

Affect variability and physical health: The moderating role of mean affect

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Abstract

Research has only begun to explore how affect variability relates to physical health and has typically not assessed long-term associations nor considered the moderating role of mean affect. Therefore, we used data from the Midlife in the United States Study waves 2 (N = 1512) and 3 (N = 1499) to test how affect variability predicted concurrent and long-term physical health while also testing the moderating role of mean affect. Results indicated that greater negative affect variability was associated concurrently with a greater number of chronic conditions ($p = .03$) and longitudinally with worse self-rated physical health ($p < .01$). Greater positive affect variability was associated concurrently with more chronic conditions ($p < .01$) and medications ($p < .01$) and longitudinally with worse self-rated physical health ($p = .04$). Further, mean negative affect played a moderating role such that at lower levels of mean negative affect, as affect variability increased, so did the number of concurrent chronic conditions ($p < .01$) and medications ($p = .03$) and the likelihood of reporting worse long-term self-rated physical health ($p < .01$). Thus, the role of mean affect should be considered when testing short- and long-term associations between affect variability and physical health.

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KEYWORDS

affect, affect dynamics, affect variability, physical health

INTRODUCTION

Affect fluctuates across time, and this temporal aspect is associated with mental health (Ebner-Priemer et al., 2009; Houben et al., 2015). For example, greater variability in negative and/or positive affect, often measured by the standard deviation of affect levels (Röcke et al., 2009), is linked to more depressive symptoms (Jenkins et al., 2020; Peeters et al., 2006) and higher levels of anxiety (Gruber et al., 2013; Houben et al., 2015). And these associations hold above and beyond mean affect levels. Although research has begun to explore affect variability in relation to physical health, this work has typically not assessed longer-term associations or considered the moderating role of mean affect. Therefore, the goals of the present study were to examine whether negative and positive affect variability predicted a diverse set of physical health outcomes in cross-sectional and longitudinal data and to explore how mean affect may alter these associations.

Existing studies in this area have found that greater negative and/or positive affect variability is associated with poorer physical health. Greater variability in positive and negative affect assessed once daily over several days has been associated with worse scores on a composite measure of physical health (Hardy & Segerstrom, 2016) and greater somatic symptoms (Jenkins et al., 2020). Similarly, in large nationally representative samples, variability in positive affect on a single day is associated with worse self-rated physical health (Chan et al., 2016), the presence of angina (Chan et al., 2016), and an increased risk of mortality (Ong & Steptoe, 2020). Moreover, affect variability is associated with worse pain outcomes. In a sample of adults with chronic pain, variability in negative affect assessed once per day over 14 days was associated with greater daily limitation due to pain (Rost et al., 2016). Affect data from adolescents with juvenile idiopathic arthritis collected three times per day for 28 days revealed that greater negative affect variability was associated with higher pain and greater functional limitations, whereas greater positive affect variability was associated with higher pain (Connelly et al., 2012). This evidence consistently demonstrates that greater affect variability is associated with worse physical health.

Further, these findings support the stability theory of affect (Gruber et al., 2013; Hardy & Segerstrom, 2016; Houben et al., 2015), which proposes that individuals with poor affect regulation capabilities will have less stable (i.e., more variable) affect and consequently worse physical health. Although the stability theory predicts a main effect of affect variability on health, the fragile positive affect theory proposes an interaction between affect variability and mean levels of affect. It suggests that high variability is particularly harmful for health when an individual also has high mean positive affect (i.e., unstable positive affect; Ong & Ram, 2017; Jones et al., 2020). This is because high but frequently fluctuating mean positive affect may indicate that the individual experiences positive affect primarily due to positive environmental contexts but has poor affect regulation skills, inhibiting the ability to maintain positive states, which then increases vulnerability to various health problems. Furthermore, whereas the fragile positive affect theory emphasizes the role of mean positive affect in the association between positive affect variability and health, negative affect could work in a similar way, with greater negative affect variability being worse for health at low levels of mean negative affect (again reflecting a

desirable environment but poor affect regulation skills to capitalize on a consistently desirable affective profile). Indeed, one study found that negative affect mean levels and variability interact to predict somatic symptoms (Jenkins et al., 2020).

Therefore, the current study hypothesizes that at higher levels of mean positive affect or lower levels of mean negative affect, greater affect variability will be associated with poor physical health. The Midlife in the United States (MIDUS) study provides ample opportunity to test these predictions related to affect variability and physical health. MIDUS was initiated in 1995 (MIDUS I) and has assessed participants during two other phases (MIDUS II [collected 2004–2006] and MIDUS III [collected 2013–2014]) to understand health and aging among U.S. adults. The National Study of Daily Experiences (NSDE) is an in-depth project within MIDUS that has sought to investigate people's day-to-day lives, including their affective experiences. Hardy and Segerstrom (2016) first analyzed this NSDE data to show that variability in positive and negative affect at NSDE I (collected from 1996 to 1997) and NSDE II (collected 2004–2009) was concurrently associated with a composite measure of physical health (including general health, chronic conditions, activities of daily living, and medications) at MIDUS I and MIDUS II, respectively. Additionally, negative affect variability at NSDE I was longitudinally associated with worse physical health at MIDUS II, but this was not true for positive affect variability.

Given the availability of MIDUS III, the present investigation builds on prior work to use affect data from NSDE II and physical health data from MIDUS II and III. This study will examine affect variability's association with individual markers of physical health (self-rated physical health, chronic conditions, pain, headaches, and medications) to test its breadth of effects. Importantly, we will test the moderating role of mean affect. We predict that greater negative and positive affect variability will be associated with worse self-rated physical health, more chronic conditions, the presence of chronic pain, more frequent headaches, and more medications, concurrently and longitudinally. We also expect mean affect will moderate these associations.

METHOD

Participants

Participants came from the MIDUS study, a national longitudinal study of U.S. adults in which participants provided appropriate informed consent (data can be accessed at <https://www.icpsr.umich.edu/web/pages/>). The current study included a subsample who participated in wave 2 (MIDUS II [2004–2006] [Ryff et al., 2007]), wave 3 (MIDUS III [2013–2014] [Ryff et al., 2015]), as well as the NSDE (NSDE II [2004–2009]; $n = 2022$), where they reported on their daily experiences and affect for eight consecutive days. Participants were excluded from analyses if they had fewer than 4 days of affect data to be used for the computation of affect variability ($n = 213$; 10.5% of the NSDE II sample) or had missing sociodemographic data (MIDUS II: $n = 297$; MIDUS III: $n = 1$). Participants who did not partake in MIDUS III were excluded from the longitudinal analyses ($n = 309$). The average length of time between participation in NSDE II and MIDUS III was 7.3 years ($SD = 1.3$). The final sample for the cross-sectional analyses consisted of 1512 participants, whereas the final sample for the longitudinal analyses consisted of 1499 participants.

Measures

Affect

The affect scales included 14 negative (restless or fidgety, nervous, worthless, so sad nothing could cheer you up, everything was an effort, hopeless, lonely, afraid, jittery, irritable, ashamed, upset, angry, frustrated) and 13 positive (in good spirits, cheerful, extremely happy, calm and peaceful, satisfied, full of life, close to others, like you belong, enthusiastic, attentive, proud, active, confident) affect items selected from validated measures (Mroczek & Kolarz, 1998) and based on theory (Watson et al., 1988). Participants reported how much they felt each emotion on a scale from 0 (none of the time) to 4 (all of the time) once per day for eight consecutive days.

Mean affect and variability

The daily mean negative affect was calculated by averaging the scores on the 14 negative affect items each day. The overall mean negative affect value was taken by averaging the mean negative affect across all available days. Mean positive affect was calculated with the same procedures using the 13 positive affect items. The affect scales in the NSDE have acceptable between-person reliability ($R_{KF} = .97$ for negative affect, $.99$ for positive affect) and within-person reliability ($R_C = .77$ for negative affect, $.86$ for positive affect; Scott et al., 2020).

Negative affect variability was calculated by taking the standard deviation of mean negative affect for each of the available days (so long as there were data for at least 50% of the available days [i.e., 4 days]); positive affect variability was similarly calculated using the standard deviation of mean positive affect.

Physical health outcomes

Physical health outcomes were self-reported in MIDUS II and III.

Self-rated physical health

Participants indicated their state of physical health with one of five categories: poor (5), fair (4), good (3), very good (2), or excellent (1). “Poor” was selected as the highest category so that positive regression estimates for independent variables could be interpreted as predicting worse health in line with other outcomes.

Number of chronic conditions

Participants were asked whether they had any chronic conditions during the past 12 months (see Table S1). Participants who indicated they had no chronic conditions were given a score of 0. Participants who responded that they had chronic conditions were prompted to indicate the number they had. Responses ranged from 0 to 20.

Chronic pain

Participants were asked if they had pain that “persists beyond the time of normal healing and has lasted anywhere from a few months to many years” (yes [“1”] or no [“0”]). 37.1% (MIDUS II: $n = 547$) and 34.8% (MIDUS III: $n = 521$) reported having chronic pain.

Headache frequency

Participants reported headaches in the past 30 days: almost every day (6), several times a week (5), once a week (4), several times a month (3), once a month (2), or not at all (1). “Almost every day” was selected as the highest category, so positive regression estimates could be interpreted as predicting worse headache frequency like other outcomes.

Number of medications taken

Participants reported whether they had taken prescription medications in the past 30 days for hypertension, diabetes, high cholesterol, heart condition, lung problems, ulcer, arthritis, hormone replacement, birth control, headaches, anxiety or depression, or pain. Affirmative responses were summed and ranged from 0 to 12.

Covariates

Participants reported their race as one of six categories: White (reference group), Black/African American, Native American or Alaska Native Aleutian Islander/Eskimo, Asian, Native Hawaiian or Pacific Islander, or other. Education was collapsed into six categories: <9th grade (reference group), some high school, high school graduate/GED, some college/Associate of Arts degree, bachelor's degree, or >bachelor's degree. Household income at MIDUS II was reported in dollars and collapsed into six categories following the U.S. Census Bureau: <\$20,000 (reference group), \$20,000–\$44,999, \$45,000–\$139,999, \$140,000–\$149,999, \$150,000–\$199,999, or ≥\$200,000. Household income at MIDUS III was reported in dollars. Marital status was reported as married (reference group), separated, divorced, widowed, or never married. The cross-sectional analyses controlled for covariates reported in MIDUS II, whereas the longitudinal analyses controlled for covariates reported in MIDUS III.

Statistical analyses

All statistical analyses were performed in R Version 4.0.2 (R Core Team, 2021). Means, standard deviations, *t*-tests, and Pearson correlations were used to calculate descriptive statistics. For the primary analyses, mean affect and affect variability were z-scored so that regression coefficients would reflect standardized beta values, thus providing effect sizes. Ordinal logistic regression modeled the outcomes of self-rated physical health and headache frequency because they included multiple ordered categories; odds ratios were used for effect sizes. Logistic regression modeled the binary outcome of chronic pain; odds ratios were used for effect sizes. Negative binomial regression modeled count outcomes, which included the number of chronic conditions and the number of medications; odds ratios and Pseudo R^2 were used for effect size. Negative binomial models were chosen over Poisson models by calculating the Pearson chi-square statistic and related dispersion statistic for each outcome; each dispersion statistic was larger than one, indicating a negative binomial model fit the data better (Meyer, 2020). Missing data of varying proportions existed across the five dependent variables (MIDUS 2: 1%–9% missing; MIDUS 3: 1%–18% missing). We used the listwise deletion approach because it could be applied to all of the regression models, whereas other approaches (e.g., full information maximum likelihood) could not.

Interaction terms for affect variability and mean affect were probed by examining the simple slope between the predictor and outcome at the 15th and 85th percentile levels of the moderator

(mean affect). Additionally, regions of significance tests were conducted using the Johnson-Neyman technique (Rast et al., 2014) for logistic and negative binomial models and the Aiken and West (1991) technique for ordinal models. All interaction terms probing (using simple slopes and regions of significance) were done on the linear scale (log-odds for logistic and ordinal logistic regression models; logs of expected counts for negative binomial models). However, to facilitate the interpretation of interactions in figures, we graphed the curvilinear predicted probabilities for logistic and ordinal models and the curvilinear predicted counts for negative binomial models. Our sample sizes of 1512 and 1499 were more than sufficient to reach adequate power based on the literature standards for logistic (UCLA Group, n.d.), ordinal logistic (Dickey et al., 2022), and negative binomial models (Aban et al., 2009).

Four separate models were used for each outcome to test the main effects of mean affect levels and affect variability as well as their interactions. First, Model 1 tested the main effects of mean negative affect and negative affect variability. Model 2 added the interaction term between mean negative affect and negative affect variability to Model 1. Model 3 tested the main effects of mean positive affect and positive affect variability. Model 4 added the interaction term between mean positive affect and positive affect variability to Model 3. All models controlled for age, sex, race, education, income, and marital status. Furthermore, longitudinal models predicting MIDUS III outcomes additionally controlled for the respective health outcome at MIDUS II (e.g., models predicting chronic pain at MIDUS III controlled for chronic pain at MIDUS II).

RESULTS

Descriptive statistics

Participant characteristics are shown in Table 1. The longitudinal sample (MIDUS III) had similar demographic characteristics, with the exception of age ($M = 64$; $SD = 11$). Among the MIDUS II analytic sample ($N = 1512$), mean negative affect was significantly lower than mean positive affect ($t = -137.01$, $p < .01$, 95% confidence interval [CI] of the difference $[-2.58, -2.51]$, Cohen's $d = 4.98$; Table 2). Similarly, negative affect variability was lower than positive affect variability ($t = -26.65$, $p < .01$, 95% CI of the difference $[-0.18, -0.15]$, Cohen's $d = 0.97$). Individuals higher in mean negative affect tended to be lower in mean positive affect and have greater affect variability regardless of valence (Table 2). In contrast, those with higher mean positive affect had lower affect variability regardless of valence. Additionally, participants with greater negative affect variability also had higher levels of positive affect variability. The longitudinal (MIDUS III) analytic sample's ($N = 1499$) affect measures showed the same pattern of associations.

Concurrent physical health outcomes

Main effects of affect variability

Participants with greater negative and/or positive affect variability were more likely to have a higher number of chronic conditions (negative affect variability: $OR = 1.08$, 95% CI $[1.01, 1.15]$, Pseudo R^2 for the overall model = 0.04, $p = .03$; positive affect variability: $OR = 1.10$, 95% CI

TABLE 1 Participant characteristics at MIDUS II.

Variable	Mean (SD) or N (%)
Age, years	55 (12)
Sex	
Female	833 (55.1%)
Male	679 (44.9%)
Race	
White	1,407 (93.4%)
Black and/or African American	37 (2.5%)
Native American or Alaska native Aleutian Islander/Eskimo	19 (1.3%)
Asian	5 (0.3%)
Other	38 (2.5%)
Education level	
<9th grade	12 (0.8%)
Some high school	48 (3.2%)
High school graduate/GED	355 (23.5%)
Some college/AA degree	451 (29.8%)
Bachelor's degree	332 (21.9%)
>Bachelor's degree	314 (20.8%)
Annual household income	
<\$20,000	693 (45.8%)
\$20,000–\$44,999	365 (24.2%)
\$45,000–\$139,999	413 (27.3%)
\$140,000–\$149,999	5 (0.3%)
\$150,000–\$199,999	12 (0.8%)
≥\$200,000	24 (1.6%)
Marital status	
Married	1110 (73.4%)
Separated	26 (1.7%)
Divorced	175 (11.6%)
Widowed	87 (5.8%)
Never married	114 (7.5%)

Abbreviations: AA, Associate of Arts; GED, General Educational Development; MIDUS, Midlife in the United States.

[1.05, 1.15], Pseudo R^2 for the overall model = 0.05, $p < .01$; Table 3, Models 1 and 3), when adjusting for mean affect. Participants with greater positive affect variability reported taking a greater number of medications ($OR = 1.12$, 95% CI [1.06, 1.19], Pseudo R^2 for the overall model = 0.05, $p < .01$; Table 3, Model 3) when adjusting for mean positive affect. There were no other main effects of affect variability on other concurrent physical health outcomes in Models 1 and 3.

TABLE 2 Descriptive statistics of mean affect and variability measures.

Measure	Mean	SD	2	3	4
1. Mean negative affect	0.18	0.22	−0.50*** (−0.43, −0.56)	0.74*** (0.70, 0.77)	0.19*** (0.10, 0.27)
2. Mean positive affect	2.73	0.69		−0.45*** (−0.51, −0.38)	−0.21*** (−0.29, −0.13)
3. Negative affect variability	0.17	0.14			0.38*** (0.31, 0.45)
4. Positive affect variability	0.33	0.19			

Note: The last three columns depict the correlation matrix of the variables. Ninety-five percent confidence intervals are in parentheses.

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

Interactions between variability and mean levels

Mean negative affect moderated the association between negative affect variability and self-rated physical health ($OR = 0.89$, 95% CI [0.83, 0.96], $p < .01$; Table 3, Model 2). However, when testing the simple slopes between negative affect variability and self-rated physical health at the 15th and 85th percentile levels of mean negative affect, as well as the regions of significance, the slopes were not significantly different from zero when mean negative affect was below the 99th percentile (e.g., simple slope at the 15th percentile of mean negative affect: $OR = 1.15$, 95% CI [0.95, 1.39]; simple slope at the 85th percentile of mean negative affect: $OR = 1.02$, 95% CI [0.86, 1.21]). Only when the mean negative affect was at or above the 99th percentile was the slope between negative affect variability and the likelihood of reporting worse self-rated health significant and negative (reflecting that as negative affect variability increased, self-rated health improved). This only encompassed 16 individuals in our sample, so we do not emphasize these results.¹

Additionally, mean negative affect moderated the association between negative affect variability and the number of chronic conditions reported ($OR = 0.95$, 95% CI [0.92, 0.98], Pseudo R^2 for the overall model = 0.05, $p < .01$; Table 3, Model 2; Figure 1). Specifically, at low mean negative affect (15th percentile), as negative affect variability increased, so did the number of chronic conditions reported (simple slope effect: $OR = 1.13$, 95% CI [1.05, 1.22], $p < .01$). In contrast, the slope at high mean negative affect (85th percentile) was not significant (simple slope effect: $OR = 1.06$, 95% CI [0.99, 1.14], $p = .07$). Regions of significance tests showed that the slope between negative affect variability and the number of chronic conditions was significant and positive when mean negative affect was at and below the 83rd percentile. Above the 83rd percentile of mean negative affect, there were no significant associations between negative affect variability and the number of chronic conditions (except for at extremely high values

¹Although we do not elaborate on these and similar results in the manuscript, fluctuations in affect during times of less ideal affective states are a natural response (Sbarra & Emery, 2005). Experiencing greater variability during high mean levels of negative affect may indicate that someone is adaptively responding to their environment, and thus, it may be less surprising that this affect profile is associated with better health.

TABLE 3 Mean and variability of negative and positive affect predicting concurrent physical health.

Outcome	Negative affect			Positive affect		
	Mean	SD	Mean*SD	Mean	SD	Mean*SD
Self-rated physical health (N = 1506)						
Model 1	.469***	.039				
Model 2	.597***	.068	-.113**			
Model 3				-.529***	.086	
Model 4				-.530***	.084*	-.009
No. of chronic conditions (N = 1506)						
Model 1	.177***	.076*				
Model 2	.239***	.091**	-.050**			
Model 3				-.209***	.097***	
Model 4				-.210***	.088***	-.033
Chronic pain (N = 1474)						
Model 1	.344***	-.054				
Model 2	.380***	-.041	-.036			
Model 3				-.236***	.087	
Model 4				-.238***	.081	-.030
Headache frequency (N = 1497)						
Model 1	.232**	.136				
Model 2	.278**	.149*	-.039			
Model 3				-.369***	.103	
Model 4				-.371***	.089	-.066
No. of medications (N = 1444)						
Model 1	.125**	.069				
Model 2	.175***	.083*	-.042*			
Model 3				-.114***	.113***	
Model 4				-.114***	.104***	-.038

Note: Regression estimates are presented. For self-rated physical health, chronic pain, and headache frequency, estimates are log-odds. For the number of chronic conditions and the number of medications, estimates are logs of expected counts. All models controlled for covariates (age, sex, race, education, income, and marital status).

Abbreviation: SD, Standard Deviation.

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

[99.6th percentile], which we do not emphasize because it represents only 10 individuals). Taken together, this indicates that for individuals with higher mean negative affect (in this case, above the 83rd percentile), variability is not associated with the number of chronic conditions, whereas for individuals with lower mean negative affect (in this case, at and below the 83rd percentile), as variability increases, so does the number of chronic conditions.

A similar pattern emerged where mean negative affect moderated the relationship between negative affect variability and the number of medications reported ($OR = 0.96$, 95% CI [0.92,

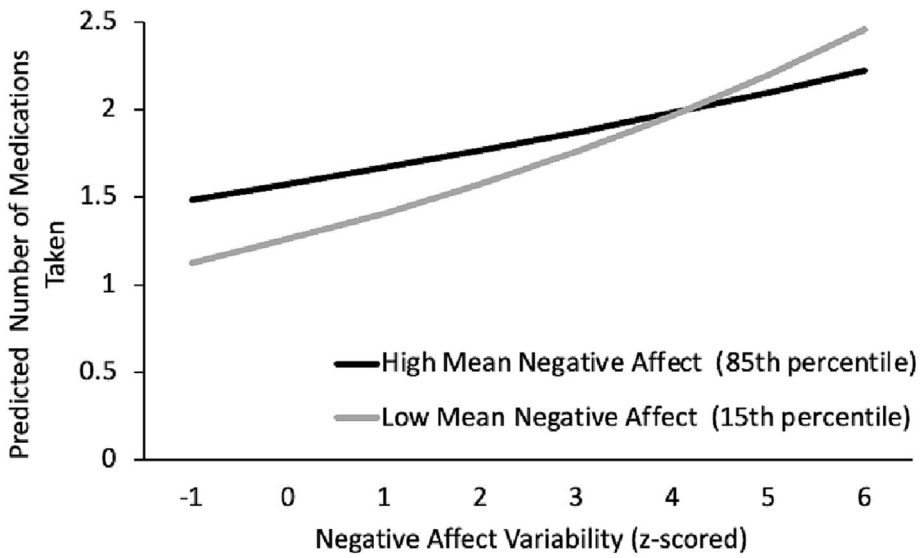


FIGURE 1 Mean negative affect moderates the association between negative affect variability and the number of concurrent chronic conditions.

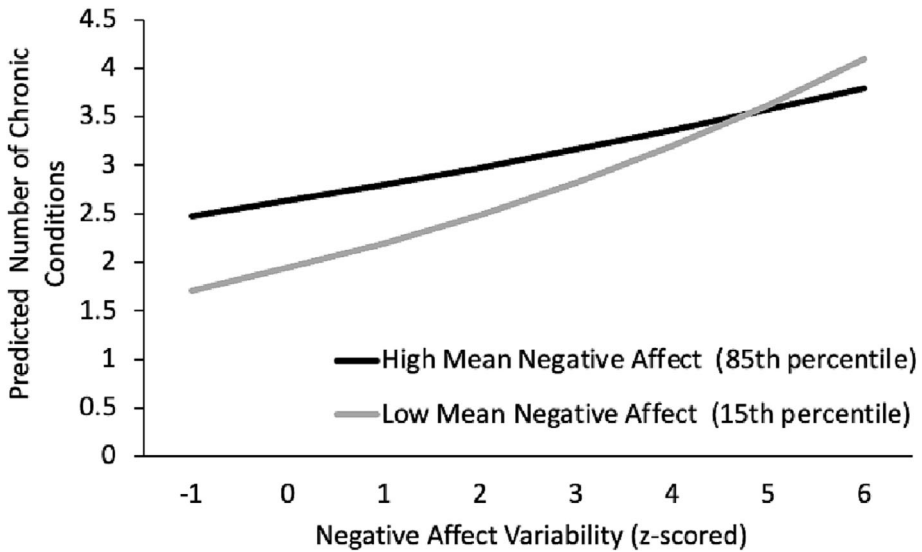


FIGURE 2 Mean negative affect moderates the association between negative affect variability and the number of concurrent medications taken.

0.99], Pseudo R^2 for the overall model = 0.05, $p = .03$; Table 3, Model 2; Figure 2). At low mean negative affect (15th percentile), as negative affect variability increased, so did the number of medications reported (simple slope effect: OR = 1.12, 95% CI [1.02, 1.22], $p = .01$). At high mean negative affect (85th percentile), the slope between negative affect variability and number

of medications was not significant (simple slope effect: $OR = 1.06$, 95% CI [0.98, 1.15], $p = .15$). Regions of significance tests revealed that the slope between negative affect variability and the number of medications was significant and positive when mean negative affect was below the 75th percentile. At and above the 75th percentile of mean negative affect, there were no significant associations between negative affect variability and the number of medications. Taken together, this indicates that for individuals with higher mean negative affect (in this case, at and above the 75th percentile), variability is not associated with the number of medications, whereas for individuals with lower mean negative affect (in this case, below the 75th percentile), as variability increases, so does the number of medications.

Mean negative affect did not moderate the associations between negative affect variability and physical health for the other outcomes (chronic pain, headache frequency), $ps > .05$. Nor were any interactions between mean positive affect and positive affect variability significant, $ps > .05$.

Long-term physical health outcomes

Main effects of affect variability

Participants with greater negative and/or positive affect variability were more likely to report worse physical health (negative affect variability: $OR = 1.35$, 95% CI [1.15, 1.60], $p < .01$; positive affect variability: $OR = 1.12$, 95% CI [1.01, 1.25], $p = .04$; Table 4, Models 1 and 3). There were no other main effects of affect variability on other long-term physical health outcomes.

Interactions between variability and mean levels

Mean negative affect moderated the association between negative affect variability and self-rated physical health ($OR = 0.84$, 95% CI [0.75, 0.93], $p < .01$; Table 4, Model 2; Figures 3a,b). Specifically, at low mean negative affect (15th percentile), as negative affect variability increased, the likelihood of reporting worse self-rated physical health increased (simple slope effect: $OR = 1.30$, 95% CI [1.07, 1.58]). There was a similar but attenuated pattern at high mean negative affect (85th percentile), such that as negative affect variability increased, so did the likelihood of reporting worse self-rated physical health (simple slope effect: $OR = 1.22$, 95% CI [1.02, 1.46]). When testing the regions of significance, the slope between negative affect variability and the likelihood of reporting worse self-rated physical health was significant and positive when mean negative affect was at and below the 88th percentile. Above the 88th percentile of mean negative affect, there were no significant associations between negative affect variability and self-rated physical health (except for at extremely high values [99.8th percentile], which represent only four individuals). Taken together, this indicates that for individuals with higher mean negative affect (in this case, above the 88th percentile), variability is not associated with self-reported physical health, whereas for individuals with lower mean negative affect (in this case, at and below the 88th percentile), as variability increases, so does the likelihood of reporting worse self-rated physical health.

Mean negative affect did not moderate the associations between negative affect variability and physical health for the other outcomes, $ps > .05$. Nor were any interactions between mean positive affect and positive affect variability significant, $ps > .05$.

TABLE 4 Mean and variability of negative and positive affect predicting long-term physical health.

Outcome	Negative affect			Positive affect		
	Mean	SD	Mean*SD	Mean	SD	Mean*SD
Self-rated physical health (N = 1487)						
Model 1	.148	.308***				
Model 2	.250	.330***	-.129*			
Model 3				-.408***	.131*	
Model 4				-.404***	.145*	-.074
No. of chronic conditions (N = 1284)						
Model 1	.119**	.016				
Model 2	.148***	.027	-.040			
Model 3				-.110***	.036	
Model 4				-.110***	.036	.000
Chronic pain (N = 1268)						
Model 1	.096	.175				
Model 2	.174	.191	-.103			
Model 3				-.250***	.125	
Model 4				-.254***	.120	-.038
Headache frequency (N = 1292)						
Model 1	.302**	-.149				
Model 2	.345**	-.132	-.060			
Model 3				-.158*	.071	
Model 4				-.158*	.279	.002
No. of medications (N = 1231)						
Model 1	.042	.035				
Model 2	.074	.044	-.041			
Model 3				-.078**	.015	
Model 4				-.078**	.017	.008

Note: Regression estimates are presented. For self-rated physical health, chronic pain, and headache frequency, estimates are log-odds. For the number of chronic conditions and the number of medications, estimates are logs of expected counts. All models controlled for covariates (age, sex, race, education, income, and marital status, respective health outcomes at MIDUS II).

Abbreviation: SD, Standard Deviation.

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

DISCUSSION

In analyses testing concurrent associations between affect variability and physical health, higher levels of negative and positive affect variability were associated with a greater number of chronic conditions, even when adjusting for mean affect. Similarly, individuals who experienced greater positive affect variability reported taking more medications. When we tested

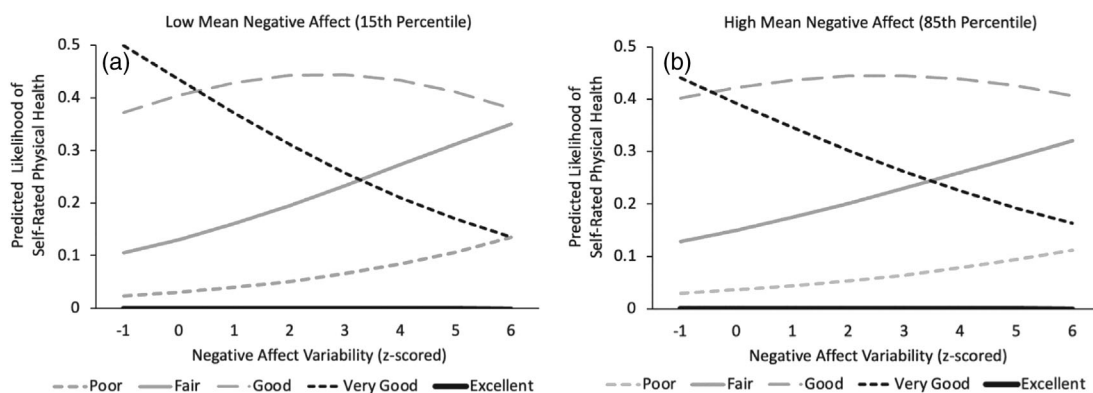


FIGURE 3 (a,b). Mean negative affect moderates the association between negative affect variability and long-term self-rated physical health. *Note:* As mentioned in the statistical analyses section of the methods, we have graphed the curvilinear predicted probabilities for ease of interpretation. When graphing curvilinear probabilities for ordinal logistic regression models, figures show the predicted probability of falling into each ordinal category. For example, Figure 3a shows the curvilinear probabilities for each of the five categories for someone at the 15th percentile of mean negative affect. These probabilities can be interpreted as follows: The probability of self-reporting “poor” physical health is generally low but has a slight increase as variability increases; the probability of self-reporting “fair” physical health is low when variability is low and increases as variability increases; the probability of self-reporting “good” physical health is generally high; the probability of reporting “very good” is high when variability is low and then decreases as variability increases; the probability of self-reporting “excellent” physical health is generally extremely low (note that it is depicted almost on top of the x-axis). In sum, as variability increases, a person is less likely to be in the “very good” category and more likely to be in the “poor” or “fair” categories.

associations prospectively (up to 10 years later), greater negative and positive affect variability were associated with worse self-rated physical health, even when adjusting for mean affect. These findings match the broader literature on affect variability and health, as well as the stability theory of affect, indicating that greater variability is associated with worse mental (Gruber et al., 2013; Houben et al., 2015; Peeters et al., 2006) and physical health (Cheng et al., 1995; Ong & Steptoe, 2020). Moreover, the current findings are in line with past work from earlier waves of the MIDUS Study, which showed that greater variability in positive and negative affect was associated with worse physical health (Hardy & Segerstrom, 2016).

This work adds to the growing literature by demonstrating the conditions under which the effects of affect variability might be most prominent. We found that at lower levels of mean negative affect, the likelihood of worse physical health increases as negative affect variability increases. In contrast, when mean negative affect was higher, physical health tended to be worse regardless of variability level. This interaction between mean affect and affect variability is consistent with the stability theory of affect and prior work on negative affect mean levels. Typically, greater levels of mean negative affect are associated with worse health (Pacella et al., 2018; Sirois & Burg, 2003; Suls & Bunde, 2005; Willroth et al., 2020). As a result, affect variability may not matter at higher levels of mean negative affect because of ceiling effects. In other words, individuals with high mean negative affect may have such poor health that their variability in negative affect does not matter. For those with lower mean negative affect, the implications of variability are consistent with views on fragile affect (Jones et al., 2020; Ong & Ram, 2017), such that greater variability in affect paired with more desirable mean levels

(e.g., low mean negative affect) is associated with worse health. For individuals with low mean negative affect, the effects of variability in affect may take their toll on health.

This study has several limitations. Affect was assessed once per day for 8 days to capture affect variability. Although prior work has used this method of once-daily assessments, it has typically done so over longer time spans (e.g., 13 [Jenkins et al., 2020] or 14 days [Rost et al., 2016]). In contrast, other studies have taken a different approach by using multiple assessments within a single day to capture variability (Chan et al., 2016; Ong & Steptoe, 2020). However, some studies have combined these approaches to capture affect multiple times per day over the course of many days (e.g., Connelly et al. [2012] assessed affect three times per day for 28 days). Nevertheless, the same pattern of association does seem to occur when these different assessment time scales are used. Despite this, future investigations may consider measuring affect variability over more daily time points and/or over the course of more days, similar to work in areas of psychological health (Peeters et al., 2006) and physiology (e.g., Human et al., 2015; Jenkins et al., 2018; Jones et al., 2020). Assessing variability over more days may capture a more stable picture of what affect variability is like for an individual. Assessing variability over more time points in each day may show what an individual's variability is like over the course of different daily events and can highlight the implications of affect variability at the daily level.

Another limitation of the current investigation includes self-reported outcomes. Although some outcomes were more concrete in nature (e.g., number of medications), future studies could use physical exams assessing objective markers of physical health to ensure reporting biases are not present. Additionally, we used the standard deviation to assess affect variability due to its ease of interpretation, its common use (Eid & Diener, 1999; Röcke et al., 2009), and evidence that more complex assessments do not add much predictive value (Dejonckheere et al., 2019). However, other variability metrics may have their own benefits (e.g., the standard deviation approach cannot assess temporal ordering of affect but the recurrence quantification analysis approach can; Jenkins et al., 2020) and may be considered in future research.

Our measure of affect had more high-arousal emotions (e.g., upset, angry, enthusiastic, and active) compared with low-arousal emotions (e.g., lonely, calm, and peaceful). Prior work on mean levels of affect has shown differential effects of arousal level on health (e.g., Pressman et al., 2017), and thus arousal level of affect variability may have differential implications as well. Although the affect measure used in the MIDUS study was not meant to create subscales based on arousal, future research could consider using affect scales such as the subcomponents of affect scale (Jenkins et al., 2021) that include arousal subscales to test how affect variability based on arousal relates to health.

Another limitation is the issue of reverse causality. Despite using affect data that was collected before the health outcomes, health status could have existed prior to the assessment of affect. Indeed, we conducted a supplemental analysis using MIDUS II (2004–2006) physical health to predict affect variability at NSDE III (2017–2019) and generally found that worse self-rated health, more chronic conditions, the presence of chronic pain, more headaches, and more medications were associated with greater negative and positive affect variability (see Table S2). These findings, paired with those presented above, demonstrate that there may be bidirectional effects between affect variability and health.

Although testing multiple outcomes required conducting multiple tests of significance, we elected not to use a correction because we had a priori reasons for running our specific models, a more restrictive alpha increases false negatives, and it may be more pertinent to describe why tests are conducted rather than statistically adjust for the number of tests (Perneger, 1998).

Given that the goal was to examine affect variability's association with several health outcomes concurrently and long-term, conducting multiple tests was necessary. Finally, although the effect sizes in this study were relatively modest, small effects may still have important implications when they accumulate over time or impact many people at the population level (Funder & Ozer, 2019).

This study had several strengths, as it used a large, national sample to test associations between affect variability and physical health while also extending existing research to examine the implications for long-term health and the moderating role of mean affect. Whereas cross-sectional associations cannot speak to the direction of effects, using longitudinal data (such as the prospective design used here) can help point us to directionality. Additionally, longitudinal data allow for an investigation of how affective influences on health may accumulate over time to impact health. Further, testing the interaction between mean and variability uncovered instances when variability can be disadvantageous. And, testing a breadth of physical health outcomes demonstrated that affect variability seemed to be related to self-rated physical health, chronic conditions, and medication use while having no statistically significant association with chronic pain or headache frequency. Although prior research has demonstrated that affect variability has implications for individuals with chronic pain (Connelly et al., 2012; Rost et al., 2016), our study is the first to test whether affect variability predicts the presence of pain in the general population. It is possible that affect variability may only have implications for those with preexisting chronic pain rather than pain more generally.

The mechanisms underlying concurrent and prospective associations between affect variability and physical health merit further investigation and could shed light on which health outcomes are relevant. For example, affect variability is associated with a range of biological mechanistic processes, including dampened profiles of cortisol output (Human et al., 2015), immunocompetence (Jenkins et al., 2018), and heart rate variability (Koval et al., 2013). All of these may have long-term implications, with some also exhibiting short-term effects (e.g., catching a cold). Likewise, greater affect variability has been linked with unhealthy behaviors such as reduced physical activity (Wen et al., 2018), worse sleep (Leger et al., 2019), and greater alcohol consumption (Mohr et al., 2015). These, in turn, may contribute to poor physical health both concurrently and, if sustained over time, longitudinally. Social support has been shown to be critical for both mean levels of affect and health (Kok et al., 2013), and new work is beginning to demonstrate that affect variability may also be tied to interpersonal wellbeing (Urganci et al., 2022). Understanding biological, behavioral, and social processes may allow precise predictions about which physical health outcomes will be impacted by affect variability over shorter and longer periods of time.

In conclusion, greater affect variability is associated with worse physical health, such as more chronic conditions and medication use concurrently and worse self-rated physical health longitudinally. Mean affect may moderate these associations such that at lower levels of mean negative affect (which is usually best for health), health outcomes are worse as affect variability increases. The present findings suggest that mean affect should be considered when testing associations between affect variability and physical health. Such findings also have implications for interventions aimed at promoting emotional well-being (Park et al., 2022) and suggest that interventions may aid in health promotion when they minimize variability in affective states as opposed to solely focusing on reducing negative affect or enhancing positive affect. Mindfulness-based stress reduction approaches may facilitate effective emotion regulation in daily life by reducing variability in negative affect (Keng et al., 2021). It is also possible that reduced variability may be a byproduct of interventions aimed at promoting positive affect and

reducing negative affect (Pressman & Cross, 2018). Thus, it is important to consider mean levels of affect and how those levels vary over time in the context of both interventions and physical health.

CONFLICT OF INTEREST STATEMENT

The authors report no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data can be accessed at <https://www.icpsr.umich.edu/web/pages/>.

ETHICS STATEMENT

The Chapman University Institutional Review Board determined the current research was not human subjects research because of the deidentified, publicly available MIDUS data and waived the need for ethics review.

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