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Bistability and Affect Shift Dynamics in the Prediction of Psychological Well-Being

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How affective experiences, such as feelings, emotions, and moods, fluctuate over time is relevant for understanding and predicting psychological well-being. Here, we present a novel approach to investigate affect dynamics grounded on the concept of multistability, a common behavior of complex systems, characterized by abrupt shifts between two or more stable states. We analyze self-report measures in two ecological momentary assessment studies from Spain ($N = 65$) and Germany ($N = 56$). Participants were asked to rate how they feel on a single bipolar visual analogue scale ranging from very bad to very good, 6 times a day over the course of 29 days in the Spanish study and 5 times a day during 21 days in the German study. We observe bistable behavior in 61.5% of the Spanish and 46% of the German sample. Further, we introduce a range of metrics to quantify the frequency and magnitude of shifts between positive and negative affect and identify the positive to negative affect shift ratio as a robust predictor of psychological well-being. Our results suggest that affective bistability is a prevalent feature of affect dynamics and highlight the potential of positive to negative affect shift ratio as a valuable tool for predicting psychological well-being both in research and clinical settings.

Keywords: affect dynamics, bistability, psychological well-being, affect shift ratio, ecological momentary assessment

One of the defining characteristics of affective experiences is their fleeting nature. Emotions, feelings, and moods can quickly shift in response to external events or internal regulatory processes. The dynamic nature of affect has prompted extensive research on the relationship between patterns of moment-to-moment affective changes and psychological well-being. Indeed, a meta-analysis of 79 related studies, involving 11,381 participants, revealed that certain measures of affect dynamics, such as variability, instability, and inertia, can effectively predict psychological flourishing and well-being (Houben et al., 2015).

Beyond their transitory character, another core attribute lying at the heart of all affective phenomena is their hedonic tone, or *valence* (Dukes et al., 2021). Valence captures the extent to which affective experiences are perceived as pleasant or unpleasant, good or bad.

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This evaluative notion of valence has been termed the "heat of emotion" (Charland, 2005) that gives experiences their subjective color and allows us to interact with the world in a meaningful way (Russell, 2003). Valence, therefore, facilitates the classification of affective phenomena, whether a concrete emotion, a fleeting feeling, or a more enduring mood, into either one of two distinct states: pleasant, referred to as positive affect (PA), and unpleasant, commonly known as negative affect (NA).[1]

The delineation of affect into two distinctive states allows for drawing parallels with other complex natural systems characterized by the coexistence of multiple stable states (Feudel, 2008). Multistability signifies that a system can exist in two or more usually contrasting states under the same conditions, where abrupt transitions from one stable state to the other can occur (Scheffer & Carpenter, 2003; Scheffer et al., 2001). For example, lakes can undergo sudden shifts between clear and turbid water states (Scheffer & van Nes, 2007), while tropical forests can rapidly transform into savannas (Hirota et al., 2011). In Figure 1a, we illustrate multistable behavior through the stability landscape of a system (e.g., a lake) that features two distinct states, represented as balls (clear or turbid water states) in two separate valleys corresponding to the basins of attraction for each state. The hilltop that divides the two valleys marks the threshold that, once crossed, triggers a tipping event causing a shift from one state to the other. The depth of each basin of attraction depicts the energy required for the system to reach the tipping point and shift to the alternative state. Empirically, it is possible to reconstruct a probabilistic stability landscape by assuming that the observed system state is the result of the system having visited most parts of its true stability landscape. The stability landscape can then be inferred through the dominant modes of the probability density of the system states (Dakos & Kéfi, 2022). In Figure 1a, the system is confined to one of the two alternate states, resulting in two deep wells and a steep tipping point. However, in Figure 1b, we observe that the system also explores the regions between the two wells, resulting in reduced stability for state A. Despite exhibiting characteristics of State A (turbid water), this behavior is less stable, making it easier for the system to transition to State B (clear water).

Drawing on this framework, it is possible to hypothesize that human affect may exhibit bistable behavior characterized by abrupt shifts between more than one stable state, in this case PA and NA. Intuitively, this would mean that individuals may not continuously traverse the full spectrum of emotional states but rather tend to remain within preferred regions of positive or negative affect. External or internal conditions—such as significant life events or changes in personal health—can then exert sufficient pressure to induce sudden transitions, moving a person abruptly from their customary region in one state to a preferred region in the opposite state. This hypothesis is not entirely new. van de Leemput et al. (2014) provided initial evidence for transitions between depressed and normal states, and Houben, Vansteelandt, et al. (2016) coined the term "emotional switching" to describe the phenomenon of transitioning between PA and NA, using regression models to estimate both switching propensity (the likelihood of a switch occurring) and magnitude (the distance between adjacent measurement occasions when a switch occurs). In a later study, they extended this idea by investigating the specificity of emotional switching in borderline personality disorder (Houben, Bohus, et al., 2016), while two other relevant studies focused on the moderator effect of mindfulness (Keng & Tong, 2016; Rowland et al., 2020).

Despite initial empirical evidence suggesting that affective shifting may be a relevant feature of affective experiences, the phenomenon of bistability, indicated by the presence of attractor basins in both positive and negative affect, has not been properly investigated. In a recent study, Haslbeck et al. (2023) identified a high prevalence of multimodality in the intensity distributions of distinct emotions (e.g., happy, excited, angry, anxious, etc), which, as explained earlier, can be used to infer bistable (two modes) or multistable (more than two modes) behavior. However, this apparent multistability within concrete emotions differs from the operationalization of bistability between PA and NA that we propose here. In addition, although the propensity and magnitude of shifts between PA and NA has been statistically inferred through regression models, no concrete indices of transitions between affective states have been proposed or tested in predicting psychological well-being.

In this study, we explore the prevalence of bistability between PA and NA and investigate whether bistable behavior and key characteristics of transitions between affective states can be used to predict psychological well-being. To test these hypotheses, we analyze data sets from two distinct ecological momentary assessment (EMA) studies. The first study includes a sample from the general Spanish population (N = 65), in which participants reported their subjective feelings 6 times a day over a period of 29 days. The second study involves undergraduate university students in Marburg, Germany (N = 56), who reported their subjective feelings 5 times a day for 21 days. After determining and codifying the presence of bistability in each data set, we develop three categories of metrics, the affect shift ratio (ASR), residence time (RT), and affect shift magnitude (ASM), to quantify the information conveyed by transitions between affective states. We evaluate the predictive validity of the presence of bistability and affect shift characteristics in relation to established predictors of psychological well-being, such as the within-person mean and standard deviation of PA and NA, which were found to have superior predictive power compared to more elaborate, time-dependent measures of affect (Dejonckheere et al., 2019).

Method

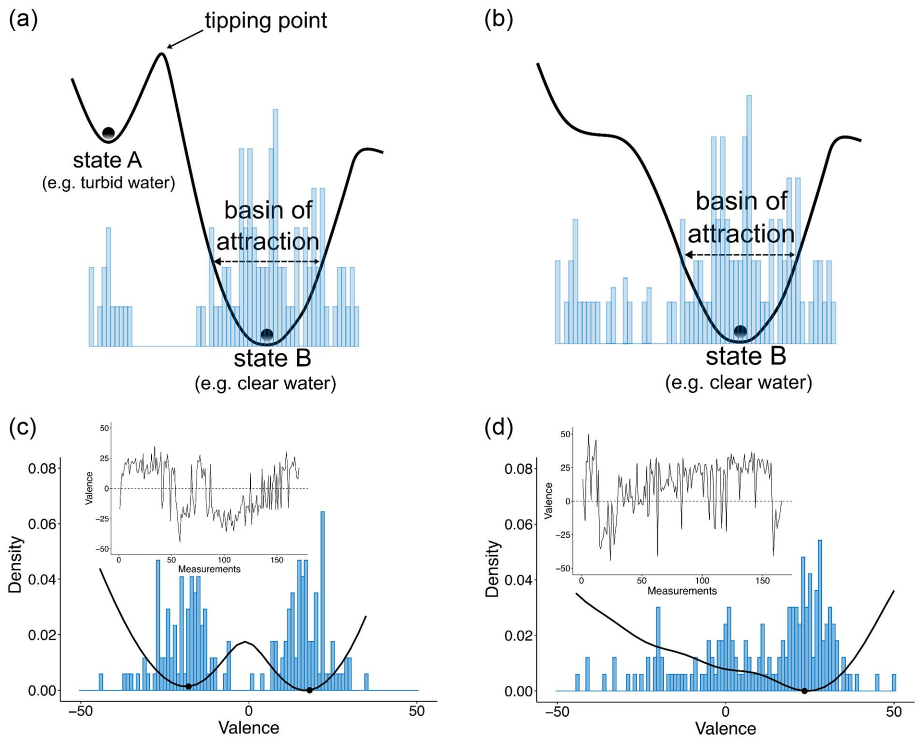
Participants

To test our research hypotheses, we analyzed data from two EMA studies, hereafter referred to as the Spanish study (Study 1) and the German study (Study 2). Both studies were approved by the ethics committees of their respective institutions: the Human Research Ethics Committee of the University of Granada in Spain (Reference: 2214/CEIH/2021) and the Department of Psychology of the Philipps-University of Marburg in Germany (Reference: 2022-22v). All participants provided informed consent after receiving complete information about the studies. Table 1 presents a detailed

[1] Note that in this study we use the term PA to refer to all positively valenced affective states (e.g., excited, relaxed, happy) and NA to encompass all negatively valenced states (e.g., distressed, sluggish, sad). This is in line with the circumplex model of affect (Russell, 1980), but contrasts with the way PA and NA are conceptualized in the rotated circumplex model by Watson and Tellegen (1985), where PA ranges from high activation, positive valence (e.g., excited) to low activation, negative valence (e.g., sluggish), and NA ranges from high activation, negative valence (e.g., distressed) to low activation, positive valence (e.g., relaxed). For a recent discussion on the pervasiveness of misunderstandings related to this issue, see (LaRowe et al., 2024).

Figure 1

Illustration of Bistability and Representative Stability Landscapes for a Bistable and a Monostable Participant



Note. Panel a: Reconstruction of the hypothetical stability landscape of a lake using the histogram of the empirical observations of a single variable (e.g., water transparency). The system's two distinct states are represented by basins of attraction. The depth of a basin indicates the "energy" required to reach the tipping point and transition to a different state. Panel b: An alternative stability landscape generated by the same generic model with parameter variations, allowing for intermediate levels of water transparency and resulting in a monostable system with reduced stability in State A. Panels c and d: Representative examples of valence time series and distributions used to reconstruct the stability landscape of a bistable (Panel c) and a positive-monostable (Panel d) participant from the Spanish study. Despite the monostable characterization, the monostable participant still exhibits transitions between affective states, albeit with a single basin of attraction in the positive affect regime. In the Spanish Study, 61.5% of participants were classified as bistable, compared to 46% in the German study. Notably, 96.7% of all participants experienced transitions between positive and negative affect, indicating the prevalence of affect shifts across the sample. See the online article for the color version of this figure.

summary of each data set, including participant information, EMA protocol, and available well-being indicators. Additional information on the assessment protocols of both studies, descriptive statistics, and distribution plots for each well-being indicator are available in the additional online material (https://osf.io/xqm84/).

The initial sample size of 103 participants in the Spanish study, determined by funding constraints, was reduced to 65 after data preprocessing (see relevant section). Participants were recruited by a survey company (QUANTICA Marketing Research) to represent the Spanish population based on gender, age, location, and annual income. Inclusion criteria were being over 18 years of age and an Android user, as the custom app used for data collection was only available on this operating system. Data were collected between November 16 and December 14, 2021.

The German study involved 56 participants from Germany, recruited through the online portal used by the Department of Psychology at the Philipps-University of Marburg, as well as flyers and posters displayed on the university campus. The sample size was determined by the time frame for recruitment based on the availability and resources of the research team. Participants were required to be over 18 years of age and either native German speakers or possess native-level German language proficiency, since the questionnaires were presented in German. Data were collected between September 14 and December 8, 2022.

Despite the lack of sufficient empirical data to calculate power requirements for our novel affect shift metrics, recently published power curves for the measure of average affect recommend 100 participants with 50 measurements per participant to detect a .3 correlation at the 0.05 significance level (Pirla et al., 2023). Although our sample size is smaller, the substantial increase in measurement frequency in our data sets likely offsets this limitation, suggesting that our study maintains adequate power to detect meaningful correlations.

Table 1
Summary of the Studies

	Participant				EMA protocol		Well-being indicator					
Study	*N*	Female %	Age	Bistable %	Day	Occasion	Life satisfaction	Resilience	Flourishing	Depression symptoms	Anxiety symptoms	Psychological inflexibility
1. Spanish	65	48	44.1 ± 17 (18–69)	61.5	29	6	SWLS.1	BRS	FS	PHQ-9	GAD-7	AAQ-II
2. German	56	79	23.9 ± 2.7 (19–32)	46.0	21	5	SWLS	BRS		DASS-21 (depression)	DASS-21 (anxiety)	AAQ-II

Note. EMA = ecological momentary assessment; SWLS.1 = one-item Satisfaction with Life Scale; SWLS = Satisfaction with Life Scale; BRS = Brief Resilience Scale; FS = Flourishing Scale; PHQ-9 = Patient Health Questionnaire–9; DASS-21 = Depression, Anxiety and Stress Scale–21; GAD-7 = Generalized Anxiety Disorder Scale–7; AAQ-II = Acceptance and Action Questionnaire–II.

Affect Measures

In both EMA studies included in our analysis, valence, a primary dimension of affect referring to the pervasive subjective experience underlying any emotionally charged episode and consisting simply of feeling good or bad (Russell, 1980), was assessed via the prompt "How do you feel right now?" using a single bipolar visual analogue scale ranging from −50 (*very bad*) to +50 (*very good*). There is ample theoretical agreement and empirical support that a single-item bipolar scale is an efficient measure to study the intraindividual dynamic patterns of momentary affect (Cloos et al., 2023) and the most appropriate to accurately and fully describe the valence of individuals at any given moment (Russell, 2017; Russell & Carroll, 1999; Watson & Tellegen, 1999).

This measurement approach, also used by Houben, Vansteelandt, et al. (2016) to assess "emotional switching," facilitates the direct detection of transitions between PA and NA, identified as crossings of the zero (neutral) point. In contrast, methods that infer PA and NA through the experience of distinct emotions previously labeled as positive or negative, for example, Houben, Bohus, et al. (2016), require an additional analytical step to deduce the overall affect state by subtracting NA from PA. This involves an extra layer of analysis, which can potentially obscure the immediate experience and detection of affect shifts.

The within-person mean and standard deviation PA and NA were obtained from the valence variable by separately averaging all positive and negative valence values, respectively. These two parameters were chosen as benchmarks based on the results of the meta-analysis by Dejonckheere et al. (2019). However, in the additional online material (https://osf.io/xqm84/), we include additional analyses that include the inertia and instability parameters as the two most prevalent time-dependent measures of affect in the literature. Due to their time-dependent nature, inertia (measured as the autocorrelation coefficient) and instability (measured as the root-mean-square of successive differences) were estimated after a linear interpolation of missing values for the entire range of the valence variable and not separately for PA and NA.

In both studies, participants were prompted to answer multiple questions using similar visual scales. However, for the purposes of this study, only the valence scale was analyzed, while responses to other questions served as a means to verify compliance with the protocol (refer to the Data Preprocessing section for more information).

Psychological Well-Being Indicators

We investigated the predictive value of the presence of bistability and affect shift metrics on six indicators of psychological well-being, five of which were common in the two studies (see Table 1). These indicators encompass both positive and negative aspects of well-being, including measures of life satisfaction, resilience, and flourishing (positive), as well as symptoms of depression, anxiety, and psychological inflexibility (negative).

Life Satisfaction

Two different instruments were used to assess people's perceived life satisfaction.

Satisfaction With Life Scale. The German study used the Satisfaction with Life Scale (SWLS; Diener et al., 1985), which includes five statements (e.g., "In most ways my life is close to my ideal") that participants rate based on their level of agreement, in a range from 1 (*strongly disagree*) to 7 (*strongly agree*). Cronbach's α was .82.

Single-Item. The Spanish study used a single-item life satisfaction scale ("In general, how satisfied are you with your life?") ranging from 1 (*very dissatisfied*) to 4 (*very satisfied*), which has been found to have comparable performance to the SWLS scale (Cheung & Lucas, 2014).

Resilience

Resilience, understood as the ability to recover from stress, was assessed in both studies by the Brief Resilience Scale (Smith et al., 2008). This questionnaire consists of six statements (e.g., "I tend to bounce back quickly after hard times") that participants rate based on their level of agreement, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Cronbach's α was .72 in the Spanish study and .85 in the German study.

Flourishing

Flourishing, the eudaimonic aspect of well-being understood as the self-perceived success in important areas such as relationships, self-esteem, purpose, and optimism, was assessed in the Spanish study by the Flourishing Scale (Diener et al., 2010). This self-report instrument includes eight items (e.g., "I lead a purposeful and meaningful life" or "My social relationships are supportive and rewarding"), ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Cronbach's α was .91.

Depression Symptoms

Two different continuous scales were used to assess participants' depression symptom levels. In the Spanish study, 27.69% of participants showed significant symptoms of depression (Patient Health Questionnaire ≥ 10), while in the German study, it was 10.71% (Depression subscale of the Depression, Anxiety and Stress Scale ≥ 7).

Patient Health Questionnaire–9. The Spanish study used the Patient Health Questionnaire (Kroenke et al., 2001), which assesses the frequency of nine prominent depression symptoms experienced over the last 2 weeks (e.g., "Feeling down, depressed, or hopeless"). Item scales range from 0 (*not at all*) to 3 (*nearly every day*). Cronbach's α was .87.

Depression, Anxiety and Stress Scales–21 (Depression). The German study used the depression subscale of the Depression, Anxiety and Stress Scales (DASS-21; Lovibond & Lovibond, 1995), which consists of seven items (e.g., "I felt down-hearted and blue") and is scored on a range from 0 (*not at all*) to 3 (*very much or most of the time*). Cronbach's α was .81.

Anxiety Symptoms

Two distinct instruments were used to assess participants' anxiety symptom levels. Significant symptoms of anxiety (Generalized Anxiety Disorder Scale ≥ 10) were indicated by 21.53% of the participants in the Spanish study, compared with 17.85% in the German study (Anxiety subscale of the Depression, Anxiety and Stress Scale ≥ 5).

Generalized Anxiety Disorder Scale–7. The Spanish study used the Generalized Anxiety Disorder Scale–7 (Spitzer et al., 2006), which is a seven-item screening tool for general anxiety symptoms in diverse settings and populations. Each item is a statement about the presence of bothersome anxiety-related symptoms during the last 2 weeks (e.g., "Not being able to stop or control worrying"). Item scales range from 0 (*not at all*) to 3 (*nearly every day*). Cronbach's α was .91.

Depression, Anxiety and Stress Scales–21 (Anxiety). The German study used the anxiety subscale of the DASS-21 (Lovibond & Lovibond, 1995), which consists of seven items (e.g., "I felt scared without any good reason") and is scored on a range from 0 (*not at all*) to 3 (*very much or most of the time*). Cronbach's α was .64.

Psychological Inflexibility

Psychological inflexibility refers to the level of experiential avoidance and was assessed in both studies by Acceptance and Action Questionnaire–II (Bond et al., 2011). This questionnaire has seven statements (e.g., "I worry about not being able to control my worries and feelings") that are rated from 1 (*never true*) to 7 (*always true*). Cronbach's α was .95 in the Spanish study and .89 in the German study.

Data Preprocessing

To ensure the quality of the affect data, we performed a series of preprocessing steps on both data sets. First, we replaced all measurement occasions where a participant left the default response options ("0" in Spanish study and "50" in the German study) on all visual analogue scales with missing values. We considered these cases to have a high probability of being invalid measurements, as it is highly likely that participants did not make a genuine effort to respond accurately to the questions. This resulted in the replacement with missing values of 356 measurement occasions in the Spanish data set and 35 in the German data set. Next, we excluded participants who showed poor compliance with the EMA protocol. Specifically, we removed participants with less than 75% of measurement occasions completed.[2] This resulted in the exclusion of 32 participants from the initial 103 in the Spanish data set and 0 participants in the German data set. Next, we excluded participants with 20 or more consecutive measurement occasions (equivalent to over 3 days in the Spanish sample and 4 days in the German sample) recording extreme values (–50, 50) or no measurement at all, assuming that such patterns indicated a lack of sincere commitment to the task. This criterion led to the exclusion of another six participants in the Spanish study and 0 participants in the German study. Finally, four participants were excluded from the initial 60 participants of the German study because they failed to properly respond to a survey item that served as a validation check. The remaining 65 participants of the Spanish study had a mean compliance

[2] To ensure that our results are robust to this criterion, we repeated the main analyses (bistability prevalence and least absolute shrinkage and selection operator [LASSO] regressions) for a less strict threshold (65%). In the additional online material (https://osf.io/xqm84/), we provide tables with regression coefficients for this different exclusion threshold.

rate of 90% (SD = 6%), and the remaining 56 participants of the German study had a mean compliance rate of 94% (SD = 5%).

Data Analyses

To account for the differences in the EMA protocols between the two studies (see Table 1), most analyses were conducted separately for each data set. The second data set (German study) was thus used as a replication to validate the findings and enhance the robustness of the conclusions.

Prevalence of Bistability

To address the prevalence of bistability in the two data sets, we reconstructed the probabilistic stability landscape of each participant using potential analysis (Livina et al., 2010) that is based on fitting a polynomial function to the probability density of individual valence time series. We used the *liv_potential()* function of the *earlywarnings* package in R to carry out this analysis. Next, we identified attractor basins as local minima of the fitted potential using a sliding window approach. For each data point, we selected a window spanning three adjacent samples centered at that point and identified the minimum value within that window. A data point was considered a local minimum if its value was smaller than all other values within the window. Participants were classified as "bistable" if at least one local minimum was found in each of the two affective regimes (PA and NA). Nonbistable participants fell under four distinct categories: "positive-monostable," if they presented only one minimum in the PA regime; "negative-monostable," with one minimum in the NA regime; "positive-multistable," if they exhibited more than one minima only in the PA regime; and "negative-multistable," if they displayed more than one minima only in the NA regime. To test the predictive validity of bistability in relation to psychological well-being, we constructed the index "type," which was treated as a categorical variable with two levels: 0 = nonbistable and 1 = bistable. Therefore, the coefficient associated with "type" in the LASSO regression reflects the differential effect of being bistable compared to nonbistable.

The effect of the window size parameter can be appreciated by a visual inspection of the valence probability density of participant number 5 (participant ID = 5), available in the additional online material (https://osf.io/xqm84/). In this participant, the default window size of three samples identifies a local minimum in the NA range, leading to a classification of the participant as "bistable." However, increasing the window size to five samples alters this interpretation, as the same data point no longer constitutes a local minimum, thereby classifying the participant as "monostable." Intuitively, one may argue that visiting the NA regime only a few times during the duration of the study is not sufficient evidence for the existence of a basin of attraction and could rather be regarded as an anomalous deviation from a unique stable state in the PA regime. Since there is inevitably a subjective element on how much evidence is required to identify a basin of attraction in the context of affect dynamics, we repeated our analyses for a window spanning five adjacent samples to account for this more conservative approach. This dropped the prevalence of bistability from 61.5% to 49.2% in the Spanish study and from 46% to 38% in the German study (see Results section).

Development of Affect Shift Metrics

We developed 10 metrics to quantify the frequency and magnitude characteristics of affect transitions for each participant. The labels, substantive descriptions, and mathematical equations for each of these metrics are listed in Table 2.

Reliability Tests

We estimated the reliability of the new affect shift metrics by calculating correlation coefficients between the first and second halves of our data sets. Most of the novel metrics demonstrated significant correlations, indicating robust internal consistency and reliability across different time intervals. The tables with the correlation coefficients and p values for each data set are included in the additional online material (https://osf.io/xqm84/).

Empirical Interdependencies

We conducted a principal component analysis (PCA) to investigate the commonalities between the affect shift metrics and understand the degree to which they represent distinct affect dimensions. Prior to the analysis, we merged the two data sets and assessed the data's suitability for PCA using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, Bartlett's test of sphericity, and the determinant of the correlation matrix to ensure adequate sample size, nonidentity, and absence of multicollinearity, respectively. The data passed all validation checks: KMO overall measure of sampling adequacy = 0.71; Bartlett's test $p < .001$; determinant correlation matrix >0.0001. We used the functions *KMO()* and *cortest.bartlett()* from the R package *psych* and the function *det()* from R's *base* package to conduct these data checks. We then used the *principal()* function from the *psych* package to perform a PCA with two factors and employed an oblique (oblimin) rotation to examine the correlation between dimensions. The analysis was executed with both scaling and centering of the data. To identify the overlap between the affect shift metrics and the within-person mean and standard deviation values of PA and NA, we computed a correlation matrix using Pearson correlations.

Explanatory Power in the Prediction of Psychological Well-Being

To determine the optimal combination of a large set of predictors, we performed a LASSO regression for each well-being indicator available in the two data sets. LASSO regression is a regularization technique that employs a penalty term to the sum of absolute values of the coefficients, which shrinks some coefficient estimates toward zero, thereby reducing model complexity and guarding against overfitting. This method has the added benefit of providing a degree of protection against Type I error by performing variable selection and reducing the chances of including irrelevant predictors in the model. We used the *caret* R package for performing a tenfold cross-validation to estimate the optimal lambda value (the tuning parameter), which minimizes the mean cross-validated error. With the optimal lambda value, we then used the *glmnet* package in R to fit the LASSO regression model to our data, allowing us to identify the most relevant predictors and their associated regression coefficients.

Table 2
Overview of Affect Shift Metrics

Metric (abbreviation)	Substantive description	Mathematical equation
1. Positive to negative affect shift ratio (P2N-ASR)	Ratio of transitions from PA to NA in relation to the total number of measurement occasions of PA.	$\text{P2N-ASR}_j = \frac{\sum_{t=1}^{T_j-1} \mathbb{I}(V_{jt}>0 \text{ and } V_{jt+1}<0)}{\sum_{t=1}^{T_j} \mathbb{I}(V_{jt}>0)}$
2. Negative to positive affect shift ratio (N2P-ASR)	Ratio of transitions from NA to PA in relation to the total number of measurement occasions of NA.	$\text{N2P-ASR}_j = \frac{\sum_{t=1}^{T_j-1} \mathbb{I}(V_{jt}<0 \text{ and } V_{jt+1}>0)}{\sum_{t=1}^{T_j} \mathbb{I}(V_{jt}<0)}$
3. Mean positive residence time (mPRT)	Average duration of consecutive PA measurement occasions.	$\text{mPRT}_j = \frac{1}{\text{TPAseq}_j} \sum_{i=1}^{\text{TPAseq}_j} d\text{PAseq}_{ij}$
4. Standard deviation positive residence time (sdPRT)	Average deviation from the mean duration of consecutive PA measurement occasions.	$\text{sdPRT}_j = \sqrt{\frac{1}{\text{TPAseq}_j} \sum_{i=1}^{\text{TPAseq}_j} (d\text{PAseq}_{ij} - \text{mPRT})^2}$
5. Mean negative residence time (mNRT)	Average duration of consecutive NA measurement occasions.	$\text{mNRT}_j = \frac{1}{\text{TNAseq}_j} \sum_{i=1}^{\text{TNAseq}_j} d\text{NAseq}_{ij}$
6. Standard deviation negative residence time (sdNRT)	Average deviation from the mean duration of consecutive NA measurement occasions.	$\text{sdNRT}_j = \sqrt{\frac{1}{\text{TNAseq}_j} \sum_{i=1}^{\text{TNAseq}_j} (d\text{NAseq}_{ij} - \text{mNRT})^2}$
7. Mean positive to negative affect shift magnitude (mP2N-ASM)	Average magnitude of transitions from PA to NA.	$\text{mP2N-ASM}_j = \frac{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}>0 \text{ and } V_{jt+1}<0)\cdot\lvert V_{jt}-V_{jt+1}\rvert}{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}>0 \text{ and } V_{jt+1}<0)}$
8. Standard deviation positive to negative affect shift magnitude (sdP2N-ASM)	Average deviation from the mean magnitude of transitions from PA to NA.	$\text{sdP2N-ASM}_j = \sqrt{\frac{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}>0 \text{ and } V_{jt+1}<0)\cdot(\lvert V_{jt}-V_{jt+1}\rvert - \text{mP2N-ASM}_j)^2}{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}>0 \text{ and } V_{jt+1}<0)}}$
9. Mean negative to positive affect shift magnitude (mN2P-ASM)	Average magnitude of transitions from NA to PA.	$\text{mN2P-ASM}_j = \frac{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}<0 \text{ and } V_{jt+1}>0)\cdot\lvert V_{jt}-V_{jt+1}\rvert}{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}<0 \text{ and } V_{jt+1}>0)}$
10. Standard deviation negative to positive affect shift magnitude (sdN2P-ASM)	Average deviation from the mean magnitude of transitions from NA to PA.	$\text{sdN2P-ASM}_j = \sqrt{\frac{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}<0 \text{ and } V_{jt+1}>0)\cdot(\lvert V_{jt}-V_{jt+1}\rvert - \text{mP2N-ASM}_j)^2}{\sum_{t=1}^{T-1} \mathbb{I}(V_{jt}<0 \text{ and } V_{jt+1}>0)}}$

Note. PA = positive affect; NA = negative affect; T = total number of measurement occasions; t = specific measurement occasion; V = valence vector; $I(P)$ = index function that takes the value of 1 if statement P is true and 0 if P is false; TPAseq = total number of PA sequences; TNAseq = total number of NA sequences; i = specific PA or NA sequence; j = participant index; dPAseq = duration (in measurement occasions) of PA sequence; dNAseq = duration (in measurement occasions) of NA sequence.

In addition to the LASSO regression, we also carried out a stepwise multiple regression to support the results obtained from the LASSO regressions and to ensure that our findings are robust across different variable selection techniques. In our analysis, we used the Akaike information criterion, available through the *stepAIC()* function in the *MASS* package in R, to guide the selection process. We considered both forward and backward steps, allowing variables to be added or removed from the model at each iteration.

Finally, we assessed the relative importance of predictor variables by calculating the Lindeman–Merenda–Gold metric (Sen et al., 1981), available through the *relaimpo* R package, which estimates the average contribution of each predictor variable to the explained variance when considering all possible orderings of the variables in the model. By normalizing the contributions, we obtained the relative importance of each predictor expressed as a percentage, indicating the proportion of the total explained variance attributed to each variable.

Transparency and Openness

The Methods section provides detailed information on the selection of the sample and the criteria for data exclusion. This study is exploratory in nature and was not preregistered. The sample sizes for the Spanish and German EMA studies were determined by budget constraints and the maximum recruitment achievable within a set period, respectively. All statistical analyses were performed using open packages and custom scripts in R (Version 4.3.1). The data and software code necessary to reproduce the results presented in this article are available on the project website on the Open Science Framework repository (Perakakis et al., 2024). Additional measures were collected for each sample but are not included in this report, as they fall outside the scope of the current research.

Results

Prevalence of Bistability in Affect Dynamics

To examine whether affect dynamics are characterized by bistability, we reconstructed the probabilistic stability landscape of each participant by fitting a polynomial function to the probability density of individual valence time series and identifying its local minima. Participants were classified as "bistable" if at least one local minimum was found in each of the two affect regimes (PA and NA).

In the Spanish study, we classified 61.5% participants as "bistable," 18.5% as "positive-monostable," 18.5% as "positive-multistable," and 1.5% as "negative-multistable." The German study showed a slightly lower prevalence of bistability, with 46% of participants classified as "bistable," 39% as "positive-monostable," 5% as "negative-monostable," 7% as "positive-multistable," while one participant (PID = 128) was classified as "undefined" due to the absence of identifiable local minima in the potential analysis. As discussed in the Methods section, we repeated this analysis for a more conservative criterion (5-sample window size), which dropped the prevalence of bistability from 61.5% to 49.2% in the Spanish study and from 46% to 38% in the German Study. Figure 1c and 1d provide examples of time series, distributions, and energy functions for a "bistable" and a "positive-monostable" participant from the Spanish Study, respectively. Interestingly, we observed that the absence of bistability does not indicate a lack of affect shifts between positive and negative affect. In fact, 117 out of 121 participants (96.7%) in both studies experienced at least one affect shift from one affective regime to the other. For a comprehensive view of the individual plots for all participants, please refer to the additional online material (https://osf.io/xqm84/).

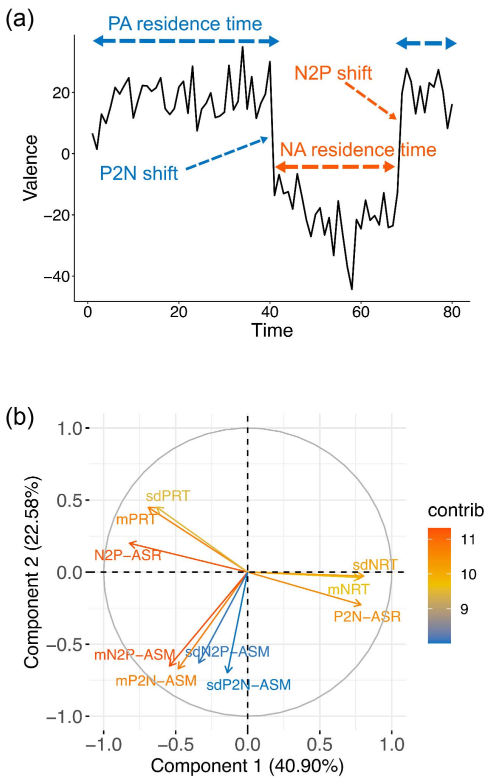
Measuring Affect Shift Dynamics

In addition to identifying the prevalence of bistable behavior, our second objective was to develop quantitative indices of transitions between the primary affective states. We first introduced the ASR as the ratio of shifts between PA and NA. This ratio can be calculated separately for PA to NA and NA to PA shifts, yielding two distinct metrics: P2N-ASR and N2P-ASR. Intuitively, these indices quantify the propensity for affective transitions between successive measurements. Specifically, the P2N-ASR is calculated by dividing the total count of PA to NA shifts by the total samples in PA, indicating the likelihood that PA will shift to NA in the next measurement occasion. Conversely, the N2P-ASR is derived by dividing the total count of NA to PA shifts by the total samples in NA, reflecting the probability that NA will transition to PA in the next measurement instance. Both indices range from 0 to 1, where 0 signifies no possibility of a transition and 1 denotes a certain transition. Our second index quantified the mean duration an individual remains in a given affective state before experiencing a shift to the alternative affective state. We called this the mean positive or negative residence time (mPRT or mNRT) and also calculated its standard deviation positive or negative residence time (sdPRT or sdNRT). Last, we devised an index to capture the mean and standard deviation of the ASM, producing another four metrics: mP2N-ASM, sdP2N-ASM, mN2P-ASM, sdN2P-ASM. Table 2 presents an overview of these metrics, including substantive descriptions and mathematical equations, while Figure 2a illustrates the rationale for their construction.

To investigate the potential overlap between the affect shift metrics and to determine whether they express different dimensions of affect dynamics, we merged the two data sets and conducted a PCA that included the six time-related metrics (P2N-ASR, N2P-ASR, mPRT, sdPRT, mNRT, sdNRT) and the four magnitude-related metrics (mP2N, sdP2N, mN2P, sdN2P). The two first PCA axes accounted for 63.48% of the total variance with time-related metrics loaded onto the first component and magnitude-related metrics loaded onto the second component (Figure 2b). Despite finding significant correlations between metrics loaded onto the same component, the low correlation between components ($r = 0.18$) indicates that our affect shift metrics indeed quantify two distinct aspects of affect dynamics, one related to the frequency and the other to the magnitude of shifts between affective states.

Next, we asked how affect shift dynamics relate to the two affect measures most predictive of psychological well-being, the within-person mean and standard deviation of PA and NA, as well as two widely studied time-dependent measures, inertia and instability. Mean PA showed a negative correlation with P2N-ASR ($r = -0.53$) and a positive correlation with N2P-ASR ($r = 0.50$). This implies that, in our sample, individuals with higher average PA are less prone to shift from PA to NA and, when such transitions occur, they are more likely to shift back to PA. Similarly, mean PA also correlated negatively with the mean and standard deviation residence time in NA (mNRT: $r = -0.35$; sdNRT: $r = -0.39$), implying again that individuals with higher average PA levels tend to "escape" sooner from the NA regime and to experience less variability in the time spent in this affective state. Regarding the average magnitude of

Figure 2
Affect Shift Metrics



Note. Panel a: Illustration of the components of a valence time series used to derive the affect shift metrics. Blue double-arrow dashed lines represent consecutive measurement occurrences within the positive affect (PA) regime, which are averaged to produce the mean and standard deviation positive residence time (mPRT and sdPRT). Similarly, a red double-arrow dashed line indicates an instance of consecutive measurement occurrences within the negative affect (NA) regime, used to calculate the mNRT and sdNRT. A blue single-arrow dashed line indicates a shift from positive to negative (P2N) affect. The total number of such shifts is divided by the total number of measurement occurrences in the PA regime to calculate the P2N affect shift ratio (P2N-ASR). The distances between two consecutive measurements when P2N shifts occur are averaged to calculate the mean and standard deviation of the P2N affect shift magnitude (mP2N-ASM and sdP2N-ASM). Likewise, a red single-arrow dashed line marks a negative to positive (N2P) shift, which is used to calculate the corresponding N2P-ASR and N2P-ASM metrics. Panel b: Principal component analysis demonstrating the separation of time-related (ASR and RT) and magnitude-related (ASM) metrics, accounting for 63.48% of the total variance. N2P-ASR = negative to positive affect shift magnitude; mNRT = mean negative residence time; sdNRT = standard deviation negative residence time; mN2P-ASM = mean negative to positive affect shift magnitude; sdN2P-ASM = standard deviation negative to positive affect shift magnitude; RT = Residence Time. See the online article for the color version of this figure.

affect shifts, mP2N and mN2P were both positively correlated with mean PA ($r = 0.73$, $r = 0.75$, respectively), alluding that individuals with larger affect shifts in both directions tend to have higher average levels of PA. These correlations can be understood intuitively if we consider that a higher mean PA generally implies more intense positive emotions. Consequently, a shift to NA would require a larger change in affective state, as the starting point in PA is further away from the NA regime.

Inertia correlated positively with mNRT ($r = 0.40$) and negatively with N2P-ASR ($r = -0.63$), which further supports its association with psychological maladaptiveness, suggesting a tendency to become entrenched in negative affective states. Instability on the other hand was positively related to sdP2N-ASM ($r = 0.55$), indicating an increased variability in the magnitude of P2N transitions. In the additional online material (https://osf.io/xqm84/), we provide a correlogram with these correlation coefficients which were all statistically significant at the $p < .001$ level.

Inferring Well-Being From Bistability and Affect Shift Metrics

We tested whether bistability and affect shift metrics could be used to predict a range of well-being indicators indexed in Table 1. To determine the optimal combination of stability and affect metrics for each well-being indicator, we conducted a series of LASSO regression analyses. The models included stability type (bistable or nonbistable) and all novel affect shift metrics together with the within-person mean and standard deviation of PA and NA, two well-established predictors of psychological well-being. The P2N-ASR metric, which quantifies the ratio of positive to negative affect transitions, emerged as a particularly important predictor, as it presented the highest coefficient in most well-being indicators across both studies. The LASSO coefficients, displayed in Table 3, reveal that a higher ratio of positive to negative affect shifts was predictive of higher levels of anxiety (Generalized Anxiety Disorder Scale in the Spanish study and Anxiety subscale of the Depression, Anxiety and Stress Scale in the German study), depression (Patient Health Questionnaire in the Spanish study and Depression subscale of the Depression, Anxiety and Stress Scale in the German study), and psychological inflexibility (Acceptance and Action Questionnaire in both studies). In contrast, higher P2N-ASR values were predictive of lower levels of psychological flourishing (Flourishing Scale in the Spanish study), lower psychological resilience (Brief Resilience Scale in both studies), and lower satisfaction with life (SWLS in the German study). Additionally, in the additional online material (https://osf.io/xqm84/), we report that calculating stability type based on a five-sample window (see Methods section on the prevalence of bistability), or including inertia and instability as predictors, did not significantly alter the main finding regarding the predictive validity of the P2N-ASR.

Next, we conducted a complementary analysis using stepwise regressions based on the Akaike information criterion to further examine the predictive value of P2N-ASR in the context of the mean and standard deviation of PA and NA. The results, shown in Figure 3a and 3b, align with and further support our previous findings from the LASSO regression models. Once again, P2N-ASR emerged as a key predictor of well-being indicators across both studies. Specifically, higher P2N-ASR values were associated with higher levels of negative well-being indicators: anxiety, depression, and psychological inflexibility in the Spanish study and higher levels of depression and psychological inflexibility in the German study. Conversely, higher P2N-ASR values were linked to lower levels of positive well-being outcomes: satisfaction with life in both studies. These results further emphasize the importance of the ASR as a predictor of psychological well-being, demonstrating the robustness of this finding across different variable selection techniques. Tables

Table 3
Coefficients of LASSO Regression Models

	Study 1 (Spanish)						Study 2 (German)				
Affect metric	GAD	PHQ	AAQ	FS	BRS	SWLS.1	DASSa	DASSd	AAQ	BRS	SWLS
Affect shift											
Type					0.14	0.14		−0.79		0.34	
P2N-ASR	6.50	17.56	39.89	−6.78	−0.92		1.95	6.85	25.57	−3.54	−15.66
N2P-ASR			8.92		−1.04	0.07			−0.03	−0.93	1.24
mPRT					0.05	0.02					
sdPRT			−0.10							−0.07	
mNRT										0.91	
sdNRT			0.70		−0.05			0.56		−0.79	
mP2N-ASM		0.07						−0.01		0.01	
sdP2N-ASM			−0.16		0.01			−0.01	0.25		
mN2P-ASM										−0.01	
sdN2P-ASM		−0.08	−0.50	0.11	0.06	0.01		−0.01		−0.01	0.09
Mean/standard deviation											
mPA						0.01				0.04	
sdPA			−0.34	0.49	0.04			−0.28		−0.03	0.45
mNA									0.13	−0.06	
sdNA			−0.13							0.01	0.20

Note. LASSO = least absolute shrinkage and selection operator; P2N-ASR = positive to negative affect shift ratio; N2P-ASR = negative to positive affect shift ratio; mPRT = mean positive residence time; sdPRT = standard deviation positive residence time; mNRT = mean negative residence time; sdNRT = standard deviation negative residence time; mP2N-ASM = mean positive to negative affect shift magnitude; sdP2N-ASM = standard deviation positive to negative affect shift magnitude; mN2P-ASM = mean negative to positive affect shift magnitude; sdN2P-ASM = standard deviation negative to positive affect shift magnitude; mPA = mean positive affect; sdPA = standard deviation positive affect; mNA = mean negative affect; sdNA = standard deviation negative affect; GAD = Generalized Anxiety Disorder Scale; PHQ = Patient Health Questionnaire; AAQ = Acceptance and Action Questionnaire–II; FS = Flourishing Scale; BRS = Brief Resilience Scale; SWLS.1 = one-item Satisfaction with Life Scale; DASSa = Anxiety subscale of the Depression, Anxiety and Stress Scale; DASSd = Depression subscale of the Depression, Anxiety and Stress Scale; SWLS = Satisfaction with Life Scale.

with the coefficients of all regression models are provided in the additional online material (https://osf.io/xqm84/).

Finally, after identifying the importance of the P2N-ASR in predicting psychological well-being through LASSO and stepwise regression analyses, we further investigated its relative contribution in simple linear regression models in comparison to mean and standard deviation PA and NA levels. To this end, we used the relative importance analysis, which allowed us to quantify the proportion of the total variance in the outcome variable explained by each predictor while accounting for the intercorrelations among the predictors. The findings shown in Figure 3c provide additional support for the significance of the P2N-ASR in predicting psychological well-being since once more this metric consistently emerged as a key contributor to the explained variance in most well-being outcomes: anxiety and depression in the Spanish study and anxiety, depression, psychological inflexibility, and satisfaction with life in the German study. In addition, the relative importance analysis also provides insight into the complementary contributions of other predictors, mostly the mean and standard deviation of PA, in the context of the ASR metric.

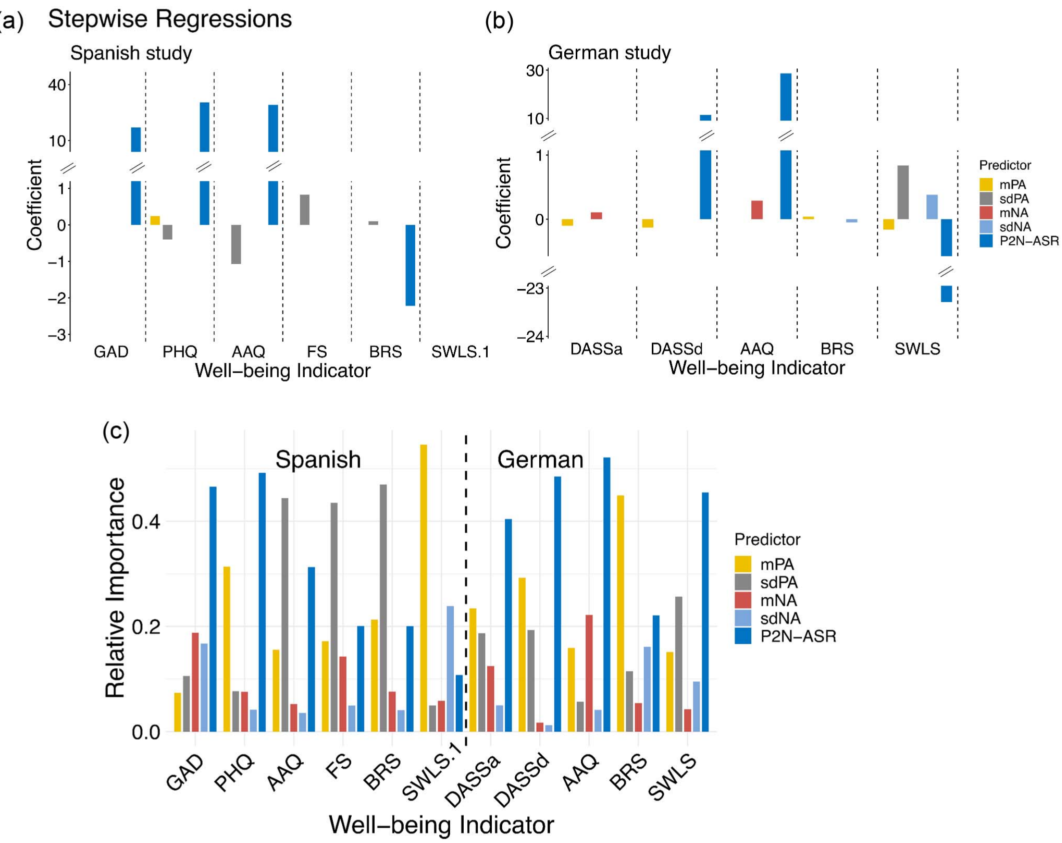
Discussion

The aim of this study was twofold. Inspired by models describing bistable behavior in natural systems (Scheffer et al., 2001), we first sought to identify the presence of "attractor basins" within the two key affective domains, PA and NA. To this end, we adapted a stability landscape analysis approach, originally developed for ecological systems (Dakos & Kéfi, 2022), and applied it to valence time series data derived from two distinct EMA studies—the "Spanish Study" and the "German Study"—where participants were prompted to rate their current affective state on a continuum from very negative to very positive. An attractor basin was identified as a distinct mode in the empirical distribution of the valence time series, demarcating an area of the affective space that the individual visits more frequently than neighboring areas. An attractor basin therefore implies that transitions to and from this area occur abruptly, which also suggests that such transitions require more energy. In psychological terms, we could say that the existence of an attractor basin indicates an affective state that "entraps" the individual, requiring a considerable internal or external "push" to move to an alternative state. This contrasts with scenarios where normal or skewed, yet mode-less distributions point to a more fluid affective experience, characterized by smoother transitions across the affective spectrum.

Our results revealed a significant percentage of individuals exhibiting at least one attractor basin in each affective regime, PA and NA. This pattern, which we called "bistable," was observed in 61.5% of participants in the Spanish Study and 46% of participants in the German Study. Despite the difference in prevalence between the two studies, the results collectively indicate that bistability is a common feature of affect dynamics. In a related vein, Haslbeck et al. (2023) recently showed that multimodal distributions are prevalent even in the time series of specific emotions that occupy only one affective regime, either positive or negative. Taken together, these observations have important implications for our attempts to model the human affective space, challenging models that depict affect as a stable system with a characteristic baseline state to which it returns following an emotional disturbance (Boker et al., 2008; Chow et al., 2005; Kuppens et al., 2010). Instead, it lends support to the

Figure 3

Predicting Well-Being From Affect Shifts



Note. Panels a and b: Stepwise regression coefficients for each well-being indicator included in the two studies. The acronyms of all well-being indicators are provided in Table 1. Predictors encompass the positive to negative affect shift ratio (P2N-ASR) metric, consistently identified as a robust predictor in previous LASSO regressions (see Table 3), and conventional mean and standard deviation values of PA and NA. The "//" symbol is used to indicate discontinuities on the *y*-axis introduced to better represent graphically the entire range of the different predictors. Panel c: Relative importance analysis of linear models illustrating the percentage contribution of each predictor variable to the explained variance in well-being. Again the novel P2N-ASR metric is compared to mean and standard deviation values of PA and NA. LASSO = least absolute shrinkage and selection operator; PA = positive affect; NA = negative affect; GAD = Generalized Anxiety Disorder Scale; PHQ = Patient Health Questionnaire; AAQ = Acceptance and Action Questionnaire–II; FS = Flourishing Scale; BRS = Brief Resilience Scale; SWLS.1 = one-item Satisfaction with Life Scale; DASSa = Anxiety subscale of the Depression, Anxiety and Stress Scale; DASSd = Depression subscale of the Depression, Anxiety and Stress Scale; SWLS = Satisfaction with Life Scale; mPA = mean positive affect; sdPA = standard deviation positive affect; mNA = mean negative affect; sdNA = standard deviation negative affect. See the online article for the color version of this figure.

notion that more complex models, such as the Affective Ising Model proposed by Loossens et al. (2020), the Flex3 model by Hollenstein et al. (2013), or the regime switching state-space models described by Hamaker and Grasman (2012), are necessary to better capture the true nature of emotional experiences.

Our second aim was to test whether affective bistability and other key characteristics of shifts between positive and negative affect predict well-being outcomes. We developed metrics that quantified the frequency and magnitude of affect shifts in both directions: from PA to NA and from NA to PA (ASR, RT, and ASM). LASSO regressions including the presence of bistability, the novel affect shift metrics, and average and standard deviation values of PA and NA consistently identified the ASR from PA to NA (P2N-ASR)—a measure of the propensity to experience an affect transition in the next measurement occasion—as the best predictor of various well-being indicators. Stepwise regressions and Relative importance analyses further supported the predictive power of P2N-ASR compared to the average and standard deviation levels of PA and NA, widely regarded as the gold standard of affect measures (Dejonckheere et al., 2019).[3]

While previous studies have utilized multilevel logistic regression models to examine emotional switching (e.g., Houben, Bohus, et al., 2016; Houben, Vansteelandt, et al., 2016), our research introduces a suite of easily quantifiable and interpretable metrics that can be used across different populations and research designs, including clinical

[3] In the additional online material (https://osf.io/xqm84/), we present LASSO regressions that include instability and inertia as predictors and further corroborate the superior predictive validity of the P2N-ASR.

settings. The P2N-ASR, in particular, is not only less computationally but also less cognitively demanding. Its calculation does not require rating emotions on a continuous scale (e.g., rating happiness from 1 to 10) but simply classifying the momentary affective state dichotomously as good or bad. This approach circumvents the ambiguity and complexity of differentiating subtle gradations on an emotion scale, like discerning between a 7 and an 8 in happiness.

Many emotion researchers might argue here that a bipolar assessment of affect is problematic since it excludes the possibility of mixed feelings—for example, the simultaneous experience of both happiness and sadness (Larsen & McGraw, 2014). However, recent studies reviewing the theoretical and empirical evidence in support of affective bipolarity argue that it does not preclude the endorsement of emotions with opposite valence in particular "bittersweet" situations (Russell, 2017; Tay & Kuykendall, 2017). In particular, psychometric evidence reveals that individuals who report feeling "ambivalent" exhibit response patterns with a single-peaked—rather than bimodal—distribution centered around the middle of a bipolar continuum. This implies that the experience of ambivalence or mixed feelings can be sufficiently captured by a single-item bipolar scale (Tay & Kuykendall, 2017). In fact, an attractor basin near the center of the bipolar valence continuum could indicate an individual with a propensity to experience mixed or ambivalent emotions. Conversely, a polarized affective experience might be characterized by a bistable pattern, with two attractors situated at the extremes of the continuum.

While it is still true that a single bipolar scale cannot distinguish between the experience of mixed emotions and the absence of emotion or "not feeling anything in particular," incorporating additional context such as experimental mood induction or supplementary affective variables (e.g., energetic and tense arousal) could help to disentangle these affective states. This suggests that, by addressing limitations inherent in the bipolar measurement of affective valence, the stability analysis framework we introduce here may also be valuable for researchers exploring individual differences in the experience of mixed emotions (e.g., Rafaeli et al., 2007), or the polarization of affective reporting in clinical populations (e.g., Coifman et al., 2012), or as a result of contextual parameters such as stress (e.g., Zautra et al., 2002).

Furthermore, single-item bipolar scales have proven to be efficient instruments to study the intraindividual dynamic patterns of momentary affect, while being indispensable for intensive longitudinal data research, as they decrease participant burden, involve fewer decisions regarding item selection or scale composition, and facilitate comparability across longitudinal studies (Cloos et al., 2023; Lucas & Donnellan, 2012). In the particular case of assessing shifts between PA and NA, a bipolar approach is methodologically more fitting. It allows individuals to directly identify and report their current affective state, rather than relying on researchers to make an indirect inference, such as by subtracting the intensities of negative emotions from those of positive ones. Furthermore, even if we accept that the intricate nuances of affect cannot be fully encapsulated by a single metric and multiple measures could contribute to a more comprehensive assessment, the reality is that the simple query, "How do you feel?" expecting a response of either good or bad, is a universally understood question. This simple classification of good or bad aligns with how people naturally summarize and communicate their affective state in everyday interactions, making it more accessible and easier to convey, an aspect that is of great value in clinical practice (Abdel-Khalek, 2006).

Building on the clinical relevance of ASR as a simple yet informative measure of affect, it is also worth considering its potential utility as an early warning signal (EWS; van de Leemput et al., 2014). EWS are indicators that can help identify individuals at risk of developing or experiencing a significant change in their mental health condition (Hofmann et al., 2016; Wichers et al., 2020). One example of EWS is increased flickering between different states, which might signal that the system is approaching a critical transition (Dakos et al., 2013; Scheffer et al., 2009). The ASR could be utilized in clinical practice as a complementary tool for monitoring mood disorders, where increases in the frequency of affect shifts might indicate the onset of an episode. Its integration into digital mental health interventions could trigger alerts for both patients and clinicians when a rise in affect shift frequency is detected, facilitating early intervention. Additionally, in high-risk populations, such as those in the prodromal phases of psychosis or with borderline personality disorder, the P2N-ASR could help identify worsening emotional regulation, allowing for more timely and targeted therapeutic interventions.

Importantly, common EWS metrics developed for detecting transitions in bistable systems (Dakos et al., 2012; Scheffer et al., 2015), such as variance and autocorrelation, involve rating emotions on a scale, which, as discussed earlier, can be challenging for some individuals. In contrast, the ASR, based on binary good/bad responses, offers a more accessible and intuitive approach to monitoring affect and potentially anticipating the closeness of a tipping point that could mark a transition to a pathological mental state.

Limitations and Future Research

Our results offer empirical support for the prevalence of bistability in human affect dynamics, a phenomenon we operationalized through the presence of attractor basins in both positive and negative affective domains. In addition, we introduced a suite of metrics to capture the frequency and magnitude of shifts between positive and negative affective states. Particularly, the ratio of shifts from positive to negative affect (P2N-ASR) emerged as an important predictor of a wide range of psychological well-being outcomes. Yet several questions remain open for exploration.

First, there is a need to replicate these preliminary findings related to bistability prevalence and the predictive power of the ASR in larger and more diverse samples. Specifically, future research should examine the impact of varying EMA protocols, including those with fewer measurement occasions per day and a reduced total number of days. For example, the observed decline in prevalence in our second data set (from 61.5% to 46%) may potentially be influenced by differences in EMA protocols, such as fewer daily measurements (5 instead of 6) and a shorter data collection period (21 days rather than 29). Sampling frequency is particularly critical, as fewer measurements per day might miss short-lived affect transitions, reducing the ability to detect bistability and affect shifts. Conversely, higher sampling frequencies could improve the detection of these dynamics by capturing more detailed temporal fluctuations. At the same time, it would be useful to also assess bistability in studies of longer duration. We based our characterization of individual stability landscapes on the assumption that participants visited most parts of their true stability landscape during the study period. A longer study duration could therefore reveal a landscape more representative of the true affective experience of individuals. However, it is also important to note that although higher sampling frequencies and longer study durations are likely to enhance the detection of bistability and affect shifts, future studies should also focus on identifying the lower limits of sampling frequency and study duration where the P2N-ASR remains a reliable predictor of well-being. Establishing these thresholds is crucial, as it will allow researchers to balance the need for accurate and informative data with minimizing participant burden.

Alternatively, differences in the results between the two samples could reflect variations in cultural, age, or gender demographics. While both Germany and Spain share a Western cultural background, distinct historical and socioeconomic contexts in each country could influence the observed prevalence of bistability and the predictive validity of the P2N-ASR. Similarly, the higher average age in the Spanish sample and the predominantly female composition of the German group (see Table 1) might also account for the differences seen in our results. To effectively address these factors, future studies need to be specifically designed to control for these variables or include sufficient variation and sample size to allow for their analysis as moderators.

Importantly, although in our studies the presence of bistability did not seem to be related to psychological well-being, it is crucial to test this relation in clinical populations. We hypothesize that mental disorder patients may exhibit pronounced attractor basins in the negative affect regime and that quantifying the characteristics of these basins could aid and guide therapeutic interventions. Conversely, identifying and quantifying attractor basins in the positive affect regime could provide novel indicators of emotional resilience, similar to those that are successfully employed in ecological systems (Scheffer et al., 2015).

Finally, future studies should focus on life factors and events that influence or trigger transitions between affective states. Although past research has highlighted the impact of stressful experiences on affect dynamics (e.g., Zautra et al., 2002), the data sets analyzed in this study did not include daily stress measures or specific event data. To address this gap, subsequent research could focus on objective assessments, for example, by using observer ratings (Connolly et al., 2007), leveraging mobile sensor data to measure daily context (e.g., Bailon et al., 2019) in combination with network analytical approaches (Lutz et al., 2018), and recording psychophysiological variables through wearable devices (Hoemann et al., 2023). Ideally, experimental studies inducing emotional contexts in naturalistic settings or the use of idiographic tools based on key biopsychosocial processes (Hayes et al., 2020), such as the Process-Based Assessment Tool (Ciarrochi et al., 2022), can help detect the causes of affect transitions at the level of the individual. This understanding could inform tailored, context-sensitive clinical interventions aimed at promoting well-being and preventing adverse mental health outcomes.

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