# Running Head: EMOTION VOCABULARY SIZE

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#### Abstract

18 To date we know little about natural emotion word repertoires, and whether or how they 19 are associated with emotional functioning. Principles from linguistics suggest that the richness or 20 diversity of individuals' actively used emotion vocabularies may correspond with their typical 21 emotion experiences. The current investigation measures active emotion vocabularies in 22 participant-generated natural speech and examined their relationships to individual differences in 23 mood, personality, and physical and emotional well-being. Study 1 analyzes stream-of-24 consciousness essays by 1,567 college students. Study 2 analyzes public blogs written by over 25 35,000 individuals. The studies yield consistent findings that emotion vocabulary richness 26 corresponds broadly with experience. Larger negative emotion vocabularies correlate with more 27 psychological distress and poorer physical health. Larger positive emotion vocabularies correlate 28 with higher well-being and better physical health. Findings support theories linking language use 29 and development with lived experience and may have future clinical implications pending further 30 research.

*Keywords:* emotion, emotion vocabulary, emotion language, affect labeling, emotion
 awareness

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# Natural Emotion Vocabularies as Windows on Distress and Well-being Introduction

In today's age of hyper-self-awareness, the ability to name emotions is often celebrated. 36 37 It is often assumed that people who use rich emotional vocabularies are emotionally and 38 physically healthier than those who express themselves using a narrower range of emotion 39 words. Self-styled emotion experts publish lengthy lists of emotion words to help people articulate feelings as precisely as possible<sup>1-4</sup>. In popular and scholarly press, it is proposed that 40 naming emotions can promote mental and physical health<sup>5-7</sup>. To capitalize on this effect, readers 41 42 are advised to "beef up your emotion concepts" and "learn as many new words as possible," to be equipped to categorize difficult emotions when they arise more flexibly and precisely<sup>5</sup>. 43 Mobile applications ensure that the most precise emotion label is only a finger-click away<sup>8</sup>. 44 45 Despite this interest in naming emotions, we still know little about natural emotion word 46 repertoires, and whether or how natural emotion vocabularies are associated with emotional 47 functioning. Most research on benefits of identifying emotions has measured self-perception of emotional abilities instead of emotion language itself<sup>9,10</sup>. The studies more concerned with 48 49 emotion language have relied on passive presentation of experimenter-generated emotion words, 50 capturing constructs other than natural emotion vocabularies. For example, emotional 51 intelligence, the ability to recognize and reason using emotions, is measured using multiple choice formats<sup>11</sup>. Emotion differentiation, the ability to distinguish same-valenced emotions 52 53 conceptually, which is correlated with positive mental health, is inferred from the structure of Likert emotion ratings<sup>12</sup>. Faster responding on such Likert-type emotion scales is also associated 54 with helpful emotion regulation<sup>13</sup>. And compared to viewing unlabeled images, viewing 55 56 upsetting images paired with a matching emotion word activates frontal lobe structures that

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dampen emotional intensity<sup>14</sup>. Such studies point compellingly to benefits related to recognizing
common emotion concepts and labels, but they have unclear relevance to natural, spontaneous
emotion word use in everyday life.

60 Linguistic approaches contribute a useful distinction to the study of emotion language: 61 degrees of verbal knowledge fall into one of two nested domains. An active vocabulary is the set 62 of words an individual produces spontaneously, which constitutes only a subset of one's passive vocabulary, or the full body of words the person can recognize<sup>15-17</sup>. Importantly, sizes of active 63 64 and passive vocabularies are not correlated; passive vocabularies increase through schooling. 65 whereas active vocabularies tend to plateau, suggesting that people re-use the words with which they are most comfortable<sup>16</sup>. Studies presenting participants with emotion labels reveal processes 66 involving passive emotion knowledge. However, as others have pointed out<sup>12,18-20</sup>, to fully 67 understand the role of emotion language in well-being, we must also extend research into active 68 69 emotion vocabularies.

70 At their most basic level, words are symbols that correspond to concepts and experiences<sup>21</sup>. From this perspective, there should be a broad alignment between active 71 vocabularies and experience. At this stage, we are agnostic about the causality in this 72 73 relationship, which could be bidirectional. Specifically, active vocabularies could correspond 74 with experiences for at least three, non-mutually-exclusive reasons. First, active vocabularies provide a window into mental habits. According to Zipf's<sup>22</sup> principle of least effort, speakers are 75 naturally economical in their use of language, with active vocabularies driven by utility. Like 76 77 carpenters who keep their most useful tools within arm's reach, speakers use most frequently the 78 words that perform their most common mental operations. This linguistic principle has become a 79 central premise of personality research: active vocabularies can tell us about the concepts people

use in their thinking most<sup>22-25</sup>. By this logic, an individual may simply have developed a wider
variety of labels for certain emotions via more frequent experiences of them.

82 Second, active vocabularies may reflect expertise or interest. The psychologist uses a rich vocabulary of psychology words, the sommelier a rich vocabulary of wine words. Lévi-Strauss<sup>26</sup> 83 84 famously recorded that indigenous hunter-gatherers in the Philippines easily named over 450 85 plants, 75 birds, and 20 varieties of ants. Lévi-Strauss reasoned that utility alone could not 86 explain such staggering vocabularies, as there would be diminishing practical returns on such 87 fine-grained classifications. Instead, he speculated that interest may have motivated these 88 exceedingly diverse taxonomies. In addition to well-established determinants of vocabulary acquisition and maintenance<sup>27,28</sup>, we similarly suggest that preoccupation with or interest in 89 one's own affective states could contribute to the development of increasingly diverse affective 90 91 taxonomies and lexica.

92 Third, it appears that experience can grow into gradual alignment with words. The strong causal view—that language fully determines experience<sup>29</sup>—has been dismissed<sup>30</sup>, but subtler 93 versions of this hypothesis are compelling. Dewey<sup>31</sup> has described the function of words as "a 94 fence, a label, and a vehicle—all in one"<sup>31</sup>, meaning that words not only divide our continuous 95 96 stream of experiences into discrete units, but also catalog experiences in memory for future use, 97 and conceptually scaffold our interpretations of future events. Several others have articulated similar roles for language in shaping experience (see language-as-context<sup>32</sup>; the mangrove 98 effect<sup>33</sup>; essence placeholders<sup>34</sup>). Initial experiments seem to confirm that verbal concepts help 99 construct perceptions of reality, including the experience and interpretation of emotional states<sup>5</sup>, 100 34-37 101

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In the present project, two studies examine the characteristics of active emotion

103	vocabularies and their relationships to individual differences in mood, personality, and physical
104	and emotional well-being. We expect a broad cross-sectional correspondence between words and
105	experience, such that large vocabularies for negative emotions would signal low well-being,
106	while large positive emotion vocabularies would signal high well-being.
107	Results
108	Study 1
109	Stream-of-consciousness writing, with its unstructured nature, presents an ideal
110	opportunity to investigate linguistic markers of individual differences <sup>24</sup> . Study 1 investigated
111	emotion vocabularies (EVs) in stream-of-consciousness writings (final N = 1,567) by: (1)
112	identifying basic properties of positive and negative EVs, including their size and test-retest
113	reliability; (2) examining the link between EVs and broad individual differences in demographic
114	characteristics, personality, and physical and emotional health; and (3) examining the
115	relationships between EVs for specific emotion families (i.e., anger, sadness, anxiety/fear,
116	happiness) and the intensity of corresponding state-level moods. Relationships are expressed
117	with standardized errors and 95% bias-corrected and accelerated confidence intervals, generated
118	using 2000 bootstrapped replicates with replacement.
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Overall, 6.11% (SD = 1.66) of words used in essays were emotionally toned, based on the positive emotion (M = 3.62, SD = 1.28) and negative emotion (M = 2.40, SD = 1.15) categories computed using Linguistic Inquiry and Word Count (LIWC)<sup>38</sup>. The actual number of unique emotion words was far smaller. Average EV was 0.55 for negative emotions (SD = 0.36, range = 0 to 5.71, 95% CI [.53, .57]), and 0.52 for positive emotions (SD = 0.34, range = 0 to 3.75, 95% CI [.29, .34]). Based on the EV algorithm, these average rates correspond to approximately one unique positive and one unique negative emotion word per 200 words of text. Test-retest correlations were modest ( $\mathbf{r}_{\text{NegEV}} = .18, 95\%$  CI [.10, .27], p < .001;  $\mathbf{r}_{\text{PosEV}} = .28, 95\%$  CI [.19, .38], p < .001), but in line with previous findings of temporal stability for traits manifested in verbal behavior  $(\mathbf{r} = .24)^{39}$ . Positive and negative EV indices were modestly correlated with each other in a positive direction, suggesting that to some extent they may reflect a unitary tendency toward greater diversity in emotion language (Table 1). As shown in Table 1, negative EV was associated with female gender, while positive EV was not. Neither negative nor positive EV were related to age.

151 152	Insert Table 1 about here
153 154	Indicating convergent validity, negative and positive EV were related to cognitive
155	processing words (see Table 1). Both positive and negative EV were also associated with general
156	vocabulary, and each index was associated with the corresponding emotional tone. These
157	convergences support our general conceptualization of EV; they are also further relevant to our
158	examination of incremental validity, below.
159	As seen in Table 1, negative EV was generally associated with prevalence of linguistic
160	markers related to poor well-being, namely, lower frequency of we-words and leisure words, and
161	higher use of I-words and illness words. Positive EV was generally associated with markers
162	related to positive well-being: high frequency of achievement, affiliation, and leisure words. A
163	few findings were not expected. Positive EV was unexpectedly related to higher mention of
164	physical illness words. Achievement words did not show the expected inverse correlation with
165	negative EV, perhaps because these concerns are common to most students in a university
166	setting.
167	As shown in Table 1, negative EV was related to higher neuroticism and depression and
168	lower overall health. Conversely, positive EV corresponded with indicators of more positive
169	experiences and higher psychosocial functioning: higher extraversion, agreeableness, and overall
170	health, and lower self-reported neuroticism and depression. For scatterplots of key relationships
171	see Supplementary Figure 2. Although not the focus of these analyses, Study 1 data were also
172	used to examine criterion validity of the text-derived indices. Correlations between text-derived
173	and self-reported indicators of well-being, reported in Supplementary Table 2, consistently
174	indicate the associations suggestive of validity (i.e., I-words and illness words with low well-
175	being; we-words, affiliation, achievement, and leisure words with high well-being).

176 Given the possibility that EV is partly a product of emotional tone of texts and/or 177 individuals' general verbal ability, the analyses reported in Table 1 were repeated using partial 178 correlations controlling for general vocabulary, negative emotional tone, and positive emotional 179 tone. As indicated in the footnotes to Table 1, many key relationships between emotion EV and 180 psychological variables remained or became significant. EV appears to be capable of explaining 181 unique variance in health and adjustment indices, above and beyond the effects of overall verbal 182 development and emotional tone. Readers interested in an exploration of the interaction between 183 negative and positive EV are directed to Supplementary Note 1.

Students used more diverse negative EV when they felt negatively before writing ( $\mathbf{r} = .19$ , SE = .02, 95% CI [.14, .24], p < .001), and larger negative EV was also related to feeling negatively after writing ( $\mathbf{r} = .21$ , SE = .02, 95% CI [.17, .26], p < .001). Similarly, the positive EV and was related to positive self-reported mood before writing ( $\mathbf{r} = .19$ , SE = .02, 95% CI [.14, .23], p < .001). and after writing ( $\mathbf{r} = .22$ , SE = .02, 95% CI [.18, .27], p < .001).

189 Emotion-specific EV scores were used to examine the relationship between variability in 190 emotion language with change in corresponding mood states. Sadness vocabularies were used to 191 predict post-writing levels of self-reported sadness, fear vocabularies to predict post-writing 192 worry, anger vocabularies to predict post-writing anger, and undifferentiated negative 193 vocabularies to predict self-reported levels of post-writing stress. To provide a stringent test of 194 the effects of sheer emotion vocabulary size, apart from overall vocabulary richness or the 195 emotionality of the writing, partial correlations controlled for general vocabulary and negative 196 and positive emotional tone. To isolate change in self-reported moods over time, each partial 197 correlation also controlled for pre-writing levels of the target mood. As shown in Table 2, as a 198 \_\_\_\_\_

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Insert Table 2 about here

200 201	function of variability in specific emotion vocabularies, the corresponding subjective feelings
202	grew stronger over the course of writing, and these subjective mood effects were highly specific
203	to the target mood. People who used more names for sadness grew sadder over the course of the
204	stream of consciousness exercise, but did not grow more worried, angry, or stressed. People who
205	used more names for fear grew more worried, but did not feel sadder, angrier, or more stressed.
206	People who used more names for anger in their writing grew angrier, but actually grew less
207	worried, and reported no change in stress. The people who grew more stressed over the course of
208	the writing exercise were those who used high rates of unique undifferentiated negative words.
209	Positive EV showed a similar correspondence with increases in positive mood.
210	
211	Study 2
212	Study 2 analyzed a large collection of public blogs (final $N = 35, 385$ ). Bloggers wrote
213	often over several years, producing text samples spanning an unrestricted range of topics-some
214	personal and emotional, others dry and factual. Relationships in Study 2 are expressed with
215	standardized errors and 95% bias-corrected and accelerated confidence intervals, generated using
216	500 bootstrapped replicates with replacement.
217	
218	The average blogger used approximately 6.55 unique negative emotion words and 5.99
219	unique positive emotion words. The negative EV rate averaged $0.29$ (SD = $0.21$ , range = 0 to
220	2.66), and the positive EV rate averaged 0.33 (SD = $0.21$ , range = 0 to 2.49), or just less than one
221	unique positive and one unique negative emotion word per 300 words of text. To assess EV

stability, each blog was split in half, and separate EV statistics were computed for each half.

223 Reliabilities ( $\mathbf{r}_{\text{NegEV}}$  = .27, SE = .01, 95% CI [.26, .29], p < .001;  $\mathbf{r}_{\text{PosEV}}$  = .28, SE = .01, 95% CI

224	[.27, .29], p < .001) exceeded both the test-retest reliability in Study 1 and rates found previously
225	for psychological linguistic variables <sup>39</sup> . As in Study 1, positive and negative EV were positively
226	correlated ( $\mathbf{r} = .22$ , SE = .01, 95% CI [.20, .23], $p < .001$ ). Examples of emotion words captured
227	appear in Supplementary Methods.
228	As in Study 1, negative EV was associated with female gender; positive EV was also
229	associated with female gender (see Table 3). Replicating Study 1, negative and positive EV were
230	related to cognitive processing words. Both positive and negative EV were associated with
231	general vocabulary, and each index was associated with the corresponding emotional tone.
232	
233	Insert Table 3 about here
234	Negative EV was again associated with linguistic markers of low well-being. As in Study
236	1, negative EV was correlated with higher use of illness and <i>I</i> -words, and lower use of we- and
237	leisure words. Exceeding effects of Study 1, negative EV was further related to lower rates of
238	achievement words. Results involving positive EV were similar to Study 1. Positive EV was
239	again related to higher rates of achievement, leisure, and affiliation words. Unexpectedly,
240	correlations with illness and I-words, which had been positive but nonsignificant in Study 1,
241	were larger and reaching significance in Study 2. For scatterplots of key relationships see
242	Supplementary Figure 2.
243	Almost all relationships between negative emotion EV and psychological variables
244	remained significant after controlling for other factors (and in the same direction), as did several
245	of the relationships involving positive emotion EV. In other words, EV again appeared to be
246	capable of explaining unique variance in health and adjustment indices.
247	Discussion
248	These studies examined whether emotion vocabularies in natural language are associated

with psychosocial functioning. Study 1 indicated that EV indices are psychometrically 249 250 acceptable. Regarding construct validity, EVs were correlated with cognitive processing 251 tendency, general vocabulary, and emotional tone in logically consistent directions. Most 252 markers of well-being were associated with use of sparser negative and more expansive positive 253 EVs. At the state level, using a wider array of emotion words was associated with intensification 254 of the corresponding mood. These effects were strikingly emotion-specific: people with varied 255 vocabularies for sadness grew sadder, people with varied anger vocabularies grew angrier, and 256 so on-even when controlling for pre-writing levels of these specific moods. These effects 257 remained above and beyond effects of potential confounds. It appears that people use larger EVs 258 to describe states they are likely to intensify. However, the student sample and stream-of-259 consciousness exercise limit generalizability. Although the topic was not constrained, the 260 exercise required some minimal degree of introspection, which could have inflated EVs. Study 2 261 addressed these concerns by analyzing a larger and more heterogeneous sample of natural 262 language.

263 In Study 2, Psychometrics of EVs generally replicated Study 1. Although people used 264 positively valenced words more frequently than negative words, EVs were again slightly larger 265 for negative emotions. Split-half reliability exceeded test-retest reliability found in Study 1, 266 suggesting stability. EVs again correlated with established markers of attention to internal 267 experience (cognitive processing), general vocabulary breadth, and emotional tone, suggesting 268 construct validity. Notably, most people tended to have small EVs, averaging about seven unique 269 emotion words per 1,000 words in their blog entries. This low rate is consistent with the limited nature of active vocabularies relative to other knowledge levels<sup>16</sup>. Negative EV was again 270 271 correlated with virtually all markers of lower adjustment. Bloggers with a larger negative EV

used language in ways consistent with people who are depressed, socially and behaviorally
withdrawn, and in poorer physical health. Similarly, and even more consistently than in Study 1,
negative EV demonstrated incremental validity in predicting well-being indices above and
beyond effects of general vocabulary and emotional tone. Relationships of positive EV with
well-being indicators were more mixed and only partially replicated Study 1.

277 Across both studies, then, people who used a wider variety of negative emotion words 278 appeared to be faring less well; they used linguistic markers of lower well-being and reported 279 greater depression, neuroticism, and poorer physical health. Conversely, people who used a 280 variety of positive emotion words appeared to be faring well; positive EV was associated with 281 linguistic markers of well-being and, in the student sample, self-reports of higher 282 conscientiousness, extraversion, agreeableness, and overall health, and lower depression and 283 neuroticism. Most relationships could not be attributed to the emotional tone of the texts, nor to 284 the size of individuals' general vocabularies, recommending EV as a unique psychological marker in its own right. The stability of EV indices, acceptable for measures of its kind<sup>39</sup>, 285 286 underscores this potential.

287 To interpret these findings, the relationship of EV to mood (Study 1) is instructive. 288 Larger EVs corresponded with state mood and its intensification, suggesting that emotion 289 vocabularies not only provide insight into frequently experienced emotions, but perhaps also 290 indicate a sort of emotional expertise: the tendency to use reflective thought to intensify alreadypresent feeling states. If vocabulary size indicates interest<sup>26</sup>, larger EVs may further reveal 291 292 emotional states preoccupying the individual. Future studies incorporating trait preoccupation 293 with moods (e.g., rumination) may be fruitful. EV's correspondence with mood is noteworthy given possible difficulties inferring momentary well-being from emotion word frequencies<sup>40,41</sup>. 294

The EV approach bypasses this issue by relying not on frequency but rather on the diversity of emotion word categories. Future research could explore whether EVs develop over time in parallel with the frequency of felt experiences, which would help confirm whether EVs serve as observable markers of familiar emotional states.

299 The current pattern of findings suggests that the relative proliferation of emotion words in 300 individuals' active vocabularies may correspond to emotional experiences, but it does not speak 301 to whether EVs were instrumental (helpful or harmful) in bringing emotional experiences about. 302 Even though moods intensified during the stream of consciousness writing (Study 1) 303 corresponding to diversity in emotion word use, the absence of experimental manipulation makes 304 it impossible to conclude that broader EVs *caused* this intensification. At the same time, it is also 305 not possible to rule out such a causal effect. Language facilitates mental processes and subtly alters experience<sup>31,33</sup>. For instance, verbalizing taste sensations aids later memory retrieval<sup>42</sup>, 306 307 suggesting words may sustain fleeting subjective states. Emotion labels, in particular, may influence which emotions individuals perceive in others and experience themselves<sup>32,34,36,43</sup>. 308 309 Future research should investigate experimentally whether the state mood intensification such as 310 we observed could have been constructed in part by more elaborative use of emotion synonyms. 311 If so, this could be interpreted in line with constructivist emotion theories: while finding a 312 precise emotion labels is presumed to aid in emotion regulation because it creates access to relevant emotion knowledge<sup>5,44</sup>, applying more than one relevant label may be counterproductive 313 314 for down-regulating negative states, given that the labels may also reify the perception and felt experience of the state being named<sup>34</sup>. 315

316 It is tempting to use the current findings to speculate about whether and how broad 317 emotion vocabularies may be psychologically adaptive (i.e., functions causally to increase

318 individuals' well-being). While we believe the current findings are a small part of a larger puzzle 319 on this topic, we caution readers against interpreting current findings strongly in terms of the 320 psychological adaptiveness of large emotion vocabularies. We take as given the existing larger 321 framework, at the intersection of evolutionary psychology and appraisal theories, holding that the 322 existence of language is advantageous because of its ability to segment and categorize experience into cognitively manageable units<sup>45-47</sup>. Recent discovery of cross-cultural universals 323 324 in the structure of emotion semantics underscores the species-wide advantageousness of lexical systems containing names for both positive and negative states<sup>48</sup>. That said, evolutionarily 325 326 advantageous behaviors do not necessarily confer advantage in social-emotional life at individual difference level<sup>49</sup>. A true test of psychological adaptiveness of large emotion vocabularies still 327 328 requires experimental evidence that this study does not provide.

329 Importantly, our findings are not incompatible with evidence of regulatory neurological effects of labeling vs. not labeling negative states<sup>14</sup>. Perhaps unhappy people use larger 330 331 vocabularies for negative emotions as attempts to down-regulate those states—maybe even 332 somewhat successfully. Negative mood intensified as a function of negative EVs (Study 1); 333 however, mood increases might have been even more pronounced had unhappy individuals not 334 deployed an arsenal of emotion words. The findings presented here are silent on the possible 335 coping function of emotion labels; rather, they complement existing literature by advancing the 336 possibility that EVs serve as trait-like indicators of familiar states. Additionally, note that 337 individual people likely rely on active and passive EV for different purposes in their everyday 338 lives. Passive EVs are likely important for recognizing and interpreting day-to-day social behaviors in the social environment<sup>50</sup>. Active EVs may be more important for decoding one's 339 340 own mental state and communicating it to oneself and others, to address one's own needs and

341 inform new behavior 51,52.

342 Limitations of this study include the use of a one-item question to assess self-reported 343 physical health and the absence of a direct measure of writers' education levels. A possible proxy 344 for education, the general vocabulary index, was correlated with the breadth of emotion 345 vocabularies, especially positive EV. However, many associations between EV and well-being 346 indicators survived the inclusion of general vocabulary size as a covariate. Future replications 347 with nuanced measures of individual differences in both well-being outcomes and intellectual 348 functioning are needed. Our current findings also suggest several new research questions that the 349 present study was not equipped to answer fully. For one, supplemental analyses using 350 complementary text analysis methods suggest that emotion vocabularies may have interesting 351 relationships with more sophisticated topic modeling approaches (Supplementary Note 2, 352 Supplementary Table 4). Relationships between EV and conceptually related traits, such as 353 emotional intelligence, also need to be articulated, as do relationships of EV dimensions to one 354 another. Post hoc moderation analyses were suggestive of a possible buffering effect of rich 355 positive emotion vocabularies, such that they may protect against maladaptive correlates of rich 356 negative emotion vocabularies with depression (Supplementary Note 1). This initial cross-357 sectional effect requires replication and extension before it can be substantively interpreted. 358 Several features of the EV method require comment. It is important to note that the words 359 captured by the EV index are not applied to mental or emotional life exclusively; for instance, 360 the word "alone" does not always refer to the feeling state. This is a natural feature of word-361 counting approaches to text analysis. Because words correspond to mental content imperfectly, 362 text-derived signals are necessarily noisy; even robust, meaningful effects are necessarily small<sup>53</sup>. Given the explicit instruction in the stream-of-consciousness essays to focus on internal 363

364 experience, it is likelier that words with multiple meanings were used for their emotional 365 meaning more in this sample than in the blogs. As with other word counting approaches, the 366 multiple meanings of words do not invalidate the EV approach, but instead simply constrain the 367 inferences it can support. As argued elsewhere, spontaneously used words should be considered 368 not explicit, but rather semi-implicit indices of thematic content, concerns, and frequent mental operations<sup>54,55</sup>. Moreover, the reliability of inferences from such data is proportional to sample 369 370 size—this approach is best suited to revealing sample-wide patterns; inferences about any 371 individual or small group should be treated with skepticism. See Supplementary Note 3 for 372 additional nuance regarding the negligible impact of imbalance and length in EV word lists. 373 Future longitudinal research can ultimately determine whether and how changes in 374 emotion vocabularies and changes in well-being are related. Intensive multilevel studies of 375 emotion language are needed that would be capable of unpacking the complex relationship of 376 emotion words to moods at contrasting temporal resolutions. Perhaps rich vocabularies for 377 negative emotions are co-activated during distressed states so as to appear correlated in the short 378 term, while in the long term these rich vocabularies could nevertheless be helpful. Future large-379 scale studies could further characterize the relationship of EVs to clinical presentations and 380 changes in clinical functioning over time. Given the distinct conceptual viewpoints afforded by 381 different measures, it would be interesting to include in such studies other measures related to emotion awareness, including traits<sup>56</sup>, emotional abilities<sup>11,57</sup>, and passive emotion word 382 knowledge and recognition<sup>12,13,44</sup>. Understanding patterning of EV development within a multi-383 384 method, multivariate context will be essential to improve theoretical models of emotion language 385 and support emerging emotion labeling-based interventions. To complement these observational 386 methods for emotion language research, there is also a clear need for experimental manipulations

of EV and other aspects of naturalistic, active emotion language generation. For example, a
recent experimental manipulation of emotion labeling suggests preliminarily that leading
individuals to generate excessive numbers of emotion labels in the context of a simulated stressor
could undermine problem solving and emotion regulation efforts<sup>20</sup>. Many more experiments are
needed before we can answer causal questions on the effects of emotion language on emotion
experience and psychological adaptation.

393 At this juncture clinical application of the present methods and present findings is 394 premature. Assessments of EV could potentially merit consideration as the basis for a future tool 395 for planning treatment and predicting patient responses to affect labeling and other emotion-396 focused interventions. However, given the current method's more appropriate use for describing 397 sample-wide patterns, the use of EV for diagnostic and intervention purposes would require 398 further validation. While cross-sectional, our findings would be consistent with the possibility 399 that distressed people may not need to increase vocabulary size, per se, for articulating their 400 unhappiness-their negative EVs appear larger already. Perhaps other features of emotion 401 language, or coordinated habits or skills, are needed instead of-or in addition to-emotion 402 language diversity. Instead of or in addition to EVs, psychological effects of emotion language 403 may hinge on several other factors, including perhaps: context-specificity/precision of emotion language selections<sup>18,44</sup>, deep conceptual emotion knowledge<sup>34</sup>, cognitive efficiency of emotion 404 405 naming processes  $^{13,20}$ , and/or accompanying mental stance (e.g., nonreactiveness  $^{58}$ : nonjudgmentalness<sup>59</sup>; perceived clarity of emotions and/or ambiguity tolerance<sup>10,60</sup>). Because 406 words may help construct experience<sup>34</sup>, we cautiously speculate, based on our positive EV 407 408 findings, that positive EV may be an especially fruitful target for mechanistic and applied study. 409 Overall, the current project highlights the potential value of big data in the multi-method

410 study of emotion language, because it can reveal broad patterning of naturally-occurring social 411 and clinical processes. Large data sets make visible relatively small effects that are difficult to 412 capture in lab samples. Our initial replication suggests that we are detecting small, but reliable, 413 phenomena at the intersection of emotion vocabularies, distress, and well-being. This project 414 also offers up a computerized tool for the quantification of active emotion vocabularies in 415 participant-generated natural speech/text, which can aid the efficiency and generalizability of 416 future efforts to understand the link between active emotion vocabularies and experience. 417 **Methods** 418 Study 1 419 Participants and procedure. Undergraduates enrolled in a large online introductory 420 psychology class completed identical writing assignments in mid-September (Time 1) and, for 421 test-retest reliability analysis, again in early December (Time 2). Most essays met criteria for 422 inclusion: of the 1,579 students who wrote the first essay, 1,567 produced analyzable texts (i.e., at least 100 words; at least 70% of words identifiable by the default LIWC<sup>38</sup> lexicon); 1,360 of 423 424 those produced analyzable essays at Time 2. Given the novelty of our research question, effect 425 sizes were not available a priori for a power analysis. However, this sample size is sufficient to 426 detect even very small-to-moderate correlations with adequate (.80) power. Students completing 427 the Time 1 essay had a mean age of 18.8 (SD = 2.0), and 60.7% identified as female. Time 2 428 essay completers differed from non-completers by sex (females more likely to complete the 429 second essay) and by reporting higher conscientiousness (independent *t*-tests, p < .01). The 430 procedure was approved by the Institutional Review Board at the University of Texas at Austin. 431 Informed consent was obtained from all participants at the start of the semester.

432 Stream of consciousness essays. Participants recorded their thoughts in writing as they

433	occurred for 20 minutes. Students completed the exercises on personal computers outside of
434	class. The instructions read:
435 436 437 438 439	During this 20-minute task, your goal is to track your thoughts, perceptions, and feelings as they occur to you. Simply write continuously for the entire time and type out your thoughts, perceptions, and feelings without censoring them. There are no right or wrong things to write. Just track what is going on in your mind for the full 20 minutes.
440 441	When 20 minutes had elapsed, students were given the option to stop or continue writing. Essays
442	averaged 665 words (SD = 241) at Time 1 and 631 words (SD = 254) at Time 2. Sample essays
443	representative of the tone/content of essays and range of EV scores appear in Supplementary
444	Methods.
445	Emotion Vocabulary (EV). Linguistic Inquiry and Word Count (LIWC) <sup>38</sup> is frequency-
446	based, meaning that it counts the number of occurrences of over 4,500 words and word stems in
447	over 70 categories. However, in its typical application, LIWC would produce the same score for
448	texts containing ten different emotion words as it would for texts repeating the same emotion
449	word ten times. We created an approach that quantifies the size of EVs by counting the rate of
450	unique, or non-repeated, emotion words. By emotion words, we mean words that are used
451	primarily for naming emotional states or feelings (e.g., happy, disheartened, embarrassed), rather
452	than referring to affectively tinged or themed content (e.g., victory, idiotic, fight). While there is
453	disagreement about the number of distinct emotional states <sup>61</sup> , this approach is flexible and can be
454	modified to include words of interest to each researcher. For the current project, the words
455	naming positive and negative emotions were identified from the initial set of 406 positive and
456	499 negative affectively tinged words in the LIWC2007 emotion dictionaries. The final list of
457	emotion words included 92 negative emotion and 53 positive emotion words (Supplementary
458	Table 1). Normative data on age-of-acquisition (AoA) drawn from Kuperman and colleagues <sup>62</sup>

459 show comparable AoA for positive (8.21yrs, SD=2.63) and negative words (8.9yrs, SD=2.79;

460 Supplementary Table 3). Note that the length and balance of final word lists can be expected to

461 impact results negligibly, thanks to properties of count-based text analyses (Supplementary Note

462 3). By unique and non-repeated, we mean that the emotion vocabulary approach is concerned

463 with the diversity—not frequency, quality, or other dimension—of emotion word use.

464 Importantly, various inflections of the same word (e.g., sad, sadness, sadly) were counted as the465 same emotion word.

466 To eliminate the confounding effect of text length, all EV scores controlled for word467 count using the following formula:

Emotion Vocabulary (EV) = 
$$\left(\frac{\# unique emotion words}{total word count}\right) \times 100$$

468

469 Thus, EV scores represent the number of unique emotion words as a percentage rate of total 470 word count. For example, the text, "he was so angry at me, but sadly there was nothing I could 471 do" would receive an EV score of  $2/14 \times 100$ , or 14.29. Scores were computed separately for 472 negative and positive emotion words (in the numerator position). To anticipate more fine-grained 473 questions related to state mood, EV rates were also computed separately for names of sadness-474 related emotions (e.g., disappointed, bitter, hopeless), anxiety- or fear-related emotions (e.g., 475 nervous, afraid, alarmed), and anger-related emotions (e.g., mad, furious, aggravated). To 476 correspond to state mood ratings for a stressed mood, which is generally considered an 477 undifferentiated negative emotional state, the EV rate was also computed for general, negatively 478 valenced words that could easily refer to an affective state (e.g., awful, terrible, bad). 479 We have developed a free, open-source software program called Vocabulate, which 480 automatically performs the text processing method described here. The software itself and

481 dictionary file from the Supplemental Online Materials are available at <u>https://osf.io/8ckyp/</u>. This
482 open source repository also contains the data supporting the findings of both studies reported in
483 this manuscript.

484 Individual difference indicators—text-derived. Several other language markers were 485 computed in order to better understand the EV construct. The first of these was computed using 486 our open-source software for computing EV (Vocabulate; see Code Availability). The rest were 487 computed using LIWC, which counts words in approximately 80 categories that have been extensively validated in psychological research<sup>25</sup>. Categories are grammatical (e.g. articles, 488 489 pronouns), thematic (e.g., social, religion), and psychological (e.g. positive and negative affect 490 words). LIWC produces scores reflecting the presence of words in each category as a percentage 491 of each individual's total word count.

492 General vocabulary size (via Vocabulate). Emotion vocabulary size might be an artifact 493 of general verbal ability or educational background. To address this possibility, we estimated each writer's general vocabulary size, which is a commonly used proxy for education level<sup>63</sup>. as 494 495 a type/token ratio (TTR). In calculating TTR, the number of unique words (types) is divided by 496 the number of total words (tokens) used in the text. Like EV, TTR is expressed as a percentage, 497 with higher values representing higher diversity in vocabulary. In this context, a unique word 498 refers to any word that appears at least once in a given text. For example, the exclamation "A 499 horse! A horse! My Kingdom for a horse!" contains 5 unique words out of 9 total words (a, 500 horse, my, kingdom, for). In order to capture the most relevant index of general vocabulary, only 501 open-class, or content, words were counted (i.e., excluding function words such as pronouns, 502 prepositions, articles, and other short and common words which are used frequently but are not 503 clearly linked with verbal ability). To avoid redundancy, all emotion words used to compute EV

were excluded. The average TTR for general vocabularies was 71.01, (SD = 7.25; range = 30.73 to 96.38).

506 *Cognitive processing (via LIWC).* Given that people may develop more expansive 507 vocabularies to describe topics they find interesting, EV size was expected to converge with the 508 tendency to reflect on internal experience. The LIWC cognitive process index, which captures 509 the frequency of words such as think, question, and because. This index is believed to indicate 510 individuals' efforts to analyze or mentally organize experience<sup>64</sup>.

511 *Emotional tone (via LIWC).* One would assume that negative emotion vocabulary size 512 might be highly correlated with the overall emotional tone of the text. To explore this possibility, 513 negative and positive emotional tone was calculated for all texts using the LIWC negemo and 514 posemo variables, which have been demonstrated in many studies to accurately reflect affective 515 traits and states<sup>65,66</sup>.

516 Language diagnostic of well-being (via LIWC). LIWC includes several non-emotion language dimensions that have been related to mental and physical health<sup>25</sup>. The category health 517 518 includes 294 health-related words (e.g., clinic, flu, pill). People who use more words in this 519 category tend to report being less healthy than people who do not. Several studies have found 520 that the use of first-person singular pronouns, or I-words, is correlated with depression, physical illness, anxiety, and even suicide<sup>54</sup>. Conversely, consistent with the social support literature, the 521 522 more people use words suggesting engagement with others, such as first-person plural, or wewords, the fewer health problems they report<sup>24,25</sup>. Additionally, words related to affiliation (e.g., 523 524 ally, friend, social), achievement (e.g., win, success, better), and leisure (e.g., cook, chat, movie) 525 were presumed to be related to higher psychosocial adjustment.

526

Individual difference indicators-self-reported. Self-report measures administered

527 over the course of the semester were used to examine the individual differences associated with
528 EV and confirm the utility of linguistic proxies for well-being.

*Personality*. Students completed the 44-item Five Factor Inventory (FFI)<sup>67</sup> midway
through the semester. The five factors include extraversion, neuroticism, agreeableness,
conscientiousness, and openness. For the current sample, the internal reliability was good (*α*s
range from .78 for conscientiousness to .85 for extraversion). *Physical health.* During the second week of the semester, participants responded to the

question, "Overall, how would you rate your health?" Responses ranged from 1 (poor) to 5 (excellent). The mean response was 3.69 (SD = 0.84).

*Emotional health.* Three weeks before the semester ended and the Time 2 essay was completed, students completed the short form of the Center for Epidemiological Studies Depression Scale, which was developed for use in the general population (CESD-10)<sup>68</sup>. Participants rate the frequency with which they experienced 10 depression symptoms in past week on a scale ranging from 0 (rarely or none of the time/less than 1 day) to 3 (most or all of the time/5-7 days). In our sample internal consistency was good ( $\alpha = 0.85$ ). The mean depression score was 10.00 (SD = 5.91).

543 State-level mood ratings. Immediately before and after the 20-minute writing exercise, 544 students rated how much they felt four negative moods (sad, worried, angry, stressed) and four 545 positive moods (happy, enthusiastic, optimistic, calm) on a Likert scale ranging from 1 (not at 546 all) to 5 (a great deal). Ratings of the same valence were averaged to create negative and positive 547 mood scores at both pre- and post-writing with acceptable-to-good internal consistency (αs .75 to 548 .83).

549 Study 2

550 **Text corpus and author characteristics.** The complete text from 37,296 blogs was 551 collected from blogger.com in August 2004. For complete information on corpus design, see Schler and colleagues<sup>69</sup>. Blogs contained all entries written from their inception to the day they 552 553 were collected. Inclusion criteria were identical to that reported in Study 1, and duplicate texts 554 collected in error were removed. The final corpus contained the full content of blogs by 35,385 555 individuals, ranging in total length from 107 to 481,983 words (M = 3,142; SD = 6,572). This 556 sample size mitigates potential issues due to small effect sizes for work of this nature. Bloggers' 557 self-identified gender and age were collected when available. Age and gender data were 558 available for 27.4% of bloggers (N = 9,688). Among these, approximately half of bloggers were 559 female (5,048; 52%), and ages ranged from 13-88 (M = 22.41; SD = 8.06). No informed consent 560 was obtained, as identifying data were not collected.

561 Emotion vocabulary. EV was computed using the same method described in Study 1.
562 Representative examples of emotion words captured appear in Supplementary Methods.

563 **Individual difference indices (text-derived).** Because self-reports were not available, 564 we relied on the text-based indices of well-being identified in Study 1. Evidence of criterion 565 validity of these text-derived indices, based on their correlations with self-report in Study 1, is 566 available online (Supplementary Table 2). Other text-based indices (cognitive processing, 567 general vocabulary, positive and negative emotional tone, and presence of well-being themes) 568 were derived for all blogs in the corpus using the same methods described for Study 1. The 569 average TTR for general vocabularies was 62.91 (SD = 13.14, range 4.66 to 95.06). 570 **Data Availability** 

571	The datasets generated during and analyzed during the current studies are available in
572	The Open Science Framework repository, at <u>https://osf.io/8ckyp/</u> . A reporting summary for this
573	Article is available as a Supplementary Information file.
574	Code Availability
575	The mathematical formulas for computing EV and related indices are provided in this
576	manuscript, and the list of word mappings are provided in the online supplements. The custom
577	open-source software we have developed to perform this computation directly, Vocabulate, is
578	available at <u>https://osf.io/8ckyp/</u> and <u>https://github.com/ryanboyd/Vocabulate</u> .
579	

# References

- 581 1. Allan, P. "Find the perfect word for your feelings with this vocabulary wheel." Available at:
- 582 http://lifehacker.com/find-the-perfect-word-for-your-feelings-with-this-vocab-1653013241
- 583 (Accessed: 30<sup>th</sup> Oct 2014).

- 584 2. Hein, S. "Feeling Words/Emotion Words." Available at: <u>http://core.eqi.org/fw.htm</u>
  585 (Accessed: 30<sup>th</sup> Oct 2014).
- 586 3. McLaren, K. *The language of emotions: What your feelings are trying to tell you*. (Sounds
  587 True, Inc., Boulder, 2010).
- 4. Ryan, P. M. *Dictionary of emotions: Words for feelings, moods, and emotions*. (PAMAXA,
  United States, 2014).
- 5. Barrett, L. F. *How emotions are made: The secret life of the brain*. (Houghton Mifflin
  Harcourt, Boston, 2017).
- 6. Goleman, D., Boyatzis, R. & McKee, A. *Primal leadership: Unleashing the power of emotional intelligence.* (Harvard Business Review, Business School Press, Boston, 2013).
- 594 7. O'Boyle, E. H., Humphrey, R. H., Pollack, J. M., Hawver, T. H., & Story, P.A. The relation
- between emotional intelligence and job performance: A meta-analysis. *J. Organ. Behav.* 32,
  788-818 (2011).
- 597 8. Brackett, M. A. & Stern, R. MoodMeter (2015). Available at: <u>http://moodmeterapp.com/team/</u>
- 598 9. Salovey, P., Mayer, J. D., Goldman, S. L., Turvey, C. & Palfai, T. P. Emotional attention,
- 599 clarity, and repair: Exploring emotional intelligence using the Trait Meta-Mood Scale. In
- 600 Emotion, Disclosure, & Health (ed. Pennebaker, J. W.) 125–154 (American Psychological
- 601 Association, 1995).
- 602 10. Vine, V. & Aldao, A. Impaired emotional clarity and psychopathology: A transdiagnostic

- 603 deficit with symptom-specific pathways through emotion regulation. J. Soc. Clin.
- 604 *Psychol.* **33**, 319-342 (2014).
- 605 11. Mayer, J. D., Salovey, P., Caruso, D. R. & Sitarenios, G. Measuring emotional intelligence
  606 with the MSCEIT V2. 0. *Emotion* 3, 97 (2003).
- 607 12. Kashdan, T. B., Barrett., L. F. & McKnight, P. E. Unpacking emotion differentiation:
- 608 Transforming unpleasant experience by perceiving distinctions in negativity. *Curr. Dir.*
- 609 *Psychol. Sci.* **24**, 10-16 (2015).
- 610 13. Lischetzke, T., Cuccodoro, G., Gauger, A., Todeschini, L. & Eid, M. Measuring affective
- 611 clarity indirectly: Individual differences in response latencies of state affect ratings. *Emotion*
- **5**, 431-445 (2005).
- 613 14. Lieberman, M. D., Inagaki, T. K., Tabibnia, G. & Crockett, M. J. Subjective responses to
- 614 emotional stimuli during labeling, reappraisal, and distraction. *Emotion*, **3**, 468–480 (2011).
- 615 15. Goldin-Meadow, S., Seligman, M. E. P. & Gelman, R. Language in the two-year-old.
- 616 *Cognition* **4**, 198-202 (1976).
- 617 16. Laufer, B. (1998). The development of passive and active vocabulary in a second language:
- 618 Same or different? *Appl. Linguist.* **19**, 255-271 (1998).
- 619 17. Marchman, V. A. & Dale, P. S. Assessing receptive and expressive vocabulary in child
- 620 language. In Research Methods in Psycholinguistics and the Neurobiology of Language: A
- 621 Practical Guide (eds de Groot, A. M. B. & Hagoort, P.) 40–67 (Wiley, 2018).
- 622 18. Ottenstein, C. & Lischetzke, T. (2019). Development of a novel method of emotion
- differentiation that uses open-ended descriptions of momentary affective states. *Assessment*(in press).
- 625 19. Bazhydai, M., Ivcevic, Z., Brackett, M. A. & Widen, S. C. Breadth of emotion vocabulary in

- 626 early adolescence. *Imagin., Cogn. Pers.* **38**, 378-404 (2019).
- 627 20. Vine, V., Aldao, A. & Nolen-Hoeksema, S. Chasing clarity: Rumination as a strategy for
  628 making sense of emotions. *J. Exp. Psychopatol.* 5, 229-243 (2014).
- 629 21. de Saussure, F. Nature of the linguistic sign. In Course in General Linguistics (eds. Meisel,
- 630 P. & Saussy, H.; trans. Baskin, W.) 65-70 (Open Court, Chicago, 2011).
- 631 22. Zipf, G. K. Human behavior and the principle of least effort: An introduction to human
- 632 *ecology*. (Addison-Wesley Press, Inc., Cambridge, 1949).
- 633 23. Boyd, R. L. & Pennebaker, J. W. Language-based personality: A new approach to
- 634 personality in a digital world. *Curr. Opin. Behav. Sci.* **18**, 63–68 (2017).
- 635 24. Pennebaker, J. W. & King, L. A. Linguistic styles: Language use as an individual difference.
  636 *J. Pers.Soc. Psychol.* 77, 1296-1312 (1999).
- 637 25. Tausczik, Y.R. & Pennebaker, J.W. (2010). The psychological meaning of words: LIWC and
- 638 computerized text analysis methods. J. Lang. Soc. Psychol. 29, 24-54 (2010).
- 639 26. Levi-Strauss, C. The Savage Mind. (University of Chicago Press, Chicago, 1966).
- 640 27. Kenji, H. & D'andrea, D. Some properties of bilingual maintenance and loss in Mexican
- background high-school students. *Appl. Linguist.* **13**, 72–99 (1992).
- 642 28. Van Overschelde, J. P. The influence of word frequency on recency effects in directed free
- 643 recall. J. Exp. Psychol. Learn. 28, 611–615 (2002).
- 644 29. Whorf, B. L. Science and linguistics. In Language, Thought, and Reality: Selected writings
- 645 of Benjamin Lee Whorf (ed. Carroll, J. B.) 207-219 (MIT Press, Cambridge, 1956).
- 646 30. Pullum, G. (1989). The great Eskimo hoax. *Nat. Lang. Linguist. Theory* 7, 257-281 (1989).
- 647 31. Dewey, J. *How we think*. (DC Heath, Boston, 1910).
- 648 32. Barrett, L. F., Lindquist, K. A. & Gendron, M. Language as context for the perception of

- 649 emotion. *Trends Cogn. Sci.* **11**, 327-332 (2007).
- 650 33. Clark, A. Magic words: How language augments human computation. In Language and
- 651 Thought: Interdisciplinary Themes (eds. Carruthers, P. & Boucher, J.) 162–83 (Cambridge
- 652 University Press, Cambridge, 1998).
- 653 34. Shablack, H., & Lindquist, K. A. The role of language in emotional development. In
- 654 Handbook of Emotional Development (eds. LoBue, V., Pérez-Edgar, K., & Buss, K. A.),
- 655 451–478 (2019).
- 656 35. Lee, K., Lindquist, K. A. & Payne, B. K. Constructing bias: Conceptualization breaks the
- 657 link between implicit bias and fear of Black Americans. *Emotion* **18**, 855–871 (2018).
- 658 36. Lindquist, K. A. & Barrett, L. F. Constructing emotion: The experience of fear as a
  659 conceptual act. *Psychol. Sci.* 19, 898–903 (2008).
- 37. Sauter, D. A. Is there a role for language in emotion perception? *Emot.* Rev. 10, 111-115
  (2018).
- 38. Pennebaker, J.W., Booth, R.J., Boyd, R.L. & Francis, M.E. *Linguistic Inquiry and Word Count: LIWC 2015* (Pennebaker Conglomerates Inc, Austin, 2015).
- 664 39. Mehl, M.R. & Pennebaker, J.W. The sounds of social life: A psychometric analysis of
- students' daily social environments and conversations. *J. Pers. Soc. Psychol.* 84, 857-870
  (2003).
- 40. Kross, E., Verduyn, P., Boyer, M., Drake, B., Vickers, B., et al. Does counting emotion
- 668 words on online social networks provide a window into people's subjective experience of
- 669 emotion? A case study on Facebook. *Emotion* **19**, 97-107 (2018).
- 41. Sun, J., Schwartz, H. A., Son, Y., Kern, M. L. & Vazire, S. The language of well-being:
- 671 Tracking fluctuations in emotion experience through everyday speech. J. Pers. Soc. Psychol

- 672 **118**, *364-387* (2020).
- 42. Melcher, J. M. & Schooler, J. W. The misrememberance of wines past: Verbal and
- 674 perceptual expertise differentially mediate verbal overshadowing of taste memory. J. Mem.
- 675 *Lang.* **35**, 231-245 (1996).
- 43. Lindquist, K. A., Satpute, A. B. & Gendron, M. Does language do more than communicate
  emotion? *Curr. Dir. Psychoi. Sci.* 24, 99-108 (2014).
- 44. Barrett, L. F., Gross, J., Christensen, T. C. & Benvenuto, M. Knowing what you're feeling
- and knowing what to do about it: Mapping the relation between emotion differentiation and
  emotion regulation. *Cogn. Emot.* 15, 713-724 (2001).
- 45. Boster, J. S. Categories and cognitive anthropology. In *Handbook of Categorization in*
- *Cognitive Science*, 2nd Ed. (eds. Cohen, H. & Lefebvre, C.) 75-106 (Elsevier, Amsterdam,
  2017).
- 46. Johnstone, T. & Scherer, K.R., Vocal communication of emotion. In *The Handbook of Emotion* (eds. Lewis, M. & Haviland, J.) 220-235 (Guilford, New York, 2000).
- 686 47. Cangelosi, A. & Harnad, S. The adaptive advantage of symbolic theft over sensorimotor toil:
- 687 Grounding language in perceptual categories. *Evol. Commun.* **4**, 117-142 (2001).
- 48. Jackson, J. C., Watts, J., Henry, T. R., List, J. M., Forkel, R., Mucha, P. J., et al. Emotion
- semantics show both cultural variation and universal structure. *Science* **366**, 1517-1522
- 690 (2019).
- 49. Buss, D.M. *Evolutionary psychology: The new science of the mind*. (Routledge, New York,
  2019).
- 50. Adolphs, R. Cognitive neuroscience of human social behaviour. *Nat. Rev. Neurosci.* 4, 165–
  178 (2003).

- 51. Hoemann, K., Xu, F. & Barrett, L. F. Emotion words, emotion concepts, and emotional
  development in children: A constructionist hypothesis. *Dev. Psychol.* 55, 1830–1849 (2019).
- 697 52. Olsson, A., & Ochsner, K. N. The role of social cognition in emotion. *Trends Cogn. Sci.* 12,
  698 65–71 (2008).
- 53. Edwards, T. & Holtzman, N. S. A meta-analysis of correlations between depression and first
  person singular pronoun use. *J. Res. Pers.* 68, 63-68 (2017).
- 701 54. Desrosiers, A., Vine, V. & Kershaw, T. "RU Mad?" Computerized text analysis of affect in
- social media relates to stress and substance use among ethnic minority emerging adult
- 703 males. Anx. Stress Coping **32**, 109-123 (2019).
- 55. Pennebaker, J. W. The Secret Life of Pronouns: What Our Words Say About Us.
- 705 (Bloomsbury Press, New York, 2011).
- 56. Taylor, G. J. & Bagby, R. M. New trends in alexithymia research. *Psychother*.
- 707 *Psychosom.* **73**, 68-77 (2004).
- 57. Lane, R. D. Neural substrates of implicit and explicit emotional processes: a unifying
- framework for psychosomatic medicine. *Psychosom. Med.* **70**, 214-231 (2008).
- 710 58. Desrosiers, A., Vine, V., Curtiss, J. & Klemanski, D. H. Observing nonreactively: A
- 711 conditional process model linking mindfulness facets, cognitive emotion regulation
- strategies, and depression and anxiety symptoms. J. Affect. Disord. 165, 31-37 (2014).
- 59. Van der Gucht, K., Dejonckheere, E., Erbas, Y., Takano, K., Vandemoortele, M., Maex, E.,
- et al. An experience sampling study examining the potential impact of a mindfulness-based
- 715 intervention on emotion differentiation. *Emotion* **19**, 123–131 (2019).
- 716 60. Vine, V., Aldao, A. & Nolen-Hoeksema, S. Chasing clarity: Rumination as a strategy for
- 717 making sense of emotions. J. Exp. Psychopathol. 5, 229-243 (2014).

- 718 61. Ortony, A. & Turner, T. What's basic about basic emotions? *Psychol. Rev.* 97, 315-331
  719 (1990).
- 62. Kuperman, V., Stadthagen-Gonzalez, H. & Brysbaert, M. Age-of-acquisition ratings for
  30,000 English words. *Behav. Res. Methods* 44, 978-990 (2012).
- 722 63. Keuleers, E., Stevens, M., Mandera, P. & Brysbaert, M. Word knowledge in the crowd:
- 723 Measuring vocabulary size and word prevalence in a massive online experiment. *Q. J. Exp.*

724 *Psychol.* 68(8), 1665–1692 (2015).

- 725 64. Kleim, B., Horn, A. B., Kraehenmann, R., Mehl, M. R. & Ehlers, A. Early linguistic markers
- of trauma-specific processing predict post-trauma adjustment. *Front. Psychiatry* 9, 645–645
  (2018).
- 65. Newell, E. E., McCoy, S. K., Newman, M. L., Wellman, J. D. & Gardner, S. K. You sound
  so down: Capturing depressed affect through depressed language. *J. Lang. Soc. Psychol.* 37,
  451–474 (2018).
- 66. Saxbe, D. E., Yang, X.-F., Borofsky, L. A. & Immordino-Yang, M. H. The embodiment of
  emotion: Language use during the feeling of social emotions predicts cortical somatosensory
  activity. *Soc. Cogn. Affect. Neurosci.* 8, 806–812 (2013).
- 734 67. John, O. P., Donahue, E. M. & Kentle, R. L. The Big Five Inventory—Versions 4a and 5.
- 735 (University of California Institute of Personality and Social Research, Berkeley, 1991).
- 736 68. Andresen, E. M., Malmgren, J. A., Carter, W. B. & Patrick, D. L. Screening for depression in
- 737 well older adults: Evaluation of a short form of the CES-D (Center for Epidemiologic
- 738 Studies-Depression Scale). Am. J. Prevent. Med. 10, 77–84 (1994).
- 69. Schler, J., Koppel, M., Argamon, S. & Pennebaker, J. Effects of age and gender on blogging.
- 740 Proceedings of the American Association for Artificial Intelligence, 2005.

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755	Author Contributions					
756	V.V. and J.W.P. developed the concept and approach for these studies using archival data					
757	collected by J.W.P. V.V., R.L.B., and J.W.P. developed the emotion vocabulary dictionary.					
758	R.L.B. parsed text samples to generate linguistic data, and V.V. conducted statistical analyses.					
759	V.V. drafted the manuscript, with critical revisions provided by R.L.B. and J.W.P.					
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761	The text analysis program LIWC is a commercial product co-owned by J.W.P. Proceeds					
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763	declare no other conflicts of interest with respect to authorship and/or publication of this article.					

# 764 Table 1

Pearson and Partial Correlations of Emotion Vocabulary (EV) with Other Study Variables for Study 1 (N = 1.567 unless marked otherwise)

	Pearson Correlations with Negative EV	Partial Correlations with Negative EV	Pearson Correlations with Positive EV	Partial Correlations with Positive EV
Negative EV				
Positive EV	.16 (.06)***	.18 (.04)***		
Demographic variables				
Age	02 (.02)	$05(.03)^{\pm}$	06 (.02)*	04 (.02)
Gender <sup>a</sup>	.20 (.02)***	.15 (.03)***	00 (.03)	.06 (.03)*
Individual differences—text-				
derived				
Cognitive processing	.08 (.03)**		07 (.03)**	
Negative emotional tone	.61 (.04)***		.01 (.06)	
Positive emotional tone	03 (.04)		.50 (.03)***	
General vocabulary size	.11 (.04)***		$.21(.03)^{***}$	
L-words	.11 (.05)***	.01(.05) 23(04)***	$.00(.04)^{+}$	10(04)***
We words	11(02)***	.23 (.04)	.05 (.04)	.10(.04)
A ffiliation words	$11(.02)^{+++}$	$00(.02)^{+}$	$03(.02)^{*}$	$00(.03)^{+}$
Annation words	.05 (.03) <sup>-</sup>	.09 (.03)***	.14 (.04)***	.00 (.03)
Achievement words	.06 (.06)*	.04 (.04) <sup>±</sup>	.11 (.04)***	.00 (.03)
Leisure words	07 (.06)**	02 (.04)	.20 (.06)***	.08 (.05)**
Individual differences—self-				
reported	02(02)	02(02)	04 (02)	01(02)
Openness	03 (.03)	02 (.03)	.04 (.03)	.01 (.03)
Conscientiousness	01 (.03)	.06 (.03)*	.06 (.03)*	.07 (.03)*
Extraversion	04 (.03)	03 (.03)	.06 (.03)*	.03 (.03)
Agreeableness	.01 (.03)	$.05(.03)^{\pm}$	.09 (.03)**	.06 (.03) <sup>±</sup>
Neuroticism <sup>b</sup>	.17 (.03)***	.08 (.03)**	09 (.03)**	02 (.03)
Depression symptoms <sup>c</sup>	.11 (.03)***	01 (.03)	07 (.03)*	01 (.03)
Overall health <sup>d</sup>	13 (.03)***	05 (.03) <sup>±</sup>	.06 (.03)*	.05 (.03)

767 *Note.* Partial correlations control for general vocabulary, negative, and positive emotional tone.

All tests are two-tailed. Coefficients are expressed as **r** (SE). For 95% confidence intervals and

result of the second se

770 \*\*\*p < .001, \*\* p < .01, \*p < .05.  $\pm p < .10$ 

- 771 <sup>a</sup> Coded 0 = male, 1 = female.
- <sup>b</sup> n = 1,341 participants based on available data.

773  $c^{n} = 1,256$  participants based on available data.

<sup>d</sup> n = 1,545 participants based on available data.

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779 Table 2

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Partial Correlations between Emotion Vocabulary (EV) for Distinct Emotion Types and Changes in Self-Rated Moods in Study 1 (N = 1,546)

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	Sadness	Worry	Anger	Stressed	Positive
Emotion Vocabulary	mood change	mood change	mood change	mood change	mood change
Sadness	.09 (.03)***	.02 (.03)	08 (.02)**	.01 (.03)	01 (.03)
Fear	03 (.02)	.09 (.03)***	12 (.02)***	.02 (.03)	.06 (.03)*
Anger	.01 (.03)	.05 (.03) <sup>±</sup>	.10 (.03)***	.05 (.03) <sup>±</sup>	10 (.03)***
Undifferentiated negative	.00 (.03)	.06 (.03)*	01 (.03)	.09 (.03)**	02 (.03)
Positive	04 (.02)	.02 (.03)	07 (.02)**	02 (.03)	$.04(.02)^{\pm}$

784 *Note.* Values are partial correlation coefficients between EV indices and post-writing ratings of

subjective mood. Each correlation controls for pre-writing levels of the target mood, as well as

general vocabulary, and negative and positive emotional tone. Sample size is based on

availability of state mood ratings. All tests were two-tailed. Coefficients are expressed as **r** (SE).

For 95% confidence intervals and exact significance values, see Supplementary Table 6.

789 \*\*\* p < .001. \*\* p < .01. \* p < .05.  $\pm p < .10$ 

790

# 792 Table 3

Pearson Correlations of Emotion Vocabulary (EV) with Other Study Variables for Study 2 (N =

794 35,385)

	Pearson Correlations	Partial Correlations	Pearson Correlations	Partial Correlations
	with Negative EV	with Negative EV	with Positive EV	with Positive EV
Negative EV				
Positive EV	.22 (.01)***	.12 (.01)***		
Demographic variables				
Age <sup>a</sup>	09 (.01)***	.01 (.01)	.05, (.01)***	07 (.01)***
Gender <sup>b</sup>	.15 (.01)***	.15 (.01)***	.07 (.01)***	.07 (.01)***
Individual differences-text-				
derived				
Cognitive processing	.21 (.01)***		.08 (.01)***	
Negative emotional tone	.51 (.01)***		03 (.01)***	
Positive emotional tone	.09 (.01)***		.35 (.01)***	
General vocabulary size	.24 (.01)***		.46 (.00)***	
Illness words	.16 (.01)***	.07 (.01)***	.07 (.01)***	.06 (.01)***
I-words	.28 (.01)***	.20 (.01)***	.13 (.01)***	.10 (.01)***
We-words	08 (.01)***	.00 (.01)	02 (.01)**	.00 (01)
Affiliation words	01 (.01)	.06 (.01)***	.08 (.01)***	.03 (.01)***
Achievement words	10 (.01)***	07 (.01)***	.06 (.01)***	01 (.01)
Leisure words	14 (.01)***	09 (.01)***	.06 (.01)***	05 (.01)***

796 *Note*. Partial correlations control for general vocabulary, negative, and positive emotional tone.

All tests are two-tailed. Coefficients are expressed as **r** (SE). For 95% confidence intervals and

result of the second se

799 \*\*\*p < .001, \*\* p < .01, \*p < .05.  $\pm p < .10$ 

800 <sup>a</sup> For analyses involving age, n = 9,805 authors' blogs.

- 801 <sup>b</sup> Coded 0=male, 1=female.
- 802