Exploring State Self-Compassion and State Negative Affect in Daily Life Using Experience Sampling Methodology: A Bivariate Cross-Lagged Panel Model Approach

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Master Thesis

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November 2024

Abstract

Background. Self-compassion (SC) has been linked to lower negative affect (NA) at the between-person trait level. As SC may function as a protective mechanism, essential in the moment and thus state level, this study investigated its underexplored within-person relationship with NA. Using experience sampling data and a bivariate cross-lagged panel approach, the bidirectional associations between state SC and state NA were examined. Additionally, the study assessed SC's within-person and between-person variability in the data.

Methods. A secondary analysis was conducted on the data collected over two weeks. State SC was measured with two items, and state NA with four items, three times per day. Linear mixed modelling (LMM) was used to analyse within-person, time-lagged associations of the sample (N = 108, M_{Age} = 28.2, 74.1% female). Intraclass correlation coefficients (ICC) were used to calculate the within-person and between-person variability of SC.

Results. LMMs showed no significant cross-lagged predictive associations between state SC and state NA at the group level. Individual analyses revealed variability, with some participants showing predictive associations. The ICC indicated substantial between-person (41%) and within-person variability (59%) in state SC.

Discussion. Despite the insignificant cross-lagged associations, the potential predictive associations cannot be entirely rejected, especially because the study used few daily measures and did not account for potential moderators such as trait SC, mindfulness, and emotion regulation strategies. The within-person and between-person variability found underscores the importance of viewing SC as both a trait and a state-level construct, challenging the traditional characterisation of SC as solely a trait. Future research should aim to replicate these findings with increased sampling frequency and investigate moderating factors to capture rapid fluctuations and better understand the dynamic interactions between SC and NA in everyday life.

Introduction

Clinical psychology has been predominantly focused on pathology in the past but has shifted to include the study of human happiness and well-being in the last decades, emerging as positive psychology (e.g. Gable & Haidt, 2005; Seligman & Csikszentmihalyi, 2000). A central concept of positive psychology is self-compassion (SC), introduced by Neff (2003), which refers to the practice of extending unconditional kindness toward oneself (Bohlmeijer & Hulsbergen, 2018; Neff, 2003a). In recent years, SC has gained attention in research as it has been connected to enhanced subjective and psychological well-being, as well as lower experience of negative emotions, such as sadness, fear and stress (Neff, 2003a; MacBeth & Gumley, 2012). One reason may be that SC plays an important role in regulating negative emotions, often called negative affect (NA; Arimitsu & Hofmann, 2015; Guan et al., 2021). NA reflects the frequency and intensity of unpleasant emotions and is also used as a measurable indicator of (reduced) affective well-being (Watson et al., 1988). Central to this regulation is the idea that SC functions as an adaptive mechanism, helping individuals navigate adversity and potentially mitigating the impact of NA (Trompetter et al., 2017). Given that psychological resilience and adaptation are inherently dynamic processes (Kalisch et al., 2017), it is crucial to investigate how SC and NA interact in everyday life. However, the dynamic interplay between SC and NA remains underexplored despite its recognised importance.

Self-Compassion and Well-being

SC can be defined by three interacting elements, namely, 1) self-kindness, 2) common humanity, and 3) mindfulness (Neff, 2003b, 2023). Self-kindness is the ability to extend kindness towards oneself, counteracting self-critical tendencies, especially during adversities. Common humanity acknowledges suffering as a universal human experience instead of an isolated and personal one. Lastly, mindfulness entails an attentive and non-judgemental awareness of emotions, preventing over-identification and becoming overwhelmed with negative feelings (Neff, 2003c, 2003a). Numerous studies highlighted the positive association between SC and well-being, as demonstrated in a meta-analysis by Zessin and colleagues (2015b). SC has also been connected to lower rates of psychopathology, such as depression, anxiety, and post-traumatic stress disorder (e.g. MacBeth & Gumley, 2012; Muris & Petrocchi, 2017; Svendsen et al., 2016), as well as greater life satisfaction, self-acceptance, social connectedness, and optimism (e.g. Keyes, 2005; Neff et al., 2007). Moreover, individuals with higher SC reported lower susceptibility and intensity of negative emotions (Arimitsu & Hofmann, 2015; Guan et al., 2021; Zessin et al., 2015b). A commonly accepted theoretical viewpoint suggests that SC functions as a resilience or adaption mechanism, potentially reducing NA, and diminishing or mitigating its impact (Trompetter et al., 2017). One possible explanation for this theory is that reacting with SC to adversity reduces its impact through a mindful attitude, as the situation is perceived as temporary, less distressing, and manageable. This perception may reduce the NA or even bring about a shift from negative to positive emotions (Terry & Leary, 2011). This explanation is also in line with the prominent set-point theory, which suggests that after positive or negative events, individuals experience a short increase or decrease in well-being before returning to their normal baseline (Luhmann et al., 2012).

State Self-Compassion and State Negative Affect in Everyday Life

To date, most studies have focused on SC as a trait, primarily using cross-sectional designs (Faustino, 2022). As a trait, SC is conceptualised as a more enduring, stable disposition that shows variability between persons (Neff et al., 2007). In recent years, studies have also demonstrated that SC is highly variable within individuals, likely due to everyday life's dynamic and ever-changing nature (Breines & Chen, 2013; Faustino, 2022). Therefore, SC can also be understood as a state, reflecting moment-to-moment variability. Additionally, researchers suggest that adaptation to daily adversities is a highly dynamic and complex process involving various resilient factors (Kalisch et al., 2017; Ong & Leger, 2022). Therefore, as SC would be framed as a dynamic adaptation process, it is essential to examine SC as such a dynamic construct and investigate its association with NA in everyday life from a state perspective. In fact, Wiesma (2024) even found that state SC plays a more significant role in moderating the relationship between daily adversities and affect than trait SC. A suitable method to investigate SC in everyday life is the experience sampling method (ESM). ESM is a diary technique that employs smartphones, in which participants must self-report their emotions and experiences in their everyday lives multiple times a day for a set period (Ader et al., 2022; Myin-Germeys & Kuppens, 2022). Data obtained from ESM makes it possible to examine temporal relations between variables over relatively short periods due to the repeated assessment of the constructs (Myin-Germeys et al., 2018). However, few studies have investigated state SC and state NA using ESM. Hanebaum (2021) found that higher levels of state SC were associated with slight increases in subjective well-being. Mey and colleagues (2023) showed that individuals who reported higher state SC momentarily experienced increased positive affect and reduced NA. Additionally, more state SC was associated with lower stress reactivity, and exploratory analysis revealed that recent SC predicted subsequent affect more strongly than the reverse (Mey et al., 2023). Similarly, Scott et al. (2024) found that state SC moderated the link between daily stressor exposure and state NA experienced by older adults. Thus, the positive association between state SC and state NA is well established.

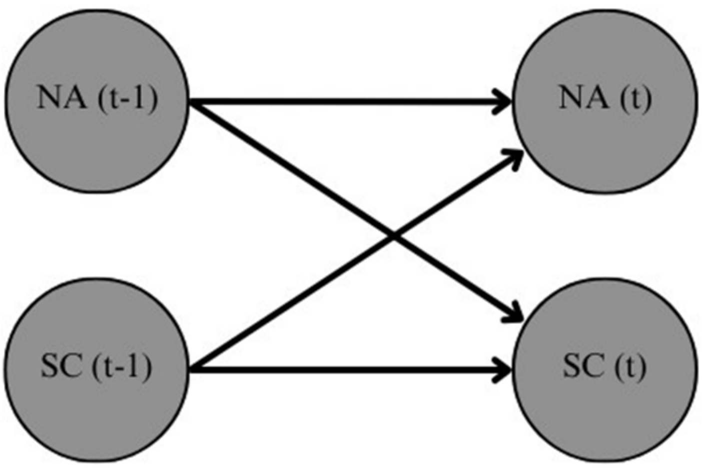
The current understanding of SC suggests that its beneficial effects on NA drive the association between SC and NA at the within-person level. However, apart from Mey et al. (2023), who found a weak association, no study has examined the temporal dynamics between state SC and state NA by investigating whether heightened state SC precedes a reduction in state NA. Research also has yet to explore the possibility of a reciprocal relationship, where fluctuations in state NA might subsequently influence state SC in everyday life. According to the adaptation hypothesis, SC is essential after individuals' baseline levels of NA are heightened, for instance, during everyday challenges. In those moments, SC can facilitate emotional adaptation. Thus, SC may be particularly elevated when an individual's NA is high. On the other hand, there may be no need for high SC to facilitate adaptation when an individual is feeling fine (Hanebaum, 2021; Odou & Brinker, 2015; Stutts et al., 2018). This suggests that, at the state level, self-compassionate individuals may show a positive association between NA and SC, where an increase in NA is followed by heightened SC in the next moment. This association would directly contrast the patterns observed at the between-person level, where SC is generally associated with lower NA (Zessin et al., 2015). This dynamic, within-person association cannot be captured through traditional cross-sectional studies. Additionally, investigating these dynamics could provide insights into how SC operates in real-time, potentially helping individuals cultivate greater SC as an adaptive strategy (Terry & Leary, 2011b). This lack of consideration for the temporal sequence and possible bidirectional relationship is a key limitation of existing research.

Bivariate Cross-lagged Panel Model of State Self-Compassion and State Negative Affect

One solution is to investigate how state SC and state NA influence each other over time in both directions using a bivariate cross-lagged analysis (Hamaker et al., 2018; see Figure 1).

Figure 1

Bivariate Cross-lagged Panel Model of Self-Compassion and Negative Affect



This model depicts a representation of a bivariate cross-lagged panel design focusing on the within dynamics between state SC and state NA (Hamaker et al., 2018). Each variable is represented twice in the figure. Once in a lagged form (t-1) corresponding to an earlier moment in time, and once in form (t). Additionally, four parameters can be seen as arrows. These include two autoregressive and cross-lagged parameters (Hamaker et al., 2018). The autoregression shows how the two variables at an earlier time point (t-1) are associated with themselves at a later time point (t). The cross-lagged parameters are particularly relevant for this thesis as they illustrate the lagged association between state SC and state NA and, therefore, allow to investigate temporal relations between these two variables. Applying this model to investigate the relationship between state SC and state NA bidirectionally provides valuable insights into whether elevated SC can reduce NA in the following moment, and whether high NA might subsequently increase SC. Thus, this approach addresses the limitations of previous studies by capturing the dynamic interplay between these variables over time.

The bivariate cross-lagged panel model is based on the assumption that SC as an adaptation mechanism shows variations in everyday life, therefore exhibiting state-like characteristics. Consequently, it is essential to investigate whether SC shows daily fluctuations. One study that examined this, conducted by Scott and colleagues (2024), revealed that 37% of the variation in SC was attributable to fluctuations within individuals over time. Thus, SC demonstrated significant variability at both the between- and within-person levels. However, they used a sample of older adults that may not be generalisable to the whole population. Similarly, Hanebaum (2021) found an ICC of 0.38 for SC in his sample, indicating that 38% of the total variance was attributable to differences between individuals, while the remaining 62% was due to fluctuations within individuals. This exploitation may also help to give insight into the trait vs state discussion regarding SC (Faustino, 2022). Thus, the variability of SC within the dataset will be examined.

Aim of this Study

To conclude, this paper aims to investigate the potential bidirectional association between state SC and state NA. While the association of state SC and state NA is fairly established, the temporal dynamics and especially the possible influence of state NA on subsequent state SC have not been investigated in depth. A bivariate cross-lagged panel model has been chosen to understand the temporal relationship between the two variables. Although Mey et al. (2023) investigated the bidirectional association, no study has used a cross-lagged approach. An assumption for this cross-lagged model is the dynamic character of SC. However, there is little research into the within and between variability of SC. Thus, the degree to which SC shows variability between and within individuals in this dataset will also be investigated. Grounded in the outline, the following research questions emerge:

RQ1: *How are state self-compassion and state negative affect associated over two weeks, as explored through a cross-lagged panel approach?*

RQ2: *How does self-compassion vary within and between individuals over the time period of two weeks?*

It is hypothesised that higher levels of state SC at one time point (t-1) will predict lower levels of state NA at subsequent time points (t1) within individuals over the two-week period. Additionally, it is hypothesised that higher levels of state NA at one time point (t-1) will predict higher levels of state SC at the subsequent time point (t1) within individuals over the two-week period. Given the lack of research investigating the reverse relationship, this hypothesis is more exploratory. Finally, it is hypothesised that SC will vary significantly within and between individuals over the two weeks period with the degree of within-person variability being greater than that of between-person variability.

Method

Participants

This study used an existing data set collected during a master thesis project regarding mental health in daily life (Faesing, 2022; Schleich, 2022). The participants were recruited through the Sona System, the test subject arrangement of the University of Twente, and from the researcher's acquaintances. Due to the rather high burden of ESM studies, individuals accessible to the researcher were recruited to increase willingness to participate (Eisele et al., 2022). Therefore, non-random convenience sampling was applied. The participation condition entailed a) ownership of a smartphone with an internet connection, b) availability of an email address, and c) sufficient command of English or German to comprehend and adhere to the study. The project aimed at a sample size of 50, deemed adequate given that the average participant size for ESM studies is 53 (Van Berkel et al., 2017). Power analyses were not conducted due to the complexities of multilevel modelling in ESM studies (Myin-Germeys & Kuppens, 2022b; Trull & Ebner-Priemer, 2020).

Design and Procedure

A within-group ESM design was employed for the longitudinal study to investigate various variables. The project received ethical approval from the Ethics Committee of Behavioural, Management and Social Sciences of the University of Twente [#211225; #220220] (Faesing, 2022; Schleich, 2022). The online research platform Avicenna Research (https://avicennaresearch.com/; called Ethica Data in 2022) was employed for the ESM data collection. After the study was set up, a three-day pilot trial was conducted using the smartphone version of the app to confirm the study setup's feasibility and identify potential problems. Consequently, an email was sent to the participants inviting them to download the Ethica app and create an account. After approving the informed consent, the actual data collection started. Participants could choose between participating in the study in English and

German. The data collection lasted 14 days (from 22/11/2021 to 05/12/2021) with the same starting date for all participants to ease the data handling. The two-week data collection period was chosen based on recommendations indicating that this duration typically yields strong response rates (Conner & Lehman, 2012; Van Berkel et al., 2017).

An the first day, the participants had to fill out a baseline questionnaire, including demographic information (age, gender, sex, education, nationality, occupation) and other questionnaires not used in this study. The baseline questionnaire was intended to be completed at the start of the study but did not expire until the end of the data collection. Participants who did not complete the questionnaire immediately received three additional reminders over the two weeks. On the same day, the ESM sampling started. The daily ESM questionnaires included 12 items and were triggered semi-randomly within three predefined time intervals: morning (10 a.m. ± 2 hours), afternoon (3 p.m. ± 2 hours), and evening (8 p.m. ± 2 hours; Faesing, 2022; Schleich, 2022). The study utilised three measurements per day to minimise participant burden and align with the specific research questions of the group, which did not necessitate more finely-tuned timeframes (Faesing, 2022; Schleich, 2022). The principle of time-contingent signal sampling was used to prevent participants from anticipating the notifications, while still maintaining a clear time frame. Moreover, a push notification was sent for each of the three trigger points, and the questionnaires expired two hours afterwards with a reminder of the expiration after 1 hour.

Measures

Baseline Questionnaires

In the original project, the baseline questionnaires consisted of 43 items measuring different trait variables and demographics. For this study, only the demographic information was utilised.

State Questionnaires

Again, multiple state measures were included in the original project, with SC and NA as the only relevant constructs for this study.

State Self-Compassion. State SC was measured with two momentary items: *'I feel kind towards myself'* and *'I currently feel self-critical'*. Participants replied on a 7-point Likert scale ranging from 1 *(not at all)* to 7 *(very much)*. The self-criticism item was reversed, and mean scores were calculated for the two items to calculate each participant's observed state SC score. A split-half correlation between the scores of the first week and second week demonstrated a high internal reliability of r = 0.80.

State Negative Affect. Consistent with previous research, state NA was measured by four items. Two low-valence, low-arousal items (How *'down', 'guilty'* do you feel right now?) and two low-valence, high-arousal items (How *'anxious', 'insecure'* do you feel right now?) were used. Participants responded on a 7-point Likert scale ranging from 1 *(not at all)* to 7 *(very much)*. The average was computed for the five items. A split-half correlation between the scores of the first and second week revealed a high reliability estimate of r = 0.85.

Data Analysis

The program R-Studio (version 2024.09.0+375) was used for all statistical analyses. Participants who completed less than 33% of the daily questionnaires were removed from the study, as this rate is commonly viewed as the minimum for ESM studies (Conner & Lehman, 2012). In terms of measures, the observed SC and NA scores were averaged to calculate the person mean (PM). Moreover, the person-mean centred score (PMC) was calculated by subtracting the individual observed state NA and SC scores from the PM scores (Hoffman & Walters, 2022). This disaggregates within-person effects by centring each participant's scores around their own mean, thus focusing on how variables change within individuals independently of differences between them (Kraiss et al., 2022). Additionally, by removing the first measure point from the variables PMC SC, PMC NA, state SC and state NA, lagged variables were created (t-1), namely, PMC SC lag, PMC NA lag, state SC lag and state NA lag.

Linear mixed models (LMM) were run with the 'nlme' package to analyse the first research question regarding the bivariate cross-lagged model. An LMM was chosen due to the random effects, which account for the hierarchical and nested structure, and for handling randomly missing values, which are typical in ESM data (Goldstein et al., 1993). Moreover, an autoregressive covariance structure (AR1) was selected to model correlations between measurements in ESM data, assuming that correlations weaken exponentially. AR1 is an important feature of the cross-lagged panel (Hamaker et al., 2018; Barnett et al., 2010). Additionally, for this analysis, random slopes were also included because the Akaike Information Criterion and the Bayesian Information Criterion indicated a better fit for the model with random intercepts and random slopes.

Subsequently, two LMM analyses were performed. For the first analysis, the dependent variable was state NA, and the independent variables were PMC SC lagged and state NA lagged. For the second LMM, state SC served as the dependent variable, PMC NA lagged, and state SC lagged were chosen as the independent variables. The two analyses were also conducted for each individual participant to examine heterogeneity in cross-lagged associations. A simple linear model (SLM) was fitted for each participant, with state NA as the dependent variable and PMS SC lag and state NA lag as independent variables. Similarly, a SLM was run for each participant with state SC as the dependent variable and PMS NA lag and state SC lag as independent variables. For the second research question, an LMM was again used to calculate the intraclass correlation coefficient (ICC) to compare the degree of within- and between variability of the observed state SC scores. In all analyses conducted, results with a p-value below 0.05 were considered statistically significant.

Results

Participants

The study collected data from 132 participants. However, 24 (18.2%) participants were removed due to not reaching the participation criteria of 33%. Thus, 108 participants were included in the final data set for the data analysis. The final sample had a mean age of 28.2 years (*SD* = 12.26), with participants ranging in age from 14 to 60 years. The average completion rate for state items among the remaining participants was 76.08% (*SD* = 42.60%, range 0.00 - 100.00%), which is considered a good response rate compared to the average response rate of 69.9% reported by Van Berkel et al. (2017). Additionally, the average completion rate for the demographics per participant was 99.62% (*SD* = 2.73%, range 80.00 - 100.00%), indicating high data completeness. An overview of the demographic information of the participants is presented in Table 1. Notably, the sample predominantly consisted of young German women.

Table 1

Overview Demographics of the Participants (N = 108)

Demographic	N (%)
Gender	
Female	80 (74.1)
Male	26 (24.1)
Other	2 (1.9)
Nationality	
German	81 (75.0)
Dutch	17 (15.7)
Other	10 (9.3)
Education	
Middle school	10 (9.3)
High school	53 (49.1)
Bachelor	30 (27.8)

Master	11 (10.2)
Other	4 (3.8)
Occupation	
Working	40 (37.0)
Student	36 (33.3)
Studying and Working	25 (23.2)
Self-employed	4 (2.8)
Other	4 (3.8)
Not Working	0 (0)

Note. Frequencies (N) and percentages (%).

Additionally, statistics regarding the measures are summarised in Table 2 and visualised in Figure 2.

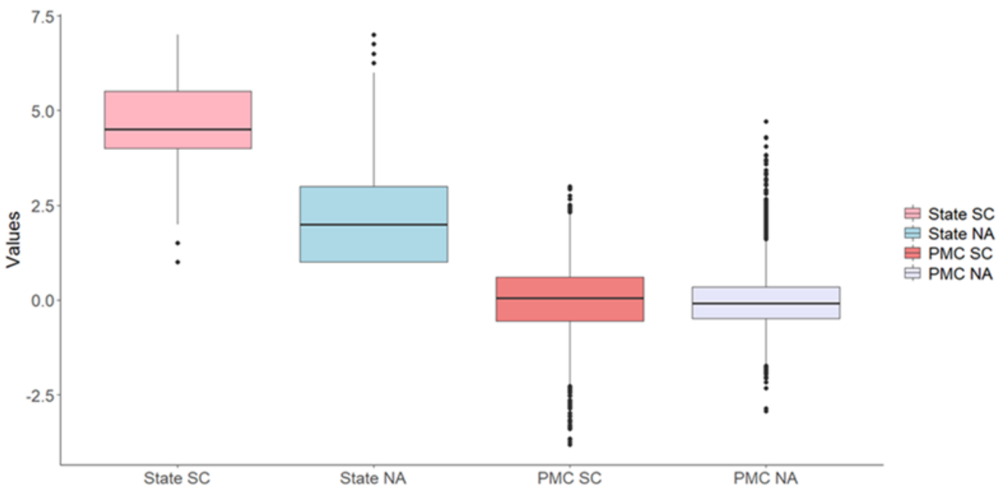
Table 2

Overview Measures

Measures	Mean	Median	SD	Range
State Self-Compassion	4.58	4.5	1.23	1- 7
Person Mean-Centred Self Compassion	0	0.05	0.93	-3.82 - 2.98
State Negative Affect	2.2	2	1.20	1- 7
Person Mean-Centred Negative Affect	0	-0.09	0.83	-2.93 - 4.71

Figure 2

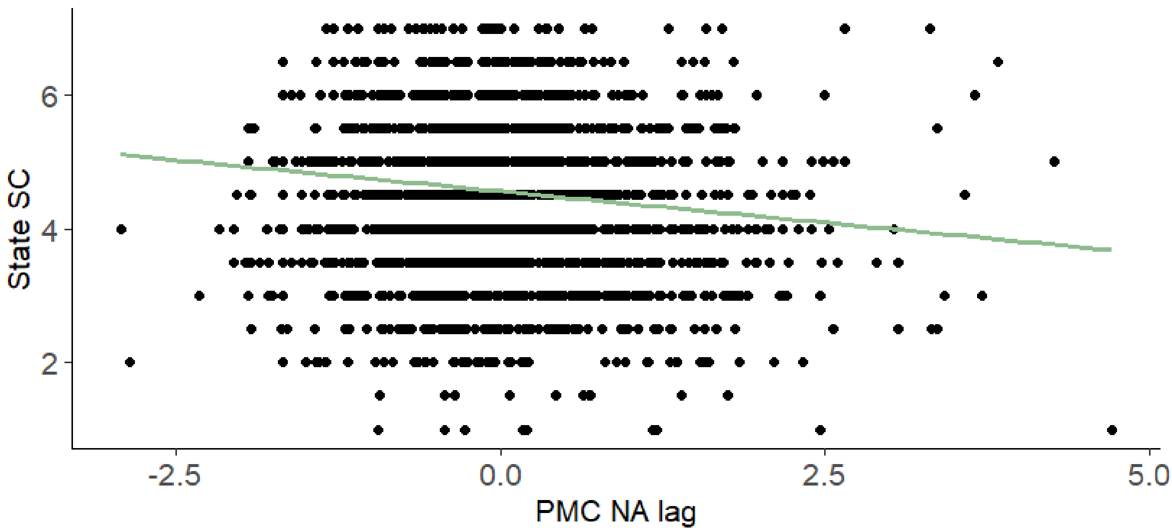
Boxplots of Measures



The relationship of state SC and PMC NA lagged is displayed in Figure 3. A weak negative relationship becomes visually apparent. Additionally, the two variables showed a correlation of r = -0.12.

Figure 3

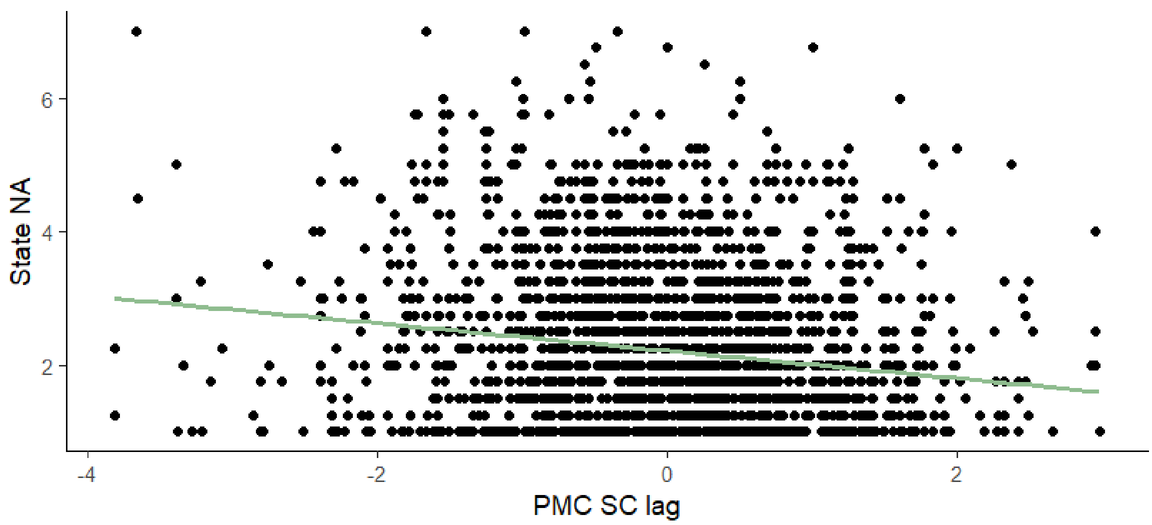
Scatterplot State Self-Compassion and Person Mean-Centred Negative Affect Lagged



In Figure 4, the relationship between state NA and PMC SC lag is shown in a scatterplot, and again, a weak negative trend becomes apparent. The correlation is r = -0.16.

Figure 4

Scatterplot State Negative Affect and Person Mean-Centred Self-Compassion Lagged



Cross-Lagged Panel Model of State Self-Compassion and State Negative Affect

The analysis results for hypothesis one can be seen in Table 2. No significant association was found between PMC SC and state NA one moment later, while controlling for autoregressive effects.

Table 2

Fixed Effects Estimates for the Relationship Between Person Mean-Centred Self-Compassion Lagged and State Negative Affect

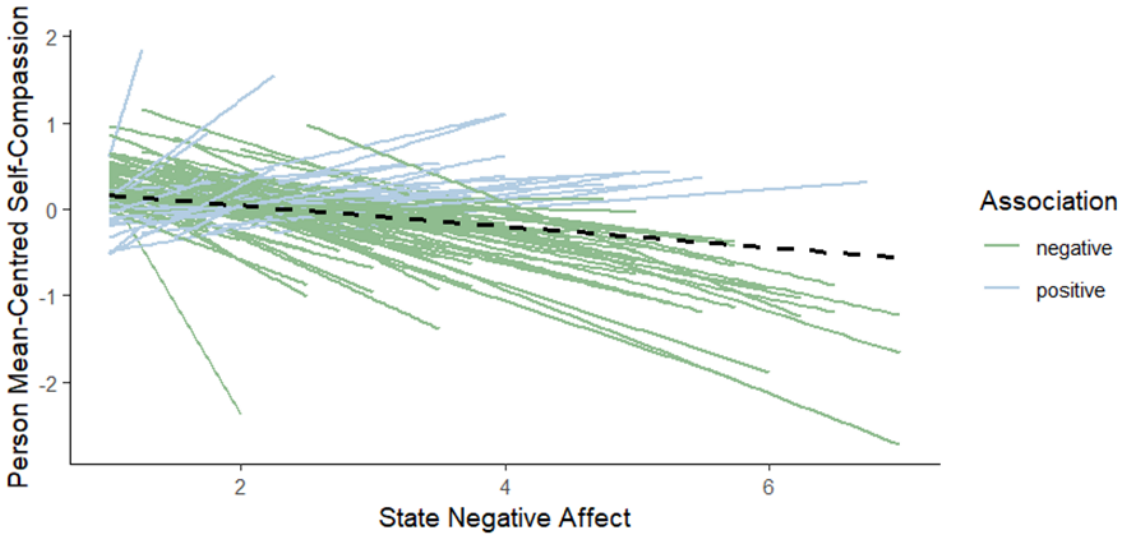
	Estimate	Std. Error	df -value	t-value	p-value
Intercept	1.54	0.01	0.075	20.58	.001***
PMC SC lag	-0.0	0.02	169.06	-0.63	.533
State NA lag	0.295	0.02	2486.75	14.81	.001***

Note. Asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

The results of the same analyses for individual participants are in Appendix A. It can be seen that PMC SC affected state NA one moment later in six participants, with three positive and three negative associations that surpassed the threshold for statistical significance. In Figure 5, individual within-person associations are shown. Negative associations (N = 63) and positive associations (N = 45) were differentiated. The lowest individual association was -1.15, and the highest one was 0.55.

Figure 5

Individual Associations Between Person Mean-Centred Self-Compassion Lagged and State



Negative Affect

Table 3 shows that for hypothesis two, no significant association was found between PMC NA and state SC one moment later, while controlling for autoregressive effects.

Table 3

Fixed Effects Estimates for the Relationship Between Person Mean-Centred Negative Affect Lagged and State Self-Compassion

	Estimate	Std. Error	df -value	t-value	p-value
Intercept	3.55	0.11	670.1	31.92	.001**
PMC Na lag	0.02	0.03	162.00	0.76	.45
State SC lag	0.23	0.02	2852.00	11.34	.001**

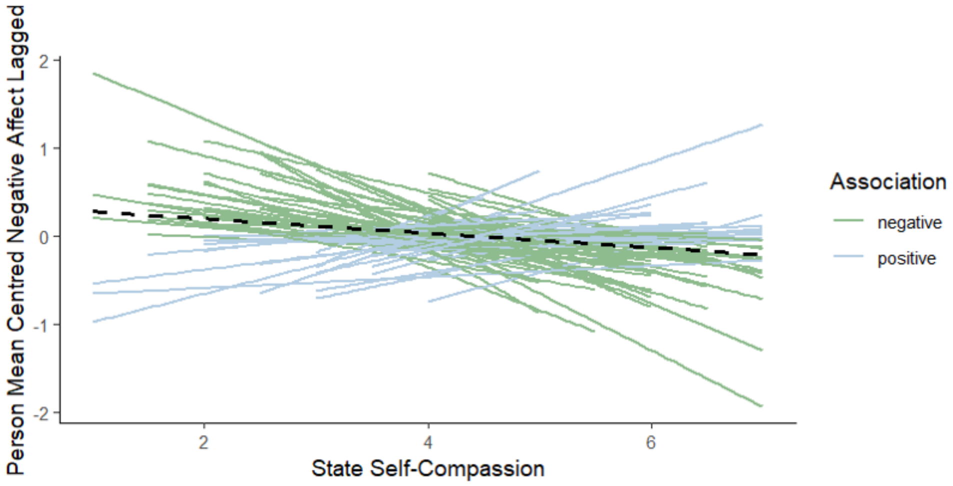
Note. Asterisks indicate statistical significance (* p < 0.05, ** p < 0.01, *** p < 0.001).

At the individual level, analyses revealed that state NA predicted state SC one moment later in eight participants, with four positive and four negative associations (see Appendix B). Individual associations are displayed in Figure 6. The associations were predominantly

negative (N = 57), while 48 associations were positive. The lowest individual association was -1.15, and the highest had a value of 1.2.

Figure 6

Individual Associations between State Self-Compassion and Person Mean-Centred Negative Affect Lagged

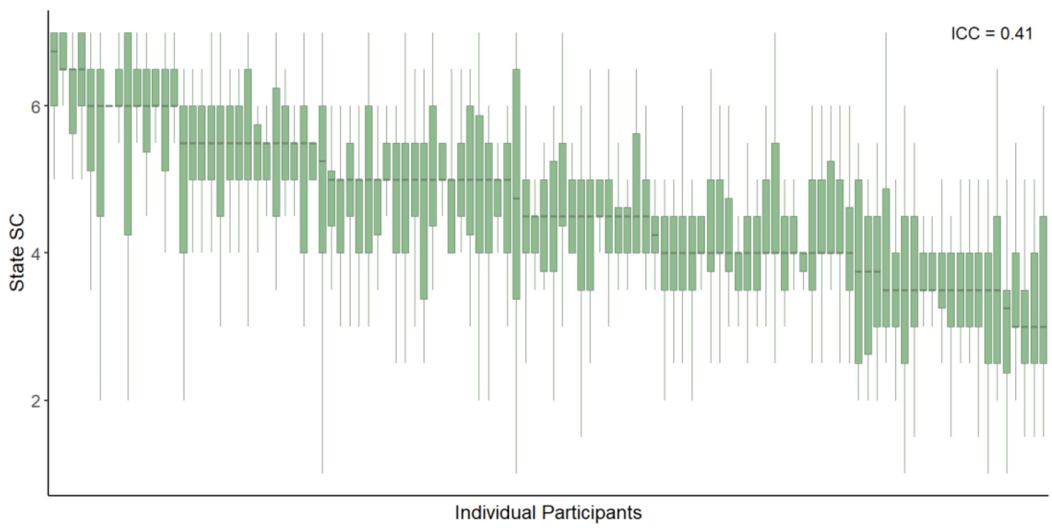


Self-Compassion Variations Between and Within Individuals

To answer the second research question, the ICC was found to be 0.41. The between-person variance was 0.64, and the within-person variance was 0.91, with standard deviations of 0.80 and 0.95. This indicates that 41% of the variance in SC scores in this data set is attributable to differences between individuals, while 59% is due to fluctuations within individuals over time. This is also visualised in Figure 7.

Figure 7

Distribution of State Self-Compassion Values by Participan



Discussion

This study examined the association between state SC and state NA in everyday life using a bivariate cross-lagged panel model ESM data. Primary analyses showed that state SC did not predict subsequent state NA, nor did state NA predict state SC, leading to the rejection of hypotheses one and two. Supporting hypothesis three, 41% of the variance in SC scores was due to between-person variability, while 59% was due to within-person fluctuations.

Cross-Lagged Panel Model of State Self-Compassion and State Negative Affect

Hypothesis one was rejected, as no significant predictive association was found between state SC and state NA. This outcome contrasts with most existing literature investigating the relationship between SC and NA at both the between-person and within-person levels. A negative association has consistently been found at the between-person level, as demonstrated in the meta-analysis by Zessin et al. (2015). Although fewer studies have explored the state level of SC and NA, most have also found a negative association at the within-person level (e.g., Mey et al., 2023; Wiesmann, 2024), with exceptions like Allen and Leary (2010) and Ferrari and colleagues (2019), who did not find a significant association. However, since only Mey et al. (2023) investigated the predictive relationship, there are few comparative studies for hypothesis one. The findings of this study contradict the understanding of state SC as an adaptive mechanism that lowers NA (e.g., Neff et al., 2007; Odou & Brinker, 2014). Theoretically, a positive association should be apparent as individuals are expected to be kind to themselves when facing difficulties (e.g., Leary et al., 2007; Neff et al., 2007). Hypothesis two aimed to determine whether state NA can predict SC. The analysis did not support this hypothesis. Given that this relationship is relatively unexplored, there are few similar studies. Only Mey et al. (2023) investigated the predictive association of state NA on subsequent state SC and found a weak association.

There may be multiple reasons for these results. Mey and colleagues (2023) used six daily notifications for their data collection. The data for this study was collected through three measurements per day (Faesing, 2022; Schleich, 2022). However, for a study utilising a cross-lagged panel model, a higher number of time points per day would have been preferable, as the current frequency may limit the depth of analysis, particularly for lagged assessments. The time between the notifications may have been too long to investigate the association momentarily. Additionally, Breines and Chen (2013) emphasise that SC can function differently across individuals, acting as a protective factor in only some contexts. So, more variables may need to be accounted for. Trait-level SC may play a key role in the moderation of the relationship. The hypothesis assumes that individuals respond to high NA with SC. However, the ability to use SC varies. Participants with low average SC might not increase in state SC following high NA if SC is not their usual coping strategy. Hanebaum (2021) found that the association between state SC and well-being depended on trait SC. A strong baseline SC level was suggested as essential for the effective use of SC during high NA moments (Hanebaum, 2025). Another moderator could be emotion regulation strategies. SC has been linked to adaptive strategies like cognitive reappraisal and negatively associated with maladaptive strategies, such as high levels of rumination (Inwood & Ferrari, 2018). Individuals who frequently engage in high levels of rumination may struggle to practice SC following high NA because rumination intensifies negative emotions and inhibits self-kindness (Raes, 2010). Conversely, those who utilise adaptive strategies are more likely to increase SC in response to NA, using it as a coping mechanism to reduce distress (Diedrich et al., 2014). A more statistical explanation for the results may be the restricted range of data. In this study, the mean state SC was high (M = 4.58 on a 7-point scale), which may indicate a ceiling effect, while the mean state NA was low (M = 2.2), potentially indicating a floor effect. This limited variability could reduce the ability to detect significant associations because there is less fluctuation in scores to reveal predictive relationships.

Predictive Associations of the Bivariate Cross-Lagged Panel Model at the Individual Level

The individual analyses for hypotheses one and two revealed a few positive and negative associations, suggesting underlying mechanisms such as differences in emotional regulation. Participants with negative associations, where higher SC predicts lower subsequent NA, may effectively use SC to alleviate negative emotions, consistent with Neff's (2003) view of SC as an adaptive mechanism. Conversely, those with positive associations, where higher SC predicts higher NA, might experience increased awareness of negative emotions (Neff, 2003). The observed variability aligns with findings by Krieger et al. (2016), who noted that individuals with more depressive symptoms often struggle to maintain SC, intensifying negative emotions. This complex interplay reflects differences in coping styles, while again, a focus is on trait-level SC potentially moderating the associations (Hanebaum, 2021; Scott et al., 2024).

Within and Between Variability in State Self-Compassion

Hypothesis three was accepted, as the ICC indicated that state SC exhibits considerable within-person variability. Specifically, 41.2% of the variance in state SC was due to stable individual differences, while 58.8% reflects fluctuations within individuals over time. This result is consistent with previous research that found considerable fluctuation at the within-person level (e.g., Hanebaum, 2021; Mey et al., 2023). This pattern is also consistent with findings for affective states, where similar proportions of within-person variance have been reported (e.g., Nezlek, 2017). NA, for instance, typically exhibits an ICC between 0.40 and 0.50, indicating that approximately 60-50% of its variance is within-person (Mroczek et al., 2003). This finding further supports the idea that SC can significantly fluctuate within individuals, influenced by daily experiences and situations. These results support the conceptualisation of SC as a state that fluctuates in response to situational factors and momentary experiences but also as a stable trait. Further, the finding underlines the decision to use a bivariate cross-lagged panel model, which necessitates within-person fluctuations.

Strengths and Limitations

To the best of current knowledge, this is the first study to examine the relationship between state SC and state NA using a cross-lagged panel approach with ESM data. By controlling for autocorrelation, often unaccounted for in prior research, a more precise depiction of the temporal dynamics between SC and NA was archived. ESM enabled the capture of moment-to-moment fluctuations, offering a nuanced view of their interplay in daily life and enhancing the ecological validity of the findings (Curran & Bauer, 2011; Shiffman et al., 2008). This approach to examining within-person, time-lagged associations sheds light on intra-individual processes and offers initial insights to inform future research in this field (Shiffman et al., 2008).

However, some limitations should be noted. The sample, primarily young, educated German women, limits generalisability to broader populations and reflects the convenience sampling used (Jager et al., 2017). State SC was measured with two items focused solely on self-kindness versus self-criticism, potentially missing dimensions of common humanity and mindfulness (Neff, 2003). Mey et al. (2023) found self-criticism to be more closely related to NA than self-kindness, aligning with research supporting a six-dimensional SC structure (Neff et al., 2021). Additionally, the sampling frequency of three times per day may not fully capture rapid fluctuations in SC and NA, potentially overlooking shorter-term dynamics. Finally, while cross-lagged panel modelling is often linked to causality, this nonexperimental longitudinal design cannot establish causal relationships (Bolger & Laurenceau, 2013).

Directions for Future Research

Future studies should aim to replicate these findings with more diverse samples to enhance the generalisability of the results. Increasing the frequency of ESM prompts may better capture rapid fluctuations in SC and NA, offering more profound insights into temporal dynamics (Myin-Germeys & Kuppens, 2022). Because the temporal dynamics between state NA and state SC are not yet clearly understood, conducting experimental studies with closely spaced time frames would be highly valuable. Additionally, expanding the number of items used to measure state SC could provide a more comprehensive assessment of the construct, capturing its multifaceted nature. Furthermore, employing experimental designs, such as micro-randomised trials, could provide causal evidence for the directionality of the relationship between SC and NA (Qian et al., 2022). Exploring potential moderating variables and mediating mechanisms could clarify the the associaton between state NA and state SC (Breines & Chen, 2013). For example, examining trait SC as a moderator or previous experience with SC or practices like SC meditation, as discussed by Mey et al. (2023). Finally, the interaction between NA and SC could be investigated by focusing specifically on moments when NA increases to provide a deeper understanding of their relationship.

Conclusion

This study explored the associations between state SC and state NA using a bivariate cross-lagged panel approach and ESM. No predictive bidirectional association between state SC and state NA was found. However, state SC showed substantial between and within-person variability, emphasising the importance of a state-level perspective. The distinctive approach of this study is the utilisation of a cross-lagged panel model to investigate the predictive associations of state SC and NA bidirectionally from a dynamic perspective, which has not been done before. Future research may conduct similar investigations using more frequent time points and experimental designs, focusing on moderating variables to investigate the bidirectional association in everyday life.

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Appendix A

Individual-Level Estimates for the Effect of Lagged Self-Compassion on State Negative Affect

Participant ID	Estimate	Standard Error	t-value	p-value
1	-0.111	0.303	-0.366	.717
3	-0.190	0.104	-1.832	.076
4	0.065	0.186	0.348	.731
5	0.156	0.299	0.522	.607
6	**0.449**	**0.213**	**2.103**	**.043***
8	-0.117	0.200	-0.586	.563
10	-0.456	0.351	-1.298	.207
11	0.176	0.339	0.519	.611
12	-0.469	0.259	-1.807	.079
13	-0.363	0.224	-1.619	.114
15	-0.152	0.248	-0.614	.544
16	-0.006	0.139	-0.042	.967
17	0.024	0.058	0.417	.679
18	0.090	0.146	0.620	.542
19	-0.650	0.528	-1.230	.234
20	-0.049	0.101	-0.488	.629
24	-0.779	0.419	-1.858	.080
25	-0.000	0.000	-0.749	.459
26	-0.076	0.080	-0.949	.349
27	-0.380	0.301	-1.264	.214
28	0.008	0.028	0.306	.762
29	0.078	0.146	0.529	.600
30	0.329	0.278	1.184	.244
31	0.044	0.102	0.434	.669
32	-0.216	0.193	-1.121	.269
33	-0.116	0.199	-0.584	.564
34	-0.181	0.113	-1.605	.117
35	-0.115	0.234	-0.493	.625
36	0.126	0.121	1.039	.312
37	-0.089	0.204	-0.436	.665
38	-0.024	0.160	-0.151	.881
39	0.151	0.252	0.599	.554
41	**-0.179**	**0.043**	**-4.142**	**<.001*****
42	0.013	0.082	0.157	.877
43	0.109	0.254	0.429	.671

Participant ID	Estimate	Standard Error	t-value	p-value
44	0.003	0.240	0.013	.990
45	-0.066	0.294	-0.225	.824
47	-0.296	0.221	-1.341	.191
48	-0.331	0.300	-1.102	.279
49	-0.151	0.183	-0.827	.414
50	-0.115	0.339	-0.339	.736
52	-0.094	0.152	-0.615	.545
53	-0.110	0.107	-1.024	.312
56	0.160	0.306	0.522	.606
57	**0.637**	**0.301**	**2.118**	**.046***
58	-0.375	0.205	-1.827	.091
59	-0.216	0.125	-1.729	.093
63	0.017	0.094	0.185	.855
64	0.320	0.283	1.130	.273
65	-0.573	0.406	-1.413	.178
66	0.316	0.247	1.277	.213
67	0.553	0.344	1.605	.137
68	-0.452	0.230	-1.968	.057
69	0.055	0.198	0.279	.783
70	-0.117	0.147	-0.795	.432
71	-0.194	0.128	-1.514	.138
72	0.118	0.193	0.613	.544
73	-0.082	0.159	-0.517	.609
74	0.199	0.236	0.841	.411
75	-0.133	0.234	-0.566	.575
76	-0.036	0.054	-0.670	.508
77	-0.384	0.255	-1.507	.146
78	-0.264	0.234	-1.130	.279
79	-0.007	0.206	-0.034	.973
81	0.027	0.054	0.504	.623
83	**-0.198**	**0.076**	**-2.594**	**.014***
84	0.062	0.074	0.846	.409
85	-0.094	0.071	-1.320	.195
86	-0.091	0.169	-0.541	.592
87	0.247	0.248	1.000	.332
88	-0.264	0.167	-1.588	.122
90	0.076	0.128	0.592	.567
91	0.035	0.220	0.158	.877
92	**0.096**	**0.046**	**2.086**	**.046***

Participant ID	Estimate	Standard Error	t-value	p-value
93	0.188	0.310	0.607	.555
94	0.145	0.204	0.712	.483
95	-0.204	0.155	-1.314	.198
96	-0.052	0.164	-0.315	.755
97	-0.168	0.160	-1.048	.301
98	0.031	0.151	0.207	.837
99	0.133	0.095	1.398	.172
101	-0.097	0.178	-0.545	.591
103	0.307	0.194	1.583	.122
104	-0.324	0.168	-1.929	.062
105	0.099	0.317	0.312	.758
106	-0.198	0.271	-0.733	.471
108	-0.098	0.071	-1.380	.178
110	-0.022	0.039	-0.567	.574
111	-0.740	0.423	-1.747	.096
112	-0.107	0.160	-0.670	.507
113	0.156	0.262	0.598	.555
114	0.012	0.160	0.076	.940
115	0.085	0.192	0.442	.662
116	-0.035	0.091	-0.390	.701
117	0.115	0.393	0.293	.774
119	-0.000	0.000	-0.531	.606
121	-0.037	0.109	-0.343	.737
122	0.113	0.066	1.708	.102
123	-0.024	0.105	-0.230	.820
124	**-0.721**	**0.274**	**-2.636**	**.020***
127	0.122	0.106	1.155	.262
128	0.103	0.089	1.158	.264
129	0.107	0.073	1.477	.153
130	0.519	0.256	2.025	.060
131	-0.154	0.193	-0.799	.431
132	-0.600	0.424	-1.416	.171

Note. Asterisks indicate statistical significance ($p < .05$, **p** < .01, ***p*** < .001).

Appendix B

Individual-Level Estimates for the Relationship Between State SC and State NA_lag

Participant ID	Estimate	Standard Error	t-value	p-value
1	-0.34	0.19	-1.81	.085
2	-0.30	0.36	-0.85	.401
3	**1.13**	**0.39**	**2.86**	**.008****
4	0.68	0.36	1.88	.082
5	0.01	0.52	0.02	.988
6	-0.26	0.20	-1.32	.198
7	-0.38	0.36	-1.03	.313
8	0.22	0.56	0.40	.693
9	0.39	0.45	0.88	.410
10	0.39	0.20	1.98	.055
11	**0.35**	**0.14**	**2.44**	**.020***
12	-0.04	0.67	-0.05	.957
13	0.11	0.19	0.56	.581
14	-0.81	0.63	-1.28	.209
15	-0.13	0.37	-0.35	.734
16	-0.34	0.49	-0.70	.506
17	-0.18	0.19	-0.99	.332
18	-0.18	0.24	-0.75	.458
19	0.06	0.18	0.35	.730
20	0.29	0.41	0.69	.492
21	-0.11	0.14	-0.78	.442
22	1.11	0.93	1.19	.242
23	0.05	0.34	0.16	.874
24	-0.16	0.25	-0.64	.527
25	-0.97	0.48	-2.03	.068
26	0.04	0.22	0.18	.857
27	0.10	0.21	0.47	.644
28	0.43	0.31	1.40	.171
29	0.16	0.23	0.68	.502
30	-0.37	0.72	-0.51	.624
31	**-0.44**	**0.16**	**-2.75**	**.009****
32	0.01	0.18	0.06	.953
33	-0.02	0.22	-0.08	.937
34	0.53	0.88	0.60	.556
35	-0.05	0.38	-0.14	.893
36	-0.20	0.18	-1.07	.294

Participant ID	Estimate	Standard Error	t-value	p-value
37	-0.36	0.25	-1.43	.164
38	0.32	0.37	0.89	.388
39	0.02	0.25	0.07	.942
40	-0.13	0.28	-0.45	.658
41	-0.12	0.29	-0.41	.688
42	0.24	0.48	0.50	.620
43	0.39	0.31	1.26	.229
44	0.21	0.25	0.85	.399
45	-0.35	0.24	-1.45	.161
46	**-0.58**	**0.24**	**-2.39**	**.036***
47	-0.61	2.21	-0.28	.828
48	-0.27	0.22	-1.21	.234
49	-0.48	0.32	-1.49	.145
50	0.52	0.39	1.33	.214
51	-0.17	0.41	-0.41	.693
52	**0.34**	**0.13**	**2.53**	**.020***
53	**-1.10**	**0.45**	**-2.48**	**.048***
54	0.07	0.12	0.58	.568
55	0.11	0.21	0.53	.602
56	-0.11	0.27	-0.42	.677
57	-0.13	0.20	-0.67	.509
58	0.21	0.20	1.06	.297
59	-0.10	0.51	-0.20	.844
60	0.09	0.15	0.61	.561
61	-0.13	0.34	-0.39	.701
62	0.62	0.49	1.26	.217
63	-0.23	0.34	-0.67	.516
64	-1.37	0.92	-1.49	.211
65	0.08	0.21	0.37	.719
66	1.00	2.20	0.46	.693
67	-0.03	0.35	-0.09	.931
68	0.30	0.68	0.45	.667
69	**1.17**	**0.57**	**2.07**	**.046***
70	-0.25	0.25	-1.00	.325
71	-0.13	0.75	-0.17	.866
72	-0.13	0.17	-0.76	.454
73	-0.31	1.47	-0.21	.843
74	0.10	0.35	0.28	.780
75	-0.12	0.58	-0.21	.838

Participant ID	Estimate	Standard Error	t-value	p-value
76	1.05	1.10	0.95	.413
77	-0.12	0.53	-0.23	.824
78	0.07	0.21	0.34	.738
79	-0.36	0.48	-0.74	.469
80	-0.17	0.16	-1.07	.293
81	-0.12	0.18	-0.67	.508
82	0.08	0.48	0.18	.861
83	**0.99**	**0.31**	**3.16**	**.005***
84	-0.09	0.12	-0.73	.469
85	-0.18	0.20	-0.92	.363
86	-0.37	0.19	-1.95	.070
87	0.06	0.31	0.19	.849
88	-0.36	0.49	-0.73	.472
89	0.42	0.60	0.69	.494
90	-0.03	0.13	-0.22	.828
91	-0.07	0.21	-0.32	.754
92	-0.21	0.37	-0.59	.564
93	0.40	0.29	1.41	.170
94	**-1.01**	**0.32**	**-3.11**	**.005***
95	-0.69	1.23	-0.56	.588
96	0.06	0.23	0.28	.787
97	-0.09	0.82	-0.11	.915
98	0.32	0.39	0.81	.424
99	0.67	0.31	2.12	.067
100	-0.85	0.74	-1.15	.270
101	-0.25	0.56	-0.43	.679
102	0.36	0.26	1.39	.183
103	0.15	0.28	0.52	.623
104	-0.05	0.25	-0.22	.829

Note. Asterisks indicate statistical significance (*p* < .05, **p** < .01, ***p*** < .001).