Emotional Regularity:

Associations with Personality, Psychological Health, and Occupational Outcomes

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Abstract

Emotional regularity is the degree to which a person maintains and returns to a set of emotional states over time. The present investigation examined associations between emotional regularity and extant emotion measures as well as psychologically relevant dimensions of personality, health, and real-world occupational outcomes. Participants included 598 U.S. adults who provided daily experience sampling reports on their emotional states for approximately two months. Results suggest that emotional regularity was related to, but distinct from, well-established measures of emotion including emotional intensity, variability, covariation, inertia, granularity, and emodiversity. Furthermore, emotional regularity significantly predicted measures of personality, psychological health, and occupational outcomes even when accounting for extant emotion measures and sociodemographic covariates. Finally, it explained modest (7.5%) improvement (in terms of cross-validated RSq.) over baseline models containing emotional intensity, variability, and sociodemographic covariates. These findings suggest that emotional regularity may provide an important indicator of healthy emotional functioning and may be a promising area for further scientific discovery.

Keywords: emotion; emotional complexity; emotion dynamics; recurrence quantification analysis; complex systems

Declarations

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1. Introduction

Consider the emotional experiences of John, George, Paul, and Ringo. John is very happy most days, George is extremely sad most days, Paul rapidly alternates between happy and sad days, whereas Ringo experiences long bouts of sadness followed by spurts of happiness. What do these emotional profiles over time tell us about their traits, psychological health, and life outcomes? Quite a bit. How people experience emotions can provide important clues into their psychological health and functioning (e.g., Bagozzi, Wong, & Yi, 1999; Kuppens, Allen, & Sheeber, 2010; Tugade, Fredrickson, & Feldman Barrett, 2004). For example, previous work has demonstrated that patterns of emotional experiences over time predict happiness and symptoms of depression across both normative and highly stressful contexts (Gruber, Kogan, Quoidbach, & Mauss, 2013; Taquet, Quoidbach, Fried, & Goodwin, 2021; Trull et al., 2008), the ability to adaptively regulate emotions (Hollenstein, 2015), and indicators of physical health (Quoidbach et al., 2014; Quoidbach et al., 2018). Here, we suggest that one important, but understudied aspect of emotional experience is the *regularity* by which people experience different patterns of emotions across time. We refer to this as *emotional regularity* and examine the ways it is unique from previous research and how it relates to individual differences and real-world psychologically-relevant outcomes.

Emotional regularity can be defined as the degree to which a person maintains and returns to a set of emotional states over time. To illustrate, consider a person's positive and negative self-reported affect levels rated on a 1 (not at all) to 5 (extremely) Likert scale for seven consecutive days represented as [pos, neg]$_{day}$: **[3, 1]**$_{D1}$, [3, 2]$_{D2}$, **[3, 1]**$_{D3}$, **[1, 4]**$_{D4}$, **[1, 4]**$_{D5}$, [2, 3]$_{D6}$, **[3, 1]**$_{D7}$. Whereas, the emotional *system* in this example can accommodate 25 possible states (2^5 as each dimensions can take on one of five values), only four ([3, 1], [1, 4], [3, 2], and [2, 3]) occur (e.g., [1, 1] or [5, 2] never occur). Of those that occur, [3, 1] and [1, 4] can be defined as "recurrent" states as they occur on multiple, though not necessarily consecutive days (i.e., D1, D3, D4, D5, and D7), whereas [3, 2] and [2, 3] each occur once on D2 and D5. Time points where the system is in the same state are said to be *recurrent* and the proportion of recurrent points (8 out of 42 or 19% in this example) is the measure of *emotional regularity* (see **Figure 1** and **Table 1** for more details and a graphical illustration)**.**

Beyond this illustrative example, emotional regularity is a construct that can be operationalized in multiple ways. For example, the above operationalization used only two affective dimensions (positive and negative affect), but alternate dimensions (e.g., valence, arousal, dominance) or discrete emotions (e.g., levels of happiness, anger, fear) can be considered instead. Similarly, whereas the example used a discrete 1-5 self-report measurement scale, the scale need not be in the 1-5 range, it can be continuous, and other measures of emotion can be used. Furthermore, the present example required perfect matches (i.e., a distance of zero) for two states to be considered recurrent, however, depending on the measurement scale and desired degree of precision, only matches within a certain threshold can be considered recurrent.

Measurement issues notwithstanding, the concept of emotional regularity is grounded in complex systems theory, which describes the behavior of dynamic systems over time and is hypothesized to reflect a central organization principle of physical, social, and psychological systems (Bar-Yam, 2019; Van Orden, Holden, & Turvey, 2003), including emotion (e.g. Camras & Witherington, 2005; Hoeksma, Oosterlaan, Schipper, & Koot, 2007; Lewis, 2005; Pessoa, 2018). This perspective emphasizes that healthy functioning is maintained through patterns of self-organized variability (Thayer & Lane, 2000) through positive and negative feedback loops that operate across multiple levels and timescales (Hollenstein, 2015; Lewis, 2005). Within this framework, an organism is composed of sub-systems which work together in a coordinated fashion (Van Orden et al., 2003). Although individual components have a high number of degrees of freedom (e.g., large number of possible facial muscle configurations), a well-functioning system self-organizes to a subset of lower dimensional *attractor* states when in the service of goal-oriented behavior (e.g., a smile or a frown).

With this framework in mind, we suggest that emotional regularity captures a critical aspect of self-organization as applied to emotion-relevant phenomena –return to a set of emotion states (these are the attractors), which can be existing states or a new recurrent state. Thus, emotion regularity reflects a form of stability across time through change, characterized by adaptive psychological, physiological, and behavioral responses to stressors, that enables an organism to return (i.e., recurrence) to a resting state (Butler & Randall, 2013; Thayer & Sternberg, 2006). In the present case, emotional states are represented along the dimensions of positive and negative affect, which form a *state space* representing all possible configurations of these two dimensions. Emotional regularity captures patterns of recurrence to a subset of attractor states from all possible states (two attractor states, [3, 1] and [1, 4], out of 25 possible states in the example).

In addition to recurrence, *multidimensionality* – multiple components of the affective experience are considered jointly– is an important aspect of emotional regularity. For example, in the present case, the two dimensions of positive and negative affect are jointly modeled rather individually considered. Multidimensionality more accurately captures the realities and complexities of emotional experience over unidimensional representations and is consistent with a complex systems approach where the unit of analysis is the entire system rather than its individual components. The presence of multiple attractors – called *multistability* – is another important component of emotional regularity although the definition is sufficiently broad to encompass a single attractor state. Finally, by considering recurrence all possible states and at all lags (i.e., time combinations), emotion regularity provides a global measure of the *structural organization* (i.e., patterning) of a complex dynamical system. Thus, with its emphasis on multidimensionality, multistability, and global structure, we suggest that the concept of emotion regularity captures an important, yet understudied, aspect of emotional processes across time that warrants greater empirical investigation in understanding its relationship to extant emotion constructs and ecological validity in predicting psychologically relevant outcomes.

The Present Investigation

In the present investigation we sought to establish empirical support for the theoretical possibility that emotional regularity might offer a new yet complementary perspective on the global structure in the patterns of emotions people experience across time. Accordingly, we examined emotional regularity in a large adult nonclinical sample of 598 participants from across the U.S. Participants provided emotion self-reports once a day for roughly 56 consecutive days using validated experience sampling methodology (ESM; Csikszentmihalyi & Larson, 1987). This design enabled us to examine two main aims: **Aim 1** established the unique, yet complementary, role of emotional regularity in understanding emotion experiences. We predicted (Hypothesis 1) that emotional regularity would be associated with, but distinct from, basic (emotional intensity and variability) and other complex measures of emotion including emotion covariation (Bagozzi et al., 1999), inertia (Kuppens, Allen, et al., 2010), granularity (Lindquist & Barrett, 2008), and diversity (Quoidbach et al., 2014); these are subsequently discussed.

Aim 2 examined associations between emotional regularity and several psychologically-relevant outcome measures including personality traits, health, and life outcomes. We predicted that emotional regularity should be associated with adaptive functioning in that it indexes maintenance of a recurrent set of emotional states through self-organized variability (Hypothesis 2). We further investigated the discriminant and incremental predictive power of emotional regularity by comparing it to and accounting for the aforementioned basic and complex measures of emotion. We also report results of cross-validated statistical models to address concerns of overfitting and quantify generalizability of the findings (Yarkoni & Westfall, 2017). It is important to clarify that Hypothesis 2 is restricted to nonclinical samples; emotional regularity might be associated with maladaptive responses in clinical samples. In particular, it might reflect an individual's inflexibility and need for predictability, where uncertainty can lead to increased stress and anxiety. And, because emotional regularity is hypothesized to be distinct from emotional intensity, clinically significant emotional states (e.g., generalized anxiety disorder) could underlie high regularity scores. Similar, mood instability, which is associated with several psychiatric disorders (Broome, Saunders, Harrison, & Marwaha, 2015), could be associated with high emotional regularity if it occurs in a predictable pattern (e.g., mood swings).

Our two aims and analytic plan were designed in accordance with the recommendations of a recent study (Dejonckheere et al., 2019) that argued that new measures of emotion dynamics tend to be interrelated and add limited (if not negligible) information in predicting psychological well-being above emotional intensity and variability. We agree that new measures of emotion should be held to a higher standard in order to avoid introducing redundant concepts based on overfit statistical models. Accordingly, we followed the criteria recommended by the authors by: (1) theoretically grounding emotional regularity within complex systems perspectives of emotion (Section 1); (2) discussing how emotion regularity is distinct from other complex emotion measures including covariation, inertia, diversity, and granularity (Section 2.3.2); (3) demonstrating that there is considerable unexplained variance in emotional regularity after accounting for positive and negative intensity and variability (Section 3.1); (4) demonstrating that emotional regularity predicts personality traits, health, and occupational outcomes (which goes beyond the mental health outcomes examined in Dejonckheere et al. (2019)) after accounting for *both* emotional intensity *and* variability (and sociodemographic covariates; Section 3.2.1); (5) showing both discriminant and incremental predictive power of emotional regularity after accounting for the other complex emotion measures (in addition to the basic emotion measures), which is a step beyond the analyses recommended in Dejonckheere et al. (2019) (Section 3.2.2); (6) reporting results of cross-validated models indicating that emotional regularity explained additional variance (an average of 7.5% improvement in cross-validated RSq.) over baseline models containing emotional intensity, variability, and sociodemographic covariates to address concerns about overfitting and providing evidence of generalizability (Section 3.2.3); and (7) demonstrating that the results are robust to parameter choices used to compute emotional regularity (Section 3.3). We therefore think that emotional regularity more than adequately crosses the threshold for introducing a new complex measure of emotion, suggesting a promising area for further scientific discovery.

2. Method

The present investigation employed a large-scale longitudinal study of 598 U.S. adults as part of a broader study on individual differences, health, and job performance. The sample size, measures, and procedures were determined by the funding agency and were out of the control of the researchers; see Mitre (2017) for details. Procedures were approved by the University of

Notre Dame, which served as the IRB on record (#17-05-3870). Data for the present study were obtained via an IRB Authorization Agreement between the University of Colorado Boulder (#17-0457) and Notre Dame.

2.1. Participants

Participants were 598 adult information workers between the ages of 21-68 from across the U.S. recruited via partnerships with their workplaces as well as informally though messaging boards and other ad platforms. An information worker is one who primarily works with data and information such as an accountant, manager, scientist, and engineer. Participants were grouped into five cohorts and included fixed monetary compensation for four cohorts (up to $750; 59% of the sample) and lottery-based monetary incentives for one cohort that disallowed direct compensation. As seen in **Table 2**, there was considerable heterogeneity in terms of gender, occupation, income, education level, job role (supervisor or not), and whether participants were born in the U.S. All participants provided informed consent.

2.2. Measures and Procedure

Whereas previous work on measures of complex emotions have focused on a few key indicators of mental health (e.g., life satisfaction, depressive symptoms, and borderline symptoms) (see review by Dejonckheere et al., 2019), we consider a much broader set of measures here. Specifically, we examined associations between emotional regularity, Big Five personality traits and three mental and physical health outcomes: stress/anxiety, substance (alcohol) abuse, and sleep deprivation. As an additional, and perhaps more critical test of its predictive validity, we also examined whether emotional regularity predicted three key dimensions of job performance: task performance, organizational and citizenship behavior, and counterproductive work behavior, even after controlling for well-known predictors, such as cognitive ability, personality, and state-trait anxiety (e.g., Barrick & Mount, 1991; Kaplan, Bradley, Luchman, & Haynes, 2009; Schmidt & Hunter, 2004). Finally, critical to our hypothesis on the unique information captured by emotional regularity, we tested whether the above relationships were maintained after accounting for a range of extant emotion measures including emotional intensity, variability, covariation, inertia, granularity, and diversity.

Table 3 provides details on all measures, which consisted of a set of widely-used and well-validated assessments; these are discussed in detail in Mitre (2017). The study was conducted in two parts – an initial battery of measures followed by a two-month experience-sampling protocol. First, participants completed an approximately 60-90 min long proctored individual difference measurement session in person at their workplace or remotely via videoconferencing software. The survey, administered in Qualtrics, included validated full-length measures of psychological constructs including Big Five personality (openness, conscientiousness, extraversion, agreeableness, and neuroticism), cognitive ability (fluid and crystallized intelligence), affect (positive and negative affect and state-trait anxiety), and health measures pertaining to alcohol and tobacco use, sleep quality, and physical activity.

Job performance was measured along the widely-used dimensions (Rotundo & Sackett, 2002) of: (1) task performance, (2) organizational and citizenship behavior, and (3) counterproductive work behaviors. Task performance pertains to completion of role-specific job duties rewarded by management and includes measures of in-role behavior and individual task proficiency (Viswesvaran & Ones, 2000). Organizational and citizenship behavior refers to specific behaviors undertaken to promote the wellness of the organization and its employees even if these are not formally rewarded (Organ, 1997), for example, filling in for a sick co-worker. Conversely, counterproductive work behaviors are those which are deliberately taken to harm the organization and its employees; they can be directed at specific individuals (interpersonal deviance – e.g., stealing a coworkers lunch) or the organization more broadly (organizational deviance – e.g., lying on timesheets) (Sackett & DeVore, 2002). It should be noted that self-reports are a standard method to measure job performance in the industrial and organizational psychology literatures. And whereas more objective methods (e.g., production rates) might be preferable to measure task performance, self-reports might be more accurate to measure counterproductive work behaviors as others might not be aware of these behaviors. Self-reports of organizational and citizenship behavior also align with informant-reports (see Carpenter, Berry, & Houston, 2014 for a meta-analysis).

Second, for the next two months, participants received one text message per day with a Qualtrics link to an ESM survey that occurred at either 8am, 12pm, or 4pm local time. The 2-4 minute ESM survey included short versions of the personality, affect, health, and job performance measures, with daily assessment frequency and assessment timing varying by measure. Participants completed an average of 78% (median = 87%; *SD* = 23%) of the surveys and were provided with an opportunity to complete additional surveys for a few days beyond the two-month timeline.

2.3. Data Treatment

We analyzed all measures reported in **Table 3** with the following exceptions. We used the 10-item ESM affect measure (i.e., Short PANAS) administered daily for two months in lieu of the PANAS-X (administered once) because we were interested in emotion patterning across time. We also did not analyze physical activity since we have no prior hypothesis about how it should be related to emotional regularity. Tobacco use was not considered since only 8.5% of our sample self-identified as a smoker.

2.3.1. Computing emotion regularity. The basic technique to compute emotional regularity outlined in the Introduction is called recurrence quantification analysis (RQA, Webber & Zbilut, 2005). RQA measures the temporal organization of a time series representing a dynamical system by identifying recurrent patterns, or repeat values, that occur over time. It indicates the extent to which a system is in a similar (recurrent) state at various time lags, as well as periods of time when the system revisits a sequence of states. This is captured in a recurrence plot (Figure 1C) where the time series is compared to itself at different time delays (as in Table 1), and points that overlap are marked as "recurrent" on the plot. Typically matches within a predefined distance called the *radius* are considered to be recurrent*;* the example above utilized exact matches (or a radius of 0) for simplicity, but we considered various radii in our analyses. The recurrence rate is the proportion of recurrent points.

This computation of emotional regularity does not impose any constraints of the ordering of the time series, and shuffling the time series (while maintaining element-wise associations between positive and negative affect) would yield the same score since each element is compared to every other element. This is *intentional* as we intend for emotional regularity to serve as a *global* measure of the structural organization (or patterning) of the affective system as a whole. It is possible to also examine local dynamics by computing recurrence rates across small bands along the main diagonal (where ordering does matter), but we were interested in global dynamics so consider the entire plot as is routinely done (e.g. Amon, Vrzakova, & D'Mello, 2019; Pellecchia & Shockley, 2005; Zhang, Anderson, & Miller, 2021). There are also additional measures that can be computed from a recurrence plot (Marwan, Romano, Thiel, & Kurths, 2007), such as *determinism,* which quantifies consecutive repetitions of states, which in the present case would be two or more consecutive days with similar affective states. However, we did not consider these measures since our selected measure of recurrence rate most closely aligns with our theoretical conceptualization of emotional regularity.

Whereas unidimensional RQA examines repetition within a single signal over time as a measure of self-similarity, we use a multidimensional extension called MdRQA (Wallot, Roepstorff, & Mønster, 2016), which quantifies the degree to which the *collective organization* of multiple signals comprising a system exhibits regular patterns of behavior. Accordingly, we used MdRQA to compute emotional regularity scores (see **Figure 2** for an example) by representing the affective states along two dimensions of positive and negative affect. Consistent with the scoring guidelines (Mackinnon et al., 1999), we constructed positive and negative affect time series as the sum of the respective items on the Short PANAS measure (alert, excited, enthusiastic, inspired, and determined for positive affect; distressed, upset, scared, afraid, and nervous for negative affect). We could have directly proceeded with a 10-dimensional emotional state space by working with non-aggregated Short PANAS data (instead of separately summing items representing positive and negative emotions) if more precise patterning across emotions was desired (e.g., distinguishing a day with high anger but low scores for the other negative emotions vs. a day with high fear but low scores for the other negative emotions). However, we deemed our level of representation sufficient for the present purposes and to avoid sparsity concerns given the number of ESMs completed (52 on average – see below). For example, our two-dimensional state space has 400 possible states (20^2 as each dimension can take on 20 values in the 5 to 25 range) whereas a 10-dimensional discrete emotion space would have 5^{10} (each discrete emotion can range from 1 to 5) or roughly 10 million (9,765,625) states.

The first step in a MdRQA analysis is to compute the distance matrix between all possible data points, which in our case was the Euclidean distance between affect [pos, neg] across all combination of days for each participant. The next step is to filter the matrix by setting a threshold (radius) for what is considered a recurrent point (i.e., distances < radius are recurrent). We opted for the simplest case where emotional state on day_i [pos_{d1}, neg_{d1}] was considered recurrent if it exactly matched (i.e., distance of 0) the emotional state on day_j [pos_{dj}, neg_{dj}]. This is equivalent to setting the MdRQA radius parameter to 0 for the main analysis, but we also report results across a range of radii as a robustness check (Section 3.3). Emotional regularity is computed as the proportion of recurrent points (i.e., the recurrence rate).

In our data, the mean participant-level Euclidean distance was 4.3 (SD = 1.5) out of a maximum possible value of 28.3 (i.e., Euclidean distance between lowest [5, 5] and highest [25, 25] possible values). There was a mean of 27 (SD = 10) unique states per participant (e.g., [5, 3] and [5, 4] are different states), out of which a mean of 10 (SD = 4) were recurrent states (i.e., unique states that occurred more than once per participant) considering exact matches only (i.e., a radius of 0). Emotional regularity scores (percent of recurrence points) ranged from 0 to 71% with a mean of 7.17% (SD = 9.26%). There was considerable variability in the distribution with a positive skew, so the median of 4.11% is a better measure of the central tendency of the distribution. We also square-root transformed the scores and report these results; however, results were similar for untransformed scores. See Supplementary Information (SI) for histograms of the pertinent measures used in computing emotional regularity.

As a comparison, we generated surrogate time series for each participant by randomly sampling (with replacement) from their positive and negative affect distributions. As expected, the random surrogate time series had significantly ($p < .001$ using a paired Wilcoxon signed rank test) lower (M = 2.69, SD = 1.11) recurrence rates than the actual time series (M = 7.17, SD = 9.26), which indicates that the observed recurrent patterns were systematic.

2.3.2. Computing comparison emotion measures. We suggest that emotional regularity as described above is *related* to but *distinct* from other measures of emotion, including emotion intensity, variability (or stability), covariation, inertia, granularity (differentiation), and diversity due to its emphasis on multidimensionality, metastability, and recurrence. To begin with the basic emotion measures, it differs from *emotion intensity* in that it is not concerned with specific emotion levels but repetitions of emotions over time. For example, timeseries with different emotional intensities, but with similar patterning of states, can have similar emotional regularity scores. Turning to measures of emotion dynamics, *emotion stability (or variability*) is the most basic measure, and is typically computed as the standard deviation of positive and/or negative affect (Grühn, Lumley, Diehl, & Labouvie-Vief, 2013; Trull et al., 2008). Whereas the standard deviation assesses deviation from a single point (the mean) in a single dimension, emotional regularity measures recurrence to multiple points (multistability) in a multidimensional (e.g., positive and negative affect) state space.

With respect to other measures of emotion dynamics, *emotion covariation* (or *dialectism*) refers to the simultaneous experience of pleasant and unpleasant states (Bagozzi et al., 1999). Its operationalization as the correlation between positive and negative affect sets it apart from emotional regularity, which is unconcerned with how these two affect dimensions covary (i.e., they could be synchronous or asynchronous).

Like us, other researchers have adopted a complex systems perspective to investigate emotion dynamics, such as the DynAffect (Kuppens, Oravecz, & Tuerlinckx, 2010) and Flex3 (Hollenstein, 2015) models, but with some key differences. Whereas DynAffect emphasizes only one fixed state (i.e., the "home base"), the existence of multiple recurrent states is a core component of emotional regularity. Multistability is a key component of the Flex3 model, but this model focuses on the time spent in the fixed states and on frequency of transitions among attractor states. In contrast, emotional regularity is concerned with "revisits" to one or more recurrent states irrespective of the number or nature of those states. The Flex3 model also emphasizes differentiating flexible from rigid emotional profiles, called *emotional inertia* or the degree to which emotions are resistant to change. Emotional inertia is computed as the lag-1 autocorrelation among consecutive time points (Kuppens, Allen, et al., 2010), which emphasizes local patterns. Conversely, regularity examines global patterns across all combinations of time points.

Jenkins, Hunter, Richardson, Conner, and Pressman (2020) recently introduced the idea of *affective predictability* – repetitions of patterns of affective experiences – within a complex systems framework. They also used an RQA framework to measure affective predictability. However, Jenkins et al. (2020) use auto-recurrence (aRQA) to *separately* compute recurrence rates for unimodal positive and negative affect, yielding two measures of *self-similarity*, whereas, we use MdRQA to *jointly* considers positive and negative affect as two dimensions of a multidimensional system to yield a *single* measure of system-level *regularity* (Amon et al., 2019). In addition to the conceptual difference, a multidimensional approach drastically reduces overlap with emotion variability, which is a major concern for measures of emotion dynamics (Dejonckheere et al., 2019). In particular, *unimodal* positive and negative recurrence rates from auto-RQA (i.e., Jenkins et al. (2020) measure) were strongly correlated with positive (r = -0.61) and negative (r = -0.75) emotion variability in our data; these correlations were even larger (rs = -0.75 and -0.76) in the data reported in Jenkins et al. (2020). However, correlations between *multimodal* recurrence (i.e., the proposed measure from a multidimensional RQA) and positive and negative affect variability were notably lower (rs of -.43 and -.46) in our data. Thus, the similarity between emotional regularity (current work) and emotion predictability (Jenkins et al., 2020) is limited to the use of RQA; the two have conceptual, methodological, and empirical differences. For these reasons, we did not examine unimodal recurrence rates (i.e., Jenkins et al. (2020) measure) further.

Beyond emotion dynamics, other complex measures of emotion focus on the awareness and experience of specific emotions (Lindquist & Barrett, 2008), including emotional granularity/differentiation and diversity. *Emotional granularity* (Lindquist & Barrett, 2008; Tugade et al., 2004), also called *emotional differentiation* (Kashdan, Barrett, & McKnight, 2015), pertains to the ability to make fine-grained differentiations among similar emotions (e.g., distinguishing between “anger” and “frustration” vs. reporting feeling “bad”). Because emotional granularity pertains to the precision with which people report/experience emotions, it should relate to emotional regularity, but the two are not redundant since granularity does not measure patterning of responses over time. Similarly, drawing from the biological concept of biodiversity (variety and abundance of biological life), the parallel concept of *emodiversity* reflects the variety and abundance of emotions a person experiences (Quoidbach et al., 2014; Quoidbach et al., 2018). This concept emphasizes the richness (number of unique emotional states) and evenness (relative proportions of different emotions), but again, not on emotion patterning across time as is central to emotional regularity.

Our final selection of comparison emotion measures (see **SI.4** for definitions of all emotion measures) including positive and negative emotion intensity, variability, covariation, inertia, granularity, and diversity was intended to represent the diversity of complex emotional measures while eliminating measures that are redundant. We computed these comparison measures following standard procedures. Specifically, similar to Grühn et al. (2013), positive and negative affect intensity and variability were computed as the mean and standard deviation of the respective time series. Some researchers have used the (root) mean squared successive difference ([R]MMSD) as a measure of variability, but this measure is often highly correlated with the standard deviation (e.g., *rs* of 0.82 and 0.90 in Jenkins et al. (2020); *rs* of .77 and .83 in Ebner-Priemer and Sawitzki (2007)), so we did not compute it here. We computed emotional covariation as the Pearson correlation between the positive and negative affect time series (Grühn et al., 2013), and positive and negative emotion inertia as the lag-1 autocorrelation of the positive and negative linearly detrended affect time series, respectively (Jahng, Wood, & Trull, 2008; Kuppens, Allen, et al., 2010). Whereas missing data complicated the computation of emotion inertia, we did not choose to impute missing data as it might contaminate the other measures. Following Tugade et al. (2004), we computed positive and negative emotional granularity (differentiation) scores as the average intra-class correlation (ICC) of the observation × item matrix and reverse scored (i.e., -1 × ICC) the resultant values such that higher scores reflect higher granularity (differentiation). Similarly, following Quoidbach et al. (2014), we computed positive and negative emotional diversity scores as Shannon's biodiversity index, one per ESM survey, and then averaged the scores across surveys.

2.3.3. Computing personality, health, and job performance measures. Recall that personality, health, and job performance measures were administered during the initial battery as well as during the subsequent weeks via ESM surveys. We merged the two to increase reliability and precision. The general procedure for merging involved: (1) computing the initial measure from the individual survey items; (2) computing the equivalent ESM measure on a per-survey basis; (3) averaging across ESM surveys to obtain a participant-level ESM score; (4) verifying that scores from steps (1) and (4) were adequately correlated, and if so, (5) z-score standardizing each and then taking the average as the final measure. In order to maximize available data, we proceeded with one measure for the few cases where the complementary measure was missing. We applied this basic approach for all measures with the following additional steps for some. For stress/anxiety, we first averaged the ESM measures as they were strongly correlated ($r = .83$, $p < .001$) before merging it with the initial STAI measure. For task performance, we averaged in-role behavior and individual task proficiency scores as they were strongly correlated ($r = .77$, $p < .001$). Because alcohol measures were zero-inflated due to participants who do not consume alcohol, we multiplied the alcohol disorder scores from the initial battery with the ESM measure that asks participants to report the number of alcoholic beverages consumed the previous day. This allowed us to preserve the shape of the distribution and the combined measure correlated strongly ($rs > .81$; $ps < .001$) with the individual items. See **SI.1, SI.2,** and **SI.3** for descriptive statistics and correlations among the pertinent measures.

2.4. Data exclusion. We required that participants complete at least 7 of the roughly 56 ESM surveys to be included in the study. Of the 598 participants in our sample, 581 (97.3 %) met this criterion and completed an average of 52 surveys (median = 57; $SD = 13$). The sample size was 581 for almost all of the analyzes with the exception of alcohol use where $N = 577$. We experimented with additional cutoffs for the minimum number of surveys for inclusion; these results are reported as well (Section 3.2). We note that the number of ESM surveys was not correlated with emotional regularity ($r = .01$, $p = .75$) but was weakly correlated with some of the other emotion measures ($rs < .16$), so we included it as a covariate in all analyses.

3. Results

3.1. Aim 1: Associations between emotion regularity with extant emotion measures.

We would expect extant emotion measures to have nonzero correlations with emotional regularity, but, there should be substantial unexplained variance in emotional regularity after accounting for these measures (Hypothesis 1). As seen in **Table 4**, we found that emotional regularity was significantly (p's < .01) associated with lower positive (r = -.27) and negative (r = -.46) emotion intensity, lower positive (r = -.43) and negative (r = -.46) emotion variability, higher covariance among the two (r = .27), making more fine grained positive (r = .14) and negative (r = .29) emotion differentiation (i.e., emotion granularity), and the tendency to experience more diverse positive (r = .19) and negative (r = .58) emotions. Emotion regularity was weakly related to positive emotion inertia (r = .09, p < .05) and was unrelated to negative emotion inertia (r = .05, p > .05).

In general, the correlations with the basic emotion measures (intensity and variability), which ranged from -.27 to -.46, were lower than similar correlations with other measures of complex emotion measures (e.g., negative affect variability was strongly correlated with negative emotional granularity [r = -.72]; see **SI.5** for the correlation matrix). To quantify this, we regressed emotional regularity on the positive and negative intensity and variability entered together. This combined model with four predictors explained 35% (adjusted *Rsq*) of the variance in emotional regularity, suggesting it captures related, but distinct (65% unexplained variance) information. Emotional regularity was also within the range (0% to 56%) of the other complex measures with respect to the amount of variance explained by the basic emotion measures (*adjusted RSqs* of 0% for positive/negative emotional inertia, 11% for emotional covariance, 14% and 28% for positive and negative emotional diversity, and 45% and 56% for positive and negative emotional granularity).

3.2. Aim 2: Associations with personality, psychological health, and occupational outcomes

We hypothesized (Hypothesis 2) that emotional regularity should be associated with adaptive functioning in nonclinical samples. Accordingly, we regressed measures of personality, psychological health, and job performance outcomes on emotional regularity after controlling for the above covariates as well as positive and negative affect intensity and variability. We also covaried the number of ESM surveys completed, cohort (five groups), demographics (age, gender, and native language [English or not], which strongly correlated [phi = .79, $p < .001$] with being born in the U.S.). All predictors were entered simultaneously in the models.

3.2.1. Comparison to basic emotion measures. The results are summarized in **Table 5** (see **SI.6, SI.7**, and **SI.8** for full models). With respect to *personality*, we found that emotional regularity was negatively related to neuroticism ($\beta = -.17$, $p < .001$), positively associated with agreeableness ($\beta = .11$, $p = .02$) and conscientiousness ($\beta = .12$, $p = .01$), and unrelated to openness ($\beta = -.06$, $p = .25$) and extraversion ($\beta = .07$, $p = .15$). For the *health variables*, emotional variability negatively predicted stress/anxiety ($\beta = -.25$, $p < .001$) and weakly predicted alcohol consumption (incidence rate ratio [IRR] = .88, $p = .06$), but was unrelated to sleep quality ($\beta = .01$, $p = .87$). For *occupational outcomes*, emotional regularity was associated with task performance ($\beta = .13$, $p = .01$) and organizational and citizenship behavior ($\beta = .20$, $p =$ $< .001$), but not reliably with counterproductive work behavior ($\beta = -.08$, $p = .09$). We applied a false-discovery rate correction (Benjamini & Hochberg, 1995) for the above 11 models and found that the patterns of significance were maintained at the $p_{fdr} < .05$ level for agreeableness, conscientiousness , neuroticism, stress/anxiety, task performance, and organizational and citizenship behavior, but not for alcohol consumption (p_{fdr} = .09).

We conducted follow-up analyses for selected models. Given that income is a reliable predictor of stress/anxiety (Ettner, 1996), we included income as an additional covariate and found a similar effect for emotional regularity (β = -.24, p < .001). We repeated the job performance models with several other covariates that have consistently been linked to job performance. Specifically, we jointly entered whether the participant was a supervisor or not, cognitive ability (Shipley abstraction and vocabulary), big-five personality, and state-trait anxiety (e.g., Barrick & Mount, 1991; Kaplan et al., 2009; Schmidt & Hunter, 2004). This approach offers a rigorous test of the incremental predictive validity of emotional regularity. The results generally held for task-performance (β = .08, p = .06) and organizational and citizenship behavior (β = .15, p < .01), but not counterproductive work behavior (β = -.03, p = .48).

To get a sense of the relative predictive power of emotional regularity compared to the four basic emotion measures, we examined the average effect per predictor. Specifically, we computed the mean of absolute value of the beta coefficients in Table 5 across the 10 (out of 11) dependent variables; we excluded alcohol consumption since the effect was an incidence rates ratio (IRR) and none were significant predictors. Overall, emotional regularity ($\beta_{\text{abs\_mean}}$ = .12) was a better predictor than positive variability ($\beta_{\text{abs\_mean}}$ = .06), was equivalent to negative intensity ($\beta_{\text{abs\_mean}}$ = .12) and negative variability ($\beta_{\text{abs\_mean}}$ = .13) and was less predictive than positive intensity ($\beta_{\text{abs\_mean}}$ = .19). Thus, when all five predictors are simultaneously entered, the predictive power of emotional regularity ($\beta_{\text{abs\_mean}}$ = .12) was within the range ($\beta_{\text{abs\_means}}$ from .06 to .19) of the four basic emotion measures.

Because emotional diversity is inherently a multidimensional measure which jointly considers positive and negative affect, it was important to ascertain that its predictive power above positive and negative emotional variability, both unimodal measures. Accordingly, we computed the covariance between positive and negative affective timeseries as a multidimensional measure of emotional variability and added it as a fifth basic affect measure in the models (i.e., covariates included positive and negative affective intensity, variability, and now, covariance). Results indicated that emotional regularity still significantly predicted agreeableness ($\beta = .13$, $p < .05$), conscientiousness ($\beta = .12$, $p < .05$), neuroticism ($\beta = -.15$, $p < .01$), stress/anxiety ($\beta = -.24$, $p < .001$), alcohol consumption (IRR = .87, $p < .05$), task-performance ($\beta = .16$, $p < .01$) and organizational and citizenship behavior ($\beta = .19$, $p < .01$), indicating that its predictive power is not solely due to it being a multidimensional measure.

3.2.2. Comparison to extant emotion measures. How does emotional regularity compare to the existing complex emotion measures in predicting personality, health, and job performance? We addressed this question in two ways. First, we repeated the above models (with the same sociodemographic and basic emotion measures as covariates) but by individually including emotional regularity (for comparison), emotional covariance, positive and negative emotion inertia, granularity, and diversity as predictor variables (eight in all). We found (see Table 6) that *none* of the emotion measures (including emotional regularity) significantly ($p < .05$) predicted openness, alcohol consumption, sleep disorders, and counterproductive work behavior, whereas conscientiousness, neuroticism, stress/anxiety, and organizational and citizenship behaviors were predicted by *at least one other* complex emotional measure in addition to emotional regularity. Extraversion was the only measure that was predicted by another complex emotion measure *but not* by emotional regularity. Importantly, emotional regularity was the *sole predictor* of agreeableness and task performance. These findings suggest that emotional regularity has discriminatory predictive power compared to the comparison complex emotion measures.

Second, to investigate the incremental predictive power of emotional regularity over the comparison emotion measures, we repeated the above models, but with both emotional regularity and *each* comparison emotion measure as a predictor. For example, we regressed agreeableness on emotional regularity and emotion covariation after controlling for the four basic emotion measures and the sociodemographic covariates. This allows us to examine the effect of emotional regularity after accounting for each comparison measure. Importantly, with one exception (specifically, the effect of emotional regularity on neuroticism was nonsignificant after including emotional diversity as a predictor), emotional regularity remained a consistent predictor of agreeableness, conscientiousness, neuroticism, stress/anxiety, task performance, and organizational and citizenship behavior, after controlling for the other measures of emotion complexity (see **SI.9** for details). To our knowledge, this is the first study to demonstrate the predictive validity of a complex emotion measure (i.e., emotional regularity) after accounting for other complex emotional measures.

3.2.3. Generalizability (Cross-validation analysis). To get a sense of generalizability and also address concerns of overfitting, we computed a 10-fold cross validated RSq. (across 100 iterations) for the regression models. This entailed dividing the participants into 10 pseudorandom folds, building models on nine of the *training* folds, generating predictions for the *held-out test fold*, and iteratively repeating the process until each fold was included as a test fold once. Predictions were pooled over the 10 folds, upon which a cross-validated RSq was computed. We repeated this process for 100 iterations and averaged results across iterations. We first computed the cross-validated *RSq*. for a baseline model with affect intensity, variability, and the other covariates (number of ESM surveys used to compute affect measures, cohort, age, gender, and native language). We then computed the percent improvement in cross-validated *RSq*. when emotional regularity was added as an additional predictor to this baseline model. We focused on the following six outcome measures where emotional regularity was a robust predictor based on the above analyses: agreeableness, conscientiousness, neuroticism, stress/anxiety, task performance, and organizational and citizenship behavior.

We found that the model with emotional regularity explained an additional (on average 7.5% of the variance) over the baseline model. As indicated in Table 7, improvements ranged from 3.1% for agreeableness to 17.0% for organizational and citizenship behaviors. These findings contrast the Dejonckheere et al. (2019) study, which reported that several measures of emotion dynamics and complexity (not including emotional regularity) yielded negligible (close to 0%) improvements in cross-validated *RSq's* compared to baseline models with affective intensity and variability. Thus, in addition to addressing concerns of overfitting, the present results provide additional evidence for generalizability and incremental contributions of emotional regularity net of the baseline affective measures.

3.3. Robustness Checks

Our modeling approach has two free parameters – the radius used to determine if affective states on any two days are recurrent (set to 0 in the above results) and the minimum number of ESM responses for inclusion (set to 7 in the current results). Because larger radii relax the criterion for recurrence, they are also more tolerant of measurement error. To investigate robustness of our findings to these parameters, we recomputed emotional regularity scores using multiple radii and minimum number of ESM responses. We first normalized positive and negative affect values to the 0 to 1 range to facilitate comparisons across different radii. We then computed emotional regularity using radii in the 0 to 0.25 range with increments of 0.05. Next, using a radius of 0, we considered the effects of different cutoffs for the minimum number of ESM surveys per participant from a low of 3 (N = 591, the minimum needed to meaningfully compute some of the affect measures), 7 (N = 581, the current threshold), and a high of 14 (N = 564).

The results are shown in Table 8. Using the default radius of 0, we found that recurrence rates were equivalent across the minimum number of ESM surveys per participant. Next, using the default minimum number of surveys to 7, we found that recurrence rates increased for larger radii (which is what was expected). We did not go beyond a radius of 0.25 because the mean recurrence rate at 11% for this radius already exceeds the recommendation value of 5% for recurrence quantification analyses (Coco & Dale, 2014; Pellecchia & Shockley, 2005).

For Aim 1, we examined the influence of the radius on the variance explained by the four basic emotion measures with minimum number of surveys set at 7 (default value). We found that the basic emotion measures explained between 7% to 35% of the variance in emotional regularity across radii. In fact, emotional regularity was even more distinct from the basic emotion measures for larger radii (e.g., RSq. was 12% for a radius of 0.2 compared to 35% for the default radius of 0 used for the main results), providing even more support for Hypothesis 1.

For Aim 2, we first recomputed the regression models from **Table 5** using emotional regularity computed at the various radii and the minimum number of ESM surveys fixed at 7. The results were largely consistent across radii with some inconsistencies emerging at a radius of 0.25, ostensibly because the mean recurrence rate at this radius (11%) exceeds the 5% recommendation (see above). Varying the minimum number of ESM surveys had no influence on the results. Thus, emotional regularity predicted agreeableness, conscientiousness, neuroticism, stress/anxiety, task performance, and organizational and citizenship behavior independent of the parameters used in the modeling.

4. Discussion

We introduced the concept of emotional regularity as the propensity to maintain and return to a set of emotional states and grounded it in complex systems perspectives that emphasize stability via self-organized variability. Researchers have introduced several complex emotion measures over the last decade, so it is important to demonstrate the utility for another emotion measure. First, we argued that emotional regularity is theoretically distinct from a host of extant measures given its focus on multidimensionality, multistability, and global structural organization. Similar to emotional regularity, one recent study also used a recurrence quantification framework analyze affective dynamics (Jenkins et al., 2020), but the present approach is methodologically (multidimensional via MdRQA vs. unidimensional via auto-RQA), conceptually (system-level regularity vs. self-similarity), and empirically (i.e., it is less correlated with emotion variability [*rs* < .46 vs. *rs* < .75]) distinct. Second, we empirically demonstrated that emotional regularity was related to but, not redundant with, emotion intensity and emotional variability – there was 65% of unexplained variance after accounting for basic emotion measures, which supports Hypothesis 1. Third, we examined the pattern of association among emotional variability and other complex measures of emotion, finding correlations ranging from .05 to .58, which suggest overlap but not redundancy.

The pattern of associations among emotional regularity and the other emotion measures was insightful. For one, emotional regularity was positively associated with emotional granularity and covariation, suggesting that it complementarily indexes adaptive functioning. For example, according to Ong, Zautra, and Finan (2017), affective experiences are more bipolar (i.e., low covariation) when stress is high. Similarly, low-levels of negative emotional granularity have been linked to a number of psychopathologies including major depressive disorder and borderline personality disorder (see Smidt and Suvak (2015) for a review). And although emotional regularity was negatively correlated with positive and negative affective variability, this does not imply that people with high emotional regularity experience a monotonous emotional life. In fact, results suggest that people with high emotional regularity experience a rich and diverse set of emotions (i.e., emodiversity). Thus, emotional regularity reflects a balance between having a rich/diverse emotional life, which will inevitably include some variability, versus experiencing emotional inertia (being stuck in the same emotional state) or extreme emotional variability (i.e., mood instability). One conclusion is that recurring to a set of emotional states (emotional regularity) while experiencing a rich and balanced set of emotions suggests adaptability and flexibility associated with healthy functioning (Hollenstein, 2015; Quoidbach et al., 2014).

To this point, we found support for the claim that emotional regularity indexes positive functioning in nonclinical samples (Hypothesis 2). Emotional regularity was associated with personality traits of (negatively) neuroticism, agreeableness and conscientiousness. By definition, the personality dimension of neuroticism (emotionally unstable) should be associated with less regular emotional profiles, which was supported in the current investigation. We also observed a significant positive association among the personality dimension of conscientiousness and emotional regularity; which is plausible in that orderliness and self-discipline – two facets of conscientiousness (Soto & John, 2017) – should extend to peoples' emotional lives. Results supporting an association between the personality dimension of agreeableness and emotional regularity was less easily explained and warrants further research. With respect to psychological health outcomes, we found that emotional regularity negatively predicted mental health (stress/anxiety), even after accounting for negative affect intensity, variability, and income, which is consistent with the hypothesis that it indexes adaptive functioning. The evidence was less compelling with respect to physical health indicators in that emotional regularity was an inconsistent predictor of substance abuse (alcohol consumption) and did not predict sleep disruptions.

We also found that emotional regularity predicted key occupational outcome measures of higher task performance and conducive organizational/citizenship behaviors, but not counterproductive/deviant behaviors in the workplace. Whereas most previous studies on other complex emotion measures have focused on predicting mental health outcomes, most commonly indicators of psychological well-being, such as life-satisfaction, borderline symptoms, and depression symptoms (Dejonckheere et al., 2019), our study is the first to associate a complex emotional measure with occupational outcomes. In this case, the predictive power of emotional regularity is quite significant given the heterogeneity of occupations in our sample and since we accounted for several known predictors of job performance, including personality (Barrick & Mount, 1991), cognitive ability (Schmidt & Hunter, 2004), and stress/anxiety (Kaplan et al., 2009). The fact that emotional regularity can predict outcomes that go beyond mental health (an emotion-related outcome) to job performance (a non-emotion-related outcome), supports our claim that it provides a viewpoint into adaptive functioning in nonclinical samples.

Many studies of complex emotion measures only control for emotional intensity, and effects become negligible when both intensity and variability are included as control variables (Dejonckheere et al., 2019). Not only did we show that our findings are robust to both positive and negative affective intensity and variability (and even covariance), in most cases, the findings were robust to seven other complex measures of emotion (covariation, and positive and negative inertia, granularity, and diversity). Additionally, whereas some of these other emotion measures did predict several outcome measures, emotional regularity uniquely predicted two measures suggesting discriminative predictive power.

Finally, using cross-validation to avoid overfitting and to provide a measure of generalizability, we found that emotional regularity explained, on average, an additional 7.5% of the variance over the baseline model of emotional intensity, variability, and pertinent covariates. Thus, we think that the present investigation addresses the central caution in Dejonckheere et al. (2019) pertaining to "disregarding any overlap with existing measures fails to evaluate the potential redundancy of new measures, which not only may lead to a dispersed and scattered research field but may also create a false sense of scientific progress in the long run" (p. 478). We conclude that emotional regularity provides a unique perspective to measuring emotional patterning and has value in predicting a range of personality, health, and occupational outcomes that go beyond the mental health outcomes examined in previous research.

The present investigation should be interpreted with respect to several limitations. First, individual differences (e.g., emotional regulation, emotional intelligence) and situational factors (e.g., situational novelty, coping potential) related to emotional regularity need to be explored. We also conducted our study with a large and moderately diverse nonclinical sample of information workers, but there is the question of how emotional regularity differs in clinical populations, such as those diagnosed with major depressive disorder or borderline personality disorder. A different pattern of results could be expected in clinical samples, as discussed in the Introduction. Second, we did not have control on the study methods and procedures as these were funder-mandated, which limited the types of data we could collect. But this also permitted us to collect a large and geographically diverse dataset on information workers to investigate emotion regularity and other measures of emotion dynamics and complexity, thereby adding to the existing literature which has focused on mental-health outcomes in clinical and student populations. For the same reason, we were restricted to self-reported measures of all key measures, including the use of the Short PANAS to measure all affect variables, which tends to focus on high-arousal emotions. Replication with alternate self-report measures of emotion is desirable. Fourth, we opted for a more coarse-grained representation of affect as a point in a two-dimensional positive-negative state space which obfuscates more fine-grained distinctions among emotions (i.e., high alertness and low values on all other emotions would yield the same score than high determination and low values on all other emotions). Hence, future work should examine alternate conceptualizations of regularity, especially when more data are available.

There are also several avenues for future research. For one, we focused on nonclinical samples and emphasized personality, general psychological health, and occupational outcomes. Much of the prior work on complex emotion measures has investigated mental health outcomes such as depressive and borderline symptoms (Dejonckheere et al., 2019) in both clinical and nonclinical outcomes, so investigating emotional regularity in this context is one avenue for future research. Second, and as elaborated below, our computation of emotional regularity is derived from a (multidimensional) recurrence quantification analysis framework (MdRQA), which is a powerful analytic tool to investigate complex dynamical systems. We focused on only one measure (recurrence rate) in this initial investigation because it best aligned with our theoretical conceptualization of emotional regularity. However, future work can investigate additional RQA measures (Marwan et al., 2007) as well as analyze local affect dynamics compared to the global patterning investigated here. Third, extant research on emotion dynamics primarily relies on self-reported affect with known limitations (Trull & Ebner-Priemer, 2009). The MdRQA approach utilized here can be applied to analyze physiological and behavioral data from any number of signals (e.g., Amon et al., 2019), so a complementary investigation using these measures would be an important line of future work. Fourth, our study adopted a diary design where the ESMs were administered once per day, presumably resulting in sampling different emotional episodes. It would be interesting to examine emotional regularity with alternate designs where ESM surveys are completed multiple times per day, ostensibly from similar episodes, as well as to examine rhythmic shifts in regularity (e.g., diurnal rhythms, weekend-weekday changes, seasonal effects). Finally, whereas the present study was correlational, understanding the precise mechanisms underlying the effects requires future work with alternate designs and measures to uncover causal relationships.

In conclusion, we suggest that emotional regularity provides a unique insight into emotion because it captures adaptive self-organization to recurrent emotional states amongst the ups and downs of life. Although a person might not always be able to control how they feel, being able to return to a set of recurrent emotional states might reflect a form of adaptive function that is associated with emotional health and well-being in nonclinical samples. Complex systems perspectives of emotion in general, and emotional regularity in particular, are a promising area for further scientific discovery.

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Table 1. Computing emotional regularity in a hypothetical example

[Pos, Neg]$_{\textbf{Day}}$	$[3, 1]_{D1}$	$[3, 2]_{D2}$	$[3, 1]_{D3}$	$[1, 4]_{D4}$	$[1, 4]_{D5}$	$[2, 3]_{D6}$	$[3, 1]_{D7}$			
$[3, 1]_{D7}$	1	0	1	0	0	0	-			
$[2, 3]_{D6}$	0	0	0	0	0	-	0			
$[1, 4]_{D5}$	0	0	0	1	-	0	0			
$[1, 4]_{D4}$	0	0	0	-	1	0	0			
$[3, 1]_{D3}$	1	0	-	0	0	0	1			
$[3, 2]_{D2}$	0	-	0	0	0	0	0			
$[3, 1]_{D1}$	-	0	1	0	0	0	1			
#Matches	2	0	2	1	1	0	2		**8**	Sum
#Possible	6	6	6	6	6	6	6		**42**	Sum
									8/42	
									19%	**Score**

Note: Emotional regularity scores - positive and negative affect levels ([pos, neg]day) - are compared across consecutive days, matches (days with similar values) are tallied, summed, and then proportionalized to compute the recurrence rate (emotional regularity score)

Table 2. Descriptive statistics for participant demographics (*N* = 598)

Cohort (%)	
Cohort 1 [Miscellaneous[1]]	156 (26.1)
Cohort 2 [Large Technology Services Firm]	246 (41.1)
Cohort 3 [Large Midwestern Tech / Engineering Firm]	143 (23.9)
Cohort 4 [Small Midwestern Software Firm]	21 (3.5)
Cohort 5 [Medium Midwestern University]	32 (5.4)
Male (%)	347 (58.0)
Age (mean (SD))	34.36 (9.39)
Born in US = Yes (%)	493 (82.6)
Native language English = Yes (%)	514 (86.0)
Education (%)	
Doctoral degree, such as PhD, MD, JD	18 (3.0)
Master''s degree	212 (35.5)
Some graduate school	48 (8.0)
College degree	277 (46.3)
Some college	37 (6.2)
High school degree (or equivalent)	4 (0.7)
Some high school (or equivalent)	2 (0.3)
Job Status = Part-time (%)	11 (1.8)
Supervisor = Yes (%)	281 (47.2)
Income (%)	
More than $150,000	131 (22.1)
$125,000 to $150,000	59 (9.9)
$100,000 to $124,999	103 (17.4)
$75,000 to $99,999	128 (21.6)
$50,000 to $74,999	126 (21.2)
$25,000 to $49,999	40 (6.7)
Less than $25,000	6 (1.0)
Occupation (%)	
Architecture and Engineering	59 (9.9)
Arts, Design, Entertainment, Sports, and Media	15 (2.5)
Business and Financial Operations	144 (24.1)
Computer and Mathematical	168 (28.1)
Education, Training, and Library Services	11 (1.8)
Healthcare Practitioners and Technical Healthcare Occupations	12 (2.0)
Management	72 (12.0)
Office and Administrative Support Occupations	24 (4.0)
Sales and Related Occupations	9 (1.5)
Other	84 (14.0)

Note. [1] Whereas the other four cohorts were recruited through their employers, the miscellaneous cohort was comprised of professionals recruited through mailing lists, word-of-mouth, and social media.

Table 3. List of measures and instruments

Domain/Construct	Initial Battery	Experience Sampling Method
Psychological		
Personality	Big-Five-Inventory-10 (BFI-10)	BFI-2 (biweekly)
Cognitive Ability		
Fluid	Shipley Abstraction	-
Crystallized	Shipley Vocabulary	-
Affect		
Positive and Negative Affect	Pos/Neg Affect Schedule Extended (PANAS-X)	PANAS-S (7/week)
Anxiety	State-Trait Anxiety Inventory (STAI)	Custom[1] (7/week)
Stress	-	Custom[1] (7/week)
Health		
Alcohol use	Alcohol Use Disorders Identification Test (AUDIT)	Custom[2] (3-4/week)
Tobacco use	Modified Global Adult Tobacco Survey (GATS)	Custom[2] (3-4/week)
Sleep	Pittsburgh Sleep Quality Index	Custom[3] (3-4/week)
Physical activity	International Physical Activity Questionnaire (IPAQ)	Custom[4] (3-4/week)
Job Performance		
Task performance	In-Role Behavior (IRB) & Individual Task Proficiency (ITP)	IRB/ITP (3/week)
Organizational Citizenship Behaviors (OCB)	OCB Checklist (OCB-C)	OCB/CWB scale (3/week)
Counterproductive Work Behavior (CWB)	Interpersonal and Organizational Deviance Scale (IOD)	OCB/CWB scale (3/week)

Notes. [1]Single item measures on current levels of anxiety or stress on a 1 to 5 scale.[2] Number of alcoholic beverages/tobacco products consumed the previous day (⩾0 or greater); [3] total hours of prior night’s sleep (range 0-24); [4] approximate MET-minutes of prior day’s exercise (⩾0).The PANAX-X, Tobacco, and Physical activity measures are not analyzed in this paper.

Table 4. Descriptive statistics and correlations between emotional regularity and the other emotion measures.

Covariate	*M (SD)*	*Range*	*r*
Basic Affect Measures			
Positive Intensity	11.78 (3.22)	[5.2, 24]	-0.270***
Negative Intensity	6.54 (1.55)	[5.0, 15]	-0.457***
Positive Variability	3.02 (0.94)	[.85, 7.5]	-0.431***
Negative Variability	1.81 (1.13)	[0, 7.7]	-0.457***
Emotional Complexity & Dynamics Measures			
Emotional Covariance	-0.01 (0.27)	[-.79, .93]	0.270***
Pos. Emo. Inertia	-0.04 (0.14)	[-.48, .34]	0.092*
Neg. Emo. Inertia	0.38 (0.25)	[-.66, .44]	0.050
Pos. Emo. Granularity	-0.75 (0.14)	[-0.98, -.10]	0.142***
Neg. Emo. Granularity	-0.62 (0.25)	[-.99, 0]	.290***
Pos. Emo. Diversity	1.56 (0.03)	[1.4, 1.6]	0.190***
Neg. Emo. Diversity	1.58 (0.02)	[1.4, 1.6]	0.579***

Notes. * indicates $p < .05$; ** indicates $p < .01$; *** indicates $p < .001$. Range refers to the observed ranged in the data.

Table 5. Standardized coefficients (effect size) for predicting personality, health, and job performance from emotional regularity compared to basic emotional measures.

Domain/Construct	**Emotional Regularity**	**Emotional Intensity**		**Emotional Variability**	
(Dependent Variable)		*Pos*	*Neg*	*Pos*	*Neg*
Personality					
Agreeableness (*β*)	0.11*	0.24**	-0.16*	0.07	-0.05
Openness (*β*)	-0.06	0.12**	-0.09	0.18**	0.05
Extraversion (*β*)	0.07	0.27**	-0.03	0.02	0
Conscientiousness (*β*)	0.12*	0.2**	0	0.06	-0.18*
Neuroticism (*β*)	-0.17**	-0.2**	0.14*	-0.01	0.26**
Health					
Stress/Anxiety (*β*)	-0.25**	-0.14**	0.42**	-0.09*	0.31**
Alcohol use [Incidence RR]	0.88†	1.03	0.86†	0.89	1.24†
Sleep (*β*)	0.01	0.09*	-0.06	-0.01	-0.19*
Job Performance					
Task performance (*β*)	0.13**	0.22**	-0.24**	0.1*	-0.07
Organizational & Citizenship Behaviors (*β*)	0.2**	0.27**	-0.02	0.09†	0.1
Counterproductive Work Behavior (*β*)	-0.08†	-0.14**	0.06	0.01	0.13†

Note. †$p < .10$; *$p < .05$; **$p < .01$; Predictors for all models include emotional regularity, positive and negative affective intensity and variability. Covariates include the number of ESM surveys used to compute affect measures, cohort [five groups], age, gender, and native language [English or not]. The model for alcohol is a negative binomial regression so Incident Rate Ratios are reported; other models are ordinary linear regressions and standardized coefficients are reported. $N = 581$ for all models except alcohol use, where $N = 577$.

Table 6. Standardized coefficients (effect size) for predicting personality, health, and job performance from emotional regularity compared to other complex emotional measures

Domain/Construct	**Emotional Regularity**	**Emo. Cov.**	**Emotional Inertia** *Pos*	*Neg*	**Emotional Granularity** *Pos*	*Neg*	**Emotional Diversity** *Pos*	*Neg*
Personality								
Agreeableness (*β*)	0.11*	-0.06	-0.02	0.03	0.09	0.08	-0.02	0.07
Openness (*β*)	-0.06	-0.05	-0.01	0.06	0.07	0.08	0.06	-0.01
Extraversion (*β*)	0.07	0.03	-0.01	-0.09*	-0.02	-0.05	0.02	0.12*
Conscientiousness (*β*)	0.12*	-0.03	-0.1*	0.04	0.02	0	-0.03	0.03
Neuroticism (*β*)	-0.17**	-0.08*	0.03	0.02	-0.03	-0.08	0	-0.24**
Health								
Stress/Anxiety (*β*)	-0.25**	-0.04	0.01	0.02	0.08*	0.04	-0.03	-0.34**
Alcohol use [Incidence RR]	0.88†	1.39	0.51	0.73	2.96	0.9	0.01	0.01
Sleep (*β*)	0.01	-0.01	-0.03	0	-0.04	0	0.04	0.05
Job Performance								
Task performance (*β*)	0.13**	-0.05	-0.03	0.07†	-0.07	-0.03	-0.07†	0.07
Organizational & Citizenship Behaviors (*β*)	0.2**	0.09*	0.07†	0.04	-0.14**	0.06	0.11**	0.1*
Counterproductive Work Behavior (*β*)	-0.08†	0.05	0.03	0.01	-0.03	-0.02	0.02	-0.04

Note. †$p < .10$; *$p < .05$; **$p < .01$; Emo. Cov. = emotional covariance. Predictors for all models include positive and negative affective intensity and variability, the number of ESM surveys used to compute affect measures, cohort [five groups], age, gender, and native language [English or not]. The model for alcohol is a negative binomial regression so Incident Rate Ratios are reported; other models are ordinary linear regressions and standardized coefficients are reported.

Table 7. Improvement in 10-fold cross-validated RSq. (mean over 100 iterations) when emotional regularity is added as a predictor to a baseline model with positive and negative emotional intensity, variability, and covariates.

Domain/ Construct	**10-fold cross-validated RSq. (%)** Model 1: No Emotional Regularity	Model 2: With Emotional Regularity	% Improvement
Agreeableness	12.1	12.5	3.6
Conscientiousness	10.3	10.8	5.2
Neuroticism	23.8	25.1	5.9
Stress/Anxiety	49.0	52.7	7.5
Task performance	17.5	18.5	5.7
Organiz. Citizenship Behaviors	12.4	14.5	17.0

Notes. % improvement computed as 100 * [(model 2 – model 1)/model 1]; Sociodemographic covariates include the number of ESM surveys used to compute affect measures, cohort [five groups], age, gender, and native language [English or not].

Table 8. Results across range of radii and exclusion criterion (i.e., minimum number of ESM responses).

	Main Result	**Min. Surveys = 7**					**Radius = 0**	
		Radius					*Min Surveys*	
	Surveys = 7; Radius = 0.	0.05	0.1	0.15	0.2	0.25	3	14
Emotional Regularity Measure								
N	581			581			591	564
Mean Recurrence Rate (%)	7.17	7.17	7.18	7.35	8.68	11	7.19	7.11
Aim 1: Variance explained by basic emotion measures (%)	35	35	34	26	12	7	35	34
Aim 2: Predicting Constructs								
Personality								
Agreeableness *(β)*	0.11 *	0.11 *	0.11 *	0.12 **	0.1 *	0.04	0.1 *	0.11 *
Openness *(β)*	-0.06	-0.06	-0.06	-0.04	-0.04	-0.07†	-0.05	-0.08
Extraversion *(β)*	0.07	0.07	0.07	0.08	0.05	0.04	0.05	0.08 †
Conscientiousness *(β)*	0.12 *	0.12 *	0.13 *	0.13 **	0.11 *	0.05	0.11 *	0.15 **
Neuroticism *(β)*	-0.17 **	-0.17 **	-0.16 **	-0.17 **	-0.08 *	-0.09 *	-0.16 **	-0.15 **
Health								
Stress/Anxiety *(β)*	-0.25 **	-0.25 **	-0.24 **	-0.24 **	-0.18 **	-0.17 **	-0.25 **	-0.26 **
Alcohol use *(IRR)*	0.86 †	0.86 †	0.86 *	0.86	0.86	0.86	0.86 *	0.86 †
Sleep *(β)*	0.01	0.01	0.01	0.01	-0.01	-0.03	0	0.04
Job Performance								
Task performance *(β)*	0.13 **	0.13 **	0.13 **	0.13 **	0.09 *	0.09 *	0.13 **	0.12 *
Organiz. Citizenship Bhv. *(β)*	0.2 **	0.2 **	0.2 **	0.18 **	0.12 **	0.11 **	0.2 **	0.2 **
Counterproductive Wk. Bhv. *(β)*	-0.08†	-0.08 †	-0.09 †	-0.11 *	-0.09 *	-0.03	-0.09 †	-0.08

Note. † $p < .10$; * $p < .05$; ** $p < .01$; Min. = Minimum. Organiz. Citizenship Bhv. = Organizational and citizenship behavior; Counterproductive Wk. Bhv. = Counterproductive work behavior; IRR = incidence rate ratio.

Figure 1. Hypothetical example to illustrate basic idea of emotional regularity, state spaces, and recurrence plots. (Top). Time series depicting positive and negative affect intensity across seven days. The person has mild positive affect on day one (i.e., D1), the same level of positive affect but with slightly elevated negative affect on D2, returns back to a mild positive state on D3. On D4 they abruptly shift to an intense negative state, maintain it on D5, and return to the original D1 state on D7 with D6 representing a transition point. (Lower left). Scatter plot (state space) of positive and negative affect. Point size is proportional to number of recurrences (different days with similar affect values). For example, positive affect was 3 and negative affect was 1 on day 3, 1, and 7. (Lower right) Recurrence plot formed by comparing emotion on each day to every other day and marking overlaps (recurrent points) with black rectangles. Empty cells reflect combinations of days where affective states were different.

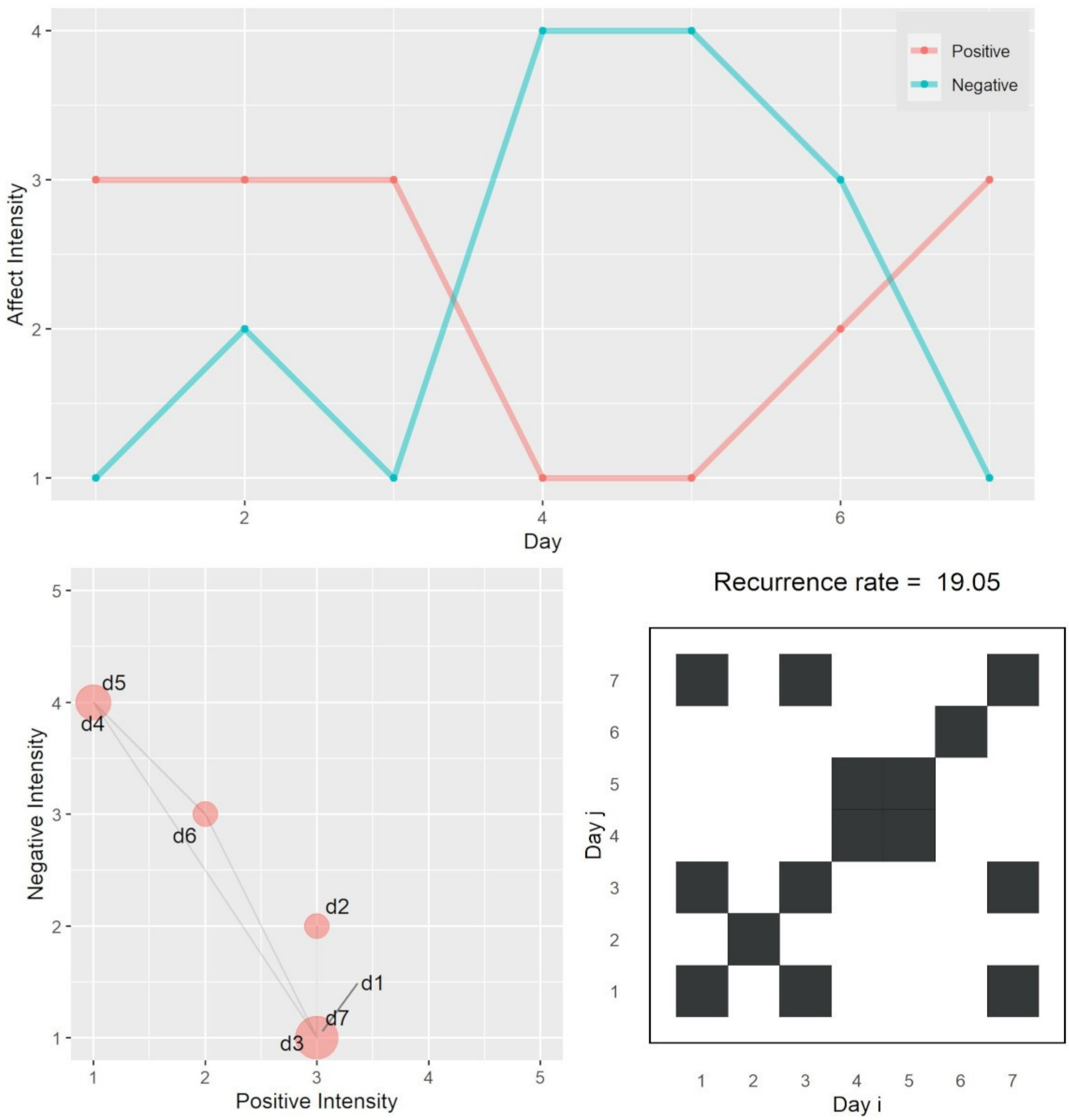

Figure 2. Time series (A), state space (B), and recurrence plot (C) for sample participant with a 11.45% recurrence rate.