Original Article

Latent State-Trait Models for Longitudinal Family Data

Investigating Consistency in Perceived Support

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Abstract. Support is key to healthy family functioning. Using the family social relations model (SRM), it has already been shown that variability in perceived support is mostly attributed to individual perceiver effects. Little is known, however, as to whether those effects are stable or occasion-specific. Several methods have been proposed within the structural equation modeling (SEM) framework for the investigation of hypotheses on stable and occasion-specific aspects of such psychological attributes. In this paper, we explore the applicability of different models for determining the consistency of SRM effects of perceived support: the multistate model, the singletrait-multistate model, and the trait-state occasion model. We provide a detailed description of the model building process and assumption verification, as well as the supporting R-code. In addition to the methodological contribution on how to combine these models with the SRM, we also provide substantive insights into the consistency of perceived family support. We rely on round robin data on relational support from the Dutch RADAR-Y (Research on Adolescent Development and Relationships – Younger Cohort) study, a 6-year longitudinal study of 500 families with a 13-year-old target adolescent at the start of the study.

Keywords: consistency, family social relations model, latent state-trait models, perceived support

Introduction

The latent State-Trait (LST) framework can be used to study longitudinal dynamics of psychological attributes that go beyond their mean change over time. LST models can, for example, determine the degree to which such attributes reflect stable effects (traits), effects of person-situation interactions (states), or random measurement error. The proportion of the psychological attribute that can be explained by stable effects is sometimes referred to as the consistency. This paper does not aim to discuss at length the formal framework of LST theory (Steyer, Ferring, & Schmitt, 1992). Rather, we explain in detail how LST models can be applied to longitudinal family data to explore consistency. We present data on perceived support from approximately 500 four-member families (father, mother, target, adolescent, and sibling) that participated in the RADAR-Y (Research on Adolescent Development and Relationships – Younger Cohort). In particular, we focus on exploring the consistency of interpersonal dynamics of perceived support within families. The goal of this paper is, therefore, threefold.

First, we want to share with family researchers our findings on consistency of perceived support within families. Second, more methodologically oriented researchers may be interested in the technical aspects of combining LST models with family data. Third, researchers interested in applying those models will find sufficient detail on the model building process and practical implementation. At the end of this Introduction, we discuss the structure of the paper in more detail. We first emphasize the importance of our substantive research question and the complexities that we may encounter in finding an answer.

While support is key to healthy family functioning, few studies have adopted a systemic approach toward a full investigation of the support exchange within family dyads (Lanz & Tagliabue, 2014). We argue that round robin data are required for such investigation. In a round robin design, each family member provides data on their relationship with the other family members. The data are called directed relationship data because the measure of person A in relationship to person B is not the same as the measure of person B in relationship to person A (Cook, 1994).

A round robin design has advantages compared to other research designs that are applied in the family literature in which the unit of analysis is the family or a specific dyad. When the study of family functioning is limited to the rating of the family as a whole, for example, when the mother is rating the overall support in the family, single family member's reports are likely to represent characteristics of the rater themselves rather than solely reflecting whole family functioning (Manders et al., 2007). When family functioning is studied at a dyadic level, one problem is that, very often, only parent-adolescent relationships are considered, typically, the mother-adolescent relationship and mostly from the perspective of the adolescent. Such a unidirectional measure is heavily influenced by the characteristics of the rater and does not account for family functioning at all relationship levels nor does it take into account the possibility that both between and within family differences may exist. In contrast, the use of a round robin design can study family functioning from multiple perspectives, across multiple family dyads, and on different levels.

The family social relations model with roles (SRM; Kenny & La Voie, 1984) offers a valuable tool to disentangle these complex family dynamics from round robin data. According to the SRM, each dyadic measurement is potentially a function of four systematic sources of variance: an actor effect, a partner effect, a relationship effect, and a family effect. For example, when an adolescent in the RADAR-Y study is asked "How much does your mother care about you?," the obtained dyadic measurement may be determined by several factors. First, it may be determined by the adolescent's general tendency to perceive support (the actor effect of the adolescent). Although the most commonly used term in the SRM literature is the "actor" effect, the alternative term that is sometimes used and is better suited to address measures of perceived relational support is the "perceiver" effect. The dyadic measurement of perceived support as reported by the adolescent in relation to the mother may further be determined by the mother's general tendency to support other family members (the partner effect of the mother), the adolescent's perceived support from the mother that is unique to their relationship (the adolescent-mother relationship effect), and the overall level of support in the family (the family effect). The SRM has already shown in other studies that perceived support is mostly driven by the perceiver rather than the partner, particularly in adolescents (e.g., Branje, van Aken, & van Lieshout, 2002).

In the RADAR-Y study, round robin data on perceived support were not obtained at a single time point but annually gathered over a period of 6 years. From a family systems' theory perspective, it is reasonable to assume that family relationships are subject to change (Cox & Paley, 2003; Olson & Gorall, 2003). Despite the long-standing acknowledgment of the importance of interpersonal interactions by developmental theorists (Bronfenbrenner, 1979; Collins & Laursen, 1999), researchers have been slow to exploit the rich potential of family data in the study of developmental processes (Card & Toomey, 2012; Nestler, Grimm, & Schönbrodt, 2015). Existing research on relationship development within families has mostly focused on one dyad (e.g., Schmitt, 2000) and often (but not always) from one perspective, thereby suffering from the same aforementioned shortcomings as in cross-sectional designs. That is, when studying families from a developmental perspective we must consider the different perspectives and levels. We concur with Hatton et al. (2008) that interactional behaviors, such as the adolescent's general perception of support, may reflect a combination of an enduring tendency to interact in characteristic fashion as well as a tendency to modulate behavior in response to the specific context.

To assess consistency in support, we need to move beyond traditional methods that assess change over time in familial support, such as growth models that are relevant for exploring mean changes. For example, in the RADAR-Y study, when an adolescent is asked at a certain moment "How much does your mother care about you?," the response may reflect a combination of a stable perception of support and a transitory perception of that moment. Occasion-specific circumstances (the adolescent may engage in a romantic relationship and, in striving for more equality, the adolescents may reach equality in the parent-adolescent relationship) may change the variability in the responses of the adolescent and, hence, the consistency.

It is, however, important to understand at what level of family dynamics those circumstances impact the consistency of the perception of support. Do the circumstances impact the consistency of perceived support in the family as a whole or just the consistency of the perception of support of the adolescent, for example?

To answer these research questions, we first use the SRM to disentangle dyadic measures at every time point into family effects, perceiver effects, partner effects, and relation-specific effects. Next we assess to what extent these effects reflect stable components versus fluctuating components over time. Ackerman, Kashy, Donnellan, and Conger (2011) studied similar positive-engagement behavior in families annually over a 3-year period, for example, and found an appreciable degree of consistency in family norms, individual characteristics, and relation-specific effects. While these authors acknowledged some fluctuations in consistency over time for the different effects, no firm conclusions on whether the consistency is constant over time could be drawn based on the three assessments alone. In the RADAR-Y study, we have annual data for adolescents and their family over a 6-year period, and we can better assess how the consistency of perceived support evolves during adolescence. We do so by placing the SRM within the earlier mentioned latent state-trait (LST) perspective.

Our paper is organized as follows. We start with a more detailed description of the RADAR-Y study and the dyadic measurement of perceived support. Next, we show how the SRM can be used to disentangle the dyadic measurements into meaningful components and fit SRM models for each wave separately. While SRM models allow us to identify the sources of variability in perceived support in family relationships at every wave, we cannot conclude anything on the consistency of the SRM effects. Accordingly, we introduce several methods that have been proposed within the structural equation model (SEM) framework for the investigation of hypotheses on stable and occasion-specific aspects of some attribute. For didactic purposes, we provide details on state-trait models in the next section and discuss the model building process and assumption verification. The steps described in this section can easily be replicated by the reader using the Electronic Supplementary Material, ESM 1. We end with an overview on the estimated consistency over time of the SRM effects of perceived support and discuss our findings in a broader perspective both from a substantive and methodological point of view.

RADAR-Y Study

Design

In the RADAR-Y study, adolescents were recruited from randomly selected schools in the province of Utrecht and four larger cities in The Netherlands. At the first measurement wave, target adolescents were attending their first year of junior high school. Participants of the current study were four-member families of 497 adolescents (i.e., mother, father, siblings, and the target adolescent, further abbreviated as "M," "F," "S," and "A," respectively) who completed questionnaires during annual home visits. During these visits, target adolescents and their mothers, fathers, and one of their siblings completed a battery of questionnaires, one of which assessed the quality of family relationships with every other participating family member. A trained research assistant provided instructions in addition to written instructions that accompanied the questionnaires. Parents provided written informed consent before their children participated. Families annually received 100 Euros as an incentive to participate.

Data from six measurement waves with a 1-year interval are used hereafter. At the first measurement, adolescents were, on average 13 years old (SD = 0.5), their siblings were, on average, 15 years old (SD = 3.1), their mothers were, on average, 44 years old (SD = 4.5), and their fathers were, on average, 47 years old (SD = 5.1). The majority of the target adolescents were Dutch according to Statistics Netherlands. At the time of the first wave of data collection, most adolescents were living with both parents, and most of their families were classified as having medium to high socioeconomic status. The number of families that could be included in the analyses presented throughout this paper dropped from 496 at wave 1 (one family had no data on support at wave 1) to 435 at wave 6.

The Network of Relationships Inventory

The Network of Relationships Inventory (NRI; Furman & Buhrmester, 1985) support scale was used to measure dyadic support in family relationships. The NRI was applied in a round robin design, meaning that every family member rated the perceived support from every other family member using the same set of questions. Because we included four-person families in the current study, this resulted in 12 dyadic ratings of perceived support per item per family. The NRI support scale consists of eight items (e.g., "How much does your mother/father/sister/brother really care about you?"), with all items answered according to a 5-point scale ranging from 1 (= *hardly at all*) to 5 (= *extremely much*). A higher score on this scale reflects higher levels of perceived relationship support in a specific family relationship. To separate state variability from measurement-error variability later in this paper, we require two measurements at every wave. Therefore, at each wave, we created two parcels of four items: the first four items on support in the questionnaire are referred to as the A-parcel, and the last four are referred to as the B-parcel. Across all family ratings and waves, the reliability of these scales was considered adequate (the mean α was equal to .65 for the A-parcels and .74 for the B-parcels).

SRM Effects of Support

The Family Social Relations Model

The SRM allows us to disentangle dyadic measurements at three different levels: the individual, the dyadic, and the family level. Let X_{ijmt} represent the dyadic measurement of the person with role i (i = mother, father, target, sibling) rating person with role j (j = mother, father, target, sibling) using indicator m (m = A-parcel or B-parcel) at time t (t = 1, . . ., 6). For ease of explanation, we describe below the SRM analysis at each time point t and for each indicator m separately and, therefore, drop the index t and m. The SRM assumes that each dyadic measurement is a function of four latent effects: a family effect *Fam*, a perceiver effect *Per*, a partner effect *Par*, and a relation-specific effect *Rel*. Figure 1 shows the four-member model with these SRM effects specified as latent variables and with arrows pointing from the latent variables toward the dyadic measurement. Note that in Figure 1, with only one indicator per dyadic measurement the relationship effect cannot be disentangled from the measurement error and is absorbed in ϵ_{AM}. In the confirmatory factor analysis that is typically used, all paths from the SRM effects to the observed measurements are fixed to one (for more details, see Kenny, Kashy, & Cook, 2006). When considering the dyadic measurement for the adolescent-mother relation X_{AM}, for example, the measurement is decomposed into the family effect *Fam* (i.e., the overall level of support in the family), the perceiver effect of the adolescent *Per* (i.e., the adolescent's general perception of support from all family members), the partner effect of the mother *Par* (the mother's general tendency to support other family members), and a residual error term ϵ_{AM}:

$$X_{AM} = \mathrm{Fam} + \mathrm{Per}_A + \mathrm{Par}_M + \epsilon_{AM}. \quad (1)$$

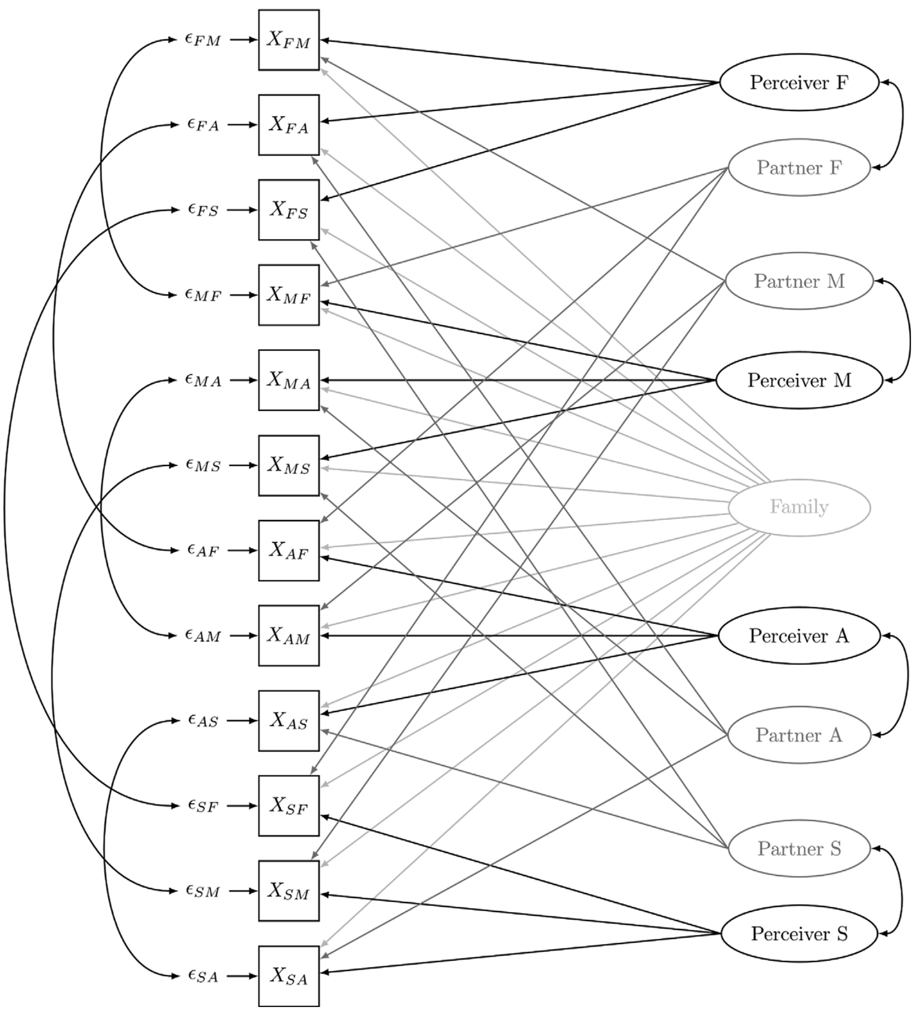

Figure 1. The family social relations model (M = mother; F = father; A = adolescent; S = sibling).

The total variability in X_{AM} can be decomposed into the sum of the variances of each of those components, that is,

$$\mathrm{Var}(X_{\mathrm{AM}}) = \mathrm{Var}(\mathrm{Fam}) + \mathrm{Var}(\mathrm{Per}_{\mathrm{A}}) + \mathrm{Var}(\mathrm{Par}_{\mathrm{M}}) + \mathrm{Var}(\epsilon_{\mathrm{AM}}), \qquad (2)$$

and can identify which level explains most of the variability. While the decomposition is illustrated here for *AM*, a similar decomposition can be done for the other 11 relationships.

In addition to the SRM variances, two types of reciprocities are also typically specified. Generalized reciprocities at the individual level (e.g., capturing whether the amount of perceived support by the adolescent is associated with the amount of support that the other family members experience in relation to the adolescent) are characterized as the correlation between a person's perceiver and partner effect in Figure 1. Reciprocities at the dyadic level (e.g., capturing whether the *A-M* relation-specific perceived support is associated with the *M-A* relation-specific perceived support) are marked as the correlation between the relationship effects (absorbed in the measurement error here) of the two members of the same dyad in Figure 1.

So far, the SRM has been discussed in terms of (co-)variances, but each of these variances measures deviations around a mean effect. In the four-member model with one indicator per relationship, we have a total of 21 SRM means (one family mean, four actor means, four partner means, and 12 relationship means), but only 12 means are observed. The family mean is typically defined as the average over the 12 dyadic measurements. Restrictions are further applied such that the mean actor effects sum to zero, the mean partner effects sum to zero, and the mean SRM relationship effects sum to zero for a given actor or a given partner. Both the actor and partner means then represent deviations from the overall grand mean (i.e., the family mean; Eichelsheim, Dekovic, Buist, & Cook, 2009; Kenny et al., 2006).

SRM Analysis of RADAR-Y Data on Support

For the RADAR-Y data, we fitted an SRM for the A-parcels and B-parcels separately at each of the six waves resulting in 12 SRM models. We considered a separate SRM for every parcel rather than a single SRM with two indicators for every dyadic measurement. Note that two indicators at every wave were necessary to separate state variance from measurement variance in the application of the LST models for the SRM effects that we will introduce in the next section.

As an example, we first discuss the SRM analysis of support for the B-parcels at wave 1 in more detail. To fit the family SRM, we used the R-package *fSRM* that is specifically tailored (Stas, Schönbrodt, & Loeys, 2015). We started from the above-described specifications for the (co-)variances (i.e., 21 variances and 10 reciprocities in Figure 1) and means. After additionally constraining the partner variance of the mother equal to zero, the model yielded a decent fit ($\chi^2(49) = 70.08$, $p = 0.026$, CFI = 0.987, SRMR = 0.050, RMSEA = 0.029).

The family variance, the perceiver variance for all roles, the partner variance of the father, and all relation-specific variances (confounded with the residual error) were all significant. Figure 2A shows the variance decomposition for the dyadic measurement in each relationship using the B-parcels at wave 1. The family effect explained 8 to 20% of the total variance; perceiver variance accounted for 17–53% of the total variance in the dyadic support variances. Partner variance was absent or very small, except for the father where it ranged between 12% and 17%. Approximately, the results are consistent with those of Branje et al. (2002) who also found evidence that perceived support depends considerably on the characteristics of the perceiver.

Similarly, the 11 SRM models for measurements at other waves and/or using the other parcel fitted relatively well. The CFI for those 11 models ranged from .94 to .99 while the SRMR ranged from .047 to .072 and the RMSEA from .033 to .061 (after constraining some of the negative partner variances equal to zero in some of the models). Moreover, the qualitative findings described above for the B-parcel at wave 1 also apply. Figure 2A–2F reveal that the variance decomposition for the B-parcels of the 12 relationship measurements is similar across time. However, this figure does not yet reveal anything about the consistency of each of these SRM effects over time. State-trait models could explore the consistency of the SRM effects. To do so, we need predicted factor scores for the SRM effects that can be used as dependent variables in the LST models.

Multiple methods, such as the regression predictor and the Bartlett predictor (Harman, 1976), exist to predict factor scores. Most software tools for SEM estimate factor scores use the regression predictor. When those factor scores are used for the dependent variable in a subsequent regression (such as in the LST model), the regression parameter will typically be biased because the degree of uncertainty inherent in the factors score is not considered. In contrast, when using the Bartlett predictor for the estimation of the factor scores, there is no longer bias when factor scores are used for the dependent variable (Devlieger, Mayer, & Rosseel, 2016). Hence, we opted for the latter.

Finally, note that we only consider the factor scores for the family effect and the perceiver effect for the father, mother, adolescent, and sibling and the partner effect of the father. The variances of other partner effects were small. We do not consider the relation-specific SRM effects either because they are confounded with measurement error.

Trait-State Models: A General Overview

Suppose we explore the consistency of the adolescent's perceiver effect of support. We have two factor scores (one based on the A-parcels and one based on the B-parcels) at every wave ($t = 1, \ldots, 6$) for this effect. Different state-trait models have been proposed for multiple indicators measured at multiple time points in the literature. This section introduces some of the models without going into details. The models discussed are graphically depicted in Figure 3. For clarity, only three occasions are shown in detail instead of the six that we use later in our example.

We start with the most general model, the multistate model (MS model), which is represented in Figure 3A. The MS model assumes that both indicators per occasion measure the same latent state variable. The different latent state variables are allowed to be correlated, but the covariance can be different for each pair.

It is possible that the latent state variables consist of a stable trait component and occasion-specific residuals. To separate those components, we need to consider a stable trait component over the course of the study. The single-trait-multistate model (STMS model) depicted in Figure 3B is the simplest type of LST model in which this is achieved. Specifically, for every latent state variable, the latent trait component can be separated from the state residual components. The proportion of variance due to the latent trait relative to the total variance of the observed variable is referred to by Steyer and colleagues as the "common consistency (CO) coefficient of the observed variable." Alternatively, the measurement error can be excluded from the calculation, and the proportion of the "state" variance that is explained by the latent trait at a given time point can be used, which is referred to as the "consistency of the latent state." We use the latter consistency coefficient. This coefficient quantifies the degree to which the latent trait determines individual differences in the latent state and is thus useful to distinguish between the stable aspects of a construct and the more temporally changing aspects. The multistate model presented in Figure 3A does not allow such disentanglement.

In STMS models, the only covariances allowed between the latent states are captured by one common trait, which might be unreasonable in some situations. The LST-AR model (Latent State-Trait Autoregressive model; Steyer & Schmitt, 1994) relaxes this assumption by including autoregressive effects between the latent state variables at each time point (Figure 3C). In this model, the covariance over time between states will typically diminish as the lag

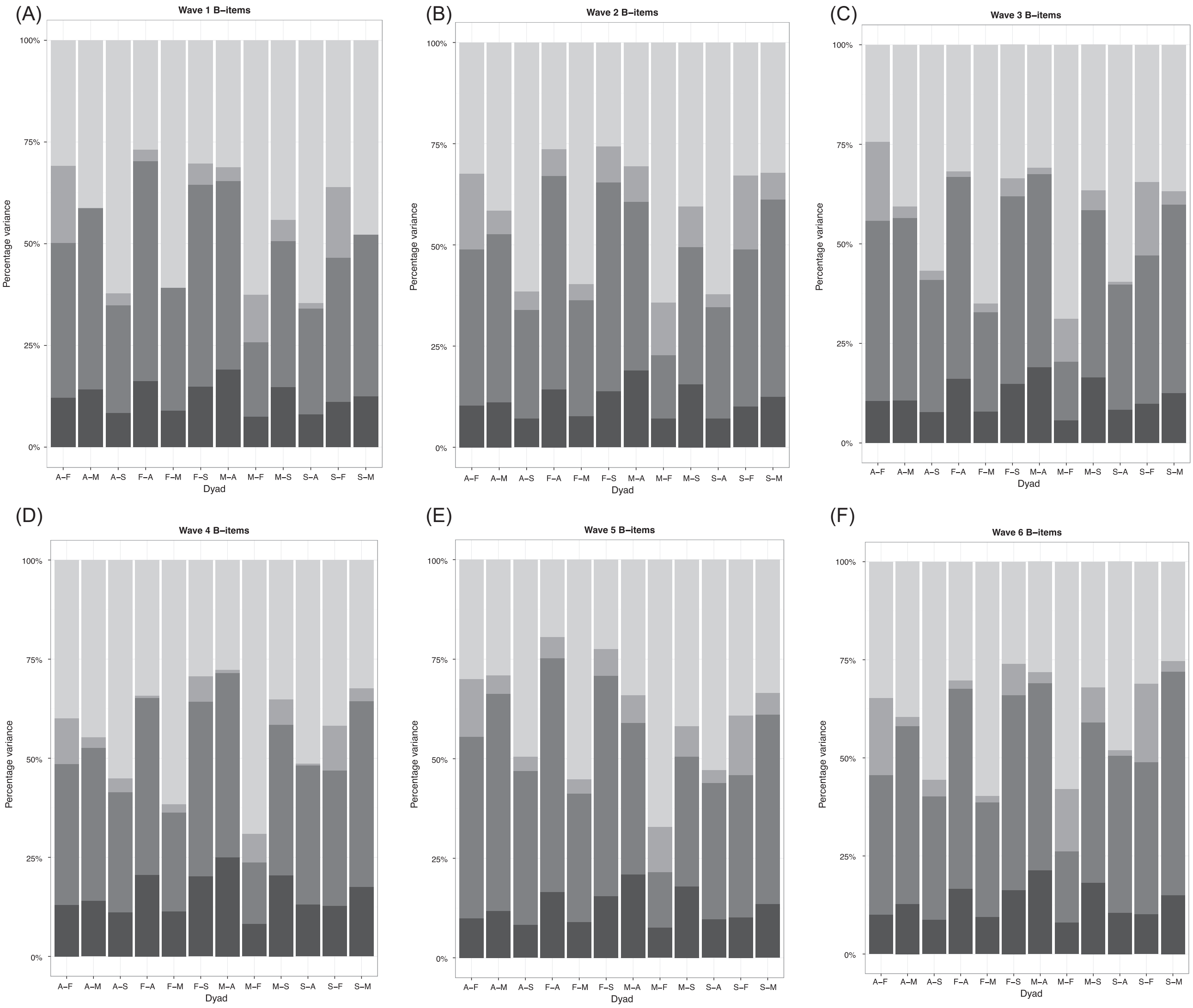

Figure 2. The variance decomposition of each dyadic relationship (Black = Family; dark gray = perceiver; gray = partner; light gray = relationship + error) for the B-parcels at every wave.

between states increases. The trait-state occasion model (TSO model, Figure 3D) was proposed by Cole, Martin, and Steiger (2005) as an alternative for the LST-AR. Both models include a latent trait variable and an autoregressive component but, in the TSO model, the autoregressive effect is added between the state residual variables rather than between the latent state variables. As we show in the next section, if the latent trait loadings are freely estimated, the LST-AR and TSO models imply the same variance covariance.

We also make some assumptions concerning the measurement error. In multiple indicator applications with repeated administration of the same indicators over time, method effects are typically present. Method effects are modeled to account for the covariance between measurements of the same indicator due to indicator-specific properties not captured by the stable component. In our study, the method effect is nothing more than a comparison of the A- and B-parcels. That is, parcels based on the same set of items at different time points may be more similar than parcels based on another set of items. There are different approaches to model the method effect; the main approaches are the CU approach and the $M - 1$ approach. In the CU approach, error variables of the same indicator correlate over time (as shown in Figure 4A). In the $M - 1$ approach, one indicator is selected as a reference for which no method factor is selected, whereas for each of the other $M - 1$ indicators a method factor is assumed (as shown in Figure 4B, with η_B as the method factor for the B-parcels). Geiser and Lockhart (2012) favored the $M - 1$ approach when method effects are not too strong (a strong method may, e.g., occur when different indicators reflect different

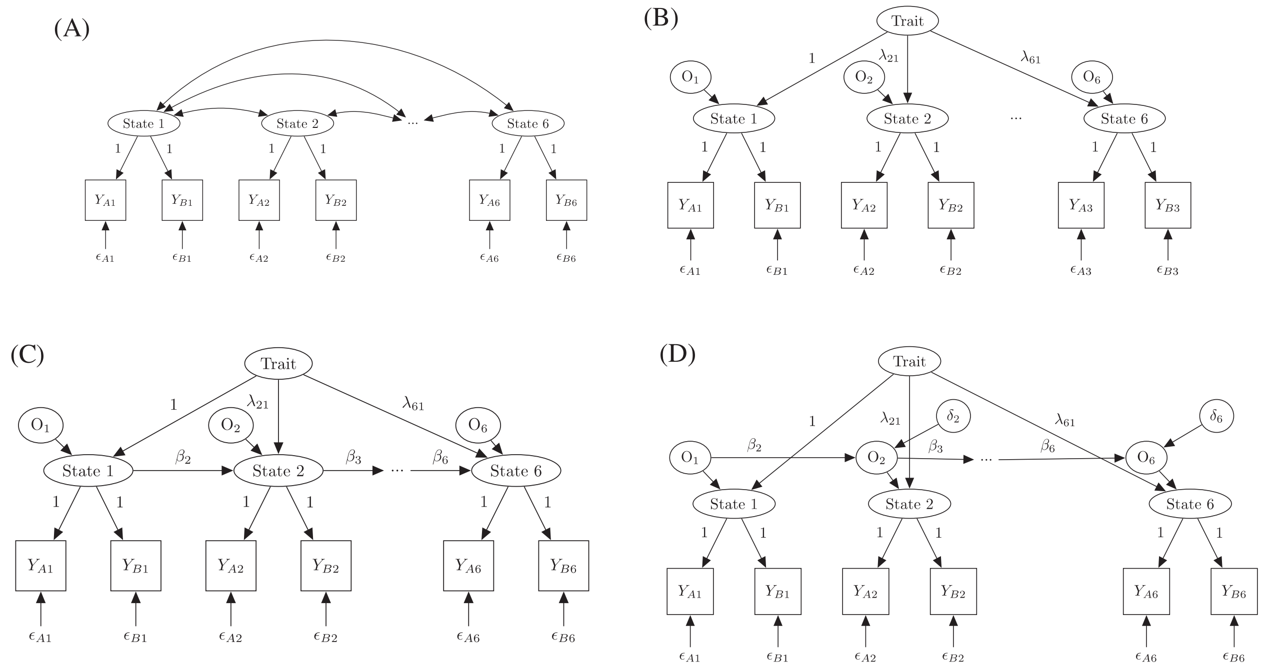

Figure 3. Longitudinal models for trait and states. Correlation between error terms is dropped for clarity. (A) Multistate model (MS). (B) Single trait multi state model (STMS). (C) Latent state-trait autoregressive model (LST-AR). (D) Trait-state occasion model (TSO).

facets of a construct). LaGrange and Cole (2008), on the other hand, concluded that the CU approach was the only model to fit all datasets well in their simulation study. Based on our model building, which is described in detail in the next section, we opted for the CU approach in all models.

In the next section, the identification, similarities, and differences between the above described LST models are discussed in more detail using a tutorial approach. Specifically, we illustrate the model building process and checking of assumptions with the analysis of the adolescent's perceiver effect of perceived support. When exploring the different state-trait models for this SRM effect, the best fitting model was the TSO model (Figure 5). Using the same model building approach for the other SRM effects, we similarly found the TSO model to be the best fitting. All models were fitted using the SEM R-package *lavaan* (Rosseel, 2012). Their fit can easily be replicated using the corresponding R-code shown in ESM 1.

Trait-State Models: A More Detailed Description

Consider a random experiment in which M indicator variables are measured at T occasions. Let Y_{mt} denote the mth indicator at the tth occasion (indicator $m = 1, \ldots, M$, time $t = 1, \ldots, T$).

The Multistate Model

The MS model in Figure 3A assumes that both indicators per occasion measure the same latent state variable, possibly up to a linear transformation. Therefore, we decompose Y_{mt} into a common time-specific latent state variable S_t and a measurement-error variable ϵ_{mt}, that is,

$$Y_{mt} = \lambda_{mt0} + \lambda_{mt1} S_t + \epsilon_{mt} \quad (3)$$

To identify the model, we make some additional constraints on the factor loadings. Specifically, we set the loadings for the A-parcels equal to one at all time points (i.e., $\lambda_{At1} = 1$) and the loadings for the B-parcels all equal to some common value λ_{B1} at all time points (i.e., $\lambda_{Bt1} = \lambda_{B1}$ for all t). Most SEM software programs (including the R-package *lavaan*) further freely estimate by default the intercepts λ_{mt0}, leading to a saturated mean structure (note that, for clarity, the intercepts are not shown in Figure 3). Alternatively, we freely estimate the mean of S_t by assuming all intercepts λ_{At} are equal to zero, and further assess, for example, whether there is a (zero) time-constant shift in the mean of the B-parcels versus the A-parcels (i.e., $\lambda_{Bt0} = \lambda_{B0}$). By constraining the loadings and the intercepts, measurement invariance can be tested (Byrne, Shavelson, & Muthén, 1989). If the invariance assumption is not met, the relation between the latent state and the indicator has the potential to change over time (Prenoveau, 2016).

Given the few assumptions that are made in the MS model, it is not surprising that the MS model for the

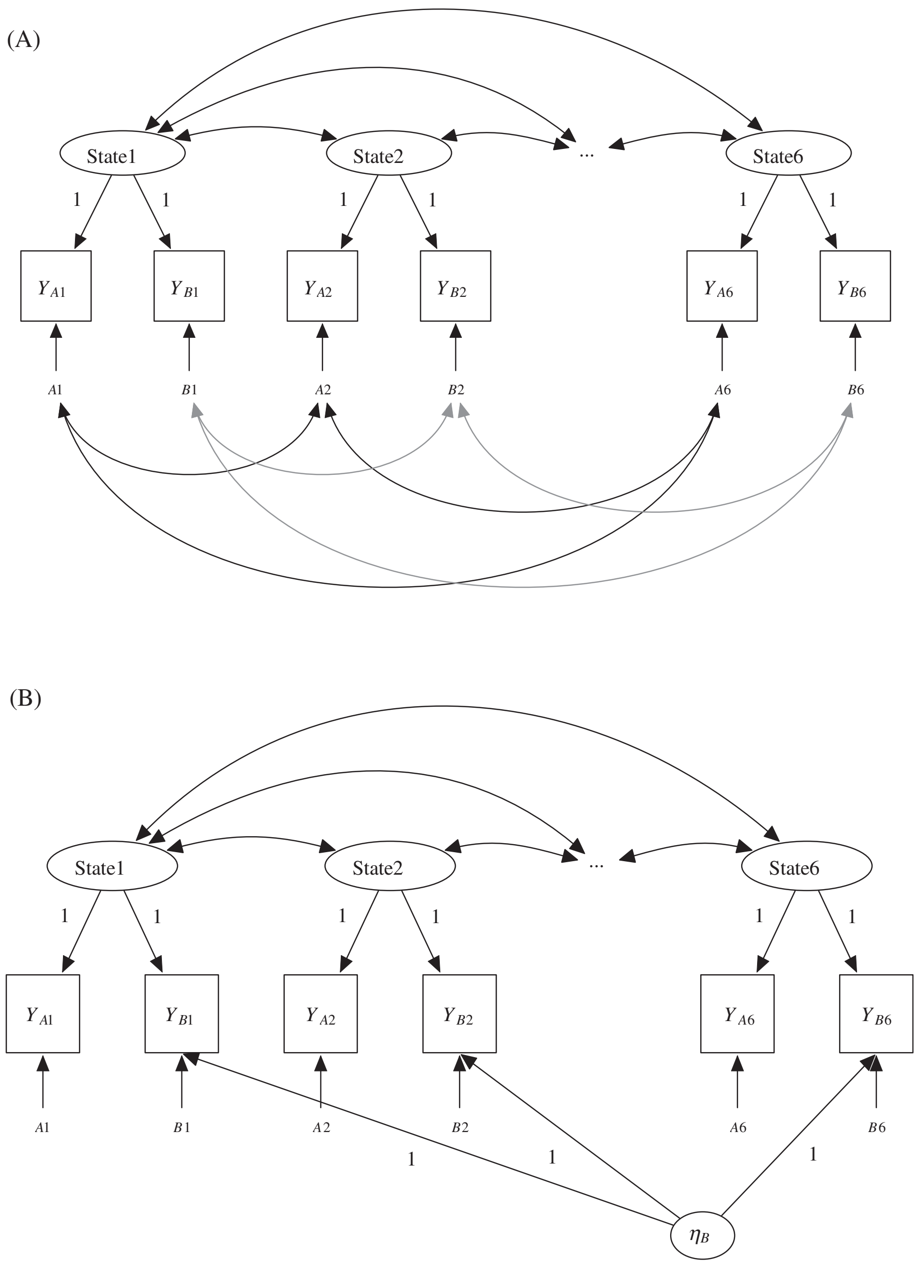

Figure 4. Modeling method effects in the multistate mode. (A) Correlated uniqueness approach (CU). (B) $M - 1$ approach ($M - 1$).

adolescent's perceiver effect of support with a saturated mean structure, a common factor loading λ_{B1} for the B-parcels and using the CU approach (see ESM 1 for the corresponding *lavaan* syntax), fits well ($\chi^2(14) = 30.94$, $p = 0.006$, CFI = .995, SRMR = .021, RMSEA = .055). From a conceptual perspective, there are no objective reasons the adolescent's perceiver effect based on the A-parcel and B-parcel at a specific time point would be expected to differ. Any difference in loadings or intercepts could be attributed to chance by randomly selecting four out of eight items to create both parcels. The model assuming $\lambda_{B1} = 1$ fits equally well (χ^2-difference test: $\chi^2(1) < .001$, $p = 1.00$). We, therefore, assume throughout the paper that the A- and B-parcels measure the latent states on the same scale. Finally, we fitted a model assuming a time-constant shift in the mean of the B-parcels versus the A-parcels. The MS model with such restricted mean structure fitted well ($\chi^2(20) = 51.85$, $p < .001$, CFI = .991, SRMR = .024, RMSEA = .063), with a shift in the mean of the B-parcels versus the A-parcels that was significant ($\hat{\lambda}_{B0} = -.040$, $SE = .011$, $p < .001$).

Next, we compare the approaches to account for method effects. When the covariances between the A indicators are set to zero over time and the covariances between the B indicators are assumed to be equal over time in the CU approach, the model-implied variance covariance of that constrained CU approach and the $M - 1$ approach with a latent method effect for the B indicators coincide.

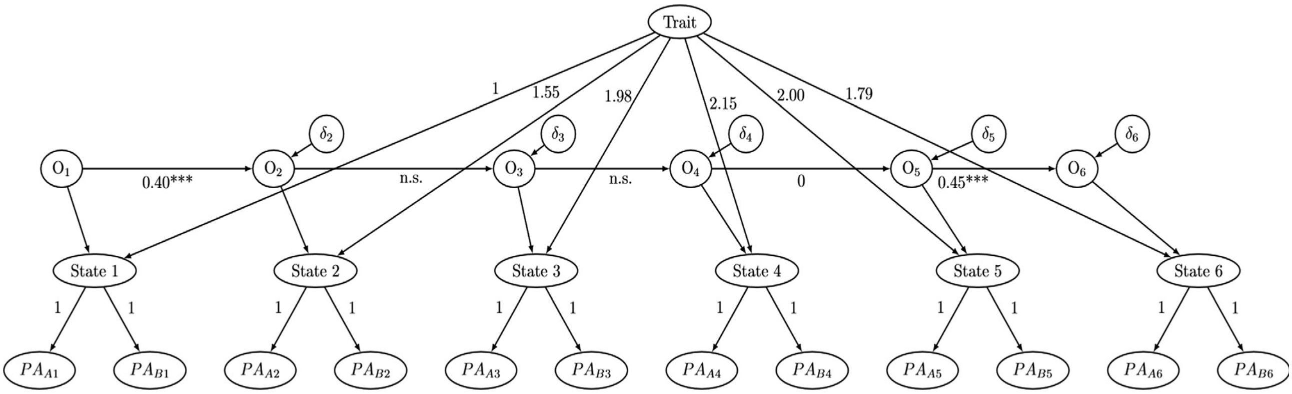

Figure 5. A latent state-trait occasion model for the perceiver effect of the adolescent (PA), where the autoregressive coefficient $\hat{\beta}_4$ is fixed to zero. The correlated errors are omitted for clarity (***p < .001; **p < .01; *p < .05; *ns* = not significant).

Table 1. The estimated covariance matrix of the latent states for the MS model of the adolescent's perceiver effect (variances are on the diagonal, correlations above the diagonal, and covariances below the diagonal)

	State 1	State 2	State 3	State 4	State 5	State 6
State 1	.118	.643	.464	.444	.449	.412
State 2	.080	.132	.661	.690	.614	.558
State 3	.064	.096	.161	.750	.730	.621
State 4	.059	.097	.116	.149	.814	.730
State 5	.062	.090	.118	.126	.161	.770
State 6	.057	.082	.101	.114	.125	.163

A χ^2-difference test can be used to test the appropriateness of the $M - 1$ method. Using the $M - 1$ method for method variance rather than CU fits significantly worse (χ^2-difference test: $\chi^2(29) = 77.30$, $p < .001$) in our example. In all subsequent models, we, therefore, always rely on the CU approach.

In the remainder of this paper, we use the MS model assuming fixed state loadings, a time-constant shift in the mean of the B-parcels versus A-parcels, and CU as the reference model.

Table 1 shows the estimated covariance matrix for the six latent state variables S_t from the reference model. While the variance of the states tends to increase over time, the correlation between states decreases as the lag increases.

As mentioned, it is possible that the latent state variables S_t are composed of latent trait components and situation-specific residuals.

The Singletrait-Multistate Model

In the STMS model in Figure 3B, the latent state variable is allowed to be composed of the latent trait component "Tr" and situation state residual components "O_t",

$$S_t = \lambda_{t0} + \lambda_{t1}\mathrm{Tr} + \mathrm{O}_t \qquad (4)$$

with λ_{t0} and λ_{t1} representing a time-specific intercept and a latent trait loading, respectively. The metric of the latent trait factor is uniquely determined by setting $\lambda_{10} = 0$ and $\lambda_{11} = 1$. Steyer, Mayer, Geiser, and Cole (2015) distinguish between three different scenarios for the values of λ_{t0} and λ_{t1}: (1) θ-equivalence assumes that $\lambda_{t0} = 0$ and $\lambda_{t1} = 1$ for all t, (2) essential θ-equivalence assumes that $\lambda_{t1} = 1$ for all t, but λ_{t0} can be freely estimated (except for $\lambda_{10} = 0$), and (3) θ-congenericity assumes no restrictions (except $\lambda_{10} = 0$ and $\lambda_{11} = 1$). As noted by Geiser et al. (2015) θ-equivalence is required in the STMS model if the goal is to establish a strict state variability model in which only systematic time-specific fluctuations around a trait are allowed but no trait changes. These authors argued, therefore, that to disentangle pure variability models from trait change processes, it is important to also consider the mean.

Combining Equation 3 with all λ_{mt1} equal to one (as we have seen that equal latent state loadings could be assigned here) and Equation 4, it follows that each observed variable Y_{mt} can be decomposed into a latent trait "Tr", a latent state residual "O_t," and a measurement-error variable ϵ_{mt}, that is,

$$Y_{mt} = \lambda_{mt0} + \lambda_{t0} + \lambda_{t1}\mathrm{Tr} + \mathrm{O}_t + \epsilon_{mt} \qquad (5)$$

with $\lambda_{At0} = 0$ for all t when freely estimating the means of the states. As mentioned above, θ-equivalence implies that the means of the states are constant over time, and the longitudinal process under consideration can be viewed as situation-specific deviations of the latent scores from the trait score.

Under model (5), it follows that the observed variance of Y_{mt} is the sum of the variance of the latent trait, occasion-specific residual variance, and measurement-error variance:

$$\mathrm{Var}(Y_{mt}) = \lambda_{t1}^2 \mathrm{Var}(\mathrm{Tr}) + \mathrm{Var}(\mathrm{O}_t) + \mathrm{Var}(\epsilon_{mt}) \quad (6)$$

Steyer and colleagues refer to the proportion of variance due to the latent trait relative to the total variance of the observed variable as the common consistency (CO) coefficient of the observed variable:

$$\mathrm{CO}(Y_{mt}) = \frac{\lambda_{t1}^2 \mathrm{Var}(\mathrm{Tr})}{\mathrm{Var}(Y_{mt})} \quad (7)$$

Sometimes, the measurement-error variance is excluded from the denominator, and the corresponding proportion is referred to as the consistency of the latent state:

$$\mathrm{CO}(S_{mt}) = \frac{\lambda_{t1}^2 \mathrm{Var}(\mathrm{Tr})}{\lambda_{t1}^2 \mathrm{Var}(\mathrm{Tr}) + \mathrm{Var}(\mathrm{O}_t)} \quad (8)$$

When fitting the STMS model assuming θ-equivalence for the adolescent's perceiver effects of support, the fit indices provide strong evidence against this model ($\chi^2(39) = 196.89$, $p < .001$, CFI = .955, SRMR = .127, RMSEA = .100). Assuming essential θ-equivalence improves the fit significantly (χ^2-difference test: $\chi^2(5) = 31.63$, $p < .001$), most fit indices still point toward a bad fit ($\chi^2(34) = 165.25$, $p < .001$, CFI = .963, SRMR = .121, RMSEA = .098). The STMS model making the least assumptions (i.e., assuming θ-congenericity) is the best fitting STMS model, but the fit indices are not yet satisfactory ($\chi^2(29)=109.09$, $p < .001$, CFI = .977, SRMR = .046, RMSEA = .083), and contrasting this model with our reference MS model yields evidence for a relatively poor fit also (χ^2-difference test: $\chi^2(9)=57.25$, $p < .001$). Substantively, these results already suggest that the adolescent's perceiver effect over time is not a pure state variability process but might be a combination of state variability and trait change.

State-Trait Models with Autoregressive Effects

The LST-AR model in Figure 3C includes autoregressive effects β between the latent state variables at each time point, that is,

$$S_t = \beta_t S_{t-1} + \lambda_{t1} \mathrm{Tr} + \mathrm{O}_t \quad (9)$$

Cole et al. (2005) argued, however, that the LST-AR model may be of limited usefulness because the correlation between adjacent state variables increases over time, and the authors alternatively proposed the TSO model in Figure 3D. In the TSO model, the autoregressive effect is added between the state residual variables O_t rather than between the latent state variable S_t, that is,

$$\mathrm{O}_t = \beta_t \mathrm{O}_{t-1} + \delta_t \quad (10)$$

By doing so, Cole et al. (2005) avoided the apparent limitation inherent in the LST-AR model.

When we allow unequal latent trait loadings, as in Figure 3, some caution with the identification of the model is required. Focusing on the higher order part in the TSO model in Figure 3D, for example, but assuming three occasions, the maximum number of parameters (ignoring the mean for now) that can be freely estimated is six (three state variances and three covariances). However, without applying any additional constraints eight parameters need to be estimated, making the model under-identified. It is easy to see that statistical identification is achieved as soon as the number of occasions is at least five.

Note that Cole et al. (2005) assumed that the latent trait loadings in the LST-AR and TSO models were all equal to one (i.e., $\lambda_{t1} = 1$ for all t). When that assumption is relaxed, the LST-AR model and TSO model have the same model-implied variance covariance and yield exactly the same autoregressive coefficients. The TSO model proposed by Cole et al. (2005) builds on the trait-state-error (TSE) model originally proposed by Kenny and Zautra (1995) and later referred to as the state-autoregressive-trait (START) model (Kenny & Zautra, 2001). The TSO extends the TSE in two ways: (1) it considers multiple indicators of the targeted construct at each time point, and (2) it relaxes the stationarity assumption by allowing for different autoregressive coefficients at each time point; otherwise, the TSO, LST-AR, and TSE are actually equivalent.

Finally, note that Steyer and colleagues in the revised LST theory (Steyer et al., 2015) no longer consider the LST-AR model because the notion of "state" in the LST-AR model and the TSO model is inconsistent with its definition in the revised LST framework. In the revised LST framework, the latent state variables S_t are defined as the conditional expectation of Y_{mt} given the person and situation variables at time t, which implies that no autoregressive dependencies between state residuals may exist.

Ignoring the strict LST framework, the TSO model specification makes determining the percentage of the purported 'state' variance that is explained by the latent trait at a given time point straightforward:

$$\mathrm{CO}(S_t) = \frac{\lambda_{t1}^2 \mathrm{Var}(\mathrm{Tr})}{\lambda_{t1}^2 \mathrm{Var}(\mathrm{Tr}) + \mathrm{Var}(\mathrm{O}_t)} \quad (11)$$

which we will refer to as the consistency of the latent state, as in the LST framework. In fact, 100% of the purported state variance at a given time point is partitioned into latent trait variance and state residual variance. The completely standardized regression pathway between the latent trait and the latent state equals their correlation, and these squared correlations provide the proportion of "state" variance explained by "trait."

Table 2. Fit indices for the MS model and the TSO model for all SRM effects (M = mother; F = father; A = adolescent; S = sibling)

	MS				TSO			
Component	χ^2-statistic, p-value	CFI	SRMR	RMSEA	χ^2-statistic, p-value	CFI	SRMR	RMSEA
Family	$\chi^2(20) = 43.85$, $p = .002$	0.995	.019	.054	$\chi^2(25) = 47.80$, $p = .004$	0.996	.019	.048
Perceiver M	$\chi^2(20) = 25.74$, $p = .18$	0.998	.017	.027	$\chi^2(24) = 30.13$, $p = .18$	0.998	.018	.025
Perceiver F	$\chi^2(20) = 26.31$, $p = .16$	0.998	.019	.028	$\chi^2(24) = 28.17$, $p = .25$	0.999	.019	.021
Perceiver A	$\chi^2(20) = 51.85$, $p < .001$	0.991	.024	.063	$\chi^2(25) = 55.84$, $p < .001$	0.991	.026	.055
Perceiver S	$\chi^2(20) = 21.55$, $p = .37$	1.000	.013	.014	$\chi^2(24) = 22.92$, $p = .53$	1.000	.014	.000
Partner F	$\chi^2(20) = 29.43$, $p = .08$	0.997	.018	.034	$\chi^2(24) = 48.07$, $p = .002$	0.994	.023	.055

Notes. CFI = comparative fit index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation.

Although the TSO model assuming θ-congenericity converged and fitted the adolescent's perceiver effects well ($\chi^2(24) = 55.33$, $p < .001$, CFI = .991, SRMR = .026, RMSEA = .057), we observed that the estimated autoregressive coefficient at the fourth time alpha was out of range and imprecise ($\hat{\beta}_4 = -0.765$, $SE = 1.92$). Cole et al. (2005) and Kenny and Zautra (2001) made similar observations for the TSE model. A smallscale simulation study (results not shown) mimicking the setting of our data revealed that out-of-range values for the autoregressive coefficients with imprecise standard error were frequently encountered. This was despite the fact that the model fitted was used to actually simulate the data and was expected to fit well. The TSO model fixing this out-of-range autoregressive coefficient with imprecise standard error to zero fitted well ($\chi^2(25)=55.84$, $p < .001$, CFI = .991, SRMR = .026, RMSEA = .055). Comparing this TSO model with our reference MS model, the model fits well (χ^2-difference test: $\chi^2(5)=3.99$, $p = .55$). Figure 5 shows the estimated factor loadings and autoregressive coefficients from our final TSO model for the adolescent's perceiver effect.

We explored the same set of state-trait models for the other SRM effects. Using the same model building approach described for the adolescent's perceiver effect, we similarly find the TSO model assuming θ-congenericity as the best fitting model. Note that for the TSO model for the family effect, an out-of-range value with an imprecise standard error was observed at the fifth wave, which was fixed to zero ($\hat{\beta}_5 = -2.45$, $SE = 15.97$). Table 2 shows the fit indices of the MS model and TSO model for all SRM effects.

Results: Consistency in SRM Effects

Relying on TSO models such as the one shown in Figure 5, Table 3 presents the estimated consistency of the SRM effects expressed as the proportion of state variance explained by the latent trait at each wave. To test the hypothesis that the consistency is constant over time, we compare the fitted TSO model shown in Table 2 with a TSO model where the consistencies are constrained to be equal across waves. The constant consistency and the χ^2-difference value comparing the constrained and unconstrained models are presented in the last two columns of Table 3.

At wave 1, the variations in the state family effect for support are due to nearly equal amounts of trait and occasion influences. Thereafter, the proportion of variance in the state family effect accounted for by the trait gradually increases up to wave 5 and slightly drops at wave 6. Although, at the 5% significance level no constant consistency over time (68%) can be assumed ($p = .046$), overall perceived family support shows no extreme variation over time.

For the perceiver effects, an interesting difference is observed between the parents and the adolescents. At wave 1, the consistency is much smaller in the adolescents than in the parents. To see how consistency in support develops in the transitional years of adolescence, it is most relevant to focus on the target adolescents because they represent a more homogeneous group of 13-year-old boys and girls while the siblings are a much more heterogeneous group with respect to age (mean age of approximately 15 years). The peak of consistency in the target adolescents is reached at the age of 16 (wave 4). In the siblings, who are older on average, this peak is reached a year earlier (at wave 3), but note the large imprecision of that estimator that might be a reflection of the more heterogeneous characteristics of the siblings. After the peak at wave 4 in the target adolescents, the consistency again drops, and the variations in support perceived by the target adolescents are due to nearly equal amounts of trait and state. Although there is some tendency in the parents of an increase in the consistency followed by some decrease, this trend is much less pronounced, particularly in the fathers.

For the partner effect of the father, we observe relatively small variation in consistency over time (despite statistical evidence against a constant consistency).

Discussion

Supportive family relationships are of key importance in the life of an individual. Perceived familial support during

Table 3. Consistency for SRM effects, expressed as the proportion of state variance explained by trait variance according to the TSO model (with 95% confidence intervals), at every wave. The last two columns present a constant consistency coefficient across waves and a χ^2-test for such constant coefficient

	Wave-specific						Constant	
SRM effect	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Overall	χ^2-diff
Family	.54 (.46, .63)	.61 (.53, .70)	.76 (.69, .83)	.86 (.78, .94)	.93 (.86, .99)	.84 (.78, .91)	.68 (.61, .75)	$\chi^2(5) = 10.93, p = .046$
Perceiver M	.50 (.40, .61)	.58 (.47, .70)	.71 (.59, .84)	.85 (.72, .99)	.83 (.63, 1.03)	.81 (.71, .92)	.67 (.61, .74)	$\chi^2(5) = 17.67, p = .003$
Perceiver F	.54 (.44, .66)	.63 (.51, .77)	.79 (.67, .91)	.72 (.61, .84)	.76 (.65, .89)	.75 (.63, .88)	.67 (.62, .73)	$\chi^2(5) = 10.44, p = .064$
Perceiver A	.25 (.16, .36)	.53 (.44, .63)	.71 (.59, .84)	.91 (.81, 1.02)	.73 (.64, .84)	.59 (.47, .69)	.49 (.40, .59)	$\chi^2(5) = 32.49, p < .001$
Perceiver S	.35 (.24, .47)	.46 (.28, .68)	.92 (.47, 1.51)	.65 (.36, 1.02)	.53 (.39, 70)	.49 (.33, .68)	.45 (.35, .55)	$\chi^2(5) = 19.40, p = .002$
Partner F	.67 (.58, .77)	.72 (.63, .82)	.89 (.77, 1.01)	.87 (.80, .94)	.78 (.67, .90)	.85 (.77, .94)	.79 (.75, .83)	$\chi^2(5) = 14.53, p = .013$

childhood and adolescence has been related to various outcomes such as well-being (Chu, Saucier, & Hafner, 2010), overall life satisfaction, mental health and stress levels (Lakey & Orehek, 2011), and the ability to engage in healthy relationships with friends and romantic partners during (emerging) adulthood (Ackerman et al., 2013). The family environment is, therefore, one of the most important environments for early socialization experiences.

Given that the family environment consists of interpersonal dynamics at different levels, we argued that it is important to first disentangle the raw observed dyadic measurements into meaningful effects on different levels rather than directly applying LST models to the raw scores. If the raw scores are used, changes in consistency are harder to interpret. In that case, we cannot conclude whether these changes in consistency are due to individual, relation-specific, or family-level changes. It is, therefore, crucial to have round robin data rather than data that are limited to the family as a whole or some specific dyad.

Based on state-trait models for SRM effects, we found in the RADAR-Y data that – particularly in the first wave – the degree to which perceiver effects of support can be attributed to stable traits rather than fluctuations over time was less for adolescents and siblings compared to parents. Moreover, consistency in the adolescent's perceptions of support was found to gradually increase until adolescents were approximately 16 years old but then dropped again. The consistency in the family effect, however, remained relatively constant over time. Based on available literature in developmental and family psychology, we discuss these findings below.

Considering adolescent normative development, it is well known that adolescent status may affect the perception of their relationship with parents (De Goede, Branje, Delsing, & Meeus, 2009). This process is also known as the separation-individuation process, which is considered extremely important for healthy identity development (Youniss & Smollar, 1990). One of the objectives of adolescence is that family relationships shift from being relatively unilateral relationships toward relationships that are characterized by mutuality (Grotevant & Cooper, 1986). Based on previous findings, we know that substantive equality in parent-adolescent relationships is generally achieved in mid- to late adolescence (De Goede et al., 2009; Steinberg & Silk, 2002; Youniss & Smollar, 1990). The studies find less occasion-specific variability in adolescents' perception of support from their family members as they grow up and, hence, increasing consistency in the adolescent's perceiver's effect until the age of 16.

However, these ideas provide no explanation yet for the drop in consistency observed around ages 17 and 18. Possible explanations may be found in the changing circumstances that naturally occur in family systems when adolescents enter emerging adulthood. The fact that adolescents (as well as siblings) spend increasing amounts of time outside the home as they mature (attending college/university, some adolescents may obtain jobs) may affect consistency in family relationships (Tsai, Telzer, & Fuligni, 2013). Moreover, adolescents and siblings may find additional support resources outside the family, for

Table 4. Consistency for SRM effects, expressed as the proportion of state variance explained by trait variance according to the STMS model (with 95% confidence intervals), at every wave

	Wave-specific					
SRM effect	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Family effect	.65 (.58, .73)	.74 (.68, .80)	.85 (.81, .90)	.88 (.85, .92)	.90 (.87, .94)	.82 (.77, .87)
Perceiver M	.60 (.51, .70)	.72 (.63, .80)	.79 (.72, .86)	.84 (.78, .91)	.78 (.71, .85)	.80 (.72, .87)
Perceiver F	.57 (.48, .67)	.65 (.57, .74)	.77 (.71, .84)	.78 (.71, .85)	.78 (.71, .85)	.78 (.71, .85)
Perceiver A	.33 (.23, .45)	.61 (.52, .70)	.68 (.60, .76)	.82 (.76, .88)	.81 (.75, .87)	.66 (.58, .75)
Perceiver S	.39 (.29, .50)	.50 (.41, .61)	.78 (.70, .86)	.70 (.62, .78)	.72 (.64, .82)	.65 (.56, .75)
Partner F	.72 (.64, .81)	.77 (.70, .84)	.86 (.81, .91)	.89 (.84, .94)	.84 (.78, .89)	.87 (.82, .93)

example, through engagement in romantic relationships. Close relationships with peers and colleagues may become visible in more occasion-specific variability in the adolescent's perceived support from their family members and, hence, cause a decrease in consistency (Collins, 2003). We explored some of these possible explanations with the RADAR-Y data. At every wave, data were available on whether adolescents or siblings were still living at home. Information on whether individuals were engaged in romantic relationships was only available for the target adolescent. Restricting the analyses to families where the adolescents and siblings lived at home during the entire study period and/or where the adolescents did not engage in a romantic relationship during the study did, however, reveal a similar pattern with a drop in consistency at wave 6. There may be many other possible occasion-specific circumstances that could have occurred around late adolescence that we could not account for.

Focusing next on the overall family effect of perceived support, we found that the consistency gradually increased up to wave 5 and then dropped slightly at wave 6, but the changes in consistency are less pronounced than in the adolescent's perceiver effect. Our results imply a stable supportive family climate across waves that is minimally affected by the developmental changes that occur during adolescence. This observation is consistent with the earlier findings of Ackerman et al. (2011) who examined the stability of SRM effects in positive engagement behavior across three waves and also found stable family effects. Godley, Kahn, Dennis, Godley, and Funk (2005) reported patterns of family cohesion that were largely stable across the period of adolescence. Note that the sample of families used in the current study consisted of well-functioning families, which may also explain why the family climate is characterized by stable support patterns. The circumplex model of marital and family systems (Olson & Gorall, 2003) assumes that healthy family systems are characterized by stability and by some flexibility in relationship patterns. Unhealthy families, on the other hand, are characterized either by too much stability (i.e., rigidity) or by too much fluctuation in family relationship patterns (i.e., chaos).

While the current article illustrates the combination of SRM and LST models using family data, the proposed approach is more broadly applicable and could also be applied in contexts were there are no family roles present. The SRM with indistinguishable members (Kenny et al., 2006) has often been applied in the analyses of interpersonal perceptions, for example in classroom settings or other social networks. Card and Hodges (2010) examined aggression and victimization using the SRM; Grafeman, Barry, Marcus, and Leachman (2015) explored perceptions of narcism and van den Berg and Cillessen (2015) explored popularity ratings. Some of these authors emphasized that future research examining the stability of these perceptions over time is required. The framework presented here allows us to do so and extends the ad hoc approaches (e.g., van den Berg & Cillessen (2015) used correlations between time point 1 and 2 to explore the stability of the SRM effects).

From a modeling perspective, several remarks deserve attention. First, we observed out-of-range autoregressive coefficients with imprecise standard error for some of the TSO models that we fitted, and in two models we fixed one of those autoregressive coefficients to zero. Importantly, we are comfortable with the consistencies derived from the models because they are consistent with those that would have been obtained from the simpler but worse fitting STMS models (see Table 4). Second, the reader may question why we have chosen to take a stepwise approach. That is, for the first step an SRM was fitted for each wave and parcel separately, and factor scores for all SRM effects were obtained. In the second step, we fitted trait-state models to those factor scores. Ideally, the 12 SRM models would be considered simultaneously adding trait-state models for every SRM effect on top. For example, for the family effect of support, a stable trait effect could be assumed that is common to the state family effects, which are themselves manifested by the A- and B-parcel specific family effects at each wave. However, a model simultaneously integrating both the SRM at every wave for every parcel and the TSO model for every SRM effect quickly becomes computationally prohibitive as the number of waves increases. We could not go beyond three waves (using a constrained TSO equivalent to an STMS for the model to be identified).

Although it was computationally prohibitive to simultaneously fit an SRM and LST model with more than three waves, the proposed sequential approach offered a valuable alternative. Moreover, simulation studies (in samples of 500 families) in settings with three waves revealed no bias for the estimator of consistency and appropriate coverage for its associated 95% confidence interval in both approaches, but the estimator in the sequential approach was more efficient. Although promising, this finding requires more formal justification.

Despite these methodological limitations, the substantive results presented in this paper indicate that state-trait models are helpful for understanding developmental aspects in relational processes within families.

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Electronic Supplementary Material

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