

**A General Framework for the Inclusion of Time-Varying and Time-Invariant  
Covariates in Latent State Trait Models**

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**Abstract**

Latent state-trait (LST) models are increasingly applied in psychology. However, existing LST models are limited and do not allow researchers to relate time-varying or time-invariant covariates, or a combination of both, to key parameters in LST models. We present a general framework for the inclusion of nominal and/or continuous time-varying and time-invariant covariates in LST models. The new framework builds on modern LST theory and Bayesian moderated nonlinear factor analysis and is termed moderated nonlinear LST (MN-LST) framework. The MN-LST framework offers new modeling possibilities and allows for a fine-grained analysis of trait change, synergistic interaction effects, as well as inter- or intra-individual variability. The new MN-LST approach is compared to multiple-indicator latent growth curve models. The advantages of the MN-LST are illustrated in an empirical application examining dyadic coping in romantic relationships. Finally, the advantages and limitations of the approach are discussed, and practical recommendations are provided.

*Keywords:* latent state-trait models, moderated nonlinear factor analysis, time-varying covariates, time-invariant covariates, synergistic interaction effects

**Translational Abstract:**

The person-situation controversy is arguably one of the most influential debates in the history of psychology. For many decades, scholars have argued about the relative importance of trait versus situation effects on human personality and behavior. Latent state-trait theory represents a firm mathematical foundation for studying trait, situation and/or person  $\times$  situation effects by means of latent variables. However, existing latent state-trait (LST) models do not allow researchers to test whether key parameters in the model vary as a function of time-varying and time-invariant covariates, or combinations of both. In this article, we introduce a general framework for relating continuous and/or nominal time-varying and time-invariant covariates to key parameters in LST models. Our framework allows for a fine-grained analysis of trait change, synergistic interaction effects, as well as inter- or intra-individual variability. The new approach is compared to multiple indicator latent growth curve (LGC) models. We highlight the advantages of the MN-LST framework using real data, investigating the effects of neuroticism and momentary stress on dyadic coping in romantic relationships over time. Finally, we discuss the advantages and limitations of the MN-LST framework and provide practical recommendations for applied researchers.

## **A General Framework for the Inclusion of Time-Varying and Time-Invariant Covariates in Latent State Trait Models**

The person-situation controversy is one of the most influential debates in the history of personality psychology (Lucas & Donnellan, 2009). For many decades, scholars have discussed the relative importance of trait versus situation effects as the driving forces of human behavior (Fleeson & Nofhle, 2009, Schmitt et al., 2003). The debate centered around two rival positions. On the one hand, the “dispositionists” believed in relatively stable interindividual differences in personality and assumed that these substantially contribute to the prediction of human behavior. On the other hand, the “situationists” were convinced that thoughts, feelings and behavior at a given moment are largely determined by the situation and even questioned the existence of personality “traits” in the sense of enduring individual differences (Lucas & Donnellan, 2009).

Today, most researchers agree that the two positions are indefensible scientific stances, as both traits and situations contribute to human behavior. More importantly, scholars have argued that their interaction might account for the largest amount of behavioral variability (Cronbach, 1975; Krueger, 2009; Schmitt et al., 2003). Many psychologists seek to better understand the interplay (or synergistic interaction effects) between the person and the situation (Schmitt et al., 2003). The term “synergistic interaction” describes a condition in which the overall effect of two contributing factors (e.g., the person and the situation) is larger than the sum of their unique effects (Schmitt et al., 2003).

Synergistic interactions are commonly investigated in diathesis-stress models, which attempt to explain why certain people develop mental disorders. According to diathesis-stress theories, persons differ in their vulnerabilities toward stressful situations and situations differ in their straining potential. The theories suggest that both effects multiply and that the stress level of a situation has a larger impact on vulnerable individuals. State-trait emotion theories

(Bushman, 1995; Stemmler, 1997) as well as motivation theories (Heckhausen, 1989) also postulate synergistic interaction effects. Both theories assume that a person's trait level (e.g., trait anxiety or motivational capacity) determines the impact of a corresponding situation.

Ideally, to study person, situation, as well as person  $\times$  situation effects, longitudinal study designs and a firm psychometric theory are needed. In the early 1990s, Steyer and colleagues proposed classical latent state-trait (LST) theory to measure inter-individual differences that are attributable to a) person-specific effects (latent trait variable), b) situation effects and/or person-situation interaction effects (latent state-residual variable), and c) unsystematic measurement error (latent error variable) (Steyer et al., 1992, 1999). More recently, Steyer, Mayer, Geiser, and Cole (2015) proposed a revised and more general LST theory (LST-R) that explicitly accounts for the dynamic nature of traits and trait change due to past experiences. It is worth noting that LST as well as LST-R theory build on a general definition of the term "situation", including both inner as well as outer situations (see Steyer et al., 1992, 1999, 2015). Outer situations refer to objectively describable and/or manipulatable external circumstances that could potentially be reproduced in experiments. Inner situations refer to subjective phenomena, for example, perceptions, feelings, beliefs, or evaluations of a specific setting (Rauthmann et al., 2015).

Another line of current research refers to the analysis of intra-individual variability processes around a fixed or changing trait. For instance, Geukes and colleagues (2017) proposed a framework to disentangle within-person variability occurring across different situations (i.e., cross-context or cross-roll variability) and within-contexts variability (i.e., internal inconsistency). Studying intra-individual variability becomes increasingly popular in many areas of psychological research, such as in personality psychology (e.g., Wundrack et al., 2018), in clinical psychology (e.g., Shalom et al., 2018), in health psychology (e.g., Hardy & Segerstrom, 2017), in organizational psychology (e.g., Lievens et al., 2018), and in

cognitive psychology (e.g., Jones et al. 2020). In sum, many researchers are interested in studying intra-individual variability around a stable or changing trait.

In this study, we present a general framework for the inclusion of time-varying and time-invariant covariates in LST-R models and the investigation of synergistic interaction effects (i.e., the combined effect of person and situational characteristics). Our approach combines Bayesian moderated nonlinear confirmatory factor analysis and LST modeling and is termed moderated nonlinear LST (MN-LST) approach. The MN-LST approach bears several advantages. First, it allows researchers to explain trait change as a function of personal characteristics, situational characteristics, and the combination of both. To this regard, it enables researchers to study synergistic interaction effects (i.e., the combined effect of personal and situational characteristics). Second, it allows researchers to examine key predictor variables of inter- or intra-individual variability processes. Third, it permits researchers to model key variance coefficients in LST-R models (i.e., consistency and specificity coefficients, or intra-individual variability) as a function of external explanatory variables. Fourth, using Bayesian estimation it is possible to jointly estimate trait change, synergistic interaction effects and intra-individual variability processes in a single analysis. Fifth, the new MN-LST framework is more general than most traditional approaches for the analysis of trait change trajectories as well as variability processes by means of time-varying and time-invariant predictors.

We believe that the new MN-LST approach will be of relevance to many applied researchers. Prior research, especially in the area of social and personality psychology, focused either on cross-sectional designs investigating inter-individual differences on well-known taxonomies *or* on longitudinal designs investigating mean change of certain traits (Cervone & Little, 2019; Costa et al., 2019). The integration of modeling interindividual differences, trait change, variability and person  $\times$  situation interactions in a common

framework would foster a better understanding of their interrelations. In health and clinical psychology, individual-centered approaches (often referred to as personalized or precision medicine) are becoming increasingly important, as many patients do not benefit sufficiently from the standard therapy. To develop individual-centered approaches, appropriate statistical models are required which enable researchers to identify personal and situational factors that moderate the effect of specific therapeutic interventions (Cuijpers et al., 2012, Schneider et al., 2015; Simon & Perlis, 2010).

Throughout this article, we will concentrate on a prototypical example in which person effects, situational effects, and person  $\times$  situation interaction effects are key moderators for the dynamics of a person's behavior over time. Specifically, we will examine the additive and multiplicative effects of neuroticism (as a trait or person-specific characteristic) and the experienced stress level at work (as an inner situational characteristic) on the longitudinal development and variability of dyadic coping (i.e., the joint and supportive coping) behavior in romantic couples. According to several empirical studies, external situational stressors, like stress at work, can spill over into the relationship and have detrimental effects on dyadic coping and marital satisfaction (Breitenstein et al., 2017; Ferguson, 2012; Fuenfhausen & Cashwell, 2013; Martos et al., 2019; Randall & Bodenmann, 2017; van Steenbergen et al., 2014). Furthermore, personality traits like neuroticism are associated with less engagement in coping strategies (Merz et al., 2014) as well as with increased intra-individual behavioral variability (Judge et al., 2014). With respect to this prototypical example, we will highlight the methodological advantages of the new MN-LST framework.

### **Overview**

The article is structured as follows. First, we provide an overview on existing methods for the inclusion of time-varying and time-invariant covariates in LST models. Second, we describe in detail how trait change is represented in two key parameters in LST-R models,

which allow for a flexible representation of different trait change trajectories. Furthermore, we show how intra-individual variability can be assessed in extended LST-R or extended latent growth curve (LGC) models. Third, we introduce the new moderated nonlinear LST approach and discuss how time-varying and time-invariant covariates can be included simultaneously to study trait change, synergistic interaction effects as well as inter- or intra-individual variability processes. Fourth, we illustrate the new MN-LST approach in an empirical application investigating time-varying and time-invariant predictors of dyadic coping in romantic relationships. Finally, we discuss the advantages and limitations of the MN-LST approach with reference to alternative modeling strategies and provide practical recommendations for applied researchers.

### **Traditional Approaches for the Inclusion of Time-Varying and Time-Invariant Covariates in LST Models**

Traditionally, explanatory variables are included in LST models using a) a multiple group approach (Geiser et al., 2016; Steyer et al., 2015), b) a multilevel approach (Geiser, Bishop et al., 2013; Holtmann et al., 2020; Koch et al., 2017), c) a finite mixture modeling approach (Courvoisier et al., 2007; Crayen et al., 2017; Eid & Langeheine, 2003; Hohmann et al., 2018; Litson et al., 2019), d) a multiple indicator multiple cause (MIMIC; Ploubidis & Frangou, 2011) or a multiple construct LST modeling approach (Courvoisier et al., 2007; Koch et al., 2018; Schermelleh-Engel et al., 2004), or e) a combination of the above.

In a multiple group LST (MG-LST) approach, a given data set is first split into the different levels of an observed, time-invariant categorical covariate (e.g., gender). The values on the observed, time-invariant nominal covariate (0 = male, 1 = female) represent the group membership. MG-LST model parameters are then estimated simultaneously in each group. Measurement equivalence assumptions can be tested using classical fit statistics for model comparisons. MG-LST models are flexible, as they allow key parameters in the model to vary

across groups (e.g., intercepts, factor loadings, factor means or factor variances and covariances). However, MG-LST models may become unpractical if the covariate is a random factor with many factor levels.

Multilevel LST (ML-LST) models can be conceived as an extension of MG-LST models, as they allow to include observed, time-invariant categorical covariates with many factor levels (e.g., a covariate with multiple factor levels that indicate different nations). In ML-LST models, a given LST model is specified on multiple levels. For example, trait and state components of well-being may be studied within nations (level 1) and between nations (level 2) using a ML-LST approach. Unobserved heterogeneity in key LST model parameters (e.g., random intercept or random slopes) can be modeled as random effects via latent variables on the between level. To explore potential predictors of heterogeneity, researchers can link additional explanatory variables to the random effects. ML-LST models are attractive whenever researchers seek to investigate heterogeneity in LST models across many randomly sampled factor levels. Examples of ML-LST applications are the study by Koch et al. (2017) and Holtmann et al. (2020), where ML-LST models were used to study the convergent and discriminant validity in longitudinal multirater measurement designs.

Finite mixture distribution LST models have been proposed to model heterogeneity in LST models as a function of a latent (hidden or unknown) nominal time-invariant covariate (Crayen et al., 2017; Eid & Langeheine, 2003; Litson et al., 2019). Contrary to multigroup and multilevel LST models, finite mixture distribution LST models allow researchers to account for heterogeneity in LST models even if the covariate is not (directly) observed. Litson et al. (2019) provide a tutorial and recommendations on how to apply mixture distribution LST models to longitudinal multirater data.

Another possibility is to include time-varying and time-invariant covariates in LST models using a MIMIC approach (see Ploubidis & Frangou, 2011) or a multiple construct

LST approach (Courvoisier, et al., 2007; Koch et al., 2018; Schermelleh-Engel et al., 2004).

Multiple construct LST approaches use latent variables as explanatory variables. Time-varying explanatory variables are decomposed into latent traits and multiple occasion-specific variables, which are linked to the latent factors in the original LST model. We will address the multiple construct LST approach in the discussion of this article. In MIMIC models, covariates are directly linked to the latent variables in LST models. The covariate can be a nominal or continuous observed variable or a continuous latent variable. Furthermore, the covariate can be time-invariant or time-varying. The main advantage of the MIMIC approach is that researchers can simultaneously include time-varying and time-invariant (continuous or nominal) covariates into LST models. However, one limitation of the MIMIC approach is that the latent variables are typically related to external variables, while the remaining parameters in the model (e.g., trait loadings, intercepts, variances) are not directly related to the covariates. Hence, it cannot be tested whether key parameters in LST models vary as a function of the external covariates in MIMIC models.

In sum, all of the aforementioned approaches are limited in some aspects: Multiple group, multilevel and finite mixture models do allow key parameters of LST models (i.e. trait factor loadings, intercepts and latent state residual variances) to vary depending on external observed (MG and ML-LST models) or unknown latent (finite mixture LST models) covariates. However, these methods require categorical and time-invariant covariates, which limits their applicability. In contrast, MIMIC or multi-construct LST models allow researchers to also include continuous and time-variable covariates. However, they do not allow to define all model parameters as a function of these covariates. The goal of the present study is to present a Bayesian approach for the joint analysis of trait-change, synergistic interaction effects as well as inter- or intra-individual variability processes by simultaneously including time-varying, time-invariant or a combination of both types of covariates in LST-R models.

### Modeling Different Types of Trait Change in LST and LGC Models

Latent state-trait (LST) models as well as latent growth curve (LGC) models are frequently applied in psychology to study long-lasting trait change as well as variability processes. Here, we summarize the key similarities and differences between LST-R and LGC models that are vital for studying different types of trait change and variability processes (see also Geiser, Bishop et al., 2013; Geiser, Keller, & Lockhart 2013; Steyer et al., 2012; Tisak & Tisak, 2000). We will focus on the meaning of LST-R model parameters representing trait change as well as situation effects and/or person  $\times$  situation effects.

The basic idea of LST-R theory (Eid et al., 2017; Steyer et al., 2015) is that an observed variable  $Y_{it}$  ( $i$ : indicator;  $t$ : time) is decomposed into a latent trait, a latent state residual, and a latent measurement error variable at each (point in) time  $t$ ,

$$Y_{it} = \tau_{it} + \epsilon_{it} = \xi_{it} + \zeta_{it} + \epsilon_{it} \quad (1)$$

where  $\tau_{it}$  is the latent true score (state) variable (with  $\tau_{it} = \xi_{it} + \zeta_{it}$ ),  $\xi_{it}$  is the latent trait factor,  $\zeta_{it}$  is the latent state-residual, and  $\epsilon_{it}$  is the latent measurement error variable pertaining to indicator  $i$  at time  $t$ . For illustrative purposes, we will explicitly denote those variables that can vary by person with an index  $p$  (for person) in the following (that is, Equation (1) corresponds to:  $Y_{itp} = \xi_{itp} + \zeta_{itp} + \epsilon_{itp}$ ).

A key feature of LST-R theory is that latent trait variables are time-specific such that a person's trait can change over time due to experiences made in the past (see Eid et al., 2017; Steyer et al., 2015). That is, LST-R models allow researchers to explicitly model trait change over time. To identify model parameters of LST-R models, several assumptions must be made, with different sets of assumptions defining different models of LST-R theory. In the following, we will focus on models that fall into the category of multistate-singletrait models, as they are discussed in Steyer et al. (2015). The most general of these models assumes that

latent trait variables of different time points are positive linear functions of each other. That is, it is assumed that a person's trait  $\xi_{itp}$  (of indicator  $i$  at time  $t$ ) is a positive linear function of the person's initial trait at  $t = 1$ ,  $\xi_{i1p}$ :

$$\xi_{itp} = \alpha_{it} + \lambda_{it}\xi_{i1p} \quad \text{for } t > 1 \quad (2)$$

with  $\lambda_{it} \geq 0$ . According to Equation (2), a person's trait score  $\xi_{itp}$  at time  $t$  changed from time point 1 by an additive constant  $\alpha_{it}$  and a multiplicative term  $\lambda_{it}$ . Furthermore, it is assumed that the latent state residual variables pertaining to different observed variables ( $\zeta_{itp}$  and  $\zeta_{i'tp}$ , where  $i \neq i'$ ) are perfectly correlated across indicators and thus can be replaced by a common latent residual variable:

$$\zeta_{itp} = \delta_{it}\zeta_{tp} \quad (3)$$

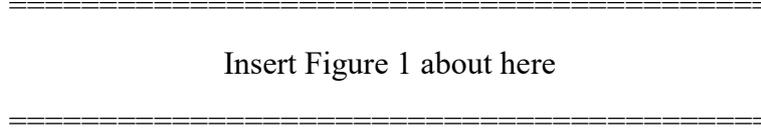
where  $\delta_{it}$  is the factor loading pertaining to the common latent state residual factor  $\zeta_{tp}$ . The values on the latent state residual factor  $\zeta_{tp}$  denote the difference of a person's trait score  $\xi_{itp}$  from the person's true score ( $\tau_{itp}$ , latent state variable) at time  $t$ . Formally, the latent state residual variables are defined as latent residual variables with respect to the corresponding latent trait variable at time  $t$ .

Inserting Equation (2) and Equation (3) into Equation (1) yields the general measurement equation of an LST-R model:

$$Y_{itp} = \alpha_{it} + \lambda_{it}\xi_{i1p} + \delta_{it}\zeta_{tp} + \epsilon_{itp} \quad (4)$$

where  $i$  refers to the indicator and  $t$  denotes the time point. Again, the index  $p$  in Equation (4) is used to indicate person-specific parameters in the model. Typically, the index  $p$  is dropped when using the standard notion of confirmatory factors analysis. The latent state residual as well as measurement error variables are defined as latent residual variables (see Steyer et al., 2015) and thus have the same properties as residual variables (e.g.,  $\mathbb{E}(\zeta_{tp}) =$

$\mathbb{E}(\epsilon_{itp}) = 0$  for all  $i, t$ ). Figure 1 shows an LST-R model with indicator-specific trait factors for a minimal measurement design with two indicators measured on three time points.



To achieve identification, commonly made restrictions are to a) either fix the intercept at the first time point or fix the expectation of the latent trait factor, and b) either fix one loading per latent factor to one (e.g.,  $\lambda_{i1} = 1$  and  $\delta_{1t} = 1$ ) or to fix the variance of the latent factors to one, that is  $Var(\xi_{i1p}) = Var(\zeta_{tp}) = 1$ . Note that the interpretation of the parameters changes with the identification restrictions chosen to set the scale of the latent variables. If, for example,  $\alpha_{i1} = 0$  and  $\mathbb{E}(\xi_{i1p})$  is freely estimated, then  $\alpha_{it}$  parameters for  $t > 1$  can be interpreted similar to the intercept parameter in a linear regression analysis with uncentered predictor variables. If  $\mathbb{E}(\xi_{i1p})$  is set to zero and all  $\alpha_{it}$  are freely estimated, then  $\alpha_{it}$  is equivalent to  $\mathbb{E}(Y_{it})$ .

In the following, we will build on the standard parametrization implemented by default in most statistical software by fixing the first factor loading to one and fixing the expectation of the latent trait variable  $\xi_{i1p}$  to zero, i.e., we freely estimate all intercepts  $\alpha_{it}$  and variances of latent variables. Hence, in our model  $\alpha_{it}$  is equivalent to  $\mathbb{E}(Y_{it})$ . Since we are not interested in  $\alpha_{it}$  measured at a certain time point but aim to model differences between  $\alpha_{it}$  and  $\alpha_{i1}$  (i.e., in the change from the first to a subsequent time point), we insert  $\alpha_{i1}$  into each measurement equation of the observed variables  $Y_{it}$  pertaining to subsequent time points  $t > 1$ , that is:

$$Y_{itp} = \Delta_{\alpha_{it}} + \lambda_{it}\xi_{i1p} + \delta_{it}\zeta_{tp} + \epsilon_{itp} + \alpha_{i1} \quad \text{for } t > 1 \quad (5)$$

In the above Equation (5),  $\Delta_{\alpha_{it}}$  denotes the additive (or mean) change parameter and is defined as the expected *difference* of the observed variables  $Y_{it}$  and  $Y_{i1}$ :

$$\Delta_{\alpha_{it}} := \alpha_{it} - \alpha_{i1} = \mathbb{E}(Y_{it}) - \mathbb{E}(Y_{i1}) \quad (6)$$

Note that  $\Delta_{\alpha_{it}}$  is equal to  $\mathbb{E}(\xi_{i1p} - \xi_{i1p})$  if  $\alpha_{i1}$  is set to zero and  $\lambda_{it}$  is set to one in the following reformulation of the above model using expected values,  $\mathbb{E}(\xi_{i1p} - \xi_{i1p}) = \Delta_{\alpha_{it}} + (\lambda_{it} - 1)\mathbb{E}(\xi_{i1p}) + \alpha_{i1}$ . The advantage of the difference score parameterization (see Equation 5) is that it allows researchers to model two distinctive trait change parameters, with  $\Delta_{\alpha_{it}}$  denoting additive (trait) change and  $\lambda_{it}$  (for  $t > 1$ ) denoting multiplicative trait change. If  $\Delta_{\alpha_{it}} \neq 0$ , then the observed scores, on average, shift upwards ( $\Delta_{\alpha_{it}} > 0$ ) or downwards ( $\Delta_{\alpha_{it}} < 0$ ) by an additive constant. The trait factor loadings  $\lambda_{it}$  in Equation (5) represent the increase or decrease of interindividual differences in the latent trait at time  $t$  as the variance of a latent trait for  $t > 1$  is a function of the latent trait at time 1:

$$Var(\xi_{it}) = \lambda_{i1}^2 Var(\xi_{i1}) \quad \text{for } t > 1 \quad (7)$$

Hence, the parameter  $\lambda_{it}$  for  $t > 1$  can be interpreted as the multiplicative (or weighted) change of the person's individual initial trait values. If  $\lambda_{it} > 1$ , initial trait values are amplified which indicates an increase of interindividual trait differences. If  $\lambda_{it} < 1$ , initial trait values are attenuated and interindividual trait differences decrease. Note that the rank order of the trait scores is invariant under positive linear transformations<sup>1</sup>.

The difference score parametrization is advantageous for various reasons: First, additive trait change is represented by a unique parameter  $\Delta_{\alpha_{it}}$  that is easy to interpret. Second, the parametrization allows for an independent consideration of additive and

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<sup>1</sup> Note, however, that the rank order of the persons with respect to the persons' time-specific true scores are not necessarily constant across time, as the model does not impose any restrictions on the (rank order of the) state residual variables (i.e., a person's time-specific deviation of his or her true score from the time-specific trait value is free to vary across time).

multiplicative trait change (i.e.,  $\Delta_{\alpha_{it}}$  always represents the difference of the expectation of two observed variables even if  $\lambda_{it} \neq 1$ ). Third, parameter equality constraints can be imposed distinctively on the two change parameters. A list of reasonable parameter constraints can be found in Appendix A.

One key limitation of the aforementioned LST-R models is that they assume that the additive and the multiplicative trait change parameters ( $\Delta_{\alpha_{it}}$  and  $\lambda_{it}$ ) are *constant* across all persons. That is, trait change is assumed to occur in terms of the same linear function of the initial trait value for all persons. Consequently, time-varying and time-invariant variables cannot be directly linked to the key parameters in LST-R models (e.g., using a MIMIC approach) to explain interindividual differences in trait change.

An alternative modeling approach are latent growth curve (LGC) models, where trait change is modeled by means of latent intercept and latent slope factors. The values on the latent intercept and slope factors in LGC models represent a person's initial trait and the amount of a person's trait change over time, respectively. While the amount of change in LGC models is modeled to be person-specific (captured in latent slope factor scores), the shape of the change trajectories across time are the same across individuals, given by the slope factor loadings and typically specified as a (linear or quadratic) function of time. External (time-invariant) variables may be linked to the latent intercept and slope factors to study key predictors of individual trait change. Figure 2 shows a multiple-indicator latent growth curve model with indicator-specific intercept and linear slope factors, for a minimal measurement design with two indicators measured on three time points.

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A key difference between LST-R and LGC models is that, instead of the assumption stated in Equation (2), a growth function  $f$  is assumed for the shape of trait change for  $t > 1$  (see also Geiser, Bishop et al., 2013):

$$\xi_{itp} = \xi_{i1p} + f(\xi_{i2p} - \xi_{i1p}) \quad (8)$$

If we assume linear change (as we do for the remainder of this article),  $\xi_{i1p}$  is defined as latent intercept factor ( $Int_{ip}$ ),  $(\xi_{itp} - \xi_{i1p})$  is defined as latent linear slope factor ( $Slo_{ip}$ ), and the state residual variables are assumed to be perfectly correlated across indicators within a time point, obtaining the following multiple indicator latent linear growth curve model (see Figure 2):

$$Y_{itp} = Int_{ip} + (t - 1)Slo_{ip} + \delta_{it}\zeta_{tp} + \epsilon_{itp} \quad (9)$$

As shown in Figure 2, the latent intercept and slope factors can correlate with each other. A negative correlation implies that higher initial values are associated with lower slope scores and lower initial values are associated with higher slope scores (Duncan & Duncan, 2004). If there are no theoretical assumptions about the growth function, researchers may also freely estimate some of the linear slope factor loadings (e.g., freely estimating the factor loadings of the linear slope factor for  $t > 2$ ) to determine the shape of change over time. These models may be termed hybrid LGC models, as the shape of trait change is not explicitly defined beforehand by the researcher, but instead estimated from the data. However, freely estimating the loadings of the linear slope factor undermines in some way the nature of latent growth curve modeling, that is, modeling and testing the shape of trait change. LST-R models represent a less restrictive variant of LGC models in that they do not require researchers to make specific assumptions regarding the shape of trait change (e.g., linear trait change) across time. Furthermore, in the MN-LST models introduced in the following, the shape of change

trajectories may vary across individuals. In the discussion, we consider the relation between MN-LST models and LGC model in greater detail.

### Modeling Different Variability Processes in LST-R and LGC Models

Both LST-R and LGC models allow researchers to study different variability processes around a stable or changing trait. In LST-R models (as given by Equations (2) – (4)), the variance of each observed variable can be decomposed as follows:

$$\sigma_{Y_{it}}^2 = \lambda_{it}^2 \sigma_{\xi_{i1}}^2 + \delta_{it}^2 \sigma_{\zeta_t}^2 + \sigma_{\epsilon_{it}}^2 \quad (10)$$

where  $\sigma_{Y_{it}}^2$  is the variance of an observed variable,  $\sigma_{\xi_{i1}}^2$  is the variance of the initial latent trait variable (weighted by  $\lambda_{it}^2$ , squared loading of the trait factor),  $\sigma_{\zeta_t}^2$  is the variance of the latent state residual variable (weighted by  $\delta_{it}^2$ , squared loading of the state-residual factor), and  $\sigma_{\epsilon_{it}}^2$  is the variance of the measurement error variable. The variance of a state residual variable  $\sigma_{\zeta_t}^2$  provides information about the extent to which persons fluctuate around their individual trait levels. Typically, this variance is conceptualized as the variance of the true scores around the trait values at a specific time point, that is, the state residuals at time  $t$  are assumed to be normally distributed with mean zero and a time-specific variance:

$$\zeta_{tp} \sim N(0, \sigma_{\zeta_t}^2) \quad (11)$$

Similarly, in LGC models, the variance of a state residual variable reflects the degree to which the true scores deviate from the person-specific trait values at a specific time point. In LST models, the specificity coefficient quantifies the proportion of reliable interindividual differences that are due to time-specific effects (i.e., situation and/or person- situation interaction effects). The specificity coefficient is computed as the proportion of true score variance ( $\sigma_{\tau_{it}}^2 = \sigma_{Y_{it}}^2 - \sigma_{\epsilon_{it}}^2$ ) that is due to variance in the state residual variables at time  $t$ :

$$Spe(\tau_{it}) = \frac{\delta_{it}^2 \sigma_{\zeta t}^2}{\sigma_{\tau_{it}}^2} \quad (12)$$

The counterpart of the specificity coefficient is the consistency coefficient. The consistency coefficient is defined as  $Con(\tau_{it}) = 1 - Spe(\tau_{it})$  and represents the proportion of reliable interindividual differences that are attributable to the latent trait factor in LST-R models or to the latent intercept and slope factors in LGC models.

An increasing number of studies are devoted to the analysis of intra-individual (within-person) variability (e.g., Geukes et al. 2017; Lievens et al., 2018; Wundrack et al., 2018). Several approaches have been proposed for estimating intra-individual variability parameters from repeated measurement data (e.g., Asparouhov et al., 2018; Driver & Voelkle, 2018; Eid & Diener, 1999; Nordgren et al., 2019; Wang et al., 2012). Recent developments in the context of dynamic structural equation modeling (see Asparouhov et al., 2018) allow researchers to estimate within-person variability in multilevel time series models using Bayesian estimation methods. In this article, we use a Bayesian approach to extend LST-R and LGC models to person-specific variances of the latent state-residual variables across time (intra-individual variability). These models will be termed *extended* LST-R and *extended* LGC models in the remainder of the article. Although we do not assume autoregressive effects in the above models, autoregressive effects may be incorporated in empirical applications. To model intra-individual variability across time, the variance of the latent state residual variables is modeled to be person-specific, that is,

$$\zeta_{tp} \sim N(0, \sigma_{\zeta p}^2) \quad (13)$$

Equation (13) states that the state-residuals of person  $p$  are assumed to be normally distributed, with a mean of zero and a person-specific variance  $\sigma_{\zeta p}^2$  which is constant across time. Note that in contrast to the time specific variance  $\sigma_{\zeta t}^2$ , the person-specific variance  $\sigma_{\zeta p}^2$

can correlate with latent trait variables  $\xi_{itp}$ . By regressing the log of the person-specific variability parameter  $\log(\sigma_{\zeta_p}^2)$  on external explanatory variables, it is possible to identify predictors of intra-individual variability. Next, we introduce a general framework for explaining trait change as well as inter-or intra-individual variability processes by external covariates using a Bayesian moderated nonlinear latent state-trait (MN-LST) approach.

### **Bayesian Moderated Nonlinear Latent State-Trait Framework**

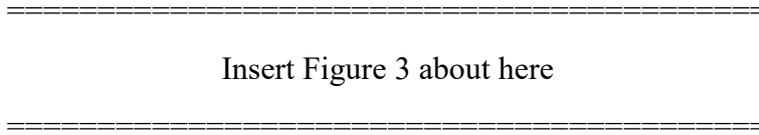
The basic idea of the MN-LST framework is to link time-varying and time-invariant covariates to *trait change* and *variability* parameters in LST models. The MN-LST framework builds on moderated nonlinear factor analysis (Bauer & Hussong, 2009; Curran et al., 2014; Hildebrandt et al., 2016; Molenaar et al., 2011) and Bayesian Markov-Chain Monte-Carlo (MCMC) sampling techniques. The MN-LST framework allows researchers to include time-varying and time-invariant (nominal or continuous) covariates, as well as interaction terms between the covariates as predictors for trait change as well as variability processes. It is also possible to include higher-order polynomial terms in MN-LST models to test nonlinear (e.g. quadratic) moderation effects.

For simplicity, we will focus on a minimal example with one time-invariant and one time-varying covariate and discuss the inclusion of the covariates in a step-by-step fashion. First, we will discuss the inclusion of time-invariant covariates in MN-LST models. Second, we will explain how time-varying covariates can be included in MN-LST models. Third, we discuss how interaction terms between the covariates can be specified in order to test synergistic interaction effects. Fourth, we clarify how external covariates can be used to predict the amount of occasion-specificity (i.e., predicting variance coefficients) and explain intra-individual variability parameters across time. Throughout the remainder of the article, we will focus on observed covariates. An extension to *latent* continuous covariates is discussed in the discussion.

### Inclusion of Time-Invariant Covariates

Consider a researcher who seeks to explain interindividual differences in coping behavior over time by a time-invariant covariate (e.g., neuroticism,  $X_{v(p)}$ ). We use the notation  $X_{v(p)}$  to make clear that the time-invariant covariate in the data set is a vector of length  $p = 1, \dots, P$ , which can take on values from  $v = 1, \dots, V$ .

Figure 3 shows a path diagram of a MN-LST model with a time-invariant covariate.



Again, trait change in LST-R models is reflected in differences between intercepts  $\Delta_{ait}$  (additive trait change parameter) and the trait loadings  $\lambda_{it}$  (multiplicative trait change parameter) pertaining to time points  $t > 1$ . In the MN-LST framework, these key parameters can vary as a (linear or nonlinear) function of the values  $v$  on the time-invariant covariate  $X_{v(p)}$ :

$$\Delta_{aitv} = \beta_{0it}^A + \beta_{1it}^A X_{v(p)} + \varepsilon_{itv}^A \quad (14)$$

$$\lambda_{itv} = \beta_{0it}^\lambda + \beta_{1it}^\lambda X_{v(p)} + \varepsilon_{itv}^\lambda \quad (15)$$

where  $\Delta_{aitv}$  and  $\lambda_{itv}$  represent the additive and multiplicative trait change parameters, respectively, for indicator  $i$  at time  $t$  for each value  $v$  of the time-invariant covariate  $X_{v(p)}$  with values ranging from  $v = 1, \dots, V$ .

The parameters  $\Delta_{aitv}$  and  $\lambda_{itv}$  do not vary across persons  $p$ , but across different values  $v$  of the external covariate  $X_{v(p)}$  that are present in a given sample. Hence, moderated nonlinear factor analysis is a generalization of multiple group analysis, where the values  $v$  on the covariate  $X_{v(p)}$  represent different groups (see Bauer, 2017). Theoretically, all parameters in LST-R models (see Equation (5)) could be regressed on a time-invariant covariate.

However, we focus on the two trait change parameters  $\Delta_{aitv}$  and  $\lambda_{itv}$ . Additionally,

researchers may relate external variables to initial intercept parameter  $\alpha_{i1}$  to model mean differences in the initial (trait) scores (i.e., mean differences in dyadic copying at time 1).

The parameters  $\beta_{0it}^A, \beta_{1it}^A, \beta_{0it}^\lambda$ , and  $\beta_{1it}^\lambda$  in Equation (14) and (15) represent regression coefficients and the error terms  $\varepsilon_{itv}^A$  and  $\varepsilon_{itv}^\lambda$  capture unexplained parameter heterogeneity in the intercept-changes and trait loadings across different values of the covariates (e.g., due to deviations from the linearity assumption, see Hildebrandt et al., 2016). Hence, we assume a stochastic relationship<sup>2</sup> between the intercepts and trait loadings on the one hand and the observed time-invariant covariate  $X_{v(p)}$  on the other hand. A more restrictive variant of the above MN-LST model can be obtained if the error terms are dropped, implying a deterministic relationship (see Bauer, 2017).

To clarify the interpretation of the coefficients in Equation (14) and (15), we refer to the simplified example of a single time-invariant, grand-mean centered covariate (neuroticism) predicting the intercept and trait factor loading of indicator 1 at time 2. In this case,  $\beta_{012}^A$  and  $\beta_{012}^\lambda$  would denote the expected *additive* trait change and the expected *multiplicative* trait change for an averagely neurotic person (i.e.,  $X_{v(p)} = 0$ ). The regression coefficients  $\beta_{1i2}^A$  and  $\beta_{1i2}^\lambda$  can be interpreted as the expected change in the corresponding trait change parameters when neuroticism increases by one unit.

### **Inclusion of Time-Varying Covariates**

Next, we consider the inclusion of a time-varying covariate (e.g., stress at work,  $X_{tv(p)}$ ) in MN-LST models. The additional index  $t$  in the subscript indicates that the explanatory variable is a time-varying covariate with values  $v = 1, \dots, V$ . Figure 4 shows a

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<sup>2</sup> To empirically model and estimate the error terms in Equations (9) and (10), it is necessary to sample a sufficient number of observations for each value on the time-invariant covariate. To this end, researchers might consider rounding the values on continuous moderating covariates to one or two decimal places before the analysis. In case the covariate is dichotomous (or covariates are dummy-coded to include nominal variables), the error terms have to be dropped from the equations.

path diagram of a MN-LST model with a single time-varying covariate measured at three time points.

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 Insert Figure 4 about here  
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It is worth noting that both  $\Delta_{\alpha_{it}}$  and  $\lambda_{it}$  can be directly linked to the time-varying covariates measured at the same time point ( $X_{tv(p)}$ ) or at previous time points (e.g.,  $X_{(t-1)v(p)}$ ) in the MN-LST framework:

$$\Delta_{\alpha_{itv}} = \beta_{0it}^{\Delta} + \beta_{1it}^{\Delta} X_{tv(p)} + \beta_{2it}^{\Delta} X_{(t-1)v(p)} + \varepsilon_{itv}^{\Delta} \quad (16)$$

$$\lambda_{itv} = \beta_{0it}^{\lambda} + \beta_{1it}^{\lambda} X_{tv(p)} + \beta_{2it}^{\lambda} X_{(t-1)v(p)} + \varepsilon_{itv}^{\lambda} \quad (17)$$

where  $\beta_{0it}^{\Delta}$ ,  $\beta_{1it}^{\Delta}$ , and  $\beta_{2it}^{\Delta}$  denote the regression coefficients with respect to the additive change parameter  $\Delta_{\alpha_{itv}}$ , and  $\beta_{0it}^{\lambda}$ ,  $\beta_{1it}^{\lambda}$ , and  $\beta_{2it}^{\lambda}$  represent the regression coefficients with respect to the trait loadings  $\lambda_{itv}$ . Note that covariates measured at lags greater than one are not included in Equations (16) and (17) for parsimony but may principally be modeled. The error terms  $\varepsilon_{itv}^{\Delta}$  and  $\varepsilon_{itv}^{\lambda}$  capture unexplained heterogeneity in the intercepts and trait loadings. Equations (16) and (17) state that  $\Delta_{\alpha_{itv}}$  as well as  $\lambda_{itv}$  may vary as a function of the values (or combinations of values) on a time-varying covariate measured at the same time point  $X_{tv(p)}$  and at the previous time point  $X_{(t-1)v(p)}$ .

An example where this general MN-LST model may be suitable is when critical life events are considered as time-varying covariates. Critical life events can have long-lasting effects on a person's trait that diminish only slowly over time (e.g., Hentschel et al., 2017). Consider, for example, a person who experiences a divorce at the first time point. Experiencing a divorce at time 1 might not only affect the person's well-being at time 1 but also at time 2 and thereby also the trait changes from time 1 to time 2 (or later time points). At the second time point, the person may for instance experience a positive life event. The

positive effect of this event might, however, be attenuated by the lasting negative effect of the foregoing divorce. The MN-LST framework allows researchers to include lagged effects of time-varying covariates. However, for simplicity, in the present study we will focus on situations where the time-varying covariate only affects the person's trait at the same time point.

The regression coefficients in Equation (16) and (17) can be interpreted in a similar way as discussed before. We generally recommend researchers to center the external covariates. There are two possible centering techniques with respect to time-varying covariates: centering at the overall grand-mean or centering at the person-specific or group-mean (Enders & Tofighi, 2007; Kreft et al., 1995). Selecting an appropriate centering technique is crucial for the interpretation of  $\beta_{0it}^A$  and  $\beta_{0it}^\lambda$  parameters, as they reflect the expected parameter for a person scoring 0 on all covariates. We recommend researchers to choose an appropriate centering technique that eases the interpretation of the model parameters and helps to answer the research question at hand. If researchers decide to center the covariate at the person-specific mean (group-mean centering), we recommend to additionally include the person-specific mean as a time-invariant covariate in the model. In the discussion, we explain how researchers may also use latent (person-centered) covariates (see Lüdtke et al., 2008) in MN-LST models.

### **Inclusion of Synergistic Person $\times$ Situation Interaction Effects**

Referring to the above example, a researcher may seek to investigate whether neuroticism (the time-invariant covariate) and stress at work (the time-varying covariate) have a multiplicative effect on (the change of) dyadic coping behavior over time. It can reasonably be assumed that stress at work has a stronger impact on the coping behavior of comparatively more neurotic than on emotionally more stable individuals. To study this synergistic interaction effect, researchers need to include a product variable of the time-invariant and the time-varying covariate as an additional explanatory variable into the MN-LST model.

Specifically, the model parameters  $\Delta_{\alpha_{itvw}}$  and  $\lambda_{itvw}$  in the MN-LST model are linked to a time-invariant covariate  $X_{1v}$ , a time-varying covariate  $X_{2tw}$ , and a product term of the two covariates ( $X_{1v}X_{2tw}$ ):

$$\Delta_{\alpha_{itvw}} = \beta_{0it}^{\Delta} + \beta_{1it}^{\Delta}X_{1v} + \beta_{2it}^{\Delta}X_{2tw} + \beta_{3it}^{\Delta}(X_{1v}X_{2tw}) + \varepsilon_{itvw}^{\Delta} \quad (18)$$

$$\lambda_{itvw} = \beta_{0it}^{\lambda} + \beta_{1it}^{\lambda}X_{1v} + \beta_{2it}^{\lambda}X_{2tw} + \beta_{3it}^{\lambda}(X_{1v}X_{2tw}) + \varepsilon_{itvw}^{\lambda} \quad (19)$$

For simplicity, we dropped the index  $p$  in the above Equation (18) and (19). The indices  $v = 1, \dots, V$  and  $w = 1, \dots, W$  are used to clarify that the time-invariant covariate  $X_{1v}$  and the time-varying covariate  $X_{2tw}$  can take on different values and the parameters  $\Delta_{\alpha_{itvw}}$  and  $\lambda_{itvw}$  may vary as a function of the combination of the values on both covariates. The coefficients  $\beta_{0it}^{\Delta}$ ,  $\beta_{1it}^{\Delta}$ ,  $\beta_{2it}^{\Delta}$ , and  $\beta_{3it}^{\Delta}$  represent regression coefficients with respect to  $\Delta_{\alpha_{itvw}}$  (additive trait change parameter), while  $\beta_{0it}^{\lambda}$ ,  $\beta_{1it}^{\lambda}$ ,  $\beta_{2it}^{\lambda}$  and  $\beta_{3it}^{\lambda}$  denote the regression coefficients with respect to  $\lambda_{itvw}$  (multiplicative trait change parameter), and  $\varepsilon_{itvw}^{\Delta}$  and  $\varepsilon_{itvw}^{\lambda}$  are the error terms.

The product term ( $X_{1v}X_{2tw}$ ) and its' coefficients  $\beta_{312}^{\Delta}$  and  $\beta_{312}^{\lambda}$  represent the synergistic (person  $\times$  situation) interaction effects between trait neuroticism and time-varying stress at work with respect to the additive  $\Delta_{\alpha_{itvw}}$  and the multiplicative  $\lambda_{itvw}$  trait change parameters. For example, the regression coefficient  $\beta_{312}^{\Delta}$  characterizes the expected change in the additive trait change parameter  $\Delta_{\alpha_{itvw}}$  of dyadic coping if both stress at work and neuroticism increase by one unit simultaneously (above and beyond the main effects). The synergistic interaction effect for the trait loading  $\lambda_{12}$  can be interpreted accordingly.

### Predicting Variance Coefficients

The MN-LST framework also allows researchers to link external covariates to different variance parameters in the model. Thereby, it is possible to explain inter- or intra-individual variability processes around a moving trait. Furthermore, consistency and occasion-specificity coefficients may be investigated as a function of external covariates.

***Explaining Inter-Individual Variability Processes***

The occasion-specificity coefficient (see Equation (12)) reflects the amount of true inter-individual variability that is due to time-specific inter-individual differences (i.e., situation and/or person  $\times$  situation effects). In the MN-LST framework, time-varying as well as time-invariant covariates can be linked to latent state residual variation using a logarithmic function. A researcher might, for instance, assume that persons with high state-stress levels show more variability and larger time-specific deviations from their dyadic coping skill traits at this time point as compared to persons with lower state-stress levels. To test such a hypothesis, researchers can regress the log (natural logarithm) of the latent state residual variance  $\log(\sigma_{\zeta tv}^2)$  on a time-varying covariate  $X_{tv(p)}$  measured at the same time point  $t$ :

$$\log(\sigma_{\zeta tv}^2) = \beta_{0t}^{\sigma} + \beta_{1t}^{\sigma} X_{tv(p)} + \varepsilon_{tv}^{\sigma} \quad (20)$$

or equivalently written as  $\sigma_{\zeta tv}^2 = \exp(\beta_{0t}^{\sigma} + \beta_{1t}^{\sigma} X_{tv(p)} + \varepsilon_{tv}^{\sigma})$ , where  $\exp(\cdot)$  refers to the (natural) exponential function. Note that the variance of the latent state residual  $\sigma_{\zeta tv}^2$  varies as a function of the *values* of the time-varying covariate  $X_{tv(p)}$ . The coefficient  $\exp(\beta_{0t}^{\sigma})$  is the expected latent state residual variance at time  $t$  given the time-varying covariate takes on the value zero. The coefficient  $\exp(\beta_{1t}^{\sigma})$  represents the expected multiplicative change in the latent state residual variance if the covariate increases by one unit.

By regressing the latent state residual variances  $\sigma_{\zeta tv}^2$  and the trait factor loadings  $\lambda_{itv}$  on time-varying or time-invariant covariates, the consistency and occasion specificity coefficients are inherently predicted as well. In sum, the MN-LST framework allows the consistency and specificity coefficients to vary as a function of time-varying and time-invariant covariates. In the empirical application, we illustrate how the consistency coefficient varies in dependence of a persons' general stress level and neuroticism.

***Explaining Intra-Individual Variability Processes***

Following a similar logic, intra-individual variability processes (i.e., person-specific variabilities around a changing trait) can be predicted by *time-invariant* covariates. In practice, researchers need to specify an *extended* MN-LST model to explain intra-individual variance in addition to the trait change parameters. The person-specific state residual variance  $\sigma_{\zeta_p}^2$  (see Equation (13)) can be considered as a trait-like coefficient for intra-individual variability. As this parameter is time-invariant, it can only be defined as a function of time-invariant covariates. Again, a log-linear function is used to relate intra-individual variability parameters  $\sigma_{\zeta_p}^2$  to a time-invariant covariate  $X_{v(p)}$  (e.g., a person trait-level of neuroticism), that is,

$$\log(\sigma_{\zeta_p}^2) = \beta_0^\sigma + \beta_1^\sigma X_{v(p)} + \varepsilon_p^\sigma, \quad (21)$$

where  $\beta_0^\sigma$  and  $\beta_1^\sigma$  are regression coefficients and the error term  $\varepsilon_p^\sigma$  captures unexplained inter-individual heterogeneity in intra-individual variability. Note that the intra-individual variability parameters  $\sigma_{\zeta_p}^2$  in Equation (21) vary across persons  $p$  (not across values  $v$  of the covariate as in Equation (14)). The coefficient  $\exp(\beta_0^\sigma)$  is the expected within-person variability across time for a person scoring zero on the time-invariant covariate  $X_{v(p)}$  (for instance, the expected intra-individual variability in coping behavior across time for a person with an average level of neuroticism). The coefficient  $\exp(\beta_1^\sigma)$  is the expected multiplicative change in  $\sigma_p^2$  if the time-invariant covariate increases by one unit, with  $\exp(\beta_1^\sigma) < 1$  indicating a decrease and  $\exp(\beta_1^\sigma) > 1$  indicating an increase in intra-individual variability with an increase in the covariate  $X_{v(p)}$ .

### Empirical Application

Next, we illustrate the MN-LST approach using real data from a large German multi-wave study. In the present application, we investigate the effect of the time-invariant covariate neuroticism and time-varying covariate stress at work on variability and change in dyadic coping behavior. As we are especially interested in the synergistic person  $\times$  situation

interaction and do not have any theoretical assumptions about the shape of trait change, we focus on the MN-LST approach.

### **Data description**

Data was taken from the Panel Analysis of Intimate Relationships and Family Dynamics (pairfam; Brüderl et al. 2019). Pairfam is a longitudinal multi-perspective study launched in 2008/09, which annually assesses partnership and family dynamics in Germany (for a detailed description of the study, see Huinink et al., 2011). We investigated the development and variability of dyadic coping behavior in romantic couples over a period of nine years with 5 occasions of measurement (including waves 1, 3, 5, 7 and 9). In this study, we focused on the self-evaluations of anchor persons of the first birth cohort, born between 1971 and 1973, as this cohort provided most data on the included variables. Participants with missing values on the covariates were excluded, resulting in a final sample of  $N = 854$ . Dyadic coping behavior was measured with 3 items stemming from the Dyadic Coping Questionnaire (FDCT-N, Bodenmann, 2000), neuroticism was assessed with 4 items from the short version of the Big Five Inventory (BFI-K; Rammstedt & John, 2005), and current stress level at work was assessed with two questions concerning time pressure and workload. All items were answered on a 5-point rating scale (1=low to 5=high).

### **Specification and Estimation**

Models were estimated using Bayesian estimation via MCMC methods based on the Gibbs Sampler, as implemented in JAGS (v4.3.0; Plummer, 2003). Estimation was carried out using the `rjags` package (v4-10; Plummer 2019) in R (R Core Team, 2018). Previous to the MN-LST analysis, we evaluated the fit of the (unmoderated) baseline LST model using the maximum likelihood robust (MLR) estimator implemented in the `lavaan` package (v0.6-4; Rosseel, 2012). The LST model was specified with indicator-specific trait factors. The

following parameter constraints were imposed:  $\lambda_{i1} = 1$ ,  $\delta_{it} = 1$ ,  $\mathbb{E}(\xi_i) = 0$ ,  $\mathbb{E}(\zeta_i) = 0$ , and  $\sigma_{\zeta t}^2 = \sigma_{\zeta tr}^2$ .

We estimated two MN-LST models. In the first model, we predicted both trait change parameters as well as the time-specific state residual variances (i.e., inter-individual variability in occasion-specific effects; model 1). In the second model, we fitted an *extended* MN-LST model to explain the intra-individual variability parameter  $\sigma_{\zeta p}^2$ , instead of the latent state-residual variance  $\sigma_{\zeta t}^2$  (model 2). In both models, we modeled intercepts at the first time point  $\alpha_{i1}$ , intercept-changes  $\Delta_{\alpha_{it}}$ , and trait loadings  $\lambda_{it}$  for  $t > 1$  as a deterministic function of the time-stable covariate neuroticism, the time-varying covariate stress at work and their synergistic interaction. Following Bauer (2017), we choose a deterministic function to reduce model complexity and facilitate model estimation.

The time-varying covariate (stress at work) was centered at the person-specific mean score. In addition, we included the person-specific mean level of stress as well as the interaction between time-invariant stress and neuroticism as time-invariant covariates. All time-invariant covariates were grand-mean centered. The effects of the covariates on the additive and the multiplicative trait change parameters were set invariant across indicators. Hence, we do not assume indicator-specific effects of the moderating covariates. Furthermore,  $\beta_0$ -coefficients for  $\Delta_{\alpha_{it}}$  and  $\lambda_{it}$  were set invariant across indicators, which together with the above restriction implies that additive and multiplicative trait change is equal for different indicators (see parameter restrictions discussed in Appendix A in Equations (A.1) - (A.4)). However, we freely estimated the  $\beta_0$ -coefficient with respect to  $\alpha_{i1}$  (the intercept at time 1), that is, indicators may differ in their initial mean level. We did not impose any longitudinal constraints on the covariate effects to allow for and investigate potential adaptation processes. Significance of trait change parameters and covariate effects was evaluated using Bayesian 95% credibility intervals.

Bayesian estimation was conducted by running three MCMC chains with 40,000 iterations and a thinning factor of 10. The first 20,000 sample iterations were discarded (burn-in). Convergence of MCMC chains was evaluated by visually inspecting autocorrelation and trace plots. MCMC chains converged well for all parameters of both models. Traceplots can be retrieved from the open science framework OSF (Link: <https://osf.io/4ejvz>). All unconstrained parameters were modeled using uninformative priors. Details on prior specifications can be found in Appendix C, annotated JAGS code is provided in the supplemental material (Link: <https://osf.io/bka6j>).

## Results

As described in the previous section, we evaluated the fit of the baseline LST model using MLR estimation. The model fitted the data well,  $\chi^2(86) = 128.05, p = .002; CFI = .987, TLI = .984, RMSEA = .027, SRMR = .032$ . Considering that the MN-LST model is less restrictive than the baseline LST model, as it permits for differences in model parameters across values of the covariates, it can be assumed that the MN-LST model fits the data at least as good as the baseline model.

Parameter estimates of model 1 are summarized in Table 1, results concerning model parameters of model 2 are summarized in Table 2. Parameters in column  $\beta_{0it}$  are the respective expected parameter values for averagely neurotic individuals at an average mean stress level, experiencing a person-specific average amount of stress at work. The parameters  $\beta_{T\_Neuro\_it}, \beta_{T\_Stress\_it}, \beta_{O\_Stress\_it}, \beta_{T\_Neuro\_x\_O\_Stress\_it},$  and  $\beta_{T\_Neuro\_x\_T\_Stress\_it}$  refer to the effects of the covariates and their interactions on the respective parameters (note that parameters are set invariant across indicators).

### *Explaining trait change parameters.*

Parameters  $a_{i1}$  in Table 1 refer to the three initial intercept parameters at time 1, additive trait change parameters  $\Delta_{\alpha_{it}}$  refer to the mean differences between time 1 and one of the four subsequent measurement occasions (T2, T3, T4, and T5; set invariant across indicators). Additive trait change is present if the  $\Delta_{\alpha_{it}}$  parameters significantly differ from 0.

$\beta_{0it}^A$  parameters indicate a significant negative additive trait change, which means that averagely neurotic and stressed individuals show a decrease in dyadic coping behavior over time. Considering the Bayesian credibility intervals, only neuroticism has a significant effect on initial values  $a_{i1}$ , with persons with a level of neuroticism above average show less dyadic coping behavior at time 1. None of the included covariates was found to predict additive trait change.

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Insert Table 1 about here  
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Recall that multiplicative trait change is present if trait factor loadings  $\lambda_{it}$  for  $t > 1$  significantly differ from 1. The parameters  $\beta_{0it}^\lambda$  indicate that averagely neurotic and averagely stressed persons experience positive multiplicative trait change at the third and fourth measurement occasions with respect to time 1. That is, the initial trait values of individuals are further enhanced, leading to an increase of inter-individual trait differences.

With respect to the effects of external covariates on multiplicative trait change, neuroticism has a significant positive effect on trait loadings of the fourth measurement occasion, i.e., an increase in neuroticism leads to increased interindividual trait heterogeneity. Furthermore, trait loadings of the third time point are predicted by the person-specific mean stress level and the neuroticism x mean stress interaction. That is, an increase in person-specific stress levels is associated with increased trait heterogeneity in dyadic coping. This

effect is mainly present for persons low on neuroticism and is attenuated under high neuroticism levels.

***Explaining consistency or occasion specificity coefficients.***

By explaining the variance of the latent state residuals in addition to trait factor loadings, we indirectly also model consistency  $Con(\tau_t)$  and specificity  $Spe(\tau_t)$  coefficients in dependence of external covariates. Figure 5 shows an illustrative example of the consistency coefficient on the third measurement occasion moderated by the (interaction) between time-stable neuroticism and time-stable stress at work. The figure reveals that consistency, that is, the amount of variance in dyadic coping attributable to reliable inter-individual trait differences, decreases with an increase in neuroticism for individuals with a high mean stress level (i.e., one standard deviation above average). That is, situation- and time-specific inter-individual variation around the trait levels increases with increasing neuroticism, in highly stressed individuals. In contrast, for persons with a low mean stress level (i.e., one standard deviation below average), the consistency increases with an increase of neuroticism. The highest consistency is expected for below-average neurotic individuals experiencing a high mean level of stress at work. In general, differences in consistency between individuals with low and high stress levels are most pronounced for individuals low on neuroticism.

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Insert Figure 5 about here

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***Explaining within-person variability parameters.***

Next, we specified an extended MN-LST model to estimate and moderate the person-specific intra-individual variability parameter (see Table 2). With respect to trait change, results of the extended MN-LST model largely parallel those of the regular MN-LST analysis.

However, instead of modeling specificity or consistency coefficients, we now predict intra-individual variability as a log-linear function of time-invariant external covariates (i.e., neuroticism, trait stress and the neuroticism  $\times$  trait stress interaction). For averagely neurotic and stressed individuals we expect an intra-individual variability of  $\exp(\beta_0^\sigma) = .057$ .

Neuroticism has a significant impact on intra-individual variability: Persons scoring one unit above average on neuroticism are expected to show an increased intra-individual variability in dyadic coping of  $(.057 * 1.262 =) .072$ . The effect of neuroticism on intra-individual variability for different trait stress levels is illustrated in Figure 6. Figure 6 reveals that the highest intra-individual variability is expected for highly neurotic individuals on a high mean-stress level. However, the effect of trait stress as well as the neuroticism  $\times$  stress interaction are not significant.

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Insert Table 2 about here  
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Insert Figure 6 about here  
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### **Discussion of the Empirical Application**

Our findings can be summarized as follows. First, there is negative additive as well as positive multiplicative trait change in dyadic coping behavior over the course of 9 years. That is, dyadic coping behavior was observed to decrease across years, with a temporary increase in interindividual differences in dyadic coping behavior after 5 and 7 years. Second, trait neuroticism has a negative effect on initial values of additive change trajectories of dyadic coping over time, suggesting that persons with a high level of neuroticism tend to have lower coping skills in general, which is in line with previous research on dyadic coping (Merz et al.,

2014). However, neuroticism was not found to affect changes in the level of dyadic coping over time. Instead, neuroticism was positively associated with within-person variability across time (i.e., the amount of person-specific fluctuations around a person's changing trait). This indicates that persons who report a higher level of neuroticism tend to show more variability in their coping behavior across time than persons that report a lower level of neuroticism. This result supports previous findings suggesting that neuroticism is associated with an increased intra-individual behavioral variability (Judge et al., 2014). Fourth, occasion-specific stress at work was neither associated with trait change nor with situational variability. Similarly, trait stress was not found to affect levels of dyadic coping behavior and was associated with an increase in interindividual differences in trait coping behavior for persons low on neuroticism at only one measurement occasion. Fifth, we found no synergistic interaction effects of neuroticism with stress on coping behavior. One possible explanation for the non-significant effects of stress-at-work might be that the variables included in the current analyses (time pressure and workload) did not serve as good indicators of a person's actually experienced overall level of stress. While some persons might experience a high workload in a job context as stressful and straining, others might experience them as positive (for instance, as they enjoy their work or interpret a high workload as a sign of a well-going business). It can be hypothesized that main effects of stress as well as synergistic effects of neuroticism and stress are more likely to occur if stress was assessed in terms of a personally experienced momentary overall stress level, considering personal as well as work-related stressors. However, the non-significant interaction effect might also be due to a lack of statistical power or because synergistic person  $\times$  situations interactions do not exist as hypothesized.

### **Overall Discussion**

Identifying key predictors of trait change and variability processes (inter- or intra-individual variability) are two central goals in psychology. In this article, we introduced a

general framework for the inclusion of nominal and/or continuous time-varying and time-invariant covariates, as well as their synergistic interactions in LST-R models. The new framework combines the advantages of modern LST theory and moderated nonlinear factor analysis using Bayesian MCMC estimation techniques. The MN-LST framework allows a fine-grained analysis of trait change, inter- or intra-individual variability, and synergistic interaction effects, which cannot be examined in a similar fashion in traditional LST modeling approaches. In the following, we discuss the advantages and limitations of the new MN-LST framework with reference to alternative modeling strategies.

### **Relation to Latent Growth Curve Models**

An alternative modeling approach are multiple-indicator latent growth curve models. Multiple-indicator LGC models can be specified as (traditional) single level or as multilevel CFA models (Geiser; Bishop et al., 2013). As explained above, the introduced MN-LST-R models is less restrictive than LGC models in that the MN-LST model allows researchers a) to flexibly model trait change without specifying a specific shape of change across time while b) shapes of trait change trajectories may differ across individuals, c) to flexibly test specific hypotheses about the shape of trait change, and c) easily integrate synergistic interaction effects of external covariates on the shape and amount of trait change. Table 3 summarizes the key differences and similarities between MN-LST and LGC analysis.

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Insert Table 3 about here  
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A key difference between the approaches is that trait change is modeled by means of latent variables (i.e., slope factor) in LGC models, whereas in MN-LST models it is represented in the intercepts and trait loadings pertaining to different time points. In LGC models, the latent intercept and slope factor may be further regressed on *time-invariant* covariates (e.g.,  $X_p$  = a person's gender):

$$Int_{ip} = \beta_{0i}^I + \beta_{1i}^I X_p + \epsilon_{ip}^I \quad (22)$$

$$Slo_{ip} = \beta_{0i}^S + \beta_{1i}^S X_p + \epsilon_{ip}^S \quad (23)$$

Accordingly, LGC models allow researchers to model and explain inter-individual differences in person-specific degrees of trait change given change trajectories of a specified shape. The coefficients  $\beta_{0i}^I$  and  $\beta_{0i}^S$  represent the expected value on the intercept and slope factors of indicator  $i$  for a person scoring zero on the time-invariant covariate. The coefficients  $\beta_{1i}^I$  and  $\beta_{1i}^S$  denote the expected change in the intercept and slope factors if the time-invariant covariate increases by one unit. The error terms  $\epsilon_{ip}^I$  and  $\epsilon_{ip}^S$  capture unexplained inter-individual heterogeneity in the initial trait values ( $Int_{ip}$ ) and growth trajectories ( $Slo_{ip}$ ). It can be shown that the same expected change trajectories given by Equations (22) and (23) can be modeled by use of MN-LST models. That is, the expected change trajectories modeled in the moderated LGC model can be reproduced by the MN-LST model given certain parameter restrictions (see Appendix B, for details). This shows that the MN-LST model is more flexible in modeling different forms or shapes of trait change. However, in MN-LST models change trajectories vary across levels of the covariate, while LGC models allow for person-specific degrees of trait change.

A limitation of the multiple-indicator LGC models is that it does not permit researchers to relate time-varying covariates or the combination of time-invariant and time-varying covariates directly to latent intercept and slope factors in the model. Hence, it is not possible to examine the effect of a time-varying covariate (e.g., daily stress) on the intercept and slope factors (i.e., trait change parameters). Furthermore, it is not possible to directly investigate synergistic interaction effects (i.e., interaction between person and situational factors) on the intercept and slope factors, as these latent variables are time-invariant. In contrast, the MN-LST framework allows researchers to relate time-varying covariates, time-

invariant covariates, and the combination of both types of covariates directly to *trait change parameters* in the model.

Another advantage of MN-LST models is that they are more flexible and allow the specification of any kind of trait change trajectories. In LGC models, researchers oftentimes assume linear trait change, which is often a too restrictive. In practice, researchers may start by fitting a MN-LST model with unrestrictive trait change to the data before fitting a traditional LGC model in order to test a specific form of trait change.

By imposing certain equality constraints on the regression coefficients in MN-LST models, researchers may test specific hypothesis concerning the shape of trait change or trait stability. For example, a MN-LST models with time-invariant intercepts and time-invariant trait loadings would suggest that the latent trait is perfectly stable over time (i.e., no additive and no multiplicative trait change). Regressing the latent trait on the time-invariant covariate, while constraining the latent state-residuals as well as the latent errors to be equal across time, yields a random-intercept multilevel CFA model with a time-invariant covariate.

Alternatively, researchers may test specific trait change patterns (e.g., adaptation processes) that may occur after an intervention or a critical life event. Consider, for example, a measurement design with three time points and an intervention which takes place between the first and the second measurement occasion. The aim of the intervention may be to reduce depression or unhealthy behavior (e.g., quitting smoking). It is reasonable to assume that individuals in the control group will not change on average over the course of the study (i.e., no additive trait change if  $X=0$ ), where individuals in the intervention group ( $X=1$ ) will experience a strong reduction (i.e., negative additive trait change) shortly after the intervention, but a less strong reduction over time. This specific additive trait change pattern can be tested in the new MN-LST framework by imposing certain parameter constraints on the regression coefficients pertaining to the additive trait change parameter. More specifically, the following constraint is needed to test whether there is no significant additive trait change

in the control group ( $\beta_{0i2}^A = \beta_{0i3}^A = 0$ ), whereas the following constraint is needed to test whether the reduction in depressive symptoms between T1 and T2 is larger than between T1 and T3 ( $|\beta_{1i2}^A| > |\beta_{1i3}^A|$  or  $|\beta_{1i2}^A| - |\beta_{1i3}^A| > 0$ ). This shows that the new MN-LST framework is very flexible for testing differential trait change hypotheses, as any kind of trait change trajectory that is supported by a well-grounded theory can be flexibly modelled.

Overall, MN-LST as well as LGC models bear advantages with respect to certain applications. To select an appropriate model in practice, researchers may focus on two key aspects. Does theory suggest a specific form of trait change? In this case, we recommend (hybrid) LGC models as they are more parsimonious and facilitate the specification of individual (person-specific) degrees of trait change. Second, do researchers aim at the investigation of synergistic interaction effects with regard to trait change parameter? That is, do researchers seek to include time-invariant variables, time-varying variables, and the interaction of both into the model in order to explain trait change? In this case, MN-LST models are recommended, as they allow for a flexible and a fine-grained analysis of synergetic interaction effects in LST-R models.

Many social and personality researchers may find MN-LST models attractive for the investigation of moderated consistency and/or moderated specificity coefficients. For example, MN-LST models may be used to examine which personality traits (e.g., neuroticism), situational factors (e.g., stress), or the combination of both are most relevant to increase or decrease the consistency of human behavior over time (e.g., dyadic copying). Additionally, extended LGC as well as extended MN-LST models can be used to study person-specific variability around a fixed or changing trait. To this regard, simulation studies are needed to examine how many time points are sufficient to accurately predict inter- or intra-individual variability parameters in MN-LST models.

In sum, the MN-LST framework represents a generalization of many traditional approaches to model parameter heterogeneity in LST models. For example, a MN-LST model with a time-invariant covariate that can take two values (e.g., 0 = male; 1 = female) is equal to a multiple group LST model. If the time-invariant covariate can take multiple values (e.g., representing different nations), the MN-LST models can be viewed as a multilevel LST model with nation as a cluster variable. On the other hand, MN-LST model may also be viewed as a generalization of finite mixture LST models, where the covariate is used to uncover heterogeneity in the model parameters. The advantages of the MN-LST framework is that both nominal and continuous time-varying and time-invariant variables can be included simultaneously in the model, which is not always possible using the discussed traditional approaches.

### **Relation to Modern Approaches to Investigate Parameter Heterogeneity**

Recently, two alternative approaches to model parameter heterogeneity in structural equation models have been suggested. The first approach uses recursive partitioning algorithms to explore possible splits of a given data set that are associated with significant differences in the model parameters. The approach is implemented in the R packages `semtree` (Brandmaier et al., 2013) and `semforests` (Brandmaier et al., 2016). SEM Trees as well as SEM Forests are exploratory approaches and allow researchers to examine parameter heterogeneity in a predefined structural equation model. Compared to our approach, SEM trees are particularly useful when researchers seek to (exploratory) identify predictors of parameter heterogeneity from a large set of potential covariates. Especially higher interactions between covariates as well as nonlinear associations are inherently modeled and accounted for when using this approach. One drawback is that continuous predictors often gain disproportionately high importance when carelessly using the default settings, as this will lead to multiple splits of the data sets. This can be circumvented by

splitting continuous covariates into theoretically meaningful parts. Using the MN-LST framework, it may be easier to impose parameter constraints and include time-varying covariates in addition to other covariates.

The second approach is termed individual parameter contribution (IPC) regression proposed by Arnold, Oberski, Brandmaier and Voelkle, 2019. The IPC approach approximates the individual parameter values for each person and regresses these IPCs on external covariates following the principle of classical linear regression analysis. The IPC approach is based on maximum likelihood estimation and requires at least two steps. First, a structural equation model (without covariates) is fit to a given data set. In a second step, the IPC are computed and regressed on external covariates. The IPC approach is implemented in the R package `ipcr` (Arnold et al., 2019). The recently proposed IPC approach is a promising alternative to MNLFA as it also accounts for parameter heterogeneity building on the principals of classical regression analysis. However, the current version of the `ipcr` package does not yet enable researchers to easily impose certain constraints on the regression coefficients. Furthermore, Bayesian estimation, as compared to maximum likelihood estimation, allows to incorporate prior information into the model, which may be beneficial to increase statistical power to identify parameter heterogeneity.

### **Inclusion of latent covariates**

The MN-LST approach can be extended to the inclusion of latent external covariates, which is another important advantage over traditional approaches like multiple group models, multilevel models, or MIMIC models. Psychological constructs are rarely assumed to be measured without measurement error. Measurement error in independent variables may lead to biased estimation of effects and may thus entail incorrect theoretical conclusions. Especially with respect to time-varying covariates, it has been recommended to include the latent person-specific mean instead of the observed person-specific mean score as a time-

invariant covariate (Lüdtke et al., 2008). In order to include latent covariates in MN-LST models we use an extended multiple construct approach, in which a LST model is specified for each time-varying covariate to separate latent trait (mean) scores from time-specific deviations. Change and variability parameters of the MN-LST model are then regressed on the respective factor scores of the additional LST models. We provide an example code for a model with the latent group mean centered time-varying covariate stress at work in the supplemental material, which can be found on OSF (Link: <https://osf.io/rdv74>).

### Conclusion

We presented a general framework for the inclusion of time-varying covariates, time-invariant covariates, and their combined interaction effects in modern LST models. The new framework makes a fine-grained analysis of trait change, synergistic interaction effects, and within- or between-person variability processes possible. Furthermore, the new modeling framework was compared to extended LGC models and illustrated with an empirical application studying dyadic coping in romantic relationships.

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Figures

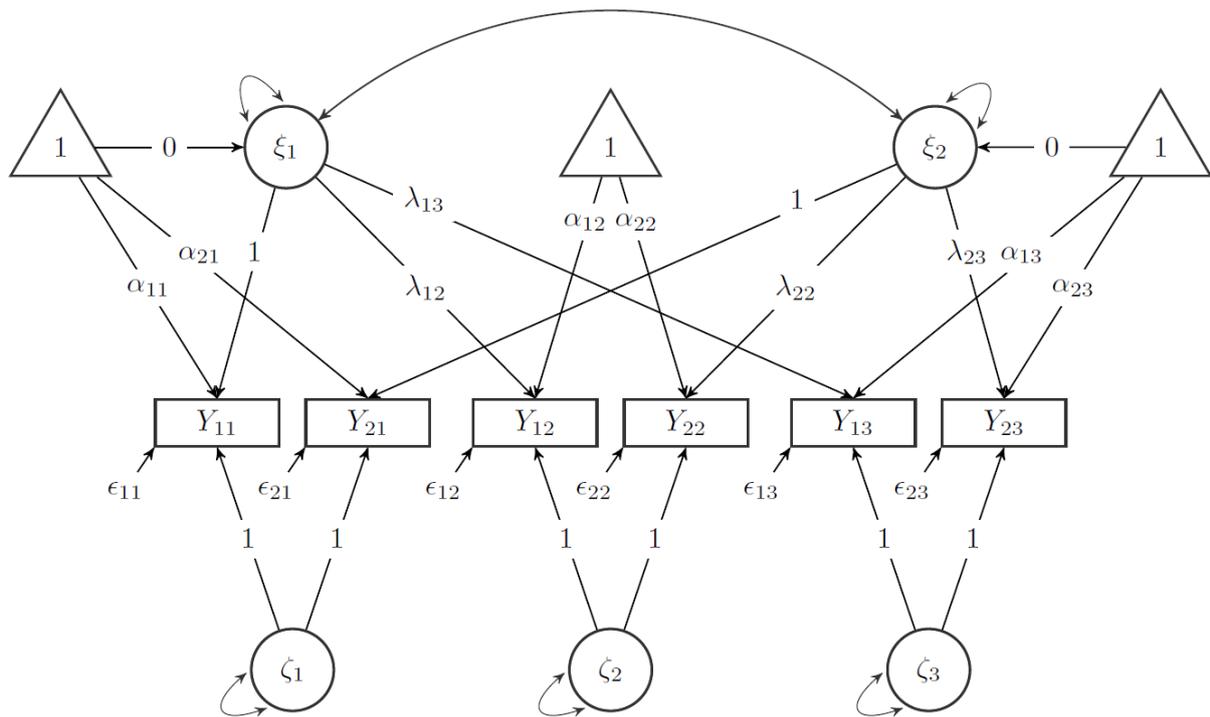


Figure 1: LST-R model of three measurement occasions with two indicators and indicator-specific trait variables.  $\alpha_{it}$ : intercept parameter of indicator  $i$  at time  $t$ ;  $\epsilon_{it}$ : measurement error variable of indicator  $i$  at time  $t$ ;  $\lambda_{it}$ : trait factor loading of indicator  $i$  at time  $t$ ;  $\xi_i$ : indicator-specific trait factors;  $Y_{it}$ : observed indicator variable  $i$  at time  $t$ ;  $\zeta_t$ : latent state-residual variable at time  $t$ ;  $i$ : indicator;  $t$ : time point.

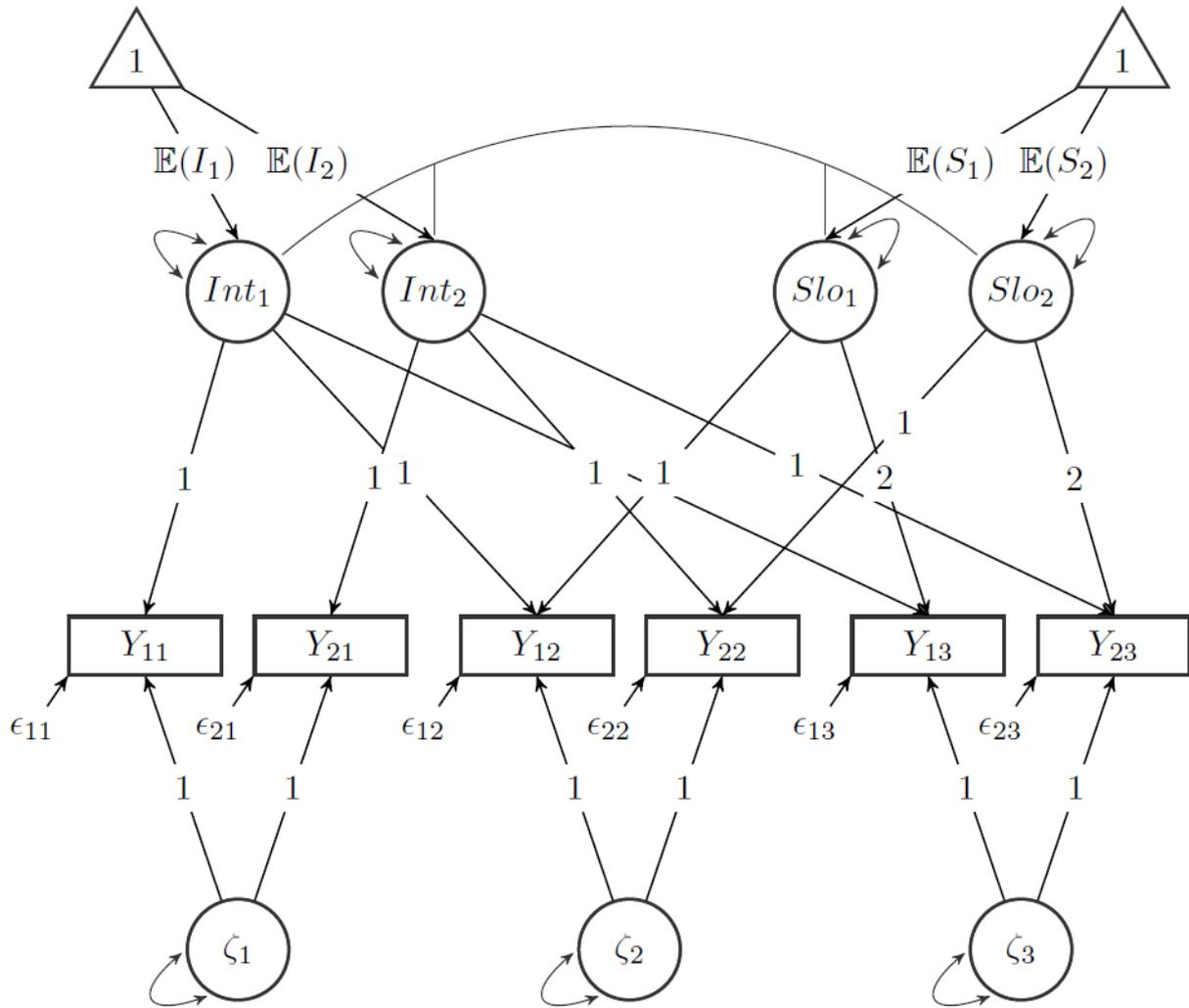


Figure 2: LGC model of three measurement occasions with two indicators. As is common practice, all intercept factor loadings and the first slope factor loading are fixed to 1. To model linear growth, slope factor loadings of the third measurement occasion are fixed to 2. Additionally, all intercepts of observed variables are fixed to 0 (they are omitted here in order to keep the figure as clear as possible).  $\alpha_{it}$ : intercept parameter of indicator  $i$  at time  $t$ ;  $\epsilon_{it}$ : measurement error variable of indicator  $i$  at time  $t$ ;  $E$ : expectation;  $\lambda_{it}$ : trait factor loading of indicator  $i$  at time  $t$ ;  $Int_i$ : indicator-specific intercept factors;  $Slo_i$ : indicator-specific slope factors;  $\xi_i$ : indicator-specific trait factors;  $Y_{it}$ : observed indicator variable  $i$  at time  $t$ ;  $\zeta_t$ : latent state-residual variable at time  $t$ ;  $i$ : indicator;  $t$ : time point.

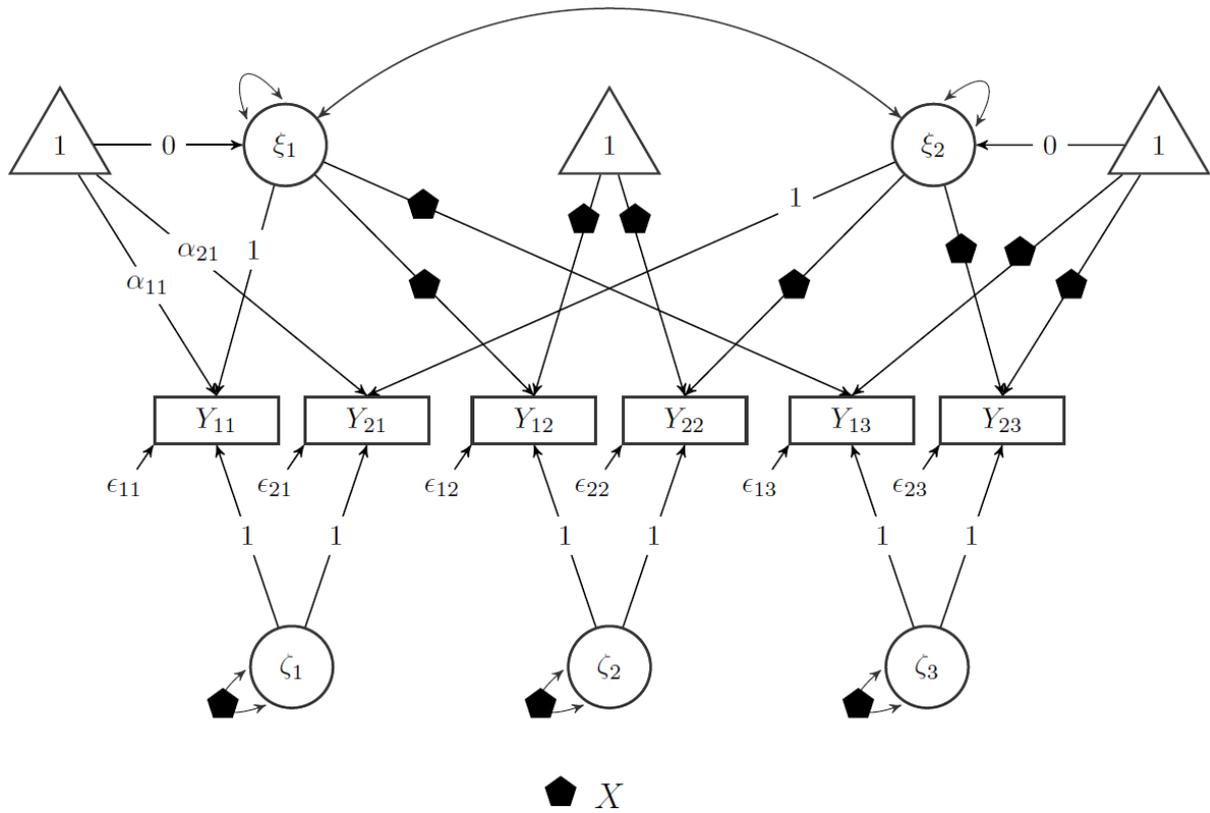
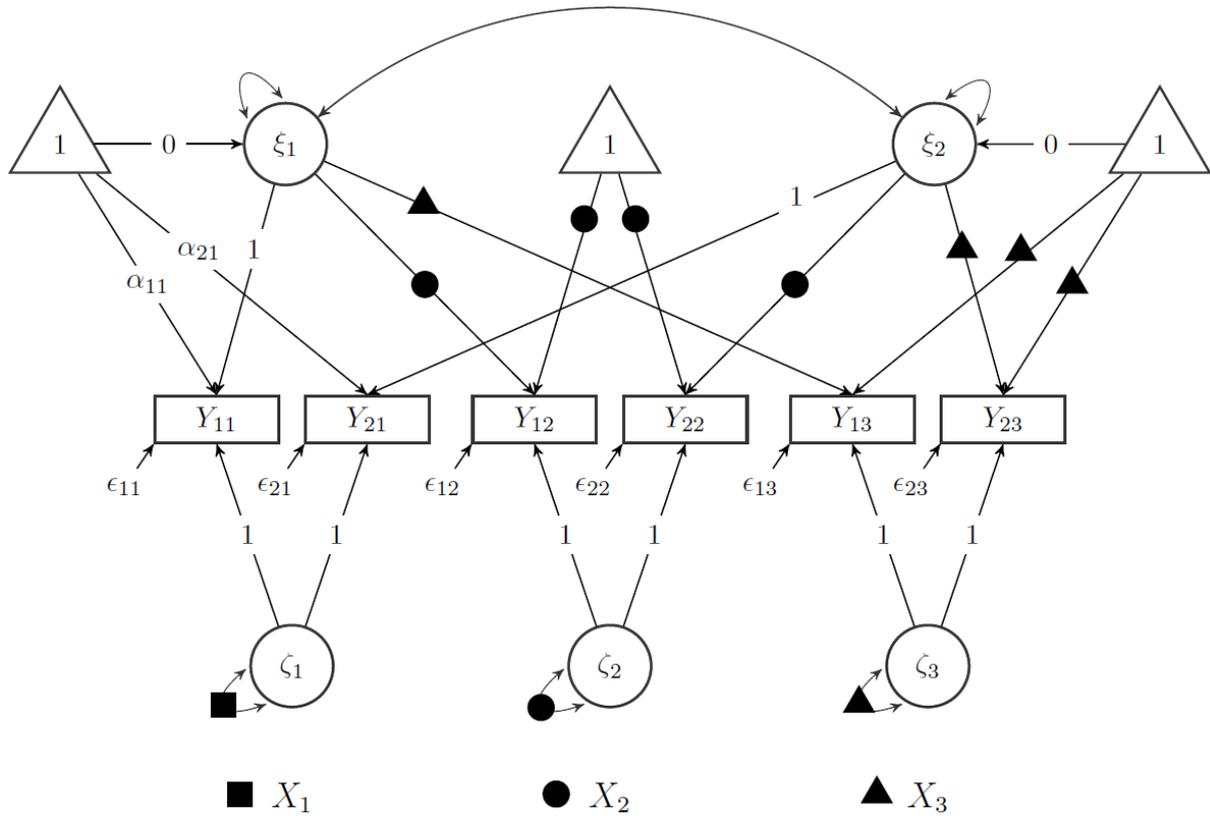
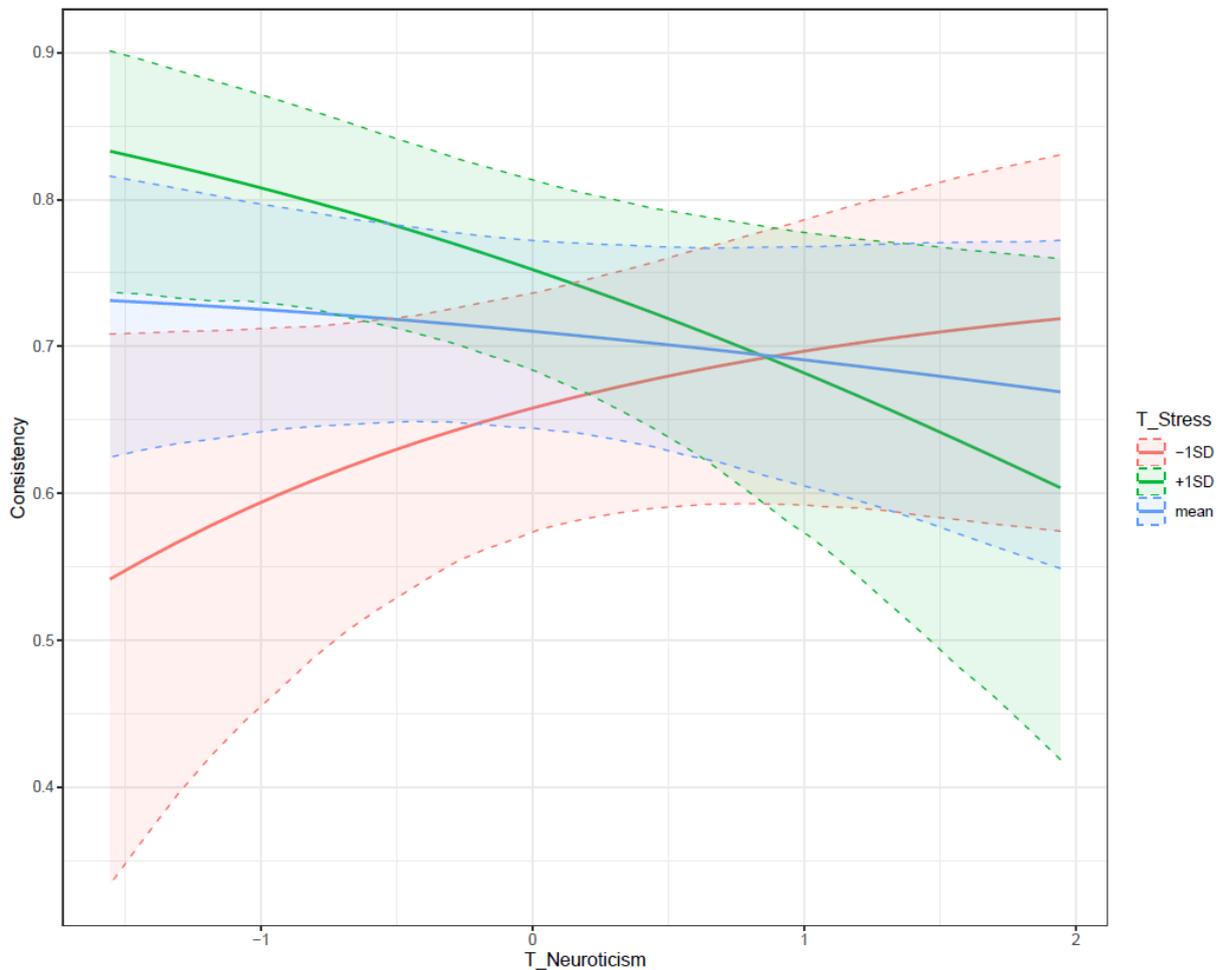


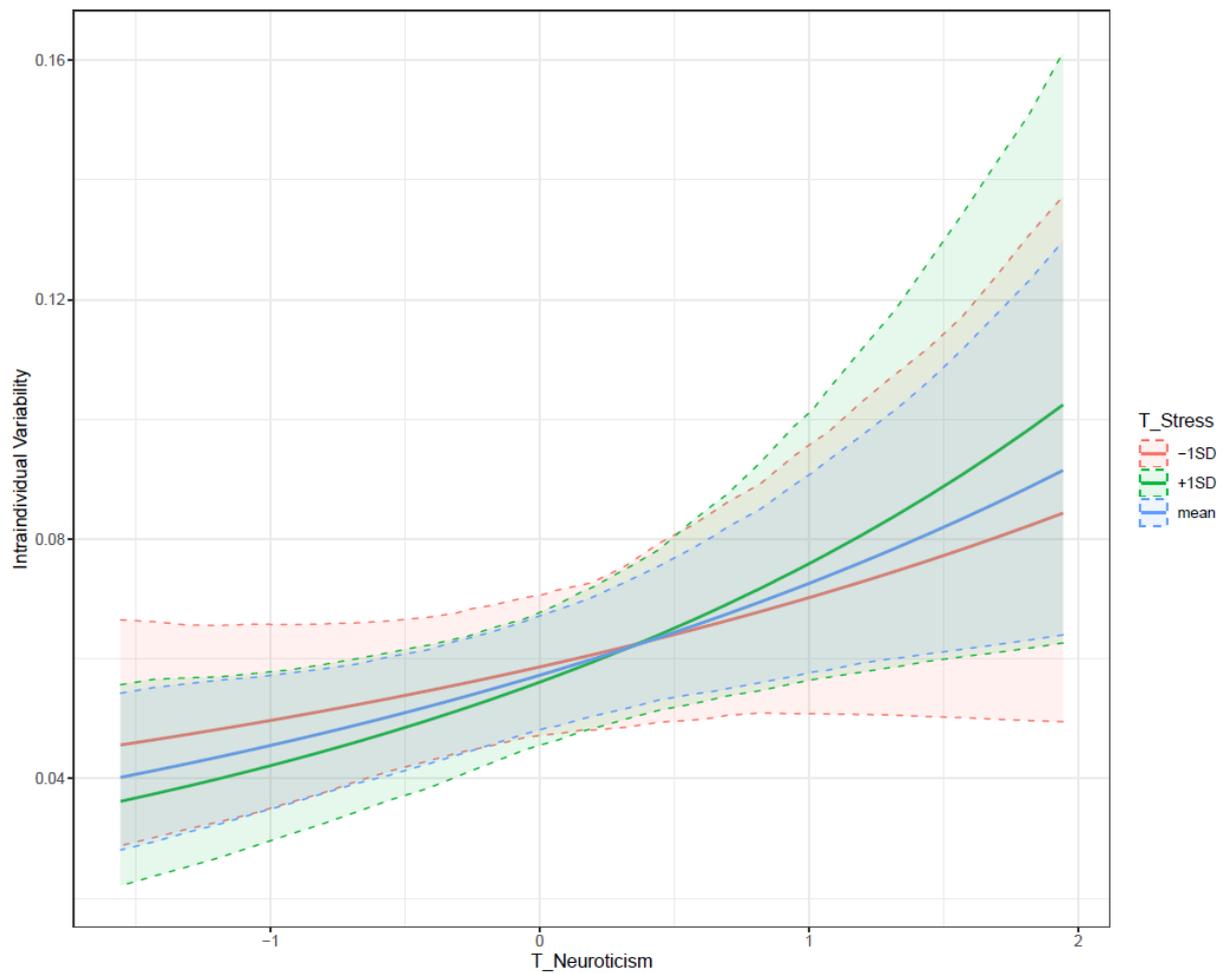
Figure 3: Nonlinear LST model with a time-invariant covariate  $X$ . Key parameters of trait change and variability (marked with a pentagon), i.e. intercepts, trait-factor loadings and latent state residual variances are allowed to vary across levels of the external covariate.  $\alpha_{it}$ : intercept parameter of indicator  $i$  at time  $t$ ;  $\epsilon_{it}$ : measurement error variable of indicator  $i$  at time  $t$ ;  $\lambda_{it}$ : trait factor loading of indicator  $i$  at time  $t$ ;  $\xi_i$ : indicator-specific trait factors;  $Y_{it}$ : observed indicator variable  $i$  at time  $t$ ;  $\zeta_t$ : latent state-residual variable at time  $t$ ;  $i$ : indicator;  $t$ : time point.



*Figure 4:* Nonlinear LST model with time-varying covariate  $X_t$ . Moderated parameters of trait change and variability are marked with geometric symbols (i.e., intercepts, trait-factor loadings and latent state-residual variances). These parameters are allowed to vary across levels of the external covariate of the corresponding measurement occasion.  $\alpha_{it}$ : intercept parameter of indicator  $i$  at time  $t$ ;  $\epsilon_{it}$ : measurement error variable of indicator  $i$  at time  $t$ ;  $\lambda_{it}$ : trait factor loading of indicator  $i$  at time  $t$ ;  $\xi_i$ : indicator-specific trait factors;  $Y_{it}$ : observed indicator variable  $i$  at time  $t$ ;  $\zeta_t$ : latent state-residual variable at time  $t$ ;  $i$ : indicator;  $t$ : time point.



*Figure 5:* Illustration of moderated Consistency at time 3 by the interaction of time-stable (within-person averaged) stress at work (i.e., T\_Stress) and time-invariant neuroticism (T\_Neuroticism), given the persons' time-specific stress level corresponds to the respective persons' average stress level (i.e., controlling for state stress). The solid lines represent the effect of neuroticism on the consistency coefficient at time 3 for averagely stressed individuals (blue line), above-average stressed persons (+ 1 SD, green line) and below average stressed persons (- 1 SD, red line). The consistency coefficient was calculated for Markov-Chain Monte-Carlo samples at each post-burn-in iteration, with solid lines representing the mean of the resulting posterior distribution and dashed lines representing the corresponding 95% credibility intervals (2.5% and 97.5% quantiles of the respective distribution).



*Figure 6:* Illustration of moderated intraindividual variability in dependence of time-invariant neuroticism (i.e.,  $T\_Neuroticism$ ) and time-invariant mean-stress (i.e.,  $T\_Stress$ ) and their interaction. The solid lines represent the effect of neuroticism on intraindividual variability for persons on an average mean stress level (blue line), persons on a mean stress level 1  $SD$  above average, green line) and persons on a mean stress level 1  $SD$  below average (red line). The specificity coefficient was calculated for Markov-Chain Monte-Carlo samples at each post-burn-in iteration, with solid lines representing the mean of the resulting posterior distribution and dashed lines representing the corresponding 95% credibility intervals (2.5% and 97.5% quantiles of the respective distribution).

## Tables

Table 1 *Unstandardized estimates from MN-LST analysis*

Moderated parameters	$\beta_{0it}$	$\beta_{T\_Neuro\_it}$	$\beta_{T\_Stress\_it}$	$\beta_{O\_Stress\_it}$	$\beta_{T\_Neuro \times O\_Stress\_it}$	$\beta_{T\_Neuro \times T\_Stress\_it}$
Initial Intercepts $\alpha_{i1}$						
$\alpha_{11}$	4.071 [4.029, 4.111]					
$\alpha_{21}$	4.203 [4.160, 4.246]	<b>-.117 [-.169, -.062]</b>	-.008 [-.051, .036]	.000 [-.034, .035]	-.021 [-.068, .024]	.005 [-.058, .065]
$\alpha_{31}$	4.412 [4.370, 4.454]					
Intercept Changes $\Delta_{\alpha_{it}}$						
$\Delta_{\alpha_{i2}}$	<b>-.042 [-.082, -.002]</b>	.013 [-.044, .070]	-.023 [-.071, .025]	-.028 [-.072, .015]	-.015 [-.077, .046]	.031 [-.038, .098]
$\Delta_{\alpha_{i3}}$	<b>-.179 [-.218, -.140]</b>	.020 [-.033, .075]	-.032 [-.077, .013]	.011 [-.036, .058]	.055 [-.012, .122]	-.013 [-.078, .052]
$\Delta_{\alpha_{i4}}$	<b>-.177 [-.218, -.138]</b>	-.005 [-.063, .052]	.007 [-.040, .053]	-.001 [-.047, .042]	.001 [-.057, .062]	-.029 [-.096, .039]
$\Delta_{\alpha_{i5}}$	<b>-.147 [-.189, -.107]</b>	.009 [-.049, .066]	.026 [-.021, .072]	.012 [-.032, .057]	.032 [-.031, .096]	-.062 [-.132, .006]
Trait factor loadings $\lambda_{it}$						
$\lambda_{i2}$	1.065 [0.957, 1.181]	.112 [-.002, .227]	.032 [-.068, .129]	.050 [-.073, .172]	.059 [-.105, .221]	-.035 [-.172, .102]
$\lambda_{i3}$	<b>1.214 [1.098, 1.338]</b>	.083 [-.025, .193]	<b>.148 [.054, .241]</b>	.063 [-.071, .195]	.003 [-.175, .177]	<b>-.150 [-.281, -.022]</b>
$\lambda_{i4}$	<b>1.184 [1.070, 1.311]</b>	<b>.118 [.008, .233]</b>	.019 [-.077, .112]	.072 [-.047, .190]	.013 [-.147, .170]	-.033 [-.167, .101]
$\lambda_{i5}$	1.065 [0.953, 1.186]	.095 [-.022, .214]	-.007 [-.108, .094]	-.075 [-.195, .048]	-.045 [-.210, .116]	-.000 [-.140, .138]
State Residual variances $\sigma_{\zeta_t}^2$						
$\sigma_{\zeta_1}^2$	.089 [.070, .111]					
$\sigma_{\zeta_2}^2$	.075 [.058, .095]					
$\sigma_{\zeta_3}^2$	.073 [.057, .092]	<b>1.249 [1.103, 1.409]</b>	0.984 [0.889, 1.090]	1.026 [0.882, 1.200]	1.017 [0.839, 1.229]	1.054 [0.918, 1.213]
$\sigma_{\zeta_4}^2$	.086 [.068, .106]					
$\sigma_{\zeta_5}^2$	.102 [.083, .124]					

## Moderated Nonlinear Latent State-Trait Models

*Note.*  $\beta_{0it}$  parameters for trait factor loadings printed in bold type significantly differ from 1 (i.e., multiplicative trait change).  $\beta_{0it}$  parameters for intercept change  $\Delta\alpha_{it}$  and effects of covariates  $k$  ( $\beta_{kit}$ ) printed in bold type significantly differ from 0. With the exception of  $\beta_{0it}$  parameters for initial intercepts  $\alpha_{i1}$ , all parameters are set invariant across indicators  $i$ . As variance-related parameters were exponentiated, values  $> 1$  indicate a positive and values  $< 1$  indicate a negative effect on situational variability (effects that significantly differ from 1 are printed in bold type).  $\beta_{0it}$ : expected parameter estimates for averagely neurotic individuals at an average inter- and intra-individual stress level.  $\beta_{T\_Neuro\_it}$ : effects of the time-stable covariate neuroticism;  $\beta_{T\_Stress\_it}$ : effects of the time-stable person-specific mean stress level;  $\beta_{O\_Stress\_it}$ : effects of the situation-specific level of stress at work;  $\beta_{T\_Neuro\_x\_O\_Stress\_it}$ : effects of the synergistic interaction between neuroticism and the situation-specific level of stress at work;  $\beta_{T\_Neuro\_x\_T\_Stress\_it}$ : effects of the interaction between neuroticism and the time-stable person-specific mean stress level.  $\alpha_{i1}$ : intercept parameter of indicator  $i$  at time 1;  $\Delta\alpha_{it}$ : intercept change between time 1 and time  $t$ ;  $\lambda_{it}$ : trait factor loading at time  $t$ ;  $\sigma_{\zeta_t}^2$ : latent state residual variance at time  $t$ ;  $i$ : indicator;  $t$ : time point.

Table 2

*Unstandardized estimates from extended MN-LST analysis*

Moderated parameters	$\beta_{0it}$	$\beta_{T\_Neuro\_it}$	$\beta_{T\_Stress\_it}$	$\beta_{O\_Stress\_it}$	$\beta_{T\_Neuro \times O\_Stress\_it}$	$\beta_{T\_Neuro \times T\_Stress\_it}$
Intercepts $\alpha_{it}$						
$\alpha_{11}$	4.075 [4.037, 4.113]					
$\alpha_{21}$	4.207 [4.167, 4.248]	<b>-.110 [-.159, -.061]</b>	-.006 [-.049, .037]	.001 [-.034, .035]	-.021 [-.067, .024]	-.010 [-.069, .050]
$\alpha_{31}$	4.416 [4.376, 4.456]					
Intercept change $\Delta_{\alpha_{it}}$						
$\Delta_{\alpha_{i2}}$	<b>-.047 [-.086, -.008]</b>	-.002 [-.055, .055]	-.021 [-.066, .024]	-.026 [-.069, .017]	-.020 [-.083, .043]	.041 [-.024, .106]
$\Delta_{\alpha_{i3}}$	<b>-.177 [-.215, -.140]</b>	.004 [-.049, .058]	-.030 [-.075, .014]	.009 [-.038, .058]	.036 [-.032, .104]	-.001 [-.063, .061]
$\Delta_{\alpha_{i4}}$	<b>-.182 [-.219, -.145]</b>	-.010 [-.064, .044]	-.001 [-.046, .043]	.007 [-.036, .050]	.005 [-.053, .061]	-.012 [-.077, .052]
$\Delta_{\alpha_{i5}}$	<b>-.154 [-.193, -.114]</b>	.001 [-.054, .057]	.028 [-.017, .072]	.016 [-.025, .059]	.030 [-.028, .087]	-.029 [-.093, .034]
Trait factor loadings $\lambda_{it}$						
$\lambda_{i2}$	1.061 [0.956, 1.173]	<b>.120 [.010, .233]</b>	.027 [-.071, .123]	.056 [-.061, .177]	.079 [-.081, .236]	-.042 [-.177, .088]
$\lambda_{i3}$	<b>1.181 [1.074, 1.296]</b>	.104 [-.006, .214]	<b>.099 [.006, .192]</b>	.041 [-.091, .168]	.023 [-.136, .183]	-.119 [-.249, .008]
$\lambda_{i4}$	<b>1.211 [1.098, 1.328]</b>	.100 [-.009, .215]	.044 [-.046, .135]	.074 [-.040, .188]	.020 [-.126, .170]	-.064 [-.197, .064]
$\lambda_{i5}$	1.079 [0.970, 1.201]	.065 [-.046, .181]	-.004 [-.103, .092]	-.056 [-.170, .053]	-.034 [-.184, .119]	-.054 [-.180, .078]
Intra-individual variability $\sigma_{\zeta_p}^2$						
$\sigma_{\zeta_p}^2$	$exp(\beta_{0it})$ 0.057 [0.048, 0.067]	$exp(\beta_{T\_Neuro\_it})$ <b>1.262 [1.067, 1.496]</b>	$exp(\beta_{T\_Stress\_it})$ 0.982 [0.852, 1.124]			$exp(\beta_{T\_Neuro \times T\_Stress\_it})$ 1.062 [0.875, 1.283]

## Moderated Nonlinear Latent State-Trait Models

*Note.*  $\beta_{0it}$  parameters for trait factor loadings printed in bold type significantly differ from 1 (i.e., multiplicative trait change).  $\beta_{0it}$  parameters for intercept change  $\Delta\alpha_{it}$  and effects of covariates  $k$  ( $\beta_{kit}$ ) printed in bold type significantly differ from 0. With the exception of  $\beta_{0it}$  parameters for initial intercepts  $\alpha_{i1}$ , all parameters are set invariant across indicators  $i$ . As variance-related parameters were exponentiated, values  $> 1$  indicate a positive and values  $< 1$  indicate a negative effect on intra-individual variability (effects that significantly differ from 1 are printed in bold type).  $\beta_{0it}$ : expected parameter estimates for averagely neurotic individuals at an average inter- and intra-individual stress level.  $\beta_{T\_Neuro\_it}$ : effects of the time-stable covariate neuroticism;  $\beta_{T\_Stress\_it}$ : effects of the time-stable person-specific mean stress level;  $\beta_{O\_Stress\_it}$ : effects of the situation-specific level of stress at work;  $\beta_{T\_Neuro\_ \times\_ O\_Stress\_it}$ : effects of the synergistic interaction between neuroticism and the situation-specific level of stress at work;  $\beta_{T\_Neuro\_ \times\_ T\_Stress\_it}$ : effects of the interaction between neuroticism and time-stable person-specific mean stress level;  $\alpha_{i1}$ : intercept parameter of indicator  $i$  at time 1;  $\Delta\alpha_{it}$ : intercept change between time 1 and time  $t$ ;  $\lambda_{it}$ : trait factor loading at time  $t$ ;  $\sigma_{\zeta_p}^2$ : person-specific intra-individual variability parameter;  $i$ : indicator;  $t$ : time point.

Table 3

*Comparison of MN-LST models and LGC models*

	<b>MN-LST Models</b>	<b>LGC Models</b>
Individual Trait Change	Trait change trajectories depend on the values of the given covariate(s).	Trait change trajectories can be modeled by means of latent variables. Individual degrees of trait change is presented in the factor score of the latent intercept and slope factors.
Shape of Trait Change	MN-LST models are general and do not assume a specific shape of trait change.	LGC models assume a specific (linear or nonlinear) form of trait change. This assumption may be relaxed in hybrid LGC models, where some factor loadings pertaining to the slope factor are freely estimated. Nevertheless, the shape of trait change is assumed to be the same across individuals.
Deterministic or Stochastic Relationships between Trait Change Parameters and External Covariates	Deterministic and stochastic relationships can be modeled. To be in line with LGC models, researchers must explicitly model error terms and allow correlations among error terms in MN-LST models.	In general, a stochastic relationship is assumed and implemented in standard SEM software. Error terms and correlations among error terms are automatically estimated.
Synergetic Interaction Effects	Synergetic person by situation interaction effects can directly be related to trait change parameters in MN-LST models.	Synergetic person by situation interaction effects cannot directly be linked to the latent factors in LGC models. Time varying covariates as well as product variables may be linked to the observed variables.

## Moderated Nonlinear Latent State-Trait Models

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Relate Covariates to Inter- and Intra-Individual Variability Processes	Yes. MN-LST models can be parameterized in such a way that external variables can be linked to inter- or intra-individual variability parameters.	Yes. LGC models can be parameterized in such way that external variables can be linked to inter- or intra-individual variability parameters.
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## Appendix A: Parameter constraints

### *Equality Restrictions Across Indicators*

A reasonable restriction in the MN-LST framework with respect to parameters of additive and multiplicative trait change is to set the effects of a time-varying covariate  $X_{tw}$  or a time-invariant covariate  $X_v$  to be equal across different indicators. We recommend imposing the following parameter equality restrictions to ensure that the effects of the covariates are invariant across different indicators ( $i$  and  $i'$ , where  $i \neq i'$ ). Note that the effects can still differ across time points ( $t$  and  $t'$  where  $t \neq t'$ ) as well as different covariates. In case of one time-invariant or time-varying covariate, the following restrictions are recommended:

$$\beta_{1it}^{\Delta} = \beta_{1i't}^{\Delta} = \beta_{1t}^{\Delta} \quad \forall i, i' \quad (\text{A.1})$$

$$\beta_{1it}^{\lambda} = \beta_{1i't}^{\lambda} = \beta_{1t}^{\lambda} \quad \forall i, i' \quad (\text{A.2})$$

The above equality restrictions (Equation A.1 and A.2) imply that the effects of the covariates on  $\Delta_{\alpha_{it}}$  and  $\lambda_{it}$  (where  $t > 1$ ) are equal across all indicators (i.e., no indicator-specific effects of the covariates) of the same construct. In addition, researchers may also impose the following equality restrictions to test whether trait change is equal across indicators if the covariate has a value of zero:

$$\beta_{0it}^{\Delta} = \beta_{0i't}^{\Delta} = \beta_{0t}^{\Delta} \quad \forall i, i' \quad (\text{A.3})$$

$$\beta_{0it}^{\lambda} = \beta_{0i't}^{\lambda} = \beta_{0t}^{\lambda} \quad \forall i, i' \quad (\text{A.4})$$

Note that  $\beta_{0it}^{\Delta}$  and  $\beta_{0it}^{\lambda}$  denote the expected intercept-change  $\Delta_{\alpha_{it}}$  and trait loadings  $\lambda_{it}$  for  $t > 1$ , respectively, given the covariates have a value of zero. Together the restrictions in Equations (A.1) – (A.4) imply that trait change is perfectly homogenous across indicators, i.e., that all indicators show the same changes across time. These constraints may be too restrictive if indicators are heterogenous in empirical applications.

### *Equality Restrictions Across Time*

Many researchers are interested in adaptation processes (e.g., adaptation to a critical life event). An adaptation process is present if the effect of a covariate on the parameters  $\Delta\alpha_{it}$  and  $\lambda_{it}$  consistently decreases over time. For instance, time-varying covariates (e.g., an intervention taking place for all persons at the same time point) may have differential effects on trait change over time. In case of a critical life event (e.g., unemployment) the lagged effects on the intercepts or trait loadings may slowly approach zero over time, indicating that the effect of the time-varying (shock) variable diminishes over time. Hypotheses regarding adaptation processes can easily be integrated into the MN-LST framework by specifying parameter restrictions with respect to diminishing effects of an intervention or life event across time (e.g., for an event / intervention taking place just before time point  $t$ :  $\beta_{kit}^A > \beta_{ki(t+1)}^A > \beta_{ki(t+2)}^A > \dots$ ). Furthermore, an event occurring at time  $t$  might cause a constant shift in trait levels that will not diminish across time, which could easily be tested by constraining the effect of the respective covariate on additive trait change parameters to be constant across time after the time of occurrence.

In other contexts, it might be more reasonable to assume that a time-invariant covariate causes a constant (i.e., time-invariant) shift in the intercepts and trait loading parameters in the MN-LST model. A time-invariant shift in the intercepts implies that the covariate has a constant positive or negative effect on the general trait level while not affecting the amount of trait change. In the difference score parameterization of the MN-LST, a time-invariant level shift caused by a time-invariant covariate is present if the initial values  $\alpha_{i1}$  are moderated by the respective covariate, while there is no effect of the covariate on the additive trait change parameters (i.e.,  $\beta_{kit}^A = 0$  for covariate  $k$ ).

Consider the example of moderating change in dyadic coping behavior by the time-invariant covariate neuroticism. If  $\alpha_{i1}$  is moderated by neuroticism but  $\beta_{kit}^A = 0$  for neuroticism, the average level of coping skills differs between neurotic and less neurotic

persons, but trait change in dyadic coping is not affected by neuroticism. If in addition  $\beta_{0it}^A = 0$ , there is no additive trait change in dyadic coping. If, in contrast,  $\beta_{0it}^A = 0$  and  $\beta_{kit}^A \neq 0$  for covariate neuroticism (centered), there is no level trait change for averagely neurotic persons over time, but neuroticism has an effect on additive trait change, that is, additive trait change differs by  $\beta_{kit}^A$  between persons that differ in neuroticism by one unit.

Following a similar logic, researchers can impose equality restrictions with regard to the trait factor loadings if all loadings are freely estimated and the variances of the latent factors in the MN-LST model are fixed to 1 (using a standardized latent variable parameterization).

To test the above parameter equality restrictions, researcher may a) use fit statistics of overall model fit (e.g., DIC, AIC, BIC, Posterior Predictive P-Values, Bayesian RMSEA), b) specify individual parameter differences as new parameters in the MCMC sampling process, or c) inspect 95% credibility intervals for the  $\beta$ -coefficients in the unrestricted MN-LST model.

## Appendix B: A Formal Comparison of LGC and MN-LST models

To highlight some key differences between LGC and MN-LST modeling, we provide a more formal comparison. The basic measurement equation of both models can be written as follows:

$$Y_{itp} = \xi_{itp} + \delta_{it}\zeta_{tp} + \epsilon_{itp} \quad (\text{B.1})$$

where  $\xi_{itp}$  is the latent trait,  $\delta_{it}\zeta_{tp}$  is the weighted state residual, and  $\epsilon_{itp}$  is the measurement error variable. Again,  $i$  denotes the indicator,  $t$  represents the time point, and  $p$  denotes the person. In LGC models, the latent trait  $\xi_{itp}$  is decomposed as follows:

$$\xi_{itp} = \xi_{i1p} + f \cdot (\xi_{i2p} - \xi_{i1p}) \quad (\text{B.2})$$

where  $\xi_{i1p} := Int_{ip}$  and  $(\xi_{i2p} - \xi_{i1p}) := Slo_{ip}$ . The function  $f$  determines the shape of trait change. For example, in case of linear trait change  $f = (t - 1)$ , the above Equation is equal to:  $\xi_{itp} = Int_{ip} + (t - 1) \cdot Slo_{ip}$ . Next, the intercept and slope factors might be regressed on a time-invariant covariate:

$$\mathbb{E}(Int_{ip}|X_{v(p)}) = \beta_{0i}^I + \beta_{1i}^I X_{v(p)} \quad (\text{B.3})$$

$$\mathbb{E}(Slo_{ip}|X_{v(p)}) = \beta_{0i}^S + \beta_{1i}^S X_{v(p)} \quad (\text{B.4})$$

with possibly correlated residual terms  $\epsilon_{ip}^I$  and  $\epsilon_{ip}^S$ .

In contrast, in MN-LST models, trait variables at  $t > 1$  are modeled as

$$\xi_{itp} = \Delta_{\alpha_{itv}} + \lambda_{it}\xi_{i1p} + \alpha_{i1v} \quad (\text{B.5})$$

where  $\Delta_{\alpha_{itv}}$  represent the additive trait change parameter,  $\lambda_{it}$  is the multiplicative trait change parameter, and  $\alpha_{i1v}$  is the initial average trait level. Note that the index  $v$  indicates that  $\Delta_{\alpha_{itv}}$  and  $\alpha_{i1v}$  may vary across values  $v$  of a moderating covariate. The above Equation can equivalently be written as follows (in terms of expectations):

$$\mathbb{E}(\xi_{itp} - \xi_{i1p}) = \mathbb{E}(\Delta_{\alpha_{itv}}) + (\lambda_{it} - 1)\mathbb{E}(\xi_{i1p}) + \mathbb{E}(\alpha_{i1v}) \quad (\text{B.6})$$

Let  $\lambda_{it} = 1$  and  $\mathbb{E}(\xi_{i1p}) = 0$ . This restriction implies that there is no multiplicative trait change and the latent trait at time 1 is centered. Similar as in LGC models, the initial trait level  $\alpha_{i1v}$  and additive trait parameter  $\Delta_{\alpha_{itv}}$  are regressed on a time-invariant covariate:

$$\mathbb{E}(\alpha_{i1v}|X_{v(p)}) = \beta_{0i}^l + \beta_{1i}^l X_{v(p)} \quad (\text{B.7})$$

$$\mathbb{E}(\Delta_{\alpha_{itv}}|X_{v(p)}) = f(\beta_{0it}^s) + f(\beta_{1it}^s) X_{v(p)} \quad (\text{B.8})$$

where  $\beta_{0i}^l, \beta_{1i}^l, \beta_{0it}^s$ , and  $\beta_{1it}^s$  represent the latent regression coefficients. For example, if  $X_{v(p)}$  is a categorical predictor which can take two values (0 = male, 1 = female), then  $\beta_{0i}^l$  reflects the expected initial trait level for males and  $\beta_{1i}^l$  represents the expected mean difference in the initial trait level. According to Equation (B.8), the regression of the additive trait change parameter on the covariate is restricted to follow a specific function. For example, to specify a linear growth function  $f = (t - 1)$ , researchers must impose the following parameter restrictions on the regression coefficients:

$$\beta_{0it}^s = (t - 1)\beta_{0i2}^s, \text{ where } t > 1 \quad (\text{B.9})$$

$$\beta_{1it}^s = (t - 1)\beta_{0i2}^s, \text{ where } t > 1 \quad (\text{B.10})$$

Equation (B.9) implies that the expected additive trait change for males  $\beta_{0it}^s$  follows a specific form (e.g. a linear form). Furthermore, Equation (B.10) states that the expected differences in the additive trait change parameter for males and females follows a specific form. These restrictions will lead to the same expected growth trajectories in the two groups as modeled in the LGC model given in Equations (B.3) and (B.4). However, in the MN-LST model it is not necessary to impose these restrictions. That is, the expected trait change trajectories modeled in the LGC model represent a restrictive variant of trajectories that could be modeled in the MN-LST framework. On the other hand, the LGC model includes person-specific residual terms for the slope factor, such that the degree of trait change is estimated as person-specific in the LGC model. Allowing for a flexible estimation of  $\beta_{0it}^s$  and  $\beta_{1it}^s$  (not imposing any restrictions as made in Equations (B.9) and (B.10)), change trajectories in the MN-LST

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model may vary across persons in dependence of their values on the included covariates. Note that person-specific initial values are also estimated in the MN-LST model in terms of the trait factor values.

In sum, the MN-LST framework is more flexible in terms of modeling different forms of trait change, whereas LGC models allow to model person-specific degrees of trait change given the specified shape of the change trajectory.

### Appendix C: Prior Settings Used in the Empirical Application

The following uninformative priors were used for the specification of the MN-LST model explaining interindividual occasion-specific variability. The following priors were set on the respective parameters for all indicators  $i$ , covariates  $k$ , and time points  $t$ :

$$\beta_{0i1}^{\alpha} \sim N(0, 0.001)$$

$$\beta_{ki1}^{\alpha} \sim N(0, 0.001)$$

$$\beta_{0it}^{\Delta} \sim N(0, 0.001)$$

$$\beta_{kit}^{\Delta} \sim N(0, 0.001)$$

$$\beta_{0it}^{\lambda} \sim N(1, 0.001)$$

$$\beta_{kit}^{\lambda} \sim N(0, 0.001)$$

$$\beta_{kt}^{\sigma} \sim N(0, 0.001)$$

$$\epsilon_{it} \sim IG(0.001, 0.001)$$

$$\begin{bmatrix} \xi_{11} \\ \xi_{21} \\ \xi_{31} \end{bmatrix} = MVN(\boldsymbol{\mu}, \mathbf{T})$$

$$\text{with } \mathbf{T} = \begin{bmatrix} \tau_1^2 & & \\ \tau_{12} & \tau_1^2 & \\ \tau_{13} & \tau_{13} & \tau_2^2 \end{bmatrix}, \boldsymbol{\mu} = \begin{matrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{matrix}, \text{ and}$$

$$\mathbf{T} \sim IW(\boldsymbol{\Psi}, \nu)$$

with  $\boldsymbol{\Psi}$  specified as a diagonal unit matrix of size  $d=3$  and  $\nu = d + 1 = 4$ ,  $N$  denoting the normal distribution,  $MVN$  denoting the multivariate normal distribution,  $IG$  the inverse gamma distribution, and  $IW$  the inverse Wishart distribution. Parameter constraints were imposed by specifying highly informative priors on the respective parameters:

$$\mu_i \sim (0, 1^{10})$$

$$\delta_{it} \sim N(1, 1^{10})$$

$$\lambda_{i1} \sim N(1, 1^{10})$$