Do complex affect dynamics improve predictions of psychological and behavioral outcomes?

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Abstract

Background There is growing interest in the use of ecological momentary assessment (EMA) as a means for quantifying how individuals' affective experiences fluctuate over time, and how such dynamics relate to mental health outcomes. A plethora of methods exist for precisely quantifying these affect dynamics, but recent work pooling data from multiple studies has suggested that most of the variance in outcome measures of depression, borderline symptoms, and life satisfaction is captured by simple measures, such as the mean (*M*) and standard deviation (*SD*) of affect ratings over time. Ever-more sophisticated approaches for measuring affect dynamics may offer little value for understanding mental health. Here, we examined a broad array of mental health outcomes and affect dynamic measures within a single cohort to comprehensively evaluate whether EMA-derived measures of affect dynamics are associated with specific psychopathological experiences.

Methods 314 adults (97 males; 18–45 years of age) completed 28 days of EMA, which included once-daily ratings on the Positive and Negative Affect Schedule (PANAS)-10 and daily measures of stress, sleep, and alcohol use. We calculated 16 established affect dynamics measures (*M*, *SD*, relative *SD*, mean-squared successive differences, autoregression, intraclass correlation, and Gini coefficient for positive affect (PA) and negative affect (NA), as well as emotion network density and PA–NA correlation) in addition to six additional measures derived using dynamic network analyses of participant responses (promiscuity and flexibility for the entire network, PA, and NA). Predictive power was assessed using cross-validated linear regression models predicting 117 outcomes spanning five cross-sectional psychometric questionnaires and EMA-based longitudinal behavioral measures. We compared models that included each complex measure against baseline models using only *M* or *M* + *SD* scores quantifying PA and NA.

Results Across all 117 outcomes, no complex affect dynamics measures improved cross-validated R^2 by more than 5.3 % beyond the *M* and *SD* of PA and NA.

Conclusion Elaborate measures of affect dynamics, as indexed by the PANAS-10, offer minimal incremental explanatory power in predicting psychopathology beyond basic summary statistics of daily affect. These findings question the added value of increasingly complex measures of affect dynamics for predicting standard psychological and behavioral outcomes.

Keywords: ecological momentary assessment, affect, well-being, psychopathology, affective dynamics

Background

Affect is inherently dynamic, changing over time in response to both internal and external influences (Kuppens, 2015). Accordingly, numerous studies have demonstrated that temporal affect dynamics, or how affect evolves over time, play a significant role in explaining individual differences in mental health and psychopathology (Koval et al., 2016; Kuppens et al., 2012; Sperry et al., 2020). Given that mental disorders are characterized by substantial heterogeneity (Segal et al., 2025), an understanding of affect dynamics may facilitate sub-typing as well as prevention and early intervention strategies.

Affect dynamics are commonly quantified using ecological momentary assessment (EMA), which involves repeated sampling of individuals' experiences in real-time and naturalistic settings (Shiffman et al., 2008). EMA-based probes can vary in terms of their duration, questionnaires used for assessment, frequency of assessment, and sampling schedules (e.g., random, fixed-interval, event-contingent) (Smyth & Smyth, 2003). EMA methodologies are increasingly used as a way of probing people’s mental health experiences and struggles in their daily lives (Myin-Germeys et al., 2018). Affective experience is one domain that is frequently quantified using EMA and is commonly quantified using measures of positive affect (PA) and negative affect (NA). PA and NA respectively represent positively- and negatively-valanced affective dimensions that capture affective experiences, such as enthusiasm, pride, and excitement, versus, guilt, nervousness, and shame. They capture the two dominant dimensions of affective experience and are typically measured because they are strongly predictive of well-being and psychopathology (De Wild-Hartmann et al., 2013; Duif et al., 2020; Juarascio et al., 2016; Koval et al., 2013; Schoevers et al., 2021; Scott et al., 2020). PA and NA are commonly assessed using standardized tools such as the Positive and Negative Affect Schedule (PANAS-10), which is widely adopted due to its brevity and extensive psychometric validation (E. R. Thompson, 2007; Watson et al., 1988).

The affect dynamics measured using the PANAS-10 and similar instruments have garnered increased attention as a promising avenue for explaining variability in psychopathology, leading to the development of progressively more complex affect dynamic measures designed to improve the predictive validity of affect metrics for mental health outcomes, capture more fine-grained temporal features of affective fluctuations, and provide stronger explanatory power for the mechanisms linking affect dynamics to psychopathology (Bringmann et al., 2013; Curtiss et al., 2019a; Hamaker et al., 2018; Kalisch et al., 2019; Kuranova et al., 2021; Naragon-Gainey, 2019; Schat et al., 2023; Scott et al., 2020; Snippe et al., 2023; Wright & Woods, 2020). These measures include quantities capturing affect variability relative to mean affect levels (relative standard deviation; (Mestdagh et al., 2018)), affect instability and temporal dependency (mean squared successive differences [MSSD]; (Jahng et al., 2008)), affective persistence or carryover effects (autoregression; (Kuppens et al., 2010)), interconnectedness of affective states (affect network density; (Pe et al., 2015)), consistency of affect across measurement occasions (intraclass correlation; (R. J. Thompson et al., 2021)), affective bipolarity (PA–NA correlation; (Dejonckheere et al., 2018)), and inequality in affect intensity distributions (Gini coefficient; (Brown & Coyne, 2017)).

Despite the promise and rapid proliferation of new and diverse affect dynamic measures, a pivotal study by Dejonckheere et al. (2019) questioned their utility for predicting commonly used measures of psychological well-being. Focusing on EMA-based measures of PA and NA derived from 15 different studies comprising 1,777 people, the authors examined 16 commonly studied measures for quantifying affect dynamics and tested whether they can significantly improve the prediction of three psychological well-being outcomes––depressive symptoms, borderline personality symptoms, and life satisfaction––relative to models that relied on simple affect measures: the mean (*M*) and standard deviation (*SD*) of affect ratings. Their findings revealed that many of the more complex measures were highly intercorrelated and that they added little (i.e., <1.4% of explained variance) to the prediction of psychological well-being beyond the simpler benchmark models relying on the *M* and *SD*.

Dejonckheere et al.'s (2019) work raises fundamental questions about the utility of complex affect dynamics in predicting psychological outcomes commonly studied in the literature, but these analysis synthesized data from 15 different datasets, each with varying inclusion criteria, frequency, and duration of EMA collection, and psychological well-being measures, meaning that it is unclear whether a unified approach to data collection and analysis would yield improved statistical power. Dejonckheere et al. (2019) also assumed that personalized affect networks are static over time, implying that within-person interactions between different affective states remain constant throughout the study period. However, this assumption is unrealistic. Empirical studies have shown that within-person affect dynamics can fluctuate over time due to both internal (e.g., negative cognitions) and external (e.g., stressful life events) factors (Bringmann et al., 2018). For example, stressful situations, such as public speaking, reduce affective inertia, which is the carryover effect (autoregression) of an affective state from one time point to the next (Koval et al., 2016; Kuppens et al., 2010). Furthermore, experiencing more intense negative affect can increase inertia over time (De Haan-Rietdijk et al., 2016). Beyond these, the structure of within-person affect networks—the connections between different affective states—may also vary over time. Although many studies have called for considering such non-stationarity of affect dynamics (Curtiss et al., 2019a; Spiller et al., 2021), this aspect has not yet been fully explored.

A final consideration is that Dejonckheere et al. (2019) only considered three psychological outcomes, leaving open the possibility that complex affect dynamic measures are informative for other dimensions of psychological and cognitive well-being, such as anxiety (Hall et al., 2021; Schoevers et al., 2021), externalizing symptoms (Hawes & Klein, 2023; Heller et al., 2021; South & Miller, 2014), personality traits (Miller et al., 2009; Wilson et al., 2017), and general intelligence (Dallman et al., 2022). In this context, it may also be important to move beyond exclusively focusing on cross-sectional outcome measures to instead consider how affect dynamics relate to daily fluctuations in mental health-related experiences and behaviors, such as stress levels (Goldschmidt et al., 2014; Määttänen et al., 2021), sleep quality and duration (Galambos et al., 2009; Triantafillou et al., 2019), and alcohol use (Duif et al., 2020; Yang et al., 2022)

In the present work, we set out to address these limitations by comprehensively evaluating the utility of 22 different affect dynamic measures, which include 6 novel measures capturing topological dynamics of non-stationary within-person affect networks, in predicting 117 different psychological outcomes and daily behaviors within a single sample of 314 community adults. Our analysis reveals that, across 12 different predictive models evaluated, no single measure of affect dynamics led to an incremental gain of predictive power that exceeded 5.3% of explained variance beyond a simple benchmark model comprising only the mean and *SD* of PA and NA scores.

Methods

Procedures

Participants. The Monash Brain & Behavior Project (MBBP) study included 314 participants (n = 97 males, 31%) aged 18–45 years (M = 28.2, SD = 7.7) drawn from the general population in Melbourne, Australia (see Table 1 for demographic statistics and affective characteristics). Inclusion criteria required participants to be right-handed, native English speakers, of European ancestry (all four grandparents of European descent), without intellectual disabilities, and with no personal history of neurological illness, steroid abuse, or clinically diagnosed substance abuse. Participants were not excluded even if they reported a personal or family history of mental illness, ensuring that our sample has a diverse range of mental health histories.

Behavioral measurements. All participants completed a 2-hour online questionnaire comprising a comprehensive battery of psychometrically-validated instruments. These questionnaires assessed personality traits, various dimensions of mental health symptoms, life satisfaction, and other psychological factors. Additionally, participants completed a 2-hour cognitive assessment battery under the supervision of trained research officers at Monash Biomedical Imaging. The cognitive battery was designed to measure several processes believed to be critical for the self-regulation of attention, thinking, emotion, and behavior—domains often impacted by mental health conditions. The target variables for this study were derived from these behavioral measurements. The measures considered in the present analysis are a subset of these collected measures, as explained below.

EMA. Individuals who completed the psychopathological assessments were invited to participate in a Daily Experience Sampling Survey (DESS), which involved a 1–2 minute daily “diary” questionnaire online, accessible via mobile phones, tablets, or computers. Participants received an electronic link to a brief online survey at 7:00 pm each day for 28 days, which included the short version of the Positive and Negative Affect Schedule (PANAS-10) to measure daily positive and negative affect. The short-form of the PANAS-10 comprises 10 items measuring PA (5 items) and NA (5 items). It has been validated through extensive psychometric evaluations, demonstrating strong internal consistency, test-retest reliability, and construct validity across diverse populations and contexts (E. R. Thompson, 2007; Watson et al., 1988). Internal consistency reliability of the subscales was high in the present sample (PA α = 0.85; NA α = 0.81).

Participants also completed questions regarding stressful events they encountered during the day and their self-rating of associated stress levels, in addition to providing ratings on the quality and duration of their previous night's sleep, any substance use (e.g., drugs or alcohol) in the past 24 hours, and their perceived level of intoxication (see Additional file 1 for DESS questions). A reminder email was sent at 8:00 pm if participants failed to complete the survey, with the link remaining active until 11:59 pm. Responses after this time were not considered. Affect dynamics in this study were calculated using data from the DESS.

Measures of affect dynamics

We considered the same set of 16 measures of affect dynamics originally evaluated by Dejonckheere et al. (2019), including Mean PA and NA (*M*), Variance or standard deviation in PA and NA (*SD*), Relative variance or standard deviation in PA and NA (*SD**), Mean Square of Successive Differences in PA and NA (*MSSD*), Auto-regression in PA and NA (AR), Emotion-network density (D), ICC for PA and NA (ICC), PA–NA correlation (ρ), and the Gini coefficient (G) for PA and NA. Brief descriptions and calculation formulas for each measure are summarized in Table 2 (see also Table 1 in Dejonckheere et al. (2019)).

We also examined six additional measures of affect dynamics derived from the network science literature (Mucha et al., 2010; Sizemore & Bassett, 2018), which treat affect networks of DESS item responses as time-varying systems, allowing us to capture how the structure of affect networks evolves over time. To calculate these measures, we first applied a sliding window method, with each window spanning 7 days, starting from the first day of valid data. The window was then moved one day at a time, generating a new overlapping window. The process was repeated and continued until the last time window reached the final day of valid data. For each participant with N valid days of data (25–28 days; see below), this procedure generated time windows. Changing the window size to 5, 10, or 14 days did not affect the main results of the study (see Supplementary Fig. 1 in Additional file 2).

Within each time window, we constructed an affect network based on the cross-product matrix of PANAS-10 responses over the 7-day period. In this matrix, each row/column, corresponding to a network node, was a PANAS-10 item, and each matrix element, corresponding to a network edge, was the cross-product of the item ratings obtained for every pair of items. One such network was defined for each time window.

We then applied a multilayer extension of the Louvain method for community detection (Mucha et al., 2010) to characterize dynamic community structure within these networks with parameters for interlayer coupling and for resolution to achieve a proper multilayer community assignment, as implemented in a freely available MATLAB code (https://github.com/GenLouvain/GenLouvain) (Mucha et al., 2010). The algorithm returns a community assignment for each time window (also called a network layer), where a community corresponds to a cluster of items sharing similar variance. The resulting time-varying community assignments were then used to calculate measures of node promiscuity and node flexibility. Node promiscuity was defined as the number of different communities in which a node participated, normalized by the total number of communities. Node flexibility was defined as the number of times a node changed communities, normalized by the total number of opportunities it had to change communities (Sizemore & Bassett, 2018). We computed promiscuity and flexibility measures averaged across the entire network, as well as just over PA and NA items. We therefore obtained a total of 6 different measures of non-stationary affect dynamics.

Target variables

We used the 22 different affect dynamics measures described above to predict 117 different indicators of psychological well-being. These indicators comprised 108 cross-sectional psychological well-being measures and 9 dynamic measures of daily fluctuations in sleep quality and alcohol use from the EMA (DESS). Detailed descriptions of all 117 psychological well-being indicators can be found in the Supplementary Table 1 in the Additional file 2.

Cross-sectional psychological well-being measures. People's life satisfaction and depressive and borderline symptoms tested in (Dejonckheere et al, 2019)'s work were assessed using the Satisfaction With Life (SWL) (Diener et al., 1985), the General Depression subscale of the Inventory of Depression and Anxiety Symptoms - Expanded Version (IDAS-II) (Watson et al., 2012), and the Computerized Adaptive Test of Personality Disorder (CAT-PD) (Simms et al., 2011), respectively. These measures were complemented by assessments of 105 additional measures of psychological well-being and behavioral outcomes derived using subscales of five commonly-used psychometric questionnaires: the IDAS-II and CAT-PD, the Eating Pathology Symptoms Inventory (EPSI) (Forbush et al., 2013), the Externalizing Spectrum Inventory - Brief Form (ESI-BF) (Patrick et al., 2013), the Big Five Inventory - Second Edition (BFI-II) (Soto & John, 2017), and the Wechsler Abbreviated Scale of Intelligence – Second Edition (WASI-II) (Wechsler, 2011).

Dynamics of sleep and alcohol use. We measured daily fluctuations in people's sleep quality and alcohol using the *M* and *SD* of their perceived sleep quality scores, sleep duration, daily stress levels, and alcohol consumption, as well as the frequency of alcohol use, during the DESS study.

Statistical analysis

Data pre-processing. Participants were excluded if they provided fewer than 25 days of DESS data, and/or if they failed to maintain a valid response rate of > 89% (); failed to provide complete answers to the DESS questionnaire items for at least one day, to ensure item-level completeness across the entire dataset (); exhibited no variability in PA or NA composite scores (); and/or rated the intensity of any same-valence emotion above 10% on the response scale, which affects estimation of the Gini coefficient (). After these steps, a final sample of 314 participants was retained for further analysis.

Predictive modelling. We first examined empirical correlations between different affect dynamic measures using pairwise Pearson correlations and hierarchical clustering. Next, following Dejonckheere et al. (2019), we evaluated the unique explanatory power of affect dynamics in predicting the 117 psychological well-being indicators through 10-fold cross-validated linear regression models. In each case, the predictive model specified the affect dynamic metric, in addition to the *M* and *SD* of PA and NA ratings. The variance explained by this model was then compared with two benchmark models incorporating only the *M*, or only the *M* and *SD* of the ratings.

Results

Correlations between measures of affect dynamics

The reordered correlation matrix of the 22 affect dynamic measures reveals a modular structure comprising four distinct clusters, which represent groups of affect dynamic measures with highly similar correlation profiles (Fig. 1a).

One cluster comprised traditional variability measures for PA, including *SD*, *SD**, and *MSSD*. A separate cluster comprised the same set of variability measures for NA, while also including ICC, forming a parallel grouping with similarly strong internal coherence. A third comprised six novel dynamic network-based measures: flexibility (F) and promiscuity (P), each computed for PA, NA, and across the entire affective network. These nonstationary-network-based measures grouped tightly, suggesting that they reflect a shared dynamic property distinct from traditional variability.

In contrast, a more loosely organized cluster brought together the *M*, G, and AR for both valences, ICC for PA, ρ, and D. These measures were less strongly interconnected (r range = -0.73 to 0.26) and showed relatively weak associations with the rest of the matrix.

Notably, the PA variability cluster (r range = 0.81 to 0.94), the NA variability cluster (r range = 0.52 to 0.81), and the nonstationary-network-based measures cluster (r range = 0.063 to 0.90) were characterized by strong positive correlations among measures within the same cluster, while correlations between clusters were generally weak or negative, indicating distinct dissociations between different dimensions of affect dynamics.

Regarding the variance explained by the *M* and *SD* of PA and NA (Fig. 1b), P (PA) has the lowest proportion accounted for by the *M* and *SD* of PA and NA (R^2 = 0.023), followed by P (network) (R^2 = 0.024). In contrast, *SD** and *MSSD* are most strongly explained by the *M* and *SD* of PA and NA (*SD**: R^2 PA = 0.91, R^2 NA = 0.84; *MSSD*: R^2 PA = 0.76, R^2 NA = 0.68). Overall, *SD**, *MSSD*, G, and ICC for both valences are strongly explained by the *M* and *SD* of PA and NA (R^2 range = 0.44 to 0.91), while AR, D, ρ, and 6 novel nonstationary-network-based measures have low proportion of variance explained by the *M* and *SD* of PA and NA (R^2 range = 0.023 to 0.11). High variance explained by the M and SD implies shared information between a complex affect dynamic measure and the most parsimonious affect dynamic measures *M* and *SD*, which suggests redundancy and limited incremental value. Conversely, low variance explained indicates that a measure may capture unique aspects of affect dynamics not accounted for by *M* and *SD*, thereby offering potentially novel insights into affective processes and their links to psychopathology.

Predictive modelling

As a first benchmark, we considered the predictive performance of models including only the *M* or *SD* of NA or PA ratings as predictors of the outcome variables. The *M* of NA generally outperformed the *M* of PA, exhibiting a slightly positive mean predicted R^2 (0.02). Among all the 117 psychological well-being and behavioral variables, the *M* of NA showed the strongest predictive performance for mean daily stress levels (predicted R^2 = 0.52,), followed by general depression (predicted R^2 = 0.30,) and dysphoria (predicted R^2 = 0.27,).

Both the *SD* of NA and *SD* of PA ratings yielded negative mean predicted R^2 values across the 117 target variables, with *SD* of NA (mean predicted R^2 = -0.035) slightly outperforming the *SD* of PA (mean predicted R^2 = -0.043). This result suggests that the *SD* of NA or PA offers little predictive utility. However, the *SD* of both PA and NA predicted the *SD* of daily stress levels, with R^2 values of 0.37 () and 0.12 (), respectively, after accounting for the effects of mean ratings.

Across all 18 models using one of the complex affect dynamics measures as a predictor, both average and median predicted R^2 values across the 117 outcomes were negative, indicating generally poor predictive performance. Some complex affect dynamics measures showed moderate effects for specific outcomes. For example, models incorporating the *MSSD* and *SD* of NA ratings on their own exhibited R^2 values of 0.30 () and 0.21 (), respectively, in predicting the *SD* of daily stress levels. The Gini coefficient of NA ratings was also associated with () in predicting mean daily stress levels. However, compared to models in which the *M* and/or *SD* of NA ratings over time were included, the more complex affect measures explained no more than 5.3% of additional outcome variance (Fig. 2).

Discussion

Our analysis of the utility of 22 different measures of EMA-based affect dynamics in predicting 117 different cross-sectional and longitudinal psychological outcomes reveals that complex measures for quantifying affect dynamics offer little additional benefit over simple measures, such as the *M* and *SD*, of daily affect fluctuations. By considering an expanded set of affect dynamic measures that account for time-varying processes, and by considering a much wider range of outcomes, our results are consistent with results of Dejonckheere et al. (2019) and support the generality of the conclusion that measures of complex affect dynamics have little power in predicting typically measured psychological outcomes.

Beyond replicating Dejonckheere et al. (2019), our findings align with other EMA research in the literature. For instance, our analysis indicated that affect dynamic measures predict depression and anxiety symptoms in IDAS-II with the highest accuracy. Specifically, mean NA showed the greatest predictive power for the general depression subscale in IDAS-II with predicted R^2 value reaching 0.30, while mean PA showed a poorer predictive effect with predicted R^2 value of 0.17 (Supplementary Fig. 2 in the Additional file 2). This result is consistent with previous findings emphasizing the critical role of negative emotion in internalizing disorders, such as depression and anxiety (Naragon-Gainey, 2019; Young et al., 2019), alongside weaker relationships between positive affect and these conditions (Gilbert, 2012; Naragon-Gainey, 2019).

We also observed domain-specific prediction of EMA-based behavioral targets (sleep, stress, and alcohol use). Mean PA was more predictive than mean NA for average sleep quality, consistent with prior studies linking better sleep primarily to PA rather than NA (De Wild-Hartmann et al., 2013; Galambos et al., 2009; Triantafillou et al., 2019). Conversely, daily stress levels were much more robustly predicted by *mean* NA, with a predicted R^2 value reaching 0.52, which was the strongest prediction in our results. For comparison, the effect of mean PA on this outcome was only 0.0047. Stress variability was also better predicted by the *SD* of NA (predicted R^2 = 0.12) than the *SD* of PA (predicted R^2 = 0.083). These findings align with previous reports indicating that daily life stress heightens NA, while maintaining relatively stable PA, particularly in individuals with major depressive disorder (Myin-Germeys et al., 2003).

Our findings may reflect a broader trend in time series analysis observed in other fields, in which investigators propose specific measures to capture a particular process of interest without first considering whether the proposed measure indexes a unique feature that is not already captured by existing approaches. The recent development of accessible approaches for highly comparative time series analysis, which allow one to compare the behavior of a given measure with thousands of other analysis methods developed in diverse scientific fields across a large library of time series recorded in different systems can be leveraged to avoid the unnecessary proliferation of redundant methods (Fulcher & Jones, 2014, 2017; Lubba et al., 2019).

Our analysis is not intended to suggest that EMA-based measures of affect dynamics are not useful. Indeed, EMA-based measures of depression and anxiety have demonstrated greater sensitivity and higher post-treatment effect sizes compared to traditional questionnaires (Moore et al., 2016). EMA may also mitigate recall biases inherent in cross-sectional measures (Solhan et al., 2009), enabling more sensitive, ecologically valid, and nuanced assessments of mood and behavior, including social interactions crucial to psychopathology research (Moskowitz & Young, 2005). A particularly promising avenue involves the use of EMA to identify early warning signals that may anticipate critical transitions in psychological states, including clinical relapses (Borsboom, 2017; Cramer et al., 2016; Hofmann et al., 2016; Kalisch et al., 2019; Dablander et al., 2023). For instance, critical slowing down in the variance or autocorrelation of PA and NA has shown promise in forecasting episodes of depression (Kuranova et al., 2020; Schreuder et al., 2020; Van De Leemput et al., 2014; Wichers et al., 2016), bipolar disorder (Bayani et al., 2017; Curtiss et al., 2019b), and sudden therapeutic gains and losses (Olthof et al., 2020), although methodological and practical challenges remain (Bos et al., 2022; Wagner & Eisenman, 2015). Our findings simply indicate that complex EMA-based measures of affect dynamics may have little value in predicting cross-sectionally assessed psychological outcomes.

Our results should be considered in relation to several limitations. First, our EMA data were collected over a relatively brief, 28-day period, potentially constraining the generalizability of our dynamical measures, especially since we were unable to characterize dynamics unfolding over longer timescales. Future studies employing longer EMA protocols could provide deeper insights into the temporal stability and predictive validity of these measures. Second, our EMA data were collected once per day. Future work should check the generality of our results using EMA data that are collected multiple times a day, given evidence that the predictive effect of affect dynamics in psychological outcomes can be improved when emotions are densely sampled (Shin et al., 2022). Third, our sample was restricted to right-handed community-dwelling adults of European ancestry without neurological disorders, potentially limiting the generalizability of our findings across more diverse populations and clinical samples. Finally, although we measured psychological outcomes using subscales and summed scores from established questionnaires, our predictive models yielded relatively small effect sizes. While this result aligns with recent work indicating that it is difficult to reliably predict psychopathology ratings assessed using cross-sectional assessments (Marek et al., 2022), such ratings, when indexed with simple summed scores, contain considerable measurement error that can be mitigated through the appropriate application of latent modelling and other psychometric tools (Tiego et al., 2023). Such approaches have been used in the context of EMA research (Abbott et al., 2024; Cushing et al., 2017; Hamilton et al., 2025) and a direct assessment of whether effect sizes can be improved by refining psychological phenotypes with these methods will be an important avenue of future work.

Conclusion

Our comprehensive evaluation indicates that complex affect dynamics measures minimally improve the predictions of psychological and behavioral outcomes beyond the simplest measures––the mean and standard deviation of PA and NA. Ongoing efforts to predict cross-sectional outcomes with ever-more complex affect dynamic measures are therefore unlikely to yield much benefit. Instead, a more thoughtful consideration of which specific outcomes may be most sensitive to EMA-based measures of affect fluctuations will be required to advance the field.

Declarations

Consent for publication

Not applicable.

Data availability

Data for The Monash Brain & Behavior Project (MBBP) used in this study can be made available upon reasonable request to the authors.

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Authors’ contributions

YS led the conceptualization, analysis, and drafting of the manuscript. PTL was responsible for the code review of all analyses. JT and TC contributed to the methodology. BH, JK, and KF assisted with data collection and processing. JCP contributed to conceptualization and methodology. MB provided funding support. AF contributed to conceptualization, methodology, and supervision. All authors contributed to reviewing and editing the manuscript.

Competing interests

The authors declare that they have no competing interests.

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Table 1. Demographic and affective characteristics of our sample (N = 314).

Variable	**Value**
Age, mean (SD)	28.18 (7.71)
Sex, n (%)	
Female	212 (67.52)

Male	97 (30.89)
Other	4 (1.27)
PA, mean (SD)	13.75 (2.66)
NA, mean (SD)	9.67 (2.38)

Table 2. Summary of 22 affect dynamic measures.

Measure (abbreviation)	Affect dynamic feature	Brief description	Mathematical description	Mathematical equation
1. Mean PA and NA (M)	Average affect level	Reflects an individual's average level of positive or negative affect across time.	The average of all affect ratings over the entire sampling period.	
2. Variance or standard deviation PA and NA (SD)	Emotional variability	Indicates the extent to which an individual’s emotional state fluctuates around their mean level of affect.	Calculated as the square root of the average squared deviation from the mean affect rating.	
3. Relative variance or standard deviation PA and NA (SD*)	Relative emotional variability	Captures emotional fluctuations while accounting for the scale's range, i.e., normalizing variability relative to the affect’s potential range.	The standard deviation divided by the maximum possible standard deviation at a given mean level.	
4. MSSD PA and NA (MSSD)	Emotional instability	Measures the extent of emotional changes between consecutive observations, capturing rapid shifts in affective states.	The square root of the average squared difference between consecutive affect ratings.	
5. Auto-regression PA and NA (AR)	Emotional inertia	Represents the persistence of affective states over time—how strongly current affect is predicted by previous states.	The within-person autoregressive slope in a multilevel AR(1) model, indicating how much a previous affect rating predicts the current one.	
6. Emotion-network density (D)	Emotional interconnectivity over time	Reflects how strongly different affective states influence each other across time, representing emotional rigidity or system-level resistance to change.	Calculated as the average absolute value of within-person auto- and cross-regressive slopes in a multilevel VAR(1) model.	
7. ICC PA and NA (ICC)	Emotional granularity/differentiation	Captures how well an individual differentiates between distinct positive or negative emotions, with higher values indicating less emotional differentiation.	Derived from the intra-class correlation of affect ratings, where low ICC reflects greater distinction between emotion types.	
8. PA–NA correlation (ρ)	Affective bipolarity or	Indicates whether PA and NA are experienced	Calculated as the within-person correlation between PA	

	dialecticism	independently or in opposition, revealing a person's emotional complexity or bipolar tendency.	and NA time series.	
9. Gini coefficient PA and NA (G)	Emodiversity	Reflects the breadth and evenness in the experience of various affective states within either valence.	A weighted Gini index across emotion frequencies, taking into account both the richness and distribution of reported affective experiences.	
10. Flexibility PA, NA, and network (F)	Affective community switching flexibility	Reflects how often affective states transition between different communities over time, indicating the dynamic reconfiguration of the emotional system.	Calculated as the number of community switches made by each node (affect item) across successive time windows, normalized by the number of transitions. Averaged separately across PA, NA, and all items.	
11. Promiscuity PA, NA, and network (P)	Affective community diversity	Indicates the extent to which affective states participate in multiple communities across time, capturing how widely each affect item integrates with varying emotional contexts.	For each node (affect item), the number of unique communities it belongs to across time windows is divided by the total number of communities it could have joined. Then averaged over PA, NA, and all items.	

PA, positive affect; NA, negative affect; ICC, intra-class correlation; E, discrete emotion; $\mathbf{E}$, vector of discrete emotions; T, total number of time points, with t, specific time point; $\mathbf{T}$, total number of time windows; N, total number of people, with j, specific person; b, intercept; $\mathbf{b}$, vector of intercepts; ^{c}, within-person centred undefined variable; ^{g}, fixed effect; ^{r}, random effect; ε, residuals; $\boldsymbol{\varepsilon}$, vector of residuals; AR, auto-regressive component; **VAR**, vector auto-regressive matrix; K, number of emotions, with k and l, indices of specific emotions; $\bar{E}_{\mathrm{PAkj}}$, mean of positive affect emotion k for person j; c_{kj}, number of times an emotion k is bigger than a threshold for person j (for example, 10% of the measurement scale), with c_{kj} c_{k+1j}; F_k, flexibility of emotion k; m, emotion k changed communities m times; P_k, promiscuity of emotion k; n, $\mathbf{N}$, emotion k participates in n of $\mathbf{N}$ total communities.

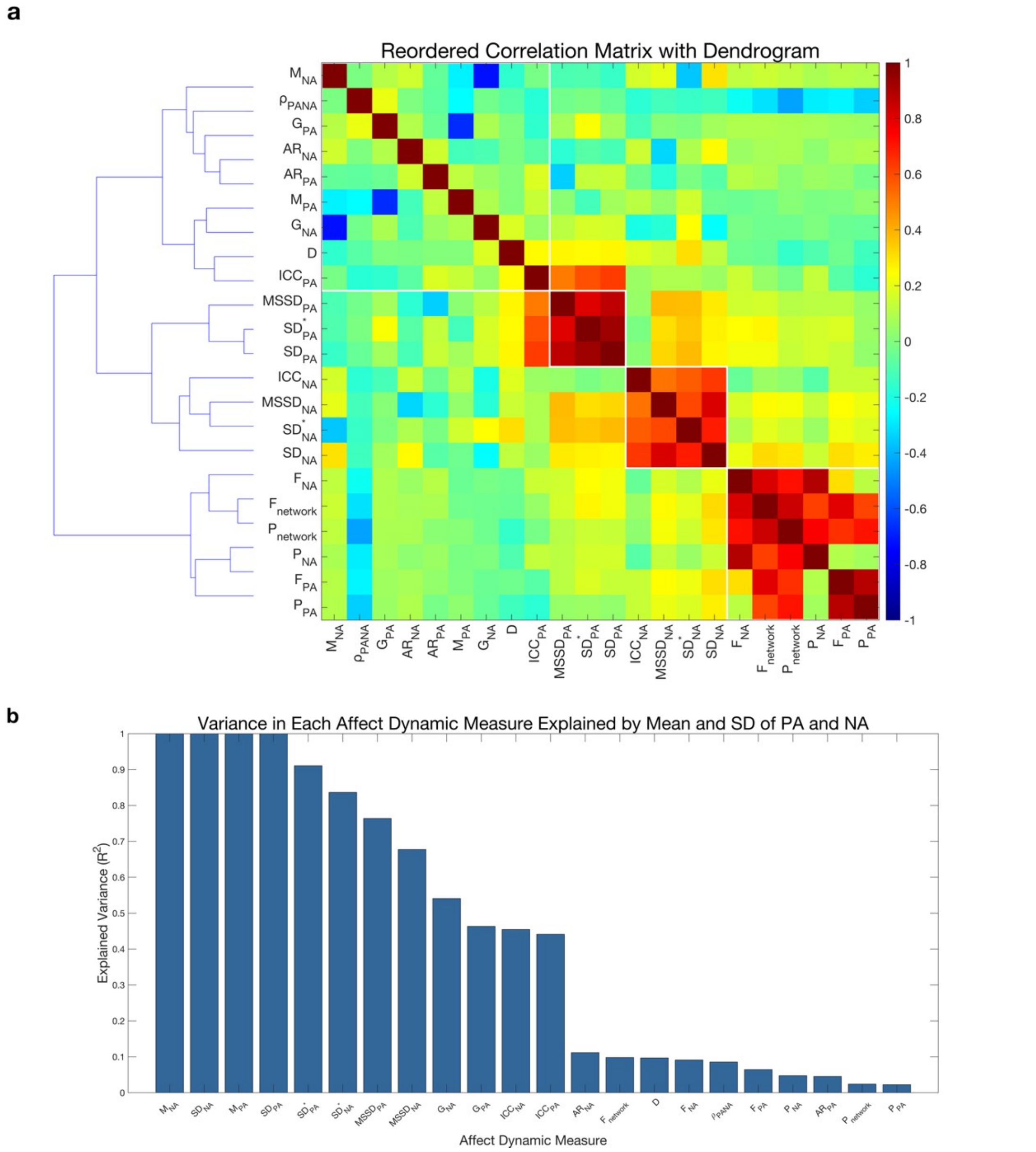

Figure 1. Empirical dependencies of the 22 affect dynamic measures. ***a. Reordered correlation matrix of all affect dynamic measures.*** *The four white boxes in the correlation matrix heatmap show the hierarchical clusters, which were identified based on Euclidean distance and Ward's linkage method. The matrix rows and columns were reordered according to the optimal leaf ordering of the resulting dendrogram to improve cluster visualization.* ***b. Variance in each affect dynamic measure explained by the Mean and SD of PA and NA.*** *The bars were ordered by descending* R^2 *values.*

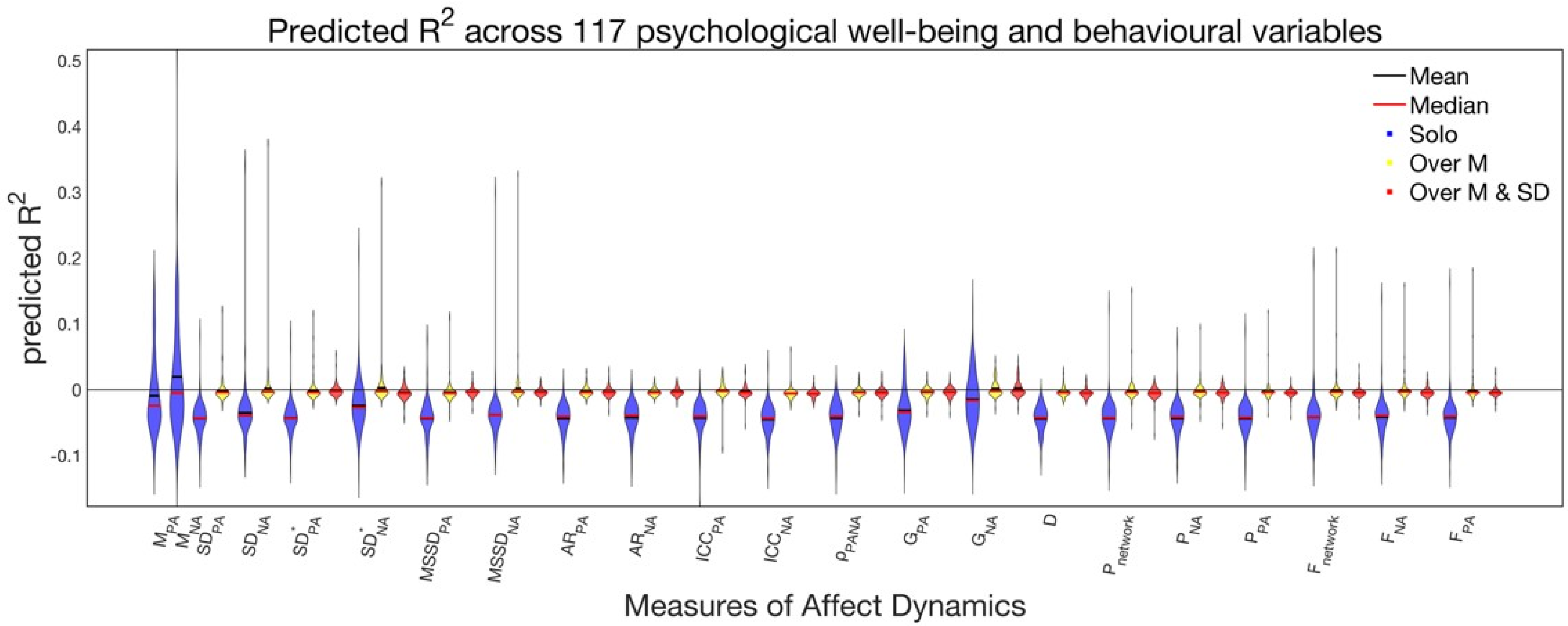

Figure 2. Added explanatory power of all affect dynamic measures in the linear prediction of 117 psychological and behavioral outcomes beyond the *M* and *SD* of PA and NA. *Blue, yellow, and red bars reflect the predicted R^2 (a negative value indicates overfitting) for each measure alone, when controlling for M in PA and NA, and when controlling for M and SD in PA and NA, respectively. Predicted R^2 across each questionnaire or domain can be found in Supplementary Fig. 2 in the Additional file 2.*