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Using Structural Equation Modeling to Study Traits and States in Intensive
Longitudinal Data

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Abstract

Traditionally, researchers have used time series and multilevel models to analyze intensive longitudinal data. However, these models do not directly address traits and states which conceptualize the stability and variability implicit in longitudinal research, and they do not explicitly take into account measurement error. An alternative to overcome these drawbacks is to consider structural equation models (state-trait SEMs) for longitudinal data that represent traits and states as latent variables. Most of these models are encompassed in the Latent State-Trait (LST) theory. These state-trait SEMs can be problematic when the number of measurement occasions increases. As they require the data to be in wide format, these models quickly become overparameterized and lead to non-convergence issues. For these reasons, multilevel versions of state-trait SEMs have been proposed, which require the data in long format. To study how suitable state-trait SEMs are for intensive longitudinal data, we carried out a simulation study. We compared the traditional single level to the multilevel version of three state-trait SEMs. The selected models were the multistate-singletrait (MSST) model, the common and unique trait-state (CUTS) model, and the trait-state-occasion (TSO) model. Furthermore, we also included an empirical application. Our results indicated that the TSO model performed best in both the simulated and the empirical data. To conclude, we highlight the usefulness of state-trait SEMs to study the psychometric properties of the questionnaires used in intensive longitudinal data. Yet, these models still have multiple limitations, some of which might be overcome by extending them to more general frameworks.

Translational abstract: Collecting data from individuals multiple times a day for several days is becoming more popular among psychological researchers. This kind of data, known as intensive longitudinal data, allows studying how people change over short periods of time. In the present study, we explored how to study traits and states in intensive longitudinal data. Traits conceptualize the stability of variables, whereas states conceptualize their variability. For this, we conducted a simulation study in which we studied three state-trait structural equation models (state-trait SEMs). State-trait

SEMs are measurement models for longitudinal data that represent traits and states as latent variables and include measurement error terms. Our results showed that the trait-state-occasion (TSO) model outperforms the other two. We concluded that the TSO model is an additional tool to consider when analyzing intensive longitudinal data.

Keywords: states and traits, intensive longitudinal data, longitudinal structural equation modeling, measurement error

Using Structural Equation Modeling to Study Traits and States in Intensive Longitudinal Data

The amount of intensive longitudinal studies has increased considerably in the last 20 years (Hamaker & Wichers, 2017). These studies, also known as *ambulatory assessments*, *experience sampling methods* (ESMs), or *ecological momentary assessments* (EMAs), include multiple measurements per person. These measurements are collected in short periods of time and are intended to study the dynamics of psychological processes. Several advantages of intensive longitudinal methods are often highlighted, such as the emphasis on the individual, the higher ecological validity, and the diminution of recall bias; these properties are discussed in depth by Hamaker (2012), Reis (2012), and Schwarz (2012).

When studying intensive longitudinal data, the terms *traits* and *states* often occur, as these terms conceptualize the stability and variability of human behaviors and attitudes across time. Although traits and states have been defined differently throughout the years (Allen & Potkay, 1981; Chaplin, John, & Goldberg, 1988; Mischel, 2004; Steyer, Schmitt, & Eid, 1999), traits are typically regarded as relatively stable dispositions and states as the observed variability due to situational conditions (Hamaker, Schuurman, & Zijlmans, 2017; Hamaker, Nesselroade, & Molenaar, 2007). Moreover, some authors have suggested that most psychological variables are not pure traits nor states but they are something “in-between” (Geiser, Götz, Preckel, & Freund, 2017; Hertzog & Nesselroade, 1987).

In order to study states and traits in intensive longitudinal data, researchers have found inspiration in the *aggregationist model* (Epstein, 1979, 1981). In short, the aggregationist model assumes that the mean score over time for each individual (i.e., intra-individual mean) is a good estimate of a person’s trait level. Although it is not explicitly mentioned, this conceptual approach has been integrated with the statistical approaches that are generally used to analyze intensive longitudinal data. This includes *time series analysis* when $N = 1$ (Fan & Yao, 2003; Hamaker & Dolan, 2009) and *multilevel modeling* when $N > 1$ (Houben, Ceulemans, & Kuppens, 2020; Nezlek, 2012;

Walls, Jung, & Schwartz, 2006). In these approaches, the intra-individual means are considered as trait scores and the deviations from that mean are considered as state scores (e.g., Hamaker & Grasman, 2015; Nesselroade, 1991; Nezlek, 2007; Schuurman, Ferrer, Boer-Sonnenschein, & Hamaker, 2016). Time series analyses and multilevel models have been extensively used to study traits and states in intensive longitudinal data (e.g., Moeller, Ivcevic, Brackett, & White, 2018; Zelenski & Larsen, 2000).

However, the aggregationist approach is not free of criticism. According to Steyer, Ferring, and Schmitt (1992), in the aggregationist model, the situational context is not an integral part of the model. This criticism also applies to some extent to the way traits and states are handled in multilevel models. As the situation is not an explicit part of the model, the state scores are confounded with other sources of variability such as measurement error and other unobserved variables. Moreover, the definitions of traits and states are rather loose, mainly because multilevel models were not especially developed to handle these concepts.

To overcome these drawbacks, longitudinal state-trait structural equation models (i.e., state-trait SEMs) can be used as an alternative approach to analyze intensive longitudinal data. State-trait SEMs are especially suited as (a) their main focus is on differentiating the trait and the state components of the observed variables and (b) they incorporate measurement error. However, applying state-trait SEMs to intensive longitudinal data is not straightforward (Geiser, Bishop, Lockhart, Shiffman, & Grenard, 2013; Geiser et al., 2015b; Nezlek, 2007) because these models have been originally developed for longitudinal data with a limited number of measurement occasions. Furthermore, even though some of these models are supposed to be useful to analyze experience sampling data (Courvoisier, Eid, Lischetzke, & Schreiber, 2010; Eid, Courvoisier, & Lischetzke, 2012; Eid, Holtmann, Santangelo, & Ebner-Priemer, 2017), there are little to no applications of these models on intensive longitudinal data.

The goal of this study was to explore the suitability of state-trait SEMs to study states and traits in intensive longitudinal data. By doing this, we also provide a comprehensive introduction to these models, which will allow more researchers to apply

them to their intensive longitudinal data. To reach this goal, we compared three state-trait SEMs through a simulation study, and we applied them to empirical data. The three models that we considered were the multistate-singletrait (MSST; Geiser et al., 2013; Steyer, Geiser, & Fiege, 2012; Steyer, Mayer, Geiser, & Cole, 2015), the common-unique trait-state (CUTS; Hamaker et al., 2017), and the trait-state-occasion model (TSO; Cole, Martin, & Steiger, 2005; Eid et al., 2017). These models were chosen because all of them require multiple indicators, which is useful when multiple items are used to measure the same construct. Moreover, the selected models are a good representation of the wide variety of state-trait SEMs, as they cover the most general aspects that are commonly accounted for in state-trait SEMs, as we will highlight in this study.

We also discuss important characteristics of state-trait SEMs that have to be addressed when analyzing intensive longitudinal data. For example, we show how state-trait SEMs can be reformulated as multilevel SEMs allowing researchers to deal with a large number of measurement occasions per person. Moreover, we discuss how state-trait SEMs allow studying the psychometric properties of the items included in intensive longitudinal studies. Currently, a multilevel version of the TSO model is lacking, hence we also introduce the multilevel version of this model. Finally, we also show how these models can be easily adjusted to the requirements of the data, such as in the case of multidimensional settings.

In what follows, we explain the theoretical and statistical background of state-trait SEMs. This includes (a) a brief overview of the *latent state-trait theory* (LST; Steyer et al., 2012; Steyer et al., 2015; Steyer et al., 1999), (b) a discussion of the difficulties of using these models with intensive longitudinal data and how they can be overcome by reformulating the models as multilevel SEMs, (c) a detailed description of the models selected for this study, and (d) an explanation of the similarities and differences among the selected models and other models and frameworks. Next, we present the simulation study and its results. After this, the empirical example is introduced by describing and analyzing the data with the three models. This empirical

example aims to show practitioners how to analyze and interpret real experience sampling data with state-trait SEMs. Finally, we conclude with a discussion of our findings, and suggestions for future research on this field. Furthermore, in order to help researchers apply these models to their own data, in the supplementary material, we provide R code to fit these models (see https://github.com/secastroal/LST_Analyses).

State-Trait SEMs

State-trait SEMs are longitudinal structural equation models, which can distinguish the trait and the state components of the observed variables. The observed variables are usually referred to as indicators in the state-trait SEM literature, which are expected to be measured on a continuous scale. They can be, for example, the sumscores of parallel tests or the items' raw scores. Furthermore, an important assumption of state-trait SEMs is that measurement time points are equally spaced over time (Geiser et al., 2013), meaning that the time elapsed between two consecutive observations is the same for all consecutive observations. Finally, an additional assumption that should be considered when analyzing intensive longitudinal data with state-trait SEMs is stationarity. A time series is (weakly) stationary if its means and variances-covariances are equal over time (Song & Zhang, 2014).

Regarding the state-trait distinction, in the state-trait SEMs, not only persons but also situations and person-situation interactions are considered important sources of variability. For example, a person's anxiety is certainly not stable over time, but highly influenced by the situation: How anxious a person feels will be completely different at a romantic dinner than at a job interview. Also, anxiety will not only be affected by the situation but also by the person-situation interaction. For instance, the effect of a stressful situation on a person who has an anxiety disorder will be different from the effect of that same situation on a person who does not have an anxiety disorder.

These sources of variability are captured by the latent variables in state-trait SEMs. Thus, a latent variable is needed to represent the effect of both the situation and the person-situation interaction for each occasion of measurement (latent states), and a

general latent variable is needed to represent the stability of the measurements per person across situations (latent trait). In other words, state-trait SEMs aim to describe the structure of the constructs measured in longitudinal studies by differentiating the proportion of the variance that is explained either by trait effects or situational effects (Steyer et al., 1999). Additionally, state-trait SEMs are useful to understand how the trait and the state components of different constructs are related and whether these relationships are different among different subpopulations (Steyer et al., 1999).

An important characteristic of state-trait SEMs is that they are useful to analyze longitudinal data in wide format (Hamaker et al., 2017; Steyer et al., 2015). This means that there are as many columns in the data set as there are measurement occasions for each variable of interest. Therefore, parameters can be allowed to change over time. Technically speaking, state-trait SEMs can be used to test for longitudinal measurement and factorial invariance (Meredith, 1993; Meredith & Teresi, 2006) of the trait and state structures. Longitudinal measurement invariance means that the conditional distribution of the observed variable given a value of the latent variable is equal over measurement occasions. Put differently, assuming longitudinal measurement invariance means that the construct of interest (e.g., positive affect) is measured equally over time (Geiser et al., 2015a). Hence, the latent scores at different occasions can be interpreted in the same way, which allows for meaningful comparisons of latent scores over time. On the other hand, if measurement invariance is not assumed, differences between latent scores over time might be due to changes in the meaning of the scale and not necessarily due to changes in the persons' attributes (i.e., the construct being measured).

Despite their similarities, state-trait SEMs differ in many ways, such as the number of indicators (i.e., variables) needed to identify the latent state variables, or the kind of effects that are accounted for (e.g., autoregressive effects, method effects, trait change). For example, the stable trait autoregressive trait and state model (STARTS; Kenny & Zautra, 1995; Kenny & Zautra, 2001) is one of the few models that only requires one indicator on each occasion to be able to measure a situational latent variable, while most state-trait SEMs require multiple indicators. In addition,

state-trait-SEMs might include *method effects* in order to account for the specific time-invariant component of an indicator that is not shared with other indicators. For instance, these effects might be present if a variable was measured through self-report and peer-rated questionnaires. In this case, each questionnaire might have its own effect, which is independent of the situation and unique to each questionnaire. A state-trait SEM that includes this kind of effects is the CUTS model (Hamaker et al., 2017), where method effects are referred to as *unique traits*. Additionally, there are also other approaches to account for method effects, which are broadly discussed by LaGrange and Cole (2008) and Geiser and Lockhart (2012).

Moreover, some state-trait SEMs account for *autoregressive effects* (Cole et al., 2005; Eid et al., 2017; Kenny & Zautra, 1995; Kenny & Zautra, 2001; LaGrange & Cole, 2008). Autoregressive effects are used to study the dependency of the variables on themselves at previous time points. In other words, an autoregressive effect evidences how an observation of a variable at time t can be affected by previous observations of that same variable at time $t - 1$, $t - 2$, and so on. For example, if a person got a raise in their salary, this would make him/her feel more cheerful during the next few days, in such a way that the person might react more positively to future unpleasant experiences. The STARTS (Kenny & Zautra, 1995; Kenny & Zautra, 2001) and the TSO (Cole et al., 2005; Eid et al., 2017) models are examples of state-trait SEMs that include autoregressive effects to account for the relationship between consecutive occasions. These effects are especially important when studying intensive longitudinal data given the short intervals of time in which observations are collected, as this makes autoregressive effects more likely to occur.

Latent State-Trait Theory

Among the wide variety of state-trait SEMs that have been proposed, it is important to highlight the so-called latent state-trait theory (LST; Steyer et al., 2012; Steyer et al., 2015; Steyer et al., 1999). This theory encompasses several of the state-trait SEMs while also providing a probabilistic framework to study states and

traits. In this probabilistic framework, the LST theory first defines what is the random experiment of interest, which is, in other terms, the set of possible outcomes (Steyer et al., 2015). The random experiment is defined in four steps: (a) A person is sampled at time 0, (b) the person has certain experiences between the moment of sampling and the assessment, (c) the person is in a certain situation at the moment of assessment, (d) the behavior of interest is observed. The last three steps (b through d) are repeated for $t > 1$. Thus, the LST theory acknowledges the dynamic nature of persons because a person at time t is different from the person at time $t + 1$ due to the experiences the person has had between consecutive measurement occasions (Steyer et al., 2015).

Secondly, the LST theory defines all the random variables involved in the random experiment. These random variables are the persons at time t (U_t), the situations at time t (S_t), the observed variables j at time t (Y_{jt}), and the conditional expectations of the observed variables given the persons or the situations (e.g., $E[Y_{jt}|U_t]$). These conditional expectations are at the basis of the formal definitions of the latent variables in the model (Steyer et al., 2015). Models encompassed by the LST theory are, for example, the MSST (Steyer et al., 2015) and the TSO (Eid et al., 2017) models.

In addition, the LST theory defines three variance coefficients as proportions of the total variance: The *consistency*, the *occasion-specificity*, and the *reliability* (Steyer et al., 2015). The consistency is the proportion of the variance due to the sources of variability that are stable over time (trait component). The occasion-specificity is the proportion of the variance due to the sources of variability that depend on the situation (state component). The consistency and the occasion-specificity indicate to what extent the observed variables are trait- or state-like, respectively. Lastly, the reliability is the sum of the consistency and the occasion-specificity. In other words, the reliability is the proportion of the variance explained by both, stable and situational sources of variability in the given situation. The proportion of the variance that is not captured by the reliability coefficient is the random measurement error. The consistency, the occasion-specificity, and the reliability are computed for each observed variable Y_{jt} , which means that the coefficients of variable j at time t might be different from the

coefficients of the same variable j at time u , for $t \neq u$. Allowing these coefficients to change over time might be interesting if there are clear trends. For example, if a researcher observes that the reliability of an item decreases over time, further inspection of that item would be required.

State-Trait SEM as Multilevel SEM

Although some authors have suggested state-trait SEMs (single-level state-trait SEMs from here on) as a way to analyze intensive longitudinal data (Courvoisier et al., 2010; Eid et al., 2012; Eid et al., 2017), others have recognized that these models become impractical when there are many measurement occasions (Geiser et al., 2013; Geiser et al., 2015b; Nezlek, 2007). In fact, studies that use these models and have intensive longitudinal data at hand consistently use fewer measurement occasions than the ones available due to the requirement of having the data in wide-format. In general, single-level state-trait SEMs are problematic when the number of measurement occasions increases as these models were developed for studies with a limited number of occasions. For instance, if a study measured three variables once a day during ten consecutive days, there will be thirty observed variables in the model. However, when the data are in long format, the number of observed variables in the model stays at three. Therefore, applying single level state-trait SEMs to intensive longitudinal data is difficult because the number of observed variables in the model becomes too large. As a consequence, the syntax to specify the models is extremely long and convergence issues are more likely to happen (Geiser et al., 2013).

To overcome these limitations, state-trait SEMs can be formulated as multilevel SEMs (e.g., Geiser, 2020; Geiser et al., 2013), which requires the data in long format. A multilevel SEM for longitudinal data defines two levels of analysis: The within-level (level 1) and the between-level (level 2). The within-level aims to model the variability within persons and the between-level aims to model the differences between persons. Thus, to specify state-trait SEMs as multilevel SEMs, one has to model the effects of the situations and person-situations interactions as well as the random measurement

error at the within-level. Furthermore, one has to model the effects that are independent of the situation, such as the effects of the persons, at the between-level (Geiser et al., 2013). In particular, multilevel state-trait SEMs have as many observed variables as there are indicators in the data, independently of the number of measurement occasions. Considering the previous example, in a study with three indicators and ten measurement occasions, there will be only three observed variables in a multilevel setting, one for each indicator.

Additionally, in the multilevel formulation of state-trait SEMs, all parameters (loadings, intercepts, variances, residual variances, and variance coefficients) are constrained to be equal over time. This restriction implies that some sort of longitudinal measurement and factorial invariance (Meredith, 1993; Meredith & Teresi, 2006) of the trait and state structure is assumed in the multilevel formulation of state-trait SEMs. This can come as a disadvantage because the assumption of measurement invariance cannot be tested. In general, researchers should be cautious when assuming measurement invariance without testing for it. For example, Geiser et al. (2015a) showed in a simulation study that when real data were characterized by a trait change process (e.g., growth curve model), state-trait SEMs assuming measurement invariance might result in well-fitting solutions. In these cases, the trait change process might be masked and the researcher might conclude that there is no trait change at all.

In conclusion, the main advantages of formulating state-trait SEMs as multilevel SEMs are that many measurement occasions are easier to handle, there are fewer parameters to estimate, and the syntax of the model remains unchanged regardless of the number of measurement occasions included in the study. Moreover, the multilevel formulation allows to easily handle missing data (Geiser, 2020; Geiser et al., 2013). However, multilevel state-trait SEMs do not allow testing for longitudinal measurement invariance, which can be tested in single-level state-trait SEMs. Thus, the previous example about observing the reliability of a variable decreasing over time would not be possible in a multilevel setting because the reliability is constrained to be equal over time.

In relation to the models of interest in this study, the multilevel version of the MSST and the CUTS models have been proposed by Geiser et al. (2013) and by Hamaker et al. (2017, Supplementary material), respectively. The multilevel CUTS model is technically a multilevel confirmatory factor analysis (see Roesch et al., 2010). However, there is, to the best of our knowledge, no multilevel version of the TSO model; below, we present such a model.

The Models

In this section, we explain in detail the models that were selected for this study: The MSST, the CUTS, and the TSO models. As mentioned before, these models were selected because all of them require multiple indicators to identify the latent state variables. Therefore, they are useful when multiple items or variables are used to measure one unique construct (e.g., positive affect). Additionally, these models cover the most general characteristics that are studied in state-trait SEMs. In particular, the MSST model is at the foundations of the LST theory. It is the simplest model that allows differentiating states from traits. The CUTS model accounts for method effects straightforwardly and intuitively, while still differentiating between traits and states. Finally, the TSO model takes into account autoregressive effects to study the relation between consecutive measurement occasions, a feature which has been extensively considered when studying intensive longitudinal data. We cover both the single-level and multilevel version of each model. This section is complemented with the supplemental material, which provides R code to simulate data based on these models and to fit both versions of each model in Mplus within the R environment.

The multistate-singletrait model (MSST). The most straightforward model within the LST framework that allows distinguishing between traits and states is the MSST model. Here, we use the version of the MSST model from Geiser and Lockhart (2012). This version does not include the latent trait variable as a second-order factor as it is usually done in the LST theory (Steyer et al., 2015); instead, it is included as a general first-order factor. In general, the MSST model is useful to

identify the variance proportions of the indicator variables that are due to either the trait component, the state component, or the random measurement error.

To start, the MSST model requires a set of observed indicator variables Y_{jt} (j = indicator, t = time), which are measured on multiple occasions and aim to measure the same construct (e.g., anxiety, positive affect, etc.) from a sample of size n . Each variable Y_{jt} , which represents an n -variate vector of the sample's responses on the j - th indicator, is decomposed as follows:

$$Y_{jt} = \tau_{jt} + \varepsilon_{jt}. \quad (1)$$

where τ_{jt} is an n -variate vector of factor scores of the latent state variable and ε_{jt} is an n -variate vector that captures the deviations of the observed scores from the factor scores of the latent state variable, namely, the random measurement error. The random measurement error variables ε_{jt} are assumed to be normally distributed with mean zero, $\varepsilon_{jt} \sim N(0, \sigma_{\varepsilon_{jt}}^2)$. Then, the latent state variable is further decomposed as follows:

$$\tau_{jt} = \alpha_{jt} + \lambda_{T_{jt}}\xi + \lambda_{S_{jt}}\zeta_t, \quad (2)$$

where α_{jt} is an n -variate vector with the intercept of indicator j at time t , ξ is an n -variate vector of the factor scores of the latent trait variable, which is assumed to be stable over time, and ζ_t is an n -variate vector that captures the deviations of the latent state variable from the latent trait variable at time t , namely, the latent state residual. The latent state residuals ζ_t reflect both the effects of the situation and the person-situation interaction. Moreover, as well as the random measurement error, the latent state residuals are assumed to be normally distributed with mean zero, $\zeta_t \sim N(0, \sigma_{\zeta_t}^2)$. Lastly, $\lambda_{T_{jt}}$ and $\lambda_{S_{jt}}$ are the factor loadings for the latent trait variable and the latent state residual, respectively. Next, by replacing Equation 2 into Equation 1, the full decomposition of the observed variables given the MSST model can be written as follows:

$$Y_{jt} = \alpha_{jt} + \lambda_{T_{jt}}\xi + \lambda_{S_{jt}}\zeta_t + \varepsilon_{jt}. \quad (3)$$

In addition, it is also assumed that the latent trait variable ξ , the latent state residuals ζ_t , and the random measurement error variables ε_{jt} are uncorrelated with each other. The MSST model is identified by fixing one factor loading parameter of the latent trait variable and of each latent state residual to 1. Thus, one factor loading parameter $\lambda_{T_{jt}}$ and the factor loading parameters $\lambda_{S_{jt}}$ associated to one of the indicators Y_j have to be equal to 1. Moreover, one of the intercepts α_{jt} of the same indicator Y_j has to be fixed to 0.

The path diagrams of the single-level and the multilevel MSST models are presented in Figure 1. Following the most common way of representing SEMs, observed variables are presented as squares and latent variables are presented as circles. Linear relationships between variables, either observed or latent, are shown through straight arrows and covariances between two variables are shown as curved arrows. The variance of a variable is represented with a looping arrow. Moreover, random measurement error variables and residual variables are represented as latent variables with their own variances. Finally, intercepts and means are represented as the effects of a constant variable 1 (triangle) on the observed or latent variables. Effects and covariances that are set to 0 are not shown in the path diagrams. In addition, in the multilevel SEM representation of the models, a path diagram is used for each level: The within-level model and the between-level model. The path diagrams of each model follow the same conventions mentioned above, the only additional element is a dot at the end of the straight arrows that come from the random measurement error variables. These dots aim to represent the intraindividual means of all individuals on the specified observed variable. These intraindividual means per variable are then represented as latent variables and used to fit the between-level model. Note that in the multilevel SEM diagram, the subscripts t are dropped due to the required assumption that parameters are time-invariant.

The common-unique trait-state model (CUTS). This model proposed by Hamaker et al. (2017) is actually equivalent to the MSST model with orthogonal methods (Steyer et al., 1992 as cited in Geiser and Lockhart, 2012). Even though it was

first proposed within the LST framework, it is not considered a proper LST model because the additional method factors can not be defined within the probabilistic principles of the LST theory (Geiser & Lockhart, 2012, Appendix A). According to the reasoning of Hamaker et al. (2017), the CUTS model is developed based on the *averaged R-technique* and the *pooled P-technique analysis* (Cattell, 1963) and its goal is to distinguish between four sources of variance, namely, the common states, the common traits, the unique states, and the unique traits. The CUTS model is also useful to test whether there is weak factorial invariance between the trait factor structure and the state factor structure (Hamaker et al., 2017). If this assumption holds, it means that the factor structure of the construct of interest obtained in a cross-sectional study adequately describes both the between-factor and the within-factor structures.

Just like the MSST model, the CUTS model requires a set of observed indicator variables Y_{jt} , which are measured on multiple occasions on a sample of size n and aim to measure the same construct. Each observed indicator variable is an n -variate vector with the observed scores of the variable j at time t . Next, in the CUTS model, the observed variables Y_{jt} are decomposed into *trait-scores* and *state-scores* as shown in Equation 4:

$$Y_{jt} = T_j + S_{jt}, \quad (4)$$

where T_j is an n -variate vector of the intraindividual means of indicator j , which are time-invariant, and S_{jt} is an n -variate vector of the deviations of the observed scores Y_{jt} from the intraindividual means of indicator j at time t . Then, the trait-scores are further decomposed as follows:

$$T_j = \alpha_j + \lambda_{T_j}\xi + \vartheta_j, \quad (5)$$

where α_j is an n -variate vector with the grand mean of indicator j , ξ is an n -variate vector of the common trait scores, which represents what is common to all indicators over all time points, λ_{T_j} is the factor loading relating the trait-scores T_j to the common trait scores ξ of indicator j , and ϑ_j is an n -variate vector that contains the part of the

trait-score that is not accounted for by the common trait scores and therefore is unique to indicator j (unique trait scores). Both the common trait ξ and the unique trait ϑ_j are assumed to be normally distributed with mean zero and variances σ_ξ^2 and $\sigma_{\vartheta_j}^2$, respectively. Moreover, the intercepts α_j and the loadings λ_{T_j} can be allowed to vary over time to test for longitudinal measurement invariance.

Similarly, the state-scores are decomposed as follows:

$$S_{jt} = \lambda_{S_{jt}} \zeta_t + \varepsilon_{jt}, \quad (6)$$

where ζ_t is an n -variate vector of the common state scores representing what is common to all indicators at time t , $\lambda_{S_{jt}}$ is the factor loading relating the state-scores S_{jt} to the common state scores ζ_t of indicator j at time t , and ε_{jt} is an n -variate vector that contains the part of the state-score that is not accounted for by the common state scores and therefore it is unique to indicator j at time t (unique state scores). Similarly to the common and unique trait scores, the common state ζ_t and the unique state ε_{jt} are assumed to be normally distributed with mean zero and variances $\sigma_{\zeta_t}^2$ and $\sigma_{\varepsilon_{jt}}^2$, respectively.

The four sources of variance distinguished by the CUTS model are clearly evident when the full model is written in one equation by replacing Equations 5 and 6 into Equation 4 as follows:

$$Y_{jt} = \alpha_j + \lambda_{T_j} \xi + \vartheta_j + \lambda_{S_{jt}} \zeta_t + \varepsilon_{jt}. \quad (7)$$

Here, each observation is decomposed into an intercept and four components that are linked to four sources of variability. The first source of variability is the common trait ξ that is invariant over time and variables. The second source is the unique trait ϑ_j that is invariant over time but specific to indicator j and can be interpreted as systematic error. The third source is the common state ζ_t that is common over all the indicators but specific at time t . Finally, the last source of variability is the unique state ε_{jt} that is specific to each indicator and each time point and can be interpreted as random measurement error. This way of disentangling different sources of error variance is

similar to the way this is done in generalizability theory (Brennan, 2005).

In the CUTS model, the four sources of variability are independent of each other, which means that common traits, unique traits, common states, and unique states are uncorrelated. The single-level CUTS model can be just-identified with as little as two measurement occasions and three indicator variables when setting one loading of the common trait variables and of each of the common state variables to 1. The path diagrams of the single-level and multilevel versions of the CUTS model are presented in Figure 2.

The trait-state-occasion model (TSO). The TSO model was developed in order to account for autoregressive effects within the LST framework. It was first proposed by Cole et al. (2005), inspired by the STARTS model (Kenny & Zautra, 1995; Kenny & Zautra, 2001) and the autoregressive LST model (Steyer & Schmitt, 1994). Also, it was recently reintroduced by Eid et al. (2017) to argue that it is effectively an LST model as all the latent variables are well defined as conditional expectations. The main innovation of the TSO model is that it introduces autoregressive effects among the latent state residuals. This creates two new sets of variables: The occasion-specific variables O_t and the occasion-specific residuals ζ_t . Thus, the TSO model is useful to describe how the trait and the state components of a construct are associated with the indicator variables while controlling for the carry-over effect that might be present between consecutive measurement occasions.

In this study, we use the version of the TSO proposed by Eid et al. (2017, Figure 3B) that does not consider the latent trait variable as a second-order factor, and that uses latent trait-indicator variables instead of a common latent trait variable for all the indicators. The TSO model first decomposes the observed variables Y_{jt} as it is done in the MSST model as in Equation 1. The difference is expressed in the decomposition of the latent state variables τ_{jt} as follows:

$$\tau_{jt} = \alpha_{jt} + \lambda_{T_{jt}}\xi_j + \lambda_{S_{jt}}O_t, \quad (8)$$

where α_{jt} is an n -variate vector with the intercept of indicator j at time t , ξ_j is an

n -variate vector that represents the latent trait-indicator variable of indicator j , O_t is an n -variate vector that represents the latent occasion-specific variable at time t , and $\lambda_{T_{jt}}$ and $\lambda_{S_{jt}}$ are the factor loadings of the latent trait-indicator variable ξ_j and the latent occasion-specific variable O_t , respectively.

Next, the latent occasion-specific variable at time O_t is regressed on the latent occasion-specific variable at the previous time O_{t-1} . In other words, the TSO model assumes that the effects of the situation and the person-situation interaction are carried-over to future situations, which is represented by the autoregressive effect between consecutive latent occasion-specific variables. This dynamic process has two main implications: (a) It is not possible to regress the latent occasion-specific variable O_1 on any other latent occasion-specific variable, therefore, $O_1 = \zeta_1$ and (b) the latent occasion-specific variable O_t is a linear combination of all the occasion-specific residuals ζ_s for $s = 1, \dots, t$. Equations 9 and 10 show how to define the latent occasion-specific variables O_2 and O_3 in terms of the latent occasion-specific residuals ζ_t :

$$O_2 = \beta_{1,2}O_1 + \zeta_2 = \beta_{1,2}\zeta_1 + \zeta_2, \quad (9)$$

$$O_3 = \beta_{2,3}O_2 + \zeta_3 = \beta_{2,3}(\beta_{1,2}\zeta_1 + \zeta_2) + \zeta_3, \quad (10)$$

where $\beta_{1,2}$ and $\beta_{2,3}$ are the autoregressive effects between two consecutive latent occasion-specific variables, and ζ_1 to ζ_3 are n -variate vectors that represent the occasion-specific residuals. These occasion-specific residuals capture the effects of the situation and the person-situation interaction, which are not explained by observations in previous situations.

In the TSO model, the latent-trait indicators ξ_j , the latent occasion-specific residuals ζ_t , and the random measurement error variables ε_{jt} are assumed to be normally distributed with mean zero and variances $\sigma_{\xi_j}^2$, $\sigma_{\zeta_t}^2$, and $\sigma_{\varepsilon_{jt}}^2$, respectively. Moreover, latent trait-indicator variables are uncorrelated with the latent occasion-specific residuals and the random measurement error variables but are allowed to correlate among themselves. In addition, the latent occasion-specific residuals and

the random measurement error variables are uncorrelated with each other. The path diagrams of the single-level and multilevel TSO model are presented in Figure 3.

Similarities and Differences

As mentioned previously, the LST theory defines a set of coefficients that are proportions of the total variance of an indicator. The three main coefficients are reliability, consistency, and occasion-specificity (Steyer et al., 2015). These coefficients are common to every LST model. However, the equations are not necessarily equal among models given how the total variance of an observed variable is defined in each model. For example, while the consistency of an indicator Y_{jt} in the MSST model only accounts for the variance of the latent trait variable $Var(\xi)$, the consistency in the TSO model accounts for both the variance of the latent trait-indicator variable $Var(\xi_j)$ and the variance of the latent occasion-specific variable of the previous measurement occasion $Var(O_{t-1})$. The equations of these variance coefficients are presented in Table 1 for each of the three models to show how they differ.

Moreover, additional coefficients can be defined depending on the complexity of the model. In the TSO model, the consistency can be further decomposed into two additional coefficients: The *predictability by trait* and the *unpredictability by trait* (Eid et al., 2017). The predictability by trait is the proportion of the variance that is due to the latent trait-indicator variable ξ . It can be interpreted as the proportion of the variance that is explained by the trait differences between persons on the first occasion of measurement. On the other hand, the unpredictability by trait is the proportion of the variance that is due to the previous occasion-specific residuals ζ_{t-u} for $u = 1, \dots, t - 1$ (recall Equations 9 and 10). In other words, it is the proportion of the variance that is explained by the carry-over effects observed in the data. The equations of the predictability by trait and the unpredictability by trait are also presented in the end of Table 1.

Lastly, the CUTS model is special in this regard because it was not developed within the LST theory. Because of this, this kind of coefficients was not defined for the

CUTS model by its authors (Hamaker et al., 2017). However, given the equivalence between the CUTS model and the MSST model with orthogonal methods, we propose to use the coefficients defined by Geiser and Lockhart (2012) with the CUTS model to facilitate the comparison of the models selected in this study (see equations in Table 1). Thus, for the CUTS model, the consistency was also decomposed into two additional coefficients: The *common consistency* and the *unique consistency*. The common consistency is the proportion of the variance due to the common trait ξ . Hence, it encompasses the effects that are stable over time and common across all the indicators. On the contrary, the unique consistency is the proportion of the variance due to the unique trait ϑ_j , which is stable over time and unique to one indicator.

In short, there are variance coefficients as proposed in the LST theory that are shared among the three models, which are the reliability, the consistency, and the occasion-specificity. Even though the equations of these coefficients are different from model to model due to how the total variance of an observed variable is computed, their interpretation remains the same across models. Moreover, additional variance coefficients can be defined for a model. In this case, both the CUTS and the TSO models allow decomposing the consistency in two new variance coefficients: The common consistency and the unique consistency for the CUTS, and the predictability by trait and the unpredictability by trait for the TSO. These new coefficients are entirely different between the two models, not only in their equations but also in their interpretations. Functions to compute these coefficients can be found in the R code.

Relation of State-Trait SEMs with Other Models for Intensive Longitudinal Data

An important advantage of formulating state-trait SEMs as multilevel SEMs, especially state-trait SEMs that account for autoregressive effects, is that it allows relating these models to other frameworks that are commonly used to analyze intensive longitudinal data. Specifically, multilevel state-trait SEMs can be compared with multilevel (vector) autoregressive models (multilevel-VAR; e.g., Bringmann et al., 2013;

Chow, Hamagani, & Nesselroade, 2007; De Haan-Rietdijk, Gottman, Bergeman, & Hamaker, 2016; Ebner-Priemer et al., 2015; Rovine & Walls, 2006), dynamic factor analysis models (DFA; Fuller-Tyszkiewicz et al., 2017; Molenaar, 1985; Song & Zhang, 2014), and more general frameworks such as state-space modeling (Chow, Hamaker, Fujita, & Boker, 2009; Kalman, 1960; Lodewyckx, Tuerlinckx, Kuppens, Allen, & Sheeber, 2011) and dynamic structural equation modeling (DSEM; Asparouhov, Hamaker, & Muthén, 2017, 2018). All these models have in common that they are specifically developed to analyze intensive longitudinal data, and they incorporate autoregressive effects to model persons' dynamics.

Firstly, multilevel-VAR models are an integration of time series and multilevel modeling, which allow modeling auto- and cross-regressive effects when $N > 1$ (Rovine & Walls, 2006). In contrast to autoregressive effects, cross-regressive effects model the dependency of a variable X at time t on a different variable Y at previous time points (e.g., Y at $t - 1$ or $t - 2$). In this framework, researchers are usually interested in understanding persons' dynamics and their relation with stable variables of the persons (e.g., gender, neuroticism). Moreover, as these models aim to acknowledge the idiosyncrasy of each individual, auto- and cross-regressive coefficients are defined as random effects. Recently, multilevel-VAR models that account for measurement error have been proposed (Schuurman & Hamaker, 2019; Schuurman, Houtveen, & Hamaker, 2015). These models differentiate the residuals of the model (known as innovations) from the random measurement error by the inclusion of latent variables, which are identified by only one indicator. These one-indicator latent variables are equivalent to the latent state variables used in state-trait SEMs. In particular, the multilevel-VAR model with measurement error (Schuurman & Hamaker, 2019) can be seen as the multilevel version of the STARTS model (Kenny & Zautra, 1995; Kenny & Zautra, 2001) with random auto- and cross-regressive effects.

Secondly, multilevel state-trait SEMs can be framed as multilevel DFA models. Initially, DFA models (Fuller-Tyszkiewicz et al., 2017; Molenaar, 1985) were inspired by the P-technique analysis proposed by Cattell (1963). These are factor analysis models

that are applied to the time series of an individual and account for the lagged structure in the data. In recent years, multilevel DFA models have been proposed (Song & Ferrer, 2012; Song & Zhang, 2014), which allow studying multivariate time series when $N > 1$. As well as in multilevel-VAR, multilevel DFA models have an emphasis on the individuals. Therefore, the lagged effects are allowed to randomly vary in the population. The multilevel TSO model, which we presented above, can be seen as a multilevel DFA model where the between factor structure is different from the within factor structure and the autoregressive effect is fixed instead of random.

Thirdly, the state-space modeling approach (Kalman, 1960) is a broader framework, which is especially useful to analyze intensive longitudinal data. In psychology, state-space models have been used to study persons' dynamics (e.g., Chow et al., 2009; Lodewyckx et al., 2011). In general, state-space models are described by two equations: The observation equation and the transition equation (Chow, Ho, Hamaker, & Dolan, 2010). In the observation equation, the measurement model is specified by incorporating latent variables at each observation, which are denominated as *states*. In the transition equation, the dynamics of the system are modeled by auto- and cross-regressive effects. Note that SEMs are also defined by two equations: The measurement model and the structural model. While the measurement model in SEM is equivalent to the observation equation in state-space modeling, the structural model is not immediately equivalent to the transition equation. As a result, SEM can be seen as a special case of state-space modeling and vice versa (Chow et al., 2010). In relation to multilevel state-trait SEMs, the latent state variables are comparable to the states in state-space modeling.

Finally, multilevel state-trait SEMs can be implemented in the DSEM framework (Asparouhov et al., 2017, 2018; Hamaker, Asparouhov, Brose, Schmiedek, & Muthén, 2018; McNeish & Hamaker, 2019). The most general DSEM is the cross-classified model (Asparouhov et al., 2018), which decomposes the observation into three components: The person's component, $Y_{2,i}$; the time component, $Y_{3,i}$; and the deviation of person i at time t , $Y_{1,it}$. A two-level DSEM model only includes the person's component and the

deviation of the person i at time t . In particular, multilevel state-trait SEMs that include lagged relationships (e.g., the multilevel TSO model) can be seen as DSEMs with fixed effects instead of random effects. DSEM has been especially developed to analyze intensive longitudinal data. It integrates time series analyses, multilevel modeling, structural equation modeling (SEM), and time-varying effect modeling (TVEM; Hastie & Tibshirani, 1993; Hoover, Rice, Colin, & Yang, 1998) into one unified framework. This results in a comprehensive and accessible framework for the analysis of intensive longitudinal data.

To conclude this section, it is also important to highlight the major differences between state-trait SEMs and the models and frameworks that were just mentioned. Firstly, the research questions that can be answered by using state-trait SEMs are considerably different from the research questions that can be answered by using multilevel VAR or state-space modeling. While state-trait SEMs are mostly useful to identify the factor structure of the scales and short questionnaires used in intensive longitudinal data, multilevel VAR and state-space models are more about explaining how a dynamic system is affected by covariates of interest. In relation to DFA models, multilevel state-trait SEMs that account for autoregressive effects can be easily formulated as DFA models, with the difference that DFA models are more flexible by allowing autoregressive effects to be random among persons. Lastly, the DSEM framework allows for bridging the gap between state-trait SEM and multilevel VAR models, and thus for answering a broad range of research questions arising from both approaches.

Simulation Study

State-trait SEMs have been rarely used to analyze intensive longitudinal data, mainly because most of the models have been proposed as single-level models. As indicated previously, single-level models become harder and practically impossible to use when there are too many measurement occasions. To the best of our knowledge, this paper presents, for the first time, a simulation study that aims to systematically

explore under which conditions state-trait SEMs can be useful to analyze intensive longitudinal data. For this, we selected three state-trait SEMs: The MSST, the CUTS, and the TSO models. While these models are some of the simplest models that allow differentiating states and traits, they also address some of the most important features that are accounted for by more complex state-trait SEMs (i.e., method effects and autoregressive effects). In the simulation, we compared both the single-level and the multilevel formulation of each model. Even though differences in the estimates between the two versions of the same model were not expected because they are mathematically identical, multilevel models can handle large numbers of measurement occasions and missing data (Geiser, 2020; Geiser et al., 2013). It is therefore important to see under which conditions (e.g., how many time points) the single-level version runs into fitting issues, and thus, the multilevel formulation of the models becomes the only possible way to fit the models to the data.

In addition, multiple factors were manipulated, such as the model used to simulate the data, the number of measurement occasions, the proportion of missing values, and the ratio between the trait variance and the state variance. To start with, we simulated separate data sets based on each model to be able to compare the model fits across different data-generating models. We expected that each model would be favored when it matches with the true or data-generating model. Next, we manipulated the number of measurement occasions and the proportion of missing values. Although it is known that the single-level models become impossible to fit as the number of measurement occasions and the proportion of missing values increases, no simulation study has yet aimed to determine the point at which this happens. Finally, the ratio between the trait and the state variances was considered to study how the models would perform if the variables were more trait-like, more state-like, or evenly trait- and state-like. Considering previous results (Cole et al., 2005), we expected no differences in the results due to this factor.

In a nutshell, this simulation study aimed to explore how suitable the selected state-trait SEMs are for analyzing intensive longitudinal data. To explore this, the

models were tested under different conditions, which represent realistic settings of intensive longitudinal studies in psychology. The models were evaluated in terms of the number of times the analysis converged to proper solutions and the quality of the estimated parameters in relation to the true population parameters. A secondary goal of the simulation was to identify what is the maximum number of measurement occasions that can be handled by the single-level models. By studying this, we expected to be able to provide practical guidelines on the usage of state-trait SEMs when analyzing intensive longitudinal data.

Method

In the simulation study, we manipulated four factors while keeping the sample size and the number of variables fixed. Thus, the sample size was fixed at 100, as it is a reasonable number of individuals to have in an intensive longitudinal study (e.g., Bos, Schoevers, & Rot, 2015; Bringmann et al., 2013; Kuppens, Allen, & Sheeber, 2010), and the number of indicators was fixed to 4¹. In relation to the manipulated factors, firstly, we manipulated the model used to generate the data to be able to fairly compare the selected models. In the following sections, the model used to generate data is referred to as the *base model*. Secondly, the number of measurement occasions was set to 10, 15, 20, 30, 60, or 90. The conditions with 20 measurement occasions or less aimed to aid in the identification of the maximum number of measurement occasions that can be handled by single-level state-trait SEMs. Note that single-level state-trait SEMs are commonly used to analyze data that have between two and eight measurement occasions (Geiser & Lockhart, 2012, Appendix B). The conditions with 30 measurement occasions or more aimed to mimic the common number of observations in psychological time series (e.g., Bringmann et al., 2016; Fuller-Tyszkiewicz et al., 2017; Schuurman et al., 2015; Song & Zhang, 2014). Thirdly, three proportions of missing values were

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¹ The number of indicators was kept fixed and small considering that intensive longitudinal questionnaires tend to be short in order to not burden the participant (Eisele et al., 2020). Thus, the number of questions measuring the same construct is likely to be small. Moreover, we ran a short simulation manipulating the number of indicators, which showed that this factor does not seem to affect the performance of the model when it increases. Results from this simulation are available in the supplementary material.

selected: 0%, 10%, and 20%². The missing values were assumed to follow an MCAR mechanism (Little & Rubin, 2019; Rubin, 1976). Finally, the approximate ratio between the trait variance and the state variance was set to 1:3, 1:1, and 3:1. This factor was manipulated in a similar way as it was done by Cole et al. (2005) in a simulation study about method effects in the TSO model. In conclusion, the simulation follows a $3 \times 6 \times 3 \times 3$ fully crossed design, where 100 replications were generated for each condition.

In relation to the true parameters, these were defined on the basis of other simulation studies with state-trait SEMs (e.g., Cole et al., 2005; Geiser & Lockhart, 2012; LaGrange & Cole, 2008) and empirical results of the models of interest (e.g., Eid et al., 2017; Geiser & Lockhart, 2012; Hamaker et al., 2017). The proportion of measurement error variance across all models and all indicator variables was set to approximately 0.2, which implies that the true reliabilities of the indicators variables were set to approximately 0.8. All true parameters were assumed to be time-invariant because this is required in the multilevel formulation of the models. In other words, measurement invariance was assumed to hold in all the generated data sets. The true parameters and true variance coefficients are included in the supplementary material of this paper.

Once a data set was simulated, it was analyzed 11 times ($3 \text{ models} \times 2 \text{ versions of each model} \times 2 \text{ estimation methods}$ – 1 for the multilevel TSO with maximum likelihood estimation). Hence, each replication was analyzed with the single-level and the multilevel version of each model. Moreover, the estimation methods were set to maximum likelihood estimation (MLE) and MCMC Gibbs sampler (Bayes). Note that the multilevel version of the TSO model can only be estimated through Bayesian methods because maximum likelihood estimation is not supported in Mplus when using the LAGGED command or the ampersand (&) command to include lagged variables in the model (Muthén & Muthén, 2017). This is why each generated data set was

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² These proportions of missing values were kept small due to several practical reasons. Firstly, in previous runs, we observed that increasing the proportion of missing values to around 10% already resulted in very long running times and convergence problems for the single-level models. Secondly, it is known in the literature that a clear advantage of the multilevel formulation is that it is able to handle missing values (Geiser, 2020; Geiser et al., 2013). Finally, these proportions of missing values aimed to resemble the proportion of missingness observed in the filtered empirical data at hand.

analyzed 11 instead of 12 times.

The simulation was performed in Mplus 8.2 (Muthén & Muthén, 2017) and R 3.6.1 (R Core Team, 2019). Mplus was used to fit the models to the data and R was used to generate the data and to analyze the results of the simulation. Furthermore, Mplus was called from within the R environment through the package MplusAutomation (Hallquist & Wiley, 2018). All the code for this study is available at https://github.com/secastroal/LST_Analyses. Note that these models can also be fitted in any SEM specialized software, for example with the R package lavaan (Rosseel, 2012). Also, to fit the models within the Bayesian framework, alternative software such as Stan (Carpenter et al., 2017) or JAGS (Depaoli, Clifton, & Cobb, 2016) can be considered. When running the analyses in Mplus, we used a maximum of 50,000 iterations when the estimation method was maximum likelihood, and we used three chains each with a minimum of 5,000 iterations with thinning 10 when the estimation method was Gibbs sampling³. These conditions and in general the complexity of the models made the analyses highly computationally demanding, especially when the number of measurement occasions and the proportion of missingness were larger. Therefore, a maximum running time of one hour per model fit was set and 4GB of RAM dedicated per core in order to be able to conduct the simulation study in a reasonable period of time. After the time limit was reached or if all the available memory was used for a specific analysis, it was interrupted and no output was saved.

Outcomes. To compare the performance of the models in the simulation study, we determined (a) the number of successful analyses, that is, the number of times a model was not interrupted, converged and provided a reasonable solution, and (b) the quality of the parameter estimates in relation to the true population parameters.

Analyses that did not finish successfully were classified into warnings/errors,

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³ In all Bayesian analyses, we used the default priors provided by Mplus, which are uninformative priors. A sensitivity analysis was done with a random sample of analyses using weak priors. Results from these analyses are included in the supplementary material and provided evidence that the weight of the priors of the estimated model is negligible. Furthermore, to be sure that the MCMC algorithm converged, we used the BITERATIONS option of MPlus. This option makes the algorithm run until all the potential scale reduction factors (also known as Rhat) are below 1.05 or 1.1 (when there is a large number of parameters) given a minimum and a maximum number of iterations (Muthén & Muthén, 2017).

non-convergence, and out of resources. The warnings/errors status might be due to negative variances, unreliable standard errors, or non-convergence of the H1 model. The H1 model is the unrestricted model, which is needed to compute the χ^2 and related fit measures in SEM (Muthén & Muthén, 2017). The non-convergence status might be due to the model being unable to compute standard errors or because the algorithm did not converge (exceeding the maximum number of iterations in MLE or not satisfying the convergence criterion in the MCMC algorithm). Finally, the out of resources status implies that the analysis was forced to stop after an hour of running time or the computing process ran out of available memory. To study the quality of the parameter estimates, we computed the average bias ($E[\hat{\theta} - \theta]$), the average relative bias ($E[(\hat{\theta} - \theta)/\theta]$), the average absolute bias ($E[|\hat{\theta} - \theta|]$), and the root mean squared error (RMSE; $\sqrt{E[(\hat{\theta} - \theta)^2]}$). Additionally, in the supplementary material, we included results about information criteria indices, which indicate the number of times a model was selected as the best fitting model.

As not all the parameters nor variance coefficients are shared across all the three models, we focused our analyses on the parameters and variances coefficients that are common to the three models. The comparable parameters across all models are the three factor loadings at the within-level λ_{S_j} , the variance of the latent state residual $var(\zeta)$, the four variances of the measurement error component $var(\epsilon_j)$, the reliabilities $Rel(Y_j)$, the consistencies $Con(Y_j)$, and the occasion-specificities $Spe(Y_j)$.

Results

Successful analyses. The percentage of analyses that finished successfully or failed per type of analysis across all conditions is shown in Table 2. This table shows the effect of the formulation of the model and the estimation method. As expected, analyses estimated via MLE were more prone to be interrupted or to present convergence issues or errors when the data were structured in wide format. For example, the single-level CUTS model estimated with MLE only retrieved an interpretable solution in 21.4% of the analyses performed. On the other hand,

single-level models estimated via Bayesian methods also failed in multiple replications but mainly due to the analyses running out of time. In contrast, when the data were structured in long format and the multilevel versions of the models were used, the analyses almost never failed independently of the estimation method. However, this is not the case for the multilevel CUTS model estimated by means of MLE, which only converged to an interpretable solution in 61.9% of the analyses.

Figures 4 through 6 show how many analyses finished successfully in the conditions with trait-state variance ratio of 1:1 given each proportion of missingness. This allows observing in detail how the number of measurement occasions and the proportion of missing values affect the convergence of the analyses. The same plots and particular results for conditions with trait-state variance ratios of 1:3 and 3:1 are included in the supplementary material. Starting with the single-level models, analyses failed to provide a solution when estimated by means of MLE and with 60 or more measurement occasions. This threshold becomes lower when including missing values. With 10% missing values, 30 or more measurement occasions become hard to handle, and with 20% missing values, 20 measurement occasions are already problematic. Moreover, when fitting the single-level CUTS model with MLE to non CUTS data, the analyses completely failed to reach a solution independently of the number of measurement occasions. When the number of measurement occasions was lower than 60, these failures were mainly because of the model estimating negative variances. This could happen due to the fact that there were not real method effects in the data. Similarly, when fitting the single-level TSO model with MLE to MSST data, the single-level TSO model completely failed to provide a reasonable solution. In general, increasing the number of measurement occasions in combination with the proportion of missing values makes the single-level models more likely to fail when estimated by means of MLE.

In contrast, when using Bayesian estimation, single-level models successfully finished independently of the number of measurement occasions or the proportion of missing values. Note that single-level models estimated by means of Bayesian methods only failed to reach a solution with 90 measurement occasions when there were missing

values. These failures were mainly due to the imposed time restriction. Hence, without the one-hour time limit, the single-level models estimated via Bayesian methods were likely to converge even with 90 measurement occasions.

In relation to the multilevel formulation of the models, the multilevel models tended to perform relatively well in most conditions independently of the estimation method. As shown in Figures 4 through 6, the multilevel models finished successfully in almost all of the replications across all conditions. However, this is not true for the multilevel CUTS model when estimated by means of MLE, which failed to provide an interpretable solution when analyzing data generated from another model. These failures were more likely because of negative variances. We conjecture again that the problem is that there are no real method effects in the data generated based on the MSST and the TSO models. As a consequence, it was difficult for the CUTS model to estimate null unique trait variances, resulting in at least one negative estimated variance. Note that the multilevel CUTS model failed completely when there were autoregressive effects in the data. As this was unexpected, we further inspected these analyses by performing some additional simulations while varying some of the true population parameters. In these additional simulations, we found that the covariances of the latent trait-indicator variables ξ_j of the TSO model had an effect on the performance of the multilevel CUTS model estimated via MLE. In other words, had we selected a different variance-covariance matrix to generate the TSO data, we would have had results where the multilevel CUTS model with MLE would converge in most of the replications. Results of these additional simulations are presented in the supplementary material.

Estimated Parameters. Bias, relative bias, absolute bias, and RMSE were used to compare the estimated parameters with the population parameters. As said previously, we used these statistics to compare the parameters that were common across all three models. Given that these different measures did not lead to different conclusions, the following section is based on the results from the average relative bias. In general, we observed that the three models fit particularly well their own data,

showing little deviation from the population parameters. Moreover, the quality of the estimated parameters was not overly affected by the proportion of missing values, the estimation method, or the version of a model, which means that the average bias of a parameter did not vary noticeably when these factors changed.

As a whole, the estimated within factor loadings λ_{S_j} showed biases close to 0 in most situations. When looking at the estimated variance of the state residual ($var(\zeta)$) and the estimated variances of the measurement error components $var(\epsilon_j)$, these estimates tended to show some bias, especially when the generation and estimation models differed. For example, the MSST was shown to perform quite poorly in those cases. Also, the CUTS model was considerably inaccurate at the estimation of the variance of the state residual ($var(\zeta)$) when analyzing data generated based on the TSO model. In contrast, the TSO was consistently accurate independently of the generating model. These observations are highlighted in Figure 7, which shows the average relative bias of the variance of the latent state residual ($var(\zeta)$) per condition when the trait-state variance ratio was 1:1 and there were no missing values.

In relation to the variance component coefficients, such as reliability, consistency, and occasion-specificity, the models did a relatively good job at recovering these parameters. For example, in Figures 8 and 9, we display the average relative bias of the reliability and the consistency for the third variable Y_3 across the conditions without missing values and a trait-state variance ratio of 1:1. For the estimates of the reliability, the MSST model tended to slightly underestimate these parameters when the data were generated based on a different model. This effect was larger when the variables were more trait-like. Similarly, the estimates of the consistency tended to show some bias when using the MSST model to analyze data based on the other models. Yet, this effect was lower in the conditions with a trait-state variance ratio of 3:1. On the other side, the CUTS model was fairly accurate at estimating the reliability regardless of the base model. However, the estimates of the consistency got worse when the model used to generate the data was the TSO and when the variables were more state-like. Finally, the accuracy of the estimates of the TSO model was high independently of the base

model, the trait-state variance ratio, and the other manipulated factors.

Additionally, we also looked at the variance component coefficients that were not common across all the three models, such as the unique consistency for the CUTS model and the unpredictability by trait for the TSO model. We expected these coefficients to be estimated close to 0 if the data were generated from a different model. In other words, if the base model was the MSST, and the data were analyzed with the CUTS model, we expected the estimate of the unique consistency to be basically 0. To some extent, our expectations were met. On the one hand, the CUTS model did estimate approximately null unique consistencies when the base model was the MSST, but it did not when the base model was the TSO. Moreover, the unique consistencies, when the base model was the TSO, tended to be larger the more trait-like the variables were.

On the other hand, the estimates of the unpredictability by trait in the TSO model when the data were not generated by itself were basically 0. This is shown in Figure 10, which plots the mean estimate across replications of the unpredictability by trait for all indicators Y_j when the model used to generate the data was the CUTS model, the trait-state variance ratio was 1:1, and the proportion of missing values was 0%. Moreover, the same observations were made about the estimates of the autoregressive effect⁴. This is evidence of the robustness of the TSO model. In other words, if there are no autoregressive effects in the data, the TSO is able to identify the lack of these effects. Thus, the TSO does not estimate unrealistic autoregressive effects even if method effects are present in the data.

Summary

Through the simulation study, we explored the suitability of the selected models at analyzing hypothetical intensive longitudinal data. This also allowed comparing the performance of the three models and to get an idea of which model can be more useful and more reliable when analyzing intensive longitudinal data. As expected, the results showed that the single-level models are harder to fit via MLE when the number of

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⁴ A plot for the bias of the autoregressive effect is included in the supplementary material.

measurement occasions and the proportion of missing values increase. On the contrary, the single-level models were able to converge when estimated via an MCMC algorithm even with 90 measurement occasions and if they failed, it was mainly due to the imposed time limit. Therefore, under the absence of missing values, single-level models can be useful at analyzing data with up to 30 measurement occasions if estimated via MLE and with up to 90 measurement occasions if estimated via an MCMC algorithm. However, when estimated through Bayesian methods, comparing models and thus testing for measurement invariance can be difficult due to the lack of fit statistics, which makes the model impractical when there are too many measurement occasions. In short, using the single-level models can be an alternative if the time series of interest is not too long (around 30 time points), as this would allow researchers to test for measurement invariance.

By any means, the multilevel formulation of the models is undeniably more practical and straightforward to use in comparison with their respective single-level formulation, although multilevel state-trait SEMs could also run into fitting problems when the fitting model did not match the data-generating model. In general, the models did a good job at recovering the population parameters, especially the multilevel TSO model, which consistently performed well across all the conditions of the simulation study. For this reason, we consider the multilevel TSO the most viable model to analyze intensive longitudinal data among the models that were studied.

Empirical Example

To present a real data application, we analyzed data from the national crowdsourcing study *HowNutsAreTheDutch* (Dutch: *HoeGekIsNL*; Krieke et al., 2016; Krieke et al., 2017), which started in May 2014. The *HowNutsAreTheDutch* (HND) project aims to study the mental health of the Dutch population by considering the mental health as “a dimensional and dynamic phenomenon” (Krieke et al., 2016, p. 124). To capture the dynamics of the mental health, the HND project includes in its design a daily diary study, from which we obtained the data. Specifically, we analyzed

the items used to measure positive affect, which are *I feel relaxed*, *content*, *calm*, *energetic*, *enthusiastic*, and *cheerful*. The first three items measure positive affect deactivation, and the last three measure positive affect activation according to the circumplex model of affect (Feldman Barrett and Russell, 1998, and Yik, Russell, and Barrett, 1999, as cited in Krieke et al., 2016). In a nutshell, the circumplex model assumes that affect can be explained by two dimensions: Valence (positive or negative) and activation. In the following analysis, we used the three state-trait SEMs discussed in this paper to determine if the positive affect items are described best by a one-factor or a two-factor measurement model. Moreover, we aimed to explore the psychometric properties of the items and to determine to what extent the items are trait- or state-like.

Method

In the diary study, participants were followed three times a day, for 30 days. Hence, each participant could have a maximum of 90 measurements. To assess the participants, a link to the questionnaire was sent through a text message every six hours given each participant's daily routine. After receiving the text message, participants had to answer the questionnaire immediately or within the next hour. The questionnaire contained 43 items that measure, for example, subjective well-being, mood, self-esteem, etc. Most of the items were rated on a visual analogue scale (VAS) from 0 to 100. Note that we only considered the six items that measure positive affect.

In this empirical example, we considered the data collected between May 2014 and December 2018. Initially, the data included 115,386 records of 1,396 participants with a mean of 43.13 observations per participant. Most of the participants had less than 20 or more than 60 observations. As some participants did the daily diary study multiple times, we decided to analyze only the first daily diary study of each participant. Furthermore, in some cases, participants have 93 observations because the study period was wrongly programmed to last 31 days during the first month of the study, from which we selected the first 90 observations. Also, given that many participants tended to drop the daily diary study during the early stages of it, we only included participants

with at least 65% of the observations (59 or more) in the analyses. This criterion is also used in the HND project to give personalized feedback (Krieke et al., 2016, p. 128).

After this selection, data were reduced to 57,945 records of 644 individuals (mean age 39.88; 83.86% women) with a mean of 74.9 observations per participant.

Results

The responses on the six positive affect items were spread over the whole range of the scale. The median of the six items varied between 50.0 and 63.8, and the standard deviation varied between 19.05 and 21.43. Moreover, their correlations ranged from 0.36 to 0.79. The distribution of the six items was very similar. Panel A of Figure 11 presents the distribution of the item *relaxed*. As shown in the histogram, the item's scores are concentrated around three main points: 40, 50, and 70. This odd distribution can be explained by the large variability of the data and the method of data collection. On the one hand, due to the nature of the variables, it was expected for people to be concentrated just a little above and below the middle point. On the other hand, the visual analogue scales were presented with the middle point pre-selected. If a person was not feeling in any particular way, they were able to just check their response in the middle point. In contrast, the distribution of the intraindividual means follows a more bell-shaped distribution as shown in panel B of Figure 11.

To give an illustration of the raw data, Figure 12 presents the trace plots of a random subsample of 30 persons on the variables *relaxed* and *energetic*. As one of the assumptions imposed by the state-trait SEMs discussed in this study is stationarity⁵, we tested for it by means of the Kwiatkowski–Phillips–Schmidt–Shin test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992), where the null hypothesis is that the observable time series is trend-stationary. By excluding individuals with at least one non-stationary time series, the sample size was reduced to 376 persons. The main analyses of this study were performed on the sample with and without the individuals with non-stationary time series. As the results did not show major differences, here, we report the results of the larger sample. The results excluding the individuals with

non-stationary time series are available in the supplementary material.

The HND data were analyzed with the multilevel versions of the three models: MSST, CUTS, and TSO. All the analyses were performed within the Bayesian framework. This means the models were estimated with the MCMC Gibbs sampler including four chains with thinning 10 and 5,000 iterations per chain. The first half of each chain was considered part of the burn-in phase, which left a total of 10,000 valid samples of the posterior distribution of the parameters. These analyses aimed to identify the factor structure and the variance component distribution of the six positive affect items.

Initially, we tried to fit the models to all items at once, assuming a unique factor of positive affect. However, the models did not fit well the data or did not converge. This was a clear indication that one factor was not enough to capture the structure of the data. Therefore, we decided to analyze the data in two sets of items as is suggested by the circumplex model: The positive affect deactivation (PAD) and the positive affect activation (PAA) sets. The results of these analyses were more promising but the mixing of the chains of the intercepts was poor as shown in Figure 13. To solve this, we centered the data and constrained the intercepts to 0 to get a better solution. Note that the intercepts do not influence the computation of the variance coefficients. Next, we report the results of the models fitted to each of the centered sets of items. The corresponding posterior predictive p -values (ppp⁶) and Deviance Information Criteria (DIC⁷) are presented in Table 3 for each set. Note that the ppp is not available for the TSO due to software limitations. Considering the DIC values, the TSO model seems to

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⁵ In the literature, different types of stationarity are mentioned, for example, weak stationarity, strict stationarity, trend stationarity, or if the data contained a random walk. Note that it is far from trivial to test for these different kinds of stationarity (see Bringmann et al., 2017). In this specific case, we opted to test for trend stationarity.

⁶ The posterior predictive p -value (ppp; Asparouhov & Muthén, 2010) is the Bayesian counterpart of the traditional p -value. It tests the model against an unspecified alternative. As implemented in Mplus, low ppp values indicate model misfit. For more details on how ppp values are computed in Mplus see Asparouhov and Muthén (2010, pp. 28-30)

⁷ The DIC as computed in Mplus should be interpreted with caution because it can be unstable, especially when the model includes latent variables (Asparouhov et al., 2018, pp. 366-368). Also, note that the DIC values of different models are not always comparable.

fit the data best for both sets of items. Hence, we follow with the interpretation of the results of the TSO analyses.

To interpret the results, we focused on the variance coefficients of the model: Reliability, consistency, predictability by trait, unpredictability by trait, and occasion-specificity. These estimates are shown in Table 4 for the two sets of items. The estimated reliability coefficients show that a large proportion of the variance of the items was explained by reliable sources of variability. In particular, the reliabilities of the items that measure positive affect activation are on average higher than the reliability of the items that measure positive affect deactivation, which means that positive emotions with high arousal are measured more precisely than positive emotions with low arousal.

Regarding the consistency and occasion-specificity, the items *content* and *calm* of positive affect deactivation have a consistency coefficient considerably larger than the occasion-specificity. This means that these items are in general more trait-like than state-like. In other words, emotions such as feeling content or calm are not as influenced by the situation as emotions such as feeling relaxed. Yet, the variation due to the situation is not negligible. On the other hand, the item *relaxed* as well as all the items of positive affect activation appear equally trait-like as they are state-like. The variability due to the person and the variability due to the situation are evenly distributed and equally important. These results can be compared with the intraclass-correlation (ICC; Houben et al., 2020) which is usually computed in an empty multilevel model. The corresponding ICCs of the six items varied between 0.32 and 0.37, which indicates that all the items were more state-like. These contradictory conclusions might be due to the fact that the state-trait SEMs do account for the random measurement error, while traditional multilevel models do not.

Finally, the unpredictability by trait of all the items was estimated close to 0.05, which means that only 5% of the variability is explained by the carry-over effects. The unpredictability by trait is directly associated with the estimated autoregressive effects, which were 0.367 for the positive affect deactivation items and 0.317 for the positive affect activation items. Despite the fact that the autoregressive effects were relatively

large and practically significant, this did not necessarily imply that the proportion of the variance explained by the dynamic process, namely the unpredictability by trait, would be practically significant as well.

Additionally, we fitted a simple extension of the TSO model in order to fit the two sets of items at once and allow including cross-regressive effects on the latent occasion-specific variables. The main goal of fitting this model was to study the possible cross-regressive effects of positive affect deactivation on positive affect activation and vice versa. This model was also fitted to the centered data to avoid divergent MCMC chains. The path diagram of this model and its estimates are presented in Figure 14. This analysis suggests that positive affect deactivation had an important effect over time on positive affect activation, but the converse was not true. In other words, when people feel positive emotions with low arousal (e.g., calm and relaxed), then people's positive emotions with high arousal (e.g., energetic and excited) are likely to increase slightly in future situations, but not the other way around.

Summary

To conclude, by analyzing the HND data with the state-trait SEMs, we found evidence supporting the thesis that the factor structure of positive affect consists of two dimensions: Positive affect activation and positive affect deactivation. This evidence supports the circumplex model of affect. Moreover, from the TSO model, we observed that all the items are reliable at measuring positive affect. The analysis also showed that most of the measured emotions are approximately as trait-like as they are state-like. This means that the trait component of these emotions is not negligible even though emotions are prone to fluctuate over time. Finally, the analysis showed that there are important auto- and cross-regressive effects that help explaining the dynamic process that governs the relationship among emotions of positive affect. These results are in concordance with the literature about emotional reactivity (see Kuppens et al., 2010; Suls, Green, & Hillis, 1998).

Discussion

In this paper, we explored how to study states and traits in intensive longitudinal data by means of state-trait SEMs. We selected three state-trait SEMs for our study: The MSST, the CUTS, and the TSO models, which represent the variety of state-trait SEMs. Our analyses showed that these models might be especially useful when formulated as multilevel SEM. This facilitates their application to intensive longitudinal data regardless of the number of measurement occasions that are included (see also Geiser, 2020; Geiser et al., 2013). Furthermore, with the empirical example, we also showed how state-trait SEMs allow studying the psychometric properties of the items used in experience sampling studies, and drawing conclusions about the nature of the variables in terms of their state and trait components. As shown in the empirical example, some modeling decisions might be required to facilitate the convergence of the models. For example, centering and constraining intercepts to zero is a safe way to simplify the models. This is possible because intercepts are not needed in the computation of the variance coefficients, which are of major interest in a state-trait SEM analysis.

In relation to our results, out of the three models, the multilevel formulation of the TSO model was the one that performed the best in both the simulation study and the empirical example. Our analyses showed that the multilevel TSO model estimated the parameters with the lower bias across the different conditions and performed equally well even when the real data did *not* have autoregressive effects. For these reasons, and considering that autoregressive effects are likely to occur in intensive longitudinal data, we can conclude that the multilevel TSO model is the most suitable state-trait SEM for analyzing intensive longitudinal data. Note that this is not the case for the single-level TSO model, which not only failed by increasing the number of measurement occasions and the proportion of missing values, but also when the data were generated based on the MSST. In contrast, the performance of both formulations of the MSST and the CUTS models was not as good. For instance, the MSST model introduced bias when there were method or autoregressive effects in the real data. These results are consistent

with the results of Geiser and Lockhart (2012), who observed that the MSST model performance is not optimal when there are method effects in the data. Similarly, the CUTS model introduced bias when there were autoregressive effects in the real data.

One of the most important results from the simulation was that both single-level and multilevel TSO models were robust to data that include method effects, meaning that unrealistic autoregressive effects were not estimated even when method effects were present in the data. This result can be explained by the fact that the versions of the TSO used in this study included latent trait indicator variables instead of a common latent trait variable. Including latent trait indicator variables is in fact a way to account for method effects in the state-trait SEM literature (Geiser & Lockhart, 2012). Therefore, this might be the reason why the TSO model as presented in this study was able to correctly deal with data that include real method effects. Basically, the real method effects were captured by the variance of the latent trait indicator variables of the TSO model.

Studying the Psychometric Properties of Intensive Longitudinal Data

One of the main advantages of analyzing intensive longitudinal data with state-trait SEMs is that these models allow studying the psychometric properties of the items used in daily diary studies. As a consequence, it is possible to account for the random measurement error in the data and to study the precision of the items at measuring what they intend to measure. In general, when measuring psychological variables, measurement error is likely to happen (Schuurman & Hamaker, 2019; Schuurman et al., 2015). Therefore, intensive longitudinal data should ideally be analyzed through models that account for measurement error, such as state-trait SEMs.

Furthermore, state-trait SEMs allow quantifying the precision of the measurements in terms of the variance coefficients proposed in the LST theory. As shown in the empirical example, one can estimate the reliability of each item and identify the proportion of random measurement error that is present in the data. In addition, the LST theory estimates the consistency and the occasion-specificity

coefficients. These coefficients allow for additional interpretations of the data and they can be used to make decisions about the items for future applications. In the empirical example, it was shown that the positive affect emotions are as trait-like as they are state-like. For example, the items *content* and *calm* had a consistency considerably larger than their occasion-specificity, which meant that they were more trait-like than state-like. Note that other measures used in traditional multilevel modeling such as ICC (Houben et al., 2020) also indicate to what extent a variable is trait- or state-like. However, these kinds of measures might be biased by the amount of random measurement error present in the data (Muthén, 1991; Roesch et al., 2010), which results in overestimation of the variability within individuals. Therefore, models that account for the random measurement error can more accurately determine the trait-state nature of the variables.

Even though one of the advantages of state-trait SEMs is the possibility to study the psychometric properties of the questionnaires used in intensive longitudinal data, this topic has also been addressed from other perspectives. Within multilevel approaches, it is common to study these psychometric properties during the pre-analysis of the data (see Geschwind, Peeters, Drukker, Os, & Wichers, 2011; Nezlek, 2007). Moreover, alternative reliability coefficients have been recently proposed. Specifically, in the multilevel-VAR model with measurement error (Schuurman & Hamaker, 2019), the authors proposed two reliability coefficients: The between-person reliability and the within-person reliability. Similarly, in the context of confirmatory factor analysis for intensive longitudinal data, Hu et al. (2016) proposed the intraindividual reliability and the interindividual reliability. While these coefficients seem similar to the consistency and the occasion-specificity coefficients of the LST theory, they are not necessarily equal. Both Schuurman and Hamaker (2019) and Hu et al. (2016) acknowledge that the reliability of a questionnaire can vary from person to person, allowing the within-person reliability or the interindividual reliability to vary over persons. This is not the case for the variance coefficients proposed within the LST theory.

Limitations and Future Research

There are some important limitations when applying state-trait SEMs to intensive longitudinal data due to the assumptions that are made. In particular, state-trait SEMs assume that measurement occasions are equally spaced over time, that parameters are equally valid for all the individuals in the sample, that parameters do not vary over time when the models are formulated as multilevel SEM, and that time series are assumed to be stationary. Next, we discuss each of these limitations and possible solutions if available.

Firstly, assuming that measurement occasions are equally spaced over time can be an unrealistic assumption for intensive longitudinal data. This is because, in most studies, individuals are required to fill the questionnaires at random intervals during the day. Therefore, assuming that the measurements are equally spaced over time does not hold and the parameter estimates can be misleading (Crayen, Eid, Lischetzke, & Vermunt, 2017; Haan-Rietdijk, Voelke, Keijsers, & Hamaker, 2017). This is especially problematic when auto- and cross-regressive effects are included because a model like the TSO can only estimate one autoregressive parameter, which is tied to a specific time interval. Thus, if the measurement occasions are unequally spaced over time, such an autoregressive effect would mean that the effect of the variable Y at time $t - 1$ on itself at time t is the same regardless of the elapsed time between occasions. One approach to deal with data collected at unequal intervals, suggested within the DSEM framework (Asparouhov et al., 2017, 2018), is to include missing values in such a way that the time interval between occasions becomes approximately equal over time. Alternatively, one can use continuous-time models to deal with unequal time intervals⁸, which is strongly suggested as ignoring the violation of this assumption results in biased estimates of the auto- and cross-regressive effects (Haan-Rietdijk et al., 2017). Some of the most common continuous-time models used to analyze intensive longitudinal data are encompassed within the hidden Markov model framework. For example, a continuous-time mixture LST Markov model has been proposed by Crayen et al. (2017)

for analyzing categorical items.

Secondly, assuming that parameters are equally valid for all the individuals in the sample violates one of the principles of intensive longitudinal methods, which is the emphasis on the individual (Hamaker, 2012). Given this principle, it is logical to expect that relationships between variables or even the factor structures are not exactly the same across all the persons. This is not taken into account when the parameters are estimated for the sample as a whole, as in state-trait SEMs. In general, to account for these individual differences, parameters can be modeled as random effects. This is the standard procedure in the multilevel vector autoregressive (ML-VAR) literature, where auto- and cross-regressive effects are treated as random slopes (Bringmann et al., 2013; De Haan-Rietdijk et al., 2016; Rovine & Walls, 2006; Schuurman et al., 2016). Recent developments also allow for random residual variances (Jongerling, Laurenceau, & Hamaker, 2015). For state-trait SEMs, an important avenue for future research is therefore to allow for random loadings, autoregressive effects, or residual variances, which can be done by extending the models within the DSEM framework (Asparouhov et al., 2017, 2018). Alternatively, some authors have suggested a more *bottom up* approach (Adolf, Voelkle, Brose, & Schmiedek, 2017; Molenaar, 2004; Ram, Brinberg, Pincus, & Conroy, 2017), where each single-subject time series is first analyzed before pooling out results for the sample.

Thirdly, assuming that parameters are time-invariant and that the time series are stationary implies the type of psychological dynamics that can be studied is very restricted. In other words, these assumptions imply that the dynamic process is static. Therefore, time series collected during a psychological intervention, where the intention is to change the dynamic process, can not be analyzed under these assumptions. Moreover, assuming that the dynamic processes of interest are static may not be accurate in most cases (Bringmann et al., 2017; De Haan-Rietdijk et al., 2016). These limitations not only apply to state-trait SEMs but also to most well-known techniques

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⁸ Selig, Preacher, and Little (2012) have proposed an interesting approach to deal with unequal time intervals in panel data, which includes the time as a moderator of the lag effect. However, this method still needs to be extended for intensive longitudinal data.

such as ML-VAR. Alternative methods that relax these assumptions are in development, for example, Bringmann et al. (2017) recently proposed a semi-parametric time-varying autoregressive model to address this problem in the ML-VAR literature. Similarly, De Haan-Rietdijk et al. (2016) proposed a model that estimates a different autoregressive effect given a threshold, which is useful to analyze persons whose dynamics vary given the strength of the psychological variable. The DSEM framework (Asparouhov et al., 2018) also allows relaxing these assumptions with the cross-classified DSEM models, which include time as an additional level of analysis. Lastly, if analyzing time series from a single individual, one can consider the extended Kalman filter with iteration and smoothing estimator (Molenaar, Sinclair, Rovine, Ram, & Corneal, 2009). Hopefully, future research will allow extending these methods to multilevel state-trait SEMs.

Finally, notice that in this study, we only covered three fundamental state-trait SEMs. This largely restricts the kind of research questions that can be addressed by these models. However, more complex state-trait SEMs have been proposed over the years. For example, Courvoisier, Eid, and Nussbeck (2007) presented a mixture LST model that can incorporate time-varying covariates. A model like this allows studying the psychological dynamics and how they are affected by other variables, which might answer similar research questions like the ones commonly seen in the multilevel literature. Also, Geiser et al. (2015b) proposed an LST model that accounts for the effects of random and fixed situations. This model allows examining to what extent traits can be specific to a situation. In addition, this model has also been formulated as a multilevel SEM model. To summarize, more complex LST models allow addressing more complex research questions but researchers might need to reformulate them as multilevel SEM in order to be able to study intensive longitudinal data with them.

Conclusion

Through this study, we explored the suitability of state-trait SEMs to analyze intensive longitudinal data. Our results showed that out of the three models included in this study, the multilevel TSO model performed the best in both the simulation study

and the empirical example. This makes the multilevel TSO model an interesting alternative, which might be useful when analyzing intensive longitudinal data if multiple items were used to measure the same construct. Particularly, we encourage the use of the multilevel versions of state-trait SEMs estimated by means of Bayesian estimation, as the analyses under these settings performed the best in terms of model convergence and accurately recovered the parameters throughout the different conditions. Yet, it might be a disadvantage that there are not enough absolute or relative fit measures that allow comparing the goodness of fit of different models.

In general, for researchers that are interested in applying state-trait SEMs to daily diary data, it is important to highlight that these models are applicable under certain specific conditions such as that (a) there should be a latent construct that is measured with multiple items on the intensive longitudinal study, (b) the variables should preferably be measured on a continuous scale, (c) the time interval between occasions should be equal over time, and (d) the time series is assumed to be stationary. Through these models, researchers can answer research questions about the factor structure of their questionnaires, the proportion of the state and trait components of their variables, and study the psychometric properties of the items used. Beware that fitting state-trait SEMs can be subject to the same modeling decisions that are made when using multilevel modeling such as data centering and item selection. In practice, if the data does not include too many measurement occasions (no more than 30), researchers can consider using the single-level models and allow for time-varying parameters to test whether measurement invariance holds.

In this study, we aimed to present state-trait SEMs as alternative tools that can be considered when analyzing intensive longitudinal data. Moreover, we connected the state-trait SEM literature to a broader literature, showing how these models are related to different frameworks that were especially developed to analyze intensive longitudinal data. We consider this is an important opportunity to integrate these different frameworks, which will allow extending state-trait SEMs to more accurately describe psychological dynamics.

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Table 1

Variance Decomposition and Components of the MSST, CUTS, and TSO

Description	Equation
MSST	
Total Variance	$Var(Y_{jt}) = \lambda_{T_{jt}}^2 Var(\xi) + \lambda_{S_{jt}}^2 Var(\zeta_t) +$ $Var(\varepsilon_{jt})$
Reliability	$Rel(Y_{jt}) = 1 - \frac{Var(\varepsilon_{jt})}{Var(Y_{jt})}$
Consistency	$Con(Y_{jt}) = \frac{\lambda_{T_{jt}}^2 Var(\xi)}{Var(Y_{jt})}$
Occasion-Specificity	$Spe(Y_{jt}) = \frac{\lambda_{S_{jt}}^2 Var(\zeta_t)}{Var(Y_{jt})}$
CUTS	
Total Variance	$Var(Y_{jt}) = \lambda_{T_{jt}}^2 Var(\xi) + Var(\vartheta_j) +$ $\lambda_{S_{jt}}^2 Var(\zeta_t) + Var(\varepsilon_{jt})$
Reliability	$Rel(Y_{jt}) = 1 - \frac{Var(\varepsilon_{jt})}{Var(Y_{jt})}$
Total Consistency	$TCon(Y_{jt}) = \frac{\lambda_{T_{jt}}^2 Var(\xi) + Var(\vartheta_j)}{Var(Y_{jt})}$
Common Consistency	$CCon(Y_{jt}) = \frac{\lambda_{T_{jt}}^2 Var(\xi)}{Var(Y_{jt})}$
Unique Consistency	$UCon(Y_{jt}) = \frac{Var(\vartheta_j)}{Var(Y_{jt})}$
Occasion-Specificity	$Spe(Y_{jt}) = \frac{\lambda_{S_{jt}}^2 Var(\zeta_t)}{Var(Y_{jt})}$
TSO	
Total Variance	$Var(Y_{jt}) = \lambda_{T_{jt}}^2 Var(\xi_j) +$ $\beta_{t-1,t}^2 \lambda_{S_{jt}}^2 Var(O_{t-1}) + \lambda_{S_{jt}}^2 Var(\zeta_t) + Var(\varepsilon_{jt})$
Reliability	$Rel(Y_{jt}) = 1 - \frac{Var(\varepsilon_{jt})}{Var(Y_{jt})}$
Consistency	$Con(Y_{jt}) = \frac{\lambda_{T_{jt}}^2 Var(\xi_j) + \beta_{t-1,t}^2 \lambda_{S_{jt}}^2 Var(O_{t-1})}{Var(Y_{jt})}$
Predictability by Trait	$Pred(Y_{jt}) = \frac{\lambda_{T_{jt}}^2 Var(\xi_j)}{Var(Y_{jt})}$
Unpredictability by Trait	$UPred(Y_{jt}) = \frac{\beta_{t-1,t}^2 \lambda_{S_{jt}}^2 Var(O_{t-1})}{Var(Y_{jt})}$
Occasion-Specificity	$Spe(Y_{jt}) = \frac{\lambda_{S_{jt}}^2 Var(\zeta_t)}{Var(Y_{jt})}$

Table 1
Variance Decomposition and Components of the MSST, CUTS, and TSO

Description	Equation
Note. These are the general equations of the variance coefficient components of the single level models. When all parameters are assumed to be invariant over time or when the models are formulated as multilevel SEM, the equations get simplified because the subscripts t are not needed anymore. The equations of the MSST and the CUTS models were retrieved from Geiser and Lockhart (2012), and the equations of the TSO model were retrieved from Eid et al. (2017).	

Table 2
Percentages of Successes and Failures per Type of Analysis on 16200 Analyses Each

Model	Est.Method	Successful	Warnings/Errors	Non-convergence	Out of Resources
MSST	MLE	56.06	9.72	1.02	33.2
ML-MSST	MLE	93.91	0.16	5.86	0.06
MSST	Bayes	81.85	0	8.25	9.91
ML-MSST	Bayes	92.81	0	5.35	1.84
CUTS	MLE	21.4	45.31	0	33.29
ML-CUTS	MLE	61.9	38.04	0.01	0.06
CUTS	Bayes	88.49	0	0.04	11.47
ML-CUTS	Bayes	99.44	0	0.04	0.52
TSO	MLE	39.12	33.15	0	27.73
TSO	Bayes	88.59	0	0	11.41
ML-TSO	Bayes	99.48	0	0	0.52

Table 3
ppp and DIC of the Three Models for the Two Sets of Items

		MSST	CUTS	TSO
PAD	ppp	0.583	0.644	-
	DIC	1185142.150	1171133.218	1129157.419
PAA	ppp	0.583	0.657	-
	DIC	1184024.092	1170988.591	1113933.571

Table 4
Variance Coefficients of the Three Models for the Two Sets of Items

Variance Coefficient		Items		
		Relaxed	Content	Calm
PAD	Reliability	0.80	0.68	0.67
	Consistency	0.40	0.41	0.39
	Predictability by Trait	0.34	0.37	0.35
	Unpredictability by Trait	0.06	0.04	0.04
	Occasion-Specificity	0.40	0.27	0.28
		Energetic	Enthusiastic	Cheerful
PAA	Reliability	0.70	0.84	0.79
	Consistency	0.35	0.39	0.39
	Predictability by Trait	0.31	0.34	0.35
	Unpredictability by Trait	0.04	0.05	0.04
	Occasion-Specificity	0.35	0.45	0.40

Figure 1. Path Diagram of the MSST Model. (A) Single level MSST. (B) Multilevel MSST.

A

B

Figure 2. Path Diagram of the CUTS Model. (A) Single level CUTS with time varying intercepts α_{jt} and trait loadings $\lambda_{T_{jt}}$. (B) Multilevel CUTS.

Figure 3. Path Diagram of the TSO Model. (A) Single level TSO. (B) Multilevel TSO.

Figure 4. Number of Successful Analyses per Condition with 0% Missingness and 1:1 Trait-State Variance Ratio

Figure 5. Number of Successful Analyses per Condition with 10% Missingness and 1:1 Trait-State Variance Ratio

Figure 6. Number of Successful Analyses per Condition with 20% Missingness and 1:1 Trait-State Variance Ratio

Figure 7. Average Relative Bias of the Variance of the Latent State Residual $var(\zeta)$ per Condition with 1:1 Trait-State Variance Ratio and 0% Missingness

Figure 8. Average Relative Bias of the Reliability of the Third Indicator Y_3 per Condition with Trait-State Ratio 1:1 and 0% Missingness

Figure 9. Average Relative Bias of the Consistency of the Third Indicator Y_3 per Condition with Trait-State Ratio 1:1 and 0% Missingness

Figure 10. Estimated Unpredictability by Trait of all Indicators when the Base Model was the CUTS Model, the Trait-State Variance Ratio was 1:1, and the Proportion of Missing Values was 0%

Figure 11. Histograms of the variable *relaxed*. (A) Histogram of the raw scores. (B) Histogram of the intraindividual means.

Figure 12. Time series of a sample of 30 individuals on the variables *relaxed* (Top) and *energetic* (Bottom). The ticked time series shows the overall means at each time point.

Figure 13. Traceplot of the chains of the intercept estimate of the variable *relaxed* when fitting the multilevel TSO model.

Figure 14. Multidimensional TSO with crosslagged effects.