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Examining the temporal dynamics of psychological flexibility on affect and stress in a transdiagnostic clinical sample: an ecological momentary assessment study

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EXAMINING THE TEMPORAL DYNAMICS OF PSYCHOLOGICAL FLEXIBILITY ON AFFECT AND STRESS IN A TRANSDIAGNOSTIC CLINICAL SAMPLE: AN ECOLOGICAL MOMENTARY ASSESSMENT STUDY

by

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EXAMINING THE TEMPORAL DYNAMICS OF PSYCHOLOGICAL FLEXIBILITY ON AFFECT AND STRESS IN A TRANSDIAGNOSTIC CLINICAL SAMPLE: AN ECOLOGICAL MOMENTARY ASSESSMENT STUDY

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ABSTRACT

Psychological flexibility (PF) is defined as one's ability to pursue valued activities despite distress. PF is a critical process of change in evidence-based treatments, and is associated with psychosocial health and functioning. Although PF is considered context-dependent, previous research often measures PF as a static construct, often by administering the Acceptance and Action Questionnaire, which may not fully capture the construct of PF and limits understanding of how PF may change over time. One approach for measuring individual dynamics over time is ecological momentary assessment (EMA), which has been applied to numerous psychological constructs, including PF recently.

This study investigated the dynamic relationship between PF, affect, and stress in a clinical sample of 39 individuals. Six items from the Process Based Assessment Tool were used to measure PF in terms of experiential avoidance and values-promoting processes. Participants completed a two-week EMA phase which included answering daily self-report items, and collecting smartphone and wearable technology data on screen time, steps, sleep quality, distance traveled, and activity. I hypothesized that PF would vary within and across time and context to predict affect and stress and expected that indicators of psychosocial health and measures of psychological processes would influence PF, affect, and stress.

Results revealed significant associations such that flexibility was generally related to higher positive affect, lower negative affect, and lower stress. Some PF-items were associated with better day-quality ratings. PF interacted with context (conflict or valued action) and type of situation, with greater PF generally associated with valued-actions. Measures of psychological and attentional processed differentially interacted with PF to predict affect and stress. Step count interacted with PF in several models. Screen time was associated with affect and stress at a given timepoint. Heart-rate variability was differentially related to stress, affect, and PF within and across time. Activity, GPS, and sleep quality data were not significant. Overall, this study supports evidence that PF is highly idiographic and related to indicators of psychosocial wellbeing over time, generally supporting my hypotheses.

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INTRODUCTION

Psychological flexibility (PF) is a critical process of clinical change in evidence-based treatments, psychosocial health, and daily functioning (Kashdan et al., 2020; Kashdan & Rottenberg, 2010). The construct has often been difficult to define given its relation to nearly every facet of life, with extant research related to affect, emotion regulation, behavior, cognition, regulation, and coping (Kashdan & Rottenberg, 2010; Doorley et al., 2020). At its core, PF is defined as one's ability to pursue valued activities despite distress or interference, and it is undoubtedly context-dependent given that one's goals and distress change constantly depending on the environment (Hayes et al., 2011; Kashdan et al., 2020).

Although utilization of this definition allows for precise measurement of the PF construct in the current study, there are numerous other facets of flexibility that contribute to the breadth of its impact on psychological functioning. For example, Bonanno and Burton (2013) discuss the importance of *regulatory flexibility* which relates to one's ability to adapt to internal or external circumstances using coping and/or emotion regulation strategies, which is closely related to Cheng's (2001) construct of *coping flexibility. Cognitive flexibility* tends to discuss the ways in which one's attention adaptively shifts between sets or may exhibit biases toward or away from certain stimuli (set-shifting; Miyake et al., 2000) and this is closely related to *affective flexibility* which identifies set-shifting ability in the context of emotion (Genet & Siemer, 2011). Affective flexibility also relates to one's ability to modulate emotions according to context or during tasks. Relatedly, work from Aldao et al. (2015) and Conroy et al. (2020) detail the importance of *emotion regulation flexibility* which measures which emotion regulation strategies are employed by people in certain situations and the degree to which skill-use may change in presence or form depending on the context (i.e., using reappraisal all the time or only in certain situations).

The construct of PF was originally coined by Acceptance and Commitment Therapy (ACT; Hayes et al., 2011) and is a primary mechanism of change in ACT and other cognitive-behavioral therapies (Arch & Craske, 2008; Arch et al., 2012). As a treatment, ACT uses mindfulness and behavior change principles to help patients learn to allow and accept their emotional experiences while working towards defining and living aligned with their values. According to this treatment, PF is achieved through the combination of skills in: acceptance, present-focused awareness, values-based living, committed actions based on values, defusion (e.g., detachment) from cognitions and beliefs, and self-as-context (e.g., viewing oneself as experiencing emotions, thoughts and behaviors instead of defining oneself by these experiences; Hayes et al., 2011). In other words, PF is achieved and maintained when individuals learn to reduce emotions, thoughts, and behaviors that move them away from their values and increase acceptance and change processes that move them toward psychosocial well-being. Altogether, the ACT model of PF serves as a primary theoretical framework from which research and treatment have evolved. A point of convergence across numerous definitions of PF is the reliance on pursuing valued activities despite distress or interference, in multiple contexts (Hayes et al., 2011; Kashdan et al., 2020).

As psychological flexibility is difficult to define as a construct, it is understandably difficult to measure comprehensively as well (Ong et al., 2019). The Acceptance and Action Questionnaire (Bond et al., 2011; AAQ-II) is the most popular measure of PF, derived from principles of ACT. It assesses one's level of flexibility or experiential avoidance across 7 items, depending on scoring. Notably, the AAQ has 28 identified variants that pertain to specific clinical and medical presentations, in part to increase the predictive power of the measure, although it also indicates the potential pitfalls of global measurements of flexibility in the literature (Ong et al., 2019; Kashdan et al., 2020). Other measures of PF include the CompACT (based specifically on ACT core processes; Francis et al., 2016), Multidimensional Psychological Flexibility Inventory (MPFI; Rolffs et al., 2018), and Personalized Psychological Flexibility Inventory (PPFI; Kashdan et al., 2020) as well as others related to values (Wilson et al., 2010), cognitive fusion (Gillanders et al., 2014), cognitive flexibility (Dennis & Vander Wal, 2010), openness and engagement (Benoy et al., 2019), coping flexibility (Cheng, 2001; Kato, 2020), and emotion regulation flexibility (Burton & Bonnano, 2016; Hofmann & Kashdan, 2010). Use of the AAQ in experimental and clinical research has undoubtedly increased our knowledge of the construct as a field, although recent research identifies strong overlap with negative affect and distress (Bond et al., 2011) at the expense of a strong relationships with acceptance and related constructs (Rochefort et al., 2018; Tyndall et al., 2019; Wolgast, 2014). Additionally, most PF measures reflect subscales of acceptance or avoidance, particularly from a thinking or feeling perspective, while more explicit measures of engagement in helpful or unhelpful behaviors within a given context are harder to find. This may, in part, explain why the majority of PF research to date has focused more on *inflexibility* and negative content in psychopathology as opposed to understanding the ways in which flexibility processes may also emerge amongst distress.

In an effort to extend research into process-based therapy (Hayes & Hofmann, 2017; Hayes et al., 2019; Hayes et al., 2020) based on evolutionary principles of behavioral selection, retention, and variation, the Process Based Assessment Tool (PBAT) was created to reflect the positive and negative processes of PF (Ciarrochi et al., 2021). Recently developed by the first three readers on this dissertation, the full and abbreviated versions of the PBAT reflect four subscales: meaning-thwarting behavior (selection of responses not in line with values), variation (choosing new behaviors), retention (engaging in behaviors that make it likely for values to continue being supported), and meaning-enhancing behavior (selection of behaviors in line with values; Ciarrochi et al., 2021). Unlike other measures of PF, the PBAT reflects only one's behaviors and goes beyond assessment of avoidance or acceptance. Additionally, the measure recognizes that individuals may choose to behave in helpful or unhelpful ways on each of the subscales depending on context.

Despite the breadth of definitions and measures of PF, research points to clear psychosocial health benefits across individuals with primary psychological disorders, medical diagnoses, and in sub-clinical or non-clinical samples (Gloster et al., 2017; Kashdan & Rottenberg, 2010; Doorley et al., 2020; Kashdan et al., 2020). On the other hand, inflexibility (i.e., low PF) has been associated with processes and diagnoses of psychopathologies (for reviews, see Mansell & Morris, 2018; Levin et al., 2012; Kashdan

& Rottenberg, 2010; Doorley et al., 2020). Namely, inflexibility has been associated with: rumination and low mindfulness, neuroticism, emotional reactivity, maladaptive emotion regulation use, attributional style, positive and negative affect, executive dysfunction, self-control, and experiential avoidance. Increases in PF over the course of treatment also show evidence for this construct as a mechanism of change and correlate of higher quality of life and psychosocial health (Arch & Craske, 2008; Arch et al., 2012; Hayes et al., 2006; Hayes et al., 2019; Hofmann & Hayes, 2019; Kashdan & Rottenberg, 2010; Gloster et al., 2017).

Given these data on the relationship between psychosocial health and PF, it is increasingly important to understand news ways of measuring the construct to account for context and individual differences in expression of flexibility to inform better treatments for increasing adaptive, flexible responses in daily life. Unfortunately, the majority of studies on PF are correlational, concerned with static measurement of PF with an emphasis on inflexibility, and limited to mostly between-group analyses. Indeed, numerous empirical and literature reviews (Kashdan & Rottenberg, 2010; Kashdan et al., 2020; Doorley et al., 2020) indicate the need to: 1) measure PF in daily life using idiographic or time-series designs, 2) make improvements to methodology and measurements that are employed to answer these questions (i.e., with the PBAT), and 3) better understand the causality of the relationship between flexibility and affective processes (i.e., does inflexibility precede negative affect and dysfunctional outcomes or vice versa).

One innovative approach for studying psychological processes over time is ecological momentary assessment (EMA). EMA collects high density time series data through the use of daily diaries, smartphone apps, and self-report packets, to name a few (Shiffman et al., 2008). Time series analysis allows for modeling dynamic processes over time, within and across individuals, through the use of multi-level models and quantification of time-lagged relationships and auto-correlations (e.g., variable X at time *t* associated with variable Y at time *t-1*) which approximate causality (Granger, 1969). Use of EMA research designs in clinical science has boomed recently (for reviews, see Shiffman et al., 2008; Wright & Woods, 2020), especially in relation to affective dynamics and psychopathology over time. Indeed, EMA designs are also equipped to passively measure objective health, activity, and social data through smartphone sensors or wearable technology, with numerous studies indicating relationships between affectivity and physical activity levels, as well as PF and wellbeing (Wichers et al., 2012; Stavrakakis et al., 2015; Kangasniemi et al., 2014; aan het Rot et al., 2012; Peltz et al., 2020). There is also a growing literature that has applied EMA designs to investigate PF in relation to psychological processes such as emotion regulation, emotional disorders, stress and wellbeing, mindfulness, and values (Benson et al., 2019; Kashdan et al., 2020; Finkelstein-Fox et al., 2020; Gregoire et al., 2020; Blanke et al., 2019; Keng et al., 2018; Levin et al., 2018; Hardy et al., 2017). Generally speaking, these studies report that greater PF is associated with adaptive coping by using different emotion regulation strategies, mindfulness, and acting toward one’s values. However, these studies often measure flexibility based on the AAQ, have not focused as much on diverse clinical samples, and tend to use daily diary approaches as opposed to randomly-pinged, in-the-moment data collection. As such, there is abundant opportunity to continue applying idiographic methodologies to better understand the nuances of PF over time.

The current study represents an innovative approach to understanding the interplay between PF, during conflict or goal pursuit, affect, and stress, through the use of an EMA design for capturing high density self-report data over a 2-week span. Using various items from the PBAT to quantify PF as well as passively collected health and activity data, this study will explore the interplay between PF as it pertains stress or values-directed actions, affect, and stress. Use of the PBAT will encourage a behavioral and evolutionary approach to studying flexible and inflexible decision-making across contexts. Data from this investigation have the potential to contribute significantly to clinical and treatment research pertaining to the directionality and causality of the relationship between PF and psychosocial health processes over time, measurement of PF as a dynamic clinical process that is context-dependent, and understanding how neuropsychological attention measures may align or differentiate from daily measures of flexibility.

Present Study

Overview

The current study investigated the temporal dynamics of PF, positive and negative affect, and momentary stress in relation to conflictual or values-based contexts in a transdiagnostic clinical sample, utilizing EMA. Study participants (n = 39) were adults presenting or diagnosed with emotional disorders at a university clinic or from the community. The study consisted of three phases: 1) baseline visit including a diagnostic interview, attention tasks, and self-report questionnaires (See Methods); 2) a two-week EMA phase; and 3) an endpoint visit consisting of the same self-report questionnaires as baseline. During the EMA phase, participants were prompted 5 times a day, at random, to rate their affect, PF in the context of stress or goals, and momentary stress. In addition, physical and social activity data were collected passively (i.e., without prompting) during the EMA phase using the Ethica app and Oura rings (See Methods). Participants earned up to $100 for completing the entire study based on rates of compliance to prompts and study procedures.

Primary Aims and Hypotheses

Aim 1. Examine the relationship between PF, affect, and stress over time in a transdiagnostic sample of adults.

Hypothesis 1a. PF will be associated with positive affect and negative affect within each time-point (i.e., flexibility at time *t* will relate to affect at time *t*).

Hypothesis 1b. It is expected that PF will differentially predict positive and negative affect at lagged time-points (i.e., flexibility at time *t* will predict affect at time *t* +1).

Hypothesis 1c. Increased PF will be associated with decreased stress over time (Grégiore et al., 2020).

Hypothesis 1d. PF in the context of stress and values-directed actions or affect will be associated with retrospective rating of quality of day.

Hypothesis 1e. Type of reported stress/conflict and values-directed actions (i.e., categorical variables) will be differentially associated with affect, stress, and PF.

Aim 2. Investigate how the temporal relationship between PF, affect, and stress varies as a function of baseline measures of processes of emotional disorders (i.e., mindfulness, emotion regulation, affective style/emotion regulation flexibility, rumination, cognitive flexibility, and experiential avoidance, attention tasks).

Hypothesis 2a. It is expected that mindfulness scores will moderate the relationship between PF, affect, and stress over time such that those scoring higher on subscales of the FFMQ will show a stronger relation between PF and positive affect or decreased stress when compared with individuals scoring lower on FFMQ subscales.

Hypothesis 2b. Emotion regulation processes will moderate the relationship between PF, affect, and stress over time such that those scoring higher on suppression and rumination will show a stronger relation between PF and negative affect or stress, while individuals scoring higher on reappraisal will show a stronger relation between PF and positive affect or decreased stress.

Hypothesis 2c. Baseline measures of flexibility (e.g., AAQ-II, CFI, ASQ) will moderate the temporal relationship between PF, affect, and stress such that such that scores indicating inflexibility will be associated with a stronger relation between PF, negative affect, and increased stress when compared with higher scores.

Hypothesis 2d. Participants exhibiting greater cognitive inflexibility on attention tasks (Emotional Stroop, Asymmetric Task Switching) will moderate the relationship between PF, affect, and increased stress, when compared to individuals exhibiting greater flexibility on those tasks (Compton et al., 2004; for reviews see, Zinchenko et al., 2020; Abramovitch et al., 2021).

Aim 3. Examine the relationship between momentary PF, affect, stress and indices of physical and social activity (e.g., GPS, steps and activity, and screen time) and physical health (sleep and heart rate variability, HRV).

Hypothesis 3a. Increased physical activity (e.g., GPS, steps, greater motion) will be associated with greater positive affect, PF, and reduced momentary stress at subsequent time points (Wichers et al., 2012; Stavrakakis et al., 2015; Kangasniemi et al., 2014).

Hypothesis 3b. Increased screen time will be associated with changes in PF, affect, and stress over time.

Hypothesis 3c. poor sleep quality will be associated with greater momentary stress, inflexibility, and negative affect at subsequent timepoints (Peltz et al., 2020).

Hypothesis 3d. It is expected that HRV will physiologically correspond with changes in PF, affect, and stress over time.

METHODS

Participants

Study participants were recruited from the greater Boston community and Boston University's Center for Anxiety and Related Disorders (CARD). The final study sample consists of 39 participants who completed all portions of the study and were included in analyses. 43 participants were recruited and enrolled in the study, having completed at least the baseline visit. The four participants not included in analyses were either deemed ineligible during the baseline visit or lost to follow-up prior to beginning the EMA phase.

The study sample consisted of 28 females (71.8%) and 8 males (20.5%), with 3 individuals (7.7%) identifying as non-binary. The mean age of the sample was 29.5 years with a range of 18-66 (missing age data for two participants). With respect to race and ethnicity, participants identified as being part of the following groups: 92.3% non-Hispanic/Latinx, 5.1% Hispanic/Latinx, and 2.5% not reported (1 participant). 79.5% identified as White, 10.3% identified as Asian, 2.6% identified as Black or African American, 10.3% identified as more than one race, and one participant did not report their race.

To achieve a breadth of clinical presentations, inclusion criteria did not specify a particular psychiatric diagnosis nor level of comorbidity. Participants presented with the following primary diagnoses: 30.8% Generalized Anxiety Disorder (GAD), 17.9% Social Anxiety Disorder, 12.8% Major or Persistent Depressive Disorders (MDD, PDD), 7.7% Obsessive Compulsive Disorder (OCD), 7.7% Specific Phobia (SPEC), 7.7% Other Specified Anxiety Disorder (OSAD), 5% Agoraphobia, 2.6% Panic Disorder (PD), 2.6% Post-traumatic stress disorder (PTSD), 2.6% Body Dysmorphic Disorder, and 2.6% Attention Deficit Hyperactivity Disorder (ADHD). There were also high rates of comorbidity in the sample, with 74.4% of participants having a comorbid diagnosis, and 61.5% having up to two comorbidities. See Table 1 for diagnostic and demographic data.

Baseline scores for psychological processes are displayed in Table 2. Highlighted baseline characteristics include an average negative affect score of 24.5 (*SD*=7.2) and positive affect score of 27 (*SD*=7.6) on the PANAS, 16.2(*SD*=10.2) on the BDI, and 99 (*SD*=20.2) on the STAI. In relation to baseline psychological flexibility, participants mean scores indicate an average AAQ (higher scores = more inflexible) score of 39.2 (*SD*=7.1) and an average CFI total score of 98.3 (*SD*=13.5).

Sample Size and Data Density

The sample size for the current study was determined based on a power analysis conducted using *EMATools* package in R, which determined that an intended N of 40 participants completing 5 sets of responses per day for 2 weeks would yield power of 0.8 for an estimated medium effect size, or over 0.99 for a large effect size, assuming compliance rates of >75%. Effect size estimates in results tables revealed small to moderate effect sizes (see Tables 6-14, 21-31). A-priori estimations were assuming an interclass correlation coefficient of 0.5, though the actual ICCs in the current study varied between 0.2-0.5 depending on the variable, which indicated sufficient power for within-person analyses by this analysis tool.

39 participants were included in final analyses, which corresponded to an average of 55 rows of data per participant for Ethica (out of a possible 70, ~78.5%). Compliance rates for Oura Ring data were high, with only two participants missing complete Oura data due to technical issues. Based on these completion rates, the current study is likely well-powered for the subsequent within-person analyses with less power for between-subjects analyses, though the effects of low power affect the interpretability of null findings as opposed to significant findings.

Inclusion and Exclusion Criteria

Participants were included in the study if they were: 1) 18 years or older, 2) self-reported normal or corrected vision, 3) owned a working smartphone (i.e. Android or Apple IOS), 4) were either stable on current psychotropic medications (or off concurrent medication for 2 weeks), received stable psychological treatment for a minimum of 6 weeks prior to study enrollment, or were not receiving any psychotherapy/medication treatment but were experiencing symptoms of an emotional disorder.

Participants were ineligible for the study if they: 1) were unable to understand study procedures or participate in the informed consent process, 2) had a serious medical or neurological illness (e.g., Alzheimer's, Parkinsons, etc), 3) had significant suicidal ideation within past 2 weeks (BDI-II Q9 >2), 4) had a history of head trauma causing loss of consciousness resulting in ongoing cognitive impairment, 5) had a history of psychotic disorder, bipolar disorder, an intellectual disability, learning disorder, communication disorder, or movement disorder (i.e., developmental disorder other than ADHD), 6) had a current substance use disorder, or 7) displayed significant personality dysfunction likely to interfere with study participation (as assessed during the clinical interview).

Procedures

Interested or referred individuals completed a brief phone screen to determine initial eligibility for the study and provide information about study procedures and EMA requirements. If eligible after the phone screen, a baseline screening visit was scheduled at CARD or via HIPAA-compliant Zoom. The baseline visit consisted of informed consent, a clinician-administered diagnostic assessment, completion of self-report questionnaires and computerized attentional tasks, and information on setting up smartphones and Oura rings to be compliant with their respective apps. Following the consent and baseline visit, participants were enrolled in the 2-week EMA phase where they were prompted 5 times per day to fill out questions pertaining to positive and negative affect, stress, and PF in the context of conflict or goals. Daily ratings were collected via the Ethica app for IOS and Android phones. The Ethica app also gathered data on participants' GPS coordinates, step count, motion-based activity, and screen time. Additionally, sleep, heart-rate, and step count data were collected using the Oura Ring and its accompanying app. After completion of the EMA phase, participants completed the same self-report questionnaires from the baseline visit and return their loaned Oura rings. Table 3 shows the measurement and EMA phase schedule.

Participants could earn up to $100 for completing the entire study based on the following cost breakdowns: $20 for the baseline visit, $10 for completion of follow-up questionnaires, and up to $70 for 2 weeks of EMA data. Participants could earn up to $35 per week for completion of EMA items ($5 per day for 100% response compliance; payment rate was dependent on percentage of prompts answered).

Measures

Clinician Administered Measure

Adult Anxiety Disorders Interview Schedule for DSM-5 (Adult ADIS-5; Brown & Barlow, 2014). The ADIS-5 is a semi-structured clinical interview that assesses adults' current symptoms to discern diagnostic information about anxiety, mood, trauma, substance, and somatic disorders. For the purposes of the current study, this interview was used to gather diagnostic data on participants for classification purposes in analyses. Diagnostic data include the presence of: major depressive disorder, persistent depressive disorder, generalized anxiety disorder, social anxiety disorder, panic disorder, agoraphobia, obsessive-compulsive disorder, body dysmorphic disorder, specific phobia, post-traumatic stress disorder, attention deficit hyperactivity disorder, and/or other specified emotional disorders.

Baseline Attentional Measures

Emotional Stroop Task (Williams, Matthew, & MacLeod, 1996; Ben-Haim et al., 2016)**.** The Emotional Stroop Task is widely used to measure attention bias toward positive, negative, and neutral threat words, particularly in psychopathology research. Words vary in terms of valence and arousal and participants were shown words in various colors and instructed to report the color while ignoring the word. Emotional interference (i.e., difficulty reporting color in the context of distraction words) in relation to error and response rates serve as metrics for attention bias in this task. The overall Stroop effect was calculated as the mean response time for all negative and positive words combined minus the mean response time for both control word blocks, not including the practice block.

The Emotional Stroop Task was administered to participants via MatLab using lab computers or online via a secure webhost through Boston University. Participants were shown a black screen with instructions in white font, which detailed that they should ignore the word and indicate the color it is printed in on the screen. Word colors included: red, green, blue, or yellow. After the instructions, a white fixation cross was presented in the middle of the screen for 750ms. Words were then presented in block format and each participant viewed the words in a random order. Block 1 included 30 practice trials, block 2 presented 40 control/neutral-word trials, block 3 included 40 negative-word trials, block 4 presented 40 control trials, and block 5 presented 40 positive-word trials. Word position was jittered over a small range around the center point of the screen so that subjects could not simply focus entirely on the center of the screen. The jitter was over a 100-pixel range horizontally and a 50-pixel range vertically. Participants did not receive correct answer feedback and the words appeared until a response was made. In-person versions of the task allowed participants to make responses on a keyboard (F=red, G=green, H=blue, J=yellow), while virtual subjects made responses by using a mouse to click buttons on the screen pertaining to colors. No substantive differences on task performance were found between virtual versus in-person participation.

Positive, negative, and neutral word stimuli were chosen from Affective Norms for English Words (ANEW), with permission, based on pleasure, arousal, and dominance ratings normed from research (Bradley & Lang, 2017). Due to ANEW regulations, the release of example words in publications prohibited, though the affective ratings and norms are mirrored after systems like the International Affective Picture System (IAPS; Lang, Bradley, & Cuthbert, 2008).

Asymmetric Task Switching (Gustavson et al., 2017; Barthel et al., 2022). The asymmetric switching paradigm asks participants to shift attention between two tasks of differential attentional demand. One task is less attentionally demanding and requires subjects to report which side of the screen an arrow is pointing. The second task is more attentionally demanding and requires identification of the direction of the arrows. An asterisk (*) or plus sign (+) cue alerts participants about which task they should follow. The "+" refers to the location procedure and the "*" refers to the direction procedure. The cue is shown 750ms before the task stimuli given research that states that more than 500-600ms are needed to anticipate and process stimuli (Rogers & Monsell, 1995). Cue arrows stay visible until a participant responds, and a feedback sound will alert them if they do not respond quick enough. Trials are presented without delays. There were a total of 8 blocks composed of 672 mixed, switching trials (112 trials per block) and 144 pure trials. All blocks contain 4 practice trials at the beginning, which are not used in analyses. This computer task used in the current study is identical to that of Gustavson et al. (2017) and Barthel et al. (2022).

Participants first performed each of the tasks without switching (72 pure trials of reporting location of the arrows and 72 pure trials of reporting direction of the arrows). Pure trials are presented first to ensure task mastery by participants. After the pure trials, participants completed 4 practice trials (not scored) that lead into 4 mixed blocks composed of location and direction trials and 2 mixed blocks with the cues reversed. 112 trials are included in each block. Trials were randomly ordered so that participants switch after 0 repeated trials, 1 repeated trial, 2 repeated trials, or 3 repeated trials. These occur, 12, 8, or 4 times per block, respectively. Each block included 28 switch trials, 16 trials that have one repeat, 8 trials that are 2-repeat, and 4 trials that are 3-repeat, in random order. Overall, each block contained 56 trials pertaining to location and 56 pertaining to direction for the full 112 trials.

Following the completion of these 4 mixed blocks, participants were oriented to a new rule that the cues indicating location or direction have been reversed. For blocks 5-6, the instructions changed, and participants now report arrow direction in response to a "+" and arrow location in response to "*". Following these new rules, participants complete 2 mixed blocks of 112 trials.

Similar to the procedure of Gustavson et al. (2017) and Barthel et al. (2022), we will also differentiated blocks of stimuli to measure the effects of task effort and attention. Trial presentation was incongruent, with arrows pointing in the opposite direction as the side the cue is shown on, 75% of the time. Incongruence is included as an attention check throughout the experiment.

Baseline and post-EMA measures

Positive and Negative Affect Scale (PANAS; Watson et al., 1988**)** This scale is a 20-item measure of one's feelings and emotions in the moment, on a five-point scale. Subscales include positive affect and negative affect.

Acceptance and Action Questionnaire (AAQ-II; Bond et al., 2011**).** This is a 7-item measure that assesses one's level of experiential avoidance versus psychological flexibility on a seven-point scale, depending on how it is scored. Higher scores indicated greater inflexibility/experiential avoidance in our study.

Cognitive Flexibility Inventory (CFI; Dennis & Vander Wal, 2010**).** The CFI is a 20-item measure assessing the following components of cognitive flexibility: 1) perceived controllability of difficult situations, 2) propensity to observe alternative explanations, and 3) ability to come up with alternative solutions and explanations under difficult circumstances.

Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990**).** This questionnaire contains 16 items that assess worry on a five-point scale. Scores are summed to create a total score ranging from 16 to 80.

State-Trait Anxiety Inventory (STAI; Spielberger, 1983**)**. The STAI is a 40-item self-report measure that is used to assess one's situational and/or general disposition towards anxiety. Subscales include state and trait anxiety which can be calculated separately or summed for a full-scale score.

Ruminative Response Scale (RRS; Treynor et al., 2003**).** This is a 22-item measure of rumination along three subscales: reflection, brooding, and depression. Items are rated on a four-point scale and participants are asked to think about when they are down and respond with how they generally act under these circumstances.

Beck Depression Inventory-II (BDI; Beck et al., 1996**)**. The BDI-II is a 21-item instrument designed to measure both the presence and severity of depressive symptoms.

Emotion Regulation Questionnaire (ERQ; Gross & John, 2003**).** The ERQ is a 10-item measure that assesses the use of two emotion regulation strategies: cognitive reappraisal and expressive suppression.

Affective Styles Questionnaire (ASQ; Hofmann & Kashdan, 2010**).** This is a 20-item questionnaire that indicates one's use of various styles of regulating emotions (i.e., emotion regulation flexibility) across three factors: concealing, adjusting, and tolerating.

Five Facet Mindfulness Questionnaire (FFMQ-15; Baer et al., 2008**).** The FFMQ-15 is a 15-item self-report scale assessing trait mindfulness, developed from the original 39-item scale (Baer et al., 2006). The measure five distinct facets of mindfulness: observing, describing, acting with awareness, non-judging of inner experience, and non-reactivity to inner experience.

Satisfaction with Life Scale (SWLS; Diener et al., 1985). The SWLS is a 5-item scale that assesses subjective evaluation of one's life. Items are rated on a 7-point Likert scale.

EMA Items

To maximize the context-specificity of this study, EMA items were chosen to reflect a theoretical model of the relationship between PF, affect, and stress in the context of conflict or goals/values. Items were chosen from based on the highest factor loadings reported in previous research or based on prior items used in EMA studies. The particular items chosen from the PBAT in this study were shown to be among the strongest predictors of negative or positive behaviors in the context of PF using a large representative sample of adults (Ciarrochi et al., 2021).

Affect items. At each of the 5 daily assessment times, participants were asked: "How *enthusiastic* do you feel right now?" and "How *nervous* do you feel right now?". These items were chosen based on the highest factor loadings for positive and negative affect on the PANAS (Watson et al., 1988; Crawford & Henry, 2004). Ratings were made according to the original PANAS 5-point scale (1 "very slightly or not at all", 2 "a little", 3 "moderately", 4 "quite a bit", 5 "extremely").

Stress Item. Experience of stress was measured using one item: "To what extent are you stressed right now?" (Gregoire et al., 2020), which was be rated on a scale of 0 (*not stressed at all)* to 10 (*very stressed*).

Coping with Stress/Conflict or Goals. To categorize experiences of conflict and goal/values-directed behaviors, an initial item to gauge whether participants thought about a stress or conflict or value was used (adapted from Stone et al., 1998). Participants were asked: "*In the past 3 hours, did you think about an issue/conflict or a goal/value? Please select the option that you thought about more at this time.*" Then participants were prompted to choose and categorize their most significant stressor or value from the following choices: *work/school, romantic relationship, friendship, family, finances, daily hassles/minor matters, health*. Next, they were prompted to answer: *"Please rate the degree to which you responded to this event on a scale of 0 (strongly disagree) to 100 (strongly agree)?"* Options included a reduced set of items from a new scale, the PBAT Items included: *1) I felt stuck and unable to change my ineffective behavior."* (**PF-stuck**)*; 2) "I did not find an appropriate outlet for my emotions."* (**PF-noout**)*; 3) "I struggled to connect with moments in my life."* (**PF-noconnect**)*; 4) "I used my thinking in ways that helped me in this situation."* (**PF-think**)*; 5) "I changed my environment in order to improve my life. (examples: removing temptation, reducing distractions, surrounding myself with positive influences)"* (**PF-environ**)*;* and *6) "I did things to connect with people who are important to me"* (**PF-yesconnect**). These items reflect four subscales: meaning-thwarting behavior, variation, retention, and meaning-enhancing behavior and were shown to be among the strongest predictors of negative or positive outcomes using a large representative sample of adults (Ciarrochi et al., 2021).

Retrospective rating. At the end of each day, participants were asked to reflect on their day and rate it's quality on a scale of 1 ("bad day") to 100 ("good day"), where 50 represents "neither good nor bad".

Ethica Sensor Data. Ethica is an app-based platform for IOS and Android smartphones that collects questionnaire data and passive, objective data from sensors. The following time-stamped data was collected during the EMA phase: global positioning systems (GPS), step count (pedometer), amount of screen time, and motion-based activity.

Oura Ring. The Oura ring is a wearable ring device that collects objective data using infrared and sensor technology, which is securely stored in an app for IOS and Android users. The following data were collected and analyzed from Oura rings: sleep stages and score, heart-rate data including HRV, and step count. See Table 3 for measurement and scheduling table

Data Reduction and Preprocessing

Attentional data. Trimming procedures were similar to those of Barthel et al. (2022) and Gustavson et al. (2017) such that RT data were computed for correct trials that exceeded 150ms. Outliers were removed if RTs were above or below six standard deviations of the group mean and were replaced with the nearest value, to eliminate bias due to extreme scores. RTs were excluded if they were 3.32 times the median RT absolute deviation by trial type within subjects (Wilcox & Keselman, 2003) to make sure that naturally occurring extreme RTs did not bias a single person's total mean RT.

Trimming procedures accounted for between-group outliers and within-subject variances. For accuracy data and error rates, error trials and the trial immediately following the error were removed when conducting the RT analyses and computing switch costs (Rogers & Monsell, 1995). To calculate a single metric for Switching Cost to enter into models, we used the following formula: switch cost = ((location-switch – location-repeat) – (direction-switch – direction-repeat)).

GPS data. Data preprocessing and computation of relevant GPS metrics were completed in RStudio and were identical to the tutorial script and methods from Müller et al. (2022). After removing missing and inaccurate coordinate data, we loaded in a Shapefile that stores geometric and coordinate projection data (Environmental Systems Research Institute, 2016) and includes the Massachusetts and northeastern United States, given the location of participants during the study. Similar to Müller et al. (2022), points outside of this projection region are removed. Although Müller et al.'s (2022) code computes numerous mobility metrics for GPS data, we focused specifically on total distance travelled in meters.

Pedometer data. Ethica collects the following data sources relevant to step count data: number of steps, accuracy of record, and duration over which the data were collected. Android devices collect data in-the-moment, per step, while iOS devices record the number of steps taken every 5 minutes. To account for the difference in sampling rates between pedometer data and Ethica self-report prompts, step data were averaged to correspond with the five Ethica prompts (i.e., averaging within 3-hour periods between prompts). The Oura rings also collects pedometer data and was considered to be a more accurate estimation of step count given that it was worn on participants' fingers instead of requiring them to remember to bring their phone everywhere. Oura step count was computed as a daily average metric. All subsequent models including pedometer data were based on Oura data, given that visual inspection of data from both apps indicated more consistent data from Oura.

Motion-based activity. Using standard sensor procedures from Android and iOS devices, Ethica recognizes and labels different types of participant activity including: stillness, device tilt, activity on-foot, walking, running, biking, and being in a vehicle. Data can be categorized into multiple activity types for a given time point depending on what the participant is doing. Confidence levels pertaining to the reported activity is also recorded, on a scale of low to high confidence. Data were averaged to correspond with the five daily Ethica self-report prompts, such that higher numbers (categorical) indicated more activity within a time window compared to lower numbers.

Screen time and state. At random sampling periods, Ethica records the state of a participant's phone (either on or off) in addition to the length of time the phone was in that specific state. Data were coded categorically (0: "screen off", 1: "screen on") and were averaged to correspond to the five daily Ethica self-report prompt windows.

Oura ring sleep data. Data for each participant was exported from the Oura cloud according to the dates of their specific study period. All data are stored and processed by Oura via proprietary algorithms. The following data were exported and used in analyses: average HRV (measured at night during sleep), total step count, and total sleep score which measures sleep quality from 0-100 with greater scores revealing higher sleep quality.

Analysis Plan and Hypothesis Testing

Study analyses were completed using RStudio version 12.0+353 (R Core Team, 2022). EMA items recorded in Ethica were nested within participants such that, positive and negative affect, and stress variables represent within-person variables. Between-group variables included scores on questionnaires measured at baseline, and baseline attentional performance metrics, for example. Given the nested observations and non-independence of data, a multi-level modeling (MLM) approach was utilized. MLM is also structured to handle missing data, which is common in EMA designs given the high density data collection (Baraldi & Enders, 2010; Enders, 2011). Given that a total sum score of PBAT items was not appropriate, and model convergence was not achieved when adding multiple items into models, each PBAT item was added into models separately for each outcome. To minimize the chances of Type 1 error, given the high number of models ran, p-value criterion were set to be conservative at $p \leq 0.02$. Due to the number of models ran, non-significant values are not reported in table format, but are included in a separate Supplemental Materials to this dissertation.

PF items from the PBAT were converted to represent trait and state scores such that trait scores represented between-person associations (individual means) and state scores represented within-person associations. That is, trait scores were computed based on the number of points per person to make up an average score and state scores represented a regression line for each person. Computation of state and trait scores followed open source code (https://quantdev.ssri.psu.edu/tutorials/analysis-experience-sampling-ema-data-chapter-31-bivariate-intraindividual-covariation) and is based on Bolger and Laurenceau (2013). Preliminary analysis began with unconditional models in which the outcome and predictors variables were entered and only the intercept was modeled to discern how much variance was due to between or within-person processes. Results from unconditional models were used to calculate intraclass correlations (ICC), which is the ratio of between-person variance to total variance (between – within). Where appropriate, variables were centered around an individual's own mean or around a grand mean in the context of between-groups variables (Wenze et al., 2009). Models accounted for autoregression on the within-person residual auto-regression (i.e., error terms at time *t* correlate with error terms at time *t-1*) by listing this as a covariate (Bolger & Laurenceau, 2013). All models were fit including a fixed effect of day, which pertained to which day data collection occurred on (e.g., 1-14). We also tested models using a fixed effect of time, which pertained to each of the 5 Ethica prompts per day. Model results did not significantly differ depending on which time variable was used, so we obtained the day variable throughout.

With respect to Aim 1, preliminary unconditional models were computed to understand potential between-person differences in the intercept over time. Next, sample-centered trait PF scores were entered individually into models predicting either PA, NA, or stress to understand if the average level of affect or stress varied by trait PF. State models were similar to trait models except within-person PF scores were entered in place of trait scores to model slope without between-person differences in slope. Finally, trait and state scores were entered in the same model as fixed effects predicting various outcomes of interest. These slope models were then compared to models that included between-person slope differences to understand if the associations between state PF and affect or stress differ across persons. Comparisons were tested using analysis of variance (ANOVA) and Likelihood Ratio Tests to determine if model fit was statistically significant with the addition of random effects, as a metric for testing ergodicity (Marshall et al., 2020).

For hypotheses pertaining to lagged variables (state and trait PF, stress, and affect), a *t-1* lag was created using the *lag* function in RStudio and was then entered into models using the same procedure as above. Specifically, we explored "antecedent" models in which each PBAT item measuring PF, and PA, NA, or stress at time *t* predicted change in affect or stress at time *T+1.* In other words, the six PF items were each modeled separately with PA, NA, and stress in antecedent models. Following the same procedure as the antecedent models, we also examined "consequence" models in which PF and PA, NA, or stress at time *t* predicted change in PF at time *T+1.* This modeling approach allowed us to explore temporal ordering of the relationship between PF, affect, and stress to discern if PF influenced change in affect and stress or vice versa (See Marshall et al., 2020). See Figure 1 for depiction of antecedent and consequence models.

With respect to hypotheses 1d and 1e, "event" and "type" variables were categorial and entered into models using the *as.factor()* R command to allow for exploration of interactions between each category/level of these variables and PF on affect, stress, or quality-of-day rating. These hypotheses pertained only to contemporaneous models.

Aim 2 builds on the models from aim 1 to inform whether there were between-person (trait) differences in the within-person (state) association that were moderated by a between-person predictors. In other words, does the addition of moderator variables explain differences in the slope of the relationship between PF items and affect or stress? Entered moderators included baseline questionnaire data (e.g., mindfulness, emotion regulation, affective style, rumination, attention tasks, cognitive flexibility, and experiential avoidance) and attentional task metrics. Moderator variables were also entered into antecedent and consequence models in addition to contemporaneous models.

For Aim 3, physical health (e.g., step count, activity, and GPS distance) and social activity (e.g., screen time) variables were added separately as fixed effects to contemporaneous models from Aim 1 to discern if there were effects on PF, affect, or stress within a given time. Then these variables were also added as interaction terms with PF to antecedent and consequence models to understand their effects on the temporal relationship between PF, affect, and stress. Thus, if greater physical activity is associated with greater PF and positive affect over time, hypothesis 3a would be supported. Similarly, hypothesis 3b would be supported if amount of screen time is associated with changes in affect, stress, and PF. Hypothesis 3c would be retained if poor sleep quality relates to momentary patterns of avoidant coping, (in)flexibility, increased stress, and negative affect over time, as measured by Oura ring data. Finally, hypothesis 3d would be supported if HRV corresponds with changes in PF and stress over time in antecedent and consequence models.

Missing Data

There were two classifications of missing data in our dataset: 1) general missingness (e.g., filled out some prompts but not others on a given day) likely due to missing a notification or failing to respond within the 30-minute time-window, and 2) specific missingness due to study design, such that participants were instructed to select context type three (e.g., "other") if they were prompted at a time that they were sleeping, showering, or otherwise not engaging with a conflict or a goal/value to preserve the validity of the context category as much as possible throughout data collection. Selection of "other" at this stage led to no further data collection for that prompt window, so missing data within that category is not random, but expected. Selection of goal/value or conflict as contexts were greater than selection of "other" type. Results of Missing Completely at Random (MCAR) Test (Little, 1988) were significant, revealing that missingness was not completely at random and is likely Missing-at-Random (MAR) or Not-Missing-at-Random (NMAR), though tests for determining true MNAR data structures are difficult and limited (Enders, 2011). MLM allows for use of Maximum Likelihood Estimation (MLE), which uses all available information for parameter estimation through model imputation (Enders, 2011). As such all, models were fit using Restricted Maximum Likelihood (REML) and were specified as with an AR1 covariance structure to remove noise due to trended data over time.

RESULTS

Descriptive Statistics

Table 1 displays the demographic characteristics of the study sample. Table 2 shows the means and standard deviations of all baseline questionnaires and EMA items. Table 4 displays the means, standard deviations, and correlations between each PF item from the PBAT. Positively worded items were more correlated with one another than with negatively worded items, and vice versa. In general, negatively worded items had the highest correlations, but Table 4 reveals that each item is related but distinct from one another, as would be expected. Relation between items also suggests that it is necessary to model both state and trait-derived scores in models. Table 5 shows the descriptive statistics for the EMA item-level data. For simplicity, non-significant model results are reported in a separate Supplemental Materials to this dissertation.

Contemporaneous Associations Between PF, Affect, and Stress

Aim 1, hypothesis 1a, contemporaneous models included an intercept, day variable, state PF (within-person), and trait PF (mean-centered between-person) as predictors of either PA, NA, or stress in intercept only models which were then compared to models including a random effect of state PF. PF was modeled separately for each PBAT item and its relation to PA, NA, and stress. For PA-PF models, results revealed significant negative within-person effects of state *in*flexibility on PA. Specifically, a one unit standardized increase in feeling stuck and unable to change behaviors (e.g., **PF-stuck**) was associated with a 0.28 standardized unit decrease in PA (*SE* = 0.04, *t*-value: -7.7, *p* <.001). A one unit standardized increase in endorsement of not finding an outlet in emotions (e.g., **PF-noout**) was associated with a 0.23 standardized unit decrease in PA (*SE* = 0.04, *t*-value: -5.6, $p < .001$), and a one unit standardized increase in struggling to connect with moments in life (e.g., **PF-noconnect**) was associated with a 0.26 unit decrease in PA (*SE* = 0.03, *t*-value: -7.90, $p < .001$). State flexibility items were associated with greater PA at time *t.* Engaging in thinking to problem-solve (e.g., **PF-think**) was associated with greater PA (β=0.22, *SE* = 0.04, *t*-value: 6.39, $p < .001$), as was changing one's environment to improve the situation (**PF-environ**; β=0.17, *SE* = 0.03, *t*-value: 5.86, $p < .001$), and doing things to connect with people who are important/meaningful (**PF-yesconnect**; β=0.25, *SE* = 0.03, *t*-value: 7.30, $p < .001$). Across all contemporaneous PF-PA models, the effect of day was negatively related to PA (all *p's* <0.01). There was also a significant positive relationship between trait PF and PA in all models except PF-environ (all *p's* <0.01; Table 6). Coupled with significant pooled within and between-person effects, the nature of within-person effects were highly variable, as shown in Figure 2, and ANOVA models comparing intercept-only and random-slope models each revealed better model fit for random-slope models.

For NA-PF contemporaneous models, results revealed significant positive associations between inflexibility items and NA, which included: PF-stuck (β=0.34, *SE* = 0.03, *t*-value: 10.34, $p < .001$), PF-noout (β=0.26, *SE* = 0.04, *t*-value: 7.37, $p < .001$), and PF-noconnect (β=0.27, *SE* = 0.03, *t*-value: 8.36, $p < .001$). PF items pertaining to flexibility were negatively associated with NA at time *t*, including: PF-think (β=-0.16, *SE* = 0.03, *t*-value: -4.68, $p < .001$), PF-environ (β=-0.10, *SE* = 0.03, *t*-value: -3.17, $p < .01$), and PF-yesconnect (β=-0.19, *SE* = 0.03, *t*-value: -7.25, $p < .001$; Table 7). Similar to PA models, within-person effects were highly variable, as shown in Figure 3, and ANOVA models comparing intercept-only and random-slope models each revealed better model fit for random-slope models.

In Stress-PF models, PBAT items pertaining to inflexibility were associated with greater stress, including: PF-stuck (β=0.41, *SE* = 0.04, *t*-value: 11.55, *p* <.001), PF-noout (β=0.33, *SE* = 0.03, *t*-value: 11.56, *p* <.001), and PF-noconnect (β=0.30, *SE* = 0.03, *t*-value: 11.09, *p* <.001). Items pertaining to flexibility were associated with decreased stress, including: PF-think (β=-0.19, *SE* = 0.03, *t*-value: -6.77, *p* <.001), PF-environ (β=-0.13, *SE* = 0.03, *t*-value: -4.35, *p* <.001), and PF-yesconnect (β=-0.24, *SE* = 0.03, *t*-value: -9.58, *p* <.001; Table 8). Similar to PA and NA models, within-person effects were highly variable, as shown in Figure 4, and ANOVA models comparing intercept-only and random-slope models each revealed better model fit for random-slope models. Overall, model results support hypothesis 1a as PF was significantly related to affect and stress at time *t*.

Temporal Associations Between PF, Affect, and Stress

Aim 1, hypotheses 1b-1c, temporal models examined the effects of PF on affect and stress over time (antecedent models) while controlling for PF earlier in the day and to model the potential ways in which PF, affect, and stress influence each other temporally (consequence models). The antecedent models were not supported for any of the PF-items predicting PA over time (See Table 9, Figure 5). The consequence models for PF-noconnect was supported, such that PF at time *t* predicted future inflexibility, when controlling for PF (β=0.18, *SE* = 0.04, *t*-value: 4.04, *p* <.001). PA at time *t* also influenced PF-noconnect by decreasing the chances of feeling this way later in the day (β=-0.14, *SE* = 0.04, *t*-value: -3.51, *p* <0.001). The day variable and intercept were also significant, evidencing differences across subjects (Figure 6). Lastly, the PF-yesconnect consequence model was supported. PF-yesconnect at time *t* predicted future increases in PF-yesconnect (β=0.24, *SE* = 0.043, *t*-value: 5.77, *p* <.001) as did PA at time *t* (β=0.13, *SE* = 0.04, *t*-value: 3.26, *p* =0.001). See Table 10 for PF-noconnect and PF-yesconnect models. All other consequence models were not significant.

Overall, antecedent models between PF-stuck, PF-noout, PF-noconnect, PF-think, PF-yesconnect and NA, respectively, were not supported though there was variability at the within-person level in terms of the nature of the effect (See Figure 7). However, the consequence models for PF-stuck and PF-noconnect were significant, such that PF at time *t* influenced PF at time *T+1* (PF-stuck: β=0.21, *SE* = 0.05, *t*-value: 3.76, *p* <.001; PF-noconnect: β=0.19, *SE* = 0.04, *t*-value: 4.45, *p* <.001) and NA and time *t* was associated with increased endorsement of feeling stuck and disconnected (β=0.12, *SE* = 0.04, *t*-value: 3.07, *p* =.002; β=0.13, *SE* = 0.04, *t*-value: 3.35, *p* <0.001, respectively). The day variable and model intercepts were significant indicating differences across persons (See Figure 7 and Table 12). The antecedent model for PF-environ and NA was supported such that PF-environ at time *t* predicted a small decrease in NA at time *T+1* (β=-0.07, *SE* = 0.03, *t*-value: -2.56, *p* =0.01), while NA at time *t* predicted greater NA at time *T+1* (β=0.23, *SE* = 0.03, *t*-value: 7.98, *p* <0.001; see Table 11). The consequence model for PF-environ and NA was not significant at the 0.02 level. The consequence model for PF-yesconnect and NA was supported, such that PF-yesconnect at time *t* predicted an increase in PF at time *T+1* (β=0.25, *SE* = 0.04, *t*-value: 6.27, p <0.001), while NA at time *t* predicted less NA at time *T+1* (β=-0.09, *SE* = 0.04, *t*-value: -2.54, p =0.01; see Table 12 and Figure 8). All other models were not significant.

For stress models, only PF-environ and PF-yesconnect exhibited significant antecedent models. A standardized one unit increase in PF-environ at time *t* was associated with a 0.06 unit decrease in stress at time *T+1* (*SE* = 0.02, *t*-value: -2.62, p =.01), and a standardized one unit increase in stress at time *t* was associated with a 0.3 unit increase in future stress (*SE* = 0.03, *t*-value: 11.02, p <.001). Results were similar in strength and direction for the PF-yesconnect and stress antecedent model (see Table 13, Figure 9). The PF-stress consequence models were significant for all PF items with the exception of PF-noout, PF-think, and PF-environ (see Table 14, Figure 10). Overall, hypotheses 1b and 1c were partially supported as PF variables were differentially related to affect and stress over time.

Contemporaneous Relationships Between PF, Affect, Stress, and Day Quality Considering Context and Event Type

Aim 1, hypotheses 1d-1e, contemporaneous models were repeated with the addition of an interaction term between either type of context (e.g., conflict/stressor or goal/value) or type of event (e.g., work/school, romantic relationship, friendship, family, finances, daily hassles/minor matters, health, other) and PF. Models were identical to original contemporaneous models with the exception of this interaction term and the addition of context or type as a random effect. Context did not significantly interact with any of the PF items to predict PA in contemporaneous models, but there was a significant positive main effects of goal/value context on PA in all models (Table 15). Context significantly interacted with PF-noconnect to reveal decreased NA (β=-0.14, *SE* = 0.04, *t*-value: -3.32, *p* =.001; Table 16). For stress models, context did not interact with any PF items to predict stress, but there was a significant negative main effect of goal/value context on stress in all models.

For models in which quality-of-day rating was the outcome of interest, there was a significant main effect of goal/value context on day quality in all PF models (all β's 0.08-0.14, *p*'s < 0.001). There was a significant small interaction between PF-environ and goal/value events (β=0.07, *SE* = 0.03, *t*-value: 2.59, *p* =.01) and between PF-yesconnect and goal/value events (β=0.09, *SE* = 0.03, *t*-value: 3.16, *p* <.01; Table 17). For type of event, there were no significant main effects of type on day quality rating with the exception of the PF-yesconnect model which showed a positive effect of daily hassle events on day quality ratings (β=0.13, *SE* = 0.05, *t*-value: 2.64, *p* = 0.01). Results also revealed significant positive interactions between PF-yesconnect and health, romantic, and friendship-related events in predicting day quality. There was a significant small interaction between each PF-stuck, PF-noout, and PF-noconnect and "other" type in the negative direction and a significant negative interaction between PF-stuck and romantic relationship events (see Table 18). Given differential relationships depending on the PF-item modeled, hypothesis 1d was partially supported.

Type of event models were identical to context models, though the random effect of type was removed to allow for models to converge. For PF-stuck and PA, there was a significant positive effect of friendship-related events on PA (β=0.20, *SE* = 0.08, *t*-value:

2.39, $p = 0.02$). In PF-think PA models, there was a significant positive effect of friendship-related events on PA (β=0.22, *SE* = 0.09, *t*-value: 2.60, $p = 0.01$). There were no significant main effects or interactions regarding event type in PF-noout, PF-noconnect, PF-yesconnect and PF-environ PA models at the 0.02 level.

With respect to NA, there was a significant negative effect of daily hassle events on NA in the PF-stuck model (β=-0.25, *SE* = 0.07, *t*-value: -3.66, $p < 0.001$). There was also a significant negative effect of daily hassles on NA in the PF-noout model (β=-0.27, *SE* = 0.07, *t*-value: -3.68, $p < 0.001$) and a significant interaction between PF-noout and daily hassles (β=-0.17, *SE* = 0.07, *t*-value: -2.32, $p = 0.02$). For PF-noconnect models, there was a significant negative effect of daily hassles on NA (β=-0.24, *SE* = 0.07, *t*-value: -3.29, $p = 0.001$) and significant positive interactions with family and "other" event type ((β=0.31, *SE* = 0.08, *t*-value: 3.64, $p < 0.001$; β=0.20, *SE* = 0.09, *t*-value: 2.32, $p = 0.02$, respectively). For PF-think and PF-environ, there were significant negative main effects of daily hassles on NA (β=-0.27, *SE* = 0.07, *t*-value: -3.59, $p < 0.001$; β=-0.25, *SE* = 0.08, *t*-value: -3.24, $p = 0.001$, respectively), but no significant interactions. Consistent with other models, there was a significant negative effect of daily hassle events on NA (β=-0.27, *SE* = 0.08, *t*-value: -3.65, $p < 0.001$), and a significant negative interaction between PF-yesconnect and friendship events on NA (β=-0.19, *SE* = 0.08, *t*-value: -2.30, $p = 0.02$). See Table 19.

With respect to stress models, there was a significant negative effect of friendship, family, and daily hassle events on stress and a positive interaction between PF-stuck and romantic-related events on stress (see Table 20). In the PF-noout stress model, there were significant negative associations between daily hassles and romantic-related event type and stress, and one significant positive interaction between PF-noout and romantic-related events (see Table 20). For the PF-noconnect stress model, there were significant negative associations between daily hassles and romantic-related event type and stress, and a positive interaction between PF-noconnect and romantic-related event type on stress (see Table 20). For the PF-think stress model, there were significant associations between romantic, friendship, and daily hassle events and stress, and no significant interactions. The same pattern of results holds for PF-environ models with the exception of the romantic and friendship event effects. For the PF-yesconnect stress model, the only main effect was daily hassles and there were two negative interactions between PF and romantic and friendship-related events on stress (see Table 20). Model results with type of event added support hypothesis 1e that context and type of event would be differentially associated with PF, affect, and stress.

Moderation Effects of Baseline Questionnaires on the Temporal and Contemporaneous Associations Between PF, Affect, and Stress

Aim 2 moderation models were identical to Aim 1 contemporaneous and temporal models, with the exception of the addition of an interaction term between a baseline questionnaire score or attentional task score and PF in prediction of affect or stress. All models included random effects of state PF, unless there were convergence issues. Non-significant Likelihood Ratio Tests from ANOVAs comparing intercept-only models to models including random intercepts revealed that including random slopes based on individual differences did not improve model fit. There were no significant effects of baseline FFMQ total score (with Observe facet included) on PA in contemporaneous models. The interaction between baseline FFMQ and each PF item was also not significant in antecedent and consequence PA models, with the exception of the antecedent model for PF-environ ($\beta=-0.06$, $SE = 0.02$, t-value: -2.84, $p < 0.01$) and PF-yesconnect ($\beta=-0.06$, $SE = 0.03$, t-value: -2.49, $p = 0.01$; Table 21, Figure 11). In contemporaneous stress models, there was one significant interaction between PF-yesconnect and FFMQ ($\beta=-0.05$, $SE = 0.02$, t-value: -2.52, $p = 0.01$; Figure 11). With respect to temporal models with PF and stress, there was a significant interaction between PF-stuck and FFMQ in the stress consequence model ($\beta=-0.12$, $SE = 0.05$, t-value: -2.26, $p = 0.02$; see Figure 11). As such, hypothesis 2a was partially supported, though effects were quite small.

Each subscale from the ERQ (e.g., reappraisal and suppression) was entered as an interaction term in contemporaneous and temporal models for PA, NA, and stress. There were no significant main effects or interactions of ERQ subscales in contemporaneous PF models predicting PA or NA. In contemporaneous models predicting stress, there was a significant interaction between PF-stuck and reappraisal ($\beta=0.10$, $SE = 0.03$, t-value: 3.58, $p < 0.001$). For PF-noout and stress, there was no significant main effects or interactions at the 0.02 level of significance. There was a small negative interaction between PF-noconnect and reappraisal in predicting stress ($\beta=-0.06$, $SE = 0.03$, t-value: -3.00, $p < 0.001$), but no interaction with suppression. There were no significant main effects or interactions between ERQ subscales and PF-think or PF-environ in stress contemporaneous models. Reappraisal and PF-yesconnect significantly interacted to predict reduced stress (β=-0.06, *SE* = 0.024, *t*-value: -2.31, $p = 0.02$), but there was no significant interaction with suppression scores. See Table 22 and Figure 12 for significant results. For temporal models between PF, affect, and stress, with the addition of ERQ subscale scores, there were no significant main effects or interactions in any model. Most temporal models revealed non-significant Likelihood Ratio Tests from ANOVAs comparing models, which increased interpretability of pooled estimates versus individual differences. Hypothesis 2b was partially supported as ERQ scores related to stress and interacted with PF-items, though these effects were not significant in temporal models.

Next, three separate baseline measures of PF (e.g., AAQ-II, CFI, and ASQ) were added as moderators into contemporaneous and temporal models in models related to PF, NA, and stress. We used the total scores from the AAQ-II (higher scores indicating greater *in*flexibility) and CFI, and used individual subscale scores from the ASQ (e.g., tolerating, concealing, adjusting) in models. There were no significant main effects or interactions of ASQ subscale scores in any contemporaneous or temporal models including PF predicting NA or stress. For the contemporaneous NA models, there was a significant main effect of AAQ score (β=0.22, *SE* = 0.08, *t*-value: -2.90, $p = 0.01$) and a significant negative interaction between AAQ and PF-environ in predicting NA (β=-0.07, *SE* = 0.02, *t*-value: -3.01, $p < 0.001$). There was also a significant positive main effect of AAQ score in the PF-yesconnect NA model (see Table 23). For contemporaneous stress models with AAQ interactions added, there were no significant main effects or interactions with AAQ scores in PF-stuck, PF-noconnect, PF-nooout, PF-environ, or PF-yesconnect models. In the PF-think and stress model, there was a significant negative interaction between PF and AAQ score (β=-0.09, *SE* = 0.02, *t*-value: -3.81, $p < 0.001$; Table 24). Most contemporaneous NA and stress models revealed non-significant ANOVA comparisons of model fit.

There were no significant main effects of or interactions between AAQ scores and PF in any antecedent or consequence PF-NA models. With the exception of the PF-yesconnect stress model, there were no significant main effects of or interactions between AAQ scores and PF over time. PF-yesconnect and AAQ score exhibited a positive interaction effect on stress in the antecedent model only (β=0.05, *SE* = 0.02, *t*-value: 2.26, $p = 0.02$).

For CFI total scores added to contemporaneous NA models, there was a significant positive interaction between PF-stuck and CFI score (β=0.08, *SE* = 0.03, *t*-value: 3.00, $p < 0.001$; Figure 14), but all other main effects and interaction terms in other PF models were not significant. For contemporaneous stress models, there was a significant negative main effect of CFI score on stress in the PF-environ model (β=-0.25, *SE* = 0.08, *t*-value: -2.85, $p = 0.01$) and the PF-yesconnect model (β=-0.23, *SE* = 0.09, *t*-value: -2.56, $p = 0.02$), but all other main effects and interactions were not significant. See Table 25. For temporal models with CFI score added, there were no significant main effects of or interactions with CFI in NA or stress models. As such, hypothesis 2c was partially supported given several significant interaction terms but overall baseline flexibility scores revealed more main effects than interactions, counter to predictions.

Lastly, a singular performance score from the Switching Task and Emotional Stroop was added into contemporaneous models to interact with the daily PF variables to predict affect and stress. For contemporaneous PF-PA models, there were significant negative interactions between Switching Cost and PF-stuck, PF-noout, and PF-noconnect, (all β's -0.09- -0.10, all *p's* <0.001; see Table 26 and Figure 15). For NA models, there were no significant main effects or interactions between Switching Cost and PF. For PF-stress models, the interaction between Switching Cost and PF-noout was significant in the positive direction (β=0.07, *SE* = 0.02, *t*-value: 2.97, *p* <0.001;see Table 26), but all other models were not significant.

There were no significant main effects of or interactions between the Stroop Effect score and PF in any affect or stress models. These results reveal partial support for hypothesis 2d which predicted that flexibility scores from the attentional tasks would moderate the relationships between PF, affect, and stress.

Effects of Physical and Social Health Indicators on the Relationship Between PF, Affect, and Stress

Aim 3 contemporaneous and temporal models were identical to Aim 1 models with the addition of various physical and social health metrics collected via the Ethica app and Oura rings added as interaction variables with each PF item to predict affect and stress. In contemporaneous PF-PA models including step count, there was a significant negative interaction between PF-noconnect and steps (β=-0.05, *SE* = 0.02, *t*-value: -2.26, *p* =0.02). In contemporaneous PF-NA models, step count interacted with PF-stuck in the positive direction (β=0.06, *SE* = 0.02, *t*-value: 2.46, *p* =0.01) and interacted with PF-yesconnect in the negative direction (β=-0.05, *SE* = 0.02, *t*-value: -2.60, *p* =0.01) See Table 27 and Figure 16 for significant models. For PF-stress contemporaneous models, there were no significant main effects of or interactions with step count in prediction of stress. There were also no main effects of or interactions with step count in any of the temporal models predicting affect or stress.

The activity metric, calculated by Ethica based on motion, was added to contemporaneous and temporal models, which yielded no significant main effects or interactions across models. Ethica GPS data were processed to extract total distance traveled in meters. This value was then added into contemporaneous and time-lagged models of PF and affect or stress. Across all contemporaneous and temporal models including GPS distance predicting affect and stress, there were also no significant main effects of or interactions with GPS-distance. Based on these results, hypothesis 3a was not supported given that GPS distance did not relate to stress and did not interact with PF to predict PA, but rather showed main effects in NA models. GPS-distance also did not significantly relate to PF, affect, and stress in temporal models, counter to prediction.

Finally, the screen time metric calculated via Ethica was entered into contemporaneous and temporal models to interact with PF in prediction of affect and stress. There were no significant main effects of or interactions with screen time in any contemporaneous model at the 0.02 level of significance. In temporal models, there was a significant main effect of screen time on PF-noout (β=-0.08, *SE* = 0.03, *t*-value: -2.39, *p* =0.02) and PF-noconnect (β=-0.09, *SE* = 0.04, *t*-value: -2.49, *p* =0.01) in PA consequence models. There were no other significant main effects or interactions in the PF-PA temporal models. In PF-stress models, there was a significant main effect of screen time on PF-noout (β=-0.08, *SE* = 0.03, *t*-value: -2.34, *p* =0.02) and PF-noconnect (β=-0.09, *SE* = 0.04, *t*-value: -2.45, *p* =0.01) in stress consequence models. Similar to PA and stress models, there was a significant main effect of screen time on PF-noout (β=-0.08, *SE* = 0.03, *t*-value: -2.43, *p* =0.02) and PF-noconnect (β=-0.10, *SE* = 0.04, *t*-value: -2.56, *p* =0.01) in NA consequence models. These results partially support hypothesis 3b stating that screen time would be related to changes in affect and stress within, but not across time.

Impact of Sleep Quality and Nighttime Heart-Rate Variability on PF, Affect, and Stress Models

Contemporaneous and temporal models were identical to aforementioned Aim 3 models with the addition of sleep score (e.g., sleep quality) or average nighttime HRV collected from Oura rings added as interaction variables with each PF item to predict affect and stress. In contemporaneous models with sleep score added, there were no significant main effects of or interactions with sleep score. In all temporal models including sleep score, there were no significant main effects of or interactions with sleep score at the 0.02 significance level. These results do not support hypothesis 3c.

For contemporaneous models with the addition of average nighttime HRV score added, PA model results revealed significant negative interactions between HRV and PF-stuck (β=-0.10, *SE* = 0.03, *t*-value: -3.31, *p* =0.001) and PF-noout (β=-0.07, *SE* = 0.03, *t*-value: -2.26, *p* =0.02). There were also significant positive interactions between HRV and PF-think (β=0.07, *SE* = 0.03, *t*-value: 2.41, *p* =0.02) and PF-environ (β=0.07, *SE* = 0.03, *t*-value: 2.39, *p* =0.02) on PA (Table 28). In contemporaneous models predicting stress, there were significant positive main effects of HRV on stress in all PF models except PF-stuck (all β's 0.11-0.16, all *p*'s < 0.01; Table 29). There were no significant main effects of or interactions with HRV in contemporaneous NA models.

With respect to temporal models, there was a significant interaction between PF-environ and HRV in the PA consequence model predicting PF-environ (β=-0.12, *SE* = 0.05, *t*-value: -2.50, *p* =0.01). For temporal stress models, there was a significant main effect of HRV on stress in all antecedent models (all β's 0.06-0.08, all *p*'s < 0.02; Table 30). There was also a significant negative interaction between PF-environ and HRV in predicting PF-environ in the stress consequence model (β=-0.11, *SE* = 0.05, *t*-value: -2.40, *p* =0.02). For temporal NA models, there was a significant main effect of HRV in all antecedent models (all β's 0.08, all *p*'s < 0.01; Table 31). There was also a significant main effect of HRV on PF-environ (β=-0.11, *SE* = 0.05, *t*-value: -2.36, *p* =0.02) in the NA consequence model.

DISCUSSION

Decades of research point to the psychosocial health benefits of PF across samples and methodologies. As the field has expanded its focus toward understanding idiographic processes over time, while moving away from nomothetic approaches that quantify group differences at the diagnostic level, it is increasingly important to understand the construct of PF in a similar way (Kashdan & Rottenberg, 2010; Kashdan et al., 2020; Doorley et al., 2020). Extant research has also called for changes in the way PF is measured, both in terms of measuring the construct over time, under different contexts, and in relation to the items or instruments used for measurement (e.g., moving beyond the AAQ). By understanding PF variability within individuals across time using measures that account for inflexible and flexible actions, we can better estimate the causality of the relationship between flexibility and affective processes (i.e., does inflexibility precede affective change and dysfunctional outcomes or vice versa?). The current study was designed to address these gaps in the literature by examining the dynamic relationship between PF, as measured by six distinct items from the PBAT, affect and stress in a clinical sample across different contexts. The aims of the current study estimated associations between PF, affect, and stress within and across time, under the contexts of conflicts or goals/values, and in the presence of various moderator variables including psychological processes, attentional metrics, and physical and social health data collected via smartphone apps. Comparison of antecedent and consequence temporal models allowed for examining whether changes in PF influenced affect or stress over time or vice versa, to estimate quasi-causal associations. A discussion of how the current study results relate more broadly to the literatures of PF and process-based therapy will follow.

Contemporaneous and Temporal Associations Between PF, Affect, and Stress

Aim 1, hypotheses 1a-1c, pertained to modeling the associations between PF, affect, and stress within and across time. For contemporaneous models, inflexible approaches to dealing with daily life (e.g., feeling stuck, having no outlet for emotions, and not connecting with life) were associated with lower positive affect, as expected. Flexible approaches to coping were associated with greater positive affect (e.g., connecting with others, changing one's environment, and thinking to problem-solve). As predicted, inflexible behaviors were associated with greater negative affect and stress while flexible behaviors were related to decreased negative affect and stress within the same time point. Across these models, there was a high degree of variability in the extent to which PF related to affect and stress and the direction of the effects within individuals, which is consistent with ACT theory such that the utility of identifying behaviors is more about function over form (Hayes, 2004), as what works for one individual may not work for another. The relationship between PF, affect, and stress in contemporaneous models was generally consistent at the within and between group levels, with a few exceptions. As such, these "proof of concept" results support decades of literature identifying a relationship between PF, affect, and stress (for reviews, see Gloster et al., 2017; Doorley et al., 2020; Kashdan et al., 2020).

To explore the temporal associations between PF, affect, and stress, separate antecedent and consequence models were tested (Marshall et al., 2020) in which lagged PF, affect, or stress variables predicted future affect, stress, or PF after controlling for previous timepoints (Figure 1). Results revealed no significant pooled effect of antecedent models between PF and PA. However, the variability amongst individuals points to the utility of understanding function over form of a behavior (Hayes, 2004) and the need to understand PF at the individual, rather than group level. Our results showed significant consequence models for PF-yesconnect and PF-noconnect, indicating that past PF predicted future PF and that PA predicted future PF. This suggests that positive affect and one's level of PF are primary driving forces behind these flexibility processes, but that PF was not predictive of PA processes. This supports treatment research that targets PA as opposed to solely focusing on reducing NA (Craske et al., 2019; Tirpak et al.,

2019) as well as efforts to increase social connection to reduce isolation and improve mental health (Cacioppo et al., 2015; Holt-Lunstad, Robles, & Sbarra, 2017).

In relation to NA, results indicated that changing one's environment predicted a small decrease in NA at future timepoints and that previous NA predicted increased future NA. This effect suggests that changing one's circumstances precedes changes in NA. In consequence models, our results revealed that previous instances of feeling stuck or disconnected and previous NA did predict future inflexibility in these domains. It was also shown that previous instances of connection were associated with feeling connected in the future, while previous NA was associated with reduced connection in the future. These effects altogether suggest that treatment efforts to reduce NA are likely helpful in increasing flexible behaviors. Overall, NA temporal models displayed high variability within individuals, even in models with non-significant pooled effects.

For stress models, only PF-environ and PF-yesconnect exhibited significant antecedent models, suggesting that changing one's environment and connecting with others as flexible behaviors decreased future stress, while endorsement of stress at time *t* was associated with increased future stress. These results are consistent with findings from evidence-based treatments that target behavior change over time to improve functioning. Additionally, our results also indicated that stress influences PF, with all consequence models significant except for PF-noout, PF-think, and PF-environ. These results seem to highlight research revealing the impacts of stressful life events or systemic inequalities on overall poorer functioning and mental health disorders (Juster, McEwen, & Lupien, 2010; Charlson et al., 2019; Gibson et al., 2021) and that changes to these stressful environments is beneficial.

Considering PF, Affect, and Stress in Context

Aim 1, hypothesis 1d examined the extent to which flexible behaviors affect overall perception of day-quality. Hypothesis 1e set to explore a basic premise of ACT, which is that PF is a contextual process. Context, specifically goals or values, was significantly related to positive quality-of-day ratings made at the end of the day in all contemporaneous PF models. Connecting with others and changing one's environment also significantly interacted with context to predict positive day quality. These results suggest that broadly engaging in or thinking about goals or values is related to increased perceptions of a "good" day and that psychological flexibility, in the context of values, provides an additive effect to perceptions of day quality. Conversely, type of event was not related to day quality, with the exception of one model which revealed a positive effect of daily hassles on day quality. This effect is counter to the expectation that more daily hassles may lead to a worse perception of the day, but it is possible that these hassles occurred within a valued-context, which could explain the positive effect. Despite an array of options for defining type of situation, there was a significant interaction between PF-stuck, PF-noout, PF-noconnect and "other" type of event in predicting worse day quality. This could suggest that unexpected or difficult to define daily experiences, when already acting inflexibly, dampen perception of the day.

For contemporaneous affect and stress models including context (with stress/conflict as the reference point), it was revealed that context did not interact with PF to predict PA, but that goal/value context was generally related to greater PA. Similarly, goal/value context was negatively associated with NA and stress. These global results suggest that engaging in or thinking about goals or values is generally beneficial and supports one of the primary mechanisms of change in ACT interventions that seek to identify, clarify, and promote values-based action. There were no significant interactions between PF and context in stress models, but there was one significant interaction between context and PF-noconnect resulting in reduced NA, which may suggest that the effect of context dampened the impact of general disconnect on overall affect. That said, contemporaneous results generally contradict context specificity in PF strategies, which was unexpected.

For contemporaneous PA models with type of event included, our results revealed significant main effects of friendship-related events on increased PA, however we did not find any significant interactions between PF and type on PA, which was similar to context effects. Interestingly, in NA contemporaneous models, daily hassles were associated with reduced NA in all models. Given that interactions between context and type were not modeled, due to insufficient power for three-way interactions, this effect could be driven by daily hassles that occurred within the context of goals or values. Alternatively, daily hassles as a categorical item may have been too broad or a "catch-all" category that actually included other event types that are more typically associated with reduced negative affect. PF significantly interacted with daily hassles, family, friendship, and "other" event-type, depending on the PBAT item modeled. Specifically, feeling like there is no outlet for emotions interacted with daily hassles to predict increased NA, and feeling disconnected interacted with family and "other" event-type to produce greater NA within time. Connection with others and friendship interacted to reduce NA within time. These data are consistent with CBT-based models of emotion that break down one's experiences into situations, thoughts, feelings, and behaviors (Beck, 2020), such that the daily events we experience interact with our abilities to act flexibly in association with affect.

In stress models, our results revealed various main effects of and interactions with friendship, family, romantic, and daily hassle event types. PF-stuck interacted with romantic events in prediction of reduced stress within time and friendship, family, and daily hassle events were related to lower stress. PF-noout interacted with romantic events to relate to increased stress and PF-noconnect interacted with romantic or family events to predict increased stress within time. PF-yesconnect interacted with romantic and friendship events in association with less stress. PF-think and PF-environ did not interact with event type to predict stress. These results may suggest that when inflexible approaches are used (and account for variance in affect or stress outcomes), event type may more obviously affect one's perception of emotions or stress. Results may also reflect how stress and affect were measured in our study, as NA was only measured using one item pertaining to level of nervousness, which could theoretically be a feeling felt under positive and negative types of events and contexts. Similarly, our stress item measured the degree of stress in a given moment, and did not qualify whether the stress was acute or more continuous or chronic. This may be an important next step in measuring stress in EMA designs, given evidence that acute and chronic stress differentially affect the hypothalamic-pituitary-adrenal (HPS) axis (Aschbacher et al., 2013; 8798 et al., 2015; Lu, Wei, & Li, 2021), which is related to expressions of psychopathology and resilience (Haglund et al., 2007; Doom & Gunnar, 2013).

Moderation Effects

Overall, our results partially supported the hypothesis that baseline mindfulness scores on the FFMQ affected PA or stress during the EMA phase. Data indicated a small, significant negative interaction between lagged PF-environ and PF-yesconnect and FFMQ scores in prediction of PA in time-lagged models. Greater PF and lower than average FFMQ scores were associated with greater PA, while lower PF and higher than average FFMQ scores were associated with less PA, so this interaction effect seems to be driven by level of PF more-so than mindfulness. Results were similar for the interaction between lagged PF-stuck and FFMQ on stress. PF-yesconnect interacted with FFMQ at the same timepoint to predict reduced stress, which was a small but significant effect driven by PF. FFMQ scores were equally predictive of stress when PF was low, but when PF was high, this effect superseded lower than average mindfulness scores.

In contemporaneous models, we did not find significant effects of baseline ERQ subscale scores on PA or NA. However, in contemporaneous stress models, we found significant positive interaction between feeling stuck and reappraisal, feeling disconnected and reappraisal (negative interaction effect), and connecting with others and reappraisal (negative interaction effect). At low levels of PF-stuck, stress was low irrespective of reappraisal, but higher than average PF-stuck scores and higher than average reappraisal scores produced greater stress. This pattern was similar for the PF-noconnect interaction. Lower PF-yesconnect scores and higher reappraisal scores were associated with higher stress, while higher PF scores were related to lower stress. In other words, it seems that general efforts to reappraise situations as a regulation tool (at baseline) did not compensate for feeling stuck or feeling disconnected in a given moment, which was associated with more stress. Counter to predictions, there were no significant main effects of or interactions with ERQ scores in temporal models, which may be reflective of the way that ERQ was measured (only at baseline) and less to do with no temporal effects, though future research should test this empirically. Even still, these results do not suggest a "one-size-fits-all" approach to understanding the interplay between emotion regulation and PF, and it seems warranted to understand how *daily* emotion regulation skill use may interact with PF.

In contrast to research identifying affective style as an emotional flexibility process that is related to psychopathology and changes over time (Hofmann & Kashdan, 2010; Hofmann et al., 2012; Totzeck et al., 2018; Totzeck et al., 2020), our results revealed no main effects of or interactions with baseline scores on the ASQ (e.g., tolerating, concealing, adjusting) in contemporaneous and temporal NA or stress models. Similar to interpretations of the emotion regulation models discussed earlier in this section, it is possible that null findings are related to only having administered the ASQ at baseline and endpoint as opposed to more frequently. Alternatively, it is possible that *changes* in affective styles may be more likely to relate to or interact with PF as opposed to one single trait score, but since the current study used a clinical sample of adults either in stable treatment or no treatment at all, ASQ scores change scores were small (less than

3 points for all subscales from pre-post on average). Future research could examine the unique or similar impacts of affective styles on PF using EMA within the context of treatment research.

In contemporaneous models predicting NA, there was a significant direct effect of AAQ score (higher score = inflexibility) in PF-environ and PF-yesconnect models. Changing one's environment to improve the moment significantly interacted with AAQ scores in NA the model in the negative direction. Higher AAQ scores were associated with greater NA at low PF levels, but this effect diminished at higher PF levels (Figure 13). That said, there were no significant main effects of or interactions between AAQ scores and PF in any temporal PF-NA models. In models predicting stress, there was a main effects of AAQ on stress in the PF-think model only. Using one's thinking in a situation also negatively interacted with AAQ score in the contemporaneous stress model, such that at low levels of PF-think, high AAQ score drove up stress, but high PF-think scores led to lower stress regardless of AAQ score. These results seem to suggest a general inflexible disposition that relates to NA and stress irrespective of time, which makes sense in light of the sample's clinical characteristics. Although, the significant negative interactions with daily PF, suggest that even individuals with general inflexible tendencies are able to behave flexibly and experience positive benefits in the form of reduced stress and negative affect in that moment. To some extent, this is part of what allows therapists to begin building motivation for change in clients, as they often have the ability to act differently, but the important step is practice and consistency. Contrary to study hypotheses, our temporal models revealed no main effects of or interactions with baseline AAQ score, with the exception of an interaction between PF-yesconnect and AAQ in predicting stress in one antecedent model. This effect was driven primarily by PF score, such that low PF (lagged) and low AAQ score was associated with greater stress and greater PF was associated with lower stress (Figure 13). NA and stress model results including CFI total score as a predictor and interaction term revealed a significant positive interaction between PF-stuck and CFI, such that at low PF-stuck levels, NA was low irrespective of CFI score, but at higher PF-stuck levels, NA was high (Figure 14). Additionally, in stress models, CFI score was associated with less stress within a given contemporaneously. These data support an association between affect and PF, but do not suggest an interaction between dispositional and daily PF in predicting affect or stress over time.

As an additional indicator of flexibility that was not dependent on self-report, we employed two attentional tasks at baseline to measure attention bias and inflexibility to use as moderators in models. Overall, our sample exhibited expected switch costs on average, indicating that the Switching Task operated as intended. In contemporaneous models predicting PA, our results revealed significant negative interaction effects between PF and Switching Cost score for the three PBAT indicators of inflexibility (PF-stuck, PF-noout, and PF-noconnect). For stress models, there were positive interaction between PF-noout and switching cost. Although interaction effects were small, they were highly reliable such that lower daily PF scores were driving the negative effects on PA, while higher degrees of feeling disconnected were driving positive effects on stress (Figure 15). Given that 30% of our population had a primary diagnosis of GAD, with original switching task papers primarily measuring the effect in trait and state anxiety (Gustavson et al. 2017; Barthel et al., 2022), our effects should be tested in other populations. Future research should also determine if performance on the Switching Task is predictive of temporal changes in psychological processes over time, as our results are only contemporaneous.

Counter to predictions based on cognitive dysfunction as a transdiagnostic feature of psychopathology (Zinchenko et al., 2020; Abramovitch et al., 2021), our results revealed no main effects of or interactions with Emotional Stroop scores in any contemporaneous affect or stress models. The average Stroop effect score for our study sample was positive, indicating a significantly slower response time to emotional words, as the task should show, though it is possible that since the words used in our task were general and not specific to each individual's clinical presentation or set of emotional concerns, our effects may have been weaker (Williams, Matthew, & MacLeod, 1996; Becker et al., 2001).

Model Associations with Physical and Social Health Indicators Included

It was hypothesized that step count would relate to and interact with PF in predicting affect and stress. Our results showed a significant interaction between PF-noconnect and steps, such that PA was higher when disconnection was lower than average, but PA was lower when individuals endorsed feeling more disconnected (Figure 16). In models predicting NA, there was a small, significant positive interaction between feeling stuck and step count, such that at low levels of feeling stuck, NA was lower than at points when feeling stuck was high (Figure 16). PF-yesconnect also negatively interacted with step count to predict NA contemporaneously, with the effect driven by PF. Models predicting stress as the outcome were not significant and our results did not support evidence for steps predicting affect or stress over time.

As an indicator of social health, we used a categorical indicator of the degree to which participants' phone screens were on and off during the study period. Screen time was unrelated to affect and stress variables in contemporaneous models. Notably, we did not know what content participants were accessing on their phones when screens were on, which may have provided richer information for including in models. However, our results did exhibit screen time effects in temporal association models. Our results indicated that screen time at time *t* was associated with reduced disconnect and feeling like there is no outlet for emotions at time *t* in consequence models for PA, NA, and stress. These data seem consistent with data that suggest the benefit of technology and social media use on reducing feelings of isolation and increased wellbeing, alongside potential pitfalls (for review, see Clark, Algoe, & Green, 2018). Future research should employ other metrics of social health such as social media use or other forms of technology use to understand if results are similar or different from ours in the context of PF, affect, and stress. As such our data do not suggest temporal relationships between step count and PF, affect, and stress nor do the data suggest that movement interacts with flexibility, which does not support hypotheses.

Contrary to our predictions, activity data were unrelated to affect and stress in contemporaneous and time-lagged models. The lack of relationship between activity data and affect or stress has been shown in other studies with similar methodologies (Moshe et al., 2021; Curtiss et al., 2022), alongside numerous studies suggesting a clearer link (Curtiss et al., 2019; Bernstein et al, 2019; Asare et al., 2022). To some degree, our results could be reflective of the way that motion-based activity was measured, via smartphone, as opposed to using a watch or actigraphy (i.e., phones may not always be present with participants when moving). To that end, visual inspection of Ethica step data indicated general low activity count, which contrasted the overall daily step count average derived from the Oura rings. An additional explanation put forth by Curtiss et al. (2022), is that physical activity is generally lower in clinical versus non-clinical samples overall, and that the very context in which our sample was derived may have led to less activity and non-significant models.

GPS-distance travelled also did not significantly relate to affect and stress in contemporaneous and temporal models, counter to predictions. Previous research by Asare et al., (2022) found that GPS-data were predictive of depressed versus non-depressed groups, so it is possible that our results were non-significant due to the fact that our sample was mostly anxious, lower sample size, or due to our lack of a non-clinical comparison group. Müller et al. (2020) found associations between distance travelled and anxiety, affect, and stress, such that greater distance travelled was associated with lower anxiety, greater affect, and less stress. Given that these authors created the code used in the current study, it is surprising that our results are not similar, especially given our sample location (e.g., city) where walking to many locations is highly likely. However, Müller et al. (2020) looked at daily movement, while our study looked at total distance traveled across the 14-day study period. Future research may benefit from breaking down daily activity and could also employ other GPS-derived metrics like those computed by Müller et al. (2022) including number of places travelled, clusters of location data, entropy, and type of location visited (home, work etc.). The intent was to compute these additional metrics in the current study, but upon initial inspection of several processed participants' data, it appeared that most location data were within a singular cluster for participants which limited the metrics we were able to compute based on Müller et al.'s code, though secondary analyses will be explored.

Model Associations with Sleep Indicators Included

Despite the importance of sleep on daily functioning and research suggesting impaired sleep in association with psychological disorders (Harvey et al., 2011), sleep score, as measured by the Oura ring, was not significantly related to PA, NA, or stress in contemporaneous or temporal models. The results were surprising given that sleep score was a metric for understanding overall sleep quality and Moshe et al. (2021) have shown significant effects of Oura ring sleep metrics in relating to depression and anxiety. That said, Moshe and colleagues centered their analyses on total sleep time, time in bed and waking after sleep onset as opposed to total sleep score. Certainly, it is also possible that Oura ring sleep data are not as reliable as other methods for measuring one's sleep, though recent studies suggest high agreement with polysomnography sleep study data (Altnini & Kinnunen, 2021). However, the high agreement rate was based on using all available Oura data and our models were simply extracting one score. Another factor that could affect results is that Oura data are surmised into one score per day based on the previous night's sleep, so each participant only had 14 days of data as opposed to PF, affect, and stress data which ranged from 40-70 datapoints per participant. It is possible that a longer sampling period or a larger sample would be preferrable for studying sleep metrics collected via Oura, though Moshe et al. (2021) also measured data over the course of two weeks. Follow-up analyses, including those planned by this author, will leverage additional Oura data to better understand how sleep measured via this system relate to affect, stress and PF more broadly.

We also examined the main and interaction effects of average nighttime HRV collected via Oura rings on contemporaneous and temporal models of PF, affect, and stress given research implicating HRV as an important biomarker in psychopathology, with greater HRV tending to be beneficial when compared to less variability (for review see, Beauchaine & Thayer, 2015). Results revealed negative interaction effects between inflexible processes and HRV and positive interaction effects between flexibility and HRV in contemporaneous PA models, with the exception of PF-stuck and PF-yesconnect models. Interaction plots show that at low levels of feeling stuck or without an outlet, participants reported higher PA regardless of HRV, while higher levels of inflexibility related to lower PA (Figure 17). The same pattern was true, in the opposite direction, for PF-environ and PF-think. For contemporaneous models with stress as the outcome variable, there were significant positive main effects of HRV in all models except PF-stuck, while nothing was significant in the NA models. Temporal model results with HRV added revealed significant interactions between PF-environ and HRV in the PA consequence model predicting reduced PF-environ at time *t*. For stress and NA consequence models, there were also negative interactions between PF-environ and HRV in predicting future PF. Our results revealed positive associations between HRV and NA or stress in all antecedent models such that HRV was associated with greater NA and stress at time *t*.

Overall HRV results are surprising in light of prior research indicating positive effects of HRV on reducing stress (Beauchaine & Thayer, 2015). However, it is important to note that HRV was collected only at nighttime and not during the day, per Oura sampling settings, so our results cannot surmise about the nature of participants' HRV throughout their daily lives. Instead, our results may suggest that general HRV during sleep interacts with daily PF. As mentioned earlier, another potential influence on our results is that our measurement of stress was focused on the extent to write participants felt stressed but was not concerned with identifying positive versus negative stress or chronic versus acute stress, so our global interaction results predicting higher stress within timepoints, could be fleshed out in future research. Using Oura rings, Moshe et al. (2021) also found positive associations between HRV and anxiety, though they did not find a link between HRV and stress or depression. Despite studies revealing that Oura rings' measurement of HRV is nearly identical to electrocardiogram (ECG) readings in healthy subjects (Kinnunen et al., 2020) and generally produces small biases despite different calculation methods, Cao et al. (2022) determined that the ratio of low frequency to high frequency HRV exhibited high error rates in health subjects. If high error rates are present in our clinical sample as well, it may affect results, though this analysis is beyond the scope of the current study. Future research is needed to better understand the nature of HRV estimates from Oura in clinical samples, as well as additional reliability and validity studies more broadly.

Limitations

There are several important limitations to consider in evaluating the results of the current study. Although multi-level modeling is a commonly employed approach for handling longitudinal data analyses due to the nested properties of the data, these models inherently assume stationarity in the data, such that they are assumed not to change over time (Hayes et al., 2022; Gates, Chow, and Molenaar, in press). Recent discussion in the field about non-ergodic data in psychological sciences (Fisher, Medaglia, & Jeronimus, 2018) point out that it is nearly impossible to assume that all individuals are influenced by the same processes over time, which limits the field's ability to deduce individual-level conclusions based on group-level models (for review see, Hayes et al., 2022). With acknowledgment of the limitation of MLM for modeling idiographic processes of change, the current study employed several novel approaches for calling attention to within-person dynamics within an MLM framework including: plotting variability of within-person estimates to compare with pooled estimates and testing temporal antecedent and consequence models to test whether specific links between PF and affect or stress varied from person to person based on methods from Marshall et al. (2020) and Sahdra et al. (2022). Although we were interested in interaction effects and group-level results, the primary goal of this dissertation was to examine individual fluctuations in PF, with within-person results of primary interest. Future research exploring the dynamics of PF, affect, and stress may consider alternative data analytic approaches including dynamic network analysis (Borsboom & Cramer, 2013; Epskamp et al., 2018), dynamic structural equation modeling (DSEM; Asparouhov et al., 2018; Hamaker et al., 2018;), or other idiographic time-series analyses, which may be more appropriate for pure idiographic research questions.

Another limitation of the current study is that activity data were mostly measured via smartphone, with the exception of step count, as opposed to via a watch or actigraphy, for example. Participants were told to take their phones with them as much as possible during the study period for optimal data collection, but visual inspection of activity data indicated windows of non-activity that we cannot be sure were due to actual non-movement or due to leaving one's phone behind during exercise. This may limit the interpretations of our activity-based data as a result. For step count, differences in counts between data collected via Ethica and Oura were observed, which may support the idea that wearable technology may be a more accurate estimate as opposed to data collected from smartphones. Secondary analysis of Oura activity estimates is planned to explore these potential differences, though these data are averaged daily as opposed to at 5 times per day or more as in the case of Ethica.

As mentioned earlier in the discussion, it is worth acknowledging the use of singular items to measure PF, affect, and stress, which counters traditional ways of measuring constructs using multiple items in consideration of multiple types of validity, reliability, and factor analysis. That said, use of brief measures or items is common in EMA research, as it is important to reduce subject burden in completing daily prompts to prioritize participant compliance and engagement. In an effort to prioritize construct validity in our study, items were selected to measure PF, affect, and stress items based on factor loadings and face validity from previous research (Ciarrochi et al., 2021). Descriptive results revealed modest correlations between PF items, though this is consistent with the idea that the items are related but distinct from one another. Another potential caveat of using singular items to measure affect and stress is that it is possible that participants experienced affect or stress in ways other than how constructs were measured, which may point to the importance of assessing these constructs in additional ways.

Moreover, our selection of six items from the larger PBAT were based on factor loadings (Ciarrochi et al., 2021), interest in modeling inflexible and flexible processes (i.e., positively and negatively worded PBAT items), and a theoretical understanding of PF, which was not consistent with totaling the items into a global PF score to enter into multi-level models. Models also did not converge when entering multiple PF-items as individual predictors into models, which led us to model each item with each outcome or interaction term separately in each contemporaneous and temporal models. Although this does not take away from the results obtained in this study, we are hopeful that future research methods allow for modeling PBAT items together to better understand their unique contribution to model effects and outcomes.

Finally, it should be noted that our study sample lacks racial, ethnic, and gender diversity, with the majority of the sample identifying as White and Female. Most participants were either students or working professionals in the Boston-area, which may further limit generalizability of findings. Unfortunately, lack of diversity in samples is common in psychological research, such that these results should be replicated in larger, more diverse study samples prior to making population-based inferences.

Final Conclusions

Overall, the current study is one of the first to examine the dynamic relationship between PF, affect, and stress in a heterogenous clinical sample, specifically using items from the PBAT. Our results support clinical and research evidence that psychological flexibility is highly idiographic and variable over time, depending on the process measured. Importantly, results also show that PF interacts with context and types of daily events to relate to affect and stress as well. Although our data did not support associations between physical activity, distance-travelled, and sleep quality in relation to PF, affect, and stress, we did find promising initial data suggesting relationships between step count, screen state, and HRV in relation to PF, affect, and stress. Despite the general correlational results of our data, we tested antecedent and consequence models (see Marshall et al., 2020) to estimate quasi-causal influences between PF and affect or stress, which showed that PF can precede or follow changes in affect and stress, depending on the behavior modeled. Data from the current study are an important first step in understanding how to best model PF as a contextual process over time in relation to other symptoms of psychopathology. Future research can continue to use idiographic methodology and wearable technologies to better understand the unique and interacting roles that physical, mental, and social health play in our overall functioning. These data are also promising for use in clinical settings as a way to potentially understand the specific flexible or inflexible behaviors that each client is walking in with, given that our data preliminarily show that different PF processes may relate differently to affect, stress, and moderator variables depending on the individual.

TABLES

Table 1 Sample demographic and diagnostic data

	Mean(SD)
Age	29.5 (11.9)
Gender(%, n)	
Male	20.5 (8)
Female	71.8 (28)
Non-binary	7.7 (3)
Race (%)	
White	79.5
Black or African American	2.6
Asian	10.3
More than one race	10.3
Not reported	2.5
Ethnicity (%)	
Non-Hispanic/Latinx	92.3
Hispanic/Latinx	5.1
Not reported	2.5
Primary Diagnosis (%, n)	
GAD	30.8 (12)
SAD	17.9 (7)
MDD or PDD	12.8 (5)
OCD	7.7 (3)
SPEC	7.7 (3)
OSAD	7.7 (3)
AG	5 (2)
PD	2.6 (1)
PTSD	2.6 (1)
BDD	2.6 (1)
ADHD	2.6 (1)

Note. GAD = Generalized Anxiety Disorder; SAD = Social Anxiety Disorder; MDD = Major Depressive Disorder; PDD = Persistent Depressive Disorder; OCD = Obsessive Compulsive Disorder; SPEC = Specific Phobia; OSAD = Other Specified Anxiety Disorder; AG = Agoraphobia; PD = Panic Disorder; PTSD = Post-Traumatic Stress Disorder; BDD = Body Dysmorphic Disorder; ADHD = Attention Deficit Hyperactivity Disorder

Table 2 Baseline scores for psychological processes

Baseline Questionnaire	Mean(SD)
STAI-Total	99(20.2)
BDI	16.2(10.2)
PANAS-PA	27(7.6)
PANAS-NA	24.5(7.2)
PSWQ	61.9(12.6)
AAQ	39.2(7.1)
RRS-Total	55(16)
ERQ-Reappraisal	23.5(6.5)
ERQ-Suppression	13.2(5.8)
CFI-Total	98.3(13.5)
ASQ	
Concealing	23(7.4)
Tolerating	15.6(4.2)
Adjusting	16.5(4.9)
FFMQ-Total (w/Observe)	45.1(7.5)
SWLS	20(8.1)

Note. FFMQ = Five Facet Mindfulness Questionnaire; PANAS = Positive and Negative Affect Scale; STAI = State-Trait Anxiety Inventory; BDI = Beck Depression Inventory; PSWQ = Penn State Worry Questionnaire; RRS = Ruminative Response Scale; ERQ = Emotion Regulation Questionnaire; AAQ-II = Acceptance and Action Questionnaire; CFI = Cognitive Flexibility Inventory; ASQ = Affective Styles Questionnaire; SWLS = Satisfaction With Life Scale

Table 3 Study measures and scheduling

Measure	Baseline Phase	EMA Phase	Endpoint
ADIS-5	X		
Emotional Stroop	X		
Task Switching	X		
FFMQ	X		X
PANAS	X		X
STAI	X		X
BDI	X		X
PSWQ	X		X
RRS	X		X
ERQ	X		X
AAQ-II	X		X
CFI	X		X
ASQ	X		X
SWLS	X		X
Stress Item		X	
Affect Items		X	
Event Categorical Items		X	
6 PBAT Items		X	
End of day rating		X	
Ethica app data (passive)		X	
Oura ring data (passive)		X	

Note. ADIS-5 = Anxiety Disorders Interview Schedule; FFMQ = Five Facet Mindfulness Questionnaire; PANAS = Positive and Negative Affect Scale; STAI = State-Trait Anxiety Inventory; BDI = Beck Depression Inventory; PSWQ = Penn State Worry Questionnaire; RRS = Ruminative Response Scale; ERQ = Emotion Regulation Questionnaire; AAQ-II = Acceptance and Action Questionnaire; CFI = Cognitive Flexibility Inventory; ASQ = Affective Styles Questionnaire; SWLS = Satisfaction With Life Scale; PBAT = Process Based Assessment Tool

Table 4 Means, standard deviations, and correlations with confidence intervals

Variable	*M*	*SD*	1	2	3	4	5	6
1. PF-stuck	42.77	27.94						
2. PF-nooutlet	36.95	26.69	.67**					
			[.64, .69]					
3. PF-noconnect	41.79	27.19	.68**	.63**				
			[.65, .71]	[.59, .66]				
4. PF-think	57.20	23.34	-.52**	-.49**	-.45**			
			[-.56, -.49]	[-.53, -.45]	[-.49, -.41]			
5. PF-environ	51.11	25.62	-.15**	-.16**	-.11**	.34**		
			[-.20, -.10]	[-.21, -.11]	[-.16, -.06]	[.29, .38]		
6. PF-yesconnect	57.86	27.38	-.41**	-.37**	-.40**	.40**	.26**	
			[-.45, -.37]	[-.42, -.33]	[-.44, -.36]	[.36, .44]	[.21, .31]	

Note. M and *SD* are used to represent mean and standard deviation, respectively. Each row represents an item from the PBAT. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

Table 5 Descriptive statistics for EMA items

vars	N	mean	sd	median	min	max	range
PA	2156	2.23	1.06	2	1	5	4
NA	2153	1.93	1.00	2	1	5	4
Stress	2149	3.75	2.53	3	0	10	10
PF-stuck	1495	42.77	27.94	40	0	100	100
PF-noout	1491	36.95	26.69	31	0	100	100
PF-noconnect	1491	41.79	27.19	41	0	100	100
PF-think	1492	57.20	23.34	60	0	100	100
PF-environ	1490	51.11	25.62	53	0	100	100
PF-yesconnect	1491	57.86	27.38	60	0	100	100
Day Quality	2225	66.31	21.22	69	0	100	100

Note. PA = Positive Affect; NA = Negative Affect; PF items pertain to items selected from the PBAT

Table 6 PF-PA contemporaneous model results

	PA			PA			PA			PA			PA			PA		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.09	-0.09 – 0.27	0.323	0.07	-0.12 – 0.26	0.456	0.06	-0.13 – 0.24	0.552	0.07	-0.11 – 0.26	0.451	0.1	-0.10 – 0.31	0.314	0.09	-0.09 – 0.28	0.334
day	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.00	**0.011**	-0.01	-0.02 – -0.00	**0.028**	-0.02	-0.03 – -0.00	**0.009**	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.01	**0.002**
PF-stuck	-0.28	-0.35 – -0.21	**<0.001**															
Trait stuck	-0.02	-0.03 – -0.01	**0.001**															
PF-noout				-0.23	-0.30 – -0.15	**<0.001**												
Trait noout				-0.01	-0.02 – -0.00	**0.005**												
PF-noconnect							-0.26	-0.32 – -0.19	**<0.001**									
Trait noconnect							-0.01	-0.02 – -0.00	**0.004**									
PF-think										0.22	0.15 – 0.29	**<0.001**						

Trait think										0.02	0.01 – 0.03	**0.002**						
PF-environ													0.17	0.11 – 0.23	**<0.001**			
Trait environ													0	-0.01 – 0.02	0.625			
PF-yesconnect																0.25	0.19 – 0.32	**<0.001**
Trait yesconnect																0.01	0.00 – 0.02	**0.019**
Random Effects																		
σ^2	0.56			0.61			0.6			0.61			0.65			0.6		
τ_{00}	0.25 $_{id}$			0.25 $_{id}$			0.25 $_{id}$			0.25 $_{id}$			0.31 $_{id}$			0.25 $_{id}$		
τ_{11}	0.03 $_{id.scale(stuck.state)}$			0.04 $_{id.scale(noout.state)}$			0.02 $_{id.scale(nocon.state)}$			0.03 $_{id.scale(think.state)}$			0.01 $_{id.scale(environ.state)}$			0.02 $_{id.scale(ycon.state)}$		
ρ_{01}	-0.61 $_{id}$			-0.64 $_{id}$			-0.50 $_{id}$			0.38 $_{id}$			0.42 $_{id}$			0.47 $_{id}$		
ICC	0.33			0.32			0.31			0.31			0.33			0.32		
N	39 $_{id}$			39 $_{id}$			39 $_{id}$			39 $_{id}$			39 $_{id}$			39 $_{id}$		
Observations	1495			1491			1491			1492			1490			1491		
Marginal R^2 / Conditional R^2	0.160 / 0.439			0.102 / 0.393			0.130 / 0.401			0.120 / 0.393			0.037 / 0.354			0.112 / 0.394		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. “PF-stuck” is the state score and “Trait stuck” is the trait score, for example. PA = Positive Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 7 PF-NA contemporaneous model results

	NA			NA			NA			NA			NA			NA		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	-0.04	-0.21 – 0.14	0.667	-0.02	-0.21 – 0.16	0.795	-0.03	-0.21 – 0.16	0.783	-0.04	-0.23 – 0.14	0.639	-0.07	-0.27 – 0.13	0.492	-0.06	-0.26 – 0.13	0.538
day	0.01	-0.00 – 0.02	0.214	0.01	-0.01 – 0.02	0.369	0.01	-0.01 – 0.02	0.373	0.01	-0.01 – 0.02	0.211	0.01	-0.00 – 0.03	0.097	0.01	-0.00 – 0.03	0.119
PF-stuck	0.34	0.28 – 0.41	**<0.001**															
Trait stuck	0.02	0.01 – 0.02	**<0.001**															
PF-noout				0.26	0.19 – 0.33	**<0.001**												
Trait noout				0.01	0.00 – 0.02	**0.047**												
PF-noconnect							0.27	0.20 – 0.33	**<0.001**									
Trait noconnect							0.01	0.00 – 0.02	**0.017**									
PF-think										-0.16	-0.22 – -0.09	**<0.001**						
Trait think										-0.01	-0.03 – -0.00	**0.009**						

PF-environ													-0.1	-0.17 – -0.04	**0.002**			
Trait environ													-0.01	-0.02 – 0.01	0.316			
PF-yesconnect																-0.19	-0.24 – -0.14	**<0.001**
Trait yesconnect																0	-0.01 – 0.00	0.306
Random Effects																		
σ^2		0.63			0.68			0.68			0.72			0.74			0.72	
τ_{00}		0.20 $_{id}$			0.22 $_{id}$			0.20 $_{id}$			0.21 $_{id}$			0.24 $_{id}$			0.24 $_{id}$	
τ_{11}		0.02 id.scale(stuck.state)			0.02 id.scale(noout.state)			0.02 id.scale(nocon.state)			0.02 id.scale(think.state)			0.02 id.scale(environ.state)			0.01 id.scale(ycon.state)	
ρ_{01}		0.74 $_{id}$			0.43 $_{id}$			0.25 $_{id}$			-0.75 $_{id}$			-0.54 $_{id}$			-0.73 $_{id}$	
ICC		0.26			0.26			0.25			0.24			0.26			0.26	
N		39 $_{id}$			39 $_{id}$			39 $_{id}$			39 $_{id}$			39 $_{id}$			39 $_{id}$	
Observations		1495			1491			1491			1492			1490			1491	
Marginal R^2 / Conditional R^2		0.189 / 0.400			0.091 / 0.327			0.109 / 0.330			0.060 / 0.289			0.020 / 0.277			0.044 / 0.289	

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. "PF-stuck" is the state score and "Trait stuck" is the trait score, for example. NA = Negative Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 8 PF-Stress contemporaneous model results

	Stress			Stress			Stress			Stress			Stress			Stress		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.12	-0.05 – 0.28	0.169	0.13	-0.04 – 0.30	0.124	0.14	-0.03 – 0.31	0.115	0.11	-0.08 – 0.30	0.257	0.09	-0.12 – 0.30	0.41	0.09	-0.12 – 0.30	0.385
day	-0.01	-0.02 – 0.00	0.054	-0.01	-0.03 – -0.00	**0.038**	-0.01	-0.03 – -0.00	**0.021**	-0.01	-0.02 – 0.00	0.16	-0.01	-0.02 – 0.01	0.309	-0.01	-0.02 – 0.01	0.258
PF-stuck	0.41	0.34 – 0.47	**<0.001**															
Trait stuck	0.03	0.02 – 0.03	**<0.001**															
PF-noout				0.33	0.27 – 0.38	**<0.001**												
Trait noout				0.02	0.01 – 0.03	**<0.001**												
PF-noconnect							0.3	0.25 – 0.36	**<0.001**									
Trait noconnect							0.02	0.01 – 0.03	**<0.001**									
PF-think										-0.19	-0.24 – -0.13	**<0.001**						

Trait think				-0.02	-0.04 – -0.01	**0.001**						
PF-environ							-0.13	-0.20 – -0.07	**<0.001**			
Trait environ							0	-0.01 – 0.01	0.86			
PF-yesconnect										-0.24	-0.29 – -0.19	**<0.001**
Trait yesconnect										-0.01	-0.02 – -0.00	**0.036**
Random Effects												
σ^2	0.5	0.57	0.58		0.65			0.68			0.63	
τ_{00}	0.19 id	0.18 id	0.20 id		0.23 id			0.32 id			0.33 id	
τ_{11}	0.03 id.scale(stuck.state)	0.01 id.scale(noout.state)	0.01 id.scale(nocon.state)		0.01 id.scale(think.state)			0.02 id.scale(environ.state)			0.01 id.scale(ycon.state)	
ρ_{01}	0.60 id	0.58 id	0.53 id		-0.47 id			-0.32 id			-0.72 id	
ICC	0.3	0.25	0.27		0.27			0.33			0.35	
N	39 id	39 id	39 id		39 id			39 id			39 id	
Observations	1495	1491	1491		1492			1490			1491	
Marginal R^2 / Conditional R^2	0.329 / 0.531	0.232 / 0.427	0.222 / 0.430		0.117 / 0.357			0.019 / 0.348			0.095 / 0.409	

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. "PF-stuck" is the state score and "Trait stuck" is the trait score, for example. Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 9 PF-PA antecedent models

	PA			PA			PA			PA			PA			PA		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.14	0.05 – 0.23	**0.003**	0.13	0.04 – 0.22	**0.006**	0.13	0.03 – 0.22	**0.007**	0.13	0.04 – 0.22	**0.006**	0.13	0.04 – 0.22	**0.005**	0.13	0.04 – 0.23	**0.005**
day	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.01	**0.001**
PA lag	0.19	0.13 – 0.25	**<0.001**	0.21	0.16 – 0.27	**<0.001**	0.22	0.16 – 0.28	**<0.001**	0.23	0.17 – 0.29	**<0.001**	0.23	0.17 – 0.28	**<0.001**	0.21	0.15 – 0.26	**<0.001**
PF-stuck lag	-0.07	-0.14 – 0.00	0.059															
Trait stuck	0.01	-0.04 – 0.06	0.677															
Trait PA	0.47	0.41 – 0.53	**<0.001**	0.45	0.39 – 0.52	**<0.001**	0.46	0.40 – 0.52	**<0.001**	0.45	0.39 – 0.51	**<0.001**	0.45	0.39 – 0.50	**<0.001**	0.46	0.40 – 0.52	**<0.001**
PF-noout lag				-0.03	-0.08 – 0.02	0.218												
Trait nooout				0	-0.06 – 0.05	0.874												
PF-noconnect lag							-0.02	-0.07 – 0.03	0.379									

Trait noconnect							0.01	-0.04 – 0.06	0.676									
PF-think lag										-0.02	-0.07 – 0.03	0.446						
Trait think										-0.01	-0.06 – 0.04	0.737						
PF-environ lag													0.02	-0.03 – 0.07	0.419			
Trait environ													0.01	-0.04 – 0.06	0.677			
PF-yesconnect lag																0.05	0.00 – 0.10	0.035
Trait yesconnect																0.01	-0.04 – 0.06	0.783
Random Effects																		
σ^2	0.6			0.63			0.63			0.62			0.62			0.62		
τ_{00}	0.00 id			0.00 id			0.00 id			0.00 id			0.00 id			0.00 id		
τ_{11}	0.02 id.scale(stuck.state.lag)			0.00 id.scale(noout.state.lag)			0.00 id.scale(nocon.state.lag)			0.00 id.scale(think.state.lag)			0.00 id.scale(environ.state.lag)			0.00 id.scale(ycon.state.lag)		
ρ_{01}	-0.17 id			0.01 id			0.00 id			0.14 id			0.08 id			-0.08 id		
ICC	0.03			0			0			0.01			0			0		
N	39 id			39 id			39 id			39 id			39 id			39 id		

Observations	1189	1187	1187	1187	1185	1186
Marginal R^2 / Conditional R^2	0.381 / 0.401	0.375 / 0.375	0.376 / 0.376	0.375 / 0.379	0.376 / 0.379	0.376 / 0.377

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1*. PA = Positive Affect; NA = Negative Affect Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 10 PF-PA consequence models

	PF-noout			PF-yesconnect		
Predictors	Estimates	CI	p	Estimates	CI	p
(Intercept)	-0.16	-0.31 – -0.02	**0.03**	0	-0.13 – 0.12	0.954
day	0.02	0.01 – 0.04	**0.01**	0	-0.01 – 0.02	0.959
PA lag	-0.07	-0.15 – 0.01	0.07	0.13	0.05 – 0.21	**0.001**
PF-noout lag	0.13	0.04 – 0.21	**<0.001**			
Trait noout	0.04	-0.04 – 0.12	0.29			
Trait PA	0.05	-0.04 – 0.14	0.28	-0.09	-0.17 – -0.00	**0.043**
PF-yesconnect lag				0.24	0.16 – 0.32	**<0.001**
Trait yesconnect				0.02	-0.05 – 0.09	0.607
Random Effects						
σ^2	0.94			0.91		
τ_{00}	0.00 id			0.00 id		
τ_{11}	0.02 id.scale(noout.state.lag)			0.01 id.scale(ycon.state.lag)		
ρ_{01}	0.72 id			0.00 id		
ICC	0.02			0.02		
N	39 id			39 id		
Observations	939			936		
Marginal R^2 / Conditional R^2	0.037 / 0.055			0.085 / 0.099		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. PA = Positive Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 11 PF-NA antecedent model results

	scale(na)		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.11	-0.22 – 0.00	0.054
day	0.01	0.00 – 0.03	**0.027**
nalag	0.23	0.17 – 0.28	**<0.001**
environ state lag	-0.07	-0.12 – -0.02	**0.011**
imean environ	0.02	-0.04 – 0.07	0.529
imean na	0.37	0.30 – 0.43	**<0.001**
Random Effects			
σ^2	0.70		
$\tau_{00\ id}$	0.00		
$\tau_{11\ id.scale(environ.state.lag)}$	0.00		
$\rho_{01\ id}$	-0.32		
ICC	0.00		
N_{id}	39		
Observations	1184		
Marginal R^2 / Conditional R^2	0.280 / 0.283		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent time *T*. environ state lag = PF-environ lag; nalag = Negative Affect lag; imean environ = Trait environ; imean na = Trait NA; NA = Negative Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 12 PF-NA consequence model results

	PF-stuck			**PF-noconnect**			**PF-environ**			**PF-yesconnect**		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	-0.18	-0.31 – -0.05	**0.005**	-0.19	-0.31 – -0.06	**0.004**	0	-0.14 – 0.13	0.944	0.02	-0.11 – 0.14	0.795
day	0.02	0.01 – 0.04	**0.002**	0.03	0.01 – 0.04	**0.001**	0	-0.02 – 0.02	0.932	0	-0.02 – 0.01	0.751
NA lag	0.12	0.04 – 0.19	**0.002**	0.13	0.05 – 0.20	**0.001**	0.08	0.01 – 0.15	**0.029**	-0.09	-0.17 – -0.02	**0.011**
PF-stuck lag	0.21	0.10 – 0.31	**<0.001**									
Trait stuck	0.02	-0.05 – 0.09	0.576									
Trait NA	-0.07	-0.15 – 0.01	0.082	-0.07	-0.15 – 0.01	0.079	-0.01	-0.09 – 0.06	0.748	0.06	-0.01 – 0.13	0.102
PF-noconnect lag				0.19	0.10 – 0.27	**<0.001**						
Trait noconnect				0.02	-0.05 – 0.09	0.519						
PF-environ lag							0.15	0.06 – 0.23	**<0.001**			
Trait environ							0.01	-0.05 – 0.08	0.677			
PF-yesconnect lag										0.25	0.18 – 0.33	**<0.001**

Trait yesconnect										0.02	-0.04 – 0.08	0.536
Random Effects												
σ^2	0.85			0.91			0.95			0.91		
τ_{00}	0.00 $_{id}$			0.00 $_{id}$			0.00 $_{id}$			0.00 $_{id}$		
τ_{11}	0.05 $_{id.scale(stuck.state.lag)}$			0.02 $_{id.scale(nocon.state.lag)}$			0.02 $_{id.scale(environ.state.lag)}$			0.01 $_{id.scale(ycon.state.lag)}$		
ρ_{01}	0.36 $_{id}$			0.94 $_{id}$			0.40 $_{id}$			-0.07 $_{id}$		
ICC	0.06			0.02			0.02			0.02		
N	39 $_{id}$			39 $_{id}$			39 $_{id}$			39 $_{id}$		
Observations	942			940			936			936		
Marginal R^2 / Conditional R^2	0.087 / 0.140			0.079 / 0.098			0.026 / 0.041			0.082 / 0.096		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. NA = Negative Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 13 PF-Stress antecedent model results

	Stress			Stress		
Predictors	Est.	CI	p	Est.	CI	p
(Intercept)	0	-0.10 – 0.09	0.952	0	-0.10 – 0.10	0.992
day	0	-0.01 – 0.01	0.962	0	-0.01 – 0.01	0.975
Stress lag	0.3	0.25 – 0.35	**<0.001**	0.29	0.24 – 0.35	**<0.001**
PF-environ lag	-0.06	-0.11 – -0.02	**0.009**			
Trait environ	0.01	-0.04 – 0.06	0.598			
Trait stress	0.4	0.34 – 0.46	**<0.001**	0.4	0.34 – 0.46	**<0.001**
PF-yesconnect lag				-0.06	-0.11 – -0.02	**0.009**
Trait yesconnect				-0.04	-0.09 – 0.00	0.074
Random Effects						
σ^2	0.6			0.59		
τ_{00}	0.00 id			0.00 id		
τ_{11}	0.00 id.scale(environ.state.lag)			0.00 id.scale(ycon.state.lag)		
ρ_{01}	0.02 id			0.02 id		
ICC	0			0		
N	39 id			39 id		
Observations	1182			1182		
Marginal R^2 / Conditional R^2	0.394 / 0.395			0.397 / 0.397		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 14 PF-stress consequence model results

	PF-stuck			PF-noconnect			PF-yesconnect		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	-0.2	-0.32 – -0.07	**0.003**	-0.21	-0.34 – -0.08	**0.001**	0.02	-0.10 – 0.15	0.706
day	0.03	0.01 – 0.04	**0.001**	0.03	0.01 – 0.04	**<0.001**	0	-0.02 – 0.01	0.652
Stress lag	0.18	0.10 – 0.26	**<0.001**	0.21	0.14 – 0.29	**<0.001**	-0.13	-0.20 – -0.05	**0.001**
PF-stuck lag	0.16	0.05 – 0.27	**0.003**						
Trait stuck	0.01	-0.08 – 0.09	0.858						
Trait stress	-0.09	-0.18 – 0.01	0.068	-0.13	-0.22 – -0.04	**0.008**	0.07	-0.00 – 0.15	0.056
PF-noconnect lag				0.14	0.06 – 0.22	**0.001**			
Trait noconnect				0.03	-0.05 – 0.11	0.49			
PF-yesconnect lag							0.24	0.16 – 0.33	**<0.001**
Trait yesconnect							0.02	-0.04 – 0.08	0.505
Random Effects									
σ^2		0.84			0.89			0.91	
τ_{00}		0.00 $_{\text{id}}$			0.00 $_{\text{id}}$			0.00 $_{\text{id}}$	
τ_{11}		0.05 $_{\text{id.scale(stuck.state.lag)}}$			0.01 $_{\text{id.scale(nocon.state.lag)}}$			0.01 $_{\text{id.scale(ycon.state.lag)}}$	
ρ_{01}		0.38 $_{\text{id}}$			0.92 $_{\text{id}}$			0.02 $_{\text{id}}$	
ICC		0.06			0.02			0.02	
N		39 $_{\text{id}}$			39 $_{\text{id}}$			39 $_{\text{id}}$	
Observations		942			940			936	
Marginal R^2 / Conditional R^2		0.092 / 0.144			0.091 / 0.108			0.087 / 0.102	

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. PA = Positive Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 15 Context as a moderator in PF-PA contemporaneous models

	Value	Std.Error	p-value
Goal/Value Context	0.358	0.051	**0**
PF-stuck	-0.2	0.038	**0**
Trait stuck	-0.013	0.004	**0.003**
Goal/Value Context*PF-stuck	-0.029	0.045	0.521
Goal/Value Context	0.444	0.063	**0**
PF-noout	-0.137	0.038	**0**
Trait noout	-0.01	0.004	**0.02**
Goal/Value Context*PF-noout	-0.041	0.044	0.353
Goal/Value Context	0.457	0.065	**0**
PF-noconnect	-0.198	0.035	**0**
Trait noconnect	-0.01	0.004	**0.013**
Goal/Value Context*PF-noconnect	0.011	0.044	0.796
Goal/Value Context	0.458	0.063	**0**
PF-think	0.146	0.033	**0**
Trait think	0.016	0.006	**0.008**
Goal/Value Context*PF-think	0.042	0.042	0.322
Goal/Value Context	0.53	0.068	**0**
PF-environ	0.105	0.03	**0**
Trait environ	0.002	0.005	0.708
Goal/Value Context*PF-environ	0.031	0.041	0.452
Goal/Value Context	0.478	0.066	**0**
PF-yesconnect	0.199	0.035	**0**
Trait yesconnect	0.011	0.004	**0.017**
Goal/Value Context*PF-yesconnect	-0.002	0.042	0.969

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Goal/Value Context = participants were thinking about or acting on a value or goal when prompted; * indicates interaction term; PA = Positive Affect. All scores are standardized for interpretability.

Table 16 Context as a moderator in PF-NA contemporaneous models

Item	Value	Std.Error	p-value
Goal/Value Context	-0.193	0.052	**0**
PF-stuck	0.31	0.039	**0**
Trait stuck	0.015	0.004	**0.001**
Goal/Value Context*PF-stuck	-0.006	0.046	0.896
Goal/Value Context	-0.329	0.065	**0**
PF-noout	0.228	0.038	**0**
Trait noout	0.008	0.005	0.11
Goal/Value Context*PF-noout	-0.047	0.046	0.306
Goal/Value Context	-0.341	0.064	**0**
PF-noconnect	0.284	0.033	**0**
Trait noconnect	0.009	0.004	0.046
Goal/Value Context*PF-noconnect	-0.144	0.043	**0.001**
Goal/Value Context	-0.375	0.07	**0**
PF-think	-0.16	0.038	**0**
Trait think	-0.012	0.005	0.026
Goal/Value Context*PF-think	0.08	0.045	0.074
Goal/Value Context	-0.438	0.075	**0**
PF-environ	-0.085	0.037	**0.022**
Trait environ	-0.004	0.005	0.43
Goal/Value Context*PF-environ	0.025	0.044	0.562
Goal/Value Context	-0.402	0.067	**0**
PF-yesconnect	-0.167	0.03	**0**
Trait yesconnect	-0.002	0.005	0.664
Goal/Value Context*PF-yesconnect	0.053	0.043	0.222

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Goal/Value Context = participants were thinking about or acting on a value or goal when prompted; * indicates interaction term; NA = Negative Affect. All scores are standardized for interpretability.

Table 17 Context as a moderator in PF models predicting day quality

	Value	Std.Error	p-value
Goal/Value Context	0.125	0.032	**0**
PF-environ	-0.016	0.023	0.497
Trait environ	0.004	0.006	0.546
Goal/Value Context*PF-eviron	0.072	0.028	**0.01**
Goal/Value Context	0.133	0.033	**0**
PF-yesconnect	-0.008	0.029	0.796
Trait yesconnect	0.025	0.004	**0**
Goal/Value Context*PF-yesconnect	0.09	0.028	**0.002**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Goal/Value Context = participants were thinking about or acting on a value or goal when prompted; * indicates interaction term. All scores are standardized for interpretability.

Table 18 Type of event as a moderator in PF models predicting day quality

	Value	Std.Error	p-value
PF-stuck	-0.1	0.029	0.001
Trait stuck	-0.028	0.004	0
Romantic event*PF-stuck	-0.136	0.057	**0.018**
Other event*PF-stuck	0.186	0.064	**0.004**
PF-noout	-0.077	0.026	0.003
Trait noout	-0.028	0.005	0
Other event*PF-noout	0.157	0.052	**0.003**
PF-noconnect	-0.087	0.032	0.007
Trait no connect	-0.023	0.004	0
Other event*PF-noconnect	0.151	0.053	**0.005**
PF-yesconnect	0.005	0.032	0.881
Trait yes-connect	0.027	0.004	0
Romantic event*PF-yesconnect	0.138	0.053	**0.009**
Friendship event*PF-yesconnect	0.131	0.052	**0.012**
Health event*PF-yesconnect	0.104	0.043	**0.017**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Event Type = participants were engaging in an activity related to that type of event; * indicates interaction term; PA = Positive Affect. All scores are standardized for interpretability.

Table 19 Type as a moderator in PF-NA contemporaneous models

	Value	Std.Error	p-value
Daily Hassles	-0.249	0.072	**0.001**
PF-stuck	0.336	0.043	**0**
Trait stuck	0.016	0.004	**0**
Daily Hassles	-0.269	0.073	**0**
PF-noout	0.268	0.045	**0**
Trait noout	0.01	0.005	0.046
Daily Hassles*PF-noout	-0.166	0.072	**0.02**
Daily Hassles	-0.241	0.073	**0.001**
PF-noconnect	0.219	0.042	**0**
Trait noconnect	0.01	0.004	**0.023**
Family Event*PF-noconnect	0.313	0.086	**0**
Other Event*PF-noconnect	0.198	0.085	**0.02**
Daily Hassles	-0.268	0.075	**0**
PF-think	-0.182	0.043	**0**
Trait think	-0.015	0.005	**0.01**
Daily Hassles	-0.246	0.076	**0.001**
PF-environ	-0.11	0.042	**0.009**
Trait environ	-0.006	0.006	0.301
Daily Hassles	-0.274	0.075	**0**
PF-yesconnect	-0.157	0.039	**0**
Trait yesconnect	-0.005	0.005	0.314
Friendship Event*PF-yesconnect	-0.186	0.081	**0.021**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Event Type = participants were engaging in an activity related to that type of event; * indicates interaction term; NA = Negative Affect. All scores are standardized for interpretability.

Table 20 Type as a moderator in PF-Stress contemporaneous models

	Value	Std.Error	p-value
Friendship Event	-0.216	0.077	**0.005**
Family Event	-0.201	0.074	**0.006**
Daily Hassles	-0.218	0.065	**0.001**
PF-stuck	0.391	0.042	**0**
Trait stuck	0.026	0.004	**0**
Romantic Event*PF-stuck	0.196	0.077	**0.011**
Romantic Event	-0.211	0.09	**0.02**
PF-noout	0.295	0.037	**0**
Trait noout	0.022	0.004	**0**
Romantic Event*PF-noout	0.262	0.076	**0.001**
Romantic Event	-0.21	0.091	**0.02**
Daily Hassles	-0.204	0.068	**0.003**
PF-noconnect	0.219	0.036	**0**
Trait noconnect	0.019	0.004	**0**
Romantic Event*PF-noconnect	0.298	0.077	**0**
Romantic Event	-0.246	0.098	**0.012**
Friendship Event	-0.197	0.083	**0.018**
Daily Hassles	-0.258	0.07	**0**
PF-think	-0.219	0.038	**0**
Trait think	-0.023	0.006	**0.001**
Daily Hassles	-0.22	0.072	**0.002**
PF-environ	-0.111	0.04	**0.006**
Trait environ	-0.001	0.007	0.887
Daily Hassles	-0.249	0.07	**0**
PF-yesconnect	-0.188	0.037	**0**
Trait yesconnect	-0.011	0.005	0.047
Romantic Event*PF-yesconnect	-0.23	0.076	**0.003**
Friendship Event*PF-yesconnect	-0.203	0.075	**0.007**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Event Type = participants were engaging in an activity related to that type of event; * indicates interaction term. All scores are standardized for interpretability.

Table 21 Significant PF-PA antecedent model results with FFMQ as moderator

	PA			PA		
Predictors	Est.	CI	p	Est.	CI	p
(Intercept)	0.13	0.04 – 0.23	**0.005**	0.14	0.04 – 0.23	**0.005**
day	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.002**
PA lag	0.23	0.17 – 0.28	**<0.001**	0.21	0.15 – 0.27	**<0.001**
PF-environ lag	0.02	-0.03 – 0.06	0.492			
FFMQ	-0.02	-0.07 – 0.03	0.476	-0.01	-0.07 – 0.04	0.611
Trait environ	0.02	-0.03 – 0.07	0.496			
Trait pa	0.45	0.39 – 0.51	**<0.001**	0.46	0.40 – 0.52	**<0.001**
PF-environ lag * FFMQ	-0.06	-0.10 – -0.02	**0.005**			
PF-yesconnect lag				0.04	-0.02 – 0.09	0.17
Trait yesconnect				0.01	-0.05 – 0.07	0.755
PF-yesconnect lag * FFMQ				-0.06	-0.11 – -0.01	**0.013**
Random Effects						
σ^2		0.62			0.62	
τ_{00}		0.00 id			0.00 id	
τ_{11}		0.00 id.scale(environ.state.lag)			0.00 id.scale(ycon.state.lag)	
ρ_{01}		0.00 id			-0.01 id	
ICC		0			0	
N		37 id			37 id	
Observations		1138			1137	
Marginal R^2 / Conditional R^2		0.381 / 0.381			0.380 / 0.380	

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. PA = Positive Affect; FFMQ = Five Facet Mindfulness Questionnaire; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 22 Significant PF-Stress model results with ERQ scores as moderators

	Stress			Stress			Stress		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.11	-0.05 – 0.28	0.18	0.14	-0.04 – 0.31	0.127	0.09	-0.12 – 0.30	0.396
day	-0.01	-0.02 – 0.00	0.065	-0.01	-0.03 – -0.00	**0.026**	-0.01	-0.02 – 0.01	0.279
ERQ-R	0.09	-0.06 – 0.24	0.233	0.03	-0.12 – 0.19	0.682	0.02	-0.20 – 0.24	0.866
PF-stuck	0.41	0.35 – 0.47	**<0.001**						
Trait stuck	0.03	0.02 – 0.03	**<0.001**						
ERQ-R * PF-stuck	0.1	0.05 – 0.16	**<0.001**						
PF-noconnect				0.3	0.25 – 0.36	**<0.001**			
Trait noconnect				0.02	0.01 – 0.03	**<0.001**			
ERQ-R * PF-noconnect				0.06	0.01 – 0.11	**0.021**			
PF-yesconnect							-0.24	-0.28 – -0.20	**<0.001**
Trait yesconnect							-0.01	-0.02 – 0.01	0.349
ERQ-R * PF-yesconnect							-0.06	-0.09 – -0.02	**0.003**

	Random Effects		
σ^2	0.5	0.58	0.63
τ_{00}	0.19 $_{\text{id}}$	0.20 $_{\text{id}}$	0.33 $_{\text{id}}$
τ_{11}	0.02 $_{\text{id.scale(stuck.state)}}$	0.01 $_{\text{id.scale(nocon.state)}}$	0.00 $_{\text{id.scale(ycon.state)}}$
ρ_{01}	0.65 $_{\text{id}}$	0.60 $_{\text{id}}$	-0.01 $_{\text{id}}$
ICC	0.29	0.27	0.34
N	39 $_{\text{id}}$	39 $_{\text{id}}$	39 $_{\text{id}}$
Observations	1495	1491	1491
Marginal R^2 / Conditional R^2	0.342 / 0.532	0.226 / 0.436	0.071 / 0.388

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. ERQ-R = Emotion Regulation Questionnaire-Reappraisal subscale; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 23 Significant PF-NA model results with AAQ score as a moderator

	scale(na)			scale(na)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.06	-0.25 – 0.12	0.492	-0.06	-0.24 – 0.13	0.552
day	0.01	-0.00 – 0.03	0.097	0.01	-0.00 – 0.03	0.120
aaq	0.22	0.07 – 0.38	**0.006**	0.21	0.05 – 0.37	**0.010**
environ state	-0.10	-0.15 – -0.06	**<0.001**			
imean environ c	-0.00	-0.01 – 0.01	0.958			
aaq * environ state	-0.07	-0.11 – -0.02	**0.003**			
ycon state				-0.20	-0.25 – -0.14	**<0.001**
imean ycon c				-0.00	-0.01 – 0.01	0.598
aaq * ycon state				0.02	-0.04 – 0.08	0.538
Random Effects						
σ^2	0.76			0.72		
τ_{00}	0.19 $_{id}$			0.20 $_{id}$		
τ_{11}	0.00 $_{id.scale(environ.state)}$			0.01 $_{id.scale(ycon.state)}$		
ρ_{01}	-0.02 $_{id}$			-0.71 $_{id}$		
ICC	0.20			0.22		
N	39 $_{id}$			39 $_{id}$		
Observations	1490			1491		
Marginal R^2 / Conditional R^2	0.069 / 0.257			0.088 / 0.289		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. NA and scale(na) = Negative Affect; AAQ = Acceptance and Action Questionnaire; * denotes interaction term; environ state = PF-environ; ycon state = PF-yesconnect; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 24 Significant PF-Stress model results with AAQ score as a moderator

	scale(stress)			scale(stress)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.12	-0.07 – 0.31	0.205	-0.00	-0.10 – 0.09	0.922
day	-0.01	-0.03 – 0.00	0.115	0.00	-0.01 – 0.01	0.927
aaq	0.10	-0.08 – 0.27	0.281	-0.01	-0.06 – 0.04	0.752
think state	-0.19	-0.24 – -0.14	**<0.001**			
imean think c	-0.02	-0.04 – -0.01	**0.003**			
aaq * think state	-0.09	-0.14 – -0.05	**<0.001**			
stresslag				0.30	0.24 – 0.35	**<0.001**
ycon state lag				-0.07	-0.12 – -0.03	**0.003**
imean ycon				-0.04	-0.09 – 0.00	0.072
imean stress				0.40	0.34 – 0.46	**<0.001**
ycon state lag * aaq				0.05	0.01 – 0.10	**0.024**
Random Effects						
σ^2	0.65			0.59		
τ_{00}	0.23_{id}			0.00_{id}		
τ_{11}	$0.01_{\text{id.scale(think.state)}}$			$0.00_{\text{id.scale(ycon.state.lag)}}$		
ρ_{01}	-0.40_{id}			0.00_{id}		
ICC	0.26			0.00		
N	39_{id}			39_{id}		
Observations	1492			1182		
Marginal R^2 / Conditional R^2	0.145 / 0.371			0.401 / 0.401		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. scale(stress) = Stress; AAQ = Acceptance and Action Questionnaire; * denotes interaction term; think state = PF-think; ycon state = PF-yesconnect; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 25 Significant PF model results with CFI score as a moderator

	scale(na)			scale(stress)			scale(stress)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.06	-0.25 – 0.12	0.507	0.06	-0.14 – 0.26	0.577	0.05	-0.16 – 0.25	0.653
day	0.01	-0.00 – 0.03	0.079	-0.01	-0.02 – 0.01	0.257	-0.01	-0.02 – 0.01	0.353
cfitotal	0.05	-0.12 – 0.23	0.554	-0.23	-0.41 – -0.05	**0.015**	-0.25	-0.43 – -0.07	**0.007**
stuck state	0.36	0.30 – 0.42	**<0.001**						
imean stuck c	0.01	0.00 – 0.02	**0.005**						
cfitotal * stuck state	0.08	0.03 – 0.13	**0.003**						
ycon state				-0.27	-0.31 – -0.22	**<0.001**			
imean ycon c				-0.00	-0.01 – 0.01	0.726			
cfitotal * ycon state				-0.03	-0.07 – 0.00	0.087			
environ state							-0.14	-0.21 – -0.07	**<0.001**
imean environ c							0.00	-0.01 – 0.01	0.780
cfitotal * environ state							-0.01	-0.08 – 0.05	0.706
Random Effects									
σ^2	0.62			0.68			0.73		
τ_{00}	0.21 $_{id}$			0.24 $_{id}$			0.23 $_{id}$		
τ_{11}	0.01 $_{id.scale(stuck.state)}$			0.00 $_{id.scale(ycon.state)}$			0.02 $_{id.scale(environ.state)}$		
ρ_{01}	0.91 $_{id}$			-0.00 $_{id}$			-0.38 $_{id}$		
ICC	0.26			0.26			0.25		
N	36 $_{id}$			36 $_{id}$			36 $_{id}$		
Observations	1374			1372			1370		
Marginal R^2 / Conditional R^2	0.180 / 0.397			0.124 / 0.350			0.075 / 0.311		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. scale(stress) = Stress; cfitotal= Cognitive Flexibility Inventory total score; * denotes interaction term; stuck state = PF-stuck; ycon state = PF-yesconnect; environ state = PF-environ; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 26 Significant PF model results with Switching Cost as a moderator

	scale(pa)			scale(pa)			scale(pa)			scale(stress)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.09	-0.09 – 0.27	0.330	0.07	-0.12 – 0.26	0.472	0.05	-0.13 – 0.24	0.570	0.13	-0.04 – 0.30	0.130
day	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.00	**0.010**	-0.01	-0.02 – -0.00	**0.027**	-0.01	-0.03 – -0.00	**0.034**
SwitchingCost	0.09	-0.09 – 0.28	0.297	0.04	-0.15 – 0.22	0.696	0.05	-0.13 – 0.23	0.576	0.07	-0.08 – 0.23	0.350
stuck state	-0.28	-0.34 – -0.21	**<0.001**									
imean stuck c	-0.02	-0.03 – -0.01	**0.001**									
SwitchingCost * stuck state	-0.10	-0.17 – -0.03	**0.004**									
noout state				-0.23	-0.30 – -0.15	**<0.001**				0.33	0.28 – 0.38	**<0.001**
imean noout c				-0.01	-0.02 – -0.00	**0.012**				0.02	0.01 – 0.03	**<0.001**
SwitchingCost * noout state				-0.09	-0.17 – -0.02	**0.016**				0.07	0.02 – 0.12	**0.003**
nocon state							-0.25	-0.31 – -0.20	**<0.001**			
imean nocon c							-0.01	-0.02 – -0.00	**0.008**			
SwitchingCost * nocon state							-0.09	-0.14 – -0.03	**0.004**			
Random Effects												
σ^2	0.56			0.61			0.60			0.57		
τ_{00}	0.24 $_{\text{id}}$			0.26 $_{\text{id}}$			0.26 $_{\text{id}}$			0.18 $_{\text{id}}$		
τ_{11}	0.02 $_{\text{id.scale(stuck.state)}}$			0.03 $_{\text{id.scale(noout.state)}}$			0.01 $_{\text{id.scale(nocon.state)}}$			0.01 $_{\text{id.scale(noout.state)}}$		
ρ_{01}	-0.61 $_{\text{id}}$			-0.70 $_{\text{id}}$			-0.57 $_{\text{id}}$			0.56 $_{\text{id}}$		
ICC	0.32			0.33			0.31			0.25		
N	39 $_{\text{id}}$			39 $_{\text{id}}$			39 $_{\text{id}}$			39 $_{\text{id}}$		
Observations	1495			1491			1491			1491		
Marginal R^2 / Conditional R^2	0.161 / 0.433			0.099 / 0.392			0.127 / 0.397			0.248 / 0.436		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. scale(stress) = Stress; scale(pa) = Positive Affect; SwitchingCost = score on Asymmetric Task Switching paradigm; * denotes interaction term; stuck state = PF-stuck; nocon state = PF-noconnect; noout state = PF-noout; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 27 Significant PF model results with step count as a moderator

	scale(pa)			scale(na)			scale(na)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.05	-0.14 – 0.24	0.635	-0.07	-0.25 – 0.12	0.475	-0.06	-0.26 – 0.13	0.533
day	-0.01	-0.02 – 0.01	0.276	0.01	-0.00 – 0.03	0.096	0.01	-0.00 – 0.03	0.091
osteps	0.06	-0.01 – 0.13	0.113	0.00	-0.07 – 0.08	0.927	-0.01	-0.08 – 0.06	0.766
nocon state	-0.26	-0.33 – -0.19	**<0.001**						
imean nocon c	-0.02	-0.03 – -0.01	**0.001**						
osteps * nocon state	-0.05	-0.10 – -0.01	**0.024**						
stuck state				0.34	0.27 – 0.41	**<0.001**			
imean stuck c				0.02	0.01 – 0.02	**<0.001**			
osteps * stuck state				0.06	0.01 – 0.10	**0.014**			
ycon state							-0.18	-0.24 – -0.12	**<0.001**
imean ycon c							-0.01	-0.01 – 0.00	0.229
osteps * ycon state							-0.06	-0.11 – -0.01	**0.009**
Random Effects									
σ^2	0.57			0.63			0.73		
τ_{00}	0.24 $_{id}$			0.19 $_{id}$			0.22 $_{id}$		
τ_{11}	0.02 $_{id.scale(nocon.state)}$			0.03 $_{id.scale(stuck.state)}$			0.01 $_{id.scale(ycon.state)}$		
	0.02 $_{id.scale(osteps)}$			0.01 $_{id.scale(osteps)}$			0.01 $_{id.scale(osteps)}$		
ρ_{01}	-0.58			0.86			-0.71		
	0.23			0.49			0.50		
ICC	0.33			0.27			0.24		
N	37 $_{id}$			37 $_{id}$			37 $_{id}$		
Observations	1350			1352			1347		
Marginal R^2 / Conditional R^2	0.164 / 0.441			0.188 / 0.405			0.049 / 0.282		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. scale(na) = Negative Affect; scale(pa) = Positive Affect; osteps = Step Count from Oura Ring; * denotes interaction term; stuck state = PF-stuck; nocon state = PF-noconnect; ycon state = PF-yesconnect; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 28 Significant PF-PA model results with HRV as a moderator

	PA			PA			PA			PA		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.16	-0.04 – 0.36	0.118	0.12	-0.09 – 0.32	0.262	0.13	-0.07 – 0.33	0.213	0.16	-0.07 – 0.38	0.173
day	-0.02	-0.03 – -0.01	**0.004**	-0.01	-0.03 – -0.00	**0.028**	-0.01	-0.03 – -0.00	**0.038**	-0.02	-0.03 – -0.01	**0.004**
HRV	-0.03	-0.15 – 0.08	0.602	-0.07	-0.18 – 0.05	0.248	-0.05	-0.16 – 0.05	0.335	-0.07	-0.20 – 0.06	0.32
PF-stuck	-0.29	-0.35 – -0.23	**<0.001**									
Trait stuck	-0.02	-0.03 – -0.01	**<0.001**									
HRV * PF-stuck	-0.1	-0.15 – -0.04	**0.001**									
PF-noout				-0.24	-0.31 – -0.17	**<0.001**						
Trait noout				-0.01	-0.02 – -0.00	**0.007**						
HRV * PF-noout				-0.07	-0.14 – -0.01	**0.024**						
PF-think							0.24	0.18 – 0.30	**<0.001**			
Trait think							0.03	0.01 – 0.04	**<0.001**			

HRV * PF-think							0.07	0.01 – 0.13	**0.016**			
PF-environ										0.19	0.13 – 0.25	**<0.001**
Trait environ										0	-0.01 – 0.02	0.857
HRV * PF-environ										0.07	0.01 – 0.13	**0.017**
Random Effects												
σ^2		0.54			0.58			0.58			0.61	
τ_{00}		0.26 id			0.27 id			0.28 id			0.35 id	
τ_{11}		0.02 id.scale(stuck.state)			0.03 id.scale(noout.state)			0.01 id.scale(think.state)			0.01 id.scale(environ.state)	
		0.04 id.scale(HRV)			0.03 id.scale(HRV)			0.03 id.scale(HRV)			0.05 id.scale(HRV)	
ρ_{01}		-0.78			-0.75			0.41			0.37	
		-0.47			-0.5			-0.84			-0.31	
ICC		0.37			0.36			0.36			0.4	
N		37 id			37 id			37 id			37 id	
Observations		1324			1322			1322			1321	
Marginal R^2 / Conditional R^2		0.195 / 0.495			0.127 / 0.441			0.180 / 0.474			0.044 / 0.430	

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. PA = Positive Affect; HRV = Heart-rate variability; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 29 Significant PF-Stress model results with HRV as a moderator

	Stress			Stress			Stress			Stress			Stress		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.17	0.00 – 0.35	**0.045**	0.18	0.00 – 0.36	**0.046**	0.17	-0.02 – 0.36	0.086	0.14	-0.06 – 0.35	0.175	0.14	-0.06 – 0.35	0.173
day	-0.02	-0.03 – -0.00	**0.017**	-0.02	-0.03 – -0.01	**0.005**	-0.01	-0.03 – 0.00	0.06	-0.01	-0.03 – 0.01	0.193	-0.01	-0.02 – 0.00	0.189
HRV	0.14	0.05 – 0.24	**0.002**	0.15	0.06 – 0.25	**0.001**	0.13	0.03 – 0.23	**0.009**	0.16	0.05 – 0.26	**0.003**	0.14	0.04 – 0.25	**0.009**
PF-noout	0.35	0.29 – 0.41	**<0.001**												
Trait noout	0.02	0.01 – 0.03	**<0.001**												
PF-noconnect				0.31	0.26 – 0.37	**<0.001**									
Trait noconnect				0.02	0.01 – 0.03	**0.001**									
PF-think							-0.23	-0.28 – -0.17	**<0.001**						
Trait think							-0.02	-0.03 – -0.01	**0.006**						
HRV * PF-think							-0.01	-0.06 – 0.05	0.795						
PF-environ										-0.14	-0.20 – -0.08	**<0.001**			
Trait environ										0	-0.01 – 0.01	0.94			

HRV * PF-environ										-0.02	-0.08 – 0.04	0.478			
PF-yesconnect													-0.24	-0.30 – -0.18	**<0.001**
Trait yesconnect													0	-0.01 – 0.01	0.593
HRV * PF-yesconnect													-0.04	-0.09 – 0.02	0.187
Random Effects															
σ^2	0.56			0.57			0.65			0.68			0.63		
τ_{00}	0.16 id			0.18 id			0.20 id			0.26 id			0.25 id		
τ_{11}	0.02 id.scale(noout.state)			0.01 id.scale(nocon.state)			0.01 id.scale(think.state)			0.02 id.scale(environ.state)			0.01 id.scale(ycon.state)		
	0.01 id.scale(HRV)			0.01 id.scale(HRV)			0.01 id.scale(HRV)			0.01 id.scale(HRV)			0.02 id.scale(HRV)		
ρ_{01}	0.48			0.37			-0.62			-0.25			-0.43		
	-0.65			-0.66			-0.74			-0.79			-0.66		
ICC	0.25			0.26			0.25			0.29			0.31		
N	37 id			37 id			37 id			37 id			37 id		
Observations	1322			1322			1322			1321			1320		
Marginal R^2 / Conditional R^2	0.249 / 0.433			0.223 / 0.429			0.138 / 0.356			0.047 / 0.327			0.087 / 0.373		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. PA = Positive Affect; HRV = Heart-rate variability; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 30 Significant PF-Stress consequence model results with HRV as a moderator

	scale(stress)			scale(stress)			scale(stress)			scale(stress)			scale(stress)			scale(stress)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.04	-0.07 – 0.14	0.521	0.03	-0.08 – 0.13	0.630	0.04	-0.07 – 0.15	0.448	0.02	-0.08 – 0.13	0.655	0.02	-0.08 – 0.13	0.660	0.02	-0.08 – 0.13	0.662
day	-0.00	-0.02 – 0.01	0.498	-0.00	-0.02 – 0.01	0.573	-0.01	-0.02 – 0.01	0.331	-0.00	-0.02 – 0.01	0.592	-0.00	-0.02 – 0.01	0.612	-0.00	-0.02 – 0.01	0.588
stresslag	0.28	0.22 – 0.35	**<0.001**	0.31	0.25 – 0.38	**<0.001**	0.31	0.25 – 0.37	**<0.001**	0.31	0.25 – 0.36	**<0.001**	0.30	0.24 – 0.35	**<0.001**	0.30	0.24 – 0.35	**<0.001**
stuck state lag	0.04	-0.02 – 0.11	0.196															
HRV	0.08	0.02 – 0.14	**0.010**	0.07	0.02 – 0.12	**0.010**	0.07	0.01 – 0.13	**0.020**	0.06	0.01 – 0.12	**0.018**	0.07	0.02 – 0.13	**0.012**	0.07	0.01 – 0.12	**0.017**
imean stuck	0.03	-0.04 – 0.09	0.423															
imean stress	0.36	0.29 – 0.44	**<0.001**	0.33	0.26 – 0.41	**<0.001**	0.34	0.26 – 0.41	**<0.001**	0.35	0.29 – 0.42	**<0.001**	0.37	0.31 – 0.43	**<0.001**	0.37	0.31 – 0.43	**<0.001**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. Each column pertains to each of the 6 PBAT items measuring PF. scale(stress) = Stress; HRV = Heart-rate variability; imean = Trait values; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability

Table 31 Significant PF-NA consequence model results with HRV as a moderator

	scale(na)			scale(na)			scale(na)			scale(na)			scale(na)			scale(na)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.09	-0.21 – 0.02	0.119	-0.10	-0.22 – 0.01	0.086	-0.09	-0.21 – 0.02	0.118	-0.09	-0.21 – 0.02	0.116	-0.10	-0.22 – 0.02	0.092	-0.10	-0.22 – 0.02	0.091
day	0.01	-0.00 – 0.03	0.078	0.01	-0.00 – 0.03	0.051	0.01	-0.00 – 0.03	0.080	0.01	-0.00 – 0.03	0.074	0.01	-0.00 – 0.03	0.056	0.01	-0.00 – 0.03	0.055
nalag	0.24	0.18 – 0.30	**<0.001**	0.25	0.19 – 0.31	**<0.001**	0.25	0.19 – 0.31	**<0.001**	0.24	0.18 – 0.30	**<0.001**	0.24	0.18 – 0.30	**<0.001**	0.24	0.18 – 0.30	**<0.001**
stuck state lag	0.03	-0.03 – 0.09	0.384															
HRV	0.08	0.02 – 0.13	**0.008**	0.08	0.02 – 0.14	**0.006**	0.08	0.03 – 0.14	**0.004**	0.08	0.02 – 0.13	**0.011**	0.08	0.03 – 0.14	**0.005**	0.08	0.02 – 0.14	**0.007**
imean stuck	0.03	-0.03 – 0.10	0.323															
imean na	0.33	0.26 – 0.40	**<0.001**	0.33	0.26 – 0.40	**<0.001**	0.32	0.25 – 0.39	**<0.001**	0.33	0.27 – 0.40	**<0.001**	0.34	0.27 – 0.40	**<0.001**	0.34	0.27 – 0.40	**<0.001**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. Each column pertains to each of the 6 PBAT items measuring PF. scale(na) = Negative Affect; HRV = Heart-rate variability; imean = Trait values; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

FIGURES

Figure 1 Depiction of antecedent and consequence models

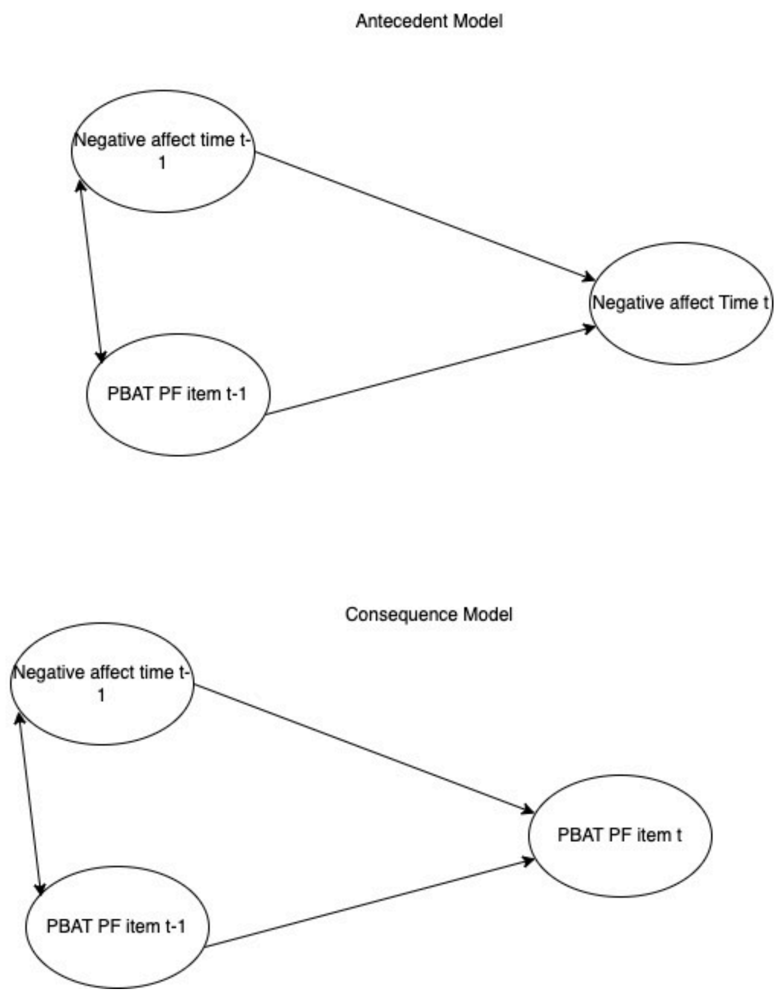
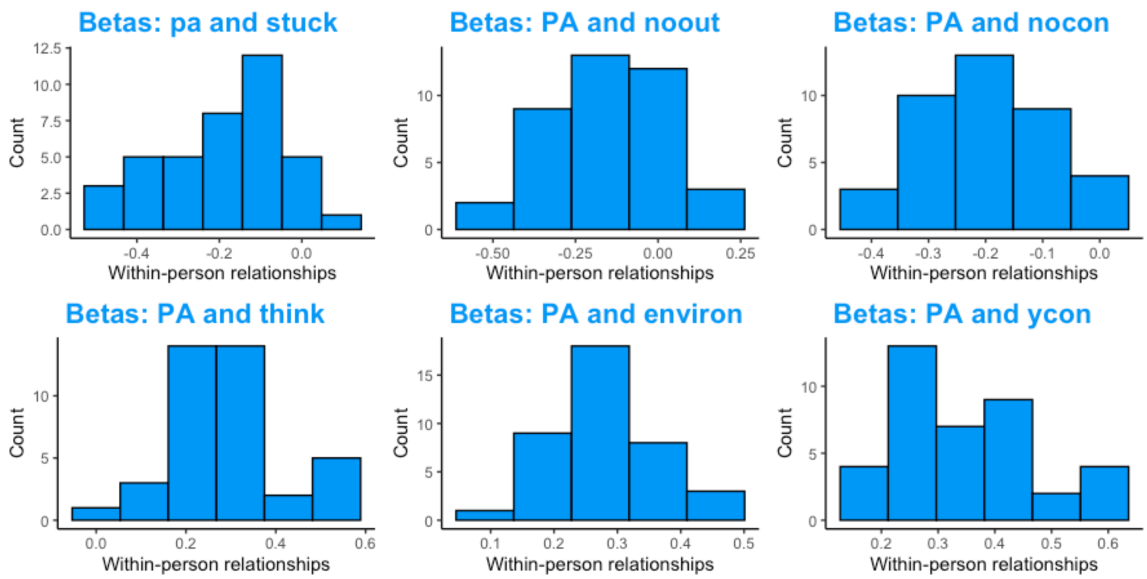
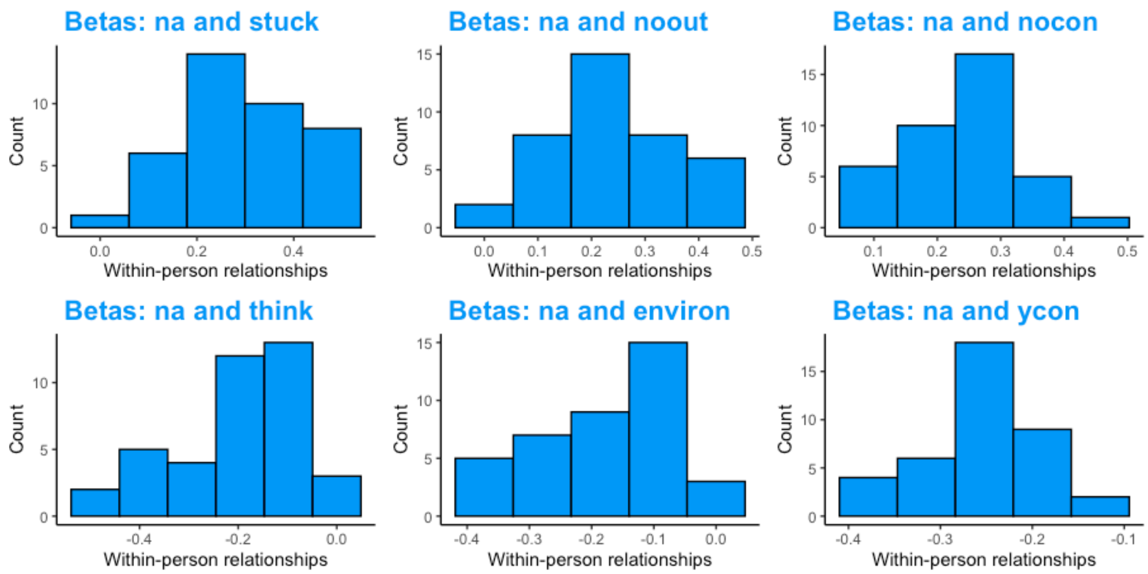


Figure 2 Within-person variability for PF-PA models



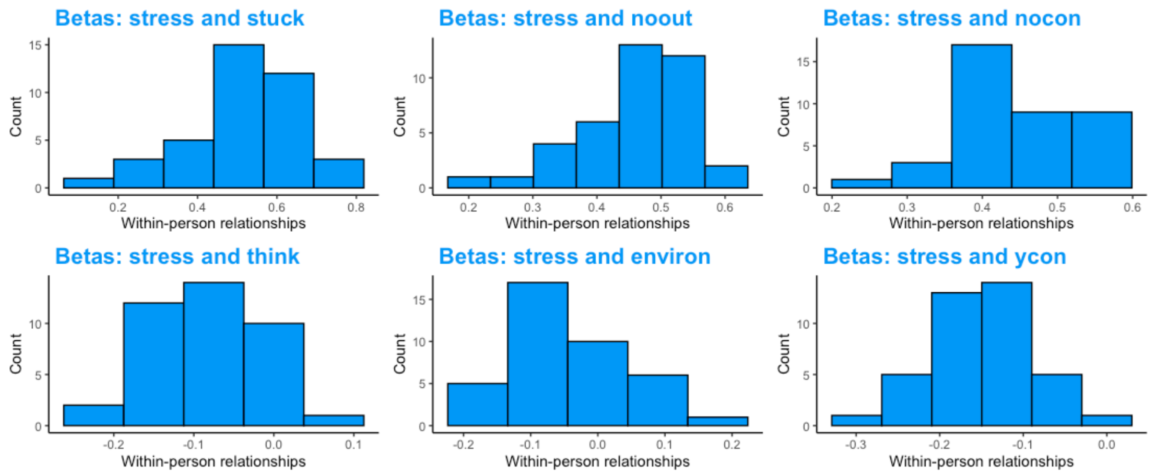
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. PA = Positive Affect

Figure 3 Within-person variability for PF-NA models



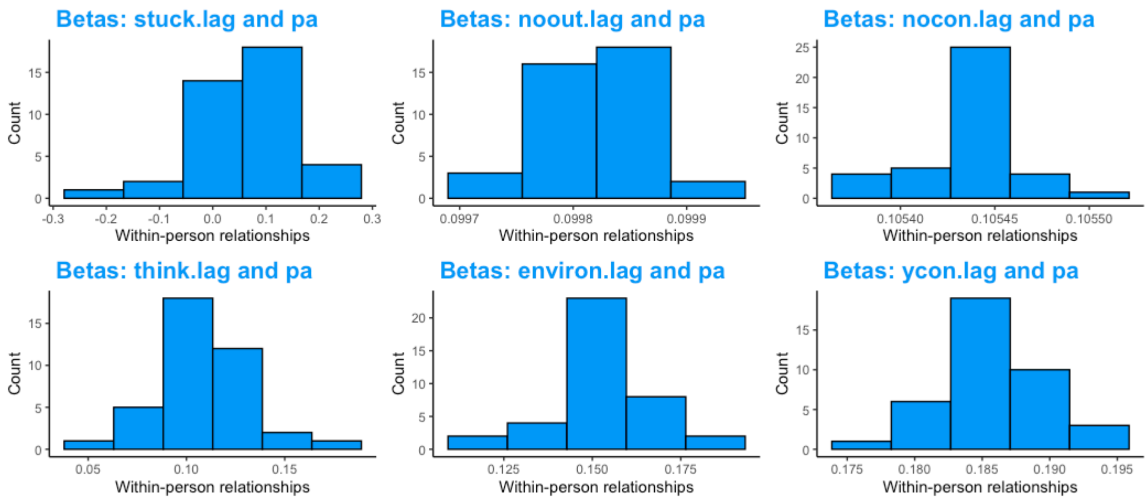
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. NA = Negative Affect

Figure 4 Within-person variability for PF-Stress models



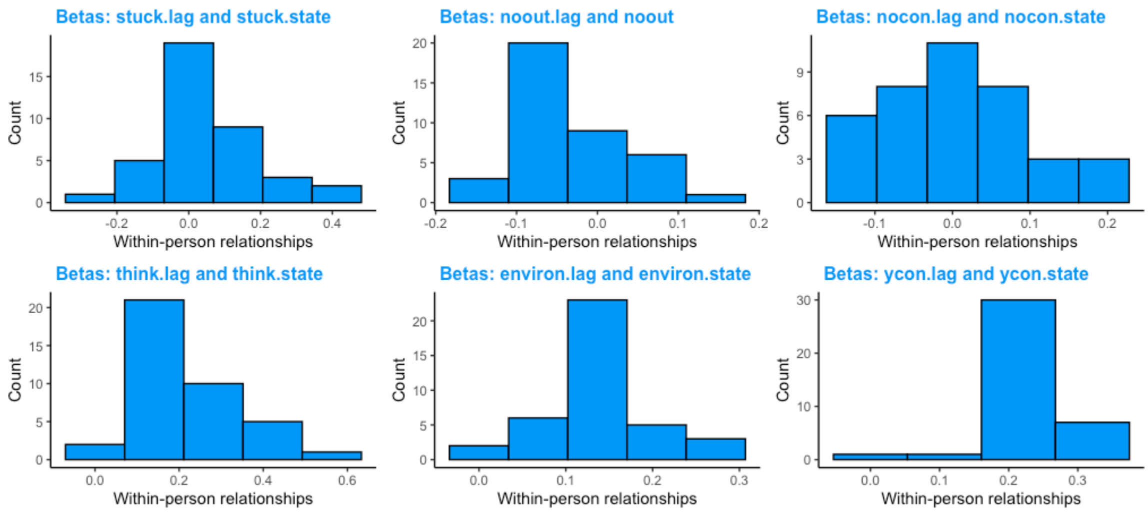
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted.

Figure 5 Within-person variability for PF-PA antecedent models



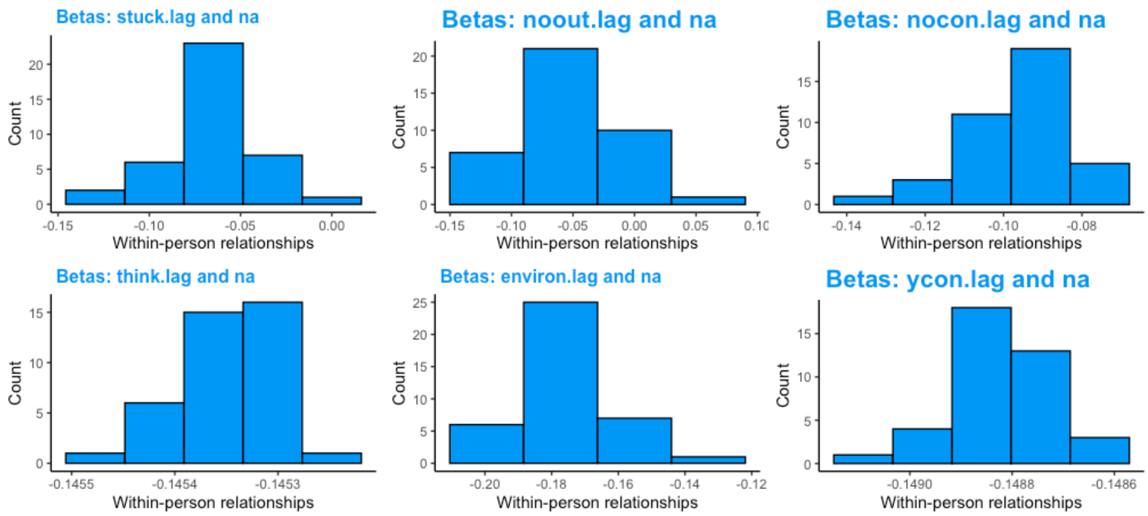
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. PA = Positive Affect

Figure 6 Within-person variability for PF-PA consequence models



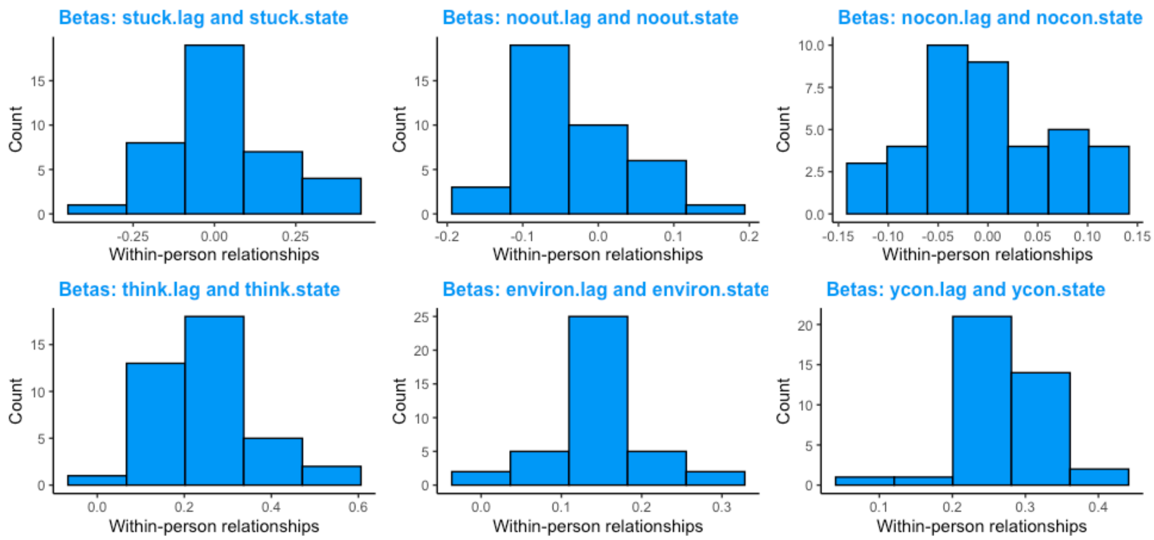
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable (PF at time T) and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. PA = Positive Affect

Figure 7 Within-person variability for PF-NA antecedent models



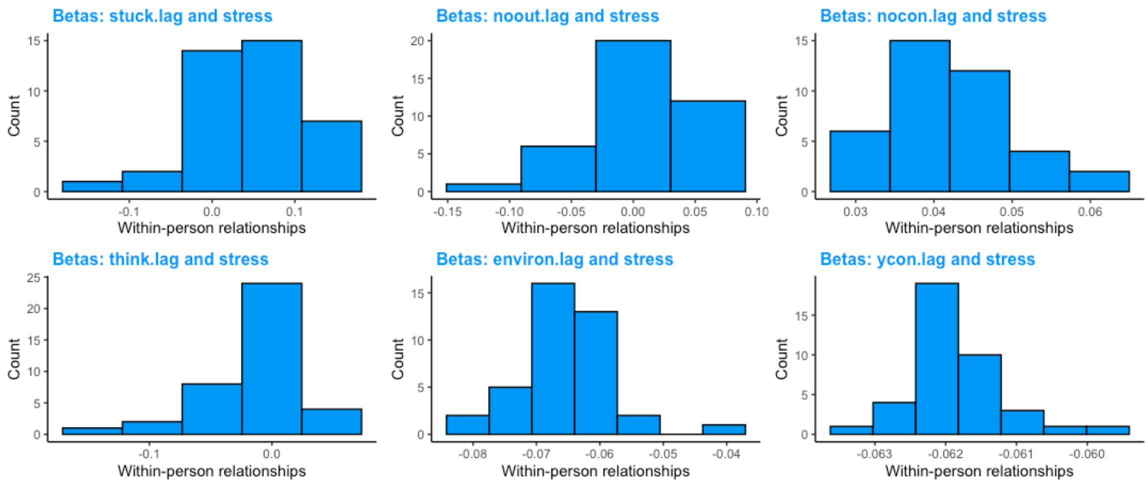
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. NA = Negative Affect

Figure 8 Within-person variability for PF-NA consequence models



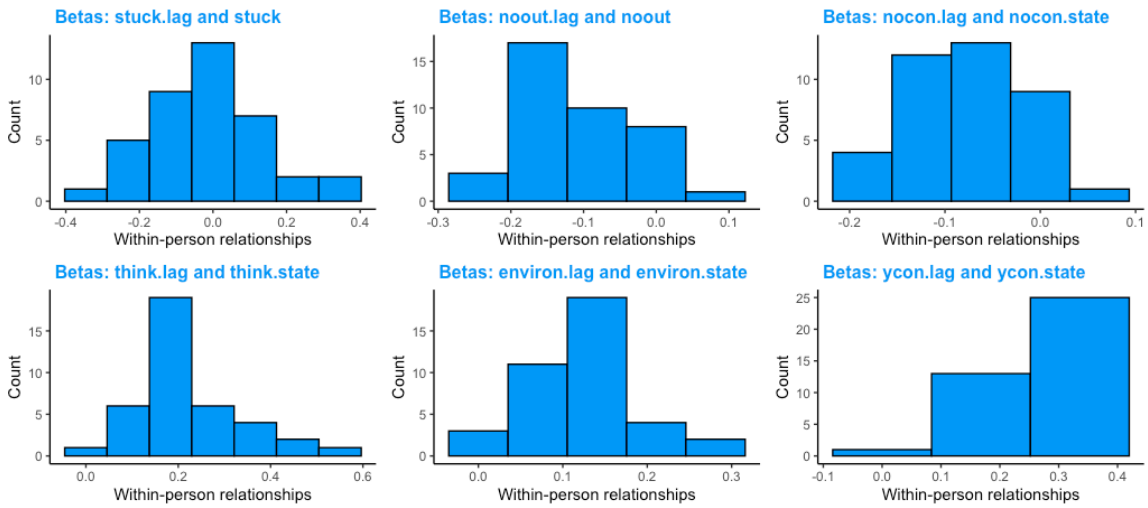
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable (PF at time T) and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. NA = Negative Affect

Figure 9 Within-person variability for PF-Stress antecedent models



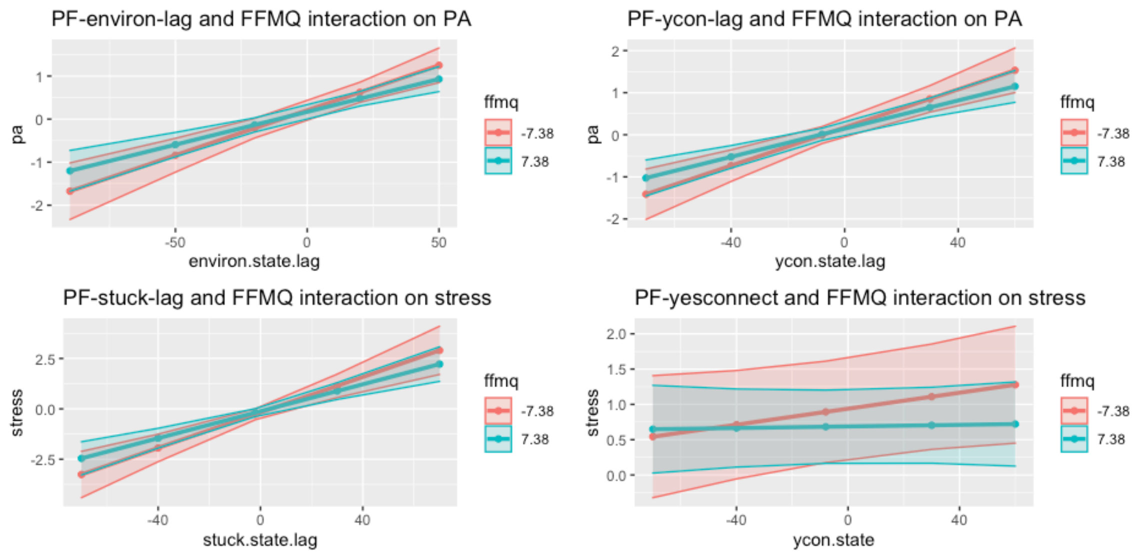
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T.

Figure 10 Within-person variability for PF-Stress consequence models



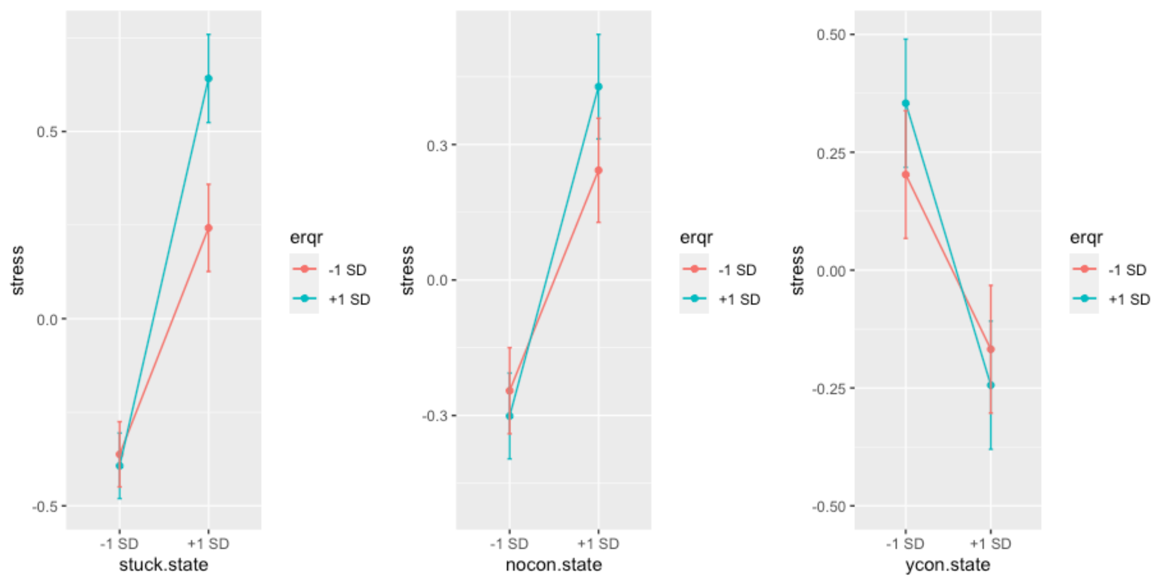
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable (PF at time T) and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T.

Figure 11 PF-FFMQ interaction plots



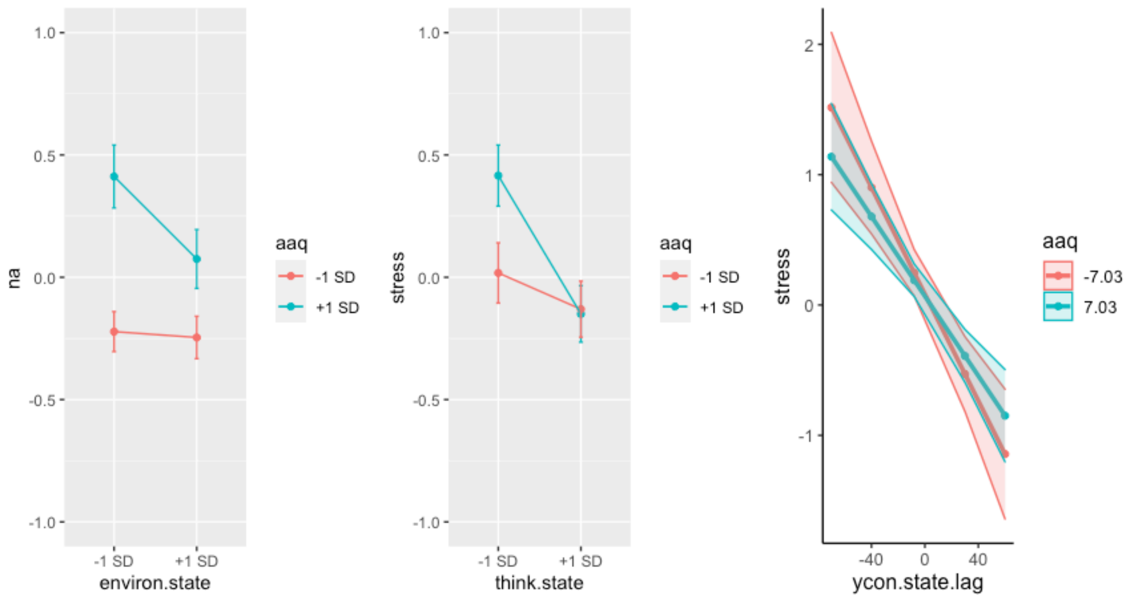
Note. Level of moderator variable is +/- 1 SD FFMQ = Five Facet Mindfulness Questionnaire

Figure 12 PF-ERQ interaction plots



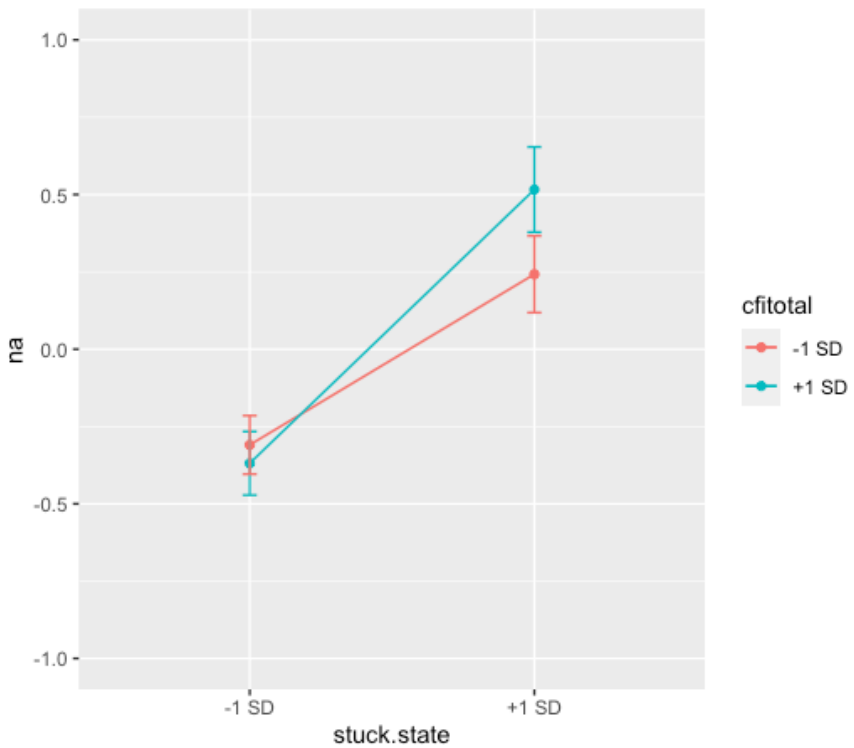
Note. Level of moderator variable is +/- 1 SD ERQ-R = Emotion Regulation Questionnaire-Reappraisal subscale score

Figure 13 PF-AAQ interaction plots



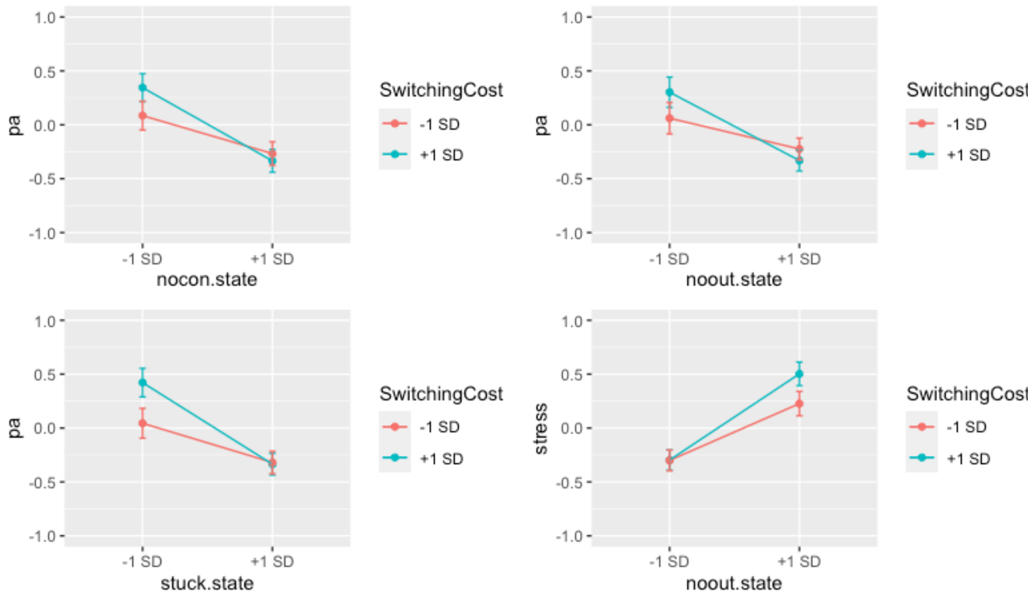
Note. Level of moderator variable is +/- 1 SD AAQ = Acceptance and Action Questionnaire

Figure 14 PF-CFI interaction plot



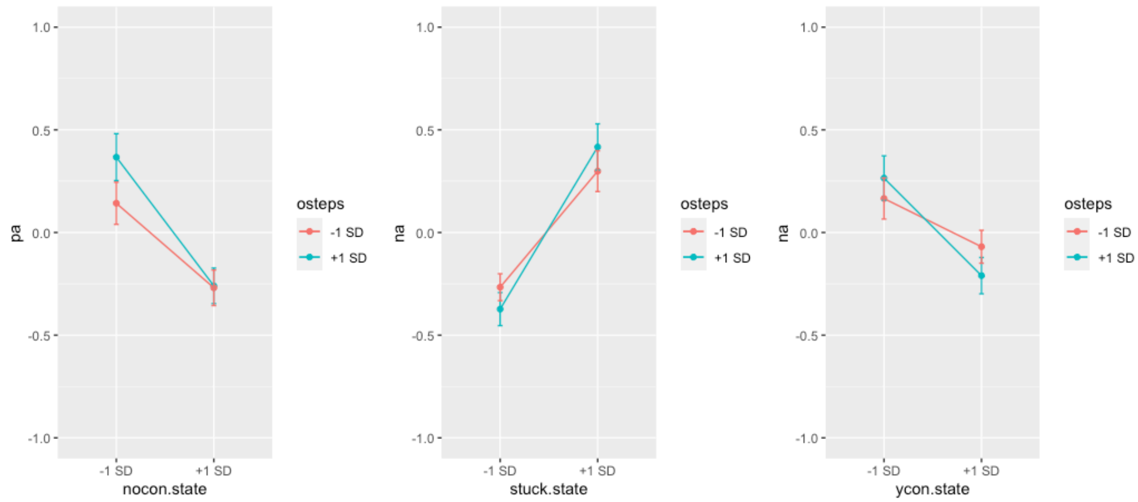
Note. Level of moderator variable is +/- 1 SD cfitotal = Cognitive Flexibility Inventory total score

Figure 15 PF-SwitchingCost interaction plots



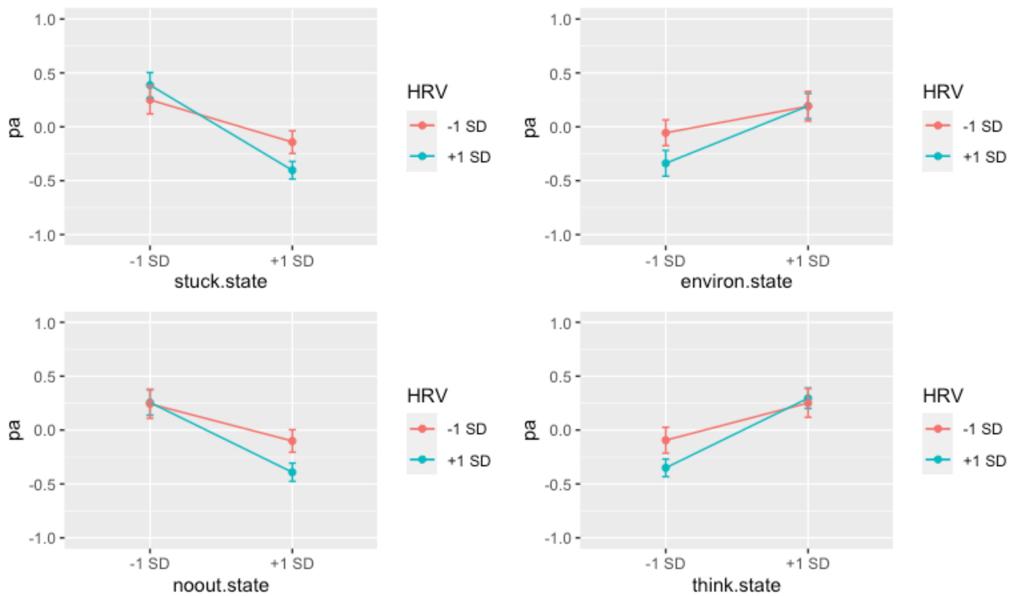
Note. Level of moderator variable is +/- 1 SD SwitchingCost = score on Asymmetric Task Switching paradigm

Figure 16 PF-Steps interaction plots



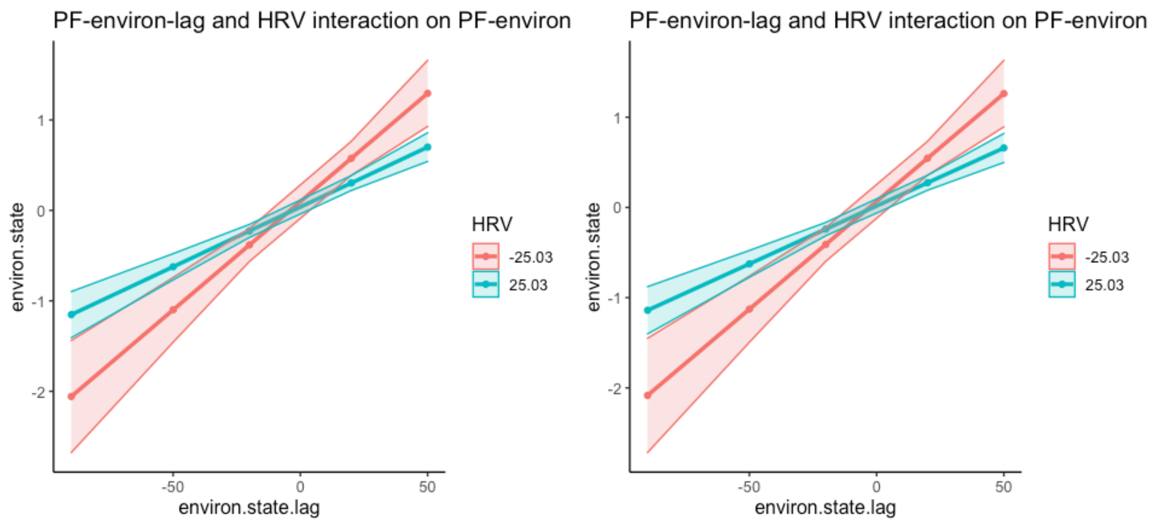
Note. Level of moderator variable is +/- 1 SD osteps = Step count from Oura Ring

Figure 17 PF-HRV interaction plots



Note. Level of moderator variable is +/- 1 SD HRV = Heart-rate variability

Figure 18 Lagged PF-HRV interaction plots



Note. Level of moderator variable is +/- 1 SD FFMQ = Five Facet Mindfulness Questionnaire

APPENDIX

Examining the Temporal Dynamics of Psychological Flexibility on Affect and Stress in a Transdiagnostic Clinical Sample: An Ecological Momentary Assessment Study

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Abstract

Psychological flexibility (PF) is defined as one's ability to pursue valued activities despite distress. PF is a critical process of change in evidence-based treatments, and is associated with psychosocial health and functioning. Although PF is considered context-dependent, previous research often measures PF as a static construct, often by administering the Acceptance and Action Questionnaire, which may not fully capture the construct of PF and limits understanding of how PF may change over time. One approach for measuring individual dynamics over time is ecological momentary assessment (EMA), which has been applied to numerous psychological constructs, including PF recently.

This study investigated the dynamic relationship between PF, affect, and stress in a clinical sample of 39 individuals. Six items from the Process Based Assessment Tool were used to measure PF in terms of experiential avoidance and values-promoting processes. Participants completed a two-week EMA phase which included answering daily self-report items, and collecting smartphone and wearable technology data on screen time, steps, sleep quality, distance traveled, and activity. I hypothesized that PF would vary within and across time and context to predict affect and stress and expected that indicators of psychosocial health and measures of psychological processes would influence PF, affect, and stress.

Results revealed significant associations such that flexibility was generally related to higher positive affect, lower negative affect, and lower stress. Some PF-items were associated with better day-quality ratings. PF interacted with context (conflict or valued

action) and type of situation, with greater PF generally associated with valued-actions. Measures of psychological and attentional processed differentially interacted with PF to predict affect and stress. Step count interacted with PF in several models. Screen time was associated with affect and stress at a given timepoint. Heart-rate variability was differentially related to stress, affect, and PF within and across time. Activity, GPS, and sleep quality data were not significant. Overall, this study supports evidence that PF is highly idiographic and related to indicators of psychosocial wellbeing over time, generally supporting my hypotheses.

Examining the Temporal Dynamics of Psychological Flexibility on Affect and Stress in a Transdiagnostic Clinical Sample: An Ecological Momentary Assessment Study

Psychological flexibility (PF) is a critical process of clinical change in evidence-based treatments, psychosocial health, and daily functioning (Kashdan et al., 2020; Kashdan & Rottenberg, 2010). The construct has often been difficult to define given its relation to nearly every facet of life, with extant research related to affect, emotion regulation, behavior, cognition, regulation, and coping (Kashdan & Rottenberg, 2010; Doorley et al., 2020). At its core, PF is defined as one's ability to pursue valued activities despite distress or interference, and it is undoubtedly context-dependent given that one's goals and distress change constantly depending on the environment (Hayes et al., 2011; Kashdan et al., 2020).

Although utilization of this definition allows for precise measurement of the PF construct in the current study, there are numerous other facets of flexibility that contribute to the breadth of its impact on psychological functioning. For example, Bonanno and Burton (2013) discuss the importance of *regulatory flexibility* which relates to one's ability to adapt to internal or external circumstances using coping and/or emotion regulation strategies, which is closely related to Cheng's (2001) construct of *coping flexibility. Cognitive flexibility* tends to discuss the ways in which one's attention adaptively shifts between sets or may exhibit biases toward or away from certain stimuli (set-shifting; Miyake et al., 2000) and this is closely related to *affective flexibility* which identifies set-shifting ability in the context of emotion (Genet & Siemer, 2011). Affective flexibility also relates to one's ability to modulate emotions according to context or during tasks. Relatedly, work from Aldao et al. (2015) and Conroy et al. (2020) detail the importance of *emotion regulation flexibility* which measures which emotion regulation strategies are employed by people in certain situations and the degree to which skill-use may change in presence or form depending on the context (i.e., using reappraisal all the time or only in certain situations).

The construct of PF was originally coined by Acceptance and Commitment Therapy (ACT; Hayes et al., 2011) and is a primary mechanism of change in ACT and other cognitive-behavioral therapies (Arch & Craske, 2008; Arch et al., 2012). As a treatment, ACT uses mindfulness and behavior change principles to help patients learn to allow and accept their emotional experiences while working towards defining and living aligned with their values. According to this treatment, PF is achieved through the combination of skills in: acceptance, present-focused awareness, values-based living, committed actions based on values, defusion (e.g., detachment) from cognitions and beliefs, and self-as-context (e.g., viewing oneself as experiencing emotions, thoughts and behaviors instead of defining oneself by these experiences; Hayes et al., 2011). In other words, PF is achieved and maintained when individuals learn to reduce emotions, thoughts, and behaviors that move them away from their values and increase acceptance and change processes that move them toward psychosocial well-being. Altogether, the ACT model of PF serves as a primary theoretical framework from which research and treatment have evolved. A point of convergence across numerous definitions of PF is the reliance on pursuing valued activities despite distress or interference, in multiple contexts (Hayes et al., 2011; Kashdan et al., 2020).

As psychological flexibility is difficult to define as a construct, it is understandably difficult to measure comprehensively as well (Ong et al., 2019). The Acceptance and Action Questionnaire (Bond et al., 2011; AAQ-II) is the most popular measure of PF, derived from principles of ACT. It assesses one's level of flexibility (higher scores) or experiential avoidance (lower scores) across 7 items. Notably, the AAQ has 28 identified variants that pertain to specific clinical and medical presentations, in part to increase the predictive power of the measure, although it also indicates the potential pitfalls of global measurements of flexibility in the literature (Ong et al., 2019; Kashdan et al., 2020). Other measures of PF include the CompACT (based specifically on ACT core processes; Francis et al., 2016), Multidimensional Psychological Flexibility Inventory (MPFI; Rolffs et al., 2018), and Personalized Psychological Flexibility Inventory (PPFI; Kashdan et al., 2020) as well as others related to values (Wilson et al., 2010), cognitive fusion (Gillanders et al., 2014), cognitive flexibility (Dennis & Vander Wal, 2010), openness and engagement (Benoy et al., 2019), coping flexibility (Cheng, 2001; Kato, 2020), and emotion regulation flexibility (Burton & Bonnano, 2016; Hofmann & Kashdan, 2010). Use of the AAQ in experimental and clinical research has undoubtedly increased our knowledge of the construct as a field, although recent research identifies strong overlap with negative affect and distress (Bond et al., 2011) at the expense of a strong relationships with acceptance and related constructs (Rochefort et al., 2018; Tyndall et al., 2019; Wolgast, 2014). Additionally, most PF measures reflect subscales of acceptance or avoidance, particularly from a thinking or feeling perspective, while more explicit measures of engagement in helpful or unhelpful behaviors within a given context are harder to find. This may, in part, explain why the majority of PF research to date has focused more on *inflexibility* and negative content in psychopathology as opposed to understanding the ways in which flexibility processes may also emerge amongst distress.

In an effort to extend research into process-based therapy (Hayes & Hofmann, 2017; Hayes et al., 2019; Hayes et al., 2020) based on evolutionary principles of behavioral selection, retention, and variation, the Process Based Assessment Tool (PBAT) was created to reflect the positive and negative processes of PF (Ciarrochi et al., 2021). Currently being developed by the first three readers on this dissertation, the full and abbreviated versions of the PBAT reflect four subscales: meaning-thwarting behavior (selection of responses not in line with values), variation (choosing new behaviors), retention (engaging in behaviors that make it likely for values to continue being supported), and meaning-enhancing behavior (selection of behaviors in line with values; Ciarrochi et al., 2021). Unlike other measures of PF, the PBAT reflects only one's behaviors and goes beyond assessment of avoidance or acceptance. Additionally, the measure recognizes that individuals may choose to behave in helpful or unhelpful ways on each of the subscales depending on context.

Despite the breadth of definitions and measures of PF, research points to clear psychosocial health benefits across individuals with primary psychological disorders, medical diagnoses, and in sub-clinical or non-clinical samples (Gloster et al., 2017; Kashdan & Rottenberg, 2010; Doorley et al., 2020; Kashdan et al., 2020). On the other hand, inflexibility (i.e., low PF) has been associated with processes and diagnoses of psychopathologies (for reviews, see Mansell & Morris, 2018; Levin et al., 2012; Kashdan & Rottenberg, 2010; Doorley et al., 2020). Namely, inflexibility has been associated with: rumination and low mindfulness, neuroticism, emotional reactivity, maladaptive emotion regulation use, attributional style, positive and negative affect, executive dysfunction, self-control, and experiential avoidance. Increases in PF over the course of treatment also show evidence for this construct as a mechanism of change and correlate of higher quality of life and psychosocial health (Arch & Craske, 2008; Arch et al., 2012; Hayes et al., 2006; Hayes et al., 2019; Hofmann & Hayes, 2019; Kashdan & Rottenberg, 2010; Gloster et al., 2017).

Given these data on the relationship between psychosocial health and PF, it is increasingly important to understand news ways of measuring the construct to account for context and individual differences in expression of flexibility to inform better treatments for increasing adaptive, flexible responses in daily life. Unfortunately, the majority of studies on PF are correlational, concerned with static measurement of PF with an emphasis on inflexibility, and limited to mostly between-group analyses. Indeed, numerous empirical and literature reviews (Kashdan & Rottenberg, 2010; Kashdan et al., 2020; Doorley et al., 2020) indicate the need to: 1) measure PF in daily life using idiographic or time-series designs, 2) make improvements to methodology and measurements that are employed to answer these questions (i.e., with the PBAT), and 3) better understand the causality of the relationship between flexibility and affective processes (i.e., does inflexibility precede negative affect and dysfunctional outcomes or vice versa).

One innovative approach for studying psychological processes over time is ecological momentary assessment (EMA). EMA collects high density time series data through the use of daily diaries, smartphone apps, and self-report packets, to name a few (Shiffman et al., 2008). Time series analysis allows for modeling dynamic processes over time, within and across individuals, through the use of multi-level models and quantification of time-lagged relationships and auto-correlations (e.g., variable X at time *t* associated with variable Y at time *t-1*) which approximate causality (Granger, 1969). Use of EMA research designs in clinical science has boomed recently (for reviews, see Shiffman et al., 2008; Wright & Woods, 2020), especially in relation to affective dynamics and psychopathology over time. Indeed, EMA designs are also equipped to passively measure objective health, activity, and social data through smartphone sensors or wearable technology, with numerous studies indicating relationships between affectivity and physical activity levels, as well as PF and wellbeing (Wichers et al., 2012; Stavrakakis et al., 2015; Kangasniemi et al., 2014; aan het Rot et al., 2012; Peltz et al., 2020). There is also a growing literature that has applied EMA designs to investigate PF in relation to psychological processes such as emotion regulation, emotional disorders, stress and wellbeing, mindfulness, and values (Benson et al., 2019; Kashdan et al., 2020; Finkelstein-Fox et al., 2020; Gregoire et al., 2020; Blanke et al., 2019; Keng et al., 2018; Levin et al., 2018; Hardy et al., 2017). Generally speaking, these studies report that greater PF is associated with adaptive coping by using different emotion regulation strategies, mindfulness, and acting toward one's values. However, these studies often measure flexibility based on the AAQ, have not focused as much on diverse clinical samples, and tend to use daily diary approaches as opposed to randomly-pinged, in-the-moment data collection. As such, there is abundant opportunity to continue applying idiographic methodologies to better understand the nuances of PF over time.

The current study represents an innovative approach to understanding the interplay between PF during conflict or goal pursuit, affect, and stress, through the use of an EMA design for capturing high density self-report data over a 2-week span. Using various items from the PBAT to quantify PF as well as passively collected health and activity data, this study will explore the interplay between PF as it pertains stress or values-directed actions, affect, and stress. Use of the PBAT will encourage a behavioral and evolutionary approach to studying flexible and inflexible decision-making across contexts. Data from this investigation have the potential to contribute significantly to clinical and treatment research pertaining to the directionality and causality of the relationship between PF and psychosocial health processes over time, measurement of PF as a dynamic clinical process that is context-dependent, and understanding how neuropsychological attention measures may align or differentiate from daily measures of flexibility.

Present Study

Overview

The current study investigated the temporal dynamics of PF, positive and negative affect, and momentary stress in relation to conflictual or values-based contexts in a transdiagnostic clinical sample, utilizing EMA. Study participants (n = 39) were adults presenting or diagnosed with emotional disorders at a university clinic or from the community. The study consisted of three phases: 1) baseline visit including a diagnostic interview, attention tasks, and self-report questionnaires (See Methods); 2) a two-week EMA phase; and 3) an endpoint visit consisting of the same self-report questionnaires as baseline. During the EMA phase, participants were prompted 5 times a day, at random, to rate their affect, PF in the context of stress or goals, and momentary stress. Participants earned up to $100 for completing the entire study based on rates of compliance to prompts and study procedures.

Primary Aims and Hypotheses

Aim 1. Examine the relationship between PF, affect, and stress over time in a transdiagnostic sample of adults.

Hypothesis 1a. PF will be associated with positive affect and negative affect within each time-point (i.e., flexibility at time *t* will relate to affect at time *t*).

Hypothesis 1b. It is expected that PF will differentially predict positive and negative affect at lagged time-points (i.e., flexibility at time *t* will predict affect at time *t* +1).

Hypothesis 1c. Increased PF will be associated with decreased stress over time (Grégiore et al., 2020).

Hypothesis 1d. PF in the context of stress and values-directed actions or affect will be associated with retrospective rating of quality of day.

Hypothesis 1e. Type of reported stress/conflict and values-directed actions (i.e., categorical variables) will be differentially associated with affect, stress, and PF.

Aim 2. Investigate how the temporal relationship between PF, affect, and stress varies as a function of baseline measures of processes of emotional disorders.

Hypothesis 2a. It is expected that mindfulness scores will moderate the relationship between PF, affect, and stress over time such that those scoring higher on subscales of the FFMQ will show a stronger relation between PF and positive affect or decreased stress when compared with individuals scoring lower on FFMQ subscales.

Hypothesis 2b. Emotion regulation processes will moderate the relationship between PF, affect, and stress such that those scoring higher on suppression and rumination will show a stronger relation between PF and negative affect or stress, while individuals scoring higher on reappraisal will show a stronger relation between PF and positive affect or decreased stress.

Hypothesis 2c. Baseline measures of flexibility (e.g., AAQ-II, CFI, ASQ) will moderate the temporal relationship between PF, affect, and stress such that such that scores indicating inflexibility will be associated with a stronger relation between PF, negative affect, and increased stress when compared with higher scores.

Hypothesis 2d. Participants exhibiting greater cognitive inflexibility on attention tasks (Emotional Stroop) will moderate the relationship between PF, affect, and increased stress, when compared to individuals exhibiting greater flexibility on those tasks (Compton et al., 2004; for reviews see, Zinchenko et al., 2020; Abramovitch et al., 2021).

Methods

Participants

Study participants were recruited from the greater Boston community and Boston University's Center for Anxiety and Related Disorders (CARD). The final study sample consists of 39 participants who completed all portions of the study and were included in analyses. 43 participants were recruited and enrolled in the study, having completed at least the baseline visit. The four participants not included in analyses were either ineligible after the baseline visit or lost to follow-up prior to beginning the EMA phase.

The study sample consisted of 28 females (71.8%) and 8 males (20.5%), with 3 individuals (7.7%) identifying as non-binary. The mean age of the sample was 29.5 with a range of 18-66 (missing age data for two participants). With respect to race and ethnicity, participants identified as being part of the following groups: 92.3% non-Hispanic/Latinx, 5.1% Hispanic/Latinx, 2.5% not reported (1 participant). 79.5% identified as White, 10.3% identified as Asian, 2.6% identified as Black or African American, 10.3% identified as more than one race, and one participant did not report their race.

To achieve a breadth of clinical presentations, inclusion criteria did not specify a particular psychiatric diagnosis nor level of comorbidity. Participants presented with the following primary diagnoses: 30.8% Generalized Anxiety Disorder (GAD), 17.9% Social Anxiety Disorder, 12.8% Major or Persistent Depressive Disorders (MDD, PDD), 7.7% Obsessive Compulsive Disorder (OCD), 7.7% Specific Phobia (SPEC), 7.7% Other Specified Anxiety Disorder (OSAD), 5% Agoraphobia, 2.6% Panic Disorder (PD), 2.6%

Post-traumatic stress disorder (PTSD), 2.6% Body Dysmorphic Disorder, and 2.6% Attention Deficit Hyperactivity Disorder (ADHD). There were also high rates of comorbidity in the sample, with 74.4% of participants having a comorbid diagnosis, and 61.5% having up to two comorbidities. See Table 1 for diagnostic and demographic data.

Baseline scores for psychological processes are displayed in Table 2. Highlighted baseline characteristics include an average negative affect score of 24.5 (SD=7.2) and positive affect score of 27 (SD=7.6) on the PANAS, 16.2(SD=10.2) on the BDI, and 99 (SD=20.2) on the STAI. In relation to baseline psychological flexibility, participants mean scores indicate an average AAQ (higher scores = more inflexible) score of 39.2 (SD=7.1) and an average CFI total score of 98.3 (SD=13.5).

Sample Size and Data Density

The sample size for the current study was determined based on a power analysis conducted using *EMATools* package in R, which determined that an intended N of 40 participants completing 5 sets of responses per day for 2 weeks would yield power of 0.8 for an estimated medium effect size, or over 0.99 for a large effect size, assuming compliance rates of >75%. Effect size estimates in results tables revealed small to moderate effect sizes. A-priori estimations were assuming an interclass correlation coefficient of 0.5, though the actual ICCs in the current study varied between 0.2-0.5 depending on the variable, which indicated sufficient power for within-person analyses by this analysis tool.

39 participants were included in final analyses, which corresponded to an average of 55 rows of data per participant for Ethica (out of a possible 70, ~78.5%). Compliance

rates for Oura Ring data were high, with only two participants missing complete Oura data due to technical issues. Based on these completion rates, the current study is likely well-powered for the subsequent within-person analyses with less power for between-subjects analyses, though the effects of low power affect the interpretability of null findings as opposed to significant findings.

Inclusion and Exclusion Criteria

Participants were included in the study if they were: 1) 18 years or older, 2) self-reported normal or corrected vision, 3) owned a working smartphone (i.e. Android or Apple IOS), 4) were either stable on current psychotropic medications (or off concurrent medication for 2 weeks), received stable psychological treatment for a minimum of 6 weeks prior to study enrollment, or were not receiving any psychotherapy/medication treatment but were experiencing symptoms of an emotional disorder.

Participants were ineligible for the study if they: 1) were unable to understand study procedures or participate in the informed consent process, 2) had a serious medical or neurological illness (e.g., Alzheimer's, Parkinsons, etc), 3) had significant suicidal ideation within past 2 weeks (BDI-II Q9 >2), 4) had a history of head trauma causing loss of consciousness resulting in ongoing cognitive impairment, 5) had a history of psychotic disorder, bipolar disorder, an intellectual disability, learning disorder, communication disorder, or movement disorder (i.e., developmental disorder other than ADHD), 6) had a current substance use disorder, or 7) displayed significant personality dysfunction likely to interfere with study participation (as assessed during the clinical interview).

Procedures

Interested or referred individuals completed a brief phone screen to determine initial eligibility for the study and provide information about study procedures and EMA requirements. If eligible after the phone screen, a baseline screening visit was scheduled at CARD or via HIPAA-compliant Zoom. The baseline visit consisted of informed consent, a clinician-administered diagnostic assessment, completion of self-report questionnaires and computerized attentional tasks, and information on setting up smartphones and Oura rings to be compliant with their respective apps. Following the consent and baseline visit, participants were enrolled in the 2-week EMA phase where they were prompted 5 times per day to fill out questions pertaining to positive and negative affect, stress, and PF in the context of conflict or goals. Daily ratings were collected via the Ethica app for IOS and Android phones. After completion of the EMA phase, participants completed the same self-report questionnaires from the baseline visit. Table 3 shows the measurement and EMA phase schedule.

Participants could earn up to $100 for completing the entire study based on the following cost breakdowns: $20 for the baseline visit, $10 for completion of follow-up questionnaires, and up to $70 for 2 weeks of EMA data. Participants could earn up to $35 per week for completion of EMA items ($5 per day for 100% response compliance; payment rate was dependent on percentage of prompts answered).

Measures

Clinician Administered Measure

Adult Anxiety Disorders Interview Schedule for DSM-5 (Adult ADIS-5; Brown & Barlow, 2014). The ADIS-5 is a semi-structured clinical interview that assesses adults' current symptoms to discern diagnostic information about anxiety, mood, trauma, substance, and somatic disorders. For the purposes of the current study, this interview was used to gather diagnostic data on participants for classification purposes in analyses. Diagnostic data include the presence of: major depressive disorder, persistent depressive disorder, generalized anxiety disorder, social anxiety disorder, panic disorder, agoraphobia, obsessive-compulsive disorder, body dysmorphic disorder, specific phobia, post-traumatic stress disorder, attention deficit hyperactivity disorder, and/or other specified emotional disorders.

Baseline Attentional Measures

Emotional Stroop Task (Williams et al., 1996; Ben-Haim et al., 2016)**.** The Emotional Stroop Task is widely used to measure attention bias toward positive, negative, and neutral threat words, particularly in psychopathology research. Words vary in terms of valence and arousal and participants were shown words in various colors and instructed to report the color while ignoring the word. Emotional interference (i.e., difficulty reporting color in the context of distraction words) in relation to error and response rates serve as metrics for attention bias in this task. The overall Stroop effect was calculated as the mean response time for all negative and positive words combined minus the mean response time for both control word blocks, not including the practice block.

The Emotional Stroop Task was administered to participants via MatLab using lab computers or online via a secure webhost through Boston University. Participants were shown a black screen with instructions in white font, which detailed that they should ignore the word and indicate the color it is printed in on the screen. Word colors included: red, green, blue, or yellow. After the instructions, a white fixation cross was presented in the middle of the screen for 750ms. Words were then presented in block format and each participant viewed the words in a random order. Block 1 included 30 practice trials, block 2 presented 40 control/neutral-word trials, block 3 included 40 negative-word trials, block 4 presented 40 control trials, and block 5 presented 40 positive-word trials. Word position was jittered over a small range around the center point of the screen so that subjects could not simply focus entirely on the center of the screen. The jitter was over a 100-pixel range horizontally and a 50-pixel range vertically. Participants did not receive correct answer feedback and the words appeared until a response was made. In-person versions of the task allowed participants to make responses on a keyboard (F=red, G=green, H=blue, J=yellow), while virtual subjects made responses by using a mouse to click buttons on the screen pertaining to colors. We found no substantive differences between task performance virtually versus in-person.

Positive, negative, and neutral word stimuli were chosen from Affective Norms for English Words (ANEW), with permission, based on pleasure, arousal, and dominance ratings normed from research (Bradley & Lang, 2017). Due to ANEW regulations, the release of example words in publications prohibited, though the affective ratings and norms are mirrored after systems like the International Affective Picture System (IAPS).

Asymmetric Task Switching (Gustavson et al., 2017; Barthel et al., 2022). The asymmetric switching paradigm asks participants to shift attention between two tasks of differential attentional demand. One task is less attentionally demanding and requires subjects to report which side of the screen an arrow is pointing. The second task is more attentionally demanding and requires identification of the direction of the arrows. An asterisk (*) or plus sign (+) cue alerts participants about which task they should follow. The "+" refers to the location procedure and the "*" refers to the direction procedure. The cue is shown 750ms before the task stimuli given research that states that more than 500-600ms are needed to anticipate and process stimuli (Rogers & Monsell, 1995). Cue arrows stay visible until a participant responds, and a feedback sound will alert them if they do not respond quick enough. Trials are presented without delays. There were a total of 8 blocks composed of 672 mixed, switching trials (112 trials per block) and 144 pure trials. All blocks contain 4 practice trials at the beginning, which are not used in analyses. This computer task used in the current study is identical to that of Gustavson et al. (2017) and Barthel et al. (2022).

Participants first performed each of the tasks without switching (72 pure trials of reporting location of the arrows and 72 pure trials of reporting direction of the arrows). Pure trials are presented first to ensure task mastery by participants. After the pure trials, participants completed 4 practice trials (not scored) that lead into 4 mixed blocks composed of location and direction trials and 2 mixed blocks with the cues reversed. 112 trials are included in each block. Trials were randomly ordered so that participants switch after 0 repeated trials, 1 repeated trial, 2 repeated trials, or 3 repeated trials. These occur, 12, 8, or 4 times per block, respectively. Each block included 28 switch trials, 16 trials that have one repeat, 8 trials that are 2-repeat, and 4 trials that are 3-repeat, in random order. Overall, each block contained 56 trials pertaining to location and 56 pertaining to direction for the full 112 trials.

Following the completion of these 4 mixed blocks, participants completed 4 more warm up trials to orient them to the fact that the cues indicating location or direction have been reversed. For blocks 5-6, the instructions changed, and participants now report arrow direction in response to a "+" and arrow location in response to "*". Following these new rules, participants complete 2 mixed blocks of 112 trials.

Similar to the procedure of Gustavson et al. (2017) and Barthel et al. (2022), we will also differentiated blocks of stimuli to measure the effects of task effort and attention. Trial presentation was incongruent, with arrows pointing in the opposite direction as the side the cue is shown on, 75% of the time. Incongruence is included as an attention check throughout the experiment.

Baseline and post-EMA measures

Positive and Negative Affect Scale (PANAS; Watson et al., 1988**)** This scale is a 20-item measure of one's feelings and emotions in the moment, on a five-point scale. Subscales include positive affect and negative affect.

Acceptance and Action Questionnaire (AAQ-II; Bond et al., 2011**).** This is a 7-item measure that assesses one's level of experiential avoidance versus psychological flexibility on a seven-point scale, depending on how it is scored. Higher scores indicated greater inflexibility/experiential avoidance in our study.

Cognitive Flexibility Inventory (CFI; Dennis & Vander Wal, 2010**).** The CFI is a 20-item measure assessing the following components of cognitive flexibility: 1) perceived controllability of difficult situations, 2) propensity to observe alternative explanations, and 3) ability to come up with alternative solutions and explanations under difficult circumstances.

Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990**).** This questionnaire contains 16 items that assess worry on a five-point scale. Scores are summed to create a total score ranging from 16 to 80.

State-Trait Anxiety Inventory (STAI; Spielberger, 1983**)**. The STAI is a 40-item self-report measure that is used to gage one's situational and/or general disposition towards anxiety. Subscales include state and trait anxiety which can be calculated separately or summed for a full-scale score.

Ruminative Response Scale (RRS; Treynor et al., 2003**).** This is a 22-item measure of rumination along three subscales: reflection, brooding, and depression. Items are rated on a four-point scale and participants are asked to think about when they are down and respond with how they generally act under these circumstances.

Beck Depression Inventory-II (BDI; Beck et al., 1996**)**. The BDI-II is a 21-item instrument designed to measure both the presence and severity of depressive symptoms.

Emotion Regulation Questionnaire (ERQ; Gross & John, 2003**).** The ERQ is a 10-item measure that assesses the use of two emotion regulation strategies: cognitive reappraisal and expressive suppression.

Affective Styles Questionnaire (ASQ; Hofmann & Kashdan, 2010**).** This is a 20-item questionnaire that indicates one's use of various styles of regulating emotions (i.e., emotion regulation flexibility) across three factors: concealing, adjusting, and tolerating.

Five Facet Mindfulness Questionnaire (FFMQ-15; Baer et al., 2008**).** The FFMQ-15 is a 15-item self-report scale assessing trait mindfulness, developed from the original 39-item scale (Baer et al., 2006). The measure five distinct facets of mindfulness: observing, describing, acting with awareness, non-judging of inner experience, and non-reactivity to inner experience.

Satisfaction with Life Scale (SWLS; Diener et al., 1985). The SWLS is a 5-item scale that assesses subjective evaluation of one's life. Items are rated on a 7-point Likert scale.

EMA Items

To maximize the context-specificity of this study, EMA items were chosen to reflect a theoretical model of the relationship between PF, affect, and stress in the context of conflict or goals. Items were chosen from based on the highest factor loadings reported in previous research or based on prior items used in EMA studies. The particular items chosen from the PBAT in this study were shown to be among the strongest predictors of negative or positive behaviors in the context of PF using a large representative sample of adults (Ciarrochi et al., 2021).

Affect items. At each of the 5 daily assessment times, participants were asked: "How *enthusiastic* do you feel right now?" and "How *nervous* do you feel right now?". These items were chosen based on the highest factor loadings for positive and negative affect on the PANAS (Watson et al., 1988; Crawford & Henry, 2004). Ratings were made according to the original PANAS 5-point scale (1 "very slightly or not at all", 2 "a little", 3 "moderately", 4 "quite a bit", 5 "extremely").

Stress Item. Experience of stress was be measured using one item: "To what extent are you stressed right now?" (Gregoire et al., 2020), which was be rated on a scale of 0 (*not stressed at all)* to 10 (*very stressed*).

Coping with Stress/Conflict or Goals. To categorize experiences of conflict and goal/values-directed behaviors, an initial item to gauge whether participants thought about a stress or conflict or goal was used (adapted from Stone et al., 1998). Participants were asked: "*In the past 3 hours, did you think about an issue/conflict or a goal/value? Please select the option that you thought about more at this time.*" Then participants were prompted to choose and categorize their most significant stressor or goal from the following choices: *work/school, romantic relationship, friendship, family, finances, daily hassles/minor matters, health*. Next, they were prompted to answer: *"Please rate the degree to which you responded to this event on a scale of 0 (strongly disagree) to 100 (strongly agree)?"* Options included a reduced set of items from a new scale, the PBAT Items included: *1) I felt stuck and unable to change my ineffective behavior."* (**PF-stuck**)*; 2) "I did not find an appropriate outlet for my emotions."* (**PF-noout**)*; 3) "I struggled to connect with moments in my life."* (**PF-noconnect**)*; 4) "I used my thinking in ways that helped me in this situation."* (**PF-think**)*; 5) "I changed my environment in order to improve my life. (examples: removing temptation, reducing distractions, surrounding myself with positive influences)"* (**PF-environ**)*; and 6) "I did things to connect with people who are important to me"* (**PF-yesconnect**). These items reflect four subscales: meaning-thwarting behavior, variation, retention, and meaning-enhancing behavior and were shown to be among the strongest predictors of negative or positive outcomes using a large representative sample of adults (Ciarrochi et al., 2021).

Retrospective rating. At the end of each day, participants were asked to reflect on their day and rate it's quality on a scale of 1 ("bad day") to 100 ("good day"), where 50 represents "neither good nor bad".

Data Reduction and Preprocessing

Attentional data. Trimming procedures were similar to those of Barthel et al. (2022) and Gustavson et al. (2017) such that RT data were computed for correct trials that exceeded 150ms. Outliers were removed if RTs were above or below six standard deviations of the group mean and were replaced with the nearest value, to eliminate bias due to extreme scores. RTs were excluded if they were 3.32 times the median RT absolute deviation by trial type within subjects (Wilcox & Keselman, 2003) to make sure that naturally occurring extreme RTs did not bias a single person's total mean RT. Trimming procedures accounted for between-group outliers and within-subject variances. For accuracy data and error rates, error trials and the trial immediately following the error were removed when conducting the RT analyses and computing switch costs (Rogers & Monsell, 1995). To calculate a single metric for Switching Cost to enter into models, we used the following formula: switch cost = ((location-switch – location-repeat) – (direction-switch – direction-repeat)).

Analysis Plan and Hypothesis Testing

Study analyses were completed using RStudio version 12.0+353 (R Core Team, 2022). EMA items recorded in Ethica were nested within participants such that, positive and negative affect, and stress variables represent within-person variables. Between-group variables included scores on questionnaires measured at baseline, and baseline attentional performance metrics, for example. Given the nested observations and non-independence of data, a multi-level modeling (MLM) approach was utilized. MLM is also structured to handle missing data, which is common in EMA designs given the high density data collection (Baraldi & Enders, 2010; Enders, 2011). Given that a total sum score of PBAT items was not appropriate, and model convergence was not achieved when adding multiple items into models, each PBAT item was added into models separately for each outcome. To minimize the chances of Type 1 error, given the high number of models ran, we set our p-value criterion to be conservative at $p \leq 0.02$. Significant model results that were between p=0.03-0.05 were not reported on in the results section.

PF items from the PBAT were converted to represent trait and state scores such that trait scores represented between-person associations (individual means) and state scores represented within-person associations. That is, trait scores were computed based on the number of points per person to make up an average score and state scores represented a regression line for each person. Computation of state and trait scores followed open source code (https://quantdev.ssri.psu.edu/tutorials/analysis-experience-sampling-ema-data-chapter-31-bivariate-intraindividual-covariation) and is based on Bolger and Laurenceau (2013). Preliminary analysis began with unconditional models in which the outcome and predictors variables were entered and only the intercept was modeled to discern how much variance was due to between or within-person processes. Results from unconditional models were used to calculate intraclass correlations (ICC), which is the ratio of between-person variance to total variance (between – within). Where appropriate, variables were centered around an individual's own mean or around a grand mean in the context of between-groups variables (Wenze et al., 2009). Models accounted for autoregression on the within-person residual auto-regression (i.e., error terms at time *t* correlate with error terms at time *t-1*) by listing this as a covariate (Bolger & Laurenceau, 2013). All models were fit including a fixed effect of day, which pertained to which day data collection occurred on (e.g., 1-14). We also tested models using a fixed effect of time, which pertained to each of the 5 Ethica prompts per day. Model results did not significantly differ depending on which time variable was used, so we obtained the day variable throughout.

With respect to Aim 1, preliminary unconditional models were computed to understand potential between-person differences in the intercept over time. Next, sample-centered trait PF scores were entered individually into models predicting either PA, NA, or stress to understand if the average level of affect or stress varied by trait PF. State models were similar to trait models except within-person PF scores were entered in place of trait scores to model slope without between-person differences in slope. Finally, trait and state scores were entered in the same model as fixed effects predicting various outcomes of interest. These slope models were then compared to models that included between-person slope differences to understand if the associations between state PF and affect or stress differ across persons. Comparisons were tested using analysis of variance (ANOVA) and Likelihood Ratio Tests to determine if model fit was statistically significant with the addition of random effects, as a metric for testing ergodicity.

For hypotheses pertaining to lagged variables (state and trait PF, stress, and affect), a *t-1* lag was created using the *lag* function in RStudio and was then entered into models using the same procedure as above. Specifically, we explored "antecedent" models in which each PBAT item measuring PF, and PA, NA, or stress at time *t* predicted change in affect or stress at time *T+1.* In other words, the six PF items were each modeled separately with PA, NA, and stress in antecedent models. Following the same procedure as the antecedent models, we also examined "consequence" models in which PF and PA, NA, or stress at time *t* predicted change in PF at time *T+1.* This modeling approach (See Marshall et al., 2020) allowed us to explore temporal ordering of the relationship between PF, affect, and stress to discern if PF influenced change in affect and stress or vice versa. See Figure 1 for depiction of antecedent and consequence models.

With respect to hypotheses 1d and 1e, "event" and "type" variables were categorial and entered into models using the *as.factor()* command to allow for exploration of interactions between each category/level of these variables and PF on affect, stress, or quality-of-day rating. These hypotheses pertained only to contemporaneous models.

Aim 2 builds on the models from aim 1 to inform whether there were between-person (trait) differences in the within-person (state) association that were moderated by a between-person predictors. In other words, does the addition of moderator variables explain differences in the slope of the relationship between PF items and affect or stress? Entered moderators included baseline questionnaire data (e.g., mindfulness, emotion regulation, affective style, rumination, attention tasks, cognitive flexibility, and experiential avoidance) and attentional task metrics. Moderator variables were also entered into antecedent and consequence models in addition to contemporaneous models.

Missing Data

There were two classifications of missing data in our dataset: 1) general missingness (e.g., filled out some prompts but not others on a given day) likely due to missing a notification or failing to respond within the 30-minute time-window, and 2) specific missingness due to study design, such that participants were instructed to select context type three (e.g., "other") if they were prompted at a time that they were sleeping, showering, or otherwise not engaging with a conflict or a goal/value to preserve the validity of the context category as much as possible throughout data collection. Selection of "other" at this stage led to no further data collection for that prompt window, so missing data within that category is not random, but expected. Selection of goal/value or conflict as contexts were greater than selection of "other" type. Results of Missing Completely at Random (MCAR) Test were significant, revealing that missingness was not completely at random and is likely Missing-at-Random (MAR) or Not-Missing-at-Random (NMAR), though tests for determining true MNAR data structures are difficult and limited (Enders, 2011). MLM is well-equipped for handling missing data and all study models were fit using all available information for parameter estimation (Enders, 2011). Per Enders (2011), use of Maximum Likelihood Estimation (MLE) is appropriate for MAR data and yields accurate estimates. As such all, models were fit using Restricted

Maximum Likelihood (REML) and were specified as with an AR1 covariance structure to remove noise due to trended data over time.

Results

Table 1 displays the demographic characteristics of the study sample. Table 2 shows the means and standard deviations of all baseline questionnaires and EMA items. Table 4 displays the means, standard deviations, and correlations between each PF item from the PBAT. Positively worded items were more correlated with one another than with negatively worded items, and vice versa. In general, negatively worded items had the highest correlations, but Table 4 reveals that each item is related but distinct from one another, as would be expected. Relation between items also suggests that it is necessary to model both state and trait-derived scores in models. Table 5 shows the descriptive statistics for the EMA item-level data.

Contemporaneous Associations Between PF, Affect, and Stress

Aim 1, hypothesis 1a, contemporaneous models included an intercept, day variable, state PF (within-person), and trait PF (mean-centered between-person) as predictors of either PA, NA, or stress in intercept only models which were then compared to models including a random effect of state PF. PF was modeled separately for each PBAT item and its relation to PA, NA, and stress. For PA-PF models, results revealed significant negative within-person effects of state *in*flexibility on PA. Specifically, a one unit standardized increase in feeling stuck and unable to change behaviors (e.g., **PF-stuck**) was associated with a 0.28 standardized unit decrease in PA (*SE* = 0.04, *t*-value: -7.7, *p* <.001). A one unit standardized increase in endorsement of not finding an outlet in emotions (e.g., **PF-noout**) was associated with a 0.23 standardized unit decrease in PA (*SE* = 0.04, *t*-value: -5.6, p <.001), and a one unit standardized increase in struggling to connect with moments in life (e.g., **PF-noconnect**) was associated with a 0.26 unit decrease in PA (*SE* = 0.03, *t*-value: -7.90, p <.001). State flexibility items were associated with greater PA at time *t.* Engaging in thinking to problem-solve (e.g., **PF-think**) was associated with greater PA (β=0.22, *SE* = 0.04, *t*-value: 6.39, p <.001), as was changing one's environment to improve the situation (**PF-environ**; β=0.17, *SE* = 0.03, *t*-value: 5.86, p <.001), and doing things to connect with people who are important/meaningful (**PF-yesconnect**; β=0.25, *SE* = 0.03, *t*-value: 7.30, p <.001). Across all contemporaneous PF-PA models, the effect of day was negatively related to PA (all *p's* <0.01). There was also a significant positive relationship between trait PF and PA in all models except PF-environ (all *p's* <0.01; Table 6). Coupled with significant pooled within and between-person effects, the nature of within-person effects were highly variable, as shown in Figure 2, and ANOVA models comparing intercept-only and random-slope models each revealed better model fit for random-slope models.

For NA-PF contemporaneous models, results revealed significant positive associations between inflexibility items and NA, which included: PF-stuck (β=0.34, *SE* = 0.03, *t*-value: 10.34, p <.001), PF-noout (β=0.26, *SE* = 0.04, *t*-value: 7.37, p <.001), and PF-noconnect (β=0.27, *SE* = 0.03, *t*-value: 8.36, p <.001). PF items pertaining to flexibility were negatively associated with NA at time *t*, including: PF-think (β=-0.16, *SE* = 0.03, *t*-value: -4.68, p <.001), PF-environ (β=-0.10, *SE* = 0.03, *t*-value: -3.17, p <.01), and PF-yesconnect (β=-0.19, *SE* = 0.03, *t*-value: -7.25, p <.001; Table 7). Similar to PA models, within-person effects were highly variable, as shown in Figure 3, and ANOVA models comparing intercept-only and random-slope models each revealed better model fit for random-slope models.

In Stress-PF models, PBAT items pertaining to inflexibility were associated with greater stress, including: PF-stuck (β=0.41, *SE* = 0.04, *t*-value: 11.55, $p < .001$), PF-noout (β=0.33, *SE* = 0.03, *t*-value: 11.56, $p < .001$), and PF-noconnect (β=0.30, *SE* = 0.03, *t*-value: 11.09, $p < .001$). Items pertaining to flexibility were associated with decreased stress, including: PF-think (β=-0.19, *SE* = 0.03, *t*-value: -6.77, $p < .001$), PF-environ (β=-0.13, *SE* = 0.03, *t*-value: -4.35, $p < .001$), and PF-yesconnect (β=-0.24, *SE* = 0.03, *t*-value: -9.58, $p < .001$; Table 8). Similar to PA and NA models, within-person effects were highly variable, as shown in Figure 4, and ANOVA models comparing intercept-only and random-slope models each revealed better model fit for random-slope models. Overall, model results support hypothesis 1a as PF was significantly related to affect and stress at time *t*.

Temporal Associations Between PF, Affect, and Stress

Aim 1, hypotheses 1b-1c, temporal models examined the effects of PF on affect and stress over time (antecedent models) while controlling for PF earlier in the day and to model the potential ways in which PF, affect, and stress influence each other temporally (consequence models). The antecedent models were not supported for any of the PF-items predicting PA over time (See Table 9, Figure 5). The consequence models for PF-noconnect was supported, such that PF at time *t* predicted future inflexibility, when controlling for PF (β=0.18, *SE* = 0.04, *t*-value: 4.04, $p < .001$). PA at time *t* also influenced PF-noconnect by decreasing the chances of feeling this way later in the day (β=-0.14, *SE* = 0.04, *t*-value: -3.51, *p* <0.001). The day variable and intercept were also significant, evidencing differences across subjects (Figure 6). Lastly, the PF-yesconnect consequence model was supported. PF-yesconnect at time *t* predicted future increases in PF-yesconnect (β=0.24, *SE* = 0.043, *t*-value: 5.77, *p* <.001) as did PA at time *t* (β=0.13, *SE* = 0.04, *t*-value: 3.26, *p* =0.001). See Table 10 for PF-noconnect and PF-yesconnect models. All other consequence models were not significant.

Overall, antecedent models between PF-stuck, PF-noout, PF-noconnect, PF-think, PF-yesconnect and NA, respectively, were not supported though there was variability at the within-person level in terms of the nature of the effect (See Figure 7). However, the consequence models for PF-stuck and PF-noconnect were significant, such that PF at time *t* influenced PF at time *T+1* (PF-stuck: β=0.21, *SE* = 0.05, *t*-value: 3.76, *p* <.001; PF-noconnect: β=0.19, *SE* = 0.04, *t*-value: 4.45, *p* <.001) and NA and time *t* was associated with increased endorsement of feeling stuck and disconnected (β=0.12, *SE* = 0.04, *t*-value: 3.07, *p* =.002; β=0.13, *SE* = 0.04, *t*-value: 3.35, *p* <0.001, respectively). The day variable and model intercepts were significant indicating differences across persons (See Figure 7 and Table 12). The antecedent model for PF-environ and NA was supported such that PF-environ at time *t* predicted a small decrease in NA at time *T+1* (β=-0.07, *SE* = 0.03, *t*-value: -2.56, *p* =0.01), while NA at time *t* predicted greater NA at time *T+1* (β=0.23, *SE* = 0.03, *t*-value: 7.98, *p* <0.001; see Table 11). The consequence model for PF-environ and NA was not significant at the 0.02 level. The consequence model for PF-yesconnect and NA was supported, such that PF-yesconnect at time *t* predicted an increase in PF at time *T+1* (β=0.25, *SE* = 0.04, *t*-value: 6.27, *p* <0.001), while NA at time *t* predicted less NA at time *T+1* (β=-0.09, *SE* = 0.04, *t*-value: -2.54, *p* =0.01; see Table 12 and Figure 8). All other models were not significant.

For stress models, only PF-environ and PF-yesconnect exhibited significant antecedent models. A standardized one unit increase in PF-environ at time *t* was associated with a 0.06 unit decrease in stress at time *T+1* (*SE* = 0.02, *t*-value: -2.62, *p* =.01), and a standardized one unit increase in stress at time *t* was associated with a 0.3 unit increase in future stress (*SE* = 0.03, *t*-value: 11.02, *p* <.001). Results were similar in strength and direction for the PF-yesconnect and stress antecedent model (see Table 13, Figure 9). The PF-stress consequence models were significant for all PF items with the exception of PF-noout, PF-think, and PF-environ (see Table 14, Figure 10). Overall, hypotheses 1b and 1c were partially supported as PF variables were differentially related to affect and stress over time.

Contemporaneous Relationships Between PF, Affect, Stress, and Day Quality Considering Context and Event Type

Aim 1, hypotheses 1d-1e, contemporaneous models were repeated with the addition of an interaction term between either type of context (e.g., conflict/stressor or goal/value) or type of event (e.g., work/school, romantic relationship, friendship, family, finances, daily hassles/minor matters, health) and PF. Models were identical to original contemporaneous models with the exception of this interaction term and the addition of context or type as a random effect. Context did not significantly interact with any of the PF items to predict PA in contemporaneous models, but there was a significant positive main effects of goal/value context on PA in all models (Table 15). Context significantly interacted with PF-noconnect to reveal decreased NA (β=-0.14, *SE* = 0.04, *t*-value: -3.32, *p* =.001; Table 16). For stress models, context did not interact with any PF items to predict stress, but there was a significant negative main effect of goal/value context on stress in all models.

For models in which quality-of-day rating was the outcome of interest, there was a significant main effect of goal/value context on day quality in all PF models (all β's 0.08-0.14, *p*'s < 0.001). There was a significant small interaction between PF-environ and goal/value events (β=0.07, *SE* = 0.03, *t*-value: 2.59, *p* =.01) and between PF-yesconnect and goal/value events (β=0.09, *SE* = 0.03, *t*-value: 3.16, *p* <.01; Table 17). For type of event, there were no significant main effects of type on day quality rating with the exception of the PF-yesconnect model which showed a positive effect of daily hassle events on day quality ratings (β=0.13, *SE* = 0.05, *t*-value: 2.64, *p* = 0.01). Results also revealed significant positive interactions between PF-yesconnect and health, romantic, and friendship-related events in predicting day quality. There was a significant small interaction between each PF-stuck, PF-noout, and PF-noconnect and "other" type in the negative direction and a significant negative interaction between PF-stuck and romantic relationship events (see Table 18). Given differential relationships depending on the PF-item modeled, hypothesis 1d was partially supported.

Type of event models were identical to context models, though the random effect of type was removed to allow for models to converge. For PF-stuck and PA, there was a significant positive effect of friendship-related events and PA (β=0.20, *SE* = 0.08, *t*-

value: 2.39, $p = 0.02$). In PF-think PA models, there was a significant positive effect of friendship-related events on PA (β=0.22, *SE* = 0.09, *t*-value: 2.60, $p = 0.01$). There were no significant main effects or interactions regarding event type in PF-noout, PF-noconnect, and PF-environ PA models at the 0.02 level.

With respect to NA, there was a significant negative effect of daily hassle events on NA in the PF-stuck model (β=-0.25, *SE* = 0.07, *t*-value: -3.66, $p < 0.001$). There was also a significant negative effect of daily hassles on NA in the PF-noout model (β=-0.27, *SE* = 0.07, *t*-value: -3.68, $p < 0.001$) and a significant interaction between PF-noout and daily hassles (β=-0.17, *SE* = 0.07, *t*-value: -2.32, $p = 0.02$). For PF-noconnect models, there was a significant negative effect of daily hassles on NA (β=-0.24, *SE* = 0.07, *t*-value: -3.29, $p = 0.001$) and significant positive interactions with family and "other" event type ((β=0.31, *SE* = 0.08, *t*-value: 3.64, $p < 0.001$; β=0.20, *SE* = 0.09, *t*-value: 2.32, $p = 0.02$, respectively). For PF-think and PF-environ, there were significant negative main effects of daily hassles on NA (β=-0.27, *SE* = 0.07, *t*-value: -3.59, $p < 0.001$; β=-0.25, *SE* = 0.08, *t*-value: -3.24, $p = 0.001$, respectively), but no significant interactions. Consistent with other models, there was a significant negative effect of daily hassle events on NA (β=-0.27, *SE* = 0.08, *t*-value: -3.65, $p <0.001$), and a significant negative interaction between PF-yesconnect and friendship events on NA (β=-0.19, *SE* = 0.08, *t*-value: -2.30, $p = 0.02$). See Table 19.

With respect to stress models, there was a significant negative effect of friendship, family, and daily hassle events on stress and a positive interaction between PF-stuck and romantic-related events on stress (see Table 20). In the PF-noout stress model, there were significant negative associations between daily hassles and romantic-related event type and stress, and one significant positive interaction between PF-noout and romantic-related events (see Table 20). For the PF-noconnect stress model, there were significant negative associations between daily hassles and romantic-related event type and stress, and a positive interaction between PF-noconnect and romantic-related event type on stress (see Table 20). For the PF-think stress model, there were significant associations between romantic, friendship, and daily hassle events and stress, and no significant interactions. The same pattern of results holds for PF-environ models with the exception of the romantic and friendship event effects. For the PF-yesconnect stress model, the only main effect was daily hassles and there were two negative interactions between PF and romantic and friendship-related events on stress (see Table 20). Model results with type of event added support hypothesis 1e that type of event would be differentially associated with PF, affect, and stress.

Moderation Effects of Baseline Questionnaires on the Temporal and Contemporaneous Associations Between PF, Affect, and Stress

Aim 2 moderation models were identical to Aim 1 contemporaneous and temporal models, with the exception of the addition of an interaction term between a baseline questionnaire score or attentional task score and PF in prediction of affect or stress. All models included random effects of state PF, unless there were convergence issues. Non-significant Likelihood Ratio Tests from ANOVAs comparing intercept only models to models including random intercepts revealed that including random slopes based on individual differences did not improve model fit. There were no significant effects of baseline FFMQ total score (with Observe facet included) on PA in contemporaneous models. The interaction between baseline FFMQ and each PF item was also not significant in antecedent and consequence PA models, with the exception of the antecedent model for PF-environ (β=-0.06, *SE* = 0.02, *t*-value: -2.84, $p < 0.01$) and PF-yesconnect (β=-0.06, *SE* = 0.03, *t*-value: -2.49, $p = 0.01$; Table 21, Figure 11). In contemporaneous stress models, there was one significant interaction between PF-yesconnect and FFMQ (β=-0.05, *SE* = 0.02, *t*-value: -2.52, $p = 0.01$; Figure 11). With respect to temporal models with PF and stress, there was a significant interaction between PF-stuck and FFMQ in the stress consequence model (β=-0.12, *SE* = 0.05, *t*-value: -2.26, $p = 0.02$; see Figure 11). As such, hypothesis 2a was partially supported, though effects were quite small.

Each subscale from the ERQ (e.g., reappraisal and suppression) was entered as an interaction term in contemporaneous and temporal models for PA, NA, and stress. There were no significant main effects or interactions of ERQ subscales in contemporaneous PF models predicting PA or NA. Most temporal models revealed non-significant Likelihood Ratio Tests from ANOVAs comparing models, which increased interpretability of pooled estimates without as much concern for disregarding individual differences. In contemporaneous models predicting stress, there was a significant interaction between PF-stuck and reappraisal (β=0.10, *SE* = 0.03, *t*-value: 3.58, $p < 0.001$). For PF-noout and stress, there was no significant main effects or interactions at the 0.02 level of significance. There was a small negative interaction between PF-noconnect and reappraisal in predicting stress (β=-0.06, *SE* = 0.03, *t*-value: -3.00, $p < 0.001$), but no interaction with suppression. There were no significant main effects or interactions between ERQ subscales and PF-think or PF-environ in stress contemporaneous models. Reappraisal and PF-yesconnect significantly interacted to predict reduced stress (β=-0.06, *SE* = 0.024, *t*-value: -2.31, $p =$ 0.02), but there was no significant interaction with suppression scores. See Table 22 and Figure 12 for significant results. For temporal models between PF, affect, and stress, with the addition of ERQ subscale scores, there were no significant main effects or interactions in any model. Hypothesis 2b was partially supported as ERQ scores related to stress and interacted with PF-items, though these effects were not significant in temporal models.

Next, we incorporated three separate baseline measures of PF (e.g., AAQ-II, CFI, and ASQ) as moderators into contemporaneous and temporal models in models related to PF, NA, and stress. We used the total scores from the AAQ-II (higher scores indicating greater *in*flexibility) and CFI, and used individual subscale scores from the ASQ (e.g., tolerating, concealing, adjusting) in models. There were no significant main effects or interactions of ASQ subscale scores in any contemporaneous or temporal models including PF predicting NA or stress. For the contemporaneous NA models, there was a significant main effect of AAQ score (β=0.22, *SE* = 0.08, *t*-value: -2.90, $p =$ 0.01) and a significant negative interaction between AAQ and PF-environ in predicting NA (β=-0.07, *SE* = 0.02, *t*-value: -3.01, $p <$ 0.001). There was also a significant positive main effect of AAQ score in the PF-yesconnect NA model (see Table 23). For contemporaneous stress models with AAQ interactions added, there were no significant main effects or interactions with AAQ scores in PF-stuck, PF-noconnect, PF-nooout, PF-environ, or PF-yesconnect models. In the PF-think and stress model, there was a significant negative interaction between PF and AAQ score (β=-0.09, *SE* = 0.02, *t*-value: -3.81, $p < 0.001$; Table 24). Again, most contemporaneous NA and stress models revealed non-significant ANOVA comparisons of model fit.

There were no significant main effects of or interactions between AAQ scores and PF in any antecedent or consequence PF-NA models. With the exception of the PF-yesconnect stress model, there were no significant main effects of or interactions between AAQ scores and PF over time. PF-yesconnect and AAQ score exhibited a positive interaction effect on stress in the antecedent model only (β=0.05, *SE* = 0.02, *t*-value: 2.26, p =0.02).

For CFI total scores added to contemporaneous NA models, there was a significant positive interaction between PF-stuck and CFI score (β=0.08, *SE* = 0.03, *t*-value: 3.00, p <0.001; Figure 14, but all other main effects and interaction terms in other PF models were not significant. For contemporaneous stress models, there was a significant negative main effect of CFI score on stress in the PF-environ model (β=-0.25, *SE* = 0.08, *t*-value: -2.85, p =0.01) and the PF-yesconnect model (β=-0.23, *SE* = 0.09, *t*-value: -2.56, p =0.02), but all other main effects and interactions were not significant. See Table 25. For temporal models with CFI score added, there were no significant main effects of or interactions with CFI in NA or stress models. As such, hypothesis 2c was partially supported given several significant interaction terms but overall baseline flexibility scores revealed more main effects than interactions, counter to predictions.

Lastly, we entered a singular performance score from the Switching Task and Emotional Stroop into contemporaneous models to interact with the daily PF variables to predict affect and stress. For contemporaneous PF-PA models, there were significant negative interactions between Switching Cost and PF-stuck, PF-noout, and PF-noconnect, (all β's -0.09- -0.10, all *p's* <0.001; see Table 26 and Figure 15). For NA models, there were no significant main effects or interactions between Switching Cost and PF. For PF-stress models, the interaction between Switching Cost and PF-noout was significant in the positive direction (β=0.07, *SE* = 0.02, *t*-value: 2.97, *p* <0.001; see Table 26), but all other models were not significant.

There were no significant main effects of or interactions between the Stroop Effect score and PF in any affect or stress models. These results reveal partial support for hypothesis 2d which predicted that flexibility scores from the attentional tasks would moderate the relationships between PF, affect, and stress.

Discussion

Decades of research point to the psychosocial health benefits of PF across samples and methodologies. As the field has expanded its focus toward understanding idiographic processes over time, while moving away from nomothetic approaches that quantify group differences at the diagnostic level, it is increasingly important to understand the construct of PF in a similar way (Kashdan & Rottenberg, 2010; Kashdan et al., 2020; Doorley et al., 2020). Extant research has also called for changes in the way PF is measured, both in terms of measuring the construct over time, under different contexts, and in terms of the items or instruments used for measurement (e.g., moving beyond the AAQ). By understanding the way PF changes within individuals across time using measures that account for inflexible and flexible actions, we can better estimate the causality of the relationship between flexibility and affective processes (i.e., does inflexibility precede affective change and dysfunctional outcomes or vice versa?). The current study was designed to address these gaps in the literature by examining the dynamic relationship between PF, as measured by six distinct items from the PBAT, affect and stress in a clinical sample across different contexts. The aims of the current study estimated associations between PF, affect, and stress within and across time, under the contexts of conflicts or goals/values, and in the presence of various moderator variables including psychological processes, attentional metrics, and physical and social health data collected via smartphone apps. Comparison of antecedent and consequence temporal models allowed for examining whether changes in PF influenced affect or stress over time or vice versa, to estimate quasi-causal associations. A discussion of how the current study results relate more broadly to the literatures of PF and process-based therapy will follow.

Contemporaneous and Temporal Associations Between PF, Affect, and Stress

Aim 1, hypotheses 1a-1c, pertained to modeling the associations between PF, affect, and stress within and across time. For contemporaneous models, inflexible approaches to dealing with daily life (e.g., feeling stuck, having no outlet for emotions, and not connecting with life) were associated with lower positive affect, as expected. Flexible approaches to coping were associated with greater positive affect (e.g., connecting with others, changing one's environment, and thinking to problem-solve). As predicted, inflexible behaviors were associated with greater negative affect and stress while flexible behaviors were related to decreased negative affect and stress within the same time point. Across these models, there was a high degree of variability in the extent to which PF related to affect and stress and the direction of the effects within individuals, which is consistent with ACT theory such that the utility of identifying behaviors is more about function over form, as what works for one individual may not work for another. The relationship between PF, affect, and stress in contemporaneous models was generally consistent at the within and between group levels, with a few exceptions. As such, these "proof of concept" results support decades of literature identifying a relationship between PF, affect, and stress.

To explore the temporal associations between PF, affect, and stress, we modeled separate antecedent and consequence models (Marshall et al., 2020) in which lagged PF, affect, or stress variables predicted future affect, stress, or PF after controlling for previous timepoints (Figure 1). Results revealed no significant pooled effect of antecedent models between PF and PA. However, the heterogeneity amongst individuals points to the utility of understanding function over form of a behavior and the need to understand PF at the individual, rather than group level. Our results showed significant consequence models for PF-yesconnect and PF-noconnect, indicating that past PF predicted future PF and that PA predicted future PF. This suggests that positive affect and one's level of PF are primary driving forces behind these flexibility processes, but that PF was not predictive of PA processes. This supports treatment research that targets PA as opposed to solely focusing on reducing NA as well as efforts to increase social connection to reduce isolation and improve mental health.

In relation to NA, results indicated that changing one's environment predicted a small decrease in NA at future timepoints and that previous NA predicted increased future NA. This effect suggests that changing one's circumstances precedes changes in NA. In consequence models, our results revealed that previous instances of previous instances of feeling stuck or disconnected and previous NA did predict future inflexibility in these domains. It was also shown that previous instances of feeling connected were associated with feeling connected in the future, while previous NA was associated with reduced connection in the future. These effects altogether suggest that treatment efforts to reduce NA are likely helpful in increasing flexible behaviors. Overall, NA temporal models displayed high heterogeneity within individuals, even in models with non-significant pooled effects.

For stress models, only PF-environ and PF-yesconnect exhibited significant antecedent models, suggesting that changing one's environment and connecting with others as flexible behaviors decreased future stress, while endorsement of stress at time *t* was associated with increased future stress. These results are consistent with findings from evidence-based treatments that target behavior change over time to improve functioning. That said, our results also indicated that stress influences PF, with all consequence models significant except for PF-noout, PF-think, and PF-environ. These results seem to highlight research revealing the impacts of stressful life events or systemic inequalities on overall functioning and symptom reduction, such that changes to these stressful environments is beneficial.

Considering PF, Affect, and Stress in Context

Aim 1, hypothesis 1d examined the extent to which flexible behaviors affect overall perception of day-quality. Hypothesis 1e set to explore a basic premise of ACT, which is that PF is a contextual process. Context, specifically goals or values, was significantly related to positive quality-of-day ratings made at the end of the day in all contemporaneous PF models. Connecting with others and changing one's environment also significantly interacted with context to predict positive day quality. These results suggest that broadly engaging in or thinking about goals or values is related to increased perceptions of a "good" day and that psychological flexibility, in the context of values, provides an additive effect to perceptions of day quality. Conversely, type of event was not related to day quality, with the exception of one model which revealed a positive effect of daily hassles on day quality. This effect is counter to the expectation that more daily hassles may lead to a worse perception of the day, but it is possible that these hassles occurred within a valued-context, which could explain the positive effect. Despite an array of options for defining type of situation, there was a significant interaction between PF-stuck, PF-noout, PF-noconnect and "other" type of event in predicting worse day quality. This could suggest that unexpected or difficult to define daily experiences, when already acting inflexibly, dampens perception of the day.

For contemporaneous affect and stress models including context (with stress/conflict as the reference point), it was revealed that context did not interact with PF to predict PA, but that goal/value context was generally related to greater PA. Similarly, goal/value context was negatively associated with NA and stress. These global results suggest that engaging in or thinking about goals or values is generally beneficial and supports one of the primary mechanisms of change in ACT interventions that seek to identify, clarify, and promote values-based action. There were no significant interactions between PF and context in stress models, but there was one significant interaction between context and PF-noconnect resulting in reduced NA, which may suggest that the effect of context dampened the impact of general disconnect on overall affect. That said, contemporaneous results generally contradict context specificity in PF strategies, which was unexpected. Further research could examine the extent to which PF strategy use interacts with context over time.

For contemporaneous PA models with type of event included, our results revealed significant main effects of friendship-related events on increased PA, however we did not find any significant interactions between PF and type on PA, which was similar to context effects. Interestingly, in NA contemporaneous models, daily hassles were associated with reduced NA in all models. Given that we did not model the interaction between context and type in our models, as we were likely not sufficiently powered for three-way interactions, this effect could be driven by daily hassles that occurred within the context of goals or values. Alternatively, daily hassles as a categorical item may have been too broad or a "catch-all" category that actually included other event types that are more typically associated with reduced negative affect. PF significantly interacted with daily hassles, family, friendship, and "other" event-type, depending on the PBAT item modeled. Specifically, feeling like there is no outlet for emotions interacted with daily hassles to predict increased NA, and feeling disconnected interacted with family and "other" event-type to produce greater NA within time. Connection with others and friendship interacted to reduce NA within time. These data are consistent with CBT-based models of emotion that break down our experiences into situations, thoughts, feelings, and behaviors, such the daily events we experience do interact with our abilities to act flexibly which is associated with overall affect.

In stress models, our results revealed various main effects of and interactions with friendship, family, romantic, and daily hassle event types. PF-stuck interacted with romantic events in prediction of reduced stress within time and friendship, family, and daily hassle events were related to lower stress. PF-noout interacted with romantic events to relate to increased stress and PF-noconnect interacted with romantic or family events to predict increased stress within time. PF-yesconnect interacted with romantic and friendship events in association with less stress. in the PF-stuck, PF-noout, and PF-noconnect models, with the only main effect in PF-yesconnect models being daily hassles. PF-think and PF-environ did not interact with event type to predict stress. These results may suggest that when inflexible approaches are used (and account for variance in affect or stress outcomes), event type may more obviously affect one's perception of emotions or stress. Results may also reflect how stress and affect were measured in our study, as NA was only measured using one item pertaining to level of nervousness, which could theoretically be a feeling felt under positive and negative types of events and contexts. Similarly, our stress item measured the degree of stress in a given moment, this distinction did not qualify whether the stress was acute or more continuous or chronic. This may be an important next step in measuring stress in EMA designs, given evidence that acute and chronic stress differentially affect the hypothalamic-pituitary-adrenal (HPS) axis (Aschbacher et al., 2013; Belda et al., 2014; Lu, Wei, & Li, 2021), which is related to expressions of psychopathology versus resilience (Haglund et al., 2007; Claes et al. 2009; Doom & Gunnar, 2013).

Moderation Effects

Overall, our results partially supported the hypothesis that baseline mindfulness scores on the FFMQ affected PA or stress during the EMA phase. Data indicated a small, significant negative interaction between lagged PF-environ and PF-yesconnect and FFMQ scores in prediction of PA in time-lagged models. Greater PF and lower than average FFMQ scores were associated with greater PA, while lower PF and higher than average FFMQ scores were associated with less PA, so this interaction effect seems to be driven by level of PF more-so than mindfulness. Results were similar for the interaction between lagged PF-stuck and FFMQ on stress. PF-yesconnect interacted with FFMQ at the same timepoint to predict reduced stress, which was a small but significant effect driven by PF. FFMQ scores were equally predictive of stress when PF was low, but when PF was high, this effect superseded lower than average mindfulness scores.

In contemporaneous models, we did not find significant effects of baseline ERQ subscale scores on PA or NA. However, in contemporaneous stress models, we found significant positive interaction between feeling stuck and reappraisal, feeling disconnected and reappraisal (negative interaction effect), and connecting with others and reappraisal (negative interaction effect). At low levels of PF-stuck, stress was low irrespective of reappraisal, but higher than average PF-stuck scores and higher than average reappraisal scores produced greater stress. This pattern was similar for the PF-noconnect interaction. Lower PF-yesconnect scores and higher reappraisal scores were associated with higher stress, while higher PF scores were related to lower stress. In other words, it seems that general efforts to reappraise situations as a regulation tool (at baseline) did not compensate for feeling stuck or feeling disconnected in a given moment, which was associated with more stress. Counter to predictions, there were no significant main effects of or interactions with ERQ scores in temporal models, which may be reflective of the way that ERQ was measured (only at baseline) and less to do with no temporal effects, though future research should test this empirically. Even still, these results do not suggest a "one-size-fits-all" approach to understanding the interplay between emotion regulation and PF, and it seems warranted to understand how *daily* emotion regulation skill use may interact with PF.

In contrast to research identifying affective style as an emotional flexibility process that is related to psychopathology and changes over time, our results revealed no main effects of or interactions with baseline scores on the ASQ (e.g., tolerating, concealing, adjusting) in contemporaneous and temporal NA or stress models. Similar to interpretations of the emotion regulation models discussed earlier in this section, it is possible that null findings are related to only having administered the ASQ at baseline and endpoint as opposed to more frequently. Alternatively, it is possible that *changes* in affective styles may be more likely to relate to or interact with PF as opposed to one single trait score, but since the current study used a clinical sample of adults either in stable treatment or no treatment at all, ASQ scores change scores were small (less than 3 points for all subscales from pre-post on average). Future research could examine the unique or similar impacts of affective styles on PF using EMA within the context of treatment research.

In contemporaneous models predicting NA, there was a significant direct effect of AAQ score (higher score = inflexibility) in PF-environ and PF-yesconnect models. Changing one's environment to improve the moment significantly interacted with AAQ scores in NA the model in the negative direction. Higher AAQ scores were associated with greater NA at low PF levels, but this effect diminished at higher PF levels (Figure 13). That said, there were no significant main effects of or interactions between AAQ scores and PF in any temporal PF-NA models. In models predicting stress, there was a main effects of AAQ on stress in the PF-think model only. Using one's thinking in a situation also negatively interacted with AAQ score in the contemporaneous stress model, such that at low levels of PF-think, high AAQ score drove up stress, but high PF-think scores led to lower stress regardless of AAQ score. These results seem to suggest a general inflexible disposition that relates to NA and stress irrespective of time, which makes sense in light of the sample's clinical characteristics. That said, the significant negative interactions with daily PF, suggest that even individuals with general inflexible tendencies are able to behave flexibly and experience positive benefits in the form of reduced stress and negative affect in that moment. To some extent, this is part of what allows therapists to begin building motivation for change in clients, as they often have the ability to act differently, but the important step is practice and consistency. Unfortunately, our temporal models revealed no main effects of or interactions with baseline AAQ score, with the exception of an interaction between PF-yesconnect and AAQ in predicting stress in one antecedent model. This effect was driven primarily by PF score, such that low PF (lagged) and low AAQ score was associated with greater stress and greater PF was associated with lower stress (Figure 13). NA and stress model results including CFI total score as a predictor and interaction term revealed a significant positive interaction between PF-stuck and CFI, such that at low PF-stuck levels, NA was low irrespective of CFI score, but at higher PF-stuck levels, NA was high (Figure 14). Additionally, in stress models, CFI score was associated with less stress within a given contemporaneously. These data support an association between affect and PF, but do not suggest an interaction between dispositional and daily PF in predicting affect or stress over time.

As an additional indicator of flexibility that was not dependent on self-report, we employed two attentional tasks at baseline to measure attention bias and inflexibility to use as moderators in models. Overall, our sample exhibited expected switch costs on average, indicating that the Switching Task operated as intended. In contemporaneous models predicting PA, our results revealed significant negative interaction effects between PF and Switching Cost score for the three PBAT indicators of inflexibility (PF-stuck, PF-noout, and PF-noconnect). For stress models, there were positive interaction between PF-noout and switching cost. Although interaction effects were small, they were highly reliable such that lower daily PF scores were driving the negative effects on PA, while higher degrees of feeling disconnected were driving positive effects on stress (Figure 15). Given that 30% of our population had a primary diagnosis of GAD, with original switching task papers primarily measuring the effect in trait and state anxiety (Gustavson et al. 2017; Barthel et al., 2022), our effects should be tested in other populations. Future research should also determine if performance on the Switching Task is predictive of temporal changes in psychological processes over time, as our results are only contemporaneous.

Counter to prior studies relating scores on the Emotional Stroop with daily flexibility metrics, our results revealed no main effects of or interactions with Emotional Stroop scores in any contemporaneous affect or stress models. The average Stroop Effect score for our study sample was positive, indicating a significantly slower response time to emotional words, as the task should show, though it is possible that since the words used in our task were general and not specific to each individual's clinical presentation or set of emotional concerns, that effects were dampened.

Overall, the current study is one of the first to examine the dynamic relationship between PF, affect, and stress in a heterogenous clinical sample, specifically using items from the PBAT. Our results support clinical and research evidence that psychological flexibility is highly idiographic and variable over time. Importantly, our results also show that PF interacts with context and types of daily events to relate to affect and stress as well. In addition to the general correlational results of our data, we tested antecedent and consequence models (see Marshall et al., 2020) to estimate quasi-causal influences between PF and affect or stress, which showed that PF can precede or follow changes in affect and stress, depending on the behavior modeled. Data from the current study are an important first step in understanding how to best model PF as a contextual process over time in relation to other symptoms of psychopathology. These data are also promising for use in clinical settings as a way to potentially understand the specific flexible or inflexible behaviors that each client is walking in with, given that our data preliminarily show that different PF processes may relate differently to affect, stress, and moderator variables depending on the individual.

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Table 1 Study measurement schedule

Measure	Baseline Phase	EMA Phase	Endpoint
ADIS-5	X		
Emotional Stroop	X		
Task Switching	X		
FFMQ	X		X
PANAS	X		X
STAI	X		X
BDI	X		X
PSWQ	X		X
RRS	X		X
ERQ	X		X
AAQ-II	X		X
CFI	X		X
ASQ	X		X
SWLS	X		X
Stress Item		X	
Affect Items		X	
Event Categorical Items		X	
6 PBAT Items		X	
End of day rating		X	
Ethica app data (passive)		X	
Oura ring data (passive)		X	

Note. ADIS-5 = Anxiety Disorders Interview Schedule; FFMQ = Five Facet Mindfulness Questionnaire; PANAS = Positive and Negative Affect Scale; STAI = State-Trait Anxiety Inventory; BDI = Beck Depression Inventory; PSWQ = Penn State Worry Questionnaire; RRS = Ruminative Response Scale; ERQ = Emotion Regulation Questionnaire; AAQ-II = Acceptance and Action Questionnaire; CFI = Cognitive Flexibility Inventory; ASQ = Affective Styles Questionnaire; SWLS = Satisfaction With Life Scale; PBAT = Process Based Assessment Tool

Table 2 Baseline scores for psychological processes

Baseline Questionnaire	Mean(SD)
STAI-Total	99(20.2)
BDI	16.2(10.2)
PANAS-PA	27(7.6)
PANAS-NA	24.5(7.2)
PSWQ	61.9(12.6)
AAQ	39.2(7.1)
RRS-Total	55(16)
ERQ-Reappraisal	23.5(6.5)
ERQ-Suppression	13.2(5.8)
CFI-Total	98.3(13.5)
ASQ	
Concealing	23(7.4)
Tolerating	15.6(4.2)
Adjusting	16.5(4.9)
FFMQ-Total (w/Observe)	45.1(7.5)
SWLS	20(8.1)

Note. FFMQ = Five Facet Mindfulness Questionnaire; PANAS = Positive and Negative Affect Scale; STAI = State-Trait Anxiety Inventory; BDI = Beck Depression Inventory; PSWQ = Penn State Worry Questionnaire; RRS = Ruminative Response Scale; ERQ = Emotion Regulation Questionnaire; AAQ-II = Acceptance and Action Questionnaire; CFI = Cognitive Flexibility Inventory; ASQ = Affective Styles Questionnaire; SWLS = Satisfaction With Life Scale

Table 3 Sample demographic and diagnostic data

	Mean(SD)
Age	29.5 (11.9)
Gender(%, n)	
Male	20.5 (8)
Female	71.8 (28)
Non-binary	7.7 (3)
Race (%)	
White	79.5
Black or African American	2.6
Asian	10.3
More than one race	10.3
Not reported	2.5
Ethnicity (%)	
Non-Hispanic/Latinx	92.3
Hispanic/Latinx	5.1
Not reported	2.5
Primary Diagnosis (%, n)	
GAD	30.8 (12)
SAD	17.9 (7)
MDD or PDD	12.8 (5)
OCD	7.7 (3)
SPEC	7.7 (3)
OSAD	7.7 (3)
AG	5 (2)
PD	2.6 (1)
PTSD	2.6 (1)
BDD	2.6 (1)
ADHD	2.6 (1)

Note. GAD = Generalized Anxiety Disorder; SAD = Social Anxiety Disorder; MDD = Major Depressive Disorder; PDD = Persistent Depressive Disorder; OCD = Obsessive Compulsive Disorder; SPEC = Specific Phobia; OSAD = Other Specified Anxiety Disorder; AG = Agoraphobia; PD = Panic Disorder; PTSD = Post-Traumatic Stress Disorder; BDD = Body Dysmorphic Disorder; ADHD = Attention Deficit Hyperactivity Disorder

Table 4 Means, standard deviations, and correlations with confidence intervals

Variable	*M*	*SD*	1	2	3	4	5	6
1. PF-stuck	42.77	27.94						
2. PF-nooutlet	36.95	26.69	.67**					
			[.64, .69]					
3. PF-noconnect	41.79	27.19	.68**	.63**				
			[.65, .71]	[.59, .66]				
4. PF-think	57.20	23.34	-.52**	-.49**	-.45**			
			[-.56, -.49]	[-.53, -.45]	[-.49, -.41]			
5. PF-environ	51.11	25.62	-.15**	-.16**	-.11**	.34**		
			[-.20, -.10]	[-.21, -.11]	[-.16, -.06]	[.29, .38]		
6. PF-yesconnect	57.86	27.38	-.41**	-.37**	-.40**	.40**	.26**	
			[-.45, -.37]	[-.42, -.33]	[-.44, -.36]	[.36, .44]	[.21, .31]	

Note. M and *SD* are used to represent mean and standard deviation, respectively. Each row represents an item from the PBAT. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

Table 5 Descriptive statistics for EMA items

vars	N	mean	sd	median	min	max	range
PA	2156	2.23	1.06	2	1	5	4
NA	2153	1.93	1.00	2	1	5	4
Stress	2149	3.75	2.53	3	0	10	10
PF-stuck	1495	42.77	27.94	40	0	100	100
PF-noout	1491	36.95	26.69	31	0	100	100
PF-noconnect	1491	41.79	27.19	41	0	100	100
PF-think	1492	57.20	23.34	60	0	100	100
PF-environ	1490	51.11	25.62	53	0	100	100
PF-yesconnect	1491	57.86	27.38	60	0	100	100
Day Quality	2225	66.31	21.22	69	0	100	100

Note. PA = Positive Affect; NA = Negative Affect; PF items pertain to items selected from the PBAT

Table 6 PF-PA contemporaneous model results

	PA			**PA**			**PA**			**PA**			**PA**			**PA**		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.09	-0.09 – 0.27	0.323	0.07	-0.12 – 0.26	0.456	0.06	-0.13 – 0.24	0.552	0.07	-0.11 – 0.26	0.451	0.1	-0.10 – 0.31	0.314	0.09	-0.09 – 0.28	0.334
day	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.00	**0.011**	-0.01	-0.02 – -0.00	**0.028**	-0.02	-0.03 – -0.00	**0.009**	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.01	**0.002**
PF-stuck	-0.28	-0.35 – -0.21	**<0.001**															
Trait stuck	-0.02	-0.03 – -0.01	**0.001**															
PF-noout				-0.23	-0.30 – -0.15	**<0.001**												
Trait noout				-0.01	-0.02 – -0.00	**0.005**												
PF-noconnect							-0.26	-0.32 – -0.19	**<0.001**									
Trait noconnect							-0.01	-0.02 – -0.00	**0.004**									
PF-think										0.22	0.15 – 0.29	**<0.001**						
Trait think										0.02	0.01 – 0.03	**0.002**						

PF-environ													0.17	0.11 – 0.23	**<0.001**			
Trait environ													0	-0.01 – 0.02	0.625			
PF-yesconnect																0.25	0.19 – 0.32	**<0.001**
Trait yesconnect																0.01	0.00 – 0.02	**0.019**
Random Effects																		
σ^2	0.56			0.61			0.6			0.61			0.65			0.6		
τ_{00}	0.25_{id}			0.25_{id}			0.25_{id}			0.25_{id}			0.31_{id}			0.25_{id}		
τ_{11}	$0.03_{\text{id.scale(stuck.state)}}$			$0.04_{\text{id.scale(noout.state)}}$			$0.02_{\text{id.scale(nocon.state)}}$			$0.03_{\text{id.scale(think.state)}}$			$0.01_{\text{id.scale(environ.state)}}$			$0.02_{\text{id.scale(ycon.state)}}$		
ρ_{01}	-0.61_{id}			-0.64_{id}			-0.50_{id}			0.38_{id}			0.42_{id}			0.47_{id}		
ICC	0.33			0.32			0.31			0.31			0.33			0.32		
N	39_{id}			39_{id}			39_{id}			39_{id}			39_{id}			39_{id}		
Observations	1495			1491			1491			1492			1490			1491		
Marginal R^2 / Conditional R^2	0.160 / 0.439			0.102 / 0.393			0.130 / 0.401			0.120 / 0.393			0.037 / 0.354			0.112 / 0.394		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. "PF-stuck" is the state score and "Trait stuck" is the trait score, for example. PA = Positive Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 7 PF-NA contemporaneous model results

	NA			NA			NA			NA			NA			NA		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	-0.04	-0.21 – 0.14	0.667	-0.02	-0.21 – 0.16	0.795	-0.03	-0.21 – 0.16	0.783	-0.04	-0.23 – 0.14	0.639	-0.07	-0.27 – 0.13	0.492	-0.06	-0.26 – 0.13	0.538
day	0.01	-0.00 – 0.02	0.214	0.01	-0.01 – 0.02	0.369	0.01	-0.01 – 0.02	0.373	0.01	-0.01 – 0.02	0.211	0.01	-0.00 – 0.03	0.097	0.01	-0.00 – 0.03	0.119
PF-stuck	0.34	0.28 – 0.41	**<0.001**															
Trait stuck	0.02	0.01 – 0.02	**<0.001**															
PF-noout				0.26	0.19 – 0.33	**<0.001**												
Trait noout				0.01	0.00 – 0.02	**0.047**												
PF-noconnect							0.27	0.20 – 0.33	**<0.001**									
Trait noconnect							0.01	0.00 – 0.02	**0.017**									
PF-think										-0.16	-0.22 – -0.09	**<0.001**						
Trait think										-0.01	-0.03 – -0.00	**0.009**						
PF-environ													-0.1	-0.17 – -0.04	**0.002**			

Trait environ													-0.01	-0.02 – 0.01	0.316			
PF-yesconnect																-0.19	-0.24 – -0.14	**<0.001**
Trait yesconnect																0	-0.01 – 0.00	0.306
Random Effects																		
σ^2	0.63			0.68			0.68			0.72			0.74			0.72		
τ_{00}	0.20 id			0.22 id			0.20 id			0.21 id			0.24 id			0.24 id		
τ_{11}	0.02 id.scale(stuck.state)			0.02 id.scale(noout.state)			0.02 id.scale(nocon.state)			0.02 id.scale(think.state)			0.02 id.scale(environ.state)			0.01 id.scale(ycon.state)		
ρ_{01}	0.74 id			0.43 id			0.25 id			-0.75 id			-0.54 id			-0.73 id		
ICC	0.26			0.26			0.25			0.24			0.26			0.26		
N	39 id			39 id			39 id			39 id			39 id			39 id		
Observations	1495			1491			1491			1492			1490			1491		
Marginal R^2 / Conditional R^2	0.189 / 0.400			0.091 / 0.327			0.109 / 0.330			0.060 / 0.289			0.020 / 0.277			0.044 / 0.289		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. “PF-stuck” is the state score and “Trait stuck” is the trait score, for example. NA = Negative Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 8 PF-Stress contemporaneous model results

	Stress			Stress			Stress			Stress			Stress			Stress		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.12	-0.05 – 0.28	0.169	0.13	-0.04 – 0.30	0.124	0.14	-0.03 – 0.31	0.115	0.11	-0.08 – 0.30	0.257	0.09	-0.12 – 0.30	0.41	0.09	-0.12 – 0.30	0.385
day	-0.01	-0.02 – 0.00	0.054	-0.01	-0.03 – -0.00	**0.038**	-0.01	-0.03 – -0.00	**0.021**	-0.01	-0.02 – 0.00	0.16	-0.01	-0.02 – 0.01	0.309	-0.01	-0.02 – 0.01	0.258
PF-stuck	0.41	0.34 – 0.47	**<0.001**															
Trait stuck	0.03	0.02 – 0.03	**<0.001**															
PF-noout				0.33	0.27 – 0.38	**<0.001**												
Trait noout				0.02	0.01 – 0.03	**<0.001**												
PF-noconnect							0.3	0.25 – 0.36	**<0.001**									
Trait noconnect							0.02	0.01 – 0.03	**<0.001**									
PF-think										-0.19	-0.24 – -0.13	**<0.001**						
Trait think										-0.02	-0.04 – -0.01	**0.001**						

PF-environ													-0.13	-0.20 – -0.07	**<0.001**			
Trait environ													0	-0.01 – 0.01	0.86			
PF-yesconnect																-0.24	-0.29 – -0.19	**<0.001**
Trait yesconnect																-0.01	-0.02 – -0.00	**0.036**
Random Effects																		
σ^2	0.5			0.57			0.58			0.65			0.68			0.63		
τ_{00}	0.19 id			0.18 id			0.20 id			0.23 id			0.32 id			0.33 id		
τ_{11}	0.03 id.scale(stuck.state)			0.01 id.scale(noout.state)			0.01 id.scale(nocon.state)			0.01 id.scale(think.state)			0.02 id.scale(environ.state)			0.01 id.scale(ycon.state)		
ρ_{01}	0.60 id			0.58 id			0.53 id			-0.47 id			-0.32 id			-0.72 id		
ICC	0.3			0.25			0.27			0.27			0.33			0.35		
N	39 id			39 id			39 id			39 id			39 id			39 id		
Observations	1495			1491			1491			1492			1490			1491		
Marginal R^2 / Conditional R^2	0.329 / 0.531			0.232 / 0.427			0.222 / 0.430			0.117 / 0.357			0.019 / 0.348			0.095 / 0.409		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. “PF-stuck” is the state score and “Trait stuck” is the trait score, for example. Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 9 PF-PA antecedent models

	PA			PA			PA			PA			PA			PA		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.14	0.05 – 0.23	**0.003**	0.13	0.04 – 0.22	**0.006**	0.13	0.03 – 0.22	**0.007**	0.13	0.04 – 0.22	**0.006**	0.13	0.04 – 0.22	**0.005**	0.13	0.04 – 0.23	**0.005**
day	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.01	**0.001**
PA lag	0.19	0.13 – 0.25	**<0.001**	0.21	0.16 – 0.27	**<0.001**	0.22	0.16 – 0.28	**<0.001**	0.23	0.17 – 0.29	**<0.001**	0.23	0.17 – 0.28	**<0.001**	0.21	0.15 – 0.26	**<0.001**
PF-stuck lag	-0.07	-0.14 – 0.00	0.059															
Trait stuck	0.01	-0.04 – 0.06	0.677															
Trait PA	0.47	0.41 – 0.53	**<0.001**	0.45	0.39 – 0.52	**<0.001**	0.46	0.40 – 0.52	**<0.001**	0.45	0.39 – 0.51	**<0.001**	0.45	0.39 – 0.50	**<0.001**	0.46	0.40 – 0.52	**<0.001**
PF-noout lag				-0.03	-0.08 – 0.02	0.218												
Trait nooout				0	-0.06 – 0.05	0.874												
PF-noconnect lag							-0.02	-0.07 – 0.03	0.379									
Trait noconnect							0.01	-0.04 – 0.06	0.676									

PF-think lag										-0.02	-0.07 – 0.03	0.446						
Trait think										-0.01	-0.06 – 0.04	0.737						
PF-environ lag													0.02	-0.03 – 0.07	0.419			
Trait environ													0.01	-0.04 – 0.06	0.677			
PF-yesconnect lag																0.05	0.00 – 0.10	0.035
Trait yesconnect																0.01	-0.04 – 0.06	0.783
Random Effects																		
σ^2	0.6			0.63			0.63			0.62			0.62			0.62		
τ_{00}	0.00 id			0.00 id			0.00 id			0.00 id			0.00 id			0.00 id		
τ_{11}	0.02 id.scale(stuck.state.lag)			0.00 id.scale(noout.state.lag)			0.00 id.scale(nocon.state.lag)			0.00 id.scale(think.state.lag)			0.00 id.scale(environ.state.lag)			0.00 id.scale(ycon.state.lag)		
ρ_{01}	-0.17 id			0.01 id			0.00 id			0.14 id			0.08 id			-0.08 id		
ICC	0.03			0			0			0.01			0			0		
N	39 id			39 id			39 id			39 id			39 id			39 id		
Observations	1189			1187			1187			1187			1185			1186		
Marginal R^2 / Conditional R^2	0.381 / 0.401			0.375 / 0.375			0.376 / 0.376			0.375 / 0.379			0.376 / 0.379			0.376 / 0.377		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1*. PA = Positive Affect; NA = Negative Affect Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 10 PF-PA consequence models

	PF-noout			PF-yesconnect		
Predictors	Estimates	CI	p	Estimates	CI	p
(Intercept)	-0.16	-0.31 – -0.02	**0.03**	0	-0.13 – 0.12	0.954
day	0.02	0.01 – 0.04	**0.01**	0	-0.01 – 0.02	0.959
PA lag	-0.07	-0.15 – 0.01	0.07	0.13	0.05 – 0.21	**0.001**
PF-noout lag	0.13	0.04 – 0.21	**<0.001**			
Trait noout	0.04	-0.04 – 0.12	0.29			
Trait PA	0.05	-0.04 – 0.14	0.28	-0.09	-0.17 – -0.00	**0.043**
PF-yesconnect lag				0.24	0.16 – 0.32	**<0.001**
Trait yesconnect				0.02	-0.05 – 0.09	0.607
Random Effects						
σ^2	0.94			0.91		
τ_{00}	0.00 id			0.00 id		
τ_{11}	0.02 id.scale(noout.state.lag)			0.01 id.scale(ycon.state.lag)		
ρ_{01}	0.72 id			0.00 id		
ICC	0.02			0.02		
N	39 id			39 id		
Observations	939			936		
Marginal R^2 / Conditional R^2	0.037 / 0.055			0.085 / 0.099		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. PA = Positive Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 11 PF-NA antecedent model results

	scale(na)		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.11	-0.22 – 0.00	0.054
day	0.01	0.00 – 0.03	**0.027**
nalag	0.23	0.17 – 0.28	**<0.001**
environ state lag	-0.07	-0.12 – -0.02	**0.011**
imean environ	0.02	-0.04 – 0.07	0.529
imean na	0.37	0.30 – 0.43	**<0.001**
Random Effects			
σ^2	0.70		
$\tau_{00\ id}$	0.00		
$\tau_{11\ id.scale(environ.state.lag)}$	0.00		
$\rho_{01\ id}$	-0.32		
ICC	0.00		
N_{id}	39		
Observations	1184		
Marginal R^2 / Conditional R^2	0.280 / 0.283		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent time *T*. environ state lag = PF-environ lag; nalag = Negative Affect lag; imean environ = Trait environ; imean na = Trait NA; NA = Negative Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 12 PF-NA consequence model results

	PF-stuck			PF-noconnect			PF-environ			PF-yesconnect		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	-0.18	-0.31 – -0.05	**0.005**	-0.19	-0.31 – -0.06	**0.004**	0	-0.14 – 0.13	0.944	0.02	-0.11 – 0.14	0.795
day	0.02	0.01 – 0.04	**0.002**	0.03	0.01 – 0.04	**0.001**	0	-0.02 – 0.02	0.932	0	-0.02 – 0.01	0.751
NA lag	0.12	0.04 – 0.19	**0.002**	0.13	0.05 – 0.20	**0.001**	0.08	0.01 – 0.15	**0.029**	-0.09	-0.17 – -0.02	**0.011**
PF-stuck lag	0.21	0.10 – 0.31	**<0.001**									
Trait stuck	0.02	-0.05 – 0.09	0.576									
Trait NA	-0.07	-0.15 – 0.01	0.082	-0.07	-0.15 – 0.01	0.079	-0.01	-0.09 – 0.06	0.748	0.06	-0.01 – 0.13	0.102
PF-noconnect lag				0.19	0.10 – 0.27	**<0.001**						
Trait noconnect				0.02	-0.05 – 0.09	0.519						
PF-environ lag							0.15	0.06 – 0.23	**<0.001**			
Trait environ							0.01	-0.05 – 0.08	0.677			

PF-yesconnect lag										0.25	0.18 – 0.33	**<0.001**
Trait yesconnect										0.02	-0.04 – 0.08	0.536
Random Effects												
σ^2	0.85			0.91			0.95			0.91		
τ_{00}	0.00 id			0.00 id			0.00 id			0.00 id		
τ_{11}	0.05 id.scale(stuck.state.lag)			0.02 id.scale(nocon.state.lag)			0.02 id.scale(environ.state.lag)			0.01 id.scale(ycon.state.lag)		
ρ_{01}	0.36 id			0.94 id			0.40 id			-0.07 id		
ICC	0.06			0.02			0.02			0.02		
N	39 id			39 id			39 id			39 id		
Observations	942			940			936			936		
Marginal R^2 / Conditional R^2	0.087 / 0.140			0.079 / 0.098			0.026 / 0.041			0.082 / 0.096		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. NA = Negative Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 13 PF-Stress antecedent model results

	Stress			Stress		
Predictors	Est.	CI	p	Est.	CI	p
(Intercept)	0	-0.10 – 0.09	0.952	0	-0.10 – 0.10	0.992
day	0	-0.01 – 0.01	0.962	0	-0.01 – 0.01	0.975
Stress lag	0.3	0.25 – 0.35	**<0.001**	0.29	0.24 – 0.35	**<0.001**
PF-environ lag	-0.06	-0.11 – -0.02	**0.009**			
Trait environ	0.01	-0.04 – 0.06	0.598			
Trait stress	0.4	0.34 – 0.46	**<0.001**	0.4	0.34 – 0.46	**<0.001**
PF-yesconnect lag				-0.06	-0.11 – -0.02	**0.009**
Trait yesconnect				-0.04	-0.09 – 0.00	0.074
Random Effects						
σ^2	0.6			0.59		
τ_{00}	0.00 $_{id}$			0.00 $_{id}$		
τ_{11}	0.00 $_{id.scale(environ.state.lag)}$			0.00 $_{id.scale(ycon.state.lag)}$		
ρ_{01}	0.02 $_{id}$			0.02 $_{id}$		
ICC	0			0		
N	39 $_{id}$			39 $_{id}$		
Observations	1182			1182		
Marginal R^2 / Conditional R^2	0.394 / 0.395			0.397 / 0.397		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 14 PF-stress consequence model results

	PF-stuck			PF-noconnect			PF-yesconnect		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	-0.2	-0.32 – -0.07	**0.003**	-0.21	-0.34 – -0.08	**0.001**	0.02	-0.10 – 0.15	0.706
day	0.03	0.01 – 0.04	**0.001**	0.03	0.01 – 0.04	**<0.001**	0	-0.02 – 0.01	0.652
Stress lag	0.18	0.10 – 0.26	**<0.001**	0.21	0.14 – 0.29	**<0.001**	-0.13	-0.20 – -0.05	**0.001**
PF-stuck lag	0.16	0.05 – 0.27	**0.003**						
Trait stuck	0.01	-0.08 – 0.09	0.858						
Trait stress	-0.09	-0.18 – 0.01	0.068	-0.13	-0.22 – -0.04	**0.008**	0.07	-0.00 – 0.15	0.056
PF-noconnect lag				0.14	0.06 – 0.22	**0.001**			
Trait noconnect				0.03	-0.05 – 0.11	0.49			
PF-yesconnect lag							0.24	0.16 – 0.33	**<0.001**
Trait yesconnect							0.02	-0.04 – 0.08	0.505
Random Effects									
σ^2	0.84			0.89			0.91		
τ_{00}	0.00_{id}			0.00_{id}			0.00_{id}		
τ_{11}	$0.05_{\text{id.scale(stuck.state.lag)}}$			$0.01_{\text{id.scale(nocon.state.lag)}}$			$0.01_{\text{id.scale(ycon.state.lag)}}$		
ρ_{01}	0.38_{id}			0.92_{id}			0.02_{id}		
ICC	0.06			0.02			0.02		
N	39_{id}			39_{id}			39_{id}		
Observations	942			940			936		
Marginal R^2 / Conditional R^2	0.092 / 0.144			0.091 / 0.108			0.087 / 0.102		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. PA = Positive Affect; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 15 Context as a moderator in PF-PA contemporaneous models

	Value	Std.Error	p-value
Goal/Value Context	0.358	0.051	**0**
PF-stuck	-0.2	0.038	**0**
Trait stuck	-0.013	0.004	**0.003**
Goal/Value Context*PF-stuck	-0.029	0.045	0.521
Goal/Value Context	0.444	0.063	**0**
PF-noout	-0.137	0.038	**0**
Trait noout	-0.01	0.004	**0.02**
Goal/Value Context*PF-noout	-0.041	0.044	0.353
Goal/Value Context	0.457	0.065	**0**
PF-noconnect	-0.198	0.035	**0**
Trait noconnect	-0.01	0.004	**0.013**
Goal/Value Context*PF-noconnect	0.011	0.044	0.796
Goal/Value Context	0.458	0.063	**0**
PF-think	0.146	0.033	**0**
Trait think	0.016	0.006	**0.008**
Goal/Value Context*PF-think	0.042	0.042	0.322
Goal/Value Context	0.53	0.068	**0**
PF-environ	0.105	0.03	**0**
Trait environ	0.002	0.005	0.708
Goal/Value Context*PF-environ	0.031	0.041	0.452
Goal/Value Context	0.478	0.066	**0**
PF-yesconnect	0.199	0.035	**0**
Trait yesconnect	0.011	0.004	**0.017**
Goal/Value Context*PF-yesconnect	-0.002	0.042	0.969

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Goal/Value Context = participants were thinking about or acting on a value or goal when prompted; * indicates interaction term; PA = Positive Affect. All scores are standardized for interpretability.

Table 16 Context as a moderator in PF-NA contemporaneous models

Item	Value	Std.Error	p-value
Goal/Value Context	-0.193	0.052	**0**
PF-stuck	0.31	0.039	**0**
Trait stuck	0.015	0.004	**0.001**
Goal/Value Context*PF-stuck	-0.006	0.046	0.896
Goal/Value Context	-0.329	0.065	**0**
PF-noout	0.228	0.038	**0**
Trait noout	0.008	0.005	0.11
Goal/Value Context*PF-noout	-0.047	0.046	0.306
Goal/Value Context	-0.341	0.064	**0**
PF-noconnect	0.284	0.033	**0**
Trait noconnect	0.009	0.004	0.046
Goal/Value Context*PF-noconnect	-0.144	0.043	**0.001**
Goal/Value Context	-0.375	0.07	**0**
PF-think	-0.16	0.038	**0**
Trait think	-0.012	0.005	0.026
Goal/Value Context*PF-think	0.08	0.045	0.074
Goal/Value Context	-0.438	0.075	**0**
PF-environ	-0.085	0.037	**0.022**
Trait environ	-0.004	0.005	0.43
Goal/Value Context*PF-environ	0.025	0.044	0.562
Goal/Value Context	-0.402	0.067	**0**
PF-yesconnect	-0.167	0.03	**0**
Trait yesconnect	-0.002	0.005	0.664
Goal/Value Context*PF-yesconnect	0.053	0.043	0.222

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Goal/Value Context = participants were thinking about or acting on a value or goal when prompted; * indicates interaction term; NA = Negative Affect. All scores are standardized for interpretability.

Table 17 Context as a moderator in PF models predicting day quality

	Value	Std.Error	p-value
Goal/Value Context	0.125	0.032	**0**
PF-environ	-0.016	0.023	0.497
Trait environ	0.004	0.006	0.546
Goal/Value Context*PF-eviron	0.072	0.028	**0.01**
Goal/Value Context	0.133	0.033	**0**
PF-yesconnect	-0.008	0.029	0.796
Trait yesconnect	0.025	0.004	**0**
Goal/Value Context*PF-yesconnect	0.09	0.028	**0.002**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Goal/Value Context = participants were thinking about or acting on a value or goal when prompted; * indicates interaction term. All scores are standardized for interpretability.

Table 18 Type of event as a moderator in PF models predicting day quality

	Value	Std.Error	p-value
PF-stuck	-0.1	0.029	0.001
Trait stuck	-0.028	0.004	0
Romantic event*PF-stuck	-0.136	0.057	**0.018**
Other event*PF-stuck	0.186	0.064	**0.004**
PF-noout	-0.077	0.026	0.003
Trait noout	-0.028	0.005	0
Other event*PF-noout	0.157	0.052	**0.003**
PF-noconnect	-0.087	0.032	0.007
Trait no connect	-0.023	0.004	0
Other event*PF-noconnect	0.151	0.053	**0.005**
PF-yesconnect	0.005	0.032	0.881
Trait yes-connect	0.027	0.004	0
Romantic event*PF-yesconnect	0.138	0.053	**0.009**
Friendship event*PF-yesconnect	0.131	0.052	**0.012**
Health event*PF-yesconnect	0.104	0.043	**0.017**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Event Type = participants were engaging in an activity related to that type of event; * indicates interaction term; PA = Positive Affect. All scores are standardized for interpretability.

Table 19 Type as a moderator in PF-NA contemporaneous models

	Value	Std.Error	p-value
Daily Hassles	-0.249	0.072	**0.001**
PF-stuck	0.336	0.043	**0**
Trait stuck	0.016	0.004	**0**
Daily Hassles	-0.269	0.073	**0**
PF-noout	0.268	0.045	**0**
Trait noout	0.01	0.005	0.046
Daily Hassles*PF-noout	-0.166	0.072	**0.02**
Daily Hassles	-0.241	0.073	**0.001**
PF-noconnect	0.219	0.042	**0**
Trait noconnect	0.01	0.004	**0.023**
Family Event*PF-noconnect	0.313	0.086	**0**
Other Event*PF-noconnect	0.198	0.085	**0.02**
Daily Hassles	-0.268	0.075	**0**
PF-think	-0.182	0.043	**0**
Trait think	-0.015	0.005	**0.01**
Daily Hassles	-0.246	0.076	**0.001**
PF-environ	-0.11	0.042	**0.009**
Trait environ	-0.006	0.006	0.301
Daily Hassles	-0.274	0.075	**0**
PF-yesconnect	-0.157	0.039	**0**
Trait yesconnect	-0.005	0.005	0.314
Friendship Event*PF-yesconnect	-0.186	0.081	**0.021**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Event Type = participants were engaging in an activity related to that type of event; * indicates interaction term; NA = Negative Affect. All scores are standardized for interpretability.

Table 20 Type as a moderator in PF-Stress contemporaneous models

	Value	Std.Error	p-value
Friendship Event	-0.216	0.077	**0.005**
Family Event	-0.201	0.074	**0.006**
Daily Hassles	-0.218	0.065	**0.001**
PF-stuck	0.391	0.042	**0**
Trait stuck	0.026	0.004	**0**
Romantic Event*PF-stuck	0.196	0.077	**0.011**
Romantic Event	-0.211	0.09	**0.02**
PF-noout	0.295	0.037	**0**
Trait noout	0.022	0.004	**0**
Romantic Event*PF-noout	0.262	0.076	**0.001**
Romantic Event	-0.21	0.091	**0.02**
Daily Hassles	-0.204	0.068	**0.003**
PF-noconnect	0.219	0.036	**0**
Trait noconnect	0.019	0.004	**0**
Romantic Event*PF-noconnect	0.298	0.077	**0**
Romantic Event	-0.246	0.098	**0.012**
Friendship Event	-0.197	0.083	**0.018**
Daily Hassles	-0.258	0.07	**0**
PF-think	-0.219	0.038	**0**
Trait think	-0.023	0.006	**0.001**
Daily Hassles	-0.22	0.072	**0.002**
PF-environ	-0.111	0.04	**0.006**
Trait environ	-0.001	0.007	0.887
Daily Hassles	-0.249	0.07	**0**
PF-yesconnect	-0.188	0.037	**0**
Trait yesconnect	-0.011	0.005	0.047
Romantic Event*PF-yesconnect	-0.23	0.076	**0.003**
Friendship Event*PF-yesconnect	-0.203	0.075	**0.007**

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Event Type = participants were engaging in an activity related to that type of event; * indicates interaction term. All scores are standardized for interpretability.

Table 21 Significant PF-PA antecedent model results with FFMQ as moderator

	PA			PA		
Predictors	Est.	CI	p	Est.	CI	p
(Intercept)	0.13	0.04 – 0.23	**0.005**	0.14	0.04 – 0.23	**0.005**
day	-0.02	-0.03 – -0.01	**0.002**	-0.02	-0.03 – -0.01	**0.002**
PA lag	0.23	0.17 – 0.28	**<0.001**	0.21	0.15 – 0.27	**<0.001**
PF-environ lag	0.02	-0.03 – 0.06	0.492			
FFMQ	-0.02	-0.07 – 0.03	0.476	-0.01	-0.07 – 0.04	0.611
Trait environ	0.02	-0.03 – 0.07	0.496			
Trait pa	0.45	0.39 – 0.51	**<0.001**	0.46	0.40 – 0.52	**<0.001**
PF-environ lag * FFMQ	-0.06	-0.10 – -0.02	**0.005**			
PF-yesconnect lag				0.04	-0.02 – 0.09	0.17
Trait yesconnect				0.01	-0.05 – 0.07	0.755
PF-yesconnect lag * FFMQ				-0.06	-0.11 – -0.01	**0.013**
Random Effects						
σ^2		0.62			0.62	
τ_{00}		0.00 id			0.00 id	
τ_{11}		0.00 id.scale(environ.state.lag)			0.00 id.scale(ycon.state.lag)	
ρ_{01}		0.00 id			-0.01 id	
ICC		0			0	
N		37 id			37 id	
Observations		1138			1137	
Marginal R^2 / Conditional R^2		0.381 / 0.381			0.380 / 0.380	

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time *T-1* and outcome variables represent score at time *T*. PA = Positive Affect; FFMQ = Five Facet Mindfulness Questionnaire; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 22 Significant PF-Stress model results with ERQ scores as moderators

	Stress			Stress			Stress		
Predictors	Est.	CI	p	Est.	CI	p	Est.	CI	p
(Intercept)	0.11	-0.05 – 0.28	0.18	0.14	-0.04 – 0.31	0.127	0.09	-0.12 – 0.30	0.396
day	-0.01	-0.02 – 0.00	0.065	-0.01	-0.03 – -0.00	**0.026**	-0.01	-0.02 – 0.01	0.279
ERQ-R	0.09	-0.06 – 0.24	0.233	0.03	-0.12 – 0.19	0.682	0.02	-0.20 – 0.24	0.866
PF-stuck	0.41	0.35 – 0.47	**<0.001**						
Trait stuck	0.03	0.02 – 0.03	**<0.001**						
ERQ-R * PF-stuck	0.1	0.05 – 0.16	**<0.001**						
PF-noconnect				0.3	0.25 – 0.36	**<0.001**			
Trait noconnect				0.02	0.01 – 0.03	**<0.001**			
ERQ-R * PF-noconnect				0.06	0.01 – 0.11	**0.021**			
PF-yesconnect							-0.24	-0.28 – -0.20	**<0.001**
Trait yesconnect							-0.01	-0.02 – 0.01	0.349
ERQ-R * PF-yesconnect							-0.06	-0.09 – -0.02	**0.003**

Random Effects

σ^2	0.5	0.58	0.63
τ_{00}	0.19 $_{\text{id}}$	0.20 $_{\text{id}}$	0.33 $_{\text{id}}$
τ_{11}	0.02 $_{\text{id.scale(stuck.state)}}$	0.01 $_{\text{id.scale(nocon.state)}}$	0.00 $_{\text{id.scale(ycon.state)}}$
ρ_{01}	0.65 $_{\text{id}}$	0.60 $_{\text{id}}$	-0.01 $_{\text{id}}$
ICC	0.29	0.27	0.34
N	39 $_{\text{id}}$	39 $_{\text{id}}$	39 $_{\text{id}}$
Observations	1495	1491	1491
Marginal R^2 / Conditional R^2	0.342 / 0.532	0.226 / 0.436	0.071 / 0.388

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. ERQ-R = Emotion Regulation Questionnaire-Reappraisal subscale; * denotes interaction term; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 23 Significant PF-NA model results with AAQ score as a moderator

	scale(na)			scale(na)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.06	-0.25 – 0.12	0.492	-0.06	-0.24 – 0.13	0.552
day	0.01	-0.00 – 0.03	0.097	0.01	-0.00 – 0.03	0.120
aaq	0.22	0.07 – 0.38	**0.006**	0.21	0.05 – 0.37	**0.010**
environ state	-0.10	-0.15 – -0.06	**<0.001**			
imean environ c	-0.00	-0.01 – 0.01	0.958			
aaq * environ state	-0.07	-0.11 – -0.02	**0.003**			
ycon state				-0.20	-0.25 – -0.14	**<0.001**
imean ycon c				-0.00	-0.01 – 0.01	0.598
aaq * ycon state				0.02	-0.04 – 0.08	0.538
Random Effects						
σ^2	0.76			0.72		
τ_{00}	0.19 $_{\text{id}}$			0.20 $_{\text{id}}$		
τ_{11}	0.00 $_{\text{id.scale(environ.state)}}$			0.01 $_{\text{id.scale(ycon.state)}}$		
ρ_{01}	-0.02 $_{\text{id}}$			-0.71 $_{\text{id}}$		
ICC	0.20			0.22		
N	39 $_{\text{id}}$			39 $_{\text{id}}$		
Observations	1490			1491		
Marginal R^2 / Conditional R^2	0.069 / 0.257			0.088 / 0.289		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. NA and scale(na) = Negative Affect; AAQ = Acceptance and Action Questionnaire; * denotes interaction term; environ state = PF-environ; ycon state = PF-yesconnect; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 24 Significant PF-Stress model results with AAQ score as a moderator

	scale(stress)			scale(stress)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.12	-0.07 – 0.31	0.205	-0.00	-0.10 – 0.09	0.922
day	-0.01	-0.03 – 0.00	0.115	0.00	-0.01 – 0.01	0.927
aaq	0.10	-0.08 – 0.27	0.281	-0.01	-0.06 – 0.04	0.752
think state	-0.19	-0.24 – -0.14	**<0.001**			
imean think c	-0.02	-0.04 – -0.01	**0.003**			
aaq * think state	-0.09	-0.14 – -0.05	**<0.001**			
stresslag				0.30	0.24 – 0.35	**<0.001**
ycon state lag				-0.07	-0.12 – -0.03	**0.003**
imean ycon				-0.04	-0.09 – 0.00	0.072
imean stress				0.40	0.34 – 0.46	**<0.001**
ycon state lag * aaq				0.05	0.01 – 0.10	**0.024**
Random Effects						
σ^2	0.65			0.59		
τ_{00}	0.23 $_{id}$			0.00 $_{id}$		
τ_{11}	0.01 $_{id.scale(think.state)}$			0.00 $_{id.scale(ycon.state.lag)}$		
ρ_{01}	-0.40 $_{id}$			0.00 $_{id}$		
ICC	0.26			0.00		
N	39 $_{id}$			39 $_{id}$		
Observations	1492			1182		
Marginal R^2 / Conditional R^2	0.145 / 0.371			0.401 / 0.401		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. scale(stress) = Stress; AAQ = Acceptance and Action Questionnaire; * denotes interaction term; think state = PF-think; ycon state = PF-yesconnect; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 25 Significant PF model results with CFI score as a moderator

	scale(na)			scale(stress)			scale(stress)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.06	-0.25 – 0.12	0.507	0.06	-0.14 – 0.26	0.577	0.05	-0.16 – 0.25	0.653
day	0.01	-0.00 – 0.03	0.079	-0.01	-0.02 – 0.01	0.257	-0.01	-0.02 – 0.01	0.353
cfitotal	0.05	-0.12 – 0.23	0.554	-0.23	-0.41 – -0.05	**0.015**	-0.25	-0.43 – -0.07	**0.007**
stuck state	0.36	0.30 – 0.42	**<0.001**						
imean stuck c	0.01	0.00 – 0.02	**0.005**						
cfitotal * stuck state	0.08	0.03 – 0.13	**0.003**						
ycon state				-0.27	-0.31 – -0.22	**<0.001**			
imean ycon c				-0.00	-0.01 – 0.01	0.726			
cfitotal * ycon state				-0.03	-0.07 – 0.00	0.087			
environ state							-0.14	-0.21 – -0.07	**<0.001**
imean environ c							0.00	-0.01 – 0.01	0.780
cfitotal * environ state							-0.01	-0.08 – 0.05	0.706
Random Effects									
σ^2	0.62			0.68			0.73		
τ_{00}	0.21 $_{\text{id}}$			0.24 $_{\text{id}}$			0.23 $_{\text{id}}$		
τ_{11}	0.01 $_{\text{id.scale(stuck.state)}}$			0.00 $_{\text{id.scale(ycon.state)}}$			0.02 $_{\text{id.scale(environ.state)}}$		
ρ_{01}	0.91 $_{\text{id}}$			-0.00 $_{\text{id}}$			-0.38 $_{\text{id}}$		
ICC	0.26			0.26			0.25		
N	36 $_{\text{id}}$			36 $_{\text{id}}$			36 $_{\text{id}}$		
Observations	1374			1372			1370		
Marginal R^2 / Conditional R^2	0.180 / 0.397			0.124 / 0.350			0.075 / 0.311		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. scale(stress) = Stress; cfitotal= Cognitive Flexibility Inventory total score; * denotes interaction term; stuck state = PF-stuck; ycon state = PF-yesconnect; environ state = PF-environ; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Table 26 Significant PF model results with Switching Cost as a moderator

	scale(pa)			scale(pa)			scale(pa)			scale(stress)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.09	-0.09 – 0.27	0.330	0.07	-0.12 – 0.26	0.472	0.05	-0.13 – 0.24	0.570	0.13	-0.04 – 0.30	0.130
day	-0.02	-0.03 – -0.01	**0.001**	-0.02	-0.03 – -0.00	**0.010**	-0.01	-0.02 – -0.00	**0.027**	-0.01	-0.03 – -0.00	**0.034**
SwitchingCost	0.09	-0.09 – 0.28	0.297	0.04	-0.15 – 0.22	0.696	0.05	-0.13 – 0.23	0.576	0.07	-0.08 – 0.23	0.350
stuck state	-0.28	-0.34 – -0.21	**<0.001**									
imean stuck c	-0.02	-0.03 – -0.01	**0.001**									
SwitchingCost * stuck state	-0.10	-0.17 – -0.03	**0.004**									
noout state				-0.23	-0.30 – -0.15	**<0.001**				0.33	0.28 – 0.38	**<0.001**
imean noout c				-0.01	-0.02 – -0.00	**0.012**				0.02	0.01 – 0.03	**<0.001**
SwitchingCost * noout state				-0.09	-0.17 – -0.02	**0.016**				0.07	0.02 – 0.12	**0.003**
nocon state							-0.25	-0.31 – -0.20	**<0.001**			
imean nocon c							-0.01	-0.02 – -0.00	**0.008**			
SwitchingCost * nocon state							-0.09	-0.14 – -0.03	**0.004**			
Random Effects												
σ^2	0.56			0.61			0.60			0.57		
τ_{00}	0.24_{id}			0.26_{id}			0.26_{id}			0.18_{id}		
τ_{11}	$0.02_{\text{id.scale(stuck.state)}}$			$0.03_{\text{id.scale(noout.state)}}$			$0.01_{\text{id.scale(nocon.state)}}$			$0.01_{\text{id.scale(noout.state)}}$		
ρ_{01}	-0.61_{id}			-0.70_{id}			-0.57_{id}			0.56_{id}		
ICC	0.32			0.33			0.31			0.25		
N	39_{id}			39_{id}			39_{id}			39_{id}		
Observations	1495			1491			1491			1491		
Marginal R^2 / Conditional R^2	0.161 / 0.433			0.099 / 0.392			0.127 / 0.397			0.248 / 0.436		

Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) and trait (between-person) scores. scale(stress) = Stress; scale(pa) = Positive Affect; SwitchingCost = score on Asymmetric Task Switching paradigm; * denotes interaction term; stuck state = PF-stuck; nocon state = PF-noconnect; noout state = PF-noout; imean = Trait values; Est. = Estimate; CI = 95% Confidence Interval. All scores are standardized for interpretability.

Figure 1 Depiction of antecedent and consequence models

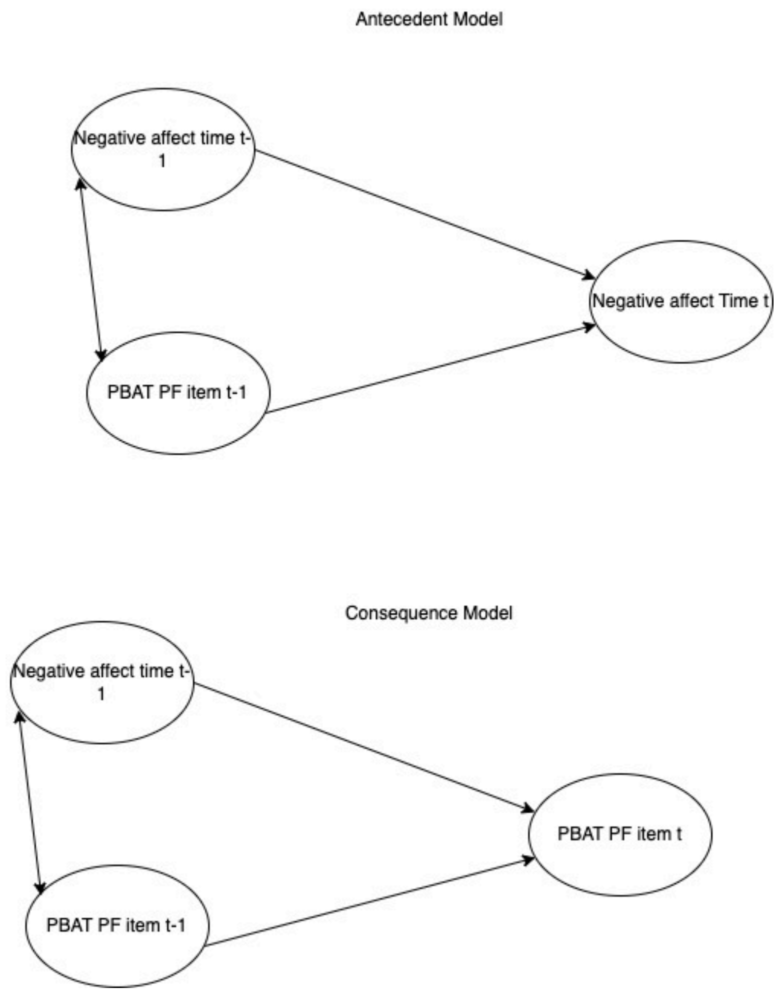
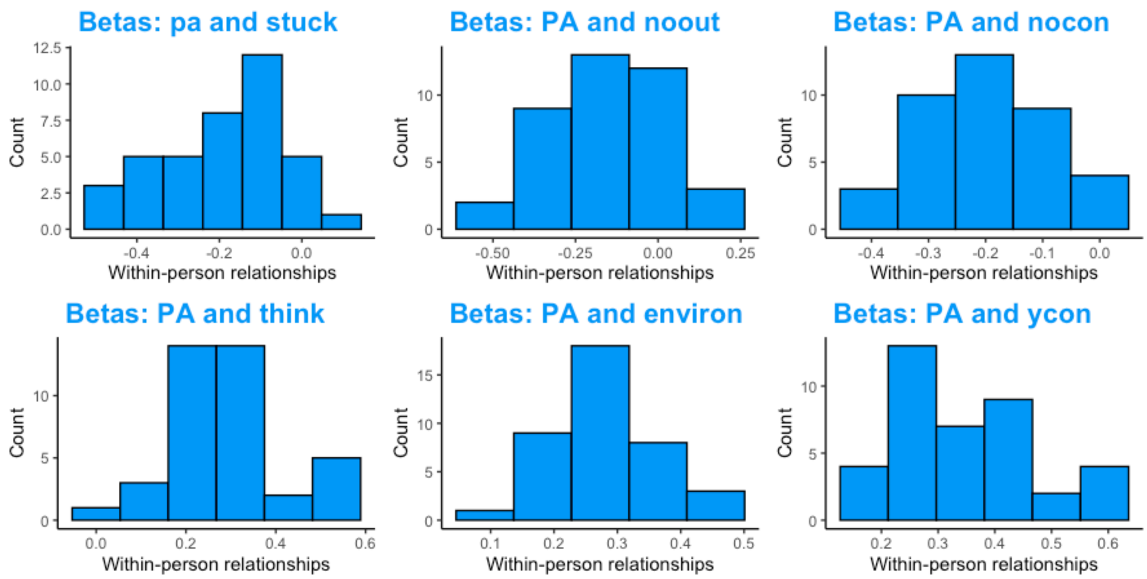
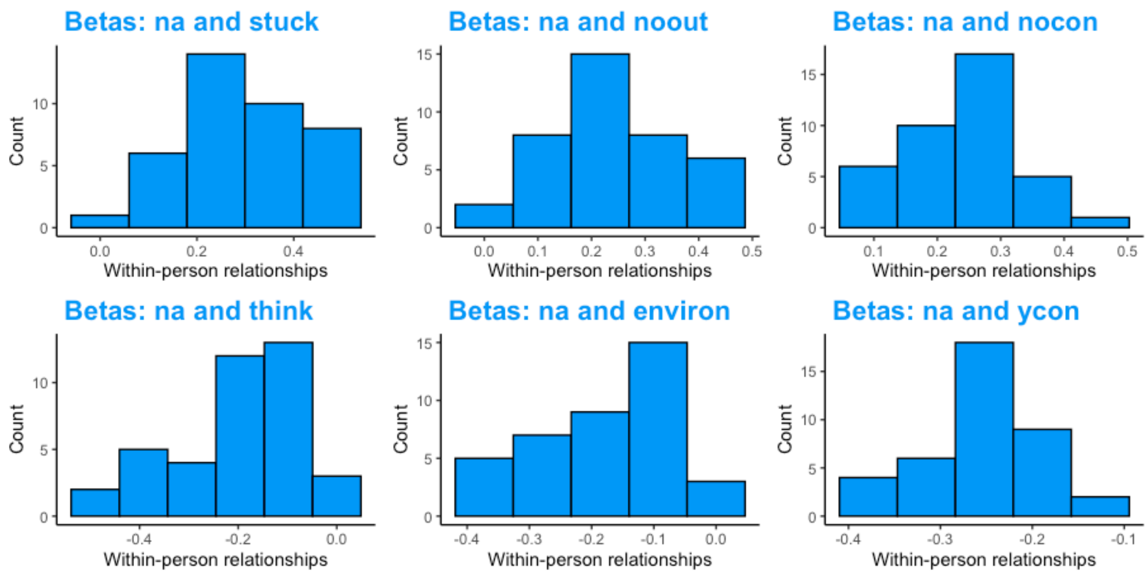


Figure 2 Within-person variability for PF-PA models



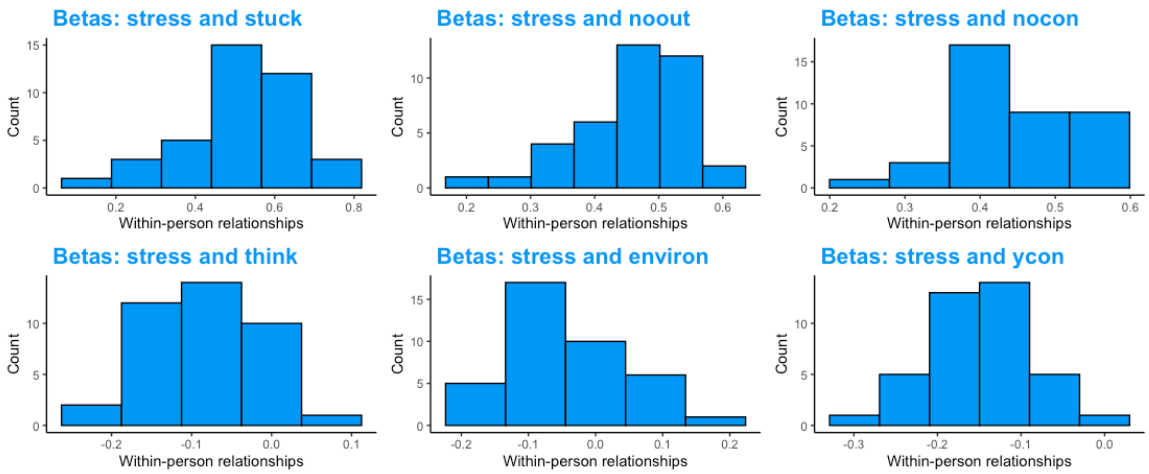
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. PA = Positive Affect

Figure 3 Within-person variability for PF-NA models



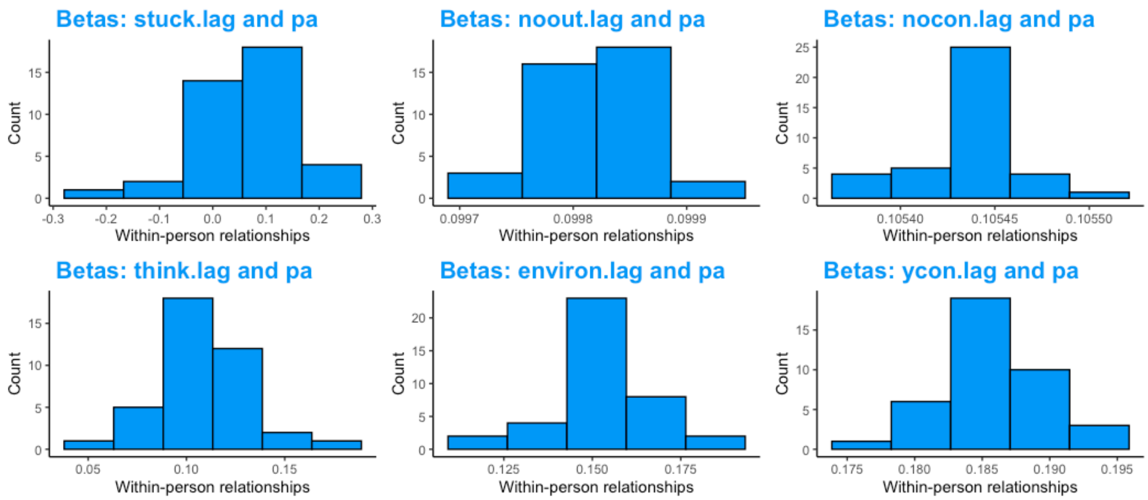
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. NA = Negative Affect

Figure 4 Within-person variability for PF-Stress models



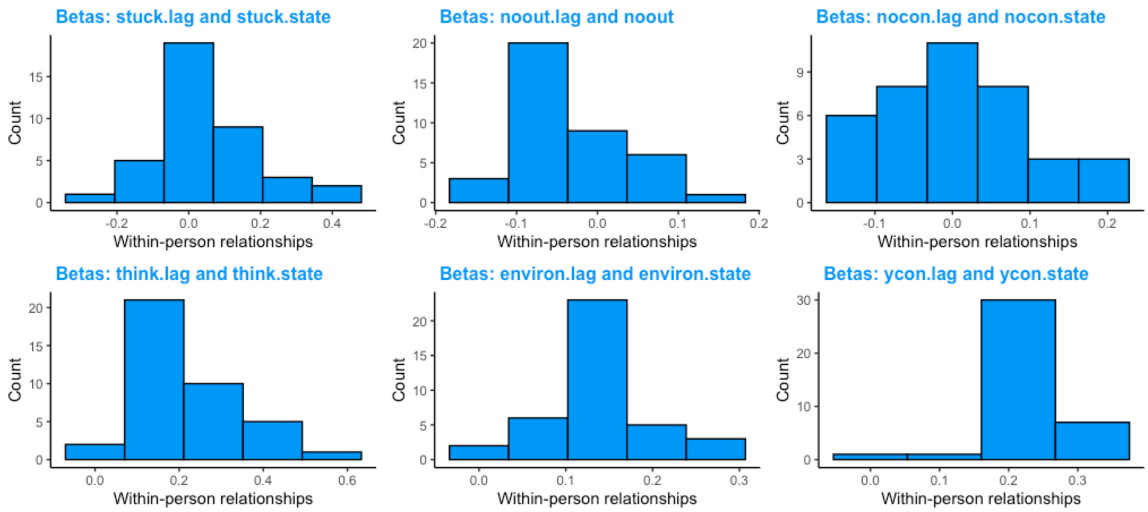
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted.

Figure 5 Within-person variability for PF-PA antecedent models



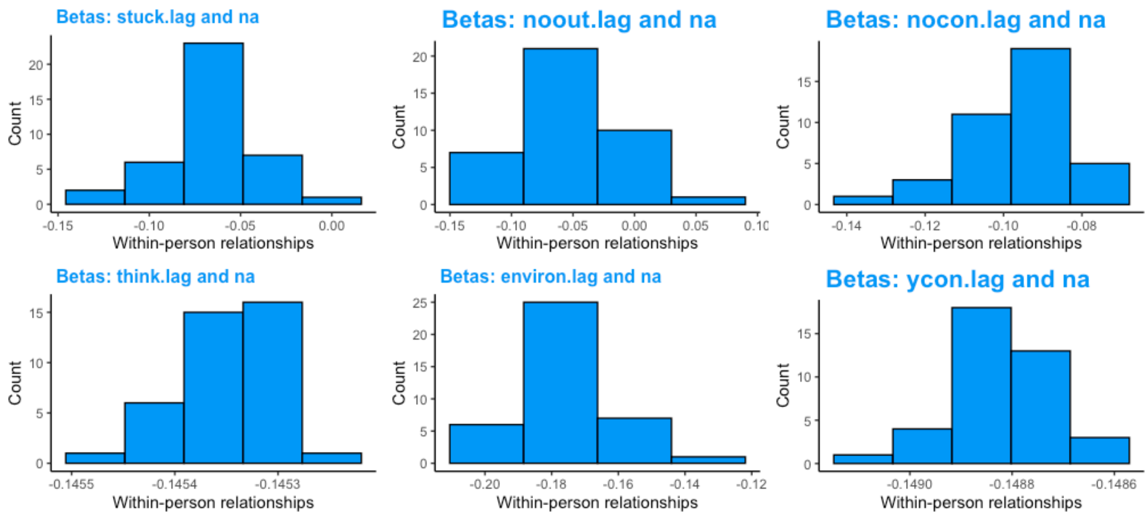
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. PA = Positive Affect

Figure 6 Within-person variability for PF-PA consequence models



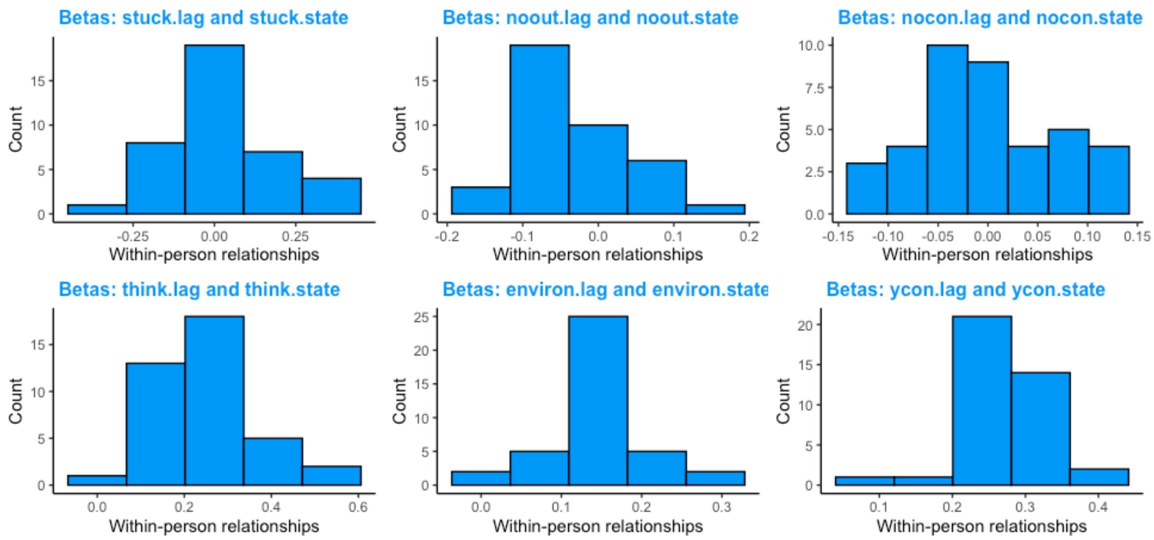
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable (PF at time T) and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. PA = Positive Affect

Figure 7 Within-person variability for PF-NA antecedent models



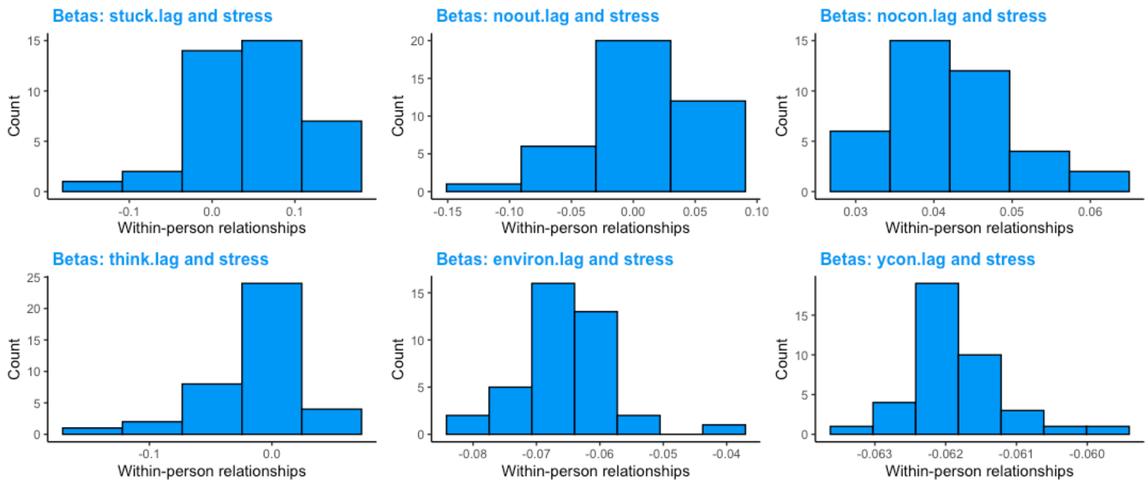
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. NA = Negative Affect

Figure 8 Within-person variability for PF-NA consequence models



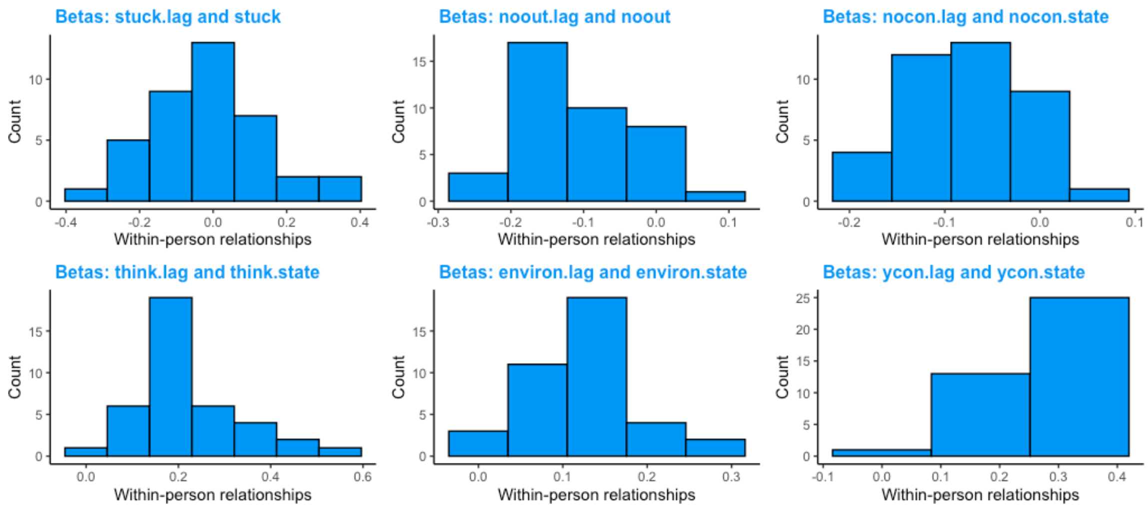
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable (PF at time T) and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T. NA = Negative Affect

Figure 9 Within-person variability for PF-Stress antecedent models



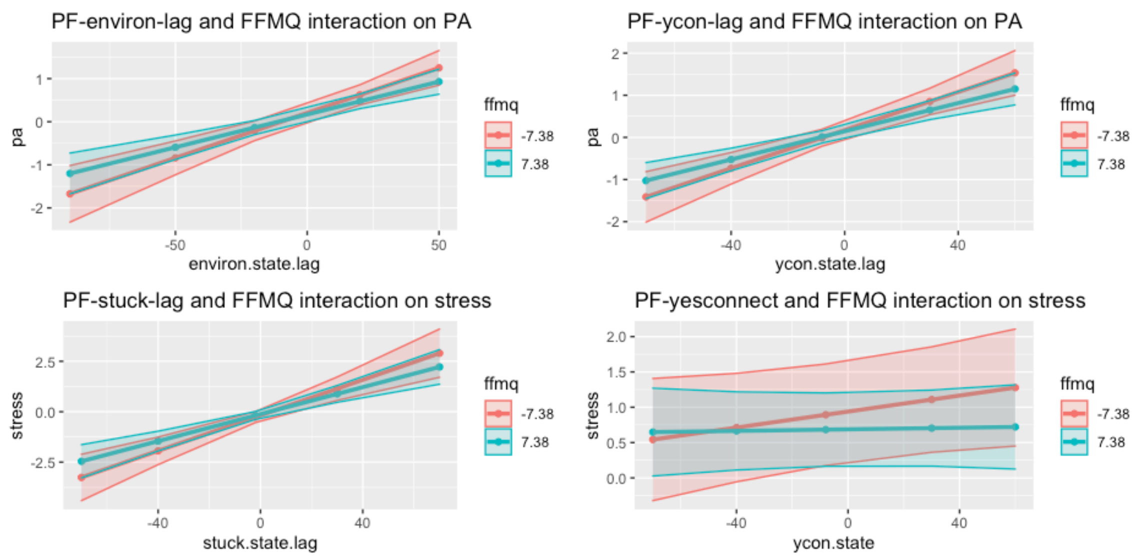
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T.

Figure 10 Within-person variability for PF-Stress consequence models



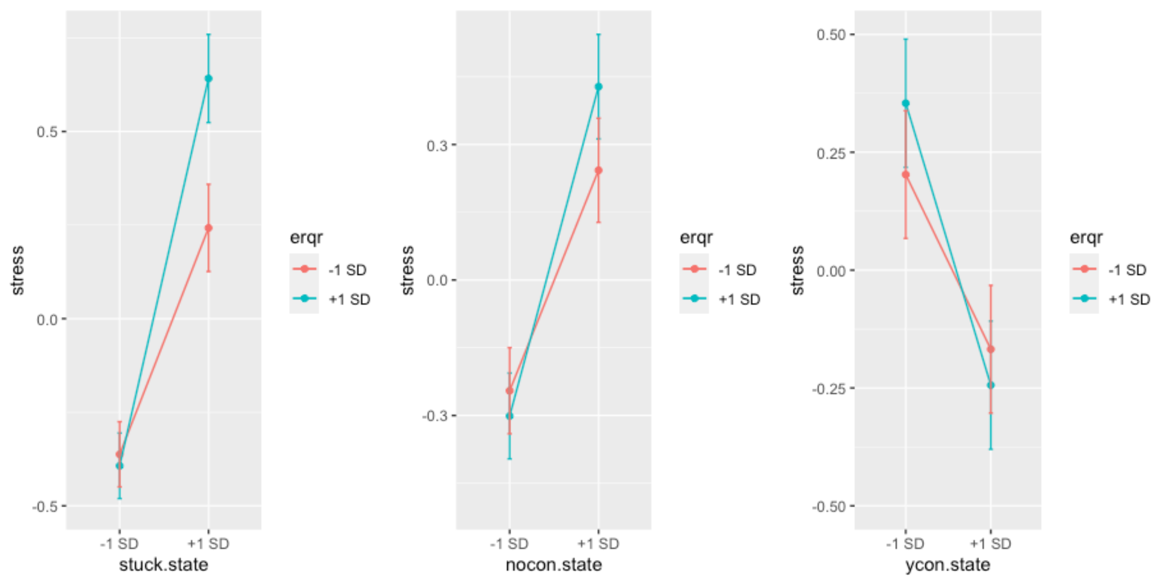
Note. PF items represent items from PBAT. Each item was calculated to reflect state (within-person) scores and the variability in relationship between outcome variable (PF at time T) and lagged PF is depicted. Lagged variables represent variable at time T-1 and outcome variables represent score at time T.

Figure 11 PF-FFMQ interaction plots



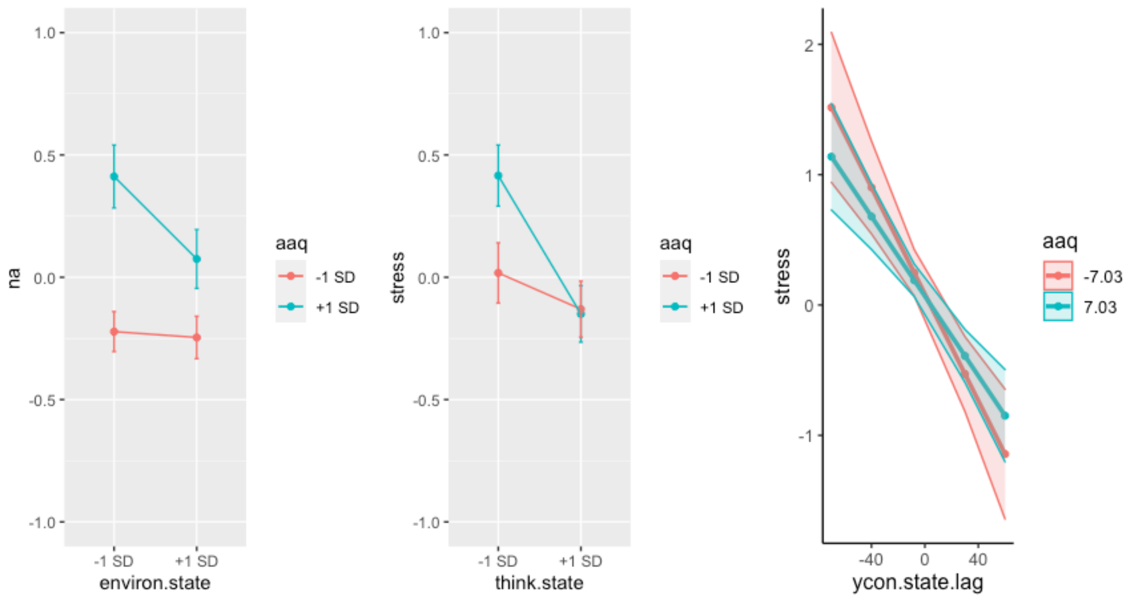
Note. Level of moderator variable is +/- 1 SD FFMQ = Five Facet Mindfulness Questionnaire

Figure 12 PF-ERQ interaction plots



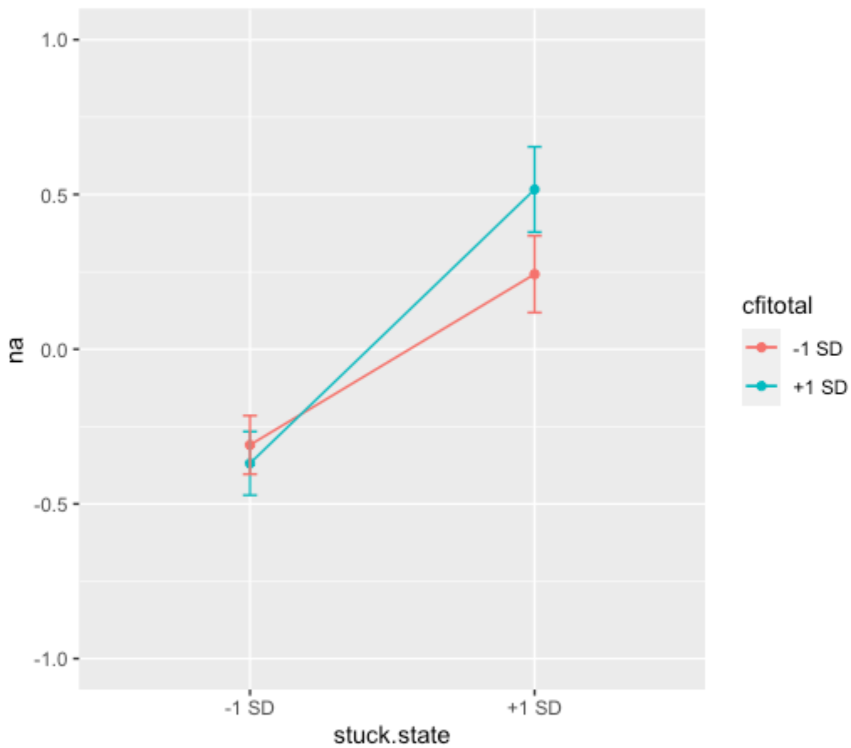
Note. Level of moderator variable is +/- 1 SD ERQ-R = Emotion Regulation Questionnaire-Reappraisal subscale score

Figure 13 PF-AAQ interaction plots



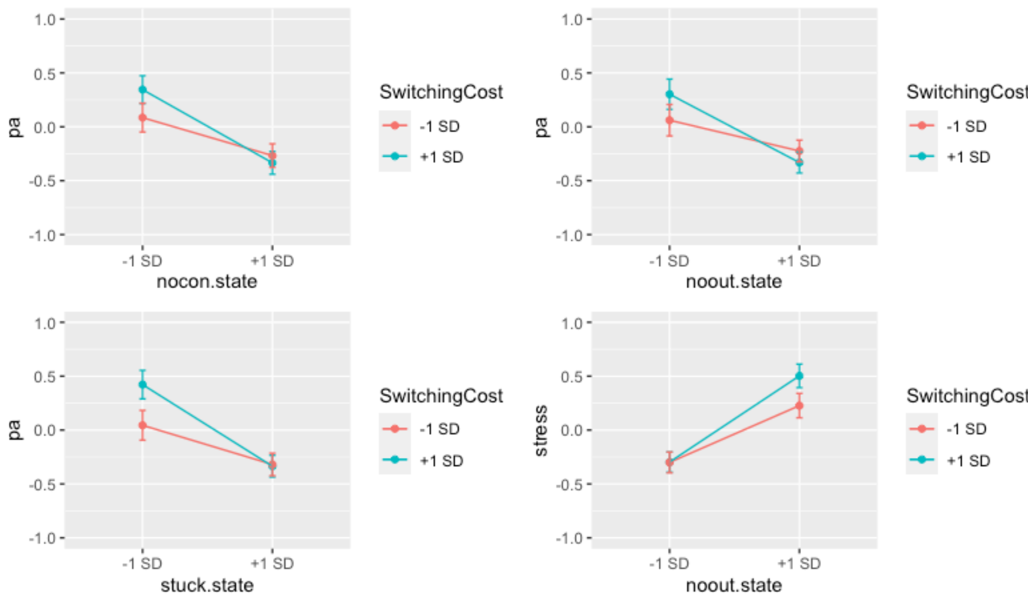
Note. Level of moderator variable is +/- 1 SD AAQ = Acceptance and Action Questionnaire

Figure 14 PF-CFI interaction plot



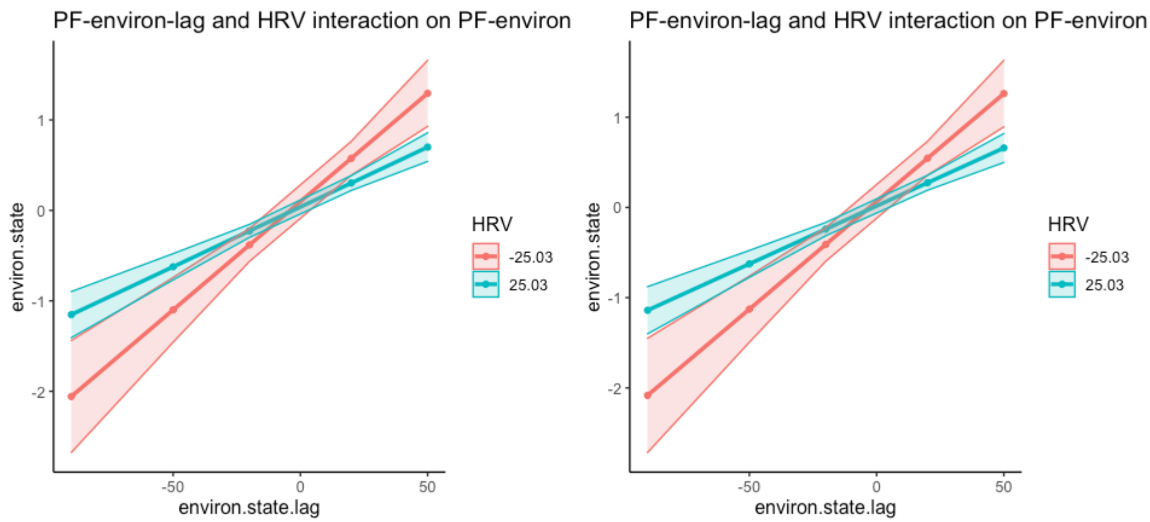
Note. Level of moderator variable is +/- 1 SD cfitotal = Cognitive Flexibility Inventory total score

Figure 15 PF-SwitchingCost interaction plots



Note. Level of moderator variable is +/- 1 SD SwitchingCost = score on Asymmetric Task Switching paradigm

Figure 16 Lagged PF-FFMQ interaction plots



Note. Level of moderator variable is +/- 1 SD FFMQ = Five Facet Mindfulness Questionnaire

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