
Methodological Innovations in Gerontology: Advances in Psychosocial Research:
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Fusing Biodiversity Metrics into Investigations of Daily Life: Illustrations and Recommendations With Emodiversity

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Abstract

Objectives: Functionalist emotion and ecological systems theories suggest *emodiversity*—the variety and relative abundance of individuals' emotion experiences—is beneficial for psychological and physical health and may change with age. This paper examines and provides recommendations for operationalization of diversity-type intraindividual variability (IIV) constructs using intensive longitudinal data, and demonstrates the utility of emodiversity by examining its links to physical health moderated by mean levels of emotion and age.

Method: Using data from a daily diary study of 138 adults (age 40 to 65 years), we consider how item selection, response scale, choice of diversity index, and number of occasions enable/constrain mapping to theory, measurement reliability, and empirical inquiry.

Results: Item selection and response scale had limited influence on rank-order differences in diversity. Reliable measurement ($r \geq .8$) required a minimum of 6 to 12 occasions depending on choice of index, theoretical conception, study design, and distribution of diversity scores. The empirical findings suggest mean level of negative affect, rather than age, moderates the relation between negative emodiversity and health.

Discussion: This study provides recommendations for the calculation of diversity-type IIV constructs and illustrates the potential for study of emodiversity to contribute to understanding of successful aging.

Keywords: Diversity—Emotion—Intraindividual variability—Longitudinal analysis

Individual differences in positive and negative emotions—quantified by overall level—relate to functional and developmental outcomes including well-being and health (e.g., [Mroczek, 2001](#)). Intraindividual variability (IIV)—measured through observation of within-person fluctuations occurring at relatively fast timescales (e.g., seconds, minutes, days)—is also connected to functional and developmental

outcomes (e.g., [Fiske & Rice, 1955](#); [Nesselroade, 2001](#); [Ram & Gerstorf, 2009](#)). For example, interindividual differences in emotion IIV (e.g., variability, instability, inertia, differentiation, flexibility, diversity) relate to psychopathology ([McConville & Cooper, 1996](#)), well-being ([Gruber, Kogan, Quoidbach, & Mauss, 2013](#)), cognition ([Ram, Gerstorf, Lindenberger, & Smith, 2011](#)), health ([Hardy & Segerstrom,](#)

2016), personality (Eid & Diener, 1999), and age (see R ocke & Brose, 2013, for a review). In most studies, emotion IIV held predictive value beyond individuals' overall levels of emotions. Thus, within-person dynamics captured by IIV represent a distinct dimension of emotional experience. This paper contributes to existing literature by identifying and examining ways to quantify diversity-type IIV.

Many methods and theories of IIV draw on work in other fields, including physics and biology (Nesselroade & Boker, 1994; Ram & Pedersen, 2008). In ecology, conception and measurement of *biodiversity*—the variety and relative abundance of species in an ecosystem—supports knowledge about how each species serves functional roles for the environment (e.g., as predator, as prey). Depletion or overabundance of any species has consequences for the functioning and health of the ecosystem (Magurran, 2004). Parallel notions of diversity found in psychology include racial diversity, stressor diversity, activity diversity, and social diversity (Budescu & Budescu, 2012; Koffer, Ram, Conroy, Pincus, & Almeida, 2016; Lee et al., 2016; Ram, Conroy, Pincus, Hyde, & Molloy, 2012). Recently, Quoidbach and colleagues (2014) quantified individuals' emotional diversity—*emodiversity*—as the variety and relative abundance of discrete emotion experiences. Functionalist emotion theory suggests the biopsychosocial environments encountered in daily life can activate a diversity of emotions (e.g., excitement, fear, anger), each serving adaptive purposes by prioritizing, organizing, and regulating behavior to optimize an individual's adjustment to situational demands (Barrett & Campos, 1987). As in nature, depletion or overabundance of an emotion(s) may have consequences for the functioning and health of the individual.

Conceptually, emodiversity sits within the broader concept of *emotional complexity*—individuals' ability to see the good and bad in situations (*emotional poignancy*), experience mixed emotions (*emotional dialecticism*), differentiate among discrete emotions (*emotional differentiation*), describe emotional experiences with precision (*emotional granularity*), experience a range of emotions (*emodiversity*), and flexibly match emotions with specific situations (Barrett, Gross, Christensen, & Benvenuto, 2001; Feldman, 1995; Larsen, McGraw, & Cacioppo, 2001; Lindquist & Barrett, 2008; Quoidbach et al., 2014). Similar to how an intraindividual standard deviation (*iSD*) quantifies the range of positive or negative emotions an individual experiences over time (i.e., variability along continuous dimensions), diversity metrics can be used to quantify the range of discrete emotions an individual experiences (i.e., variability across categories). Unlike many other aspects of emotional complexity, emodiversity explicitly places experience within a discrete emotion space where different emotions are categorically unique (like different animal or plant species).

Given the relevance of emotional complexity in theories of successful aging, emodiversity may also have implications

for life-span development. Socioemotional selectivity theory (SST; Carstensen, 2006) suggests that, with increasing age, adults tend toward emotionally beneficial and meaningful situations as they prioritize emotional goals over information-seeking goals. Similarly, the strength and vulnerability integration model (SAVI; Charles, 2010) suggests age-related increases in emotion-regulation capacity allow individuals to maintain emotional well-being by avoiding high arousal situations. Therefore, lower emodiversity may be associated with better health among older adults who prioritize specific types of emotional experiences to maintain physiological homeostasis, whereas higher emodiversity may be associated with better health among younger adults seeking new and arousing experiences.

The Present Study

This paper explores and provides recommendations for articulating diversity-type IIV constructs using intensive longitudinal data. In the context of emodiversity, we consider how item selection, measurement scale, choice of diversity index, and number of occasions enable or constrain theory testing, measurement reliability, and empirical inquiry. Throughout, we provide recommendations for how researchers might approach the operationalization of diversity-type IIV constructs and demonstrate the utility of emodiversity as an organizing construct for understanding how emotions contribute to downstream and potentially age-specific impacts on health.

Before delving into methodological considerations, we illustrate the basic calculation of diversity across categories using the Gini (1912) coefficient,

$$GiniDiversity_i = G_i = 1 - \left(\frac{2 \sum_{j=1}^m j c_{ij}}{m \sum_{j=1}^m c_{ij}} - \frac{m+1}{m} \right) \quad (1)$$

where c_{ij} is the count of individual i 's experiences within $j = 1$ to m categories (e.g., emotion types) indexed in non-decreasing order ($c_{ij} \leq c_{ij+1}$). Diversity scores range from 0 to 1, with higher values indicating more diverse (emotional) ecosystems. Figure 1 depicts individual differences in emodiversity. Using a circumplex approach, emotion labels are placed at specific angular locations with positive emotions on the right side and negative emotions on the left side (Russell, 1980). The "petal" length indicates the number of occasions an individual experienced a particular discrete emotion. Coloring indicates the proportion of occasions the particular emotion was rated at low (blue) to high (pink) intensities. As indicated by the relative sparsity of petals, Person A (left) has lower emodiversity in both negative and positive emotions than Person B. Theories of successful aging suggest healthy older adults might be more like Person A, whereas healthy younger adults might be more like Person B. A step-by-step implementation guide for all

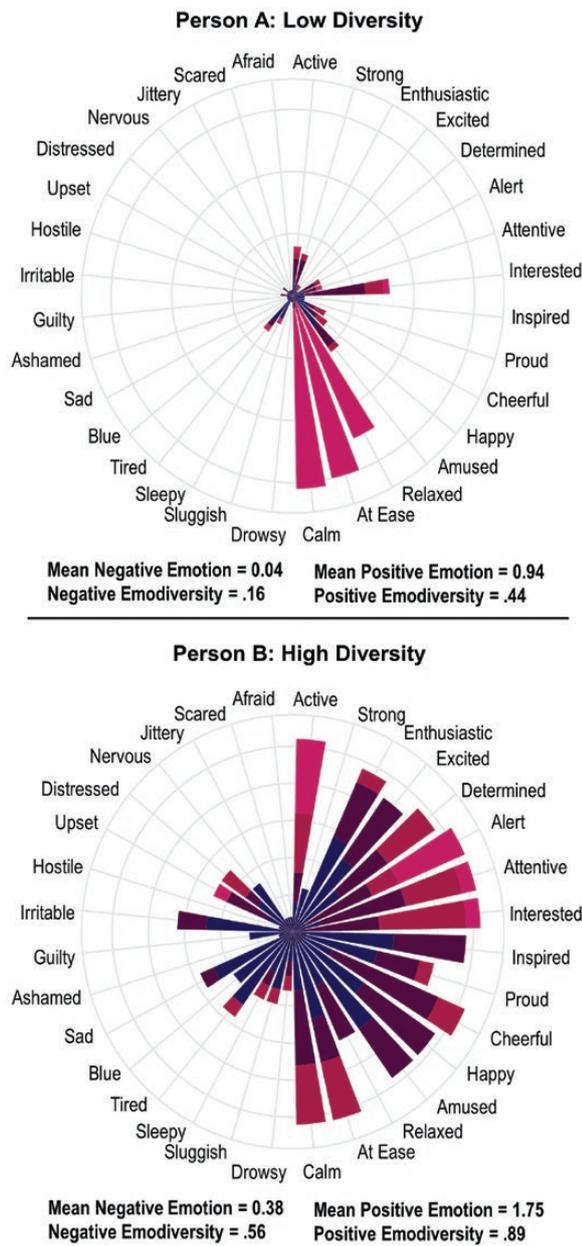


Figure 1. Self-reports of two individual's emotion experiences obtained through end-of-day reports. The length and coloring of each "petal" indicates the number of occasions each emotion was experienced and the proportion of occasions the emotion was rated at low (= darker shades closer to center) to high (= lighter shades, closer to edges) intensities. Emodiversity is the variety and relative abundance of emotions that individuals experience within a given space and time frame. Person A (left) is relatively low in emodiversity compared to Person B (right). Mean levels of positive and negative emotions are approximately equal between the two individuals. We created all figures using the ggplot2 R package (Wickham, 2009).

procedures covered can be found in the Supplementary Materials and at www.quantdev.ssri.psu.edu.

Method

Our example data are drawn from the As U Live Study, an investigation of healthy aging in a community-based

sample of middle-aged adults that included home-based interviews, laboratory assessments, and daily diary questionnaires (Sturgeon, Zautra, & Okun, 2014).

Participants

Drawing from the larger study ($N = 680$), we utilize data from the 30-day daily diary protocol and 6-month follow-up interview incorporating ($n = 138$) participants (55% female, $M_{Age} = 53.50$, $SD_{Age} = 7.50$, range = 40 to 65 years) who completed 6+ days ($M_{Days} = 29.32$, $SD_{Days} = 6.5$, range = 6 to 58) of the diary protocol, along with the follow-up interview. Participants self-identified as White or Euro-American (71%), Black/African American (2%), Hispanic/Latino (8%), Asian (2%), and mixed background (17%). Education spanned high school degree or less (14%), trade/vocational/technical school (9%), some college (23%), college degree (28%), graduate or professional training (25%), with 1% not reporting.

Procedure and Measures

The 30-day diary protocol involved answering questionnaires on a tablet computer each night. The follow-up interview occurred approximately 6 months later, including an assessment of emotions and physical health. Descriptives are presented in Table 1.

Discrete emotions

Discrete emotions were assessed using 32 items from the Positive Affect-Negative Affect Schedule (PANAS and PANAS-X; Watson, Clark, & Tellegen, 1988; + amused). Each night, participants rated the extent to which they experienced 16 positive emotions (*enthusiastic, interested, determined, excited, inspired, alert, active, strong, proud, attentive, happy, relaxed, cheerful, at ease, calm, amused*; underlined items constitute a 10-item subset), and 16 negative emotions (*scared, afraid, upset, distressed, jittery, nervous, ashamed, guilty, irritable, hostile, tired, sluggish, sleepy, blue, sad, drowsy*), using a 5-point scale, 1 = "very slightly or not at all" to 5 = "extremely" (recoded 0 to 4).

During the follow-up interview, participants reported once on a subset of 20 PANAS items (underlined in list above), rating their experience "over the past four weeks" using the same 5-point scale (also recoded 0 to 4).

Mean emotion

Mean positive and negative emotion scores for the daily repeated measures were calculated using the continuous Likert-type ratings (0–4). Within each day, the 16 positive emotion items were averaged to obtain daily composite scores that were then averaged across occasions to obtain an overall *mean positive emotion* score for each individual. The same procedure was used to obtain a *mean negative emotion* score for each individual.

Table 1. Descriptives and Correlations for Emotion, Health, and Demographic Variables

| Construct | Min | Max | Mean | SD | 1. | 2. | 3. | 4. | 5. | 6. |
|--------------------------|-------|--------|-------|-------|------------|------------|------------|------|------|------|
| 1. Global Emodiversity | 0.27 | 0.93 | 0.61 | 0.10 | .90 | <i>.44</i> | <i>.70</i> | | | |
| 2. Positive Emodiversity | 0.44 | 1.00 | 0.92 | 0.11 | <i>.39</i> | .94 | <i>.08</i> | | | |
| 3. Negative Emodiversity | 0.12 | 0.89 | 0.48 | 0.17 | <i>.76</i> | <i>.01</i> | .76 | | | |
| 4. Mean Positive Emotion | 0.20 | 3.96 | 2.09 | 0.76 | .28 | .92 | -.07 | — | | |
| 5. Mean Negative Emotion | 0.01 | 2.51 | 0.36 | 0.34 | .84 | -.09 | .72 | -.15 | — | |
| 6. SF-36 PCS | 12.06 | 100.00 | 77.59 | 21.30 | -.12 | .36 | -.15 | .45 | -.34 | — |
| 7. Age | 40.00 | 65.00 | 53.50 | 7.50 | -.22 | .07 | -.24 | .10 | -.20 | -.10 |

Note: $N = 138$; SD = standard deviation; SF-36 PCS = for the Short-Form 36 Physical Component Summary score; the box contained in rows labeled 1–3 contains correlations among diversity indices based on number and valence. The diagonal (in bold) contains correlations among indices calculated using the full set of 32 emotion items and the reduced set of 10 emotion items; the lower triangle (plain text) contains correlations among indices using the full set items; the upper triangle (italics) contains correlations among indices using the reduced set of items.

Physical health

Physical health was measured once during the follow-up interview using the MOS 36-Item Short-Form Health Survey (SF-36; Ware & Sherbourne, 1992), specifically the Physical Component Summary (PCS) score of the physical functioning, role limitations due to physical functioning, bodily pain, and general perception of health subscales. Higher scores on the 0 to 100 scale indicate better physical health.

Studying (Emo)diversity Using Intensive Longitudinal Data

In this section, we examine how study design and analyses afford/constrain study of diversity-type IIV constructs: item selection, measurement scale, number of occasions, choice of diversity index, and examination of interindividual differences.

Item Selection

Research question

Which items should be used to measure diversity? Selecting which emotion items to include is often a vexing problem in emotion research. Functionalist emotion frameworks consider all emotions as equally distinct, whereas core affect frameworks suggest distinctions among positive and negative valence emotions. A merging of these frameworks suggests consideration of positive and negative emodiversity as separate constructs. Thus, we examine the methodological implications of using all items to calculate a *global emodiversity* score, and separating items by valence to calculate *positive emodiversity* and *negative emodiversity* scores.

In addition, researchers often consider the number of items needed to measure a construct. From a practical perspective, fewer items lower participant burden but may miss key experiences (Conner & Lehman, 2012). From a theoretical perspective, reducing the number of items concentrates focus on particular portions of the emotional space (e.g., high arousal or positive valence). For example, many items in this study indicate “sleepiness” (e.g., sleepy, sluggish, tired, drowsy), but this focus may also overemphasize diversity with respect to this particular sub-facet.

We therefore examined whether the number of items influenced rank ordering of emodiversity scores.

Empirical illustration

To examine concordance across functionalist- and core-affect-operationalizations of emodiversity, we used 32 emotion items to calculate global, positive, and negative emodiversity scores (Equation 1). The lower triangle within the Table 1 box shows correlations among indices. In line with the core affect view that positive and negative dimensions are orthogonal, positive and negative emodiversity were uncorrelated ($r = .01$). From a functionalist perspective, global emodiversity should have covered the full range of emotional experiences, but instead was driven more by diversity on the negative side ($r = .76$) than diversity on the positive side ($r = .39$) of the circumplex.

To examine whether number of items influenced emodiversity scores, we re-calculated global, positive, and negative emodiversity scores using 10 emotion items (*enthusiastic, amused, proud, interested, calm, sad, ashamed, guilty, hostile, and nervous*). Shown in bold on the diagonal in the Table 1 box, the match between 32- and 10-item scores was high for global and positive emodiversity ($r_s \geq .90$), and moderately high for negative emodiversity ($r = .76$). As seen in the relative symmetry of the upper (italics) and lower triangles of Table 1, overlap of the three operationalizations remained the same when using the smaller item set.

Recommendations

In line with functionalist emotion and core affect theories, the correlations among scores calculated with different item sets suggest construct distinction between positive and negative emodiversity. The number of items however did not affect rank ordering of diversity scores. We thus move forward with all emotion items, but separating by valence.

Measurement Scale

Research question

Does response scale matter? Original formulations of biodiversity utilize observational data coded as presence versus absence of each species. Translation to emotions

suggests using checklists where participants rate their emotions as binary “yes/no” experiences. However, most studies ask participants to indicate the frequency or intensity of each emotion using a Likert-type (e.g., 1 to 5) scale. Noting potential incongruence between data streams, we examined whether response-coding (binary vs Likert-type scale) influences calculation of emodiversity.

Empirical illustration

In our example data, participants rated the intensity of their experience of discrete emotions over the current day using a 1 = “very slightly or not at all” to 5 = “extremely” scale. The semi-continuous Likert-type response scale option was invoked using a 0 to 4 recoding (for positive Likert-type items, $M_{\text{skew}} = -0.21$, $SD_{\text{skew}} = 0.18$; for negative Likert-type items, $M_{\text{skew}} = 2.96$, $SD_{\text{skew}} = 1.15$). The binary response scale was invoked by recoding to 0 when participants indicated “very slightly or not at all” and to 1 for all other responses (for positive binary items, $M_{\text{skew}} = -2.31$, $SD_{\text{skew}} = 0.61$; for negative binary items, $M_{\text{skew}} = 1.58$, $SD_{\text{skew}} = 0.96$). Rank order of the emodiversity scores for the two response-types was very similar for positive ($r = .96$) and negative ($r = .98$) emodiversity.

Recommendations

High correlations between the binary and Likert-type scales suggest it matters little which scale-type is used. Binary coding may provide more comparability across studies using different response scales as long as one option has some type of “none of the time” label. Alternatively, researchers interested in diversity in the intensity of emotion experiences should utilize the Likert-type ratings. We move forward in this analysis using the binary version.

Choice of Diversity Metric

Research question

Which diversity metric? An expansive literature exists concerning the utility and measurement of diversity (see Magurran, 2004 for a review of applications in biology). Many indices are similar, with nuances as to which may be useful in particular contexts. Budescu and Budescu (2012) reviewed psychology-based applications, underscoring how choice of index may influence conclusions reached within a study and/or limit generalizability across studies. In general, diversity metrics indicate evenness of species (the distribution of emotion experiences across emotion types), richness of species (the total number of emotion types), or a combination of both evenness and richness. To examine similarity/dissimilarity among metrics, we calculated positive and negative emodiversity scores using the Gini coefficient (evenness only; Equation 1), richness index, Simpson’s (1949) index (evenness and richness), and Shannon’s (1948) entropy (evenness and richness).

In simplest form, the richness component of emodiversity, labeled here *richness diversity*, is quantified as the total number of emotion types an individual experiences,

$$\text{RichnessDiversity}_i = R_i = \sum_{j=1}^m q_{ij} \quad (2)$$

where $j = 1$ to m categories and $q_{ij} = 1$ for all $c_{ij} > 0$, and $= 0$ otherwise. Richness scores can range from 0 to m , with higher scores indicating greater diversity. Shannon’s entropy, is calculated as

$$\text{ShannonDiversity}_i = H_i = -\sum_{j=1}^m p_{ij}(\ln p_{ij}) \quad (3)$$

where m is the number of discrete emotion types, and p_{ij} is the proportion of an individual’s experiences of each discrete emotion type. Scores can range from 0 to $\ln(m)$, with higher scores indicating greater diversity. Simpson’s index has two parameterizations that, although scaled differently, denote the probability that any two randomly selected experiences are of different emotion types. The *inverse* version is calculated as,

$$\text{Simpson’sIndex}_i = D_i = 1 - \sum_{j=1}^m p_{ij}^2 \quad (4)$$

and ranges from 0 to 1. Higher scores indicate greater diversity.

Selection of a diversity metric is facilitated through consideration of one’s theoretical conception of diversity, practicalities of the study design, and scaling and distributional properties of scores. Theoretical definition requires considering whether to prioritize evenness, richness, or both aspects of diversity. The Gini coefficient emphasizes the evenness component of diversity and may be best suited for theories/research questions that concern differences in abundances across types, rather than the actual number of emotions represented. Alternatively, richness may be suited for theories/research questions that concern the range of emotion experiences across types. Shannon’s entropy and Simpson’s index are useful in situations where researchers are interested in both richness and evenness components of diversity.

Practical aspects of the study design, particularly with respect to how emotions are sampled also inform metric selection. For example, when there are many rare “species,” Simpson’s index may better differentiate among ecologies than Shannon’s entropy (Magurran, 2004). Richness diversity, Shannon’s entropy, and Simpson’s index may be useful when emotions are sampled through open-ended entry (e.g., *which emotions did you feel today?*), a situation similar to the animal trapping techniques used in ecological studies. In contrast, the Gini coefficient may be useful when measurement of all entities occurs on all occasions (e.g., the present study design used a preset, fixed length adjective list that defined the emotional ecosystem).

Finally, researchers may consider the scaling and distributional properties of diversity scores. Comparisons across samples (e.g., across individuals, across studies) is

facilitated by metrics that scale independently of sample size (e.g., number of items; Hill, 1973). The Gini coefficient, Simpson's index, and Shannon's entropy are all purposively bounded (e.g., between 0 and 1). Richness diversity, however, is purposively reliant on sampling scheme and length of study. As well, there is a general preference for metrics where the diversity scores are relatively normally distributed, especially when used as an outcome variable.

Empirical illustration

We calculated the four diversity indices using the binary measurement scale (implementation with the `vegan` and `ineq` packages in R; Oksanen et al., 2015; Zeileis, 2014). If the total number of emotion experiences across all occasions was zero, the diversity score was coded as missing. Correlations among the positive emodiversity indices were all $\geq .66$ (correlations with richness lower than the rest, which were $\geq .93$), and correlations among the negative emodiversity indices were all $\geq .86$. Sample-level distributions for each index are shown in Figure 2. Most panels

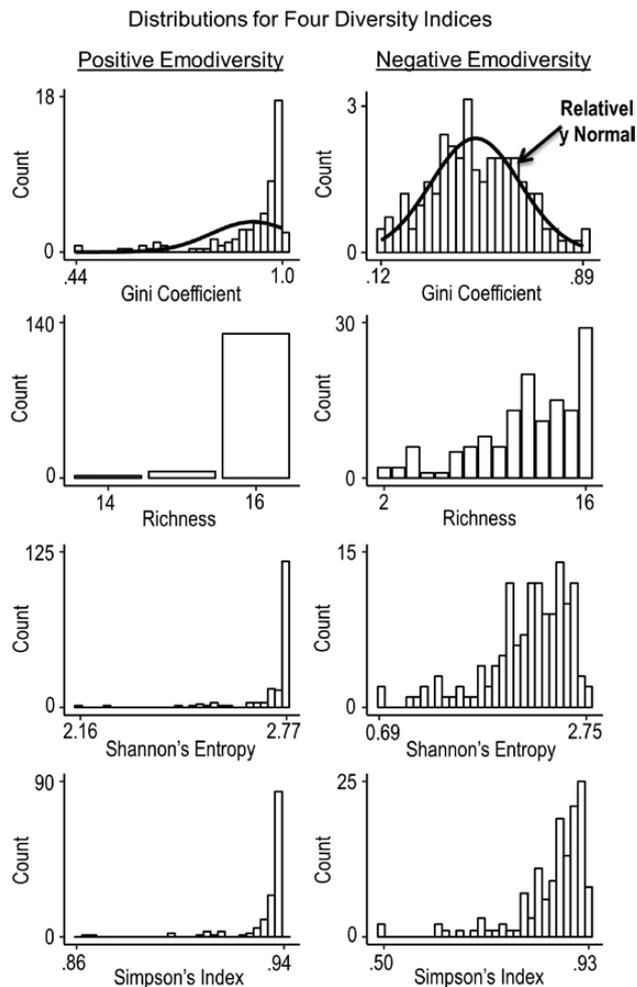


Figure 2. The Gini coefficient, richness diversity, Shannon's entropy, and Simpson's index were used to calculate emodiversity scores. Distributions of scores for each index are presented using positive valence (left column) and negative valence (right column) emotion items.

show severe skew, with only the Gini coefficient for negative emodiversity resembling a normal distribution.

Recommendations

In the context of emodiversity, we found high rank-order stability across metrics. Inspection of the distributions in Figure 2 indicates the Gini coefficient may be suitable for use as an outcome variable. Breaking with our own and others' prior research using Shannon's entropy, we move forward in the analysis using the Gini coefficient. This choice underscores the often-unintended interplay among theoretical definitions, study design, and scaling and score distributions. The present study data correspond to a pre-set, fixed length adjective list design. Implicitly, the design invokes a particular emotion theory (e.g., functionalist emotion theory; Barrett & Campos, 1987) implying importance of evenness diversity since individuals cannot invent or discover new emotions. The fixed ceiling for richness means that evenness is the only aspect of diversity that can really differ between persons. Thus, the study design and score distributions push us towards a specific theoretical conception of diversity.

Number of Occasions

Research question

How many occasions are needed to reliably measure diversity? Research has demonstrated the need for examining reliability of emotion IIV metrics (Mejía et al., 2014; Wang & Grimm, 2012). For example, Eid and Diener (1999) showed that reliable measurement of individual differences in emotion IIV (i.e., *iSD*) required more measurement occasions ($T = 51$) when using a single item than when using multiple items ($T = 7$).

Prior research (e.g., Brose, Lindenberger, & Schmiedek, 2013) comparing affective trait and state reports suggests that single versus multi-occasion assessments of affective experiences are related, but may differ in their underlying processes. For example, an individual's current mood may heavily influence a trait assessment, whereas multiple state assessments may reflect a broader range of the individual's experiences over time. Past research on emodiversity utilized a single-occasion "trait-based" design where scores indicated diversity across items (Quoidbach et al., 2014). With a repeated measures "state-based" design, emodiversity scores indicate diversity of experiences across time. Here, we make use of the combined study design, daily diary (state), and 6 month follow-up (trait) to examine concordance between the state- and trait-based emodiversity scores.

Empirical illustration

To examine the reliability of emodiversity based on a daily diary data, we calculated scores using 1-occasion, 2-occasion, ..., up to 30-occasion data and tracked rank-order stability across calculations. Given our departure from prior literature,

we examined both the Gini coefficient and Simpson’s index (which has similar properties with Shannon’s entropy). Figure 3 depicts correlations with the assumed 30-day true-score. As indicated by the intersections between horizontal and vertical dashed lines, reliability of positive emodiversity calculated using the Gini coefficient crossed a .8 threshold using 3-occasion data and a .9 threshold using 7-occasion data. For negative emodiversity, the same thresholds were crossed using 6- and 13-occasion data, respectively. Positive emodiversity scores calculated using Simpson’s index crossed .8 and .9 reliability thresholds using 7- and 9-occasion data, respectively. For negative emodiversity, the same thresholds were crossed using 12- and 24-occasion data.

Second, we examined correlations between diary-based “state” and follow-up-based “trait” emodiversity scores. Re-calculated with the 20 overlapping items, daily diary data positive ($M = 0.92, SD = 0.12$) and negative ($M = 0.48, SD = 0.17$) emodiversity, and follow-up single-assessment positive ($M = 0.94, SD = 0.14$) and negative ($M = 0.51, SD = 0.29$) emodiversity yielded similar sample averages. However, correlations between the state-based and trait-based scores were only moderate, $r = .43$ for positive emodiversity and $r = .38$ for negative emodiversity.

Recommendations

We recommend collecting at least 6 occasions to obtain reliable emodiversity scores using the Gini coefficient. More occasions may be necessary for metrics emphasizing evenness and richness. Reliability also differed by valence,

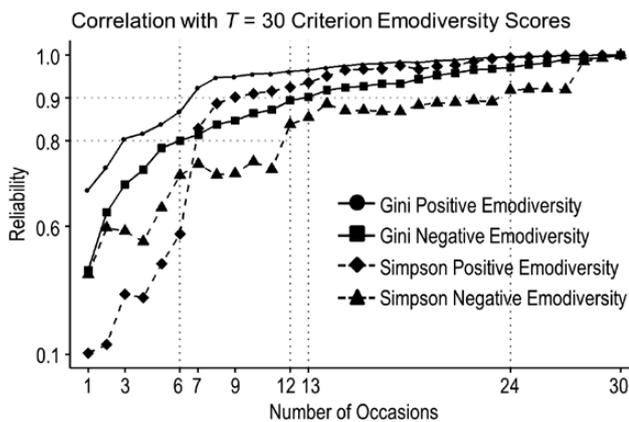


Figure 3. Reliability for diversity scores calculated using the Gini coefficient (solid lines) and Simpson’s index (dashed lines) based on correlations among number of occasions of data included (ranging from $T = 1$ to $T = 30$) and the total number of occasions designated by the study protocol ($T = 30$). Horizontal dashed lines appearing at y-axis values .8 and .9 represent two reliability thresholds for each index: Gini positive emodiversity (circles; 3- and 7-occasions), Gini negative emodiversity (squares; 6- and 13-occasions), Simpson positive emodiversity (diamonds; 7- and 9-occasions), and Simpson negative emodiversity (triangles; 12- and 24-occasions). Horizontal dashed lines appearing at y-axis values .8 and .9 represent two reliability thresholds for each index: Gini positive emodiversity (circles; 3- and 7-occasions), Gini negative emodiversity (squares; 6- and 13-occasions), Simpson positive emodiversity (diamonds; 7- and 9-occasions), and Simpson negative emodiversity (triangles; 12- and 24-occasions).

with fewer occasions needed to obtain reliable positive emodiversity scores. However, as also highlighted in other studies of emotion (e.g., Ready, Weinberger, & Jones, 2007; Solhan, Trull, Jahng, & Wood, 2009), with only moderate correlations between criterion state and trait scores, there is concern emodiversity may not be a trait. Rather, emodiversity may change substantially over time, within-person.

Interindividual Differences in Diversity

Research question

Are interindividual differences in emodiversity related to other interindividual difference characteristics? IIV metrics operationalize a variety of constructs—dynamic characteristics—that may be associated with health, well-being, etc. Here, we illustrate how an analysis might proceed. Building on theories and prior findings (e.g., Quoidbach et al., 2014), suggesting diversity is health protective, we test three hypotheses. Functionalist emotion theory and notions of biodiversity suggest that depletion or overabundance of an emotion(s) is detrimental to the individual’s health. Therefore, a general hypothesis is higher positive and negative emodiversity are associated with better health (H1). Stressor diversity research indicates that high exposure to the same stressors (i.e., chronic stressors) is worse for well-being than high exposure to diverse stressors (Koffler et al., 2016). Extension to emotion suggests the association between emodiversity and health will be stronger among individuals with high mean levels of positive and/or negative emotion (H2). Age-related increases in emotion-regulation capacity and prioritization of emotional experiences that maintain physiological homeostasis (Carstensen, 2006; Charles, 2010) suggest age will moderate the association between emodiversity and health (H3).

Empirical illustration

We calculated positive and negative emodiversity using (a) all available items, separated by positive and negative valence, (b) a binary response scale, (c) the Gini coefficient, and (d) 6 or more occasions. Model 1,

$$PhysicalHealth_i = \beta_0 + \beta_1(PositiveEmodiversity_i) + \beta_2(NegativeEmodiversity_i) + \epsilon_i \tag{5}$$

was fit to examine associations between health and positive and negative emodiversity (H1). The model was then expanded to test whether mean levels of emotion (H2) and age (H3) moderated those associations. Specifically, Model 2 was specified as,

$$PhysicalHealth_i = \beta_0 + \beta_1(PositiveEmodiversity_i) + \beta_2(NegativeEmodiversity_i) + \beta_3(PositiveEmotion_i) + \beta_4(NegativeEmotion_i) + \beta_5(Age_i) + \beta_6(PositiveEmodiversity_i * PositiveEmotion_i) + \beta_7(NegativeEmodiversity_i * NegativeEmotion_i) + \beta_8(PositiveEmodiversity_i * Age_i) + \beta_9(NegativeEmodiversity_i * Age_i) + \epsilon_i \tag{6}$$

All predictors were sample mean centered and significance was evaluated at $\alpha = .05$.

Table 2 displays results for both models. Model 1 indicated presence of significant associations, $F(2, 135) = 11.89$, $p < .001$, adjusted $R^2 = .14$. As hypothesized, higher positive emodiversity was significantly associated with better physical health ($\beta_1 = 67.17$, $p < .05$), but unexpectedly, negative emodiversity was not associated with physical health ($\beta_2 = -18.52$, $p = .06$).

Model 2 also indicated significant associations, $F(9, 128) = 9.64$, $p < .001$, adjusted $R^2 = .36$. Unexpectedly, after accounting for mean positive and negative emotion (and age), positive emodiversity was not uniquely associated with physical health. In contrast, negative emodiversity was significantly associated, in the hypothesized direction, with physical health ($\beta_2 = 27.65$, $p < .05$). Also as hypothesized (H2), mean negative emotion moderated this association ($\beta_7 = 90.72$, $p < .05$). Figure 4 shows simple slopes for average (solid line), low and high levels of mean negative emotion (dashed lines). Higher negative emodiversity was associated with better physical health among individuals with high mean negative emotion (+1 SD ; $b = 58.73$, $SE = 16.69$, $p < .001$), but not among individuals with low mean negative emotion (-1 SD ; $b = -3.43$, $SE = 13.07$, $p = .79$). Contrary to expectations (H3), associations between positive and negative emodiversity and physical health did not differ with age when controlling for other model covariates. However, the correlation between negative emodiversity and age ($r = -.24$) was stronger than the correlation between positive emodiversity and age ($r = .07$).

Recommendations

We found a significant association between positive emodiversity and physical health. However, only negative emodiversity held unique value after accounting for covariates. Notably, the multicollinearity induced by the high correlation ($r = .92$) between positive emodiversity and mean

positive emotion suggests reconsideration of how the two constructs can be differentiated. For negative emotions, results from Model 1 indicated that negative emodiversity was not associated with physical health. Results from Model 2 suggested a more complex relation, with the extent of association differing across individuals' level of mean negative emotion. Although we did not find evidence of age moderation in this study, we found a noteworthy correlation between negative emodiversity and age, which suggests future healthy aging research should continue to examine how emodiversity and other diversity-type constructs contribute to the dynamic interplay between age, emotional experience, and health.

Discussion

In this paper, we illustrate and provide recommendations for study of diversity-type IIV constructs. Using intensive longitudinal data, we examined how theoretical and methodological considerations inform item selection, use of binary or Likert-type measurement scales, choice of diversity index, number of measurement occasions, and discovery of associations among emotional experience, physical health, and age.

Operationalizing Emodiversity Using Intensive Longitudinal Data

First, we compared operationalizations of emodiversity based on a pure functionalist emotion framework (global) and a combination of functionalist emotion and core affect frameworks (positive and negative). Splitting by valence resulted in distinct indices, whereas the global index mapped more closely to negative emodiversity. Other theoretical frameworks, such as those specifically addressing age-related changes in arousal (e.g., SAVI) suggest further consideration of how emotion experiences map to

Table 2. Results From Regression Model Examining Associations Between Physical Health and Diversity Metrics

| | Model 1 | | | Model 2 | | |
|---|----------|-------|----------|----------|-------|----------|
| | Estimate | SE | <i>p</i> | Estimate | SE | <i>p</i> |
| Intercept | 77.59 | 1.68 | <.001 | 77.03 | 2.27 | <.001 |
| Positive Emodiversity | 67.17 | 14.87 | <.001 | -40.33 | 36.02 | .265 |
| Negative Emodiversity | -18.52 | 9.92 | .064 | 27.65 | 11.88 | .022 |
| Mean Positive Emotion | — | — | — | 8.07 | 3.34 | .017 |
| Mean Negative Emotion | — | — | — | -48.10 | 7.98 | <.001 |
| Age | — | — | — | -0.58 | 0.21 | .006 |
| Positive Emodiversity * Mean Positive Emotion | — | — | — | -41.72 | 24.54 | .092 |
| Negative Emodiversity * Mean Negative Emotion | — | — | — | 90.72 | 26.67 | .001 |
| Positive Emodiversity * Age | — | — | — | 1.69 | 1.63 | .303 |
| Negative Emodiversity * Age | — | — | — | 0.10 | 1.38 | .941 |
| Residual SE | 19.78 | | | 17.01 | | |
| Adjusted R^2 | .14 | | | .36 | | |

Note: $N = 138$; SE = standard error.

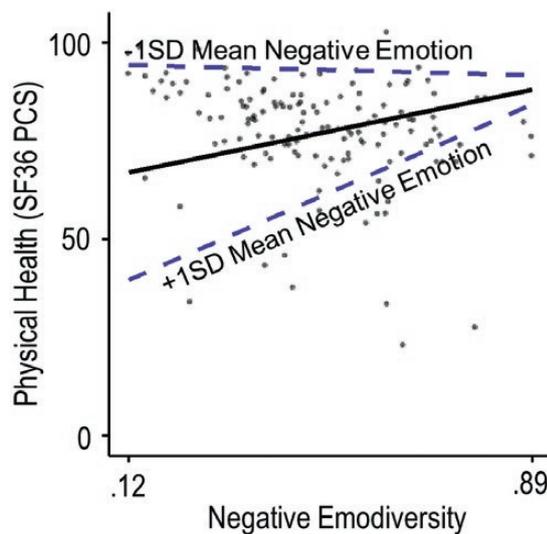


Figure 4. Simple slopes for the regression of physical health on negative emodiversity and mean negative emotion, with other covariates held constant. SF-36 PCS stands for SF-36 Physical Component Summary Score.

emodiversity constructs. We also examined operationalizations of emodiversity using all emotion items and a reduced set. Scores were highly correlated, suggesting emodiversity calculation is robust to the number of items included.

Second, we compared calculation of emodiversity using binary and Likert-type rating scales. High concordance between the scores suggests choosing a scale-type based on whether the research objective is to examine emotions as on/off states or as varying degrees of intensity.

Third, we presented a framework for selecting a diversity index based on the theoretical conception of diversity (evenness, richness, or both), practicalities of the study design, and the scaling and distributional properties of diversity scores. We evaluated similarity of scores across metrics, finding that scores were highly correlated across the four metrics. However, as seen in Figure 2, the distributions were highly skewed. Only the Gini coefficient for negative emodiversity provided a relatively normal distribution of between-person differences. We used emodiversity as a predictor, so this was not a major concern, but future research should evaluate the distribution of emodiversity scores before using them as an outcome. Breaking with prior research using Shannon's entropy, we propose, at least for emodiversity, the Gini coefficient may provide a more efficient representation of between-person differences, especially when data are collected using a study design that inherently imposes a ceiling on richness.

Fourth, we examined reliability of Gini coefficient and Simpson's index operationalizations of emodiversity by comparing scores calculated using sequentially increasing numbers of occasions to scores obtained using the 30-day study design maximum. We found differences based on valence and the type of diversity metric used. Whereas 3- and 7-occasion data achieved .8 and .9 reliabilities, respectively,

for positive emodiversity (calculated using Gini coefficient), 6- and 9-occasion data were needed for negative emodiversity. One explanation is that negative emotions are easier to differentiate than positive emotions (Barrett et al., 2001), meaning that the extent of inter-item differences does not stabilize until more data are available. Reliability also differed between diversity metrics. For positive emodiversity, .8 reliability was achieved using 6-occasion data for Gini coefficient scores and 12-occasion data for Simpson's index scores. The Gini coefficient's sole focus on evenness may make it better able to pull apart between person differences with fewer occasions compared to the joint richness/evenness focus of Simpson's index. These results may be useful for deciding on how many occasions are needed in future work on emodiversity and also suggest the need for future investigation into reliability in other domains of diversity (e.g., social, activity). Additionally, we found only moderate overlap among state and trait calculations of emodiversity, suggesting daily emodiversity provides unique information not captured by trait reports. These findings highlight the importance of articulating the timescale of assessment and differentiating between state and trait conceptualizations of emotion experiences (Brose et al., 2013).

Fifth, the empirical example provided evidence for links between emodiversity and health. Higher positive emodiversity was associated with better physical health, but not after accounting for mean positive emotion and other covariates. Higher negative emodiversity was not associated with physical health in Model 1, but was uniquely indicative of better physical health after accounting for mean negative emotion and other covariates (Model 2). In essence, the mean level of negative emotion "unlocked" an additional meaning of negative emodiversity. Simple slopes displayed in Figure 4 suggest negative emodiversity is significantly associated with physical health at high but not low levels of mean negative emotion. These findings align with hypotheses driven by functionalist emotion theory and notions of chronicity. Given the correlational nature of the present study, future research should examine whether the potential causal influence of negative emodiversity on health is limited to individuals who chronically experience negative emotions.

These results also add to the emotional complexity literature, providing some evidence that emodiversity operates similarly to psychological flexibility and emotion differentiation. Each construct broadly focuses on individuals' capacities to identify and be in tune with the nuances of their emotion experiences, with evidence that higher levels of flexibility and differentiation are associated with better physical health (e.g., Hardy & Segerstrom, 2016). One explanation for the nonsignificant association between positive emodiversity and health (Model 2), and the high correlation between positive emodiversity and mean positive emotion may be that individuals were reporting on their positive emotions in a way that was not contextually driven or differentiated (see e.g., Gruber et al., 2013). Future work

examining the designs, contexts, and samples where positive emodiversity differentiates from mean positive emotion will allow for better understanding of their associations with physical health. Overall, research on emodiversity at multiple timescales (e.g., months, years, decades) would benefit from consideration of what emodiversity indicates about the emotion-situation fit.

Surprisingly, positive and negative emodiversity did not moderate the association between age and physical health. First, the relative age homogeneity in this sample (age 40–65) may have limited our ability to detect age-related differences. Second, our conceptualizations of positive and negative emodiversity incorporated both low and high arousal emotions. But, lower emodiversity in high arousal emotions may be health protective for older adults, whereas greater emodiversity in low arousal emotions may be health protective for younger and older adults. Third, the daily diary method may have influenced the findings. Charles and colleagues (2016) showed age advantages in emotion experiences, particularly the tendency for older adults to experience lower negative affect, were more pronounced when participants reported over longer timescales (i.e., monthly) compared to faster timescales (i.e., daily).

Limitations and Opportunities for Future Research

A cautionary note about these analyses concerns visual inspection of the distributions presented in Figure 2. There are severe restrictions in the range of positive emodiversity scores, for both binary and continuous response scales. Many individuals have maximum (or near maximum) diversity—indicating total equality of experience across positive emotions. This may be because individuals do not differentiate among positive emotions, the diversity in positive emotion eliciting contexts, or because participants use a general valence focus (Barrett, 1998) when rating their positive emotional states. It may be that emotional differentiation and granularity are necessary precursors of emodiversity (Quoidbach et al., 2014). These findings further indicate that negative emotions hold more differentiated functional value than positive emotions (e.g., Barrett et al., 2001). How that (lack of) differentiation changes with age remains an open question.

Participants in the As U Live Study were a relatively homogenous sample in terms of age (40 to 65 years), ethnicity (primarily White), and education (53% college obtained college or graduate degrees). These participants were also healthier ($M = 77.62$, $SD = 21.3$) than the general population ($M = 49.22$, $SD = 15.13$) in terms of their SF-36 physical quality of life scores. In addition to future research on age-related differences/changes in emodiversity, future work should examine emodiversity in other characteristics including ethnicity, educational experiences, and physical functioning to further differentiate unique contributions to the human experience, beyond what is captured by other emotion IIV constructs.

Building on past research using a single-occasion design, this analysis used data on individuals' discrete emotion experiences across 30 days to operationalize emodiversity as a dynamic characteristic, assuming stability of diversity over time. Although this approach may better reflect of individuals' emotion experiences over a specific period (e.g., the past day), it is inherently a recall-self-report design, susceptible to memory and other recall biases. Additionally, emodiversity may itself change over fast (e.g., day-to-day, week-to-week) and/or slow (e.g., year-to-year, across decades) timescales (Ram & Gerstorf, 2009). With ecological momentary assessments, experience sampling, measurement-burst, and other designs wherein participants provide repeated measurements, multilevel modeling and other dynamic models could provide insight into how health covaries with changes in emodiversity.

Emodiversity theory ties the adaptiveness of an emotion experience to context. The present study data did not include indicators of context (where the emotions occurred) or whether the reported emotions were accurate/adaptive reflections of the biopsychosocial inputs. Mapping emodiversity to environmental and developmental features of the context will allow for better understanding of for whom and in what contexts emodiversity is adaptive. The degree to which emodiversity is beneficial may depend on the complexity of one's environmental context and how that complexity facilitates or constrains opportunities for emotional experience. For example, facing positive events and challenges are key components of learning and developmental processes in educational and work place settings (Vygotsky, 1978). Exploring individual, environmental, and developmental contexts will provide an empirical base supporting the design of interventions to foster the specific types of diversity contributing to optimal functioning in daily life and healthy aging across the life span. We hope future research continues to expand the study of diversity-type IIV constructs into other domains where discrete feelings and behaviors manifest (e.g., types of stressors, types of activities, types of locations, types of social partners), to better understand how the range of experiences an individual encounters contributes to health, well-being, and successful aging.

Supplementary Material

Supplementary data is available at *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences* online.

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