs_pos_7 scs_neg_8 neg_aff_Moment neg_aff_Day neg_aff_Person;
  CLUSTER = user_id;  ! Clustering at the subject level
  WITHIN = neg_aff_Moment neg_aff_Day;  ! Covariates at the moment and day level
  BETWEEN = neg_aff_Person;  ! Covariate at the person level

MISSING = .;

ANALYSIS:
  TYPE = TWOLEVEL;  ! Multilevel model with user_id as the cluster
  ESTIMATOR = ML;  ! Maximum likelihood estimation

MODEL:
  %WITHIN%  ! Level 1: Within-subject and within-day variation
    PositiveSelfCompassion_w BY scs_pos_1 scs_pos_3 scs_pos_6 scs_pos_7;
    ! Positive self-compassion factor on within level
    NegativeSelfCompassion_w BY scs_neg_2 scs_neg_4 scs_neg_5 scs_neg_8;
    ! Negative self-compassion factor on within level
    PositiveSelfCompassion_w ON neg_aff_Moment neg_aff_Day;
    ! Regress positive factor on momentary and daily negative affect
    NegativeSelfCompassion_w ON neg_aff_Moment neg_aff_Day;
    ! Regress negative factor on momentary and daily negative affect

  %BETWEEN%  ! Level 2: Between-subject variation
    PositiveSelfCompassion_b BY scs_pos_1 scs_pos_3 scs_pos_6 scs_pos_7;
    ! Positive self-compassion factor on between level
    NegativeSelfCompassion_b BY scs_neg_2 scs_neg_4 scs_neg_5 scs_neg_8;
    ! Negative self-compassion factor on between level
    PositiveSelfCompassion_b ON neg_aff_Person;
    ! Regress positive factor on person-level negative affect
    NegativeSelfCompassion_b ON neg_aff_Person;
```

```
      ! Regress negative factor on person-level negative affect

OUTPUT:
   TECH1 TECH8 STANDARDIZED MODINDICES;
```

Mplus script for the Bifactor Model

```
TITLE: Multilevel Bifactor Model with covariates at moment, day, and person level;

DATA:
   FILE = "/Users/corrado/Documents/bipolar_continuum/data/mplus_data/neff_2.dat";

VARIABLE:
   NAMES = uid day tw scp1 scn2 scp3 scn4 scn5 scp6 scp7 scn8 na_mom na_day na_per;
   USEVARIABLES = scp1 scn2 scp3 scn4 scn5 scp6 scp7 scn8 na_mom na_day na_per;
   CLUSTER = uid;
   WITHIN = na_mom na_day;
   BETWEEN = na_per;

   MISSING = .;

ANALYSIS:
   TYPE = TWOLEVEL;
   ESTIMATOR = ML;

MODEL:
   %WITHIN%
     Gen_w BY scp1* scn2 scp3 scn4 scn5 scp6 scp7 scn8;
     Pos_w BY scp1* scp3 scp6 scp7;
     Neg_w BY scn2* scn4 scn5 scn8;

     ! Fix variances to help with model identification
     Gen_w@1;  ! Fix variance of the general factor
     Pos_w@1;  ! Constrain variance of the positive factor
     Neg_w@1;  ! Constrain variance of the negative factor

     ! Ensure no covariance between factors
     Pos_w WITH Gen_w@0;
     Neg_w WITH Gen_w@0;
     Pos_w WITH Neg_w@0;
```

```
   ! Regress factors on covariates
   Gen_w ON na_mom na_day;
   Pos_w ON na_mom na_day;
   Neg_w ON na_mom na_day;

%BETWEEN%
   Gen_b BY scp1* scn2 scp3 scp4 scn5 scp6 scp7 scn8;
   Pos_b BY scp1* scp3 scp6 scp7;
   Neg_b BY scn2* scn4 scn5 scn8;

   ! Fix variances on the between level as well
   Gen_b@1;  ! Fix variance of the general factor
   Pos_b@1;  ! Constrain variance of the positive factor
   Neg_b@1;  ! Constrain variance of the negative factor

   ! Ensure no covariance between factors
   Pos_b WITH Gen_b@0;
   Neg_b WITH Gen_b@0;
   Pos_b WITH Neg_b@0;

   ! Regress factors on covariates
   Gen_b ON na_per;
   Pos_b ON na_per;
   Neg_b ON na_per;

OUTPUT:
  TECH1 TECH8 STANDARDIZED MODINDICES(ALL);
```

Bayesian hierarchical model

Here we provide a detailed description of the Bayesian hierarchical model used to test the relationship between compassionate (CS) and uncompassionate (UCS) self-responding in the context of Neff's bipolar hypothesis. The model's structure incorporates multiple levels of variation, capturing momentary and daily changes in emotional and contextual factors, as well as individual differences in baseline CS and UCS levels.

The core structure of the model can be described as follows:

1. **Data Structure**:

   - *CS and UCS* are measured repeatedly over time via Ecological Momentary Assessment (EMA), with participants reporting their CS and UCS scores multiple times a day.
   - The model also includes momentary and day-level predictors such as negative affect (`neg_aff`) and context evaluation (`context_eval`).

2. **Model Parameters**:

   - **Fixed Effects**: The model includes an overall effect of CS on UCS (`beta_cs`), reflecting the hypothesized inverse relationship between these two constructs. A negative `beta_cs` would support Neff's hypothesis that higher CS predicts lower UCS.
   - **Random Effects**: The model allows for individual-level deviations in this relationship, captured by the random slopes for CS (`z_participant_slope_cs`), as well as individual differences in baseline UCS levels (`z_participant`).
   - **Interaction Terms**: The model includes an interaction between CS and momentary negative affect (`beta_interaction`), allowing us to test whether the inverse CS-UCS relationship is modulated by emotional states.
   - **Contextual Effects**: To account for fluctuations across time and context, the model includes three levels of predictors for negative affect and context evaluation:
     - *Momentary (within-day)*: Measures the effect of immediate negative affect and context on UCS.
     - *Daily (between-days)*: Measures the effect of average negative affect and context across a given day.
     - *Person-level (between-participants)*: Captures individual differences in baseline negative affect and context evaluations.

3. **Bayesian Structure**:

   - The model is implemented using Bayesian inference, which allows for posterior distributions of all parameters to be computed. This provides a full probabilistic representation of uncertainty around the estimated effects.

- *Hierarchical Priors*: The hierarchical structure of the model allows for individual-specific estimates of the relationship between CS and UCS. Random slopes are modeled with normal distributions centered on the group-level fixed effects, capturing the variability across participants.

4. **Generated Quantities**:

   - The model includes a *generated quantities* block to compute posterior predictions for UCS (`pred_UCS`) at each measurement occasion, based on the estimated relationships between CS, negative affect, and context.
   - *Log-likelihoods* (`log_lik`) for each observation are computed, enabling posterior predictive checks and model comparison using *leave-one-out cross-validation* (LOO).

5. **Sampling**:

   - The model was estimated using Markov Chain Monte Carlo (MCMC) sampling. Four chains were run with 2000 iterations each for burn-in and 2000 iterations for sampling. This approach provided efficient approximation of the posterior distribution.

Key Parameters and Interpretation

- `beta_cs`: Represents the overall effect of CS on UCS. A negative value would indicate that, on average, increases in CS are associated with decreases in UCS, supporting Neff's hypothesis.
- `beta_interaction`: Tests the interaction between CS and negative affect, indicating whether the CS-UCS relationship becomes stronger or weaker depending on momentary emotional states.
- `sigma_participant_slope_cs`: The standard deviation of the random slopes for CS, indicating how much the effect of CS on UCS varies across individuals.
- **Random Intercepts**: Variability in UCS across participants (`sigma_participant`), days (`sigma_day`), and measurement occasions (`sigma_measurement`), capturing how uncompassionate responses fluctuate due to time or context.

Posterior Predictive Checks and Model Fit Assessment. To evaluate model fit, we employed posterior predictive checks and leave-one-out cross-validation (LOO). Pareto k statistics were calculated to quantify how well each data point was predicted by the model. There were no divergent transitions. Maximum Rhat: 1.0150; mean Rhat: 1.0006.

The full Stan code for the model is provided below.

```
data {
  int<lower=0> N; // Total number of observations
  int<lower=0> P; // Number of participants
```

```stan
  int<lower=0> D; // Number of days
  int<lower=0> M; // Number of measurements per day per participant
  array[N] int<lower=1, upper=P> participant; // Participant index for each observation
  array[N] int<lower=1, upper=D> day; // Day index for each observation
  array[N] int<lower=1, upper=M> measurement; // Measurement index for each observation
  array[N] real CS; // Compassionate Self measures
  array[N] real UCS; // Uncompassionate Self measures

  // Scaled and centered negative affect variables
  array[N] real neg_aff_Moment; // Negative affect moment-centered
  array[N] real neg_aff_Day; // Negative affect day-centered
  array[N] real neg_aff_Person; // Negative affect person-centered

  // Scaled and centered context evaluation variables
  array[N] real context_eval_Moment; // Context evaluation moment-centered
  array[N] real context_eval_Day; // Context evaluation day-centered
  array[N] real context_eval_Person; // Context evaluation person-centered
}

parameters {
  // Fixed effects
  real alpha_ucs; // Intercept for UCS
  real beta_cs; // Overall effect of CS on UCS
  real beta_interaction; // Effect of interaction between CS and NA

  // Coefficients for the three negative affect components
  real beta_neg_aff_Moment;
  real beta_neg_aff_Day;
  real beta_neg_aff_Person;

  // Coefficients for the three context evaluation components
  real beta_context_eval_Moment;
  real beta_context_eval_Day;
  real beta_context_eval_Person;

  // Random intercepts
  vector[P] z_participant; // Random intercept for participants
  vector[D] z_day; // Random intercept for days
  vector[M] z_measurement; // Random intercept for measurements

  // Random slopes for CS at the participant level
```

```stan
    vector[P] z_participant_slope_cs;

    // Random slopes for NA at the participant level
    vector[P] z_participant_slope_na;

    // Variance parameters
    real<lower=0> sigma_participant; // SD of participant intercepts
    real<lower=0> sigma_day; // SD of day intercepts
    real<lower=0> sigma_measurement; // SD of measurement intercepts
    real<lower=0> sigma_participant_slope_cs; // SD of participant slopes for CS
    real<lower=0> sigma_participant_slope_na; // SD of participant slopes for NA
    real<lower=0> sigma_ucs; // Error term for UCS model

    real<lower=0> nu; // Degrees of freedom for t-distribution
}

model {
  // Priors for fixed effects
  alpha_ucs ~ normal(0, 1);
  beta_cs ~ normal(0, 1);
  beta_interaction ~ normal(0, 1); // Prior for interaction term
  beta_neg_aff_Moment ~ normal(0, 1);
  beta_neg_aff_Day ~ normal(0, 1);
  beta_neg_aff_Person ~ normal(0, 1);
  beta_context_eval_Moment ~ normal(0, 1);
  beta_context_eval_Day ~ normal(0, 1);
  beta_context_eval_Person ~ normal(0, 1);

  // Priors for random effects (latent variables)
  z_participant ~ normal(0, 1);
  z_day ~ normal(0, 1);
  z_measurement ~ normal(0, 1);
  z_participant_slope_cs ~ normal(0, 1);
  z_participant_slope_na ~ normal(0, 1);

  // Priors for variances
  sigma_participant ~ exponential(1);
  sigma_day ~ exponential(1);
  sigma_measurement ~ exponential(1);
  sigma_participant_slope_cs ~ exponential(1);
  sigma_participant_slope_na ~ exponential(1);
```

```stan
    sigma_ucs ~ exponential(1);
    nu ~ gamma(2, 0.1);

    // Likelihood for UCS using a t-distribution
    for (n in 1:N) {
      UCS[n] ~ student_t(
        nu,
        // Random intercepts
        alpha_ucs +
        sigma_participant * z_participant[participant[n]] +
        sigma_day * z_day[day[n]] +
        sigma_measurement * z_measurement[measurement[n]] +

        // Main effect of CS with individual random slope
        (beta_cs + sigma_participant_slope_cs *
          z_participant_slope_cs[participant[n]]) * CS[n] +

        // Main effect of NA (including random slope for NA)
        (beta_neg_aff_Moment + sigma_participant_slope_na *
          z_participant_slope_na[participant[n]]) * neg_aff_Moment[n] +
        beta_neg_aff_Day * neg_aff_Day[n] +
        beta_neg_aff_Person * neg_aff_Person[n] +

        // Interaction term between CS and NA (Moment-level)
        beta_interaction * CS[n] * neg_aff_Moment[n] +

        // Main effect of context evaluation components
        beta_context_eval_Moment * context_eval_Moment[n] +
        beta_context_eval_Day * context_eval_Day[n] +
        beta_context_eval_Person * context_eval_Person[n],

        // Error term
        sigma_ucs
      );
    }
}

generated quantities {
  array[N] real pred_UCS; // Posterior predictions for UCS
  array[N] real log_lik; // Log-likelihood for UCS
```

```
  for (n in 1:N) {
    pred_UCS[n] = student_t_rng(
      nu,
      alpha_ucs +
      sigma_participant * z_participant[participant[n]] +
      sigma_day * z_day[day[n]] +
      sigma_measurement * z_measurement[measurement[n]] +
      (beta_cs + sigma_participant_slope_cs *
        z_participant_slope_cs[participant[n]]) * CS[n] +
      (beta_neg_aff_Moment + sigma_participant_slope_na *
        z_participant_slope_na[participant[n]]) * neg_aff_Moment[n] +
      beta_neg_aff_Day * neg_aff_Day[n] +
      beta_neg_aff_Person * neg_aff_Person[n] +
      beta_interaction * CS[n] * neg_aff_Moment[n] +
      beta_context_eval_Moment * context_eval_Moment[n] +
      beta_context_eval_Day * context_eval_Day[n] +
      beta_context_eval_Person * context_eval_Person[n],
      sigma_ucs
    );

    log_lik[n] = student_t_lpdf(
      UCS[n] |
      nu,
      alpha_ucs +
      sigma_participant * z_participant[participant[n]] +
      sigma_day * z_day[day[n]] +
      sigma_measurement * z_measurement[measurement[n]] +
      (beta_cs + sigma_participant_slope_cs *
        z_participant_slope_cs[participant[n]]) * CS[n] +
      (beta_neg_aff_Moment + sigma_participant_slope_na *
        z_participant_slope_na[participant[n]]) * neg_aff_Moment[n] +
      beta_neg_aff_Day * neg_aff_Day[n] +
      beta_neg_aff_Person * neg_aff_Person[n] +
      beta_interaction * CS[n] * neg_aff_Moment[n] +
      beta_context_eval_Moment * context_eval_Moment[n] +
      beta_context_eval_Day * context_eval_Day[n] +
      beta_context_eval_Person * context_eval_Person[n],
      sigma_ucs
    );
  }
}
```

In summary, the idiographic approach enabled by this model allows for a deeper exploration of Neff's bipolar hypothesis, testing whether the CS-UCS relationship holds not only at the group level but also at the individual level, across different time frames and contexts.

Additional Model Results

In this section, we provide a comprehensive overview of the additional results from the Bayesian hierarchical model.

Posterior Estimates of Fixed Effects

The core fixed effects in the model include β_{CS} and $\beta_{\text{interaction}}$, which have been discussed in the main manuscript.

Random Effects and Variability Across Individuals

One of the strengths of this hierarchical model is its ability to capture individual variability in the relationship between CS and UCS.

- $\sigma_{\text{participant\_slope\_cs}}$: This parameter has been discussed in the main text.
- **Random Intercepts**:
  - $\sigma_{\text{participant}}$: The posterior mean of this parameter is 0.458, with an 89% CI of [0.437, 0.480], indicating substantial variation in baseline UCS levels across individuals.
  - σ_{day}: The posterior mean of this parameter is 0.089, with an 89% CI of [0.076, 0.102], capturing daily fluctuations in UCS.
  - $\sigma_{\text{measurement}}$: The posterior mean of this parameter is 0.067, with an 89% CI of [0.059, 0.075], capturing within-day, moment-to-moment variability in UCS.

Contextual Effects: Negative Affect and Context Evaluation

To account for contextual variability, the model includes momentary, daily, and person-level predictors for both negative affect and context evaluation.

- **Negative Affect (NA)**:
  - $\beta_{\text{neg\_aff\_Moment}}$: The momentary effect of negative affect on UCS was estimated to have a posterior mean of 0.092, with an 89% CI of [0.071, 0.113], indicating that higher momentary negative affect is associated with increased levels of UCS.

- $\beta_{\textbf{neg\_aff\_Day}}$: The day-level effect of negative affect on UCS was estimated to have a posterior mean of 0.047, with an 89% CI of [0.026, 0.068], indicating that higher average negative affect across the day contributes to increased UCS.
- $\beta_{\textbf{neg\_aff\_Person}}$: The person-level effect of negative affect was estimated to have a posterior mean of 0.067, with an 89% CI of [0.045, 0.089], capturing how individuals with higher baseline levels of negative affect tend to have higher levels of UCS.

- **Context Evaluation**:

  - $\beta_{\textbf{context\_eval\_Moment}}$: The momentary effect of context evaluation on UCS was estimated to have a posterior mean of -0.061, with an 89% CI of [-0.082, -0.040], suggesting that more positive context evaluations at a given moment are associated with lower levels of UCS.
  - $\beta_{\textbf{context\_eval\_Day}}$: The day-level effect of context evaluation on UCS was estimated to have a posterior mean of -0.042, with an 89% CI of [-0.064, -0.021], indicating that days characterized by more positive evaluations tend to be associated with lower levels of UCS.
  - $\beta_{\textbf{context\_eval\_Person}}$: The person-level effect of context evaluation was estimated to have a posterior mean of -0.056, with an 89% CI of [-0.078, -0.034], indicating that individuals with more positive overall evaluations of their context tend to experience lower levels of UCS.

Posterior Predictive Checks and Model Fit

To assess the fit of the model, we performed *posterior predictive checks* using density overlays and histogram comparisons between the observed data and the posterior predictions. The results indicated that the model accurately captures the distribution of UCS scores, providing confidence in the model's predictive performance. The MCMC sampling did not produce any divergent transitions.

We also computed *leave-one-out cross-validation (LOO)* for model comparison and fit assessment. The Pareto k statistics indicated that all observations were well predicted, with no problematic points (i.e., $k < 0.5$ for all data points). The maximum $\hat{R}$ value across all parameters was 1.0150, with a mean $\hat{R}$ value of 1.0006, suggesting good convergence.

Idiographic versus Nomothetic Approaches

We believe that, for the purposes of testing Neff's hypothesis, using a Bayesian multilevel model in the present study is both justified and appropriate. While more specialized idiographic approaches, such as the GIMME method (Wright et al. 2019), offer specific advantages, these are not necessary for the current analysis. Wright et al. (2019) highlight two main strengths of GIMME over multilevel modeling: (1) it does not require assuming that all individuals follow the same functional form, and (2) it avoids assuming normally distributed random effects.

However, in our case, assuming a linear relationship between UCS and CS aligns with the theoretical basis of our study and allows us to directly test the hypothesis that motivated our research.

Regarding the assumption of normally distributed random effects, while it is true that all statistical analyses are conditional on the model assumptions, our results are strongly supported by the good fit of the model, as evidenced by posterior predictive checks, R-hat values, and the absence of convergence issues. Thus, these assumptions do not undermine the validity of our conclusions. Moreover, multilevel modeling provides an additional advantage over purely data-driven idiographic methods by greatly attenuating the risk of overfitting. GIMME, while excellent for uncovering individual-level variation without prior assumptions, can sometimes risk overfitting when dealing with complex, noisy data, as noted by Wright et al. (2019). Given our specific research question—testing the hypothesized relationship between CS and UCS—a simpler multilevel model is better suited, as it effectively bridge nomothetic and idiographic approaches, because they simultaneously estimate within-person associations among variables (e.g., daily stress→negative affect) and between-person differences in those associations (Conner et al. 2009).

Response to Reviewer Comments

Reviewer 1

- Point 2: "The introduction provides a reasonable rationale for testing the bipolar continuum hypothesis using EMA. However, I wonder if the authors could provide a brief review of recent self-compassion research using EMA (e.g., Mey et al., 2023; DOI: 10.1007/s12671-022-02050-y, which was in the reference list but was not cited) and explain how previous research might inform hypotheses."

  - *Thank you for this helpful suggestion. We have added a brief review of recent work on self-compassion using EMA to the introduction of the manuscript, drawing particularly on Mey et al. (2023). This work highlights that, while self-compassion (SC) has traditionally been viewed as a stable trait, there is growing evidence that SC fluctuates within individuals over time and that these fluctuations impact well-being. For instance, individuals report healthier eating behaviors, better body image, less perceived stress, and a lower likelihood of clinical impairment due to eating habits on days when they report higher SC than usual.*

  - Mey et al. (2023) utilized EMA to investigate the implications of momentary self-compassion (SC) for affective dynamics and well-being in daily life, finding that higher recent SC was related to higher momentary positive affect and lower momentary negative affect. Moreover, they found that higher recent SC was associated with lower stress reactivity to daily hassles. The study importantly shows that SC may not only be a beneficial trait but also a helpful state that can be cultivated in daily life to enhance well-being and mitigate the negative impact of stress. This is significant because it highlights the potential for individuals to experience the benefits of SC regardless of their general level of self-compassion. Mey et al. (2023) also discovered that SC fluctuates over time within the same individual, challenging the traditional view of SC as a static trait. This dynamic nature of SC supports our present design, which uses EMA to examine how the CS and UCS covary across different contexts to evaluate the hypothesis of a bipolar continuum. Furthermore, the study's findings suggest that repeatedly increasing one's momentary SC could potentially lead to increases in trait levels of SC, offering more enduring well-being benefits. This aligns with research on mindfulness, which has shown that repeatedly increasing state mindfulness in brief meditations over several weeks led to heightened trait mindfulness at the end of the intervention. The sources also note a "paradox" within the SC concept. While SC aims to alleviate suffering, it also emphasizes acceptance of the current moment, creating a potential tension between these two aspects. The findings of Mey et al. (2023) thus demonstrate the value of EMA as a method to explore the dynamic nature of SC and its implications for well-being. This method captures the fluctuation of SC within individuals, which might not be revealed by static, trait-based measures.

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