The Well-Being Profile (WB-Pro): Creating a Theoretically-based multidimensional measure of well-being to advance theory, research and policy-practice

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Abstract

There is no universally agreed definition of well-being as a subjective experience, but Huppert and So (2013) adopted and systematically applied the definition of well-being as positive mental health–the opposite of the common mental disorders described in standard mental health classifications (e.g., Diagnostic and Statistical Manual). We extended their theoretical approach to include multi-item scales, using two waves of nationally representative US adult samples to develop, test and validate our multidimensional measure of well-being (WB-Pro). This resulted in a good-fitting *a priori* (48-item 15-factor) model that was invariant over time, education, gender, and age; showed good reliability (coefficient alphas .81-.93), test-retest correlation (.73-.85; *M* = .80), and convergent/discriminant validity based on a multitrait-multimethod analysis, and relations with demographic variables, selected psychological measures, and other multidimensional and purportedly unidimensional well-being measures. Further, we found that items from two widely used, purportedly unidimensional well-being measures loaded on different WB-Pro factors consistent with *a priori* predictions based on the WB-Pro factor structure, thereby calling into question their claimed unidimensionality and theoretical rationale. Because some applications require a short global measure, we used a machine-learning algorithm to construct two global well-being short versions (5- and 15-item forms) and tested these formative measures in relation to the full-form and validity criteria. The WB-Pro appears to be one of the most comprehensive measures of subjective well-being, based on a sound conceptual model and empirical support, with broad applicability for research and practice, as well as providing a framework for evaluating the breadth of other well-being measures.

Keywords: Multiple dimensions of well-being; convergent and discriminant validity; formative, reflective and unidimensional scales; factor analysis; machine-learning.

Public Significance Statement: Based on a systematic and coherent theoretical approach to defining well-being, we have used state-of-the-art psychometric techniques to develop and validate a new multidimensional well-being measure (WB-Pro). The full professional version (48-items, 15-factors) is recommended for high-quality well-being research. It is also available in shorter versions (15 and 5-items) that can be utilized where is it not practical to use the full version.

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There are many approaches to conceptualizing well-being, and each has different implications for how well-being should be measured. Some researchers use the term well-being very broadly to include objective circumstances, including economic and social conditions (e.g. income, housing and education) or lack of mental ill-health symptoms (e.g. depression and anxiety), but our focus is on well-being as a subjective experience beyond simply neutral levels of mental ill-health. We briefly review the many different approaches to conceptualizing well-being in its subjective sense in order to set the context for the present study.[1]

Conceptual Framework for Defining Well-Being

At its broadest level, well-being refers to our perception of how well our life is going. For some researchers, this concept is best captured by a global evaluation of how satisfied we are with our life. This evaluation most frequently relies on a single question, and it appears the earliest reference to such a survey measure is Cantril (1965). Some scholars prefer to use several questions to evaluate life satisfaction (e.g. Diener, Emmons, Larsen, & Griffin,1985; Cummins,1996). For certain purposes, this global evaluation, particularly when it results in a single number, can be very useful. For example, economists are increasingly interested in measuring subjective well-being in national and cross-national surveys to supplement the traditional reliance on economic indicators as the principal drivers of policy. In this context, they argue that a single numerical estimate of subjective well-being is necessary to place alongside a single numerical estimate of measures such as GDP (e.g. Clark, Flèche, Layard, Powdthavee & Ward., 2018)

[1] The literature contains some unhelpful terminology, with some authors using the terms ‘subjective well-being’ and ‘psychological well-being’ in very restrictive ways and strictly differentiated from each other. However, since our focus is on well-being in its general subjective sense, and since each of these terms actually refers to experiences that are both subjective and psychological, we use the terms interchangeably. On the occasions when we use the term ‘well-being’ on its own, it refers to these subjective aspects of well-being as opposed to objective aspects of well-being. It is worth noting that there is some overlap between the terms ‘well-being’ and ‘quality of life,’ although the later is typically used in the context of healthcare. Quality of life scales may include questions about how people feel and aspects of their psychological functioning, but in contrast to well-being measures, they emphasize health status, physical capability, and ability to function in a sociocultural context (WHOQOL Group, 1994).

In contrast, some scholars view well-being as the presence of positive emotions such as happiness, rather than as a global evaluation of life (e.g. Bradburn, 1969; Fredrickson, 2009; Kahneman, Diener & Schwarz, 1999; Layard, 2005). This is the hedonic view of well-being. Among the earliest scales that measure this construct are Bradburn's Affect Balance Scale (1969) and the Positive and Negative Affect Scale (PANAS) of Watson, Clark and Tellegen, and Sarason (1988), while the Scale of Positive and Negative Experience (SPANE) of Diener et al. (2010) is among the most recent. One of the critiques of the view that well-being can be equated with positive affect is that emotions are ephemeral, whereas a longer perspective is needed to establish how well our life is going. In addition, happiness can be achieved in ways that are very unhelpful to the individual in the longer term, such as the use of mood enhancing drugs.

Another conceptual approach is that well-being cannot be reduced to either happiness or life satisfaction alone, but that well-being comprises a number of different components (Huppert, 2014). According to Diener, Suh, Lucas, & Smith (1999), 'subjective well-being' is the combination of life satisfaction, the presence of pleasant affect and the absence of unpleasant affect. Other scholars postulate that the subjective experience of well-being is more than the combination of feeling good and being satisfied; it also includes functioning well both personally and socially. This is sometimes referred to as eudaimonic well-being (Ryan & Deci, 2001). Some scholars conceptualize well-being purely in terms of eudaimonic well-being. This includes Ryff's (1989) Psychological Well-being, which describes six dimensions of personal and social functioning: autonomy, environmental mastery, personal growth, positive relationships, purpose in life, and self-acceptance. Another example of a eudaimonic conceptualization is self-determination theory (Ryan & Deci, 2000), which postulates that the fulfillment of three basic psychological needs—autonomy, competence, and relatedness—is both essential and sufficient for well-being. However, a number of leading authorities (e.g. Seligman, 2002, 2011; Keyes & Waterman, 2003) argue that true well-being requires the combination of hedonic well-being (positive affect) and eudaimonic well-being. This framework has also been adopted by the Organization for Economic Co-operation and Development (OECD), which regularly undertakes cross-national well-being surveys. Their guidelines state that well-being measures should include positive affect, eudaimonic well-being and life evaluation (OECD, 2013).

In a pragmatic approach to creating a consensus on the components of well-being, Su, Tay & Diener (2014) undertook a review that combined all the existing approaches. They describe a multicomponent model with 18 facets of positive functioning, representing 7 dimensions of psychological well-being: subjective well-being (satisfaction with life, positive emotions), relationships (positive relations with others, belonging), meaning (purpose in life), engagement, mastery (competence, self-efficacy, self-esteem), optimism, and autonomy (need for autonomy, control). Despite this pragmatic effort of Su et al. (2014), there remains a lack of a consensus on an appropriate theoretical framework.

One theoretical framework with a long history defines psychological well-being as equivalent to positive mental health, and includes both eudaemonic and hedonic aspects of well-being. This approach has been adopted by many organisations and individuals, including the World Health Organization (1947), where mental well-being was equated with mental health and the term, 'mental health' was used to refer to a positive state, and not just the absence of mental disorders. Jahoda (1958) contrasted psychological well-being with psychological ill-being and defined six elements of positive psychological functioning: attitudes of an individual toward his/her own self, personal growth or self-actualization, integration, autonomy, perception of reality, and environmental mastery. A similar approach was taken by Ryff (1989), who also proposed six dimensions of psychological well-being.

The present study builds on the theoretical approach that defines well-being as equivalent to positive mental health. One of the benefits of the positive mental health approach is that, in contrast to the lack of agreement on the components of psychological well-being, there is international agreement on the components (symptoms) of psychological ill-being as listed in the International Classification of Diseases (ICD) Mental and Behavioural Disorders (World Health Organization, 1990;2018) and the Diagnostic and Statistical Manual (DSM) of Mental Disorders (American Psychiatric Association, 1994, 2013). The basic lists of symptoms of mental disorders remain virtually unchanged across different editions of these manuals, even though there is continued debate on whether and how individual diseases should be classified (Kotov et al. 2017). We acknowledge that we did not include symptoms from all mental disorders which could have broadened the model. However, our focus was on the disorders which are regarded as common mental disorders not only in the sense of their high prevalence, but also in the sense that they can affect anyone in the general population, which is not the case with most other mental disorders.

Building on this body of knowledge about the symptoms of ill-being, Huppert and So (2013) suggested that well-being goes beyond a neutral point which merely reflects an absence of mental ill-being symptoms, proposing a typology of well-being that is the opposite of the symptoms of the common mental disorders. They began with a list of the psychological symptoms and criteria used to describe the most common mental disorders, depression and anxiety, as described in the two widely used international classifications of diseases (DSM, ICD). They focused on categories of Major Depressive Episode (DSM) and Depressive Episode (ICD), and on Generalized Anxiety Disorder (terminology common to both systems) that were most prevalent and had logical polar opposites. Conceiving well-being as lying at the opposite end of the spectrum to the common mental disorders, Huppert and So (2013) identified features such as happiness and hopefulness (the opposite of specific depression symptoms) or calmness and resilience (the opposite of core symptoms of generalized anxiety). In addition, they included DSM Axis V- Global Assessment of Functioning, which rates an individual's general level of personal and social functioning, and which the ICD classification includes within their diagnostic criteria.

This systematic approach yielded ten features of positive well-being. It was found that these ten features combined positive feeling and positive functioning (i.e. hedonic and eudaimonic aspects of well-being): competence, emotional stability, engagement, meaning, optimism, positive emotion, positive relationships, resilience, self-esteem, and vitality.

Framework for Measuring Well-Being

As can be seen from the preceding brief review of the different approaches to conceptualizing well-being, there seems to be widespread agreement that well-being is best understood as a multidimensional construct, so measures of well-being need to reflect this. Of course, it would be convenient if we could measure how well a person perceives their life to be going using a single construct or better still, a single question such as a life satisfaction or happiness question, but this would not be very illuminating if well-being is really a multidimensional construct. A single construct or single item could not provide useful information about the profile of different components that make up well-being, and as a result, it could not provide practical guidance to policy makers about which components of well-being need to be improved, nor specific interventions to improve these components. The need for a multidimensional approach to measuring well-being is evident in large scale studies showing that groups or countries can obtain identical scores on a life satisfaction measure, but display completely different profiles on well-being dimensions (Huppert & So, 2018).

A number of scales specifically recognize the multidimensional nature of well-being and provide subscales for measuring different dimensions. This includes the PERMA Profiler (Butler & Kern, 2016) based on Seligman's (2011) five proposed pillars of well-being (positive emotion, engagement, relationships, meaning, accomplishment), Ryff and Singer's (1996) Psychological Well-being scales, and Ryan & Deci's (2000) Basic Psychological Needs Satisfaction Scale, as well as the Comprehensive Inventory of Thriving (CIT) of Su et al. (2014).

Other popular scales, although not providing subscales for measuring specific dimensions, have nevertheless recognized the multidimensional nature of well-being, by including multiple items which cover a range of well-being constructs. These include, the Warwick-Edinburgh Mental Well-being Scale of Tennant et al. (2007) and the Flourishing Scale of Diener et al. (2010). However, the way in which these scales are scored usually results in a single, total score. While it is important to use a range of items to capture the diversity of processes and characteristics that underpin well-being, converting these items into a single score does not provide insight into how an individual is doing on the various dimensions of well-being. As emphasized by Marsh (2007), if a survey instrument is an ill-defined mix of different items that are not supported by a well-established factor structure and are summarized by an average of these items, then there is no basis for knowing what is being measured. Here we take an alternative approach, starting with a systematic conceptual framework for measuring well-being.

Huppert and So (2013) developed an operational definition of flourishing based on psychometric analysis of indicators of 10 components of well-being, using data from well-being questions that were administered to a representative sample of 43,000 Europeans who participated in The European Social Survey (ESS). There were striking differences in country profiles across the 10 features. Huppert and So concluded that their profiles offered fresh insights into cultural differences in well-being as well as promising targets for policies to improve well-being. Their comparison with a life satisfaction measure showed that valuable information would be lost if well-being had been measured only by life satisfaction. Taken together, their findings reinforce the need to measure subjective well-being as a multidimensional construct in future surveys. However, as previously mentioned, one weakness in their study is that each component/dimension is represented by only a single item.

The Present Investigation

Components of Well-Being

The overarching purpose of our research is to develop a concise measure of well-being that produces reliable and valid scores on each of the theoretically derived dimensions of well-being, with particular emphasis on those proposed by Huppert and So (2013). Following Goglo et al. (2014) and others (e.g., Marsh, Ellis, Parada, Richards & Heubeck, 2005), we argue that in relation typically limited testing time and cost effectiveness for large surveys, brief scales of 3 or 4 items are desirable as long as psychometric support is strong. Based on our review of the well-being literature, we identified five important constructs that had not been included in the original list. Three of these, competence, self-acceptance and autonomy, have an individual focus like the ten original constructs, while two of the new components (empathy and prosocial behavior) have an interpersonal focus. The importance of these additional constructs for positive mental health was independently supported through consultations with several clinical psychologist colleagues.

The term ‘competence’ was included in Huppert and So's (2013) original list of constructs, but it could more accurately have been described as ‘clear thinking’, since the DSM/ICD criteria from which it was derived concern the ability to think, concentrate and make decisions. In the current version, we added a more traditional measure of ‘competence’ arguably a core component of general well-being and thriving (Marsh, Martin, Yeung & Craven, 2017; Ryan & Deci, 2017). People who feel a sense of general competence have higher self-esteem (Thøgersen-Ntoumani & Ntoumanis, 2007), and greater satisfaction with life (Meyer, Enstrom, Harstveit, Bowles, & Beevers, 2007). Conversely, individuals with anxiety and depression have difficulty achieving goals and report feeling a lack of general competence (e.g., Ryan & Deci, 2017; Wei, Shaffer, Young, Zakalik & Hansen, 2005).

Considerable theory and research based on the SDT (Ryan & Deci, 2001, 2017) argues a lack of autonomy underpins all of the common mental disorders. Depression and anxiety are associated with decrements in perceived volition and control over one's life, and the tendency to make decisions out of shame, guilt or avoidance, rather than one's longer term values and aspirations (Ryan & Deci, 2017). All of these tendencies are linked to an absence of autonomy, meaning a general sense of autonomy is a core component of healthy functioning (Ryan & Deci, 2017).

Further, depression and anxiety are linked to a general non-acceptance of oneself and one's life (Hayes, Strosahl, & Wilson, 1999; Hayes, Strosahl, & Wilson, 2012). In clinical and non-clinical samples, non-acceptance is strongly correlated with measures of general psychopathology (Hayes et al., 2004) and specific measures of anxiety and depression (Forsyth, Parker, & Finlay, 2003; Marx & Sloan, 2005; Roemer, Salters, Raffa, & Orsillo, 2005; Tull, Gratz, Salters, & Roemer, 2004). Indeed, third-wave behavioral theories of psychopathology such as Acceptance and Commitment Therapy have identified the tendency toward the avoidance and non-acceptance of one's internal states (i.e., thoughts and emotions) as a generalized process underlying all psychopathology (Hayes et al., 1999). In this way, self-acceptance is a core feature of subjectively experienced well-being, wherein one's internal states are acknowledged and not suppressed.

Empathy and prosocial behavior were included on the basis that prosocial emotions and behaviors are central to human functioning and vitality (Eisenberg, Fabes, & Spinrad, 2007; Weinstein & Ryan, 2010). Empathy is the tendency to vicariously experience other individuals' emotional states (Davis, 1994). Individuals with some mental health disorders have difficulty feeling the emotions of others and taking the perspective of others (e.g. Baron-Cohen, 2011; Caligor, Levy & Yeomans, 2015). In contrast, empathy is essential to positive social functioning (Batson, 1991; Eisenberg et al., 2007) and has been associated with group cohesion (Henry, Sager, & Plunkett, 1996), relationship satisfaction (Davis & Oathout, 1987), and prosocial behavior (Sahdra, Ciarrochi, Parker, Marshall & Heaven, 2015), and as such is an important feature of healthy individual functioning.

Prosocial behavior has been defined as “voluntary behavior intended to benefit another” (Eisenberg et al., 2007, p. 646). It is related to empathy but conceptually distinct from it, in that the former describes observable behavior, whereas the latter describes an internal state. Depression and anxiety have also been negatively linked to prosocial behavior, including social withdrawal, and less capacity to respond to the needs of others (Eisenberg et al., 2007).

Based on the above considerations, it was decided to add these five constructs to the ten described by Huppert and So (2013). Although not directly derived from the inverse of DSM/ICD classifications, all are at least indirectly related to these classifications, and vetted by clinical psychologists. This provides an opportunity to examine how the original constructs and the newer constructs are related to each other, how each is related to a standard measure of well-being such as life satisfaction, and to test the independence of the 15 constructs.

WB-Pro: Development and Refinement of a Preliminary Item Pool

The preliminary development and refinement of an item pool took place in three stages. In the first stage, an extensive pool of a total of 195 items was prepared by the authors to represent the 15 WB-Pro factors—the 10 originally proposed by Huppert and So (2013) and the additional five factors added in the present investigation. In an initial evaluation, 29 leading academic colleagues with relevant backgrounds were provided with the 15 constructs and sorted each of 195 items into what they considered to be the most appropriate construct (or constructs) and commented on the suitability of each item. On the basis of this feedback, we refined the item pool to a total of 132 items representing the 15 constructs. A Qualtrics survey was then developed in which the order of items was randomized for each participant and administered electronically to a large, representative sample of US adults. Using the standard procedures for developing a "short form" (see Marsh, Ellis et al., 2005; Marsh, Martin & Jackson, 2010), the item pool used at Time 1 (T1) was reduced to an item pool of 60 items to represent the 15 constructs, and these were the basis of the survey administered at Time 2 (T2). In particular, items were retained that: loaded substantially on the factor they were designed to measure; contributed to the reliability of the scale; did not cross-load substantially on other scales; and did not have substantial correlated uniquenesses with other items. Care was also taken to select items that maintained the breadth of the original construct. Using a similar procedure, the set of 60 WB-Pro items retained at T2 was further reduced to the 48 items comprising the final version of the WB-Pro. All analyses presented here are based on this final set of 48 items (see Figure 1).

In summary, based on these selection procedures and traditional criteria of a psychometrically sound instrument, we sought to construct the WB-Pro instrument such that it demonstrates:

- Good reliability: Median Cronbach's coefficient alpha ≥ .80 across the scales (T1 & T2);
- Good test-retest stability over three months: median test-retest correlation ≥ .70 across the 15 scales (repeat sample from T1 & T2);
- A well-defined, replicable factor structure as shown by structural equation modelling in relation to traditional indices of fit (Marsh, Hau & Wen, 2004; T1 & T2);
- A factor structure that is invariant over gender, age, level of education, and time as shown by multiple-group structural equation models (T1 & T2);
- Applicability for participants across the age range from late-adolescent/young adult, middle-age, and older adults (combined sample from T1 and T2);
- Convergent and discriminant validity in relation to: (a) multitrait-multimethod (MTMM) analyses of WB-Pro responses in relation to time (test-retest stability, T1 and T2); (b) other multidimensional measures of well-being (e.g., PERMA, Basic Psychological Needs, T2); (c) multi-item, purportedly unidimensional well-being instruments (e.g., WEMWBS, Flourishing, T2); (d) other selected psychological measures (depression, stress; life satisfaction, happiness, sleep, life-event changes); and selected demographic variables (gender, age, marital status, English fluency, education).

Finally, we recognize that some applications require a short global measure rather than the full multidimensional WB-Pro. This might be because particular applications might not be able to include the full 48-item measure due to time constraints, or because researchers are only interested in a global measure of well-being. For this reason, we used a novel machine learning approach to construct two global well-being short-forms. The 15-item version (WB-Pro15), maintains the full range of dimensions by selecting the best item from within each of the 15 dimensions. The even shorter 5-item version (WB-Pro5) selects the best 5 items from among the 48-items. We offer these short, global measures as formative indices of well-being, but emphasize that the full version WB-Pro provides a more reliable and robust, multidimensional representation of well-being.

Further, we note there has been considerable theoretical and statistical confusion in the construction and evaluation of global measures of well-being based on single-item indicators of selected components of well-being, as in the 14-item WEMWBS (Tennant et al., 2007), and 8-item Flourishing Scale (Diener et al, 2010). It is our contention that these multi-item global measures, like the WB-Pro5 and WB-Pro15, should be considered formative rather than reflective measures, and that psychometric criteria like unidimensionality are inappropriate and, perhaps, even counter-productive in the construct and evaluation of formative scales. In support of these claims, we demonstrate that WEMWBS and Flourishing measures really are multidimensional measures. First, we conceptually map the 14 WEMWBS items and the 8 Flourishing items onto the 15 WB-Pro factors based on item content. Then we provide empirical support for this a priori conceptual mapping based on factor analyses of all 60 items (14 WEMWBS, 8 Flourishing, 48 WB-Pro). Implications of this distinction between formative and reflective measures are then discussed.

Methods

Participants

Data were collected from a nationally representative sample of U.S. adults sourced by Qualtrics, an enterprise survey technology solution entity. Ethical approval for the study was granted by the Research Ethics Board (2018-288H & 2018-289H). Qualtrics sourced the participants from several traditional and online market research panels and provided with a small monetary benefit for completing the surveys (between $2-5 USD worth of points that could be traded for merchandise). Participants were provided with a unique survey weblink to allow for them to be identified and matched for completed surveys in T1 and T2. Qualtrics used preliminary data screening to ensure that there were not multiple responses by the same respondent on the basis IP addresses and other preliminary data screening in relation to completion of the survey. Based on the data provided by Qualtrics, we used preliminary data screening filters to eliminate questionable responses: two validity check items instructing respondents to select a specific response; and a visual check for response patterns such as straight-lining or (i.e., selecting the same response in a row) or diagonal-lining. On this basis 3.2% of the respondents were eliminated.

As part of the first survey (T1), participants were also asked to indicate whether they would wish to be involved in the follow up survey (T2). The T2 survey was conducted 3 months after the T1 survey. Participants completed an online anonymous survey in exchange for points they received from the survey company, which could then be redeemed for merchandise. All participants provided basic demographic information (i.e., age, gender, marital status, education level, employment status, English fluency, and ethnic background). To increase the likelihood of the collected sample being representative of the general U.S. population, quota aims were established to align with the U.S. population breakdown of age and gender demographics, based on the figures published by the U.S. Census Bureau, with the samples collected for this study. There was minimal difference between the demographic breakdowns of the samples we used in both T1 and T2 and the national demographic data published by the U.S. Census Bureau.

A total of 1,035 participants completed the online survey at time T1; 51% female with a mean age of 45.5 years (SD = 16.5). Of these 1,035 participants, 444 also completed the T2 online survey, in addition to 1,082 newly sourced participants, making a total of 1,524 participants for T2; 49% female participants with a mean age of 47.7 years (SD = 16.9). In total, we considered 2559 sets of responses by 2117 participants that we divided into three groups: 1 (N = 591, T1 surveys by those completing surveys at T1 only); 2 (N = 444, T1 surveys by participants completing surveys at T1 and T2), and 3 (N = 444, T2 surveys by participants completing surveys at T1 and T2). Different sets of analyses were based on different groups of respondents.

Measures: key correlates and determinants of our 15 well-being factors

Life Changes. As part of the surveys at both T1 and T2, participants were asked: "Please indicate whether you have experienced any major changes in your life, whether positive or negative, during the past three months." Across the 2,559 sets of responses, only 24% indicated that there had been a major change. We then classified these as negative (10.3%), neutral (5.3%), positive (6.1%), or no significant events (78%; i.e., respondents who did not list a significant life change). For present purposes we constructed four dummy variables (with no significant events being the "no-events" category) and regressed these on the 15 well-being factors such that coefficients represent the effect a negative, neutral, or positive life change (compared to not having a significant life change).

Alternative measures and correlates of well-being. At T2, we added a set of psychological measures designed to test the convergent and discriminant validity of interpretations of the WB-Pro factors: well-being, measured using the standard life satisfaction question from the UK Office for National Statistics (Self, Thomas & Randall, 2012), the Warwick Edinburgh Mental Well-being Scale (WEMWBS -Tennant et al., 2007), the Flourishing Scale (Diener et al, 2010), the PERMA-Profiler (Butler & Kern, 2016); basic psychological need satisfaction and thwarting, measured with the Psychological Need Satisfaction and Frustration Scale (Chen et al., 2014); personality, measured via the Big Five Personality Inventory (see Marsh, Nagengast & Morin, 2013; Marsh, Lüdtke et al., 2010); psychological stress, measured with the ‘stress’ items of the Copenhagen Psychosocial Questionnaire II (Dicke, Marsh, et al., 2018; Pejtersen, Kristensen, Borg, & Bjorner, 2010;); depression, measured via the Center for Epidemiologic Studies Depression scale (8-item CES-D; Radloff, 1977; Steffick, 2000); sleep quality measured using items from the Sleep Quality Scale (Cappelleri et al, 2009); and general health adapted from a question from the European Social Survey (ESS, 2013).

Statistical Analysis

Factor Analysis. In addition to traditional descriptive statistics and reliability estimates, factor analysis was our primary statistical tool. As noted in their classic Annual Review of Clinical Psychology article, Marsh, Morin, Parker & Kaur (2014) emphasized that exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), path analysis, and structural equation modelling (SEM) have long histories in psychological research. Although CFA has seemed to largely supersede EFA, CFAs of multidimensional constructs typically fail to meet standards of good measurement: goodness of fit, measurement invariance, lack of differential item functioning, and well-differentiated factors in support of discriminant validity. Part of the problem is undue reliance on overly restrictive CFAs in which each item loads on only one factor. Using both “real” and simulated data, previous research has shown that when this assumption of CFA is violated, CFA factor correlations tend to be positive biased and that in some cases this bias can be substantial (Marsh, Morin, et al., 2014; also see Marsh, Guo, et al., 2019; Morin, Marsh & Nagengast, 2013). Exploratory SEM (ESEM), an overarching integration of the best aspects of CFA/SEM and traditional EFA, provides confirmatory tests of a priori factor structures, and relations between latent factors and multi-group/multi-occasion tests of full measurement invariance (e.g., configural, metric, and scalar invariance). Due in part to the bias in CFA when assumptions that each item loads on only a single factor, ESEM tends to result in better differentiation among the multiple factors. It incorporates all combinations of CFA factors, ESEM factors, covariates, grouping/multiple-indicator multiple-cause (MIMIC) variables, latent growth, and complex structures that typically have required CFA/SEM. Thus, ESEM has broad applicability to psychological research that is not appropriately addressed either by traditional EFA or CFA/SEM. For present purposes, the 2,559 sets of responses are based on participants who completed the survey only at Time 1 (N = 593), only at Time 2 (N = 1082), or both Times 1 and 2 (N = 884 sets of responses by 442 individuals). To maximize the number of cases, some of the factor analyses was done for the entire set of 2,559 responses in which that data was in the "long" (or stacked) format. For these long format analyses, because 442 participants contributed responses at both T1 and T2, we used the Mplus complex design option to adjust standard errors for the fact there were two sets of responses for these participants (Muthén & Muthén, 2017). However, to evaluate the test-retest stability of responses and the invariance of the factor structure over time, we structured the data into wide format.

In the present investigation, we combined and compared CFA and ESEM solutions in the selection of items to be used in the final WB-Pro, testing psychometric properties, test-retest stability, and MTMM analyses of convergent and discriminant validity. A detailed presentation of the application of ESEM and its extension is beyond the scope of this study (but see Marsh et al., 2014 for an overview of the wide applicability of ESEM; also see Marsh, Lüdtke et al. 2010; Marsh et al., 2009; Marsh et al., 2013; also see *Supplemental Materials*, Section 1). Particularly, the application of ESEM for the development of a short form is apparently a new application of ESEM that will provide an important methodological contribution to instrument construction more generally. Assessment of goodness-of-fit was based on indices that are relatively independent of the sample-size (Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004; Marsh, Hau, & Grayson 2005). The population values of Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) vary along a 0-to-1 continuum, such that values greater than .90 and .95 typically reflect acceptable and excellent fits to the data, respectively. Values smaller than .08 and .06 for the Root Mean Square Error of Approximation (RMSEA) support acceptable and good model fits, respectively.

Convergent and discriminant validity: Multitrait-multimethod analyses. The multitrait-multimethod (see Campbell & Fiske, 1959) design is used widely to assess convergent and discriminant validity, and also is a standard criterion for evaluating psychological instruments. The MTMM design provides a particularly strong approach to evaluating stability of responses to a multidimensional instrument, as emphasized by Campbell and O'Connell (1967) who specifically operationalized the multiple methods in their MTMM paradigm as multiple occasions. Marsh (Marsh, Ellis, Parada, Richards & Heubeck, 2005; Marsh, Martin & Jackson, 2010) also recommended this approach to evaluate support for the convergent and discriminant validity in relation to temporal stability over time. In this regard, convergent validities refer to stability over time (i.e., test-retest correlations) and the "method" factor is time. Although the design might be considered weak in relation to providing support for convergence based on maximally different methods (e.g., multiple respondents—self, peer; multiple instruments designed to measure the same traits), it provides a "best case" test in relation to discriminant validity. Thus, if there is no support for discriminant validity in relation to convergent validities based on time as the method factor, support for discriminant validity is unlikely to be found with other, more demanding tests of convergent validity.

Based on test-retest data from Time 1 and 2 (N=442 participants), we assessed convergent and discriminant validity in relation to time from a within-network perspective. For these analyses, "convergent validity" is test-retest correlation, whereas the different methods refer to time (see Marsh, Martin & Jackson, 2010 for an example of this approach). Marsh, Martin and Jackson (2010) demonstrated new and evolving latent-variable approaches that allow convergent and discriminant validity to be assessed using the traditional Campbell & Fiske (1959) criteria (the original and most widely used basis of assessing MTMM data) while still overcoming subsequent criticisms of these criteria. Further rationale for the MTMM approach we used in the present analyses appears in Section 4 of *Supplemental Materials*.

Convergent and discriminant validity: Relations with other Constructs. In subsequent analyses, we added demographic variables (marital status, gender, age, education, English fluency) and covariates to the WB-Pro factor structure. The covariates included multidimensional (PERMA, Psychological Need Satisfaction and Frustration Scale) and purportedly unidimensional measures of well-being (Flourishing, WEMWBS), as well as other measures (Big-Five personality, stress, depression, life satisfaction, happiness, sleep problems, general health, and exercise). The multidimensional measures of well-being included specific components of well-being that were included on the WB-Pro, providing a basis for testing convergent (agreement on matching factors) and discriminant (correlations for non-matching factors) validity.

Of particular interest were the multi-item purportedly unidimensional measures of well-being – in this study, we focused on the Flourishing Scale (Diener et al., 2010) and WEMWBS (Tennant et al., 2007) measures. We began by relating these measures to our WB-Pro factors and testing the claims that these measures are unidimensional. However, the nature of the items and the basis of their selection in the original construction of these measures suggested that items were included to reflect different components of well-being. Each of the co-authors of the present study undertook a priori classification of the 22 items (8 from the Flourishing, 14 from the WEMWBS) as being associated with one or more of the 15 WB-Pro classifications. These a priori classifications were then used to test ESEM models in which the 22 items from the Flourishing and the WEMWBS were "absorbed" into the WB-Pro ESEM using target rotation in which the target factor loadings were specified based on a priori classifications (i.e., items hypothesized to load on a particular factor were given a target of .8 and all others were given targets of zero). This 15-factor solution, with the Flourishing and WEMWBS items absorbed into the WB-Pro15-factor structure, was compared with separate factor structures in which Flourishing and/or WEMWBS items were used to define separate factors (i.e., with items not cross-loading on the WB-Pro factors). The goodness-of-fit and factor loadings based on these alternative models provided a more rigorous test of the unidimensionality of the Flourishing and the WEMWBS but also provided further tests of the convergent and discriminant validity of the WB-Pro factors.

Development of a short-form of WB-Pro. Recognizing the usefulness of a much briefer measure of well-being than the WB-Pro (based on 48 items), we undertook some additional analyses. Here the intent was to develop a formative measure of well-being based on a single global measure rather than a multidimensional profile of distinct factors. We applied a novel machine-learning approach based on genetic algorithms (GA) to the selection of the "best" items to reflect the measure. More specifically, we implemented the GA method in R, an open source statistical computing environment (R Core Team, 2018), using the GAabbreviate package (Scrurra & Sahdra, 2015; for further discussion see *Supplemental Materials*; Section 8). The GA implement the principles of biological evolution (e.g., mutation, crossover, and selection based on fitness) in a computational framework to find a suitable short form of the long form that is reliable, valid, and preserves most of the variance in the data of the original questionnaire (Sahdra, Ciarrochi, Parker & Scrucca, 2016; Yarkoni, 2010). The GA have been employed to abbreviate long forms of several psychological constructs, including personality traits (Yarkoni, 2010), psychopathy (Eisenbarth, Lilienfeld & Yarkoni, 2015), experiential avoidance (Sahdra et al., 2016), body image (Basarkod, Sahdra & Ciarrochi, 2018), and mindfulness in sports (Noetel, Ciarrochi, Sahdra & Lonsdale, 2019). For present purposes, we constructed two versions of WB-Pro-Short, one based on the best 5 items, and another based on the best 15 items subject to the constraint that at least one item was included from each of the 15 WB-Pro factors.

Results

Factor structure

Confirmatory Factor Analysis (CFA) and Exploratory Structural Equation Modelling (ESEM). A critical initial step was to evaluate the factor structure underlying the responses to 48-item WB-Pro instrument, and to compare results based on CFA and ESEM.

Factor Structure: Total Group. Two sets of factor analyses–CFA and ESEM–were conducted on the entire set of 2559 responses from participants at T1 and T2. Critical features of these analyses were the goodness-of-fit indices (see *Supplemental Materials*, Section 3, Table 2, Models 1A & 1B). The highly restrictive CFA structure in which each item was allowed to load on one and only one factor provided a remarkably good fit (CFI=.97, TLI=.96, RMSEA = .037) in relation to traditional criteria for a good fitting model. Nonetheless, the fit of the less restrictive ESEM was even better (CFI=.99, TLI=.99, RMSEA = .023). However, the ESEM (711 parameter estimates) was less parsimonious that the CFA (249 parameter estimates). Nevertheless, even goodness-of-fit indices that control for parsimony (RMSEA and TLI) were better for the ESEM than the CFA.

Based on goodness-of-fit, both the ESEM and CFA solutions were good, with the ESEM solution having best fit, and the CFA solution being most parsimonious. Further, parameter estimates based on the CFA and ESEM both demonstrate that the WB-Pro factors are well defined. Together, both CFA and ESEM solutions provide support for the a priori factor structure relating the 48 items to the WB-Pro factors. A complete presentation of these fit statistics and parameter estimates, is in *Supplemental Materials*, Section 3, Tables 2, 3A and 3B.

Multiple Group Tests of Factorial Invariance. In the initial tests of invariance (invariance over stacked groups; Models 2A – 2C in *Supplemental Materials*, Section 3, Table 2), we evaluate whether the factor structures for these three groups completing WB-Pro at T1, at T2, or at both T1 and T2, are invariant. Because these groups are each nationally representative samples from the same population, it is not surprising that there is good support for even the most restrictive model of scalar invariance (i.e., invariance of factor loadings and intercepts) as well as the less restrictive models of metric (i.e., invariance of factor loadings) and configural invariance (i.e., no invariance constraints). Because scalar invariance is substantially more parsimonious than the metric and particularly the configural model, support for scalar invariance is particularly strong based on the TLI and RMSEA indices that control for parsimony.

In the next three sets of invariance tests (Models 3 – 5 in Table 2, *Supplemental Materials*), we evaluate the invariance of the factor solution over three educational categories (‘high school’, ‘some tertiary education’, and ‘a four-year tertiary degree’), four age groups, and two gender groups (males and females). Importantly, each of these grouping variables are substantively different, and tests of invariance provide potentially demanding tests of the generalizability of the WB-Pro factor structure in relation to these demographic variables. Nevertheless, the patterns of results for each of these tests of invariance are quite similar. In each case, there is good support for even the most restrictive model of scalar invariance (Models 3C, 4C and 5C in Table 2, *Supplemental Materials*), as well as the less restrictive models of metric and configural invariance. Again, this support for invariance is particularly strong for the TLI and RMSEA indices that control for parsimony. Although presented only briefly here, it is important to emphasize that results of these tests of invariance demonstrated that the WB-Pro factor structure is very robust.

Convergent and Discriminant Validity in Relation to Time: Multitrait-Multimethod Analyses

As noted earlier, that MTMM design in relation to time provides a "best case" test of the discriminant validity of a multidimensional measure. Furthermore, many of the traditional problems with the original criteria proposed by Campbell and Fiske (1959) are overcome when they are applied to a latent correlation matrix based on a well-fitting factor analysis in which each factor is based on multiple items. The MTMM analysis starts with an ESEM of the 15 WB-Pro factors administered at T1 and T2. The fit of the model was good, showing strong support for invariance (configural, metric, and scalar) over time (see Models 6A, B & C in Table 2 of *Supplemental Materials*, Longitudinal Invariance).

In this MTMM analyses, the critical feature is the 30x30 MTMM of correlations among the 15 WB-PRO factors at T1 and T2 (Table 1). With time as the method factor, the convergent validities are the 15 test-retest correlations between matching T1 and T2 factors (correlations shaded in gray in Table

1). These are consistently substantial (.73 to .86; M r = .80). This provides strong support for convergent validity in relation to time as the method factor.

In the MTMM paradigm, discriminant validity is established by comparing convergent validities to the other correlations in the MTMM matrix (Table 1); correlations among the 15 factors among at T1 (05 to .59; *M r* = .34), correlations among the 15 factors at T2 (-.05 to .65, *M r* = .35), and correlations between T1 and T2 non-matching factors (-.07 to .48; *M r* = .29). Because every convergent validity is substantially greater than all remaining correlations, there is strong support for both the convergent and discriminant validity of all 15 WB-Pro factors in relation to time. In summary, even though some of the WB-PRO factors are substantially correlated, there is clear evidence that all the factors are well differentiated based on this MTMM analysis.

Relations to Background/Demographic Characteristics

A set of 10 background/demographic characteristics were regressed on the set of WB-Pro factors (see Table 3, Section 5 of *Supplemental Materials*). Although the resulting 150 regression coefficients are mostly modest in size, nearly half are statistically significant (due in part to the moderately large sample size). In support of our multidimensional perspective, age and gender were positively related to some WB-Pro factors and negatively related to others—results that would not be evident with unidimensional approaches to well-being. Thus, for example, males had significantly higher scores for emotional stability, resilience, vitality, and self-acceptance, but significantly lower scores for empathy, prosocial behavior, and self-esteem. However, the gender-by-age interactions demonstrated that gender difference in favor of males declined with age for emotional stability, resilience, vitality, and self-acceptance, whereas the gender difference in favor of prosocial behavior for females became larger with age. Also, in support of a multidimensional perspective, older participants had higher scores for emotional stability, clear thinking, positive emotions, resilience, and self-acceptance, but lower scores for optimism and vitality. However, there were also some quadratic effects associate with age. For example, competence increased with age, levelled out and then declined in old age, whereas optimism initially declined with age, levelled out and then increased in old age.

The largest positive effects were associated with marital status (married = 1, not married = 0; there were significantly positive correlations for 7 of the 15 factors), education (significantly positive correlations for 10 of 15 factors), and English fluency (significantly positive correlations for 8 of the 15 factors, but negatively related to resiliency). The positive effects of being married did not vary as a function of age, but the advantages were slightly larger for males than females on three well-being factors (engagement, resilience, and prosocial behavior).

Relations with Significant Life Change Events

Participants indicated whether they had experienced major life events in the last three months. Across the 2,559 sets of responses, we classified these as negative (10.3%), neutral (5.3%), positive (6.1%), or no significant events (78%; i.e., respondents who did not list a significant life change). We contrasted the effects of not having a significant life event (“left out" category) with those for negative, neutral, or positive life events (bottom of Table 3, Section 5 of *Supplemental Materials*).

Particularly, as most reported life events were negative, the effect of negative life events on well-being was negative for 12 of 15 WB-Pro factors, the largest being on resilience, optimism, and emotional stability (see Table 4, Section 6 of *Supplemental Materials*). Interestingly, experiencing negative life events had small positive effects on empathy and prosocial behavior (although the prosocial behavior effect was not statistically significant in relation to having no life events, but was clearly significantly different from the negative effect for most other factors). Experiencing positive life events was positively associated with well-being, although the effects were significant for only four of 15 factors (prosocial behavior, vitality, positive relations, and optimism). Not surprisingly, there were almost no differences in well-being associated with experiencing a neutral life-event change compared to not having experienced one at all (significant for only one of 15 WB-Pro factors, empathy).

Convergent and Discriminant Validity in Relation to Other Constructs

The main results from the convergent validity analysis are based on correlations in a factor analysis based on the large number of items (143) and factors (40 = 15 WB-Pro factors plus 25 covariate factors) summarized in Table 2. For the set of 375 correlations (15 WB-Pro factors x 25 external criteria), 15 are for external criteria specifically chosen to reflect a WB-Pro factor as a test of convergent validity. In support of the convergent and discriminant validity of the WB-Pro factors (see Table 2), each of the 15 convergent validities is higher than the correlation between the specific criterion of any the other WB-Pro factors. For the remaining 10 external criteria (e.g., Big-Five factors and global measures of well-being), no single WB-Pro factor was chosen to be most logically associated with each criterion. The overarching finding is that WB-Pro dimensions were generally most strongly correlated with the scales that we a prior predicted to show large associations, especially in the case of PERMA, Basic Psychological Needs, life satisfaction and happiness. A more detailed presentation of the relations between the WB-Pro factors and scales testing convergent and divergent validity (e.g., PERMA, Basic Psychological Needs, Big-Five Personality, and other single-scale measures including depression, stress, life satisfaction, happiness, sleep, general health and exercise) is included Section 4 of *Supplemental Materials.*

A Profile Approach: Relations Between WB-Pro15 Factors and Selected Demographic Variables

In this section (see Table 3) we evaluate a multidimensional profile approach to the representation of the WB-Pro15 scales in relation to three demographic variables (marital status, gender, and age) and compare it to a unidimensional approach. For present purposes, we represent the unidimensional approach with responses to the Life Satisfaction measure. To be useful, the correlations between the background variable and at least some—hopefully many—of the WB-Pro15 factors must be different from the correlation with life satisfaction. Thus, for example, married respondents were non-significantly lower (-.10) on competence but significantly higher on life satisfaction (.23); and the difference between the two (-.10 - .23 = -.33) was significant. More generally, significantly positive difference scores (shaded dark grey) indicate that the effect of the demographic variable was significantly more positive than the corresponding effect on life satisfaction, significantly negative difference scores (shaded light grey) mean that the effect of demographic variable was more negative than for life satisfaction.

If most of the difference scores were non-significant, it could be argued that most of the profile of WB-Pro effects could be explained in terms of overall life satisfaction. However, a majority of the difference scores are statistically significant for all three demographics (some differences positive and others negative) and there are significant differences for all 15 WB-Pro factors. These results demonstrate good support for the multidimensional rationale underpinning WB-Pro: the profile of effects for each of these demographic variables across the WB-Pro factors cannot be explained in terms of a global measure of life satisfaction. We examine these profile differences for each of the three demographics in more detail in Section 7 of *Supplemental Materials*.

Purportedly Unidimensional Measures of Well-Being

Of particular interest are the two widely used measures of global well-being that are purportedly unidimensional: the Diener et al. (2010) 8-item Flourishing Scale and the 14-item Warwick-Edinburgh Mental Well-being Scale (Tennant et al. 2007). Again, it is not surprising that both these global measures of well-being are substantially correlated with all WB-Pro scales (*r*s > .70 in **bold** in Table 4) and also substantially correlated with each other (r = .78). For the WEMWBS instrument the highest three correlations with WB-Pro factors are positive emotions (.82), optimism (.80), and engagement (.79), whereas for the Diener et al. (2010) instrument the largest three correlations are for meaning (.78), positive emotions (.77), and engagement (.76). For both instruments, the lowest correlations were with empathy (.25, .30) and prosocial behavior (.43, .46). Again, the patterns of correlations relating the WB-Pro items to each of these global measures of well-being is very similar, with a profile similarity index of .97 (i.e., the correlation between the 15 correlations relating WEMWBS to WB-Pro factors, and the corresponding 15 correlations based on Flourishing responses).

Tests of the Unidimensionality of the WEMWBS and the Flourishing. Both the WEMWBS and the Flourishing scales are sometimes claimed to be unidimensional measures of well-being. Although each is intended to provide a global summary score that represents global well-being, it is unclear whether these reflect unidimensional measures of a reflective well-being construct or an index of a formative measure representing different constructs. Although both reflective and formative measures can be used as global measures, the logic of their appropriate construction and derivation of psychometric properties differ substantially (for further discussion of reflective and formative measures see *Supplemental Material*, Section 9).

We began by testing the unidimensionality of the 8-item Flourishing and 14-item WEMWBS scales, separately and in combination. Based on typical measures of goodness-of-fit (see *Supplemental Materials,* Section 3, Table 2) and consistent with previous research, there was at least reasonable support for the unidimensionality of both the Flourishing (CFI = .96, TLI = .94, Model 8A) and WEMWBS (CFI = .93, TLI = .92, Model 8B) scales considered separately. In a CFA model with two factors based on responses to all 22 items from both instruments, the fit was somewhat poorer (CFI = .91, TLI = .89, Model 8C). In this model the Flourishing and WEMWBS factors correlate .78 with each other. The relatively poorer fit of the model with both instruments was because some items from each instrument related more strongly to some items in the other instrument than could be explained by the correlation between the two global factors. This finding is consistent with the design of each instrument to include different components of well-being that were overlapping in the two instruments, but calls into question the claims that each is a unidimensional measure.

Next, we added the WB-Pro ESEM factor structure to each of these three unidimensional models (Models 9A-C in *Supplemental Materials,* Section 3, Table 2). Hence, in each of these models, the Flourishing items and the WEMWBS items each defined separate factors which were not allowed to cross-load on the WB-Pro factors. Thus, for example, the first WEMWBS item "I've been feeling optimistic about the future" was not allowed to load on the WB-Pro optimism factor, the factor that it was most logically related to, based on a priori classifications by the co-authors. The relation of this item to the WB-Pro optimism factor could only take place through the WEMWBS global well-being factor defined by all 14 WEMWBS items. Similarly, the first Flourishing item "My social relationships are supportive and rewarding" was not allowed to load on the WB-Pro positive relations factor and could only be related to this factor through the Flourishing Scale global well-being factor based on defined by all 8 Flourishing Scale items. Again, there was at least reasonable support for the unidimensionality of the Flourishing and WEMWBS measures based on these models. For the model with one Flourishing well-being factor defined by the eight Flourishing items and 15 WB-Pro factors defined by ESEM of the 48 WB-Pro items, the fit was reasonable by typical standards of fit (CFI = .96, TLI = .92, Model 9A, Table 2 of *Supplemental Materials*), as were the models based on the 14

WEMWBS items (CFI = .95, TLI = .92, Model 9B) and, to a lesser extent, the combination of Flourishing Scale and WEMWBS items (CFI = .91, TLI = .90). It is interesting to note that the fit of each of these models that included the WB-Pro items was roughly similar to the fit of the models based on the Flourishing Scale and WEMWBS items that did not include the WB-Pro items. However, in each case, the fit of these three models was noticeably poorer than the fit of models considered earlier based on only the WB-Pro items.

Absorption of WEMWBS and Flourishing Items into WB-Pro

Our final set of models (10A – 10C,Table 2, *Supplemental Materials*) was specifically designed to test our a priori hypothesis that the Flourishing Scale and WEMWBS are multidimensional instruments. More specifically, we tested extended target ESEM models in which the Flourishing Scale and WEMWBS items were fully "absorbed" into the WB-Pro factors, completely eliminating the Flourishing Scale and WEMWBS global factors. As with the WB-Pro, each of the WEMWBS and Flourishing Scale items was designated a priori as a "target item" to the most closely related to a WB-Pro factor or as a "non-target item" based on the co-authors’ a priori classifications of items into WB-Pro factor factors (see Table 4; also see Mplus syntax, Section 11). Thus, all three models (48 WB-Pro items with 8 Flourishing items, Model 10A, Table 2 of *Supplemental Materials*; with 14 WEMWBS items, Model 10B; or with 22 items from both Flourishing Scale and WEMWBS items, Model 10C) posited only the 15 WB-Pro factors, such that all the additional WEMWBS and Flourishing items were absorbed into the WB-Pro factors. The critical evaluations of these models are: first, do these "absorption models" fit systematically better than those already considered in which the WEMWBS and Flourishing Scale items define separate factors; and second, do the WEMWBS and Flourishing Scale items load on the WB-Pro factors with which they are most logically related (based on a priori classifications by the co-authors)?

For each of the three models, the absorption models fit substantially better than the corresponding models hypothesizing separate global well-being factors defined by the WEMWBS or Flourishing Scale items (see Models 8, 9 and 10 in Table 2 of *Supplemental Materials*). Of particular relevance are the models based on the 48 WB-Pro items, 14 WEMWBS items, and 8 Flourishing Scale items. As already noted, the model based on 17 factors (15 WB-Pro, 1 WEMWBS, 1 Flourishing) provided a marginal fit to the data (RMSEA = 0.066, CFI = .91, TLI = .89, Model 9C). In contrast the corresponding absorption model based on only 15 factors provided a much better fit to the data (RMSEA = 0.022, CFI = .98, TLI = .97, Model 10C). A similar pattern of results is evident for corresponding models that considered the WEMWBS and Flourishing Scale items separately.

In Table 4, we present the factor loadings for the 14 WEMWBS and 8 Flourishing Scale items on the WB-Pro factors. (To facilitate presentation, those over .20 are shaded in grey and those greater than .35 are bolded). Also presented are the a priori predictions regarding the 22 items of WB-Pro factors that would be most correlated (the highest possible score is 4). Thus, for example, the first WEMWBS item “I've been feeling optimistic about the future” was classified as fitting into the optimism WB-Pro factor (classification score = 3.33) and the item loaded .73 on this factor. Similarly, the first Flourishing Scale item, "I lead a purposeful and meaningful life", was classified into the ‘meaning’ WB-Pro factor (classification score = 3.00) and the item loaded .76 on this factor. All 22 Flourishing and WEMWBS items load at least moderately or substantially on one or more WB-Pro factors. The pattern of factor loadings of the 22 items on the 15 factors is closely aligned to the a priori classifications. Thus, the profile similarity index, the correlation between the set of 330 (22 items x 15 factors) factor loadings and the corresponding set of 330 classifications, is .81.

Although there is good support for the a priori classification of the Flourishing Scale and WEMWBS items into different WB-Pro factors, the coverage of items across the 15 WB-Pro factors is not uniform. WEMWBS items are substantially related to competence, engagement, positive emotions and self-esteem with very little representation of meaning, resilience, self-acceptance, autonomy, empathy, or prosocial behavior. The Diener et al. (2010) Flourishing Scale items are most strongly represented in the WB-Pro self-esteem factor (6 of 8 items load substantially on this factor—those shaded in Table 3). However, 7 of the 8 items load most substantially on a single WB-Pro factor (the item "People respect me" loads substantially on both WB-Pro factors positive relations and self-esteem). Nevertheless, the Diener et al. (2010) instrument has relatively little coverage of emotional stability, positive emotions, resilience, vitality, self-acceptance, autonomy, or empathy. This analysis of the Flourishing and WEMWBS instruments also highlights differences, as well as similarities, in the components of well-being covered by each of these instruments. Thus, for example, the Flourishing – but not the WEMWBS—instrument has items specifically targeted to reflect engagement, meaning, self-esteem and prosocial behavior. In contrast, the WEMWBS—but not the Flourishing—instrument has items specifically targeted to reflect clear thinking, competence, vitality, and, perhaps, autonomy.

Development of a short-form of WB-Pro

Recognizing the usefulness of a much briefer measure of well-being than the WB-Pro (with 48 items), we sought to develop an explicitly formative measure of well-being based on a single global measure rather than a multidimensional profile of distinct factors. It is not our intention to develop a relatively unidimensional (reflective) measure of well-being based on items that are highly internally consistent, rather we aim here to develop a formative index measure of well-being that most appropriately encompasses the range of content covered by all WB-Pro factors. This has been accomplished with an innovative machine-learning approach based on selections of subsets of items that explain the maximum amount of variance in the total set of 48 WB-Pro items (for further discussion see *Supplemental Materials*, Section 8).

For present purposes, we constructed two global scales from the 48 WB-Pro items, one based on the best 15 items subject to the constraint that one item was included from each of the 15 WB-Pro factors, and one based on the best 5 items. In evaluating these short forms, we focused on two issues: First, we examined how related the global scales are to each of the 25 external criteria (*Supplemental Materials, Table 5*); second, we examined whether the global scales are as highly related to any of the criteria as the highest correlating WB-Pro factor. This second step is a test of the multidimensionality of well-being, since support for the multidimensional perspective requires that the global scores are less correlated with the external criteria than the highest correlating WB-Pro factor. The pattern and even the size of correlations between the set of 25 external criteria and each of the two global scores is similar (*Supplemental Materials, Table 5*). Although the 15-item global scale does marginally better than the 5-item global scale, the difference is minimal, and the 5-item scale actually does better for some of the criteria (for further discussion see *Supplemental Material*, Section10).

Discussion

We aimed to develop a robust multidimensional measure of well-being, based on the dimensions identified in the systematic approach used by Huppert and So (2013), and drawing on an extensive review of the subjective well-being literature. Defining psychological well-being as the opposite of psychological ill-being (the common mental disorders of anxiety and depression), our approach is among the most systematic attempts to-date to define and measure well-being, and resulted in a novel, theory-based measure of subjective well-being.

Contrasting Purportedly Unidimensional and Multidimensional Measures of Well-Being

The multidimensional approach we have used to measure well-being is in sharp contrast to unidimensional approaches. In one of the unidimensional approaches, well-being is inferred from responses to a single item (e.g. "happiness" or "life satisfaction") or a tightly-worded set of items designed to measure a narrowly defined construct. Such an approach is truly unidimensional, highly parsimonious and expedient. However, this approach provides a very narrowly defined measure of well-being and does not provide useful information about the profile of different components that make up well-being. As a result, it cannot provide practical guidance with respect to policy, or the choice of specific interventions to improve well-being components.

In a second unidimensional approach, illustrated by the widely used Flourishing Scale (Diener et al., 2010) and WEMWBS (Tennant et al., 2007), well-being is based on responses to a set of items implicitly designed to cover the well-being construct in greater breadth. Clearly, this approach results in a more broadly defined measure of well-being; however, because well-being is still represented by a single score, it does not provide useful information about the profile of different components that make up well-being, or even the components used to construct the measure. The range of well-being content sampled by these measures has been compromised to maximize internal consistency (i.e., items were dropped that were not internally consistent). Furthermore, although purportedly unidimensional, the explicit logic of the design of these instruments is multidimensional—covering a range of different components of well-being. Additionally, the rationale for what components of well-being are included or not in the implicit definition of well-being based on a single total score, is often unclear.

Our study demonstrated the limitations of treating purportedly multidimensional scales as unidimensional. While our study focused on the WEMWBS and Flourishing scales as illustrations of this, our findings may have implications for other widely-used well-being scales (e.g., the Comprehensive Inventory of Thriving; Su et al., 2014).

A Multidimensional Perspective: The WB-Pro Factor Structure

We found very strong empirical support for the multidimensional factor structure of the WB-Pro instrument. First, the factor structure of the 48-item instrument, using both ESEM and CFA, provided an extremely good fit to the data and support for the a priori 15-factor structure. Although the CFA structure was more parsimonious (i.e., required fewer parameter estimates), the ESEM structure fit the data somewhat better and resulted in more differentiates, distinct (i.e., less correlated) factors. Whereas we prefer the ESEM factor structure, results based on both are very similar and both provide strong support for the a priori WB-Pro factor structure.

Second, we found very strong support for the invariance (metric and scalar as well as configural) of the factor structure over levels of education, age, gender, and time for our nationally representative sample of U.S. adults. This support for invariance demonstrated the robustness of the WB-Pro factor structure and the appropriateness of comparing scores across these different demographic groups.

Relations with Demographic Variables. In support for our multidimensional perspective (but also substantively relevant), we found distinct patterns of relations between the 15 WB-Pro factors and 10 demographic variables (including age, gender, education, and marital status). Although this pattern of relations is substantively interesting in its own right, the overarching insight is that this pattern of relations could not be represented with a single global measure of well-being, thereby underscoring the value of taking a multidimensional approach to the study of well-being.

Life-change events. To examine how the WB-Pro dimensions relate differentially to the experience of significant life-events, we asked participants to describe significant life events experienced during the previous three months. These were classified as positive, negative, neutral or not having occurred. Consistent with our finding of differential relations between the WB-Pro dimensions and demographic variables, we found that having negative life experiences were negatively associated with most of the WB-Pro well-being factors (especially optimism, resilience, and emotional stability), whereas negative life events were unrelated to competence and positively related to empathy and pro-social behavior. This suggests that life set-backs may inhibit more hedonic aspects of well-being, but strengthen eudaemonic aspects, such as connecting with and assisting others. There were fewer responses for positive and neutral events, limiting the conclusions we can draw from these, but the overall picture suggests a varied pattern of associations between the 15 WB-Pro dimensions and significant life events—positive, negative and neutral—further reinforcing the value of a multidimensional approach to the study of well-being.

A Multidimensional Perspective: Support for Convergent and Discriminant Validity

MTMM Analysis in Relation to Time. The MTMM paradigm (Campbell & Fiske, 1959) is specifically designed to test for convergent and discriminant validity. Here, we operationalized the multiple methods in relation to time such that convergent validity was based on test-retest correlations. The MTMM design in relation to time provides a strong basis for evaluating test-retest stability and discriminant validity. Across the WB-Pro factors, we found strong support for test-retest stability. However, stability over time would normally be classified as falling near the reliability end of the reliability-validity continuum. For that reason, we now turn to validity criteria that provide a stronger test of external validity.

Relations with Selected Set of 25 External Validity Criteria. We evaluated the construct (convergent and discriminant) validity of the WB-Pro factors in relation to a purposively selected set of 25 external validity criteria. Across all WB-Pro factors and 25 criteria (375 correlations in Table 2), 15 criteria were selected a priori as closely matching different WB-Pro factors—convergent validities. In support of convergent and discriminant validity, each of these 15 convergent validities was statistically significant and larger than correlations with any other WB-Pro factor.

The WB-Pro factors overlap substantially with four of five PERMA factors (all but accomplishment) and the SDT’s six basic psychological needs factors (particularly the needs satisfaction measures but also, to a lesser extent the needs frustration measures). Consistent with this a priori matching, all 10 of these convergent validities are substantial (*r*s = .70 to .90 for the seven positively oriented external criteria, and -.50 to -.58 for the three negatively oriented need frustration factors). In support of discriminant validity, all 10 convergent validities are higher than correlations with any of the other WB-Pro factor. Also, given the focus of the WB-Pro on positive well-being, it is not surprising that the needs frustration factors are less correlated with WB-Pro factors than the corresponding need satisfaction factors.

Several of the single-scale measures (i.e., depression, stress, happiness, general health, and exercise) were specifically selected a priori as being most closely associated with specific WB-Pro factors (positive emotions, emotional stability, positive emotions, vitality and vitality, respectively). Although the convergent validities relating these two sets of measures tend to be smaller, the pattern of results again supports both the convergent and discriminant validity of the WB-Pro responses. Other external validity criteria were not specifically linked to particular WB-Pro factors, but the results demonstrate that there was a clear, logical pattern of relations in support of convergent and discriminant validity. Thus, for example, the Big-Five agreeableness factor was most highly correlated with WB-Pro pro-social behavior and empathy, whereas the Big-Five conscientiousness factor was most highly correlated with WB-Pro competence and clear thinking. In summary, relations between the WB-Pro factors and the set of 25 external criteria provide strong support for both the convergent and discriminant validity of WB-Pro responses.

Global Measures of Well-Being: Reflective vs. Formative Measures

Are the WEMWBS and Flourishing Scale Measures Really Global Unidimensional Measures? The well-being research literature is divided on the use of multidimensional and global approaches to well-being. The problem with the multidimensional approach is that there is no consensus on the factors that should be included in the instrument, nor even a conceptual or theoretical framework to guide these decisions. Among those who opt for a global measure, some use a very narrow unidimensional approach based on a single item or a small number of highly internally consistent items (e.g., measures of life satisfaction or happiness considered here). However, others define a global measure of well-being as a broad formative index based on diverse components of well-being (e.g., Flourishing Scale and WEMWBS measures considered here). Furthermore, there appears to be confusion in the use of global unidimensional and global formative measures. Thus, for example, the Flourishing Scale and WEMWBS measures are sometimes claimed to be unidimensional. However, to the extent that these are designed to be broad, formative indices of well-being, unidimensionality (and high internal consistency) is an inappropriate criterion and antithetical to the rationale underlying formative indices. Indeed, the logic of formative indices is to specifically choose a number of highly differentiated indicators that cover as broad a range of relevant content as possible. Hence, if unidimensionality was used to select items in these measures, it would detract from their usefulness. This confusion is evident, for example, with the WEMWBS instrument in which a short 7-item version (Stewart-Brown et al., 2009) of the longer 14-item (Tennant et al., 2007) version of the instrument was constructed based on strategies to maximize internal consistency. In contrast, a good formative measure should be designed to minimize redundancy (and internal consistency) among indicators in order to cover as much of the relevant content with as few items as possible.

In the present investigation, we demonstrated apparent problems with the widely used Flourishing Scale and WEMWBS measures, as global, unidimensional measures of well-being. In particular, we began by showing marginal support for unidimensionality of both instruments in relation to goodness-of-fit criteria. However, we also demonstrated that both of the instruments cover a broad selection of WB-Pro factors, which clearly supports a multidimensional perspective. We then considered factor analyses that combined the items from these instruments with the 48 items from the WB-Pro instrument. In these analyses, models that constrained the WEMWBS or the Flourishing Scale items to be a single factor fit worse than models that allowed WEMWBS and/or Flourishing Scale items to load on the WB-Pro factors selected a priori as being most closely associated with each of the items. In this way, the WEMWBS and/or Flourishing Scale items were absorbed into the WB-Pro factor structure. Not only did these absorbed models provide a much-improved fit to the data, but the empirical factor loadings (relating the WEMWBS and/or Flourishing Scale items to the WB-Pro factors) closely matched our a priori predictions based on the content of each of the Flourishing Scale and/or WEMWBS items. These results apparently resolve at least some of the confusion about the inappropriate role of unidimensionality in formative index measures that are intended to sample from diverse content.

Global Formative Measures based on the WB-Pro. In addition to our 48-item WB-Pro instrument, we specifically constructed two global, formative-index measures based on subsets of the 48 WB-Pro items using an innovative machine-learning approach. The rationale for this approach was to sample diverse content from within the item pool to maximize variance explained in the 48 items with a minimal subset of items. Using this method, we constructed two global measures, one consisting of 15 items and another 5 items. We then evaluated these global scales in relation to our set of 25 external criteria (that were not used in the selection of items in these global scales). Consistent with the proposed usefulness of the global measures, both global measures were substantially related to each of the 25 external criteria. Not surprisingly, the 15-item scale did marginally better than the 5-item scale in terms of predicting most—but not all—of the 25 criteria. However, consistent with our multidimensional perspective, neither of the global measures was as highly correlated with the most logically related WB-Pro factor.

What are the implications of these results in terms of future application of the WB-Pro?

Clearly, if researchers are interested in the multidimensionality of well-being and can justify the inclusion of all 48 WB-Pro items, then we recommend the use of the entire instrument. Because of our focus on a multidimensional perspective, we are loath to recommend the use of a global scale instead of the full WB-Pro instrument. However, if researchers can only justify the use of a relatively small number of items, we recommend the use of a broadly defined formative index of well-being such as our 15-item measure (WB-Pro15) which incorporates all 15 WB-Pro dimensions, or the very brief 5-item measure (WB-Pro5). Nevertheless, because the 15- and 5-item global WB-Pro measures are new, it is important that further research juxtaposes their usefulness in relation to more widely used measures of global well-being, such as the WEMWBS (Tennant et al., 2007) and the Flourishing Scale (Diener et al., 2010) and the BIT. However, it is also important that such further research explores in greater detail the apparent confusion between global unidimensional and global formative measures of well-being.

Using WB-Pro to Map the Content of Alternative Measures of Well-being

The analyses we have reported, particularly those based on the items in the WEMWBS (Tennant et al., 2007) and Flourishing Scale (Diener et al., 2010), also provide a heuristic demonstration that the WB-Pro provides a suitable base to map the content of alternative measures of well-being and related constructs. Extending this mapping metaphor, Marsh, Hau, Artelt, Baumert & Peschar (2006) suggested that a broadly-based multidimensional instrument can provide the latitude and longitude for mapping the content of different measures widely used within research literature. Also, related to this issue are jingle-jangle fallacies where two factors with the same name do not necessarily measure the same content (jingle fallacy), or two factors with different labels might measure the same content (jangle fallacy). Using this approach, we were able to map the content covered by WEMWBS and the Flourishing Scale. In particular, by mapping the WEMWBS and Flourishing items onto the WB-Pro factors, we not only demonstrated that neither of these global measures should be considered unidimensional, but also demonstrated that the content covered by each was not the same. Using the same approach, we were also able to map the content of the Big-five, PERMA and SDT factors onto WB-Pro factors. This use of the WB-Pro instrument to map the content of alternative measures seems particularly relevant in an area like well-being measurement that Diener and Seligman (2004, p. 2) described as "haphazard, with different studies assessing different concepts in different ways."

Limitations, Conclusions and Directions for Further Research

WB-Pro is a 15-factor comprehensive measure of subjective well-being, based on a sound conceptual model and strong empirical support. The 15 factors showed good reliability, test-retest correlation, convergent/discriminant validity in relation to stability over time and relevant psychological measures, and a good a priori fit to the data that was invariant over time, education, gender and age. We note however, that our systematic approach to selection of factors might have excluded some potentially important factors. Furthermore, substantial correlations among some factors might detract from their discriminant validity. Also, the sample of respondents was U.S. adults so that further research is needed to test the generalizability to other ages and nationalities.

There are a number of ways in which this new measure, the WB-Pro, can advance research and policies related to well-being. First, it facilitates an understanding of how multidimensional profiles vary between individuals and groups. Second, it will allow us to track change and explore how different dimensions change over time, as a result of societal/cultural change, or following an intervention program. Further, having identified differences between individuals or groups, we can design policies and programs to enhance well-being that are tailored to the profiles we observe. For example, if one group obtains high scores on measures such as engagement, competence, or meaning but low scores on other measures such as autonomy, emotional stability or self-acceptance, we can tailor programs to focus on those dimensions where they show weakness rather than on dimensions where they show strength. On the other hand, we acknowledge that not all research studies are able to include a 48-item measure of well-being, and we have accordingly used a machine-learning approach (genetic algorithm methodology) to develop two shorter forms based on these 48 items: the WB-Pro5 and the WB-Pro15. Both the 5- and 15-item measures are robust short measures of well-being that represent the range of WB-Pro factors, and can each be used as a single total score. Similar to our claims in relation to the WEMWBS and Flourishing Scale, we stress that these short measures based on the WB-Pro instrument should be considered formative rather than reflective measures. Our short global measures can be used where there are strict limitations on survey length, but it is worth recognizing that the full WB-Pro instrument provides more reliable and robust, multidimensional representations of well-being.

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Table 1

Test-Retest Correlations Among 15 Well-being Factors: A Multitrait-Multimethod (MTMM) Matrix

Latent Factors	CO	CT	ES	EN	ME	OP	PE	PR	RE	SE	VI	AC	AU	EM	PS
	Correlations Between Time 1 & 2 Constructs: Convergent validities in diagonal (shaded), Heterotrait-Heteromethod Correlation in off-diagonals														
Competence (CO)	.77	.33	.20	.22	.42	.24	.37	.26	.25	.31	.19	.56	.46	.15	.21
Clear thinking (CT)	.38	.75	.48	.39	.33	.34	.28	.36	.41	.36	.18	.45	.36	.15	.22
Emot Stability (ES)	.19	.41	.84	.24	.32	.33	.31	.12	.44	.30	.24	.34	.23	.04	.16
Engagement (EN)	.09	.39	.36	.78	.32	.49	.25	.35	.34	.43	.25	.31	.34	.18	.19
Meaning (ME)	.32	.33	.30	.42	.83	.59	.51	.39	.35	.38	.34	.43	.30	.15	.14
Optimism (OP)	.21	.26	.32	.54	.42	.83	.38	.35	.33	.49	.31	.34	.32	.14	.15
Pos Emotions (PE)	.28	.29	.41	.42	.53	.54	.86	.37	.33	.34	.34	.50	.36	.12	.18
Pos Relations (PR)	.29	.37	.36	.34	.41	.39	.44	.81	.23	.50	.17	.47	.36	.27	.26
Resilience (RE)	.25	.22	.43	.28	.32	.43	.34	.23	.78	.25	.27	.38	.28	-.07	.13
Self-Esteem (SE)	.21	.23	.45	.43	.39	.42	.33	.36	.28	.80	.09	.41	.35	.18	.18
Vitality (VI)	.15	.26	.22	.37	.24	.44	.30	.16	.34	.15	.85	.24	.24	.05	.07
Acceptance (AC)	.35	.42	.41	.36	.36	.34	.29	.31	.45	.44	.18	.82	.43	.14	.35
Autonomy (AU)	.30	.35	.31	.38	.36	.35	.34	.36	.31	.31	.15	.43	.73	.11	.16
Empathy (EM)	.12	.02	.01	.13	.12	.01	.03	.23	-.04	.08	-.03	.09	.02	.82	.41
Pro-social (PS)	.14	.18	.17	.21	.27	.24	.11	.24	.21	.23	.08	.23	.24	.40	.73
	Correlations Among Time 1 factors (below diagonal) and Among Time 2 factors (above diagonal): Heterotrait-Monomethod Correlations														
Competence (CO)	1.0	.61	.28	.26	.52	.31	.51	.37	.29	.42	.21	.56	.49	.15	.25
Clear thinking (CT)	.43	1.0	.47	.48	.46	.34	.44	.49	.34	.49	.26	.54	.48	.10	.29
Emot Stability (ES)	.31	.42	1.0	.35	.34	.27	.38	.30	.50	.33	.24	.50	.39	.15	.20
Engagement (EN)	.14	.41	.38	1.0	.49	.60	.40	.49	.30	.57	.34	.45	.54	.20	.29
Meaning (ME)	.49	.38	.36	.34	1.0	.57	.65	.51	.33	.44	.32	.45	.43	.09	.26
Optimism (OP)	.22	.29	.40	.54	.54	1.0	.46	.46	.37	.50	.29	.35	.47	.06	.21
Pos Emotions (PE)	.42	.36	.47	.36	.59	.54	1.0	.52	.40	.42	.36	.47	.41	.09	.22
Pos Relations (PR)	.35	.37	.29	.34	.47	.41	.45	1.0	.30	.57	.13	.42	.45	.28	.32
Resilience (RE)	.30	.40	.55	.44	.44	.41	.44	.27	1.0	.28	.35	.42	.31	-.05	.15
Self-Esteem (SE)	.28	.41	.39	.58	.31	.46	.36	.41	.30	1.0	.06	.51	.47	.10	.26
Vitality (VI)	.20	.25	.30	.43	.34	.42	.39	.19	.31	.18	1.0	.22	.19	.01	.13
Acceptance (AC)	.45	.47	.50	.37	.50	.38	.44	.43	.49	.45	.25	1.0	.49	.15	.27
Autonomy (AU)	.39	.44	.30	.39	.42	.37	.38	.42	.34	.40	.22	.50	1.0	.11	.16
Empathy (EM)	.16	.11	.09	.15	.17	.09	.11	.29	.06	.15	.07	.22	.16	1.0	.52
Pro-social (PS)	.28	.28	.21	.28	.22	.20	.17	.31	.23	.31	.08	.35	.28	.51	1.0

Note: Table 1 is a multitrait-multimethod matrix of correlations between the 15 WB-Pro factors at time 1 (T1) and time 2 (T2) for the longitudinal analysis (see Model 6, Table 2 of *Supplemental Materials*) with time as the method factor. In the upper box, the diagonal (highlighted in grey) correlations are convergent validities (T1-T2 test-retest correlations; (.73 to .86; $M\ r = .80$); the off-diagonal values are heterotrait-heteromethod (different traits, different methods) correlations between T1 and T2 factors (-.07 to .48; $M\ r = .29$). In the lower box are heterotrait-heteromethod (different trait, different method) correlations among T1 factors (below the main diagonal, .05 to .59; $M\ r = .34$) and among T2 factors (above the main diagonal; -.05 to .65, $M\ r = .35$). Because every convergent validity is greater than all remaining (heterotrait-monomethod and heterotrait-monomethod) correlations, there is strong support for the convergent and discriminant validity of all 15 WB-Pro factors in relation to time.

Table 2

Correlates of Well-Being: Support for the Convergent and Discriminant Validity of 15 Well-Being Factors

	Well-Being Profile 15 Factors														
Well-Being Correlates	Competence	Clear Thinking	Emot Stability	Engagement	Meaning	Optimism	Pos Emotion	Pos Relations	Resilience	Self-Esteem	Vitality	Self-Acceptance	Autonomy	Empathy	Pro-Social
PERMA															
Positive Emotion	.68	.67	.70	.82	.81	.83	**.90***	.72	.71	.73	.72	.72	.68	.28	.43
Engagement	.69	.68	.62	**.84***	.75	.75	.80	.68	.64	.71	.66	.67	.65	.31	.46
Positive Relations	.56	.58	.56	.67	.71	.69	.73	**.83***	.56	.62	.57	.59	.58	.31	.39
Meaning	.70	.65	.65	.82	**.90***	.83	.82	.70	.67	.74	.69	.70	.68	.29	.46
Accomplishment	**.72**	.69	.65	**.79**	**.81**	**.79**	**.78**	.65	.69	.71	.71	.70	.66	.24	.44
Psychological Needs															
Satisf Autonomy	.65	.63	.56	.75	.70	.68	.67	.59	.56	.62	.57	.60	**.70***	.23	.36
Satisf Relation	.59	.58	.51	.60	.62	.59	.62	**.81***	.47	.64	.42	.57	.58	.36	.42
Satisf Competence	**.79***	.71	.59	.67	.64	.65	.62	.57	.57	.74	.50	.67	.63	.19	.39
Frust Autonomy	-.43	-.47	-.40	-.50	-.45	-.47	-.50	-.43	-.39	-.43	-.37	-.43	**-.50***	.01	-.15
Frust Relation	-.44	-.48	-.40	-.40	-.42	-.40	-.46	**-.59***	-.35	-.50	-.25	-.43	-.41	-.07	-.20
Frust Competence	**-.58***	-.56	-.48	-.50	-.52	-.49	-.52	-.48	-.46	-.59	-.38	-.55	-.48	.02	-.19
Big Five															
Openness	.44	.39	.31	**.43**	.31	.33	.30	.30	.28	.40	.29	.37	.32	.39	**.42**
Conscientiousness	**.68**	**.65**	.45	.53	.48	.43	.44	.46	.39	.56	.39	.52	.50	.23	.42
Extraversion	.43	.38	.32	**.51**	.49	.46	**.51**	.45	.43	.48	.48	.43	.37	.26	.41
Agreeableness	.48	.45	.50	.44	.40	.37	.43	.48	.33	.50	.23	.45	.40	**.61**	**.66**
Neuroticism	-.48	-.51	**-.62**	-.48	-.47	-.48	**-.52**	-.39	**-.59**	-.48	-.44	**-.55**	-.45	.12	-.18
Single Scale Measures															
WEMWBS	.69	.69	.67	**.79**	**.78**	**.80**	**.82**	.72	.68	.73	.70	.72	.67	.25	.43
Flourishing	.71	.64	.62	.76	.78	.76	.77	.69	.61	.72	.62	.67	.64	.30	.46
Depression*	-.45	-.53	**-.53**	-.50	-.55	-.55	**-.62***	-.48	-.51	-.51	-.50	-.54	-.45	.02	-.15
Stress	-.43	-.51	**-.60***	-.51	-.46	-.48	**-.57**	-.43	-.54	-.46	-.47	-.53	-.45	-.02	-.17
Life Satisfaction	.64	.60	.60	.75	.77	**.81**	**.80**	.66	.65	.62	.69	.62	.62	.20	.35
Happiness*	.51	.52	.52	.63	.63	.65	**.72***	.59	.53	.58	.52	.54	.52	.17	.35
Sleep	.07	.11	.15	.16	.18	.22	.22	.18	.17	.07	**.27**	.10	.10	.05	-.03
General Health	-.37	-.35	-.36	-.42	-.40	-.46	-.41	-.31	-.39	-.32	**-.56***	-.34	-.31	-.10	-.18
Exercise	.21	.21	.25	.29	.27	.28	.25	.18	.24	.20	**.40***	.21	.20	.11	.21

Note. Correlations are based on a large confirmatory factor analysis model (143 items and 40 factors--15 WB-Pro15 plus 25 covariate factors). Correlations in bold are for those relations most logically and highly related to each of the WB-Pro15 factors, whereas underlined correlations are for external criteria specifically chosen a priori to reflect a WB-Pro15 factor as a test of convergent validity.

Table 3

A Profile Perspective on Relations Between the 15 factors of WB-Pro and selected Demographic variables

	Married			Difference			Male			Difference			Age			Difference		
	Est	SE		Est	SE		Est	SE		Est	SE		Est	SE		Est	SE	
Competence	-.10	.06		-.33	.06	**	.08	.04	*	.02	.04		.09	.06		.07	.06	
Clear Thinking	.12	.06	*	-.11	.06	*	.05	.03	*	-.01	.03		.16	.03	**	.15	.03	**
Emot Stability	.15	.04	**	-.08	.04		.12	.03	**	.05	.03		.12	.04	**	.10	.04	**
Engagement	.25	.04	**	.02	.04		-.01	.04		-.08	.04	**	.00	.05		-.01	.05	
Meaning	.03	.06		-.25	.06	**	.07	.04	*	.01	.04		.09	.06		.07	.06	
Optimism	.30	.03	**	.07	.03	*	.00	.04		-.06	.03	*	-.10	.05	*	-.11	.05	*
Pos Emotions	.03	.05		-.26	.05	**	.05	.03		-.01	.03		.13	.05	*	.12	.05	*
Pos Relations	.17	.03	**	-.06	.03	*	-.03	.03		-.10	.02	**	.07	.03	**	.05	.02	*
Resilience	.14	.04	**	-.09	.04	*	.13	.03	**	.07	.02	**	.07	.03	**	.05	.02	*
Self-Esteem	.23	.05	**	.00	.05		-.06	.03		-.12	.03	**	.12	.06	*	.11	.06	
Vitality	.11	.03	**	-.11	.03	**	.16	.02	**	.10	.02	**	-.04	.03		-.06	.02	*
Self-Acceptance *	.04	.04		-.19	.04	**	.12	.03	**	.05	.03	*	.15	.03	**	.14	.03	**
Autonomy*	.04	.04		-.19	.04	**	.04	.03		-.03	.02		.12	.03	**	.10	.03	**
Empathy *	.04	.03		-.19	.04	**	-.14	.03	**	-.21	.03	**	.00	.03		-.01	.03	
Pro-Social	.04	.03		-.19	.04	*	-.10	.03	**	-.16	.03	**	.04	.03		.02	.03	
Life Satisfaction	.23	.02	**				.06	.02	**				.02	.02				

Note. For each WB-Pro factor, we tested the effect of three demographic variables (Married, Male, and Age) and the difference between that effect and the corresponding effect on Life Satisfaction. Thus, for example, Married respondents were non-significantly lower (-.10) on competence but significantly higher on life satisfaction (.23); the difference between the two (-.10 - .23 = -.33) was significant. More generally, significantly positive difference scores (shaded dark grey) indicate that the effect of the demographic variable was significantly more positive than the corresponding effect on life satisfaction, significantly negative difference scores (shaded light grey) mean that the effect of demographic variable was more negative than for life satisfaction. * p value <.05; ** p value <.01.

Table 4

Relations between the 15 WB-Pro Factors and Individual items from the WEMWBS and from The Flourishing Scale: The Multidimensionality of Unidimensional Scales

WB-Pro Factors		W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	F1	F2	F3	F4	F5	F6	F7	F8
Competence	FL	.18	.39	.13	.18	.19	.37	.31	.23	.09	**.48**	**.45**	.13	.35	.11	.02	-.21	-.08	-.01	.36	.15	.00	.10
	PFL	.00	1.43	.00	.00	.00	1.17	1.00	.00	.00	1.73	.17	.00	.00	.00	.00	.00	.00	.00	1.67	.00	.00	.30
Clear Think	FL	-.07	.08	.03	-.03	-.07	.13	**.59**	-.07	-.12	.00	.36	.00	.13	-.11	-.12	-.02	.20	.06	.32	.11	-.11	.04
	PFL	.00	.00	.00	.00	.00	.66	3.00	.00	.00	.00	1.67	.00	.00	.00	.00	.00	.00	.00	1.17	.00	.00	.00
Emot Stab	FL	.08	.05	.29	.08	.06	.21	.32	.10	.01	.05	.11	-.02	-.08	.13	.02	-.02	-.04	-.08	-.08	.07	.10	.07
	PFL	.00	.00	1.67	.00	.00	.30	.00	.00	.00	.00	.00	.33	.00	.33	.00	.00	.00	.00	.00	.00	.00	.00
Engagement	FL	.12	.24	.33	.37	.39	.11	.25	.17	.08	.20	.14	-.03	**.53**	.24	.15	.19	**.61**	.19	.14	-.09	-.16	-.16
	PFL	.00	.30	.67	1.43	.67	.00	.00	.00	.00	.10	.00	.00	2.83	.00	.33	.00	2.67	.00	.00	.00	.00	.00
Meaning	FL	.09	.22	-.07	-.05	-.06	.02	.01	.04	-.10	.13	.02	-.03	-.07	-.05	**.76**	.09	.17	.14	.15	.21	.33	.22
	PFL	.33	1.57	.00	.00	.00	.00	.00	.17	.00	.00	.00	.00	.33	.00	3.00	.00	.67	.17	.33	2.00	.67	.00
Optimism	FL	**.73**	.04	.04	.04	.04	-.01	.00	.11	-.04	.00	-.02	.01	.23	.11	-.05	-.12	-.07	.03	.05	.06	**.63**	-.09
	PFL	3.33	.00	.00	.00	.00	.00	.00	.17	.00	.00	.00	.00	.33	.00	.00	.00	.00	.00	.00	.00	3.00	.00
Pos Emot	FL	.12	.20	.36	.14	.07	.20	.09	.39	.20	.20	.06	.18	.10	**.50**	.13	.07	.14	-.05	-.22	.08	-.02	-.08
	PFL	.33	.00	1.33	.00	.67	.00	.00	1.00	.33	.47	.00	1.33	.17	3.33	.33	.00	.00	.00	.00	.17	.33	.10
Pos Relat	FL	.02	.10	.04	.31	-.02	.01	.05	.07	**.74**	.02	-.03	**.83**	-.03	.12	.14	**.82**	.13	.33	.12	.15	.07	**.42**
	PFL	.00	.00	.00	1.57	.00	.00	.00	.00	2.67	.00	.00	2.33	.00	.00	.00	3.67	.00	1.67	.00	.00	.00	1.87
Resilience	FL	-.06	.06	.04	.03	-.05	.19	-.11	-.06	-.05	.09	.02	-.08	.07	-.03	-.08	-.06	-.05	-.01	.01	-.03	-.13	.03
	PFL	.00	.00	.00	.00	.00	1.51	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Self-Esteem	FL	.00	.16	.01	-.08	-.04	.23	.03	.22	-.07	.31	.19	-.02	-.05	.18	.25	.02	.14	.25	**.61**	**.72**	.35	**.47**
	PFL	.00	.70	.00	.00	.00	.59	.00	2.67	.00	1.70	.00	.00	.00	.00	.33	.00	.00	.00	.83	1.83	.00	1.40
Vitality	FL	-.08	.02	.04	-.06	**.58**	.01	-.03	.07	-.03	.03	-.11	-.07	.03	.07	.10	.11	*.21*	.01	.02	.03	.05	.14
	PFL	.00	.00	.00	.00	2.67	.00	.00	.00	.00	.00	.00	.00	.00	.33	-.03	-.05	-.02	-.15	-.07	-.07	.00	.06
Self-Accept	FL	-.05	-.07	-.02	-.10	-.06	-.10	-.05	.09	.00	.11	-.07	-.08	-.10	-.06	-.09	-.04	-.01	-.02	-.03	-.05	-.07	-.13
	PFL	.00	.00	.33	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Autonomy	FL	-.01	-.12	.05	-.04	-.02	.06	.05	.03	-.01	.01	.31	-.02	-.01	.06	-.05	-.10	-.01	-.16	-.02	-.01	-.04	.07
	PFL	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	2.17	.00	.33	.00	.00	.00	.33	.00	.00	.00	.00	.00
Empathy	FL	.02	.04	.08	.33	.18	.01	-.04	-.07	.19	-.03	-.09	.08	.13	.10	-.08	.08	-.06	-.02	-.06	-.04	-.09	-.03
	PFL	.00	.00	.00	.53	.00	.00	.00	.00	.50	.00	.00	.00	.00	.00	.00	.00	.00	.33	.00	.00	.00	.00
Pro-Social	FL	.02	.11	.02	.22	.04	.04	.03	.10	.22	.00	.05	.13	.16	.05	.04	.11	.07	**.44**	.03	.03	-.01	.09
	PFL	.00	.00	.00	.47	.00	.00	.00	.00	.50	.00	.00	.00	.00	.00	.00	.33	.00	1.83	.00	.00	.00	.33

Note. FL = actual factor loadings of the 14 WEMWBS and 8 Flourishing items on each of the WB-Pro factors (those over .20 are in bold and the highest for each item is highlighted in grey). PFL = predicted factor loading, summated values from four co-authors as to which WB-Pro factors the 22 items would be most correlated with (highest possible score is 4). Correlation = the correlation between FL and PFL values for each the 15 WB-Pro factors (last column) and for each of the 14+8 =24 items (the last row); the correlation across all 330 (22 items x 15 factors) sets of FLs and EFLs is .81.

14 WEMWBS (W) Items: W1, I've been feeling optimistic about the future. W2, I've been feeling useful. W3, I've been feeling relaxed. W4, I've been feeling interested in other people. W5, I've had energy to spare. W6, I've been dealing with problems well. W7, I've been thinking clearly. W8, I've been feeling good about

myself. W9, I've been feeling close to other people. W10, I've been feeling confident. W11, I've been able to make up my own mind about things. W12, I've been feeling loved. W13, I've been interested in new things. W14, I've been feeling cheerful.
8 Flourishing (F) Items: F1, I lead a purposeful and meaningful life. F2, My social relationships are supportive and rewarding. F3, I am engaged and interested in my daily activities. F4, I actively contribute to the happiness and well-being of others. F5, I am competent and capable in the activities that are important to me. F6, I am a good person and live a good life. F7, I am optimistic about my future. F8 , People respect me.

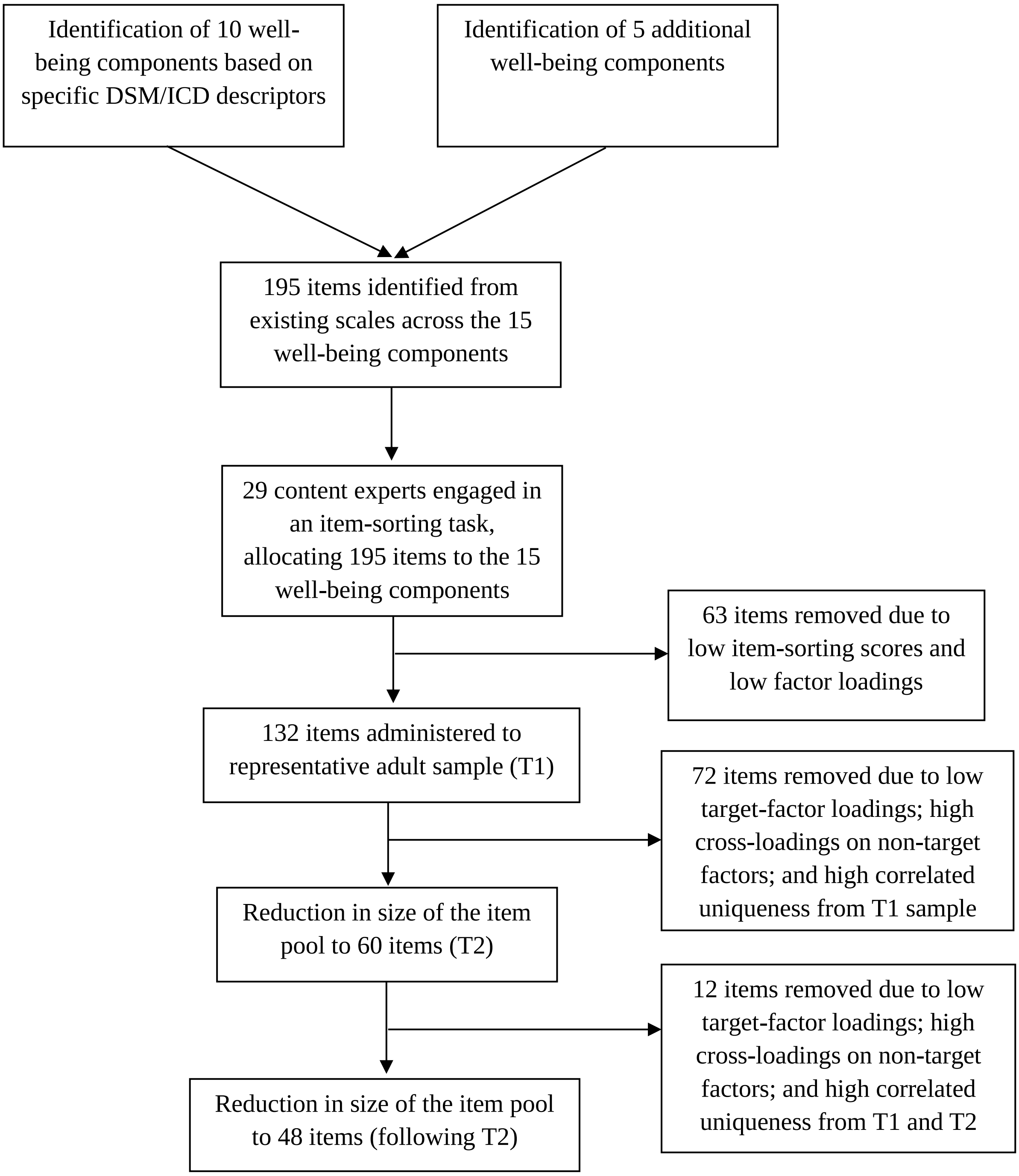

Figure 1. Flow diagram of processes for selection of items used in the WB-Pro 48.

Supplemental Materials

Section 1: Development of an Initial Pool of Items and Its Refinement

Stage :1 Initial Item Construction and Selection. The purpose of Stage 1 was to develop a large pool of items designed to measure each of these 10 components, to trial the item pool on a large, national representative sample, and to use evolving statistical analyses to select the best items to measure each of the 10 constructs. Starting with the 10 construct definitions items, the research team constructed additional items and adapted appropriate items from existing instruments designed to measure similar constructs (see subsequent discussion). In preparing items for the present study, we started with Huppert and So's (2013) ten original constructs but asked ourselves the question whether the inverse of the DSM/ICD criteria really covered well-being adequately.

Based on our review of the literature and in discussion with several clinical psychologist colleagues, we concluded that there were five important constructs missing from the original list. The additional factors were based on our review of the well-being literature in which we included positive psychology constructs that are not well-represented in clinical taxonomies of ill-being that were the basis of the original 10 constructs. We then independently verified the importance of these additional constructs through consultations with clinical psychologists. Three of these, Competence, Self-acceptance and Autonomy, have an individual focus like the ten original constructs, while two of the new components empathy and prosocial behavior- have an interpersonal focus.

Competence was included in Huppert and So's (2013) original list of constructs, but the most suitable item available in the ESS was subsequently classified as "clear thinking" leading us to retain that component but to still add a more traditional measure of competence. Competence is arguably a core component of general wellness and thriving (Ryan & Deci, 2017). People who feel a sense of general competence have higher self-esteem (Thøgersen-Ntoumani & Ntoumanis, 2007), and greater satisfaction with life (Meyer, Enstrom, Harstveit, Bowles, & Beevers, 2007). Conversely, individuals with anxiety and depression have difficulty achieving goals and report feeling a lack of general competence (e.g., Ryan & Deci, 2017; Wei, Philip, Shaffer, Young, Zakalik & Hansen, 2005).

Considerable theory and research based on Self-Determination Theory (see overview by Ryan & Deci, 2017) argues that a lack of autonomy underpins all of the common mental disorders, even if it is not specifically mentioned as a symptom. Depression and anxiety are associated with decrements in perceived volition and control over one's life, and the tendency to make decisions out of shame, guilt or avoidance, rather than one's longer term values and aspirations (Ryan & Deci, 2017). All of these tendencies are linked to an absence of autonomy, meaning a general sense of autonomy is a core component of healthy functioning (Ryan & Deci, 2017).

Empathy and prosocial behaviour were included on the basis that prosocial emotions and behaviours are central to human functioning, vitality and wellness (Eisenberg, Fabes, & Spinrad, 2007; Weinstein & Ryan, 2010). Empathy is the tendency to vicariously experience other individuals' emotional states (Davis, 1994). Individuals with mental health disorders have difficulty feeling the emotions of others and taking the perspective of others (Baron-Cohen, 2011). In contrast, empathy is essential to positive social functioning (Batson, 1991; Eisenberg et al., 2007) and has been associated with group cohesion (Henry, Sager, & Plunkett, 1996), and relationship satisfaction (Davis & Oathout, 1987), and as such is an important feature of healthy individual functioning.

Prosocial behavior has been defined as "voluntary behavior intended to benefit another" (Eisenberg et al., 2007, p. 646). It is related to empathy but conceptually distinct from it, in that the former describes observable behaviour, whereas the latter describes an internal state (Eisenberg et al., 2007). Depression and anxiety have also been negatively linked to prosocial behaviour, including social withdrawal, and less capacity to respond to the needs of others (Eisenberg et al., 2007). Although not directly derived from the inverse of DSM/ICD classifications, all are at least indirectly related to these classifications.

This large item pool for each of the 15 WB-Pro15 components was then be critiqued by an expert panel of well-being researchers (colleagues of the authors). Each item was evaluated in relation to clarity of expression and an assessment of the factor to which it belongs. These responses were used to cull potentially inappropriate items and to revise the wording of potentially ambiguous items. This revised item pool was then administered to a large, representative sample of adult participants and advanced statistical analyses was used to select the best items.

Stage 2: Final Item Selection and Testing. The purpose of stage 2 was two-fold. Firstly, we sought to replicate, refine, and test the generalisability of the WB-Pro15 factor structure with a new, nationally representative sample of adults. Part of this sample consisted of some of participants from Stage 1 that allowed us to evaluate the test-retest stability of the WB-Pro15 constructs in addition to reliability. Based on the WB-Pro15 items from Stage 1 on the final WB-Pro15, we used "best practice" procedures (see Marsh, Ellis, Parada, Richards & Heubeck, 2005; Marsh, Martin & Jackson, 2010) to develop a brief instrument WB-Pro15 instrument, retaining only 3 or 4 items per factor that provide a well-defined, good-fitting factor structure, items that: Best measured the intended construct as inferred on the basis of corrected item-total correlations (available in most reliability procedures) and the size of standardized factor loadings in CFA (these two criteria are combined as they provide essentially the same information); Had minimal cross-loadings as evidenced by Mplus's modification indexes based on CFA and cross-loadings based on ESEM, indicating the extent to which the fit would be improved if an item were allowed to load on a factor other than the one that it was intended to measure, and expected size of the cross-loading; Had minimal correlated uniquenesses, particularly with other items in the same scale (if two items within the same scale had a substantial correlated uniqueness, only one item was retained); Maintained the breadth of content of the original construct (based on subjective evaluations of the content of each item); and had a sufficient number of items to maintain a coefficient α estimate of reliability of at least .80 (and to retain more items for scales found to be less reliable). Based on these selection procedures and traditional criteria of a psychometrically sound instrument, we sought to construct the WB-Pro15 instrument such that it demonstrates:

- Good reliability: Median coefficient alpha ≥ .80 across the scales (Stages 1 & 2);
- Good test-retest stability over one year: median test-retest correlation ≥ .70 across the 15 scales (repeat sample from Stages 1 & 2);
- A well-defined, replicable factor structure as shown by structural equation modelling in relation to traditional indices of fit (Marsh, Hau & Wen, 2004; Stages 1 & 2);
- A factor structure that is invariant over gender, age, level of education, and time as shown by multiple-group structural equation models (Stages 1 & 2);
- Applicability for participants across the age range from late-adolescent/young adult, middle-age, and older adults (combined sample from stages 1 and 2);
- Convergent and discriminant validity as shown by multitrait-multimethod (MTMM) studies of WB-Pro15 responses in relation to time (test-retest stability) and to selected scales from other well-being instruments and indicators of well-being (Stage 2);

Section 2: Wording of Selected Items and Constructs Considered in the Present Investigation

Table 1

Wording of Selected Items and Constructs Considered in the Present Investigation

Construct definitions of the original 10 constructs (Huppert & So, 2013).

Competence: Feeling that one is a capable person (e.g. thinking clearly, concentrating, making decisions).
Emotional stability: Balanced emotional responses; feeling calm or relaxed; even-tempered.
Engagement: Being actively involved or taking an interest in most activities.
Meaning: The sense that one's activities serve a wider purpose than self-interest.
Optimism: Having a positive attitude about the future; feeling hopeful.
Positive emotion: Tendency to experience positive feelings (e.g. happy, cheerful, contented).
Positive relationships: Experiencing good connections with people; having meaningful relationships.
Resilience: Ability to manage or recover from setbacks or from anxiety and worry.
Self-esteem: Positive evaluation of oneself as a person e.g. feelings of worth.
Vitality: Having sustained energy, particularly in relation to mental energy.

15 Dimensions and 48 items for the WB-Pro

Autonomy	I feel free to do whatever I decide to do.
Autonomy	I feel free to make my own choices. (A)
Autonomy	I feel I can decide for myself how to live my life.
Clear Thinking	I am able to think clearly
Clear Thinking	I am able to stay focused when I need to.
Clear Thinking	I am easily able to concentrate when necessary. (A)
Competence	I am competent and capable in the activities that are important to me.
Competence	Most things I do, I do well. (A)
Competence	I am able to perform well and be successful in most things that I do
Emotional Stability	I do not get easily upset. (A) (B)
Emotional Stability	I usually maintain my composure.
Emotional Stability	I am emotionally balanced and even-tempered.
Empathy	My heart goes out to people who are unhappy.
Empathy	I feel others' emotions.
Empathy	Other people's misfortunes usually disturb me a great deal.
Empathy	I easily get caught up in other people's feelings. (A)
Engagement	Most of the time I am really interested in what I am doing. (A)
Engagement	I am almost always engaged and interested in my daily activities.
Engagement	I feel excited by many of the things I do.
Meaning	I lead a purposeful and meaningful life.
Meaning	I feel I have a sense of direction in my life.
Meaning	My life has a clear sense of purpose. (A)
Optimism	I feel very optimistic about my future. (A)
Optimism	My future looks very bright to me.
Optimism	I am always optimistic about my future. (B)
Positive Emotions	I generally feel cheerful.
Positive Emotions	I am happy most of the time.
Positive Emotions	All things considered, I would describe myself as a happy person. (A)
Positive Relationships	There are people in my life who really care about me. (A)
Positive Relationships	I have close and secure relationships.
Positive Relationships	There are people with whom I can discuss intimate and personal matters. (B)
Positive Relationships	I receive help and support from others when I need it.
Prosocial Behavior	I frequently offer help to others.
Prosocial Behavior	I willingly give of my time to others in need. (A)
Prosocial Behavior	If a person needs help, I would do almost anything I could to assist. (B)

Resilience	I tend to bounce back quickly after hard times.
Resilience	It does not take me long to recover from a stressful event.
Resilience	I quickly get over and recover from significant life difficulties. (A)
Self-Acceptance	I am accepting of my own flaws and inadequacies.
Self-Acceptance	I can admit my shortcomings without shame or embarrassment. (A)
Self-Acceptance	I can see my own problems and shortcomings without getting distressed by them.
Self-Acceptance	I am accepting of who I am.
Self-Esteem	I feel that I'm a person of worth. (A)
Self-Esteem	A lot of things about me are good.
Self-Esteem	I feel that I have a number of good qualities. (B)
Vitality	I feel full of energy most of the time.
Vitality	I generally have a lot of energy. (A)
Vitality	I generally feel active and vigorous.
14 WEMWBS Items	
WMWB1	I've been feeling optimistic about the future.
WMWB2	I've been feeling useful.
WMWB3	I've been feeling relaxed.
WMWB4	I've been feeling interested in other people.
WMWB5	I've had energy to spare.
WMWB6	I've been dealing with problems well.
WMWB7	I've been thinking clearly.
WMWB8	I've been feeling good about myself.
WMWB9	I've been feeling close to other people.
WMWB10	I've been feeling confident.
WMWB11	I've been able to make up my own mind about things.
WMWB12	I've been feeling loved.
WMWB13	I've been interested in new things.
WMWB14	I've been feeling cheerful.
8 Flourishing Items	
FLOURISHING1	I lead a purposeful and meaningful life.
FLOURISHING2	My social relationships are supportive and rewarding.
FLOURISHING3	I am engaged and interested in my daily activities.
FLOURISHING4	I actively contribute to the happiness and well-being of others.
FLOURISHING5	I am competent and capable in the activities that are important to me.
FLOURISHING6	I am a good person and live a good life.
FLOURISHING7	I am optimistic about my future.
FLOURISHING8	People respect me.

Note. A = Item included in 15 item WB-Pro scale. B = Item included in 5 item WB-Pro scale.

Section 3: Application and Results of Exploratory and Confirmatory Structural Equation Modeling

Full- and Set-Exploratory Structural Equation Modeling (ESEM) parameters can be identified with the maximum likelihood (ML), weighted least square, or with robust alternatives. Within a given model, is possible to posit a combination of Confirmatory Factor Analysis **(**CFA), Full-ESEM and Set-ESEM factors within the same model. If the model contains only a single factor, then CFA, Set-ESEM and Full-ESEM are equivalent.

In ESEM models when there is more than one factor (m > 1) with cross-loadings, model identification requires additional constraints (see Asparouhov & Muthén 2009; Marsh et al., 2009; Marsh, Martin & Martin, 2010; Sass & Schmitt, 2010). The initial (unrotated) unconstrained factor structure requires a total of m^2 constraints to achieve identification. This initial, unrotated solution is then rotated using any one of a wide set of orthogonal and oblique rotations (Asparouhov & Muthén, 2009, Sass & Schmitt, 2010). Because the fit of the ESEM model does not depend on the particular rotation, goodness-of-fit does not provide a basis for choosing a particular rotation (Sass & Schmitt, 2010; also see Marsh, Morin, Parker & Kaur, 2014; Marsh, Guo et a., in press). However, comparison of fit with alternative model is facilitated by the fact that the traditional CFA model is nested under the Set-ESEM model which is nested under the Full-ESEM model. Geomin ration was used in early applications of ESEM (Marsh et al., 2009, 2010). However, more recently target rotation has been used to provide a compromise between the mechanical approach to EFA rotation and the a priori CFA model, based on partial knowledge of the factor structure. This is consistent with the emphasis of ESEM as a confirmatory tool rather than an exploratory tool.

Full- and Set-ESEM are highly flexible but, as initially operationalized, many CFA analyses could not be done with ESEM. Marsh, Lüdtke, Nagengast, Morin & Von Davier (2013; Morin, Marsh, & Nagengast, 2013) proposed ESEM within CFA (EwC) to resolve most of these limitations of ESEM. Identification of the ESEM requires m^2 constraints where M = number of factors. Marsh and colleagues (2013) proposed that this could be accomplished that by retaining parameters estimates in the final ESEM solution, and fixing m^2 factor loadings in initial solution. Thus, for example, fixing the all the factor loadings for the item with the highest factor loading for each factor for all the factors results in m^2 constraints (i.e., there are m constraints associated with each of the m factors). The EwC solution is equivalent to the ESEM solution in terms of *df*, goodness of fit, and parameter estimates. However, the EwC is actually a CFA model based on the ESEM solution, thereby facilitating further models that are possible with CFA. Although previously applied in relation to Full-ESEM the some rationale can be applied to each set of ESEM factors within a Set-ESEM analysis (Marsh, Guo et a., in press), as illustrated in in the present investigation.

Results of factor analyses in the present investigation

Two sets of factor analyses – CFA and ESEM – were conducted on the entire set of 2,559 responses from participants at T1 and T2. Critical features of these analyses were the goodness-of-fit indices (see Models 1A & 1B in Table 2, below) and parameter estimates for both ESEM and CFA models (shown in Table 3A & 3B, below).

For the ESEM solution, all items load more highly on the factor that it was designed to measure (target loadings) than on other factors (non-target loadings; target loading are shown in Table 3A, and the full set of target and non-target loadings is presented in Section 6, below). The target loadings are all substantial, varying from .520 to .909 (median = .710). Nevertheless, some of the factor correlations are substantial, varying from .011 to .815 (Mean r = .476), with 8 of the 105 correlations greater than .700. Thus the ESEM solution is well-defined.

For the CFA solution (see Table 3B, below), all the factor loadings are substantial, varying from .691 to .910 (Mean = .831; non-target loadings are all constrained to be zero in the CFA). However, the factor correlations are very high, varying from .284 to .918 (Mean r = .692), with 66 of 105 being greater than .700. Hence, although CFA structure is well-defined and well-fitting, the large factor correlations detract from the potential usefulness of the factors.

Both the ESEM and CFA solutions are well-defined in terms of goodness-of-fit and well-defined factors. Although the CFA solution is preferable in terms of parsimony, the ESEM solution is better fitting and resulted in more distinct factors. However, both CFA and ESEM solutions provide support for the a priori factor structure relating the 48 items to the WB-Pro factors.

Table 2

Goodness of Fit for Models in the Present Investigation

Model	N Parms	CHI	df	RMSEA	CFI	TLI	Description
			1 Total (stacked) Group Analysis				
1A	711	1207	513	.023	.994	.986	ESEM-Total Group
1B	249	4397	975	.037	.968	.963	CFA-Total Group
1C	30	10128	.90	.236	.613	.548	HO Factor Analysis*
			2 Multiple Group Invariance over Four Stacked Groups				
2A	2844	3498	2052	.035	.976	.946	Configural-4 groups
2B	1359	4531	3537	.021	.985	.981	Metric-4 groups
2C	1260	4744	3636	.022	.984	.980	Scalar -4 groups
			3 Multiple Group Invariance over Three Educational Groups				
3A	2133	2543	1539	.028	.984	.965	Configural-3 Educ Groups
3B	1143	3264	2529	.018	.988	.984	Metric-3 Educ Groups
3C	1077	3358	2595	.019	.988	.984	Scalar -3 Educ Groups
			4 Multiple Group Invariance over Four Age Groups				
4A	2844	3358	2052	.032	.981	.958	Configural-4 Age Groups
4B	1359	4588	3537	.022	.985	.980	Metric-4 Age Groups
4C	1260	4747	3636	.022	.984	.980	Scalar -4 Age Groups
			5 Multiple Group Invariance over Two Gender Groups				
5A	1422	1599	1026	.021	.98	.979	Configural-2 Gender Groups
5B	927	1988	1521	.016	.992	.988	Metric-2 Gender Groups
5C	894	2042	1554	.016	.992	.988	Scalar -2 Gender Groups
			6 Longitudinal Invariance & Multitrait-Multimethod Analyses				
6A	1695	5522	3057	.02	.978	.967	Configural-2 Waves
6B	1200	6335	3552	.019	.975	.968	Metric-2 Waves
6C	1152	6686	3600	.02	.973	.965	Scalar -2 Waves
			7 Total (stacked) Group Analysis Relating Demographic Variables to WB-Pro 15 Factors				
7	926	1186	843	.015	.995	.99	Demographic Variables
			8 Tests of Unidimesionality of WEMWBS & Flourishing Instruments				
8A	24	190	20	.075	.955	.937	Deiner (D) 8-item (1 Factor)
8B	42	641	77	.069	.934	.921	Warwick (W) 14-Item (1 Factor)
8C	67	1589	208	.066	.906	.891	W+D 22 items (2 factors)
			9 WB-Pro 15 + Unidimentional WEMWBS & Flourishing Instruments				
9A	750	2891	902	.038	.955	.923	D+WB- Pro 15 (1+15 Factors)
9B	768	3911	1247	.037	.947	.920	W+WB- Pro 15 (2+15 Factors)
9C	807	6396	1748	.042	.921	.891	W+D+WB- Pro 15 (2+15 Factors)
			10 WB-Pro 15 Absorbing WEMWBS & Flourishing Items				
10A	847	1491	805	.024	.984	.970	D+WB-Pro 15 (15 Factors)
10B	949	1723	1066	.020	.987	.977	W+WB- Pro 15 (15 Factors)
10C	1085	2554	1470	.022	.982	.970	W+D+WB- Pro 15 (15 Factors)

Note. Summary of Goodness-of-fit statistics for the different factor analyses considered in the present investigation. ESEM = exploratory factor analysis; CFA = confirmatory factor analysis; Parms = number of freely estimated parameters; *Chi* = chi-square; df = degrees of freedom ratio; CFI = Comparative fit index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation. Model. Models 1-6 were based on stacked (long format) data, using robust maximum likelihood estimator and type = complex to account for fact that some students had two sets of responses.

Table 3A

WB-Pro15 Factor Structure: Exploratory Structural Equation Model (ESEM)

	Comp etence	Clear Thinking	Emot Stablity	Engage ment	Mean ing	Optim ism	Pos Emot	Pos Relat	Resil ience	Self-Esteem	Vitality	Self-Accep	Auton omy*	Emp athy	Pro-Social
	CO	CT	ES	EN	ME	OP	PE	PR	RE	SE	VI	AC	AU	EM	PS
Target Factor Loadings															
Item 1	.520	.534	.803	.678	.557	.766	.656	.807	.732	.581	.819	.855	.755	.564	.775
Item 2	.687	.809	.666	.656	.57	.661	.668	.755	.744	.58	.909	.923	.909	.788	.821
Item 3	.607	.902	.723	.476	.66	.598	.720	.784	.848	.596	.665	.546	.681	.78	.733
Item 4								.791				.544		.872	
Factor Correlations															
CO	1														
CT	.536	1													
ES	.259	.685	1												
EN	.075	.518	.627	1											
ME	.724	.448	.284	.013	1										
OP	.032	.441	.612	.799	.137	1									
PE	.689	.533	.446	.114	.815	.244	1								
PR	.436	.677	.601	.514	.523	.555	.600	1							
RE	.372	.638	.751	.515	.441	.545	.555	.584	1						
SE	.086	.547	.619	.760	.011	.707	.169	.584	.444	1					
VI	.365	.558	.579	.505	.494	.529	.583	.518	.644	.318	1				
AC	.632	.722	.669	.383	.611	.381	.659	.690	.685	.460	.559	1			
AU	.487	.695	.607	.528	.464	.522	.529	.696	.598	.540	.522	.713	1		
EM	.345	.381	.349	.279	.323	.217	.339	.542	.289	.268	.301	.490	.405	1	
PS	.324	.47	.415	.378	.263	.318	.295	.535	.389	.402	.313	.508	.431	.731	1
Higher-Order Factor Loadings and Residual Variances															
Loading	.563	.829	.793	.615	.580	.617	.680	.825	.787	.621	.695	.856	.812	.520	.571
Residual	.683	.313	.371	.622	.664	.620	.538	.320	.381	.614	.517	.268	.341	.729	.674

Note. Presented are target loadings relating each of the 48 items to the factor that it was designed to measure. Items 1 to 3 (or 4) refer to the three or four items designed to measure each factor. Cross-loadings are not shown here but are available in Supplemental Materials, section 6. The higher-order factor analysis was based on fitting a single factor to the latent correlation matrix of correlations among the 15 first-order factors shown here. Whereas all 15 factors loaded substantially on the higher-order factor (loadings .520 to .856), much of the variance in each of the factors could not be explained by the higher-order factor (residual variance components = .268 to .729). We also note that the fit of the higher-order factor model was extremely poor (RMSEA = 236; CFI = .613; TLI = .548)

Table 3B
Summary of Confirmatory Factor Analysis (CFA) Model

	Competence	Clear Thinking	Emot Stablity	Engagement	Meaning	Optimism	Pos Emot	Pos Relat	Resilience	Self-Esteem	Vitality	Self-Accep	Autonomy	Empathy	Pro-social
	CO	CT	ES	EN	ME	OP	PE	PR	RE	SE	VI	AC	AU	EM	PS
Factor Loadings															
item 1	.855	.837	.788	.816	.888	.91	.91	.766	.879	.853	.927	.77	.825	.724	.837
Item 2	.798	.832	.865	.846	.879	.901	.901	.831	.859	.827	.918	.706	.871	.784	.857
item 3	.848	.809	.742	.796	.894	.891	.891	.74	.887	.843	.882	.853	.815	.664	.815
Item 4				.852				.744						.691	
Factor Correlations															
CO	1														
CT	.861	1													
ES	.733	.775	1												
EN	.86	.798	.771	1											
ME	.806	.739	.748	.918	1										
OP	.78	.698	.732	.878	.916	1									
PE	.782	.748	.827	.889	.88	.889	1								
PR	.727	.711	.675	.786	.797	.758	.785	1							
RE	.751	.721	.786	.792	.771	.762	.799	.65	1						
SE	.889	.819	.766	.84	.833	.794	.831	.798	.732	1					
VI	.667	.655	.685	.825	.754	.778	.777	.59	.726	.632	1				
AC	.836	.799	.787	.808	.792	.748	.782	.739	.752	.882	.641	1			
AU	.792	.755	.686	.797	.761	.736	.737	.717	.687	.766	.616	.786	1		
EM	.405	.361	.379	.432	.394	.342	.359	.504	.282	.433	.284	.424	.375	1	
PS	.587	.528	.501	.582	.555	.496	.504	.59	.478	.583	.429	.565	.496	.756	1

Section 4: Convergent and discriminant validity

Multitrait-multimethod approach: A supplemental rationale

The multitrait-multimethod (see Campbell & Fiske, 1959) design is used widely to assess convergent and discriminant validity, and also is a standard criterion for evaluating psychological instruments. Although Campbell and Fiske's original guidelines are still widely used to evaluate MTMM data, important problems with their guidelines are well known (see reviews by Marsh, 1988, 1993; Marsh & Grayson, 1995). Ironically, even in highly sophisticated CFA approaches to MTMM data, a single scale score—often an average of multiple items—is typically used to represent each trait–method combination. Marsh (1993; Marsh et al., 2005; Marsh & Hocevar, 1988), however, argued that it is stronger to incorporate the multiple indicators explicitly into the MTMM design. When multiple indicators are used to represent each scale, CFAs and ESEMs at the item level results in a MTMM matrix of latent correlations, thereby eliminating many of the objections to the Campbell–Fiske guidelines. We argue that because our analysis starts with a latent correlation matrix in which factors are represented by multiple items, our approach overcomes most of the limitations widely attributed to the original Campbell & Fiske (1959) guidelines. For this reason, the actual summary of the MTMM results based on the latent MTMM correlation matrix better represents the logic and intuitive appeal of the original Campbell-Fiske guidelines than do most current approaches to MTMM data.

Multitrait-multimethod approach: Supplemental discussion of results

The 30x30 correlation matrix based on this factor analysis (see Table 3 in the main manuscript) represents a MTMM matrix with 15 traits (the WB-Pro factors) and two methods (T1 and T2). The 15 test-retest correlations (.73 to .85; Mn = .80; the main diagonal in Table 3) represent convergent validities. These results provide good support for convergent validity in relation to time. The remaining correlations between T1 and T2 responses (.02 to .56; Mean r = .29; off-diagonal correlations in Table 3) represent heterotrait-heteromethod correlations in Campbell-Fiske terminology. Correlations among T1 factors (Mean r = .34) and among T2 factors (Mean r = .35) represent heterotrait-monomethod correlations (not shown to conserve space, but see Table 2, above). Because the convergent validities are substantially higher than the either heterotrait-heteromethod or heterotrait-monomethod correlations, there is good support for divergent validity.

Because the correlations among different factors at each wave (Mean rs = .34 & .35) are slightly higher than correlations among different factors for different waves (Mean r = .29), there is some evidence for a small method-halo effect associated with each wave considered separately.

Relations with other Constructs

Here, we discuss results (presented in Table 2 of the manuscript) of our tests of convergent and divergent validity of the 15 WB-Pro dimensions with other relevant scales.

PERMA. Four of the five PERMA factors (engagement, meaning, positive emotions and positive relations—all but accomplishment) directly parallel four of the WB-Pro factors. In support of the convergent validity of these four factors, correlations among each pair of PERMA and WB-Pro factors (.834 to .899) are extremely high. Correlations between these four PERMA factors and other WB-Pro factors are substantial, but systematically lower. The fifth PERMA factor, accomplishment, is highly correlated with WB-Pro factors to which it is most logically related (competence, engagement, meaning, optimism, and positive emotions—correlations of .721 to .808). Although correlations between PERMA and WB-Pro factors support the validity of the factors, we note that correlations among the five PERMA factors are very high (.768 to .937), meaning they are not ideally suited to testing discriminant validity in relation to other measures, or differentiating between the five PERMA factors.

Basic Psychological Needs. This instrument measures need satisfaction and need frustration in relation to three basic psychological needs—a total of 6 (3 needs x 2 directions). Each of the three psychological needs (autonomy, relatedness, and competence) matches a corresponding WB-Pro (autonomy, positive relations, and competence). Logically, the positively oriented WB-Pro factors should be most strongly (positively) related to the corresponding need satisfaction factors, and less strongly (negatively) related to the corresponding need frustration factors. Consistent with a priori predictions, the correlations between matching need satisfaction and WB-Pro factors are substantial (.700, .812, .786), whereas the corresponding correlations for need frustration are smaller in size and negative in direction (-.500, -.585, -.582). In each case, the WB-Pro factor is more positively related with the matching need satisfaction factor than to any other psychological need factor, and more negatively correlated with the matching need frustration factor than to any other psychological need factor. These results provide strong support for the convergent and discriminant validity of responses to both instruments.

Big-Five Personality. As noted earlier, there is not such a clear a priori matching of Big-Five personality and WB-Pro factors. Highlighted in Table 6 are the WB-Pro factors that are logically most related and highly correlated with each Big-Five personality factor. Thus, openness is most strongly related to engagement and prosocial behavior; conscientiousness is most highly correlated with competence and clear thinking; extraversion is most highly correlated with engagement and positive emotions; agreeableness is most highly correlated with empathy and prosocial behavior; and neuroticism is most highly correlated (negatively) with particularly emotional stability, but also with positive emotions, resilience, and self-acceptance. Particularly the correlations of agreeableness with prosocial behavior and empathy are larger than the correlations of between these WB-Pro factors and any of the PERMA or Psychological Needs factors (or any of the additional single-scale measures that were considered). This is not surprising as these well-being factors are not represented in the other measures, but the correlations between Big-Five and WB-Pro factors provide support for the convergent as well as discriminant validity of particularly these two WB-Pro factors. In summary, although not strictly a priori, this logical pattern of relations between Big-Five personality factors and WB-Pro factors provides support for the convergent and discriminant validity of the responses to the WB-Pro.

Single-Scale Measures. Next we evaluate convergent and discriminant validity in relation to selected single-scale measures (but see analyses of WEMWBS and flourishing, described below). Two multi-item single-factor instruments (CES-D and stress) reflect widely used measures of ill-being. Hence, it is logical that these measures are negatively correlated with most of the WB-Pro measures of well-being. Interestingly, the exception is the empathy scale that is nearly uncorrelated with these measures of ill-being. Logically and empirically, these two measures of ill-being are most negatively correlated with emotional stability (particularly stress) and positive emotions (particularly depression).

Life satisfaction and happiness are sometimes used as single-item constructs (or single construct if based on multiple items). Not surprisingly, both these measures are positively related with all WB-Pro factors. Although we did not postulate a priori predictions about the pattern of correlations, correlations greater than .700 are highlighted in Table 7. Life satisfaction tends to be more correlated with WB-Pro factors, with seven correlations greater than .700 (the highest being optimism, .812; and positive emotions, .799). In contrast, happiness is only correlated greater than .700 with positive emotions. Nevertheless, the pattern of correlations relating these two measures to WB-Pro is very similar (the profile similarity index, the correlation between the 15 correlations with happiness and the corresponding 15 correlations with life satisfaction, is .970).

Although sleep problems, general health, and exercise are not highly correlated with any of the WB-Pro factors, each of these three items are most highly correlated with the WB-Pro factor of vitality-- particularly general health (.559) and exercise (.394).

Section 5: Goodness-of-fit, Golden Rules, and Interpretation of Parameter Estimates

In applied CFA/SEM studies, applied researchers have sought universal “golden rules” as to what constitutes an acceptable goodness of fit (Marsh, Balla & McDonald, 1988; Marsh, Hau, & Wen, 2004). Generally, given the known sensitivity of the chi-square test to sample size, to minor deviations from multivariate normality, and to minor misspecifications, applied SEM research focuses on indices that are relatively sample-size independent (Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004; Marsh, Hau, & Grayson 2005), such as the Root Mean Square Error of Approximation

(RMSEA), the Tucker-Lewis Index (TLI), and the Comparative Fit Index (CFI). Population values of TLI and CFI vary along a 0-to-1 continuum, in which values greater than .90 and .95 typically reflect acceptable and excellent fits to the data, respectively. Values smaller than .08 and .06 for the RMSEA support acceptable and good model fits respectively.

The chi-square difference test can be used to compare two nested models, but this approach suffers from even more problems than does the chi-square test for single models—problems that led to the development of other fit indices (see Marsh, Hau et al., 2005). Cheung and Rensvold (2002) and Chen (2007) suggested that if the decrease in fit for the more parsimonious model is less than .01 for incremental fit indices such as the CFI, there is reasonable support for the more parsimonious model. For indices that incorporate a penalty for lack of parsimony, such as the RMSEA and the TLI, it is also possible for a more restrictive model to result in a better fit than would a less restrictive model. However, it is emphasized that these cut-off values constitute rough guidelines only, rather than "golden rules" (Marsh et al., 2004). Indeed, this emphasis of treating these cut-off values as rough guideline rather than golden rules applies even more strongly to Full- and Set-ESEM where there has not been a sufficient history of application to fully support the usefulness of cut-offs based on CFA models.

The basic CFA model is nested under the corresponding Set-ESEM, and the Set-ESEM is nested under the Full-ESEM. This nested structure facilitated conventional model comparisons which can be used to compare the fit of three models– along with a detailed evaluation of parameter estimates based on the three approaches. The Set- and Full-ESEMs are most appropriate when they fit the data better than the corresponding CFA model, the multiple ESEM factors are well-defined in the measurement model, and there are substantively important differences in parameter estimates based on the CFA and the ESEM models. Starting with the initial ESEM publications (Asparouhov & Muthén, 2009; Marsh et al., 2009), Marsh et al. (2014) argued that factor correlations were typically positively biased unless the CFA assumption is met (all cross-loadings are exactly equal to zero in the population). Indeed, even when the ICM-CFA model apparently fits well, CFA factor correlations tend to be larger than ESEM factor correlations. Importantly, simulation studies show that ESEM is typically better at recovering known factor correlations and that even small cross-loadings can result in biased estimates of factor correlations when based on CFAs (Marsh et al., 2014). If ESEMs are sufficiently similar to CFA results, then there is robust support for the factor structure based on the CFA solution. Thus, it is always appropriate to test ESEMs even when CFA models are retained.

Marsh et al. (2014) also acknowledged that ESEM might lack parsimony (particularly in large, complex models based on moderate sample sizes). Set-ESEM was developed in part to achieve a better balance between the goodness-of-fit for the Full-ESEM and the parsimony of the CFA. However, because of the nesting relationship between the three models, parsimony based on the number of freely estimated parameters will always be best for CFA, followed by Set-ESEM, and then Full-ESEM, whereas the goodness of fit for indices that do not control for parsimony (e.g., the chi-square statistics and indices like the CFI that are monotonic with it) will always be better for ESEM, followed by Set-ESEM, and then CFA. However, for indices that control for parsimony (e.g., TLI and RMSEA), it is possible for the CFA model to fit better than the ESEM models, or for Set-ESEM to fit better than the Full-ESEM. Nevertheless, when these three models vary substantially in relation to parsimony, model evaluation should not rely solely – or even primarily – on the basis of goodness of fit.

Section 6: Relations of the WB-Pro Dimensions with 10 Demographic Variables

In support for our multidimensional perspective (but also substantively relevant), we found distinct patterns of relations between the 15 WB-Pro factors and 10 demographic variables. These patterns of relations appear in Table 4, below, and demonstrate a complex pattern of associations between the 15 WB-Pro dimensions and various demographic factors. For example, males reported more vitality, resilience and emotional stability than females, whereas females reported greater empathy than males. Similarly, there were positive correlations with age for self-acceptance, positive emotions, clear thinking and autonomy, while other WB-Pro factors (e.g., optimism) showed weaker or even negative relations with age. Further, there were also some quadratic effects associated with age. For example, competence initially increased, levelled out and then declined in older age (i.e. an inverted ‘U-shape’), whereas optimism, engagement, positive relations, vitality and resilience initially declined, levelled out and then increased in older age (i.e., a ‘U-shape’). Although most WB-Pro factors were positively related to education (the strongest were emotional stability, vitality, clear thinking, optimism, positive relations, self-esteem and engagement), others had little or no association. Lastly, being married was positively related to many WB-Pro factors (the largest associations were optimism, engagement and self-esteem) but were uncorrelated with other factors. Although these complex patterns of relations are substantively important in their own right, the overarching issue for present purposes is that these patterns of relations support our multidimensional approach to well-being. In particular, the complex multidimensional pattern of relations could not be represented with a single global measure of well-being.

Table 4

Association between 15 WB factors and Background/Demographic Variables

Predictor Variables	Competence CO	clear thinking CT	Emot Stablity ES	Engagement EN	Meaning ME	Optimism OP	Pos Emot PE	Pos Relat PR	Resilience RE	Self-Esteem SE	Vitality VI	Self-Accept AC	Autonomy* AU	Empathy EM	Pro-social PS
Demographic															
Married	-.106	.088	.***131***	.***247***	-.048	.***287***	-.031	.***157***	.***136***	.***204***	.***100***	.035	.041	.038	.042
Male	.***088***	.057	.***115***	-.018	.066	-.003	.052	-.033	.***140***	-.***056***	.***156***	.***120***	.045	-.***140***	-.***095***
Education	.054	.***143***	.***161***	.***123***	.081	.***136***	.044	.***125***	.***082***	.***130***	.***148***	.***058***	.052	.***066***	.023
English Fluency	-.***104***	-.***119***	-.054	-.020	-.022	-.029	-.055	-.079	-.***052***	-.***081***	-.028	-.***082***	-.***093***	-.***048***	-.***096***
AGE-linear	.***097***	.***143***	.***083***	-.033	.***091***	-.***135***	.***131***	.042	.046	.***08***9	***-.058***	.***143***	.***101***	-.018	.020
AGE-quad	-.***082***	.011	.058	.***091***	-.021	.***115***	-.001	.***066***	.***059***	.011	.***065***	-.031	.034	.038	.005
Married x AGE	-.049	-.029	-.022	-.035	-.005	.003	-.025	-.011	-.029	-.053	-.004	-.039	-.048	-.042	-.037
Education x AGE	.039	-.019	-.***057***	-.009	.015	-.047	.010	-.034	-.032	-.***062***	.019	-.001	-.004	-.011	.011
Male x Age	-.026	-.028	-.***071***	-.065	-.042	-.004	-.058	-.051	-.***066***	-.012	-.***087***	-.***096***	-.045	-.***1***01	-.***056***
Married x Male	-.013	.016	.024	.***080***	-.013	.053	-.026	.***059***	.028	.060	.021	-.003	.033	.041	.***077***
Life Event Changes															
Negative	0.07	***-0.42***	***-0.52***	***-0.38***	***-0.23***	***-0.56***	***-0.36***	***-0.34***	***-0.56***	***-0.28***	***-0.4***	***-0.32***	***-0.24***	***0.26***	0.2
Neutral	0.08	-0.04	-0.36	0.05	-0.09	0.15	-0.17	0.04	-0.2	0.01	-0.08	-0.11	0.02	***0.26***	0.12
Positive	0.17	0.09	-0.05	0.21	0.19	***0.33***	0.24	***0.28***	0.15	0.1	***0.28***	0.16	0.17	0.35	***0.37***

Note. In the structural equation model, each of the WB-Pro15 scales was represented by a latent factor and regressed on the eight predictor variables. To facilitate interpretation all first-order predictor variables were standardized and all interaction terms were the product of standardized predictor variables (but not restandardized). A separate analysis was done predicting each WB-Pro 15 factor from the set of three life event change scores. Statistically significant ($p < .05$) coefficients are presented in bold and underlined.

Section 7: A Profile Approach to the Relation Between WB-Pro15 Factors and Selected Demographic Variables

In this section (see Table 6) we evaluate a multidimensional profile approach to the representation of the WB-Pro15 scales in relation to three demographic variables (Married, Male, and Age) and compare it to a unidimensional approach.

The effect of being married was positive for life satisfaction (.228); however, it was even more positive for optimism, but less positive for all the other WB-Pro factors (significantly so for 11 factors). This differentiated profile of effects of being married on WB-Pro factors cannot be explained in terms of global Life Satisfaction.

Gender differences (male) were weakly positive for life satisfaction (.063); however, they were significantly more positive for vitality, emotional stability, and acceptance, but significantly negative for self-esteem, positive relations, optimism, engagement, and particularly empathy, pro-social behaviour. This differentiated profile of gender differences on WB-Pro factors cannot be explained in terms of global Life Satisfaction.

Age was not significantly related to life satisfaction (.016); however, age effects were significantly more positively for clear thinking, emotional stability, positive relations, positive emotions, reliance, acceptance and autonomy, but more negative for optimism and vitality. This differentiated profile of age effects on WB-Pro factors cannot be explained in terms of global Life Satisfaction.

In summary, this profile approach to the relation between the WB-Pro15 factors and selected demographic variables provides strong support for the multidimensional perspective underpinning the WB-Pro15 instrument. The differentiated effects of these demographic variables could not be explained in terms of a unidimensional perspective of well-being.

Section 8: WB-Pro Short Forms: Machine Learning Genetic Algorithms

To create a short-form of the WB-Pro, we utilized the latest advances in machine-learning methods in psychometrics employing genetic algorithms (GA). First introduced by Holland (1975) as optimization tools for game theory and pattern recognition problems, the GA have recently gained popularity in psychometrics for being highly convenient optimization tools for efficiently finding a short form of a long form (Sahdra, Ciarrochi, Parker & Scrucca, 2016; Schroeders, Wilhelm, & Olaru, 2016; Yarkoni, 2010). The GA implement the principles of biological evolution (e.g., mutation, crossover, and selection based on fitness) in a computational framework to find a suitable short form of the long form that is reliable, valid, and preserves most of the variance in the data of the original questionnaire (Sahdra et al., 2016; Yarkoni, 2010). The GA have been employed to abbreviate long forms of several psychological constructs, including personality traits (Yarkoni, 2010), psychopathy (Eisenbarth, Lilienfeld & Yarkoni, 2015), experiential avoidance (Sahdra et al., 2016) and body image (Basarkod, Sahdra & Ciarrochi, 2018).

We implemented the GA method in R, an open source statistical computing environment (R Core Team, 2018), using the GAabbreviate package (Scrurra & Sahdra, 2015). The details of the genetic algorithms procedure for questionnaire abbreviation are described in Yarkoni (2010), and the details of the GAabbreviate package can be found in Sahdra et al. (2016). Briefly, the GAabbreviate aims to minimise the ‘cost’ of an item in the abbreviated scale based on the ‘fitness function’ below, as described by Sahdra et al. (2016):

$$Cost = Ik + \sum_{i=1}^{s} w_i \, (1 - R_i^2)$$

Here, I is the item cost, k is the number of items to be retained, s is the number of subscales in the measure (if applicable), w_i are the weights associated with the each subscale (if applicable), and R^2 is the variance that a linear combination of individual item scores can explain in the ith subscale or the original full scale if there are no subscales or the multidimensional structure is ignored. Consistent with the cross-validation recommendations for machine learning applications to minimize over-fitting

(James, Witten, & Hastie, 2014), the GAabbreviate implements cross-validation by default by training the GA on 50% of the sample and testing the variance-explained criterion on the remaining 50%.

In our case, the GA procedure of finding a 15-item measure from the pool of 48 items of WB-Pro began with a random selection of several sets consisting of 15 items. Borrowing the terminology from genetics, the items of the original full scale represent the genes and the item sets of randomly selected short forms represent chromosomes. Two of the selected item sets represent two parents of an offspring, a short form that is a product of several computational procedures analogous to natural selection in biological evolution. Subsetting and recombining item sets is analogous to two chromosomes exchanging one or more of their genetic sequences. As in biological evolution, in which spontaneous changes in the genes alter the gene sequence, in the GA method, the mutated items are replaced with items of the initial item pool to alter the short forms. After such manipulations, the next generation of the short versions were evaluated using a fitness function (as described above). The best performing offspring was selected, representing ‘survival of the fittest’ in evolutionary terms. We following the same procedure for generating the 5-item measure, expect no constraint was set for item selection within subscales. The correlation of the 15-item short form with the long form (in the validation subset) was .90, and that of the 5-item version with the full form was .96.

Section 9: Formative vs Reflective Measures

A starting point of the present investigation is that understanding the causes of well-being and how to enhance it requires clear conceptual framework and definitions for the multiple well-being factors. This multidimensional approach is in sharp contrast to unidimensional approaches. In one of the unidimensional approaches well-being is inferred from responses to a single item (e.g., "happiness" or "life satisfaction") or a tightly-worded set of items designed to measure a narrowly defined construct. Such an approach is truly unidimensional, highly parsimonious and expedient. However, this approach provides a very narrowly defined measure of well-being and does not provide useful information about the profile of different components that make up well-being. In a second unidimensional approach, illustrated by the widely used Flourishing and WEMWBS measures, well-being is based on responses to a set of items implicitly designed to cover more broadly the breadth of the well-being construct. Clearly this approach results in a more broadly defined measure of well-being. However, because well-being is still represented by a single score, it does not provide useful information about the profile of different components that make up well-being, not even the components used to construct the measure. Furthermore, although purportedly unidimensional, the explicit logic of the design of these instruments is multidimensional—covering a range of different components of well-being. At best, the rationale underlying these measures is an expedient—not entirely satisfactory-- compromise between a truly unidimensional and multidimensional measures of well-being.

Indeed, Flourishing and WEMWBS measures (as well as our WB-PRO15 short measures) should be considered formative rather than reflective measures of well-being, and this has caused considerable confusion in their appropriate description and application. The rationale for a formative measure (for further discussion see Bollen & Lennox, 1991; Edwards & Bagozzi, 2000) is to provide a composite index constructed from independent, albeit correlated indicators. In the factor structure the causal flow (the direction of the arrows in the path diagram) is from indicators to the composite construct. For a reflective the construct the causal flow is from the latent construct to the indicators so that correlations among indicators are zero once the after partialing out the latent factor. The theoretical rationale for reflective measures is that the indictors are essentially interchangeable so that deletion or addition of indicators does not change the nature of the construct, whereas for formative constructs "omitting an indicator is omitting a part of the construct" (Bollen & Lennox, 1991). For formative constructs, unidimensionality and internal consistency are inappropriate – even counter-productive— criteria for assessing a formative measure. Particularly if indicators for a formative construct are selected so as to be internally consistent and form a unidimensional construct, it is likely that the breadth of the construct has been compromised and that potentially important indicators of the formative construct have been excluded.

We argue that the Flourishing and WEMWBS measures should be considered formative rather than reflective measures. Support for this argument comes from the manner in which the measures were constructed, the nature of the items, and the results of our analyses showing that the measures reflect diverse components of well-being rather than a unidimensional construct. However, we do not argue that they are "bad" measures, but only that the internal consistency and undimensionality criteria used to support their usefulness are inappropriate. The critical evaluation of a formative measure is how well the indicators cover the breadth of content the index is intended to cover. This was an explicit basis of the selection of items for the WB-Pro15 short forms (see earlier discussion), but appears to be implicit at best in the construction of the Flourishing and

WEMWBS measures. Furthermore, the use of internal consistency and undimensionality to reduce the length of the 14-item WEMWBS measure to the more widely used 7-item version (Stewart-Brown et al., 2009) is completely antithetical of the theoretical rationale of a formative measure and is likely to compromised the breadth of the measure. For example, WEMWBS item 5 (I've had energy to spare) was the only item that was a priori and empirically related to the WB-Pro15 vitality factor (see Table 6). However, this item was excluded from the 7-item version, apparently on the basis of providing a better fit to a unidimensional scale—removing the most misfitting items. Although a full evaluation of the construct validity of the Flourishing, and WEMWBS measures (or WB-Pro15 short measures) from the perspective of a formative measure is beyond the scope of the present investigation, this is an important direction for further research.

Section 10: Additional Information on Validity of WB-Pro Short Forms

Here, we provide supplementary presentation of the results of the development and validation of 5- and 15-item versions of the WB-Pro, in which these versions were validated against the WB-Pro (48-items) and selected external validation scales (see Table 5, below). Not surprisingly, the WB-Pro global 5- and 15-item scales are highly correlated with the single-scale measures designed to reflect a global sense of well-being (i.e., WEMWBS, Flourishing, life satisfaction—*r*s = 0.660 to 0.800). It is also interesting to note that the global scores are also highly correlated with the five PERMA factors (*r*s = .700 to .814) even though PERMA is designed to reflect distinct factors. This reflects, in part, the observation that correlations among the PERMA factors are very high. Nevertheless, the correlations between PERMA factors and the most logically related WB-Pro factor (r's = .808 to .899) are systematically higher. In contrast, the psychological needs satisfaction factors are less correlated with the WB-Pro global scales (*r*s = 652 to .695) due in part to the fact that the needs satisfaction factors are more distinct than the PERMA factors. However, the basic psychological need satisfaction factors are also somewhat more highly correlated with the mostly logically related WB-Pro factor (r's = .700 to .812) than with either of the WB-Pro global scales. It is also interesting to note that the pattern of results with psychological need frustration factors is similar to the pattern for need satisfaction factors. However, the sizes of the correlations with need satisfaction are systematically higher than the corresponding correlations with need frustration.

Table 5

Comparisons between WB-Pro Short Global Measures and the full WB-Pro Scale. Correlations between each of the WB-Pro measures and existing measures of well-being and related constructs

Well-Being Correlates	WB-Pro-Short Global Summary Scores		Predicted Highest Correlating WB-Pro15 Factor	
	15 item	5 item	Factor	Corr
PERMA				
Positive Emotion	.820	.745	Positive emotions	.899
Engagement	.779	.697	Engagement*	.842
Pos Relationships	.700	.644	Pos relationships*	.834
Meaning	.814	.733	Meaning*	.899
Accomplishment	.794	.693	Meaning	.808
Psychological Needs				
Satisf Autonomy	.695	.605	Autonomy*	.700
Satisf Relation	.652	.620	Pos Relations*	.812
Satisf Competence	.693	.634	Competence*	.788
Frust Autonomy	-.464	-.408	Autonomy*	-.500
Frust Relation	-.454	-.420	Positive Relations*	-.585
Frust Competence	-.534	-.469	Competence*	-.582
Big Five				
Openness	.405	.402	Engagement	.426
Conscientiousness	.554	.477	Competence	.677
Extraversion	.508	.460	Engagement	.511
Agreeable	.523	.559	Pro-Social	.664
Neurotic	-.510	-.480	Emotional Stability	-.617
Single Scale Measures				
WEMWBS	.800	.731	Positive Emotions	.818
Depression	-.543	-.480	Positive Emotions*	-.620
Stress	-.521	-.468	Emotional Stability	-.595
Diener (WB)	.763	.699	Meaning	.783
Life Satisfaction	.733	.660	Optimism	.812
Happy	.628	.569	Positive Emotions	.720
Sleep	.160	.142	Vitality	.274
General Health	.414	.358	Vitality*	-.559
Exercise	.281	.236	Vitality*	.394

Note. Correlations between global scores and well-being correlates are based on a large CFA with all 40 factors (15 WB-Pro plus 25 covariate factors). One short global score is based on the best 15 items, subject to the constraint that one item from each scale was included: the other is based on the best 5 items.

Section 11: Mplus Syntax and Output For Model 1A in Table 2 and Full set of Factor Loadings For Factor Analysis Results in Table 3A

```
USEVARIABLES ARE
 CO2 CO5 CO6
 CO9 CO10 CO11
 ES2 ES4 ES7
 EN2 EN3 EN7
 ME1 ME5 ME9
 OP2 OP3 OP5
 PE2 PE3 PE7
 PR2 PR6 PR7 PR8
 RE3 RE5 RE6
 SE1 SE2 SE3
 VI1 VI4 VI7
 AC1 AC4 AC7 AC9
 AU2 AU3 AU5
 EM1 EM2 EM4 EM5
 HG1 HG3 HG5
;
define: standardize all;
  ANALYSIS:  ESTIMATOR = ML; ROTATION = TARGET; PROCESSORS =2;
 MODEL:
  CO by    CO2-CO6~.80  CO9-hg5~0              (*t1);
  COx by   CO9-CO11~.80 es2-hg5~0   CO2-CO6~0 (*t1);
  ES by    ES2-ES7~.80   EN2-hg5~0  CO2-CO11~0(*t1);
  EN by    EN2-EN7~.80  ME1-hg5~0   CO2-ES7~0(*t1);
  ME by    ME1-ME9~.80  OP2-hg5~0   CO2-EN7~0(*t1);
  OP by    OP2-OP5~.80  PE2-hg5~0   CO2-ME9~0(*t1);
  PE by    PE2-PE7~.80  PR2-hg5~0   CO2-OP5~0(*t1);
  PR by    PR2-PR8~.80  RE3-hg5~0   CO2-PE7~0(*t1);
  RE by    RE3-RE6~.80  SE1-hg5~0   CO2-PR8~0(*t1);
  SE by    SE1-SE3~.80  VI1-hg5~0   CO2-RE6~0(*t1);
  VI by    VI1-VI7~.80  AC1-hg5~0   CO2-SE3~0(*t1);
  AC by    AC1-AC9~.80  AU2-hg5~0   CO2-VI7~0(*t1);
  AU by    AU2-AU5~.80  EM1-hg5~0   CO2-AC9~0(*t1);
  EM by    EM1-EM5~.80  HG1-hg5~0   CO2-AU5~0(*t1);
  HG by    HG1-HG5~.80              CO2-EM5~0(*t1);
 OUTPUT:  stdyx mod TECH1 tech4 sval MODINDICES (ALL);
THE MODEL ESTIMATION TERMINATED NORMALLY
MODEL FIT INFORMATION
Number of Free Parameters                  711
Loglikelihood
 H0 Value                  -120791.378
 H1 Value                  -120187.619
Information Criteria
 Akaike (AIC)               243004.756
 Bayesian (BIC)             247162.237
 Sample-Size Adjusted BIC      244903.196
  (n* = (n + 2) / 24)
Chi-Square Test of Model Fit
 Value                     1207.518
 Degrees of Freedom                513
 P-Value                    0.0000
RMSEA (Root Mean Square Error Of Approximation)
 Estimate                    0.023
 90 Percent C.I.               0.021  0.025
 Probability RMSEA <= .05          1.000
CFI/TLI
```

CFI	0.994
TLI	0.986

Chi-Square Test of Model Fit for the Baseline Model

Value	108152.958
Degrees of Freedom	1128
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value	0.006

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
CO BY				
CO2	0.520	0.036	14.396	0.000
CO5	0.687	0.043	16.168	0.000
CO6	0.607	0.059	10.232	0.000
CO9	0.114	0.029	3.870	0.000
CO10	0.062	0.032	1.931	0.053
CO11	-0.041	0.038	-1.094	0.274
ES2	0.072	0.032	2.271	0.023
ES4	0.177	0.032	5.593	0.000
ES7	-0.027	0.030	-0.900	0.368
EN2	0.284	0.033	8.517	0.000
EN3	0.136	0.030	4.546	0.000
EN7	0.136	0.031	4.358	0.000
ME1	-0.128	0.028	-4.623	0.000
ME5	-0.059	0.027	-2.186	0.029
ME9	-0.168	0.030	-5.540	0.000
OP2	0.162	0.029	5.634	0.000
OP3	0.158	0.023	6.797	0.000
OP5	0.102	0.026	3.991	0.000
PE2	-0.118	0.028	-4.198	0.000
PE3	-0.125	0.028	-4.446	0.000
PE7	-0.094	0.025	-3.836	0.000
PR2	0.099	0.029	3.366	0.001
PR6	0.004	0.031	0.139	0.889
PR7	0.033	0.031	1.081	0.280
PR8	-0.086	0.032	-2.659	0.008
RE3	0.058	0.026	2.219	0.026
RE5	0.074	0.025	2.906	0.004
RE6	-0.043	0.028	-1.547	0.122
SE1	0.009	0.032	0.269	0.788
SE2	0.177	0.036	4.939	0.000
SE3	0.298	0.033	8.904	0.000
VI1	-0.018	0.021	-0.872	0.383
VI4	0.017	0.020	0.830	0.406
VI7	-0.005	0.023	-0.204	0.838
AC1	-0.106	0.031	-3.381	0.001
AC4	-0.053	0.035	-1.510	0.131
AC7	-0.074	0.030	-2.450	0.014
AC9	0.034	0.029	1.191	0.234
AU2	0.028	0.027	1.052	0.293
AU3	-0.051	0.026	-1.928	0.054
AU5	0.052	0.029	1.787	0.074
EM1	-0.024	0.034	-0.702	0.482
EM2	0.035	0.031	1.148	0.251
EM4	-0.067	0.033	-2.009	0.045
EM5	-0.031	0.032	-0.984	0.325

HG1	0.027	0.027	1.014	0.311
HG3	-0.023	0.026	-0.876	0.381
HG5	0.039	0.028	1.422	0.155
COX BY				
CO9	0.534	0.030	17.677	0.000
CO10	0.809	0.037	21.728	0.000
CO11	0.902	0.033	27.440	0.000
ES2	-0.042	0.023	-1.794	0.073
ES4	0.038	0.029	1.329	0.184
ES7	0.074	0.024	3.058	0.002
EN2	0.059	0.032	1.846	0.065
EN3	0.040	0.027	1.488	0.137
EN7	-0.023	0.030	-0.779	0.436
ME1	-0.020	0.024	-0.812	0.417
ME5	0.088	0.025	3.574	0.000
ME9	0.001	0.027	0.031	0.975
OP2	0.046	0.025	1.856	0.063
OP3	0.019	0.020	0.985	0.324
OP5	0.000	0.024	-0.013	0.990
PE2	0.039	0.024	1.657	0.098
PE3	0.028	0.023	1.205	0.228
PE7	0.039	0.020	1.970	0.049
PR2	0.027	0.026	1.056	0.291
PR6	-0.041	0.027	-1.527	0.127
PR7	-0.025	0.028	-0.910	0.363
PR8	0.017	0.028	0.608	0.543
RE3	-0.033	0.022	-1.522	0.128
RE5	-0.014	0.020	-0.666	0.505
RE6	0.047	0.018	2.536	0.011
SE1	0.079	0.024	3.313	0.001
SE2	0.050	0.029	1.704	0.088
SE3	-0.012	0.029	-0.407	0.684
VI1	0.021	0.017	1.219	0.223
VI4	-0.003	0.015	-0.192	0.848
VI7	0.047	0.020	2.330	0.020
AC1	0.042	0.025	1.637	0.102
AC4	-0.023	0.026	-0.893	0.372
AC7	0.022	0.027	0.821	0.412
AC9	0.007	0.025	0.261	0.794
AU2	-0.031	0.022	-1.398	0.162
AU3	0.079	0.019	4.064	0.000
AU5	-0.023	0.025	-0.928	0.353
EM1	0.049	0.032	1.537	0.124
EM2	-0.011	0.028	-0.399	0.690
EM4	0.048	0.030	1.635	0.102
EM5	-0.087	0.027	-3.190	0.001
HG1	0.005	0.023	0.232	0.817
HG3	0.024	0.021	1.142	0.254
HG5	-0.054	0.024	-2.211	0.027
CO2	0.114	0.027	4.176	0.000
CO5	0.023	0.032	0.740	0.459
CO6	0.076	0.036	2.093	0.036
ES BY				
ES2	0.803	0.033	24.606	0.000
ES4	0.666	0.037	18.065	0.000
ES7	0.723	0.034	21.205	0.000
EN2	-0.063	0.034	-1.854	0.064
EN3	0.087	0.025	3.508	0.000
EN7	-0.106	0.029	-3.713	0.000

ME1	0.068	0.026	2.583	0.010
ME5	0.092	0.026	3.585	0.000
ME9	0.110	0.027	4.001	0.000
OP2	-0.076	0.025	-3.071	0.002
OP3	-0.013	0.021	-0.605	0.545
OP5	0.023	0.025	0.924	0.356
PE2	0.045	0.026	1.696	0.090
PE3	0.134	0.025	5.335	0.000
PE7	0.073	0.022	3.312	0.001
PR2	-0.016	0.027	-0.594	0.553
PR6	0.010	0.027	0.360	0.719
PR7	-0.053	0.029	-1.824	0.068
PR8	0.029	0.029	1.007	0.314
RE3	-0.051	0.024	-2.149	0.032
RE5	0.093	0.022	4.162	0.000
RE6	-0.017	0.021	-0.807	0.419
SE1	-0.043	0.025	-1.684	0.092
SE2	-0.033	0.031	-1.082	0.279
SE3	-0.023	0.031	-0.722	0.470
VI1	0.036	0.018	2.060	0.039
VI4	-0.025	0.017	-1.521	0.128
VI7	0.044	0.022	2.065	0.039
AC1	-0.016	0.029	-0.570	0.569
AC4	0.003	0.029	0.087	0.930
AC7	0.096	0.029	3.328	0.001
AC9	0.033	0.027	1.234	0.217
AU2	0.038	0.024	1.596	0.111
AU3	-0.021	0.021	-0.986	0.324
AU5	-0.001	0.027	-0.053	0.958
EM1	0.051	0.034	1.508	0.132
EM2	0.000	0.029	0.008	0.993
EM4	0.073	0.032	2.267	0.023
EM5	-0.093	0.029	-3.198	0.001
HG1	-0.034	0.024	-1.392	0.164
HG3	0.046	0.023	2.012	0.044
HG5	0.018	0.026	0.690	0.490
CO2	0.074	0.027	2.708	0.007
CO5	0.096	0.031	3.130	0.002
CO6	0.090	0.031	2.916	0.004
CO9	0.167	0.027	6.158	0.000
CO10	-0.013	0.027	-0.474	0.636
CO11	-0.085	0.023	-3.628	0.000
EN BY				
EN2	0.678	0.052	13.080	0.000
EN3	0.656	0.056	11.724	0.000
EN7	0.476	0.051	9.382	0.000
ME1	0.281	0.033	8.541	0.000
ME5	0.128	0.038	3.403	0.001
ME9	0.204	0.042	4.907	0.000
OP2	-0.138	0.032	-4.272	0.000
OP3	-0.072	0.028	-2.560	0.010
OP5	-0.058	0.033	-1.773	0.076
PE2	0.212	0.029	7.331	0.000
PE3	0.124	0.029	4.310	0.000
PE7	0.135	0.026	5.115	0.000
PR2	-0.169	0.032	-5.217	0.000
PR6	0.086	0.037	2.285	0.022
PR7	0.037	0.036	1.031	0.303
PR8	0.034	0.038	0.896	0.370

RE3	0.016	0.031	0.499	0.618
RE5	-0.013	0.029	-0.430	0.667
RE6	-0.002	0.029	-0.071	0.944
SE1	-0.108	0.032	-3.373	0.001
SE2	-0.132	0.037	-3.612	0.000
SE3	-0.056	0.038	-1.465	0.143
VI1	0.003	0.027	0.097	0.922
VI4	0.010	0.024	0.392	0.695
VI7	0.121	0.029	4.241	0.000
AC1	0.124	0.036	3.482	0.000
AC4	0.028	0.035	0.798	0.425
AC7	0.006	0.036	0.178	0.858
AC9	-0.050	0.034	-1.479	0.139
AU2	0.079	0.031	2.546	0.011
AU3	-0.067	0.030	-2.257	0.024
AU5	0.031	0.034	0.915	0.360
EM1	-0.079	0.041	-1.919	0.055
EM2	-0.022	0.037	-0.592	0.554
EM4	-0.029	0.040	-0.710	0.478
EM5	0.104	0.037	2.815	0.005
HG1	0.026	0.031	0.820	0.412
HG3	-0.026	0.030	-0.862	0.388
HG5	-0.010	0.033	-0.308	0.758
CO2	0.151	0.036	4.224	0.000
CO5	0.227	0.036	6.226	0.000
CO6	0.177	0.036	4.883	0.000
CO9	-0.054	0.036	-1.511	0.131
CO10	0.005	0.036	0.153	0.878
CO11	0.047	0.038	1.252	0.210
ES2	-0.087	0.035	-2.512	0.012
ES4	-0.030	0.040	-0.748	0.454
ES7	-0.058	0.034	-1.738	0.082
ME BY				
ME1	0.557	0.035	15.995	0.000
ME5	0.570	0.034	16.608	0.000
ME9	0.660	0.039	16.774	0.000
OP2	0.209	0.031	6.689	0.000
OP3	0.215	0.027	7.968	0.000
OP5	0.150	0.029	5.248	0.000
PE2	-0.127	0.026	-4.928	0.000
PE3	-0.091	0.027	-3.410	0.001
PE7	-0.112	0.023	-4.871	0.000
PR2	-0.011	0.031	-0.372	0.710
PR6	-0.013	0.030	-0.430	0.668
PR7	-0.021	0.034	-0.612	0.540
PR8	0.062	0.034	1.830	0.067
RE3	-0.014	0.028	-0.490	0.624
RE5	-0.071	0.026	-2.697	0.007
RE6	0.102	0.030	3.416	0.001
SE1	0.270	0.030	8.985	0.000
SE2	0.091	0.034	2.682	0.007
SE3	0.171	0.033	5.124	0.000
VI1	-0.061	0.022	-2.753	0.006
VI4	-0.065	0.022	-2.938	0.003
VI7	0.075	0.025	3.052	0.002
AC1	-0.023	0.035	-0.667	0.505
AC4	-0.146	0.032	-4.501	0.000
AC7	0.014	0.032	0.417	0.677
AC9	0.013	0.031	0.408	0.683

AU2	-0.046	0.027	-1.663	0.096
AU3	0.017	0.030	0.568	0.570
AU5	0.082	0.030	2.779	0.005
EM1	-0.034	0.037	-0.910	0.363
EM2	-0.034	0.033	-1.011	0.312
EM4	0.036	0.036	0.998	0.318
EM5	-0.044	0.035	-1.249	0.212
HG1	0.012	0.028	0.409	0.683
HG3	0.055	0.028	1.952	0.051
HG5	0.023	0.030	0.779	0.436
CO2	-0.037	0.032	-1.145	0.252
CO5	-0.208	0.035	-5.989	0.000
CO6	-0.134	0.041	-3.295	0.001
CO9	0.008	0.031	0.251	0.802
CO10	-0.041	0.035	-1.190	0.234
CO11	0.022	0.038	0.581	0.561
ES2	0.062	0.034	1.814	0.070
ES4	0.065	0.036	1.805	0.071
ES7	0.092	0.032	2.881	0.004
EN2	0.139	0.053	2.637	0.008
EN3	0.291	0.032	9.108	0.000
EN7	0.183	0.034	5.450	0.000
OP BY				
OP2	0.766	0.030	25.334	0.000
OP3	0.661	0.028	23.418	0.000
OP5	0.598	0.030	19.969	0.000
PE2	0.108	0.025	4.351	0.000
PE3	0.150	0.024	6.153	0.000
PE7	0.183	0.023	7.913	0.000
PR2	-0.019	0.027	-0.702	0.483
PR6	-0.037	0.029	-1.266	0.205
PR7	0.028	0.029	0.957	0.339
PR8	-0.004	0.031	-0.116	0.907
RE3	0.045	0.024	1.850	0.064
RE5	0.030	0.024	1.239	0.215
RE6	-0.085	0.026	-3.244	0.001
SE1	-0.034	0.027	-1.277	0.202
SE2	-0.099	0.029	-3.421	0.001
SE3	-0.116	0.028	-4.187	0.000
VI1	0.073	0.019	3.748	0.000
VI4	0.009	0.019	0.461	0.644
VI7	0.021	0.023	0.925	0.355
AC1	-0.047	0.030	-1.541	0.123
AC4	0.076	0.029	2.597	0.009
AC7	0.077	0.029	2.618	0.009
AC9	0.042	0.028	1.504	0.133
AU2	0.067	0.025	2.716	0.007
AU3	-0.059	0.025	-2.371	0.018
AU5	-0.025	0.027	-0.930	0.353
EM1	-0.021	0.034	-0.608	0.543
EM2	0.040	0.030	1.322	0.186
EM4	-0.035	0.033	-1.056	0.291
EM5	0.009	0.031	0.301	0.763
HG1	0.021	0.025	0.840	0.401
HG3	-0.003	0.025	-0.119	0.905
HG5	-0.030	0.026	-1.143	0.253
CO2	0.061	0.028	2.148	0.032
CO5	0.130	0.037	3.526	0.000
CO6	0.233	0.029	7.912	0.000

CO9	-0.029	0.027	-1.065	0.287
CO10	0.027	0.028	0.936	0.349
CO11	0.001	0.034	0.022	0.983
ES2	0.039	0.029	1.362	0.173
ES4	-0.078	0.030	-2.589	0.010
ES7	-0.119	0.026	-4.539	0.000
EN2	-0.127	0.042	-3.033	0.002
EN3	-0.153	0.026	-5.871	0.000
EN7	0.011	0.030	0.355	0.723
ME1	0.081	0.028	2.910	0.004
ME5	0.282	0.026	10.722	0.000
ME9	0.215	0.029	7.365	0.000
PE BY				
PE2	0.656	0.030	21.695	0.000
PE3	0.668	0.030	22.603	0.000
PE7	0.720	0.028	26.020	0.000
PR2	0.015	0.027	0.550	0.582
PR6	0.078	0.028	2.752	0.006
PR7	-0.080	0.029	-2.734	0.006
PR8	0.013	0.030	0.419	0.675
RE3	0.052	0.024	2.159	0.031
RE5	0.033	0.024	1.398	0.162
RE6	-0.025	0.025	-1.008	0.314
SE1	0.098	0.029	3.428	0.001
SE2	0.186	0.030	6.144	0.000
SE3	0.070	0.029	2.391	0.017
VI1	0.031	0.019	1.601	0.109
VI4	-0.024	0.018	-1.342	0.180
VI7	0.000	0.022	0.015	0.988
AC1	-0.051	0.029	-1.750	0.080
AC4	-0.095	0.030	-3.204	0.001
AC7	-0.021	0.029	-0.728	0.467
AC9	0.067	0.028	2.447	0.014
AU2	0.016	0.025	0.635	0.526
AU3	0.004	0.024	0.174	0.862
AU5	0.012	0.027	0.446	0.655
EM1	0.040	0.033	1.183	0.237
EM2	-0.002	0.030	-0.070	0.944
EM4	-0.042	0.032	-1.308	0.191
EM5	-0.044	0.030	-1.458	0.145
HG1	-0.007	0.025	-0.258	0.796
HG3	-0.009	0.025	-0.346	0.730
HG5	0.035	0.026	1.337	0.181
CO2	-0.119	0.028	-4.313	0.000
CO5	-0.110	0.034	-3.259	0.001
CO6	-0.086	0.029	-2.954	0.003
CO9	0.029	0.027	1.061	0.289
CO10	-0.018	0.028	-0.651	0.515
CO11	0.034	0.031	1.079	0.281
ES2	-0.004	0.030	-0.125	0.900
ES4	0.037	0.032	1.176	0.240
ES7	0.167	0.029	5.697	0.000
EN2	0.224	0.030	7.400	0.000
EN3	0.055	0.027	2.020	0.043
EN7	0.196	0.028	6.955	0.000
ME1	0.026	0.026	0.975	0.330
ME5	-0.184	0.024	-7.823	0.000
ME9	-0.118	0.026	-4.615	0.000
OP2	0.161	0.026	6.287	0.000

OP3	0.050	0.023	2.155	0.031
OP5	0.239	0.024	10.003	0.000
PR BY				
PR2	0.807	0.030	26.907	0.000
PR6	0.755	0.031	24.222	0.000
PR7	0.783	0.033	24.056	0.000
PR8	0.791	0.032	24.402	0.000
RE3	-0.022	0.021	-1.084	0.278
RE5	0.029	0.020	1.449	0.147
RE6	0.031	0.018	1.702	0.089
SE1	0.036	0.024	1.479	0.139
SE2	0.027	0.027	1.027	0.304
SE3	-0.013	0.024	-0.522	0.602
VI1	0.033	0.016	2.041	0.041
VI4	0.004	0.015	0.294	0.769
VI7	-0.014	0.020	-0.695	0.487
AC1	0.006	0.025	0.242	0.808
AC4	-0.011	0.024	-0.475	0.635
AC7	0.021	0.027	0.788	0.431
AC9	0.023	0.025	0.893	0.372
AU2	0.020	0.022	0.919	0.358
AU3	0.018	0.019	0.913	0.361
AU5	-0.031	0.025	-1.258	0.208
EM1	0.046	0.032	1.427	0.154
EM2	-0.054	0.028	-1.934	0.053
EM4	-0.022	0.030	-0.719	0.472
EM5	-0.003	0.027	-0.095	0.924
HG1	0.041	0.023	1.804	0.071
HG3	0.008	0.021	0.376	0.707
HG5	-0.013	0.024	-0.552	0.581
CO2	0.102	0.026	3.878	0.000
CO5	0.026	0.024	1.084	0.278
CO6	0.003	0.023	0.119	0.905
CO9	0.046	0.026	1.788	0.074
CO10	-0.005	0.022	-0.206	0.837
CO11	-0.035	0.020	-1.788	0.074
ES2	-0.058	0.023	-2.538	0.011
ES4	0.002	0.025	0.075	0.940
ES7	0.051	0.023	2.271	0.023
EN2	0.012	0.022	0.558	0.577
EN3	0.031	0.022	1.398	0.162
EN7	0.044	0.025	1.719	0.086
ME1	0.055	0.022	2.484	0.013
ME5	0.049	0.022	2.210	0.027
ME9	0.028	0.022	1.288	0.198
OP2	0.037	0.018	2.035	0.042
OP3	0.096	0.020	4.887	0.000
OP5	-0.057	0.021	-2.780	0.005
PE2	0.017	0.021	0.799	0.424
PE3	0.032	0.020	1.620	0.105
PE7	0.071	0.019	3.777	0.000
RE BY				
RE3	0.732	0.025	28.990	0.000
RE5	0.744	0.024	30.729	0.000
RE6	0.848	0.024	34.870	0.000
SE1	0.030	0.021	1.403	0.161
SE2	0.072	0.024	2.963	0.003
SE3	0.049	0.024	2.032	0.042
VI1	-0.001	0.015	-0.082	0.935

VI4	0.019	0.014	1.394	0.163
VI7	0.024	0.018	1.308	0.191
AC1	-0.010	0.024	-0.415	0.678
AC4	-0.049	0.023	-2.152	0.031
AC7	0.224	0.025	9.139	0.000
AC9	-0.080	0.023	-3.473	0.001
AU2	0.003	0.020	0.125	0.901
AU3	0.029	0.017	1.701	0.089
AU5	-0.003	0.022	-0.118	0.906
EM1	0.009	0.029	0.320	0.749
EM2	-0.028	0.025	-1.140	0.254
EM4	-0.003	0.027	-0.116	0.907
EM5	-0.009	0.024	-0.365	0.715
HG1	0.029	0.021	1.391	0.164
HG3	-0.026	0.019	-1.376	0.169
HG5	0.009	0.022	0.408	0.683
CO2	0.002	0.024	0.075	0.941
CO5	0.072	0.025	2.829	0.005
CO6	0.061	0.026	2.314	0.021
CO9	-0.060	0.023	-2.612	0.009
CO10	-0.019	0.020	-0.969	0.332
CO11	0.063	0.018	3.513	0.000
ES2	0.099	0.023	4.330	0.000
ES4	-0.062	0.024	-2.534	0.011
ES7	-0.029	0.022	-1.351	0.177
EN2	-0.002	0.026	-0.073	0.942
EN3	0.005	0.022	0.224	0.823
EN7	0.062	0.024	2.544	0.011
ME1	0.014	0.021	0.638	0.524
ME5	0.036	0.021	1.728	0.084
ME9	0.036	0.022	1.630	0.103
OP2	0.003	0.020	0.132	0.895
OP3	0.028	0.018	1.539	0.124
OP5	0.028	0.021	1.343	0.179
PE2	0.050	0.020	2.475	0.013
PE3	0.024	0.020	1.203	0.229
PE7	0.036	0.017	2.059	0.039
PR2	-0.036	0.023	-1.570	0.116
PR6	0.039	0.023	1.700	0.089
PR7	-0.030	0.025	-1.207	0.228
PR8	0.026	0.025	1.042	0.297
SE BY				
SE1	0.581	0.040	14.488	0.000
SE2	0.580	0.045	12.910	0.000
SE3	0.596	0.043	13.803	0.000
VI1	0.002	0.022	0.114	0.909
VI4	0.037	0.021	1.741	0.082
VI7	0.054	0.025	2.127	0.033
AC1	0.075	0.036	2.084	0.037
AC4	-0.010	0.038	-0.273	0.785
AC7	-0.063	0.032	-1.994	0.046
AC9	0.287	0.030	9.477	0.000
AU2	-0.126	0.027	-4.668	0.000
AU3	0.020	0.027	0.741	0.459
AU5	0.042	0.031	1.373	0.170
EM1	0.057	0.037	1.555	0.120
EM2	0.061	0.033	1.876	0.061
EM4	0.010	0.036	0.273	0.785
EM5	-0.051	0.035	-1.469	0.142

HG1	-0.035	0.028	-1.256	0.209
HG3	0.010	0.027	0.353	0.724
HG5	-0.017	0.030	-0.558	0.577
CO2	0.117	0.033	3.538	0.000
CO5	0.185	0.039	4.755	0.000
CO6	0.183	0.036	5.042	0.000
CO9	0.118	0.030	3.957	0.000
CO10	0.014	0.033	0.409	0.682
CO11	-0.085	0.036	-2.368	0.018
ES2	-0.153	0.031	-4.957	0.000
ES4	-0.047	0.036	-1.334	0.182
ES7	0.023	0.031	0.759	0.448
EN2	-0.174	0.042	-4.109	0.000
EN3	-0.093	0.032	-2.892	0.004
EN7	-0.012	0.034	-0.353	0.724
ME1	0.238	0.027	8.830	0.000
ME5	0.111	0.029	3.831	0.000
ME9	0.184	0.030	6.100	0.000
OP2	-0.110	0.027	-4.028	0.000
OP3	-0.060	0.025	-2.412	0.016
OP5	-0.063	0.027	-2.332	0.020
PE2	0.096	0.029	3.369	0.001
PE3	0.145	0.027	5.441	0.000
PE7	0.110	0.026	4.285	0.000
PR2	0.109	0.031	3.462	0.001
PR6	0.040	0.034	1.194	0.232
PR7	-0.040	0.032	-1.242	0.214
PR8	-0.157	0.033	-4.780	0.000
RE3	0.117	0.027	4.359	0.000
RE5	-0.096	0.025	-3.819	0.000
RE6	0.084	0.030	2.807	0.005
VI BY				
VI1	0.819	0.019	43.519	0.000
VI4	0.909	0.018	49.242	0.000
VI7	0.665	0.019	34.776	0.000
AC1	-0.024	0.019	-1.230	0.219
AC4	-0.024	0.019	-1.285	0.199
AC7	0.020	0.021	0.963	0.336
AC9	0.044	0.020	2.209	0.027
AU2	0.021	0.017	1.238	0.216
AU3	-0.004	0.015	-0.254	0.799
AU5	-0.010	0.019	-0.519	0.604
EM1	-0.068	0.025	-2.761	0.006
EM2	-0.041	0.021	-1.949	0.051
EM4	0.037	0.023	1.605	0.109
EM5	0.019	0.021	0.909	0.364
HG1	0.025	0.017	1.455	0.146
HG3	0.027	0.016	1.654	0.098
HG5	-0.003	0.018	-0.165	0.869
CO2	0.023	0.021	1.138	0.255
CO5	-0.008	0.020	-0.384	0.701
CO6	0.013	0.020	0.641	0.521
CO9	0.043	0.020	2.167	0.030
CO10	-0.002	0.017	-0.141	0.888
CO11	-0.004	0.016	-0.267	0.790
ES2	0.017	0.018	0.929	0.353
ES4	-0.025	0.020	-1.268	0.205
ES7	0.034	0.018	1.956	0.050
EN2	-0.013	0.021	-0.627	0.531

EN3	0.104	0.022	4.703	0.000
EN7	0.092	0.022	4.134	0.000
ME1	0.006	0.017	0.337	0.736
ME5	0.030	0.017	1.722	0.085
ME9	-0.022	0.017	-1.311	0.190
OP2	0.029	0.016	1.745	0.081
OP3	0.088	0.016	5.568	0.000
OP5	0.038	0.017	2.231	0.026
PE2	0.043	0.016	2.607	0.009
PE3	0.022	0.016	1.397	0.163
PE7	-0.021	0.014	-1.489	0.136
PR2	-0.058	0.019	-2.999	0.003
PR6	0.041	0.020	2.120	0.034
PR7	-0.024	0.021	-1.147	0.252
PR8	0.016	0.021	0.744	0.457
RE3	-0.032	0.016	-2.017	0.044
RE5	0.028	0.016	1.794	0.073
RE6	0.029	0.014	1.999	0.046
SE1	0.069	0.018	3.837	0.000
SE2	0.038	0.020	1.920	0.055
SE3	0.011	0.019	0.554	0.579
AC BY				
AC1	0.855	0.042	20.476	0.000
AC4	0.923	0.038	24.292	0.000
AC7	0.546	0.036	15.363	0.000
AC9	0.544	0.034	16.053	0.000
AU2	0.055	0.026	2.092	0.036
AU3	-0.031	0.023	-1.378	0.168
AU5	0.067	0.029	2.289	0.022
EM1	-0.063	0.036	-1.764	0.078
EM2	0.026	0.031	0.849	0.396
EM4	-0.084	0.034	-2.488	0.013
EM5	0.008	0.031	0.255	0.798
HG1	-0.005	0.026	-0.179	0.858
HG3	0.021	0.025	0.835	0.403
HG5	0.001	0.027	0.051	0.960
CO2	0.022	0.030	0.720	0.472
CO5	-0.017	0.032	-0.539	0.590
CO6	-0.096	0.030	-3.218	0.001
CO9	0.039	0.029	1.350	0.177
CO10	0.037	0.026	1.440	0.150
CO11	-0.013	0.025	-0.535	0.592
ES2	0.064	0.028	2.299	0.022
ES4	0.022	0.031	0.702	0.482
ES7	0.045	0.028	1.588	0.112
EN2	0.096	0.030	3.252	0.001
EN3	0.052	0.026	1.998	0.046
EN7	0.027	0.029	0.906	0.365
ME1	-0.014	0.026	-0.527	0.598
ME5	0.000	0.026	-0.007	0.994
ME9	-0.006	0.027	-0.211	0.833
OP2	0.097	0.023	4.179	0.000
OP3	0.004	0.023	0.179	0.858
OP5	0.114	0.025	4.615	0.000
PE2	0.021	0.025	0.839	0.401
PE3	-0.028	0.024	-1.192	0.233
PE7	-0.002	0.022	-0.091	0.928
PR2	-0.004	0.029	-0.139	0.889
PR6	-0.062	0.029	-2.117	0.034

PR7	0.070	0.031	2.265	0.024
PR8	0.021	0.031	0.689	0.491
RE3	0.081	0.024	3.304	0.001
RE5	0.086	0.024	3.589	0.000
RE6	-0.048	0.023	-2.120	0.034
SE1	0.144	0.029	4.967	0.000
SE2	0.078	0.034	2.278	0.023
SE3	0.136	0.033	4.180	0.000
VI1	0.001	0.019	0.039	0.969
VI4	0.022	0.018	1.243	0.214
VI7	0.034	0.023	1.491	0.136
AU BY				
AU2	0.755	0.028	27.423	0.000
AU3	0.909	0.026	34.449	0.000
AU5	0.681	0.028	24.398	0.000
EM1	0.005	0.027	0.192	0.847
EM2	0.025	0.023	1.075	0.282
EM4	-0.055	0.025	-2.186	0.029
EM5	-0.010	0.022	-0.432	0.666
HG1	-0.009	0.019	-0.464	0.643
HG3	-0.018	0.018	-0.979	0.327
HG5	0.045	0.020	2.224	0.026
CO2	0.048	0.023	2.069	0.039
CO5	-0.004	0.023	-0.195	0.845
CO6	0.059	0.024	2.429	0.015
CO9	0.048	0.021	2.263	0.024
CO10	-0.002	0.019	-0.100	0.920
CO11	-0.022	0.017	-1.285	0.199
ES2	-0.026	0.019	-1.347	0.178
ES4	0.077	0.022	3.510	0.000
ES7	-0.035	0.019	-1.819	0.069
EN2	0.057	0.024	2.337	0.019
EN3	0.019	0.020	0.935	0.350
EN7	0.047	0.023	2.060	0.039
ME1	0.029	0.019	1.492	0.136
ME5	0.047	0.019	2.432	0.015
ME9	0.061	0.019	3.177	0.001
OP2	0.006	0.018	0.315	0.753
OP3	0.022	0.017	1.284	0.199
OP5	0.035	0.019	1.891	0.059
PE2	0.044	0.018	2.420	0.016
PE3	0.054	0.018	3.040	0.002
PE7	-0.005	0.016	-0.315	0.753
PR2	0.013	0.021	0.603	0.546
PR6	-0.024	0.021	-1.129	0.259
PR7	0.030	0.023	1.301	0.193
PR8	-0.040	0.023	-1.736	0.083
RE3	0.030	0.017	1.723	0.085
RE5	-0.023	0.017	-1.345	0.179
RE6	0.038	0.016	2.415	0.016
SE1	0.018	0.020	0.908	0.364
SE2	0.001	0.022	0.059	0.953
SE3	-0.014	0.021	-0.661	0.508
VI1	0.037	0.014	2.729	0.006
VI4	0.029	0.013	2.305	0.021
VI7	-0.031	0.017	-1.833	0.067
AC1	-0.061	0.022	-2.843	0.004
AC4	0.005	0.022	0.237	0.813
AC7	0.034	0.023	1.492	0.136

AC9	0.096	0.022	4.470	0.000
EM BY				
EM1	0.564	0.031	17.912	0.000
EM2	0.788	0.030	26.511	0.000
EM4	0.780	0.032	24.459	0.000
EM5	0.872	0.029	30.574	0.000
HG1	0.028	0.022	1.305	0.192
HG3	0.007	0.021	0.341	0.733
HG5	0.095	0.023	4.223	0.000
CO2	0.005	0.023	0.223	0.824
CO5	0.003	0.022	0.114	0.909
CO6	0.000	0.022	-0.017	0.987
CO9	0.025	0.022	1.148	0.251
CO10	0.017	0.019	0.877	0.380
CO11	0.005	0.018	0.287	0.774
ES2	0.010	0.020	0.479	0.632
ES4	0.024	0.023	1.027	0.304
ES7	0.041	0.020	2.046	0.041
EN2	0.036	0.022	1.642	0.101
EN3	-0.043	0.021	-2.085	0.037
EN7	0.058	0.023	2.519	0.012
ME1	-0.015	0.019	-0.784	0.433
ME5	0.024	0.019	1.258	0.209
ME9	0.014	0.020	0.723	0.470
OP2	0.026	0.017	1.549	0.121
OP3	0.014	0.017	0.815	0.415
OP5	0.013	0.018	0.704	0.482
PE2	0.030	0.018	1.618	0.106
PE3	0.001	0.018	0.074	0.941
PE7	0.002	0.016	0.098	0.922
PR2	-0.053	0.022	-2.439	0.015
PR6	-0.045	0.022	-2.049	0.040
PR7	0.069	0.024	2.896	0.004
PR8	0.042	0.024	1.762	0.078
RE3	0.016	0.018	0.880	0.379
RE5	-0.016	0.018	-0.880	0.379
RE6	0.011	0.016	0.703	0.482
SE1	0.020	0.021	0.960	0.337
SE2	0.075	0.023	3.333	0.001
SE3	0.050	0.022	2.299	0.022
VI1	-0.006	0.014	-0.449	0.654
VI4	0.005	0.013	0.349	0.727
VI7	0.002	0.018	0.094	0.925
AC1	-0.003	0.022	-0.138	0.890
AC4	-0.010	0.021	-0.492	0.623
AC7	-0.015	0.023	-0.659	0.510
AC9	-0.034	0.022	-1.539	0.124
AU2	0.017	0.019	0.866	0.387
AU3	-0.008	0.017	-0.480	0.631
AU5	0.007	0.021	0.330	0.742
HG BY				
HG1	0.775	0.024	31.798	0.000
HG3	0.821	0.024	33.760	0.000
HG5	0.733	0.025	29.305	0.000
CO2	0.010	0.022	0.456	0.648
CO5	0.033	0.022	1.447	0.148
CO6	0.045	0.023	1.954	0.051
CO9	-0.091	0.021	-4.449	0.000
CO10	0.002	0.018	0.109	0.913

CO11	0.060	0.017	3.531	0.000
ES2	0.005	0.019	0.237	0.812
ES4	0.077	0.022	3.525	0.000
ES7	-0.055	0.019	-2.901	0.004
EN2	-0.004	0.023	-0.171	0.864
EN3	0.005	0.019	0.253	0.800
EN7	0.041	0.022	1.906	0.057
ME1	0.082	0.019	4.253	0.000
ME5	0.010	0.019	0.503	0.615
ME9	0.043	0.020	2.137	0.033
OP2	-0.002	0.018	-0.124	0.901
OP3	-0.003	0.016	-0.209	0.834
OP5	0.039	0.018	2.142	0.032
PE2	0.027	0.018	1.513	0.130
PE3	0.008	0.017	0.490	0.624
PE7	0.015	0.016	0.956	0.339
PR2	0.045	0.021	2.190	0.029
PR6	0.072	0.021	3.456	0.001
PR7	-0.059	0.022	-2.612	0.009
PR8	-0.050	0.022	-2.239	0.025
RE3	0.029	0.017	1.662	0.097
RE5	0.001	0.017	0.079	0.937
RE6	-0.013	0.015	-0.870	0.384
SE1	-0.028	0.020	-1.446	0.148
SE2	-0.001	0.022	-0.039	0.969
SE3	0.034	0.022	1.588	0.112
VI1	0.024	0.013	1.795	0.073
VI4	0.034	0.013	2.708	0.007
VI7	0.004	0.017	0.264	0.792
AC1	0.020	0.021	0.949	0.342
AC4	0.073	0.021	3.516	0.000
AC7	-0.038	0.022	-1.744	0.081
AC9	-0.053	0.021	-2.573	0.010
AU2	-0.040	0.018	-2.143	0.032
AU3	0.024	0.016	1.488	0.137
AU5	0.029	0.020	1.431	0.152
EM1	0.174	0.028	6.237	0.000
EM2	0.002	0.025	0.063	0.950
EM4	-0.060	0.026	-2.278	0.023
EM5	-0.084	0.024	-3.566	0.000
COX WITH				
CO	0.536	0.083	6.459	0.000
ES WITH				
CO	0.259	0.062	4.187	0.000
COX	0.685	0.037	18.285	0.000
EN WITH				
CO	-0.075	0.058	-1.298	0.194
COX	0.518	0.083	6.239	0.000
ES	0.627	0.046	13.579	0.000
ME WITH				
CO	0.724	0.015	48.289	0.000
COX	0.448	0.054	8.362	0.000
ES	0.284	0.069	4.121	0.000
EN	-0.013	0.090	-0.145	0.885
OP WITH				
CO	-0.032	0.061	-0.519	0.604
COX	0.441	0.050	8.877	0.000
ES	0.612	0.035	17.304	0.000
EN	0.799	0.014	58.889	0.000

ME	0.137	0.077	1.788	0.074
PE WITH				
CO	0.689	0.020	35.007	0.000
COX	0.533	0.051	10.443	0.000
ES	0.446	0.071	6.269	0.000
EN	0.114	0.070	1.623	0.105
ME	0.815	0.017	48.065	0.000
OP	0.244	0.066	3.689	0.000
PR WITH				
CO	0.436	0.043	10.129	0.000
COX	0.677	0.014	48.956	0.000
ES	0.601	0.023	26.565	0.000
EN	0.514	0.050	10.355	0.000
ME	0.523	0.048	10.871	0.000
OP	0.555	0.035	15.947	0.000
PE	0.600	0.040	15.037	0.000
RE WITH				
CO	0.372	0.062	5.967	0.000
COX	0.638	0.016	40.692	0.000
ES	0.751	0.023	32.149	0.000
EN	0.515	0.059	8.729	0.000
ME	0.441	0.045	9.898	0.000
OP	0.545	0.039	13.934	0.000
PE	0.555	0.044	12.612	0.000
PR	0.584	0.016	36.446	0.000
SE WITH				
CO	0.086	0.099	0.865	0.387
COX	0.547	0.064	8.479	0.000
ES	0.619	0.038	16.179	0.000
EN	0.760	0.018	41.497	0.000
ME	0.011	0.058	0.188	0.851
OP	0.707	0.014	50.997	0.000
PE	0.169	0.084	2.011	0.044
PR	0.584	0.053	10.968	0.000
RE	0.444	0.040	11.009	0.000
VI WITH				
CO	0.365	0.048	7.533	0.000
COX	0.558	0.017	33.695	0.000
ES	0.579	0.023	24.828	0.000
EN	0.505	0.063	7.991	0.000
ME	0.494	0.040	12.476	0.000
OP	0.529	0.042	12.690	0.000
PE	0.583	0.037	15.908	0.000
PR	0.518	0.017	30.841	0.000
RE	0.644	0.014	45.853	0.000
SE	0.318	0.033	9.739	0.000
AC WITH				
CO	0.632	0.043	14.701	0.000
COX	0.722	0.020	35.363	0.000
ES	0.669	0.048	13.970	0.000
EN	0.383	0.061	6.241	0.000
ME	0.611	0.045	13.507	0.000
OP	0.381	0.045	8.554	0.000
PE	0.659	0.028	23.651	0.000
PR	0.690	0.018	38.005	0.000
RE	0.685	0.024	28.863	0.000
SE	0.460	0.082	5.598	0.000
VI	0.559	0.020	28.306	0.000
AU WITH				

CO	0.487	0.059	8.221	0.000
COX	0.695	0.014	50.301	0.000
ES	0.607	0.023	26.130	0.000
EN	0.528	0.064	8.274	0.000
ME	0.464	0.042	11.025	0.000
OP	0.522	0.042	12.556	0.000
PE	0.529	0.041	13.020	0.000
PR	0.696	0.013	54.504	0.000
RE	0.598	0.016	37.364	0.000
SE	0.540	0.039	13.855	0.000
VI	0.522	0.017	31.089	0.000
AC	0.713	0.022	32.973	0.000
EM WITH				
CO	0.345	0.042	8.162	0.000
COX	0.381	0.021	17.751	0.000
ES	0.349	0.035	9.936	0.000
EN	0.279	0.056	5.032	0.000
ME	0.323	0.033	9.649	0.000
OP	0.217	0.038	5.717	0.000
PE	0.339	0.032	10.703	0.000
PR	0.542	0.019	28.283	0.000
RE	0.289	0.023	12.739	0.000
SE	0.268	0.044	6.029	0.000
VI	0.301	0.021	14.109	0.000
AC	0.490	0.019	25.914	0.000
AU	0.405	0.021	19.129	0.000
HG WITH				
CO	0.324	0.045	7.119	0.000
COX	0.470	0.019	24.406	0.000
ES	0.415	0.022	19.208	0.000
EN	0.378	0.042	8.984	0.000
ME	0.263	0.037	7.099	0.000
OP	0.318	0.031	10.177	0.000
PE	0.295	0.032	9.205	0.000
PR	0.535	0.017	30.799	0.000
RE	0.389	0.020	19.884	0.000
SE	0.402	0.034	11.731	0.000
VI	0.313	0.020	15.318	0.000
AC	0.508	0.023	22.454	0.000
AU	0.431	0.019	22.846	0.000
EM	0.731	0.017	42.445	0.000
Intercepts				
CO2	0.000	0.020	-0.004	0.997
CO5	0.000	0.020	0.007	0.994
CO6	0.000	0.020	-0.005	0.996
CO9	0.000	0.020	0.011	0.992
CO10	0.000	0.020	0.012	0.990
CO11	0.000	0.020	-0.004	0.997
ES2	0.000	0.020	-0.003	0.997
ES4	0.000	0.020	-0.004	0.997
ES7	0.000	0.020	-0.004	0.997
EN2	0.000	0.020	0.009	0.993
EN3	0.000	0.020	0.009	0.993
EN7	0.000	0.020	0.009	0.993
ME1	0.000	0.020	0.006	0.995
ME5	0.000	0.020	0.010	0.992
ME9	0.000	0.020	-0.005	0.996
OP2	0.000	0.020	0.012	0.991
OP3	0.000	0.020	-0.005	0.996

OP5	0.000	0.020	-0.005	0.996
PE2	0.000	0.020	-0.005	0.996
PE3	0.000	0.020	0.003	0.998
PE7	0.000	0.020	-0.005	0.996
PR2	0.000	0.020	0.005	0.996
PR6	0.000	0.020	-0.005	0.996
PR7	0.000	0.020	0.006	0.995
PR8	0.000	0.020	0.007	0.994
RE3	0.000	0.020	-0.004	0.997
RE5	0.000	0.020	-0.004	0.997
RE6	0.000	0.020	-0.004	0.997
SE1	0.000	0.020	-0.005	0.996
SE2	0.000	0.020	0.006	0.995
SE3	0.000	0.020	0.007	0.994
VI1	0.000	0.020	-0.004	0.997
VI4	0.000	0.020	-0.004	0.997
VI7	0.000	0.020	-0.004	0.997
AC1	0.000	0.020	-0.004	0.996
AC4	0.000	0.020	-0.004	0.996
AC7	0.000	0.020	-0.004	0.997
AC9	0.000	0.020	-0.005	0.996
AU2	0.000	0.020	0.006	0.995
AU3	0.000	0.020	-0.005	0.996
AU5	0.000	0.020	-0.004	0.996
EM1	0.000	0.020	0.008	0.993
EM2	0.000	0.020	-0.004	0.997
EM4	0.000	0.020	-0.003	0.997
EM5	0.000	0.020	0.009	0.992
HG1	0.000	0.020	-0.005	0.996
HG3	0.000	0.020	-0.005	0.996
HG5	0.000	0.020	0.008	0.993
Variances				
CO	1.000	0.000	999.000	999.000
COX	1.000	0.000	999.000	999.000
ES	1.000	0.000	999.000	999.000
EN	1.000	0.000	999.000	999.000
ME	1.000	0.000	999.000	999.000
OP	1.000	0.000	999.000	999.000
PE	1.000	0.000	999.000	999.000
PR	1.000	0.000	999.000	999.000
RE	1.000	0.000	999.000	999.000
SE	1.000	0.000	999.000	999.000
VI	1.000	0.000	999.000	999.000
AC	1.000	0.000	999.000	999.000
AU	1.000	0.000	999.000	999.000
EM	1.000	0.000	999.000	999.000
HG	1.000	0.000	999.000	999.000
Residual Variances				
CO2	0.372	0.012	30.442	0.000
CO5	0.321	0.021	15.662	0.000
CO6	0.252	0.019	13.258	0.000
CO9	0.316	0.011	29.088	0.000
CO10	0.286	0.015	18.649	0.000
CO11	0.269	0.019	14.406	0.000
ES2	0.352	0.016	22.082	0.000
ES4	0.359	0.014	25.451	0.000
ES7	0.266	0.013	20.730	0.000
EN2	0.254	0.025	10.200	0.000
EN3	0.255	0.013	19.590	0.000

EN7	0.292	0.011	27.342	0.000
ME1	0.209	0.008	25.264	0.000
ME5	0.223	0.008	26.234	0.000
ME9	0.184	0.010	19.267	0.000
OP2	0.136	0.010	13.713	0.000
OP3	0.194	0.008	25.401	0.000
OP5	0.210	0.008	26.341	0.000
PE2	0.194	0.008	25.114	0.000
PE3	0.160	0.007	22.106	0.000
PE7	0.160	0.007	22.047	0.000
PR2	0.353	0.015	23.304	0.000
PR6	0.313	0.013	24.219	0.000
PR7	0.430	0.016	26.740	0.000
PR8	0.411	0.016	25.630	0.000
RE3	0.233	0.010	23.963	0.000
RE5	0.240	0.010	23.288	0.000
RE6	0.190	0.011	16.908	0.000
SE1	0.270	0.011	25.678	0.000
SE2	0.312	0.012	25.506	0.000
SE3	0.254	0.012	21.298	0.000
VI1	0.143	0.007	19.197	0.000
VI4	0.129	0.008	15.246	0.000
VI7	0.226	0.008	29.581	0.000
AC1	0.355	0.017	20.987	0.000
AC4	0.392	0.020	19.935	0.000
AC7	0.354	0.012	29.708	0.000
AC9	0.302	0.011	28.422	0.000
AU2	0.314	0.014	22.980	0.000
AU3	0.194	0.016	12.140	0.000
AU5	0.351	0.013	27.067	0.000
EM1	0.500	0.016	30.331	0.000
EM2	0.388	0.016	23.740	0.000
EM4	0.526	0.020	26.419	0.000
EM5	0.425	0.020	21.543	0.000
HG1	0.302	0.013	23.517	0.000
HG3	0.255	0.013	19.443	0.000
HG5	0.328	0.013	24.856	0.000

R-SQUARE

Observed Variable	Estimate	S.E.	Two-Tailed Est./S.E.	P-Value
CO2	0.628	0.013	47.136	0.000
CO5	0.679	0.021	32.022	0.000
CO6	0.748	0.020	38.113	0.000
CO9	0.684	0.012	56.450	0.000
CO10	0.714	0.016	44.110	0.000
CO11	0.731	0.019	37.690	0.000
ES2	0.648	0.017	38.612	0.000
ES4	0.641	0.015	42.455	0.000
ES7	0.734	0.014	53.116	0.000
EN2	0.746	0.025	29.440	0.000
EN3	0.745	0.014	53.326	0.000
EN7	0.708	0.012	59.383	0.000
ME1	0.791	0.009	84.168	0.000
ME5	0.777	0.010	80.425	0.000
ME9	0.816	0.010	78.642	0.000
OP2	0.864	0.010	82.821	0.000
OP3	0.806	0.009	92.078	0.000
OP5	0.790	0.009	86.490	0.000

PE2	0.806	0.009	91.317	0.000
PE3	0.840	0.008	103.607	0.000
PE7	0.840	0.008	103.152	0.000
PR2	0.647	0.016	40.219	0.000
PR6	0.687	0.014	49.180	0.000
PR7	0.570	0.017	34.081	0.000
PR8	0.589	0.017	35.211	0.000
RE3	0.767	0.011	71.033	0.000
RE5	0.760	0.011	66.736	0.000
RE6	0.810	0.012	67.560	0.000
SE1	0.730	0.012	62.392	0.000
SE2	0.688	0.013	51.535	0.000
SE3	0.746	0.013	57.715	0.000
VI1	0.857	0.008	104.888	0.000
VI4	0.871	0.009	96.613	0.000
VI7	0.774	0.009	86.401	0.000
AC1	0.645	0.018	36.293	0.000
AC4	0.608	0.020	29.946	0.000
AC7	0.646	0.013	49.403	0.000
AC9	0.698	0.012	58.719	0.000
AU2	0.686	0.015	46.698	0.000
AU3	0.806	0.017	48.639	0.000
AU5	0.649	0.014	46.238	0.000
EM1	0.500	0.016	30.356	0.000
EM2	0.612	0.017	35.750	0.000
EM4	0.474	0.020	24.179	0.000
EM5	0.575	0.020	28.438	0.000
HG1	0.698	0.014	50.271	0.000
HG3	0.745	0.014	53.024	0.000
HG5	0.672	0.014	47.140	0.000

Section 12: Mplus Syntax Used for analyses presented in Table 4 of the main manuscript (Relations between Individual items from the WEMWBS and The Flourishing and the 15 WB-Pro Factors: The Multidimensionality of Unidimensional Scales)

```
            USEVARIABLES ARE
   t2CO2  t2CO5  t2CO6
   t2CO9 t2CO10 t2CO11
   t2ES2  t2ES4  t2ES7
   t2EN2  t2EN3  t2EN7
   t2ME1  t2ME5  t2ME9
   t2OP2  t2OP3  t2OP5
   t2PE2  t2PE3  t2PE7
   t2PR2  t2PR6  t2PR7 t2PR8
   t2RE3  t2RE5  t2RE6
   t2SE1  t2SE2  t2SE3
   t2VI1  t2VI4  t2VI7
   t2AC1  t2AC4  t2AC7 t2AC9
   t2AU2  t2AU3  t2AU5
   t2EM1  t2EM2  t2EM4 t2EM5
   t2HG1  t2HG3  t2HG5
      t2WMWB1 t2WMWB2 t2WMWB3 t2WMWB4 t2WMWB5 t2WMWB6
     t2WMWB7 t2WMWB8 t2WMWB9 t2WMWB10 t2WMWB11 t2WMWB12
     t2WMWB13 t2WMWB14
  ;
   define: standardize all;
 t2DIEN1 = -t2DIEN1  ;
 t2DIEN2 = -t2DIEN2  ;
 t2DIEN3 = -t2DIEN3  ;
 t2DIEN4 = -t2DIEN4  ;
 t2DIEN6 = -t2DIEN6  ;
 t2DIEN7 = -t2DIEN7  ;
 t2DIEN8 = -t2DIEN8  ;
 t2DIEN9 = -t2DIEN9  ;
   ANALYSIS:  ESTIMATOR = MLR;
    ROTATION = TARGET;
       PROCESSORS =4;
  MODEL:
  CO by t2CO2-t2CO6~.80 t2CO9-t2hg5~0  t2WMWB1-t2DIEN9~0
        T2WMWB2~.8 T2WMWB6~.8 T2WMWB10~.8 T2DIEN6~.8 (*t1);
  CT by t2CO9-t2CO11~.80 t2es2-t2hg5~0 t2CO2-t2CO6~0 t2WMWB1-t2DIEN9~0
        T2WMWB7~.8 T2WMWB11~.8  T2DIEN6~.8            (*t1);
  ES by t2ES2-t2ES7~.80 t2EN2-t2hg5~0 t2CO2-t2CO11~0 t2WMWB1-t2DIEN9~0
        T2WMWB3~.8     (*t1);
  EN by t2EN2-t2EN7~.80 t2ME1-t2hg5~0 t2CO2-t2ES7~0 t2WMWB1-t2DIEN9~0
        T2WMWB3-T2WMWB5~.8 T2WMWB13~.8 T2DIEN3~.8         (*t1);
  ME by t2ME1-t2ME9~.80 t2OP2-t2hg5~0 t2CO2-t2EN7~0 t2WMWB1-t2DIEN9~0
        T2WMWB2~.8  T2DIEN1~.8 T2DIEN7~.8 T2DIEN8~.8  (*t1);
  OP by t2OP2-t2OP5~.80 t2PE2-t2hg5~0 t2CO2-t2ME9~0 t2WMWB1-t2DIEN9~0
        T2WMWB1~.8  T2WMWB13~.8 T2DIEN8~.8 (*t1);
  PE by t2PE2-t2PE7~.80 t2PR2-t2hg5~0 t2CO2-t2OP5~0 t2WMWB1-t2DIEN9~0
        T2WMWB3~.8     T2WMWB8~.8  T2WMWB12~.8  T2WMWB14~.3 T2DIEN1~.8  (*t1);
  PR by t2PR2-t2PR8~.80 t2RE3-t2hg5~0 t2CO2-t2PE7~0 t2WMWB1-t2DIEN9~0
        T2WMWB4~.8 T2WMWB9~.8 T2WMWB12~.8 T2DIEN2~.8 T2DIEN4~.8 T2DIEN9~.8        (*t1);
  RE by t2RE3-t2RE6~.80 t2SE1-t2hg5~0 t2CO2-t2PR8~0 t2WMWB1-t2DIEN9~0
        T2WMWB6~.8     (*t1);
  SE by t2SE1-t2SE3~.80 t2VI1-t2hg5~0 t2CO2-t2RE6~0 t2WMWB1-t2DIEN9~0
        T2WMWB8~.8 T2WMWB10~.8  T2DIEN6~.8 T2DIEN7~.8 T2DIEN9~.8    (*t1);
  VI by t2VI1-t2VI7~.80 t2AC1-t2hg5~0 t2CO2-t2SE3~0 t2WMWB1-t2DIEN9~0
        T2WMWB5~.8     (*t1);
```

```
AC by t2AC1-t2AC9~.80 t2AU2-t2hg5~0 t2CO2-t2VI7~0 t2WMWB1-t2DIEN9~0
(*t1);
AU by t2AU2-t2AU5~.80 t2EM1-t2hg5~0 t2CO2-t2AC9~0 t2WMWB1-t2DIEN9~0
      T2WMWB11~.8   (*t1);
EM by t2EM1-t2EM5~.80 t2HG1-t2hg5~0 t2CO2-t2AU5~0 t2WMWB1-t2DIEN9~0
      T2WMWB5~.8 T2WMWB9~.8       (*t1);
HG by t2HG1-t2HG5~.80   t2CO2-t2EM5~0 t2WMWB1-t2DIEN9~0
      T2WMWB4~.8 T2WMWB9~.8 T2DIEN4~.8    (*t1);
 OUTPUT: sampstat  stdyx mod TECH1 tech4 sval;! MODINDICES (ALL);
```

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