**Disentangling Trait and State Psychological Inflexibility: A Longitudinal Multilevel Approach**

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Data is available upon reasonable request.

**Abstract**

An individual’s trait-like thoughts, feelings, and behaviors are characteristic patterns that occur across time, whereas state-like iterations of these variables are isolated to specific moments in time. Although highly correlated, variables at the trait and state levels measure different phenomena and should be examined separately. In this longitudinal study, we examine the disaggregation of trait and state-level psychological inflexibility among college students. Specifically, we investigated which psychological inflexibility subprocess would significantly predict positive affect, negative affect, and meaningful activity, both at the trait and state-levels. In addition to pre- and post-assessments, participants (*n* = 168) completed ecological momentary assessment (EMA) surveys (*n* = 2,251) assessing each of these variables via text message three times per day over the course of a week. Results suggested that while a greater number of state-like subprocesses significantly predict negative affect, positive affect, and meaningful activity, trait-like subprocesses hold more weight. Dominance analyses showed trait-level inaction to be the most important predictor for positive and negative affect, and trait-level of lack of contact with values to be the most important predictor for meaningful activity. Differentiating trait and state variables can enable contextual behavioral scientists to better understand pathological and therapeutic processes of change.

 *Keywords:* psychological inflexibility, ecological momentary assessment, value-based actions, affect, state, trait

WORD COUNT (tables and references not included): 7,409

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Psychological inflexibility is a conceptual model of psychological processes associated with Acceptance and Commitment Therapy (ACT). It is defined as “the rigid dominance of psychological reactions, over chosen values and contingencies, in guiding action” (Bond et al., 2011, p.678). Thus, an individual can be described as psychologically inflexible when their behaviors are controlled by their internal experiences (e.g., thoughts, feelings, and urges) at the cost of engaging in a meaningful life driven by personal values. For example, a psychologically inflexible way of responding to social anxiety would be staying home instead of going to a party, even though connecting with friends at the party would be more consistent with their values. The psychological inflexibility model consists of six sub-processes: experiential avoidance (e.g., being unwilling to have negative thoughts or feelings), cognitive fusion (e.g., treating thoughts as facts that determine one’s behavior), lack of present moment awareness (e.g., dominance of the future or past), self-as-content (e.g., attachment to the “story” of oneself), lack of contact with values (e.g., being unsure of what one’s values are), and inaction (e.g., lack of valued action; Klimczak & Levin, 2022). ACT uses the psychological inflexibility model to conceptualize psychopathology and explain suffering. In ACT, clients are guided through how to engage with valued actions even when difficult thoughts and feelings are getting in the way, instead of letting these internal experiences dictate whether they engage with valued actions or not.

Understanding the function of psychological inflexibility is critical to better understanding the mechanisms targeted in ACT interventions and psychopathology treatment more broadly. This includes an understanding of the six subprocesses’ associations with well-being, as conceptualized through a holistic lens which includes both affective and meaningful experiences (Diener et al., 1999; Joseph Sirgy & Wu, 2009). Research in this area has generally focused on psychological inflexibility and well-being at the trait-like level, with less attention to these variables at the state-like level (Howell & Demuynck, 2022; Kashdan et al., 2014; Twiselton et al., 2020). There is a need for research examining these variables at both levels, given that the two can function quite differently from one another which may lead to different magnitudes or even directions.

Additionally, a major limitation to trait-level research is that the direction of effects is unclear, particularly when the research is cross-sectional in nature. Analysis of state-level variables in a longitudinal design can provide greater insight into temporal effects, given that we can examine whether state-level variables predict the state-level outcomes that temporally follow. It is important to note however that there is a difference between prediction and causation, as only randomized controlled trials can truly shed light on the latter.

Examination of trait-like variables gives us insight into an individual’s typical patterns of behavior and their associations with typical patterns of internal experiences. In contrast, examination of state-like variables allows us to examine individual instances of behavior and internal experiences, which enables the examination of these variables at a finer-grain level. Individual change in a variable at the state-like level over time can build up to changes at the trait-like level, leaving the two highly correlated (Geiser et al., 2015). For example, as an individual repeatedly engages in experientially avoidant behaviors over time (state-like), they will be more likely to self-report as someone who tends to engage in such behaviors (trait-like).

However, it is problematic to confuse this correlation with the idea that state and trait levels are measuring the same phenomena and are redundant (Curran & Bauer, 2011; Wang & Maxwell, 2015). When state and trait levels are conflated, the results represent aggregated population average effects which are difficult to interpret (Enders & Tofighi, 2007), reduce clarity on potential causes of findings, and contribute to the phenomena of mixed findings in the psychotherapy literature (Fisher et al., 2018; Zilcha-Mano & Webb, 2021). By disaggregating state and trait-level variables, the overlapping variance is essentially removed, and thus each of the resulting variables more “purely” represents their respective phenomena.

Disaggregation of variables is also important given that trait-level variables may function differently than at the state-level. Recent research has begun to disentangle trait and state-level processes of change to shed light on mechanisms of change and the personalization of traditional cognitive behavioral therapy (CBT; Zilcha-Mano, 2021; Zilcha-Mano & Webb, 2021). Specifically, greater state-level experiences of affect in therapy predict symptom improvement while broader trait-level endorsements of affective experiences predict symptom stagnation (Rubel et al., 2017). Prior literature has conceptualized trait-level variables (e.g., demographics, patterns of pathology and psychological process) to have utility in the prediction of treatment effectiveness, as well as shape the individual context that therapy takes place in from the lens of a case-conceptualization. State-level variables may instead represent the specific mechanisms and processes most critical to target in intervention for a given individual, with these targets shifting and changing throughout treatment (Zilcha-Mano, 2021).

Disaggregation of trait and state-level variables poses implications outside of treatment related research, as trait and state-level effects have been conceptualized differently. For instance, prior research has found that both trait and state-level negative affect are associated with anxiety and depressive symptoms (Merz & Roesch, 2011). This means that both longstanding patterns of negative affect (e.g., a more neurotic personality) as well as fluctuations in negative affect not explained by traits (e.g., one-off occurrences of poor mood) each play unique roles in the phenomenon of anxiety and depression. Research on a given predictor and outcome may find effects for only the trait-level, state-level, or both, with each of these configurations posing different conclusions for the analyzed variables.

To better understand mechanisms of ACT and its underlying process target of psychological inflexibility, it is critical that a disaggregated understanding of psychological inflexibility is developed. Learning how psychological inflexibility and its subprocesses function at both trait and state-levels to influence affect and valued behavior may set the foundation for future research regarding processes of change. If a subprocess of psychological inflexibility operates in opposite directions for the trait and state-levels in predicting affect or behavior, this is important to account for in future studies of psychological inflexibility to avoid producing null effects due to aggregation. Additionally, it is important to clarify whether isolated expressions of psychological inflexibility matter in predicting affect and behavior, or if broader patterns of behavior over time have a more important role.

Thus, in an exploratory fashion we sought to examine which of the six psychological inflexibility subprocesses would significantly predict negative affect, positive affect, and meaningful affect at the trait- and state-level, and in which direction. We additionally examined the magnitude of effects by exploring which processes and at which levels held the most importance relative to each other. This was accomplished through an ecological momentary assessment (EMA) design, also known as intensive longitudinal methods. In an EMA design, participants’ behavior is studied within the context of their natural environment (Shiffman et al., 2008). Thus, participants receive prompts to complete multiple surveys over a span of time (e.g., three prompts per day for one week in the present study) within their daily life so that state-level "in the moment" variables may be analyzed. This methodology is appropriate for answering the present study’s questions given that it allows for the analysis of state-level variables within the context of the individual participant. Specifically, the multiple data points collected for each participant allow us to determine whether an individual’s given score on a variable is more than, less than, or approximately typical for that individual, and thus appropriately account for these within-person variations.

**Method**

**Participants**

The present study was approved by the university’s Institutional Review Board, and informed consent was obtained from all participants. Data collection took place from October 2020 to April 2021, which coincided with the COVID-19 pandemic. Participants were recruited through the university-wide online research participation platform and received up to 3 research credits towards their courses. While a variety of courses on campus accept extra credit that is awarded through the research participation platform, the majority of these are introductory psychology courses. Eligibility criteria included being 18 years of age or older, a current college student, and owning an android or iPhone they could use to respond to EMA surveys. A sample of201 college students at a large public university in the Western United States initially participated in this study. However, two participants were excluded for completing the baseline assessment too quickly (in less than 272 seconds, providing a minimum of 2 seconds per item; Huang et al., 2012) , and 31 were excluded due to having completed less than two eligible EMA surveys, leaving 168 participants whose data were included in our analyses.

See Table 1 for a listing of sample characteristics. Participants identified primarily as White (92.9%) women (75.6%) with an average age of 24 (SD = 8.9). Observed baseline depression, anxiety, and stress scores characterize the sample as experiencing somewhat higher psychopathology than typical college students (Kia-Keating et al., 2018; Norton, 2007). Participants seemed to vary regarding COVID-19 distress, however the majority of participants indicated that COVID-19 did not affect their participation in the study, with responses being highly right-skewed.

**Procedures**

All research procedures were completed online, with surveys being completed via Qualtrics. Participants completed a brief screening and informed consent prior to being automatically directed to a baseline assessment. Participants were provided with instructions on how to complete the daily EMA surveys via a text message to their mobile phone with a link to the Qualtrics survey. For the next week, survey prompts were delivered via text message on a semi-random schedule, once each at a randomly selected morning time between 9 AM to 1 PM, midday time between 1 to 5 PM, and evening time between 5 to 9 PM. To be included in analyses, responses had to be completed within two hours of the prompt being sent and the individual must have completed at least two EMA surveys in total. A prior guide to cleaning EMA data used a one hour response time window, however we have chosen to relax this to a two hour window given the context of using a college student sample (McCabe et al., 2012). We anticipated that students may be in classes or involved with other academic activities which may delay the response time, and did not want to unnecessarily limit our sample size through a more stringent window. Surveys were labeled as either morning, midday, or evening based on the time the prompt was sent, as opposed to time the survey was completed.

Additionally, surveys must have been completed within 72 seconds to be included in our analyses, which was determined by allocating two seconds per item. Prior research has demonstrated that fast responding of under two seconds per item indicates careless responding and consequently unreliable data (Huang et al., 2012). A similar study specific to EMA data have indicated less stringent criteria of one second per item for determining careless responding, however we chose to maintain the stricter criteria of two seconds per item to better ensure that MPFI items measuring psychological inflexibility were answered with discretion given that these six items measure distinct constructs (Jaso et al., 2021).

 EMA surveys assessed psychological inflexibility processes and meaningful activity as experienced since the last prompt, as well as current positive and negative affect. A research assistant (*initials masked*) contacted each participant during the EMA period to assess and address any issues in completing the EMA prompts. After the one-week EMA period, participants were asked to complete a post online assessment questionnaire.

**Measures**

Surveys included in our study assessed demographic characteristics (i.e., age, gender, race, academic year, marital status), COVID-19 related variables (i.e., baseline impairment in functioning from COVID-19, Likert scale rating of how much COVID-19 affected their ability to fully participate in the study, and financial and psychological distress caused by COVID-19 at baseline and post-assessment) and other mental health related variables (i.e., psychological distress, positive mental health, overly valuing happiness, striving for positive experiences, and psychological flexibility and inflexibility).

***Multidimensional Psychological Flexibility Inventory (MPFI)***

The MPFI is a 60-item global, trait-like measure designed to assess each psychological flexibility and psychological inflexibility subprocess in detail (Rolffs et al., 2018). Items are rated on a 6-point Likert scale from 1 (*never true*) to 6 (*always true*) and assess experiences from the past two weeks. There are twelve subscales, including six subscales for psychological flexibility and six subscales for psychological inflexibility, with these constructs being inverses of one another. The psychological flexibility subscales include acceptance, present moment awareness, self-as-context, defusion, contact with values, and committed action. The psychologic inflexibility subscales include experiential avoidance, lack of contact with the present moment, self-as-content, fusion, and lack of contact with values. Subscale scores are produced by averaging its items’ responses, and composite psychological flexibility and inflexibility scores are similarly produced by averaging the corresponding subscales. Thus, these total scores range from 1 to 6 with higher scores indicating higher levels of the dimension being assessed. For the purpose of this study, only psychological inflexibility items were analyzed. The MPFI was distributed at both baseline and post assessment. Internal consistency for the psychological inflexibility subscale at baseline was found to be excellent (α = .95).

***EMA Measures***

 Between and within internal reliability for EMA measures was evaluated using coefficient omega, with this approach utilizing all EMA timepoints (Geldhof et al., 2014). Coefficient omegas were calculated using the omegaSEM function from the multilevelTools package (Wiley, 2020).

**Shortened MPFI.** To assess psychological inflexibility in the moment, one item from each of the psychological inflexibility subscales of the MPFI (Rolffs et al., 2018) was included (see Appendix A). The first two items of each of its subscales in the MPFI can be used in place of the full measure when a briefer assessment is preferred. However, to reduce participant burden, we further reduced the scale to the first item from each of the psychological inflexibility subscales, for a total of six MPFI items. Items were prefaced by “Since the last prompt…” (e.g., “Since the last prompt… I tried to distract myself when I felt unpleasant emotions”). Items were analyzed individually as opposed to as a summed score given the aims of the study. While we are unaware of any other studies that similarly use a similarly abbreviated version of the MPFI, prior research has supported the use of single items in EMA designs (Song et al., 2022). Our EMA item validation as reported in the results section additionally supports the convergent validity of our single-item use of MPFI items.

**Positive and Negative Affect Schedule-Expanded Form (PANAS-X).** Ten items from the PANAS-X were administered to assess positive and negative affect in the moment (Clark & Watson, 1994). Each item was phrased as “Right now, how \_\_\_\_\_ do you feel?,” and were rated on a 5-point Likert scale from 1 (*not at all*) to 5 (*very much so*). This included four items assessing positive affect (happy, excited, joyful, confident) and six items assessing negative affect (nervous, ashamed, sad, angry, guilty, irritable), with theses specific items having been used and assessed for validity in a previous EMA study (Levin et al., 2018). These items of the PANAS-X were originally selected by the prior study to represent a broad range of emotions, including primary, high arousal, and low arousal feelings. Items from each subscale of positive and negative affect were summed, producing totals ranging from 4-20 and 6-30 respectively, with higher scores indicating higher affect. Regarding negative affect, internal consistency was acceptable for ωwithin (ω = 0.71; 95% C.I. = [0.69 – 0.73]) and good for ωbetween (ω = 0.87; 95% C.I. = [0.83 – 0.91]). For positive affect, internal consistency was good for ωwithin (ω = 0.87; 95% C.I. = [0.86 – 0.88]) and excellent for ωbetween (ω = 0.93; 95% C.I. = [0.91 – 0.95]).

**Meaningful Activity.**Three items previously used by Levin et al. (2018) were administered to assess meaningful activity. While this prior study specifically used the term “valued action” as opposed to “meaningful activity”, we chose to use the latter to differentiate these items more clearly from the values and committed action related psychological inflexibility items of the MPFI previously discussed. These three items included “Since the last prompt, were you able to do what matters to you?”, “Since the last prompt, how content were you with the amount and types of things you did?”, and “Since the last prompt, were your actions in line with the kind of person you want to be?,” and were rated on a 5-point Likert scale from 1 (*not at all*) to 5 (*very much so*). Items were summed to form a total score ranging from 3 to 15, with higher scores indicating greater meaningful action. Internal consistency was found to be good for ωwithin (ω = 0.84; 95% C.I. = [0.83 – 0.85]) and excellent for ωbetween (ω = 0.97; 95% C.I. = [0.96 – 0.98]).

**Data Analysis**

Statistical analyses were conducted with R (v 4.2.2; R Core Team, 2022) in RStudio (v 2023.03.0; Posit team, 2023). The R script for the present analyses is available online at https://osf.io/pwa9b/?view\_only=633f7cba1ae849fabbfd45d4752d1146. Multiple regression was used to test whether any of the variables collected at baseline or post-assessment predicted the number of surveys completed, to account for any potential confounding variables through inclusion as a covariate in primary analyses.

To characterize the proportion of between and within-person variance (e.g., variance explained by the trait and state-levels respectively) for each EMA measure, intraclass correlation coefficients (ICCs) using the icc function from the performance package (Lüdecke et al., 2021) were calculated from null multilevel models (MLMs), with EMA observations nested within individuals. These null multilevel models were constructed with the lmer function from the lme4 package (Bates et al., 2015). Only within-person variances are reported, as between-person variances can be calculated by subtracting the within-person variance from one (e.g., the sum of within- and between-person variance is one). Calculating within-person variances helped confirm that there was enough moment-to-moment variation in psychological inflexibility processes, affect, and meaningful activity to warrant investigation at this level (Podsakoff et al., 2019).

***EMA Item Validation***

To our knowledge, no prior study has used a single-item iteration of the MPFI as was implemented in our study, with only one item being used per psychological inflexibility subprocess. Thus, to assess the convergent and divergent validity of these single-item measures, we used multilevel modeling approach with the lmer function from the lme4 package (Bates et al., 2015) in which six models were run, one for each psychological inflexibility subprocess. Models nested EMA observations within days (given that up to 3 observations could be collected in a day), and again nested within participants for this and all proceeding multilevel analyses, except when otherwise specified. All six baseline scores of the in the moment psychological inflexibility subprocesses were included as predictors for each model, with the outcome variable for the six models being the single-item measures for experiential avoidance, cognitive fusion, lack of present moment awareness, self-as-content, lack of contact with values, and inaction as measured by the full MPFI. All variables were standardized through a Z transformation to produce standardized beta coefficients, however it is important to note that variables were not standardized for other analyses aside from item validation. If a baseline trait-measure of a process variable significantly predicts its corresponding single-item EMA measure, this would indicate convergent validity, with a lack of significance from the other baseline variables suggesting discriminant validity.

To assess the construct validity in treating the person-mean average of a given psychological inflexibility process variable as a trait-level indicator, we examined the correlation between the person-mean average for each subprocess item and that same process as measured by the full MPFI at baseline and post assessment.

***Mixed-effect Location Scale Models***

A multilevel approach was used given that EMA observations were nested within days, nested within participants. Given the wide person-to-person variation in each of the studied outcomes, using an analysis such as multilevel modeling that assumes homogeneity of variance among participants would not be appropriate (Hedeker et al., 2008). Thus, Bayesian linear mixed-effect location scale models were used to test whether each facet of psychological inflexibility predicts negative affect, positive affect, and meaningful activity in the moment. This allowed for differences in variation among and within participants to be accounted for as covariates in the model, treating this variation as meaningful information as opposed to random noise (Lester et al., 2021).

For each of these three outcomes, a separate model was run using the brmsformula function from the brms package (Bürkner, 2017). To disaggregate between-person and within-person effects, two versions of each facet of psychological inflexibility were included in the model, including a person-mean average (i.e., trait-level) and a person-mean centered (i.e., state-level) version. The person-mean average of responses given through EMA surveys was preferred as a representation of trait-level psychological inflexibility (as opposed to cross-sectional baseline measurements) on account of the accuracy afforded in the moment reports as compared to retrospective recall (Ebner-Priemer & Trull, 2009). Time (operationalized as which of the 21 timepoints the EMA survey was delivered) and the variance (i.e., sigma) for each predictor were included as covariates in the model. A leave-one-out *R2* value was calculated with the loo\_R2 function from the brms package for each of the models to represent explained variance (Bürkner, 2017).

To see if our three-level approach (level 1: EMA observations, level 2: days, level 3: individual participants) was justified in representing the data and improving model fit, we additionally ran two-level versions of each model (level 1: EMA observations, level 2: individual participants) and compared each set of models with one another using leave-one-out cross-validation methods. This was accomplished using the loo\_compare function from the brms package, in which an expected log predictive density (ELPD) was calculated for each model using leave-one-out (LOO) model fit criteria (Bürkner, 2017). Larger ELPDs indicate greater model fit, with a difference in ELPDs greater than four indicating a non-negligible difference between model performance (Sivula et al., n.d.).

***Dominance Analysis***

While regressive models (e.g., mixed-effect location scale models) allow us to investigate which relationships between independent (i.e., psychological inflexibility subprocesses) and dependent (i.e., affect and meaningful activity) variables are significant, a limitation is that the relative importance of these variables are unknown. For example, a mixed-effect location scale model may hypothetically reveal that three psychological inflexibility subprocesses significantly predict negative affect, but the magnitude of these three effects are unknown. It is possible that one of these significant subprocesses contributes twice as much or more to negative affect, compared to another significant subprocess. Knowing which significant subprocesses contribute more or less to affect and meaningful action is important information, as this may shed light on which subprocesses are most important to intervene on in efforts to improve affect or meaningful action.

Thus, to determine relative importance (i.e., which predictors play a larger role in predicting the analyzed outcome), a dominance analysis (Budescu, 1993) was performed using the dominanceAnalysis function from the dominanceanalysis package (Bustos Navarrete & Coutinho Soares, 2020). Predictors in a model may explain more or less variance (e.g., *R2*) in the outcome variable dependent on what other predictors are included. This is due to collinearity, suppressor variables, and other issues. This leaves common approaches for assessing relative importance such as comparison of standardized beta coefficients flawed given that only the full model is being assessed (Azen & Budescu, 2009). Dominance analysis addresses this problem by examining each individual predictor’s contribution to the explained variance produced by all possible subsets of the model (Azen & Budescu, 2003). For the purpose of increased interpretability and flexibility, only general dominance (in which mean contributions across all model subsets are compared) is reported in the present study.

 Given that the dominanceanalysis package is not compatible with the mixed-effect location scale models previously described, the 3-level mixed-effect location scale model for each of the three outcomes was run once more as a multilevel model using the lmer function (Bates et al., 2015), so that these multilevel models could be plugged into the dominanceAnalysis function. Only significant predictors were used in these models, as is common practice for dominance analysis given that the purpose of dominance analysis is only to determine relative importance among predictors that have already been determined to be important (e.g., unimportant or non-significant variables should not be included; Mange et al., 2021). It should be noted that given the change in analytic approach and subsequent lack of accounting for heterogeneity in variance, results from the multilevel models did slightly change. However, the estimates, direction, and level of significance for all other variables were approximately similar. The $S\&B R\_{1}^{2}$ measure of contribution to outcome variance was used, given that it was developed for analyzing level-1 outcomes (e.g., in the moment affect and meaningful experiences) with both level-1 (e.g., state-level) and level-2 predictors (e.g., trait-level; Luo & Azen, 2013; Snijders & Bosker, 1994).

**Results**

**Preliminary Analyses**

 A total of 3,159 EMA surveys were collected. Individual surveys were removed if they were completed too quickly (*n* = 235; Huang et al., 2012), completed when unprompted (*n* = 234), completed more than 2 hours after the corresponding prompt (*n* = 420), or were incomplete (n = 9). Participants were excluded if less than two EMA surveys remained after this cleaning (*n* = 9). Thus, a total of 2,252 EMA surveys were included in the current analysis across 168 participants, resulting in 64% compliance regarding assessment completion. This is relatively poor compared to the 81.9% average, however it is important to note that there is much heterogeneity amongst EMA studies’ compliance rates, with 7% of published EMA studies having a compliance rate of 64% or below (Williams et al., 2021). On average, participants completed 13.4 EMA surveys (*SD* = 6.06, range = 2-21), with 43% responding to at least 80% (17 out of 21) of surveys. Mean latency between receiving an EMA prompt and completion of the survey was 23 minutes (*SD* = 29 minutes).

Greater endorsement of the statement “​​​​​​​COVID-19 reduced my ability to fully participate in the study (due to distractions, stress, or other challenges from the pandemic)” at post assessment was significantly associated with a lower number of EMA surveys completed (*p* = .049), thus this item was included as a covariate in all mixed-effect location scale model and dominance analyses. Given that multilevel analyses depend on complete data respective to predictors, and not all participants completed the post-assessment survey which asked this covariate item, sample size was reduced to 1,913 EMA observations across 134 participants for all multilevel analyses. See Table 2 for the proportion of within-person variance for each EMA variable, represented by the ICC. The proportion of within-person variances for affect found approximately matches the 53% established by a prior meta-analysis on within-person variance (Podsakoff et al., 2019).

**EMA Item Validation**

The baseline scores for experiential avoidance (*b* = 0.29, *p* < .001), cognitive fusion (*b* = 0.43, *p* < .001), lack of present moment awareness (*b* = 0.36, *p* < .001), self-as-content (*b* = 0.36, *p* < .001), lack of contact with values (*b* = 0.35, *p* < .001), and inaction (*b* = 0.34, *p* < .001) as assessed with the full MPFI were each significant predictors of the their single-item counterparts as assessed with the full MPFI, suggesting convergent validity for all psychological inflexibility EMA items. However, baseline inaction was also a significant predictor for in the moment experiential avoidance (*b* = 0.27, *p* = .002), and baseline lack of contact with values was also a significant predictor for in the moment self-as-content (*b* = 0.15, *p* = .020). Thus, the divergent validity of the experiential avoidance and self-as-content single-item measures may be subject to question; however, it is also reasonable that some subprocesses may predict one another given the interrelatedness of subprocesses within psychological inflexibility model.

 See Table 2 for a full listing of average baseline, post-assessment, and momentary scores for each psychological inflexibility subprocess, along with Pearson’s *r* correlations between momentary and baseline, as well as momentary and post-assessment scores. Each of the psychological inflexibility person-mean averages held moderately strong positive relationships with their baseline assessment counterparts (Pearson’s *r* ranging from0.51 to 0.58 except for experiential avoidance with 0.39) and moderate to fairly strong positive relationships with their post-assessment counterparts (Pearson’s *r* ranging from0.70 to 0.86), indicating appropriate construct validity regarding conceptualization of these averages as trait-level variables. This makes sense, given that the full MPFI asks individuals to base their responses on the past two weeks, with EMA surveys falling within this timeframe for post but not baseline assessment. Additionally, retrospective recall of the individual’s experiences may have been enhanced through completion of the daily EMA surveys. Given the lower correlation between person-mean average and baseline experiential avoidance, as well as issues with baseline inaction and in the moment experiential avoidance converging, the experiential avoidance single-item measure may be an invalid measure of the intended construct.

**Mixed-effect Location Scale Analyses**

Model comparisons demonstrated greater model fit for the 3-level models, as compared to 2-level iterations of the models that did not nest observations within days. This was observed for all outcome variables’ models, including positive affect (ELPD3-level = -565.8, ELPD2-level = -642.8), negative affect (ELPD3-level = -1934.5, ELPD2-level = -1995.0), and meaningful activity (ELPD3-level = -4064.2, ELPD2-level = -4103.9). ELPD differences between compared modules exceeded the benchmark of 4, with differences ranging from 39.7 to 77, indicating a non-negligible difference between the models. Thus, results from the 3-level model were used for the present study. See Table 3 for a full listing of mixed-effect location scale model results.

***Negative Affect***

The model predicting negative affect produced a leave-one-out R2value of 0.51, indicating that 51% of variance in negative affect can be explained by our model.Regarding within-person effects, higher levels of state-level cognitive fusion (95% C.I. = [0.09 – 0.15]), lack of present moment awareness (95% C.I. = [0.01 – 0.04]), self-as-content (95% C.I. = [0.02 – 0.07]), and inaction (95% C.I. = [0.05 – 0.10]) were all significant predictors of greater negative affect in the moment. Experiential avoidance and lack of contact with values were not significant predictors of negative affect in the moment (*p* > .05). Regarding between-person effects, higher trait-level cognitive fusion (95% C.I. = [0.08 – 0.25]) and inaction (95% C.I. = [0.08 – 0.28]) were significant predictors of greater negative affect in the moment. Trait-level experiential avoidance, lack of present moment awareness, self-as-content, and lack of contact with values were not significant predictors of negative affect (all *p* > .05).

***Positive Affect***

Our model with positive affect as the outcome produced a leave-one-out R2value of 0.50, indicating that 50% of variance in positive affect can be explained by our model.Regarding within-person effects, higher state-level cognitive fusion (95% C.I. = [-0.22 – -0.12]), lack of present moment awareness (95% C.I. = [-0.12 – -0.04]), lack of contact with values (95% C.I. = [-0.12 – -0.02]), and inaction (95% C.I. = [-0.19 – -0.09]) were all significant predictors of lesser positive affect in the moment. State-level experiential avoidance and self-as-content were not significant predictors of position affect in the moment (*p* > .05).Regarding between-person effects, higher trait-level inaction was the only significant predictor of lesser positive affect in the moment (95% C.I. = [-2.29 – -0.99]). Trait-level experiential avoidance, cognitive fusion, lack of present moment awareness, self-as-content, and lack of contact with values were not significant predictors of positive affect (all *p* > .05).

***Meaningful Activity***

Results indicated that 45% of variance in meaningful activity can be explained by our model, given the produced leave-one-out R2value of 0.45. Regarding within-person effects, higher state-level cognitive fusion (95% C.I. = [-0.42 – -0.28]), lack of present moment awareness (95% C.I. = [-0.41 – -0.17]), lack of contact with values (95% C.I. = [-0.68 – -0.37]), and inaction (95% C.I. = [-0.53 – -0.24]) were all significant predictors of lesser positive affect in the moment. It is notable that these were the same significant state-level predictors for positive affect in the moment as well.Regarding between-person effects, higher lack of contact with values (95% C.I. = [-1.54 – -0.33]) and inaction (95% C.I. = [-1.48 – -0.15]) predicted less meaningful activity in the moment. Trait-level experiential avoidance, cognitive fusion, lack of present moment awareness, and self-as-content were all not significant predictors of meaningful activity (all *p* > .05).

**Dominance analyses**

For the following results, each subprocess had established general dominance over all other subprocesses with a lower contributed variance. Thus, subprocesses that were found to have a higher contributed variance than another can be deemed more important than the compared variable in each respective model. Self-reported effect that COVID-19 had on study participation was included as a covariate in analyses for statistical control purposes. See Table 4 for a full listing of dominance analyses rankings and contributed variance.

Our dominance analyses suggested that trait-level inaction was the most important predictor of negative affect in the moment (contributed *R2* = .122), followed by trait-level cognitive fusion (contributed *R2* = .119), state-level cognitive fusion (contributed *R2* = .052), state-level inaction (contributed *R2* = .038), state-level self-as-content (contributed *R2* = .013), and finally state-level lack of present moment awareness (contributed *R2* = .005) being the least important. For positive affect in the moment, trait-level inaction appeared to be the most important predictor (contributed *R2* = .054), followed by state-level cognitive fusion (contributed *R2* = .031), state-level inaction (contributed R2 = .025), state-level lack of present moment awareness (contributed *R2* = .011), with state-level lack of contact with values (contributed *R2* = .008) being the least important. Regarding meaningful activity in the moment, we found trait-level lack of contact with values to be the most important predictor (contributed R2 = .070), followed by trait-level inaction (contributed *R2* = .053), state-level lack of contact with values (contributed *R2* = .025), state-level inaction (contributed *R2* = .018), state-level cognitive fusion (contributed *R2* = .013), and finally state-level lack of present moment awareness (contributed *R2* = .011) being the least important.

**Discussion**

 It is well established that psychological inflexibility holds important implications for wellbeing and psychopathology, with greater inflexibility predicting poorer outcomes (Howell & Demuynck, 2021; Levin et al., 2014). However, research on how both trait and state-like manifestations of psychological inflexibility is lacking in the literature, with the majority of research focusing on trait-like manifestations or an aggregation of the two. This has led to a lack of clarity in how psychological inflexibility subprocesses in the moment affect the human experience, relative to long standing averaged patterns. This is problematic given that psychological inflexibility processes are conceptualized as dynamic constructs that vary from moment to moment. To our knowledge, a few studies have investigated intra-individual variation in psychological flexibility (Hardy & Segerstrom, 2017; Luoma et al., 2020). In our study, the proportion of within-person variance for psychological inflexibility subprocesses ranged from 44 to 51.9%, providing empirical evidence for the dynamic, moment-to-moment nature of these variables.

To address the gap in knowledge, the present study served as an exploratory investigation of how psychological inflexibility subprocesses predict affect and meaningful activity at both the trait and state-level. This was accomplished using an EMA approach with participants being prompted to answer items up three times a day for the duration of one week, regarding in the moment affect, whether they engaged in meaningful action since the last prompt, and to what degree they engaged in each of the six psychological inflexibility processes.

We found a greater number of state-level psychological inflexibility process effects (4 for negative affect, 4 for positive affect, and 4 for meaningful activity) as compared to trait-level effects (2 for negative affect, 1 for positive affect, 2 for meaningful activity). Processes that were significant predictors at the trait-level tended to hold greater importance than those at the state-level, and contributed a higher proportion of variance to negative affect and meaningful activity when summed together than processes at the state-level despite being fewer in number. Specifically, trait-level processes accounted for 69.1% of the variance in negative affect contributed by psychological inflexibility processes, 41.9% for positive affect, and 64.7% for meaningful activity. This may mean that many (if not all) psychological inflexibility variables hold some influence over affect and meaningful activity, but that for a few of these processes in particular the building of long-standing patterns is particularly important. Given that less than half of the contributed variance came from trait variables for positive affect, positive mood may be more easily influenced by in the moment variables that are not necessarily connected to long-standing patterns (e.g., happenstance lack of present moment awareness).

 The majority of findings made conceptual sense, with trait-level inaction and cognitive fusion being the most important predictors of negative affect, trait-level inaction being the most important predictor of positive effect, and trait-level lack of contact with values and inaction being the most important predictors of meaningful action. While other subprocesses including those at the state-level were also found to be significant predictors, the processes listed were found to be at least twice as important (e.g., contribute at least twice the amount of variance) as all other significant predictors, indicating the magnitude of these trait-processes. It is interesting that trait-level inaction was one of the most important contributors of variance for all three outcomes. This may point to the important link between behavior and broader wellbeing, as highlighted by therapeutic approaches such as behavioral activation which seek to intervene on inaction.

It was surprising that experiential avoidance was not found to be a significant predictor for any outcomes at either of the two levels. One prior study found contradicting results, in which nonacceptance predicted greater negative affect at both between and within-person levels (Pavlacic et al., 2022). Given that our item validation analyses revealed in the moment inaction to also be a predictor for baseline experiential avoidance, its measurement item may be functioning similarly to experiential avoidance and thus suppressing its effects. This is further supported by the results of the convergent item validation, in which person-mean-average experiential avoidance had a relatively low correlation with its corresponding baseline measurement.

The heavier weights attributed to trait-level variables may point to these being viable targets for clinical intervention, particular in reference to clinical needs that map onto the predicted variable. For example, individuals struggling with engaging in meaningful activity may benefit most from values clarification work, while those struggling more with experiencing positive affect may benefit most from work targeting behavioral committed action strategies. State-level effects holding greater weight may be especially well-suited to be targeted by tailored in-the-moment interventions (Levin et al., 2019). This may be an especially powerful method for optimizing the efficiency of intervention, as such in-the-moment interventions can assess necessary targets (e.g., negative affect, positive affect, meaningful activity) and provide relevant skills that are most likely to result in immediate change.

Several limitations exist within our study. First, convenience sampling was used, with the present data being collected from university students using an online research participation platform for course extra credit. Additionally, 76% of our sample identified as a woman and 93% as White, given that the university that our research was conducted in is a predominantly White institution with 84% of the student body identifying as such. This limits the generalizability of our results, particularly in regards to non-college students and minoritized individuals (Weigold & Weigold, 2022). COVID-19 may be another factor to consider as well, potentially escalating psychopathology in the sample as compared to the same population under non-pandemic conditions.

Second, many of the EMA items we had used have yet to have been formally validated in a full study on psychometric properties. The specific configuration of affect items, as well as the meaningful action items, have only been used in one prior study (Levin et al., 2018) which provided preliminary support for appropriate concurrent and divergent validity. Similarly, the present study provides preliminary evidence that most of the single items of the MPFI chosen to measure in the moment psychological inflexibility subprocesses represent the same construct as the full subscales. The exception to this is the item chosen for experiential avoidance, with evidence suggesting that it may not necessarily measure the intended construct. However, these studies were not designed specifically to assess the validity of these measures, and the reliability and degree of sensitivity to change for these measures remain unclear. It should be noted that the single-item measures for both experiential avoidance and inaction specifically referenced negative emotion, potentially biasing the relationship between these variables and negative affect. It is recommended that similar studies use the full brief two-item scale to assess subprocesses.

Third, our study observed a 64% compliance rate, which is relatively poor in comparison the average 81.9% (Williams et al., 2021). While strong participant endorsement of COVID-19 affecting participation was generally infrequent, this item was still a significant predictor of noncompliance. Additionally, our two-hour allowed time window between receiving a prompt and responding leaves open the possibility for participants to answer EMA prompts when convenient, albeit we had an appropriate average latency of 23 minutes. Regardless, the ecological validity of the data remains questionable. It is also unclear whether a one-week period of assessment is long enough to accurately capture trait-level variables. Finally, multiple models were implemented without adjusting p-values for multiple comparisons, potentially inflating the family-wise error rate (Ranganathan et al., 2016). However, given the exploratory nature of the present study this approach was appropriate.

Future longitudinal research on psychological flexibility should attempt to analyze phenomena at both the state and trait-levels, given the differences between the two found by our study. Even if only state-level variables are of interest, it is still important to include trait-level variables in the analysis, otherwise the individual context in which state-level effects are occurring (e.g., traits of the participant) is not accounted for, leading to potentially misleading results (Hoffman & Stawski, 2009). If only trait-level variables are of interest, then cross-sectional designs as opposed to longitudinal ones may be better suited to answer the research question (Podsakoff et al., 2019). However, even variables conceptualized as stable (i.e., personality traits) vary to a notable degree on a day-to-day level, calling for research on state-level effects (Judge et al., 2014; Podsakoff et al., 2019).

These exploratory results lay the foundational groundwork for future research on how individual psychological inflexibility subprocesses operate in the moment, allowing for a greater fine-grain examination of the differing components of psychological flexibility. This line of research is in line with the multilevel facet of the Association of Contextual Behavioral Science (ACBS) Task Force recommendations (Hayes et al., 2021), and offers bother theoretical implications (e.g., supporting assumptions that all six sub-processes matter and form a coherent, useful construct) as well as clinical implications in regards to treatment and intervention optimization. While a greater number of state-level subprocesses may predict in the moment affect and meaningful activity, the few significant trait-level processes carry greater weight. It is notable that experiential avoidance was not found to be a significant predictor at both the state and trait-level, but that trait-level inaction was a relatively important predictor with strong magnitude for all examined outcomes. Further research is called for in order to see if these findings can be replicated, as well as assess their directionality.

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**Tables**

**Table 1**

*Sample demographics and baseline measurements*

|  |  |
| --- | --- |
|  | Total Sample |
| Age (*M* (*SD*)) | 24 (8.9) |
| Gender (%) |  |
|  *Woman* | 75.6 |
|  *Man* | 24.4 |
| Race (%) |  |
|  *White* | 92.9 |
|  *Asian* | 1.8 |
|  *Black/African American* | 0 |
|  *Native Hawaiian/Pacific Islander* | 0.6 |
|  *Multiracial* | 3.6 |
| Ethnicity (%) |  |
|  *Hispanic/Latino* | 4.8 |
|   *Not* *Hispanic/Latino* | 95.2 |
| Student status\* (%) |  |
|  *Taking classes primarily in-person* | 1.2 |
|  *Taking classes primarily online* | 69.6 |
|  *Taking a combination of classes online and in-person* | 47 |
|  *First generation student* | 10.7 |
|  *International student* | 0.6 |
| Academic year (%) |  |
|  *First year* | 44.6 |
|  *Second year* | 26.2 |
|  *Third year* | 16.1 |
|  *Fourth year* | 5.4 |
|  *Fifth year or higher* | 0.6 |
|  *Graduate student* | 0.6 |
|  *Non-degree seeking* | 4.8 |
| Depress, Anxiety, and Stress Scale (DASS; *M* (*SD*)) |  |
|  *Depression* | 10.3 (9.4) |
|  *Anxiety* | 8.3 (7.6) |
|  *Stress* | 14.2 (8.7) |
| COVID-19 distress (Scale 1 – 6; *M* (*SD*)) | 3.3 (1.6) |
| COVID-19 effect on study participation (Scale 1 – 6; *M* (*SD*)) | 2.1 (1.4) |

\*Participants could select more than one option

**Table 2**

*Descriptive statistics for baseline and momentary psychological inflexibility, affect, and meaningful activity*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Psychological Inflexibility Subprocess | Baseline*M* (*SD)* | Post-assessment*M* (*SD)* | Avg. Momentary*M* (*SD)* | Baseline & Avg. Momentary *r* | Post-assessment & Avg. Momentary *r* | Momentary Within-person ICC |
| Experiential avoidance | 3.22 (0.91) | 3.34 (1.08) | 3.08 (1.31) | 0.39 | 0.70 | 0.51 |
| Cognitive fusion | 3.18 (1.03) | 2.49 (1.08) | 2.12 (1.25) | 0.59 | 0.78 | 0.43 |
| Lack of present moment awareness | 3.75 (1.08) | 2.39 (1.07) | 2.49 (1.23) | 0.56 | 0.77 | 0.45 |
| Self-as-content | 3.87 (1.06) | 2.32 (1.14) | 1.92 (1.14) | 0.55 | 0.86 | 0.44 |
| Lack of contact with values | 4.19 (0.98) | 2.02 (0.88) | 1.94 (1.03) | 0.51 | 0.77 | 0.49 |
| Inaction | 4.16 (1.03) | 2.08 (1.01) | 1.94 (1.16) | 0.58 | 0.80 | 0.45 |
| Negative affect | - | - | 1.55 (0.59) | - | - | 0.55 |
| Positive affect | - | - | 3.01 (0.98) | - | - | 0.58 |
| Meaningful activity | - | - | 10.03 (2.93) | - | - | 0.57 |

**Table 3**

*Mixed models of negative affect, positive affect, and meaningful activity: Location/Means*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Negative affect | Positive affect | Meaningful activity |
|  | Mean (β) | Lower95% CI | Upper95% CI  | Mean (β) | Lower95% CI | Upper95% CI | Mean (β) | Lower95% CI | Upper95% CI |
| Intercept | 0.68\* | 0.51 | 0.86 | 3.48\* | 3.03 | 3.93 | 12.62\* | 11.41 | 13.83 |
| Time | 0.00 | 0.00 | 0.01 | -0.02\* | -0.03 | -0.01 | -0.03\* | -0.05 | -0.01 |
| Effect of COVID-19 on study participation | 0.03 | 0.00 | 0.06 | -0.09\* | -0.17 | -0.01 | -0.34\* | -0.56 | -0.14 |
| *State-like Level* |
| Experiential avoidance | 0.02 | 0.00 | 0.03 | -0.03 | -0.07 | 0.01 | -0.03 | -0.13 | 0.08 |
| Cognitive fusion | 0.12\* | 0.09 | 0.15 | -0.17\* | -0.22 | -0.12 | -0.28\* | -0.42 | -0.14 |
| Lack of present moment awareness | 0.02\* | 0.01 | 0.04 | -0.08\* | -0.12 | -0.04 | -0.29\* | -0.42 | -0.16 |
| Self-as-content | 0.05\* | 0.02 | 0.07 | 0.01 | -0.03 | 0.06 | -0.07 | -0.21 | 0.07 |
| Lack of contact with values | 0.03 | 0.00 | 0.05 | -0.07\* | -0.12 | -0.02 | -0.51\* | -0.68 | -0.34 |
| Inaction | 0.07\* | 0.05 | 0.10 | -0.14\* | -0.19 | -0.09 | -0.36\* | -0.51 | -0.21 |
| *Trait-like Level* |
| Experiential avoidance | 0.04 | -0.01 | 0.09 | 0.14 | 0.00 | 0.27 | 0.25 | -0.12 | 0.62 |
| Cognitive fusion | 0.16\* | 0.08 | 0.25 | -0.08 | -0.28 | 0.12 | 0.11 | -0.43 | 0.64 |
| Lack of present moment awareness | -0.04 | -0.10 | 0.01 | 0.04 | -0.09 | 0.18 | 0.05 | -0.32 | 0.42 |
| Self-as-content | 0.00 | -0.07 | 0.08 | 0.15 | -0.04 | 0.33 | 0.35 | -0.13 | 0.82 |
| Lack of contact with values | 0.00 | -0.09 | 0.10 | -0.06 | -0.29 | 0.17 | -0.95\* | -1.55 | -0.33 |
| Inaction | 0.18\* | 0.08 | 0.28 | -0.31\* | -0.55 | -0.07 | -0.82\* | -1.48 | -0.15 |

*Note.* \**p* < .05

**Table 4**

*Dominance analyses ranked importance and contributed variance*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Psychological Inflexibility Subprocess | Negative affect ranked importance | Negative affect $S\&B R\_{1}^{2}$ | Positive affect ranked importance | Positive affect $S\&B R\_{1}^{2}$ | Meaningful activity ranked importance | Meaningful activity $S\&B R\_{1}^{2}$ |
| Experiential avoidance (State) | - | - | - | - | - | - |
| Experiential avoidance (Trait) | - | - | - | - | - | - |
| Cognitive fusion (State) | 3 | .052 | 2 | .031 | 5 | .013 |
| Cognitive fusion (Trait) | 2 | .119 | - | - | - | - |
| Lack of present moment awareness (State) | 6 | .005 | 4 | .011 | 6 | .011 |
| Lack of present moment awareness (Trait) | - | - | - | - | - | - |
| Self-as-content (State) | 5 | .013 | - | - | - | - |
| Self-as-content (Trait) | - | - | - | - | - | - |
| Lack of contact with values (State) | - | - | 5 | .008 | 3 | .025 |
| Lack of contact with values (Trait) | - | - | - | - | 1 | .070 |
| Inaction (State) | 4 | .038 | 3 | .025 | 4 | .018 |
| Inaction (Trait) | 1 | .122 | 1 | .054 | 2 | .053 |

*Note.* For ranked importance, 1 represents the most important subprocess for explaining variance in the variable listed in the column, and 6 represents the least important subprocess.

**Appendix A**

List of Chosen MPFI Items Included in EMA Surveys

|  |  |  |
| --- | --- | --- |
| Psychological Inflexibility Subprocess |  | Item |
| Experiential avoidance |  | I tried to distract myself when I felt unpleasant emotions |
| Fusion |  | Distressing thoughts tended to spin around in my mind like a broken record |
| Present moment awareness |  | I did most things on “automatic” with little awareness of what I was doing |
| Self-as-content |  | I thought some of my emotions were bad or inappropriate and I shouldn’t feel them |
| Lack of contact with values |  | My priorities and values often fell by the wayside |
| Inaction |  | Negative feelings often trapped me in inaction |