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Analyzing Longitudinal Multirater Data with Individually Varying Time Intervals

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Abstract

Numerous models have been proposed for the analysis of convergent validity in longitudinal multimethod designs. However, existing multimethod models are limited to measurement designs with equally spaced time intervals. We present a new multirater latent state-trait model with autoregressive effects (MR-LST-AR) for designs with structurally different raters and individually varying time intervals. The new model is illustrated using the German Family Panel pairfam. By means of stochastic differential equations, we show how key coefficients of convergent and discriminant validity can be examined as a function of time. We compare the results from continuous and discrete time analysis and provide code to fit the new model in ctsem. Finally, the advantages and limitations of the model are discussed, and practical recommendations are provided.

Article Info

Keywords: Continuous time modeling; latent state-trait modeling; longitudinal multimethod data; structurally different methods

A single method is often not optimal to capture the complexity and multifaceted nature of human development over time. As Burns and Haynes (2006) noted “a single method (rating scale) with a single source (parent) at a single time point provides little information about the time course of the particular problem. The behavior could be stable, increasing, or decreasing as well as changing rapidly or slowly across time” (p. 417). To accurately assess construct validity in the measurement of change and stability, scholars have repeatedly stressed the need for multiple methods in longitudinal measurement designs (Eid & Diener, 2006).

Today, the advantages of multimethod measurement designs are well-known (Eid & Diener, 2006; Vazire, 2010; Vazire & Mehl, 2008) and are increasingly applied in many areas of psychology (e.g., Burns & Haynes, 2006; Connelly & Ones, 2010; Hawkins et al., 2014; Lance et al., 2008; Zald & Curtis, 2005). Furthermore, numerous confirmatory factor analysis (CFA) models have been proposed for analysing longitudinal multirater designs over the last decades (Bohn et al., 2021; Courvoisier et al., 2008; Geiser et al. 2010; Holtmann, et al., 2017, 2020; Koch et al., 2014, 2017, 2020). In the present study, we concentrate on *design-oriented* CFA models for longitudinal multitrait-multirater (MTMR) designs (Eid et al., 2016; Koch et al., 2018).

The basic idea of the design-oriented modeling approach is that there is *no* single CFA model that is suited for all measurement designs, but different models must be considered for different designs (see Eid et al., 2008, 2016). Eid et al. (2016) argued for the distinction between designs with structurally different raters *vs.* designs with interchangeable raters. According to Eid et al. (2016), structurally different raters do not stem from the same rater population and may have different perspectives on a target person. Examples of structurally different raters are self-reports, partner reports, and parent reports. Structurally different raters can be conceived as fixed raters because they are predetermined once a target person has been sampled. Designs with structurally different (or fixed) raters are typically analyzed using single-level CFA models. In contrast, interchangeable (or random) raters imply a multistage sampling procedure (Eid et al., 2016). Examples of interchangeable raters are multiple peers, colleagues, or friend ratings. In this article, we will focus on measurement designs with structurally different raters, as they are frequently used in psychology.

One central goal of longitudinal multirater research refers to the analysis of convergent validity (rater consistency), method specificity (rater consistency), and discriminant validity across time. So far, several models have been presented that combine the advantages of CFA-MTMR modeling and latent state-trait (LST) theory (see Bohn et al., 2021; Courvoisier et al., 2008; Holtmann et al., 2020; Koch et al., 2017). In a recent study, Bohn et al. (2021) introduced a multirater latent state-trait model with autoregressive effects, which has been termed the MR-LST-AR model. The MR-LST-AR model was formulated on the principles of the revised LST-R theory (see Eid et al., 2017; Steyer et al., 2015). The basic idea of the LST-R theory is that traits may change due to past experiences and that “there is no person without a past” (Steyer et al., 2015, p. 71). In LST-R theory, the time-ordering of events and variables plays a crucial role. However, LST-R models are typically specified as discrete time models, in which time is implicitly incorporated by the *ordering* of the observed variables, and latent processes are assumed to only interact when observations occur. This means that the exact time intervals between observations are not explicitly considered, and the same temporal coefficients or covariances apply regardless of whether time intervals are shorter or longer.

As a result, currently available CFA-MTMR models are strictly correct only for measurement designs with *equally spaced time-intervals*. The assumption of equal time intervals is highly questionable and regularly violated in empirical applications (see Oud & Delsing, 2010; Oud & Jansen, 2000; Voelkle et al., 2012), especially if multiple raters are considered. Ignoring differences in unequally spaced measurement intervals may bias parameter estimates and may lead to incorrect conclusions (Driver, 2022). In addition, without adequately accounting for (unequally spaced) measurement intervals, it becomes impossible to compare, or replicate, findings from different studies with different measurement designs (cf. Voelkle et al., 2012).

Consider, for example, a researcher who is interested in the analysis of dyadic coping over time. Dyadic coping can be defined "as couples' mutual, interpersonal stress regulation and the dyadic capacity to deal with couple external stressors" (Zietlow et al., 2018). Traditionally, dyadic coping is measured using self-reports and other reports from the so-called anchor person and the partner, respectively. One important question in couples research concerns the overlap (or rater consistency) between the anchor's and the partner's reported dyadic coping skills over time. It stands to reason that key outcomes regarding dyadic coping skills strongly depend on the chosen time interval in a study. Ignoring the concrete time intervals when investigating the dynamics of dyadic coping over time can be problematic and may provide limited information about the rater consistency and rater specificity over time. By means of stochastic differential equations, continuous time methods account for individually varying time intervals in longitudinal multirater studies and can be used to determine the discrete time interval when the rater consistency (or other key coefficients in the model) reaches its maximum.

The goal of the present study is 3-fold. First, we extend the conventional discrete time multimethod latent state-trait model with autoregressive effects (MR-LST-AR model) by Bohn et al. (2021) to measurement designs with individually varying time intervals. The new continuous time dynamic MR-LST-AR model correctly accounts for individually varying time intervals and allows for a fine-grained analysis of rater consistency and rater specificity as a function of time. Second, we show how the continuous time dynamic MR-LST-AR model can be extended to MTMR designs to examine the interrelationship between multiple constructs at the trait and the occasion-specific level. Third, we illustrate the new approach using data from the German Family Panel *pairfam* (Brüderl et al., 2018) and discuss its advantages and limitations for the analysis of longitudinal multirater data. To facilitate the applicability of the new model, we provide a step-by-step tutorial and code to specify the model in R.

1. Discrete Time Multirater Latent State Trait Models with Autoregressive Effects

We start by reviewing the MR-LST-AR model by Bohn et al. (2021), as this model is quite complex and includes many other longitudinal CFA models as special cases, which we review in the discussion. Later, we extend the MR-LST-AR model into a more general continuous time dynamic model. For simplicity, we introduce the conventional MR-LST-AR model for a reduced measurement design including three indicators ($i = 1, 2, 3$), one construct (e.g., dyadic coping), two structurally different raters ($k = 1, 2$; self-report and other reports), and three discrete measurement occasions[1] ($u = 1, 2, 3$). Figure 1 displays an MR-LST-AR model for the above measurement design. Note that Figure 1 displays the MR-LST-AR model as a path diagram of a confirmatory factor model.

The basic idea of the MR-LST-AR model is to contrast structurally different raters against a reference method (or rater group) at the trait and the occasion-specific level following a correlated trait correlated method minus one [CTC(M-1)] modeling approach (Eid et al., 2003; 2008). According to Geiser et al. (2008), the choice of a reference method should be based on theoretical considerations to ease the interpretation of the results, to answer key research questions, or to replicate previous findings. Without loss of generality, we select the first rater group (e.g., self-reports, $k = 1$) as the reference method and contrast the other report (e.g., partner report, $k \neq 1$) against this reference method. According to Figure 1, the observed variables Y_{i11} pertaining to the reference method ($k = 1$) at the first measurement occasion ($u = 1$) are decomposed as follows (see Y_{111}, Y_{211}, and Y_{311} in Figure 1):

$$Y_{i11} = \alpha_{i11} + S_{i11} + \varepsilon_{i11} \tag{1}$$
$$S_{i11} = T_{i11} + \lambda_{Oi11}\zeta_{11} \tag{2}$$

Plugging Equation (2) into Equation (1) yields

$$Y_{i11} = \alpha_{i11} + T_{i11} + \lambda_{Oi11}\zeta_{11} + \varepsilon_{i11} \tag{3}$$

where α_{i11} is an intercept parameter (not shown in Figure 1), S_{i11} is a latent state variable that can be decomposed into a latent trait T_{i11} and a weighted latent state residual variable $\lambda_{Oi11}\zeta_{11}$ (see Equation (2)), and ε_{i11} is an error (residual) term. Following our example, the trait T_{i11} characterizes the dyadic coping trait of the target person at time 1. Note that T_{i11}has a mean of zero. The state residual ζ_{11} captures occasion-specific deviations from the initial trait due to situational and/or person-situation-interaction effects. The state residual is defined as a residual variable with a mean of zero and is uncorrelated with the latent trait. The error variables ε_{i11} capture measurement error influences. For identification purposes, it is common to fix the loading parameter λ_{O111} to 1 and freely estimate the variances of the latent trait and state residual variables.

According to LST-R theory, the measurement equation of the observed variables pertaining to the reference method $(k = 1)$ at later measurement occasions $(u > 1)$ can be written as follows:

$$Y_{i1u} = \alpha_{i1u} + S_{i1u} + \varepsilon_{i1u} \quad u > 1 \tag{4}$$

[1] In this article, we use the index *u* to refer to a measurement occasion indiscrete time. The index *t* is used to refer to an exact time point in continuous time.

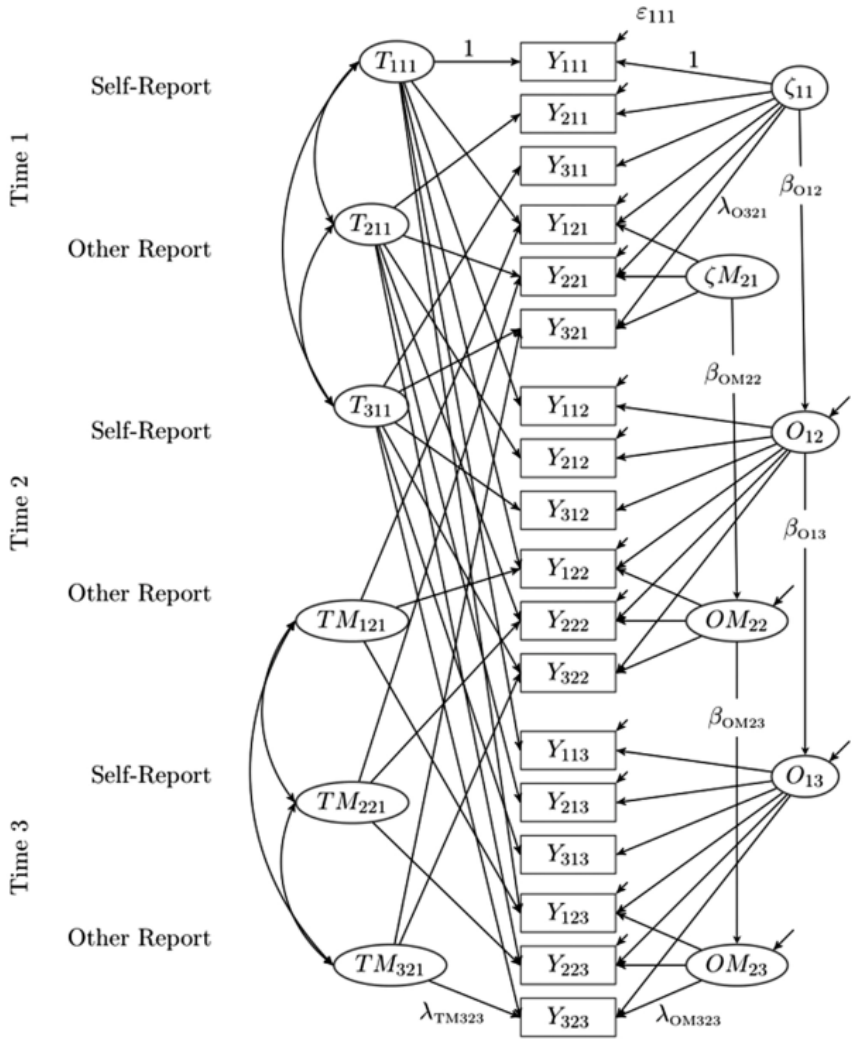

Figure 1. Path diagram of a single-construct MR-LST-AR model. A single-construct MR-LST-AR model with indicator-specific trait and trait-method factors. T_{i11}: indicator-specific trait variables pertaining to the reference rater group (here: self-report); TM_{i21}: indicator-specific trait method variables pertaining to the non-reference rater group (here: other reports); ζ_{11}: state-residual variable measured at time 1; O_{1u}: occasion-specific variables; ζM_{21}: state-residual method variable measured at time 1; OM_{2u}: occasion-specific method variable; λ_{Tiku}: loading pertaining to the trait variable; λ_{TMiku}: loading pertaining to the trait method variable; λ_{Oiku}: loading pertaining to the occasion-specific variable; λ_{OMiku}: loading pertaining to the occasion-specific method factor; β_{O1u}: autoregressive effect of the occasion-specific variable; β_{OM2u}: autoregressive effect of the occasion-specific method variable; ε_{iku}: residual (error) variable; Y_{iku}: observed variable; *i*: indicator; *k*: structurally different raters (where $k = 1$ refers to the reference rater group, $k \neq 1$ refers to the non-reference rater group); *u*: discrete measurement occasion.

$$S_{i1u} = \lambda_{\mathrm{T}i1u} T_{i11} + \lambda_{\mathrm{O}i1u} O_{1u}.\ u > 1 \tag{5}$$

Inserting Equation (5) into Equation (4) yields

$$Y_{i1u} = \alpha_{i1u} + \lambda_{\mathrm{T}i1u} T_{i11} + \lambda_{\mathrm{O}i1u} O_{1u} + \varepsilon_{i1u}, u > 1 \tag{6}$$

where α_{i1u} is an intercept, $\lambda_{Ti1u} T_{i11}$ is a weighted trait factor, $\lambda_{Oi1u} O_{1u}$ is a weighted occasion-specific factor, and ε_{i1u} is the error term. For identification purposes, the trait loading $\lambda_{\mathrm{T}i11}$ is fixed to 1 for all indicators measured at time 1 and the occasion-specific loading λ_{O11u} pertaining to the first indicator is fixed to 1. According to Equation (5), later states S_{i1u} are influenced by the trait T_{i11} of the first time point and accumulated situational influences O_{1u} (see Eid et al., 2017, for details). The O_{1u}-factors are defined as follows:

$$O_{1u} := \beta_{\mathrm{O}1u} O_{1(u-1)} + \zeta_{1u} \quad u > 1 \tag{7}$$

with β_{O1u} denoting the autoregressive effect of an occasion-specific variable $O_{1(u-1)}$ at the previous measurement occasion, and ζ_{1u} is an occasion-specific residual term. Note that Equation (7) simplifies to $O_{11} = \zeta_{11}$ if $u = 1$ (i.e., first measurement occasion). High values of the autoregressive parameters β_{O1u} indicate strong carry-over effects of past occasions. For example, past experiences due to inner and outer influences (e.g., critical life events like unemployment, promotion, stress, etc.) may affect the present dyadic coping behavior of the target. The state-residual ζ_{1u} captures occasion-specific effects that cannot be explained by previous occasions, but that is specific to the present occasion.

Oftentimes the autoregressive parameters β_{O1u}, the variances of the state residuals ζ_{1u}, respectively, are constrained to equality across measurement occasions.

Expressing Equation (7) and Equation (5) in terms of variances shows that a person's state variance (or true score variance) can be decomposed into three parts (for all $u > 1$):

$$Var(S_{i1u}) = \underbrace{\lambda_{Ti1u}^2 Var(T_{i11})}_{trait\ predictable} + \underbrace{\lambda_{Oi1u}^2 \beta_{O1u}^2 Var(O_{1(u-1)})}_{trait\ unpredictable} + \underbrace{\lambda_{Oi1u}^2 Var(\zeta_{1u})}_{occasion-specific} \quad (8)$$

The first component refers to the amount of state variation that is attributable to the initial trait. According to Eid et al. (2017) a *trait predictability coefficient* ($Pred_{trait1}$) is defined as follows:

$$Pred_{trait1}(S_{i1u}) := \frac{\lambda_{Ti1u}^2 Var(T_{i11})}{Var(S_{i1u})} \quad (9)$$

A high trait predictability coefficient would mean that dyadic coping is primarily attributable to trait-like effects measured at the first time point. The second component refers to the proportion of state variance that is *not* predictable by the initial trait but is attributable to accumulated effects of past occasion-specific influences (i.e., carry-over effects). In LST-R theory, the trait unpredictable (or dynamic) component captures trait change due to accumulated experiences (Eid et al., 2017). A measure of how much state variance is attributable to accumulated experiences is the *trait unpredictability coefficient*
($UPred_{trait1}$), which is defined for all $u > 1$:

$$UPred_{trait1}(S_{i1u}) := \frac{\lambda_{Oi1u}^2 \beta_{O1u}^2 Var(O_{1(u-1)})}{Var(S_{i1u})} \quad (10)$$

A high $UPred_{trait1}$-coefficient would suggest that there are strong carry-over effects of past occasions. The trait predictability and unpredictability coefficient add up to the *time consistency coefficient* ($TCon$):

$$TCon(S_{i1u}) := \frac{\lambda_{Ti1u}^2 Var(T_{i11}) + \lambda_{Oi1u}^2 \beta_{O1u}^2 Var(O_{1(u-1)})}{Var(S_{i1u})} \quad (11)$$

The consistency coefficient $TCon(S_{i1u})$ represents the amount of state variance that is attributable to influences of the initial trait as well as carry-over effects of past occasions. The counterpart of the consistency coefficient is the occasion-specificity coefficient $OS(S_{i1u}) = 1 - TCon(S_{i1u})$.The occasion-specificity coefficient $OS(S_{i1u})$ is based on the third component of state variability (see Equation 8) and characterizes unexplained occasion-specific influences that cannot be predicted by the initial trait nor by previous occasions. The *occasion-specificity coefficient* $OS(S_{i1u})$ is defined as follows:

$$OS(S_{i1u}) := \frac{\lambda_{Oi1u}^2 Var(\zeta_{1u})}{Var(S_{i1u})} \quad (12)$$

The occasion-specificity coefficient $OS(S_{i1u})$ captures the amount of variation in dyadic coping that is attributable to occasion-specific influences (e.g., situational effects and/or person-situational interaction effects) at the present measurement occasion.

Next, we turn to the measurement equations pertaining to the non-reference rater group ($k \neq 1$, e.g., partner report). Following a CTC(M-1) modeling approach (Eid et al., 2003, 2008), the latent trait of the partner is regressed on the latent trait of the target person. Similarly, the occasion-specific variable (momentary dyadic coping) of the partner is regressed on the occasion-specific variable (momentary dyadic coping) of the target person. The latent linear regressions are represented by the factor loadings from reference trait or reference occasion-specific factors to non-reference indicators, respectively. The residuals of these latent linear regressions are defined as latent method factors on the trait and the occasion-specific level. The trait method factor represents trait-like interindividual differences in dyadic coping measured by the partner report that is not shared with the target's self-report. A high value of the TM_{ik1}-factor indicates that the partner tends to overestimate the dyadic coping trait of the target person than one would expect based on the trait of the target person. Similarly, the occasion-specific method factor reflects the partner's view on the target person's momentary dyadic coping that is not shared with the target's self-report. A high value on the ζM_{11}-factor suggests that the partner tends to overestimate the momentary dyadic coping skill of the target than expected based on the target's self-report. Note that the trait *method* factors are necessarily uncorrelated with the latent traits pertaining to the reference method in the MR-LST-AR model. Similarly, the occasion-specific *method* variables are necessarily uncorrelated with the occasion-specific variables pertaining to the reference method in the MR-LST-AR model (see Bohn et al., 2021).

In sum, the measurement equation of the observed variables Y_{iku} can be written as follows for all $k \neq 1, u > 1$:

$$Y_{iku} = \alpha_{iku} + \lambda_{Tiku} T_{i11} + \lambda_{TMiku} TM_{ik1} + \lambda_{Oiku} O_{1u} + \lambda_{OMiku} OM_{ku} + \varepsilon_{iku} \quad (13)$$

$$O_{1u} := \beta_{O1u} O_{1(u-1)} + \zeta_{1u} \quad (14)$$

$$OM_{ku} := \beta_{OMku} OM_{k(u-1)} + \zeta M_{ku} \quad (15)$$

where α_{iku} is an intercept, $\lambda_{Tiku} T_{i11}$ is a weighted trait factor, $\lambda_{TMiku} TM_{ik1}$ is a weighted trait method factor, $\lambda_{Oiku} O_{1u}$ is a weighted occasion-specific factor, $\lambda_{OMiku} OM_{ku}$ is a weighted occasion-specific method factor, and ε_{iku} is the error term. Following the principles of LST-R theory, the occasion-specific variables (see Equation (14)) and occasion-specific method variables (see Equation (15)) are introduced to model autoregressive effects (carry-over effects). The occasion-specific factors O_{1u} characterizes the target's momentary dyadic coping assessed by the partner report that is shared with the target's self-report. The occasion-specific method factors OM_{ku} capture the part of the partner's perceived momentary dyadic coping that is not shared with the target's self-report.

Due to the definition of the latent variables in the MR-LST-AR model, the variance of the observed variables can be decomposed as follows (for all $k \neq 1, u > 1$):

$$
\begin{aligned}
Var(Y_{iku}) = {} & \lambda_{\mathrm{T}iku}^2 (T_{i11}) + \lambda_{\mathrm{TM}iku}^2 Var(TM_{ik1}) \\
& + \lambda_{\mathrm{O}iku}^2 \beta_{\mathrm{O}1u}^2 Var(O_{1(u-1)}) + \lambda_{\mathrm{O}iku}^2 Var(\zeta_{1u}) \\
& + \lambda_{\mathrm{OM}iku}^2 \beta_{\mathrm{OM}ku}^2 Var(OM_{k(u-1)}) \\
& + \lambda_{\mathrm{OM}iku}^2 Var(\zeta M_{ku}) + Var(\varepsilon_{iku})
\end{aligned} \tag{16}
$$

Based on Equation (16), it is possible to define several variance coefficients. To not distract readers with detailed technical information, we provide the formulas of these variance coefficients in Table 1 and discuss their meaning in the text. Note that we only present a selection of variance coefficients that allow researchers to study rater consistency at different levels. For additional variance coefficients see Bohn et al. (2021).

Again, it is possible to define different rater consistency coefficients (as measures of convergent validity or rater congruency) based on components that are *trait predictable* (i.e., due to the initial trait), *trait unpredictable* (i.e., due to autoregressive effects), or *occasion-specific* (i.e., due to situation and/or person-situation interaction effects of the present time point). The *rater-consistent predictability by trait1 coefficient (RConPredtrait*1*)* represents the rater consistency at the trait level at the first measurement occasion. The *RConPredtrait*1-coefficient refers to the proportion of trait variance of the non-reference method at the first measurement occasion that is shared by the reference method at that occasion. A high *RConPredtrait*1-coefficient would indicate high convergent validity (rater congruency) at the trait level at the first measurement occasion.

The *rater-consistent unpredictability by trait1 coefficient (RConUPredtrait*1*)* refers to the amount of rater consistency at the level of dynamic interindividual differences. A high *RConUPredtrait1*-coefficient suggests that anchor and partner reports overlap at the level of dynamic interindividual differences. This coefficient may be of particular importance whenever researchers are interested in the convergent validity (or rater congruency) at the dynamic (or autoregressive) level. The *rater-consistent time consistency coefficient (RConTCon)* is a measure of rater congruency at the level of time consistent interindividual differences. Time consistent interindividual differences refer to variation in the partner reports that is attributable to the initial trait and/or carry-over effects of past occasions. The *RConTCon*-coefficient is defined as the proportion of time-consistent interindividual differences in the partner reports that can be explained by the time-consistent effects of the reference method (self-reports). A high *RConTCon*-coefficient suggests high rater congruency at the time consistent level (i.e., interindividual differences that are predictable by the initial trait and/or by previous measurement occasions). The counterpart is the *rater-consistent occasion-specificity coefficient (RConOS)*: It is defined as the proportion of occasion-specific interindividual differences of the partner reports that are shared with occasion-specific interindividual differences measured by the targets' self-reports. Occasion-specific interindividual differences refer to situational effects and/or person-situation-interaction effects that are *not* attributable to the initial trait nor due to carry-over effects of past occasions. Finally, the *reliability (Rel)* is defined as the ratio of the latent state variance (or true score variance) divided by the total variance of an observed variable and can be computed for all observed variables. The MR-LST-AR model and the above variance coefficients assume equally spaced time intervals. In the case of unequally spaced time intervals, many parameters in the discrete time MR-LST-AR model will be biased. Next, we show how this limitation can be overcome using a continuous time modeling approach.

Table 1. Variance Coefficients in discrete time MR-LST-AR models.

Rater	Coefficients	Formula
All Raters	*Reliability (Rel)*	$Rel(Y_{iku}) := 1 - \frac{Var(\varepsilon_{iku})}{Var(Y_{iku})} = \frac{Var(S_{iku})}{Var(Y_{iku})}$
For reference rater group ($k = 1$)	*Predictability by Trait 1* ($Pred_{trait1}$)	$Pred_{trait1}(S_{i1u}) := \frac{\lambda_{\mathrm{T}i1u}^2 Var(T_{i11})}{Var(S_{i1u})}$
	Unpredictability by Trait 1 ($UPred_{trait1}$) for $u > 1$	$UPred_{trait1}(S_{i1u}) := \frac{\lambda_{\mathrm{O}i1u}^2 \beta_{\mathrm{O}1u}^2 Var(O_{1(u-1)})}{Var(S_{i1u})}$
	Time Consistency (TCon)	$TCon(S_{i1u}) := \frac{\lambda_{\mathrm{T}i1u}^2 Var(T_{i11}) + \lambda_{\mathrm{O}i1u}^2 \beta_{\mathrm{O}1u}^2 Var(O_{1(u-1)})}{Var(S_{i1u})} = Pred_{trait1}(S_{i1u}) + UPred_{trait1}(S_{i1u})$
	Occasion-Specificity (OS)	$OS(S_{i1u}) := \frac{\lambda_{\mathrm{O}i1u}^2 Var(\zeta_{1u})}{Var(S_{i1u})} = 1 - TCon(S_{i1u})$
For non-reference rater group ($k \neq 1$)	*Rater-consistent predictability by trait 1 (RConPredtrait1)*	$RConPredtrait1(S_{iku}) := \frac{\lambda_{\mathrm{T}iku}^2 \mathrm{Var}(T_{i11})}{\lambda_{\mathrm{T}iku}^2 \mathrm{Var}(T_{i11}) + \lambda_{\mathrm{TM}iku}^2 \mathrm{Var}(TM_{ik1})}$
	Rater-consistent unpredictability by trait 1 (RConUPredtrait1) for $u > 1$	$RConUPredtrait1(S_{iku}) := \frac{\lambda_{\mathrm{O}iku}^2 \beta_{\mathrm{O}1u}^2 Var(O_{1(u-1)})}{\lambda_{\mathrm{O}iku}^2 \beta_{\mathrm{O}1u}^2 Var(O_{1(u-1)}) + \lambda_{\mathrm{OM}iku}^2 \beta_{\mathrm{OM}ku}^2 Var(OM_{k(u-1)})}$
	Rater-consistent time consistency (RConTCon)	$RConTCon(S_{iku}) := \frac{\lambda_{\mathrm{T}iku}^2 \mathrm{Var}(T_{i11}) + \lambda_{\mathrm{O}iku}^2 \beta_{\mathrm{O}1u}^2 Var(O_{1(u-1)})}{\lambda_{\mathrm{T}iku}^2 \mathrm{Var}(T_{i11}) + \lambda_{\mathrm{TM}iku}^2 \mathrm{Var}(TM_{ik1}) + \lambda_{\mathrm{O}iku}^2 \beta_{\mathrm{O}1u}^2 Var(O_{1(u-1)}) + \lambda_{\mathrm{OM}iku}^2 \beta_{\mathrm{OM}ku}^2 Var(OM_{k(u-1)})}$
	Rater-consistent occasion specificity (RConOS)	$RConOS(S_{iku}) := \frac{\lambda_{\mathrm{O}iku}^2 Var(\zeta_{1u})}{\lambda_{\mathrm{O}ikl}^2 Var(\zeta_{1u}) + \lambda_{\mathrm{OM}iku}^2 Var(\zeta M_{ku})}$

Note. The above variance coefficients refer to a selection of the discrete time coefficients discussed in the study by Bohn et al. (2021). All coefficients are defined with respect to the true score variance (i.e., state variance) of a manifest variable, except for the reliability coefficients. Y_{iku}: manifest variable; S_{iku}: state variable; T_{i11}: initial trait; TM_{ik1}: initial trait method variable; ζ_{1u}: latent state-residual; ζM_{ku}: latent state-residual method variable; $O_{1(u-1)}$: occasion-specific variable of the previous time point; $OM_{k(u-1)}$: occasion-specific method variable of the previous measurement occasion; ε_{iku}: error term; λ: factor loadings;β: autoregressive effects; *i*: indicator; *k*: method; *u*: discrete measurement occasion.

2. Continuous Time Dynamic Multirater Latent State-Trait Models with Autoregressive Effects

Next, we introduce a continuous time dynamic MR-LST-AR model that does not rest on the assumption of equally spaced time intervals and, thus, represents a generalization of its discrete time version. The new model will be termed the CT-MR-LST-AR model (continuous time dynamic multirater latent state-trait model with autoregressive effects). The term *dynamic* model refers to a model that accounts for changes in a system of variables over time as a function of the past. The nature of the change is typically defined as a difference or differential equation (Voelkle et al., 2018). The key idea of *continuous time* dynamic models is that the constructs of interest (e.g., dyadic coping) and their interrelationships continue to exist between measurement occasions even when they are not directly observed. In contrast, discrete time models imply that the construct of interest only exists at the concrete measurement occasion and that time jumps in discrete and equidistant steps. We believe that the assumption of continuous time dynamic models is often more realistic and fits well with the revised version of the latent state-trait theory by Steyer et al. (2015). If time intervals are equidistant, the conventional discrete time MR-LST-AR and the continuous time version are identical in terms of model fit, as we will show later in the application.

The extension of the MR-LST-AR model consists of four steps and has not been proposed before: First, we reformulate the MR-LST-AR model in state-space format (e.g., Molenaar, 2003). Second, we constrain the discrete time parameters in line with the underlying continuous time dynamic model (i.e., to the solution of the stochastic differential equation for a given starting point and time interval). To this end, we use the powerful machinery of existing continuous time modeling approaches (e.g., Oud & Jansen, 2000; Voelkle et al., 2012) and software (e.g., Driver & Voelkle, 2018). Third, we analytically derive the continuous time analog of the variance coefficients introduced earlier in the text. Fourth, we back-translate the continuous time coefficients to the corresponding discrete time coefficients for any arbitrary time interval. The back-translation allows easy communication and interpretation of results, for example by plotting coefficients as a function of a given time interval.

To facilitate understanding, we focus on presenting the general idea of the new approach in the main text and use figures to illustrate the models. Technical details and the exact definitions of the continuous time versions of all variance coefficients discussed above are provided in Appendix A. A comprehensive introduction to continuous time dynamic modeling is beyond the scope of this article. For this we refer the reader to the existing literature (e.g., Voelkle et al. 2012; van Montfort et al., 2018). For applied researchers who are interested in fitting CT-MR-LST-AR models to their own data (possibly with individually varying time intervals), we provide a short tutorial along the lines of an empirical example in the next section.

Unlike discrete time models (e.g., the discrete time MR-LST-AR model), which focus on modeling the actual (discrete time) observations, a continuous time dynamic model starts with formulating a model of *change* (cf. McArdle,2009; Voelkle et al., 2018). The dependent variable (denoted by $\boldsymbol{\eta}$ in the following) is thus the *change* (denoted by $\mathrm{d}\boldsymbol{\eta}$) over a given time interval (denoted by Δt). If we let the time interval go toward zero ($\Delta t \rightarrow 0$) we write $\mathrm{d}t$ instead of Δt: Note that we introduce the new index t to refer to an exact time point in continuous time, whereas u refers to a discrete occasion of measurement, as defined above. Consequently, our dependent variable is the derivative $\frac{\mathrm{d}\boldsymbol{\eta}(t)}{\mathrm{d}t}$: The boldface notation $\boldsymbol{\eta}(t)$ indicates that $\boldsymbol{\eta}$ is a vector of one or (typically) more variables, which may be latent with an underlying measurement model or directly observed. This vector $\boldsymbol{\eta}$ is also referred to as the state vector.[2] A basic continuous time dynamic model can thus be written as

$$\frac{\mathrm{d}\boldsymbol{\eta}(t)}{\mathrm{d}t} = \mathbf{A}\boldsymbol{\eta}(t) \tag{17}$$

Equation (17) is a linear differential equation, that is, the change in $\boldsymbol{\eta}$ is predicted by the level of $\boldsymbol{\eta}$, weighted by the so-called drift matrix $\mathbf{A}$. Usually, however, such predictions are not perfect, and Equation (17) needs to be augmented by a stochastic error term $\mathbf{G}\mathrm{d}\mathbf{W}(t)$: Formally, this is written as:

$$\mathrm{d}\boldsymbol{\eta}(t) = \left(\mathbf{A}\boldsymbol{\eta}(t)\right)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{18}$$

Equation (18) is a general stochastic differential equation that can be used to define latent state-trait models with stable traits and an autoregressive structure, as frequently used to study variability processes (Geiser et al., 2015). Equation (18) can be extended in various ways, for example, to capture trends in the data. This can be achieved by adding intercepts to the equation along with expanding the state vector and constraining the elements in $\mathbf{A}$ accordingly. For a more general expression and a more detailed explanation of the underlying mathematics, see Voelkle et al. (2012) and Driver Voelkle (2018). For our purposes, it suffices to note that Equation (18) can be solved for any starting point and time interval between discrete measurement occasions t_u and t_{u-1} (i.e., $\Delta t_u = t_u - t_{u-1}$). This yields the following equation (for all $u \geq 1$):

$$\boldsymbol{\eta}_u = \mathbf{A}^*_{\Delta t_u}\boldsymbol{\eta}_{u-1} + \boldsymbol{\upsilon}_u \text{ with } \boldsymbol{\upsilon}_u \sim \mathrm{N}\left(0, \mathbf{Q}^*_{\Delta t_u}\right) \tag{19}$$

As before u denotes the discrete measurement occasion and $\boldsymbol{\upsilon}_u$ the vector of discrete time error terms with covariance matrix $\mathrm{Q}^*_{\Delta t_u}$. The matrix $\mathbf{A}^*_{\Delta t_u}$ connects the elements of the state-vector over time, containing autoregressive parameters in the main diagonal and cross-lagged parameters in the off-diagonals. The asterisk $(*)$ indicates that the parameter matrices are constrained in line with the solution of the differential Equation (18). Especially for the error terms, these constraints are well-known but somewhat complicated. To avoid distracting readers with technical details, these are found in Appendix A.

Importantly, any identified model that can be expressed in terms of Equations (18) and (19) can readily be estimated as a continuous time dynamic model. This also applies to

[2] Note, that the vector notation permits the easy extension to higher-order derivatives. Prominent examples include the damped linear oscillator (e.g., Voelkle & Oud, 2013) or CARMA (*p,q*) models (e.g., Oud et al., 2018).

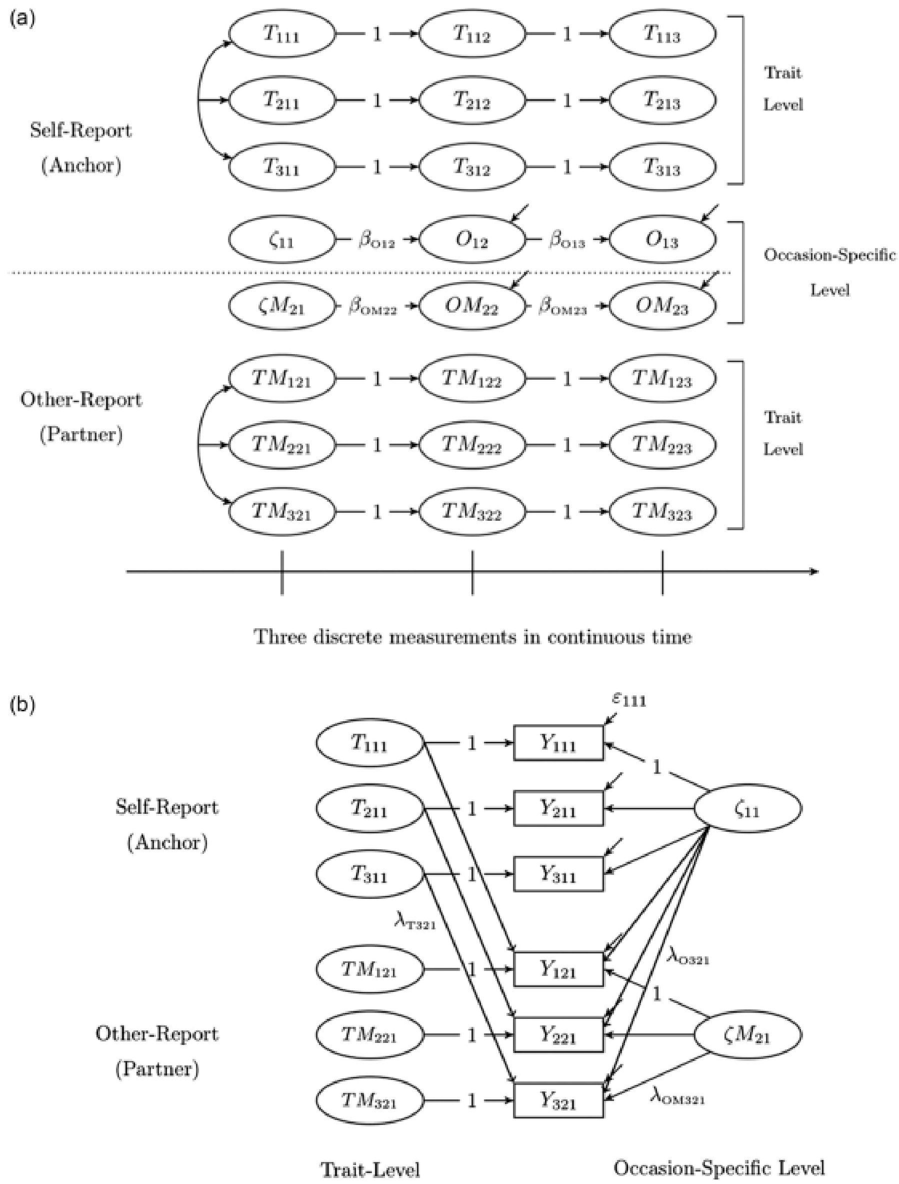

Figure 2. (a) Structural part of a single-construct MR-LST-AR model for three discrete measurement occasions. The figure displays the structural part of the MR-LST-AR model in a state-space format, where the autoregressive effects of the indicator-specific trait and trait method variables are fixed to 1. T_{i1u} indicator-specific trait variables pertaining to the reference rater group (here: self-report); TM_{iku} : indicator-specific trait method variables pertaining to the non-reference rater group (here: other reports); ζ_{11}: state-residual variable measured at time 1; O_{1u}: occasion-specific variables; ζM_{21}: state-residual method variable measured at time 1; OM_{2u}: occasion-specific method variable; β_{O1u}: autoregressive effect of the occasion-specific variable; β_{OM2u}: autoregressive effect of the occasion-specific method variable; *i*: indicator; *k*: structurally different methods/raters (where $k = 1$ refers to the reference rater group, $k \neq 1$ refers to the non-reference rater group); *u*: discrete measurement occasion. (b) Measurement part of a single-construct MR-LST-AR model for the first time point. The figure displays the measurement part of the MR-LST-AR model for the first time point, the measurement model can be replicated for later time points. T_{i11}: indicator-specific trait variables pertaining to the reference rater group (here: self-report); TM_{i21}: indicator-specific trait method variables pertaining to the non-reference rater group (here: other reports); ζ_{11}: state-residual variable measured at time 1; ζM_{21}: state-residual method variable measured at time 1; λ_{Tik1}: loading pertaining to the trait variable; λ_{TMik1}: loading pertaining to the trait method variable; λ_{Oik1}: loading pertaining to the occasion-specific variable; λ_{OMik1}: loading pertaining to the occasion-specific method factor; ε_{ik1}: residual (error) variable; Y_{iku}: observed variable; *i*: indicator; *k*: structurally different methods/raters (where $k = 1$ refers to the reference rater group, $k \neq 1$ refers to the non-reference rater group); *u*: discrete measurement occasion.

the MR-LST-AR model shown in Figure 1. To this end, we represent the structural part of the model expressed in Equations (18) and (19) in Figure 2a in a state-space format. The measurement part of the model is displayed in Figure 2b. To display the structural part in a state-space format, we simply expand the state vector to p dimensions, with p denoting all latent variables in the MR-LST-AR model shown in Figure 1, apart from the measurement error terms. Hence, Figure 2a illustrates the structural part of the discrete time MR-LST-AR model (i.e., connections between the trait and occasion-specific factors) in a state-space format. According to Figure 2a, in our example, the state vector is a vector of $p = 8$ dimensions that contains all latent variables in the MR-LST-AR model (i.e., indicator-specific trait variables, indicator-specific trait method variables, occasion-specific variables, and occasion-specific method variables).

As shown in Figure 2a, not all variables in the MR-LST- AR model change over time. Specifically, it is assumed that the latent trait and latent trait method variables do not change over time, as they represent time-invariant components in the model. This assumption is implemented by constraining the corresponding elements in $\mathbf{A}^*_{\Delta t_u}$ to 1 (see Figure 2a).

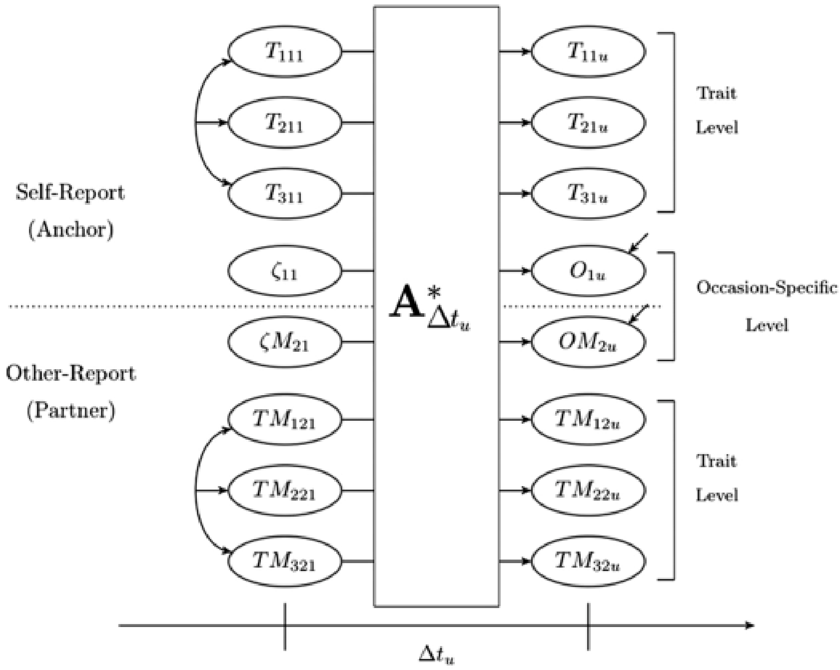

Figure 3. Graphical illustration of the discrete time parameters underlying a continuous time process. The figure illustrates how discrete time parameters underly a continuous time process. The box denoted by $\mathrm{A}^*_{\Delta t_u}$ is a matrix containing the appropriate autoregressive effects of the latent processes for an arbitrary time interval Δt_u: To fix the autoregressive effects between subsequent trait variables to 1, the corresponding values in the drift matrix were fixed to −0.0001. The rectangle in the middle schematically illustrates how the discrete time parameters are constrained to match the underlying continuous time dynamic process. Note that this representation is a simplification of how the parameters in the structural part of the discrete time model need to be constrained to obtain the continuous time dynamic model. The exact mathematical formulation of the model is expressed in Equation (18), respectively the solution of Equation (18) is provided in Equation (19).

However, at the occasion-specific (i.e., time-dependent) level, we allow for autoregressive effects of the reference method $\beta_{\mathrm{O}1u}$ as well as autoregressive effects of the non-reference method $\beta_{\mathrm{OM}1u}$, which correspond to auto regressive effects in $\mathbf{A}^*_{\Delta t_u}$ (see Figure 2a). The separation of the reference and non-reference methods is done at the measurement level.

The measurement part of the model is illustrated in Figure 2b. Formally, the latent variables $\boldsymbol{\eta}(t)$ are connected to the observed variables $\boldsymbol{y}(t)$ using the following measurement model (see Figure 2b):

$$\boldsymbol{y}(t) = \boldsymbol{\mu} + \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\varepsilon}(t) \quad \text{where} \quad \boldsymbol{\varepsilon}(t) = \mathrm{N}(\mathbf{0}_q, \boldsymbol{\Theta}) \tag{20}$$

where $\boldsymbol{y}(t)$ is a vector of manifest or observed variables with size $q = 6$ dimensions (where q denotes the number of manifest variables at time t), $\boldsymbol{\mu}$ represents the vector of the manifest intercepts (here containing zeros as we consider centered manifest variables), $\boldsymbol{\Lambda}$ is a matrix containing the factor loadings, and $\boldsymbol{\varepsilon}(t)$ is a vector of residual terms with a covariance matrix $\boldsymbol{\Theta}$: The measurement model (see Equation 20 as well as Figure 2b) corresponds to the measurement part of the MR-LST-AR model displayed in Figure 1.

Together, the model illustrated in Figures 2a and b corresponds to the discrete time MR-LST-AR model shown in Figure 1 if certain parameter constraints are imposed (i.e., equal loadings across time, equal error variances across time, equal state-residual variances across time, equal state-residual method variances across time, equal autoregressive effects across time pertaining to method *k*). The full specification of Equations (18) and (20) for the MR-LST-AR model shown in Figures 2a and b is provided in Appendix A. This concludes step 1, the reformulation of the MR-LST-AR model in a state-space format.

In step 2, the parameters of the CT model are constrained as shown in Appendix A. This idea is illustrated in Figure 3 in a simplified way. The discrete time matrix $\mathbf{A}^*_{\Delta t_u}$ is related to the drift matrix $\mathbf{A}$ via the matrix exponential equation $\mathbf{A}^*_{\Delta t_u} = \mathrm{e}^{\mathbf{A}\Delta tu}$, which is illustrated by the box in Figure 3. Thus, fixing autoregressive elements in $\mathbf{A}^*_{\Delta t_u}$ to one, corresponds to fixing the diagonal, auto effects in $\mathbf{A}$ to zero.[3] Note that the auto-effects pertaining to the reference method a_{22} in $\mathbf{A}$ (i.e., drift matrix) correspond to the auto-regressive effects $\beta_{\mathrm{O}1u}$ in $\mathbf{A}^*_{\Delta t_u}$, whereas the auto-effects pertaining to the non-reference method a_{22} in $\mathbf{A}$ correspond to the auto-regressive effects $\beta_{\mathrm{OM}1u}$ in $\mathbf{A}^*_{\Delta t_u}$.

Given that this is a standard continuous time dynamic model, we can use any appropriate software to estimate the model. An example with the package ctsem (Driver & Voelkle, 2018; version 3.3.10) will be provided in the next section. Given the parameters of the continuous time dynamic model, we can now derive the continuous time variance coefficients of the MR-LST-AR model (step 3). For simplicity, we provide all formulas for the computation of the continuous time variance coefficients in Appendix A.

Finally (step 4), we derive the traditional discrete time MR-LST-AR coefficients from the underlying continuous time coefficients for any arbitrary time interval via the constraints given in Appendix A. This will be illustrated with

[3] For technical reasons, the corresponding values in the drift matrix **A** are usually fixed to a very small negative number close to zero (e.g., −0.0001 in the present manuscript).

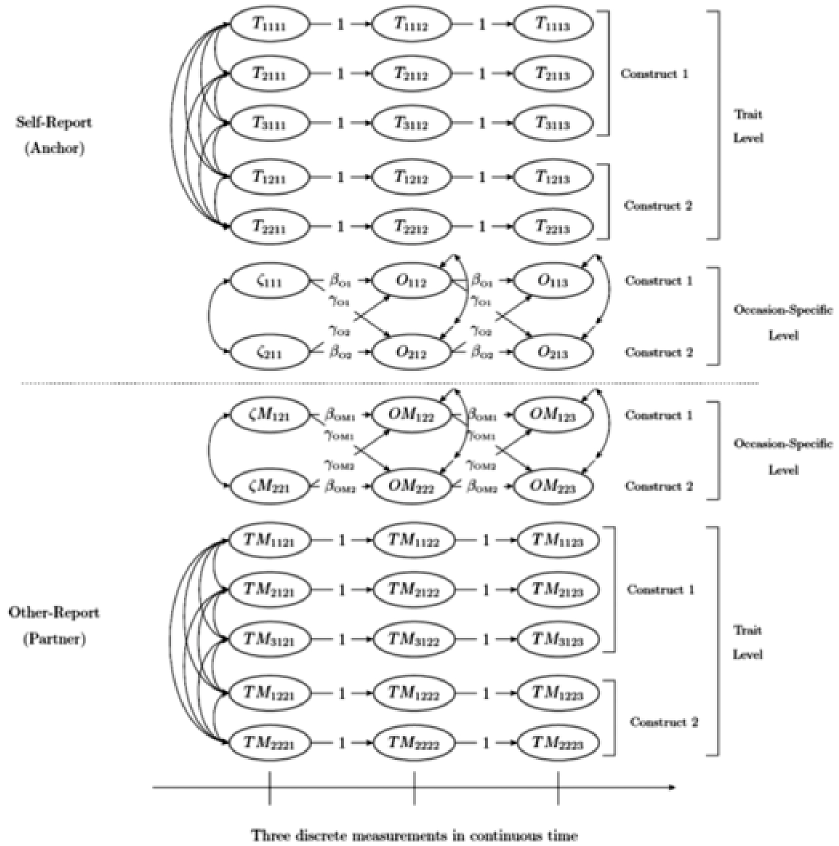

Figure 4. Structural part of an MTMR-LST-AR model with indicator-specific trait and trait-method variables. The figure displays the structural part of an MTMR-LST-AR model with indicator-specific trait and trait-method variables in a state-space format. T_{ij1u}: indicator-specific trait variables pertaining to the reference rater group (here: self-report); TM_{ijku}: indicator-specific trait method variables pertaining to the non-reference rater group (here: other reports); ζ_{j11}: state-residual variable measured at time 1; O_{j1u}: occasion-specific variables; ζM_{j21}: state-residual method variable measured at time 1; OM_{j2u}: occasion-specific method variable; β_{Oj} and γ_{Oj}: autoregressive effect of the occasion-specific variable; β_{OMj} and γ_{OMj}: autoregressive effect of the occasion-specific method variable; *i*: indicator; *k*: structurally different methods/raters (where $k = 1$ refers to the reference rater group; $k \neq 1$ refers to the non-reference rater group); *u*: discrete measurement occasion.

empirical data in the next section (e.g., see Figures 5-8). Importantly, this only works in one direction: We can correctly estimate the underlying continuous time parameters and then back-translate these parameters to discrete time parameters for any time interval. In the case of unequally spaced time intervals, however, the discrete time parameters from the MR-LST-AR model are incorrect (because the model assumes an equally spaced sampling design) and there is no way to infer the underlying continuous time parameters (e.g., Hamerle et al., 1993). Only in the special case of equally spaced time intervals, the continuous time and the discrete time version of the MR-LST-AR model will yield identical results. In the case of unequally spaced time intervals, only the continuous time dynamic MR-LST-AR parameters are valid. The degree to which the parameters in the continuous time and the discrete time version of the model will differ in the case of unequal time intervals is an empirical question (de Haan-Rietdijk et al., 2017).

3. Continuous Time Dynamic Multitrait-Multirater-Latent State-Trait Models

To examine relationships among multiple constructs and to evaluate the discriminant validity over time, researchers need to include at least two constructs. Here, we extend the state-space model shown in Figure 2a to a longitudinal multitrait-multirater (MTMR) design including two constructs (e.g., dyadic coping and intimacy as a measure of relationship quality), two structurally different raters, and three time points. The new model will be termed continuous time dynamic MTMR-LST-AR model and represents a complete continuous time dynamic multitrait-multirater latent state-trait model. For brevity, we only illustrate the structural part of the model. The measurement part has the same structure as the model presented in Figure 2b, except for the fact that the measurement model is duplicated for each construct that is added to the design. Note that each construct-method-unit may comprise a different number of observed variables.

According to Figure 4, the state space vector of the MTMR-LST-AR model is now a vector of $p = 14$ dimensions, including all latent variables (i.e., five indicator-specific trait variables, five indicator-specific trait method variables, two occasion-specific variables, and two occasion-specific method variables). Again, it is assumed that the latent trait, as well as the latent trait method variables, are time-invariant, which is implemented by constraining the corresponding elements in $\mathbf{A}^{*}_{\Delta t_u}$ to 1 (see Figure 4). Autoregressive and cross-lagged effects are permitted at the occasion-specific level. The autoregressive effects represent carry-over effects (i.e., accumulated situational effects from past occasions), whereas the cross-

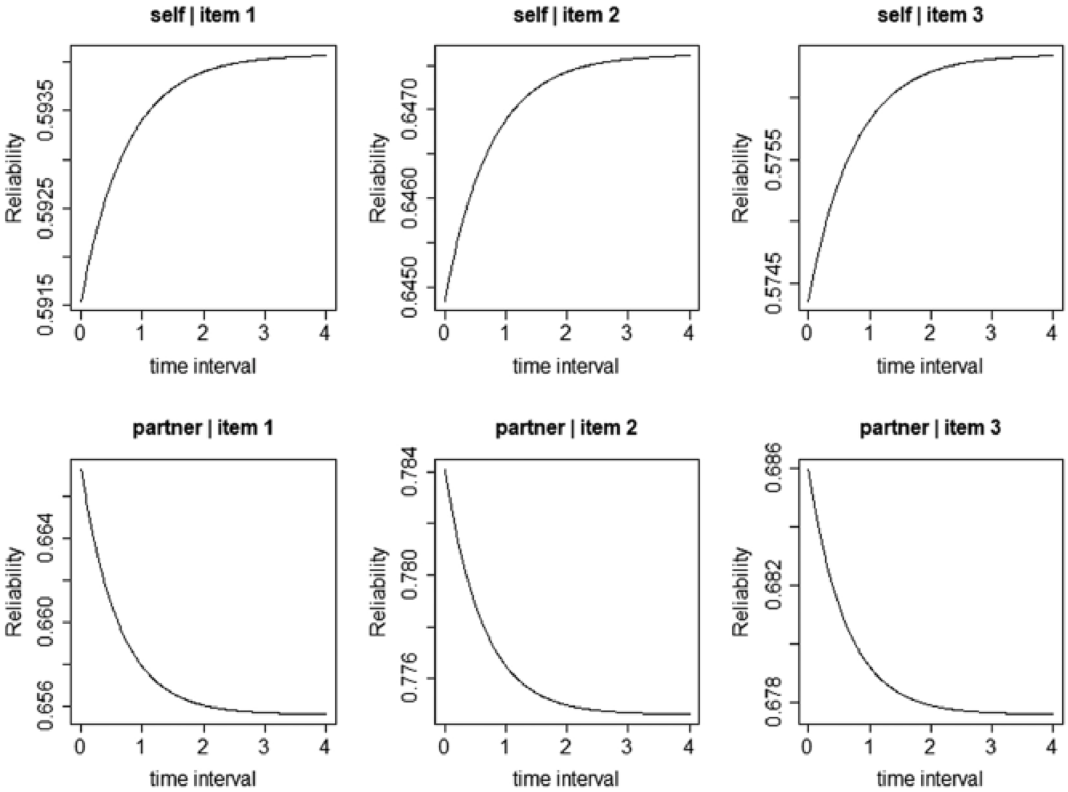

Figure 5. Reliability coefficients as a function of time in the anchor model. Results refer to the continuous time MR-LST-AR model using ctsem. The upper panel refers to the reliability coefficients of the reference rater indicators (anchor's self-report) and the lower panel refers to the reliability coefficients of the non-reference rater indicators (partner report). The *x*-axis denotes the time intervals (0-4). The limits of the *y*-axis are not adjusted to visualize the shape of the curve.

lagged effects reflect how these carry-over effects transmit to other constructs. For example, past situational effects may not only affect the momentary dyadic coping behavior of the target person but may also influence the momentary intimacy, and vice versa. The autoregressive and cross-lagged effects of the occasion-specific method variables represent carry-over effects that are specific to the non-reference method (e.g., partner report) after correcting for the influence of the reference method (e.g., target person's view).

In addition, the following covariances (or correlations) between the latent variables are permissible and can be investigated.[4] Correlations between latent traits belonging to the same construct j, but different indicators i and i' indicate heterogeneity among the reference method indicators. Similarly, correlations between the latent trait method factors belonging to the same construct j, but different indicators i and i' reflect heterogeneity among the non-reference method indicators. High correlations suggest low heterogeneity among the indicators. For a detailed discussion on how to specify indicator-specific effects in LST models see Geiser & Lockhart (2012).

Correlations between latent traits belonging to different constructs j and j' can be interpreted as a measure of discriminant validity at the trait level. High correlations indicate low discriminant validity at the trait level as measured by the reference method (e.g., anchor's self-reports). Correlations between latent trait method factors belonging to different constructs j and j' can be interpreted as a measure of partial discriminant validity (after correcting for the reference method) at the trait level. These correlations may also be interpreted as the generalizability of rater effects at the trait level. For example, high correlations would suggest that there is a general tendency that partners over- or underestimate the anchor person's trait values with respect to the expected trait value given the anchor person's self-report.

Correlations between the state residuals pertaining to different constructs j and j' can be interpreted as discriminant validity at the occasion-specific level with respect to the reference method. High correlations suggest low discriminant validity at the occasion-specific level with respect to the reference method (e.g., anchor's self-reports). Similarly, correlations between the state residual *method* factors can be interpreted as partial discriminant validity at the occasion-specific level. High correlations indicate low partial discrimination or a strong tendency that rater effects generalize across different constructs at the occasion-specific level. Formally, correlations between trait factors and trait method factors pertaining to different constructs j and j' are permissible. Similarly, correlations between state residuals and state method residuals pertaining to different constructs j and j' measured at the same

[4] Note that we focus on the covariances structure $\mathbf{\Phi}_{t_0}$ between the latent variables at time 1 (t_0 : starting point of the process) in Figure 4, as this covariance structure will be weighted by the matrix $\mathbf{A}^*_{\Delta t_u}$, and thus, become a function of time.

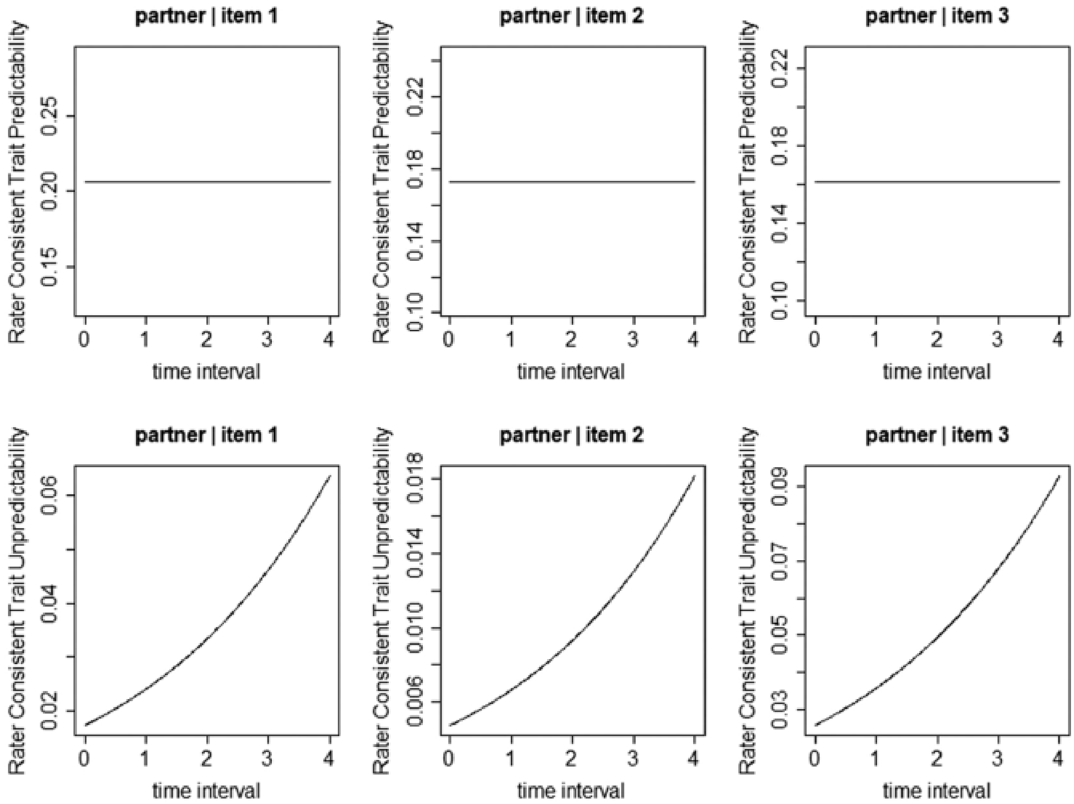

Figure 6. Rater-consistent (un)predictability by trait1 coefficients as a function of time in the anchor model. Results refer to the continuous time MR-LST-AR model using ctsem. The upper panel refers to rater consistent predictability by trait 1 coefficients and the lower panel refers to the rater-consistent unpredictability by trait 1 coefficients in the anchor model. The *x*-axis denotes the time intervals (0-4). The limits of the *y*-axis are not adjusted to visualize the shape of the curve. Note that the rater-consistent trait unpredictability by trait 1 coefficients at t0 represent the rater consistent occasion-specificity at t0.

time point are permissible. However, these correlations are oftentimes small and close to zero in empirical applications. For parsimony, we recommend fixing non-significant correlations to zero in empirical applications. This can also facilitate the estimation of more complex models including multiple traits and multiple raters.

4. Empirical Illustration

4.1. Data and Measures

In this section, we illustrate the discrete and continuous time dynamic MR-LST-AR model using data from the German Family Panel (pairfam release 9.0; Brüderl et al., 2018). A detailed description of the data and study design can be found in Huinink et al. (2011). We used a subset of the pairfam data set including waves 1, 3, 5, 7, and 9. Although the average sampling interval was about two years (mean of 1.98 and standard deviation of 0.12), not all individuals could be assessed on the same day, creating individually varying time intervals. The minimum time interval was 1.57 years, and the maximum was 2.48 years (with a range of .91 years). For our illustration, we selected couples in a stable relationship, that is, couples who were present on all occasions of measurements. This was done because anchor and partner persons could enter or leave the study at any time point. To avoid an overly complicated data structure including a mixture of stable and changing raters (see Koch et al., 2020), we decided to limit our study to stable couples. We note, however, that including all couples in the pairfam study would have led to a more unequally spaced measurement design, highlighting the practical relevance of the newly proposed approach.

In total, data from 426 couples were available on all occasions of measurement. We focused on the assessment of dyadic coping using 12 items from the Dyadic Coping Questionnaire (Bodemann, 2000) included in the pairfam study. Six out of the 12 items formed the anchor scale, while the remaining six items formed the partner scale. Item 1-3 of the anchor scale describes the anchor's self-reported behavior toward the partner in stressful situations (i.e., self- report), whereas item 4-6 of the partner scale describes the partner's perception of the anchor's behavior toward the partner (i.e., partner report). Similarly, item 1-3 of the partner scale refers to the self-reported dyadic coping of the partner, and item 4-6 of the anchor scale refers to the anchor's perceived dyadic coping behavior of the partner. In addition, we used two items to assess the quality of the relationship using the subscale Intimacy of the Network of Relationship Inventory (NFI; Furman & Buhrmester, 1985).

All items were measured using a 5-point rating scale (i.e., 1 = never to 5 = always) and were treated as continuous observed variables in the analysis. For the partner model, we used the self-reports of the partner as the reference method. The reports of the anchor person served as the non-reference method. All scripts for preparing the data are

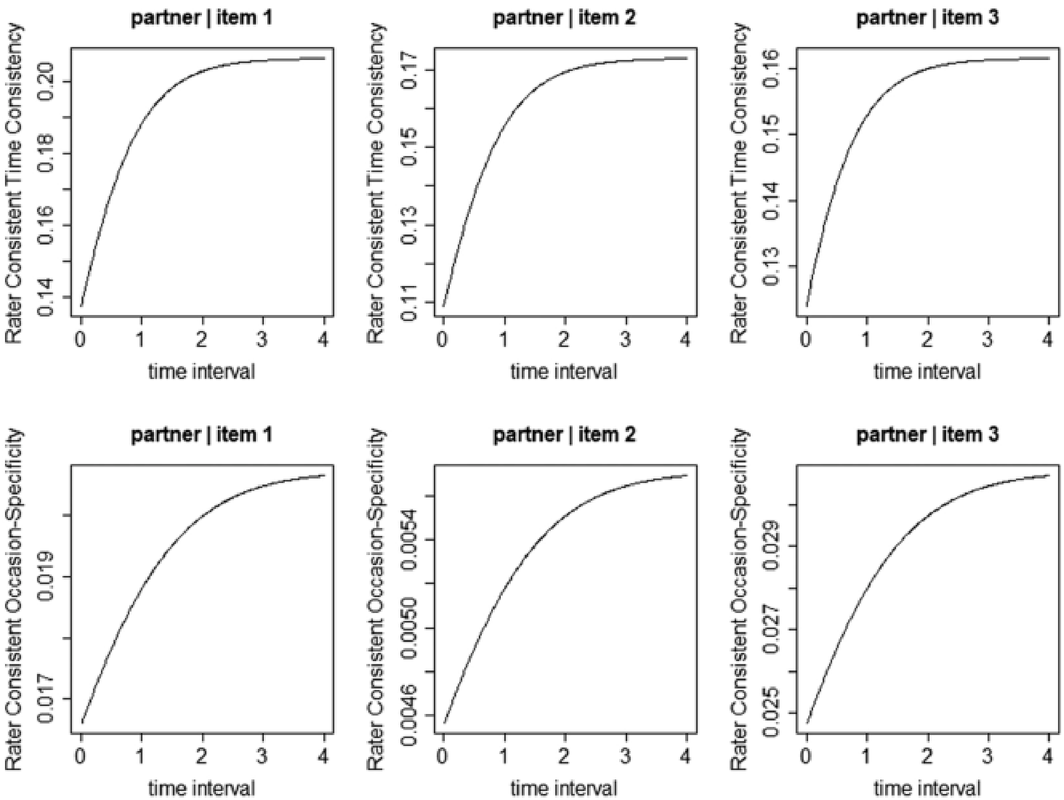

Figure 7. Rater consistent time consistency and rater consistent occasion-specificity as a function of time. Results refer to the continuous time MR-LST-AR model using ctsem. The upper panel refers to the rater consistent time consistency coefficients and the lower panel refers to the rater consistent occasion-specificity coefficients. The *x*-axis denotes the time intervals (0-4). The limits of the *y*-axis are not adjusted to visualize the shape of the curve.

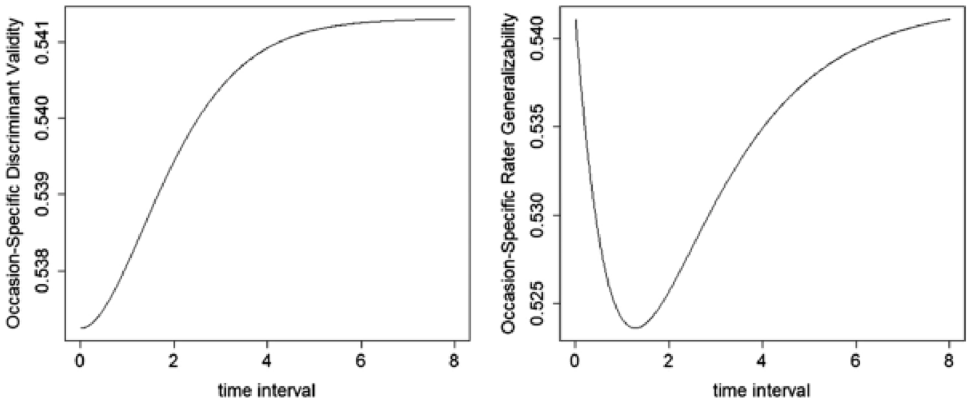

Figure 8. Discriminant validity and rater generalizability as a function of time. Results refer to the continuous time MTMR-LST-AR model using ctsem. The left figure refers to the occasion-specific correlation between the latent state residuals pertaining to different constructs (dyadic copying and intimacy) and can be interpreted as time-specific discriminant validity. The right panel refers to the occasion-specific correlation between the latent state residual method variable pertaining to different constructs (dyadic copying and intimacy) and can be interpreted as the generalizability of rater effects at the occasion-specific level.

provided on the OSF website (https://osf.io/3wuyq/?view_only=d0b2d1c975a4497bbba6e50d118dfb6a).

4.2. Analysis

The analysis was carried out in the following steps. First, we fitted the discrete time MR-LST-AR model to the data. This model served as a baseline model. Second, we fitted a continuous time dynamic MR-LST-AR model using a fixed time lag of 1. As noted earlier, in this special situation (i.e., if we assume that all time intervals are equal) the parameters of the continuous time dynamic model should perfectly recover the discrete time parameters from the baseline model. Depending on whether the assumption of equal time intervals is correct or incorrect, however, the parameter estimates (of both modeling approaches) will be correct or incorrect. Third, we refitted the continuous time dynamic MR-LST-AR model by taking into account the exact (individually varying) time intervals. To this end, we used the exact timestamps from the anchor data. Due to missing timestamps of the partner reports, we exclusively used the timestamps of the anchor reports. In this application, we assume that anchors and partners are assessed at the same time points. Note, however, that the continuous time dynamic MR-LST-AR model does not require the timestamps to be the same across raters. The above procedure was repeated for the anchor (i.e., anchors' self-reports served as the reference method) and the partner models (i.e., partners' self-reports served as the reference method). In a fourth and final step, we extended the discrete and continuous time dynamic MTMR-LST-AR models by adding the intimacy items into the anchor model.

All discrete time models were estimated using robust maximum likelihood estimation implemented in the package lavaan (Rosseel, 2012; version 0.6-7). All continuous time dynamic models were estimated using the package ctsem (Driver & Voelkle, 2018; version 3.4.2). Note that ctsem also allows researchers to estimate discrete time models. The code for fitting the models and calculating key variance coefficients is provided on the OSF website (https://osf.io/3wuyq/?view_only=d0b2d1c975a4497bbba6e50d118dfb6a)

4.3. Results

Table 2 shows the unstandardized parameter estimates in the continuous time dynamic models for the anchor and the partner perspective of dyadic coping when accounting for individually varying time intervals. According to the 95% credible intervals, all parameters in the models differ significantly from zero. To ease interpretation, we can translate the continuous time parameters back into discrete time for any given time interval (see Table 3). Importantly, the parameters in Table 2 can be used to compute the coefficients provided in Table 1 as a function of different time intervals. This feature is of great importance as researchers can evaluate how the reliability coefficients, as well as different types of rater-consistency and rater-specificity coefficients, change as a function of different time intervals. Figure 5 illustrates this fact by showing how the reliability coefficients in the anchor model change as a function of the time interval. According to Figure 5, the reliabilities of the self-reports increase marginally over time while the reliabilities of the other reports decrease marginally over time. Note that in our empirical example, the reliabilities only differ by a margin of .02 units or less.

Figure 6 shows the rater-consistent predictability by trait 1 coefficients (see upper panel, RConPredtrait1 and the rater consistent unpredictability by trait 1 coefficients (see lower panel, RConUnpredtrait1) in the anchor model. The rater-consistent predictability by trait 1 coefficients refers to the convergent validity at the initial trait level. The rater consistent unpredictability by trait 1 coefficients represents the convergent validity at the level of accumulated situational effects (i.e., interindividual differences in dyadic coping that are attributable to dynamic or autoregressive effects).

In our empirical application, the rater-consistent predictability by trait 1 coefficients ranged between .16 and .20, implying that 16% to 20% of the true variance in the partner reports could be predicted by the initial trait factor measured by the anchor self-reports. This corresponds to a latent correlation of .40 to .45, which indicates convergent validity at the initial trait level. Because, by definition, the rater-consistent predictability by trait 1 coefficients refers to the convergent validity at the initial trait level it will always be constant over time (i.e., a flat line in the upper panel of Figure 6). The rater-consistent *unpredictability* by trait 1 coefficients was substantially lower (see lower panel in Figure 6). However, the rater-consistent unpredictability by trait 1 coefficients increased over time and ranged between .00 and .03. This result suggests that there is little or no convergent validity at the level of dynamic interindividual differences. The findings may be partly explained by the fact that the measurement waves in the pairfam study were 2 years apart. An alternative explanation is that partners are not able to judge the dynamic changes in the anchor persons' dyadic coping behavior. Note that the RConUnpredtrait1-coefficients are not defined for t_0 in discrete time LST-R models (see Table 1). In continuous time dynamic models, the unpredictability coefficients correspond

Table 2. Unstandardized parameter estimates of the continuous time MR-LST-AR models for the anchor and the partner perspective.

	Anchor model			Partner model		
	Estimate	2.5%	97.5%	Estimate	2.5%	97.5%
λ_{T1kt}	0.57	0.45	0.73	0.46	0.35	0.59
λ_{T2kt}	0.57	0.42	0.73	0.42	0.32	0.56
λ_{T3kt}	0.53	0.41	0.68	0.33	0.24	0.44
λ_{O21t}	1.17	0.93	1.42	1.50	1.18	1.83
λ_{O31t}	0.92	0.76	1.08	0.78	0.64	0.92
λ_{O1kt}	0.18	0.08	0.34	0.19	0.10	0.33
λ_{O2kt}	0.12	0.03	0.32	0.22	0.11	0.37
λ_{O3kt}	0.20	0.10	0.36	0.15	0.06	0.31
λ_{OM2kt}	1.19	1.03	1.36	1.18	1.02	1.32
λ_{OM3kt}	0.93	0.81	1.06	1.01	0.88	1.14
$Var(\varepsilon_{11t})$	0.17	0.15	0.19	0.22	0.20	0.24
$Var(\varepsilon_{21t})$	0.16	0.14	0.18	0.15	0.12	0.19
$Var(\varepsilon_{31t})$	0.19	0.18	0.21	0.23	0.21	0.24
$Var(\varepsilon_{1kt})$	0.20	0.18	0.22	0.15	0.13	0.16
$Var(\varepsilon_{2kt})$	0.14	0.12	0.17	0.15	0.13	0.17
$Var(\varepsilon_{3kt})$	0.21	0.19	0.22	0.21	0.19	0.23
β_{O1t}	−0.70	−1.06	−0.44	−0.67	−0.95	−0.45
β_{OM2t}	−0.83	−1.14	−0.59	−0.95	−1.38	−0.63
$Var(T_{111})$	0.16	0.13	0.19	0.18	0.15	0.22
$Var(T_{211})$	0.17	0.14	0.22	0.21	0.17	0.25
$Var(T_{311})$	0.19	0.16	0.23	0.23	0.19	0.27
$Var(TM_{1k1})$	0.20	0.16	0.24	0.16	013	0.20
$Var(TM_{2k1})$	0.27	0.22	0.32	0.20	0.16	0.24
$Var(TM_{3k1})$	0.27	0.23	0.33	0.18	0.14	0.22
$Var(\zeta_{11})$	0.09	0.06	0.13	0.10	0.07	0.14
$Var(\zeta_{1t})$	0.12	0.08	0.18	0.11	0.08	0.15
$Var(\zeta M_{k1})$	0.14	0.10	0.19	0.10	0.07	0.13
$Var(\zeta M_{kt})$	0.20	0.14	0.28	0.22	0.15	0.31
$Cov(T_{111}, T_{211})$	0.15	0.12	0.18	0.18	0.15	0.22
$Cov(T_{111}, T_{311})$	0.14	0.12	0.17	0.15	0.13	0.19
$Cov(T_{211}, T_{311})$	0.15	0.12	0.19	0.18	0.15	0.22
$Cov(TM_{1k1}, TM_{2k1})$	0.22	0.18	0.26	0.16	0.13	0.20
$Cov(TM_{1k1}, TM_{3k1})$	0.20	0.17	0.25	0.14	0.11	0.17
$Cov(TM_{2k1}, TM_{3k1})$	0.24	0.20	0.28	0.16	0.13	0.20

Note. Estimates refer to the parameter estimates in the continuous time dynamic MR-LST-AR model accounting for individually varying time intervals using the ctsem package. λ_{Tikt}: trait factor loadings; λ_{TMikt}: trait method factor loadings; λ_{Oikt}: occasion-specific factor loadings; λ_{OMikt}: occasion-specific method factor loadings; ε_{ikt}: measurement error variable; β_{O1t}: auto-effect (reference method); β_{OMkt}: auto-effect (non-reference method); T_{i11}: latent trait factor (indicator-specific); TM_{ik1}: latent trait method factor (indicator-specific); ζ_{1t}: latent state-residual variable; ζM_{kt} : latent state-method residual variable; $Cov(\cdot)$: covariance; $Var(\cdot)$: variance; *i*: indicator; *k*: rater; *t*: continuous-time; 2.5%: lower bound of the 95% credible interval; 97.5%: upper bound of the 95% credible interval.

Table 3. Unstandardized parameter estimates of the discrete and continuous time MR-LST-AR models for the anchor and the partner perspective.

	Anchor model			Partner model		
Parameters	lavaan & ctsemOMX (two year fixed interval; $\Delta_t = 2$)	ctsemOMX (Δ_t varying)	ctsem (Δ_t varying)	lavaan & ctsemOMX (two year fixed interval; $\Delta_t = 2$)	ctsemOMX (Δ_t varying)	ctsem (Δ_t varying)
λ_{T1ku}	0.572	0.571	0.573	0.456	0.456	0.458
λ_{T2ku}	0.567	0.565	0.569	0.420	0.418	0.421
λ_{T3ku}	0.525	0.524	0.526	0.326	0.326	0.328
λ_{O21u}	1.188	1.178	1.181	1.489	1.492	1.494
λ_{O31u}	0.918	0.914	0.917	0.773	0.772	0.771
λ_{O1ku}	0.166	0.167	0.169	0.188	0.188	0.186
λ_{O2ku}	0.102	0.102	0.104	0.207	0.207	0.207
λ_{O3ku}	0.193	0.191	0.193	0.138	0.138	0.139
λ_{OM2ku}	1.187	1.184	1.181	1.175	1.174	1.182
λ_{OM3ku}	0.929	0.929	0.928	1.009	1.009	1.015
$Var(\varepsilon_{11u})$	0.167	0.167	0.167	0.218	0.218	0.218
$Var(\varepsilon_{21u})$	0.160	0.161	0.160	0.147	0.146	0.146
$Var(\varepsilon_{31u})$	0.195	0.195	0.195	0.225	0.225	0.225
$Var(\varepsilon_{1ku})$	0.195	0.195	0.195	0.147	0.146	0.147
$Var(\varepsilon_{2ku})$	0.142	0.142	0.142	0.145	0.145	0.145
$Var(\varepsilon_{3ku})$	0.206	0.205	0.206	0.206	0.206	0.206
β_{O1u}	0.264	0.262	0.267	0.277	0.266	0.268
β_{OM2u}	0.202	0.192	0.190	0.153	0.155	0.155
$Var(T_{111})$	0.157	0.157	0.156	0.179	0.180	0.179
$Var(T_{211})$	0.173	0.173	0.171	0.206	0.207	0.206
$Var(T_{311})$	0.191	0.191	0.190	0.227	0.227	0.227
$Var(TM_{1k1})$	0.196	0.197	0.196	0.163	0.163	0.162
$Var(TM_{2k1})$	0.263	0.264	0.265	0.195	0.194	0.193
$Var(TM_{3k1})$	0.272	0.272	0.273	0.178	0.177	0.177
$Var(\zeta_{11})$	0.085	0.086	0.086	0.102	0.101	0.101
$Var(\zeta_{1u})$	0.082	0.083	0.083	0.078	0.078	0.078
$Var(\zeta M_{k1})$	0.141	0.140	0.140	0.102	0.102	0.102
$Var(\zeta M_{ku})$	0.116	0.116	0.116	0.112	0.112	0.112
$Cov(T_{111}, T_{211})$	0.151	0.151	0.149	0.177	0.178	0.176
$Cov(T_{111}, T_{311})$	0.143	0.143	0.142	0.155	0.155	0.154
$Cov(T_{211}, T_{311})$	0.150	0.150	0.148	0.182	0.183	0.182
$Cov(TM_{1k1}, TM_{2k1})$	0.214	0.215	0.214	0.165	0.164	0.163
$Cov(TM_{1k1}, TM_{3k1})$	0.203	0.204	0.203	0.138	0.138	0.137
$Cov(TM_{2k1}, TM_{3k1})$	0.236	0.237	0.237	0.165	0.164	0.163
$-2{\cdot}\text{logLik}$	21002.9	21002.4	21002.3	21279.5	21262.6	21262.5
AIC	21130.9	21071.4	21070.3	21405.5	21330.6	21330.5
Computation time	6.29 s	32.60 min	32.26 s	4.59 s	35.85 min	33.31 s

lavaan: discrete time MR-LST-AR model using the lavaan package; ctsemOMX: continuous time MR-LST-AR model accounting for individually varying time intervals using the ctsemOMX package; ctsem: continuous time MR-LST-AR model accounting for individually varying time intervals using the ctsem package; λ_{Tiku}: trait factor loadings; λ_{TMiku}: trait method factor loadings; λ_{Oiku}: occasion-specific factor loadings; λ_{OMiku}: occasion-specific method factor loadings; ε_{iku}: measurement error variable; β_{O1u}: autoregressive effect (reference method); β_{OMku}: autoregressive effect (non-reference method); T_{i11}: latent trait factor (indicator-specific); TM_{ik1}: latent trait method factor (indicator-specific); ζ_{1u}: latent state-residual variable; ζM_{ku}: latent state-method residual variable; $Cov(\cdot)$: covariance; $Var(\cdot)$: variance; *i*: indicator; *k*: rater; *u*: discrete measurement occasion; $-2\log\text{Lik}$: model fit in terms of deviance; AIC: Akaike information criterion. The discrete time models fitted the data acceptably well, $x^2(431, N = 426) = 535.93,\ p < .001, \text{CFI} = .984,\ \text{RMSEA} = 0.024\,[.017;\ .030]; \text{SRMR} = 0.62$ for the anchor model and $x^2(431, N = 426) = 542.52,\ p < .01, \text{CFI} = .981,\ \text{RMSEA} = 0.025\,[.018;\ .031]; \text{SRMR} = 0.064$ for the partner model. All manifest variables were centered and the factor loadings, error variances, and autoregressive effects, as well as the occasion-specific residual variances for $u > 1$ were set to be equal across time in the discrete time models.

to the occasion-specificity at t_0: Hence, from a continuous time perspective, the occasion-specificity at t_0 is a special case of the unpredictability coefficients.

Figure 7 illustrates the rater-consistent time consistency coefficients (upper panel in Figure 7) and the rater-consistent occasion-specific coefficients (lower panel in Figure 7). The rater-consistent time consistency coefficients reflect the convergent validity between raters at the level of interindividual differences that are predictable by previous states. In our application, the rater-consistent time consistency coefficients ranged between .11 (11% shared variance) and .20 (20% shared variance), revealing considerable overlap between self-reported and partner-reported dyadic coping skills at this level. The counterpart of rater-consistent time consistency is rater-consistent occasion-specificity. The rater-consistent occasion-specificity coefficients reflect the convergent validity at the level of occasion-specific interindividual differences at a specific time point. The rater-consistent occasion-specificity coefficients are comparably lower than the rater-consistent time consistency coefficients (see lower panel of Figure 7) and range between .00 and .03. These results indicate low convergent validity at the occasion-specific level. Generally speaking, because the occasion-specificity coefficients were consistently low and close to zero, dyadic coping seems to be a “trait-like” construct in our application.

As discussed above, if we assume a constant time interval of one unit, the discrete time MR-LST-AR model is a special case of the continuous time dynamic model. Thus, both models will fit the data equally well, and it is possible to compare the results. However, when making such comparisons it is important to note that the discrete time model is agnostic of the time units. That is, in our example a one-unit interval in the discrete time model corresponds to an interval of two years, thus an interval $\Delta_t = 2$ in the continuous time dynamic model. Table 3 shows the unstandardized parameter estimates in the discrete and continuous time dynamic MR-LST-AR models for the anchor and the partner perspective, using three different R packages. The second and fifth columns refer to the discrete time models using lavaan. For the reasons discussed above, these results are (up to rounding errors) identical to the results of the corresponding continuous time dynamic model when using a time interval of 2. This was verified by using the package ctsemOMX (Driver et al., 2017). Since the results were identical, we do not repeat them, but refer to the second and fifth columns as "lavaan & ctsemOMX ($\Delta_t = 2$)" in Table 3 (the separate results are provided in the Supplemental Material). The remaining columns in Table 3 (columns 3, 4, 6, and 7) show the results of continuous time dynamic models when properly accounting for individually varying time intervals. According to Table 3, the results of the discrete time and continuous time dynamic models when accounting for individually different time intervals are very similar, especially for the anchor model.

Next, the MTMR-LST-AR models were fitted to the data to study the relationship between dyadic coping and intimacy. The discrete time MTMR-LST-AR model fitted the data acceptably well, $x^2(1200, N = 426) = 1524.96, p < .001, \mathrm{CFI} = .972, \mathrm{RMSEA} = 0.025\ [.021; .029]; \mathrm{SRMR} = 0.072.$ The continuous time dynamic model fitted the data equally well. Table B1 in the Appendix summarizes the unstandardized parameter estimates in the discrete and the continuous time dynamic MTMR-LST-AR model. Again, when choosing the same time interval ($\Delta_t = 2$) , the discrete and continuous time dynamic MTMR-LST-AR model provides similar results. Interestingly, the new version of the ctsem package allows researchers to compute even complex models, like the MTMR-LST-AR model, in a reasonable time (here: < 2 min). Table B2 provides the covariances and correlations among the latent variables in the continuous time dynamic MTMR-LST-AR model.

Again, based on the parameters in the continuous time dynamic model, it is possible to compute the correlations between the latent factors in the CT-MTMR-LST-AR as a function of the time interval. According to Figure 8, the correlations between the occasion-specific residual variables (see left panel) increase with larger time intervals, indicating the discriminant validity at the occasion-specific level decreases. However, the correlation between the occasion-specific method variables (see right panel) first decreases and then increases with increased time intervals.

4.4. Discussion of the Empirical Illustration

The results of our application suggest that dyadic coping in romantic couples can be conceived as a trait-like construct. The trait predictability coefficients were relatively large and the trait unpredictability coefficients were rather low or close to zero. The occasion-specificity coefficients measured by the anchors' self-reports were below 50%, revealing high consistency of the self-reported dyadic coping across time.

The highest convergent validity (rater consistency coefficients) between self-reported and partner-perceived dyadic coping skills were found at the trait level measured at time 1. The rater consistency coefficients were comparably lower at the dynamic and at the occasion-specific level. The low rater congruency at the dynamic and at the occasion-specific level can be partially explained by the fact that the measurement intervals were ~ 2 years apart in the pairfam study. To capture dynamic and occasion-specific influences in dyadic coping, it is recommended to use shorter time intervals between measuring waves in the assessment of dyadic coping. It can be expected that the occasion-specific influences on dyadic coping skills will be greater in studies with shorter time intervals (e.g., ambulatory assessment studies or experience sampling studies).

The results of the continuous time dynamic MTMR-LST-AR model revealed that intimacy and dyadic coping are positively correlated at the trait level and at the occasion-specific level. As expected, the correlations between intimacy and dyadic coping at the occasion-specific level decreases with increasing time intervals. The results suggest discriminant validity at both the trait and the occasion-specific level.

5. General Discussion

The analysis of convergent and discriminant validity in the measurement of change is becoming increasingly important in psychology. However, existing design-oriented modeling approaches assume *equally spaced time intervals* within and between individuals. This assumption is frequently violated in empirical applications, especially if multiple raters are considered. To fill this gap, we propose a continuous time dynamic multirater latent state-trait model with autoregressive effects that explicitly accounts for individually varying time intervals. The new model is termed the continuous time dynamic MR-LST-AR model and bears several advantages for complex longitudinal multimethod (or multirater) analyses.

First, our model is a generalization of the discrete time MR-LST-AR model by Bohn et al. (2021) to measurement designs with individually varying time intervals. Many other LST models (with or without autoregressive effects) could be derived as special cases from the proposed continuous time dynamic models. For example, the random intercept cross-lagged panel (RI-CLPM) model by Hamaker et al. (2015), the STARTS model by Kenny & Zautra (2001), the multimethod LST model by Courvoisier et al. (2008), as well as a single trait-multistate or multitrait-multistate models (see e.g., Steyer et al. 2015) represent special cases of the continuous time dynamic MTMR-LST-AR model.

Second, the proposed continuous time dynamic models allow for a fine-grained analysis of convergent validity, discriminant validity, as well as rater-specific effects at the trait level and at the occasion-specific level as a function of time. Researchers are now able to examine key variance coefficients of rater consistency (or rater specificity) at the level of interindividual differences that are (a) predictable by the initial trait, (b) attributable to dynamic effects, or (c) attributable to occasion-specific effects. More importantly, researchers could use the proposed models to determine which rater group has the highest congruency (convergent validity) with the reference rater group at both the trait and the occasion-specific level and how this overlap changes over time. This feature is especially relevant for applied researchers who are interested in determining the optimal time interval to achieve a certain rater agreement in discrete time (Dormann & Griffin, 2015).

Third, the proposed models are built on the principles of modern LST-R theory (Steyer et al., 2015, Eid et al., 2017). Following LST-R theory, the latent traits in the continuous-time dynamic MR-LST-AR model represent *time-specific* dispositions (traits) that may change as a result of past experiences. The autoregressive effects denote carry-over effects or accumulated situation effects due to past occasions. The latent residual variables denote occasion-specific effects that are neither predictable by the initial trait nor by past experiences. Overall, the presented continuous time MR-LST-AR models complement the existing discrete time LST-AR models by combining the advantages of LST-R theory, design-oriented modeling approaches, and continuous time modeling approaches.

Both discrete and continuous time dynamic modeling approaches have their strength and weaknesses. Discrete time models are advantageous if the measurement design comprises few and equally spaced time points and inference about underlying continuous processes is not desired. Oftentimes the estimation of classical (discrete time) MR-LST-AR models is not computationally demanding and usually takes only a few seconds. Furthermore, discrete time MR-LST-AR models can be extended to more complex measurement designs, including a combination of structurally different and interchangeable raters (Koch et al., 2017), categorica observed variables (Holtmann et al., 2020), or finite mixture distribution models (Litson et al., 2019).

In contrast to discrete time models, continuous time dynamic MR-LST-AR models do not rely on the oftentimes unrealistic assumption of equally spaced multirater measurement designs or latent processes that only interact when observed. By considering the exact time point of measurement, the proposed model readily extends to individualized designs with possibly completely different measurement occasions across raters and across time. Moreover, continuous time dynamic MR-LST-AR models implicitly account for incomplete data if the missingness follows a missing (completely) at random mechanism (Oud & Voelkle, 2014; Voelkle, 2016). Continuous time dynamic MR-LST-AR models could also be extended to hierarchical formulations (see Driver & Voelkle, 2018, 2021) that allow parameters in the model to vary across individuals. Granted a sufficient amount of data, such an extension would allow researchers to investigate convergent validity at a within-person level. On the downside, differential continuous time dynamic models can be complex to set up, difficult to understand, and computationally more demanding. Moreover, just like any statistical model, the continuous time dynamic modeling approach assumes that the model at hand is correctly specified, that is, that the CT-MR-LST-AR model as defined via Equations (18) and (20) holds captures the data-generating process. In practice, this assumption can be violated, and the model may be misspecified resulting in biased parameter estimates and possibly wrong conclusions. Continuous time dynamic modeling offers great flexibility in extending the basic model employed in this article, for example to higher-order models (Oud et al., 2018) fully hierarchical models (Driver & Voelkle 2018), or oscillating patterns with individually varying time intervals (e.g., Voelkle & Oud, 2013). For an overview of some recent developments, see van Montfort et al. (2018). With the present article, we hope t to make continuous time dynamic models more accessible to readers aiming to analyze complex longitudinal multimethod (or multirater) data.

5.1. Practical Recommendations

In the case of few and equally spaced time intervals, applied researchers may be fine with discrete time MR-LST-AR models, if the measurement interval is meaningful. This is important because all parameter estimates will be bound to this time interval, prohibiting a comparison across other intervals (e.g., other studies). Following Geiser and Lockhart (2012) we recommend researchers use models with indicator-specific factors. The guidelines by Geiser and Lockhart (2012) can be implemented in both discrete and continuous time dynamic models presented in this article. In our application, we specified indicator-specific trait and indicator-specific trait method factors to account for heterogeneity in the manifest variables. Alternatively, latent indicator-specific factors that are orthogonal to all other latent variables in the model could be specified (see Geiser & Lockhart, 2012).

If the design is not equally spaced, we recommend using continuous time dynamic MR-LST-AR models. To check whether the continuous time dynamic model has been correctly specified (at least in classic SEM terms), researchers can compare the results of the discrete time model with those of the continuous time version using a time lag of one unit (cf. Table 2), although once expectations and implied covariation vary across subjects comparisons to a single fit value from a saturated covariance do not always give intuitive results. A prerequisite for using our continuous time dynamic multirater approach is that the data set contain identifying variables that denote the time stamp of the measurement. Researchers should collect the time stamps for each rater separately, as they may differ, and this can provide important information for estimation. In addition, we recommend starting with models including only a single construct (i.e., mono-construct-multimethod designs). Adding multiple constructs increases the complexity of the model and the time of the estimation considerably. Researchers may also consider constraining small and unimportant correlations to zero when specifying complex MTMR-LST-AR models.

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Appendix A: Variance Coefficients in Continuous Time MR-LST-AR Models

The model-implied covariance matrix of the continuous time MR-LST-AR model discussed in Section *Continuous Time Multirater Latent State-Trait Models with Autoregressive Effects* can be expressed as follows:

$$\mathbf{\Sigma}_{\mathbf{y}_{t_u}} = \mathbf{\Lambda}\left(\mathbf{A}^*_{\mathbf{\Delta t_u}}\mathbf{\Phi}_{t_0}\left(\mathbf{A}^*_{\mathbf{\Delta t_u}}\right)^{\mathrm{T}} + \boldsymbol{Q}_{\Delta t_u}\right)\mathbf{\Lambda}^{\mathrm{T}} + \mathbf{\Theta}_{\mathbf{y}} \text{ for } \Delta t_u = t_u - t_0$$

where $\mathbf{\Sigma}_{y_{t_u}}$ is the model-implied covariance matrix of the observed variables, $\mathbf{\Lambda}$ is the time-independent loading matrix with $\mathbf{\Lambda}^{\mathrm{T}}$ being the transposed loading matrix, $\mathbf{\Theta}_{\mathrm{y}}$ is a diagonal residual (error) matrix of the manifest variables, $\mathbf{A}^*_{\mathbf{\Delta}t_u}$denotes the autoregressive-cross lagged matrix constrained to the underlying drift matrix via $\mathbf{A}^*_{\mathbf{\Delta}t_u} = \mathrm{e}^{\mathrm{A}\Delta t_u}$ with $\left(\mathbf{A}^*_{\mathbf{\Delta}t_u}\right)^{\mathrm{T}}$ being the transposed matrix, $\mathbf{\Phi}_{t_0}$ is the covariance matrix of the latent variables, and $\mathbf{Q}_{\Delta t_u}$denotes the covariance matrix constrained to underlying continuous time parameters with $\mathbf{Q}_{\Delta t_u} = \mathrm{irow}\left((\mathbf{A}\otimes\mathbf{I} + \mathbf{I}\otimes\mathbf{A})^{-1}\left(\mathrm{e}^{(\mathbf{A}\otimes\mathbf{I}+\mathbf{I}\otimes\mathbf{A})\Delta t_u} - \mathbf{I}\right)\mathrm{row}(\mathbf{Q})\right)$. Based on the above model-implied covariance matrix, we can now define the variance coefficients described in the main text. In the online Supplemental Materials, we provide a convenient R function to compute the variance coefficients in an empirical application. The reliability coefficients can be defined as follows:

$$Rel\left(\mathbf{y}_{t_u}\right) := \frac{\mathbf{\Psi}_{\Delta t_u}}{\mathbf{\Psi}_{\Delta t_u} + \mathbf{\Theta}_{\mathbf{y}}}$$

where $\mathbf{\Psi}_{\Delta t_u}$ denotes the covariance matrix of the latent variables, that is, $\mathbf{\Psi}_{\Delta t_u} = \boldsymbol{A}^*_{\boldsymbol{\Delta t_u}}\mathbf{\Phi}_{t_0}\left(\boldsymbol{A}^*_{\Delta t_u}\right)^{\mathrm{T}} + \boldsymbol{Q}_{\Delta t_u}$. The trait predictability coefficients can be defined as follows:

$$Pred_{trait1}\left(\mathbf{y}_{\boldsymbol{t_u}}\right): = \frac{\boldsymbol{\xi}_{\mathrm{ref}}}{\mathbf{\Psi}_{\boldsymbol{\Delta t_u}}}$$

with $\boldsymbol{\xi}_{\mathrm{ref}} = \mathbf{\Lambda}_{\xi\mathrm{ref}}\mathbf{\Phi}_{t_0}\mathbf{\Lambda}^{\mathrm{T}}_{\xi\mathrm{ref}}$ is the covariance matrix of the latent trait variables pertaining to the reference method indicators. Note that $\mathbf{\Lambda}_{\xi\mathrm{ref}}$ is a submatrix of $\mathbf{\Lambda}$, where only loadings pertaining to the latent traits measured by the reference method are freely estimated and all remaining loadings are fixed to zero. The trait unpredictability coefficients are defined as follows:

$$Unpred_{trait1}\left(\mathbf{y}_{t_u}\right) := \frac{\mathbf{U}_{\mathrm{ref}}}{\mathbf{\Psi}_{\Delta t_u}}$$

where $\boldsymbol{U}_{\mathrm{ref}} = \mathbf{\Psi}_{\Delta t_u} - \boldsymbol{\xi}_{\mathrm{ref}} - \boldsymbol{\zeta}_{\mathrm{ref}}$ and $\boldsymbol{\zeta}_{\mathrm{ref}} = \mathbf{\Lambda}_{\zeta\mathrm{ref}}\mathbf{Q}_{\Delta t_u}\mathbf{\Lambda}^{\mathrm{T}}_{\zeta\mathrm{ref}}$.Again, $\mathbf{\Lambda}_{\zeta\mathrm{ref}}$ is a submatrix of $\mathbf{\Lambda}$, where all loadings are fixed to zero, except for those pertaining to the occasion-specific factor of the reference method. The time consistency coefficients are computed as follows:

$$TCon\left(\mathbf{y}_{\boldsymbol{t_u}}\right) := \frac{\boldsymbol{\xi}_{\mathrm{ref}} + \mathbf{U}_{\mathbf{ref}}}{\mathbf{\Psi}_{\boldsymbol{\Delta t_u}}} = \frac{\mathbf{\Psi}_{\Delta t_u} - \boldsymbol{\zeta}_{\mathrm{ref}}}{\mathbf{\Psi}_{\Delta t_u}}$$

The occasion-specificity coefficients are defined as follows:

$$OS\left(\mathbf{y}_{t_u}\right) := 1 - TCon\left(\mathbf{y}_{t_u}\right) = \frac{\boldsymbol{\zeta}_{\mathrm{ref}}}{\mathbf{\Psi}_{\Delta t_u}}$$

Following a similar logic, the variance coefficients pertaining to the non-reference method indicators can be computed. The rater-consistent predictability by trait 1 coefficients can be computed as follows

$$RConUPredtrait1\left(\mathbf{y}_{t_u}\right) := \frac{\boldsymbol{\xi}_{\mathrm{nref}}}{\boldsymbol{\xi}_{\mathrm{nref}} + \boldsymbol{\xi}\mathbf{M}_{\mathrm{nref}}}$$

where $\boldsymbol{\xi}_{\mathrm{nref}} = \mathbf{\Lambda}_{\xi\mathrm{nref}}\mathbf{\Phi}_{t_0}\mathbf{\Lambda}^{\mathrm{T}}_{\xi\mathrm{nref}}$ and $\boldsymbol{\xi}\mathbf{M}_{\mathrm{nref}} = \mathbf{\Lambda}_{\boldsymbol{\xi}\mathbf{M}\mathrm{nref}}\mathbf{\Phi}_{t_0}\mathbf{\Lambda}^{\mathrm{T}}_{\boldsymbol{\xi}\mathbf{M}\mathrm{nref}}$. Again, the loadings matrices $\mathbf{\Lambda}_{\boldsymbol{\xi}\mathrm{nref}}$ and $\mathbf{\Lambda}_{\boldsymbol{\xi}\mathbf{M}\mathrm{nref}}$ are special cases of $\mathbf{\Lambda}$ with certain elements being fixed to zero. The $RConUPredtrait1$-coefficients are given as follows:

$$RConUPredtrait1\left(\mathbf{y}_{t_u}\right) := \frac{\mathbf{U}_{\mathrm{nref}}}{\mathbf{U}_{\mathrm{nref}} + \mathbf{UM}_{\mathrm{nref}}}$$

Table A1. Unstandardized parameter estimates of the discrete and continuous time MTMR-LST-AR model (anchor model).

Parameters	lavaan & ctsemOMX (two year fixed interval; $\Delta_t = 2$)	ctsem (Δ_t varying)	Parameters	lavaan & ctsemOMX (two year fixed interval; $\Delta_t = 2$)	ctsem (Δ_t varying)
λ_{T112u}	0.496	0.499	$Var(T_{1111})$	0.155	0.154
λ_{T212u}	0.468	0.465	$Var(T_{2111})$	0.176	0.176
λ_{T312u}	0.423	0.422	$Var(T_{3111})$	0.192	0.192
λ_{T122u}	0.112	0.111	$Var(T_{1211})$	0.274	0.273
λ_{T222u}	0.263	0.265	$Var(T_{2211})$	0.472	0.469
λ_{O211u}	1.080	1.066	$Var(\zeta_{111})$	0.098	0.100
λ_{O311u}	0.857	0.848	$Var(\zeta_{211})$	0.177	0.174
λ_{O112u}	0.155	0.153	$Var(\zeta M_{121})$	0.147	0.145
λ_{O212u}	0.101	0.100	$Var(\zeta M_{221})$	0.168	0.168
λ_{O312u}	0.182	0.180	$Var(TM_{1121})$	0.198	0.199
λ_{OM212u}	1.131	1.129	$Var(TM_{2121})$	0.268	0.270
λ_{OM312u}	0.918	0.916	$Var(TM_{3121})$	0.277	0.278
λ_{O221u}	0.886	0.891	$Var(TM_{1221})$	0.250	0.252
λ_{O122u}	0.182	0.179	$Var(TM_{2221})$	0.406	0.409
λ_{O222u}	0.145	0.150	$Var(\varepsilon_{111u})$	0.158	0.158
β_{O1}	0.226	0.231	$Var(\varepsilon_{211u})$	0.166	0.167
β_{O2}	0.304	0.317	$Var(\varepsilon_{311u})$	0.195	0.195
γ_{O1}	0.055	0.051	$Var(\varepsilon_{112u})$	0.190	0.190
γ_{O2}	−0.041	−0.045	$Var(\varepsilon_{212u})$	0.150	0.150
β_{OM1}	0.148	0.140	$Var(\varepsilon_{312u})$	0.204	0.203
β_{OM2}	0.636	0.632	$Var(\varepsilon_{121u})$	0.189	0.190
γ_{OM1}	0.158	0.152	$Var(\varepsilon_{221u})$	0.265	0.265
γ_{OM2}	−0.105	−0.102	$Var(\varepsilon_{122u})$	0.163	0.164
$Var(\zeta_{112})$	0.091	0.093	$Var(\varepsilon_{222u})$	0.264	0.264
$Var(\zeta_{212})$	0.085	0.084	−2·logLik	36756.7	36757.34
$Var(\zeta M_{112})$	0.120	0.121	AIC	37006.7	36907.35
$Var(\zeta M_{212})$	0.095	0.095	Computation time	54.87 s	1.86 min

lavaan: discrete time MTMR-LST-AR model using the lavaan package; ctsem: continuous time MTMR-LST-AR model accounting for individually varying time intervals using the ctsem package; λ_{Tijku}: trait factor loadings; λ_{TMijku} : trait method factor loadings; λ_{Oijku}: occasion-specific factor loadings; λ_{OMijku} : occasion-specific method factor loadings; ε_{ijku}: measurement error variable; β_{O1u}: autoregressive effect (reference method); β_{OMku}: autoregressive effect (non-reference method); T_{ij11}: latent trait factor (indicator-specific); TM_{ijk1}: latent trait method factor (indicator-specific); ζ_{j1u}: latent state-residual variable; ζM_{jku}: latent state-method residual variable; $Cov(\cdot)$: covariance; $Var(\cdot)$: variance; *i*: indicator; *j*: construct; *k*: rater; u = discrete measurement occasion; $-2 \cdot \log \mathrm{Lik}$: model fit in terms of deviance: AIC: Akaike information criterion.

Table A2. Covariances and correlations between the latent variables in the continuous time MTMR-LST-AR model (anchor model) at T0.

	1	2	3	4	5	6	7	8	9	10	11	12	12	14
T_{1111}	**0.15**	0.15	0.14	0.13	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
T_{2111}	0.90	**0.18**	0.15	0.13	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
T_{3111}	0.81	0.81	**0.19**	0.14	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
T_{1211}	0.64	0.58	0.60	**0.27**	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
T_{2211}	0.62	0.53	0.57	0.80	**0.47**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ζ_{111}	0.00	0.00	0.00	0.00	0.00	**0.10**	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ζ_{211}	0.00	0.00	0.00	0.00	0.00	0.25	**0.17**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ζM_{121}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.15**	0.05	0.00	0.00	0.00	0.00	0.00
ζM_{221}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	**0.17**	0.00	0.00	0.00	0.00	0.00
TM_{1121}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.20**	0.22	0.20	0.11	0.16
TM_{2121}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	**0.27**	0.24	0.15	0.17
TM_{3121}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.87	0.88	**0.28**	0.17	0.19
TM_{1221}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.51	0.56	0.63	**0.25**	0.24
TM_{2221}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.55	0.52	0.57	0.75	**0.41**

Note. Bold coefficients in the diagonal are the variances of the latent variables. Latent covariances are provided in the upper triangular. Latent correlations are represented in lower triangular. Correlations denoted by 0.00 were fixed to zero based on the definition of the model.

where $\mathbf{U}_{\mathrm{nref}} = \mathbf{\Lambda}_{\zeta\mathrm{nref}}\left(\mathbf{A}^{*}_{\Delta t_u}\mathbf{\Phi}_{t_0}\left(\mathbf{A}^{*}_{\Delta t_u}\right)^{\mathrm{T}}\right)\mathbf{\Lambda}^{\mathrm{T}}_{\zeta\mathrm{nref}}$ and $\mathbf{UM}_{\mathrm{nref}} = \mathbf{\Lambda}_{\zeta\mathbf{M}\mathrm{nref}}\left(\mathbf{A}^{*}_{\Delta t_u}\mathbf{\Phi}_{t_0}\left(\mathbf{A}^{*}_{\Delta t_u}\right)^{\mathrm{T}}\right)\mathbf{\Lambda}^{\mathrm{T}}_{\zeta\mathbf{M}\mathrm{nref}}$. Finally, the rater-consistent occasion specificity

$$RConOS(\mathbf{y}_{t_u}) := \frac{\boldsymbol{\zeta}\mathrm{nref}}{\boldsymbol{\zeta}\mathrm{nref} + \boldsymbol{\zeta}\mathbf{M}\mathrm{nref}}$$

where $\boldsymbol{\zeta}_{\mathrm{nref}} = \mathbf{\Lambda}_{\zeta\mathrm{nref}}\mathbf{Q}_{\Delta t_u}\mathbf{\Lambda}^{\mathrm{T}}_{\zeta\mathrm{nref}}$ and $\boldsymbol{\zeta}\mathbf{M}_{\mathrm{nref}} = \mathbf{\Lambda}_{\zeta\mathrm{nref}}\mathbf{Q}_{\Delta t_u}\mathbf{\Lambda}^{\mathrm{T}}_{\zeta\mathrm{nref}}$.

Appendix B: Results of the MTMR-LST-AR Models

According to Table A2, the dyadic coping traits were positively correlated with the intimacy traits at the starting point of the process. The correlation ranged between .53 and .64 and can be interpreted as a measure of discriminant validity at t_0. Similarly, the trait method factors pertaining to dyadic coping measures were positively correlated with the trait method factors pertaining to the intimacy measures at t_0: These correlations can be interpreted as rater generalizability at the initial trait level. A positive correlation suggests that the partner-specific judgment on the anchor's trait can be generalized across constructs when correcting for the anchor's self-report. The correlations ranged between .52 and .63 and support the fact that partners tend to generalize their judgments across both constructs (dyadic coping and intimacy). A similar correlation pattern was found at the occasion-specific level. However, the correlations at the occasion-specific level were lower as compared to the correlations at the trait level. The correlations between the occasion-specific (method) factors at t_0 ranged between .24 and .34. Figure 8 shows how the model-implied occasion-specific correlations change as a function of the time interval.