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Longitudinal Profiles of Affect Dynamics in Middle and Later Life: A Latent Transition Analysis

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Affect dynamics are key indicators of health and well-being across adulthood, yet little is known about their longitudinal changes and correlates. Combining mean levels and daily variability, this study examined latent profiles of affect dynamics and patterns of profile transitions over a 10-year span among middle-aged and older adults. We examined longitudinal data from the Midlife in the United States study, consisting of the second and third waves of daily diary assessments (National Study of Daily Experiences). The analytic sample included 950 U.S. adults with 7,222 days for Wave 2 and 7,580 days for Wave 3 (mean age at Wave 2 = 53 years, range: 34–81; 58% women; 86% White). Two affect dynamic indicators—affective variability and affect mean levels—were derived from eight daily dairy interviews at each wave. Latent profile analyses identified three profiles of affect dynamics: *stable positivity*, *moderately variable*, and *highly variable negativity*. Latent transition analysis revealed that all profiles exhibited moderate transition stability, with individuals generally transitioning toward less variable affectivity profiles 10 years later. Older age was associated with more stable and favorable affectivity profiles, whereas higher depressive symptoms and greater number of chronic conditions were associated with more variable and unfavorable affectivity profiles. These findings highlight the dual aspects of aging in affective well-being, including the benefits of improved affective stability and regulation with age and persistent vulnerabilities contributing to individual differences in affect dynamics. Our study underscores the importance of examining multiple affect dynamic indicators simultaneously to capture the complexity of longitudinal changes in affect dynamics.

Public Significance Statement

Human affectivity is inherently dynamic, with affective states fluctuating in daily life. Aging is associated with enhanced affective well-being, indicated by more favorable and stable affectivity. However, mental and physical health challenges can undermine these benefits of aging, leading to unfavorable and unstable affectivity patterns. Our findings contribute to the understanding of socioemotional aging by highlighting the dynamic nature of affect and the dual facets of aging.

Keywords: affect dynamics, daily diary, longitudinal design, latent profile analysis, latent transition analysis

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The present study was based on secondary data analyses from a publicly available data set. Raw data are available to the public through the Inter-University Consortium for Political and Social Research (https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/203) and the Colectica portal (https://midus.colectica.org/). Mplus output of all models is provided at https://osf.io/bfuyt/?view_only=a060d69d89e8486fab53a4bcc65079c2. This study's design and its analysis were not preregistered. All procedures were approved by the institutional review boards of the University of Wisconsin–Madison (Madison Institutional Review Board Protocol number: 2016-1051) and Pennsylvania State University (Madison Institutional Review Board Protocol number: PRAMS00042558). The original idea of the present study was presented at the 2023 Annual Scientific Meeting of the Gerontological Society of America by Sun Ah Lee.

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A balance of losses and gains is central to the aging process (Baltes, 1987). Accumulated impairments in physical functions and cognitive flexibility with age lead to readjustments in one's life goals and reallocation of resources (Baltes & Baltes, 1990). Adaptation to age-related challenges occurs when individuals optimize and adjust their resources to meet the revised goals and maintain their performance. Socioemotional theories posit that despite the challenges of balancing growth and decline, older age is often associated with enhanced well-being. Socioemotional selectivity theory suggests that the perception of limited time remaining in life prompts aging individuals to prioritize goals to maintain their socioemotional well-being over those focused on acquiring knowledge and information (Carstensen et al., 1999). As such, as individuals grow older, they increasingly seek meaningful and positive experiences while minimizing exposure to stressful experiences. Expanding on this perspective, the strength and vulnerability integration (SAVI) theory highlights the strength of aging in terms of affective regulation. SAVI posits that both time left and time lived contribute to improved affective regulation with age by shaping one's attention, appraisals, and behaviors to focus away from stressors (Charles, 2010). SAVI theory also underscores the vulnerabilities of aging, including reduced physiological flexibility and major and chronic psychosocial challenges, which contribute to substantial variability in well-being within the aging population (Charles & Piazza, 2024).

Previous studies examining age-related changes in well-being provide evidence of the benefits of aging, showing that affective well-being increases with age, as indicated by lower levels of distress, anger, and anxiety and stable levels of positive affect (Charles & Carstensen, 2010). Older adults employ adaptive affective regulation strategies to enhance their well-being. Older age is associated with a greater tendency to avoid situations that evoke high levels of distress. In addition, when facing stressful situations, older adults tend to appraise the situation as less threatening, withdraw from the situations, and prevent further escalation of stress (Charles & Piazza, 2024). However, these age-related benefits are not universal and are contingent upon various factors such as physical health, social support, and socioeconomic status. For example, individuals who experienced a loss of social support, such as spousal bereavement, reported increased distress over time (Stroebe et al., 2007). In addition, the accumulation of multiple vulnerabilities, such as being placed in a caregiving role while managing their own physical health issues, can negate the benefits of aging. Thus, while older age is generally related to improved affective well-being, the intricate interplay of individual and environmental vulnerabilities exerts a substantial heterogeneity.

Affect Dynamics in Aging Research

Affect dynamics have received mounting attention to address the inherent time-dynamic nature of affective experiences in daily life. While traditional measures of affective well-being often assess trait components of affect—stable dispositions to experience certain moods or emotions—affect dynamic research examines state components of affect by repeatedly measuring moods or emotions within a shorter timeframe (e.g., moments, hours, or days), capturing the time-dynamic aspects of affect (Kuppens & Verduyn, 2015, 2017; Lischetzke et al., 2011). Affect dynamics reflects the capability of responding to environmental challenges and regulating our emotions in everyday life (Kuppens & Verduyn, 2015). Data on affect dynamics collected in more frequent, intensive, and naturalistic settings have the advantages of reducing recall bias, improving ecological validity, and enabling the analysis of patterns and variability in real-world contexts (Kuppens et al., 2009). In examining age-related changes, affect dynamics allow an exploration of how the temporal structure of affect evolves across the lifespan, offering unique insights into the mechanisms underlying emotional regulation and well-being in daily life.

Dynamic characteristics of affect not only reflect one's emotional health but also are linked to various psychological and physical health outcomes. For example, studies have demonstrated that higher affective variability (i.e., greater fluctuations in daily affect) was associated with higher depressive symptoms (Peeters et al., 2006) and higher levels of anxiety symptoms (Houben et al., 2015). In addition, higher affective variability was associated with poor physical health (Hardy & Segerstrom, 2017), heightened inflammatory markers (Jones et al., 2020), and increased risk of mortality (Ong & Steptoe, 2020). These findings indicate that altered affect dynamics may signal maladaptive or dysregulated emotional systems that lead to maladjustment in multiple health domains.

Prior studies found that average levels of negative affect (NA) generally decrease with age, with different NA items showing distinct trajectories (e.g., a decreasing trend in anger vs. stable and slightly increasing trend in sadness after the age of 70) and slight increase in old–old age (Charles et al., 2001, 2023; Kunzmann et al., 2013; Mroczek & Kolarz, 1998). The average level of positive affect (PA) appears to follow *U*-shaped pattern, such that PA remains stable or increases until mid- to old age but declines in old–old age (e.g., decline after the peak at the age of 64; Carstensen et al., 2011; Charles et al., 2023; Gana et al., 2015). However, less has been explored regarding age-related changes in dynamic characteristics of affect, such as the range of fluctuations (i.e., affective variability) or emotional response to external events (i.e., affective reactivity). Existing evidence suggests that PA and NA variability were lower in older adults than younger adults (Brose et al., 2013, 2015; Röcke et al., 2009). A recent study (Le Vigouroux et al., 2022) found nonlinear age-related differences in affective intensity (i.e., mean levels) and variability, such that individuals experience less NA and more PA after 35–40 years and a decreasing trend in NA and PA variability with age. Similarly, a recent longitudinal analysis revealed a general decreasing trend in NA reactivity to daily stressors across 20 years, where those under the age of 54 showed a rapid decrease in NA reactivity (Almeida et al., 2023). These patterns are indicative of a general stabilization and enhanced affective regulation in everyday affective experiences across middle and older adulthood. Yet, the evidence on age-related changes in affect dynamics remains mixed.

One possible explanation underlying the current inconclusive empirical findings regarding age-related changes in affect dynamics is limited availability of data and less consideration of the interplay between different affect dynamic indicators. The scarcity of data is often attributed to the substantial burden associated with collecting repeated measures data over extended periods, which are essential for capturing changes in affect dynamics over time. Furthermore, existing studies often considered affect dynamic indicators as separate constructs, examining each indicator independently in separate models or studies (Dejonckheere et al., 2019). However, different affect dynamics indicators reflect different aspects of the affective system, which may jointly contribute to affective regulation and well-being. Recent discussion has explicated the interactive effects of different indicators on various health outcomes. For instance, greater affective variability was associated with worse health outcomes when combined with overall favorable affective states (Farmer & Kashdan, 2014; Jenkins et al., 2023; Maciejewski et al., 2023; Maher et al., 2018). This suggests that a single affect dynamic measure may not provide unique information due to the empirical overlaps between dynamic measures. In particular, considering overall mean levels of affect is crucial in understanding dynamic features of affect (Dejonckheere et al., 2019). Yet, existing studies on age-related changes in affect dynamics often focused on longitudinal changes in one dynamic indicator or changes in multiple indicators in isolation. These studies assumed a homogeneity of changes in these affect dynamic indicators across middle and later life, which leads to one single trajectory that represents the study population and ignores the variability in affective processes during these life stages. This fragmented approach limits our understanding of the multifaceted nature of affect dynamics across middle and later adulthood, suggesting the need for more integrative perspectives on emotional aging.

Person-Centered Approaches for Affect Dynamics

Person-centered approaches can offer a valuable framework for understanding longitudinal changes in affect dynamics. While most prior studies have relied on variable-centered approaches that focus on average trends across individuals, often assuming homogeneity within the population, person-centered approaches are better suited to characterizing heterogeneity by identifying subgroups of individuals with similar profiles or characteristics (Bergman & Trost, 2006; von Eye & Bogat, 2006). This strategy is particularly useful for informing interventions by detecting subgroups characterized by elevated multidimensional risk (Lanza et al., 2011, 2013). In addition, incorporating intensive longitudinal methods with person-centered approaches has been recently advanced, allowing for novel opportunities to examine heterogeneous patterns in microlevel (e.g., day- or momentary-level) processes. This includes identifying microlevel patterns of indicators (e.g., Linden-Carmichael et al., 2022) and person-level patterns using microlevel data (e.g., Lanza et al., 2022). Using affect dynamic indicators derived from daily diary data for person-centered analytic models provides empirical insight into how individuals' dynamic affective characteristics are expressed in the real world. Grouping individuals by these shared patterns allows for a better understanding of affective processes over time and informs the targeted interventions for those at highest risk.

The Present Study

The present study sought to adopt person-centered approaches to examine how different affect dynamic indicators co-evolve, accounting for heterogeneity within these patterns across individuals. Despite the prevailing notion that aging is associated with improved affective well-being, individual differences need further examination (Charles, 2010). Dynamic characteristics of affect, which capture one's affective system in daily life, provide insights into affective regulation and well-being. In the present study, we utilized longitudinal data of daily diary assessments across two waves from the National Study of Daily Experiences (NSDE) to assess affect dynamic indicators. Using latent transition analysis, we aimed (a) to identify daily affect dynamic profiles of middle-aged and older adults, (b) to explore potential predictors of these profiles, and (c) to evaluate the longitudinal transitions from one profile to another profile across 10 years.

Method

Transparency and Openness

Participants for the present study were drawn from the Midlife in the United States (MIDUS) study data set. Raw data are publicly accessible through the Inter-University Consortium for Political and Social Research (https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/203) and the Colectica portal (https://midus.colectica.org/) upon registration (Ryff et al., 2019, 2021). The study's design, hypotheses, and analytic plan were not preregistered. Mplus syntax is available at https://osf.io/bfuyt/?view_only=05b5227829d24da38b911c3c252d1c6d. We outline the criteria for determining sample size, any data exclusions, data preparation procedures, and all measures used in the analyses. The broader MIDUS study protocol was reviewed and approved by the Education and Social/Behavioral Sciences and the Health Sciences Institutional Review Boards at the University of Wisconsin–Madison. The present study was exempt from an institutional review board review, as we used publicly available deidentifiable data.

Sample and Procedure

The data for the present study were from the second and third waves of the MIDUS study. The MIDUS study is a national survey designed to examine the health and well-being across mid- and older adulthood (Radler, 2014). We used the data drawn from the NSDE daily diary project. At Wave 2 of the parent investigation (2004–2006), a sample of 4,953 English-speaking adults aged 35–86 in the United States, and an additional sample of 592 African Americans from Milwaukee, WI completed an in-depth interview and self-reported questionnaires. Among them, a random sample of 2,022 participants was invited to enroll in the NSDE 2 (2004–2009), a daily diary study comprised of telephone interviews on eight consecutive evenings (Almeida et al., 2002). At Wave 3 of the parent investigation (2013–2014), participants again completed an in-depth interview and self-reported questionnaires. Using the same daily diary protocol, a random sample of 1,236 adults completed 8-day diary interviews about their daily experiences (NSDE 3; 2017–2019).

Inclusion criteria for the present study were that participants completed at least 2 days of daily diary interviews at both NSDE 2 and NSDE 3 and provided data on predictors at MIDUS 2 parent survey. This resulted in a final analytic sample of 950 participants, 7,222 daily interview days at NSDE 2 and 7,580 days at NSDE 3. At Wave 2, the study sample had a mean age of 53.5 years ($SD = 10.25$; range: 34–81) and was 58% female, 86% White, and 45% having a bachelor's degree or higher (Table 1). Participants reported an average of 0.63 depressive symptoms ($SD = 1.76$; range: 0–7) and 2.29 chronic conditions ($SD = 2.27$; range: 0–16). Compared to the

Table 1
Descriptive Statistics and Correlations (N = 950)

Variable	*M (SD)*/*n* (%)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. T1 Age, years	53.48 (10.25)	—													
2. Gender, female	552 (58.11%)	−.01	—												
3. Race, White	814 (85.68%)	.04	−.05	—											
4. Education, Bachelor's degree or higher	428 (45.05%)	−.08*	−.09**	.09**	—										
5. T1 Depressive symptoms	0.63 (1.76)	−.10**	.10**	.01	−.03	—									
6. T1 Chronic conditions	2.29 (2.27)	.16***	.16***	−.09**	−.08*	.29***	—								
7. T1 PA mean levels	2.71 (0.72)	.25***	−.00	.03	−.03	−.26***	−.20***	—							
8. T1 PA variability	0.33 (0.19)	−.11***	.14***	−.09**	−.05	.17***	.15***	−.25***	—						
9. T1 NA mean levels	0.20 (0.24)	−.21***	.06*	−.13***	−.00	.32***	.26***	−.56***	.24***	—					
10. T1 NA variability	0.17 (0.14)	−.16***	.09**	−.12***	−.02	.23***	.22***	−.47***	.40***	.77***	—				
11. T2 PA mean levels	2.67 (0.70)	.14***	−.01	−.00	−.06*	−.24***	−.23***	.70***	−.16***	−.42***	−.32***	—			
12. T2 PA variability	0.32 (0.20)	−.04	.10**	−.05	−.07*	.15***	.17***	−.14***	.22***	.15***	.18***	−.32***	—		
13. T2 NA mean levels	0.19 (0.25)	−.14***	.03	−.16***	−.00	.25***	.29***	−.39***	.15***	.64***	.46***	−.55***	.26***	—	
14. T2 NA variability	0.15 (0.14)	−.09**	.08*	−.11**	−.05	.21***	.23***	−.31***	.17***	.44***	.44***	−.46***	.46***	.72***	—

Note. T1 = Time 1 (MIDUS Wave 2); T2 = Time 2 (MIDUS Wave 3); NA = negative affect; PA = positive affect; MIDUS = Midlife in the United States.
* $p < .05$. ** $p < .01$. *** $p < .001$.

excluded participants (i.e., 1,072 participants from NSDE 2), the final analytic sample was younger ($t = 9.98$, $df = 1985.18$, $p < .001$), more likely to have a bachelor's or higher degree ($\chi^2 = 33.74$, $df = 1$, $p < .001$), and reported fewer number of chronic conditions ($t = 4.44$, $df = 1935.04$, $p < .001$). Informed consent was obtained from all participants, and research procedures were approved by institutional review boards at the participating institutions. Study documentations are publicly available at https://doi.org/10.3886/ICPSR26841.v2 and https://doi.org/10.3886/ICPSR38529.v1.

Measures

Daily Affect

During daily diary interviews, daily positive and negative affect were assessed using measures developed for the MIDUS study (Kessler et al., 2002; Mroczek & Kolarz, 1998; Watson et al., 1988). On each day of the telephone interview, participants were asked to rate the frequency of positive affect and negative affect on a 5-point scale ranging from 0 (*none of the time*) to 4 (*all of the time*). Positive affect was assessed with 13 items asking how much of the time they felt: in good spirits, cheerful, extremely happy, calm and peaceful, satisfied, full of life, close to others, like you belong, enthusiastic, attentive, proud, active, and confident. Negative affect was assessed with 14 items: restless or fidgety, nervous, worthless, so sad nothing cheer you up, everything was an effort, hopeless, afraid, jittery, irritable, ashamed, upset, angry, and frustrated. Ratings for positive and negative affect were averaged across their respective items, providing a daily affect score for each day. For NSDE 2, the within-person reliability was 0.85 for positive affect and 0.78 for negative affect, and the between-person reliability was 0.97 for positive affect and 0.91 for negative affect. For NSDE 3, the within-person reliability was 0.85 for positive affect and 0.80 for negative affect, and the between-person reliability was 0.97 for positive affect and 0.94 for negative affect (Geldhof et al., 2014).

For the present study, two affect dynamic indicators were used: affective variability and affect mean levels. Affective variability was calculated as the within-person standard deviation to represent person-level scores for variability of daily affect across the daily diary assessments. Affect mean levels were calculated as within-person mean to represent person-level scores for the average affect across the daily diary assessments. To adjust the skewness of the distribution of the variables, six affect dynamic indicators (PA mean level, PA variability, NA mean level, and NA variability at Wave 2 and Wave 3) were log-transformed. To further enhance the interpretability, affect dynamic indicators were then transformed into z-scores at each time point, with values reflecting standard deviation units relative to the sample distribution.

Covariates

Several variables from the parent survey at Wave 2 were included as predictors of the profiles at Wave 2 and the transition probabilities. Sociodemographic variables, including age at baseline (centered at sample mean), gender (1 = female, 0 = male), education level (1 = college graduate or higher, 0 = less than college graduate), and race (1 = White, 0 = non-White), were included as predictors of identified profiles in the model. Mental and physical health indicators at Wave 2 were also included as predictors, which were depressive symptoms and the number of chronic conditions. Depressive symptoms, including depressed affect and anhedonia, were assessed using the Composite International Diagnostic Interview–Short-Form (Kessler et al., 1998). Participants who responded "yes" to either of the initial screening questions regarding whether they experienced depressed affect or loss of interest (anhedonia) for 2 weeks or more in the past 12 months were subsequently asked about the presence of associated symptoms, such as changes in appetite, sleep disturbances, fatigue, feelings of worthlessness, difficulty concentrating, and suicidal thoughts. If depressed affect was endorsed, seven associated symptoms were assessed (including anhedonia), and if only anhedonia was endorsed, it was not counted again, and six symptoms were assessed. Symptom scores reflect the number of endorsed items, and participants who endorsed neither screening items were coded as 0. During the parent survey at Wave 2, participants were also asked whether they had experienced or been treated for any of 30 separate chronic health conditions (e.g., migraine headaches, neurological disorder, stroke, tuberculosis, joint/bone diseases, varicose veins) in the past 12 months. The total number of chronic conditions was included as covariates in the analyses.

Analytic Plan

The present study conducted a latent transition analysis (LTA) to examine longitudinal patterns in age-related changes in affect dynamics. The LTA approach is a longitudinal extension of latent class/profile analysis (LCA/LPA) to model transitions in co-occurring behaviors or symptoms (Collins & Lanza, 2010). LCA/LPA is a multivariate model based on measurement theory, which posits that there is an unobserved grouping variable (i.e., latent class/profile) that can be deduced from a set of categorical (for LCA) or continuous (for LPA) indicators (Goodman, 1974; Lazarsfeld & Henry, 1968). LTA extends LCA/LPA to model longitudinal data; in addition to estimating the prevalence of latent classes/profiles at each time, LTA estimates transitions over time in latent class/profile membership (Lanza et al., 2003, 2013). Using LTA, multiple aspects of affect dynamics across two occasions will be used jointly to describe affect dynamic profiles of individuals with distinct affective characteristics over time. Further, predictors of latent affect dynamic profile membership and transition probabilities can be estimated simultaneously in LTA using logistic regression (Lanza et al., 2010). To our understanding, one study applied LPA to daily diary data to identify different profiles in affect dynamic indicators among youth (Schepers et al., 2020). The present study extended this approach to address longitudinal changes in affect dynamic profiles and their associated factors among middle-aged and older adults.

The analyses were conducted in three steps. The first step was to identify latent profiles of affect dynamics separately at each wave using LPA. Affect mean levels and affective variability were jointly modeled to identify distinct profiles of individuals with shared patterns of affective characteristics. Several indices were used to determine the optimal model, including Akaike information criteria (Akaike, 1974), Bayesian information criterion (Schwarz, 1978), sample size-adjusted Bayesian information criteria (Bozdogan, 1987), Entropy, Vuong–Lo–Mendell–Rubin test (Vuong, 1989), and the bootstrap likelihood ratio test (McLachlan & Peel, 2000). Lower values of information criteria indicate more optimal model fit and higher entropy corresponds to more precise classification (Berlin et al., 2014). The significant results for Vuong–Lo–Mendell–Rubin test and bootstrap likelihood ratio test indicate a better fit of the model compared to the model with one fewer profile. In addition, the size of the classes within each profile, the theoretical interpretability of the classes, and parsimony were considered when selecting the optimal number of profiles.

The second step extended the selected LPA model longitudinally by applying LTA to data across two time points. Measurement invariance across time was examined to ensure that the latent profiles remained comparable across both waves. Measurement invariance was tested using a likelihood ratio test, comparing a model with freely estimated parameters at each time point to a model in which parameters at Time 1 (i.e., MIDUS Wave 2) were constrained to be equal at Time 2 (i.e., MIDUS Wave 3). The nonsignificant likelihood ratio test result indicates that the constraints imposed on the model (i.e., measurement invariance) are appropriate. Transition probabilities were estimated to examine whether participants tended to remain within the same affect dynamic profiles or shift to a different profile.

Finally, predictors of latent profile membership and transitions were incorporated into the LTA model using multinomial logistic regression. A series of predictors, including age, gender, race, education level, depressive symptoms, and chronic conditions, were examined to determine their associations with profile membership at Time 1 and the likelihood of transitioning between profiles. The LPA and LTA models were estimated using Mplus 8.8 (Muthén & Muthén, 1998–2017) with the robust maximum likelihood estimator. The figures were generated in R (Version 4.3.2) using RStudio (Version 2024.09.0, Boston, MA, United States; R Core Team, 2023).

Results

Table 1 presents descriptive data on daily affect dynamics, sociodemographic characteristics, and mental and physical health status. For daily affect dynamic measures, all measures at Time 1 were positively correlated with their corresponding measures at Time 2. PA mean levels were negatively correlated with PA variability, NA mean levels, and NA variability at both time points, and were positively correlated with PA mean levels. PA variability showed positive correlations with NA mean levels and NA variability at both time points. NA mean levels were positively correlated with NA variability.

Latent Profile Analyses of Daily Affect Dynamics at Time 1 and Time 2

The summary of model fit indices and criteria of LPA models with one to six profiles is presented in Table 2. At both time points, Akaike information criterion, Bayesian information criterion, and sample size-adjusted Akaike information criterion values decreased as additional profiles were included, with less pronounced improvement observed beyond the three-profile model. The Vuong–Lo–Mendell–Rubin test and bootstrap-likelihood ratio test were not significant for the four-profile model, indicating that the four-profile model did not provide a significant improvement in model fit compared to the three-profile model.

Table 2
Model Fit Information and Model Selection Criteria for Latent Profile Analyses

Number of profile	LL	AIC	BIC	SABIC	Entropy	VLMR (p)	BLRT (p)
Time 1							
1	−5404.909	10825.817	10864.669	10839.261			
2	−4867.204	9760.408	9823.542	9782.255	0.839	<.001	<.001
3	**−4635.540**	**9307.081**	**9394.497**	**9337.330**	**0.835**	**.003**	**.003**
4	−4519.104	9084.207	9195.906	9122.859	0.859	.071	.074
5	−4453.095	8962.190	9098.171	9009.244	0.819	.029	.031
6	−4402.400	8870.799	9031.062	8926.256	0.837	.058	.062
Time 2							
1	−5401.640	10819.281	10858.132	10832.725			
2	−4870.647	9767.294	9830.428	9789.140	0.848	<.001	<.001
3	**−4615.450**	**9266.900**	**9354.316**	**9297.149**	**0.845**	**<.001**	**<.001**
4	−4527.060	9100.119	9211.818	9138.771	0.847	.764	.767
5	−4448.795	8953.589	9089.570	9000.644	0.848	.102	.104
6	−4386.264	8838.527	8998.791	8893.984	0.868	.392	.398

Note. The selected final model is presented in bold. LL = Log likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = Sample size-adjusted Akaike information criterion; VLMR (p) = p value for the Vuong–Lo–Mendell–Rubin test; BLRT (p) = p value for the bootstrap likelihood ratio test.

The assumption of measurement invariance across two time points was assessed using a likelihood ratio test. The LTA model with measurement invariance imposed across time (LL = −8542.394, df = 68) was compared to the LTA model without measurement invariance (LL = −8539.035, df = 80). The G^2 statistic difference was not significant ($G^2 = 6.718$, $df = 12$, p = .876), indicating that measurement invariance held over time; thus, the more parsimonious model was used to describe the incidence of transitions.

Latent Transition Analyses

Table 3 summarizes the parameter estimates for the selected three-profile LTA models, and Figure 1 illustrates three-profile solutions at each time point. Profile 1 was labeled *stable positivity*, characterized by low NA mean levels, high PA mean levels, and low PA and NA variability (23.1% prevalence at T1, 24.1% at T2). Profile 2 was labeled *moderately variable*, as their PA and NA mean levels and variability were moderate (52.3% at T1, 52.0% at T2). Profile 3 was labeled as *highly variable negativity*, characterized by high NA mean levels, low PA mean levels, and high PA and NA variability (24.6% at T1, 23.9% at T2).

Transition probabilities between latent profiles across two time points are also presented in Table 3. These probabilities reflect the likelihood of participants shifting from one profile at Time 1 to another at Time 2. The diagonal values represent the proportion of participants who remained in the same profile across both time points. Specifically, participants in the *stable positivity* profile at Time 1 exhibited moderate stability, with 58.0% remaining in the same profile at Time 2, while 35.0% transitioned to the *moderately variable* profile, and 7.1% moved to the *highly variable negativity* profile. The *moderately variable* profile at Time 1 exhibited the highest stability, with 67.7% remaining in the same profile at Time 2. In addition, 17.5% of this profile shifted to the *stable positivity* profile, and 14.8% transitioned to the *highly variable negativity* profile. Participants in the *highly variable negativity* profile at Time

Table 3
Parameter Estimates for Latent Transition Analysis With Three-Profile Model (N = 950)

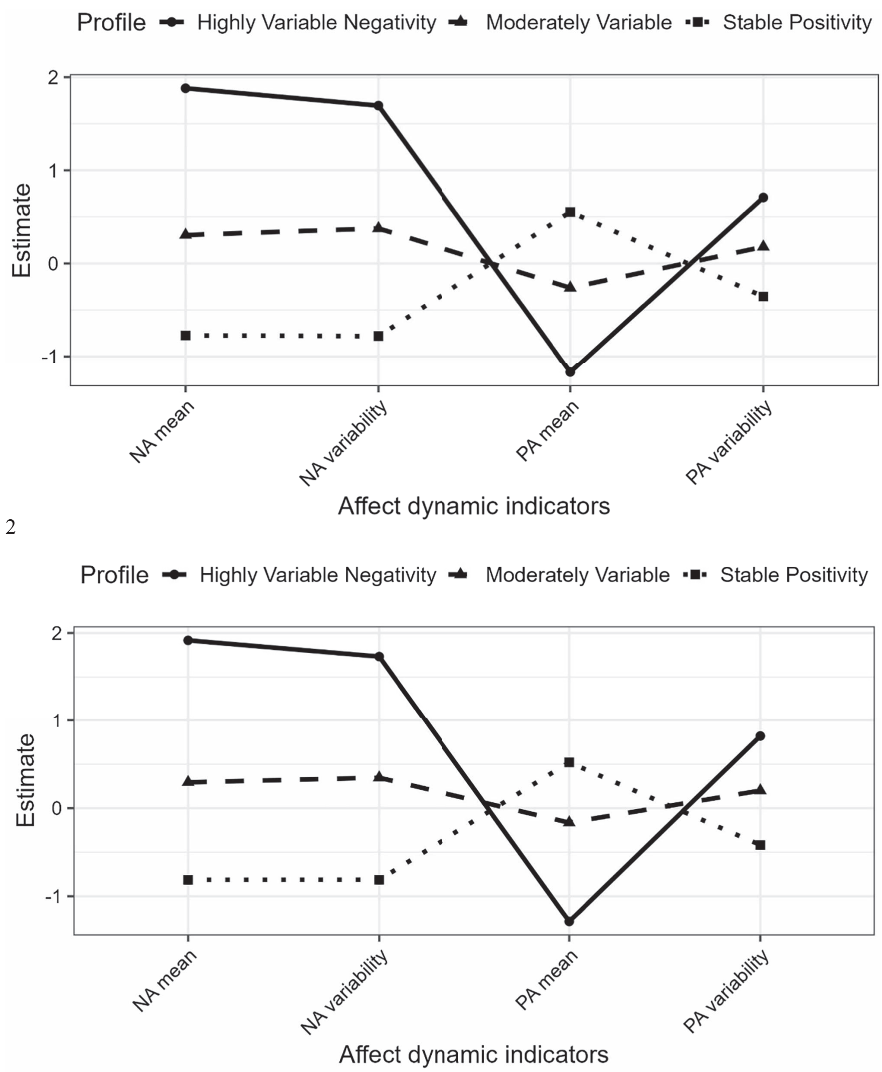
Parameter	Latent profile: Stable positivity	Moderately variable	Highly variable negativity
Estimated means (z-scores)			
PA mean levels	0.737	0.145	−0.971
PA variability	−0.493	−0.085	0.635
NA mean levels	−1.057	−0.147	1.293
NA variability	−1.160	−0.056	1.210
Prevalence of latent profiles			
Time 1	23.1%	52.3%	24.6%
Time 2	24.1%	52.0%	23.9%
Transition probabilities		Time 2	
Time 1			
Stable positivity	0.580	0.350	0.071
Moderately variable	0.175	0.677	0.148
Highly variable negativity	0.019	0.388	0.592

Note. PA = positive affect; NA = negative affect.

Figure 1
Latent Profiles of Affect Dynamics at Time 1 and Time 2

Time 1

Time 2



Note. Estimates represent *z*-scored affect dynamic indicators. NA = negative affect; PA = positive affect; Time 1 = NSDE 2; Time 2 = NSDE 3; NSDE = National Study of Daily Experiences.

1 were mostly likely to remain in the same profile at Time 2 (59.2%), followed by a transition to the *moderately variable* profile (38.8%) and *stable positivity* profile (1.9%).

Predictors of Profile Membership at Time 1

Table 4 presents the effects of sociodemographic and mental and physical health characteristics on profile membership at Time 1. The reference group was selected as the *stable positivity* profile. Compared to the *stable positivity* profile, younger participants were more likely to belong to the *moderately variable* profile, with every 1-year decrease in age associated with a 4.5% increase in the odds of being in this profile at Time 1 ($OR = 0.955$, 95% CI [0.937, 0.974], $p < .001$). Similarly, younger participants were more likely to be in the *highly variable negativity* profile, with every 1-year decrease in age linked to an 8.7% increase in the odds of being in this profile at Time 1 ($OR = 0.913$, 95% CI [0.889, 0.938], $p < .001$). Participants with higher depressive symptoms at Time 1 were more likely to be in the *highly variable negativity* profile, with a 56.9% increase in odds for each unit increase in depressive symptoms ($OR = 1.569$, 95% CI [1.155, 2.131], $p = .004$). In addition, participants with a greater number of chronic conditions at Time 1 were more likely to belong to the *moderately variable* profile, with a 32.1% increase in odds for each additional chronic condition ($OR = 1.321$, 95% CI [1.166, 1.497], $p < .001$) and the *highly variable negativity* profile, with a 58.0% increase in odds for each additional chronic condition ($OR = 1.580$, 95% CI [1.354, 1.843], $p < .001$), compared to the *stable positivity* profile.

Table 4
Associations of Covariates With Latent Profiles of Affect Dynamics at Time 1

Variable	Stable positivity *OR*	Moderately variable *OR* [95% CI]	Moderately variable *p*	Highly variable negativity *OR* [95% CI]	Highly variable negativity *p*
Age	1.000	**0.955 [0.937, 0.974]**	**<.001**	**0.913 [0.889, 0.938]**	**<.001**
Gender, female	1.000	1.082 [0.677, 1.728]	.741	1.156 [0.666, 2.007]	.607
Race, White	1.000	1.463 [0.763, 2.807]	.252	1.070 [0.483, 2.370]	.867
Education, bachelor's degree or higher	1.000	0.756 [0.471, 1.212]	.245	0.763 [0.458, 1.272]	.300
Depression at T1	1.000	1.251 [0.907, 1.726]	.173	**1.569 [1.155, 2.131]**	**.004**
Chronic conditions at T1	1.000	**1.321 [1.166, 1.497]**	**<.001**	**1.580 [1.354, 1.843]**	**<.001**

Note. The results indicate exponentiated multinomial logistic regression coefficients for the predictors of Time 1 profile membership. Bolded values indicate significance at $p < .05$. *OR* = odds ratio; CI = confidence interval; T1 = Time 1.

Predictors of Profile Transitions From Time 1 to Time 2

The effects of sociodemographic and mental and physical health characteristics on profile transitions from Time 1 to Time 2 are presented in Table 5. Race was excluded from the analyses due to the low frequency of certain categories (e.g., no non-White participants transitioning from Profiles 3 to 1); this sparseness impeded the logistic regression estimation. Among the predictors, age and the number of chronic conditions were significantly associated with certain profile transitions over time.

Older participants had 2.3% higher odds per year of transitioning to the *stable positivity* profile than remaining in the *moderately variable* profile (*OR* = 1.023, 95% CI [1.001, 1.045], *p* = .038), and had 2.2% lower odds per year of shifting from the *stable positivity* profile to the *moderately variable* profile (*OR* = 0.978, 95% CI [0.957, 0.999], *p* = .042). In addition, participants with fewer chronic conditions had 21.8% higher odds of transitioning from the *highly variable negativity* to the *stable positivity* profile (*OR* = 0.782, 95% CI [0.668, 0.915], *p* = .002) and 11.1% higher odds of transitioning to the *moderately variable* profile (*OR* = 0.889, 95% CI [0.815, 0.969], *p* = .008). In contrast, participants with a greater number of chronic conditions had 27.9% higher odds of shifting to the *highly variable negativity* profile from the *stable positivity* profile (*OR* = 1.279, 95% CI [1.092, 1.497], *p* = .002) and 12.5% higher odds of transitioning to the *highly variable negativity* profile from the *moderately variable* profile (*OR* = 1.125, 95% CI [1.032, 1.227], *p* = .008).

Discussion

Previous literature has demonstrated the benefits of aging for affective well-being while highlighting persistent age-related vulnerabilities that contribute to substantial variation across the adult lifespan. Despite growing recognition of affect dynamics as critical indicators of health and well-being, little is known about the longitudinal changes in affect dynamics and the interplay among different dynamic indicators. To address this gap, the present study employed latent transition analysis to investigate age-related changes in patterns of daily affect dynamics across middle and later adulthood.

Using 10-year longitudinal data of daily diary assessments, we identified three latent profiles of daily affect dynamics: a *stable positivity* profile (Time 1: 23.1%, Time 2: 24.1%), a *moderately variable* profile (Time 1: 52.3%, Time 2: 52.0%), and a *highly variable negativity* profile (Time 1: 24.6%, Time 2: 23.9%). Similarly, a study examining daily mood profiles in a youth sample aged 8–17 using LPA identified profiles akin to those found in our study (Schepers et al., 2020). However, the youth study also revealed an additional profile, *stable negative mood*, distinguished by consistently high mean levels of negative affect. While the demographic and developmental characteristics of the two samples differ, it is notable that similar affective dynamic profiles emerge across study populations, suggesting some consistency in affective patterns. In addition, previous research exploring the interplay of affect dynamics and health outcomes has suggested that high

Table 5
Associations Between Covariates at Time 1 and Affect Profile Transition Probabilities From Time 1 to Time 2

Predictor and profile	Time 2: Stable positivity	Time 2: Moderately variable	Time 2: Highly variable negativity
Time 1			
Age			
Stable positivity	1.000 [1.000, 1.000]	**0.978 [0.957, 0.999]**	0.982 [0.955, 1.011]
Moderately variable	**1.023 [1.001, 1.045]**	1.000 [1.000, 1.000]	1.005 [0.981, 1.029]
Highly variable negativity	1.018 [0.989, 1.047]	0.995 [0.972, 1.019]	1.000 [1.000, 1.000]
Number of chronic conditions			
Stable positivity	1.000 [1.000, 1.000]	1.137 [0.977, 1.322]	**1.279 [1.092, 1.497]**
Moderately variable	0.880 [0.757, 1.023]	1.000 [1.000, 1.000]	**1.125 [1.032, 1.227]**
Highly variable negativity	**0.782 [0.668, 0.915]**	**0.889 [0.815, 0.969]**	1.000 [1.000, 1.000]

Note. The results indicate exponentiated multinomial logistic regression coefficients for predictors on transition probabilities. Estimates represent odds ratio [95% confidence intervals]; bolded values indicate significance at $p < .05$.

affective variability may have different health implications based on mean levels (e.g., Jenkins et al., 2023; Maciejewski et al., 2023). In particular, high affective variability could be maladaptive when combined with high mean PA or low mean NA, as fluctuations from desirable affective status signal disruption or a lack of affective regulation skills (fragile positive affect; Ong & Ram, 2017). Our findings urge the importance of further investigation into these individuals who exhibit high variability coupled with high PA or low NA, as these groups were underrepresented in our sample. Future studies need to replicate the current analyses on different study samples and expand on the nuanced roles of dynamic characteristics of fragile positive affect in shaping health and well-being.

While the proportions of individuals within each profile remained relatively consistent over time, the profiles demonstrated moderate stability, with 58%–68% of participants maintaining their initial profile classification over the 10-year period. These findings underscore the substantial variability in affective well-being in mid- to later life, as highlighted by the SAVI theory, which recognizes both the benefits of aging on affective well-being and the persistent vulnerabilities that contribute to individual differences (Charles, 2010). Although previous studies have reported an overall decreasing trend in affective variability with age (Le Vigouroux et al., 2022), our findings emphasize the importance of examining heterogeneous trajectories in affect rather than assuming a single, homogeneous developmental pathway. The observed shifting patterns among profiles further shed light on the dynamic nature of affective well-being over the life span, suggesting that individuals do not remain in a single profile but instead experience fluctuations. Notably, transitions were observed in both directions: from more stable profiles to less stable ones, and vice versa. For example, 42% of participants in the *stable positivity* profile at Time 1 transitioned to either the *moderately variable* or *highly variable negativity* profile at Time 2. In contrast, 18% of participants transitioned from the *moderately variable* to the *stable positivity* profile, and 39% moved from the *highly variable negativity* to the *moderately variable* profile. These transitions provide empirical support for the SAVI theory, which suggests that while age-related strengths in affective regulation and stability may emerge, vulnerabilities, such as heightened stress or contextual challenges, can lead to individual differences in these strengths (Charles, 2010; Charles & Piazza, 2024).

Our study also revealed the effects of sociodemographic characteristics, as well as mental and physical health factors, on profile membership and transition patterns. Findings suggest that individuals who were older at baseline were more likely to belong to the *stable positivity* profile compared to the other two profiles. In addition, older individuals at baseline were more likely to transition from the *moderately variable* to *stable positivity* profile, while being less likely to shift from the *stable positivity* to *moderately variable* profile over time. These findings again highlight the benefits of aging in the dynamic nature of affect, as evidenced by lower affective variability in older adults compared to younger adults (Brose et al., 2013, 2015; Röcke et al., 2009). The emotion regulation literature explicates that older adults often report better emotional control than younger adults (Gross et al., 1997; Urry & Gross, 2010) by selecting positive social contexts (Carstensen et al., 2003; Charles et al., 2009), focusing on positive information (Isaacowitz et al., 2008), and reappraising situations in constructive ways (Shiota & Levenson, 2009).

Moreover, greater mental and physical health challenges at baseline were associated with less likelihood of being in the *stable positivity* profile. Individuals with higher depressive symptoms at baseline were more likely to be in the *highly variable negativity* profile. Among individuals in the *highly variable negativity* profile at Time 1, those with a greater number of chronic conditions were less likely to transition to the *stable positivity* or *moderately variable* profile at Time 2. Rather, those with a greater number of chronic conditions were likely to transition to the *highly variable negativity* profile over time. These results suggest that not only age itself but also underlying factors, such as mental and physical health symptoms, play a critical role in shaping one's affective well-being. Previous findings indicate that individuals experiencing chronic illness or mental health problems exhibit less favorable affect and greater day-to-day fluctuations in their affective states (Houben et al., 2015; Kircher et al., 2023; Mukherjee et al., 2023; Peeters et al., 2006). Our results are consistent with these findings, reinforcing that aging is accompanied by health challenges that can disrupt one's daily life. This echoes the significance of further research into the mechanisms underlying these transitions. However, it is important to note that we did not examine the effects of different affective profiles on health outcomes. Emerging evidence suggests that affective variability, or reactivity to daily minor events, may have differential implications for health, depending on individuals' baseline affective states (Jenkins et al., 2023; Ong & Ram, 2017). Further, moderate levels of negative affective states or psychological distress sometimes reflect active coping and engagement with one's environment and high resilience, thus related to better health outcomes (Fredrickson, 2001; Rush et al., 2024). Therefore, researchers should be cautious to conclude that transitions to affective profiles with greater affective variability or higher NA mean levels necessarily result in negative health consequences based on the current findings. Future investigation should consider the interplay of psychological, physiological, and environmental factors that drive changes in affect dynamics trajectories, as well as their implications on long-term health.

It is also noteworthy that the associations among affect mean levels and variability varied between positive and negative affect in the present study. Several theoretical frameworks, such as the dual-continuum model of mental health (Keyes, 2002) and the dynamic model of affect (Zautra et al., 1997), highlight that positive and negative emotional processes occur through distinct systems and do not necessarily co-occur. In line with this perspective and with prior findings (e.g., Hardy & Segerstrom, 2017), our results show that the correlations between PA and NA mean levels were moderate and negative (rs = −.56, −.55), whereas the correlations between PA and NA variability were smaller and positive (rs = .40, .46). These patterns underscore that PA and NA are not merely opposites but rather separable yet partially dependent affective systems.

Further, NA variability was highly correlated with higher NA mean levels (rs = .77, .72) and lower PA mean levels (rs = −.47, −.46), suggesting that NA variability may reflect overall mood states and a broader pattern of emotional dysregulation. In contrast, PA variability exhibited weaker correlations with mean affect (rs = .24, .26 with NA; rs = −.25, −.32 with PA). In addition, consistent with previous studies (Hardy & Segerstrom, 2017), we also observed that PA variability was greater than NA variability, which may indicate that PA variability reflects different mechanisms that are more responsive to contextual factors, rather than reflecting one's personal characteristics. These findings may help explain the recent discussion that the predictive value of affective variability, especially NA variability, for health outcomes diminished once mean affect was adjusted (Dejonckheere et al., 2019). Importantly, these patterns were evident across different affective profiles we identified: in each profile, the associations among mean levels and variability and between PA and NA aligned with the broader correlational trends. That is, we did not identify affective profiles characterized by combinations, for instance, high PA and high NA mean levels or low PA and low NA mean levels. While our findings support the distinctiveness of PA and NA systems, we did not find nuanced evidence on when or how these systems operate independently in daily life. Future research may build on these findings by exploring whether identified profiles emerge consistently across diverse populations.

Findings from the present study need to be interpreted considering several limitations. First, we used two dynamic indicators of affect due to the limited number of daily diary assessments per individual. Previous studies suggest that with eight daily assessments, it may not be feasible to reliably measure dynamic indicators such as affective inertia (Reed et al., 2022). Future studies with a greater number of repeated assessments are needed to incorporate a broader range of affect dynamic indicators. Such designs would also enhance the ecological validity of the findings and reduce recall bias. Second, although the current data benefits from a large sample size and longitudinal daily diary assessments across extended periods, its generalizability is constrained by the sample's racial and socioeconomic homogeneity. The MIDUS sample predominantly consists of relatively healthy, White adults, which restricts the ability to draw conclusions across diverse populations. In addition, given the nature of longitudinal designs in studying an aging population, attrition may reflect the natural processes of aging or mortality, with healthier individuals or those experiencing fewer major life events being more likely to remain in the study over time. Moreover, as this is among the first studies to explore the heterogeneity in affect dynamic profiles, the profile labels in the present study represent relative distinctions rather than absolute cut-off points. Therefore, future research in more racially, ethnically, and socioeconomically diverse and more targeted samples is needed to enhance generalizability and to establish reference standards or normative thresholds for affect dynamics. Third, we only included covariates to examine their effects on profile membership and transitions. Future studies can consider concurrent longitudinal trajectories of more diverse covariates (e.g., changes in marital status) and affect dynamics, which will further elucidate their relationship over time. In addition, as noted in the previous study (Almeida et al., 2023), the effects of age on longitudinal changes in affect dynamics may differ across age groups. While the present study did not examine whether the benefits of aging on affective profiles and transitions between profiles vary by age, future research should expand this work to clarify whether the influences of aging on affect dynamics operate uniformly or vary across the adult lifespan. Last, methodologically, we employed a two-step approach, where affect dynamic indicators were calculated separately and subsequently used in further analyses. With advancements in computational power and methodological tools, future research should consider simultaneously modeling affect dynamic indicators within latent growth or mixture models (e.g., Feng & Hancock, 2024). This integrated approach could provide methodological and substantive insights into the dynamic interplay of affective processes.

Conclusion

Affect dynamics capture the time-dynamic fluctuating nature of affect that traditional one-time measures could not capture. The present study aimed to evaluate longitudinal profiles of affect dynamics across middle and later adulthood and their associated factors. By identifying three distinct dynamic profiles and their transition patterns, our findings underscore the nuanced trajectories of affect dynamics and individual differences in these patterns. While aging is associated with improved affective regulation and greater affective stability, factors such as mental and physical health challenges significantly impact affect dynamics trajectories over time. Our findings contribute to the growing body of literature that examines affect dynamics as critical indicators of health and well-being and offer empirical support for the socioemotional theories such as SAVI. Future studies should incorporate diverse samples, richer affect dynamic measurements, and advanced modeling techniques to further elucidate the mechanisms underlying the interplay of affect dynamics and their health implications throughout the lifespan.

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