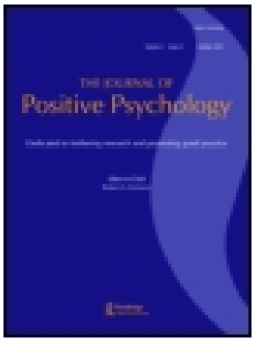

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Measuring well-being: A comparison of subjective well-being and PERMA

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ABSTRACT
We compared Seligman's PERMA model of well-being with Diener's model of subjective well-being (SWB) to determine if the newer PERMA captured a type of well-being unique from the older SWB. Participants were 517 adults who completed self-report measures of SWB, PERMA, and VIA character strengths. Results from four analytic techniques suggest the factor underlying PERMA is capturing the same type of well-being as SWB. Confirmatory factor analysis yielded a latent correlation of r = 0.98 between SWB and PERMA. Exploratory structural equation modeling found two highly related factors (r = 0.85) that did not map onto PERMA and SWB. SWB and PERMA factors showed similar relationships with 24 character strengths (average correlation difference = 0.02). Latent profile analyses yielded subgroups of people who merely scored high, low, or mid-range on well-being indicators. Our findings suggest that while lower-order indicators SWB and PERMA have unique features, they converge onto a single well-being factor.

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Well-being; happiness; flourish; character strengths; positive psychology

For years, psychologists have been conceptualizing theories to understand what contributes to a fulfilling life and conducting empirical tests of their merit. These efforts have led to a proliferation of new definitions, models, and measures of well-being (for reviews, see Cooke, Melchert, & Connor, 2016; Diener, Scollon, & Lucas, 2003; Hone, Jarden, Schofield, & Duncan, 2014; Jayawickreme, Forgeard, & Seligman, 2012; Lent, 2004; Ryan & Deci, 2001). While such research has yielded a vast, informative body of work, overlapping conceptual and measurement models stymie researchers and practitioners. It remains unclear if multiple well-being models capture distinct or similar types of well-being. In the current study, we tested whether a new proposed model of well-being – Seligman's (2011) Flourish model (i.e. 'PERMA') – represented a unique type of well-being that differs from Diener's (1984) widely used and accepted model of subjective well-being (SWB).

Modeling and measuring well-being

Researchers tend to disagree on what constitutes well-being. Bradburn's (1969) 'hedonic balance' model suggests well-being is maximized by a high ratio of positive to negative affect. Diener's tripartite model of SWB model adds to Bradburn's emotional focus by including a cognitive component on the degree to which one's life is viewed as satisfactory or close to ideal. Offering a more nuanced approach, Ryff's[1] (1989) model of psychological well-being (PWB) articulates six dimensions that are proposed to be more directly tied to the philosophical traditions of ancient Greeks and psychological theories from humanistic, existential, and developmental traditions. PWB captures six components that are proposed to engender positive functioning: self-acceptance, environmental mastery, positive relations with others, autonomy, purpose in life, and personal growth. Offering additional breadth, Keyes (1998) combined Diener's SWB dimensions with Ryff's PWB dimensions but felt neither captured a third, purportedly distinct type of well-being – social well-being (even though one of the PWB dimensions is about the depth of one's social relationships). Compton (2001) also argues for three types of well-being, identifying them as SWB, personal growth, and religiosity; using terminology similar to Diener and Ryff but with different connotations. Although incomplete, this list of models illustrates the broad range of terminology and conceptual confusion in well-being research.

Beyond the models of well-being already outlined, Seligman (2011) developed his own model, labeled 'Flourish', a model first detailed in his best-selling trade book before being widely adopted by positive psychology practitioners. Seligman (2011) identified five components

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of well-being: positive emotions, engagement, relationships, meaning, and accomplishment – hence the PERMA acronym. He suggests that each of these five components are intrinsically rewarding, representing worthwhile ends for doing anything. Together, the combination of these five indicators of well-being purportedly gives rise to human flourishing. As Forgeard, Jayawickreme, Kern, and Seligman (2011) note, 'Just as we do not have a single indicator telling us how our car is performing (instead, we have an odometer, a speedometer, a gas gauge, etc.), we suggest that we do not want just one indicator of how well people are doing' (Forgeard et al., 2011, p. 97). Seligman (2011) argues his model of well-being integrates components of hedonia (the experience of positive emotional states and satisfaction of desires) and eudaimonia (the presence of meaning and development of one's potentials) into one model, and argues that most prior models include either one or the other (e.g. SWB as hedonia, PWB as eudaimonia).

Two studies of PERMA provide preliminary support for the hypothesized structure of well-being. In a sample of 153 Australian school employees, each component of PERMA loaded onto its own factor (Kern, Waters, Adler, & White, 2014); albeit a small sample for a 36-item measure. In a larger online community sample ($N = 831$), PERMA converged onto a higher-order well-being construct (Coffey, Wray-Lake, Mashek, & Branand, 2016). Nonetheless, it is unclear if the type of well-being (flourishing) created by PERMA is the same or different than that proposed by other models of well-being. Coffey et al. (2016) found 0.92 and 0.80 latent correlations between PERMA and vitality and life satisfaction, respectively. These high correlations suggest that PERMA and SWB might be synonymous.

Most research that has directly compared models of well-being suggests an absence of discriminant validity between them. Confirmatory factor analytic (CFA) studies comparing two types of well-being have yielded high latent correlations, ranging from 0.76 to 0.97 (Disabato, Goodman, Kashdan, Short, & Jarden, 2016; Gallagher, Lopez, & Preacher, 2009; Keyes, Shmotkin, & Ryff, 2002; Linley, Maltby, Wood, Osborne, & Hurling, 2009; Longo, Coyne, Joseph, & Gustavsson, 2016). The largest of these studies (N = 41,461) found a latent correlation of 0.97 between positive feelings and positive functioning (Longo et al., 2016).[2] The second largest of these studies ($N = 7617$), found correlations greater than 0.90 between hedonic and eudaimonic well-being in each of 7 world regions that covered 6 of the 7 continents (Disabato et al., 2016).

Despite this evidence, the choice of analytic procedure influences the extent to which researchers find support for multiple types of well-being. For example, using an exploratory factor analysis, Compton (2001) found latent correlations between 0.08 and 0.42 between SWB, personal growth, and religiosity. Joshanloo (2016b) used exploratory structural equation modeling and found latent correlations between 0.36 and 0.60 among SWB, PWB, and social well-being. These results were replicated in Dutch, New Zealand, and Iranian samples, with no latent correlation exceeding 0.71 (Joshanloo & Lamers, 2016; Joshanloo, Jose, & Kiepikowski, 2017; Joshanloo, 2016a). Tests of discrimination should not be limited to confirmatory factor analysis, and exploratory procedures can offer unique additional information about constructs of interest.

Types of well-being versus types of well people

Most tests of discriminant validity between well-being models involve variable centric analyses that test whether well-being variables are related in a pool of individuals (e.g. factor analyses) and if there are distinct correlates between well-being variables (e.g. nomological network analysis). An alternative way to test discrimination between models is to examine if different types of well *people* emerge using latent profile analyses, cluster analyses, and other person-centric approaches. Person-centered analyses test whether subgroups of individuals can be distinguished by their profile of scores on well-being dimensions, which more clearly maps onto 'types'. Most models of well-being propose that optimal functioning occurs when someone is high on several types of well-being, yet few studies have explored the existence of unique well-being profiles that occur within subsets of people (see Keyes et al., 2002 for an example). Person-centric analyses may map onto theories of well-being better than variable-centric analyses (Kashdan, Biswas-Diener, & King, 2008).

Person-centric analyses yield profiles of people that can differ along indicators either quantitatively or qualitatively (Marsh, Lüdtke, Trautwein, & Morin, 2009). Qualitatively distinct profiles vary in their relative standing on profile indicators. If multiple types of well-being exist (e.g. SWB and PERMA) then there should be profiles of individuals high on one type and low to medium on another type. For example, one profile could contain people high on SWB, but low on PERMA, while another profile contains people high on both SWB and PERMA. Additionally, it is possible to yield profiles of individuals with varying intensities of well-being facts across domains that do not map perfectly onto SWB and PERMA (e.g. high scores on meaning in life and engagement but low scores on all other subscales). In contrast to qualitatively distinct profiles, quantitatively distinct profiles vary in the absolute level of profile indicators. One profile could contain people who score low on all well-being scales, and another profile could contain people who score high on all well-being scales. These results would suggest there are not different types of well people, but only well and unwell people along a continuum from low to high general well-being (e.g. Chen & Page, 2016). Person-centric approaches allow researchers to identify distinct subgroups of people that differ on the quality (shape) and/or quantity (level) of profile indicators.

The present study

We examined the differences between a dominant model of well-being (SWB) and a more recently developed model (PERMA). We hypothesized that results across four different analytical approaches would provide evidence that they capture the same overarching type of well-being. First, we conducted two types of factor analyses and hypothesized that the SWB and PERMA factors would demonstrate negligible discriminant validity as evidenced by a high latent correlation and similar fitting one- and two-factor models. Second, we conducted nomological network analyses to examine how SWB and PERMA separately related to known correlates of well-being (i.e. character strengths; Park, Peterson, & Seligman, 2004). If SWB and PERMA are distinct sources of variation, then each should have its own nomological network and correlate differently with character strengths (Cronbach & Meehl, 1955). Third, we conducted latent profile analysis and hypothesized that results would yield subgroups of people who vary only in levels of well-being as a whole (quantitatively different) rather than distinct profiles of people who differ in unique ways across well-being indicators (qualitatively different). If our predictions are borne out, our findings would add to a growing body of empirical evidence suggesting that when well-being is measured via subjective self-reports, few differences emerge between competing conceptual frameworks (Longo, Coyne, & Joseph, 2017).

Method

Participants and procedures

Participants were 517 adults recruited from Amazon's Mechanical Turk (MTurk; see Buhrmester, Kwang, & Gosling, 2011). Participants were restricted to 18 + adults living in the United States. Participants completed a battery of trait questionnaires as part of a larger project on personality and well-being; this survey was administered by the Quiet Revolution (http://www.quietrev.com). Institutional Review Board (IRB) was first obtained from the University of Melbourne. Following this approval, University of Pennsylvania IRB determined that continued IRB oversight was not required. Ages ranged from 18 to 71 years (M = 36.54, SD = 11.99), with 57.4% women. For self-identified race/ethnicity, 76.4% identified as Caucasian, 7.5% mixed race, 6.0% Black or African American, 5.03% Asian, 4.3% Hispanic, and 0.01% other. Of the 517 total participants, 10 (1.9%) had missing data on satisfaction with life and 55 (10.6%) had missing data on VIA character strengths. Individuals with and without satisfaction with life or character strength data did not differ on study variables ($ps > 0.11$). Missing values were handled using full information maximum likelihood estimation (FIML), which reduces parameter estimate bias and increases statistical power.

Measures

For consistency and to minimize cognitive burden, all scales were scored on a Likert scale ranging from 1 = 'Not like me at all' to 5 = 'Very much like me'.

Diener's model of SWB

Diener's (1984) tripartite model of SWB contains three components: life satisfaction, positive affect, and negative affect. Life satisfaction was measured with the 5-item Satisfaction with Life Scale (SWLS; Diener, Emmons, Larsen, & Griffin, 1985; $\alpha = 0.92$). Positive affect was measured with a 1-item measure of happiness ('Taking all things together, how happy would you say you are?'). Negative affect was measured with a 3-item measure of negative emotion ('In general, how often do you feel sad?'; $\alpha = 0.76$).

Seligman's PERMA model of flourishing

The PERMA-Profiler (Butler & Kern, 2016) was developed to measure Seligman's (2011) PERMA model of flourishing: (P)ositive emotions (general tendency to feel contentment and joy; $\alpha = 0.90$), (E)ngagement (being absorbed or interested in an activity, state of flow; $\alpha = .58$), (R)elationships (feeling loved, supported, and valued by others; $\alpha = 0.86$), (M)eaning (sense of direction and purpose in life; $\alpha = 0.91$), and (A)accomplishment (feelings of mastery, achievement; $\alpha = 0.79$). Participants responded to 3 items per subscale. The PERMA-Profiler subscales have demonstrated acceptable reliability, test-retest stability, and construct validity (Butler & Kern, 2016; Sun, Kaufman, & Smillie, in press).

Character strengths

The Values in Action Inventory of Strengths (VIA-IS; Peterson & Seligman, 2004) is a self-report measure containing 24 subscales that correspond to different character strengths. Participants respond to 5 items per character strength (120 items total). Coefficient alphas for each subscale indicate adequate reliability (αs = 0.78–0.92). Prior research supports the construct validity of the VIA-IS, with positive associations with life satisfaction, happiness, and recovery from physical illness, and negative associations with depression (Peterson, Park, & Seligman, 2006; Peterson, Ruch, Beermann, Park, & Seligman, 2007;

Proyer, Gander, Wellenzohn, & Ruch, 2013). We conducted confirmatory factor analyses for each individual character strength and had acceptable model fit for each (CFI ≥ 0.95; TLI ≥ 0.95; RMSEA ≤ 0.10) along with strong standardized factor loadings all greater than 0.4.

Data analytic overview

Three types of analyses were used to test for similarities and differences between the PERMA and SWB models: factor analyses, nomological net analyses, and Latent Profile Analysis (LPA). All analyses were conducted using Mplus Version 7.3 (Muthén & Muthén, 1998–2015). We conducted one and two-factor CFAs of SWB and PERMA together. Model specification was evaluated using conventional fit indices: −2 log-likelihood adjusted χ^2 value, comparative fit index (CFI), Tucker-Lewis Index (TLI), root-mean-square error of approximation (RMSEA), and standardized root-mean-square residual (SRMR). Conventional cutoffs for the CFI, TLI, RMSEA, and SRMR model fit indices exist (e.g. Hu & Bentler, 1999; CFI and TLI ≥ 0.95; RMSEA and SRMR ≤ 0.08) and were considered. However, they were not used as strict decision rules because the purpose of our analyses was model comparisons rather than covariance matrix hypothesis testing (Marsh, Hau, & Wen, 2004). Because the chi-square difference test is influenced by sample size, changes in the CFI, TLI, RMSEA, and SRMR were used to determine significant improvement in model fit. Robust standard errors and the adjusted chi-square test were used to account for non-normality because many of the well-being variables were negatively skewed. We anticipated a correlation between the happiness and positive emotions errors due to high conceptual similarity (e.g. positive emotions are sometimes considered a manifest indicator of the broad construct of happiness; Busseri & Sadava, 2011). Therefore, a residual covariance was modeled in both the one-factor and two-factor models. An additional model was tested comparing SWB + P and ERMA factors given that positive emotions are defined as a part of SWB. In this model, no residual covariance was added between happiness and positive emotions.

Statistical simulations of CFAs have shown that constraining non-zero cross-loadings to zero can upwardly bias latent correlations (Marsh, Morin, Parker, & Kaur, 2014). To minimize biases in structural parameter estimates, researchers have proposed conducting exploratory structural equation modeling (ESEM). ESEM is an exploratory factor analysis given a pre-specified number of factors within a structural equation modeling framework. ESEM allows for a riskier test of the hypothesis that SWB and PERMA represent the same type of well-being. This approach also allows for more heterogeneous types of well-being that might not correspond to the SWB and PERMA models.

Discriminant validity between two constructs can be demonstrated by examining each construct's relationships to other variables. Even if the correlation between two constructs is high, validity can be shown by placing a construct in a unique nomological network of related constructs (Cronbach & Meehl, 1955). Thus, after selecting the best measurement model, nomological net analyses were conducted to determine whether the two models of well-being diverge in their associations with measures of character strengths. Each character strength was added to the best measurement model as a manifest variable and correlated with the latent SWB and PERMA variables. Small correlation differences between the two correlations suggest the two models of well-being are capturing the same type of well-being.

Last, we conducted LPAs to determine whether important information could be gained by studying well-being at the person rather than variable level. One latent profile was specified, and in subsequent iterations, the number of profiles increased by one until the model fails to converge or failed to replicate across starting values[3] (Masyn, 2013; Nylund, Asparouhov, & Muthén, 2007). Models were evaluated by examining six fit statistics: log likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), sample-size-adjusted BIC (SSA–BIC), and Lo-Mendell-Rubin likelihood ratio test (LMR; Lo, Mendell, & Rubin, 2001). We also examined the number of replicated log likelihood values, entropy, and relative profile sizes.

Results

Descriptive statistics

Means, standard deviations, and the observed correlation matrix for well-being variables are displayed in Table 1. Data for all variables were slightly negatively skewed (excluding negative emotions, which demonstrated the opposite pattern), indicating that participants generally reported high well-being. All bivariate correlations were significantly positively correlated (negative emotions was inversely correlated) at $p < 0.01$. Absolute values ranged widely from $|r| = 0.27$ to $|r| = 0.87$ (average: $|r| = 0.61$).

Well-being measurement models

Table 2 details the various factor analytic models A–F delineated below.

One-factor CFA model

Well-being was modeled as a single factor indicated by the 3 SWB subscales and the 5 PERMA subscales with a

Table 1. Zero-order correlations, means, and standard deviations for well-being measures.

Construct		Measure	1	2	3	4	5	6	7	8
SWB	1	Satisfaction with life								
	2	Happiness	0.74							
	3	Negative emotions	−0.53	−0.62						
PERMA	4	Positive emotions	0.75	0.87	−0.64					
	5	Engagement	0.38	0.49	−0.27	0.52				
	6	Relationships	0.67	0.73	−0.49	0.72	0.37			
	7	Meaning	0.69	0.72	−0.56	0.78	0.51	0.63		
	8	Accomplishment	0.66	0.69	−0.52	0.74	0.53	0.60	0.79	
		Mean	15.82	3.69	6.97	10.61	11.64	11.05	10.79	11.45
		SD	5.47	1.21	3.01	3.23	2.23	3.08	3.25	2.50

Note: All correlations are significant at $p < 0.01$.

Table 2. Factor analytic models of well-being.

Model	Type	Name	Notes
A	CFA	One-factor model	Correlated error between happiness and positive emotions
B	CFA	Two-factor model: SWB & PERMA	Correlated error between happiness and positive emotions
C	CFA	Two-factor model: SWB + P & ERMA	Including positive emotions from PERMA with SWB
D	CFA	Two-factor model: SWB (no Hap) & ERMA	Excluding happiness and positive emotions
E	ESEM	Two-factor model: Oblique Geomin Rotation	Results contained a Heywood case
F	ESEM	Two-factor model: Oblique Geomin Rotation	Excluding happiness

Notes: CFA = Confirmatory factor analysis; ESEM = Exploratory structural equation modeling; SWB = Subjective well-being; Hap = Happiness; PERMA = Flourishing; P = positive emotions.

correlation between the happiness and positive emotion errors ($r = 0.33$) (Model A). Model fit: χ^2 (19) = 111.97, $p < 0.001$; CFI = 0.96; TLI = 0.94, RMSEA = 0.10; SRMR = 0.03. Figure 1(A) depicts the standardized factor loadings.

Two-factor CFA models

Well-being was modeled as a correlated two-factor model using SWB subscales as one factor and PERMA subscales as the other (Model B).[4] Again the hypothesized correlation between the happiness and positive emotion errors was added ($r = 0.40$). Model fit: χ^2 (18) = 106.89, $p < 0.001$; CFI = 0.96; TLI = 0.94, RMSEA = 0.10; SRMR = 0.03; latent correlation = 0.98 (Figure 1(B)).

A second two-factor CFA model was conducted in which positive emotions loaded onto the SWB factor rather than the PERMA (Model C). Although positive emotions are explicitly included in PERMA, it is also included in SWB. In the above CFA model, happiness was used in place of positive emotions for SWB; however, one could argue for positive emotions to be with SWB. A CFA model was conducted where one factor was SWB with positive emotions and a second factor was each facet of PERMA except positive emotions ('ERMA'). Model fit: χ^2 (19) = 104.71, $p < 0.001$; CFI = 0.96; TLI = 0.94, RMSEA = 0.09; SRMR = 0.03; the latent correlation was 0.94. No correlated error between happiness and positive emotion was added because they were now nested under the same factor[5] (Figure 1(C)). A third two-factor CFA was conducted in which both happiness and positive emotions were removed from the model (Model D). The goal was to determine whether the large correlation between the SWB and PERMA factors was solely due to sharing the same facet of positive affect/emotions. The SWB factor only had two indicators of satisfaction with life and negative affect, while the PERMA factor was again reduced to 'ERMA' similar to Model C. Model fit: χ^2 (8) = 46.18, $p < 0.001$; CFI = 0.97; TLI = 0.94, RMSEA = 0.10; SRMR = 0.03; the latent correlation was 0.95 (Figure 1(D)).

Two-factor ESEM model

All well-being variables were modeled as a two-factor solution with no indication of which variables pertain to which factor (Model E). No residual covariances were modeled, as ESEM seeks to improve model fit via cross-loadings rather than residual covariances. The two-factor ESEM model demonstrated excellent model fit, χ^2(13) = 34.54 $p < .01$; CFI = 0.99; TLI = 0.98; RMSEA = 0.06; SRMR = 0.02. However, it contained a Heywood case (i.e. standardized factor loading > 1) for happiness with the first factor. The pattern of factor loadings did not map into the SWB and PERMA models of well-being. The first factor corresponded most strongly to SWB with standardized loadings above 0.60 in magnitude for satisfaction with life, happiness, negative emotions, positive emotions, and positive relationships. The second factor corresponded most strongly to PERMA with standardized loadings above 0.45 in magnitude for engagement, meaning in life, and accomplishments. Two loadings were inconsistent with theoretical predictions: positive emotions only loaded on the 'SWB' factor (standardized loading on second factor = 0.12) when we would expect it to load onto both factors, and positive relationships loaded onto the 'SWB' factor (standardized loading on second factor = 0.00) rather than the 'PERMA' factor. Thus, the two factors reflect SWB plus positive relationships

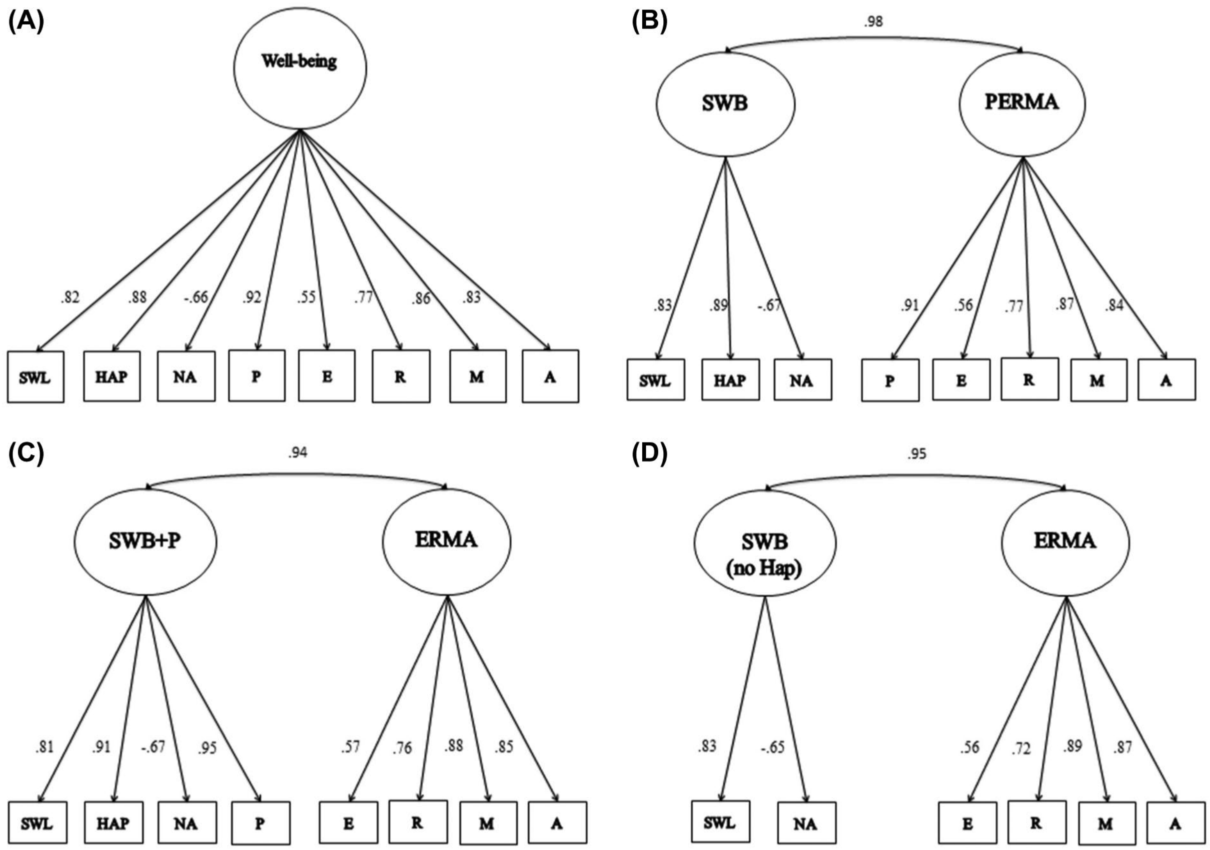

Figure 1. Standardized factor loadings from the one-factor, initial and alternative two-factor models of subjective well-being (SWB) and PERMA. SWL = satisfaction with life; HAP = happiness; NA = negative affect; P = positive emotions; E = engagement; R = positive relationship; M = meaning; A = accomplishment.

and 'EMA'. These two factors appear redundant – the latent correlation was 0.85.

An alternative two-factor ESEM model was run without happiness (the source of the Heywood case) (Model F). Results were very similar to the initial ESEM model, but with no Heywood cases. The first factor corresponded to SWB plus positive relationships with standardized loadings greater than 0.65. The second factor corresponded to 'EMA' with standardized loadings greater than 0.60. The latent correlation was still very large (r = 0.86).

Model comparisons

Absolute and relative model fit indices were compared across the one- and two-factor CFA models to determine which model best represented the data. A Satorra-Bentler scaled chi-square difference test comparing the one-factor and initial two-factor CFA models was significant ($\Delta\chi^2$ (1) = 5.28, p = 0.022); however, fit indices (CFI, TLI, RMSEA, SRMR) remained the same, suggesting the fit differences are negligible. The alternative two-factor CFA fit slightly better than the initial two-factor CFA model with less degrees of freedom as well as the one-factor CFA with equal degrees of freedom. Other than the RMSEA, the fit indices were identical for the alternative two-factor CFA, suggesting that all three models equally represent the data. Differences in standardized factor loadings across models were very small (i.e. 0.01 or 0.02). In both two-factor models, the latent correlations between SWB and PERMA factors (rs = 0.98 and 0.94) were very high, suggesting that the two factors were essentially identical – sharing over 88% of their variance. Therefore, the two factors were collapsed and the one-factor model was selected.

A Satorra-Bentler chi-square difference test was used to compare the ESEM model against the one-factor CFA. The test was significant ($\chi^2(5)$ = 67.84; p < 0.001), suggesting the two-factor ESEM better fit the data. However, the ESEM model contained a Heywood case. With large sample sizes (as in the present study), Heywood cases often indicate model misspecification, and it is generally recommended that these models not be accepted (Chen, Bollen, Paxton, Curran, & Kirby, 2001). In factor analytic models, statistical simulations have shown Heywood cases can result from trying to over-extract too many factors (Rindskopf, 1984). This explanation might be true of our data such that the correctly specified number of factors is 1. On the other hand, when happiness was removed from the ESEM model, the model contained no Heywood case. Regardless, in both models the non-theorized factor loadings of positive emotions and positive relationships suggest the two ESEM factors did not map onto the SWB and PERMA models.

Two-factor model correlations with character strengths

Despite the $r = 0.98$ and 0.94 latent correlations between SWB and PERMA, an additional validity test for the two-factor model was conducted by comparing how each factor related to the 24 VIA character strengths. The initial two-factor CFA model was used to compare character strength correlations because it best reflected the theoretical models of SWB and flourishing.[6] Each character strength was added separately to the initial two-factor CFA measurement model, in which factor loadings were fixed to the solution with 2 correlated errors. The average correlation difference between SWB and PERMA was 0.02. Moreover, 23 of 24 correlation differences between the two types of well-being were 0.05 or less, and no correlation difference exceeded 0.07, indicating substantial similarity. For each character strength, hypothesis tests (Steiger's *z*-test) were conducted to determine differences between SWB and PERMA correlations. Of the 24 strengths tested, 15 correlations were significantly different, although given the large sample size, the correlation difference only had to be less than 0.02 to be non-significant. Results are presented in Table 3.

Table 3. Correlations of SWB and PERMA with VIA strengths.

Variable	SWB	PERMA	$\lvert\Delta r\rvert$	Steiger's z	*p*-Value	B–H cutoff
Hope	0.38	0.38	0.00	0.00	N/A	N/A
Love	0.32	0.32	0.00	0.00	N/A	N/A
Humility	0.08	0.08	0.00	0.00	N/A	N/A
Humor	0.26	0.26	0.00	0.00	N/A	N/A
Gratitude	0.39	0.38	0.01	0.00	N/A	N/A
Fairness	0.16	0.15	0.01	1.07	0.285	N/A
Spirituality	0.20	0.19	0.01	1.08	0.280	N/A
Leadership	0.19	0.20	0.01	1.08	0.280	N/A
Kindness	0.21	0.22	0.01	1.09	0.276	N/A
Judgment	0.10	0.12	0.02	2.14	0.032	0.003
Prudence	0.10	0.12	0.02	2.14	0.032	0.007
Honesty	0.19	0.21	0.02	2.17	0.030	0.010
Zest	0.33	0.35	0.02	2.26	0.024	0.013
Perseverance	0.18	0.21	0.03*	3.25	0.001	0.017
Social intelligence	0.21	0.24	0.03*	3.27	0.001	0.020
Teamwork	0.25	0.22	0.03*	3.28	0.001	0.023
Appreciation beauty	0.14	0.18	0.04*	4.30	<0.000	0.027
Creativity	0.13	0.17	0.04*	4.30	<0.000	0.030
Love of learning	0.16	0.20	0.04*	4.32	<0.000	0.033
Bravery	0.18	0.22	0.04*	4.34	<0.000	0.037
Forgiveness	0.22	0.18	0.04*	4.34	<0.000	0.040
Perspective	0.19	0.23	0.04*	4.35	<0.000	0.043
Curiosity	0.22	0.26	0.04*	4.38	<0.000	0.047
Self-regulation	0.08	0.15	0.07*	9.65	<0.000	0.050

Notes: Values presented in columns SWB and PERMA represent correlations between the latent well-being factor and observed character strength composite; N/A = not applicable; *significant by the Benjamin–Hochberg (B–H) type I error correction procedure starting with $\alpha = 0.05$.

Latent profile analysis

Negative emotions were reverse coded prior to analyses to enhance graphical interpretation. Happiness was excluded due to statistical problems with latent profile analysis resulting from single-item measures.[7] Variances were allowed to differ across profiles and covariances were fixed to zero. Fit statistics for latent profile structures are presented in Table 4. The final model chosen was a three-profile solution. Compared with the one- and two-profile solutions, the three-profile solution had lower LL, AIC, BIC, and SSA-BIC values, no reduction in entropy, and the LMR test remained significant ($p < 0.05$). Although the 4-profile model converged and had lower LL, AIC, BIC, and SSA-BIC values than the 3-profile solution, it was not chosen because the LMR test was non-significant ($p = 0.54$) and there was a 14% decrease in the number of log likelihood values replicated. Figure 2 displays the standardized means of each of the 7 well-being variables across the three latent profiles. As demonstrated by the absence of overlap between any profile lines, the well-being variables clustered together, such that if participants scored low on one indicator of well-being, they scored low on the others. No qualitatively distinct well-being profiles emerged. Participants differed only on their degree of general well-being: low, medium, or high. The majority of participants were assigned to the Medium group (51.5%), followed by the Low group (28.6%), then High group (19.9%).

Discussion

A large number of researchers have developed their own theoretical models of well-being and measurement approaches to operationalize their models. Until recently (Disabato et al., 2016; Jovanovic, 2015; Longo et al., 2016), what has been missing from the literature is direct, comprehensive tests comparing models. This study presents evidence from four analytical techniques that Seligman's (2011) model of PERMA and Diener's (1984) model of SWB represent the same type of well-being. Confirmatory factor analyses (CFA) yielded a very strong correlation (*rs* between 0.94 and 0.98) between SWB and PERMA. Exploratory structural equation modeling (ESEM),

Table 4. Fit statistics for latent profile structures.

Classes	LL	# of replications	AIC	BIC	SSA-BIC	Entropy	LMR test	LMR *p*-value	Class 1 probability (subsample size)	Class 2 probability (subsample size)	Class 3 probability (subsample size)	Class 4 probability (subsample size)
1	−9231.77	50/50	18,491.53	18,551.01	18,506.57				1.00 (517)			
2	−8419.03	50/50	16,896.06	17,019.25	16,927.20	0.90	1608.32	0	0.53 (273)	0.47 (244)		
3	−8088.22	42/50	16,264.44	16,451.35	16,311.69	0.91	654.632	0.01	0.51 (266)	0.20 (103)	0.29 (148)	
4	−7889.22	36/50	15,896.43	16,147.07	15,959.79	0.91	393.81	0.54	0.14 (70)	0.33 (172)	0.39 (201)	0.14 (74)

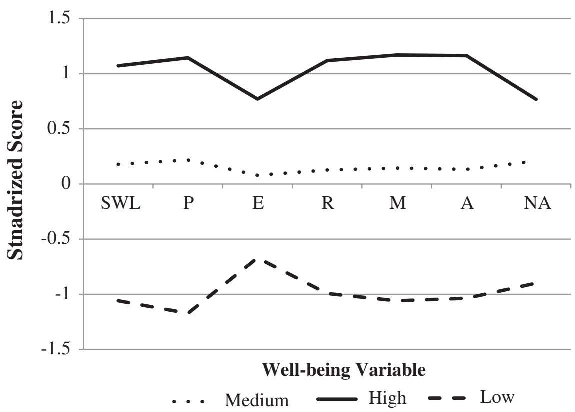

Figure 2. Latent profile analysis (LPA) of types of well-being. SWL = satisfaction with life; HAP = happiness; NA = negative affect (reverse coded); P = positive emotions; E = engagement; R = positive relationship; M = meaning; A = accomplishment.

arguably a more conservative factor analytic approach than CFA, offered similar support for considerable overlap between the two well-being models (*r*s between 0.85 and 0.86). Nomological net analyses showed that correlations between each model of well-being and various character strengths were nearly identical. Latent profile analyses (LPA) yielded three profiles of people who differed only in degrees of well-being across all indicators (low, medium, and high). No qualitatively unique profiles of well-being emerged. Results from this study suggest that PERMA does not represent a different type of well-being than SWB.

Well-being factors and facets

Following Diener's (1984) seminal SWB model put forth more than 30 years ago, researchers have sought to construct new models to capture types or parts of well-being excluded from SWB. Results from the present study suggest PERMA and SWB capture the same type of well-being when measured with self-report scales. The findings add to a growing body of work (Disabato et al., 2016; Jovanovic, 2015; Longo et al., 2016) that suggests well-being is best conceptualized as one factor consisting of unique facets (i.e. one factor with different facets) rather than consisting of unique types of well-being exist (i.e. different factors). In the case of PERMA and SWB, our results do not suggest that the lower-order facets are different from one another. The average correlation magnitude between any two well-being facets was 0.61, which indicates some discrimination. Prior research supports this notion; for example, positive affect and meaning in life are distinct facets that have demonstrated unique predictive validity (King, Hicks, Krull, & Del Gaiso, 2006; McGregor & Little, 1998). Our results do not suggest these two facets are identical or redundant. Rather, results of the present study and others suggest that models that attempt to *combine* these facets together into unique 'types' of well-being are substantially correlated with one another and often tap into the same type of well-being.

An analogue can be drawn from basic personality science. Different models of the broad personality traits contain different facets, but often contain the same Big 5 factors (plus or minus one): Extraversion, neuroticism, conscientiousness, agreeableness, and openness to experience. In Costa and McCrae's (1995) NEO model the facets of extraversion are warmth, gregariousness, assertiveness, activity, excitement seeking, and positive emotions. In Ashton et al.'s (2004) HEXACO model the facets of extraversion are social self-esteem, social boldness, sociability, and liveliness. In Saucier and Ostendorf's (1999) lexical model the facets of extraversion are sociability, unrestraint, assertiveness, and activity-adventurousness. While many of the facets are different, most personality scientists would argue the models all capture the same 'type' of extraversion.

Because models of well-being tend to capture the same type of well-being, the incremental benefit of a new model derives from the theoretically meaningful combination of facets. Models of well-being require precise descriptions of why certain facets should be combined together. Regarding PERMA, there is a lack of theoretical or empirical rationale about why these particular five facets (i.e. positive emotions, engagement, relationships, meaning, accomplishment) were chosen above others. Although Seligman (2011) reviews empirical literature linking each component with well-being, these five facets do not represent an exhaustive list of variables that are positively related to well-being. Other researchers argue that 16 basic desires underlie human behavior (Reiss, 2004), or that ten features underlie well-being (Huppert & So, 2013). A recent thematic review of self-report measures of well-being further underscores this problem – of the 99 self-report measures analyzed, 196 facets of well-being were identified (Linton, Dieppe, Medina-Lara, Watson, & Crathorn, 2016). How many possible unique five-facet combinations can be created from the 196 facets Linton et al. (2016) found? A mere 2,289,653,184.

As for which facets of well-being are 'better' or 'more important', it is up to the researcher (and ultimately, the individual) to theorize, test, and decide (Biswas-Diener, Kashdan, & King, 2009; Kashdan et al., 2008). The mere notion of developing consensus on what is and what is not well-being is a topic of debate embedded with personal beliefs and biases. Inevitably, people will value certain well-being facets above others – positive affect more than meaning in life, social relationships more than autonomy, and so on. Relatedly, there is the issue of tautology (Kashdan, 2004; Kashdan et al., 2008). If accomplishment is used to measure well-being, then accomplishment cannot be studied as a predictor of well-being. Perhaps this issue is one reason that some researchers have advocated for SWB and subjective happiness as the sole facets of well-being itself and other constructs (e.g. accomplishment, positive relationships) as predictors (Sheldon, 2016). Regardless of one's values and preferences, rigorous empirical examination of well-being facets serves to advance the science of well-being. Indeed, critiques of Diener's (1984) SWB model (among others) have led to an important outcome – the empirical investigation of areas of well-being beyond life satisfaction and emotions (e.g. meaning and purpose in life, autonomy; Ryan & Huta, 2009).

Future research on well-being

The majority of studies on well-being are comprised of self-report global questionnaires. It remains unclear whether behavioral and economic indicators of well-being represent aspects of well-being distinct from what is commonly captured by self-reports. Assessing a person's well-being using different measures or from multiple perspectives (i.e. informant reports) might yield distinct types of well-being (although the only empirical study we are aware of with informant reporting found no evidence for different well-being types; Nave, Sherman, & Funder, 2008). Assessments of discrete behaviors, either through observational measures, heart-rate variability, experience-sampling, or performance tests, potentially offer unique insights into well-being that global, subjective measures do not (e.g. Steger, Kashdan, & Oishi, 2008). As one example, nearly every study of character strengths does not use behavioral measures of what people actually do. If character strengths were measured by density distributions of how people acted in everyday moments, we might find that self-regulation and perseverance are in fact strongly related to achievement facets of well-being (e.g. Carver & Scheier, 1998; Roberts, Walton, & Bogg, 2005).

In regards to analytic approaches, the principle of critical multiplism promotes multiple types of statistical models to test the same hypothesis (Patry, 2013). The present study used four different statistical analyses – CFA, ESEM, nomological net, and LPA – to answer our central research question: Is PERMA a distinct type of well-being from SWB? The emergence of ESEM has allowed for greater critical multiplism in measurement research. However, some researchers have only used ESEM and largely ignored other statistical analyses. Joshanloo & colleagues (Joshanloo, 2016a, 2016b; Joshanloo, Jose, & Kiepikowski, 2017; Joshanloo & Lamers, 2016) have argued that 'ESEM is a more appropriate method than CFA in the study of multi-dimensional constructs, such as mental well-being' (Joshanloo, 2016b; abstract). This statement ignores the vast quantitative research on CFA models, in particular second-order and bifactor models for multi-dimensional constructs (e.g. Chen, West, & Sousa, 2006). Both confirmatory and exploratory factor analytic approaches have strengths and weaknesses that must be thoughtfully balanced. Rather than assuming one type of factor analysis is 'better', critical multiplism encourages the use and interpretation of both analytic approaches, along with non-factor analytic approaches (e.g. LPA).

Limitations

Several limitations of the present study warrant mentioning. MTurk was used to recruit participants from the United States and all measures were completed with online surveys. It is unclear how representative MTurk populations are to the United States at large, not to mention other countries. Although demographically diverse (Buhrmester et al., 2011), MTurk participants are often elevated on clinical traits such as depression and social anxiety (Arditte, Çek, Shaw, & Timpano, 2016). In addition, participant motivation and attention have shown to be worse for online surveys compared to in-person surveys (Johnson, 2005). Although the present study included attention check items to remove careless responders, it is possible participants rushed through the survey to quickly finish. This could have resulted in artificially similar response patterns across measures due to participants not thinking about the nuanced differences between measure instructions and item wording. We conducted analyses at the subscale level rather than the item level due to sample size restrictions. Studies with larger samples could try to fit models with all of the well-being and character strength items. Additionally, we used a one-item measure of happiness to capture positive affect, which did not include a variety of positive emotions nor allow us to examine subscale reliability. Finally, as with intelligence, different types of well-being may exist, but are difficult to measure scientifically (e.g. reaching one's full potential). Different scales than those used in the present study might be better suited to capture various types of well-being or well people.

Conclusion

For many individuals, their primary life aim is to experience high levels of well-being on a consistent basis. In the modern era, there is a surge of interest in measuring well-being as the primary target of coaching, interventions in schools and business organizations, and as an index of the quality of nations to supplement economic indicators. Yet, as demonstrated in this study and others, the empiricism of well-being is less straightforward. Our findings suggest new models of well-being do not necessary yield new types of well-being. Scientific progress is made when new models of well-being offer new insights beyond existing models such as SWB (Diener et al., 2017). New models of well-being that include either novel facets, theoretically justified combinations of facets, or truly distinct types of well-being are likely to offer the greatest contributions to our understanding of a life well-lived.

Notes

1. Ryff's (1989) Scales of Psychological Well-being is most often used to operationalize eudaimonic well-being, but the theoretical and conceptual ideas stem from Jahoda (1958). Jahoda proposed the inclusion of positive states in defining and measuring mental health. Her model of 'Ideal mental health' includes six components (that have a great degree of overlap with Ryff's PWB model): efficient self-perception, realistic self-esteem and acceptance, voluntary control of behavior, true perception of the world, sustaining relationships and giving affection, and self-direction and productivity.
2. As Long et al. (2016) described in their paper, they originally found a latent correlation of 0.76. While at first glance this correlation suggests some (albeit weak) discrimination, Longo et al. (2016) found that the correlation was attenuated by method variance: most of the positive feelings items were normally coded and most of the positive functioning items were reverse coded. Negatively worded items have been shown to load onto their own factors for purely methodological reasons (Marsh, 1996; Woods, 2006). After correcting for the method variance by replicating the study with all normal coded items, the latent correlation was 0.97, suggesting negligible discriminant validity between the two constructs of well-being.
3. Finite mixture models such as LPA are prone to converging on local maxima of the log likelihood function rather than the global maxima. To increase confidence that the expectation-maximization algorithm has converged onto the global maxima, it is recommended that researchers do the analysis 50 times or more with unique starting values and determine if the algorithm converged on the same log likelihood function. If yes, then there is some support (although not definite proof) that the algorithm has found the global maxima. If not, the results are suspect and should be interpreted with caution.
4. When conducting the factor analyses at the item level, results were very similar. We used polychoric correlations with the weighted least squares estimator with a scale-shifted chi-square value (WLSMV in Mplus). We created a bifactor measurement model for SWB and bifactor measurement model for PERMA. The two general factors had a latent correlation of 0.98 (CFI = 0.98, TLI = 0.97, RMSEA = 0.08).
5. Inclusion of an error between happiness and positive emotions (r = 0.20) barely changed the results. The factor loadings for happiness and positive emotions were slightly less and the latent correlation was 0.95.
6. Results were nearly identical when the alternative two-factor CFA model was used.
7. Results for the two and three-profile models were nearly identical when happiness was included. Four and five-profile models did not converge.

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