

Beyond Main Effects? Affect Level as a Moderator in the Relation Between Affect Dynamics and Depressive Symptoms

Dominique F. Maciejewski^{1*}, Eeske van Roekel¹, Thao Ha², Kalee De France³, Lauren Lin⁴, Hannah K. Lennarz⁵, Hester Trompetter⁶, Wim Meeus⁷, Anna Lichtwarck-Aschoff⁸, Susan Branje⁷, Tom Hollenstein⁹, Maaïke Verhagen¹⁰

¹ Department of Developmental Psychology, Tilburg University, the Netherlands

² Department of Psychology, Arizona State University, USA

³ Center for Emotional Intelligence, Yale University, USA

⁴ Michael G. DeGroot School of Medicine, McMaster University, Canada

⁵ Rhine-Waal University of Applied Sciences, Kleve, Germany

⁶ Center of Research on Psychological and Somatic disorders, Department of Medical and Clinical Psychology, Tilburg University, the Netherlands

⁷ Department of Youth and Family, Utrecht University, the Netherlands

⁸ Department of Child and Family Welfare, University of Groningen, the Netherlands

⁹ Department of Psychology, Queen's University, Canada

¹⁰ Department of Developmental Psychopathology, Behavioural Science Institute, Radboud University, the Netherlands

Abstract

The current study examined the role of mean levels of affect in the relation between affect dynamics and depressive symptoms. We analyzed data from seven studies that measured affect in daily life in adolescents and young adults ($N = 1,448$, age range = 11.7-29.9 years, 64.8% females). We tested main and interaction effects of affect dynamics (variability and inertia) and affect level on depressive symptoms, separately for positive affect (PA) and negative affect (NA). For PA, we found mostly main, but no interaction effects. Depressive symptoms were associated with more PA variability and less PA inertia, indicating that depressive symptoms in young people may be characterized by more variable and less lingering PA, independent of PA mean levels. For NA, we found a significant moderation effect between NA variability and NA levels for depressive symptoms at baseline. For individuals with low NA levels, high NA variability was associated with more depressive symptoms. In contrast, for individuals with high NA levels, high NA variability was associated with fewer depressive symptoms. These results suggest that the relative adaptiveness of NA variability depends on overall NA levels and underscores the need for a more nuanced understanding of affect variability in depression.

Keywords: affect dynamics, experience sampling, depressive symptoms, adolescence, young adulthood

Adolescence and young adulthood are periods of emotional, cognitive, and social development. Adolescence is characterized by rapid hormonal changes, increases in parent-adolescent conflicts, and

identity formation (Arnett, 1999; Hollenstein & Loughheed, 2013; Patton et al., 2016). Young adulthood is characterized by key transitions related to the adoption of adult roles, such as moving from home,

*Corresponding Author: Dominique Maciejewski ✉ d.f.maciejewski@tilburguniversity.edu

Received: 5 May 2023 | Revision Received: 7 August 2023 | Accepted: 8 August 2023

Handling Editor: David A. Preece

Published by Black Swan Psychological Assessments Pty Ltd

www.emotionandpsychopathology.org | ISSN: 2653-7583

gaining financial independence and entering the workforce (Arnett, 2000; Patton et al., 2016). Such changes are emotionally demanding and studies have shown that the prevalence of depression increases sharply during that period (Thapar et al., 2022). While such an increase in depressive symptoms may be normative to a certain extent, for some it is associated with problems later in life, such as recurrence of depression, emergence of other psychopathology, and impaired psychosocial functioning (Thapar et al., 2022). Research emphasizes that depression is characterized by altered affect dynamics (i.e., how affect fluctuates across time; Wichers et al., 2015). However, although depression often originates in adolescence and affect dynamics undergo significant changes with temporarily more variable and intense affect (Reitsema, Jeronimus, van Dijk, et al., 2022), the role of affect dynamics in depressive symptoms is particularly understudied in that age group (Reitsema, Jeronimus, van Dijk, et al., 2022).

Altered Affect Dynamics as Characteristics of Depression

It is well established that depression involves alterations in affect. Low levels of positive affect (PA) and high levels of negative affect (NA) are core symptoms of depression (i.e., anhedonia and depressed mood; American Psychiatric Association, 2013). However, affect fluctuates across time, and these fluctuations, called affect dynamics, contain important information about how we respond to events and regulate our emotions (Kuppens & Verduyn, 2015). Research has increasingly focused on the role of affect dynamics in depression (Wichers et al., 2015). Typically, affect dynamics are studied using daily diary and experience sampling methods (ESM), in which participants are asked to rate their emotions once or multiple times per day in daily life, for instance using smartphones (Shiffman et al., 2008). Based on the resulting affective time-series, affect dynamics are often calculated by aggregating information about the pattern of change within individuals (Hamaker et al., 2015). Two affect dynamic indicators that have been studied most often and are particularly relevant for

depression are affect variability and inertia (Houben et al., 2015; Koval et al., 2013; van de Leemput et al., 2014; Wichers et al., 2015). *Variability* refers to the average fluctuation of affect around one's mean level and is commonly calculated with the within-person standard deviation (*SD*) across the time-series. *Inertia* reflects how much affect carries over from one timepoint to another and is often calculated as the first-order autocorrelation or autoregressive (AR(1)) slope (Kuppens & Verduyn, 2015). The *SD* gives information about the *amount* of changes, independent of when changes happen, whereas the AR(1) slope gives information about the *rate* of changes, without information about the overall variance (Jahng et al., 2008). Importantly, inertia and variability are not two opposites, but provide different information about patterns of affective change¹.

In the empirical literature, there is evidence that both variability and inertia play a role in depression. A prominent meta-analysis found that depressive symptoms were univariately related to both higher variability *and* higher inertia in affect (Houben et al., 2015), a finding that was replicated in children and adolescents (Reitsema, Jeronimus, van Dijk, et al., 2022). While this may seem paradoxical and has been described as such by earlier scholars (e.g., Bos et al., 2019; Koval et al., 2013), such a dynamical signature (i.e., high variability and high inertia) could indicate slow, but large changes in affect (Nelson et al., 2020) which could be indicative of high emotional reactivity with little emotional regulatory control to facilitate recovery to a homeostatic baseline (Houben et al., 2015; Kuppens & Verduyn, 2015). In line with this, one study showed that variability and inertia can co-exist and individuals with psychopathology can get stuck in stable periodic fluctuations in affect, where they experience rigid patterns of large fluctuations in affect day in and day out (Fisher & Newman, 2016).

Historically, there are two seemingly opposing views on the adaptiveness of affective change and its role in depression (for reviews see Houben et al., 2015; McKone & Silk, 2022)². According to the first view, changing affect is broadly considered maladaptive.

¹ The *SD* and *AR(1)* slope are mathematically related, because the total variance of a time-series is defined as a function of the *AR(1)* slope and the innovation variance (i.e., the residual). The latter describes the perturbation not explained by previous scores and may function as a cleaner measure of variability (Jongerling et al., 2015; Koslowski & Holtmann, 2023). Due to this, interpretations of the total *SD* are difficult, because differences can arise due to differences in the *AR(1)* slope (i.e., inertia), the innovation variance (i.e., residual variability), or both. The main reason for including the intraindividual *SD* and *AR(1)* slope as indicators of affect dynamics in the present study, was to maximize comparability with earlier studies, which have operationalized variability and inertia in the same way (Dejonckheere et al., 2019; Houben et al., 2015).

² Note that the terms adaptation and maladaptation technically require the measurement of context (e.g., in terms of emotionally responding to some form of context). In the present paper, we refer to the term adaptation, when affect dynamics are associated with less psychopathology and to the term maladaptation, when affect dynamics are associated with more psychopathology. In this paper, we can only make statements with regard to *general* adaptive/maladaptive patterns of affect dynamics, but without the inclusion of context, it is impossible to determine when variability denotes flexibility and when it denotes instability (see also Kalokerinos & Koval, in press; McKone & Silk, 2022).

Here, high affect variability is conceptualized as an indicator of failures in the emotional regulatory and/or reactivity systems (Houben et al., 2015; Kuppens & Verduyn, 2015). According to the second view, changing affect is indicative of flexibility and broadly considered adaptive. That position emphasizes that precisely a resistance to change is problematic and signifies a lack of adaptability to changes in the environment (Kuppens & Verduyn, 2015). For instance, in the case of affect variability, while it is often seen as a sign of dysregulated emotions in ESM research, some degree of variability may be adaptive and a sign of flexible responding to the environment (McKone & Silk, 2022).

Affect Levels as a Moderator in the Relation between Affect Dynamics and Depression

In the present study, we propose an explanation for the conflicting views on the relative adaptability of affect dynamics, namely that not all individuals with heightened depressive symptoms show the same pattern of altered affect dynamics. Specifically, we suggest that one's overall affect level (i.e., the intra-individual mean across all affect ratings) is a key moderator influencing the relation between affect dynamics and depression. Considering affect levels as a moderator could explain why for some individuals higher variability may indicate adaptive and for others maladaptive emotional functioning (for a theoretical framework see Ong & Ram, 2017). Specifically, in the presence of overall positive mood (i.e., high PA or low NA levels), high variability may constitute a "hidden vulnerability" (Ong & Ram, 2017, p. 266). Individuals who feel good on average might experience variability as disturbing, because it signals deviations from overall positive mood states. In contrast, in the presence of overall negative mood (i.e., high NA or low PA levels), higher variability may indicate a "mood-brightening" effect (Ong & Ram, 2017, p. 266). Individuals with overall negative mood might experience fluctuations as a sign that their system is responsive to context and that they can still experience better mood (Maher et al., 2018).

Previous research has mostly examined affect levels as a confound and have found that the association between affect dynamics and depressive symptoms was highly reduced or even disappeared when controlling for affect level (Bos et al., 2019; Koval et al., 2013; Dejonckheere et al., 2019). We are only aware of two studies that have studied affect level as a moderator to examine whether affect dynamics have different implications for psychopathology depending on affect levels. One eight-day ESM study among young mothers found that among those with high PA levels, higher PA variability was associated

with more depressive symptoms, whereas among those with low PA levels, higher PA variability was associated with fewer depressive symptoms (Maher et al., 2018). Another 14-day daily diary study found that among individuals with low NA levels, more NA variability was related to more social anxiety symptoms, whereas among individuals with high NA levels, more NA variability was related to fewer social anxiety symptoms (Farmer & Kashdan, 2014). Collectively, these studies suggest that the functionality of affect variability may differ as a function of affect levels: High variability may signal maladaptation and as such could be related to more depression among those with positive moods (i.e., low NA or high PA levels), whereas it may signal adaptation and as such be related to less depression among those with negative moods (i.e., high NA or low PA levels).

We also propose a competing hypothesis. Given their univariate association with depressive symptoms (Dejonckheere et al., 2019), a combination of high variability and overall negative mood (i.e., high NA or low PA levels) could constitute a double-risk and thus be associated with more depressive symptoms (Ong & Ram, 2017). There is circumstantial evidence for this from the self-esteem literature, where one study showed that among individuals with low self-esteem levels, self-esteem variability was more strongly related to depressive symptoms than among individuals with high self-esteem levels (Oosterwegel et al., 2001). Based on the positive overlap between self-esteem and PA (Watson & Clark, 1984), it is plausible that high affect variability may be especially associated with more depressive symptoms among individuals with low PA or high NA levels.

The Present Study

The central aim of the present study was to examine the interaction between affect dynamics and affect level in explaining interindividual differences in depressive symptoms. Analyzing seven datasets that measured affect in daily life using daily diary (one assessment per day; one dataset) or ESM protocols (multiple assessments per day; six datasets), we assessed the interaction of diurnal affect dynamics (variability and inertia) and affect level on depressive symptoms in adolescents and young adults (four and three datasets, respectively). PA and NA are not two sides of the same coin (Lonigan et al., 1999) and might render differential associations with depressive symptoms (Houben et al., 2015). Additionally, alterations in PA seem to play a unique role in psychopathology in adolescence (Reitsemá, Jeronimus, Dijk, et al., 2022). As such, we examined associations separately for PA and NA.

We pre-registered two competing hypotheses. First, high variability could be associated with more depressive symptoms among those with overall positive affect levels (i.e., high PA or low NA levels). Here, higher variability could be perceived as disturbing and be associated with more depression, because these individuals might want to keep their positive affect levels high (Hypothesis 1). Second, high variability could be associated with more depressive symptoms among those with overall negative affect levels (i.e., low PA or high NA levels). Here, the combination of high variability with overall negative affect levels could indicate a double-risk and thus be associated with more depression (Hypothesis 2). Due to a lack of studies on inertia, we did not form any hypothesis regarding the interaction between inertia and levels at the time of the pre-registration. While we expected stronger main effects of affect dynamics on depressive symptoms for NA compared to PA (Houben et al., 2015), we had no hypothesis regarding the strength of the interaction effects for NA versus PA. Lastly, we conducted analyses for depressive symptoms measured at baseline and follow-up as outcomes (four datasets had follow-up data; range = six months to five years), but we did not formulate hypotheses on whether moderation effects would differ in strength between baseline and follow-up.

Methods

Transparency and Openness

Data for this paper had already been collected, but we conducted an a-priori power-analysis showing that our pooled sample was powered to find small to medium interaction effects (Supplementary Material A). The study's hypotheses and analysis plan have been pre-registered

(https://osf.io/4dvsc?view_only=09bb925cdef242e4a59466fb4f82cf31). All data and code are available at https://osf.io/djufr/?view_only=09bb925cdef242e4a59466fb4f82cf31. While some datasets have examined associations between affect dynamics and psychopathology (described in pre-registration), none of them have examined the interaction between affect level and affect dynamics. We report all data exclusions and all measures central to our hypotheses.

There were several deviations from the pre-registration, none of which were substantial and changed our conclusions. Here, we summarize the most important ones (Supplementary Material B provides more detail). First, we initially planned to only include participants with at least 50% completed affect assessments (Dejonckheere et al., 2019). However, based on this, we would have needed to

exclude 20% of our participants from our main analyses ($n = 328$). To maximize power for moderation effects, we adopted a less stringent compliance threshold that has been more commonly employed, namely at least 33% completed assessments. Final effects were re-analyzed with the initial criterion of 50% compliance as well as where no participants were excluded based on compliance, because it has been suggested that exclusion based on compliance can lead to biased conclusions (Jacobson, 2020). Results are reported in the paper.

Second, we pre-registered pooling the results of all datasets using a two-stage meta-analysis (i.e., analyzing each dataset separately, then pooling effect sizes). However, we decided for a one-stage mega-analysis (i.e., pooling all data into one dataset, then analyzing), since research has shown that this approach has narrower confidence intervals and smaller standard errors than two-stage meta-analyses and is thus preferred (Boedhoe et al., 2019). We re-analyzed final effects with the two-stage approach, leading to identical conclusions (Supplementary Material C).

Third, upon receiving the data after the pre-registration, we noticed that two datasets (datasets 6 and 7) differed from all other datasets (datasets 1 to 5) in how affect was assessed. First, datasets 6 and 7 did not measure PA, so we conducted PA analyses only for datasets 1 to 5. Moreover, in datasets 1 to 5, participants rated the intensity of multiple NA items, whereas in datasets 6 and 7, participants only rated the intensity of the most negative emotion since the previous assessment. Due to these differences, we conducted analyses on NA as per pre-registration pooling data from all datasets versus pooling data from datasets 1 to 5 only. We discuss both results in the paper.

Fourth, we pre-registered to also conduct analyses for the mean squared successive difference (*MSSD*), which refers to the average deviation between adjacent assessments, and is often referred to as affect instability. Unlike the *SD*, the *MSSD* takes into account the temporal ordering of assessments and is as such a temporal-dependent variability measure (Jahng et al., 2008). While the *MSSD* is also frequently researched in depression (Houben et al., 2015), recent research suggests the temporal order of affect ratings is less important in depression and that instability (*MSSD*) and variability (*SD*) are so highly correlated that they are essentially redundant (Bos et al., 2019; Dejonckheere et al., 2019; Koval et al., 2013). Because variability (*SD*) and inertia (*AR*) represent separate, partially independent dynamic patterns that are relevant for depression (Wichers et al., 2015), we focused on them as simultaneous predictors of

depressive symptoms in our main analyses and report analyses using the *MSSD* in Supplementary Material D.

Participants and Procedures

Data for the present mega-analysis come from seven different datasets (see Supplementary Material E for details on participants and procedures). Table 1 gives an overview of the demographics per dataset. Four samples included adolescents; three included young adults. The mean age across all participants was 16.03 years ($SD = 3.38$; range: 11.7 to 29.9 years)³ and 64.8% were females (range across datasets: 43% to 91%)⁴. Five studies were conducted in the Netherlands and two in Canada. All studies had predominately European/European American participants. After applying our inclusion criterion of at least 33% completed assessments, the mean percentage of included participants was 91% per dataset (range = 76% to 100%; total $N = 1,448$).

One dataset used a daily diary design to assess affect in daily life (one assessment per day), the remaining six an ESM design (multiple assessments per day, ranging from 3 to 10 assessments per day). The daily diary dataset included 75 data collection days, and the ESM studies ranged between 6 and 14 days. The total number of assessments ranged from 42 to 75. In all studies, participants completed self-report questionnaires about depressive symptoms at baseline. Additionally, four datasets had data on depressive symptoms at follow-up (6-months, 8-months, 1-year, or 5-years after baseline). The respective ethical committees approved all studies.

Measures

Affect

The studies differed in how many items were used to assess affect (see Supplementary Material F for all items and scales). Datasets 1 to 5 used multiple items with unipolar scales to assess PA and NA, ranging from 3 to 7 items for PA and 6 to 9 items for NA. In datasets 6 and 7, PA was not assessed, and NA was assessed with one item only by asking participants to identify the most negative emotion they had felt since the last assessment (selecting from anger, sadness, and anxiety) and subsequently rate the intensity of that emotion. Within each dataset, PA and NA items were

rescaled before analyses to a scale of 1 to 9 to ensure pooling across studies.

Supplementary Material F gives detailed results of psychometric analyses. Multilevel Confirmatory Factor Analyses showed that the PA and NA structure was replicated on a between-person and within-person level. Based on the results, we deleted one PA item from dataset 5 (“admiration”), because it did not load significantly on the PA factor. All other factor loadings on the corresponding PA or NA factors were moderate to high ($ps < .001$). Within-person reliability ranged from .76 to .91 for PA and .69 to .91 for NA. Between-person reliability ranged from .90 to .97 for PA and .91 to .98 for NA. For further analyses, we averaged PA and NA items into overall composite PA and NA scores. Across all datasets, the ICC ranged from 41% to 49% for PA scales and from 33% to 53% for NA scales, indicating that one-third to half of the variance was explained by differences between individuals.

Depressive symptoms

Depressive symptoms were measured using widely used self-report questionnaires (Supplementary Material F). The internal consistency of the depression questionnaires ranged from $\alpha = .76 - .94$. The items were computed into an overall score by averaging all items, with higher values indicating more depressive symptoms.

Compliance ESM and Daily Diary

Average compliance of individuals to the ESM and daily diary protocol ranged from 70% to 89% across datasets (Table 1). Pooling within-study associations between compliance and study variables with the *metafor* package (Viechtbauer, 2010) showed that males had slightly fewer valid assessments than females (standardized mean difference = $-.18$, $p = .009$). Moreover, higher compliance was associated with lower NA levels, PA variability, and NA variability ($r = -.12$ to $-.16$, $ps < .01$). Compliance was not associated with PA levels, PA and NA inertia, age and depressive symptoms ($ps > .33$).

Strategy of Analyses

Calculation of Affect Dynamics and Level Indices

We calculated affect dynamics and levels following common procedures (Houben et al., 2015), separately

³ Participants over 30 years of age were excluded due to our focus on adolescence and young adulthood ($n = 43$ in dataset 4 and $n = 3$ in dataset 6). The cut-off of 30 years was based on a definition of Arnett, who has suggested an age range of 18-29 years for the period of emerging adulthood for the European and Canadian context, because in those countries the median age for milestones such as marriage and parenthood are close to 30 (Arnett, 2012). Because participants from our samples were from the Netherlands and Canada, we used that age cut-off. We defined the lower bound as 10 years of age, which has typically been described as the lower bound of adolescence (Patton et al., 2016). No participants had to be excluded based on that cut-off.

⁴ In line with recommendations of the American Psychological Association (2019) we use the terms male and female when describing the whole group of our participants, because the age range of our participants is broad (i.e., instead of using boys/men and girls/women).

Table 1. Overview of Study Characteristics of Included Datasets

Study	Final <i>n</i>	% included cases ^a	Country	Study type	Beeps / day	# days	Total # beeps	Compliance ^b	Affect items	FU Depression	Age (<i>M, SD</i>)	% female
Dataset 1 (RADAR)	372	76.4%	NL	DD	1	75	75	75.4%	PA & NA	5-yrs	13.01 (0.44)	43.3%
Dataset 2 (Swinging moods)	283	93.4%	NL	ESM	10	6	54	70.2%	PA & NA	8-mths	14.19 (0.54)	59.5%
Dataset 3 (Mood in emerging adults)	228	100%	NL	ESM	5	11	55	88.6%	PA & NA	1-yr	19.58 (1.48)	90.8%
Dataset 4 (Emotions in daily life)	156	78.4%	NL	ESM	5	14	70	71.8%	PA & NA	N/A	21.42 (2.56)	75.6%
Dataset 5 (Emotion regulation in action)	68	100%	NL	ESM	4/9 ^c	6	44	71.6%	PA & NA	N/A	13.95 (0.94)	70.6%
Dataset 6 (LASER)	173	95.1%	CA	ESM	3	14	42	79.3%	NA ^d	N/A	18.84 (1.64)	86.6%
Dataset 7 (YES)	168	93.9%	CA	ESM	3	14	42	73.1%	NA ^d	6-mths	13.93 (0.88)	50.9%

Note. Total *N* = 1,448. ESM = Experience Sampling Method, DD = Daily diaries, FU = Follow-up, yr(s) = year(s), mths = months.

^a *n* = 3 participants were excluded due to zero-variance in PA or NA scales.

^b Refers to average percentage of answered beeps per participant. After exclusion of participants with least 33% compliance.

^c Four beeps on Friday, nine beeps on Saturday/Sunday.

^d Most intense negative emotion since the previous beep was rated (selected from sadness, anger, anxiety).

for PA and NA per dataset. *Affect level* and *variability* were calculated as the mean and standard deviation, respectively, of all data-points within individuals using the *psych* package (Revelle, 2021). *Affect inertia* was calculated by computing the AR(1) slope using multilevel models. The lagged affect items (*t*-1) were created using the *lagvar* function of the *esmpack* (Viechtbauer, 2021) and were used as a predictor in a multilevel model with random intercepts and slopes predicting affect at *t* using the *lme4* package (Bates et al., 2015). Individual slopes were saved as the inertia index. We deleted missing values within days/weeks, to increase comparability between datasets, because not all studies had recorded their missing data and to increase scores that could be used in the calculation for the inertia scores (e.g., so that lags between for instance the 1st and 3rd measurement were still calculated if the 2nd measurement was missing). When repeating analyses where missing data-points within days/weeks were not removed, results were virtually identical (see https://osf.io/djufr/?view_only=09bb925cdef242e4a59466fb4f82cf31).

Mega-Analysis

After data preparation per dataset, data were pooled into an overall dataset for the one-stage mega-analysis. Before pooling, outliers in affect dynamics and level and depressive symptoms outside the 1% and 99% percentile were winsorized. Initially, we planned to conduct the one-stage mega-analysis using a multilevel model with dataset as a random factor. However, the model did not converge, likely due to the small number of clusters (max. seven datasets). With few clusters, a fixed-effects approach is recommended (McNeish & Stapleton, 2016). Here, the dataset variable is dummy coded (i.e., *k*-1 dummy dataset variables for *k* datasets) and used as predictors in a regression model. Although the fixed-effects approach is associated with slightly lower model fit compared to the multilevel approach, both approaches are superior to the two-stage meta-analysis (Boedhoe et al., 2019).

We fitted linear regression models with affect level and dynamics as predictors and depressive symptoms as outcome. In all models, age, gender, and *k*-1 dummy variables indicating the dataset were included as covariates. Depressive symptoms at baseline were included as a covariate when examining depressive symptoms at follow-up. In Model 1, covariates and affect variability and inertia were included as simultaneous predictors to account for their overlap. In Model 2, affect level was included as an additional predictor to assess the unique effect of affect dynamics over affect level. In Model 3, the interaction terms affect variability × affect level and affect inertia × affect level were added. Affect dynamics and level

were mean centered within datasets to avoid multicollinearity and for better interpretation of the moderation effect. Depressive symptoms were standardized within datasets. Models were fitted separately for depressive symptoms at baseline and follow-up as outcomes and separately for PA and NA. With depressive symptoms at baseline as outcome, five datasets could be included for PA and seven datasets for NA. With depressive symptoms at follow-up as outcome, three datasets could be included for PA and four datasets for NA (Table 1). All analyses were conducted in *R* (R Core Team, 2022).

Results

Descriptive Statistics

Descriptive statistics and correlations of affect dynamics, affect level, and depressive symptoms per dataset can be found in Supplementary Material G. Descriptive statistics confirm that the two datasets (6 and 7) that differed in assessing NA also showed on average higher NA levels and NA variability (all Tukey post-hoc tests $ps < .001$) and fewer floor effects than datasets 1 to 5 (see Supplementary Material H for histograms). Pooled correlations across all datasets indicated that higher PA levels were associated with lower PA variability, but not with PA inertia (Table 2; see Supplementary Material I for correlations without datasets 6 and 7). Higher NA levels were associated with higher NA variability and higher NA inertia. Variability and inertia were not correlated (for both PA and NA). Depressive symptoms at baseline and follow-up were correlated with lower PA and higher NA levels, higher PA and NA variability, lower PA inertia (at baseline only) and higher NA inertia.

Association between Affect Dynamics and Level with Depressive Symptoms

Positive Affect

Results of the mega-analysis can be found in Table 3. Without controlling for PA level, higher PA variability and lower PA inertia were related to more depressive symptoms (for PA inertia at baseline only; Model 1). When controlling for PA level (Model 2), all associations diminished in size. PA inertia, but not PA variability, remained a significant predictor for depressive symptoms at baseline, and PA variability remained a significant predictor for depressive symptoms at follow-up. None of the interaction terms between PA dynamics and PA levels were significant ($ps > .09$; Model 3), indicating that the association between PA dynamics and depressive symptoms did not differ as a function of PA levels.

Negative Affect

As datasets 6 and 7 differed from datasets 1 to 5 in measuring NA, we conducted analyses as pre-registered, pooling data from all available datasets, and analyses excluding datasets 6 and 7 (Table 3). Without controlling for NA levels (Model 1), higher NA variability and higher NA inertia were associated with more depressive symptoms (for NA inertia only at baseline), both when all datasets or when only datasets 1 to 5 were included. NA variability, but not NA inertia, remained a significant predictor of depressive symptoms after adding NA levels as predictor pooling all datasets (Model 2). In contrast, pooling data from datasets 1 to 5 only, NA variability and NA inertia both became non-significant predictors.

Table 2. Pooled Correlations of Study Variables Across all Datasets

Variable	1	2	3	4	5	6	7
1. PA level							
2. PA variability	-.36**						
3. PA inertia	.09	-.01					
4. NA level	-.45***	.26***	-.11				
5. NA variability	-.36***	.56***	-.12**	.57***			
6. NA inertia	-.20***	.02	.28***	.36***	.14		
7. Dep Baseline	-.36***	.21***	-.08**	.39***	.30***	.13*	
8. Dep Follow-up	-.40***	.28***	-.02	.34***	.27***	.13***	.54***

Note. PA = Positive affect, NA = Negative affect, Dep = Depressive symptoms. Correlations were calculated per dataset and then pooled with a random-effects model using the *metafor* package (Viechtbauer, 2010). Sample sizes per pooled correlation ranged from 1,448 to 883, because not all measures were available for each dataset. Depression follow-up data were not available for datasets 4, 5 & 6. PA data were not available for datasets 6 & 7.

*** $p < .001$, ** $p < .01$, * $p < .05$.

Table 3. Mega-Analysis of Affect Dynamics and Affect Levels as Predictors of Depressive Symptoms

	Depressive symptoms baseline			Depressive symptoms follow-up		
	<i>B</i> (<i>SE</i>)	<i>p</i>	<i>b</i> * [95% CI]	<i>B</i> (<i>SE</i>)	<i>p</i>	<i>b</i> * [95% CI]
Positive Affect – Datasets 1 to 5	<i>N</i> = 1095 (5 datasets)			<i>N</i> = 718 (3 datasets)		
<i>Model 1</i>				0.43 (0.08)	<.001	.19 [.12, .25]
PA variability	0.43 (0.07)	<.001	.18 [.12, .24]	-0.08 (0.27)	.77	-.01 [-.07, .05]
PA inertia	-0.64 (0.24)	.01	-.08 [-.14, -.02]			
<i>Model 2</i>				0.20 (0.08)	.01	.09 [.02, .16]
PA variability	0.11 (0.07)	.16	.04 [-.02, .11]	0.02 (0.27)	.95	.002 [-.06, .06]
PA inertia	-0.48 (0.23)	.04	-.06 [-.11, -.003]	-0.23 (0.04)	<.001	-.24 [-.31, -.16]
PA level	-0.31 (0.03)	<.001	-.32 [-.39, -.26]			
<i>Model 3</i>				-0.11 (0.06)	.09	-.05 [-.11, .01]
PA variability × PA level	-0.01 (0.06)	.91	-.003 [-.05; .05]	-0.03 (0.25)	.89	-.004 [-.07, .06]
PA inertia × PA level				0.43 (0.08)	<.001	.19 [.12, .25]
Negative Affect – All Datasets	<i>N</i> = 1428 (7 datasets)			<i>N</i> = 867 (4 datasets)		
<i>Model 1</i>				0.31 (0.07)	<.001	.14 [.08, .20]
NA variability	0.55 (0.06)	<.001	.25 [.20, .30]	0.18 (0.23)	.43	.02 [-.04, .08]
NA inertia	0.72 (0.21)	.001	.09 [.04, .14]			
<i>Model 2</i>				0.18 (0.08)	.03	.08 [.01, .15]
NA variability	0.23 (0.07)	.001	.10 [.04, .16]	-0.07 (0.24)	.77	-.01 [-.07, .05]
NA inertia	0.10 (0.21)	.64	.01 [-.04, .06]			
NA level	0.31 (0.03)	<.001	.30 [.24, .36]	0.13 (0.04)	.002	.12 [.04, .20]
<i>Model 3</i>				0.11 (0.06)	.08	.05 [-.01, .10]
NA variability × NA level	-0.04 (0.05)	.48	-.02 [-.06, .03]	-0.04 (0.24)	.86	-.01 [-.06, .05]
NA inertia × NA level	0.06 (0.21)	.77	.01 [-.04, .06]			
Positive Affect – Datasets 1 to 5	<i>N</i> = 1095 (5 datasets)			<i>N</i> = 718 (3 datasets)		
<i>Model 1</i>				0.43 (0.08)	<.001	.18 [.11, .25]
NA variability	0.64 (0.07)	<.001	.27 [.21, .33]	0.04 (0.25)	.86	.01 [-.06, .07]
NA inertia	0.70 (0.23)	.002	.09 [.03, .15]			
<i>Model 2</i>				0.17 (0.10)	.11	.07 [-.02, .16]
NA variability	0.09 (0.09)	.33	.04 [-.04, .11]	-0.41 (0.27)	.14	-.06 [-.13, .02]
NA inertia	-0.23 (0.24)	.34	-.03 [-.09, .03]			
NA level	0.47 (0.05)	<.001	.39 [.31, .47]	0.24 (0.06)	<.001	.20 [.10, .30]
<i>Model 3</i>				-0.01 (0.09)	.90	-.004 [-.07, .06]
NA variability × NA level	-0.23 (0.08)	.004	-.08 [-.13, -.03]	-0.10 (0.27)	.71	-.01 [-.07, .05]
NA inertia × NA level	-0.07 (0.24)	.77	-.01 [-.06, .04]			

Note. PA = Positive affect. NA = Negative affect. Depression follow-up data were not available for datasets 4, 5 & 6. PA data were not available for datasets 6 & 7. Covariates were age, gender, dataset number (dummy variables, $k - 1$ for k datasets) and depressive symptoms at baseline (for follow-up). Cases with missing data on age, gender, and/or depressive symptoms were excluded. VIF for affect dynamics and levels across all models < 3.2. Significant results at $p < .05$ are printed in **bold**.

When including the interaction between NA dynamics and NA level, results differed depending on the inclusion of datasets. When pooling data from all datasets, none of the interactions were significant (all $ps > .08$). When pooling data from datasets 1 to 5 only, a significant interaction emerged between NA variability \times NA level for depressive symptoms at baseline (Cohen's $f^2 = 0.009$). The interaction was robust with different compliance inclusion criteria (50% compliance threshold: $B = -0.22$, $SE = 0.09$, $b^* = -.07$, $p = .01$, $N = 995$, no compliance threshold: $B = -0.19$, $SE = 0.07$, $b^* = -.07$, $p = .004$, $N = 1,256$). We visualized this interaction using the *interActive* shiny app by McCabe et al (2018). Results indicated that the association between NA variability and depressive symptoms was positive for low NA levels (-0.55 SDs from the mean; 34% of the sample), whereas it was negative for very high NA levels ($+2.1$ SDs from the mean, 6% of the sample; Figure 1). For individuals with NA levels between -0.55 SDs and $+2.1$ SDs, the association was not significant (60% of the sample). Figure 2 provides simple slopes with individual data-points for five different values of NA level.

Discussion

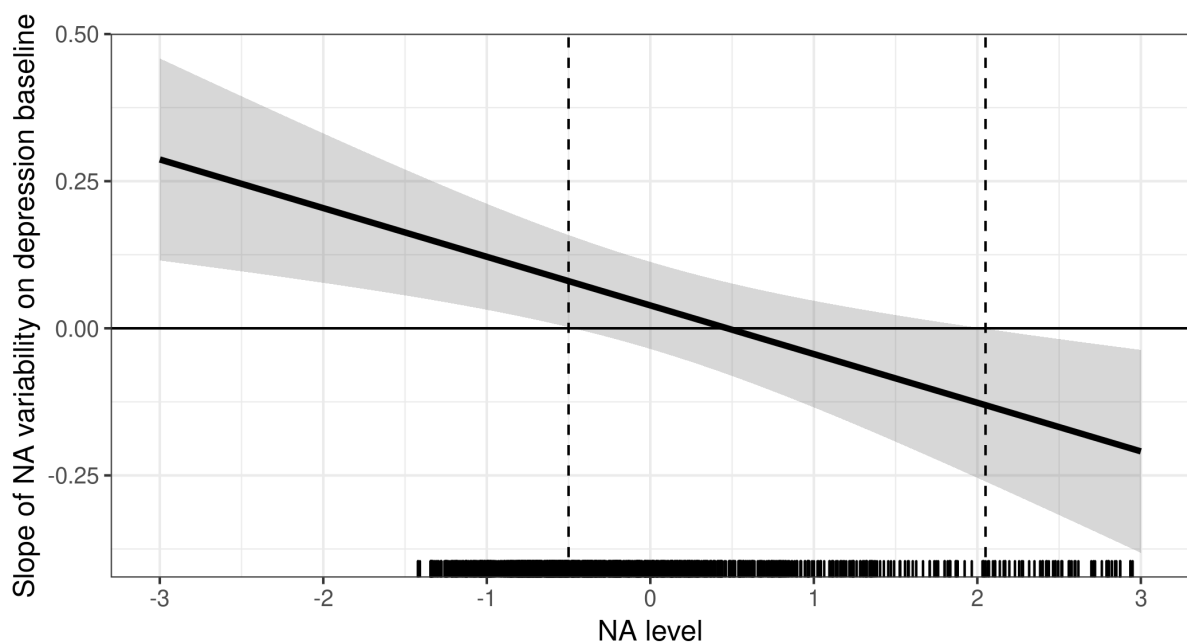
Although earlier research has shown that depressive symptoms are characterized by altered affect dynamics, seemingly conflicting views exist on the relative adaptiveness of affective change and its role in

depression (for reviews see Houben et al., 2015; McKone & Silk, 2022). The present study aimed to provide an explanation for these inconsistent views by considering affect levels as a moderator in the relation between affect dynamics and depression. Analyzing seven datasets that measured affect in daily life in adolescents and young adults, we found evidence that the association between NA variability (but not NA inertia) and depressive symptoms varied as a function of NA levels. Importantly, this interaction effect only held when excluding datasets 6 and 7, a finding which we discuss in greater detail below. Among individuals with low NA levels, higher NA variability was related to more depressive symptoms, whereas among individuals with very high NA levels, higher NA variability was related to fewer depressive symptoms. For PA, we did not find moderation effects. Instead, higher PA variability and lower PA inertia were related to more depressive symptoms irrespective of average PA levels. Overall, the present study provides evidence that the role of NA variability in depressive symptoms during adolescence and young adulthood is more complex than originally thought and that depressive symptoms may be primarily characterized by more variable and less lingering PA during that age period.

The Role of NA Variability in Depressive Symptoms May Depend on NA Levels

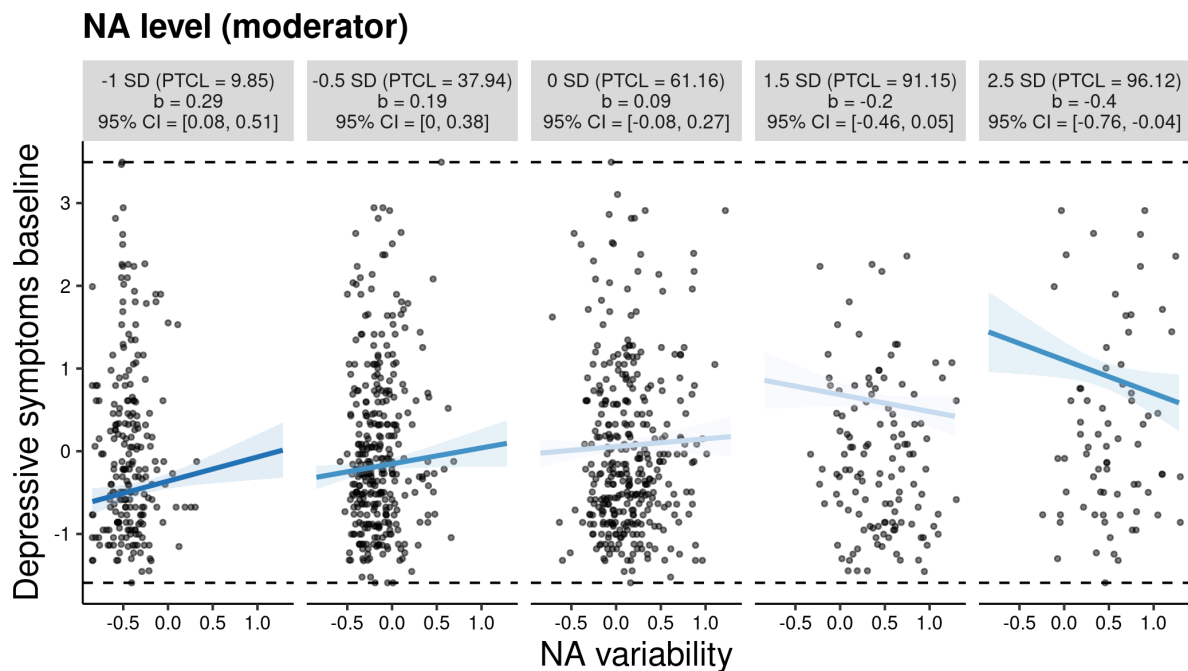
Previous research regarding the role of affect dynamics in depression have been dominated by two opposing

Figure 1. Marginal Effects Plot for Negative Affect Level as Moderator in the Relation Between Negative Affect Variability and Depressive Symptoms



Note. $N = 1,095$. Figure illustrates the direction and significance of the slope of NA variability on depressive symptoms at baseline for different values of NA level.

Figure 2. Simple Slopes Plot for Negative Affect Level as Moderator in the Relation Between Negative Affect Variability and Depressive Symptoms



Note. $N = 1,095$. Figure illustrates the association between NA variability and depressive symptoms at baseline for five different values of NA level.

views on the relative adaptiveness of affective change. Some scholars view change as maladaptive, because it may signal weaknesses in emotional reactivity and/or regulatory systems, whereas others see change as adaptive, because it may indicate flexible responding to the environment (see Houben et al., 2015; Kuppens & Verduyn, 2015; McKone & Silk, 2022). The present study offers a possible explanation for such conflicting views, at least when looking at the affect dynamic indicator variability as operationalized with the intraindividual SD. Specifically, our results show that variability can be both beneficial (i.e., associated with fewer depressive symptoms) and harmful (i.e., associated with more depressive symptoms), depending on overall mean levels.

In line with a previous study (Farmer & Kashdan, 2014), our results showed that the association between NA variability and depressive symptoms depended on NA levels. Specifically, for participants with average and moderately higher than average NA levels, NA variability did not explain interindividual differences in depressive symptoms. For those individuals, fluctuations in affect may simply be a normal part of their lives. However, when NA levels dropped below the mean, higher NA variability was associated with more depressive symptoms at baseline, suggesting a “hidden vulnerability” (Ong & Ram, 2017, p. 266) among individuals with low NA levels. Individuals

with low NA might have a higher tendency to keep their NA levels low, and variability might signal unwanted deviations from that desired state (i.e., low NA baseline levels). Those individuals might be pre-occupied to protect and maintain low negative feelings (Paradise & Kernis, 2002). Conversely, when NA levels became very high (+2.1 SDs from the mean), the direction of effects flipped into the opposite direction, with higher NA variability being associated with fewer depressive symptoms, insinuating a curvilinear effect. These results suggest that for individuals with very high NA levels, high NA variability could be beneficial and represent a “mood-brightening” effect (Ong & Ram, 2017 p. 266). Here, high variability might indicate that one can deviate into a positive direction from overall high NA levels – likely a much appreciated change – and be a sign that the system is responsive to changing contexts (Maher et al., 2018). As such, these results are in line with Hypothesis 1. In light of our findings, statements of previous research that there is little added value of affect dynamics over mean levels of affect (e.g., Dejonckheere et al., 2019) need to be nuanced. Our study suggests that this statement, at least in the case of NA variability, is only correct when variability and mean levels are investigated separately. When examined in concert, variability does explain interindividual differences in depressive symptoms and that effect depends on mean

levels. As such, future research and theories on affect dynamics may benefit from more explicitly considering how variability and level work in concert (for an example see Ong & Ram, 2017).

Importantly, based on our results, we can only draw conclusions regarding associations on a between-person level, which does not inform us how affect dynamics and level interact within one person. Relations on a between-person level can be vastly different from relations on a within-person level (Moeller, 2022). As such, a critical area for future research is to extend these findings to a within-person level to examine whether higher variability is associated with reductions in depressive symptoms for individuals with high levels of NA and whether variability could be associated with increases in depressive symptoms for individuals with low levels of NA.

Depressive Symptoms in Youths Are Characterized by Variable and Less Lingering PA

For PA, a different image emerged. Here, we mostly found main effects of PA level and dynamics, but no interaction effects between them. Specifically, when controlling for PA levels, depressive symptoms were characterized by high PA variability (at follow-up only) and low PA inertia (at baseline only). This is in contrast to other studies in mostly adult samples that find that depressive symptoms are related to both higher PA variability *and* higher PA inertia (Houben et al., 2015). As such, our findings suggest that in young people, depressive symptoms may be better characterized by overall *more fluctuating PA* (i.e., more variable and less lingering PA). It is possible that the role of PA dynamics changes across development and that anhedonia (i.e., low PA variability) plays a greater role in depression beyond adolescence. Unlike for NA, we found no significant interaction effect between PA dynamics and levels, which suggests higher PA variability and lower PA inertia are associated with more depressive symptoms irrespective of PA levels. This is in line with a prior study that only found significant variability \times level interactions for NA, but not PA in predicting social anxiety (Farmer & Kashdan, 2014). Although another study found that PA variability interacted with PA levels in predicting depression in working mothers with young children (Maher et al., 2018), it did not report associations for NA. It might be that developmental differences might account for the fact that we found no PA interaction effects. Overall, our findings underscore that PA and NA are not just opposite poles (Lonigan et al., 1999) and suggest that PA dynamics play a unique role in depression during adolescence and young adulthood (Reitsema, Jeronimus, Dijk, et al., 2022; Reitsema,

Jeronimus, van Dijk, et al., 2023). However, more research is needed into the potential differences in the relation between PA and NA regarding depression during that period.

Methodological Considerations

Two additional findings are worth noting. First, the moderation effect was found for NA variability, but not NA inertia. This is in line with several studies, which have found greatest effects for variability compared to other indices of affect dynamics (Bos et al., 2019; Dejonckheere et al., 2019; Koval et al., 2013). The *SD* (i.e., the variability index) does not actually capture change across consecutive assessments, whereas change across assessments is considered in the *AR(1)* slope calculations (i.e., the inertia index). As such, these results suggest that the interaction effect could mostly be explained by the variance and not the temporal dependency of affective change. This is especially important in the context of the different samples we used, which differed on their time-interval for the affect assessment (one to ten assessments per day). Given that variability does not actually capture change across consecutive assessments, whereas change across assessments are considered in inertia calculations, the *SD* might represent more of a non-dynamic dimension that independent of different time-scales carries some signal (see Supplementary Material D for a more thorough discussion). Overall, due to the differences in time-scale (ranging from hours to days), the current study may have been more suitable to address the construct of variability than inertia. In particular, another explanation for the null findings of inertia with regard to the interaction is that the effect for inertia was averaged out when combining the studies with different time-scales. Inertia is usually assessed and interpreted across shorter time-scales (for a discussion on time-scales in affect dynamics see Hollenstein (2021)) and is especially susceptible to missing data, which may have undermined the validity of the inertia index, particularly in the daily diary study (dataset 1). However, because both inertia and variability are key affect dynamic indicators in relation to depressive symptoms and because earlier research has indicated that the time-scale does not significantly moderate the role of affect dynamics in psychopathology (Houben et al., 2015), we included inertia as a predictor variable. In supplementary analyses, we checked whether differences in sampling frequencies had an influence on our results. Overall, we found limited evidence for that. For instance, the effect of inertia was very comparable between the different sampling frequencies. However, we need to note that these analyses are likely underpowered because sampling frequency is a stable between-study

moderator with limited variability (see Supplementary material J for results and a more thorough discussion). Nevertheless, the (null) results with regard to inertia could reflect more a problem with the measurement than content-related explanations and should be interpreted with caution.

Second, the interaction effect between NA variability and NA level was only found when pooling data from datasets 1 to 5, whereas it was not significant when pooling data from all datasets (i.e., including datasets 6 and 7, which only assessed the intensity of the most intense negative emotion). Additionally, NA dynamics became non-significant predictors after controlling for NA levels in datasets 1 to 5, whereas NA variability remained a significant predictor when all datasets were included. The time-scale was not particularly different for those datasets and while there were differences in nationality (dataset 6 and 7 were collected in Canada, datasets 1 to 5 in the Netherlands), we do not expect that this is an explanation for the differences in findings, since both Canada and the Netherlands are countries with relatively comparable cultures (i.e., with Western, individualistic values). We suspect that these findings are more explained by methodological differences. Specifically, the findings parallel results on PA, where we found mostly main, but no interaction effects. Descriptive statistics showed that NA scales in dataset 1 to 5 had more floor effects than NA scales in datasets 6 and 7 as well as PA scales (Supplementary Material H)⁵. Restricted variance makes dynamics more confounded with the mean (Mestdagh et al., 2018; also reflected in lower mean-variability correlations of PA versus NA; Table 2), which might explain why main effects of NA dynamics were more often wiped out after controlling for NA levels in datasets 1 to 5. Taken together, this suggests that if affective experiences show fewer floor effects within a sample, dynamics may have an effect beyond mean levels of affect, whereas in case of more restricted variance, level and variability may work together in explaining interindividual differences in depression. More broadly, this stresses that differences in assessing affect can lead to great differences in results (Kuppens et al., 2022).

Limitations and Future Directions

The current study has several important limitations. First, the samples included in this mega-analysis predominantly consisted of European/European American, middle-class adolescents and young adults.

One factor contributing to that homogeneity in samples was that the datasets were identified based on earlier collaborations and did not include all ESM datasets available in the research community. Thus, it is important to study how results generalize to more diverse populations, including broader socio-economic or ethnic groups. Additionally, even though, the age group we focused on is known for emerging depression (Thapar et al., 2022) and more variable affective landscapes (Reitsema, Jeronimus, van Dijk, et al., 2022), our samples contained relatively healthy participants. While our results aimed to inform theoretical frameworks of depression, we only assessed the relation between affect dynamics and depressive symptoms in a non-clinical sample. As such, to truly inform results on depression as a clinical phenomenon, current findings should be replicated in clinical samples.

Second, although pooling across studies strengthens the robustness of the findings, methodological differences between datasets should not be neglected. For instance, datasets differed on the item wording and scale types (Supplementary Material F) as well as the timescales on which affect was measured (ranging from one to ten assessments per day; Table 1), which might also explain why strongest effects were found for the time-independent variability index *SD*. While the large sample size also provided us with enough power to detect small to medium interaction effects, the effects we found were overall small. Additionally, like much previous research, we collapsed different emotions into overall NA and PA scales. This prevented us from examining whether effects were specific to distinct emotions or whether transitions between them may also play a role in depression. Overall, measurement in ESM studies is a heavily understudied topic (Kuppens et al., 2022), which is why future research needs to systematically evaluate measurement properties in ESM research. The ESM repository is an excellent example of that (Kirtley et al., 2018).

Second, although we treated depressive symptoms as the outcome in our regression analyses, our results do not allow any conclusions about the direction of effects. Furthermore, depressive symptoms at baseline were measured *before* the ESM period. In our study, we did not attempt to disentangle the direction of effects, but primarily saw altered affect dynamics as a characteristic of depressive symptoms. Although there is some evidence that altered affect dynamics precede

⁵ When one uses an index of all negative emotion items, the overall NA scale mean might be low, if a participant only felt very angry, but not sad and anxious. When the scale only exists of the one item of the strongest emotion, the overall index is naturally higher, also due to the forced choice. It is possible that due to the different assessments of affect, datasets 1 to 5 lead to an underestimation of NA while datasets 6 and 7 lead to an over-estimation.

depression (e.g., van de Leemput et al., 2014), more research is needed into the temporal order of associations (McKone & Silk, 2022).

Third, operationalizing variability as the intraindividual *SD* was mainly done to increase comparability with other studies (e.g., Houben et al., 2015), but although widely used, this operationalization may be problematic for several reasons. For one, there is a mathematical overlap between the *SD* and *AR(1)* slope, because the net variability of a time-series is defined as a combination of the *AR(1)* slope and the innovation variance or residual (Jongering et al., 2015). To check whether the overlap between the *SD* and *AR(1)* was influential in our analyses, we conducted additional models in which we tested the influence of the *SD* and *AR(1)* slope separately (see Supplementary Material D, Table S2-S4). Both approaches yielded highly similar regression estimates and identical conclusions, highlighting that while the measures may overlap, including both as simultaneous predictors does not affect the estimates. In addition to the overlap between *AR(1)* and the net *SD*, the mean and variability are also confounded, especially in studies using bounded scales. To check robustness of our conclusions, we have also repeated analyses using the relative *SD* as an indicator of variability, which has been proposed by Mestdagh et al. (2018) as a measure that corrects for the mean-variability confound (see Supplementary Material K). In analyses with the relative *SD*, the main effect of NA variability flipped in direction and the interaction effect became non-significant. However, the relative *SD* has been criticized recently for overcorrecting the mean (Mader et al., 2023). Clearly, an important area for future research is to examine how to capture variability in time-series, although recent research points towards promising alternatives. For instance, Koslowski and Holtmann (2023) highlight the utility of using a multilevel *AR(1)*, which allows to simultaneously model the *AR(1)* slope and the innovation variance. Mader and colleagues (2023) suggest Bayesian censored location-scale models, which allow simultaneous modelling of the mean (location) and residual standard deviation (scale).

Relatedly, although the affect dynamic indices used here are based on time-series affect data, they constitute merely a descriptive statistic of an individual's affective experience and do not provide information about the process itself (Hamaker et al., 2015). Summarizing many time-points into one measure neglects the complexity of affect during daily life and likely misses the "ebb and flow of affect" (Trull et al., 2015, p. 359). Future research should focus more on how affect dynamics operate at and change across different timescales. For instance, moving window

approaches could be beneficial to examine how level and dynamics change within individuals over time and how that associates with depression on a macro-level (Olthof et al., 2020; Wichers et al., 2020).

Fourth, like many other studies in the field of affect dynamics, we did not consider the context in which affect occurred, although explanations surrounding affect dynamics usually include context (i.e., there is an emotional response to an event). In the present paper, we often used the terms adaptation and maladaptation, however these terms technically require the measurement of context (e.g., in terms of emotionally responding to some form of context). Indeed, this context-insensitivity of many ESM studies in affect dynamics research may explain the relatively weak associations with mental health found in previous research (for more discussion on the role of context in affect dynamics research see Dejonckheere et al., 2020; Lapate & Heller, 2020; Mestdagh & Dejonckheere, 2021). As such, adding context is an important step in future studies (Silk, 2019) in order to truly determine when variability denotes flexibility and when it denotes instability (see also Kalokerinos & Koval, in press; McKone & Silk, 2022). This is especially important in this age group, especially because the interpersonal context changes considerably during adolescence (e.g., youth seek independence from parents and spend more time with peers) (Hollenstein & Loughheed, 2013).

Lastly, a more general note with regards to studying affect dynamics using ESM. The term *dynamic* usually describes changes across time, which often postulates that we are able to detect such changes when they happen (Hollenstein, 2021). However, even if we sample participants 20 times a day, which is unlikely due to a high burden for participants, we are still not measuring affect continuously and might thus not capture change as it happens. The question also remains in how far more frequent sampling would capture meaningful change or merely noise. As illustrated by Schiepek et al. (2016), dynamics in longitudinal ratings seem to get more and more stable with increasing lags between assessments, which might explain the finding that the mean is a better predictor than variability at less frequent sampling. Although ESM is suited for studying daily life and has higher ecological validity than laboratory settings, we must be cautious with our interpretations and remember that we still do not measure the whole movie, but "pictures of movies" (Hollenstein, 2021).

Conclusion

In conclusion, this study shows that the functionality of NA variability differs as a function of NA levels, which provides an alternative explanation for conflicting views on the role of affect variability in depressive

symptoms. Our findings suggest that higher NA variability may be a vulnerability factor among those with low NA levels, whereas higher variability may be beneficial among those with high NA levels. However, this interaction effect was only found when excluding datasets 6 and 7, highlighting the importance of methodological differences between samples. Additionally, higher PA variability and lower PA inertia were associated with more depressive symptoms independent of overall PA levels, indicating that depressive symptoms in young people seem to be mostly characterized by more variable and less lingering PA. Together, these results point towards a more nuanced understanding of the role of affect dynamics in depressive symptoms during adolescence and young adulthood.

Supplementary Materials

The supplementary material can be found on the Open Science Framework under https://osf.io/djufr/?view_only=09bb925cdef242e4a59466fb4f82cf31

Additional Information

Author Note

The study's hypotheses and analysis plan have been pre-registered (https://osf.io/4dvsc?view_only=09bb925cdef242e4a59466fb4f82cf31). All data, code and output are available at https://osf.io/djufr/?view_only=09bb925cdef242e4a59466fb4f82cf31

Findings have been presented at the SRCD conference 2021, the JRA conference 2022, and SAA conference 2022. A pre-print of this manuscript is available via <https://psyarxiv.com/42uzq>.

Funding

RADAR (dataset 1) has been financially supported by main grants from the Netherlands Organisation for Scientific Research (GB-MAGW 480-03-005) and Stichting Achmea Slachtoffer en Samenleving (SASS) to RADAR PI's, and from the Netherlands Organisation for Scientific Research to the Consortium on Individual Development (CID; 024.001.003). LASER (dataset 6) and YES (dataset 7) have been financially supported by a Natural Sciences and Engineering Research Council of Canada grant (04560-2017) awarded to Tom Hollenstein.

Conflict of Interest

The authors declare no conflict of interest.

Ethical approval

Dataset 1 (RADAR): The study was approved by Medical Ethical Committee University Medical Centre Utrecht (Protocol number: 05/159-K)

Dataset 2 (Swinging moods): The study was approved by the Medical Ethical Committee Medical Ethical Committee CMO Arnhem-Nijmegen (Protocol number: 285)

Dataset 3 (Mood in emerging adults): The study was approved by the Ethical Committee of the Faculty of Social Sciences, Radboud University Nijmegen (Protocol number: ECG2012-2711-061)

Dataset 4 (Emotions in daily life): The study was approved by the Ethical Review Board of the Tilburg School of Social and Behavioral Sciences (Protocol number: EC-2017.95)

Dataset 5 (Emotion regulation in action): The study was approved by the Ethical Committee of the Faculty of Social Sciences of Radboud University Nijmegen (Protocol number: ECG2012-2606-042)

Dataset 6 (LASER): The study was approved by the Queen's University Internal Review Board (Protocol number: GPSYC-817-17)

Dataset 7 (YES): The study was approved by the Queen's University Internal Review Board (Protocol number: GPSYC-817-17)

Data Availability

Data are available on the Open Science Framework under https://osf.io/djufr/?view_only=09bb925cdef242e4a59466fb4f82cf31

Author CRediT Statement

Maciejewski: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft, Writing – Editing, Visualization

van Roekel: Data Curation, Investigation, Methodology, Writing – Editing

Ha: Data Curation, Investigation, Methodology, Writing – Editing

De France: Data Curation, Investigation, Methodology, Writing – Editing

Lin: Data Curation, Investigation, Methodology

Lennarz: Data Curation, Investigation, Methodology, Writing – Editing

Trompeter: Data Curation, Investigation, Methodology

Meeus: Supervision, Methodology, Writing – Editing, Funding acquisition

Lichtwarck-Aschoff: Supervision, Methodology, Writing – Editing

Branje: Supervision, Methodology, Writing – Editing, Funding acquisition

Hollenstein: Supervision, Methodology, Writing – Editing, Funding acquisition

Verhagen: Project Administration, Supervision, Methodology, Writing – Editing

Copyright

The authors licence this article under the terms of the Creative Commons Attribution (CC BY) licence.

© 2023

References

- American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders*. American Psychiatric Publishing.
- American Psychological Association. (2019). *Publication Manual of the American Psychological Association* (7th ed.). American Psychological Association.
- Arnett, J. J. (1999). Adolescent Storm and Stress, Reconsidered. *American Psychologist*, *54*(5), 317–326.
- Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. *American Psychologist*, *55*(5), 469–480. <https://doi.org/10.1037/0003-066X.55.5.469>
- Arnett, J. J. (2012). New Horizons in Research on Emerging and Young Adulthood. In A. Booth, S. L. Brown, N. S. Landale, W. D. Manning, & S. M. McHale (Eds.), *Early Adulthood in a Family Context* (pp. 231–244). Springer. https://doi.org/10.1007/978-1-4614-1436-0_15
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. <https://doi.org/10.18637/jss.v067.i01>
- Boedhoe, P. S. W., Heymans, M. W., Schmaal, L., Abe, Y., Alonso, P., Ameis, S. H., Anticevic, A., Arnold, P. D., Batistuzzo, M. C., Benedetti, F., Beucke, J. C., Bollettini, I., Bose, A., Brem, S., Calvo, A., Calvo, R., Cheng, Y., Cho, K. I. K., Ciullo, V., ... Twisk, J. W. R. (2019). An empirical comparison of meta- and mega-analysis with data from the ENIGMA obsessive-compulsive disorder working group. *Frontiers in Neuroinformatics*, *12*(9), 102. <https://doi.org/10.3389/fninf.2018.00102>
- Bos, E. H., de Jonge, P., & Cox, R. F. A. (2019). Affective variability in depression: Revisiting the inertia-instability paradox. *British Journal of Psychology*, *110*(4), 814–827. <https://doi.org/10.1111/bjop.12372>
- Dejonckheere, E., Mestdagh, M., Houben, M., Rutten, I., Sels, L., Kuppens, P., & Tuerlinckx, F. (2019). Complex affect dynamics add limited information to the prediction of psychological well-being. *Nature Human Behaviour*, *3*(5), 478–491. <https://doi.org/10.1038/s41562-019-0555-0>
- Dejonckheere, E., Mestdagh, M., Kuppens, P., & Tuerlinckx, F. (2020). Reply to: Context matters for affective chronometry. *Nature Human Behaviour*, *4*(7), Article 7. <https://doi.org/10.1038/s41562-020-0861-6>
- Farmer, A. S., & Kashdan, T. B. (2014). Affective and self-esteem instability in the daily lives of people with generalized social anxiety disorder. *Clinical Psychological Science*, *2*(2), 187–201. <https://doi.org/10.1177/2167702613495200>
- Fisher, A. J., & Newman, M. G. (2016). Reductions in the diurnal rigidity of anxiety predict treatment outcome in cognitive behavioral therapy for generalized anxiety disorder. *Behaviour Research and Therapy*, *79*, 46–55. <https://doi.org/10.1016/j.brat.2016.02.006>
- Hamaker, E. L., Ceulemans, E., Grasman, R. P. P. P., & Tuerlinckx, F. (2015). Modeling affect dynamics: State of the art and future challenges. *Emotion Review*, *7*(4), 316–322. <https://doi.org/10.1177/1754073915590619>
- Hollenstein, T. (2021). Affect dynamics and time scales: Pictures of movies. In C. E. Waugh & P. Kuppens (Eds.), *Affect Dynamics* (pp. 117–129). Springer International Publishing. https://doi.org/10.1007/978-3-030-82965-0_6
- Hollenstein, T., & Loughheed, J. P. (2013). Beyond storm and stress: Typicality, transactions, timing, and temperament to account for adolescent change. *American Psychologist*, *68*(6), 444–454. <https://doi.org/10.1037/a0033586>
- Houben, M., Van Den Noortgate, W., & Kuppens, P. (2015). The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological Bulletin*, *141*(4), 901–930. <https://doi.org/10.1037/a0038822>
- Jacobson, N. C. (2020, January 14). *Compliance thresholds in intensive longitudinal data: Worse than listwise deletion: Call for action*. Society for Ambulatory Assessment Conference, Melbourne, Australia. http://www.nicholasjacobson.com/files/talks/SAA_2020_Compliance_Thresholds.pdf
- Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in ecological momentary assessment: Indices using successive difference and group comparison via multilevel modeling. *Psychological Methods*, *13*(4), 354–375. <https://doi.org/10.1037/a0014173>
- Jongerling, J., Laurenceau, J.-P., & Hamaker, E. L. (2015). A Multilevel AR(1) Model: Allowing for Inter-Individual Differences in Trait-Scores, Inertia, and Innovation Variance. *Multivariate Behavioral Research*, *50*(3), 334–349. <https://doi.org/10.1080/00273171.2014.1003772>

- Kalokerinos, E., & Koval, P. (in press). Emotion regulation flexibility. In B. Q. Ford & J. J. Gross (Eds.), *Handbook of emotion regulation* (3rd ed.).
- Kirtley, O., Hiekkaranta, A. P., Kunkels, Y. K., Eisele, G., Lüken, M., Verhoeven, D., Nierop, M. V., & Myin-Germeys, I. (2018). *The Experience Sampling Method (ESM) Item Repository*. <https://doi.org/10.17605/OSF.IO/KG376>
- Koslowski, K., & Holtmann, J. (2023). *Unique Contributions of Dynamic Affect Indicators – Beyond Static Variability*. PsyArXiv. <https://doi.org/10.31234/osf.io/t6xqk>
- Koval, P., Pe, M. L., Meers, K., & Kuppens, P. (2013). Affect dynamics in relation to depressive symptoms: Variable, unstable or inert? *Emotion, 13*(6), 1132–1141. <https://doi.org/10.1037/a0033579>
- Kuppens, P., Dejonckheere, E., Kalokerinos, E. K., & Koval, P. (2022). Some recommendations on the use of daily life methods in affective science. *Affective Science, 3*(2), 505–515. <https://doi.org/10.1007/s42761-022-00101-0>
- Kuppens, P., & Verduyn, P. (2015). Looking at emotion regulation through the window of emotion dynamics. *Psychological Inquiry, 26*(1), 72–79. <https://doi.org/10.1080/1047840X.2015.960505>
- Lapate, R. C., & Heller, A. S. (2020). Context matters for affective chronometry. *Nature Human Behaviour, 4*(7), Article 7. <https://doi.org/10.1038/s41562-020-0860-7>
- Lonigan, C. J., Hooe, E. S., David, C. F., & Kistner, J. A. (1999). Positive and negative affectivity in children: Confirmatory factor analysis of a two-factor model and its relation to symptoms of anxiety and depression. *Journal of Consulting and Clinical Psychology, 67*(3), 374–386. <https://doi.org/10.1037/0022-006X.67.3.374>
- Mader, N., Arslan, R. C., Schmukle, S. C., & Rohrer, J. M. (2023). Emotional (in)stability: Neuroticism is associated with increased variability in negative emotion after all. *Proceedings of the National Academy of Sciences, 120*(23), e2212154120. <https://doi.org/10.1073/pnas.2212154120>
- Maher, J. P., Ra, C. K., Leventhal, A. M., Hedeker, D., Huh, J., Chou, C.-P., & Dunton, G. F. (2018). Mean level of positive affect moderates associations between volatility in positive affect, mental health, and alcohol consumption among mothers. *Journal of Abnormal Psychology, 127*(7), 639–649. <https://doi.org/10.1037/abn0000374>
- McCabe, C. J., Kim, D. S., & King, K. M. (2018). Improving present practices in the visual display of interactions. *Advances in Methods and Practices in Psychological Science, 1*(2), 147–165. <https://doi.org/10.1177/2515245917746792>
- McKone, K. M. P., & Silk, J. S. (2022). The emotion dynamics conundrum in developmental psychopathology: Similarities, distinctions, and adaptiveness of affective variability and socioaffective flexibility. *Clinical Child and Family Psychology Review, 25*, 44–74. <https://doi.org/10.1007/s10567-022-00382-8>
- McNeish, D., & Stapleton, L. M. (2016). Modeling clustered data with very few clusters. *Multivariate Behavioral Research, 51*(4), 495–518. <https://doi.org/10.1080/00273171.2016.1167008>
- Mestdagh, M., & Dejonckheere, E. (2021). Ambulatory assessment in psychopathology research: Current achievements and future ambitions. *Current Opinion in Psychology, 41*, 1–8. <https://doi.org/10.1016/J.COPSYC.2021.01.004>
- Mestdagh, M., Pe, M., Pestman, W., Verdonck, S., Kuppens, P., & Tuerlinckx, F. (2018). Sidelining the mean: The relative variability index as a generic mean-corrected variability measure for bounded variables. *Psychological Methods, 23*(4), 690–707. <https://doi.org/10.1037/met0000153>
- Moeller, J. (2022). Averting the next credibility crisis in psychological science: Within-person methods for personalized diagnostics and intervention. *Journal for Person-Oriented Research, 7*(2), 53–77. <https://doi.org/10.17505/jpor.2021.23795>
- Nelson, J., Klumpp, A., Doebler, P., & Ehring, T. (2020). Everyday emotional dynamics in major depression. *Emotion (Washington, D.C.), 20*(2), 179–191. <https://doi.org/10.1037/emo0000541>
- Olthof, M., Hasselman, F., Strunk, G., van Rooij, M., Aas, B., Helmich, M. A., Schiepek, G., & Lichtwarck-Aschoff, A. (2020). Critical fluctuations as an early-warning signal for sudden gains and losses in patients receiving psychotherapy for mood disorders. *Clinical Psychological Science, 8*(1), 25–35. <https://doi.org/10.1177/2167702619865969>
- Ong, A. D., & Ram, N. (2017). Fragile and enduring positive affect: Implications for adaptive aging. *Gerontology, 63*(3), 263–269. <https://doi.org/10.1159/000453357>
- Oosterwegel, A., Field, N., Hart, D., & Anderson, K. (2001). The relation of self-esteem variability to emotion variability, mood, personality traits, and depressive tendencies. *Journal of Personality, 69*(5), 689–708. <https://doi.org/10.1111/1467-6494.695160>
- Paradise, A. W., & Kernis, M. H. (2002). Self-esteem and psychological well-being: Implications of fragile self-esteem. *Journal of Social and Clinical Psychology, 21*(4), 345–361. <https://doi.org/10.1521/jscp.21.4.345.22598>

- Patton, G. C., Sawyer, S. M., Santelli, J. S., Ross, D. A., Afifi, R., Allen, N. B., Arora, M., Azzopardi, P., Baldwin, W., Bonell, C., Kakuma, R., Kennedy, E., Mahon, J., McGovern, T., Mokdad, A. H., Patel, V., Petroni, S., Reavley, N., Taiwo, K., ... Viner, R. M. (2016). Our future: A Lancet commission on adolescent health and wellbeing. *Lancet*, 387(10036), 2423–2478. [https://doi.org/10.1016/S0140-6736\(16\)00579-1](https://doi.org/10.1016/S0140-6736(16)00579-1)
- R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing [Computer software]. <https://www.R-project.org/>.
- Reitsema, A. M., Jeronimus, B., Dijk, M., Ceulemans, E., Roekel, E., Kuppens, P., & Jonge, P. (2023). Distinguishing dimensions of emotion dynamics across 12 emotions in adolescents' daily lives. *Emotion*, 23(6), 1549–1561. <https://doi.org/10.1037/emo0001173>
- Reitsema, A. M., Jeronimus, B. F., van Dijk, M., & de Jonge, P. (2022). Emotion dynamics in children and adolescents: A meta-analytic and descriptive review. *Emotion*, 22(2), 374–396. <https://doi.org/10.1037/emo0000970>
- Revelle, W. (2021). *psych: Procedures for Psychological, Psychometric, and Personality Research* (2.1.9) [Computer software]. <https://CRAN.R-project.org/package=psych>
- Schiepek, G., Aichhorn, W., Gruber, M., Strunk, G., Bachler, E., & Aas, B. (2016). Real-time monitoring of psychotherapeutic processes: concept and compliance. *Frontiers in Psychology*, 7. <https://www.frontiersin.org/article/10.3389/fpsyg.2016.00604>
- Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *Annual Review of Clinical Psychology*, 4(1), 1–32. <https://doi.org/10.1146/annurev.clinpsy.3.022806.091415>
- Silk, J. S. (2019). Context and dynamics: The new frontier for developmental research on emotion regulation. *Developmental Psychology*, 55(9), 2009–2014. <https://doi.org/10.1037/dev0000768>
- Thapar, A., Eyre, O., Patel, V., & Brent, D. (2022). Depression in young people. *The Lancet*, 400(10352), 617–631. [https://doi.org/10.1016/S0140-6736\(22\)01012-1](https://doi.org/10.1016/S0140-6736(22)01012-1)
- Trull, T. J., Lane, S. P., Koval, P., & Ebner-Priemer, U. W. (2015). Affective dynamics in psychopathology. *Emotion Review*, 7(4), 355–361. <https://doi.org/10.1177/1754073915590617>
- van de Leemput, I. A., Wichers, M., Cramer, A. O. J., Borsboom, D., Tuerlinckx, F., Kuppens, P., van Nes, E. H., Viechtbauer, W., Giltay, E. J., Aggen, S. H., Derom, C., Jacobs, N., Kendler, K. S., van der Maas, H. L. J., Neale, M. C., Peeters, F., Thiery, E., Zachar, P., & Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences*, 111(1), 87–92. <https://doi.org/10.1073/pnas.1312114110>
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, 36(3), 1–48. <https://doi.org/10.18637/jss.v036.i03>
- Viechtbauer, W. (2021). *esmpack: Functions that Facilitate Preparation and Management of ESM/EMA* (Version 1-17) [Computer software]. <https://rdr.io/github/wviechtb/esmpack/>
- Watson, D., & Clark, L. A. (1984). Negative affectivity: The disposition to experience aversive emotional states. *Psychological Bulletin*, 96(3), 465–490.
- Wichers, M., Smit, A. C., & Snippe, E. (2020). Early warning signals based on momentary affect dynamics can expose nearby transitions in depression: A confirmatory single-subject time-series study. *Journal for Person-Oriented Research*, 6(1), 1–15. <https://doi.org/10.17505/jpor.2020.22042>
- Wichers, M., Wigman, J. T. W., & Myin-Germeys, I. (2015). Micro-level affect dynamics in psychopathology viewed from complex dynamical system theory. *Emotion Review*, 7(4), 362–367. <https://doi.org/10.1177/1754073915590623>