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Beyond the average: Idionomic evidence of individual-specific variability in the psychological flexibility-mood relationship

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ABSTRACT

Past research has relied on normative analyses for establishing the positive relationship between psychological flexibility (PF) process and well-being. These analyses, however, assume that aggregate-level effects (i.e., this positive relationship) also apply to most individuals, limiting our ability to explore the dynamic and complex nature of PF processes that interact with individual factors. Idionomic analyses, which use idiographic effects as a foundation from which to draw normative conclusions, provide a possible solution. This study used idionomic analysis to assess the degree of non-random individual heterogeneity in the relationship between each PF process and mood, how this relationship changes over time, and the unique effects of each process. From a pre-existing dataset, we analysed data from 103 psychiatric patients (M_{age} = 37 years, SD = 11.7 years; 47% male) who completed an ACT intervention. Experience sampling methods were used to repeatedly measure PF processes and mood at pre- and post-intervention. Traditional normative analyses showed an average positive relationship between each PF process and mood. However, idionomic analyses uncovered significant person-specific heterogeneity for several PF processes. The strength and direction of each relationship varied depending on the person, the specific PF process, and the temporal effects that were masked in the aggregate findings. We highlight the value of idionomic analyses in capturing, with greater depth and precision, within-person heterogeneity in the PF process-mood relationship. Idionomics has the potential to advance our development of empirically-based and personalised interventions, thus going beyond the general statement of "it depends" to a specification of how it does so.

1. What is psychological flexibility?

Psychological flexibility (PF) is the ability to stay present, openly engage with experiences—both pleasant and unpleasant—and adapt behaviour in ways that align with personal values and situational demands (Hayes et al., 2012). PF incorporates greater engagement in behaviours that align with one's personal values, even if it might trigger psychological distress (Ciarrochi et al., 2010; Hayes et al., 2006). In the formulation linked to classical forms of Acceptance and Commitment Therapy (ACT; Hayes et al., 1999, 2012), this construct comprises of six dynamic processes of change: Acceptance, Defusion, Present Moment Awareness, Self-as-Context, Values and Committed Action (Cherry et al., 2021; Hayes et al., 1999). These processes can be leveraged by the individual as skills in response to a given context (Hayes et al., 2019; Ong & Eustis, 2021, p. 176). PF is the key mechanism of change that underpins ACT (Ciarrochi et al., 2010). The ACT clinician will target specific PF processes based on the person's problems, context, and goals, and use intervention strategies known to impact these processes (Gloster et al., 2021; Hayes et al., 1999).

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1.1. The relationship between psychological flexibility and well-being

Robust literature exists demonstrating the positive relationship between PF and well-being outcomes, including positive affect (Twiselton et al., 2020), work burnout (Kent et al., 2019), self-efficacy (Jeffords et al., 2020), emotion regulation (Cobos-Sánchez et al., 2022), and general psychological health (Fonseca et al., 2020; Usubini et al., 2021). Moreover, PF has been shown to mediate positive treatment outcomes, particularly in the context of ACT (Gloster et al., 2020; Hayes et al., 2006; Kashdan & Rottenberg, 2010; Stenhoff et al., 2020; Stockton et al., 2019). Studies have further sought to investigate the relationship between specific PF processes and well-being, including demonstrating the positive relationship between well-being and Present Moment Awareness (Lomas et al., 2017a, 2017b, 2018), Values (Branstetter-Rost et al., 2009; Gloster et al., 2017; Veage et al., 2014), Acceptance (Casier et al., 2011; Levitt et al., 2004) and Self-as-Context (Bennett et al., 2021; Moran et al., 2018). When studied collectively, research has also shown dissimilar effects of each process depending on individual factors, such as population (Wang et al., 2023) and the presenting problem (Ciarrochi et al., 2014; Ding & Zheng, 2022; Peñacoba et al., 2021; Zakiei et al., 2024). For example, Zakiei et al. (2024) conducted a systematic review and meta-analysis to explore the link between the six PF processes and poor sleep outcomes. They found that across all studies, while all six processes were linked with quality of sleep and insomnia severity, Acceptance demonstrated a stronger role than the other processes.

What is important to note is that targeting PF processes, however, requires knowledge of how they apply to the well-being of a particular person, couple, or group seeking help, not to an arbitrary collection of people. Pursuing this knowledge is not without methodological challenges.

1.2. Challenges in understanding psychological flexibility

Psychometrically speaking, PF can often be viewed as a unitary construct (Ciarrochi et al., 2014; Kashdan & Rottenberg, 2010; Levin et al., 2012), but clinically speaking, these processes are targeted more specifically. Methods of measuring PF have increasingly become more multifaceted and time- and context-sensitive. Examples include the Psy-Flex measure (Gloster et al., 2021), or more dynamic methods of measurement, such as experience sampling methods (ESM; Myin-Germeys et al., 2018). ESM involves prompting individuals to complete short measures assessing daily experiences, several times a day, over multiple days (Myin-Germeys et al., 2018). Literature has demonstrated the advantage of using ESM to measure dynamic psychological outcomes (e.g., thoughts, feelings, behaviours) in the day-to-day context with robust ecological and external validity (Bartels et al., 2023; Beames et al., 2025; Myin-Germeys et al., 2018). This method provides greater precision for capturing the PF processes of change within the individual and over time, and facilitates within-person statistical modelling (Larson & Csikszentmihalyi, 1983; Sahdra et al., 2023; Van Berkel et al., 2017).

While these more dynamic methods of measurement have evolved to investigate the relationship between PF and well-being, analytic and statistical methods are lagging behind. Research to date largely relies on normative analytic methods, which involve comparing the differences between group averages (e.g., the average effect found in treatment versus control groups) to estimate treatment effects. Variation that exists between individuals in the group (between-person variation), or how these variations can change over time (within-person variation), are pooled across the group average (Sahdra et al., 2024). Moreover, non-random individual heterogeneity that deviates from the average of the ensemble or collective is commonly categorised as unexplained variability or "error," which is then used as a metric to determine the statistical significance of effects seen at the level of the collective. In effect, this sets aside possibly insightful information on person-specific idiographic effects – precisely the kind of information of importance to treatment providers (Sahdra et al., 2024). Aggregate-based normative methods have been criticised on the grounds for their use in evaluating process-based therapies (PBTs), like ACT, with implications in both research (Ciarrochi et al., 2022) and practice (Ciarrochi et al., 2024c).

PBTs focus on identifying and shifting the biopsychosocial processes that drive a person's suffering and wellbeing, rather than applying a fixed protocol aimed at a normative diagnostic category. Providers ask what processes matter for this particular person, couple, or family, in this situation, and how can these processes change over time. ACT fits squarely within this approach because it specifies both an overarching target, PF, and the set of modifiable processes that build it: defusion *(cognitive)*, acceptance *(affective)*, contact with the present moment *(attention)*, values *(motivation)*, and committed action *(overt behaviour)*, mapped cleanly onto the Extended Evolutionary Meta-Model of a process-based approach (Hayes et al., 2020; Ong et al., 2024). Each process is defined, measurable, and changeable, which gives ACT the structure required for a PBT. Although ACT researchers have developed many standardised protocols in a wide variety of areas, ACT is trained in a process-oriented way that allows personalisation rather than through protocols linked to syndromes. Only a fifth of the first 1000 randomised trials targeted traditional psychiatric syndromes (Hayes & King, 2024), and scores of ACT outcome studies are based on single-case designs. As a form of PBT, ACT providers identify which processes are most relevant for the client at that point in time and adjusts their work accordingly and ongoingly. For example, clients unsure as to why they are in therapy may benefit from values work first. When clients struggle to name or track their emotions, they may engage with mindful awareness of emotions and acceptance work. Conversely, clients who are able to recognise their thoughts and feelings easily, but who struggle to engage in concrete behaviour change, may focus on working through committed action.

Person-specific functional analysis is where normative methods alone fall short. They assume that people share the same processes, that those processes are stable over time, and that change unfolds in uniform ways across particular people (Molenaar, 2004). These assumptions rarely hold in clinical practice (Beltz et al., 2016; Sahdra et al., 2024). To evaluate PBTs like ACT, researchers need methods that track how these specific processes shift within the person, rather than merely comparing ensemble averages that may hide critical differences.

In PF literature, typical normative statistical approaches used include mediation analysis and multilevel modelling (MLM) in longitudinal designs (Ciarrochi et al., 2024c). In addition to the limited generalisability of their findings to particular cases, these methods exhibit unique limitations in capturing non-random person-specific heterogeneity within treatment effects. For example, mediation analysis studies may establish that PF mediates treatment effects between ACT interventions and well-being outcomes (e.g., mood; Stockton et al., 2019). These effects, however, are inherently based on the analyses of aggregates and are typically captured at single time points, thereby assuming that PF is static and ensemble averages apply (Ciarrochi et al., 2024c). Moreover, as mediation analyses assume all analysed variables are unidirectional and stable (Hofmann et al., 2020), any bidirectional or dynamically changing relationship between variables becomes masked underneath a supposedly overall effect that may apply to only a small portion of the collective being analysed (Hofmann et al., 2020). Correlational analyses encounter similar difficulties (Ciarrochi et al., 2024c).

Statisticians have endeavoured to address some of these problems using approaches such as MLM that capture and attempt to measure both within- and between-person variation longitudinally. However, in MLM, individual-level effects that significantly deviate from the group average are "shrunk" towards the overall mean and thus become biased in the context of group-level effects (Ciarrochi et al., 2024c; Liu et al., 2021). For example, Fledderus et al. (2013) found that PF served as a process of change in ACT for improving anxiety, and these effects strengthened over time. If a specific participant in the ACT condition exhibited high anxiety scores that increased throughout treatment, MLM would shrink their effects closer to the group-average to help derive an overall individual-level finding. Thus, even when normative statistical approaches attempt to model the particular person, they do so in ways that muffle the voices of persons who are different compared to ensemble averages. A new approach appears to be needed to properly model the relationship between PF and well-being for particular people that applies to the actual applied use case of providers helping specific people. A solution has recently been proposed to address this: the idionomic approach (Hayes et al., 2022).

1.3. The idionomic approach

Idionomics involves first employing idiographic statistical analyses, and then seeking normative generalisations, retaining those only if they comport with and increase our understanding of the idiographic findings. The idiographic step models the longitudinal data of one particular person (or couple, family, or group) at a time (Hayes et al., 2022; Sahdra et al., 2024). The normative step can involve summarising idiographic findings, looking for relations seen at the level of the ensemble and then retesting these, one at a time, to see if idiographic modelling improves for most people when these relations are included, or identifying subgroups of people studied idiographically for whom an overall pattern is meaningful (Ciarrochi et al., 2024b; Ciarrochi et al., 2024c; Hayes, Sahdra, Ciarrochi, Hofmann, & Sanford, 2024; Sahdra et al., 2024). For PBTs, idionomic approaches have shown superiority over normative approaches due to their ability to granularly explore the relationship between processes of change and outcomes within particular persons (Sahdra et al., 2024). For example, Ciarrochi et al. (2024c) analysed the relationship between three process measures and various well-being measures. They found that normative and idionomic analyses revealed inconsistent findings and severe violations of the "ergodic assumption" that must be met to reliably generalise from ensemble averages to particular people (Hernández et al., 2025). For instance, normative analysis showed that social behaviour processes (e.g., assertiveness) had no significant relationship with loneliness at the level of the collective or population. Idionomic analysis, however, showed that significant relationships existed between the two in multiple (negative and positive) directions within individuals in the sample, nullifying each other when calculating the average (Ciarrochi et al., 2024a). The authors described this as an "equisyncratic" process (Ciarrochi et al., 2024a) that is relevant idiosyncratically in both directions, such that it zeroes out at the level of the collective. Other studies exploring the relationship between process and outcome measures have similarly demonstrated inconsistency between average ensemble and idionomic findings. This includes the relationship between valued action and hedonic well-being (Sahdra et al., 2024), processes of compassion and romantic attraction (Ciarrochi et al., 2024b) and self- and other-compassion and well-being (Sahdra et al., 2023). No study to date, however, has idionomically explored the relationship between PF processes and mood. This includes whether person-specific differences exist beyond the aggregate relations.

1.4. The current study

Our primary aim was to investigate the presence of non-random person-specific heterogeneity in the relationship between the six PF processes and mood using an idionomic approach and explore how these relationships may change over time. We termed the strength of the contemporaneous, within-person relationship between a PF process and mood as "importance." We define person-specific heterogeneity as non-random between- and within-person variability that exists in effects found in the importance of the relationship between PF processes and mood (PF process-mood relationship). Our secondary aim was to explore whether the processes of PF were uniform in the strength of their relationship with mood and how this changed over time. Based on past research, we hypothesised that high levels of non-random individual heterogeneity would exist in the relationship between each PF process and mood. Further, we sought to explore whether such relationships changed over time, within-person. Due to the relative dearth of literature surrounding this issue (cf. Chin, 2023), no hypothesis was made respectively. The study was pre-registered at Open Science Framework (OSF; https://osf.io/g48qu/?view_only=c2cce7cf0ad246538b0d69b54bfaad48).

2. Method

The current study serves as a secondary study analysing archival data from Gloster et al.'s (2023) 'Choose Change' effectiveness trial that ran from May 2016 to May 2021 (full details can be found in Villanueva et al., 2019). The primary study investigated the short- and long-term effectiveness of ACT on a range of treatment outcomes within a trans-diagnostic sample of patients. In light of our aims, we obtained data from the primary study exclusively pertaining to the process and outcome measures collected at pre-intervention (the first week following treatment commencement) and post-intervention (the week following treatment conclusion) using ESM. Ethics approval was provided by the Australian Catholic University Human Research Ethics Committee (2024-3570X).

2.1. Participants

Two hundred patients were recruited from an inpatient and outpatient psychiatry clinic in Switzerland specialising in ACT (M_{age} = 37, SD = 11.7; 47% male). Participants were patients referred into these clinics via their intake procedure and were approached to participate in the primary study if they met inclusion criteria. Inclusion criteria included being over 17 years old, having local language skills, ability to attend therapy, and prior engagement in therapy and/or medication. Exclusion criteria included having acute suicidal intent, acute substance dependency, active mania, previous engagement with ACT and inability to read. Participants were further excluded when they did not provide at least 10 observations of ESM data and did not complete all measures relevant to our study. Subsequently, 103 participants were included in our analyses. This within-person sample size is comparable to past research (Ciarrochi et al., 2024b; Jones et al., 2019). In estimating power, we considered two questions: (a) our ability to detect between-person heterogeneity (e.g., I^2) and (b) our ability to detect contemporaneous associations within individuals. For heterogeneity, we retained as many individual cases as possible because even nonsignificant effects provide valuable information about the spread of effects across people. To evaluate individual-level power, we conducted a Monte Carlo ARIMAX simulation that created thousands of synthetic time-series datasets resembling the kinds of day-to-day data collected in intensive longitudinal designs. In each simulated dataset, a single individual was measured repeatedly over time. The predictor variable (x) followed a stationary AR(1) process, meaning that values changed smoothly from one time point to the next, as is typical for psychological processes; x was standardised so that one unit equalled one standard deviation. The outcome (y) was generated by combining a true effect of x (β ranging from 0.20 to 0.80) with an error term that also followed an AR(1) structure, allowing y to reflect both the influence of x and its own temporal dynamics. For each effect size and sample size (e.g., 10 or 20 observations per person), we simulated 5000 datasets and analysed each using the same ARIMAX model applied in the primary study. Power was defined as the proportion of simulations in which the model correctly detected the true effect at $\alpha = .05$. With $n = 10$, we observed modest power for medium-to-large effects ($\beta = 0.60$, power = 0.55; $\beta = 0.70$, power = 0.65; $\beta = 0.80$, power = 0.73). As expected, power increased with more observations; when participants provided at least 20 assessments, power to detect effects of $\beta \geq 0.60$ exceeded 0.73.3.

2.2. Intervention

All participants received 12 weeks of intensive ACT, consisting of one or two individual in-person sessions in the clinic by psychotherapists. Additionally, inpatients received additional daily group sessions and supportive nursing care that was consistent with ACT by a multidisciplinary team. To improve ecological validity, treatment was non-manualised and personalised, such that therapists tailored treatment and targeted PF processes based on their client's problems (Villanueva et al., 2019).

2.3. Procedure

Next, we detail the procedures entailed from pre-to post-intervention from the primary study (see Villanueva et al., 2019 for the full procedure). After participants provided informed consent, they completed a battery of measures not included in the present study, but reported elsewhere (Villanueva et al., 2019). They were then given a smartphone and instructed on the use of a mobile application on the phone to use for ESM data collection. Participants were to keep these phones throughout the duration of the study. ACT was then delivered to all participants. Process and outcome measures (PF processes and mood, respectively) were collected using ESM during the week of pre-intervention and post-intervention. Within each day of the week, participants received six identical ESM prompts on their smartphone to respond to daily, or every 3 h (see Appendix A for a codebook of prompts used). While we were interested in the changes in the relationship between PF and mood over time following ACT intervention, the efficacy of ACT was not the focus of this study and has been reported elsewhere (Gloster et al., 2023).

2.4. Measures

2.4.1. Mood

At each ESM prompt, participant's state mood was measured by asking “How would you rate your current mood?” Responses were provided on a 6-point Likert scale from 0 (*very bad*) to 5 (*very good*).

2.4.2. Psychological flexibility

The Psy-Flex is a six-item questionnaire used to assess the presence of each process of PF within the individual at that point in time (Gloster et al., 2021). Responses are provided on a 5-point scale from 1 (*very rarely*) to 5 (*very often*). Higher scores indicate more presence of a PF process within the individual. The Psy-Flex has demonstrated high reliability, convergent, divergent and incremental validity and treatment sensitivity (Gloster et al., 2021). The Psy-Flex is time- and context-sensitive, suited for swiftly capturing individual fluctuations of PF processes using ESM (Gloster et al., 2021). In the primary study, the Psy-Flex was adapted to measure more momentary fluctuations of PF processes via ESM. The administration frequency increased from once to six times a day, thus followed by modification of the tool's wording from “in the last seven days*”* to “*in the last 3 h*” The Psy-Flex has previously been used as a state measure in an event-sampling study of transdiagnostic outpatients, where it was administered six times per day over one week with items adapted to the “last 3 h” and rated on a 0–100 scale (Villanueva et al., 2024). In that study, higher momentary psychological flexibility was associated with better mood and buffered the negative impact of frequent upsetting events and being in the hospital on mood. Together with its original validation as a contextually sensitive measure intended for use in daily life (Gloster et al., 2021), this supports the suitability of Psy-Flex for ESM designs.

2.5. Data analyses

Analyses were conducted in R(R Core Team, 2024). Data files and the analysis of R script are available upon reasonable request and may require submission of a data analysis plan and signing a data sharing agreement to protect the identity of participants in the rich, multiple-timepoint data set. These analyses focused on the importance of each PF process for each individual, and comprised of a preliminary analysis followed by main analyses. Our preliminary analyses examined the simple (correlational) normative relationships between each PF process and outcome. Our main analyses involved two steps: first, an *idiographic* analysis, which examined the relationship between PF process and mood within each individual separately; and second, an *idionomic* analysis, which integrated idiographic and normative findings to identify patterns of individual heterogeneity across the sample. The idiographic analysis assessed the strength of the relationship between each of the six PF processes and mood within each person for each time point. These relationships were estimated using autoregressive integrated moving average models with an exogenous variable (I-ARIMAX; Chatfield & Xing, 2019; see Ciarrochi et al., 2024c; Sahdra et al., 2024 for further details). Each participant received a beta estimate and accompanied standard error for each PF process at each time point (pre versus post), resulting in 12 effects per person. I-ARIMAX estimated the relationship between PF process and mood for each individual (hence the “I”) while controlling for the autoregressive (p), differencing (d), and moving average (q) components of the time series. The autoregressive (p) and moving average (q) terms account for temporal dependencies in Y (i.e., our dependent variable, mood), while the differencing (d) term controls for trends (e.g., pattern of natural changes unique to mood). This approach isolates the unique contribution of X (i.e., PF), ensuring that observed relationships are not confounded by these factors (Ciarrochi et al., 2024c).

After estimating the I-ARIMAX models, we extracted each participant's beta coefficient and standard error for every PF process at both pre- and post-treatment. These idiographic estimates formed the complete dataset that fed into the Bayesian meta-analytic models. Although we do not present all individual coefficients—both because of their volume and limited standalone interpretability—we include example forest plots to illustrate how these individual-specific estimates are distributed. Here, we capture the complex nature of the relationship between PF processes and mood over time. While these plots show a representative PF process at a given timepoint, the Bayesian models reported in Tables 4 and 5 were fit to the *full set* of idiographic estimates.

The Bayesian meta-analyses (Kruschke & Liddell, 2018) allowed us to estimate a pooled “normative” effect of each PF process-mood relationship, whilst also being able to test for non-random heterogeneity of the effects both within-person and over time. The key omnibus test compared a fixed-effects model and a random-effects model to assess whether the relationship between PF processes, time, and mood varied across individuals. The fixed-effects model assumed that the effects of the predictor (*Variable*), time (*Time*), and their interaction (*Variable:Time*) were uniform and applied equally across each individual. The only source of individual variability in this model was a random intercept, which accounted for baseline differences in mood but did not allow the relationships between predictors and mood to vary across participants. In contrast, the random-effects model allowed individual differences in both intercepts and slopes, meaning the effects of *Variable*, *Time*, and their interaction could vary across participants. This approach provided a more flexible framework for capturing individual heterogeneity in the PF process-mood relationship. See Appendix B for further details of LOO and ELPD.

The predictive performance between data modelled on the fixed and random effects models were evaluated using Leave-One-Out (LOO) cross-validation and Expected Log Pointwise Predictive Density (ELPD; Wagenmakers et al., 2018).

Both models were then estimated using a Bayesian approach with **weakly informative priors**. The intercept prior (average link between process and outcome) followed a normal distribution ($M = 0.5$, $SD = 0.3$), centering estimates around a reasonable range based on prior literature. The standard deviation priors for the random effects followed a Student's t distribution ($df = 3$, $M = 0$, $SD = 1$), providing weak regularisation while allowing for extreme values if justified by the data. These priors helped stabilise estimates without overly constraining the results, ensuring that model inference was driven primarily by the observed data rather than strong prior assumptions.

As aforementioned, we lastly present this data using forest plots to visually capture the complex nature of the relationship between PF processes and mood over time. Of note, inpatient and outpatient participant data were combined for analysis in the current study as their distinction was not the primary focus.

3. Results

3.1. Preliminary analyses

The mean, standard deviation and distribution of each variable is displayed in Table 1. Participants' age was positively skewed with platykurtic kurtosis. Averaged state mood and PF processes were negatively skewed with platykurtic kurtosis. We did not transform our data as this would interfere with our aims to investigate individual heterogeneity.

Table 2 demonstrates output of between- and within-person correlational analysis between processes and mood. Within-persons correlations revealed a significant moderate positive correlation between each PF process and mood, when averaged across time. On average, or when pooled across individuals, greater engagement in a PF process at a given moment was associated with higher positive mood compared to moments of lower engagement in that process. This significant effect was observed for all PF processes ($p < .001$). All within-persons correlations fell between $r = 0.41$ and 0.47. Similarly, between-person correlations revealed a significant positive and large PF process-mood relationship for each PF process, when averaged across time ($p < .001$, $r = 0.61$ to 0.74). This suggests that individuals who were more likely to endorse higher levels of a PF process were more likely to have positive mood over time, compared to others.

We next explored the stability (variability) of the strength of the within-person relationship between a PF process and mood from pre- and post-intervention. We found small to moderate stability ($r = 0.21$ to 0.34) for all processes except Present Moment (Table 3). Based on the r^2 value of these correlation coefficients, this suggests that only about 4% to 9% of the variance between the PF process-mood relationship at post-intervention could be explained by such relationship at pre-intervention.

3.2. Main analyses

Using Bayesian meta-analysis, we compared the fit of a Fixed-Effect Model (FEM) and a Random-Effects Model (REM) to assess individual variation in the relationship between PF processes and mood. The FEM assumes that the effects of each process on mood, Time, and their interaction (*Variable:Time*) are constant across individuals, meaning all participants share the same estimated effect sizes. In contrast, the REM allows these effects to vary across individuals, capturing person-specific differences in how PF processes influence mood over time (see Data Analyses section). We fit the data to both models and evaluated their predictive performance using Leave-One-Out (LOO) cross-validation (see Table 4).

Table 1
Descriptive statistics: Sample size, means, standard deviations and distributions.

Variable	*n*	*M*	*SD*	Skewness	Kurtosis
Age	103	37	11.7	0.43	−0.87
Current Mood	103	3.24[a]	0.99	−0.54	0.29
Psychological Flexibility Process					
Present Moment	103	67.9	21.0	−0.69	0.21
Acceptance	103	62.9	23.2	−0.54	−0.20
Defusion	103	61.5	24.0	−0.49	−0.36
Self-as-Context	103	60.1	26.1	−0.43	−0.59
Values	103	70.1	21.1	−0.78	0.40
Committed Action	103	70.2	22.0	−0.85	0.37

Note. n = number of participants. *M* = mean. *SD* = standard deviation.
[a] Current Mood scores ranged from 0 (*very bad*) to 5 (*very good*).

Table 2
Correlations between psychological flexibility and mood, averaged across time.

Psychological flexibility process	Mood	
	Within-person	Between-person
Present Moment	0.45	0.67
Acceptance	0.41	0.70
Defusion	0.47	0.74
Self-as-Context	0.48	0.70
Values	0.45	0.68
Committed Action	0.44	0.61

Note. M = Mean. *SD* = standard deviation, respectively.
All correlations were significant, $p < .001$.
Within-person correlations reflect all participants' mood responses obtained via ESM across both pre- and post-intervention. This is similarly the case for between-person correlations.

Table 3
Bootstrap analyses: Stability of the importance of psychological flexibility within individuals over time.

Psychological flexibility process	*r*	*SE*	BCa 95% CI	
			LL	UL
Present Moment	0.15	0.11	−0.05	0.39
Acceptance	0.22*	0.09	0.00	0.41
Defusion	0.21*	0.10	0.02	0.40
Self-as-Context	0.21*	0.08	0.04	0.36
Values	0.34*	0.09	0.17	0.50
Committed Action	0.34*	0.08	0.18	0.47

Note. r = Pearson correlation. *SE* = standard error. *BCa* = Bias-Corrected and Accelerated.
CI = 95% confidence interval. *UL* = Upper limit. *LL* = Lower limit.
* Confidence intervals that do not include 0 indicate statistical significance, where $p < .05$.

The REM performed better than the FEM and fit more accurately to the data, indicated by the REM showing lower Leave-One-Out Information Criterion (LOO-IC) and higher Expected Log Pointwise Predictive Density (ELPD) than the FEM. However, the higher parameters in the LOO model (P_LOO) in the REM indicates increased model complexity. While this suggests a more intricate model structure, the superior fit justifies the added complexity, as it captures substantial individual heterogeneity in how PF processes relate to mood over time. All observed estimate-to-standard-error ratios were greater than three. The REM results indicate that individuals differed in how they attributed importance to each PF process and how these relationships evolved over time, challenging the assumption that average or pooled effects accurately describe individuals.

We present the REM results in Table 5. The model captures (a) overall between-person variability in PF–mood effects (random intercept), (b) process-specific deviations from this baseline (person-level random effects), and (c) changes in these relationships over time (interaction effects). The random intercept was substantial (SD = 0.22, 95% CI [0.19, 0.26]), indicating that individuals differed meaningfully in their overall PF–mood association at baseline. On average, higher PF predicted better mood, but the strength of this link varied across participants.

Process-specific random effects showed additional heterogeneity for Present Moment (0.10), Values (0.14), and Committed Action (0.15), meaning individuals differed in how strongly these processes related to mood relative to Acceptance, the reference category. Note that using Acceptance as the reference category was arbitrary and did not affect the estimated differences among the remaining processes. These deviations represent person-level variation that sits above and beyond the general

Table 4
Comparison of Model Performance: Bayesian Fixed vs Random Effects Models.

Bayesian Model	ELPD (*SE*)	P_LOO (*SE*)	LOO-IC (*SE*)	Elapsed Difference (*SE*)
Fixed Effects	−317.9 (10.6)	286.2 (16.7)	635.8 (21.2)	554.6 (66.8)
Random Effects	236.7 (7.5)	423.3 (10.7)	−473.4 (15)	0.0 (0)

Note.
ELPD = Expected Log Pointwise Predictive Density. Measures log probability density of new data points based on the model. Higher values indicate better predictive accuracy.
P_LOO = Parameters in the Leave-One-Out model. Higher values indicate increased model complexity.
LOO-IC = Leave-One-Out Information Criterion. A measure used to assess the predictive performance of a model. Lower values indicate better fit to the model.
SE = Standard Error of the respective estimates.

Table 5
Random effects modelling: Intercept, fixed effects, and interaction effects.

Effects	Standard Deviation of Effect			
	Estimate	*SE*	2.5% CI	97.5% CI
Population-Level Effects				
Intercept	0.35	0.02	0.32	0.39
Person-Level (Random) Effects				
Intercept*	0.22	0.02	0.19	0.26
Present Moment*	0.10	0.03	0.05	0.15
Defusion	0.03	0.02	0.00	0.08
Self-as-Context	0.05	0.03	0.00	0.10
Values*	0.14	0.02	0.10	0.19
Committed Action*	0.15	0.02	0.11	0.20
Interaction Effects (PF Process x Time)				
Pre to Post-Intervention*	0.25	0.02	0.21	0.29
Present Moment*	0.10	0.04	0.02	0.19
Defusion	0.05	0.03	0.01	0.12
Self-as-Context*	0.18	0.03	0.12	0.24
Values	0.07	0.04	0.01	0.15
Committed Action*	0.11	0.04	0.00	0.21

Note. Number of group-level effects = 103 levels, representing each participant in the study. *SD* = standard deviation. *SE* = standard error. *CI* = credibility interval.
Intercept refers to the baseline value of the outcome variable (mood), prior consideration of the effects of other variables. Interaction Effects refers to how time interacts with the strength of the relationship between a PF process and mood. In other words, how this strength of the relationship changes over time, from pre-to post-intervention.
Acceptance was not included as a separate variable as it served as the reference category in the model. However, its effect is captured by the model intercept: the intercept reflects the expected outcome when all other process indicators are zero, which corresponds to the Acceptance condition.
* Indicates significant effect. Significant effects are indicated by having an estimate that is more than twice its standard error.

between-person variability captured by the random intercept. Defusion (0.03) and Self-as-Context (0.05) did not show strong evidence of additional variation relative to Acceptance. However, because each process's total variability is the sum of the random intercept and its process-specific deviation, even processes with small or non-significant deviations (e.g., Defusion, Self-as-Context) still exhibit meaningful between-person differences in their PF process–mood associations. Taken together, these results show that individuals vary considerably in how PF processes relate to mood, with especially large variability for Present Moment, Values, and Committed Action. This pattern reinforces our finding that pooled (population-level) estimates (see Table 2) obscure substantial non-random heterogeneity and highlights the value of modelling both shared and process-specific variability in PF process–mood relationships.

Beyond the main effects, we examined how the strength of each PF process–mood link changed over time (PF Process × Time interaction effects). The random time effect (SD = 0.25, 95% CI [0.21, 0.29]) indicated substantial between-person variability in pre–post change: individuals differed meaningfully in how their mood shifted over time. The process-specific interaction terms showed that this variability was not uniform across PF processes. Self-as-Context (0.18), Committed Action (0.11), and Present Moment (0.10) all displayed significant interaction effects, meaning that individuals differed in how strongly these processes shaped their change in mood over time, relative to Acceptance. Defusion (0.05, 95% CI [0.01, 0.12]) showed little evidence of additional time-specific variability beyond the baseline time effect, while Values (0.07, 95% CI [0.01, 0.15]) showed modest but uncertain variation. Together, these findings indicate that individuals not only differ in how PF processes relate to mood at a single time point, but also in how these process–mood relationships evolve across time.

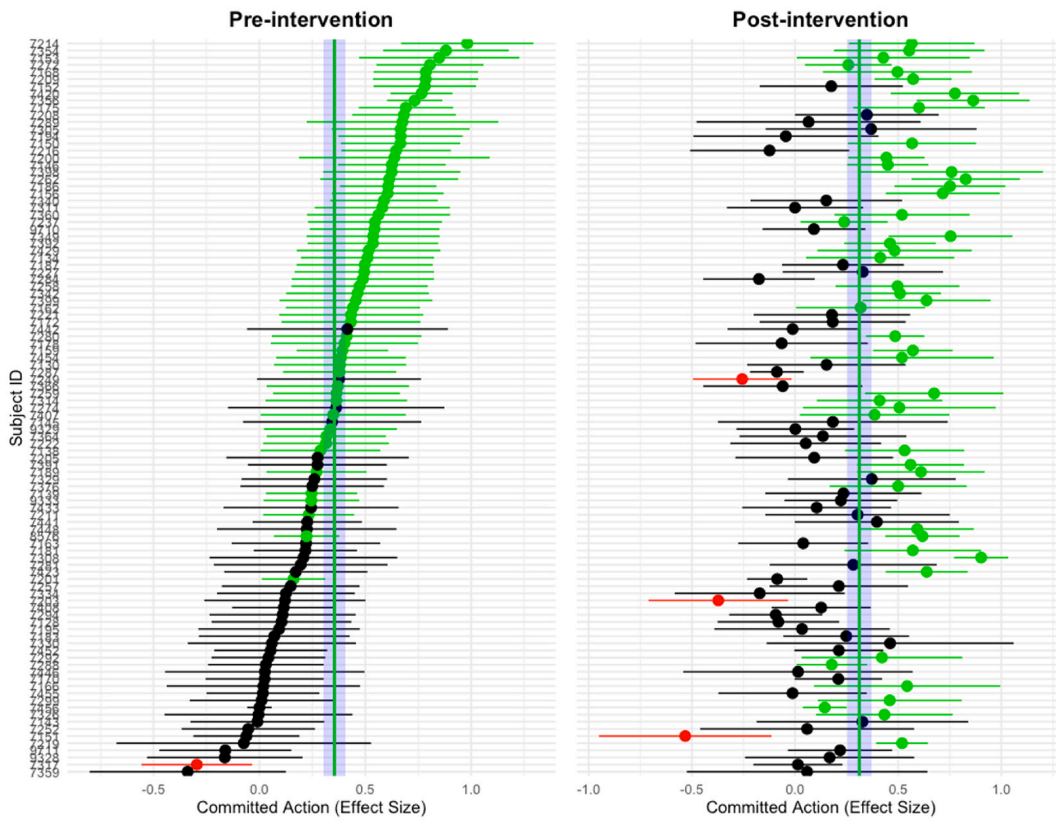
Lastly, we visualised our findings using forest plots to contrast the complex nature of person-specific variability observed in the PF-mood relationship, to the pooled effect obtained when averaging across participant's individual effects. Fig. 1 displays two panels of forest plots (Panel A and B) that present the same data in different ways. Both panels display the relationship between a specific PF, Committed Action, and mood at pre- and post-intervention for each participant. Here, the vertical green line represents the pooled effect, while the wider blue line behind represents its confidence interval. These were derived from the meta-analysis.

Panel A demonstrates participants' change in effect sizes of the Committed Action-mood relationship from pre-to post-intervention, organised according to effect size estimates. We observed that for each time point, individuals significantly deviated from the pooled effect (i.e., their confidence intervals did not overlap with the vertical green line), suggesting that the average effect does not adequately describe individual differences. While the overall pooled effect remained similar at pre- and post-intervention, individual trajectories varied considerably–Committed Action became more influential for some, while for others, its impact diminished or even became negative.

Panel B presents the same data alternatively organised by grouping participants based on how their effect size changed from pre-to post-intervention. We observed two groups: participants whose effect size remained stable over time (stable group) and those who changed over time (changing group). For the stable group, clustered at the lower portion of the forest plots, effect sizes remained either significant (green to green) or nonsignificant (black to black) from pre-to post-intervention. That is, for some participants, the importance of Committed Action was consistent over time. For the changing group, clustered at the upper portion of Panel B, we observed that for some participants, Committed Action became more important over time (non-significant to significant) or less important over time (significant to non-significant). For a smaller portion of the changing group at the upper portion of Panel B, we additionally observed that for some participants, Committed Action changed from having no significant effect on mood (black) to a negative effect (red), or vice versa, over time. We highlight the equisyncratic effect (Ciarrochi et al., 2024a), where rich underlying individual differences in the relationship between Committed Action and mood could not accurately be captured within a single, pooled effect, and how this changed over time.

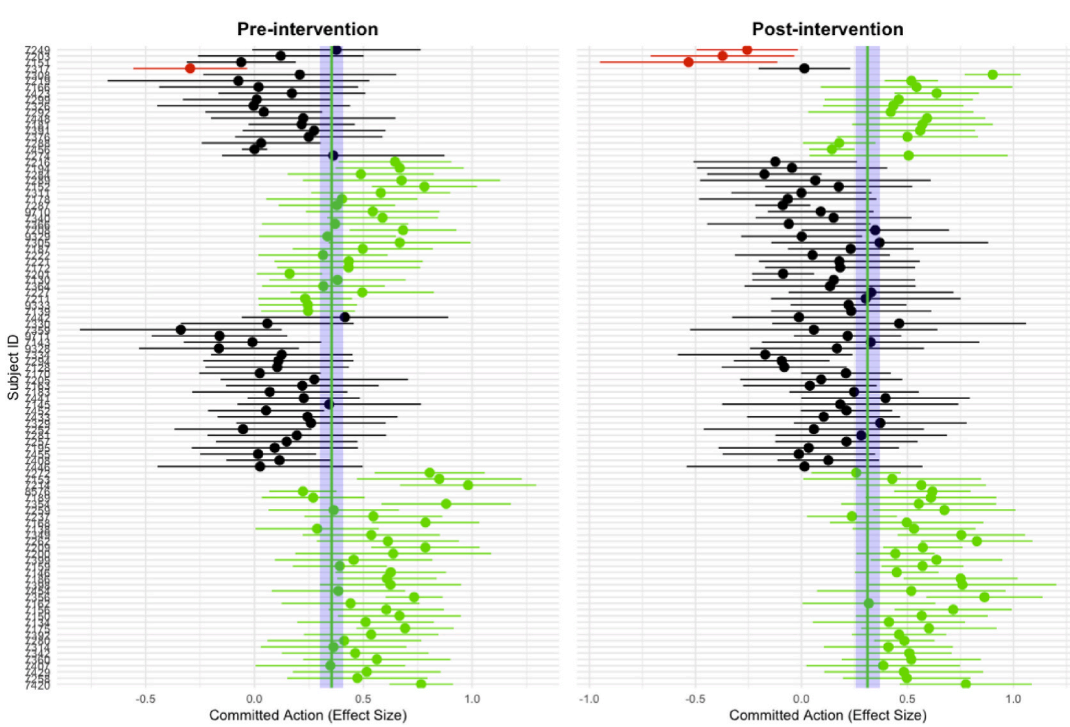
Panel A highlights the limitations of relying solely on average effect sizes to capture individual differences and change over time. Rather, there existed a notable level of non-random heterogeneity at pre- and post-intervention. Our findings further draw on the significance of being able to identify meaningful patterns of data within groups without forgoing individual heterogeneity. Panel B highlights that idiographic subgroups may exist in the nature of how one's relationship between Committed Action and mood changes from pre-to post-intervention. Temporal invariance in the importance of Committed Action held for some but not for others. While Committed Action was used for illustrative purposes, we detail similar patterns of process-mood links across

A



BEYOND THE AVERAGE: IDIONOMIC EVIDENCE

B



(caption on next page)

Fig. 1. Within-person Relationship between one example process, Committed Action and Mood Over Time. Note. Fig. 1 displays two panels of forest plots (Panel A and B) containing the same data visualised in different ways. Both panels display the specific PF, Committed Action, and its relationship with mood at pre- and post-intervention for each participant. Panel A displays participants' change in effect sizes of the Committed Action-mood relationship from pre-to post-intervention, organised according to ascending effect size estimates. Panel B presents the same data alternatively organised by grouping participants based on how their effect size changed from pre-to post-intervention. De-identified participants are indicated on the left side of each panel. The vertical line for each forest plot represents the pooled (average) effect size between Committed Action and mood for each participant. The wider blue shaded line behind indicates its 95% confidence interval. Individual estimates are represented by colour-coded dots: green indicates significant positive effects, red indicating significant negative effects, and black indicating non-significant effects. Their corresponding coloured horizontal lines indicate their confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the other PF processes in our supplementary materials.

4. Discussion

Our study employed an idionomic approach to examine how daily fluctuations in distinct PF processes influence daily mood in an ESM dataset during ACT treatment. Specifically, we explored the presence of individual heterogeneity in this relationship, and whether these effects were unique to each PF process. In comparing the pooled and idiographic findings, the aggregate analysis revealed a significant positive correlation between each PF process and mood between- and within-persons, and averaging across time. This replicates past research (Gloster et al., 2024). This conclusion generalised poorly, however, to the level of particular people, as reflected by our idiographic analysis.

The random effects model outperformed the Bayesian fixed effects model in capturing variability. While the fixed effects model suggested little-to-no significant relationship between each PF process and mood when controlling for between-person differences, it still identified a significant positive association on average. However, the significance of the random effects model indicates that pooled estimates failed to account for individual variability, highlighting the limitations of a fixed-effects approach in describing person-specific effects. The results underscore the need to account for non-random individual heterogeneity, challenging the ergodic assumption of homogeneity—the idea that ensemble-level findings apply equally to persons. Instead, our findings suggest that different underlying mechanisms may govern PF-mood relationships across individuals and these effects may often be equisyncratic when the direction of idiographic effects balance out (Ciarrochi et al., 2024a). Furthermore, the random effects model revealed individual-specific variations in how the importance of a PF process changed over time, violating the ergodic assumption of stationarity, which assumes that within-person dynamics remain stable. Crucially, the within-person profiles of importance changed. The drivers that mattered most for a given person before treatment were often not the same ones afterward, suggesting the intervention itself may have perturbed the system, either by changing how flexibility worked in daily life or how people understood and used it. Fig. 1 further supported these findings, demonstrating the substantial non-random heterogeneity in effect sizes observed for several participants in their relationship between Committed Action and mood, and how this changed over time. This heterogeneity was pooled across an averaged effect size.

Past literature consistently supports a positive relationship between increased PF and improved mood (Hayes et al., 2006; Kashdan & Rottenberg, 2010; Stockton et al., 2019). These studies rely on ensemble statistical methods (e.g., mediation analyses, MLM) that do not consider individual heterogeneity (Doorley et al., 2020; Kashdan & Rottenberg, 2010; Sahdra et al., 2024). These findings are consistent with findings from the present study obtained using correlational analysis and fixed-effects modelling. Conventionally, normative research would stop here to generalise ensemble-level findings to particular people and to provide research and clinical implications (Sahdra et al., 2024). For example, we might conclude that engaging in Committed Action increases mood by approximately 0.35 standard deviations based on the pooled estimate, implying that this likely applies to the mood of specific cases. However, idionomic analysis revealed substantial systematic variability. Engaging in Committed Action was reliably linked to worse mood for some, had no effect for others, and produced strong positive effects (effect sizes of 0.40 or higher) for others.

Our idionomic conclusions are consistent with emerging research showing how the relationship between PF and well-being outcomes may be sensitive to difference between particular people, their context, and the specific PF process explored (Ciarrochi et al., 2014; Ding & Zheng, 2022; Levin et al., 2012; Zakiei et al., 2024). For the most part, if one were asked whether PF is helpful to clients, the initial answer has to be *it depends*. Our findings are consistent with past literature employing idionomic methods to determine the degree of individual heterogeneity in the relationship between processes and outcomes, and its inconsistency with the findings from traditional biostatistical methods (Ciarrochi et al., 2024c; Sahdra et al., 2023, 2024). Moreover, using measures like Psy-Flex and an ESM study design facilitated our ability to sensitively capture the dynamic processes underlying PF and measure changes over time in relation to mood. Our findings illuminate the complexity that exists within the lives of particular people, within the PF construct, and its relationship with mood. We highlight the need for innovative methods and analyses to address this complexity, and for clinicians to consider this when personalising treatment.

Our findings have important implications. We encourage researchers and clinicians to reflect on the use of traditional statistical approaches to explore the relationship between PF and mood, where violations to the ergodic assumption exist. Although well-done normative research can inform aggregate-level decisions (e.g., in public policy), these findings may not generalise to the particular people and thus may have limited value when informing clinical practice. The present study validates the common struggle that providers face when attempting to translate existing research findings to the care of their individual clients. If the growing database on idionomic analysis is to be believed, the vast majority of existing psychological research violates its own statistical assumptions when it is generalised to particular people. The present findings provide empirical justification and endorsement for ACT practitioners who have long worked within a process-based framework: interventions need to be personalised by drawing on the PF skills of individuals, couples, or families to dynamically address their needs within the context they function. This is impossible when applying only the conclusions drawn from ensemble-based analyses. ACT providers need to be flexible in tailoring ACT interventions, across the full range of relevant PF processes (including their biophysiological and sociocultural extensions; Hayes, 2025) to best fit the idiosyncratic needs of the individual client. PBT frameworks provide an explicit guide to develop and implement this tailored process.

Regarding our conceptualisation of PF, researchers must continue to recognise and explore the unique and dynamic relationship that each PF process has with mood, and how this is unique within each individual and over time (Ciarrochi et al., 2014; Ding & Zheng, 2022; Levin et al., 2012; Zakiei et al., 2024). This includes the use of time- and context-sensitive methods and PF-specific tools. Further, our findings highlight the utility of using tools of PF that distinctly measure each process. For researchers, it may be sufficient to use aggregate measures of PF if process specificity is not required to address their aims. However, from an intervention perspective, these aggregate measures have less utility in the practical world of behaviour change where clinicians need to understand the role of processes of change within particular people (individual, couples, families, and groups) to guide intervention and measure progress.

5. Limitations and future directions

Various limitations exist within our study. Firstly, while we focused on the PF process-mood relationship over time, we did not account for the fact that these relationships were analysed within the context of ACT treatment. While it may be impossible to isolate all contextual factors related to treatment, future studies should seek to understand more precisely the extent to which the PF-mood relationship is stable over time by understanding the impact of treatment and related factors contextualising it. For example, the lack of a sampled no-treatment control undermines our ability to rule out time or measurement effects. Future studies should aim to include such a control condition to test how stable these flexibility-outcome links are without intervention and whether the within-person processes reliably shift following training. Another example includes the fact that our study did not randomise or standardise modalities, so we cannot isolate treatment-specific contributions to change in PF–mood coupling. To manage this, future research should aim to collect treatment fidelity data or modelling treatment-by-time effects. Moreover, a related limitation is that we also did not consider the role of covariates in the PF process-mood relationship and how this changes over time. Our findings may be influenced by unaccounted client factors (e.g., diagnostic problem, psychological inflexibility), clinician factors (e.g., clinical experience) or contextual factors (e.g., world events). Further research considering contextual factors is vital as PF is theoretically grounded by contextual functionalism (Gloster et al., 2021).

Second, our findings would benefit from further research to establish its clinical utility. How does knowledge of individual differences in the relationship between PF and mood improve clinical outcomes in PBTs like ACT? Our findings highlight a chasm that exists between science and practice, the specifics of which, until now, have largely gone unnoticed and have been addressed solely by a clinician's own judgement. Thus, we recommend the ongoing use of current or new measurement and statistical methods to idionomically explore this relationship. For example, past literature has employed classification methods (e.g., deep Gaussian mixture modelling and multilevel vector autoregression modelling) to explore whether subgroups of individuals exist possessing similar heterogeneous effects (Ciarrochi et al., 2024b, 2024c; Gloster et al., 2024; Sahdra et al., 2023, 2024). A program of idionomic research may be able to identify subgroups of individuals with synchronised PF process profiles (e.g., Fig. 1b) or identify common differences in how individuals respond to an ACT intervention, and how this changes over time.

Identification of meaningful subgroups in data, without ignoring individual variability, stands as an important next step in idionomic research. We limited our study to the analysis of these patterns visually, rather than statistically, in order to contain the scope of our research to examine the importance of idionomics for future research to build upon. Such a step has the potential to support evidence-based clinicians in personalising treatment to suit the individual's needs, goals and context, which may be vital for treatment effectiveness in PBTs (Li et al., 2024; Nye et al., 2023). In research and implementation, these methods can guide clinical training and education and support the development of assistive clinical tools (see Ciarrochi et al., 2024c; Hofmann & Hayes, 2024). Additional future directions of research may involve time-lagged analyses to understand temporal ordering and potential causal relationships between PF processes and mood. Using larger samples or designs optimised for temporal dynamics can help facilitate this.

Idionomic approaches have become central to the PBT agenda since a process-based approach requires being able to capture evolving psychological processes that function within the ever-evolving individual. Moreover, advancements in these approaches have the potential to equip providers with empirically derived hypotheses when formulating and treatment planning. Currently, these are solely informed by clinical judgement and a research literature that cannot reliably address the practical use case that providers face. That cannot be allowed to continue.

6. Conclusion

The current study emphasises the importance of investigating within- and between-person variability to understand the relationship between PF processes and mood. We also highlight the need to view PF as a construct with non-uniform processes (Ciarrochi et al., 2014; Levin et al., 2012). Our findings align with a growing body of literature challenging the use of group averages to draw conclusions about clients in clinical research and practice. This underscores the limitations of normative statistical methods when applied to particular people (Ciarrochi et al., 2024c; Gloster et al., 2023; Sahdra et al., 2023, 2024). Our findings also indicate that ensemble research demonstrating the positive association between PF and mood almost always violates the ergodic assumptions on which traditional statistical analyses depend on for their clinical relevance. Idionomic methods revealed a new, unexplored territory for investigating the relationship between PF and mood at the individual level. They serve as the ship to help us navigate with greater scope, depth and sensitivity the unchartered waters of what happens at the level of particular clients during therapy, including their processes of change. We are at the forefront of a shift towards using idionomic approaches to revolutionise the development of more personalised and effective treatments and empirically inform the “it depends” mantra we have grown accustomed to in clinical practice.

CRediT authorship contribution statement

Hannah F. Yee: Writing – review & editing, Writing – original draft, Project administration. **Madeleine I. Fraser:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Joseph Ciarrochi:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Baljinder Sahdra:** Writing – review & editing, Supervision. **Keong Yap:** Writing – review & editing, Supervision, Conceptualization. **Steven C. Hayes:** Writing – review & editing, Conceptualization. **Cristóbal Hernández:** Writing – review & editing, Conceptualization. **Andrew T. Gloster:** Writing – review & editing, Resources, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Baljinder K. Sahdra and Cristóbal Hernández are co-authors of the current research article and also part of the editorial board of the current journal. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcbs.2026.100993.

Appendix A

Codebook for Experience Sampling Methods

Time = Pre = 1; post = 2
Age = age_at_entry
Mood How would you rate your current mood?
0 = Very bad, 1 = Bad, 2 = Rather bad, 3 = Rather good, 4 = Good, 5 = Very good

clinical_type 1-inpatient; 2-outpatient
Psychological Flexibility measures:

FocusImportantMoments (Present Moment) = *Even when I was lost in thought, I could focus on what's happening in important moments.*
AllowFeelings (Acceptance) = *When it mattered, I could let unpleasant feelings and experiences happen without having to get rid of them immediately.*
ObserveThoughtsDistance (Defusion) = *I could observe problematic thoughts at a distance without letting them control me.*
SelfPole (Self-as-Context) = *Even when thoughts and experiences were confusing me, I could notice something like a resting pole within me.*
ChoseValue (Values) = *I decided what's important to me and I decided what I wanted to use my energy for.*
CommitAction (Committed Action) = *I put in a lot of effort for what I think is important, useful or meaningful.*

Appendix B

Predictive Performance between the Bayes Fixed and Random Effects Models

Leave-one-out cross-validation (LOO) is a statistical procedure for evaluating how well a model performs when making predictions on unseen data, and in turn, determining how generalisable the model is (Sun, 2025). This involves repeatedly partitioning the data into two parts, a training set (of which the data is used to train the model) and test set (of which data used to test the model's performance). In a dataset of n observations, the model is first trained on n - 1 observations (training set), and then this model is tested on the one left out (test set). This is then repeated n times. Each partition's performance is then averaged to establish the model's overall performance (Antoniadis & Simic, 2025; Sun, 2025). Lower LOO values indicate better model fit.

We can then use LOO to calculate the model's Expected Log Pointwise Predictive Density (ELPD) – a metric indicative of the model's predictive accuracy. Higher ELPD values indicate better predictive accuracy as the model assigns higher likelihoods to observed outcomes.

In the context of our study, LOO and ELPD were used to compare whether the fixed and random effects model fit better to the data obtained from our participants. Details on LOO and ELPD calculations can be requested from the corresponding author.

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