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Detecting Well-Being via Computerized Content Analysis of Brief Diary Entries

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Two studies evaluated the correspondence between self-reported well-being and codings of emotion and life content by the Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, & Francis, 2011). Open-ended diary responses were collected from 206 participants daily for 3 weeks (Study 1) and from 139 participants twice a week for 8 weeks (Study 2). LIWC negative emotion consistently correlated with self-reported negative emotion. LIWC positive emotion correlated with self-reported positive emotion in Study 1 but not in Study 2. No correlations were observed with global life satisfaction. Using a co-occurrence coding method to combine LIWC emotion codings with life-content codings, we estimated the frequency of positive and negative events in 6 life domains (family, friends, academics, health, leisure, and money). Domain-specific event frequencies predicted self-reported satisfaction in all domains in Study 1 but not consistently in Study 2. We suggest that the correspondence between LIWC codings and self-reported well-being is affected by the number of writing samples collected per day as well as the target period (e.g., past day vs. past week) assessed by the self-report measure. Extensions and possible implications for the analyses of similar types of open-ended data (e.g., social media messages) are discussed.

Keywords: well-being, emotion, satisfaction, content analysis, linguistic analysis

Diary studies have made important contributions in both clinical (Thiele, Laireiter, & Baumann, 2002) and social–personality (Bolger, Davis, & Rafaeli, 2003) psychology. Diary methodology enables researchers to assess the ongoing experience of participants in their natural environment while mitigating potential biases in recall (Shiffman, Stone, & Hufford, 2008). Although most diary studies employ closed-ended items such as checklists and rating scales, open-ended items have also been useful—particularly in allowing participants to record personally meaningful thoughts and experiences. Lavallee and Campbell (1995) suggested that such experiences, though idiosyncratic and subjective, may correlate more strongly with measures of stress and emotional well-being than the objective items that tend to make up event checklists. The content of open-ended responses can be analyzed for particular themes. For instance, Craske, Rapee, Jackel, and Barlow (1989) asked people with generalized anxiety disorder (GAD) to record their most significant worry episodes over a 3-week period. Content analyses revealed that GAD participants reported more concerns about their health and less concerns about financial issues than did control participants. Similarly, Lavallee and Campbell's (1995) participants described a negative event twice a day for 2 weeks. These written descriptions were then coded for the degree of self-focus. The authors showed that negative events were more likely to induce self-focus if they were related to important goals.

Despite the unique insights afforded by open-ended responses, a major drawback is the time required to develop a coding scheme and train research assistants to code the data accurately. The problem is further compounded in diary studies due to the potentially large volume of responses. Over the past decade, computerized programs such as the Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, & Francis, 2011) have greatly facilitated the content analysis of written responses. LIWC analyzes written samples by counting words that fall into various categories (e.g., social, achievement, future tense, and so on) as defined by an internal dictionary. Because writing samples vary in length, word counts in each category are taken as a percentage of the total number of words in the sample.

Computerized content analysis can handle large volumes of open-ended responses at greatly reduced speeds, without sacrificing consistency in coding. Despite the promise of such methods, little is known about the applicability of LIWC to the sort of brief, written entries that are collected in diary studies. To date, many researchers have used LIWC to analyze narratives or descriptions of singular experiences (for a review, see Tausczik & Pennebaker, 2010). However, the structure of diary data may pose unique challenges. LIWC counts words in various categories but fails to consider the context in which they appear. Thus, two phrases like

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"I had a really good time" and "I didn't have a good time" are coded equally for positive emotion. Though these shifts in meaning are no doubt present in written narratives, they may occur with increased frequency in brief diary entries due to the greater variety of topics, contexts, and, hence, *word meanings* that these data may capture. A similar issue applies to text messages from pagers and social media sites that have been analyzed by previous researchers (e.g., Back, Küfner, & Egloff, 2010; Golder & Macy, 2011).

In the present research, we evaluated the validity of using LIWC to detect the subjective well-being of participants in two diary studies. Subjective well-being consists of positive emotion, negative emotion, global life satisfaction, and satisfaction with specific life domains (Diener, Suh, Lucas, & Smith, 1999). Therefore, we also examined the ability of LIWC to code for *life-content themes*—topics concerning family, friends, work, health, leisure, and financial matters. As we will discuss later, the correspondence between LIWC codings and self-reported experience deserves more attention than it has received in the past. Moreover, such an assessment is timely as past studies relied on an older version of LIWC (Pennebaker, Francis, & Booth, 2001). In 2007, the LIWC dictionary was revised with several rarely used categories removed (e.g., optimism, grooming, and television) and new ones added (e.g., health, negations, inhibitions, and discrepancy; Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007). This change resulted in a recategorization of some words. For example, the word *work* was coded into the present tense, occupation, job, and achievement categories in LIWC2001 but was recategorized into the work and achievement categories in LIWC2007. For several categories, word coverage also expanded from LIWC2001 to LIWC2007: positive emotions (from 265 to 407), negative emotions (from 345 to 500), anxiety (from 61 to 91), anger (from 120 to 185), sadness (from 72 to 101), friend (from 29 to 37), and leisure (from 103 to 228). Therefore, LIWC2007 may provide a more comprehensive analysis of word use than LIWC2001.

Validity of LIWC Emotion Codings as Measures of Emotional Experience

A major application of LIWC is quantifying the emotional content of written expression (for a review, see Tausczik & Pennebaker, 2010). Researchers have validated such applications in various ways. In a series of experiments, participants either wrote about a personal experience or described film clips that were emotionally positive, negative, or neutral (Kahn, Tobin, Massey, & Anderson, 2007). Those in the positive (negative) group used more positive (negative) emotion words than those in the other two groups. Bantum and Owen (2009) analyzed messages from an online discussion board for breast cancer patients. They compared LIWC emotion codings with those made by human coders. Overall, LIWC detected a high proportion ($> 77\%$) of positive and negative emotion words identified by human coders. Nevertheless, false-positive rates were also substantial (from 57% to 76%). Thus, there are occasional discrepancies between the degree of emotionality estimated by LIWC and the emotional meaning perceived by human readers. A particularly acute example is provided by Back et al.'s (2010) analysis of text messages sent during the September 11th attacks. The frequency of anger words counted by LIWC rose sharply as events unfolded during the day. However, upon closer inspection (Pury, 2011), a large number of "angry" comments came from an automated technical message sent repeatedly to a single pager. The message contained the word *critical*, which is coded by LIWC as an anger word even though the message did not actually express human emotion.

Researchers have also examined the correspondence between LIWC emotion codings and self-reported emotional experience. Here the evidence is inconclusive. In Kahn et al.'s (2007) study, LIWC positive emotion correlated with self-rated amusement after watching a comedy clip, but not with positive mood assessed by the Positive Affect and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988). Moreover, LIWC negative emotion did not correlate significantly with either self-reported sadness or negative mood (PANAS) after watching a sad film clip. Alvarez-Conrad, Zoellner, and Foa (2001) examined rape narratives from women suffering from posttraumatic stress disorder. LIWC negative emotion correlated with self-reported anger but not with anxiety or depression. Mehl (2006) also failed to observe a relation between LIWC negative emotion and scores on the Beck Depression Inventory–Short Form (Beck, Rial, & Rickels, 1974). Finally, LIWC emotion codings have not consistently correlated with personality traits that are commonly associated with positive and negative affectivity such as extraversion and neuroticism (Kahn et al., 2007; Mehl, Gosling, & Pennebaker, 2006; but see Pennebaker & King, 1999, for an exception).

The lack of consistent associations between LIWC emotion codings and self-reported emotion is somewhat surprising, given the large number of studies in which the program has been used to examine emotional expression (Tausczik & Pennebaker, 2010). Recently, Golder and Macy (2011) used LIWC to analyze the emotional content of over 500 million messages ("tweets") from the social media site Twitter. They observed fluctuations in LIWC positive and negative emotions throughout the course of the day, which they partly attributed to the effects of circadian rhythm on mood. However, this conclusion assumes that the use of emotion words truly expresses the internal experience of the writer. Unfortunately, the current literature does not clearly support such an assumption.

We suggest three reasons why LIWC codings have not consistently correlated with self-reported emotion. One factor is the nature of the writing sample. Whereas autobiographical narratives by definition must refer to personal experiences, the same cannot be said of messages from pagers, discussion boards, and social media that other researchers have examined (Back et al., 2010; Bantum & Owen, 2009; Golder & Macy, 2011). Such messages often contain comments on a range of topics that have little to do with the sender's emotional experience. Second, the number of writing samples collected affects how well they represent the emotional experience of the writer. Narratives about particular events—even if autobiographical (e.g., Alvarez-Conrad et al., 2001; Kahn et al., 2007)—may not capture the full range of experiences that shapes the writer's emotional life. Mehl et al.'s (2006) study is noteworthy in this regard. Participants wore an audio recorder that randomly sampled sounds from their daily life four or five times per hour, over a 2-day period. The audio samples were transcribed and coded by LIWC. Despite the fine-grained temporal resolution of these data, LIWC emotion codings did not correlate with broad personality traits such as extraversion or neuroticism. Thus, a third factor may be the *match* between the event-sampling period and the target period assessed by the self-report measure. Though the samples collected by Mehl et al. (2006) were highly representative of participants' experience during the 2-day period, participants did not rate how they felt during the same period. LIWC codings might correlate more strongly with the latter measures than with the personality scales examined by Mehl et al.

In the present research, participants described everyday personal experiences for a period of weeks. They also reported their emotions *concurrently* throughout the event-sampling period; *retrospectively* at the end of the study; and *in general*, providing us with, global trait-based measures of their affective dispositions. We expected LIWC codings to correlate most strongly with concurrent measures (when target and sampling period were closely aligned); and least strongly with global measures (when the target period extended beyond the sampling period).

LIWC Codings of Life Content

In addition to emotional content, LIWC codes for life-content themes like work and family. We present a novel application of such codings to open-ended diary data: detecting satisfaction in specific life domains. A unique feature of short written entries is that they typically refer to a single event, providing a microcontext for the words that are used. Thus, it may be possible to detect positive (negative) events in specific areas of life by coding for the co-occurrence of positive (negative) words and a particular life-content word (e.g., work). To examine the validity of this approach for detecting satisfaction, we correlated these event codings (e.g., positive work events) with self-reported satisfaction in each domain.

Life content provides more detail about a person's quality of life. An expanded view of subjective well-being not only includes emotional experience and life satisfaction, but satisfaction with specific life domains as well (Diener et al., 1999). Such information is often of interest to counselors and clinicians who wish to know not simply if their clients are feeling well but also whether they are encountering difficulties in specific areas. For example, the Quality of Life Inventory (Frisch, Cornell, Villanueva, & Retzlaff, 1992) assesses satisfaction in 17 domains including work, friends, health, recreation, and standard of living. Moreover, well-being covaries more with positive and negative experiences in some domains than in others (Stone, 1987). A quick method of coding life-content information would enrich the analysis of open-ended diary entries and broaden quality of life research by opening up new sources of data for investigation (e.g., social media and online blogs). To our knowledge, this is one of the first studies to make use of LIWC health, money, and leisure categories and one of a handful in which LIWC family, friends, and work categories have been used (see Tausczik & Pennebaker, 2010).

We evaluated the validity of using LIWC emotion and life-content codings as indicators of well-being. Our analyses relied on data from two diary studies that were previously described by Tov (2012). In Study 1, participants described two events each day for 21 days. They also reported their emotional experience and satisfaction in various domains on a daily basis. In Study 2, similar measures were collected twice a week for 2 months. Retrospective and global measures were obtained at the end of both studies. Given the autobiographical nature of the writing samples, the relatively large number of samples per person, and the concurrent reports of emotion and domain satisfactions that were collected, these data provide a rich assessment of the potential and limitations of LIWC. In addition, previous LIWC studies have relied heavily on American samples (one exception is Golder & Macy, 2011). In contrast, our participants were English-speaking students in Singapore, thus affording an assessment of how well LIWC emotion codings capture the self-reported emotional experience of a non-Western sample.

We divided our presentation into two major sections. First, we focused on LIWC emotion codings and evaluated their correspondence with self-reported emotional experience. In the second section, we evaluated the potential of using LIWC content codings to detect satisfaction with specific life domains.

LIWC Emotion Codings and Self-Reported Emotional Experience

Study 1

Method.

Participants. Students at Singapore Management University (SMU) were recruited for a 3-week daily diary study. The final sample consisted of 206 participants (121 females) with a mean age of 21.6 years. The majority of the sample (82.5%) was ethnically Chinese. All participants were fluent in spoken and written English as this is the language of instruction at SMU. For more details on the samples for Studies 1 and 2, see Tov (2012).

Measures and procedure. Each night for 21 days, participants logged into a website (between 9 p.m. and 3 a.m.) and completed a short survey. They rated the extent to which they had experienced positive (*happy*, *pleased*, *proud*, *affectionate*, *relaxed*, *cheerful*) and negative emotions (*sad, angry, stressed, depressed*) during the day from 0 (*not at all*) to 6 (*extremely*). Emotion terms were selected to reflect a range of arousal levels (Russell, 1980). The response scale was adapted from the PANAS (Watson et al., 1988). For each participant, responses were aggregated across all daily surveys (M = 19.27). We combined the positive emotion items but separately examined the negative emotion items and their correlation with LIWC sadness, anger, and anxiety. The reliability of the concurrent emotion scores, aggregated across the 21 days (Raudenbush & Bryk, 2002), was high: positive emotion = .94, sad = .91, angry = .92, stressed = .93, and depressed = .92. Finally, participants reported two events (one positive, one negative) that occurred during the day. A total of 7,703 events were reported. Each participant averaged 48.26 characters (SD = 26.07) or 9.23 words (SD = 5.02) per event.

After the 21-day sampling period, participants attended a final survey session. They were asked to retrospect over the previous 3-weeks and rate (0 = *not at all*; 6 = *extremely*) the extent to which they had experienced positive emotions (using the same six items from the daily survey; α = .85) and negative emotions (*sad*, *upset*, *ashamed*, *angry*, *stressed*, and *depressed*; α = .88). They also rated from 1 to 7 their satisfaction during this period (i.e., their level of *satisfaction—dissatisfaction* and how *terrible—excellent* the period was; α = .83). Next, they rated the extent to which they experienced positive and negative emotions in general using the same emotion terms from the retrospective measures. Finally, participants completed the Satisfaction with Life Scale (SWLS; Diener, Emmons, Larsen, & Griffin, 1985). All global well-being scores were reliable ($\alpha_{GlobalPositive} = .85$; $\alpha_{GlobalNegative} = .88$; $\alpha_{SWLS} = .87$).

LIWC emotion codings. We were interested in how well LIWC emotion codings captured the self-reported emotional experience of participants over the entire sampling period. Therefore, LIWC word counts for each emotion category were computed as a percentage of the total number of words written by each participant, across all events. Essentially, we combined all the event descriptions written by a participant into a single writing sample to obtain an overall estimate of emotional expression during the 3-week period.

Results and discussion. Descriptive statistics are presented in Table 1. LIWC positive emotion was significantly higher than LIWC negative emotion, $t(205) = 15.61$, $p < .001$, $d = 1.41$. Similarly, self-reported positive emotions were experienced to a greater extent than negative emotions (all $ps < .001$). One exception was stress, which was fairly common at moderate levels. Retrospective satisfaction correlated with retrospective positive ($r = .60$) and negative ($r = -.52$) emotion. Similarly, global life satisfaction correlated with global positive ($r = .55$) and negative ($r = -.35$) emotion. All correlations were significant ($p < .002$) and are consistent with theories of subjective well-being (Diener et al., 1999). Next, we examined the correlation between LIWC emotion codings and self-reported emotion.

Daily self-reported emotion. LIWC positive emotion was associated with higher levels of daily positive emotion and lower levels of sadness and stress (see Table 2). LIWC negative emotion was associated with greater daily sadness, anger, and depression. Similarly, LIWC anger and anxiety correlated with daily negative emotions. Given that negative emotions tend to covary (Diener & Iran-Nejad, 1986), we examined how LIWC anger and anxiety correlated with daily anger and stress, controlling for all other self-report measures. These analyses revealed that LIWC anger was uniquely related to daily anger ($r = .17$, $p = .02$) above and beyond daily anxiety, sadness, depression, and positive emotion. However, LIWC anxiety was not uniquely related to daily stress ($r = .07$, $p = .34$) after all other daily emotions had been controlled.

Table 1
Means and Standard Deviations for Linguistic Inquiry and Word Count Emotion Codings and Self-Report Measures

Variable	Study 1 *M*	Study 1 *SD*	Study 2 *M*	Study 2 *SD*
LIWC coding				
Positive emotion	4.73	2.12	4.99	2.01
Negative emotion	2.24	1.29	2.28	1.26
Sadness	0.66	0.61	0.76	0.71
Anxiety	0.39	0.52	0.32	0.39
Anger	0.46	0.57	0.51	0.60
Concurrent well-being				
Positive emotion	2.73	0.88	3.35	0.79
Angry	1.29	1.00	1.96	1.01
Sad	1.58	0.99	2.25	0.96
Stressed	3.05	1.20	3.45	1.01
Depressed	1.66	1.10	—	—
Retrospective well-being				
Positive emotion	2.99	1.05	3.47	0.98
Negative emotion	2.10	1.17	2.90	1.06
Satisfaction	4.53	0.98	4.46	0.93
Global well-being				
Positive emotion	4.38	1.01	3.43	1.05
Negative emotion	3.13	1.12	2.33	0.97
Life satisfaction	4.44	1.24	4.39	1.15

Note. LIWC = Linguistic Inquiry and Word Count.

Retrospective and global self-reported well-being. LIWC positive emotion correlated with retrospective and global positive emotion (Table 3). Similarly, LIWC negative emotion correlated with retrospective and global negative emotion. With one exception, the satisfaction measures generally did not correlate with LIWC emotion codings. We also compared the correlations of LIWC emotion codings with concurrent, retrospective, and global self-report emotion measures. For these analyses, daily sadness, anger, anxiety, and depression were averaged into a single measure of concurrent negative emotion ($\alpha = .89$). We expected LIWC emotion codings to correlate more strongly with concurrent than with global self-report measures. Contrary to our prediction, the size of the correlation between LIWC emotion and self-reported emotion did not significantly differ among the three target periods (all $ps > .12$).

The results of Study 1 provide important evidence that LIWC emotion codings correspond with self-reported emotional experience. Participants who used positive (negative) emotion words in their event descriptions also experienced positive (negative) emotions as assessed by the concurrent measures. Moreover, LIWC emotion codings predicted how participants *remembered* feeling during the 3-week period and how they reported feeling in general. One exception is LIWC sadness, which was unrelated to daily sadness and depression.

Study 2

We attempted to replicate the findings of Study 1 using data from an 8-week diary study. These data were previously collected for a separate study on well-being and memory (Tov, 2012). Self-report measures of well-being were collected concurrently (each week during the event-sampling period), retrospectively (at the end of the sampling period), and at a global level (3 weeks later). Unlike Study 1, events were reported only twice a week to reduce participant burden. Replication in Study 2 would suggest that the detection of emotional experience via LIWC is robust across target periods and event-sampling frequency.

Method.

Participants. SMU students were recruited for a diary study spanning 4 months. The final sample consisted of 139 students (91 women). On average, students were 21.3 years old, and 75.5% were ethnically Chinese. All participants were fluent in spoken and written English.

Measures and procedure. Twice a week for 8 weeks, participants logged into a website to complete a short survey. On Wednesdays, they reported two events (one positive, one negative) that occurred during the period of Sunday through Tuesday. On Sundays, they reported two events that occurred during the period of Wednesday through Saturday. A total of 4,073 events were reported. Each participant averaged 48.28 characters ($SD = 18.99$) or 9.08 words ($SD = 3.71$) per event.

On Sundays, participants rated the extent to which they experienced positive (*happy*, *pleased*, *relaxed*, and *cheerful*) and negative (*angry*, *sad*, and *stressed*) emotions during the week from 0

Table 2
Correlations Between Linguistic Inquiry and Word Count Emotion Codings and Concurrent Emotion Measures

	Concurrent emotion measure				
LIWC coding	Positive emotion	Sad	Angry	Stressed	Depressed
Study 1 (Average daily emotion)					
Positive emotion	.19**	−.15*	−.12	−.23**	−.13
Negative emotion	−.00	.32**	.32**	.09	.28**
Sadness	−.05	.05	.03	−.11	.05
Anxiety	.05	.16*	.14*	.16*	.18**
Anger	−.02	.21**	.26**	.12	.19**
Study 2 (Average weekly emotion)					
Positive emotion	.05	−.02	.01	.00	—
Negative emotion	−.20*	.21**	.30**	.22**	—
Sadness	−.17*	.08	.08	.04	—
Anxiety	−.07	.07	.22*	.23**	—
Anger	−.12	.18*	.31**	.24**	—

Note. LIWC = Linguistic Inquiry and Word Count.
* $p < .05$. ** $p < .01$.

(*not at all*) to 6 (*extremely*). As in Study 1, we averaged the positive emotion items but examined the negative emotions separately. Responses were aggregated across the 8 weeks of the study ($M = 7.94$). The reliability of these aggregated scores (Raudenbush & Bryk, 2002) was adequate: positive emotion = .84, sad = .80, angry = .82, and stressed = .83.

At the end of the 8-week diary period, participants retrospectively rated their positive emotions (*happy*, *pleased*, *relaxed*, and *cheerful*; $\alpha = .83$), negative emotions (*angry*, *sad*, *stressed*, and *upset*; $\alpha = .81$), and satisfaction (*satisfied—dissatisfied*; *terrible—excellent;* $\alpha = .81$) over the past 2 months of the study. Response scales were identical to Study 1. Three weeks later, participants attended a final session and completed global measures of emotional experience (using identical items; $\alpha_{GlobalPositive} = .86$, $\alpha_{GlobalNegative} = .74$), and the SWLS ($\alpha = .87$).

Results and discussion. Descriptive statistics are presented in Table 1. As in Study 1, both LIWC codings and self-report measures suggested that positive emotions were experienced to a greater extent than negative emotions (all ts ≥ 4.322, ps $< .001$). The lone exception was average weekly stress, which was experienced at similar levels as positive emotions ($p = .41$). Retrospective satisfaction correlated .65 and –.35 with retrospective positive and negative emotion, respectively; global satisfaction correlated .51 and –.29 with global positive and negative emotion, respectively. All correlations were significant ($p < .001$).

Table 3
Correlations Between Linguistic Inquiry and Word Count Emotion Codings and Well-Being Measures

	Study 1 LIWC coding		Study 2 LIWC coding	
Self-reported well-being	Positive	Negative	Positive	Negative
Retrospective				
Positive emotion	.21**	−.03	−.00	−.13
Negative emotion	−.16*	.22**	.04	.27**
Satisfaction	.06	−.21**	.10	−.07
Global				
Positive emotion	.15*	.01	−.02	−.13
Negative emotion	−.18**	.22**	.05	.16
Life satisfaction	.04	−.11	.06	−.08

Note. LIWC = Linguistic Inquiry and Word Count.
* $p < .05$. ** $p < .01$.

Weekly self-reported emotion. Although LIWC negative emotion correlated with weekly negative emotion, LIWC positive emotions did not correlate with weekly positive emotion (Table 2). As in Study 1, LIWC anxiety and anger were correlated with multiple measures of weekly negative emotion. However, even after controlling for all other self-reported emotions, LIWC anxiety and anger were uniquely related to weekly stress ($r = .18$) and anger ($r = .23$), respectively (ps $< .05$). In contrast, LIWC sadness was unrelated to weekly sadness.

Retrospective and global self-reported well-being. LIWC negative emotion correlated with retrospective negative emotion and marginally with global negative emotion ($p = .07$; see Table 3). No other correlations were observed. We also examined whether LIWC emotion codings correlated more strongly with concurrent than with either retrospective or global self-report measures. Weekly sadness, anger, and stress were averaged into a single concurrent score ($\alpha = .82$). No significant differences between correlations were observed (all ps $> .08$).

Study 2 replicated the correlation between LIWC and self-report measures for negative emotions only. In both studies, all scores derived from self-report measures were reliable ($\geq .74$). The correlations between self-reported satisfaction and emotion support their validity as well-being measures. Given this finding, two other factors can be considered. First, events were sampled less frequently in Study 2 than in Study 1. In Study 1, we collected 42 events over 21 days (two events/day). In Study 2, however, 32 events were collected over 56 days (0.57 events/day). Second, the target period for the concurrent self-report measure was broader in Study 2 (past *week*) than in Study 1 (past *day*). Thus, in Study 2, the target period was not covered by as many events as in Study 1. This increases the likelihood that unreported events impinged on participants' overall emotional experience during the past week.

Also, positive events reported at midweek may not have been recalled at the end of the week, when self-reports were collected. Despite the reduced coverage in Study 2, LIWC negative emotions correlated with concurrent and retrospective emotions. We offer some possible explanations in the General Discussion.

LIWC Life-Content Codings and Self-Reported Domain Satisfaction

Next we evaluated a method for detecting satisfaction in specific life areas using LIWC life-content codings. We assumed that people are more (less) satisfied in a given domain if they frequently report positive (negative) events in that domain. The data are taken from Studies 1 and 2. In the following, we describe the procedure for coding the co-occurrence of words indicating (a) the valence of an event and (b) its relevance for a particular domain (e.g., family).

Method

Identifying valence-relevant words. As participants were instructed to provide one positive and one negative event when they wrote their diary entries, the valence of each event was already known. However, we sought to develop an approach that could be applied to other types of data. In social media, for example, the valence of a message is unknown and must somehow be *inferred* from its content. Therefore, we examined the LIWC2007 dictionary and identified categories that could disambiguate the valence of events.

A major impetus for our coding procedure was to extend applications of LIWC beyond coding for emotional content. Thus, we were interested in words that distinguished the valence of an event, regardless of whether they expressed emotion. It is possible to cognitively evaluate an event as negative or positive without a strong emotional reaction. A similar distinction is made between satisfaction judgments and emotional experience (Diener et al., 1999). Moreover, an approach that relies only on emotion words is problematic because negative emotion words were less frequent than positive emotion words (see Table 1). As a result, fewer negative events would be coded if only negative emotion words are used to identify them. In addition to LIWC positive and negative emotion, we selected three categories: negations (e.g., *aren't*, *cannot*, *did not*), inhibition (e.g., *avoid*, *block*), and discrepancy (e.g., *could've, mistake*). These categories generally imply that an event did not occur in a desirable manner.

We submitted each event description to LIWC and obtained codings on the five valence-relevant word categories. To determine how well the five categories distinguished between events that were *actually* positive or negative (as specified by participants), we entered them simultaneously as predictors in a logistic regression model. All categories significantly predicted valence. The raw regression coefficients (Study 1/Study 2) were positive emotion (b = .13/.10); negative emotion (b = –.19/–.22); negations (b = –.25/–.28); discrepancy (b = –.06/–.07); and inhibition (b = –.12/–.14), all ps $\leq$ .001. Hence, an event was coded as negative if it (a) contained any "negative words" (i.e., negative emotion, negations, inhibitions, or discrepancies) and (b) did not contain a positive emotion word. An event was coded as positive if it contained positive emotion and did not contain negative words.[1] Thus, this coding procedure results in mutually exclusive categories: an event can only be coded as positive, negative, or neither.

Coding for the co-occurrence of domain-relevant words and valence. To determine which *domain* an event was relevant to, we employed six categories in the LIWC2007 dictionary: family, friends, work, money, health, and leisure. We then coded for the co-occurrence of valence and domain-relevant words. For example, a negative event that contained a leisure word was coded as a *negative leisure* event (e.g., "*Movie* ticket seller tried to *fool* me"). A positive event that contained a leisure word was coded as a *positive leisure* event (e.g., "My *swimming* skills *improved* a lot").

Self-reported domain satisfaction. On each day of Study 1, participants rated from 1 (*extremely dissatisfied*) to 7 (*extremely satisfied*) their satisfaction with various life domains (*family, friends, health, leisure time, financial situation, grades/academic performance, what was learned in courses,* and *campus activities*). The latter three items were averaged into an index of academic satisfaction. Using formulas provided by Shrout and Lane (2012), we estimated the reliability of the daily academic satisfaction score to be R_{1R} = .66.

Similar items were administered in Study 2, with two differences. First, participants rated their satisfaction with reference to the *past week* (instead of the past day, as in Study 1). Second, we replaced *campus activities* with *progress in completing assignment/projects*. This item was combined with *learning* and *grades* to obtain an index of academic satisfaction (R_{1R} = .60).

Results and Discussion

First, we examined the percentage of events that participants reported in each domain (Table 4). On average, around 14%–15% of events were negative work-related events. In the context of our college student sample, *work* largely referred to school work (e.g., projects, exams, and assignments). Across both studies, negative work and health events were more frequently reported than positive events in these domains. In contrast, positive friend and leisure events were more frequently reported than negative events.

These differences may reflect the nature of the various domains. For example, a student can spend countless hours every day studying and working on projects. These activities may appear less pleasant than socializing or even sleeping, and the payoff may not be evident until weeks later (e.g., getting an A on the midterm). Thus, in the work domain, negative events are more frequent than positive events. Negative health events may not be more frequent than positive health events but are often more noteworthy. The words coded by LIWC health also tend to be negative (e.g., *pain, ache, sick*). Even positive health words like *heal* presuppose a negative condition. Time spent in leisure or with friends, on the other hand, may be more frequently positive because it often

[1] Unfortunately, other than LIWC positive emotion, we were unable to identify additional categories that predicted positive events. One potential category in the LIWC2007 dictionary was *assent* words (e.g., *yeah*, *okay*, *absolutely*, and so on). However, many of these words overlap with LIWC positive emotion and did not predict valence when both categories were entered into a logistic regression.

Table 4
Average Percentage of Events Reported by Participants in Each Domain by Valence

Study/domain	Positive events *M*	Positive events *SD*	Negative events *M*	Negative events *SD*	t^a
Study 1					
Family	1.71	2.76	1.16	2.30	2.50*
Friends	8.62	6.68	1.32	2.52	14.31**
Work	7.58	5.21	15.07	7.35	−12.68**
Money	2.70	3.33	2.64	3.64	0.21
Health	0.43	1.16	2.00	2.85	−7.60**
Leisure	6.32	4.93	2.40	2.94	9.86**
Study 2					
Family	1.47	2.93	1.76	3.19	−0.92
Friends	11.82	8.31	2.04	3.46	12.74**
Work	7.58	5.50	14.73	7.71	−8.83**
Money	2.47	3.48	2.40	3.58	0.16
Health	0.44	1.28	1.44	2.55	−4.25**
Leisure	6.57	6.04	2.22	2.99	7.85**

[a] Degrees of freedom = 205 (Study 1) and 138 (Study 2).
* $p < .05$. ** $p < .001$.

involves activities or people whose company is enjoyed the most.[2] When we inspected the negative leisure events, we observed that the negativity often did not stem from the leisure activity itself (e.g., "Conquered *fear* of swimming in the sea").

Next, we examined how well LIWC-derived event codings corresponded to self-reported satisfaction in each domain. In Study 1, as participants reported two events per day, we summed the event codings across events reported on the same day. We then analyzed the association between these daily event frequencies and daily domain satisfaction through multilevel regression models with daily measures nested within participants. In Table 5, each coefficient represents the change in satisfaction associated with reporting a single event in that domain. Thus, on days when a positive family event was reported, daily family satisfaction increased by 0.64 points. Positive events predicted daily satisfaction with family, friends, academics, and leisure. Negative events predicted daily satisfaction with family, financial situation, and health.

In Study 2, participants reported four events per week. Therefore, event codings were summed across events reported in the same week. These *weekly* frequencies were entered as predictors of weekly domain satisfaction in multilevel regression models. Overall, the coefficients in Study 2 were smaller than those in Study 1. These differences might be due to the target period of the self-report measures. For example, a single positive friend event was associated with a 0.40 increase in friend satisfaction on the *particular day* it was reported (Study 1) but with only a 0.15 increase in friend satisfaction over the *entire week* (Study 2). Because more events transpire during the course of a week (vs. a day), the effect of any one event is diminished. Nevertheless, positive friend and work events and negative health events still predicted weekly satisfaction, replicating our results in Study 1.

Although negative work events were more frequently reported than positive work events, the latter and not the former predicted academic satisfaction in both studies. This may reflect the results-oriented nature of school work. Long hours of studying and occasional setbacks are experienced as stressful and unpleasant, but a single positive outcome (e.g., a good grade on a project) can make the time invested worthwhile. Furthermore, though work is typically believed to be unpleasant, it also provides a sense of challenge and opportunities to experience flow (Csikszentmihalyi & LeFevre, 1989).

General Discussion

Using data from two diary studies, we have provided important validity evidence for old and new applications of LIWC. For example, LIWC negative emotion not only predicted how negatively participants were feeling when they wrote their diary entries (concurrently) but also how negatively they remembered feeling over the entire diary period (retrospectively). LIWC anger and anxiety also correlated with self-reported emotion. In addition, we introduced a method for combining LIWC codings to estimate the frequency of positive and negative events in six life domains. We showed that these LIWC-derived event frequencies corresponded with how satisfied participants were with friends, academics, and health. Though further studies are needed to validate this approach, co-occurrence codings offer a promising way to extract information that is more specific than the emotional content of open-ended responses.

Although the results are encouraging in many respects, the inconsistencies between Studies 1 and 2 are informative. Generally, the correspondence between LIWC and self-reported well-being was stronger in Study 1 than in Study 2. In Study 1, LIWC positive and negative emotion predicted concurrent, retrospective, and global self-report measures. Furthermore, in all six life domains, self-reported satisfaction correlated with either positive or negative LIWC-derived event frequencies. However, in Study 2, LIWC positive emotion was unrelated to self-reported emotion, and event frequencies had smaller effects on domain satisfaction.

As we noted previously, a major difference between Studies 1 and 2 is the density with which the self-report target period was covered by the diary entries. In Study 1, participants rated their emotion each day and reported two events per day. In Study 2, participants rated their emotion over the past week. Not only was the target period broader, but the coverage density was sparser (0.57 events per day). The reduced coverage in Study 2 may have exacerbated two sources of error that weakened the relation between LIWC and self-reported well-being. First, events reported on Wednesdays may not have been recalled when self-report items were assessed on Sundays. Second, the self-report measures may have been influenced by additional events that were not measured because participants could only report four events per week. These observations have both theoretical and methodological implications for future researchers.

The greater correspondence between LIWC and *daily* self-report measures (Study 1)—relative to *weekly* self-report measures

[2] An important caveat of our procedure is that the stem *friend** is itself coded by LIWC as a positive emotion word. Because we only coded negative events that did not contain any positive emotion words, the frequency of negative friend events is somewhat underestimated. Thus, "quarreled with a friend" would not be coded as a negative event. When we recoded the negative events to include those entries that contained the stem *friend**, the frequency of negative friend events increased in Studies 1 (M = 2.96) and 2 (M = 4.58). However, positive friend events were still more frequent in both studies, ts > 9.40, ps < .001.

Table 5
Multilevel Regression Coefficients Predicting Domain Satisfaction From Event Frequencies Derived From Linguistic Inquiry and Word Count

	Event frequency	
Satisfaction	Positive	Negative
Study 1: Daily satisfaction		
Family	.64**	−.50*
Friends	.40**	−.01
Academic	.15**	−.04
Financial	−.09	−.23*
Health	.00	−.45**
Leisure	.65**	.13
Study 2: Weekly satisfaction		
Family	.21†	−.23
Friends	.15*	−.10
Academic	.16*	−.05
Financial	−.05	−.09
Health	.22	−.47*
Leisure	.09	.10

Note. Regression coefficients are unstandardized.
† $p < .10$. * $p < .05$. ** $p < .001$.

(Study 2)—suggests that LIWC codings of diary entries tend to reflect momentary feelings and attitudes more than stable affective traits. The use of words that describe particular emotions or life domains can reveal how participants currently feel about a specific experience without indicating how participants feel more generally. This accords with the purpose of diary studies: to capture ongoing or recent experiences. We believe that the discrepancy between Studies 1 and 2 underscores the importance of coverage density. On this basis, a few recommendations can be made to future researchers who wish to estimate emotional experience or attitudes using brief open-ended diary entries or other similar types of data. In such cases, researchers must consider the target period they wish to generalize to (e.g., past day, week, or month). Researchers should then ensure that they obtain a sufficient number of writing samples to cover the target period. Our findings suggest that 0.57 samples per day may be too few (particularly for assessing positive emotion and domain satisfaction). More consistent results may be obtained with at least two samples per day. Moreover, although LIWC codings of diary entries tend to reflect momentary feelings, it may still be possible to obtain measures of general attitudes and affective traits if coverage is sufficiently dense over an extended period of time. In Study 1, with writing samples collected each day for 3 weeks, both LIWC positive and negative emotion correlated with global self-reports.

Apart from the issue of coverage density, it is noteworthy that LIWC negative emotion consistently correlated with both concurrent and retrospective negative emotional experience across both studies. This pattern might reflect a negativity bias in the processing and memory of emotional events (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). Negative experiences tend to be more differentiated than positive experiences in that there are more words to describe the former than the later (Rozin & Royzman, 2001). This asymmetry is mirrored in the greater number of words contained in LIWC negative emotion (500) than in LIWC positive emotion (407). Consequently, negative experiences may result in more distinctive written descriptions compared with positive experiences. Furthermore, negative arousal may enhance attention, encoding, and subsequent retrieval of the specific details of a negative event (Kensinger, 2009). Arousal-enhanced processing might also explain why LIWC anger and anxiety tended to correlate consistently with self-reported anger and stress. Fear (which is coded by LIWC anxiety) and anger may implicate fight-or-flight arousal mechanisms, rendering such experiences more memorable. In contrast, both sadness and general positive emotions can range from high to low arousal—producing inconsistent enhancements in attention and encoding.

Limitations

The participants in our study were explicitly instructed to write positive and negative events. It is fair to ask whether such instructions artificially sensitized participants to the valence of their experiences and inflated the detectability of emotions through word use. We think this is unlikely given that participants reported an equal number of positive and negative events. If our instructions inflated participants' use of emotion words, LIWC positive and negative emotion should be equally frequent. Instead, LIWC positive emotion was higher than LIWC negative emotion, a pattern that is consistent with the observation that self-reported positive emotions are more frequent than negative emotions in large cross-national surveys (Diener & Tov, 2009).

Given the low frequency of LIWC sadness, anxiety, and anger, it is possible that a lack of variation in these measures attenuated their correlation with self-reported negative emotion. The standard deviations for these LIWC categories were smaller than those observed for the broader positive and negative emotion categories (see Table 1). Nevertheless, we observed significant correlations between LIWC and self-reported anger and anxiety, but not sadness—even though there was more variation in the latter. Still, we acknowledge that greater variation in these LIWC categories could result in a stronger correspondence with self-report measures.

The lack of correspondence between LIWC sadness and self-reported sadness could also be due to the particular design of our study. Our participants had to describe their experiences in a relatively concise manner. It is unknown whether brevity invites a certain style of verbal processing that makes sadness less detectable. In contrast, Rodriguez, Holleran, and Mehl (2010) instructed participants to write about their personality in a stream-of-consciousness manner. They found that LIWC sadness correlated substantially with self-reported depression. Furthermore, the effect was observed when participants were told to write an entry for a private diary but not when they wrote for an online blog post that could be read by others. Perhaps private, stream-of-consciousness writing provides better cues for the detection of sadness and depression because such writing is conducive to rumination. Other forms of writing might yield more reliable linguistic cues for positive emotion. Clearly, more research is needed on how the communicative context of writing affects emotional expression and word use.

We introduced a coding method for identifying positive and negative events in specific life domains. This approach revealed that positive events were more frequently reported in some domains, whereas negative events were more frequently reported in others. The method is fairly simple to apply, but it requires caution in its use and interpretation. Our approach relies on four LIWC categories (negative emotion, negation, inhibition, and discrepancy) to identify negative events, but only one category (positive emotion) to identify positive events. As there are more words across the four categories of "negative words" than there are in LIWC positive emotion, it is possible that more negative events are identified than positive events simply because a wider net is cast for the former than the latter. In the present studies, this potential bias was partly offset by the lower frequency of negative words relative to positive emotion words.[3] Future researchers should take note of these potential biases and consider ways to mitigate them if necessary (e.g., by identifying more cues for positive events).

Possible Extensions and Applications

We focused on the validity of LIWC codings as estimates of well-being during a particular *target period*. However, diary studies also permit the study of within-person, momentary *change*s in feelings. We did not evaluate the validity of using LIWC codings to track daily or weekly changes in well-being because our data were suboptimal for such analyses. To estimate daily change reliably would require a greater number of writing samples *per day* than the two events our participants reported each day in Study 1 (see Shrout & Lane, 2012, for relevant formulas). This is especially important given that LIWC codings are affected by the length of the writing sample. A single instance of the word *happy* results in a higher score for LIWC positive emotion when the entry contains just three words instead of 30. The more samples there are per day, the more such sources of error will be minimized. Alternatively, all writing samples from a single day might be combined into a longer sample to reduce the noise associated with extremely brief entries. We took a similar approach by combining all diary entries collected over the target period into a single writing sample reflecting that period.

Although we evaluated LIWC in the context of short, open-ended diary responses, the present findings may be applicable to social media messages. There has been growing interest in measuring well-being from social media (e.g., Burke, Marlow, & Lento, 2010; Kramer, 2010). Social media messages provide numerous writing samples that can be retrieved in an unobtrusive manner. However, findings thus far have been inconsistent when emotion word counts have been correlated with self-reported life satisfaction (Kramer, 2010; Wang, Kosinski, Stillwell, & Rust, in press). Our analyses suggest that emotion word counts are more consistently related to self-reported emotional well-being (especially negative emotion) than broad cognitive well-being (i.e., life satisfaction). Moreover, as we noted, diary entries are more likely to reflect momentary feelings than global feelings and attitudes unless the coverage density is sufficiently high. In social media, emotional experiences are often shared in real time; thus, they are likely to reflect momentary feelings. Although social media studies often include large numbers of participants, this does not fully address the issues highlighted by our research. If only two or three writing samples are obtained per person and a global measure of well-being is administered, then it should not be surprising if correlations between word counts and self-reported well-being are low—even if thousands of participants are examined.

In addition, the coding of social media might be improved by using the co-occurrence method to distinguish personal from nonpersonal events. Positive personal events might contain positive emotion words and first-person pronouns (e.g., *I*, *my*, *me*). Other information could also be coded. On Facebook, messages often include information such as "place of check-in" and friends who were "tagged." This information could be coded and combined. A check-in at a conference hall might signal an academic event; tagging might signal a social event. Despite these potential applications, a remaining challenge in utilizing social media is that people tend to selectively present their emotions (Qiu, Lin, Leung, & Tov, 2012). Thus, additional validation studies will be required to evaluate the usefulness of our approach in these contexts.

The present studies provided a rich analysis of the validity of LIWC codings as measures of well-being. Our results were generally encouraging but also highlighted certain methodological considerations that could improve future applications. Given that the sample consisted of non-Western, English-speaking students, the present research provides preliminary support for the robustness of the LIWC2007 English dictionary across cultures. We hope the co-occurrence methodology introduced in this article offers researchers new ways of extracting information from open-ended responses. The present research took advantage of the unique structure of diary data. How this approach fares with other types of data remains to be seen.

[3] We also recoded the events using only two categories (negative emotion and negations) to identify negative events. Although this procedure actually led to more positive events than negative events being identified overall, negative events were still more frequently reported in the domains of work and health.

References

Alvarez-Conrad, J., Zoellner, L. A., & Foa, E. B. (2001). Linguistic predictors of trauma pathology, and physical health [Special issue]. *Applied Cognitive Psychology, 15,* S159–S170. doi:10.1002/acp.839

Back, M. D., Küfner, A. C. P., & Egloff, B. (2010). The emotional timeline of September 11, 2001. *Psychological Science, 21,* 1417–1419. doi:10.1177/0956797610382124

Bantum, E. O., & Owen, J. E. (2009). Evaluating the validity of computerized content analysis programs for identification of emotional expression in cancer narratives. *Psychological Assessment, 21,* 79–88. doi:10.1037/a0014643

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology, 5,* 323–370. doi:10.1037/1089-2680.5.4.323

Beck, A. T., Rial, W. Y., & Rickels, K. (1974). Short form of Depression Inventory: Cross-validation. *Psychological Reports, 34,* 1184–1186.

Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology, 54,* 579–616. doi:10.1146/annurev.psych.54.101601.145030

Burke, M., Marlow, C., & Lento, T. (2010). Social network activity and social well-being. In E. Mynatt (General Chair), G. Fitzpatrick, S. Hudson, K. Edwards, T. Rodden (Program Chairs), & L. Dabbish (Session Head), *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1909–1912). New York, NY: ACM. doi:10.1145/1753326.1753613

Craske, M. G., Rapee, R. M., Jackel, L., & Barlow, D. H. (1989). Qualitative dimensions of worry in *DSM-III–R* generalized anxiety disorder subjects and nonanxious controls. *Behaviour Research and Therapy, 27,* 397–402. doi:10.1016/0005-7967(89)90010-7

Csikszentmihalyi, M., & LeFevre, J. (1989). Optimal experience in work and leisure. *Journal of Personality and Social Psychology, 56,* 815–822. doi:10.1037/0022-3514.56.5.815

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment, 49,* 71–75. doi:10.1207/s15327752jpa4901_13

Diener, E., & Iran-Nejad, A. (1986). The relationship in experience between various types of affect. *Journal of Personality and Social Psychology, 50,* 1031–1038. doi:10.1037/0022-3514.50.5.1031

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin, 125,* 276–302. doi:10.1037/0033-2909.125.2.276

Diener, E., & Tov, W. (2009). Well-being on planet earth. *Psychological Topics, 18,* 213–219.

Frisch, M. B., Cornell, J., Villanueva, M., & Retzlaff, P. J. (1992). Clinical validation of the Quality of Life Inventory: A measure of life satisfaction for use in treatment planning and outcome assessment. *Psychological Assessment, 4,* 92–101. doi:10.1037/1040-3590.4.1.92

Golder, S. A., & Macy, M. W. (2011, September 30). Diurnal and season mood vary with work, sleep, and daylength across diverse cultures. *Science, 333,* 1878–1881. doi:10.1126/science.1202775

Kahn, J. H., Tobin, R. M., Massey, A. E., & Anderson, J. A. (2007). Measuring emotional expression with the Linguistic Inquiry and Word Count. *The American Journal of Psychology, 120,* 263–286. doi:10.2307/20445398

Kensinger, E. A. (2009). Remembering the details: Effects of emotion. *Emotion Review, 1,* 99–113. doi:10.1177/1754073908100432

Kramer, A. D. I. (2010). An unobtrusive behavioral model of "gross national happiness." In E. Mynatt (General Chair), G. Fitzpatrick, S. Hudson, K. Edwards, T. Rodden (Program Chairs), & S. Kiesler (Session Head), *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 287–290). New York, NY: ACM. doi:10.1145/1753326.1753369

Lavallee, L. F., & Campbell, J. D. (1995). Impact of personal goals on self-regulation processes elicited by daily negative events. *Journal of Personality and Social Psychology, 69,* 341–352. doi:10.1037/0022-3514.69.2.341

Mehl, M. R. (2006). The lay assessment of subclinical depression in daily life. *Psychological Assessment, 18,* 340–345. doi:10.1037/1040-3590.18.3.340

Mehl, M. R., Gosling, S. D., & Pennebaker, J. W. (2006). Personality in its natural habitat: Manifestations and implicit folk theories of personality in daily life. *Journal of Personality and Social Psychology, 90,* 862–877. doi:10.1037/0022-3514.90.5.862

Pennebaker, J. W., Booth, R. J., & Francis, M. E. (2011). LIWC2007: Linguistic Inquiry and Word Count (Version 1.12) [Computer software]. Austin, TX: LIWC.net.

Pennebaker, J. W., Chung, C. K., Ireland, M., Gonzales, A., & Booth, R. J. (2007). *The development and psychometric properties of LIWC2007*. Austin, TX: LIWC.net.

Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). *Linguistic Inquiry and Word Count: LIWC2001* [Computer software]. Mahwah, NJ: Erlbaum.

Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology, 77,* 1296–1312. doi:10.1037/0022-3514.77.6.1296

Pury, C. L. S. (2011). Automation can lead to confounds in text analysis: Back, Küfner, and Egloff (2010) and the not-so-angry Americans. *Psychological Science, 22,* 835–836. doi:10.1177/0956797611408735

Qiu, L., Lin, H., Leung, A. K., & Tov, W. (2012). Putting their best foot forward: Emotional disclosure on Facebook. *Cyberpsychology, Behavior, and Social Networking, 15,* 569–572. doi:10.1089/cyber.2012.0200

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*. (2nd ed.). Thousand Oaks, CA: Sage Publications.

Rodriguez, A. J., Holleran, S. E., & Mehl, M. R. (2010). Reading between the lines: The lay assessment of subclinical depression from written self-descriptions. *Journal of Personality, 78,* 575–598. doi:10.1111/j.1467-6494.2010.00627.x

Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review, 5,* 296–320. doi:10.1207/S15327957PSPR0504_2

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39,* 1161–1178. doi:10.1037/h0077714

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology, 4,* 1–32. doi:10.1146/annurev.clinpsy.3.022806.091415

Shrout, P. E., & Lane, S. P. (2012). Psychometrics. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 302–320). New York, NY: Guilford Press.

Stone, A. A. (1987). Event content in a daily survey is differentially associated with concurrent mood. *Journal of Personality and Social Psychology, 52,* 56–58. doi:10.1037/0022-3514.52.1.56

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29,* 24–54. doi:10.1177/0261927X09351676

Thiele, C., Laireiter, A.-R., & Baumann, U. (2002). Diaries in clinical psychology and psychotherapy: A selective review. *Clinical Psychology & Psychotherapy, 9,* 1–37. doi:10.1002/cpp.302

Tov, W. (2012). Daily experiences and well-being: Do memories of events matter? *Cognition and Emotion, 26,* 1371–1389. doi:10.1080/02699931.2012.660135

Wang, N., Kosinski, M., Stillwell, D. J., & Rust, J. (in press). Can well-being be measured using Facebook status updates? Validation of Facebook's Gross National Happiness Index. *Social Indicators Research*. doi:10.1007/s11205-012-9996-9

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS Scales. *Journal of Personality and Social Psychology, 54,* 1063–1070. doi:10.1037/0022-3514.54.6.1063

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