Supplementary Information

State Self-Compassion Dynamics: Evidence for the Bipolar Continuum Hypothesis

Study 1

Baseline Maesures

To exclude the possibility of emotional disorders or psychological conditions, we administered a series of validated psychological assessment questionnaires.

Depression Anxiety Stress Scale-21 (DASS-21). The DASS-21 (Lovibond & Lovibond, 1995) is a 21-item self-report questionnaire to assess depression (*i.e.*, "I felt down-hearted and blue"), anxiety (*i.e.*, "I felt I was close to panic") and stress (*i.e.*, "I found it difficult to relax") symptoms, over the past week. Items are rated on a 4-point Likert scale ranging from 0 ("It never happened to me") to 3 ("It happened to me almost always"). Both the original and its Italian version (Bottesi et al., 2015) demonstrate adequate reliability.

Rosenberg Self - Esteem Scale (RSES). The RSES (Rosenberg, 1965) assesses individual self-esteem levels through a 10-item scale (*e.g.,* "I feel that I'm a person of worth, at least on an equal basis with others"). Respondents rate each statement on a 4-point Likert scale, ranging from 4 (Strongly Agree) to 1 (Strongly Disagree). Higher total scores indicate higher self-esteem.

Self-Compassion Scale (SCS). The SCS (Neff, 2003), is a self-report questionnaire comprising 26 items designed to assess individuals' enduring Self-Compassion traits in their daily lives. The SCS encompasses six subscales: Self-Kindness, Common Humanity, Mindfulness, Self-Judgment, Isolation, and Over-Identification. Respondents were instructed to rate the frequency of their Self-Compassionate attitudes using a 5-point scale, ranging from 1 ("almost never") to 5 ("almost always"). To ensure consistency in scoring, negative items were reverse coded, with higher scores indicating a greater absence of negative Self-Compassion traits. The psychometric properties of the SCS have been found to be robust. For the total score, the Cronbach's alpha coefficient was reported as 0.96 in the original work by Neff (2003). Additionally, the test-retest reliability demonstrated adequate results, with a correlation coefficient (r) of 0.93 for the total score and ranging from 0.80 to 0.88 for the subscales.

Difficulties in Emotion Regulation Scale (DERS). The DERS is a 36-item self-report measure developed to assess the complexities in emotion regulation processes among individuals (Gratz & Roemer, 2004). This scale is divided into six subscales, each targeting a specific dimension of emotion regulation difficulties: Nonacceptance of Emotional Responses (NER), Difficulties Engaging in Goal-Directed Behavior (DEGB), Impulse Control Difficulties (ICD), Lack of Emotional Awareness (LEA), Limited Access to Emotion Regulation Strategies (LAERS), and Lack of Emotional Clarity (LEC). Respondents are asked to rate each item on a 5-point Likert scale that ranges from 0 ("Never") to 4 ("Always"), reflecting the frequency with which they experience each emotion regulation difficulty. The higher the score, the greater the difficulties in emotion regulation an individual is likely to have. Both the original version and its Italian adaptation (Sighinolfi et al., 2010), have demonstrated strong psychometric properties, including adequate reliability and validity.

The following table presents the descriptive statistics for all the aforementioned measures. It includes the estimated posterior mean (Estimate), Standard Error, and the 95% credibility interval, computed using a Bayesian model. Bayesian modeling was employed to account for deviations from Gaussianity.

Variable	Estimate	Std. Error	95% CI Lower	95% CI Upper
$DASS-21_{Stress}$	7.58	0.45	6.92	8.14
$DASS-21_{Anxiety}$	1.04	0.19	0.89	1.93
$DASS-21_{Depression}$	2.97	0.29	2.02	3.63
$RSES$	28.05	0.26	27.53	28.55
$SCS_{total-score}$	17.45	0.21	17.05	17.87
$SCS_{Self-Kindness}$	2.98	0.04	2.89	3.06
$SCS_{Common-Humanity}$	3.11	0.04	3.02	3.20
$SCS_{Mindfulness}$	3.11	0.04	3.03	3.20
$SCS_{Self-Judgment}$	2.74	0.04	2.65	2.82
$SCS_{Isolation}$	2.74	0.05	2.65	2.84
$SCS_{Over-Identification}$	2.78	0.05	2.68	2.88
$DERS_{totalscore}$	67.89	2.07	63.79	71.64
$DERS_{NER}$	6.23	0.43	5.95	7.02
$DERS_{DEGB}$	13.41	0.78	12.46	15.78
$DERS_{ICD}$	4.99	0.02	4.95	5.00
$DERS_{LEA}$	11.52	0.82	9.91	12.98
$DERS_{LAERS}$	13.01	0.67	11.52	14.11
$DERS_{LEC}$	9.91	0.65	8.36	11.14

There is no evidence of emotional disorders among participants. The obtained scores are consistent with those reported in other studies using the same measures within community samples (Bottesi et al., 2015; Neff et al., 2017; Sica et al., 2021; Sighinolfi et al., 2010).

EMA Survey Questions

For each notification in the Ecological Momentary Assessment (EMA) protocol, participants were prompted to answer the following questions.

1. Think about the most notable event that has occurred since you last received a notification. If this is your first notification of the day, consider the most significant event from the start of the day. How would you evaluate this event?

    1) Very unpleasant
    2) Unpleasant
    3) Neither unpleasant nor pleasant
    4) Pleasant
    5) Very pleasant

2. At this moment I feel NERVOUS.

    1) Not at all
    2) A little
    3) Moderately
    4) Quite a bit
    5) Very much

3. At this moment I feel UPSET.

    1) Not at all
    2) A little
    3) Moderately
    4) Quite a bit
    5) Very much

4. At this moment I feel SATISFIED.

    1) Not at all
    2) A little
    3) Moderately
    4) Quite a bit
    5) Very much

5. At this moment I feel CHEERFUL.

    1) Not at all
    2) A little
    3) Moderately
    4) Quite a bit
    5) Very much

6. I'm giving myself the caring and tenderness I need.

1) Completely false
2) Moderately false
3) Slightly false
4) Slightly true
5) Moderately true
6) Completely true

7. I'm obsessing and fixating on everything that's wrong.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

8. I'm remembering that there are lots of others in the world feeling like I am.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

9. I feel like I'm struggling more than others right now.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

10. I feel intolerant and impatient toward myself.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

11. I'm keeping things in perspective.

    1) Completely false
    2) Moderately false

3) Slightly false
4) Slightly true
5) Moderately true
6) Completely true

12. At this moment I am able to accept my flaws and weaknesses.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

13. At this moment I let myself be carried away by my emotions.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

Model Convergence Diagnostics

To ensure that the model parameters accurately reflected participants' behavior in our task, we conducted posterior predictive checks, which were adequate for all examined models.

To confirm satisfactory convergence of the Markov chain Monte Carlo (MCMC) procedure for parameter estimation, we employed the convergence statistic $\hat{R}$ and monitored the number of divergent transitions during sampling. We verified that all population-level parameters had $\hat{R} < 1.01$. Additionally, posterior sampling of the models did not result in any divergent transitions.

Multilevel Correlations between CS and UCS components of State Self-Compassion

We conducted a multilevel analysis to compute the correlation between the Compassionate Self (CS) and Uncompassionate Self (UCS) components of state self-compassion, and each of the six subscales of the Self-Compassion Scale (Neff, 2003).

Multilevel correlations provide a more accurate estimate of the relationships between variables in hierarchical or clustered data compared to simple bivariate correlations. In our study, participants were assessed multiple times across different moments and days, creating a nested data structure where measurements are clustered within individuals. A multilevel approach accounts for this clustering by separating within-person variation from between-person variation, which leads to more precise estimates of the associations. In contrast, a simple bivariate correlation would not distinguish between these sources of variation, potentially conflating individual-level effects with population-level patterns and resulting in biased estimates.

By using multilevel correlations, we estimated an average effect across participants, adjusting for the random intercepts attributable to individual differences in the hierarchical model. For both components of state self-compassion, the correlations with the subscales of the Self-Compassion Scale were modest. For CS, the largest multilevel correlation was with self-kindness, r = 0.24, 89% CI [0.15, 0.32]; for UCS, the largest multilevel correlation was with isolation, r = 0.21, 89% CI [0.10, 0.31].

CS Component of State Self-Compassion

```
fit_cs <- brm(
  state_cs ~ self_kindness + common_humanity + mindfulness +
    self_judgment + isolation + over_identification +
    (1 | user_id),
  data = d,
  family = student(),
  backend = "cmdstanr",
  iter = 10000,
  chains = 4
)
```

Variable	Estimate	Std. Error	89% CI Lower	89% CI Upper
Intercept	0.06	0.04	0.00	0.12
Self-Kindness	0.23	0.06	0.13	0.32
Common Humanity	0.18	0.05	0.10	0.26
Mindfulness	0.06	0.05	-0.03	0.14

Variable	Estimate	Std. Error	89% CI Lower	89% CI Upper
Self-Judgment	-0.04	0.05	-0.13	0.04
Isolation	-0.11	0.05	-0.19	-0.02
Over-Identification	-0.00	0.06	-0.10	0.09

UCS Component of State Self-Compassion

```
fit_ucs <- brm(
  state_ucs ~ self_kindness + common_humanity + mindfulness +
    self_judgment + isolation + over_identification +
    (1 | user_id),
  data = d,
  family = student(),
  backend = "cmdstanr",
  iter = 10000,
  chains = 4
)
```

Variable	Estimate	Std. Error	95% CI Lower	95% CI Upper
Intercept	-0.02	0.04	-0.10	0.06
Self-Kindness	-0.14	0.06	-0.24	-0.02
Common Humanity	-0.03	0.05	-0.14	0.07
Mindfulness	-0.01	0.06	-0.13	0.10
Self-Judgment	0.10	0.06	-0.01	0.23
Isolation	0.21	0.05	0.10	0.31
Over-Identification	0.12	0.06	0.00	0.25

The Impact of Negative Affect and Event Unpleasantness on State Self-Compassion

In this section, we describe the statistical analysis used to assess the impact of contextual variables on state self-compassion. Our analysis specifically focuses on three key areas: differences across individuals, variations between days within the same individual, and fluctuations within a single day for each individual.

Prior to implementing the final Bayesian hierarchical models, we performed a model selection process for determining the most fitting structures for both random and fixed effects within our dataset. In the final models, we examined the CS and UCS aspects of SSC as a function of six predictors: negative affect and context evaluation. Each of these predictors was uniquely centered to distinctly capture and differentiate the three dimensions of variance we were interested in – namely, inter-individual differences, between-day variations within individuals, and within-day fluctuations for each individual.

We started by exploring the full fixed-effect structure and proceeded with a systematic comparison of models featuring varying degrees of random-effect complexity. Once we determined the optimal random-effect structure, we turned our attention to assessing models with different fixed-effects configurations. To facilitate model comparison, we used the Leave-One-Out (LOO) method, a robust Bayesian model selection technique implemented within Stan.

This technique evaluates out-of-sample prediction accuracy by sequentially excluding individual observations from the dataset and assessing the model's performance on these excluded points. Models demonstrating lower LOO values were interpreted as having superior fit and enhanced predictive accuracy. In our modeling process, we integrated regularizing priors, which served to mitigate overfitting by applying constraints that direct the model towards more plausible outcomes. Additionally, we employed partial pooling to boost the accuracy of estimations across various groups. We fitted the models using the cmdstan interface and with the brms package, which leverages the computational power of Stan for Bayesian inference.

CS Component

Random effects

Model	elpd_diff	se_diff	elpd_loo	se_elpd_loo	p_loo	se_p_loo	looic	se_looic
Model 1: Basic Model	0.00	0.00	-8383.79	114.38	2760.33	23.56	16767.57	228.77
Model 2: Add Random Effect user_id	-281.13	55.04	-8664.92	123.20	24642.01	87.90	17329.84	246.39
Model 3: Add Random Effects for user_id and user_id:day	-551.34	45.91	-8935.13	110.27	2312.90	19.53	17870.25	220.54
Model 4: Add Random Slopes for na_moment, na_day on user_id	-1666.63	71.51	-10050.41	105.37	369.61	3.49	20100.83	210.75

Model 5: Complex Random Effects Structure	-6024.44	114.52	-14408.22	85.91	9.62	0.16	28816.44	171.81

The model comparison, utilizing the LOO method, indicates that there is no valid justification for employing a random-effect structure more complex than participant-level clustering. In other words, the simpler approach of clustering at the participant level provides an adequate representation for our data, as evidenced by the minimal improvements gained from more intricate random-effect structures.

Fixed-Effects

Model	elpd_diff	se_diff	elpd_loo	se_elpd_loo	p_loo	se_p_loo	looic	se_looic
Model 1: Full Fixed Effects	0.00	0.00	-10050.04	105.34	368.99	3.49	20100.07	210.69
Model 2: Only na	-21.57	7.81	-10071.61	105.26	366.92	3.48	20143.21	210.52
Model 3: Only con	-1580.99	64.59	-11631.03	110.22	378.08	3.39	23262.05	220.43

Based on the model comparison using the LOO method, the best-fitting model is "Model 1: Full Fixed Effects." It exhibits the highest estimated log pointwise predictive density (elpd_loo) and the lowest Leave-One-Out Information Criterion (looic), suggesting superior predictive performance compared to the other models.

The final model for predicting the compassionate responding component of state self-compassion is as follows:

$$
\begin{aligned}
sc &\sim \text{Student-t}(\mu, \sigma, \nu) \\
\mu &= \beta_0 + \\
&\quad \beta_{\text{na\_moment}} \times \text{na\_moment} + \beta_{\text{na\_day}} \times \text{na\_day} + \beta_{\text{na\_person}} \times \text{na\_person} + \\
&\quad \beta_{\text{context\_moment}} \times \text{context\_moment} + \beta_{\text{context\_day}} \times \text{context\_day} + \\
&\quad \beta_{\text{context\_person}} \times \text{context\_person} + \\
&\quad b_{\text{user\_id}}[j] + b_{\text{bysubj\_day}}[k] \\
b_{\text{user\_id}}[j] &\sim \mathcal{N}(0, \Sigma_{\text{user\_id}}) \\
b_{\text{bysubj\_day}}[k] &\sim \mathcal{N}(0, \sigma^2_{\text{bysubj\_day}}) \\
\beta &\sim \text{priors1} \\
\sigma &\sim \text{Half-Cauchy}(0, \text{scale}) \\
\nu &\sim \text{Exponential}(\text{rate})
\end{aligned}
$$

$$
\begin{aligned}
&\text{Where:} \\
\Sigma_{\text{user\_id}} &= \text{Full covariance matrix for random effects within user\_id} \\
\sigma^2_{\text{bysubj\_day}} &= \text{Var}(b_{\text{bysubj\_day}}[k])
\end{aligned}
$$

USC Component

In parallel with our analysis of the SC component, we conducted a model comparison for the USC component.

Random-Effects

Model	elpd_diff	se_diff	elpd_loo	se_elpd_loo	p_loo	se_p_loo	looic	se_looic
Model 1: Basic Model	0.00	0.00	-8325.73	103.75	2507.22	22.25	16651.46	207.50
Model 2: Add Random Effect user_id	-393.72	36.24	-8719.45	101.44	2181.38	18.63	17438.91	202.89
Model 3: Add Random Effects for user_id and user_id:day	-539.99	93.24	-8865.73	140.28	37464.65	116.55	17731.46	280.56
Model 4: Add Random Slopes for na_moment, na_day on user_id	-1646.63	64.84	-9972.36	96.36	345.11	3.36	19944.72	192.72
Model 5: Complex Random Effects Structure	-5363.17	98.42	-13688.90	77.90	8.61	0.15	27377.80	155.79

Our evaluation of random-effect structures using the LOO method yielded results consistent with those observed for the SC component. The model comparison for USC indicates that there is no compelling justification for employing a random-effect structure more complex than clustering at the participant level. This echoes the findings from the SC component analysis, where participant-level clustering proved sufficient to adequately represent our data.

Fixed-Effects

Model	elpd_diff	se_diff	elpd_loo	se_elpd_loo	p_loo	se_p_loo	looic	se_looic
Model 1: Full Fixed Effects	0.00	0.00	-9973.73	96.34	346.60	3.37	19947.46	192.67
Model 2: Only na	-18.65	6.72	-9992.38	96.39	346.37	3.40	19984.75	192.79
Model 3: Only con	-1938.50	69.27	-11912.23	101.58	363.87	3.46	23824.47	203.15

When considering fixed-effect structures for the USC component, our analysis identified 'Model 1: Full Fixed Effects' as the best-fitting model. This model exhibited the highest estimated log pointwise predictive density (elpd_loo) and the lowest Leave-One-Out Information Criterion (looic) among the options. These results closely mirror the findings from the SC component analysis, where 'Model 1: Full Fixed Effects' also emerged as the preferred model.

The congruence in results between the SC and USC components underscores the consistency and reliability of our modeling approach. For both SC and USC, we have selected 'Model 1: Full Fixed Effects' as the optimal model, demonstrating superior predictive performance compared to more complex alternatives.

The final model for predicting the uncompassionate responding component of state self-compassion is as follows:

$$
\begin{aligned}
usc &\sim \text{Student-t}(\mu, \sigma, \nu) \\
\mu &= \beta_0 + \\
&\quad \beta_{\text{na\_moment}} \times \text{na\_moment} + \beta_{\text{na\_day}} \times \text{na\_day} + \beta_{\text{na\_person}} \times \text{na\_person} + \\
&\quad \beta_{\text{context\_moment}} \times \text{context\_moment} + \beta_{\text{context\_day}} \times \text{context\_day} + \\
&\beta_{\text{context\_person}} \times \text{context\_person} + \\
&\quad b_{\text{user\_id}}[j] + b_{\text{bysubj\_day}}[k] \\
b_{\text{user\_id}}[j] &\sim \mathcal{N}(0, \Sigma_{\text{user\_id}}) \\
b_{\text{bysubj\_day}}[k] &\sim \mathcal{N}(0, \sigma^2_{\text{bysubj\_day}}) \\
\beta &\sim \text{priors1} \\
\sigma &\sim \text{Half-Cauchy}(0, \text{scale}) \\
\nu &\sim \text{Exponential}(\text{rate})
\end{aligned}
$$

Where:

$$
\begin{aligned}
\Sigma_{\text{user\_id}} &= \text{Full covariance matrix for random effects within user\_id} \\
\sigma^2_{\text{bysubj\_day}} &= \text{Var}(b_{\text{bysubj\_day}}[k])
\end{aligned}
$$

The two models were estimated using a Student's t-distribution with identity links for the mean (μ), scale (σ), and degrees of freedom (ν). The analysis was based on 12621 observations, 326 participants, with the posterior distribution derived from 12000 post-warmup draws across four chains.

In both cases, the model diagnostics indicate satisfactory convergence with Rhat values close to 1 for all parameters. The Bulk_ESS and Tail_ESS values suggest adequate effective sample sizes for reliable estimation and inference.

Direct Test of the BCH for State Self-Compassion

We employed a Bayesian hierarchical model in which UCS was the linear predictor of CS to examine the association between the two components of state SC. This model also incorporated covariates such as within-day centered negative affect and context evaluation. Random effects were included to account for variability across participants, days, and measurements, which is crucial for capturing the inherent fluctuations in state self-compassion. The use of EMA data, enriched with relevant covariates, allowed for a thorough examination of the CS-UCS relationship under diverse conditions.

The predictive outcomes from this model directly tested the BCH. A credible negative fixed-effect slope for CS would validate the hypothesis, showing that increases in CS are associated with decreases in UCS, thus supporting the bipolar nature of state self-compassion. Conversely, a non-credible or positive fixed-effect slope for CS would challenge the BCH, suggesting that CS and UCS might function independently or even synergistically, rather than as opposing elements on a single continuum (Figure 1). The central finding was a robust negative association between CS and UCS, with a median estimate of -0.44 (89% CI [-0.47, -0.42]). This result validates the BCH by demonstrating that higher levels of CS are associated with lower levels of UCS.

After controlling for CS, negative affect showed a modest positive influence on UCS (= 0.12, 89% CI [0.116, 0.13]), while the unpleasantness of the event had a minimal impact on UCS (= 0.01, 89% CI [0.002, 0.02]). These findings indicate that contextual factors and negative affect play nuanced roles in shaping state self-compassion. Substantial variability was observed in the random-effect slopes for CS across participants, with a median estimate of 0.29 (89% CI [0.26, 0.32]). This variability suggests substantial individual differences in how CS impacts UCS, reflecting the complex interplay between personality, context, and self-compassion.

Additionally, the analysis highlighted notable variability in UCS levels among participants (= 0.63, 89% CI [0.59, 0.67]), underscoring considerable individual differences in state self-compassion responses. UCS also exhibited day-to-day variability (= 0.04, 89% CI [0.02, 0.06]), albeit to a lesser extent than individual variability. This emphasizes the influence of daily emotional states and contextual stressors on self-compassion levels, reinforcing the state-dependent nature of self-compassion. Finally, the model reported minimal measurement error (median estimate: 0.01, 89% CI [0.001, 0.039]), attesting to the reliability of the assessment tools used.

In summary, the robust variability in UCS across participants and the credible random slope effects for CS indicate that the relationship between CS and UCS is influenced by a variety of factors. The moderate level of unexplained variability in UCS (median estimate: 0.41, 89% CI [0.40, 0.414]) suggests that additional factors, potentially outside the scope of this model, influence UCS levels. These factors may include unmeasured psychological variables such as personal beliefs, coping mechanisms, or external social support.

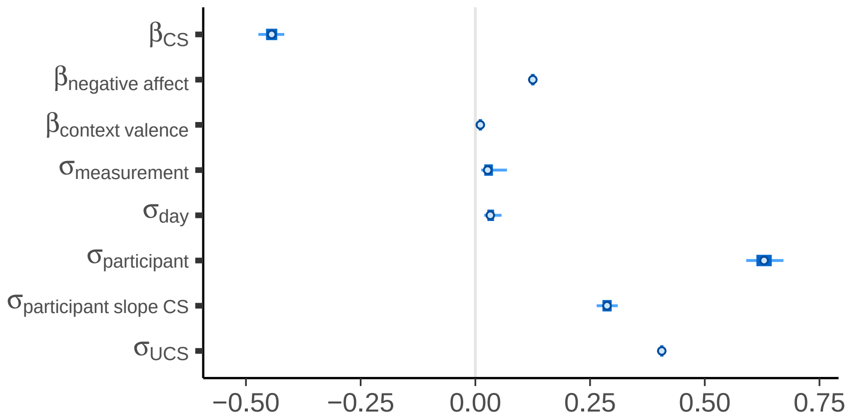

Figure 1: The estimates are expressed in terms of inter-individual differences and intra-individual variations, both within a day and across different days. The bars represent 89% credibility intervals. _(CS) represents the beta coefficients for CS; _(negative affect) and _(context valence)denote the beta coefficients for NegAff and context valence, respectively; _measurement is the standard deviation of the distribution of random effects coefficients for the 5 daily observations; _(day)represents the standard deviation of the distribution of random effects coefficients across 10 days; _(participant)indicates the standard deviation of the distribution of random effects coefficients across participants (subjects); _(participant slope CS) is the standard deviation of the slopes describing the effect of CS on UCS for each participant; _UCS is the estimated standard deviation of the population residuals distribution.

We employed a hierarchical Bayesian model to explore the relationship between state self-compassion components (CS and UCS) and their interactions with other covariates (negative affect, decentering, and context evaluation). By incorporating both fixed and random effects, our model aims to capture variability at the levels of individual participants, days, and measurements, providing a comprehensive understanding of the dynamics underlying the BCH.

In our model, the uncompassionate component (UCS) is represented using a t-distribution, which accommodates potential outliers and enhances the robustness of our analysis. This distribution is parameterized with a degree of freedom parameter (`nu`), an error term (`sigma_ucs`), and is influenced by both fixed and random effects.

The priors for the model parameters were selected to facilitate regularization:

$$\begin{aligned}
\alpha_{ucs} &\sim \text{Normal}(0, 1) \\
\beta_{cs}, \beta_{covariates} &\sim \text{Normal}(0, 1) \\
z_{participant}, z_{day}, z_{measurement}, z_{participant_slope_cs} &\sim \text{Normal}(0, 1) \\
\sigma_{participant}, \sigma_{day}, \sigma_{measurement}, \sigma_{participant_slope_cs}, \sigma_{ucs} &\sim \text{Exponential}(1) \\
\nu &\sim \text{Gamma}(2, 0.1)
\end{aligned}$$

The Stan implementation is provided below:

```
data {
  int<lower=0> N; // Total number of observations
  int<lower=0> P; // Number of participants
  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
  array[N] real neg_affect; // Negative Affect measures
  array[N] real decentering; // Decentering measures
  array[N] real context_eval; // Context evaluation measures
}

parameters {
  real alpha_ucs; // Intercept for UCS
  real beta_cs; // Overall effect of CS on UCS
  array[3] real beta_covariates; // Coefficients for other covariates
```

```
  // Random intercepts
  vector[P] z_participant;
  vector[D] z_day;
  vector[M] z_measurement;

  // Random slopes for CS at the participant level
  vector[P] z_participant_slope_cs;

  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_ucs; // Error term for UCS model
  real<lower=0> nu; // Degrees of freedom for t-distribution
}

model {
  // Priors
  alpha_ucs ~ normal(0, 1);
  beta_cs ~ normal(0, 1);
  beta_covariates ~ normal(0, 1);

  z_participant ~ normal(0, 1);
  z_day ~ normal(0, 1);
  z_measurement ~ normal(0, 1);
  z_participant_slope_cs ~ normal(0, 1);

  sigma_participant ~ exponential(1);
  sigma_day ~ exponential(1);
  sigma_measurement ~ exponential(1);
  sigma_participant_slope_cs ~ exponential(1);
  sigma_ucs ~ exponential(1);
  nu ~ gamma(2, 0.1);

  // Likelihood for UCS using t-distribution
  for (n in 1:N) {
    UCS[n] ~ student_t(
      nu,
      alpha_ucs +
      (beta_cs + sigma_participant_slope_cs *
        z_participant_slope_cs[participant[n]]) * CS[n] +
```

```
      beta_covariates[1] * neg_affect[n] +
      beta_covariates[2] * decentering[n] +
      beta_covariates[3] * context_eval[n] +
      sigma_participant * z_participant[participant[n]] +
      sigma_day * z_day[day[n]] +
      sigma_measurement * z_measurement[measurement[n]],
      sigma_ucs
    );
  }
}

generated quantities {
  array[N] real pred_UCS;
  array[N] real log_lik;

  for (n in 1:N) {
    pred_UCS[n] = student_t_rng(
      nu,
      alpha_ucs +
      (beta_cs + sigma_participant_slope_cs *
        z_participant_slope_cs[participant[n]]) * CS[n] +
      beta_covariates[1] * neg_affect[n] +
      beta_covariates[2] * decentering[n] +
      beta_covariates[3] * context_eval[n

] +
      sigma_participant * z_participant[participant[n]] +
      sigma_day * z_day[day[n]] +
      sigma_measurement * z_measurement[measurement[n]],
      sigma_ucs
    );

    log_lik[n] = student_t_lpdf(
      UCS[n] |
      nu,
      alpha_ucs +
      (beta_cs + sigma_participant_slope_cs *
        z_participant_slope_cs[participant[n]]) * CS[n] +
      beta_covariates[1] * neg_affect[n] +
      beta_covariates[2] * decentering[n] +
      beta_covariates[3] * context_eval[n] +
```

```
      sigma_participant * z_participant[participant[n]] +
      sigma_day * z_day[day[n]] +
      sigma_measurement * z_measurement[measurement[n]],
      sigma_ucs
    );
  }
}
```

Through the integration of multiple levels of random effects and the adoption of a robust likelihood function via the t-distribution, our hierarchical Bayesian model provides a nuanced analysis of the interaction between CS and UCS, shedding light on the dynamics underlying state self-compassion within a broader psychological context.

Study 2

Descriptive Statistics

Variable	Estimate	Std. Error	95% CI Lower	95% CI Upper
$DASS-21_{Stress}$	7.24	0.73	6.10	9.37
$DASS-21_{Anxiety}$	3.43	1.55	0.95	6.32
$DASS-21_{Depression}$	3.00	0.36	2.17	3.92
$RSES$	22.88	0.52	21.84	23.86
$SCS_{total-score}$	17.00	0.42	16.19	17.84
$SCS_{Self-Kindness}$	2.88	0.10	2.70	3.07
$SCS_{Common-Humanity}$	3.00	0.09	2.83	3.17
$SCS_{Mindfulness}$	3.07	0.09	2.89	3.23
$SCS_{Self-Judgment}$	2.69	0.09	2.51	2.87
$SCS_{Isolation}$	2.69	0.09	2.50	2.87
$SCS_{Over-Identification}$	2.67	0.09	2.50	2.85

There was no indication of emotional disorders among the participants. The obtained scores aligned with those found in previous studies that used the same assessment tools in community samples (Bottesi et al., 2015; Neff et al., 2017; Sica et al., 2021).

EMA Survey Questions

For each notification in the Ecological Momentary Assessment (EMA) protocol, participants were prompted to answer the following questions.

1. Think about the most notable event that has occurred since you last received a notification. If this is your first notification of the day, consider the most significant event from the start of the day. How would you evaluate this event?

   1) Very unpleasant
   2) Unpleasant
   3) Neither unpleasant nor pleasant
   4) Pleasant
   5) Very pleasant

2. At this moment I feel NERVOUS.

   1) Not at all
   2) A little
   3) Moderately
   4) Quite a bit
   5) Very much

3. At this moment I feel UPSET.

   1) Not at all
   2) A little
   3) Moderately
   4) Quite a bit
   5) Very much

4. At this moment I feel SATISFIED.

   1) Not at all
   2) A little
   3) Moderately
   4) Quite a bit
   5) Very much

5. At this moment I feel CHEERFUL.

   1) Not at all
   2) A little
   3) Moderately
   4) Quite a bit
   5) Very much

6. I’m giving myself the caring and tenderness I need.

1) Completely false
2) Moderately false
3) Slightly false
4) Slightly true
5) Moderately true
6) Completely true

7. I'm obsessing and fixating on everything that's wrong.

   1) Completely false
   2) Moderately false
   3) Slightly false
   4) Slightly true
   5) Moderately true
   6) Completely true

8. I'm remembering that there are lots of others in the world feeling like I am.

   1) Completely false
   2) Moderately false
   3) Slightly false
   4) Slightly true
   5) Moderately true
   6) Completely true

9. I feel like I'm struggling more than others right now.

   1) Completely false
   2) Moderately false
   3) Slightly false
   4) Slightly true
   5) Moderately true
   6) Completely true

10. I feel intolerant and impatient toward myself.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

11. I'm keeping things in perspective.

    1) Completely false
    2) Moderately false

3) Slightly false
4) Slightly true
5) Moderately true
6) Completely true

12. At this moment I am able to accept my flaws and weaknesses.
    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true
13. At this moment I let myself be carried away by my emotions.
    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true
14. Recently, I have been able to observe my thoughts and feelings without being drawn in.
    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true
15. Recently, I have struggled with my thoughts and feelings.
    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true
16. Recently, I have experienced my thoughts and feelings as separate from myself.
    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true

5) Moderately true
6) Completely true

17. Recently, I have been caught up in my thoughts.

    1) Completely false
    2) Moderately false
    3) Slightly false
    4) Slightly true
    5) Moderately true
    6) Completely true

Model Convergence Diagnostics

Models diagnostics produced similar results as in Study 1.

Impact of Academic Exam on State Self-Compassion

We employ a hierarchical Bayesian model to compare the CS or UCS components of state self-compassion across two time points: the day before and the day after an academic exam. This model accounts for the hierarchical structure of the EMA data, which includes repeated measures across multiple days and times. Specifically, we compare 12 administration distributed over separate days, each containing 5 notifications at different times, against a single notification on the evening following the exam.

Our model incorporates random intercepts for subjects, days, and measurement times, as well as random slopes for the exam day effects:

$$sc_n \sim \text{SkewNormal}\left(\mu_n, \sigma, \text{skewness}\right),$$

where

$$\mu_n = \alpha + \alpha_j[\text{subj}_n] + \alpha_d[\text{day}_n] + \alpha_m[\text{meas}_n] + (\beta_{\text{pre}} + \beta_{j,\text{pre}}[\text{subj}_n]) \cdot \text{exam\_day\_pre}_n + (\beta_{\text{post}} + \beta_{j,\text{post}}[\text{subj}_n]) \cdot \text{exam\_day\_post}_n.$$

For the model's parameters, we used regularization priors:

$$\begin{aligned}
\alpha &\sim \mathcal{N}(0, 2.5) \\
\alpha_j &\sim \mathcal{N}(0, \sigma_j) \\
\alpha_d &\sim \mathcal{N}(0, \sigma_d) \\
\alpha_m &\sim \mathcal{N}(0, \sigma_m) \\
\beta_{\text{pre}} &\sim \mathcal{N}(0, 1) \\
\beta_{\text{post}} &\sim \mathcal{N}(0, 1) \\
\beta_{j,\text{pre}} &\sim \mathcal{N}(0, \sigma_{\beta_{j,\text{pre}}}) \\
\beta_{j,\text{post}} &\sim \mathcal{N}(0, \sigma_{\beta_{j,\text{post}}}) \\
\sigma &\sim \text{Exponential}(1) \\
\sigma_j &\sim \text{Exponential}(1) \\
\sigma_d &\sim \text{Exponential}(1) \\
\sigma_m &\sim \text{Exponential}(1) \\
\sigma_{\beta_{j,\text{pre}}} &\sim \text{Exponential}(1) \\
\sigma_{\beta_{j,\text{post}}} &\sim \text{Exponential}(1) \\
\text{skewness} &\sim \mathcal{N}(0, 1)
\end{aligned}$$

Belows is shown the Stan implementation of the model:

```
data {
  int<lower=1> N; // Number of observations
  int<lower=1> J; // Number of subjects
  int<lower=1> D; // Number of days
  int<lower=1> M; // Number of measurements per day
  array[N] int<lower=1, upper=J> subj; // Subject index
  array[N] int<lower=1, upper=D> day; // Day index
  array[N] int<lower=1, upper=M> meas; // Moment index
  array[N] real sc; // Dependent variable
  array[N] real exam_day_pre; // 1 if exam day is 'pre', 0 otherwise
  array[N] real exam_day_post; // 1 if exam day is 'post', 0 otherwise
}

parameters {
  real alpha; // Global intercept
  array[J] real alpha_j; // Random intercepts for subjects
  array[D] real alpha_d; // Random intercepts for days
  array[M] real alpha_m; // Random intercepts for measurements
  real beta_pre; // Main effect of exam day 'pre'
  real beta_post; // Main effect of exam day 'post'
  array[J] real beta_j_pre; // Random slopes for exam_day_pre
  array[J] real beta_j_post; // Random slopes for exam_day_post
  real<lower=0> sigma; // Standard deviation for psc
  real<lower=0> sigma_j; // SD for subject random intercepts
  real<lower=0> sigma_d; // SD for day random intercepts
  real<lower=0> sigma_m; // SD for measurement random intercepts
  real<lower=0> sigma_beta_j_pre; // SD for random slopes (pre)
  real<lower=0> sigma_beta_j_post; // SD for random slopes (post)
  real skewness; // Skewness parameter for the skew normal distribution
}

model {
  // Priors
  alpha ~ normal(0, 2.5);
  alpha_j ~ normal(0, sigma_j);
  alpha_d ~ normal(0, sigma_d);
  alpha_m ~ normal(0, sigma_m);
  beta_pre ~ normal(0, 1);
  beta_post ~ normal(0, 1);
  beta_j_pre ~ normal(0, sigma_beta_j_pre);
  beta_j_post ~ normal(0, sigma_beta_j_post);
```

```
  sigma ~ exponential(1);
  sigma_j ~ exponential(1);
  sigma_d ~ exponential(1);
  sigma_m ~ exponential(1);
  sigma_beta_j_pre ~ exponential(1);
  sigma_beta_j_post ~ exponential(1);
  skewness ~ normal(0, 1);

  // Likelihood
  for (n in 1:N) {
    sc[n] ~ skew_normal(
      alpha + alpha_j[subj[n]] + alpha_d[day[n]] + alpha_m[meas[n]] +
      (beta_pre + beta_j_pre[subj[n]]) * exam_day_pre[n] +
      (beta_post + beta_j_post[subj[n]]) * exam_day_post[n],
      sigma, skewness
    );
  }
}

generated quantities {
  array[N] real y_rep;
  array[N] real log_lik;

  for (n in 1:N) {
    y_rep[n] = skew_normal_rng(
      alpha + alpha_j[subj[n]] + alpha_d[day[n]] + alpha_m[meas[n]] +
      (beta_pre + beta_j_pre[subj[n]]) * exam_day_pre[n] +
      (beta_post + beta_j_post[subj[n]]) * exam_day_post[n],
      sigma, skewness
    );

    log_lik[n] = skew_normal_lpdf(
      sc[n] |
      alpha + alpha_j[subj[n]] + alpha_d[day[n]] + alpha_m[meas[n]] +
      (beta_pre + beta_j_pre[subj[n]]) * exam_day_pre[n] +
      (beta_post + beta_j_post[subj[n]]) * exam_day_post[n],
      sigma, skewness
    );
  }
}
```

This hierarchical Bayesian model was also applied to the UCS component of state self-compassion, following the same structure and parameterization.

Impact of Academic Exam on Negative Affect

In a separate analysis, we found a large effect of academic examinations on students' negative affect. Specifically, we observed a pronounced decrease in negative affect from the day before to the day after the exams. This pattern was consistent across two separate examinations. For the first exam, we found a substantial standardized decrease in negative affect on the day following the exam, relative to the day prior. The magnitude of this decrease was -0.92 (Standard Error, $SE = 0.10$), translating to a Cohen's d value of -0.98, with an 89% CI of [-1.23, -0.78]. A parallel trend was observed for the second exam, where the standardized decrease in negative affect mirrored that of the first exam, being -0.39 ($SE = 0.08$). This yielded a Cohen's d value of -0.54, with the 89% CI of [-0.75, -0.36].

Testing the BCH Through Contextual Influences of the State Self-Compassion.

For our analyses, we employed the identical models utilized in Study 1.

Direct Test of the BCH for State Self-Compassion

As observed in Study 1, both negative affect and contextual valence are key indicators of an individual's position on the bipolar continuum of state self-compassion, ranging from CS to UCS. Specifically, high levels of NegAff were associated with proximity to the UCS pole, while low levels of NegAff suggested alignment with the CS pole. A similar pattern can be expected with contextual valence. Decentering, a core aspect of mindfulness, is expected to show that higher degrees of decentering are linked to the CS pole, whereas lower degrees indicate proximity to the UCS pole. Thus, it is reasonable to expect also in Study 2 that NegAff and decentering would demonstrate inverse relationships with state self-compassion components. To replicate the analysis from Study 1 for testing the BCH, we conducted a Bayesian hierarchical analysis. In this model, the UCS component of state self-compassion was predicted linearly from the CS component. We included as covariates the within-day centered NegAff, decentering, and the level of unpleasantness of the event. Random effects were incorporated for participants, days, and the level of unpleasantness of the event to account for individual variability and measurement precision – see Figure 2. The analysis revealed several key fixed effects. A strong negative relationship was observed (= -0.43, 89% CI [-0.47, -0.39]), corroborating the hypothesis that higher levels of CS correspond to lower levels of UCS, thus supporting the Bipolar Continuum Hypothesis (BCH). Higher levels of NegAff were associated with increased UCS (= 0.07, 89% CI [0.06, 0.08]), indicating a modest positive influence. Higher levels of decentering were linked to reduced UCS (= -0.08, 89% CI [-0.09, -0.07]), suggesting an inverse relationship. The impact of event unpleasantness was slight and marginally negative (= -0.005, 89% CI [-0.016, 0.005]). The random effects analysis provided additional insights. There was substantial variability in baseline UCS levels among participants, with a median estimate of 0.61 (89% CI [0.56, 0.67]). Daily fluctuations were negligible, with a median estimate of 0.04 (89% CI [0.02, 0.06]). The data showed high reliability, as indicated by a median estimate of 0.01 (89% CI [0.001, 0.039]). There were individual differences in how CS influences UCS, with a median estimate of 0.29 (89% CI [0.26, 0.32]). There was moderate unexplained variability in UCS, with a median estimate of 0.39 (89% CI [0.38, 0.41]). These results highlight the complex interplay between compassionate and uncompassionate self-responding, as well as the robust individual differences and minimal daily fluctuations in these components. The findings provide strong support for the BCH. The consistent negative relationship between CS and UCS, alongside the observed impacts of negative affect and decentering, underscores the validity of the BCH across different contexts and individual differences. These conclusions align with those from Study 1, reinforcing the inverse relationship between compassionate and uncompassionate self-responding as proposed by the BCH. The robust negative correlation between CS and UCS, even when accounting for momentary NegAff and other contextual factors, emphasizes the dynamic interplay between these components of state self-compassion. This supports the idea that self-compassion operates as a bipolar construct rather than as independent or synergistic elements. The observed individual differences and stable relationships across various contexts further substantiate the BCH, highlighting its applicability and relevance in understanding self-compassion dynamics.

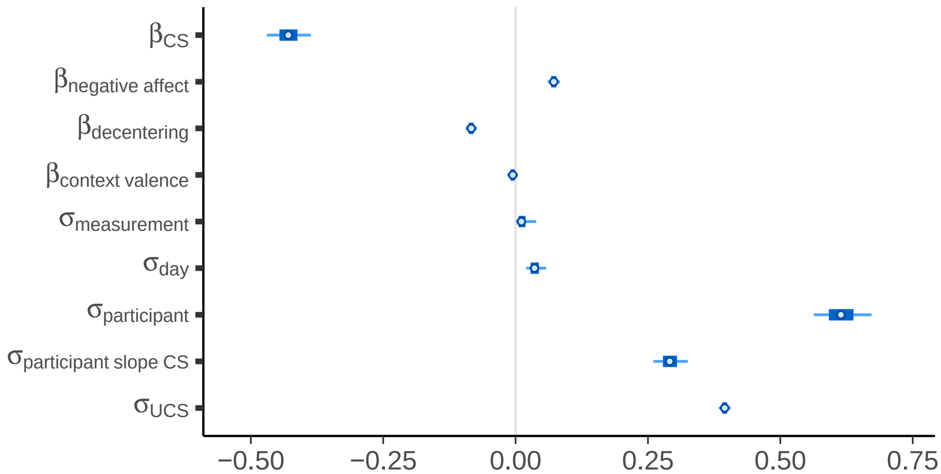

Figure 2: . The estimates are expressed in terms of inter-individual differences and intra-individual variations, both within a day and across different days. The bars represent 89% credibility intervals. _(CS) represents the beta coefficients for CS; _(negative affect), _(context valence) and _(decentering)denote the beta coefficients for NegAff, context valence and decentering respectively; _measurement is the standard deviation of the distribution of random effects coefficients for the 5 daily observations; _(day)represents the standard deviation of the distribution of random effects coefficients across 10 days; _(participant)indicates the standard deviation of the distribution of random effects coefficients across participants (N subjects); _(participant slope CS) is the standard deviation of the slopes describing the effect of CS on UCS for each participant; _UCS is the estimated standard deviation of the population residuals distribution.

For our analysis, we employed the identical Stan model utilized in Study 1.

Levels of Personal Concern

This section details the script used to test the hypothesis that the correlation between the SC and USC components of state self-compassion is influenced by the level of personal concern. The same statistical model was applied to three distinct datasets, each representing different time points relative to an examination period:

1. **Pre-Exam Dataset**: Data collected one day before the exam.
2. **Post-Exam Dataset**: Data collected one day after the exam.
3. **Baseline Dataset**: Data collected during a period unrelated to any exam.

```r
bform <-
  bf(mvbind(psc, nsc) ~ 1 + (1 | user_id)) +
  set_rescor(TRUE)

mod <- brm(
  bform,
  data = d,
  backend = "cmdstanr",
  chains = 4
)
```

Decentering and SC and USC Correlation

Decentering (Bennett et al., 2021; Bernstein et al., 2015) and self-compassion are related constructs. Both constructs contribute to psychological well-being through slightly different mechanisms. Decentering aids in diminishing identification with negative thoughts and feelings, enabling individuals to observe them without judgment or automatic reactions. This detachment can create space for self-compassion to emerge, as individuals can acknowledge their challenging experiences with greater kindness and understanding. Self-compassion, in turn, can facilitate the decentering process by offering a gentler and more welcoming approach to difficult emotions and thoughts. When individuals can treat themselves with compassion, they may find it easier to observe their internal experiences without being overwhelmed. Self-compassion allows individuals to confront failures, mistakes, and self-criticism with kindness and understanding rather than judgment or reproach. This approach can facilitate decentering, as individuals learn to view such experiences as common to all humans, rather than reflections of their personal worth. Both decentering and self-compassion contribute to psychological resilience. Decentering helps maintain a more balanced and objective perspective, while self-compassion provides emotional support and a more positive response to challenges. Mindfulness plays a key role in connecting decentering and self-compassion. Mindfulness practice encourages both decentering and self-compassion by promoting non-judgmental observation of internal experiences and greater self-kindness.

Dimensionality Test

Previous research has extensively explored the bipolar continuum hypothesis by investigating the dimensionality of *trait* self-compassion using various psychometric approaches (Brenner et al., 2017; Cleare et al., 2018; Neff, 2016; Neff et al., 2017, 2019; Petrocchi et al., 2014). These studies consistently show that models including a general factor yield superior fit indices, offering strong empirical support for Neff's hypothesis.

The current study seeks to build upon this foundation by conducting a novel psychometric evaluation of the dimensionality of *state* self-compassion. Our analysis is unique in that it examines repeated measurements of *state* self-compassion within the same participants. To address the multilevel nature of the data, we applied a series of multilevel Confirmatory Factor Analysis (CFA) models to the combined datasets from both studies. This approach allows for a precise representation of the hierarchical structure, where repeated measurements are nested within days, which are further nested within individuals.

We specified and compared three distinct models to determine the underlying structure of state self-compassion:

- The **One-Factor Model** hypothesizes that state self-compassion can be represented by a single latent factor, capturing variance at both the within-person and between-person levels.
- The **Two-Factor Model** conceptualizes state self-compassion as comprising two correlated but distinct latent factors—CS (compassionate self-responding) and UCS (uncompassionate self-responding)—functioning at both the within-person and between-person levels.
- The **Bifactor Model** examines whether state self-compassion is best characterized by a general self-compassion factor along with orthogonal specific factors (CS and UCS), isolating the variance explained by the general factor from that explained by the specific factors.

Mplus script for the One-Factor Model

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

DATA:
  FILE = "data.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;
```

Table: Standardized Factor Loadings for Multilevel One-Factor Model

Item	Within-Level Standardized Loadings	Between-Level Standardized Loadings
SCS_POS_1	0.579	0.778
SCS_NEG_2	0.673	0.925
SCS_POS_3	0.274	0.363
SCS_NEG_4	0.567	0.795
SCS_NEG_5	0.652	0.934
SCS_POS_6	0.550	0.738
SCS_POS_7	0.587	0.835
SCS_NEG_8	0.279	0.262

Additional Summary Statistics

- **Within-Level Explained Variance for SELFCOMP**: 19.6%
- **Between-Level Explained Variance for SELFCOMP**: 21.7%
- **Effect of Negative Affect on SELFCOMP (within level)**:
  - **NEG_AFF_MOMENT**: -0.272
  - **NEG_AFF_DAY**: -0.350
- **Effect of Negative Affect on SELFCOMP (between level)**:
  - **NEG_AFF_PERSON**: -0.466

Mplus script for the Two-Factor Model

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

DATA:
  FILE = "data.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;
```

Table: Standardized Factor Loadings for Multilevel Two-Factor Model

Item	Within-Level Standardized Loadings	Between-Level Standardized Loadings
CS Factor		
SCS_POS_1	0.632	0.902
SCS_POS_3	0.270	0.321
SCS_POS_6	0.581	0.749
SCS_POS_7	0.639	0.959
UCS Factor		
SCS_NEG_2	0.710	0.949
SCS_NEG_4	0.582	0.796
SCS_NEG_5	0.682	0.945
SCS_NEG_8	0.279	0.278

Additional Summary Statistics

- **Within-Level Correlation between POSITIVE and NEGATIVE factors**: 0.825
- **Between-Level Correlation between POSITIVE and NEGATIVE factors**: 0.817
- **Residual Variances (Within Level)**:
  - **SCS_POS_1**: 0.601, **SCS_NEG_2**: 0.497, **SCS_POS_3**: 0.927, **SCS_NEG_4**: 0.661, **SCS_NEG_5**: 0.535, **SCS_POS_6**: 0.662, **SCS_POS_7**: 0.591, **SCS_NEG_8**: 0.922
- **Residual Variances (Between Level)**:
  - **SCS_POS_1**: 0.187, **SCS_NEG_2**: 0.100, **SCS_POS_3**: 0.897, **SCS_NEG_4**: 0.367, **SCS_NEG_5**: 0.106, **SCS_POS_6**: 0.439, **SCS_POS_7**: 0.080, **SCS_NEG_8**: 0.923

Mplus script for the Bifactor Model

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

DATA:
  FILE = "data.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 scn4 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);
```

Table: Standardized Factor Loadings for Multilevel Bifactor Model

Item	Within-Level Standardized Loadings	Between-Level Standardized Loadings
General Factor (GEN_W / GEN_B)		
SCP1	0.614	0.860
SCN2	0.579	0.774
SCP3	0.327	0.410
SCN4	0.490	0.697
SCN5	0.585	0.819
SCP6	0.583	0.781
SCP7	0.623	0.935
SCN8	0.210	0.143

Item	Within-Level Standardized Loadings	Between-Level Standardized Loadings
Positive Factor (POS_W / POS_B)		
SCP1	0.219	0.215
SCP3	-0.313	-0.329
SCP6	-0.009	-0.073
SCP7	0.246	0.322
Negative Factor (NEG_W / NEG_B)		
SCN2	0.473	0.626
SCN4	0.291	0.378
SCN5	0.310	0.422
SCN8	0.208	0.288

The table presents standardized loadings for both the general factor and the specific positive and negative factors at the within and between levels. These loadings illustrate the bifactor structure and how each item loads onto the general and specific factors.

Goodness-of-fit indices

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 solely on statistical fit indices but should also incorporate the substantive significance of each factor (Ferrando & Lorenzo-Seva, 2018; Rodriguez et al., 2016). Although more complex models often exhibit better statistical fit, they may overfit the data, especially when an excessive number of factors are included (Ferrando & Lorenzo-Seva, 2019). Therefore, achieving a balance between model complexity and interpretability is crucial for drawing meaningful conclusions.

To determine whether the data support a unidimensional or multifactorial structure for *state* self-compassion, we applied several criteria:

1. **Factor Correlation**:
   In the Two-Factor Model, the within-level correlation between the Compassionate Self (CS) and Uncompassionate Self (UCS) factors was 0.825, while the between-level correlation was 0.817. These high correlations suggest a strong overlap between the two factors, which might indicate a common underlying construct at both the within- and between-person levels.

2. **Explained Common Variance (ECV)**:
   ECV quantifies how much of the shared variance among items is explained by the general versus specific factors. In the Bifactor Model, the general factor (Gen_w) exhibited high standardized loadings on items (e.g., SCP1 = 0.614, SCN2 = 0.579 at the within-person level), indicating that it accounts for the majority of the common variance. By comparison, the loadings of the specific factors (POS_w and NEG_w) were notably lower, suggesting that they explain less variance. This finding underscores the dominance of the general factor in accounting for self-compassion.

3. **Omega Hierarchical (ω_H)**:
   ω_H estimates how much of the variance in total scores is attributable to the general factor. In the Bifactor Model, the general factor explained a substantial proportion of the variance (e.g., SCP1 = 0.614, SCN2 = 0.579), while the specific factors contributed relatively little. This suggests that the general factor plays a predominant role in explaining individual differences in self-compassion, further supporting the interpretation of a primarily unidimensional construct.

4. **Bifactor Model Analysis**:
   The Bifactor Model highlights the predominance of the general factor, as the loadings of the specific factors were consistently lower (e.g., POS_w on SCP3 = -0.313, NEG_b on SCN8 = 0.288). This indicates that the specific factors (CS and UCS) provide limited explanatory power beyond the general self-compassion factor. Consequently, the Bifactor Model supports a conceptualization where a single general factor underlies the variance in self-compassion, with the specific factors adding relatively small additional value.

5. **Change in R-squared**:
   The Bifactor Model shows that the general factor accounts for a large proportion of the variance (e.g., R-squared for SCP1 = 0.425 at the within-person level, 0.786 at the between-person level). The specific factors contribute only marginally to the overall variance explained, suggesting that a unidimensional structure may be more parsimonious without significantly compromising the model's explanatory power.

In summary, the results of the multilevel CFA analyses lend support to Neff's hypothesis that, also for *state* self-compassion, CS and UCS are related at the global level. The strong correlations between CS and UCS at the latent level indicate that individuals who exhibit high levels of CS tend to have lower levels of UCS, and vice versa, reinforcing the notion that these two aspects are inversely related at a general level.

However, it is important to emphasize that multilevel CFA focuses on *latent, person-level relationships*, which capture broader, long-term patterns. The present findings show that, for *state* self-compassion, CS and UCS are correlated at a global, trait-like level across individuals. In contrast, analyses targeting *momentary dynamics* may reveal that, for *state* self-compassion, CS and UCS operate more independently within individuals during short-term, context-specific situations. This distinction highlights that while Neff's hypothesis may hold at the global level, further investigation is necessary to explore the relationship between CS and UCS at the momentary, within-person level.

Modeling the Dynamic Relationship Between Compassionate and Uncompassionate Self-Responding: An Idionomic Approach

The analyses described in the previous section provided evidence supporting the "essential unidimensionality" (Reise et al., 2013) of state self-compassion. Our multilevel framework, which accounted for repeated measurements within individuals over a three-month period, demonstrated that compassionate and uncompassionate self-responding (CS and UCS) are inversely related at the *nomothetic level* – that is, when examined across the entire sample.

Our psychometric evaluations, using purely *internal criteria* (fit indices for item scores), revealed that more complex models improved statistical fit. However, these improvements do not fundamentally challenge Neff's hypothesis of a bipolar continuum. While minor deviations and better fit indices were observed with more complex models, their practical importance was limited, and the overall pattern of findings remained aligned with the notion of CS and UCS as opposing dimensions.

This conclusion is further corroborated when considering *external criteria*, including covariates such as momentary negative affect and context evaluation, as described in our two studies. These situational factors did not substantially disrupt the core relationship between CS and UCS proposed by the bipolar continuum hypothesis.

It is important to note, however, that all these previous analyses were conducted at a *nomothetic* level, focusing on group-level patterns. This approach, while valuable, may obscure important differences in how self-compassion operates in the everyday life of individuals. The variability in how individuals experience and express self-compassion across different contexts might not be fully captured in these broad, averaged analyses.

To address this limitation and gain deeper insights into person-specific dynamics, we conducted an *idionomic analysis* to examine the relationship between UCS and CS at the individual level (Ciarrochi et al., 2024; Ferrari et al., 2022; Sahdra et al., 2024). This approach allows us to explore potential heterogeneity in self-compassion processes that may be masked by nomothetic analyses, providing a more nuanced understanding of how the CS and UCS constructs interact within individuals over time.

Idionomic Analysis of the Relationship Between UCS and CS

For the present purposes, an idionomic analysis was conducted in two stages. The first stage involved a strictly idiographic approach, focusing on the individual-level patterns. In the second stage, we applied a nomothetic approach to examine and describe group-level regularities as well as the variability in these effects across individuals (e.g., Ciarrochi et al., 2024; Sahdra et al., 2024).

Step 1: Fitting Individual-Level Hierarchical Bayesian Models. For each participant separately, we implemented a hierarchical Bayesian model using Stan to estimate the relationship between UCS and CS. The model incorporated additional covariates, including negative affect and context evaluation, as well as lagged effects of CS from the previous measurement within the same day. The model for each participant was specified as follows:

$$\begin{aligned}\mathrm{UCS}_n \sim t_\nu\Big(\alpha + \gamma_{\mathrm{CS}} \cdot \mathrm{CS}_n + \gamma_{\mathrm{neg\_aff}} \cdot \mathrm{neg\_aff}_n \\ + \gamma_{\mathrm{context}} \cdot \mathrm{context}_n + \phi \cdot \mathrm{lag\_CS}_n \\ + \gamma_{\mathrm{interaction}} \cdot \mathrm{CS}_n \cdot \mathrm{neg\_aff}_n, \sigma\Big),\end{aligned}$$

where:

- UCS_n represents the CS score for observation n,
- α denotes the intercept,
- γ_{CS} is the coefficient for the primary predictor, CS (CS_n),
- $\gamma_{\mathrm{neg\_aff}}$ and $\gamma_{\mathrm{context}}$ are coefficients for negative affect ($\mathrm{neg\_aff}_n$) and context evaluation ($\mathrm{context}_n$), respectively,
- ϕ represents the autoregressive coefficient for the lagged CS within the same day ($\mathrm{lag\_CS}_n$),
- σ is the scale parameter (standard deviation) of the distribution,
- ν denotes the degrees of freedom of the Student's t-distribution,
- $\gamma_{\mathrm{interaction}}$ is the coefficient for the interaction term between CS and negative affect.

This model allows for the examination of the association between UCS and CS while controlling for the effects of negative affect, context evaluation, lagged CS effects within the same day, and the CS $\times$ negative-affect interaction. We employed a Student's t-distribution (t_ν) to account for potential outliers or heavy-tailed distributions in the data.

For each participant, we examined the posterior distribution of the `gamma_CS` coefficient to estimate the proportion of posterior draws that were negative. This enabled us to evaluate whether there was evidence of a negative association between UCS and CS at the individual level, in line with Neff's bipolar continuum hypothesis. Additionally, we computed the mean posterior estimates for the `gamma_neg_aff`, `gamma_context`, and `gamma_interaction` parameters, which represent the effects of negative affect, context evaluation, and the interaction between CS and negative affect, respectively, on UCS for each participant.

Step 2: Aggregate Analysis Using a Hierarchical Model. After the idiographic analysis, we used a hierarchical model (e.g., Ciarrochi et al., 2024) in the `brms` package (R) to summarize the proportion of negative estimates for the `gamma_CS` parameter across participants. This model employed a binomial distribution, with the total number of posterior samples as the denominator and the proportion of negative estimates as the response. A random intercept for participants was included to account for individual variability.

Hierarchical models were also applied to the mean posterior estimates of the `gamma_neg_aff`, `gamma_context`, and `gamma_interaction` parameters, representing the influences of negative affect, context evaluation, and the interaction between CS and negative affect on UCS. Each model included a fixed effect (intercept) and random intercepts for participants, capturing individual differences. A Student-t likelihood was used to account for potential outliers and accommodate the heavy-tailed nature of the effect distributions, providing robust aggregate estimates of each parameter and the heterogeneity of their relationships with UCS.

Results

The analysis of the `gamma_CS` parameter across participants indicated that 81.0% (89% CI [0.796, 0.823]) of the posterior estimates for the association between uncompassionate self-responding (UCS) and compassionate self-responding (CS) were negative. This supports Neff's bipolar continuum hypothesis, which posits an inverse relationship between UCS and CS. However, the variability in individual effects (`sd(Intercept)` = 1.25, corresponding to 0.196 on the probability scale) suggests moderate heterogeneity in the strength of this relationship across participants.

For the influence of negative affect on UCS, represented by the `gamma_neg_aff` parameter, the analysis revealed a positive overall effect (intercept = 0.38, 89% CI [0.34, 0.42]), indicating that higher levels of negative affect are generally associated with increased UCS. The variability between individuals (`sd(Intercept)` = 0.19, corresponding to 0.547 on the probability scale) suggests substantial heterogeneity in how strongly negative affect influences UCS.

The analysis of context evaluation showed a small but credible negative effect on UCS (mean = -0.04, 95% CI [-0.07, -0.01]), suggesting that higher context evaluation scores are associated with a slight reduction in UCS. The variability in individual responses (`sd(Intercept)` = 0.17, corresponding to 0.543 on the probability scale) also indicates substantial heterogeneity in the relationship between context evaluation and UCS across participants.

Finally, the interaction between CS and negative affect was negligible, with the 89% credible interval spanning zero (-0.03, 0.00), suggesting no meaningful interaction effect between these variables on UCS.

Discussion

Our idionomic analysis provides insight into the complex, momentary relationship between CS and UCS. Although the group-level results generally support Neff's bipolar continuum hypothesis, substantial heterogeneity emerged in the strength and direction of the CS-UCS association across individuals. While most participants displayed the anticipated inverse relationship between CS and UCS, a notable proportion showed no clear association, and a smaller subset exhibited positive correlations—indicating that, for some individuals, CS and UCS may vary together rather than oppositely, which contradicts the bipolar continuum hypothesis [Ferrari et al., 2023; Ullrich et al., 2020]. This variability suggests that Neff's hypothesis may not be universally applicable and underscores the importance of idiographic approaches in revealing the nuanced patterns often obscured in aggregate, group-level analyses.

Additionally, our analysis revealed that negative affect consistently increased UCS across participants, indicating that elevated negative emotional states tend to intensify uncompassionate self-responding. However, the variability observed across individuals highlights that the influence of negative affect on UCS is not uniform. Contrary to expectations, we found no credible evidence that negative affect moderated the CS-UCS relationship, suggesting that momentary emotional states do not substantially alter how CS influences UCS within individuals (Dejonckheere et al., 2021).

Idiographic Analysis

This section details the specification of the model fitted separately to individual data from both experiments, constituting the first step of our idiographic analysis.

Model Structure

We employed a hierarchical Bayesian model with the following characteristics:

1. **Response Variable**: Uncompassionate Self-Responding (UCS).
2. **Primary Predictor**: Compassionate Self-Responding (CS).
3. **Covariates**:
    - `neg_aff_Moment`: Momentary negative affect.
    - `context_Moment`: Context evaluation.
    - `lag_CS_same_day`: Lagged CS from the same day.
4. **Distribution**: Student's t-distribution to account for potential outliers or heavy-tailed response distributions
5. **Temporal Dependency**: Incorporated an AR(1) component to account for autoregressive effects of UCS.

Model Parameters

- `gamma_CS`: Coefficient representing the association between CS and UCS.
- `gamma_neg_aff`: Slope for negative affect (`neg_aff_Moment`).
- `gamma_context`: Slope for context evaluation (`context_Moment`).
- `phi`: Autoregressive coefficient for the lagged CS effect.
- `nu`: Degrees of freedom for the Student's t-distribution (estimated by the model).
- `alpha`: Intercept term.
- `sigma`: Scale parameter of the Student's t-distribution.

Stan Model Specification

```
data {
  int<lower=1> N;
  vector[N] CS;
  vector[N] UCS;
  vector[N] neg_aff_Moment;
  vector[N] context_Moment;
  vector[N] lag_CS_same_day;
}

parameters {
  real alpha_raw;
  real gamma_CS_raw;
  real gamma_neg_aff_raw;
  real gamma_context_raw;
  real phi_raw;
  real<lower=0> sigma;
  real<lower=2> nu;
}

transformed parameters {
  real alpha = alpha_raw;
  real gamma_CS = gamma_CS_raw;
  real gamma_neg_aff = gamma_neg_aff_raw;
  real gamma_context = gamma_context_raw;
  real phi = phi_raw * 0.5;  // Constraining phi to [-0.5, 0.5] for stability
}

model {
  // Priors
  alpha_raw ~ normal(0, 1);
  gamma_CS_raw ~ normal(0, 1);
  gamma_neg_aff_raw ~ normal(0, 1);
  gamma_context_raw ~ normal(0, 1);
  phi_raw ~ normal(0, 1);
  sigma ~ cauchy(0, 2.5);
  nu ~ gamma(2, 0.1);

  // Likelihood
  UCS ~ student_t(nu, alpha + gamma_CS * CS + gamma_neg_aff * neg_aff_Moment +
```

```
                    gamma_context * context_Moment + phi * lag_CS_same_day, sigma);
}
```

This Stan code implements the hierarchical Bayesian model described above. The model uses weakly informative priors for all parameters and constrains the autoregressive coefficient `phi` to the interval [-0.5, 0.5] to ensure model stability. The degrees of freedom parameter `nu` is constrained to be greater than 2 to ensure finite variance of the Student's t-distribution.

Hierarchical Model Analysis

In the second step of our idiographic analysis, we employed a hierarchical model approach, analogous to a meta-analysis (Ciarrochi et al., 2024). This method allowed us to synthesize the individual-level results across all participants, providing both an aggregate estimate of the effects and a measure of heterogeneity among participants.

Model Specification

We fitted a hierarchical binomial model to the proportion of negative posterior draws for the `gamma_CS` parameter. In this framework, each participant was treated as a unique "study," enabling us to estimate:

1. The aggregate proportion of negative effects across all participants.
2. The degree of heterogeneity in these effects among participants.

The model was implemented using the `brms` package in R.

R Code for Model Fitting

```r
fit_gamma_cs_binom <- brm(
  bf(n_negative | trials(n_total) ~ 1 + (1 | id), family = "binomial"),
  data = beta_cs_df,
  prior = c(
    prior(normal(0, 1), class = "Intercept"),
    prior(normal(0, 1), class = "sd")
  ),
  iter = 100000, warmup = 2000, chains = 4, cores = 4,
  backend = "cmdstanr",
  control = list(adapt_delta = 0.99, max_treedepth = 15)
)
```

Model Components

- **Formula**: `n_negative | trials(n_total) ~ 1 + (1 | id)`
  - `n_negative`: Count of negative posterior draws.
  - `n_total`: Total number of posterior draws
  - `(1 | id)`: Random intercept for each participant.
- **Family**: Binomial, appropriate for modeling proportions.

- **Priors**:
  - `normal(0, 1)` for the intercept and standard deviation of random effects.
  - These priors are weakly informative, allowing the data to drive the results while providing some regularization.
- **MCMC Settings**:
  - 100,000 iterations with 2,000 warmup.
  - 4 chains run in parallel.
  - Increased `adapt_delta` and `max_treedepth` for improved MCMC convergence.

Extension to Other Parameters

We applied a similar hierarchical modeling approach to analyze the posterior distributions of other key parameters from the idiographic analyses:

- `gamma_neg_aff`: Coefficient for negative affect.
- `gamma_context`: Coefficient for context evaluation.
- `gamma_interaction`: Coefficient for potential interaction effects.

Posterior Predictive Checks

In the following sections, we present the results of the Posterior Predictive Checks for the four models used to assess the aggregate effects and heterogeneity in our idiographic analysis. These models evaluate the linear association between UCS and CS, the effect of negative affect, the influence of contextual evaluation, and the interaction between CS and negative affect.

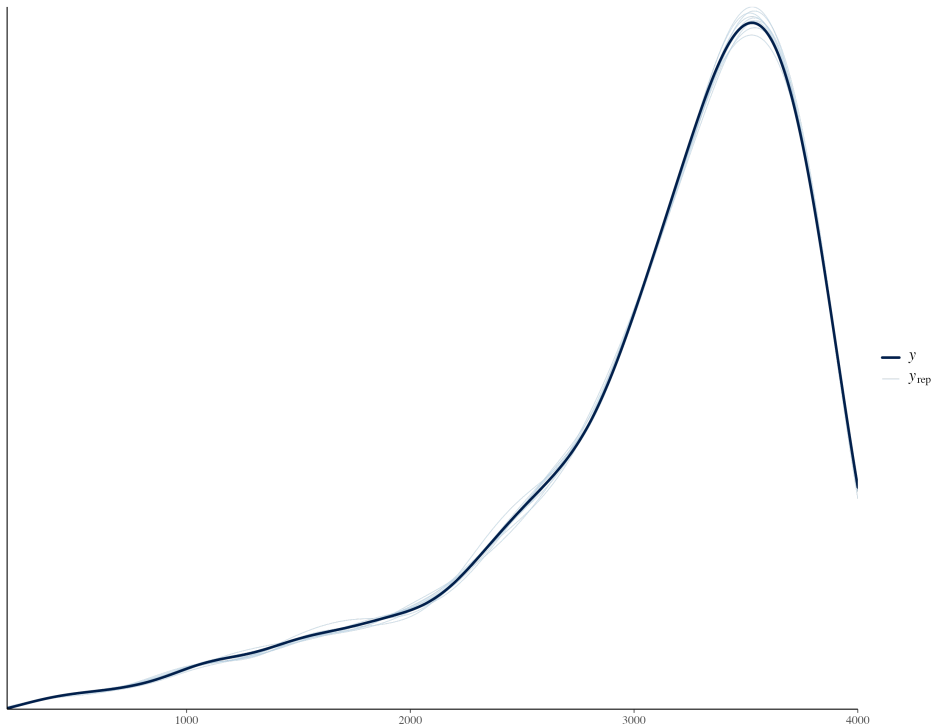

Figure 3: Idiographic analysis. Posterior Predictive Check for the hierarchical model fitted to the proportion of posterior draws of the `gamma_CS`parameter that were negative.

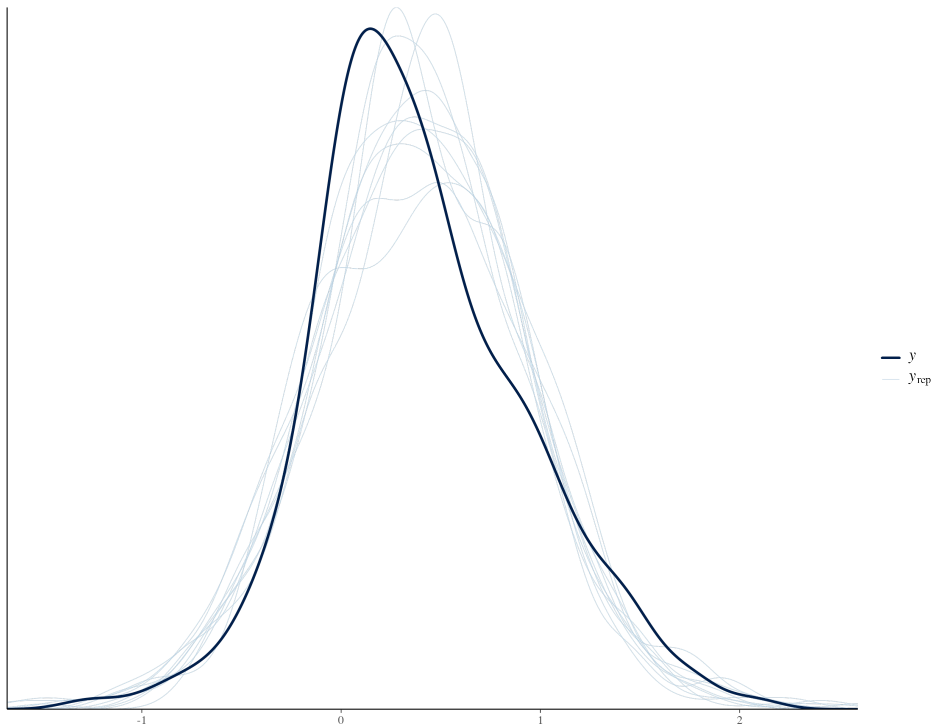

Figure 4: Idiographic analysis. Posterior Predictive Check for the hierarchical model fitted to the mean of the posterior draws of the `gamma_neg_aff` parameter.

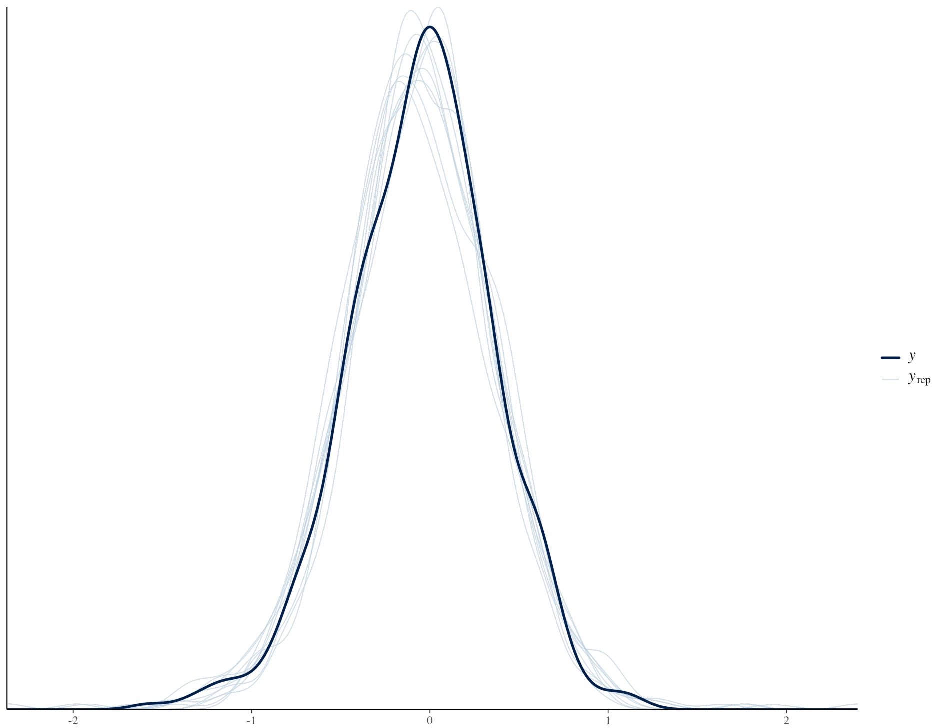

Figure 5: Idiographic analysis. Posterior Predictive Check for the hierarchical model fitted to the mean of the posterior draws of the `gamma_context` parameter.

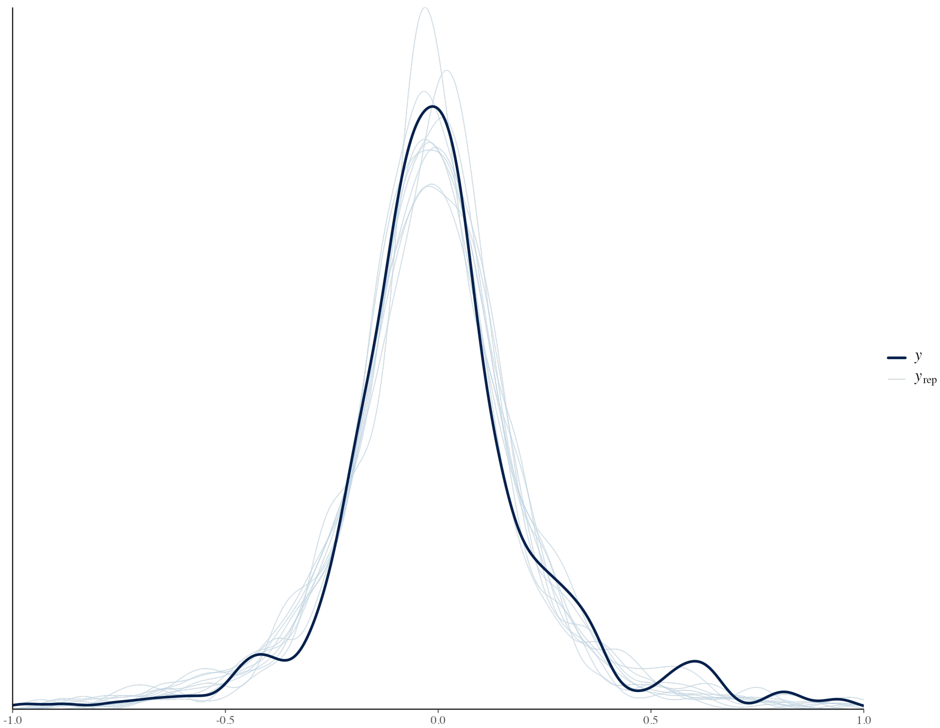

Figure 6: Idiographic analysis. Posterior Predictive Check for the hierarchical model fitted to the mean of the posterior draws of the `gamma_interaction` parameter.

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