Profiles of daily positive emotion dynamics and associations with flourishing

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Disclosure statement

The authors have no conflicts of interest to declare.

Data availability statement

The data and code that support the findings of this study are available on the open science framework: https://osf.io/6c2pe/?view_only=e2fdb8dbdb414910851adf8be95e690d

Abstract

The present study investigated between-person differences in daily positive emotion dynamics and their associations with flourishing across two studies (Study 1: *n*=244, Study 2: *n*=265). Three between-person indices of daily positive emotion dynamics were created: average intensity, variability, and inertia. Using latent profile analysis, a data-driven technique that identifies subgroups (referred to as profiles) within a population, four common ways in which these three emotion dynamics cluster at the person level were identified. Testing for associations between flourishing and the observed profiles of emotion dynamics revealed that people with high levels of positive emotion that were stable over time were highest in flourishing, followed by low-intensity but variable positive emotions, followed by individuals with low-intensity positive emotions. By considering how three key emotion dynamic indices cluster within individuals, we find that understanding both the average intensity and the extent of stability in daily positive emotion is necessary for understanding flourishing.

Keywords: positive emotion; flourishing; latent profile analysis; emotion dynamics; ecological momentary assessment

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Flourishing is a state of well-being that constitutes feeling good (hedonic or subjective well-being) and functioning well (eudaimonic or psychosocial well-being) (Fredrickson & Losada, 2005; Keyes, 2002). Longitudinal studies reveal that positive emotions are key enablers of flourishing (Lyubomirsky et al., 2005). Associations between flourishing and positive emotion are interpreted through the lens of the broaden-and-build theory, which posits that the experience of positive emotions comes with advantages distinct from the absence of negative emotions (Fredrickson & Losada, 2005). This theory asserts that, in contrast to negative emotions, which narrow an individual's attention toward threats to well-being in the immediate environment, positive emotions can broaden an individual's behavioral flexibility (Fredrickson & Losada, 2005). People who experience more positive emotions experience greater expansion of their cognitive and behavioral repertoires through their engagement with the world. This growth, in turn, can allow individuals to build more social connections and to develop stronger coping strategies, thereby preparing them to manage future threats, and hence promoting flourishing (Fredrickson & Branigan, 2005).

As emotions and their regulation reflect the operation of dynamic processes, ongoing research aims to investigate how *dynamics*, or the extent of fluctuations, in positive emotion are associated with flourishing (Lyubomirsky et al., 2005). The dynamic nature of emotions reflects their roles in alerting us to important changes in the environment and facilitating responses to these changes (Kashdan & Rottenberg, 2010; Izard, 2009). Emotion dynamics also reflect the ways we manage our emotions (Frijda, 1986), including processes that modulate the occurrence, intensity, and duration of emotional experiences (Cicchetti et al., 1995; Cole et al., 2004; Thompson, 1990) to accommodate changing environmental demands and goals (Thompson, 1994). Emotion dynamics are increasingly being measured by ecological momentary assessment approaches that allow individuals to report their affective experiences as they go about their daily lives (Van Genugten et al., 2021). Reporting on emotional experiences in everyday environments, as compared to a laboratory setting, lends ecological validity to the data collected.

Linking emotion dynamics to flourishing is complicated by the fact that the temporal flow of emotion can be quantified in several ways, and each way could relate differently to flourishing. Once a time series capturing fluctuations in emotion ratings across time is acquired, a plethora of indices are available to quantify emotion dynamics (Kuppens & Verduyn, 2015). Three well-known operationalizations (see Dejonckheere et al., 2019 for others) are average emotion intensity, emotion variability, and emotion inertia (Van Genugten et al., 2021). Quantifying the mean of a person's emotion intensity ratings in their emotion time series captures one's average level of positive emotion. Quantifying the standard deviation of an emotion time series captures the average deviation from one's mean level of emotion and is termed emotion variability. High variability indicates greater deviations in emotion from one's average emotion, while low variability indicates smaller deviations from one's average emotion intensity (Jahng et al., 2008; Vansteelandt & Verbeke, 2016). By using autoregressive models to capture how the intensity of an emotion at the previous time point (t-1) predicts emotion intensity at the current timepoint (t), emotion inertia is captured and reflects the extent to which emotion intensity is carried from one instance to the next (Kuppens et al., 2010).

Flourishing individuals experience positive emotions regularly as they succeed in their daily lives, experience high purpose and meaning in life, and give back to the world around them (Keyes, 2007). As such, we may anticipate that the positive emotion dynamics of people who flourish are characterized by high average positive emotion intensity. In terms of both variability and inertia in positive emotion, expectations for what people high in flourishing might exhibit relative to those low in flourishing are less clear. High variability may be expected given that people high in flourishing may have more positive reactions to day-to-day activities than others (Catalino & Fredrickson, 2011). In this case, high variability in positive emotion would indicate deviations from average levels of positive emotion as people savor the positive experiences they encounter in everyday life. High variability in positive emotion may also be indicative of an ability to react flexibly to changing circumstances (Waugh et al., 2001), a flexibility key to achieving and sustaining states of well-being like flourishing (Kashdan & Rottenberg, 2010). However, variability in positive affect also has been associated with lower well-being and higher levels of psychopathology (Gruber et al., 2013), suggesting that positive emotion variability indicates a type of fragile positive emotion that is difficult to sustain and easily affected by changing circumstances (Ong & Ram, 2017). A similar picture emerges for positive emotion inertia, or the persistence of an emotional state over time. Although high emotion inertia is thought to represent an inflexibility in affect and resistance to change (Hollenstein et al., 2013), there is some evidence that high positive emotion inertia is indicative of an ability to sustain positive emotion and is associated with good outcomes (Hohn et al., 2013). However, this association is not observed consistently (Houben et al., 2015; Kuppens et al., 2010).

Complicating our understanding of positive emotion dynamics in flourishing, but also providing a potential way forward to reconcile mixed findings, is the increasing recognition of the need to consider multiple indices of positive emotion dynamics in conjunction. For example, prior research distinguishes between one type of fragile positive emotion, consisting of variable high-average intensity positive emotion, and a second form of fragile positive emotion, consisting of high-average intensity positive emotion associated with frequent changes in positive emotion (e.g., low inertia) across time and contexts (Ong & Ram, 2017; see also Maciejewski et al., 2023). Despite this increasing focus on typologies, research on emotion dynamics has mainly taken a variable centered-approach (Bergman & Magnusson, 1997), asking whether the standard deviation of positive emotion, for example, predicts life satisfaction above and beyond the mean of positive emotion (Dejonckheere et al., 2019; Houben et al., 2015). This variable-centered approach allows researchers to quantify the independent contribution of one variable over another when predicting an outcome of interest. However, variables, rather than people, risk becoming the central units of most interest in this approach. Person-centered approaches highlight that humans are made up of parts that interact, and conclusions drawn from variable-centered approaches may fail to do justice to the complexity of the individual (Von Eye & Bergman, 2003). Person-oriented approaches facilitate consideration of the hanging together of different variables in an integrated manner (Bergman & Magnusson, 1997). Practically, this holistic assessment entails considering the integrated nature of multiple indices of emotion dynamics within persons (e.g., an individual with certain configurations of multiple aspects of emotion dynamics including levels of positive emotion *and* variability in positive emotion) and treating the person, rather than the variable, as the unit of interest (Magnusson, 1999; Magnusson & Cairns, 1996).

Few studies have taken a person-centered approach to emotion dynamics but there are several notable exceptions (Ernst et al., 2020; van Genugten et al., 2021). One highly relevant paper (Winter, Conner, & Jose, 2020) constructed profiles of emotion dynamics including the mean and variability of both positive and negative emotion. A three-profile solution was observed with a *Positive Profile* (named by the investigators) associated with high levels of positive emotion and low levels of negative emotion, a *Negative Profile* with high levels of negative emotion and low levels of positive emotion, and a *Mixed Profile* with high levels of positive emotion and moderate levels of negative emotion. Negative emotion variability showed some differences across the three profiles, with the *Positive Profile* showing the highest negative emotion variability of all three groups. Notably, positive emotion variability appeared similar across the three profiles. Profile membership was associated with flourishing such that individuals with the *Positive Profile* and *Mixed Profile* reported high levels of flourishing and individuals with the *Negative Profile* reported low levels of flourishing. This study suggests the feasibility of taking a person-centered approach and its ability to provide insight into positive emotion dynamics in flourishing. By including negative emotion and excluding indices of inertia, however, the existence of profiles of positive emotions characterized by differing levels of mean intensity, variability, and inertia is unclear. Together these novel applications of person-centered approaches demonstrate the existence of unique emotion dynamic configurations that may be useful for uncovering between-person differences in flourishing.

The Present Study

The present study extends current research by identifying profiles defined by differing constellations of positive emotion dynamics and testing the association between these profiles and flourishing. By surveying daily positive emotion, we generated data that allowed us to quantify the average intensity of positive emotion, variability in positive emotion, and positive emotion inertia. Using latent profile analysis, we identify common ways in which these three variables cluster in people. We next test for associations between flourishing and the observed profiles. Given the novelty of our study, we took an exploratory approach. To test the robustness of the findings and the extent to which they replicated across samples, we undertook the same approach in two studies.

Method

Study 1 combined data from the Knowledge Networks Over Time (KNOT) Study and Networks of Daily Experiences (NODE) Study. Data were combined across these studies because their protocols were very similar, making their combination to achieve a large sample size feasible. We provide details relevant to the present analyses below and direct readers to existing work for a more comprehensive overview of the study protocols (Lydon-Staley et al., 2020; McGowan et al., 2022). Institutional Review Board approval was obtained at the University of Pennsylvania.

Study 2 used data from the Social Health Impact of Network Effects (SHINE) Study. We provide details relevant to the present analyses below and direct readers to existing work for a more comprehensive overview of the protocol (Cosme et al., 2022; McGowan et al., 2021). The SHINE study was approved by the University of Pennsylvania, Columbia University, and the Army Research Office's Human Research Protection Office.

Participants

Participants in Study 1 came from two studies with similar protocols. Participants in the KNOT Study were 167 (136 women, 29 men, 2 genders not listed in the demographic survey) individuals recruited through poster, Facebook, Craigslist, and university research site advertisements in Philadelphia and the surrounding university community. Individuals were eligible if they met 4 criteria: (a) aged between 18 and 65 years, (b) having consistent access to a computer with internet access at home, (c) being willing to complete 21 consecutive days of surveys, and (d) being willing to visit the research laboratory for a one hour visit. Participants in the NODE Study were 77 young adults (63 women, 14 men) recruited through poster, Facebook, Craigslist, and university research site advertisements. Participants were eligible if they met 5 criteria: 1) aged between 18 and 25 years of age; 2) having consistent home access to a desktop or laptop with internet; 3) owning a smartphone; 4) willing to complete a 2-hour laboratory visit; and 5) willing to install a free app on their smartphone. Data on key variables for the current study were available for 244 participants (mean age = 24.05 years, *SD* = 6.45; gender = 199 women, 43 men, 2 genders not listed in the demographic survey) from the combined KNOT and NODE samples.

Participants in Study 2 were undergraduate students recruited from campus-based social groups (e.g., Greek organizations, sports clubs, and performance groups) at the University of Pennsylvania and Columbia University. Eligible social groups included on-campus organizations containing 20-100 members, with at least 80% of members interested in participating in the study. The study was advertised through flyers, university websites, in-person information sessions, and email communication. To reach campus groups, the researchers contacted group leaders and then employed a snowball sampling approach, such that participating students could share recruitment information with their peers who were members of on-campus social groups. Participants were eligible to enroll in the study if they were a member of one of the social groups invited to participate. Data on key variables for the current study were available for 265 participants (mean age = 20.22 years, *SD* = 1.98; gender = 180 women, 61 men, 24 missing information).

Procedure

For Study 1, interested KNOT Study participants first provided consent online and then completed a baseline survey containing demographic questionnaires and the flourishing measure used in the present study online. Participants then completed a laboratory session where they received training in the daily assessment protocol. Following the laboratory study, a 21-day diary assessment protocol was initiated. The 21-day diary assessment consisted of two components. The first was a daily diary consisting of survey questionnaires that took approximately 5 min to complete. The second came immediately after the daily diary component and was a 15 min internet browsing task (Lydon-Staley et al., 2021) that we do not report on in the present manuscript. Links to the daily assessments were emailed to participants at 6:30 p.m. each evening. Participants requesting reminders received a text message at 6:40 p.m. to notify them that survey links had been emailed. Participants were instructed to complete the daily assessments before going to bed, but were also told that links would remain open until 10:00 a.m. the next morning. In cases where participants completed the surveys the following morning, they were instructed to report as if they were completing the survey on the previous evening. Daily questionnaires took approximately 5 minutes to complete. Data collection began in October 2017 and ended in July 2018.

The protocol of the NODE study (McGowan et al., 2022), was very similar to the KNOT study, with participants attending a laboratory visit and then completing 21 days of daily diaries. As in the KNOT study, links to the end of day, daily diary surveys were sent via email at 6.30 p.m. each evening. Participants in the NODE study also completed an experience-sampling assessment throughout the day but we do not report on these data in this manuscript. Data collection began in July 2019 and ended in March 2020 when laboratory visits were no longer possible due to COVID-19.

For Study 2 (the SHINE study), interested participants were asked for their consent and completed a baseline survey assessing their demographics, among other measures (see for more details the SHINE study protocol paper: Cosme et al., 2022). An ecological momentary assessment was deployed between May 2020 and October 2020 in response to the emergence of the COVID-19 pandemic. For this round, all participants contacted initially and any new members that joined the social groups were invited to complete an online survey. At the end of the COVID survey, participants began a 28-day EMA protocol, with instructions on how to setup the EMA protocol on their phone (using the LifeData app) provided online.

Measures

We made use of participants' reports of demographic and trait characteristics and their daily diary (Study 1) or EMA (Study 2) reports. To allow for comparison between both studies, we focused on similar measures across both studies.

Daily Positive Emotion. In Study 1, daily positive emotion was measured using an item adapted from the Profile of Mood States (Terry, Lane, & Fogarty, 2003): “Today I felt Happy”. This item has been used in previous daily diary studies (Fosco & Lydon-Staley, 2019) and was common to both the KNOT and NODE datasets. In the NODE Study, participants rated how much they felt each emotion that day using a slider ranging from 0 (“Not at all”) to 100 (“Very”) in increments of 1. In the KNOT Study, participants used a slider ranging from 0 to 10 in increments of 0.1. To facilitate combining these data, the NODE data happiness raw scores were divided by 10.

In Study 2, daily positive emotion was measured as part of the EMA protocol. During the EMA, a morning survey was sent at 8 AM and an evening survey was sent at 6 PM. At each assessment positive emotion was measured using one item asking, “How POSITIVE do you feel right now?” Participants reported their positive emotion on a sliding scale from 1 (“Not at all”) to 100 (“Extremely”).

Flourishing. In both Study 1 and Study 2, flourishing was measured using an 8-item flourishing scale (Diener et al., 2010). The flourishing scale contains items related to important aspects of human functioning, including positive relationships, feelings of competence, and having meaning and purpose in life. Flourishing scale items are answered on a 1 (“Strong Disagreement”) to 7 (“Strong Agreement”) scale. The mean value of all 8 items was taken as a measure of flourishing, with higher values indicating relatively higher levels of flourishing.

Data Preparation

For Study 1, the daily diary positive emotion data were prepared to create three positive emotion dynamics indices: average intensity, variability, and inertia. Average intensity was computed by taking the intraindividual mean of each person’s positive emotion time series. Variability was computed as the intraindividual standard deviation. Inertia was computed by regressing day’s positive emotion on the previous day’s positive emotion in a multilevel model to accommodate the nested nature of the data (i.e., multiple days nested in multiple participants; Snijders & Bosker, 2012). Prior to running the models, the day’s positive emotion was separated into time-varying (within-person; which we refer to as day’s positive emotion) and time-invariant (between-person; which we refer to as usual levels of positive emotion) components to allow a focus on how the previous day’s positive emotion (*t*-1) predicted the current days (*t*) positive emotion (Bolger & Laurenceau, 2013).

At level 1 (day-level variables), the formal model equation was constructed as:

$$Day'sPositiveEmotion_{it} = \beta_{0i} + \beta_{1i}Day'sPositiveEmotion_{i,t-1} + \beta_{2i}Day_{it} + e_{it}, \quad (1)$$

where $Day'sPositiveEmotion_{it}$ is positive emotion for person *i* on day *t*; β_{0i} indicates the expected positive emotion on a typical day in the study; β_{1i} indicates the prediction of today’s positive emotion by yesterday’s positive emotion; β_{2i} indicates the effect of study on positive emotion in order to account for time as a third variable (Bolger & Laureneau, 2013). Finally, e_{it} are day-specific residuals that were allowed to be autocorrelated (AR1).

Person-specific intercepts and associations (from Level 1) were specified (at Level 2) as:

$\beta_{0i} = \gamma_{00} + u_{0i}$

$\beta_{1i} = \gamma_{10} + u_{1i}$

$\beta_{2i} = \gamma_{20}$,

where γ denotes a sample-level parameter and u denotes residual between-person differences that may be correlated but are uncorrelated with e_{it}. Positive emotion inertia was operationalized as $\gamma_{10} + u_{1i}$, providing a person-specific indication of the extent to which yesterday's positive emotion predicted today's positive emotion. The multilevel model was fit using nlme in R (Pinheiro et al., 2018). The three between-person indices were then standardized to have mean 0 and standard deviation 1.

For Study 2, a day-level positive emotion was computed by aggregating the morning and evening reports of positive mood. Once this day-level positive emotion variable was created, positive emotion intensity, variability, and inertia were calculated in the same manner as that for Study 1.

Data Analysis

Data from Study 1 and Study 2 were analyzed separately. However, the same analytic approach was taken across both studies. As such, we present the general data analysis approach across both studies here. Analysis consisted of identifying latent profiles of positive emotion dynamics using latent profile analysis and examining associations between profile membership and outcomes of interest, including flourishing. Latent profile analysis is a subgroup identification approach that matched our interest in capturing the co-occurrence of types of emotion dynamics (i.e., intensity, variability, inertia) within the participants. Latent profile analysis focuses on identifying subgroups of individuals with similar patterns of co-occurring characteristics (i.e., profiles), rather than focusing on single variables or interactions among variables across all individuals within a sample. Latent profile analysis is a type of mixture model that uses manifest items to divide a population into mutually exclusive and exhaustive latent classes (i.e., profiles; Gibson, 1959). Outputs of interest of latent profile analysis are the latent profile membership probabilities, which describe the distribution of profiles in the population, and the item-response means (and variances), which describe the profile-specific item means (and variances). Profiles are named and interpreted based on the pattern of item means.

Models with 1-7 profiles were compared. The final model was selected based on the Akaike information criterion (AIC; Akaike, 1974), Bayesian information criterion (BIC; Schwarz, 1978), sample-size adjusted BIC (a-BIC; Sclove, 1987), entropy (Celeux & Soromenho, 1996), a bootstrapped likelihood ratio test (McLachlan & Peel, 2000), and the sample size in each class, as well as the stability, interpretability, and parsimony of the models. Lower values for AIC, BIC, and a-BIC were taken as evidence of more optimal balance between model fit and model parsimony, higher values for entropy indicated higher classification utility, and a significant bootstrapped likelihood ratio test assessed model fit compared to a model with one fewer profile. Emphasis was also placed on the utility and theoretical interpretation of a solution as well as parsimony, given that parsimony provides greater generalizability to other samples (Lanza & Cooper, 2016). All models were estimated using Mplus version 8.1 and model identification for all models was checked with 800 initial stage starts and 400 final stage starts.

First, the number of profiles was selected, and profiles were identified and interpreted. To examine associations between profile membership and outcomes of interest, modal assignment and adjustment for classification error using the Bolck, Croon, and Hagenaars approach (BCH;

Bakk & Vermunt, 2016) was used. This approach is currently recommended for predicting continuous outcomes from profile membership (Dziak et al., 2016). The BCH approach classifies individuals to profiles based on posterior probabilities and adjusts an outcome analysis that uses these classifications for classification error. Associations between profile membership and flourishing are expressed as pairwise differences between profiles in mean levels of flourishing conditional on latent profile membership.

Results

Descriptive statistics for key study variables are shown in Table 1. Model fit information and model selection criteria are shown in Table 2.

Profile identification and description.

For Study 1, model fit criteria, profile size, and profile separation suggested the 4-profile model was best suited to the data. The BIC minimized for the 6-profile model. The AIC and a-BIC were minimized for the 7-profile model. The bootstrapped likelihood ratio tests were no longer significant after the 5-profile versus 4-profile comparison. Entropy ranged from 0.73 (4-profile model) to 0.92 (2-profile model). Therefore, we considered models with 4 to 7 profiles. To further aid in model selection, we examined the profile-specific item means across all profiles in all models (see Supplemental Material). Compared to the 4-profile model, the 5- and 6-profile models included a profile that was quite small (n=9, 4%) and had a similar interpretation to a profile existing previously in the 4-profile model (high variability and low inertia). This similarity suggests that extraction of additional profiles beyond 4 is unnecessary due to reduced parsimony and limited theoretical interpretability of a mostly redundant profile. In comparing the 3- and 4-profile models, the 4-profile model had lower AIC, BIC, and a-BIC values, indicating more optimal model fit. Thus, we selected the 4-profile model for theoretical interpretation and additional analysis.

Parameter estimates and within-profile item means are presented in Table 3 (and also visualized in Figure 1). Profile 1 (*n*=25) was characterized by lower than average levels of positive emotion, higher than average variability, and lower than average inertia. We labeled this profile *Low-Intensity Variable*. Profile 2 (*n*=22) was characterized by higher than average variability, and higher than average inertia. We labeled this profile *Variable-Inert*. Profile 3 (*n*=108) was characterized by lower than average levels of positive emotion intensity. We labeled this profile *Low Intensity*. Profile 4 (*n*=89) was characterized by higher than average positive emotion intensity and lower than average variability. We labeled this profile *High Intensity-Low Variability*.

For Study 2, model fit criteria, profile size, and profile separation again suggested the 4-profile model was best suited to the data. The BIC minimized for the 5-profile model. The AIC and a-BIC minimized for the 7-profile model. The bootstrapped likelihood ratio tests were significant after all profile models, thereby providing no discriminatory information between models. Entropy ranged from 0.56 (2-profile model) to 0.82 (7-profile model). Therefore, we considered models with 4 to 7 profiles. To further aid in model selection, we examined the profile-specific item means across all profiles in all models (see Supplementary Material). Compared to the 4-profile model, the 5-profile model included two profiles characterized by higher than average variability and inertia that had a similar interpretation to a profile existing previously in the 4-profile model characterized by high variability and inertia. This finding suggests that extraction of additional profiles beyond 4 is unnecessary due to reduced parsimony and limited theoretical interpretability of a mostly redundant profile. Thus, we selected the 4-profile model for theoretical interpretation and additional analysis.

Parameter estimates and within-profile item means are presented in Table 3 (see also Figure 1), which demonstrated three profiles similar to those uncovered in Study 1. For Study 2, profile 1 (*n*=129) was characterized by lower than average levels of positive emotion, higher than average variability, and lower than average inertia. We labeled this profile *Low-Intensity Variable*. Profile 2 (*n*=12) was characterized by higher than average variability, and higher than average inertia. We labeled this profile *Variable-Inert*. Profile 3 (*n*=122) was characterized by lower than average levels of positive emotion intensity. We labeled this profile *Low Intensity*. Profile 4 (*n*=112) was characterized by high than average positive emotion intensity, lower than average variability and inertia. We labeled this profile *High Intensity-Inert*. This was the only profile that was distinct from profiles uncovered in Study 1.

Associations between profile membership and flourishing

For Study 1, profile membership was associated with differences in flourishing (χ^2=8.87, p=0.03). Pairwise comparisons (Table 4) between profiles revealed *Low Intensity* had lower levels of flourishing than *High Intensity-Low Variability* and *Low Intensity Variable*.

For Study 2, profile membership was associated with differences in flourishing (χ^2=37.30, p<0.001). Pairwise comparisons (Table 4) between profiles showed *Low Intensity-Variable* had lower levels of flourishing than *High Intensity-Inert*. Participants in *Low Intensity* had lower flourishing than *High Intensity Inert and Low-Intensity Variable*.

Discussion

This study used intensive repeated measures data coupled with a person-centered framework to capture between-person differences in the multidimensional nature of daily positive emotion dynamics. Guided by theories highlighting roles for positive emotion dynamics in flourishing, we expanded upon existing work by identifying subgroups of individuals characterized by different patterns of average intensity, variability, and inertia in positive emotion, and testing how these between-person differences were associated with a common measure of well-being known as flourishing.

Across two different samples, our analysis revealed four profiles of positive emotion dynamics. Three subgroups were common across both samples. The first, *Low Intensity* group, was characterized by low average levels of positive emotion across the EMA periods. The second, *Low Intensity Variable* group, was also characterized by low average levels of positive emotion but showed higher than average variability around that mean and lower than average inertia. The third, *Variable Inert* group, was characterized by high variability and high inertia of positive emotions. The fourth group differed across the two samples analyzed. In one sample, a *High Intensity-Low Variability* group was observed, characterized by high overall positive emotion that did not vary substantially around the mean of the positive emotion time series. In the second sample, a *High Intensity-Inert* group emerged, characterized by high overall positive emotion that was slow-changing. Although the *High Intensity-Low Variability* and *High Intensity-Inert* groups differed, they are conceptually similar, as can be seen in Figure 1, with relatively high-intensity and stable levels of positive emotion.

Of particular interest are the *Variable-Inert* and the *High Intensity-Low Variability* and *High Intensity-Inert* groups for the insight they provide into the added value of considering indices that capture variability and inertia. Variability captures the overall range of an emotion over time, without taking the temporal order of emotion intensity levels into account. Inertia, by contrast, captures the day-to-day predictability or temporal dependency of emotion across time. Given mathematical and empirical associations among variability and inertia, researchers have been urged to control for variability when testing for associations between inertia and outcomes of interest when taking a variable-centered approach to ensure that variance attributed to inertia is not due to its overlap with variability (Koval et al., 2016). By using person-centered analyses, the current study finds that, although inertia and variability produce similar effects at high levels of positive emotion, as seen in the similarity of the *High Intensity-Low Variability* and *High Intensity-Inert* groups, distinctions are observed at lower intensity levels, as observed in the *Variable-Inert* group characterized by a relatively wide range in positive emotion (i.e., high variability) that changed relatively slowly over time (i.e., low inertia).

In testing associations between the identified emotion dynamic profiles and flourishing, both Study 1 and 2 revealed that the profiles characterized by high average positive emotion that changed little over time (the *High Intensity-Low Variability* group in Study 1 and the *High Intensity-Low Inertia* group in Study 2) had the highest levels of flourishing as compared to the *Low Intensity* groups. Findings for the *Low Intensity-Variable* group were interesting, with flourishing in this group higher than in the *Low Intensity* group. This finding suggests that variability in emotion dynamics at low average levels of intensity may be protective against the lowest levels of well-being, an interpretation that is plausible considering work suggesting that variability, at least in some contexts, may reflect an ability to react flexibly to changing circumstances (Kashdan & Rottenberg, 2010; Waugh et al., 2001).

No significant differences in flourishing emerged between the variable-inert group and any of the other profiles. This observed independence may stem from the lack of power available in examining differences with this group given how infrequent it was across both studies (9% of the sample in Study 1 and 5% in Study 2) and will benefit from examination in larger samples.

Limitations and future outlook

Findings should be interpreted considering the study's strengths and limitations. The study sample was generally high in well-being (mean flourishing was 5.91 in Study 1 and 5.60 in Study 2), tended to be white, and had a high percentage of women as compared to other genders, and thus may be limited in generalizability. The study was cross-sectional and observational. As such, causal associations between flourishing and positive emotion profiles cannot be established. Bidirectional associations between positive emotion dynamics and flourishing may be anticipated given that positive emotion is theorized to facilitate flourishing and that states of flourishing may facilitate more frequent experiences of positive emotion (Fredrickson & Joiner, 2002; Lyubomirsky et al., 2005), testing of which would benefit from longitudinal data. The positive emotion measures did not differentiate between hedonic and eudaimonic positive emotions, a distinction that may be important given that flourishing constitutes feeling good (hedonic well-being) and functioning well (eudaimonic well-being). Person-specific approaches emphasize that individuals are unique, differing in the levels they might exhibit across different emotion dynamics. The latent profile analysis approach assumes that, despite this uniqueness, it is appropriate to group individuals who are more similar to one another than they are to other individuals. This grouping reduces complexity, assumes some differences between individuals are sufficiently minimal as to be ignorable, and provides interpretable profiles between the two extremes of an aggregation that is applied to the entire population and an analysis of individuals (Von eye & Bergman, 2003).

Conclusion

We identified four profiles of individuals who differed in their patterns of three key positive emotion dynamics: average intensity, variability, and inertia. Individuals with high average levels of positive emotion that was stable over time had the highest levels of flourishing. Individuals with low intensity positive emotion had the lowest levels of flourishing. Individuals with low but variable positive emotions had intermediate levels of flourishing, higher in flourishing than participants with low but not variable positive emotion and lower in flourishing than participants with high and stable positive emotion. By considering how three key emotion dynamic indices cluster within individuals to differing degrees, we capture the richness and multidimensional nature of daily positive emotion dynamics and its relevance for well-being.

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Table 1.

Descriptive statistics and correlations of key study variables.

STUDY 1				
Variables	**1**	**2**	**3**	**4**
1. Intensity	-			
2. Variability	-0.35*	-		
3. Inertia	0.09	0.01	-	
4. Flourishing	0.35*	0.11	0.06	-
Mean	5.67	1.69	0.00	5.91
SD	1.95	0.66	0.07	0.82
STUDY 2				
Variables	**1**	**2**	**3**	**4**
1. Intensity	-			
2. Variability	-0.34*	-		
3. Inertia	0.32*	0.04	-	
4. Flourishing	0.51*	-0.08	0.10	-
Mean	62.87	12.84	0.00	5.60
SD	13.77	5.34	0.06	0.85

Notes: *SD* = standard deviation; **p*<0.05

Table 2.

Model Fit Information for Latent Profile Analysis

Study 1								
No. of Profiles	No. Free Parameters	Log-likelihood	AIC	BIC	a-BIC	Entropy	BLRT	# Profiles <10%
1	6	-1037.16	2086.32	2107.30	2088.28	-	-	0
2	10	-1014.55	2049.10	2084.07	2052.37	0.92	<.001	0
3	14	-970.03	1968.06	2017.02	1972.64	0.89	<.001	1
4	18	-951.86	1939.71	2002.66	1945.60	0.73	<.001	1
5	22	-939.32	1922.64	1999.58	1929.84	0.76	0.01	1
6	26	-925.28	1902.55	1993.48	1911.06	0.80	0.05	2
7	30	-919.05	1898.10	2003.01	1907.92	0.81	0.09	3
Study 2								
No. of Profiles	No. Free Parameters	Log-likelihood	AIC	BIC	a-BIC	Entropy	BLRT	# Profiles <10%
1	6	-1126.55	2265.11	2286.56	2267.56	-	-	0
2	10	-1100.30	2220.59	2256.39	2224.68	0.56	<0.001	0
3	14	-1070.86	2169.72	2219.84	2175.45	0.72	<0.001	1
4	18	-1056.85	2149.70	2214.14	2157.07	0.72	<0.001	2
5	22	-1045.02	2134.04	2212.79	2143.04	0.74	0.01	2
6	26	-1036.38	2124.75	2217.82	2135.39	0.76	<0.001	3
7	30	-1027.21	2114.42	2221.81	2126.70	0.79	<0.001	3

Notes: Dashes indicate criterion was not applicable. AIC = Akaike information criterion; BIC = Bayesian information criterion; SSA-BIC = sample size adjusted BIC; BLRT = Bootstrapped likelihood ratio test. The chosen solution is shaded in gray.

Table 3.

Parameter Estimates for the Four-Profile Model

Study 1				
	Within-profile means			
Profile Indicators	**Low-Intensity Variable**	**Variable-Inert**	**Low Intensity**	**High Intensity-Low Variability**
Average Positive Emotion Intensity	-0.57^{b}	-0.24	-0.48^{b}	0.83^{a}
Positive Emotion Variability	$1.19^{\boldsymbol{a}}$	1.32^{a}	0.08	-0.80^{b}
Positive Emotion Inertia	$-1.68^{\boldsymbol{b}}$	$1.97^{\boldsymbol{a}}$	-0.01	0.02
Profile *N*s	25 (10%)	22 (9%)	108 (44%)	89 (36%)

Study 2				
	Within-profile means			
Profile Indicators	**Low-Intensity Variable**	**Variable-Inert**	**Low Intensity**	**High Intensity-Inert**
Average Positive Emotion Intensity	-0.70^{b}	-0.14	-0.60^{b}	0.73^{a}
Positive Emotion Variability	$0.76^{\boldsymbol{a}}$	1.52^{a}	0.21	-0.52^{b}
Positive Emotion Inertia	$-1.82^{\boldsymbol{b}}$	$2.29^{\boldsymbol{a}}$	-0.26	0.34^{a}
Profile *N*s	19 (7%)	12 (5%)	122 (46%)	112 (42%)

Notes: Within-item variances were constrained to be equal across profiles. Indicator variables were standardized to have a mean of 0 and a standard deviation of 1. $Est^{\boldsymbol{a}}$ Significantly higher than the overall item mean at p<.05. $Est^{\boldsymbol{b}}$ Significantly lower than the overall item mean at p<.05

Table 4.

Means and Standard Errors of Flourishing across Daily Positive Emotion Profiles

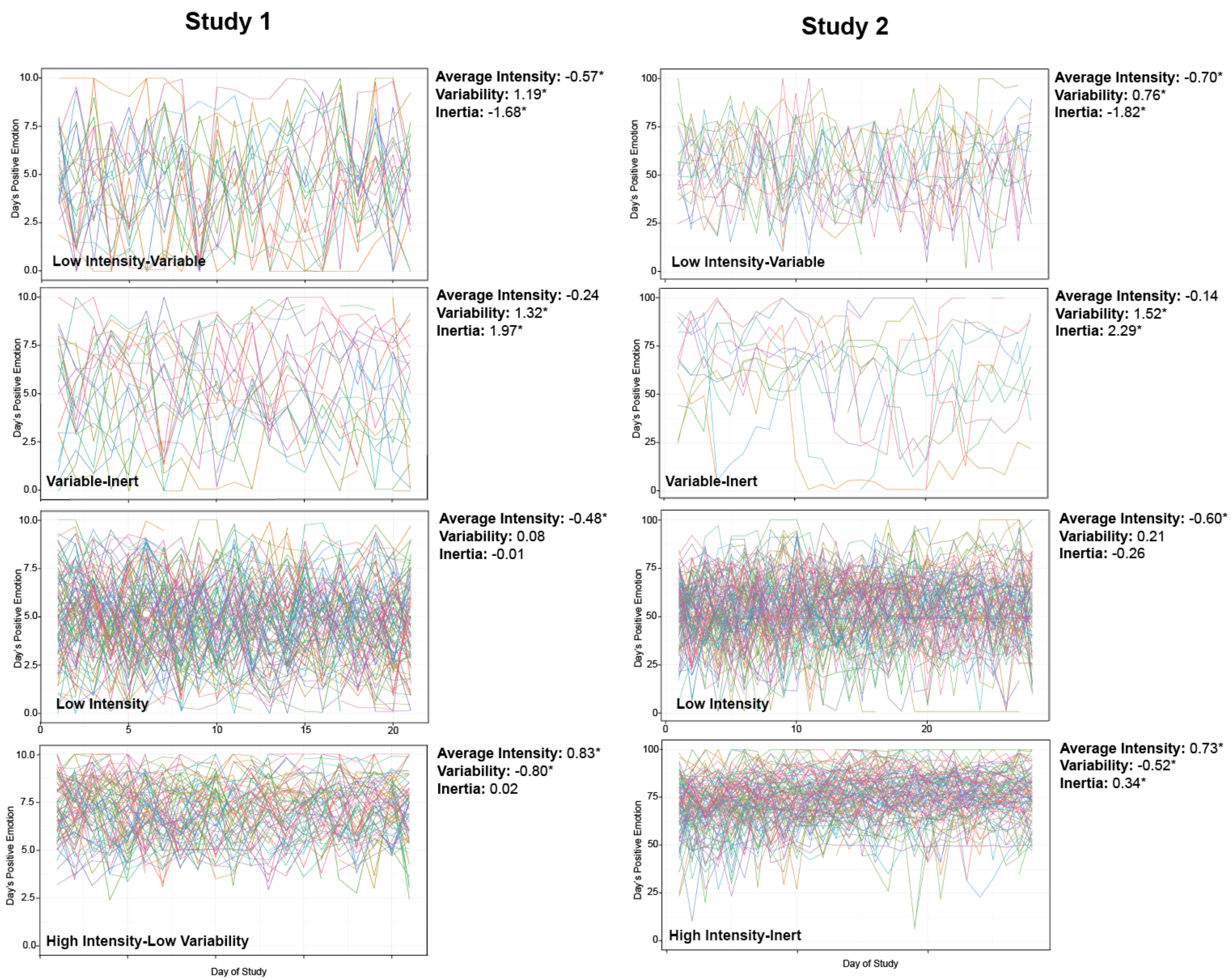
Study 1			
Low-Intensity Variable	**Variable-Inert**	**Low Intensity**	**High Intensity-Low Variability**
6.09 (0.15)	6.04 (0.20)	$5.66^{a,b}$ (0.12)	6.15 (0.08)
Study 2			
Low-Intensity Variable	**Variable-Inert**	**Low Intensity**	**High Intensity-Inert**
5.55^{c} (0.22)	5.78 (0.20)	$5.14^{b,c}$ (0.11)	6.04 (0.08)

Notes: [a]significantly different from *High Intensity-Low Variability*; [b]significantly different from *Low-Intensity Variable*; [c]significantly different from *High Intensity-Inert*.

Figure captions.

Figure 1. An illustration of the four-profile solutions for Study 1 and Study 2. Each box contains the raw positive emotion time series data for participants assigned to each profile based on posterior probability of profile membership and modal assignment for the purpose of visualization. Day's positive emotion going from low to high (x-axis) is shown across each day of the study (x-axis) for each participant (each line is a participant). The estimated average emotion intensity, variability, and inertia is shown to the right for each group (variables were standardized at the group level). *Note*: *significantly different than the sample mean at $p<0.05$.

Figure 1.


Study 1
Study 2
Low Intensity-Variable
Average Intensity: -0.57*
Variability: 1.19*
Inertia: -1.68*
Low Intensity-Variable
Average Intensity: -0.70*
Variability: 0.76*
Inertia: -1.82*
Variable-Inert
Average Intensity: -0.24
Variability: 1.32*
Inertia: 1.97*
Variable-Inert
Average Intensity: -0.14
Variability: 1.52*
Inertia: 2.29*
Low Intensity
Average Intensity: -0.48*
Variability: 0.08
Inertia: -0.01
Low Intensity
Average Intensity: -0.60*
Variability: 0.21
Inertia: -0.26
High Intensity-Low Variability
Average Intensity: 0.83*
Variability: -0.80*
Inertia: 0.02
High Intensity-Inert
Average Intensity: 0.73*
Variability: -0.52*
Inertia: 0.34*
Day's Positive Emotion
Day of Study