Journal of Research in Personality 96 (2022) 104177

Contents lists available at ScienceDirect

Journal of Research in Personality

journal homepage: www.elsevier.com/locate/jrp

The structure of everyday happiness is best captured by a latent subjective well-being factor

Michael A. Busseri[a,*], Jordi Quoidbach[b]

[a] Department of Psychology, Brock University, 1812 Sir Isaac Brock Way, St. Catharines, Ontario, Canada

[b] Ramon Llull University, ESADE Business School, Department of People Management and Organisation, Avenida de Torre Blanca, 59, 08172 Sant Cugat, Barcelona, Spain

ARTICLE INFO

Keywords:
Subjective well-being
Structure
Experience sampling

ABSTRACT

We examined the structure of subjective well-being (SWB), comprising life satisfaction (LS), positive affect (PA), and negative affect (NA), in everyday life. 4,286 French adults (M_{age} = 30 years; 72% female) rated momentary LS, PA, and NA on at least four occasions over 25 days (average). A random intercept cross-lagged panel model revealed strong loadings from LS, PA, and NA on latent SWB factors within and across occasions, but weak and inconsistent cross-lagged effects. Correlations among LS, PA, and NA were consistent across age, sex, day of the week, and time of day. Further, most individuals were characterized by a positive LS-PA correlation along with negative LS-NA and PA-NA correlations, providing evidence of generalizability across individuals.

1. Introduction

The nature of happiness has been the province of philosophers, poets, and grandmothers for millennia. But in the last 40 years, there's been a growing scientific consensus that this elusive concept is best operationalized as *subjective well-being* (SWB): individuals' overall positive versus negative evaluations and experiences of their lives. Following Diener (1984), SWB is typically studied with respect to three main components: a global assessment of one's life, assessed in terms of life satisfaction (LS), along with individuals' positive and negative affective experiences (PA and NA, respectively). Self-report ratings of LS, PA, and NA are typically moderately correlated, with a positive correlation between LS and PA, and negative correlations between LS and PA with NA (Busseri, 2018; Schimmack, 2007, 2008). From this perspective, people vary along a continuum from low (i.e., low LS, low PA, high NA) to high (i.e., high LS, high PA, low NA) SWB levels. Despite the simplicity of this tripartite formulation, fundamental questions remain unresolved concerning the structure of SWB, that is, how LS, PA, and NA together comprise, reflect, and/or combine to represent the construct of SWB (Busseri & Sadava, 2011). This critical issue has implications for what kind of construct SWB is considered to be; how it should be operationalized, including measured and analyzed; and how results concerning SWB are tabulated and synthesized. In the present work we provide new evidence concerning the structure of SWB based on individuals' daily experiences, analyzed using a state-of-the-art statistical approach to provide the most rigorous test to date of prominent competing structural models of SWB.

Over the past four decades, SWB has become one of the most widely-used approaches to studying well-being (Disabato, Goodman, Kashdan, Short, & Jarden, 2016; Martela & Sheldon, 2019). A very large amount of research employing self-report measures of LS, PA, and NA has addressed the correlates, causes, and consequences of higher (vs. lower) levels of SWB (Diener, Oishi, & Lucas, 2015; Eid & Larsen, 2008). In general, this research suggests that individuals reporting higher (vs. lower) SWB are characterized by more (vs. less) positive functioning in psychological, physical, mental, interpersonal, and professional domains, as well as with more favourable socioeconomic conditions at both individual and societal levels (Diener et al., 1999, 2009). Apparently with good reason, therefore, most individuals place high value on living a satisfying and enjoyable life (Balestra, Boarini, & Tosetto, 2018; Diener, 2009).

Whereas many researchers agree that SWB encompasses PA, NA, and LS, there is still no consensus on how these components relate to one another, nor on how they should be studied (Busseri & Sadava, 2011). Some researchers interested in SWB examine the correlates of LS, PA, and NA individually (the *separate component conceptualization*; e.g., Heintzelman et al., 2020; Joshanloo, 2016; Kapteyn, Lee, Tassot, Vonkova, & Zamarro, 2015). Other researchers model SWB as a single entity,

* Corresponding author.
E-mail addresses: mbusseri@brocku.ca (M.A. Busseri), jordi.quoidbach@esade.edu (J. Quoidbach).

https://doi.org/10.1016/j.jrp.2021.104177
Received 29 July 2021; Received in revised form 30 November 2021; Accepted 1 December 2021
Available online 7 December 2021
0092-6566/

creating a simple composite variable (e.g., LS + PA – NA ratings; Avidor, Ayalon, Palgi, & Bodner, 2017; Deng et al., 2019; Jiang, Song, Ke, Wang, & Liu, 2016) or a more advanced latent factor, consistent with a *hierarchical conceptualization* (e.g., Chmiel, Brunner, Martin, & Schalke, 2012; Linley, Maltby, Wood, Osborne, & Hurling, 2009; Olesen, Thomsen, & O'Toole, 2015). Finally, some researchers study SWB based on a *causal systems conceptualization* in which the affective components, PA and NA, are treated as inputs to LS (e.g., Jovanović & Joshanloo, 2021; Luhmann & Kalitzki, 2018; Schimmack, Diener, & Oishi, 2002; Schimmack & Oishi, 2005).

Each of these approaches make fundamentally different assumptions about the nature of SWB. Imagine Charlotte, a 35-year-old who wants to be happier. Conversations with her therapist reveal that Charlotte experiences few moments of joy (i.e., low PA), undergoes tremendous stress at home (i.e., high NA), and feels profoundly dissatisfied with the way her professional life is going (i.e., low LS). The separate components conceptualization suggests that the associations among LS, PA, and NA are irrelevant to understanding SWB and that knowledge about SWB can accrue by examining findings based on the separate components (e.g., Anglim, Horwood, Smillie, Marrero, & Wood, 2020; Luhmann, Hofmann, Eid, & Lucas, 2012; Schneider & Schimmack, 2009). According to this perspective, SWB is just an umbrella term. If Charlotte wants to address her different problems she needs to start socializing more (i.e., increasing PA), sign up for a meditation course (i.e., decreasing NA), *AND* ask for a promotion (i.e., increasing LS). That is, to achieve high SWB, she needs to work on all three components separately.

In contrast, according to the hierarchical conceptualization, the associations among LS, PA, and NA are critical to understanding SWB; this approach employs a latent SWB factor in order to account for both the shared and unique aspects of LS, PA, and NA (e.g., Busseri, Sadava, & DeCourville, 2007; Gere & Schimmack, 2013; Linley et al., 2009). According to this perspective, Charlotte may be able to increase her overall level of SWB by socializing, meditating, *OR* getting a promotion. That is, changes made to one component can affect the underlying SWB of the person, although the precise impact of these activities is difficult to estimate given that intervention research rarely reports results based on latent SWB factors indicated by LS, PA, and NA. Alternatively, the causal systems conceptualization assumes a unidirectional flow of effects from PA and NA to LS (but not vice-versa) and emphasizes LS as the primary outcome of interest in studies of SWB (e.g., Luhmann & Kalitzki, 2018; Schimmack et al., 2002; Schimmack, Krause, Wagner, & Schupp, 2010). According to this perspective, Charlotte's best bet to boost her SWB is to boost her positive emotion, or aim to reduce her negative emotion, either or both of which will help indirectly boost her LS. In contrast, an attempt at increasing her LS will not improve her emotional life

Beyond Charlotte's fictitious example, the lack of consensus or consistency across studies concerning how SWB should be conceptualized and studied (in terms of operationalization, measurement, and analysis), as well as how research results concerning SWB should be synthesized impedes scientific progress (Busseri & Sadava, 2011). Different approaches to operationalizing SWB can impact conclusions concerning its correlates, predictors, and consequences (Busseri, 2015). For example, basic conclusions about how demographic and personality factors relate to SWB differ depending on whether LS, PA, and NA are treated as three separate components, as comprising a (presumed) causal system, or as indicators of a latent SWB factor (Metler & Busseri, 2017). Studies examining SWB may focus on only one or two of its components (e.g., LS only, or PA and NA without LS) rather than all three, or report and tabulate results based on the components separately, rather than jointly or with respect to a latent SWB factor. Consequently, whether or how the huge body of extant research findings concerning LS, PA, and NA inform our understanding of SWB per say is unclear – ultimately limiting the interpretation, synthesis, and application of such findings.

Despite its fundamental importance, the structural nature of SWB is rarely the focus of direct investigation. Moreover, studies evaluating the structure of SWB rely primarily on cross-sectional designs to examine patterns of covariance among LS, PA, and NA (e.g., Albuquerque, de Lima, Figueiredo, & Matos, 2012; Busseri, 2018; Jovanović, 2015). Cross-sectional designs can provide useful information concerning the direction and magnitude of the correlations among LS, PA, and NA, as well as estimates of the shared and unique variance in each of these components at a given point in time (Busseri et al., 2007). Critically, however, such designs cannot be used to adequately compare and contrast among competing structural approaches. For example, to test the directional flow of effects proposed by the causal systems conceptualization (i.e., PA and NA to LS), an experimental approach (e.g., gauging the impact of manipulating changes in one or more SWB components) or a longitudinal design (e.g., assessing LS, PA, or NA at two or more time points) is required in order to determine if PA and NA predict or lead to changes in LS over time (Busseri & Sadava, 2011). Further, with respect to evaluating the hierarchical conceptualization of SWB, cross-sectional designs do not allow for assessing stability and change over time in the latent SWB factor and each of its indicators; here again, experimental or longitudinal approaches are necessary.

To date, however, only a handful of studies have compared competing structural models of SWB based on longitudinal and/or experimental (rather than cross-sectional) designs. The results of these studies provide converging evidence that of the various prominent structural approaches, a hierarchical conceptualization, in which SWB is operationalized as a latent factor indicated by LS, PA, and NA, provides the most robust way to conceptualize and study SWB (Busseri, 2015; Metler & Busseri, 2017). In contrast, critical short-comings were observed to studying SWB through examining LS, PA, and NA only as individual components, or as a causal system in which PA and NA are assumed to influence LS.

Despite this progress, conclusions concerning the structure of SWB are limited by a number of factors, including (1) the small number of studies comparing competing structural models of SWB, (2) lack of an integrative analytic framework for evaluating competing structural conceptualizations of SWB, and (3) the longer-term time frame typical of studies employing a longitudinal approach.

A number of longitudinal studies have examined SWB over time in relation to other variables of interest. In such studies, a variety of approaches have used to operationalize SWB, including: examining LS, PA, and NA over time in separate models (e.g., Hudson, Lucas, & Donnellan, 2017; Moreno-Agostino et al., 2021; Zacher & Rudolph, 2021); assessing LS, PA, and NA separately but simultaneously over time in the same model (e.g., Daukantaite & Zukauskiene, 2012; Spindler, Stopsack, Aldinger, Grabe, & Barnow, 2016; Yang, Yan, Jia, Wang, & Kong, 2020); computing a composite SWB score at each wave (e.g., Elliot, Thrash, & Murayama, 2011; Jiang et al., 2016; Zhou, Huebner, & Tian, 2020); and estimating a latent SWB factor at each wave indicated by LS, PA, and NA ratings (e.g., Joshanloo, 2018; Joshanloo, Sirgy, & Park, 2018; Molnar, Busseri, Perrier, & Sadava, 2009). Also noteworthy, some longitudinal studies have used cross-lagged panel models (CLPM) to examine reciprocal effects between SWB (or its components) and various other variables, including academic engagement (e.g., Datu & King, 2018), health (Hudson, Lucas, & Donnellan, 2019), prosocial behavior (Chen, Tian, & Huebner, 2020), psychological well-being (Joshanloo, 2018), and needs satisfaction (Tian, Chen, & Huebner, 2014). A few longitudinal studies have also used CLPMs to estimate predictive effects among the three SWB components over time (e.g., Casas & González, 2020; Jia, Li, Zhang, & Kong, 2021; Yang et al., 2020). Despite this diversity of approaches and variables examined in extant longitudinal studies of SWB, none these studies compared results based on different conceptualizations of the structure of SWB.

Further, even in the small number of studies directly contrasting competing structural approaches (e.g., Busseri, 2015; Metler & Busseri, 2017), results were compared based on different analytic models – that is, a higher-order latent SWB factor model to test the hierarchical conceptualization, and a CLPM to test the causal systems model – rather than evaluated simultaneously within the same model. Testing competing models in this manner limits our ability to make conclusions based on direct comparisons of each structural approach *within the same analytic model*. However, recent advances in longitudinal data analysis now provide an opportunity to test the main features of different structural approaches within the same analytic model through examining the covariance among LS, PA, and NA based both of the variation between and within individuals over time.

Such advances are notable in light of growing recognition that CLPMs do not adequately account for the stability in each repeatedly assessed variable. Consequently, the resulting cross-lagged predictive effects confound (i) differences between individuals in their rank ordering on the level of the variable of interest over time (i.e., between-individual rank order stability/change), and (ii) variation within individuals in the occasion-to-occasion level (i.e., within-individual change) of the variable of interest. As a result, CLPMs can result in biased (if not uninterpretable) estimates of the effect from one variable at a given occasion to *changes* in another variable at a subsequent occasion (including if there is rank order change in the absence of within-individual changes for some individuals; Berry & Willoughby, 2017; Hamaker, Kuiper, & Grasman, 2015; Usami, Murayama, & Hamaker, 2019).[1]

Such short-comings can be addressed through use of a 'random intercept cross-lagged panel model' (RI-CLPM; Hamaker et al., 2015). This approach accounts for stability through estimating a latent random intercept factor for each repeatedly-assessed variable of interest, indicated by fixed loadings from each repeated assessment. The random intercept factor thus represents variability between individuals in the stable (i.e., time-invariant or trait-like) levels of the variables of interest. When such random intercept factors are modeled for two or more variables, the covariation between such factors can be estimated to account for associations involving between-individual differences in levels of each factor.

The RI-CLPM also captures within-person variability through isolating variance in each repeated assessment that is independent of the latent intercept factors (and their covariation). Further, the RI-CLPM provides estimates of the within-time covariation among the variables of interest, along with auto-regressive and cross-lagged predictive effects involving the occasion-specific variance in each of the repeated-assessed variables. Because the RI-CLPM accounts for between-individual variation and rank-order stability via the latent random intercept factors (and their covariation), and because the cross-lagged predictive effects are tested based on (residual) within-individual variance in each variable of interest that is independent of such between-individual effects, estimates of cross-lagged effects in a RI-CLPM are more informative concerning the predictive effect of one variable from one occasion on within-individual changes in another variable at a subsequent occasion.

Accordingly, a RI-CLPM could provide an integrative test of competing views concerning the structure of SWB through evaluating simultaneously the primary features of both the hierarchical conceptualization (i.e., treating LS, PA, and NA as indicators of a latent SWB factor based on variance between and within individuals) *and* the causal systems model (i.e., specifying cross-lagged predictive effects among LS, PA, and NA) within the same analysis. Despite the advantages of an RI-CLPM over a CLPM, we note that, when based on correlational research designs, neither of these covariance-based approaches provide a sufficient test of the underlying causal dynamics presumed by the causal systems model (i.e., that momentary experiences of PA and NA influence momentary evaluations of LS) – evidence for which requires use of a different type of research design, as discussed further below.

To date, only one study has reported results from a RI-CLPM involving SWB, in this case testing the reciprocal associations between SWB and physical health over a three-year period (Hudson et al., 2019). In this study LS, PA, and NA were examined in separate analytic models. Consequently, results from this study provide little information relevant to evaluating the structure of SWB. Toward resolving the structure of SWB, therefore, studies employing a RI-CLPM to examine LS, PA, and NA over time would provide an important advance.

Another important consideration concerns the timeframe of longitudinal studies examining SWB. In studies to date comparing competing approaches to the structure of SWB (e.g., Busseri, 2015; Metler & Busseri, 2017), the separation between measurement occasions has ranged between several months and years, to one decade. Similarly, in other longitudinal studies of SWB (not comparing structural models) the spacing between assessments occasions has varied between several months (e.g., Jia et al., 2021; Zacher & Rudolph, 2021) and several years (e.g., Casas & González, 2020; Joshanloo, 2018). Further, in such studies assessment of SWB is typically based on individuals' LS evaluations concerning their lives overall, and their PA and NA experiences 'in general' or based on the past several weeks. These details are important because, although such general assessments of LS, PA, and NA provide valuable information about SWB, they may not fully reflect individuals' evaluations and affective experiences as they live their lives day to day (Robinson & Clore, 2002). Indeed, studies comparing global assessments versus daily or momentary reports of LS, PA, and NA find positive but moderate correlations between timeframes (e.g., Anusic, Lucas, & Donnellan, 2017; Hudson et al., 2016, 2017; Lucas, Wallsworth, Anusic, & Donnellan, 2021).

Importantly, therefore, results and conclusions concerning SWB based on global reports of LS, PA, and NA may not be fully consistent with results obtained in the shorter-term contexts, including daily or momentary assessments (Diener & Tay, 2014; Hudson, Lucas, & Donnellan, 2016). Accordingly, with respect to the structure of SWB, it is possible that the associations among LS, PA, and NA assumed by a hierarchical conceptualization of SWB may be less robust with respect to individuals' daily experiences of their lives, compared with differences between individuals over longer periods of time. It is also possible that the dynamics implied by the causal systems approach (i.e., PA and NA impacting LS) might be better supported in shorter-term contexts (vs. over periods of months or years) as momentary affective reactions might play a stronger and more consistent role in shaping individuals' evaluations of their lives in a given moment.

A number of studies have employed experience sampling or daily dairy methods to assess individuals' momentary or daily experiences of LS, PA, and NA over shorter-term periods (e.g., ranging between one week or two months). In some of these studies, LS, PA, and NA were examined in separate statistical models (e.g., Berlin & Connolly, 2019; Jiang et al., 2016; Magee & Biesanz, 2019; Tončić & Anić, 2015). In other studies, PA and NA were treated as predictors of LS, consistent with the causal systems model (e.g., Bruehlman-Senecal, Ayduk, & John, 2016; Hofman et al., 2014; Jayawickreme, Tsukayama, & Kashdan, 2017). Although such studies provide valuable information concerning momentary or daily changes in LS, PA, and NA, none of these studies compared competing approaches to operationalizing SWB or modelled momentary SWB using a latent factor approach. Consequently, extant experience sampling and daily diary studies provide little information concerning the structure of SWB, including with respect to the shared (vs. unique) aspects of LS, PA, and NA, as well as the associations among all three components within and across multiple moments. Addressing these questions would provide important theoretical and practical insights about the nature of SWB in everyday life.

We report results from a large-scale experience sampling study in which over 4,000 individuals provided momentary ratings of LS, PA,

[1] Note, however, that if one is not interested in estimating or making inferences concerning changes within individuals from one occasion to the next independent of between-individual variation and covariation in stable (or trait-like) levels of each variable, the cross-lagged effects from a standard CLPM may not necessarily be 'biased' estimates of the relative associations between variables across time.

and NA at four or more occasions. We use these ratings to evaluate competing conceptualizations of SWB, including: (1) a hierarchical model in which SWB is operationalized as a latent factor, estimated using a higher-order latent factor approach; (2) a causal systems model in which PA and NA are treated as inputs to LS, estimated using the standard CLPM; and (3) an integrative model based on a RI-CLPM which combines the primary features of the hierarchical and causal systems models in a single analysis.

With respect to our approach, we note that the causal processes presumed by the causal systems model, in which PA and NA influence LS, cannot be adequately tested by using covariance-based approaches such as a CLPM or a RI-CLPM (as noted by Hamaker et al., 2015). A more rigorous test would involve experimentally manipulating PA and NA, and gauging the resulting impact on LS (e.g., Metler & Busseri, 2017, Study 2). However, to maintain consistency with previous studies testing competing structural models of SWB (e.g., Busseri, 2015; Metler & Busseri, 2017), in the present work we continue to refer to this particular structural conceptualization of SWB as a 'causal systems model'.

Based on previous studies examining associations among LS, PA, and NA (e.g., Busseri, 2018; Schimmack & Crites, 2005; Schimmack, 2008), we expected substantial correlations among all three SWB components both within and across measurement occasions, including positive correlations between LS and PA, and negative correlations between both LS and PA with NA. Further, consistent with studies comparing competing structural models of SWB (e.g., Busseri, 2015; Metler & Busseri, 2017), we anticipated that a hierarchical conceptualization would provide good fit to the data, including substantial loadings from LS, PA, NA on latent SWB factors at each measurement occasion. With respect to anticipated effect sizes, a recent empirical review encompassing 40 samples and 34,298 participants reported meta-analytic estimates of 0.53, −0.37, and −0.49, respectively, for the correlations between LS and PA, LS and NA, and PA and NA, along with factor loadings of 0.63, 0.84, and −0.54, respectively, for LS, PA, and NA on a latent SWB factor (Busseri, 2018).

In contrast, we expected that a (presumed) causal system in which PA and NA predict LS over time (but not vice-versa) would not be supported, particularly in the context of a RI-CLPM in which stability in each SWB component is accounted for through specifying latent random intercept factors, and cross-lagged predictive effects are based on (residual) changes within individuals from one occasion to the next. Rather, based on research concerning the short-comings of CLPM (e.g., Hamaker et al., 2015; Hudson et al., 2019), we expected that estimates concerning cross-lagged predictive effects among LS, PA, and NA derived from the CLPM would differ in both direction and magnitude compared to results based on the RI-CLPM.

Exploratory analyses were also used to assess the generalizability of our findings across persons and contexts. A hierarchical conceptualization of SWB assumes a specific pattern of correlations among the three SWB components, that is, a positive correlation between LS and PA, and negative correlations between LS and NA and between PA and NA. To evaluate the generalizability of such a pattern, we examined whether person-based (age, sex) or situational factors (day of week, time of day) moderated the associations among LS, PA, and NA. In addition, we computed intraindividual correlations among LS, PA, and NA to examine the generalizability of the associations among the three SWB components within individual participants.

2. Method

2.1. Participants and procedure

Data were drawn from a large-scale experience sampling study conducted in France during 2013 and 2014. Publicized on a nationally broadcast television program, individuals were invited to volunteer for the study by downloading a free francophone smartphone application. At sign up, participants gave informed consent, provided basic demographic information, and indicated on which days and during what times they wished to receive questionnaire requests (with the defaults set at seven days a week, and between 9 a.m. and 10p.m.). Participants also indicated how often each day they wished to receive questionnaire requests (with the default set of four per day, ranging from a minimum of 1 to a maximum of 12).

At each randomly determined moment (i.e., randomly selected on each day for each individual based on their reported preferences for day, time, and number of requests per day; and based on a minimum of one hour between requests), individuals were sent an alert through the study app to provide information on several aspects of their lives at that moment, including (in some instances) ratings of LS, PA, and NA as described below, along with information concerning what they were doing and who they were with. At each request, participants were presented with between four and six questions drawn from a larger battery (see Quoidbach, Taquet, Desseilles, de Montjoye, & Gross, 2019 for the detailed list of items). The number and type of SWB component ratings requested at a given occasion ranged from 0 (i.e., no ratings of LS, PA, or NA) to 3 (i.e., ratings for LS, PA, and NA). At each request, participants had the choice to complete the requested information, delay up to 9 min, or reject the request. All information was provided and completed in French. Ethics approval was provided by the ESADE Business School.

Of the 64,132 individuals who provided responses from at least one moment during the 18-month period during which the phone app was available for download, we examined results from individuals who provided ratings of LS, PA, and NA at each of four or more occasions. Although the statistical models tested in the present work could be estimated with a minimum of three time points, the inclusion of four time points eliminated the need to employ various equality constraints in order statistically identify the RI-CLPM (see Mulder & Hamaker, 2021). The analysis sample comprised 4,286 participants (M_{age} = 29.91 years, SD = 10.24; 71.7% female; 92.0% from France, 5.8% from Switzerland or Belgium, 2.1% other). These participants had an average of 5.55 occasions with ratings of all three SWB components, range = 4 to 66 occasions. Note that for participants rating all three components of more than four occasions, only the first four such occasions were examined in order to ensure that the time period encompassed by the present analyses was as compressed as possible, and thus maximally relevant to everyday life (median separation between occasions was 5 days, 10 days, 5 days, and 25 days, respectively, between occasions 1 and 2, occasions 2 and 3, occasions 3 and 4, and occasions 1 and occasion 4). Sample size was not determined a priori based on a power analysis. However, a (post hoc) sensitivity analysis indicated that this sample size provided statistical power of 0.80 to detect as statistically significant (α = . 05, two-tailed) correlations of 0.04 or larger (absolute magnitude).[2]

Results from the larger study from which the current data were drawn have been published in previous reports (Quoidbach et al., 2019; Taquet et al., 2016, 2020; Trampe, Quoidbach, & Taquet, 2015). However, no previous publication based on the larger study has examined the structure of SWB based on ratings of LS, PA, and NA.

2.2. Measures

Ratings of LS, PA, and NA were based on how individuals were currently feeling and were completed using a visual slider ranging from 0 to 100, with lower values indicating lower amounts and higher values indicated higher amounts. For the LS ratings, the following statement was provided: "Here and now I am …"; scale anchors were 0-*unsatisfied*

[2] The present study was not pre-registered. The first author conducted the main analyses and wrote the first draft of this manuscript; the second author was responsible for designing the study and data collection, as well as data analysis and editing.

with my life and 100- *satisfied with my life*; for PA and NA, the following statement was provided: "Are you currently experiencing positive / negative emotion"; scale anchors were 0-*not at all* to 100-*absolutely*. By default, the cursor was centered at the middle point of the scale (50). Given the way the app was coded, it was not possible to distinguish whether participants skipped the question (resulting in a default score of 50) or actively selected this middle point. Taking a conservative approach, we excluded ratings of 50 from the analyses.

2.3. Open materials

The data examined in the present work, along with an analysis code file, are available at: https://osf.io/3v6bh/?view_only=a95ca8bf13fc4172a3d6cfc18e30c894.

3. Results

3.1. Evaluating competing structural models

Descriptive statistics and correlations among the LS, PA, and NA ratings are shown in Table 1. Correlations among the three SWB components were moderate to large in magnitude and each was in the expected direction within each occasion and across occasions.

3.1.1. Examining the causal systems conceptualization: cross-lagged panel model (CLPM)

Consistent with the causal systems conceptualization, we first estimated a CLPM (see Fig. 1) in which the LS, PA, and NA ratings from a given measurement occasion (i.e., Time 1, Time 2, or Time 3) were specified as predictors of the LS, PA, and NA ratings at the next measurement occasion (i.e., Time 2, Time 3, and Time 4, respectively). Correlations among the three ratings were estimated at Time 1, as were correlations among the within-time residual variances in the three ratings at each subsequent wave (i.e., within Time 2, Time 3, and Time 4).

As shown in Table 2, this model provided poor fit to the data (other than with respect to the CFI). In addition, there were several large residual associations among the LS, PA, and NA ratings from non-adjacent occasions (i.e., lag-2 or lag-3 associations) that were not accounted for the by model (i.e., residual correlations ranging from −0.20 to 0.25). Despite these issues, for completeness we report the cross-lagged predictive effects estimated from this model in Table 3. As shown, results included positive predictive effects from PA to LS and negative predictive effects from NA to LS, but also positive and negative predictive effects from LS to PA and NA. There were also large correlations among LS, PA, and NA at Time 1 (rs = 0.76, −0.72, and −79, respectively for correlations between LS and PA, LS and NA, and PA and NA; $ps < 0.001$), as well as large correlations among the residual variances in LS, PA, and NA at each subsequent time point: At Time 2, rs = 0.71, −0.64, and −0.71, respectively, $ps < 0.001$; at Time 3, rs = 0.71, −0.63, and −0.71, respectively; $ps < 0.001$; at Time 4, rs = 0.69, −0.60, and −0.67, respectively; $ps < 0.001$.[3]

[3] Results were similar when based on a modified model in which all cross-lagged effects were estimated, including lag-2 and lag-3 effects (e.g., effects of LS, PA, and NA from Time 1 on Time 3 and Time 4), creating a saturated model (df = 0). As shown in Supplemental Table 1 in the Appendix, across adjacent and non-adjacent occasions there were positive predictive effects from PA to LS and negative predictive effects from NA to LS, but also positive and negative predictive effects from LS to PA and NA. There were also large correlations among the residual variances in the LS, PA, and NA ratings at: Time 2, rs = 0.72, −0.64, and −0.71, respectively, for correlations between LS and PA, LS and NA, and PA and NA; $ps < 0.001$; at Time 3, rs = 0.70, −0.60, and −0.70, respectively; $ps < 0.001$; at Time 4, rs = 0.68, −0.58, and −0.66, respectively; $ps < 0.001$.

3.1.2. Examining the hierarchical conceptualization: higher-order latent SWB model

Consistent with a hierarchical conceptualization of SWB, we next examined a model (see Fig. 2) in which a latent SWB factor was specified at each of the four occasions, each indicated by the occasion-specific ratings of LS, PA, and NA. The loading for the LS rating was fixed to 1 at each occasion to identify each latent factor. Across occasions, the four latent SWB factors were specified as loading onto a higher-order latent SWB factor. To identify this higher-order factor, the loading from the Time 1 latent SWB factor was fixed to 1. Correlations were estimated among the residual variances within each SWB component (e.g., among the residuals in four LS ratings) to account to covariation within each component over time that was independent of the latent SWB factors.

This model provided good fit to the data (see Table 2). Further, the residual correlations revealed no large correlations among the LS, PA, and NA ratings that were not accounted for the by model (i.e., residual correlations ranged from −0.09 to 0.11). As shown in Table 4, at each occasion the LS, PA, and NA ratings had very strong loadings on the latent SWB factor. In addition, each occasion-specific latent SWB factor had a strong and positive loading on the higher-order latent SWB factor. Correlations among the residual variances within the specific SWB components were generally small to moderate in magnitude: For LS, rs ranged from 0.29 to 0.41, $ps < 0.001$; for PA, rs ranged from −0.01 to 0.07; for NA, rs ranged from 0.23 to 0.36, $ps < 0.001$.

3.1.3. Jointly testing the causal systems and hierarchical conceptualizations: random-intercept cross-lagged panel model (RI-CLPM)

The third model we tested was estimated following specifications for a RI-CLPM provided by Mulder and Hamaker (2021). This model (see Fig. 3) specified latent intercept factors for LS, PA, and NA, as indicated by the corresponding ratings from each occasion (e.g., the latent LS intercept factor was indicated by the LS ratings from Time 1, Time 2, Time 3, and Time 4). All four loadings on each latent intercept factor were fixed to 1 to identify the factors, and to specify each factor as having a fixed influence on the relevant rating over time. Correlations were estimated among the three latent intercept factors. The LS, PA, and NA ratings from each occasion were specified with residual (error) variance terms fixed to 0, and a latent time-specific variable was estimated corresponding to each rating and occasion (e.g., a latent Time 1 LS variable was indicated by the Time 1 LS rating and the variance for the Time 1 LS rating was fixed to 0). Residual variances were estimated for each of these time-specific latent variables. Correlations were estimated between the three latent Time 1 variables, and between the residual variances in these three latent variables within each occasion (i.e., among the residual variances in the latent Time 2 LS, PA, and NA variables). Cross-lagged predictive effects were estimated between the time-specific latent LS, PA, and NA variables from one occasion to the next (e.g., from the Time 1 latent LS, PA, and NA variables to the three latent T2 variables).

This model provided excellent fit to the data (see Table 2) and superior fit than either of the other two models. Further, the residual correlations revealed no large correlations among the LS, PA, and NA ratings that were not accounted for the by model (i.e., residual correlations ranged from −0.03 to 0.03). As shown in Table 5, each latent intercept factor had strong loadings from the corresponding occasion-specific ratings of LS, PA, or NA. The correlations among the three latent intercept factors were also very strong: rs = 0.92, −0.91, and −0.91, respectively, for LS and PA, LS and NA, and PA and NA; $ps <$ 0.001. Further, the correlations among the time-specific latent LS, PA, and NA variables were moderate to strong within each occasion: At Time 1, rs = 0.58, −0.53, and −0.69, respectively, for LS and PA, LS and NA, and PA and NA; at Time 2, rs = 0.59, −0.59, and −0.69, respectively; at Time 3, rs = 0.66, −0.63, and −0.72; at Time 4, rs = 0.66, −0.62, and −0.68. In addition, as shown in Table 6, the cross-lagged predictive effects were generally weak in magnitude and inconsistent in direction between each pair of occasions. These effects included positive and non-

Table 1
Descriptive Statistics and Correlations among Study Measures.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. T1 LS	61.25	26.08	–											
2. T1 PA	60.70	25.60	0.78	–										
3. T1 NA	37.99	26.89	−0.70	−0.77	–									
4. T2 LS	63.43	26.69	0.60	0.50	−0.47	–								
5. T2 PA	62.75	25.62	0.49	0.48	−0.43	0.80	–							
6. T2 NA	36.00	27.23	−0.47	−0.43	0.48	−0.73	−0.78	–						
7. T3 LS	64.61	27.33	0.58	0.49	−0.47	0.68	0.57	−0.55	–					
8. T3 PA	64.13	26.63	0.49	0.47	−0.44	0.56	0.53	−0.49	0.82	–				
9. T3 NA	35.12	28.25	−0.46	−0.42	0.47	−0.51	−0.47	0.53	−0.74	−0.79	–			
10. T4 LS	64.72	28.11	0.54	0.45	−0.44	0.61	0.52	−0.51	0.71	0.61	−0.58	–		
11. T4 PA	64.76	27.25	0.45	0.43	−0.40	0.51	0.50	−0.46	0.60	0.58	−0.52	0.82	–	
12. T4 NA	34.59	28.94	−0.41	−0.37	0.43	−0.46	−0.42	0.49	−0.54	−0.48	0.57	−0.74	−0.76	–

Note. $N = 4286$. T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. $p < .001$ for each correlation.

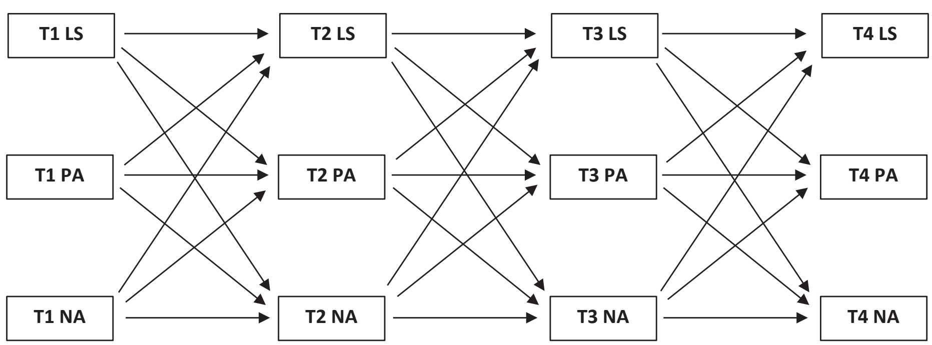

Fig. 1. Cross-Lagged Panel Model (Model 1). *Note.* T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. Not shown for ease of presentation but specified as part of the model testing are correlations among the Time 1 LS, PA, and NA ratings, and among the within-time residual variances at Time 2, Time 3, and Time 4.

Table 2
Model Fit Statistics for Structural Models.

Model	model χ^2 (*df*), *p* value	CFI	SRMR	RMSEA, *p* close fit	AIC	BIC
1. CLPM	1319.53 (27), $p <$ .001	0.97	0.09	0.11, $p <$ .001	441,038	441,039
2. Higher-order model	804.54 (32), $p <$ .001	0.98	0.04	0.08, $p <$ .001	440,513	440,882
3. RI-CLPM	42.49 (21), $p = .004$	0.99	0.01	0.02, $p >$ .999	439,773	440,212

Note. $N = 4286$. CLPM = cross-lagged panel model. RI-CLPM = random intercept cross-lagged panel model.

significant predictive effects from PA to LS, and non-significant predictive effects from NA to LS, as well as positive and negative predictive effects from LS to PA and NA.

Note that the strong correlations among the three latent intercept factors suggest that these factors could be modeled as indicators of a higher-order SWB factor; similarly, the strong correlations among the time-specific LS, PA, and NA suggest that these variables could be specified as indicators of a latent SWB factor within each occasion. To evaluate these notions directly, a modified RI-CLPM model was estimated in which (a) the correlations among the three latent intercept factors were replaced by three loadings on a higher-order latent SWB factor, with a fixed loading of 1 from the latent LS intercept factor; and (b) the correlations among the time-specific latent LS, PA, and NA variables were replaced by loadings on a time-specific latent SWB factor at each occasion, with a fixed loading of 1 from the latent LS variable (see Fig. 4). The fit of this modified RI-CLPM was identical to the original. As shown in Table 5, in such a model strong loadings were observed for all three latent intercept factors on a higher-order latent SWB factor, as were strong loadings from the time-specific latent LS, PA, and NA variables on the latent SWB factor at each occasion. The cross-lagged predictive effects between each pair of occasions were identical to the original model (see Table 6).

3.2. Exploratory analyses - moderating factors

To evaluate whether the specific pattern of associations among the three SWB components implied by a latent SWB factor was generalizable, we examined correlations among the LS, PA, and NA ratings from the first occasion reported by each participant as a function of: participant age (using a median split: younger, $M = 21.87$ years vs. older, $M = 38.28$ years), gender (male vs. female), day of the week (i.e., 61.1% on weekdays vs. 38.9% on the weekend), and time of day (four 6-hour blocks: 2.4% from 12 a.m. to 5:59 a.m., 19.1% from 6 a.m. to 11:59, 39.1% from 12p.m. to 5:59p.m., and 39.4% from 6 pm to 11:59p.m.). Within each level of a given factor (e.g., among younger and older adults), we freely estimated the covariances among the LS, PA, and NA ratings and then compared the fit of this model with a model in which each of the corresponding covariances were constrained to be equal across the levels of each factor (e.g., the covariance between LS and PA

Table 3
Cross-Lagged Predictive Effects from CLPM (Model 1).

	Criterion								
Predictor	T2 LS	T2 PA	T2 NA	T3 LS	T3 PA	T3 NA	T4 LS	T4 PA	T4 NA
T1 LS	0.52	0.27	−0.28						
T1 PA	0.02	0.20	0.03						
T1 NA	−0.10	−0.09	0.31						
T2 LS				0.58	0.35	−0.28			
T2 PA				0.04	0.19	0.03			
T2 NA				−0.09	−0.09	0.35			
T3 LS							0.60	0.36	−0.30
T3 PA							0.04	0.23	0.09
T3 NA							−0.10	−0.06	0.42

Note. $N = 4286$. T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. Standardized path coefficients are shown for each predictor (row variable) by criterion (column variable). Effects 0.05 or larger (absolute magnitude) are statistically significant at $p < .05$.

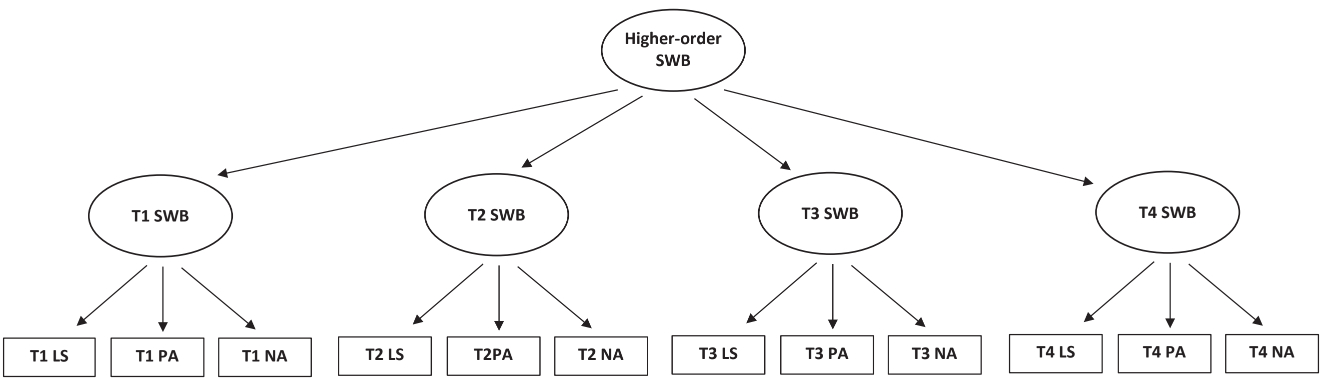

Fig. 2. Higher-Order Model (Model 2). *Note.* SWB = subjective well-being. T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. Not shown for ease of presentation but specified as part of the model testing are correlations among the within-component residual variances in LS, PA, and NA.

Table 4
Factor Loadings from Higher-Order Model (Model 2).

	Latent SWB factor				
Indicator	T1	T2	T3	T4	HO
T1 LS	0.83				
T1 PA	0.93				
T1 NA	−0.83				
T2 LS		0.86			
T2 PA		0.92			
T2 NA		−0.85			
T3 LS			0.87		
T3 PA			0.93		
T3 NA			−0.85		
T4 LS				0.88	
T4 PA				0.92	
T4 NA				−0.82	
T1 latent SWB					0.70
T2 latent SWB					0.79
T3 latent SWB					0.86
T4 latent SWB					0.80

Note. $N = 4286$. T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. SWB = subjective well-being. HO = higher-order. Standardized factor loadings are shown for each indicator (row variable) by latent factor (column variable). All loadings are statistically significant at $p < .001$.

was first freely estimated among younger and older adults, and then constrained to be equal between younger and older adults).

Model fit results for the constrained models are shown in Table 7. The constrained model did not differ significantly from the freely estimated model for participant age, gender, day of the week, or time of day. That is, the strength of the associations among LS, PA, and NA at the first measurement occasion did not vary significantly as a function of these factors. For age, the chi-square difference test between the constrained and unconstrained models was statistically significant; however, the other fit indices did not indicate a significant decrement in model fit and the residual covariances in the constrained model were small in magnitude (range = −0.02 to 0.02).

Next, we tested the generalizability of the associations among the three SWB components within participants by examining the intra-individual correlations between LS, PA, and NA for each individual in the subsample of 262 participants who provided LS, PA, and NA ratings at 10 or more occasions. Mean within-person correlations (and *SDs*) were 0.62 (0.28) for LS and PA, −0.53 (0.30) for LS and NA, and −0.62 (0.30) for PA and NA. The vast majority of participants were characterized by a positive correlation between LS and PA (94.3% of individuals), and negative correlations between LS and NA (90.1%), and PA and NA (93.1%). Further, 87.0% of individuals were characterized by the combination of a positive correlation between LS and PA, a

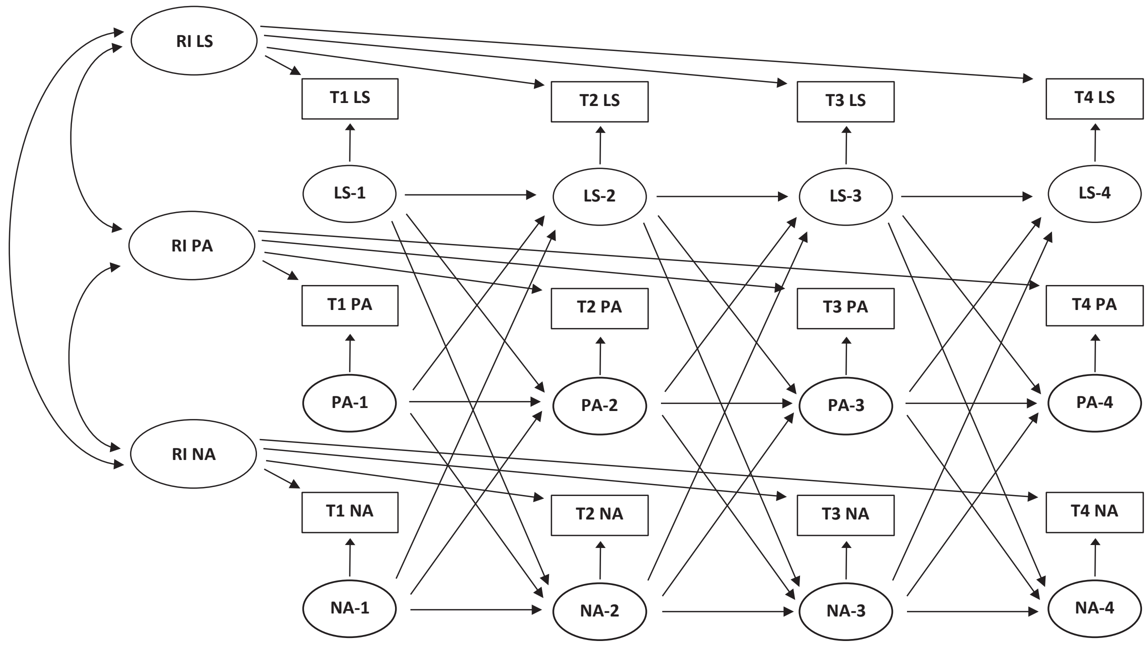

Fig. 3. Random-Intercept Cross-Lagged Panel Model (Model 3). *Note.* T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. RI = random intercept. Not shown for ease of presentation but specified as part of the model testing are: residual variances in each LS, PA, and NA rating (fixed to 0); residual variances in each time-specific latent LS, PA, and NA variables; correlations among the within-time variances in the Time 1 latent LS, PA, and NA variables; and within-time correlations among the residual variances in the time-specific latent LS, PA, and NA variables.

Table 5
Factor Loadings from RI-CLPM (Model 3).

	Latent intercept factor			Latent SWB factor (modified model)				
Indicator	LS	PA	NA	T1	T2	T3	T4	HO
T1 LS	0.77			0.67				
T2 LS	0.77				0.72			
T3 LS	0.75					0.75		
T4 LS	0.72						0.73	
T1 PA		0.70		0.91				
T2 PA		0.71			0.87			
T3 PA		0.68				0.89		
T4 PA		0.66					0.84	
T1 NA			0.70	−0.72				
T2 NA			0.70		−0.75			
T3 NA			0.67			−0.77		
T4 NA			0.65				−0.72	
RI LS								0.96
RI PA								0.97
RI NA								−0.92

Note. $N = 4286$. T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. RI = latent random intercept factor. HO = higher order. SWB = subjective well-being. Standardized factor loadings are shown for each indicator (row variable) by latent factor (column variable). All loadings are statistically significant at $p < .001$.

negative correlation between LS and NA, and a negative correlation between PA and NA.[4]

4. Discussion

Establishing the inner-structure of SWB is a fundamental step in advancing happiness research—from theorizing and measurement, to how findings should be tabulated, synthesized, and applied. We examined prominent competing structural models of SWB in daily life using large experience-sampling data and an integrative analytic approach. Results reveal that the structure of everyday happiness is best captured as a latent subjective well-being factor. These findings generalized across demographic groups and situations. Moreover, almost 9 out of 10 people displayed the expected pattern of correlations between LS, PA, and NA, suggesting that the hierarchical conceptualization of SWB

[4] Individuals who were (vs. were not) characterized by the correct combination of correlations did not differ significantly in age or sex ($ps = 0.165$ and 0.065, respectively). Note also that even when within-individual correlations were counted as being in the 'correct' direction only if they were each at least 'large' in magnitude (i.e., $r = 0.30$ or larger in absolute value; see Fredrickson, 2019), 67.2% of individuals were characterized by a combination of a positive correlation between LS and PA, and negative correlations between LS and NA, and between PA and NA.

Table 6
Cross-Lagged Predictive Effects from RI-CLPM (Model 3).

Predictor	Criterion T2 LS	T2 PA	T2 NA	T3 LS	T3 PA	T3 NA	T4 LS	T4 PA	T4 NA
T1 LS	0.03	−0.05	0.02						
T1 PA	−0.01	0.01	0.01						
T1 NA	−0.03	0.01	−0.01						
T2 LS				0.21	0.14	−0.09			
T2 PA				−0.01	−0.01	0.03			
T2 NA				−0.03	−0.02	0.07			
T3 LS							0.28	0.21	−0.16
T3 PA							0.04	0.07	0.08
T3 NA							−0.08	−0.04	0.21

Note. N = 4286. T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. Standardized path coefficients are shown for each predictor (row variable) by criterion (column variable). Effects>0.05 (absolute magnitude) are statistically significant at $p < .05$.

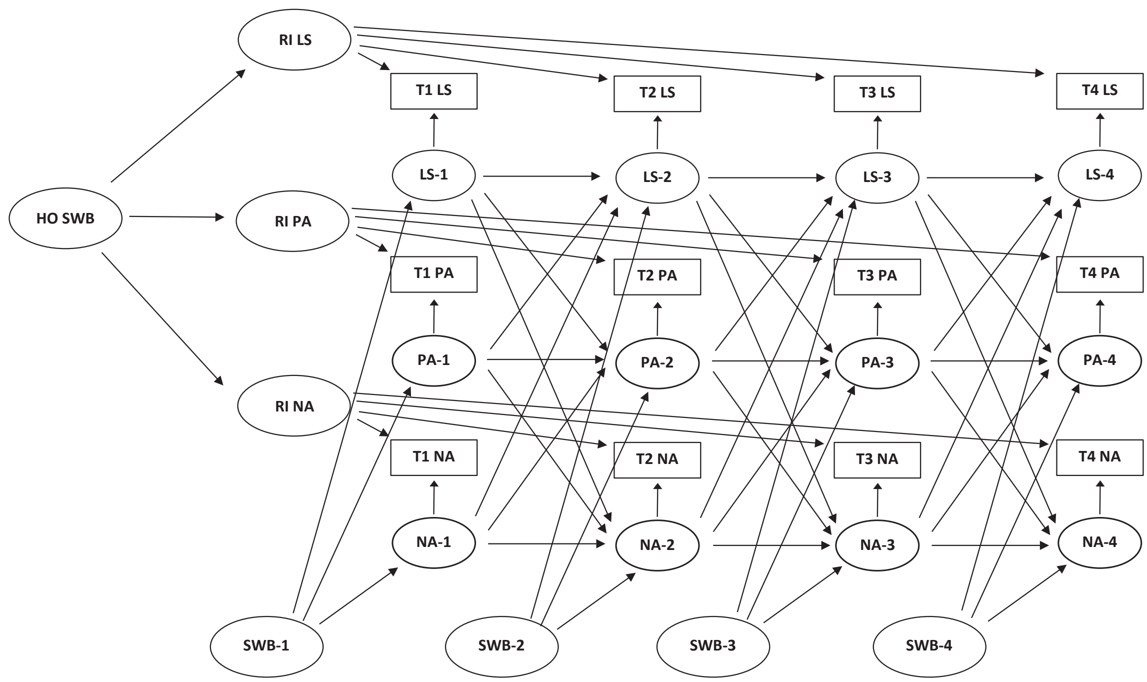

Fig. 4. Modified Random-Intercept Cross-Lagged Panel Model (Model 4). *Note.* T = time (measurement occasion). LS = life satisfaction. PA = positive affect. NA = negative affect. RI = random intercept. HO = higher-order. Not shown for ease of presentation but specified as part of the model testing are: residual variances in each LS, PA, and NA rating (fixed to 0) and residual variances in each time-specific latent LS, PA, and NA variables.

Table 7
Fit Statistics from Constrained Models Evaluating Moderators of the Associations Among LS, PA, and NA at First Occasion.

Moderator	model χ^2 (*df*), *p* value	CFI	RMSEA, *p* close fit
Gender (male vs. female)	2.41 (3), $p = .49$	>0.99	<0.01, $p > .99$
Age (younger vs. older)	8.46 (3), $p = .04$	>0.99	<0.03, $p > .92$
Day of week	2.22 (3), $p = .53$	>0.99	<0.01, $p > .99$
Time of day	6.17 (9), $p = .73$	>0.99	<0.01, $p > .99$

Note. N = 4286. Model fit indices from constrained models are shown. Model chi-square values can be interpreted as difference tests between the freely estimated (*df* = 0) and constrained models.

applied to the vast majority of participants.

4.1. Comparing structural models of SWB

The robust correlations observed among LS, PA, and NA at each occasion and across occasions are consistent with previous reviews examining associations among the three SWB components (e.g., Busseri, 2018; Schimmack & Crites, 2005; Schimmack, 2008). Such findings provide further evidence *against* conceptualizing and studying SWB as three separate components. Further, as in previous studies comparing competing structural models of SWB (Busseri, 2015; Metler & Busseri, 2017), there was little support for the (presumed) causal systems conceptualization of SWB based on individuals' momentary experiences of LS, PA, and NA in their daily lives. The original CLPM provided poor fit to the data because it did not account for associations among non-adjacent (i.e., lag 2 and lag 3) assessments. Even ignoring such issues related to model fit, the cross-lagged predictive effects suggest small reciprocal associations among *all three* SWB components over time (see also Busseri, 2015), including predictive effects of LS on both PA and NA, rather than directional predictive effects only from PA and NA to LS. We note that such results were obtained even in a modified CLPM which included all possible cross-lagged (i.e., lag-2 and lag-3) effects (see Note 1). There were also large associations observed among the residuals in

LS, PA, and NA within each occasion. These associations suggest that all three SWB components strongly covary within each occasion, independent of the mutual influence they may each have over time. Such results suggest robust underlying commonality among LS, PA, and NA.

Indeed, a hierarchical conceptualization of SWB, in which SWB is examined as a latent factor indicated by LS, PA, and NA, provided good fit to the data, and superior fit to the CLPM. Further, the factor loadings from LS, PA, and NA were strong at each occasion, as were the loadings from all four latent SWB factors on a higher-order SWB factor. Together, such findings suggest the presence of underlying commonality among LS, PA, and NA within each measurement occasion and across occasions. Such evidence provides strong support for the defining feature of the hierarchical conceptualization of the structure of SWB, consistent with previous studies comparing structural models for SWB (Busseri et al., 2007; Busseri, 2015; Metler & Busseri, 2017). An important disadvantage of this model, however, is that it does not directly inform the associations among LS, PA, and NA over time – a short-coming that is addressed in the RI-CLPM.

The RI-CLPM provided excellent fit and was superior in fit to the hierarchical model. Further, in combining the main features of each of the two other structural models we examined, the RI-CLPM accounted for underlying commonality among LS, PA, and NA within and across time, as well as cross-lagged effects. The strong loadings on the random intercept factors for each SWB component suggest stability in LS, PA, and NA across the four occasions. There was also substantial covariation among these intercepts, and between the time-specific variance in LS, PA, and NA. Further, the RI-CLPM can be modified to incorporate (i) a higher-order latent SWB factor based on the stable between-person variation in LS, PA, and NA, as well as (ii) latent SWB factors reflected in the occasion-specific covariation among the three components. Present findings based on this modified approach converge with results from the hierarchical model in providing strong support for an underlying commonality among the SWB components, both across time and within each occasion.

Independent of such associations, cross-lagged predictive effects – the defining feature of the causal systems model – were also observed. However, several of these effects were not statistically significant and their directions were inconsistent, both for a given component across occasions and among components within occasions. Thus, although the presence of such effects suggests (or is at least consistent with the possibility of) a small degree of mutual influence among LS, PA, and NA from one occasion to the next, findings from the RI-CLPM provide *no consistent support* for a causal systems account in which PA and NA are inputs to LS (rather than vice-versa).

4.2. Structure of SWB within moments, across individuals

The present findings provide strong support for an underlying latent SWB factor, both within and across moments from individuals' lives. Such a latent SWB factor assumes a particular pattern of covariation among LS, PA, and NA – that is, a positive correlation between LS and PA, and negative correlations between LS and PA with NA. To test the generalizability of this pattern, we evaluated several potential moderators of the associations among LS, PA, and NA, including person-based (age, gender) and situational factors (day of week, time of day) at the first measurement occasion. Results suggested that the covariation pattern was consistent across each of these factors. Such findings provide evidence that the underlying structure of SWB at a given moment was generalizable across participant age and gender, and regardless of factors such as the day of the week or time of day of the report.

4.3. Structure of SWB within individuals, across moments

To further test the generalizability of our findings, we evaluated the intraindividual associations among LS, PA, and NA within each individual reporting multiple momentary experiences. Several previous studies have evaluated the within-person correlation between PA and NA based on repeated sampling of moments within individuals (e.g., Carstensen, Pasupathi, Mayr, & Nesselroade, 2000; Diener & Emmons, 1984; Hershfield, Scheibe, Sims, & Carstensen, 2013). Such studies have found that, in general, more strongly negative correlations between PA and NA are more characteristic of individuals with less resilience and less positive psychosocial functioning (for a review, see Hülür et al., 2015). However, no previous studies to date have used this approach to examine intraindividual correlations among all three SWB components. Although our results were limited to the subset of respondents who reported 10 or more occasions, findings were clear and compelling: The pattern of correlations implied by a hierarchical conceptualization of SWB – a positive correlation between LS and PA, and negative correlations between LS and NA, and between PA and NA – was found among 87% of people. Such findings provide additional evidence that the defining feature of the hierarchical conceptualization of SWB – a latent SWB factor, with positive loadings from LS and PA, and a negative loading from NA, based on individuals' momentary experiences of their lives – was viable among almost every participant.

4.4. Implications for theory, research, and practice

With respect to competing conceptualizations, SWB does not appear to be structured as a causal system in which momentary experiences of PA and NA feed into LS (but not vice-versa), as previously assumed (e.g., Bruehlman-Senecal et al., 2016; Hofman et al., 2013; Jayawickreme et al., 2017). Indeed, in the RI-CLPM, the cross-lagged predictive effects were typically very small in magnitude and also inconsistent in direction and statistical significance. The inclusion of such effects did result in a better-fitting statistical model for the RI-CLPM versus the hierarchical model. Nonetheless, in both of these models the predominant findings included robust loadings of momentary experiences of LS, PA, and NA onto time-specific latent SWB factors, as well as strong covariation among such momentary experiences of SWB across time consistent with a higher-order SWB factor. Findings based both on the higher-order model and the RI-CLPM thus support a hierarchical conceptualization of the structure of SWB with respect to individuals' momentary experiences of LS, PA, and NA.

From this perspective, SWB as a momentary experience encompasses an underlying dimension ranging from low (low LS, low PA, high NA) to high (high LS, high PA, low NA) levels. Further, although not interchangeable, the three components of SWB have a strong degree of covariation, reflecting the common influence of the latent SWB factor. Additionally, from this perspective, SWB should be operationalized as a latent factor reflecting the commonality among momentary experiences of LS, PA, and NA, as well as in the commonality of such experiences across time. Notwithstanding such underlying commonality within and across moments, there are also unique aspects of LS, PA, and NA that are independent of each other. Such unique aspects of LS, PA, and NA may be both meaningful and substantive (e.g., Busseri et al., 2007; Busseri, 2015). Taken together, such notions suggest that understanding individuals' momentary experiences of SWB requires consideration of, and attention to, both the shared and unique aspects of LS, PA, and NA.

To this end, future studies examining SWB as a momentary experience would benefit from (1) assessing all three components at each moment, and (2) modeling LS, PA, and NA as indicators of a latent SWB factor. We are not aware of any other experience sampling studies to take this approach. Yet the present findings suggest that such an approach to studying individuals' momentary experience of SWB would be more appropriate, both conceptually and empirically, than ignoring such commonality (e.g., by examining only one or two components, or only examining LS, PA, and NA individually) or assuming a causal system in which PA and NA serve as positive and negative inputs (respectively) to LS. Further, it would likely prove useful to revisit results from previous studies employing such approaches in order to determine how results differ if SWB was operationalized as a latent factor, both within and across moments. To such ends, we urge researchers to report the correlations among all three SWB components, and any other variables of interest examined in a given study, in order to permit supplemental analyses involving a latent SWB factor.

From a methodological perspective, the present findings also provide further evidence that results concerning cross-lagged predictive effects derived from a standard CLPM may be very different in their magnitudes and/or directions from those derived from a RI-CLPM (Hamaker et al., 2015; see also Hudson et al., 2019). Such differences underscore the importance of modeling latent intercept factors in order to more fully account for the underlying stability that characterizes many psychological variables when assessed at multiple occasions over time. Indeed, as the present findings demonstrate, ignoring such stability – for example, through relying on two-wave panel designs or testing a CLPM without the use of random intercepts – may lead to biased estimates of cross-lagged effects concerning associations involving changes within individuals over time (e.g., due to the confounding of between-individual rank-order stability and within-individual change in a standard CLPM) and, ultimately, produce very different conclusions concerning fundamental issues related to SWB, including its structure, stability, causes, and consequences.

The present findings also have implications for synthesizing research findings. Meta-analyses and other reviews of SWB-related literature have typically tabulated and reported findings concerning SWB based on LS, PA, and NA as separate outcomes (e.g., Anglim et al., 2020; Klug & Maier, 2015). However, such findings do not address SWB based on the commonality among LS, PA, and NA, as reflected in a latent SWB factor, or with respect to the unique aspects of any of the three components independent of a latent SWB factor. Critically, therefore, although the typical approach informs LS, PA, and NA as separate components, *it does not inform SWB per say*, that is, based on the commonality among (and unique aspects of) its components. It is possible, for example, that conclusions concerning unique associations between LS, PA, or NA and other variables such as basic personality dimensions (e.g., Anglim et al., 2021) would differ once a latent SWB factor is included in the model (e.g., Busseri, 2015). Consequently, syntheses of extant SWB-related findings are needed in which results are tabulated not only based on LS, PA, and NA separately, but also (and perhaps most importantly) based on SWB as a latent factor along with the unique aspects of (i.e., residual variation in) LS, PA, and NA independent of the latent factor. Such an approach would provide much needed information concerning the correlates, predictors, and consequences of SWB as a latent factor, as well as the unique aspects of LS, PA, and NA.

Related, intervention studies aimed at boosting SWB typically report findings based on analysis of LS, PA, as NA as separate outcomes (e.g., Bolier et al., 2013; Heintzelman et al., 2020; Sin & Lyubomirsky, 2009). What is needed is a better understanding of the implications of such interventions with respect to the underlying construct of SWB from the perspective of a hierarchical conceptualization based on SWB as a latent factor (e.g., Metler & Busseri, 2017). Such an approach will be critical to determining whether, and if so how, interventions and applied techniques can help individuals achieve greater happiness in their daily lives in terms of (a) their underlying sense of SWB, and/or (b) the unique aspects of experiences of LS, PA, or NA. In this regard, the present results highlight various possible sources that account for variation in SWB, including stable traits (as reflected in the higher-order latent SWB factor and random intercept factors), time-specific experiences of SWB (as reflected in the occasion-specific latent SWB factor), and carry-over effects (i.e., auto-regressive and cross-lagged effects) between LS, PA, and NA from one occasion to the next. Each of these aspects of SWB should be considered in the context of intervention studies, particularly with respect to opportunities for impacting individuals' daily experiences of SWB. The present findings suggest, for example, that the most likely impact would be found with respect to individuals' experiences of SWB on a given day or at a given moment, even if such experiences do not accumulate over time or result in durable changes across moments.

Finally, beyond informing the structure of SWB, the approach we employed in the best work could be useful in addressing issues related to well-being more generally. For example, new insights concerning the meaning of the association between hedonic and eudaimonic well-being (e.g., Disabato et al., 2016) could be gleaned from studying their shared and unique aspects, as well as reciprocal relations over time, using a RI-CLPM. Such an approach could also prove useful to informing the structure of psychopathology, for example, with respect to a higher-order 'p factor' representing the commonality among multiple forms of distress and disturbance (e.g., Caspi et al., 2014).

4.5. Limitations

Despite the large size of the present study sample, recruitment was voluntary and sampling was not random. Consequently, it is not clear whether our findings would generalize to all participants from the countries in which the data were collected, or to individuals from other countries or geographical regions. The magnitude of the associations among LS, PA, and NA, and the loadings on the latent SWB factors, observed in the present work are consistent with recent meta-analytic results encompassing samples from multiple countries (Busseri, 2018). However, as ours is the first study to examine the structure of SWB in individuals' daily lives using an experience-sampling approach, whether the present findings will generalize to other studies employing experience-sampling approaches is unknown. Also, given that data collection was conducted over a single 18-month period, it is unclear whether our results would replicate during other historical periods. For example, a similar study conducted during the current global COVID pandemic may reveal stronger associations among momentary experiences of LS, PA, and NA, given the heightened and on-going stress or threat that individuals may be experiencing (Reich, Zautra, & Davis, 2003).

Further, all three SWB components were assessed with single-item ratings. Previous studies have provided evidence in support of the reliability and validity of this measurement approach (e.g., Cheung & Lucas, 2014; Hudson et al., 2019; Lucas & Donnellan, 2012). Further, brevity and ease of completion are important features of effective experience sampling studies. Nonetheless, the use of concise multi-item measures (e.g., Hudson et al., 2019; Hülür et al., 2015) may have provided more reliable scores at each occasion, and thus more robust estimates of the correlations among the SWB components. Such an approach might also provide broader coverage of each of the construct domains of interest (i.e., LS, PA, and NA).

We also note that the results concerning the within-individual correlations among the SWB components was based on the subsample of participants who provided LS, PA, and NA ratings at 10 or more occasions. Whether such results would be obtained based on participants reporting a high number of momentary experiences (e.g., 30 or more; Hülür et al., 2015) needs to be determined. Future research employing an experience sampling approach in which all three SWB components are assessed at a larger number of occasions from every participant would also permit more nuanced analyses of the structure of SWB within each individual (e.g., Jackson & Beck, 2021; Mejía, Hooker, Ram, Pham, & Metoyer, 2014; Ram, Brose, & Molenaar, 2013).

Finally, given the correlational nature of the study design, we can draw no conclusions concerning whether the cross-lagged predictive effects estimated in the RI-CLPM represent causal effects. These estimates are independent of stable individual differences in LS, PA, and NA (as reflected in the corresponding latent random intercept factors) and their covariation, and are also independent the occasion-specific commonality among the components. Nonetheless, they reflect associations based on naturally-occurring (rather than experimentally induced) within-individual changes over time, and thus do not provide clear evidence of causal influence. Consequently, additional research is needed employing experimental manipulation of individuals' momentary experiences of LS, PA, and NA in order to gauge their influence on each other over time.

4.6. Conclusions

Notwithstanding these limitations, the present findings provide strong support for a hierarchical conceptualization of SWB. Indeed, it appears that operationalizing SWB as a latent factor indicated by momentary ratings of LS, PA, and NA is viable not only across individuals within a given moment of their lives, but also across the daily experiences in the lives of most individuals.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Research by the first author is supported by an Insight grant from the Social Sciences and Humanities Reseach Council of Canada. The second author thanks the Ministerio de Economía, Industria y Competitividad, Gobierno de España (RYC-2016-21020) and the BBVA Foundation for financial support.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrp.2021.104177.

References

Albuquerque, I., de Lima, M. P., Figueiredo, C., & Matos, M. (2012). Subjective well-being structure: Confirmatory factor analysis in a teachers' Portuguese sample. *Social Indicators Research, 105*(3), 569–580.

Anglim, J., Horwood, S., Smillie, L. D., Marrero, R. J., & Wood, J. K. (2020). Predicting psychological and subjective well-being from personality: A meta-analysis. *Psychological Bulletin, 146*(4), 279.

Anusic, I., Lucas, R. E., & Donnellan, M. B. (2017). The validity of the day reconstruction method in the German socio-economic panel study. *Social Indicators Research, 130*(1), 213–232.

Avidor, S., Ayalon, L., Palgi, Y., & Bodner, E. (2017). Longitudinal associations between perceived age discrimination and subjective well-being: Variations by age and subjective life expectancy. *Aging & Mental Health, 21*(7), 761–765.

Balestra, C., Boarini, R., & Tosetto, E. (2018). What matters most to people? Evidence from the OECD Better Life Index users' responses. *Social Indicators Research, 136*, 907–930.

Berlin, M., & Connolly, F. F. (2019). The association between life satisfaction and affective well-being. *Journal of Economic Psychology, 73*, 34–51.

Berry, D., & Willoughby, M. T. (2017). On the practical interpretability of cross-lagged panel models: Rethinking a developmental workhorse. *Child Development, 88*(4), 1186–1206.

Bolier, L., Haverman, M., Westerhof, G. J., Riper, H., Smit, F., & Bohlmeijer, E. (2013). Positive psychology interventions: A meta-analysis of randomized controlled studies. *BMC Public Health, 13*(1), 1–20.

Bruehlman-Senecal, E., Ayduk, Ö., & John, O. P. (2016). Taking the long view: Implications of individual differences in temporal distancing for affect, stress reactivity, and well-being. *Journal of Personality and Social Psychology, 111*(4), 610.

Busseri, M. A. (2015). Toward a resolution of the tripartite structure of subjective well-being. *Journal of Personality, 83*, 413–428.

Busseri, M. A. (2018). Examining the structure of subjective well-being through meta-analysis of the associations among positive affect, negative affect, and life satisfaction. *Personality and Individual Differences, 122*, 68–71.

Busseri, M. A., & Sadava, S. W. (2011). A review of the tripartite structure of subjective well-being: Implications for conceptualization, operationalization, and synthesis. *Personality and Social Psychology Review, 15*, 290–314.

Busseri, M. A., Sadava, S. W., & DeCourville, N. (2007). A hybrid model for research on subjective well-being: Examining common- and component-specific sources of variance in life satisfaction, positive affect, and negative affect. *Social Indicators Research, 83*, 413–445.

Carstensen, L. L., Pasupathi, M., Mayr, U., & Nesselroade, J. R. (2000). Emotional experience in everyday life across the adult life span. *Journal of Personality and Social Psychology, 79*(4), 644.

Casas, F., & González, M. (2020). Do relationships between subjective well-being scales change over time? Analysis of a longitudinal sample. *Current Psychology*, 1–14.

Caspi, A., Houts, R. M., Belsky, D. W., Goldman-Mellor, S. J., Harrington, H., Israel, S., … Moffitt, T. E. (2014). The p factor: One general psychopathology factor in the structure of psychiatric disorders? *Clinical Psychological Science, 2*(2), 119–137.

Chen, X., Tian, L., & Huebner, E. S. (2020). Bidirectional relations between subjective well-being in school and prosocial behavior among elementary school-aged children: a longitudinal study. In *Child & Youth Care Forum* (Vol. 49, No. 1, pp. 77–95). Springer US.

Cheung, F., & Lucas, R. E. (2014). Assessing the validity of single-item life satisfaction measures: Results from three large samples. *Quality of Life Research, 23*(10), 2809–2818.

Chmiel, M., Brunner, M., Martin, R., & Schalke, D. (2012). Revisiting the structure of subjective well-being in middle-aged adults. *Social Indicators Research, 106*(1), 109–116.

Datu, J. A. D., & King, R. B. (2018). Subjective well-being is reciprocally associated with academic engagement: A two-wave longitudinal study. *Journal of School Psychology, 69*, 100–110.

Daukantaitė, D., & Zukauskiene, R. (2012). Optimism and subjective well-being: Affectivity plays a secondary role in the relationship between optimism and global life satisfaction in the middle-aged women. Longitudinal and cross-cultural findings. *Journal of Happiness Studies, 13*(1), 1–16.

Deng, Y., Xiang, R., Zhu, Y., Li, Y., Yu, S., & Liu, X. (2019). Counting blessings and sharing gratitude in a Chinese prisoner sample: Effects of gratitude-based interventions on subjective well-being and aggression. *The Journal of Positive Psychology, 14*(3), 303–311.

Diener, E. (1984). Subjective well-being. *Psychological Bulletin, 95*, 542–575.

Diener, E. (2009). Subjective well-being. In E. Diener (Ed.), *The Science of Well-Being* (vol. 37, pp. 11–58).

Diener, E., & Emmons, R. A. (1984). The independence of positive and negative affect. *Journal of Personality and Social Psychology, 47*(5), 1105.

Diener, E., Lucas, R., Helliwell, J. F., Schimmack, U., & Helliwell, J. (2009). *Well-being for Public Policy*. Oxford University Press.

Diener, E., Oishi, S., & Lucas, R. E. (2015). National accounts of subjective well-being. *American Psychologist, 70*(3), 234–242. https://doi.org/10.1037/a0038899

Diener, E., & Tay, L. (2014). Review of the day reconstruction method (DRM). *Social Indicators Research, 116*(1), 255–267.

Disabato, D. J., Goodman, F. R., Kashdan, T. B., Short, J. L., & Jarden, A. (2016). Different types of well-being? A cross-cultural examination of hedonic and eudaimonic well-being. *Psychological assessment, 28*(5), 471.

Eid, M., & Larsen, R. J. (2008). *The science of subjective well-being*. New York, NY: Guilford.

Elliot, A. J., Thrash, T. M., & Murayama, K. (2011). A longitudinal analysis of self-regulation and well-being: Avoidance personal goals, avoidance coping, stress generation, and subjective well-being. *Journal of Personality, 79*(3), 643–674.

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions. *American Psychologist, 56*(3), 218.

Gere, J., & Schimmack, U. (2013). When romantic partners' goals conflict: Effects on relationship quality and subjective well-being. *Journal of Happiness Studies, 14*(1), 37–49.

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods, 20*(1), 102.

Heintzelman, S. J., Kushlev, K., Lutes, L. D., Wirtz, D., Kanippayoor, J. M., Leitner, D., … Diener, E. (2020). ENHANCE: Evidence for the efficacy of a comprehensive intervention program to promote subjective well-being. *Journal of Experimental Psychology: Applied, 26*(2), 360.

Hershfield, H. E., Scheibe, S., Sims, T. L., & Carstensen, L. L. (2013). When feeling bad can be good: Mixed emotions benefit physical health across adulthood. *Social Psychological and Personality Science, 4*(1), 54–61.

Hofmann, W., Luhmann, M., Fisher, R. R., Vohs, K. D., & Baumeister, R. F. (2014). Yes, but are they happy? Effects of trait self-control on affective well-being and life satisfaction. *Journal of Personality, 82*(4), 265–277.

Hudson, N. W., Lucas, R. E., & Donnellan, M. B. (2016). Getting older, feeling less? A cross-sectional and longitudinal investigation of developmental patterns in experiential well-being. *Psychology and Aging, 31*(8), 847.

Hudson, N. W., Lucas, R. E., & Donnellan, M. B. (2017). Day-to-day affect is surprisingly stable: A 2-year longitudinal study of well-being. *Social Psychological and Personality Science, 8*(1), 45–54.

Hudson, N. W., Lucas, R. E., & Donnellan, M. B. (2019). Healthier and happier? A 3-year longitudinal investigation of the prospective associations and concurrent changes in health and experiential well-being. *Personality and Social Psychology Bulletin, 45*(12), 1635–1650.

Hülür, G., Hoppmann, C. A., Ram, N., & Gerstorf, D. (2015). Developmental associations between short-term variability and long-term changes: Intraindividual correlation of positive and negative affect in daily life and cognitive aging. *Developmental Psychology, 51*(7), 987.

Jackson, J. J., & Beck, E. D. (2021). Using idiographic models to distinguish personality and psychopathology. *Journal of Personality*.

Jayawickreme, E., Tsukayama, E., & Kashdan, T. B. (2017). Examining the within-person effect of affect on daily satisfaction. *Journal of Research in Personality, 71*, 27–32.

Jia, N., Li, W., Zhang, L., & Kong, F. (2021). Beneficial effects of hedonic and eudaimonic motivations on subjective well-being in adolescents: A two-wave cross-lagged analysis. *The Journal of Positive Psychology*, 1–7.

Jiang, J., Song, Y., Ke, Y., Wang, R., & Liu, H. (2016). Is disciplinary culture a moderator between materialism and subjective well-being? A three-wave longitudinal study. *Journal of Happiness Studies, 17*(4), 1391–1408.

Joshanloo, M. (2016). Factor structure of subjective well-being in Iran. *Journal of Personality Assessment, 98*(4), 435–443.
Joshanloo, M. (2018). Longitudinal associations between subjective and psychological well-being in Japan: A four-year cross-lagged panel study. *Personality and Individual Differences, 134*, 289–292.
Joshanloo, M., Sirgy, M. J., & Park, J. (2018). Directionality of the relationship between social well-being and subjective well-being: Evidence from a 20-year longitudinal study. *Quality of Life Research, 27*(8), 2137–2145.
Jovanović, V. (2015). A bifactor model of subjective well-being: A re-examination of the structure of subjective well-being. *Personality and Individual Differences, 87*, 45–49.
Jovanović, V., & Joshanloo, M. (2021). The Contribution of Positive and Negative Affect to Life Satisfaction across Age. *Applied Research in Quality of Life*, 1–14.
Kapteyn, A., Lee, J., Tassot, C., Vonkova, H., & Zamarro, G. (2015). Dimensions of subjective well-being. *Social Indicators Research, 123*(3), 625–660.
Klug, H. J., & Maier, G. W. (2015). Linking goal progress and subjective well-being: A meta-analysis. *Journal of Happiness Studies, 16*(1), 37–65.
Linley, P. A., Maltby, J., Wood, A. M., Osborne, G., & Hurling, R. (2009). Measuring happiness: The higher order factor structure of subjective and psychological well-being measures. *Personality and Individual Differences, 47*(8), 878–884.
Lucas, R. E., & Donnellan, M. B. (2012). Estimating the reliability of single-item life satisfaction measures: Results from four national panel studies. *Social Indicators Research, 105*(3), 323–331.
Lucas, R. E., Wallsworth, C., Anusic, I., & Donnellan, M. B. (2021). A direct comparison of the day reconstruction method (DRM) and the experience sampling method (ESM). *Journal of Personality and Social Psychology, 120*(3), 816.
Luhmann, M., Hofmann, W., Eid, M., & Lucas, R. E. (2012). Subjective well-being and adaptation to life events: A meta-analysis. *Journal of Personality and Social Psychology, 102*(3), 592.
Luhmann, M., & Kalitzki, A. (2018). How animals contribute to subjective well-being: A comprehensive model of protective and risk factors. *The Journal of Positive Psychology, 13*(2), 200–214.
Magee, C., & Biesanz, J. C. (2019). Toward understanding the relationship between personality and well-being states and traits. *Journal of personality, 87*(2), 276–294.
Martela, F., & Sheldon, K. M. (2019). Clarifying the concept of well-being: Psychological need satisfaction as the common core connecting eudaimonic and subjective well-being. *Review of General Psychology, 23*(4), 458–474.
Mejía, S., Hooker, K., Ram, N., Pham, T., & Metoyer, R. (2014). Capturing intraindividual variation and covariation constructs: Using multiple time-scales to assess construct reliability and construct stability. *Research in Human Development, 11*(2), 91–107.
Metler, S., & Busseri, M. A. (2017). Further evaluation of the tripartite structure of subjective well-being: Evidence from longitudinal and experimental studies. *Journal of Personality, 85*, 192–206.
Molnar, D. S., Busseri, M. A., Perrier, C. P., & Sadava, S. W. (2009). A longitudinal examination of alcohol use and subjective well-being in an undergraduate sample. *Journal of Studies on Alcohol and Drugs, 70*(5), 704–713.
Moreno-Agostino, D., de la Torre-Luque, A., de la Fuente, J., Lara, E., Martín-María, N., Moneta, M. V., … Ayuso-Mateos, J. L. (2021). Determinants of subjective wellbeing trajectories in older adults: A growth mixture modeling approach. *Journal of Happiness Studies, 22*(2), 709–726.
Mulder, J. D., & Hamaker, E. L. (2021). Three extensions of the random intercept cross-lagged panel model. *Structural Equation Modeling: A Multidisciplinary Journal*, 1–11.
Olesen, M. H., Thomsen, D. K., & O'Toole, M. S. (2015). Subjective well-being: Above neuroticism and extraversion, autonomy motivation matters. *Personality and Individual Differences, 77*, 45–49.
Quoidbach, J., Taquet, M., Desseilles, M., de Montjoye, Y. A., & Gross, J. J. (2019). Happiness and social behavior. *Psychological Science, 30*(8), 1111–1122.
Ram, N., Brose, A., & Molenaar, P. C. (2013). Dynamic factor analysis: Modeling person-specific process. *The Oxford Handbook of Quantitative Methods, 2*, 441–457.
Reich, J. W., Zautra, A. J., & Davis, M. (2003). Dimensions of affect relationships: Models and their integrative implications. *Review of General Psychology, 7*(1), 66–83.
Robinson, M. D., & Clore, G. L. (2002). Belief and feeling: Evidence for an accessibility model of emotional self-report. *Psychological Bulletin, 128*(6), 934.
Schimmack, U. (2007). Methodological issues in the assessment of the affective component of subjective well-being. In A. D. Ong, & M. H. M. Dulmen (Eds.), *Oxford Handbook of Methods in Positive Psychology* (pp. 96–110). Oxford, UK: Oxford University Press.
Schimmack, U. (2008). The structure of subjective well-being. In M. Eid, & R. J. Larsen (Eds.), *The science of subjective well-being* (pp. 97–123). New York, NY: Guilford Press.
Schimmack, U., & Crites, S. L., Jr. (2005). The Structure of Affect. In D. Albarracín, B. T. Johnson, & M. P. Zanna (Eds.), *The handbook of attitudes* (pp. 397–435). Lawrence Erlbaum Associates Publishers.
Schimmack, U., Diener, E., & Oishi, S. (2002). Life-satisfaction is a momentary judgment and a stable personality characteristic: The use of chronically accessible and stable sources. *Journal of Personality, 70*, 345–384.
Schimmack, U., Krause, P., Wagner, G. G., & Schupp, J. (2010). Stability and change of well being: An experimentally enhanced latent state-trait-error analysis. *Social Indicators Research, 95*(1), 19.
Schimmack, U., & Oishi, S. (2005). The influence of chronically and temporarily accessible information on life satisfaction judgments. *Journal of Personality and Social Psychology, 89*(3), 395.
Schneider, L., & Schimmack, U. (2009). Self-informant agreement in well-being ratings: A meta-analysis. *Social Indicators Research, 94*(3), 363–376.
Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis. *Journal of Clinical Psychology, 65*(5), 467–487.
Spindler, G., Stopsack, M., Aldinger, M., Grabe, H. J., & Barnow, S. (2016). What about the "ups and downs" in our daily life? The influence of affective instability on mental health. *Motivation and Emotion, 40*(1), 148–161.
Taquet, M., Quoidbach, J., De Montjoye, Y. A., Desseilles, M., & Gross, J. J. (2016). Hedonism and the choice of everyday activities. *Proceedings of the National Academy of Sciences, 113*(35), 9769–9773.
Taquet, M., Quoidbach, J., Gross, J. J., Saunders, K. E., & Goodwin, G. M. (2020). Mood homeostasis, low mood, and history of depression in 2 large population samples. *JAMA Psychiatry, 77*(9), 944–951.
Tian, L., Chen, H., & Huebner, E. S. (2014). The longitudinal relationships between basic psychological needs satisfaction at school and school-related subjective well-being in adolescents. *Social Indicators Research, 119*(1), 353–372.
Tončić, M., & Anić, P. (2015). Everyday activities: Beneficial effects of eudaimonic and hedonic motivation on subjective well-being. *Current Psychology, 34*(4), 644–653.
Trampe, D., Quoidbach, J., & Taquet, M. (2015). *Emotions in everyday life. PloS one, 10* (12), Article e0145450.
Usami, S., Murayama, K., & Hamaker, E. L. (2019). A unified framework of longitudinal models to examine reciprocal relations. *Psychological Methods, 24*(5), 637.
Yang, K., Yan, W., Jia, N., Wang, Q., & Kong, F. (2020). Longitudinal relationship between trait gratitude and subjective well-being in adolescents: Evidence from the bi-factor model. *The Journal of Positive Psychology*, 1–9.
Zacher, H., & Rudolph, C. W. (2020). Individual differences and changes in subjective wellbeing during the early stages of the COVID-19 pandemic. *American*. Psychologist.
Zhou, J., Huebner, E. S., & Tian, L. (2020). Longitudinal associations and mechanisms between achievement goals and subjective well-being in school in Chinese adolescents. *School Mental Health, 12*(2), 353–365.