Modeling the dynamics of SWB in daily life

In the third phase of the project, we will tailor a *process model for capturing dynamics in SWB dimensions*. Our framework provides an easily interpretable structure that allows us to quantify the underlying dynamics of an observed process. Classical modeling techniques reduce the data to statistical aggregates such as mean, variability, and autocorrelation, but these quantities are strictly descriptive and not necessarily useful in understanding *why* and *how* components interact. Process models, on the other hand, translate the observed data into parameters with well-understood interpretations.

In particular, we will develop a multidimensional stochastic differential equation model to jointly model the time evolution of the five SWB components, taking into account such properties as homeostasis, adaptation, and mutual reinforcement or inhibition. We will use hierarchical Bayesian methods to develop the statistical inference framework for the model. A simpler form of the proposed model has already been introduced by Oravecz, Vandekerckhove, and Tuerlinckx (2011) and we will build upon that work to develop an extended, *n*-dimensional *Bayesian Ornstein-Uhlenbeck model.* The formal mathematical details of the base model are mostly omitted here (see section 3.3 for the foundational equations), but can be found in Oravecz et al. (2009, 2011).

Moreover, we will conduct a longitudinal study based on the developed PERMA measurement instrument to collect on SWB elements twice daily for 60 days during participants' everyday lives. The data will be analyzed within the novel dynamical framework and will be compared to existing modeling approaches.

1. The Bayesian statistical framework

Bayes' theorem was developed by Thomas Bayes, an English mathematician and Presbyterian minister. While his work dates back to the early 18th century and was controversial throughout the 19th and 20th century (Cox, 2005), in recent decades his influential theory and methods were re-introduced into scientific inquires. Bayesian statistics have now started to dominate scientific research and are becoming widely accepted. Working with the Bayesian method has brought about something of a paradigm shift in scientific methodology: subjective beliefs are considered to be valid part of data analysis, hypothesis testing can be confirmatory, parameter estimates are viewed probabilistically, and so on.

In the Bayesian method we formally express the researcher's *prior knowledge* and use this as a useful starting point. The existence of prior knowledge is not merely something to acknowledge; rather it is integral to Bayesian inference and seen as part of the model. The Bayesian statistical procedure relies on the existence of prior information with the researcher (vague though that prior information may be), in that it is the prior information that is updated due to observing the data. The major contribution of Thomas Bayes is the formula that expresses how knowledge is updated with new information. According to Bayes' theorem, the probability that a theory *m* is correct given the data x, $P(m|x)$, is proportional to the product of its prior probability $P(m)$ and the likelihood of the data x under the theory $P(x|m)$. Formally: $P(m|x) = P(x|m)\, P(m) / P(x)$.

Unfortunately, classical statistics does not afford us with a true ability to confirm hypotheses—as a fundamentally falsificationist method, the classical statistical paradigm is only able to make predictive statements about data under the assumption of no true effect (the "null hypothesis"). The classical statistician will then seek to probabilistically falsify, and often reject, the null hypothesis upon which those calculations were based. A critical insight of Bayesian statistics is that the statistical unlikelihood of one particular theory does not imply the statistical likelihood of any other theory, and that it is instead possible to assign relative probabilities to different models.

Furthermore, Bayesian parameter estimation is facilitated by recent advancements in computing power, Monte Carlo methods, and software applications such as WinBUGS (Lunn, Thomas, Best, & Spiegelhalter, 2000), JAGS (Plummer, 2003) and Stan (Stan Development Team, 2013). This allows researchers to fit fairly complex hierarchical models that would not be feasible to carry out in the classical statistical framework (e.g., Vandekerckhove, Verheyen, & Tuerlinckx, 2010). For introductions to Bayesian statistics see Gelman, Carlin, Stern, and Rubin (2004) and Lee and Wagenmakers (2013), and for applications to hierarchical/multilevel models (see also in section 3.2) see Gelman and Hill (2007) and Hamaker and Klugkist (2011).

2. Longitudinal modeling in daily-life studies

With principled formal models, we are able to translate empirical research questions into statistically testable hypotheses. In a recent address on the current state of SWB research, Diener (2012) explicitly mentioned the need for methodological improvements, citing particularly longitudinal and multimethod approaches as having the largest potential.

For example, from early on SWB research has been concerned with the notion of the *set point*: people react and adjust to a flow of continuously occurring life circumstances and then return to a state of balance called a set point (see, e.g., the hedonic treadmill model; Brickman & Campbell, 1971). The topic is presently investigated from several angles: is the set point neutral, do individuals have substantially different set points, can one person have multiple set points, and so on (see, e.g., Diener, Lucas, & Scollon, 2006). Currently, studies focus on only a subset of these aspects. However, with our comprehensive approach, several empirical research directions on set point, adaptation, inter- and intra-individual variation can be described in one coherent, formal framework, while also allowing for interactions between the different mechanisms.

Longitudinal studies of well-being have typically been restricted to a handful of time-points (see, e.g., Elliot, Trash, & Murayama, 2011; Layous et al., 2012; Lucas, 2007; Lyubomirsky et al., 2011; Sheldon & Lyubomirsky, 2012) often spanning a period of years (see, e.g., Gardner & Oswald, 2007; or a collection of studies in Diener & Chan, 2011), making them inappropriate for investigating temporal dynamics of well-being in daily life.

Intensive longitudinal data studies typically restrict themselves to measuring only limited dimensions of well-being. Most generally, it is positive and negative emotions that are measured most frequently (see, e.g., Tugade & Fredrickson, 2004; Kashdan & Steger, 2006), sometimes combined with documenting actual social activity, akin to early social interaction diary research (Tidwell, Reis, & Shaver, 1996; Vittengl & Holt, 1998).

As data from daily studies typically consists of several measurements from multiple individuals, they yield intensive longitudinal data (ILD). For a detailed overview on statistical models for ILD, see Bolger and Laurenceau (2013), Mehl and Conner (2012), and Walls and Schafer (2006). To provide a short overview here, large part of these models falls into the category of *multilevel/hierarchical models* (Raudenbush & Bryk, 2002 Snijders & Bosker, 1999). They include multilevel random coefficient models that separate intra- and inter-individual variability, model multiple error terms simultaneously and can allow for the inclusion of lagged coefficients to model time-dependency; however, this is not typically done. These models generally focus on inter-individual differences only in terms of the mean level (for flexible ways to model time-varying effects, see, Tan, Shiyko, Li, Li, & Dierker, 2012) and most often deal with changes in one variable (except models of dyadic interaction as described by, e.g., Laurenceau & Bolger, 2011).

Another major area in ILD data analysis is *structural equation modeling* (SEM; see, e.g., Bollen, 1989; Kline, 2010; see Voelkle, Oud, Davidov, & Schmidt, 2012, for a recent longitudinal application). The SEM framework has been used for a wide variety of models. In ILD it can be used to distinguish variability due to measurement error from systematic influences due to environmental and temporal components. Time-dependency is routinely investigated in the SEM framework primarily through latent autoregressive modeling (see, e.g., Hamaker, Dolan, & Molenaar, 2003).

The Ornstein-Uhlenbeck process model we present below shows a correspondence to multilevel models with time-series analysis components (such as Wang, Hamaker, & Bergeman, 2012), models with differential equations (the oscillator model; Chow, Ram, Boker, Fujita, & Clore, 2005; and the reservoir model; Deboeck & Bergeman, 2012) and the dynamical factor analysis model with time-varying parameters (Chow, Zu, Shifren, & Zhang, 2011). However, our approach is tailored for accounting for the complexity of modeling changes in all elements of SWB simultaneously and to capture multifaceted inter-individual differences. Next, we provide a non-technical description of the core process of our proposed modeling framework.

3. Dynamical process modeling of SWB with the Ornstein-Uhlenbeck process

Within a person (i.e., at the individual level) we propose to account for changes over time with a stochastic process model known as the *Ornstein-Uhlenbeck process* (OUP; Uhlenbeck & Ornstein, 1930). There are several reasons to opt for an OUP based model. First of all, its parameterization is substantively meaningful and sufficient: its parameters capture crucial aspects of SWB. Second, given its continuous time and continuous state space property it can flexibly handle unbalanced, unstructured and unequally spaced data that often stem from longitudinal studies. Finally, while the OUP model is novel for SWB research, it has been successfully applied to changes in core affect (Russell, 2003), a concept related to positive affect (for details see Kuppens, Oravecz, & Tuerlinckx, 2010). The OU model does not require equally-spaced or balanced measurements (contrary to multivariate time-series models), and it can account for individual differences with respect to intra-individual variation, regulation and synchronicity parameters among the dimensions. Whereas classical models can capture inter-individual variation only with respect to the mean structure, our process model approach allows for conclusions regarding dynamics, such as the relationship between an individual's capacity for short-term adaptation in their PERMA state and their ability to cope with loss .

The model accounts for change over time based on three main parameters: a *set point*, an instantaneous *regulatory component* or adaptation towards the set point and *intra-individual variation* around the set point (for an exact mathematical description of the model see Oravecz et al., 2009, 2011).

3.1. Set point

The proposed model assumes a set point for each individual in each SWB dimensions. To illustrate the concept of the set point in the proposed framework, we plotted measurement profiles of two synthetic participants' accomplishment measures in Figure 4. The set point here means an average position—an attractor to which the process is drawn over time. As can be seen, one of the participants can be described by a rather high measurement set-point (around 80 for the light green profile), while the other one has a low set point (around 40 for the dark green profile).

3.2. Intra-individual variation

Figure 5 illustrates two hypothetical accomplishment measurement profiles with different levels of intra-individual variation: the dark green profile shows low levels of intra-individual variation while the light green profile shows higher levels. Eid and Diener (1999) have shown that intra-individual variation is a distinct trait in positive affect. Our aim is to investigate intra-individual variation in other important aspects of SWB elements as well. Moreover, inter-individual differences in intra-individual variation might be meaningfully connected to personality and other characteristics that we will explore.

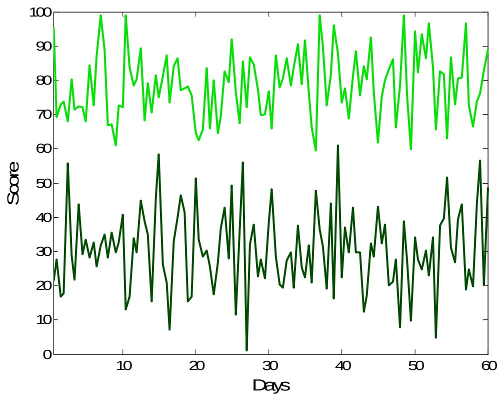

Figure 4. Illustration of the set point parameter and of inter-individual differences therein in the accomplishment dimension. Dark green: low set point. Light green: high set point.

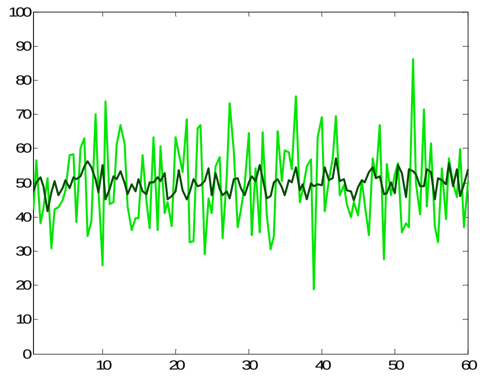

Figure 5. Illustration of the intra-individual variation parameter and of inter-individual differences therein in the accomplishment dimension. Dark green: low variation. Light green: high variation.

3.3. Short-term adaptation

Our process modeling framework also allows for instantaneous adaptation of SWB: that is, at any moment there is some amount (that for some people might be very low, for others stronger) of regulation of SWB that occurs. Figure 6 depicts two hypothetical accomplishment profiles: the dark green profile exhibits low levels of short-term regulation, while the light green profile shows high levels. We note that the intra-individual variance parameter is a distinct dynamical property of the temporal change and was set to the same value in the two simulations. As can be seen adaptation in the dark green (low short-term adaptation) profile the process wanders away for a prolonged time from the set-point. In contrast, the light green profile with higher level of adaptation can be described with frequent returns to the set point. This short-term adaptation component is typically called *damping* in the differential equation modeling literature. It has the property that the farther the current position is from the set-point, the stronger the dampening (or self-regulation) becomes. We also plan on extending the model to be able test whether the strength of the short-term adaptation differs as a function of the qualitative deviation from set-point (e.g., do we adapt to negative emotions faster than to positive ones?).

In our framework, we can mathematically separate this short-term regulatory component from long-term changes in the mean-level, introduced next.

3.4. Time-varying set-point and long-term adaptation profiles

The OUP model allows for testing the existence of multiple set points in one dimension over time. This assessable long-term temporal change in the set points will be labeled *long-term adaptation*. For example, when a significant life-event (see Luhmann, Hofmann, Eid, & Lucas, 2012, for a meta-analysis on the topic) takes place, the proposed framework will allow testing whether the set point changes in the long term in one or more elements of SWB. Mathematically, the elapsed time after a life event would be used as predictor and the set point in multiple dimensions would be made a function of this predictor. In this project for example, we will examine the effect of positive psychology interventions over time by looking at possible changes in the set-point over time (see also in Section 4). We propose to capture set point adaptation in terms of polynomial coefficients, which can subsequently be tested to credibly differ from 0 or not. Figure 7 depicts a profile in dark green in which long-term adaptation is present (SWB increasing steadily over time), while there was no long-term adaptation in the light green profile.

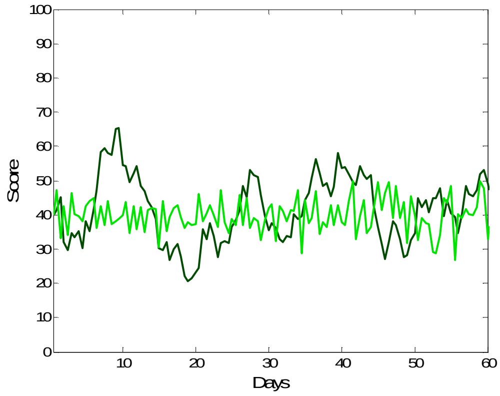

Figure 6. Illustration of the short-term adaptation parameter and of inter-individual differences therein in the accomplishment dimension. Dark green: low short-term adaptation. Light green: high short-term adaptation.

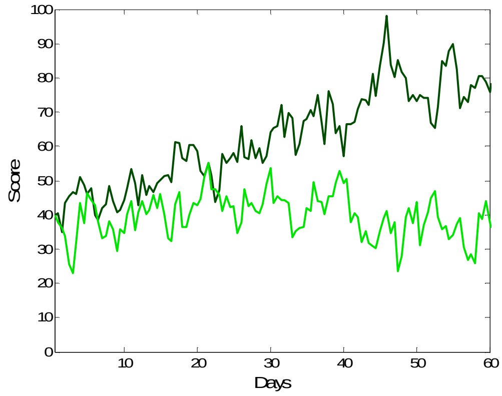

Figure 7. Illustration of long-term adaptation in the set point parameter in the accomplishment dimension. Dark green: long-term adaptation. Light green: no long-term adaptation.

3.5. Measurement error

The presented model so far described SWB dynamics on a latent level, as the changes in the true underlying score of the PERMA dimensions. Formally, this transition equation part of the model is written in the form of a first order stochastic differential equation:

$$d\mathbf{\Theta}(t) = \mathbf{B}(\boldsymbol{\mu} - \mathbf{\Theta}(t))dt + \boldsymbol{\sigma} d\boldsymbol{W}(t),$$

where vector $\mathbf{\Theta}$ represents the multidimensional latent PERMA scores, matrix $\mathbf{B}$ governs the short-term adaptation, vector $\boldsymbol{\mu}$ is the set-point, and vector $\boldsymbol{\sigma}$ controls the intra-individual variation. The self-report measures $\boldsymbol{Y}$ at time t_s are modeled through the following measurement equation:

$$\boldsymbol{Y}(t_s) = \mathbf{\Theta}(t_s) + \boldsymbol{\varepsilon}(t_s),$$

where $\boldsymbol{\varepsilon}(t_s)$ represents a normally distributed measurement error with mean 0.

By adding a measurement level to the model that assumes variation due to measurement error around the latent level, we can partial out measurement error variance from the intra-individual variance that is inherent in the process (for further mathematical details, such as the inclusion of explanatory covariates, see Oravecz et al., 2011). This extension is important, since we cannot discount the possibility that observed fluctuations in some SWB scores might be due to only measurement error. The proposed framework allows for testing this hypothesis.

3.6. Extensions to the base OUP model: a hierarchical Bayesian multidimensional modeling framework

So far we have described how the proposed framework accounts for mechanisms of SWB within an individual. In order to study inter-individual differences, we formulate a hierarchical[1] Bayesian extension to the basic model. The hierarchical/multilevel framework provides the flexibility that each participant can have their own set of OU parameters. That is, we will describe each participant's SWB elements in terms of *person-specific* set points, intra-individual variation, and adaptation. A literature review by Lyubomirsky, King, and Diener (2005) summarized correlational findings between mean-based components of SWB and personality and socio-demographic characteristics. The proposed framework can contribute to this line of inquiry by also investigating if inter-individual differences in intra-individual variability and adaptation can be associated with stable characteristics, such as age, gender, or personality traits. Also, while existing studies have typically used a two-step procedure to derive these relationships (first estimating SWB values and then correlating them with covariates), our Bayesian OUP model allows a single-step approach as OU process parameters and regression coefficients will be estimated at the same time in one model. This approach leads to more accurate results as uncertainty in the parameter estimates is directly taken into account (and it avoids generated regressor bias; Pagan, 1984). Moreover, we will be able to use covariate information on wealth, health, employment, and so on as control covariates when the focus is to *assess the effect of positive psychology interventions* (see below).

As pointed out earlier, the developed framework will be able to capture the dynamic interplay of SWB elements over time. Figure 8 depicts generated data of repeated measurements of PERMA dimensions from a synthetic study participant. As can be seen, the dimensions differ from each other in set-points, as well as in variation. Moreover, we might notice different short-term adaptation patterns as well: low levels in the accomplishment dimension and high levels in the engagement and positive relationship dimensions. We will also test whether there is dependency among the dimensions. For example: do changes in the positive emotions dimension co-occur with changes in engagement? To capture dependency among the dimensions, the intra-individual variation parameter of SWB will be formalized as an *n*-dimensional covariance matrix. These parameters describing dimension dependencies (off-diagonal elements of the matrix) can turn out to be zero, and our proposed Bayesian statistical inference framework (see below) provides a straightforward way of testing whether parameters credibly differ from 0.

While in the proposed project we plan to develop an *n*-dimensional variant of the OU model, we note here that substantial statistical and methodological work has already been carried out on a two-dimensional variant of the OU model, especially incorporating a multilevel approach into the model to account for individual variability (Oravecz, Vandekerckhove, & Tuerlinckx, 2009, 2011); as well as substantive work (Kuppens, Oravecz, & Tuerlinckx, 2010).

[1] The hierarchical version of a uni-dimensional OU model shows some similarity to the large class of linear mixed models (LMM; Verbeke & Molenberghs, 2000), although it has proven to be more flexible (Oravecz & Tuerlinckx, 2011). This flexibility is further increased by extending it to multiple dimensions.

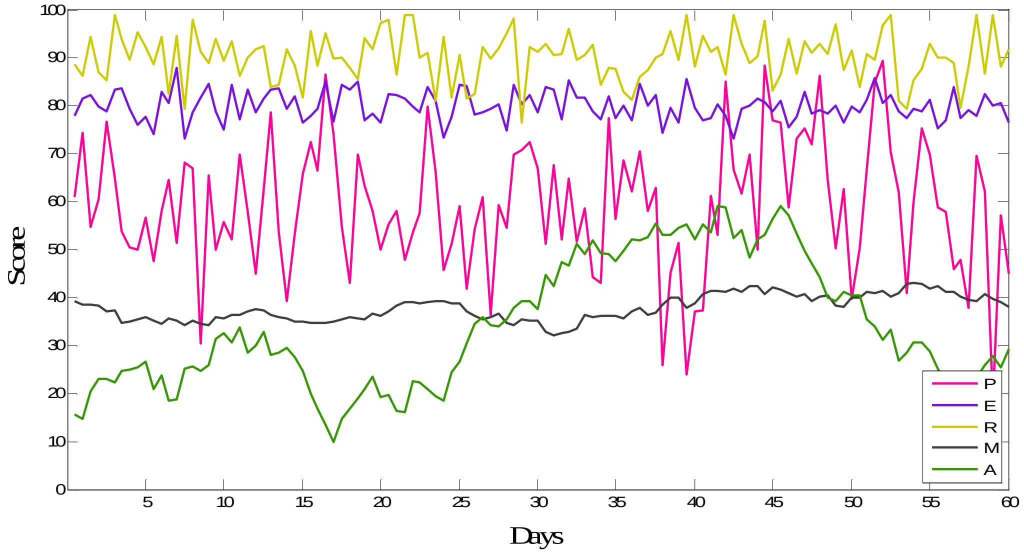

Figure 8. Synthetic data on the time evolution of the five PERMA dimensions for a person in a 60 day longitudinal study. As can be seen, this person's *positive emotions* (magenta line) dimension has the highest variation, with set point above medium level. Furthermore, their SWB can be described with high scores in the *relationship* (yellow line) and *engagement* (blue line) dimensions, with somewhat lower intra-individual variation in engagement. The *meaning* element (dark grey line) is consistently measured below medium level, with little variation in it. Finally, with respect to *accomplishment* (green line) element, the values are rather low, and the shape suggests low levels of short-term adaptation, causing a clear autocorrelation effect.

4. Proposed study to collect data on SWB changes in the PERMA dimensions

We propose a longitudinal study to measure the five SWB components and their interaction in people's everyday lives. We will design a two month long daily-life study in which we will measure the SWB components twice each day (once around lunchtime and once in the evening) using the methods developed in the first phase. We will recruit 50 participants for the study, who will be given financial incentive to complete their participation. To avoid attrition or large amounts of missing data, we will minimize the participants' workload by providing a convenient way to fill out surveys. Through a web-based experience sampling research tool for smartphones, such as Survey Signal (surveysignal.com) in combination with online survey providers (e.g., qualtrics.com), participants will be instructed to assess SWB items on their smartphones. Participants who do not own a smartphone will temporarily be provided with one by one of the participating research labs.

4.1. Studying sources of interindividual differences in the well-being dynamics through covariates

A novelty of our approach is that we look at several elements of well-being and changes therein over time. While well-being has only been studied in terms of mean values, we will consider intra-individual variation and adaptation mechanisms as well.

We select covariates (social variables and personality characteristics) based on already published findings on well-being concepts. However, most PERMA components have not been statistically related to these covariates. The covariates that we consider include attachment, social support (enhances well-being, see e.g., Helliwell & Putnam, 2004), relationship closeness, spirituality (enhances well-being, see e.g., Ryff, Singer, & Palmersheim, 2004), Big Five traits satisfaction (general overview in Steel, Schmidt, & Shultz, 2008), self-esteem and so on. We anticipate that generally, more positive social characteristics (e.g., secure attachment, greater support, altruistic behavior, compassion for others) will be tied to higher levels of positive emotions, relationship satisfaction and meaning of life from the PERMA. Personality characteristics like extraversion will most likely be related only to positive emotions and relationship (if anything). Social measures (e.g., perceived support) have also been tied to a number of positive well-being outcomes (e.g., better health, more success); therefore, we anticipate that these will be related to higher levels of wellbeing in the other subcomponents. Since these specific subcomponents together in an experience sampling set-up have yet been untested, questions on variability dynamics will be addressed in an exploratory fashion.

Finally, we would like to emphasize a key novelty in the framework here: synchronicity in the changes between PERMA elements will be modeled (e.g., the degree to which changes in achievement effect changes in positive relationships), individuals will have person-specific parameters to account for these, and sources of heterogeneity can be related to predictors. For example, levels of covariation between engagement and meaningful life might be explained through predictors such as prosocial tendencies, spirituality, and so on.

5. Summary of aims, expected output, and target audience of the third phase

The aim of the third phase is twofold. On the one hand, we will gather longitudinal data in an experience sampling study. On the other hand, we will develop a flexible OUP-based formal framework for modeling SWB over time. The framework will be constructed to operate on PERMA-based measures, but will be sufficiently flexible to accommodate future measures that become relevant in SWB research.

The expected output consists of three academic publications: first, a technical paper describing the extended OUP model; and second, a substantive paper detailing our conclusions and novel insights regarding SWB. Additionally, we will produce software to fit the multidimensional OUP model, and write the associated manuals and tutorials, and a technical paper on the software development for a corresponding journal.

The target audience of the technical papers will be one of psychometricians and mathematical and computational psychologists. The substantive paper will be geared towards SWB researchers, as will the software and training materials.

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