Non-Traditional Measures of Subjective Well-Being and Their Validity: A Review

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Abstract:
This chapter reviews a variety of methods for assessing subjective well-being beyond traditional global self-reports. The chapter examines indicators of SWB such as brain activity, smiling, cognitions, memory, and momentary experience. The author discusses the practical costs and benefits of each. Lastly, the chapter reviews new forms of data such as social media and internet searches and how they can reveal information about the subjective well-being of groups. While no single measure is perfect, this chapter aims to equip researchers with the knowledge to make informed decisions in their research designs and projects.

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Traditionally, subjective well-being (SWB) has been measured with global self-reports. There are good philosophical foundations for using self-reports of SWB. After all, the construct refers to subjective, not objective well-being, and who is best to judge how someone feels about her life other than the person herself? Global self-reports such as those captured by life satisfaction questions are especially relevant because it is these broader cognitive evaluations of one's life as a whole that are arguably at the heart of SWB. Similarly, other self-reports such as frequency and degree of positive and negative emotions provide information about the affect component of SWB. Nevertheless, there are good reasons to explore alternative measures of SWB. For example, global self-reports of SWB can be vulnerable to memory biases, social desirability, or focusing illusions. Another reason is that newer technologies may allow scientists to collect SWB data through less burdensome, more economical means. No matter the case, alternative measures of SWB can complement traditional self-reports. This chapter will explore these alternative measures and their validity.

Brain Activity

Since the 1990s techniques such as functional magnetic resonance imaging (fMRI) and electroencephalogram (EEG) have revolutionized the field of psychology. What can a window into brain processes reveal about SWB? Specifically, can fMRI and EEG be used to measure SWB? In order to address this question, we must first determine whether reliable patterns of brain activation exist for happiness or other emotions. Feldman Barrett and Wager (2006) pointed out that conditions such as consistency (i.e., activation that is not due to emotion induction procedures) and specificity (i.e., activation patterns that are non-overlapping for various states) must be met in order to establish the validity of the measures.

A handful of studies have used meta analytic techniques to examine the many fMRI and positron emission tomography (PET) studies to identify neural profiles for happiness and other emotions. Unfortunately, there remains no consensus among meta analytic studies. For example, Murphy, Nimmo-Smith, and Lawrence (2003) identified the rostral supracallosal anterior cingulate cortex (ACC) and dorsomedial prefrontal cortex (PFC) as highly involved in happiness, whereas Phan, Wager, Taylor, and Liberzon (2002) identified the basal ganglia as consistently involved in happiness. More recently, Vytal and Hamann (2010) used a more sensitive meta-analytic method to determine if any consistent activation exists for specific emotions. For happiness, the most frequently activated structure was the right superior temporal gyrus (STG).

Often it is difficult to separate activation due to the emotion itself and activation due to other cognitive processes invoked during the emotion induction procedure. For example, Suardi, Sotgiu, Costa, Cauda, and Rusconi (2016) reviewed 15 studies which used fMRI and PET on subjects who had been asked to recall happy memories. They found that remembering happy autobiographical events was associated with activation in the PFC, ACC, and insula. However, these structures were also implicated in the experience of negative emotions. Indeed, autobiographical recall is a complex task that requires memory retrieval, self-referencing, and cognitive processes such as appraisal. Not surprisingly, these very regions (PFC, ACC, and insula) have also been identified as relevant to these complex processes. Similarly, Phan et al. (2002) identified the medial PFC as generally involved in emotion processes, and activation of the ACC and insula as due to emotion recall procedures.

Despite the vast number of studies, neuroscience has yet to converge on any clear brain markers of happiness or any other emotion for that matter. In fact, the most agreed upon finding is that the amygdala is involved in fear (Murphy et al. 2003; Phan, et al. 2002), but even then, there is disagreement among scientists. For instance, the conditions of consistency and specificity have been hard to meet. There are conditions under which amygdala activation occurs which do not involve fear and sometimes even involve positive stimuli (see Feldman Barrett & Wager, 2006).

Part of the challenge in identifying which brain structures are associated with happiness is that most structures are involved in multiple emotions and serve multiple functions. Few distinct patterns exists that characterize a particular state or trait. However, there is evidence to suggest neural correlates of broader affective categories as there appear to be differences in brain activation in approach-related emotions (e.g., happiness, anger) as compared to avoidance-related emotions (e.g., fear, sadness). For instance, Richard Davidson's lab uses EEG to measure asymmetry of frontal lobe activation. His team has consistently found that greater left than right PFC activity is associated with positive affect (Urry et al., 2004). Similarly, Feldman Barrett and Wager (2006) noted that some studies found greater left-side activation for approach-related (as opposed to avoidance-related) affect. The findings are consistent with Gray's (1970) neurobiological theory which posits the existence of a Behavioral Activation System that governs appetitive, reward seeking behavior, and a Behavioral Inhibition System that governs avoidance behavior.

Smiling

What can a smile reveal about a person's SWB? Two detailed studies provide strong evidence that smiling in photographs is a valid measure of SWB. Harker and Keltner (2001) examined yearbook photos of women from the Mills College Study. Expert raters used the Facial Action Coding Scheme (FACS: Ekman, Friesen, & Hager, 1978) to rate the photographs, including the extent to which the women exhibited Duchenne smiles, or genuine smiles. Photographic ratings correlated with self-reports of personality and emotion. Individuals who expressed more positive emotionality in their yearbook photos reported less negative emotionality—and this relation held over time even when comparing self-reported emotionality 20 years after the photographs were taken. Photographic expressions also correlated with scores on the Well-Being Scale of the California Psychological Inventory (CPI: Gough, 1990) which contains items about emotional and physical health and has been shown to be highly related to life satisfaction.

Another study by Seder and Oishi (2012) compared photographs from Facebook profiles and self-reported life satisfaction. Expert raters judged participants' photographs for displays of positive emotionality. Smile intensity not only correlated with concurrent life satisfaction, but it also predicted changes in life satisfaction. Individuals with greater and more genuine smiles at Time 1 had greater increases in life satisfaction over a two-year period than those with less intense or no smiles. Moreover, it was demonstrated that the effect was not due to extraversion.

Abel and Kruger (2010) and Scollon, Sim, Shin, Koh, and Stevens (2016) also used smiling in photographs as a measure of SWB, but these studies did not have self-reported data to validate their measure. They did, however, find that smiling predicted longevity (Abel & Kruger, 2010) and teaching performance (Scollon et al., 2016)—results which are consistent with a broader literature demonstrating the links between positive emotionality and desirable life outcomes (e.g., Danner, Snowdon, & Friesen, 2001; Lyubomirsky, King, & Diener, 2005). These authors have argued that the photographs indeed capture stable individual differences in SWB.

Other research suggests a need for caution when making inferences about smiling. Labroo, Mukhopadhyay, and Dong (2014) demonstrated that people differ in their lay theories about smiling. Whereas some people smile when they *are* happy (emotion expression theory), others smile in an attempt to *become* happy (emotion regulation theory). In a series of experiments, Labroo et al. (2014) found that smiling made people with the expression theory feel happier (probably based on a facial feedback mechanism) whereas smiling made people with the regulation theory feel worse. By this rationale, smiling might be less informative about the SWB of a person who holds the emotion regulation theory, compared to people who hold the expression theory. Labroo et al. (2014)'s study, however, was a laboratory experiment where smiling was manipulated. Assessing smiling in photographs may be less of a problem because there is a strong expectation to express how one feels, rather than regulate internal states at that moment.

In short, smiling appears to be a valid indicator of SWB. Relative to other measures, smiling is not widely used as a measure of SWB in research. However, as the technology for automatic coding of facial expressions improves, reducing or removing the need for human coders, the science of SWB may see more studies using smiling in the future (see big data section).

Experience Sampling Methodology

Experience Sampling Methodology (ESM) involves participants answering questions about their affect and activities in real-time several times a day over several days. For example, respondents in a typical ESM study may receive 4-7 signals or alerts during the waking day. When respondents receive an alert, they complete a brief questionnaire about what they are doing at that moment, how they are feeling, etc., that typically takes less than a minute to complete. Technologies such as smart phones or personal data devices (e.g., Palm Pilot) make it easy for scientists to sample affect, behaviors, and time use by automatically sending alerts to participants and storing participants' responses either directly on the device or on a server. Smartphone technologies can even allow researchers to capture multimedia data and location information as well. These advances have made ESM more convenient for participants and reduced error and data loss leading to a greater response rate overall. Smart phones in particular are convenient for both researchers and participants. A 2015 Pew Survey found that 68% of Americans now own a smartphone. Among smartphone owners, 81% report that they keep their smartphone near them almost all the time during waking hours, and more than 70% report checking their smartphone a minimum of once per hour (Gallup, 2015). Never before in the history of social science research have scientists been able to track daily lives so closely and frequently. For a comprehensive review of ESM see Scollon, Kim-Prieto, and Diener (2003).

The advantage to using ESM is that respondents report on their feelings and activities in real-time or close to real time. This reduces the memory biases that often plague retrospective or global reports of well-being (Feldman Barrett, 1997; Oishi, 2002; Robinson, Johnson, & Shields, 1998; Scollon, Diener, Oishi, & Biswas-Diener, 2004). The richness of the repeated measures also allows scientists to investigate dynamic and within-person processes (e.g., Tov & Lee, 2016).

To examine the validity of ESM, we need to consider not only the psychometric evidence but also the philosophical underpinnings of the construct of SWB and its measures. The studies that have measured both ESM and global self-reports of SWB have shown there is a positive moderate correlation among the measures (Scollon et al., 2004). The less than perfect correlation either means that ESM and global self-reports are not exactly the same, or that one or both of these measures is poor. Because ESM relies on repeated measures, the aggregated data yield high reliability estimates, typically in the .90s. Therefore, the assumption is usually that ESM is the gold standard and that global self-reports are the fallible measure.

Assuming ESM is the gold standard, what can it be compared to for validation? Ultimately, researchers need to look at the entire nomological network of measures. Wirtz, Krueger, Scollon, & Diener (2003) examined ESM, global/retrospective ratings, and behavioral choice in their study which tracked students before and after a Spring Break experience. Students reported on their feelings before, during, and after the vacation. Three weeks after returning from their vacation, respondents reported the extent to which they would like to have a similar Spring Break experience to the one they just had. Wirtz et al. (2003) found the expected intercorrelations among all the SWB measures. However, and most intriguingly, ESM reports during the vacation were completely unrelated to wanting to repeat the experience. Only students' memories of the vacation predicted wanting to repeat the same (or similar) experience. At first glance, the findings may seem to defy conventional wisdom, not to mention behaviorism which posits that human beings should seek to repeat experiences they enjoy and avoid experiences they didn't enjoy. However, the results highlight the fundamental difference between what Kahneman (2010) calls experienced versus remembered utility. ESM captures experienced utility, the enjoyment that occurs during an experience, whereas global and retrospective reports capture remembered utility, how one remembers an experience. Whereas experienced utility is fleeting and lasts only as long as short-term memory lasts, remembered utility remains and continues to influence behavior long after the experience is over. The two types of utility are independent, and although ESM may have greater veracity or accuracy for experience utility, it is not necessarily superior depending on the outcome measure.

Unlike global self-reports of SWB, ESM has a greater potential for reactivity effects. Because the methodology draws attention to the respondent's internal states, perhaps with high frequency and intensity, ESM may actually change people's well-being during the course of a study. For example, depressed participants in a two-week experience sampling became less happy over time with greater frequency of emotion reporting (Conner & Reid, 2012). By contrast, non-depressed participants showed the opposite pattern and became happier over time with greater emotion reporting.

There are practical limitations to ESM as well. First, the methodology is intensive. Participants can find the frequent questioning to be invasive, even irritating. For this reason, researchers must keep the number of questions in each momentary assessment to a minimum. Second, the methodology requires considerable compliance from participants, which means some groups will be over-represented in ESM studies (e.g., conscientious people with not too chaotic lives), and even then researchers must typically offer good incentives for people to participate. Technological advances that make ESM more convenient for participants (such as using a smart phone app on the participant's own phone) will help narrow the gap between those who can and those who cannot complete an ESM study, but there are some limitations which will always remain. For scientists interested in starting their first ESM study, see Conner and Lehman (2012).

The Day Reconstruction Method

The Day Reconstruction Method or DRM (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) has been heralded as offering the richness of ESM with the convenience of a single-time assessment. The DRM guides respondents through a detailed moment-by-moment reconstruction of the previous day's activities. Participants record the location, duration, and affect experienced during each episode. Experienced affect can be weighted as a function of duration, and researchers can estimate affect in specific activities (e.g., childcare, commuting). The DRM is designed to minimize memory biases by being close in proximity to the previous day's experiences and by relying on cued recall. Several studies have now examined its validity.

Individual Difference Studies

Responses on the DRM consistently correlate with individual difference measures in expected ways. Depressed patients report more negative and less positive affect in the DRM compared to non-depressed patients (Bylsma, Taylor-Clift, & Rottenberg, 2011). Likewise, the relation between PA and Extraversion has been replicated using the DRM (Srivastava, Angelo, & Vallereux, 2008). Diurnal patterns of affect using the DRM (Daly, Delaney, Doran, & MacLachlan, 2011; Kahneman et al., 2004) mirror studies using ESM. Other studies have shown that the DRM can be used successfully and meaningfully in a variety of cultures (Caballero et al., 2014; Mellor-Marsa et al., 2015). On the other hand, Hoffenaar, van Balen, and Hermanns (2010) compared the DRM and global measures in a sample of women pre- and post-partum and found only modest convergence among the two types of reports. The authors concluded it is important to measure both global and experienced affect.

Is the DRM a Good Substitute for ESM?

In order to answer this question, researchers need to directly compare ESM data and DRM data. Dockray et al. (2010) was one of the few studies to have done this, and they found consistent within-person variation in affect across the two types of measures. Specifically, affect, especially reports of happiness, in both the DRM and ESM corresponded with one other over the course of the day. Fisher R to Z correlations were generally around .60, before adjusting for unreliability, lending strong support to the idea that the DRM may, in fact, provide equivalent information to ESM. However, Diener and Tay (2014) pointed out that completing the ESM together with DRM may inflate the convergence of measures. By drawing attention to people's emotions using ESM, responses on the DRM may be more accurate than usual.

Bylsma et al. (2011) found moderate to strong correlations among ESM and DRM measures in a sample of depressed and non-depressed participants. They also tested for reactivity to events and found reactivity effects replicated across the two methods. Srivastava et al. (2008) also tested for reactivity using the DRM and found that extraverts do not display greater reactivity to social events. Srivastava's study replicated what Lucas and Baird (2004) established using ESM, lending further support to the DRM as a decent substitute for ESM.

Abbreviated DRM

Although the DRM is significantly less time intensive than ESM, it still takes typically one hour to complete, which makes it impractical for large scale studies. Anusic, Lucas, and Donnellan (2016) examined the validity of a random sampling DRM. In this abbreviated format, respondents list the previous day's episodes or events, similar to the original DRM. However, instead of providing affect ratings for all episodes, respondents rate a randomly selected subset of episodes. Most promising, the shortened version of the DRM was shown to converge with other SWB measures and yielded results comparable to the original DRM studies.

Caveats

At the heart of these validation studies lies a more fundamental question about what specific measures mean within a theory of subjective well-being. In comparisons of the DRM with ESM, the assumption is that ESM is the gold standard. As described earlier, ESM has been shown to be a poor predictor of behavioral choices (Wirtz et al., 2003). If the DRM is supposed to yield ESM-like data, is there any reason to suspect that the DRM would be any better at predicting behavioral choices?

Another limitation of the DRM is the common practice of weighting affect by duration of the episode. While there is a logic to this practice, it also presupposes that psychological duration can be counted in the same units as time. Lastly, one of the chief advantages of the DRM over ESM is that the DRM can provide nearly as much information as ESM without the time/resource intensity. However, smart phone apps and more widely available passive data may erode this gap or at least narrow it.

Memory Measures

A memory task can be a subtle, yet powerful way to assess SWB as demonstrated by Sandvik, Diener, and Seidlitz (1993). They gave subjects 2 minutes to recall all the positive things that had happened in their lifetime, and later another 2 minutes to recall all the negative things that had happened. The balance of frequency of positive memories over negative memories was shown to correlate with self-reports of life satisfaction. In other words, happy people recalled a preponderance of positive events over negative events compared to unhappy people. Seidlitz and Diener (1993) found this individual difference was stable across samples, and the mechanisms behind the effect stemmed from differences in experience and interpretation of events. Happy people simply experience more positive events than unhappy people in general, and happy people interpret the same events as more positive than unhappy people. The belief that happy people recall more positive events because they are in a happy mood at the time of recall was not supported. There was also little evidence for the notion that happy people rehearse positive information more, thereby strengthening their retrieval of happy events.

From a practical standpoint, memory measures have a lot to offer researchers with little cost. Because they are an indirect indicator of SWB, they are not susceptible to social desirability artifacts the way asking someone how happy they are can be. Memory measures can also be implemented easily, cheaply, and quickly. To avoid priming effects, however, researchers should place memory tasks before other items that may influence accessibility of positive or negative information. Relative to other types of SWB measures, memory measures are underused in the literature, but the evidence shows they may be a good alternative.

Cognitive Accessibility

Two studies suggest that people with higher SWB organize positive emotions differently from their less happy counterparts, and this may point the way toward innovations in measurement. Robinson and Kirkeby (2005) devised a method of measuring cognitive organization based on a reaction-time paradigm. In their study, people with high life satisfaction were faster to report their positive emotions when the question followed another question about positive emotion. For example, they were faster to report how much joy they experience in general if this question followed a question about how much excitement they experience in general. By contrast, when a question about negative emotion was followed by a question about positive emotion, happy people were relatively slower to respond (e.g., how much anxiety do you experience in general, followed by how much happiness do you experience in general). The decreased reaction times suggest that positive emotions are organized in a tighter associative network for happy people.

In an independent set of studies, Koo and Oishi (2009) adapted the classic Deese-Roediger-McDermott "false memory" paradigm to examine how people organize happiness-related concepts. For example, participants learned several word lists, one of which included words related to happiness (e.g., excited, joy, smile). Importantly, each list omitted a critical word that was associated with the content of the rest of the words. In the case of the happiness-related list, the word happiness (known as the 'critical lure') was intentionally omitted so participants would not study it. Compared to unhappy people, happy people falsely recalled "happiness" as being part of the studied word list. In other words, they were more susceptible to having false memories but only for a category related to positive emotions. They were no more likely to have false memories for other categories.

These two studies demonstrate that activation of happiness-related concepts may automatically lead to activation of other parts of an associative network in happy individuals. Although no studies have used cognitive accessibility or the false memory paradigm to capture stable individual differences in SWB, these two studies show how they can be useful.

Informant Reports

Most theories of SWB hold that the individual is the best judge of his or her own happiness. Nevertheless, can other people be a valuable source of information about a person's happiness? Most studies show modest to moderate correlations among self-reports and informant reports of SWB. For instance, Zou, Schimmack, and Gere (2013) compared students' self-reports of SWB with parents' reports of the student's SWB and found convergent correlations of .30 to .36. In a meta-analysis, Schneider and Schimmack (2010) found an overall correlation of .42 among self and informant reports of life satisfaction. Similarly, Koydemir and Schütz (2012) also found moderate convergence (*r*s .42 to .46) among informant and self-ratings of life satisfaction. The highest convergence (in the .5s) was from Sandvik et al. (1993) whose participants had a minimum of 7 informants each, including at least one parent and one friend. Sandvik et al. (1993) noted that more informants and more items increase the convergence of self and informant reports.

Informant reports have even been used to study the well-being of primates (Robinson et al., 2016; Weiss, King, & Perkins, 2006). Of course, primates cannot supply self- report ratings to compare with the informant reports. However, primate studies of SWB demonstrate the psychometric reliability of observer measures. Weiss et al. (2006) reported an intraclass correlation (equivalent to Cronbach's alpha) of .83 for chimpanzee SWB when at least 3 raters provided judgments about the animal.

Importantly, however, the degree to which SWB is visible may vary by person and culture making informant reports a better indicator for some than others. Saeki, Oishi, Maeno, and Gilbert (2014) examined the convergence of self and informant reports of SWB and personality in Japanese and American samples. While self and informant reports converged in general, the convergence was lower among Japanese samples than among American samples. Self and informant reports of life satisfaction also had lower convergence than traits such as extraversion. Their findings highlight the unobservable nature of SWB, which appears to be less visible than say extraversion, and which may be more or less visible depending on one's culture.

Implicit Measures

The implicit association test (IAT) was first developed by Anthony Greenwald and colleagues (1998) to measure implicit or unconscious racial bias. The IAT uses reaction times to measure the strength of positive and negative associations towards a particular category, such as African Americans, the elderly, women, obese people, the self, or even one's own life. The Implicit Life Satisfaction (ILS: Kim, 2004) measure adapts the original IAT framework by pairing "my life" with the evaluative categories of "good" versus "bad" to measure an individual's automatic evaluation of his or her life. Whereas self-reports of life satisfaction often invite socially desirable responses, implicit measures of SWB can circumvent this problem.

Kim (2004) reported that the ILS showed reasonable internal consistency (*r*s ranging in the .70s and .80s) and modest test-retest correlations (r = .41). Implicit life satisfaction did not correlate with self-reported life satisfaction. In general, many of the IAT variants have low test-retest correlations, especially in comparison to their explicit counterparts. In addition, within the IAT paradigm, implicit measures are not necessarily expected to correlate with explicit measures as they are independent processes.

Interestingly, individuals who recently escaped North Korea had higher levels of explicit life satisfaction compared to South Koreans or resettled North Korean defectors (Jang & Kim, 2011). The high explicit life satisfaction was attributed to the recent dramatic and positive changes in defectors' living conditions. However, both recent and resettled North Korean defectors showed similar low levels of implicit life satisfaction, which the authors attributed to chronic negative living conditions. Although results from this unique study are consistent with theories of SWB and IAT research, more studies are needed to confirm the validity of the ILS.

As to whether respondents can fake responses on the ILS, Kim (2004) found that respondents could suppress their implicit life satisfaction scores when instructed to do so by slowing down their responses. However, respondents could not enhance their responses to achieve higher life satisfaction scores by responding faster. Thus, while the ILS may not be susceptible to socially desirable responding, it is not entirely immune from conscious control.

Big Data

One of the most exciting areas to provide new insight and ways of measuring SWB is through big data, particularly big data from social networking sites such as Facebook and Twitter or search engines such as Google. Big data have been described as having high "volume, velocity, and variety," (Laney, 2001) making them rich sources of information about human behavior. Information can be obtained unobtrusively on millions of users, enabling social scientists to overcome methodological problems such as under-powered designs, non-representative sampling, participant selection and fatigue, etc. This sounds like a social scientist's dream, but it may be worth taking a closer look at the validity of such measures. To date, a handful of studies have examined the validity of Facebook status updates or Twitter tweets as sources of information about a person's SWB.

Facebook

Wang, Kosinski, Stillwell, and Rust (2014) correlated Facebook Gross National Happiness scores with daily life satisfaction scores from Facebook users in 2009 and found few significant correlations. The authors concluded that Facebook status updates were not a valid way of measuring well-being or mood. However, the daily FBGNH ratings were not necessarily derived from the same Facebook users who provided the life satisfaction ratings, which may explain why Wang et al.'s results were inconsistent with data reported by Facebook scientist Adam Kramer (2010).

Kramer (2010) also compared the SWLS with the FGNH in a group of over 1,000 of the same respondents. According to Kramer (2010), life satisfaction correlated 0.17 with positivity in status updates. Considering the sample size, the magnitude of the correlation was surprisingly weak. Lending to its face validity, however, FGNH overall showed an increase during holidays and dips during national tragedies. Also, consistent with traditional studies of SWB (Larsen & Kasimatis, 1990), FBGNH showed a cyclical day-of-the-week effect where mood is highest on Fridays and lowest on Mondays.

Perhaps one explanation for the weak correlations between social media posts and life satisfaction is that social media biases users to post positive content. Liu, Tov, Kosinski, Stillwell, and Qiu (2015) postulated that self-presentation norms increase people's desire to post positive status updates, rendering positive updates less indicative of a person's true SWB. However, negative emotions are more 'honest' reflections of SWB because they are not subject to self-presentational concerns. Indeed, they found that negative, but not positive, emotion in Facebook status updates were related to life satisfaction. In addition, only status updates from the past 9 months or earlier were related to life satisfaction, a finding which corroborates Suh, Diener, and Fujita (1996) who found that only recent events contribute to SWB.

Twitter

Yang and Srinivasan (2016) directly sampled a subset of Twitter users who tweeted life satisfaction content and completed the SWLS. People who made more life satisfaction tweets had higher life satisfaction scores than those who tweeted dissatisfaction (e.g., "I hate my life"). High life satisfaction also related to tweeting more positive and fewer negative words overall, and using fewer first-person singular pronouns. Overall, the number of life satisfaction tweets was low compared to the total number of tweets (only .13%). This is not surprising given that researchers have to rely on the spontaneous mention of life satisfaction in tweets, which may make for unnatural language in the Twitter world. This may explain why there are more Twitter studies using affect instead of life satisfaction, although life satisfaction and affect tweets showed discriminant validity. Importantly, researchers need to select their words for searches carefully when trying to examine SWB from tweets.

Yang and Srinivasan's study (2016) also revealed that Twittered life satisfaction did not fluctuate with events over two-year time frame, consistent with the stability of traditional life satisfaction measures. Replicating the findings that religiosity contributes to SWB, Twitter users with high life satisfaction also posted more about religion than unhappy ones. Like Kramer's study, these findings indicate good face validity of tweets as a source of information about SWB. Unfortunately, Yang and Srinivasan (2016) only had a response rate of .46% in their study. Responders might conceivably be more consistent overall than non-responders. In any event, there appears to be promising evidence that Twitter can be used to gather meaningful data about life satisfaction.

Using a different approach, Schwartz et al. (2013) examined Tweets from over 1,000 U.S. counties with at least 30,000 Tweets per county. Their data spanned a period of 14 months and compared the

Twitter data to surveys of life satisfaction from people in the same counties. Like Wang et al. (2014), the Twitter users were not necessarily the same individuals who provided the life satisfaction data. Nevertheless, the two sources were correlated, and Twitter word use predicted county level life satisfaction above and beyond demographic variables such as median age and income. Moreover, topics that were most strongly associated with life satisfaction—for example, physical activity, social engagement, and prosocial activity—were the very ones that have consistently been found to be related to well-being using more traditional data sources.

In addition to Facebook and Twitter, other platforms such as Instagram have potential as well because the information posted by individuals are publicly available. Given the usefulness of smiling in photographs (e.g., Seder & Oishi, 2012), researchers could easily gather smiling data from Instagram as a measure of the user's SWB. With improvements in machine learning technology, the extraction of psychological information will become easier and easier, eventually removing the need for human coders entirely. Some commercially available software already exists (e.g., Noldus). To give one example of what can be done, Redi, Quercia, Graham, and Gosling (2015) identified the ambience of cafes using profile pictures of the cafes' customers. For example, a hipster café might attract more customers who wear glasses. Cleverly, the researchers used machine learning to teach computers to extract visual information from profile pictures that had previously been found to correlate with ambience. Other sources of big data, even those that are outside the realm of social media or those that have yet to be invented, may also prove to be useful to SWB science. The possibilities are endless and only constrained by our imagination.

Google Searches

Whereas Kramer (2010) described the Facebook status update as a "self-descriptive text modality, optimized and designed to elicit updates about the self," and the "strongest signal of the emotional well-being of the poster," Ruths and Pfeffer (2014) cautioned that social media distorts human behavior. Not only are the platforms themselves explicitly designed to shape human behavior (e.g., social network sites aim to increase homophily through the recommendation of friends and sites), but there is a heightened sense of self-presentation in social media (e.g., Liu et al., 2015), which may lead to the data not accurately reflecting people's true thoughts and feelings. By contrast, when people conduct internet searches, they do so in privacy, making the study of internet searches one of the rare glimpses into private behaviors that is available to scientists. Furthermore, unlike self-reports internet searches do not require introspection. Thus, by examining what people in a population are searching for on the internet, researchers may be able to estimate the well-being of that population.

Ford, Jebb, Tay, and Diener (2017) were the first to examined Google search activity and its relation to well-being. Indeed, regions with greater frequency of searches containing words such as *depression*, *afraid*, or *anxiety* had lower self-reported affect and more incidences of coronary heart disease and depression. This pattern emerged at both state and metropolis levels. Although internet searches are a powerful and inexpensive way of capturing people's deepest concerns, there are limitations on the capacity of internet searches to represent SWB. Mainly, people whose search queries include words such as *depression* are likely to be experiencing negative emotions and thus seeking ways to resolve them. By contrast, someone with high life satisfaction is unlikely to Google positive emotion terms. Ford et al.'s study, in fact, was limited to internet searches of negative terms.

Overall, big data have enormous potential for understanding SWB, and they are constantly being generated with no incentives at all from scientists. Compared to surveys or ESM which can be very costly, social media data and internet searches are potentially economical sources of information. Despite these advantages, there are limitations. For instance, social media users will tend to be younger and more tech savvy than the general population. In addition, Twitter only releases a small sample of tweets to the public. Twitter also limits the number of words users can post. However, these limitations are small in comparison to the enormous information big data can provide.

Skepticism and Caution

These new forms of data are already raising some novel and potentially serious ethical concerns for scientists. Privacy, consent, and data ownership, are just a few of the known challenges, and these too are constantly evolving. With just a bit of reflection on the amount of passive data generated by modern individuals, it is easy to sense the "creep factor" of big data (Gumbus & Grodzinsky, 2016). Unlike in a traditional survey design or laboratory experiment, when people generate social media content (such as posts and likes), do they even realize they are providing data? Chances are not. Often no explicit consent is obtained from those who provide data. In the case of internet searches, there is no way for potential subjects to opt out, short of not searching for the information in the first place. Even if it is possible to obtain consent from users for social media content, participants may not grasp the details of the research at the time of consent because in some cases, the data precede the research questions. Even when data are anonymized, people may be uncomfortable with their social media data being used for research purposes. Scholars have warned of inequities in accessibility to big data and proprietary algorithms for public data that may over represent or under represent some populations or behaviors (Ruths & Pfeffer, 2014) and potentially widen disparities between groups (Gumbus & Grodzinsky, 2016). Not to mention, if big data fall into the wrong hands, there is enormous potential for misuse. Even if there were a way to solve these problems, there may remain broader implications of conducting research in a big data world. For instance, does the datafication of our lives erode free will? For this reason and others, psychologists should forge a dialogue with ethicists, social media experts, and ordinary users to understand how best to use big data, especially as social norms evolve and new forms of data arise.

Conclusion

Thanks to advancements in technology researchers now have at their disposal many new methods for measuring SWB. While neurological approaches to assessing SWB remain far from useful or practical at present, other techniques such as big data and momentary assessments are growing more economical and accessible each day. These non-self-report methods can, at times, reduce the social desirability and introspection inherent in self-reports of SWB. However, it is important to consider that all the measures offer different vantage points of the underlying phenomenon, and no single method is a direct measure of SWB. A variety of methods allows researchers to triangulate on a picture of SWB, but they should not entirely replace self-reports of SWB. After all, the construct is *subjective* well-being.

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