No adolescent is an island: conceptualizing the family system in adolescent depression with the network approach

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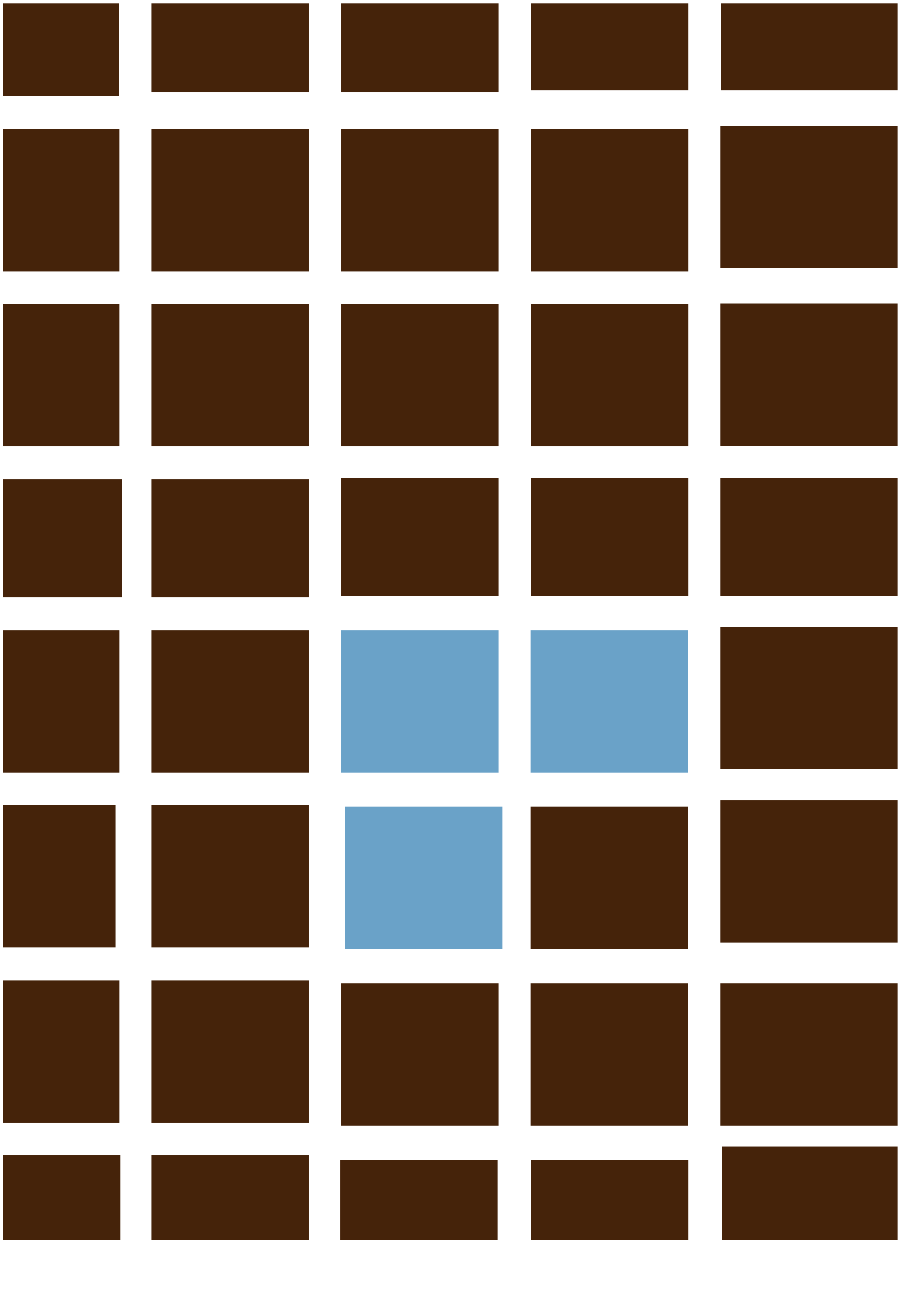

Chapter 3

A Network Study of Family Affect Systems in Daily Life

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Abstract

Adolescence is a time period characterized by extremes in affect and an increasing prevalence of mental health problems. Prior studies have illustrated how affect states of adolescents are related to interactions with parents. However, it remains unclear how affect states among family triads, that is, adolescents and their parents, are related in daily life. This chapter investigated affect state dynamics (happy, sad, relaxed, and irritated) of 60 family triads, including 60 adolescents ($M_{age} = 15.92$, 63.3% females), fathers and mothers ($M_{age} = 49.16$). The families participated in the RE-PAIR study, where they reported their affect states in four ecological momentary assessments per day for 14 days. First, we used multilevel vector-autoregressive network models to estimate affect dynamics across all families, and for each family individually. Resulting models elucidated how family affect states were related at the same moment, and over time. We identified relations from parents to adolescents and vice versa, while considering family variation in these relations. Second, we evaluated the statistical performance of the network model via a simulation study, varying the percentage of missing data, the number of families, and the number of time points. We conclude with substantive and statistical recommendations for future research on family affect dynamics.

Keywords: Network, Multilevel, Ecological Momentary Assessment, Adolescence, Family, Affect

Introduction

Adolescence is a critical developmental period characterized by physical (e.g., growth spurt), biological (e.g., hormone activity; Buchanan et al., 1992), cognitive (e.g., abstract thinking; Keating, 2004) and social changes (e.g., risk behaviour; Van Nieuwenhuijzen et al., 2009). These changes may influence daily affect states of adolescents and are potential risk factors for the onset of mental disorders (Kessler et al., 2001; Rapee et al., 2019; Ullsperger & Nikolas, 2017), including emotional disorders such as depression (Costello et al., 2003) that show increased prevalence during adolescence and continue to have problematic consequences throughout adulthood (Pine et al., 1998; Hofstra et al., 2001).

The family environment and parents in particular play an important role during adolescence (Sheeber et al., 1997; Yap & Jorm, 2015). While adolescents strive towards greater autonomy and peer contact, parents remain support providers (Furman & Buhrmester, 1992). Much attention has been paid to the influence of parenting behavior and styles, such as parental control (Janssens et al., 2015; Van Heel et al., 2019; Yap & Jorm, 2015) and criticism (Berla et al., 2022; Harris & Howard, 1984; Nelemans et al., 2014). A meta-analysis by Laursen and colleagues (2017) indicated a moderate decrease in parent-adolescent conflict during adolescence, but an increase in intensity of conflict-related negative affect from early-adolescence (10-12 years old) to mid-adolescence (13-16 years old). In addition, Van der Cruijsen and colleagues (2019) found a temporary increase in parental negativity, such as disagreement, during mid-adolescence (15-17 years old). Parental warmth (i.e., positive, accepting and supportive behavior) has been highlighted as a potential protective factor during adolescence (Lippold et al., 2016; Viner et al., 2012), in part due to the positive relation between parental support and adolescents' effective emotion regulation (Morris et al., 2017).

Extant literature has focused on adolescent affect states and their relation with adolescent mental health (Kuppens et al., 2012; Maciejewski et al., 2014). Affect states are momentary feelings, such as happiness or sadness, that are responsive to events or interactions (Kuppens et al., 2010). Positive affect states (e.g., being happy and relaxed) can be distinguished from negative affect states (e.g., being sad and irritated). Reitsema and colleagues (2021) indicated that, compared to children, adolescents show more variability in positive affect and a higher intensity of negative affect, both of which decreased in late adolescence.

Not only parental behavior, such as perceived parental warmth and criticism

(Janssen et al., 2020[1], 2021a), but also the affect states of parents themselves have been linked to affect states of adolescents (Larson & Almeida, 1999). For example, associations were found between the reported affect states of adolescents and their parents (Larson & Richards, 1994), and during interactions, parents and adolescents showed a co-occurrence of affect states (Bodner et al., 2018). In this chapter, we focus on the interrelatedness of the affect states of adolescents and their parents.

Family as dynamic system

Affect states may be the drivers of family dynamics, referring to the influence that family members, such as adolescents and their parents, have on each other. This is in line with the family system theory (or ecological system theory; Bronfenbrenner, 1977) stating that child development is affected by interactions with the environment. Parents are one of the more proximal factors in this environment (Bronfenbrenner, 1986). So far, most studies have focused on mother-adolescent relations, while other studies highlighted the role of fathers for adolescent mental health (e.g., Sheeber et al., 2007). This aligns with family system theory, stressing the importance of both parents (e.g., Bodner et al., 2018). For instance, if only looking at mother-adolescent relations, we might find that the mother's irritation results in a decrease in the adolescent's relaxation. However, the decrease in relaxation might be dependent on irritation of the other parent. Learning more about the family dynamics during adolescence, therefore, requires looking at the family, instead of focusing only on specific parent-adolescent dyads.

The family system theory not only highlights the interrelatedness of family members, but also the direction of influence, which may often be reciprocal rather than just one-directional (Bronfenbrenner, 1977, 1986; Restifo & Bögels, 2009). An action of the adolescent could result in parental response, which may in turn influence the adolescent. For instance, van Hale and colleagues (2008) found that adolescents' depressive symptoms predicted perceived parental rejection that, in turn, predicted adolescents' aggression in early adolescence. In the case of affect states, prior work found relations among family members' momentary affect states (Bodner et al., 2018); directed relations from adolescents to parents (Larson & Almeida, 1999; Larson & Richards, 1994) and from parents to adolescents (Almeida et al., 1999). Families can thus be understood as a dynamical system (Van Geert & Lichtwarck-Aschoff, 2005), with family members as interacting components (Cox & Paley, 1997).

[1]The study by Janssen et al. (2020) investigated partly the same sample as investigated in this chapter.

In addition to the importance of focusing on the family system rather than on dyads (e.g., Lougheed et al., 2020), we see four further challenges. First, while previous studies only focused on one variable of interest (e.g., Marker & Bailey, 2021), family systems are multivariate, calling for the analyses of multiple affect states. Second, family dynamics are often investigated in the lab (e.g., Bodner et al., 2018). It remains unclear how multivariate family systems evolve in daily life. Third, dynamic systems unfold over time (Schmittmann et al., 2013), which requires the investigation of multiple moments over longer periods. A method that has increasingly been used to gather this type of longitudinal information is Ecological Momentary Assessment (EMA; Larson & Csikszentmihalyi, 1983; Stone & Shiffman, 1994). EMA facilitates the distribution of questionnaires and the collection of self-report information. It enables assessing affect on the momentary level in a natural context without recall bias. Fourth, previous studies emphasized the need for an idiographic approach to studying systems, that is, illustrating that there are important differences between individuals (e.g., Molenaar, 2004) and that crucial information may get lost at the group level. When it comes to family dynamics, the idiographic perspective highlights the importance of studying each family individually from the others. Janssen et al. (2020)[1] showed that the effect of the COVID-19 pandemic on affect and parenting differed substantially between families.

This chapter aims to tackle the four aforementioned challenges by using multivariate EMA data to investigate family affect states of adolescents and their parents as dynamic systems, both at the level of each individual family and at the group-level of all families.

Network model

A promising statistical method to study family systems is the multilevel vector autoregressive network model (mlVAR; Bringmann et al., 2013). The model estimates a contemporaneous network featuring the relations between variables in the same window of measurement, and a temporal network showing the relations between variables over time (Epskamp et al., 2018d). Estimated networks can be visualized as network graphs, where variables (such as affect states of family members) are represented as nodes, and the relations among those variables are drawn as edges. The relations in the mlVAR model are corrected for the influence of all other variables in the network. Next to a network on the group level (i.e., nomothetic effects), the model also provides contemporaneous and temporal networks on the level of each individual (i.e., idiographic effects). Therefore, the mlVAR is well fitted to study family affect dynamics.

So far, the mlVAR model has been used extensively to study relations between variables over time in single individuals, or groups of individuals (e.g., Bringmann et al., 2016, Aalbers et al., 2019). However, studies investigating relations between people have remained scarce. Recently, two studies have shown that the mlVAR network model can be applied to dyads, such as romantic relationships and therapeutic relations (Bar-Kalifa & Atzil-Slonim, 2020; Bar-Kalifa & Sened, 2020). The aim of this chapter is to take the approach one step further: applying the mlVAR network to triadic family relations. Such an endeavour may pave the way to a broad range of studies into group dynamics, from families, siblings, friends, and colleagues.

Present study

This chapter has two main goals. First, we utilize the mlVAR network model to study family affect dynamics using data from the RE-PAIR study (*https://www.re-pair.org/*) (Janssen et al., 2020, 2021b). In this study, adolescents and their parents (80 families with 231 individual family members) rated four affect states (i.e., happy, sad, irritated, and relaxed) four times a day over 14 days, resulting in 56 time points. In the networks we estimate, the nodes represent four affect states for adolescents, mothers, and fathers, resulting in 12 affect states in total. We estimate relations between affect states at the same moment in time (contemporaneous effects) and over time (temporal effects) based on all families (nomothetic network) and for each family separately (idiographic networks).

Second, as the mlVAR model has not been applied much in the context of dyadic or triadic relations, we will assess the statistical performance of the statistical model in a simulation study, under three scenarios: different levels of missing data, varying families/participants in the data, and varying time-points.

Methods

Participants

Eighty adolescents and 151 parents participated in the EMA of the RE-PAIR study. In this section, we will only provide the relevant information for the sample and variables used in this study. For more information on the RE-PAIR study, we refer to Janssen et al. (2021b). In nine families, only one of the parents participated (8 mothers and 1 father). The age of the adolescents ranged from 11 to 17 years. The inclusion criteria to participate were that adolescents lived at home with at least one parent, went to high school or secondary vocational or higher education, were fluent in Dutch, were not currently diagnosed with a mental disorder, did not have a history of major depressive disorder or dysthymia, and were not diagnosed with any other mental disorder in the last two years. The parents also had to be fluent in Dutch. They did not have to be biological parents, but they had to play a significant role in the upbringing of the adolescent. Same-sex couples were included; however, only one parent participated, and therefore, the sample used in this study does not contain information on same-sex couples.

Of the 80 families that participated, 60 families (i.e., 60 adolescents, 60 mothers, 60 fathers) met the inclusion criteria for this study (i.e., both parents participated in the EMA and participants met the missingness criteria explained below). This sample was used for the family network estimation. Details on the sample are provided in Table 3.2 of the *Appendix*.

Procedure

Participants were recruited through social media and advertisements (e.g., flyers). For the EMA study, they received four questionnaires a day for 14 days: one in the morning, two in the afternoon, and one in the evening. The morning questionnaire was sent at 7 a.m. on weekdays and 9 a.m. on weekend days. The time of the other surveys was randomized within a certain time frame: between 12 a.m. and 1 p.m. and between 4 p.m. and 7 p.m. for the afternoon surveys; the evening questionnaire for adolescents between 8:15 p.m. and 8:45 p.m.; and the evening questionnaire for parents between 9 p.m. and 9:30 p.m. The participants had two hours to respond to the morning questionnaire, one hour for the afternoon questionnaires, and three hours for the evening questionnaire (see Table 3.3 in the *Appendix* for an overview). For the EMA, participants used the smartphone app Ethica (https://ethicadata.com/) on their own phone. Parents received €20 and adolescents €10 as compensation for their participation. In addition, participants had the chance of winning one of the four €75 gift cards. Adolescents and parents both provided informed consent. If adolescents were below 16 years of age, parents also had to provide consent for the participation of their child. The RE-PAIR project was conducted in line with the principles of the Declaration of Helsinki. The study was approved by the Medical Ethics Committee (METC) of Leiden University Medical Center (LUMC) in Leiden, the Netherlands (research protocol: P17.241; approval code: NL62502.058.17).

Measurement

Parents and adolescents rated four affect states: two positive affect states, happy and relaxed, and two negative affect states, sad and irritated. As described in Janssen et al. (2021b), participants were asked to rate how happy/sad/relaxed/irritated they felt at that specific moment on a Likert scale from 1 (*not at all*) to 7 (*very*). The items were slightly adapted versions of the Positive and Negative Affect Schedule for Children (PANAS-C; Ebesutani et al., 2012; Watson et al., 1988).

Statistical analysis

Descriptive statistics

The mean and standard deviation of the affect states per family member were calculated using the same procedure as Aalbers et al. (2019). Missing values were deleted pairwise, which resulted in 60 means and standard deviations per variable, of which we calculated the mean and standard deviation (also referred to as within-person mean and within-person standard deviation), described in Table 3.1.

Missing data

To overcome power problems when excluding rows containing missing values, and avoiding the unnecessary exclusion of valid data, we used the Kalman filter for data imputation (Harvey, 1990). This procedure is elaborated in the *Appendix*. The Kalman filter provides us with continuous data. In the preregistration, we stated that we would round the imputations to one decimal to obtain integer data, similar to the gathered data. However, we later learned that this is not common practice, and therefore, we decided to deviate from the preregistration and use the continuous data instead. To check if this would influence the results, we also performed the analysis using the integer data and compared it to the results based on the continuous data in the *Appendix*.

Assumption checks

The mlVAR model assumes equal time spans between EMA surveys, multivariate normality, and stationarity. First, our design does not feature exactly equal spacing, given some random variation in surveys, but it is expected that the model can deal with smaller deviations. A bigger concern is that evening and morning surveys are separated by a night. To account for that, the network model does not estimate relations between evening and morning surveys. Second, we used the Kolmogorov–Smirnov test to test for univariate normality[2] Third, stationarity implies that means, variances and autocorrelations are stable over time (Bringmann et al., 2016; Chatfield, 2003; Hamaker & Dolan, 2009). We applied the Kwiatkowksi-Phillips-Schmidt-Shin unit root test to test for trends in the data (as done by Bringmann et al., 2016)[2].

Network estimation

3

We constructed multilevel networks using mlVAR models in R with the package *mlVAR* (Epskamp et al., 2021) and visualized them with the package *qgraph* (Epskamp et al., 2012a). The networks include the affect states (happy, sad, relaxed, and irritated) for each family member (adolescent, mother, and father), resulting in networks that consist of 12 nodes. To test if the adolescent's and parents' momentary affect states are related at the same time point and over time, we estimated a temporal and contemporaneous network using the method *lmer* (sequential univariate multilevel estimation) with orthogonal estimation, recommended for networks with more than five nodes (Epskamp et al., 2021).

The model estimation is similar to Bar-Kalifa and Sened (2020), but adjusted to the family triadic data. The observations for a specific variable i of family f at the time point t are represented by $y^f_{i,t}$. For instance, reported sadness ($i = 3$) by the adolescent of family f on time point t is defined by $y^f_{3,t}$, while reported sadness by the mother of family f on time point t is defined by $y^f_{k+3,t}$. One's affect state i of family f at time point t is represented by the following Ml-VAR level 1 equation:

$$y_{[t,f,i]} = \mu_{[f,i]} + \beta_{[f,i]}(y_{[t-1,f]} - \bar{y}_f) + \varepsilon_{[t,f,i]}, \tag{3.1}$$
$$\varepsilon_{[t,f,i]} \sim N(0, \theta_{[f,i]}),$$

where $\mu_{[f,i]}$ represents the intercept of affect state i of family f, $\beta_{[f,i]}$ the vector of all estimated lagged slopes predicting affect state i of family f (e.g., estimated association between adolescent's sadness at time t - 1 and mother's irritation at time t for family f), $y_{[t-1,f]}$ the vector of all affect states reported at time t - 1 for this family, which are family-mean centered around their mean $\bar{y}_f$. $\varepsilon_{[t,f,i]}$ represents the level 1 residual error that is normally distributed around a mean of 0 with a variance of $\theta_{[f,i]}$. We assume that the data is grand-mean centred, and we end up with the following multilevel level 2 equation:

[2]We used a significant level of $\alpha = 0.05$ on which we applied the Bonferroni correction to adjust for multiple testing.

$$\begin{bmatrix} \mu_{[f,i]} \\ \beta_{[f,i]} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ \beta_{[*,i]} \end{bmatrix}, \begin{bmatrix} \omega_{\mu_i} & \omega^{(\beta_i,\mu_i)^{\mathrm{T}}} \\ \omega^{(\beta_i,\mu_i)} & \Omega^{(\beta_i)} \end{bmatrix} \right), \tag{3.2}$$

where $\beta_{[*,i]}$ represents the vector of fixed/group effects, or as we call them, the nomothetic effects. The nomothetic effects are the average effects across all families and form the sample's temporal network. $\beta_{[f,i]} - \beta_{[*,i]}$ represents the deviation from nomothetic effects. $\beta_{[f,i]}$ forms the family's individualized temporal network, the idiographic effects.

The nomothetic contemporaneous network was estimated using the level 1 residuals of the variables of the temporal network $\hat{\boldsymbol{\varepsilon}}_{[t,f,-(i)]}$, in our case affect states, to predict the level 1 residual of a variable/affect state $\hat{\varepsilon}_{[t,f,i]}$ at the same point in time, using the equation:

$$\hat{\varepsilon}_{[t,f,i]} = \boldsymbol{\beta}^{(\boldsymbol{\theta})}_{[f,i]} \hat{\boldsymbol{\varepsilon}}_{[t,f,-(i)]} + \varepsilon^{\boldsymbol{\theta}}_{[t,p,i]}, \tag{3.3}$$

where $(\boldsymbol{\theta})_{[f,i]}$ represents the vector with the contemporaneous effects (association between the variables at the same point in time) and $\varepsilon^{\boldsymbol{\theta}}_{[t,p,i]}$ the level 1 residual of the contemporaneous network. Similar to the temporal model, we can obtain the nomothetic $\beta_{[*,i]}$ and family deviation $\beta_{[f,i]} - \beta_{[*,i]}$ from the level 2 model where a multivariate normal distribution is assigned to $(\boldsymbol{\theta})_{[f,i]}$. This results in a contemporaneous network of the sample and per family. An emerging edge in this network is interpreted as two affect states are related at the measurement occasion, controlling for all other affect states in the network. Contemporaneous effects are undirected, denoted by edges without arrows. In the temporal network, if a positive edge emerges, for example, from adolescent sadness to mother sadness, the interpretation is that adolescent sadness at time point t statistically predicts mother sadness at the next time point $t + 1$ while controlling for all other affect states in the network.

To obtain additional information about the type of relations within each network, we calculated an adjusted version of the InterIntra density ratio index applied by Bar-Kalifa and Sened (2020). This index represents the ratio between the average strength of the absolute inter-individual effects (edges between family members) and the intra-individual effects (edges within family members). When this index is higher than 1, it means that the relations between family members (e.g., between adolescents and mothers) are stronger than the relations within family members (e.g., within adolescents), and vice versa.

Next to the nomothetic networks, we estimated idiographic contemporaneous and temporal networks and compared the networks of two particular families with the least missing time points. To allow for a visual comparison, the networks have the same layout settings.

Simulation

The aim of the simulation study is to assess the influence of three features on the performance of mlVAR family network estimation: 1) the percentage of missing data (i.e., 10%, 25%, and 50%), 2) the number of families in the data (i.e., 30, 45, and 59)[3], and 3) the number of time points (i.e., 20, 56, and 100)[4]. We used the retrieved nomothetic and idiographic contemporaneous and temporal networks shown in Figure 3.6 of the *Appendix* as 'true networks'. Based on these networks, we simulated data using the *mlVARsample* function from the mlVAR package (Epskamp et al., 2021) in R. In this function, data per family is simulated based on their idiographic effects (often referred to as random effects) using the *graphicalVARsim* function from the R package graphicalVAR (Epskamp, 2020). We constructed mlVAR networks based on the simulated data (containing information of all the families). To fit the models, we applied the same methods as in the empirical study, using the *lmer* estimation method with orthogonal estimation for contemporaneous and temporal effects, except that missing data were not imputed. To assess the retrieval of the true network structure, we compared the obtained network structure of the nomothetic contemporaneous and temporal networks to the true network structure of these networks on the following measures (as used by e.g., Mansueto et al., 2023; De Ron et al., 2021; Isvoranu & Epskamp, 2021):

- Bias: The absolute mean difference between the estimated edge weights and the edge weights in the true network.
- Correlation: The relation between the estimated edge weights and edge weights in the true network.

[3] Our method does not allow the number of families to extend the maximum number of families in the 'true network'. We intended, as preregistered, to use the estimated networks based on all 60 families presented in the Results section. Unfortunately, a lack of stationarity in one family led to model convergence problems, and the family was therefore removed from the simulation, resulting in a maximum of 59 families instead of 60. For the simulation, the contemporaneous and temporal networks were estimated again based on 59 families.

[4] The number of time points were based on the number of time points per family in the 'true network'. We decided to use (roughly) half and double of this number. Mansueto et al. (2023) illustrated the difficulties with estimating networks with a low number of observations. Varying the number of time points per family allowed us to check if this also applied to the multilevel network model.

- Precision: The proportion of edges that are detected by the estimated network that are also in the true network, compared to all the edges in the estimated network (true positive / (false positive + true positive)).
- Sensitivity: The proportion of edges that appeared in the estimated network compared to the total edges that appeared in the true network (true positive / (true positive + false negative)).
- Specificity: The proportion of edges that did not appear in the estimated network compared to the total edges that did not appear in the true network (true negative / (true negative + false positive)).

We also compared the obtained network structure of the idiographic contemporaneous and temporal networks to their true network structure, but due to the estimation method of idiographic networks, we could only consider bias and correlation. We repeated this process from data generation to network model estimation 1,000 times per variation (i.e., combination of % missingness, number of families and time points per family).

Results

Descriptives

The means and standard deviations of the positive and negative affect states per family member ($n = 60$) are presented in Table 3.1. The frequency of the responses on the affect state variables is shown in Figure 3.9 of the *Appendix*.

Assumption checks

The Kolmogorov–Smirnov test was significant for all variables ($p < 0.001$; see Figure 3.9). This means that the data distribution was not univariate normal, and indicates that the assumption of multivariate normality was violated. It is common to estimate VAR models on variables that do not fully meet multivariate normality, given the typical nature of such data. However, this may somewhat reduce the power to detect small edges in the data. The Kwiatkowksi-Phillips-Schmidt-Shin unit root test to test for trends in the data was not significant for any variable in any participant, indicating that all data are stationary, that is, all means and variances were stable over time.

Table 3.1. *Mean and Standard Deviation of Family Means and Standard Deviations for All Variables per Family Member*

		Adolescent	Mother	Father
Happy	M (SD)	5.40 (0.80)	5.14 (0.67)	5.12 (0.72)
	SD (SD)	0.89 (0.30)	0.90 (0.32)	0.83 (0.34)
Sad	M (SD)	1.37 (0.55)	1.49 (0.65)	1.60 (0.74)
	SD (SD)	0.58 (0.49)	0.67 (0.47)	0.62 (0.43)
Relaxed	M (SD)	5.57 (0.85)	5.28 (0.69)	5.25 (0.68)
	SD (SD)	0.93 (0.42)	1.01 (0.33)	0.93 (0.36)
Irritated	M (SD)	1.52 (0.60)	1.57 (0.52)	1.62 (0.64)
	SD (SD)	0.82 (0.53)	0.98 (0.50)	0.75 (0.50)

Note. M = Mean, SD = Standard Deviation.

3

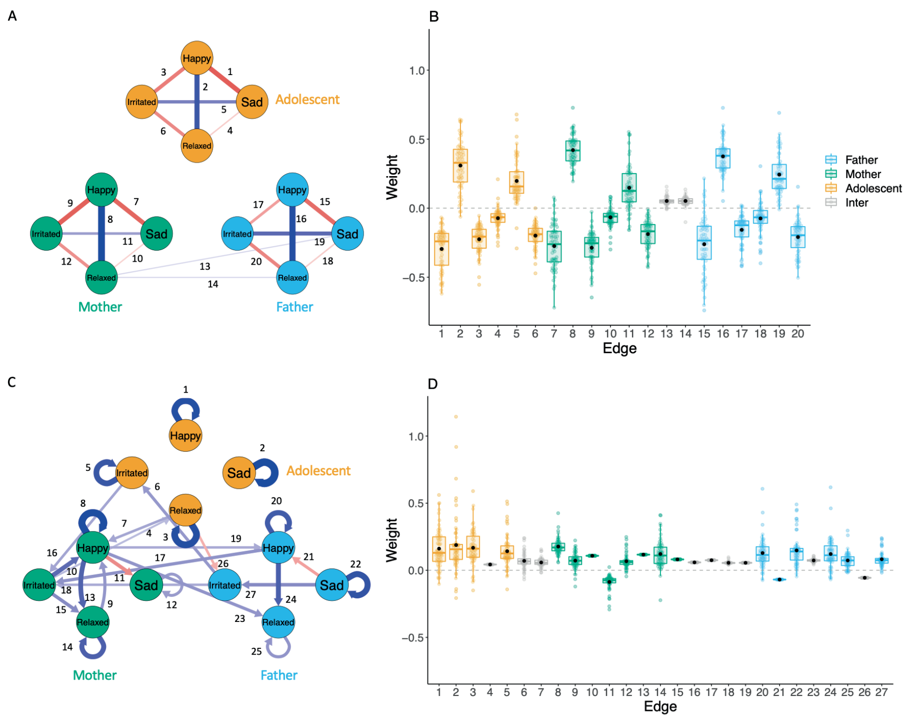
Contemporaneous network

Panel A of Figure 3.1 shows the nomothetic contemporaneous network that demonstrates how affect states relate to each other at the same time point. The *Appendix* contains an overview of the edge labels. The network contains relatively strong intra-individual effects, which are in part positive relations between affect states of the same valence, such as happy and relaxed (edges 2, 8, and 16). There are also negative relations between affect states that belong to the opposite affect valence. For example, when adolescents report being irritated at time point t, they are less likely to report being happy at that same time point t, and vice versa (edge 3).

The network contains two inter-individual effects, which are relatively weak (edges 13 and 14). If fathers report being more relaxed at time point t, it is likely that mothers will also report being more relaxed at this same time point t, and the other way around. Second, when mothers report being relaxed, fathers are more likely to report being sad at the same moment, and when fathers report being sad, mothers are more likely to report being relaxed.

We used the adjusted InterIntra density ratio to obtain information on the strength of inter- and intra-individual effects by comparing the average strength of the absolute edge weights of the temporal relations between family members (inter-individual effects) to the absolute edge weights of the temporal relations within family members (intra-individual effects). The InterIntra density ratio of the contemporaneous network was 0.234 (i.e., 1 representing equal strength), indicating that the intra-individual contemporaneous effects were around four times stronger than the inter-individual contemporaneous effects.

Figure 3.1. *Panel A: Nomothetic Contemporaneous Network. Panel B: Idiopgraphic Contemporaneous Effects. Panel C: Nomothetic Temporal Network. Panel D: Idiographic Temporal Effects.*



Note. Panels A and C: Orange nodes represent affects states of adolescents, green nodes affect states of mothers, and blue nodes affect states of fathers. The figure only shows the significant edges. Blue edges indicate positive relations between affect states and red edges negative temporal relations. The strength of the relation is represented by the thickness of the edge, with thicker edges indicating stronger relations. The numbers on the edges correspond to the edge numbers on the x-axis in panels B and D. Panels B and D: The colored dots represent parameters of all individual families and their spread is illustrated by box plots. Orange dots and boxplots represent the intra-adolescent effects, green dots and boxplots intra-mother effects, blue dots and boxplots intra-father effects, and gray dots a boxplots inter-individual effects. The black dots represent the nomothetic effects – edges in panels A and C.

Family variation in the contemporaneous network

To gain insights into the degree to which the nomothetic contemporaneous network is representative of the networks of all families, we inspected the idiographic effects. We checked which idiographic effects were present within the nomothetic network, and whether these effects were of the same sign (i.e., positive versus negative value). Next, we inspect the effects within specific families and the deviation from the nomothetic effects (Panel B of Figure 3.1).

There was considerable variation in the estimated contemporaneous effects. For instance, in some idiographic networks, there is a positive relation between sadness and irritation for mothers (edge 11), while other idiographic networks contain a negative effect or no effect at all. For other edges, such as the negative relations between happiness and sadness, and happiness and irritation of the adolescent (edges 1 and 3), there is variation in the edge weight but not in the direction of the effect. The idiographic estimates are mostly in line with the estimated nomothetic effect: the idiographic estimates are clustered around the nomothetic effect. Except for some edges, where there is a greater variation in the idiographic estimates. For instance, the distribution of the idiographic point estimates of edge weight 15, the relation between sadness and happiness of fathers, was relatively large, ranging from -0.75 to 0.25, with relatively few estimates with the same estimated edge weight as for the nomothetic effect.

Temporal network

Panel C of Figure 3.1 shows the nomothetic temporal network containing the relations between affect states of parents and adolescents over time. The figure shows relatively strong autoregressive effects, that is, temporal effects of a variable on itself. For instance, the intensity of sadness is associated with sadness at the next time point. All the family members have autoregressive effects for almost all variables, except for irritation.

The network contains temporal intra-individual effects, such as mothers being happy at time point t is positively related to mothers being relaxed at the next time point (edge 8). Irritation of adolescents at time point t is positively related to irritation at time point $t+1$ (edge 5). Fathers being sad at time point t is negatively related to fathers being happy at the next time point (edge 21). One counterintuitive relation worth noting is the small positive effect of the irritation of mothers on their happiness (edge 10). No temporal intra-individual effects between affect states of adolescents were found.

The network also yields smaller temporal inter-individual effects. There is a positive relation between the irritation of fathers at time point t and the irritation of adolescents at the next time point (edge 6). Irritation of adolescents at time point t, in turn, is positively related to irritation of mothers at time point $t+1$ (edge 16). Irritation of fathers at time point t is also positively related to irritation of mothers at time point $t+1$ (edge 18). Other temporal inter-individual effects are the positive relation between irritation of mothers and relaxation of adolescents (edge 4), the positive relation between relaxation of adolescents and happiness of mothers (edge 7), the positive relation between happiness of mothers and happiness and relaxation of fathers (edges 19 and 23), and the negative relation between relaxation of adolescents and irritation of fathers (edge 26).

The InterIntra density ratio of the temporal network was 0.516, indicating that the intra-individual temporal effects were around twice as strong as the inter-individual temporal effects.

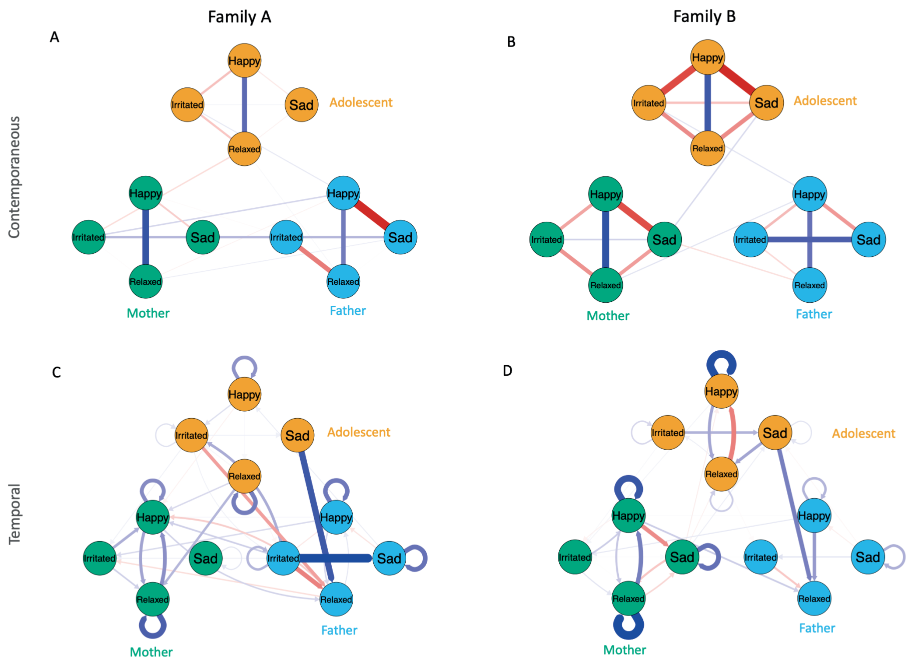
Family variation in temporal network

Panel C of Figure 3.1 shows the estimated edge weights for the temporal effects that are present in both the idiographic networks and the nomothetic network. We found variation in the estimated effects. For instance, for edge 24, the relation from happiness at time point t on relaxation at time point $t+1$ in fathers, some families have a positive effect, while others have a negative effect, or no effect at all. There are also estimated edge weights with hardly any variation resulting in a nomothetic effect that is representative of specific idiographic effects, such as the positive relation from irritation of mothers at time point t to relaxation of adolescents at the next time point (edge 4), the positive relation from irritation at time point t to happiness at time point $t+1$ of mothers (edge 10), and the positive relation from irritation of fathers at time point t to irritation of mothers at the next time point (edge 18).

Family comparison

Considering the substantial variation in estimated idiographic contemporaneous and temporal effects, we compared two example families (those with the fewest missing data) in detail. The adolescent in family A was 16 years old at the time of participation and male, while the adolescent in family B was a 17-year-old female. For each of the adolescents, both biological parents participated in the study.

Figure 3.2. *Contemporaneous and Temporal Networks of Families A and B*



Note. The figure only shows the significant edges. Blue edges indicate positive relations between affect states, and red edgesindicate negative relations. The strength of the relation is represented by the thickness of the edge, with thicker edges indicating stronger relations.

The family affect state trajectories show differences in responses and per family member and in variation of the responses (see Figures 3.11 and 3.12 in the *Appendix*).

When comparing the networks of the two families, differences in relations, the number of relations, and the strength of relations are visible (see Figure 3.2). The contemporaneous networks of the families do not contain the same inter-individual effects (see Panels A and B of Figure 3.2). For example, the negative relation between irritation of the mother and relaxation of the adolescent in family A is not present for family B, in that the edge weight did not pass the threshold. Of the effects that are present for both family A and family B, the strength of the effects differs between the families. This is mostly the case for intra-individual effects, such as the relation between happiness and sadness.

The network of family B contains slightly more temporal relations than the network for family A (i.e., 43 against 41). A noticeable difference between the networks is the negative relation between the irritation of the adolescent at time point t and the relaxation of the father at the next time point for family A, and the absence of this relation for family B. However, there are also many relations present in both family networks. For instance, the mother's positive intra-individual relations and the positive inter-individual relation between the sadness of the adolescent at time point t and the relaxation of the father at the next time point.

Simulation study

For the simulation scenarios with 30 and 45 families in combination with 20 time points and 50% missing data, the model did not converge for almost all repetitions due to non-positive definite matrices.[5] Results should therefore be interpreted with care. This issue also occurred in other simulation scenarios, but less frequently. An overview of the successful repetitions per scenario, the number of repetitions the results are based on, can be found in Table 3.5 of the *Appendix*. The results of the simulations for the scenario with 59 families, similar to our sample, are shown in 3.3. The results of the other scenarios with 30 and 45 families are shown in Figures 3.7 and Figure 3.8 of the *Appendix*. In general, the distribution of the point estimates increased (i.e., greater distance between minimum and maximum estimated value and a greater Interquartile range) when there was less data (fewer families, fewer time points and more missing data). For example, when comparing precision of nomothetic temporal networks in scenario with 45 families, 56 time points, and 0% missing data ($Mdn = 0.43$, $M = 0.43$, $SD = 0.10$) to 45 families, 56 time points, and 50% missing data ($Mdn = 0.33$, $M = 0.34$, $SD = 0.19$). In addition, there was a difference between the performance of the contemporaneous and temporal networks. Temporal networks had lower median values and greater variability in the measures of correlation, precision, and sensitivity. For instance, in the scenario of 45 families, 100 time points and 10% missing data, the median sensitivity of nomothetic temporal networks was 0.78 ($M = 0.77$, $SD = 0.14$), and the median sensitivity of nomothetic contemporaneous networks was 0.96 ($M = 0.94$, $SD = 0.04$).

Zooming in on the different measures we see, first, that the bias remained below 0.2 in every scenario. Its value only increased slightly in the scenarios with 20 time points and 50% missing data. The bias was somewhat higher for both the idiographic

[5] Non-positive definite means that the eigenvalues of a variance-covariance matrix are not greater than zero. For example, this could happen when the number of observations is smaller than the number of estimated variables (see Epskamp & Fried, 2018b, for more information).

contemporaneous and temporal networks compared to the nomothetic networks. For example, in the scenario with 45 families, 56 time points, and 25% missing data, the median bias of the idiographic contemporaneous networks was 0.04 ($M = 0.04$, $SD = 0.002$), and the median bias of the nomothetic contemporaneous networks was 0.01 ($M = 0.01$, $SD = 0.003$).

The correlation between the estimated edge weights and edge weights in the 'true network' we simulated from was lower in scenarios where there were fewer time points and families, and decreased when the percentage of missing data increased. While the correlation of the contemporaneous networks remained stable for the different scenarios, and only became more variable in the scenario with 30 families and 20 time points, the correlation of the temporal networks varied more widely. In scenarios with less data, the correlation of especially the nomothetic temporal networks dropped below zero. In the scenario with the 59 families, 100 time points and no missing data, the correlation of the temporal network was moderate to large, but still varied considerably from .606 to .857. This correlation is substantially lower than the correlation for the contemporaneous network ($Mdn = .992$, $Min = .988$, $Max = .996$). The correlation of the idiographic contemporaneous networks was slightly lower than for the nomothetic contemporaneous network, but the variation was comparable. The correlation of the idiographic and nomothetic temporal networks was similar, in some scenarios even higher for the family networks (e.g., Figure 3.7). The correlation of the nomothetic temporal network varied more widely compared to the correlation of the idiographic temporal networks. For instance, in the scenario of 45 families, 56 time points, and 25% missing data, the median correlation of nomothetic temporal networks was .54 ($M = .52$, $SD = .15$), and the median correlation of idiographic temporal networks was .59 ($M = .59$, $SD = .03$).

Precision of the estimated edges did not increase for scenarios with more time points and families, but the variability did decrease. An increase in missing data resulted in an increase in the variability. This is especially visible for temporal networks in scenarios with 56 and 100 time points. In the scenario with the 59 families and 56 time points, the standard deviation for the nomothetic temporal network with 50% missing data was 0.19, while the standard deviation was 0.08 with 0% missing data.

The proportion of edges that appeared both in the true and estimated network, sensitivity, increased when the number of time points increased, and decreased with more missing data. The estimated sensitivity of the temporal networks was lower and more variable than that of the contemporaneous networks. For instance, in the scenario with 59 families, 56 time points and 0% missing data, the median sensitivity of nomothetic temporal networks was 0.78 ($M = 0.73$, $SD = 0.14$), while the median sensitivity of nomothetic contemporaneous networks was 0.92 ($M = 0.93$, $SD = 0.05$).

The proportion of edges that did not appear in both the estimated network and true network, specificity, remained stable in every scenario. In scenarios with 56 and 100 time points, the specificity increased slightly when the percentage of missing data increased. For example, in the scenario with 59 families, 56 time points, and 0% missing data, the median specificity for nomothetic temporal networks was 0.84 ($M = 0.83$, $SD = 0.05$), while it increased to 0.93 ($M = 0.92$, $SD = 0.04$) with 50% missing data. There were no considerable differences between the contemporaneous and the temporal networks regarding the value and the variability of specificity.

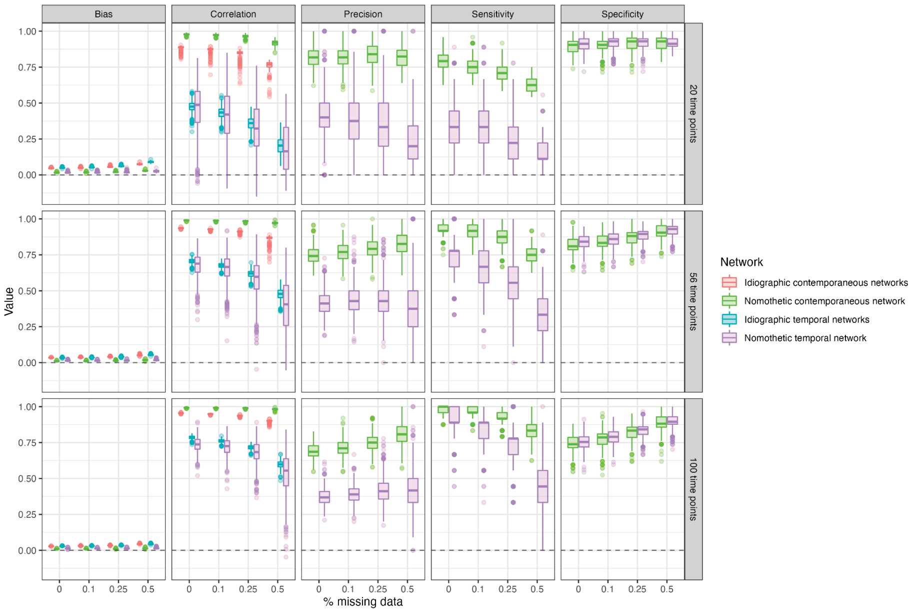
Discussion

Summary of findings and implications

This chapter illustrated the use of mlVAR network models to study triads to provide insights into family affect dynamics. The EMA data from the RE-PAIR study provided unique information on the daily affect states dynamics of adolescents and their parents. We showed how the reported affect states within families participating in the RE-PAIR study were related between the adolescent, mother, and father at the same moment in time and over time, and investigated whether these relations were consistent across families. To showcase variation across families, we utilized data from two particular families—those with the lowest amount of missing data—highlighting both similarities and differences.

Our results extended previous findings on relations between affect states of family members (Almeida et al., 1999; Larson & Almeida, 1999; Larson & Richards, 1994) to family triad relations in daily life. Next to relations within individual family members, intra-individual relations, we observed inter-individual affect state relations, for both positive and negative effect. Especially interesting are the relations between the affect states relaxation and irritation of the family members. When mothers reported being relaxed, fathers were also likely to report being relaxed, and vice versa. In addition, the temporal network with relations over time suggested that relaxation of adolescents was followed by a decrease in irritation of fathers. In turn, when fathers reported being less irritated, mothers were likely to report being less irritated at the next moment in time. In addition, if adolescents reported being irritated, mothers were likely to report being irritated at the next moment in time, while irritation of mothers was followed

Figure 3.3. *Network Estimation Results of the Simulation with 59 Families for Different Scenarios of Missing Data and Total Time Points.*



Note. The x-axis represents the percentage of missing data. The boxes on the right y-axis represent the different scenarios for the total number of time points.

by relaxation of adolescents over time, completing what could be interpreted as a triadic cycle of family affect state relations.

The families varied evidently, and especially in intra-individual relations. The contemporaneous relations—relations at the same moment in time—were largely consistent over families, with positive relations between affect states of the same type (e.g., when adolescents were sad they were more likely to also feel irritated) and negative relations between affect states of different type (e.g., when adolescents were sad they felt less happy at that same moment). However, the strength of the relations varied between families. This was also the case for the temporal relations - relations over time. Estimated temporal relations between the affect states were generally small, especially the inter-individual relations.

The intra-individual contemporaneous effects were stronger (i.e., larger absolute edge weights) in comparison to the intra-individual temporal effects, whereas the inter-individual effects were similar in strength for both networks (though the contemporaneous network contained fewer inter-individual effects), resulting in a lower

InterIntra density ratio for the contemporaneous effects. However, for both the temporal and contemporaneous networks, the inter-individual relations were less strong than the intra-individual effects, indicating logically that one's own affect states had a greater influence on one's momentary affect state than affect states of other people.

The contemporaneous network captures the effects after the estimation of the temporal effects. This means that effects that are not captured by the temporal network are likely to be identified by the contemporaneous network. Arguably, affect states could change in a smaller time frame than we accounted for in this study (Borsboom, 2022; Ryan & Hamaker, 2021), with individual differences in affect variability (Kuppens et al., 2007). For example, irritation of adolescents and parents could change in minutes instead of in hours (as measured in this study). As our temporal networks account for changes in hours, relations on smaller timescales (e.g., minutes) are likely not captured by the temporal network and therefore 'left' for the contemporaneous network. As a result, the contemporaneous relations could represent both relations over time as in the same moment; therefore, the nature of these contemporaneous relations is unclear. This issue calls for methods that regard differences in time spans in the estimation of temporal relations, such as extensions of continuous models (Ryan & Hamaker, 2021) to multilevel purposes.

Simulation

In addition to the empirical analyses, our simulation study assessed the statistical performance of the mlVAR network model when applied to triadic relations in the family context. The performance of the triadic mlVAR network model in three scenarios was evaluated: different levels of missing data, varying number of families in the data, and varying number of time points. The aim of the simulation study was to check whether this model was suitable to investigate family affect dynamics. The estimated affect state networks in this study are similar to the scenario in the simulation with 59 families, 56 time points, and 0% missing data. In this scenario, the bias remained low for all types of networks with good precision, which is in line with the general findings. Regarding correlation, precision and sensitivity, the contemporaneous networks performed well, while the performance of the temporal networks was highly variable. Especially, the detection of true edges (precision) was more difficult for temporal networks.

The network model performed worse when there was less data to base the model estimation on. Less data means less power to estimate the network structure, resulting in unstable estimations (Epskamp et al., 2018a). However, bias and specificity were almost not affected by decreases in sample size. This is in line with the results of the simulation study on a different longitudinal network: the graphical VAR (Mansueto et al., 2023). Based on these results, Mansueto and colleagues concluded that the network does well in excluding false edges. In case of specificity, the proportion of the edges of the estimated network that were correctly identified as zero, taking the true network as a reference, with less data, fewer edges will be estimated, resulting in sparse or even empty networks. Consequently, the specificity becomes high. This explains the slight increase in specificity in our simulation when the sample size decreased due to increases in the percentage of missing data. Especially, the correlation, precision, and sensitivity were affected by decreases in sample size. This indicates that the accurate detection of true edges becomes harder. In most cases, the correlations stayed in an acceptable range. To follow the conclusion of Mansueto and colleagues (2023), this means that although the full network (i.e., all true edges) could not be retrieved, the global network structure could (i.e., similar edge weights).

Finally, we observed differences between the types of networks. First, there were differences between nomothetic (based on 60 families) and idiographic networks (based on one family). Specifically, the correlation was higher for nomothetic contemporaneous networks compared to idiographic contemporaneous networks, while bias was slightly higher for idiographic networks. This can be explained by differences in the estimation method. While edges are thresholded in the nomothetic networks, edges in the idiographic networks are not thresholded. This results in denser idiographic networks: all the possible edges are estimated. When calculating the bias and correlations for idiographic networks, more edges are being compared, which results in a higher bias and lower correlation compared to nomothetic networks. Second, the temporal networks performed generally worse in retrieving the true network structure than the contemporaneous networks, in terms of correlation, precision, sensitivity, and variability. This could be due to power differences: effects in the true temporal network we simulated from were smaller than those in the contemporaneous network, and thus harder to accurately recover. The results of the simulation imply that inferences of temporal networks require careful consideration, especially for fewer time points (i.e., fewer than 100 time points).

Limitations and next steps

In the following section, we discuss limitations of our study and, where possible, recommendations that follow from our work. Given that family systems are likely highly multivariate, and most effects are small in nature, especially between family members, our investigation likely failed to uncover some relations between family members due to power issues related to 1) skewed data, 2) missing data, and 3) non-equidistant responses.

First, a fairly common statistical challenge is that data, especially negative affect items, are highly skewed at the population level (e.g., Haslbeck et al., 2023). While estimating VAR models on variables that do not fully meet multivariate normality frequently occurs, given the nature of EMA data, which is often ordinal, it likely reduces the power to detect small relations in the data. Therefore, we encourage research into measurement validation of EMA items, such as initiatives as The Experience Sampling Method (ESM) Item Repository by Kirtley et al. (2022).

Second, gathering family data is a complex issue. As explained in the section *Missing Data* of the *Appendix*, the percentage of missing data is likely to increase when combining data from different individuals. In this study, combining the data of adolescents and their parents would have resulted in 47% missing time points in total, while this would be 20% when looking at the individual level. Recently, more and more studies are looking at the application of data imputation for psychology data (e.g., Mansueto et al., 2023). In addition, the issue calls for research into (factors of) attrition and ways to incentivize participation, such as studies by Rintala et al. (2019) and Eisele et al. (2022), as well as large-scale collaborative data collection (e.g., McPhetres & Nguyen, 2018). However, it is unlikely that this issue will be solved entirely; therefore, especially in the context of mental health and psychological disorders, environmental factors related to missing data should be studied, as was, for instance, done by Sun et al. (2021).

Third, random sampling of questionnaires results in unequal time spans between responses, an issue common for individuals or groups of individuals. Overcoming this issue becomes even more difficult when it involves dyadic or triadic data, especially when surveys are not sent at the exact same time for parents and adolescents, as was done in the RE-PAIR study. However, even if surveys were sent at the exact same time, it cannot be expected that family members will respond simultaneously. This emphasizes the need for extensions on continuous models, such as proposed by Ryan and Hamaker (2021) to multilevel purposes.

As a next step in linking family affect states, contextual factors that are considered important influences on family affect dynamics by the family system theory (Bronfenbrenner, 1986) could be taken into account. For instance, it would be interesting to incorporate whether there was contact between the family members and how adolescents and parents perceived this contact in the family affect state networks. Were the family members in the same room? Did they talk to each other? Or did they have contact over social media? When family members have not been in touch, we cannot assume that their affect states are related. The question of how these time-varying moderators could be implemented into, for instance, the current network model is crucial and should be explored further. Furthermore, a question that has been raised is how these affect states are related to the development of mental disorders, such as depression (Kuranova et al., 2021). Following, our plan is, therefore, to compare the family affect state dynamics to the family affect state dynamics of adolescents diagnosed with depression.

Finally, there are limitations regarding the simulation study. An important aspect in calculating the power to retrieve edges is the number of nodes in a network (Epskamp et al., 2018a; Mansueto et al., 2023). In this simulation study, we decided not to vary the number of nodes for practical reasons and chose to focus on the number of families versus the number of time points instead. However, we assume that despite the multilevel structure of the model, the number of nodes has a great influence on the power to retrieve the true edges. Second, this simulation study used a simplified method to simulate data, which limited the possibility of varying the number of families. Therefore, this simulation should be seen as a first step to validate family triad networks.

Conclusion

In this chapter, we investigated family affect states dynamics by the application of a network model using EMA data of the RE-PAIR study. This data is distinctive in that it contains information on affect states of adolescents and their parents in daily life. The networks of multiple affect states of family triads showed how the affect states of adolescents and their parents are related at the same moment and over time. With a simulation study, we provided information on the validity of the family networks and guidance on the use of the mlVAR network model to study inter-person dynamics. This chapter illustrated how networks of triad relations can provide insights into family-specific processes and, therefore, how they can be potentially helpful as a feedback method providing family members with information on their affect dynamics, for instance, in clinical settings. As this method is not limited to the family context, it has the potential to provide insights into other types of multivariate triad dynamics.

Appendix

This section provides additional information on the sample, methods, and results. Information that is too extensive to present (e.g., preregistration, family networks and R code) is available online: *https://osf.io/72c9x/*.

Participants and procedure

A table with demographic information on the participants in the study and a table with an overview of the questionnaire schedule of the EMA are presented below.

Table 3.2. *Participant Information*

	Adolescents	Parents
N	38 females 22 males	58 biological mothers 2 adoption mothers 53 biological fathers 5 stepfathers 2 adoption fathers
Age	$M = 15.92$ ($SD = 1.32$)	$M = 49.16$ ($SD = 6.06$)
Country of birth	59 in The Netherlands 1 other	114 in The Netherlands 6 other
Education	5 vocational 19 advanced secondary 31 pre-university	7 lower vocational 25 intermediate vocational 88 higher vocational/ scientific (university)
Living situation	52 living with biological father and mother 2 living with biological mother 6 other*	

Note. N = Number of Participants, M = Mean, SD = Standard Deviation, *living with parent and stepparent, alternating between father and mother, or living with adoptive/foster parents.

Table 3.3. Questionnaire schedule EMA

Questionnaire		Time	Duration
1: Morning	Weekday	7 a.m.	2 hours
	Weekend day	9 a.m.	2 hours
2: Afternoon		12 a.m. - 1 p.m.	1 hour
3: Afternoon		4 p.m. - 7 p.m	1 hour
4: Evening	Adolescents	8:15 p.m. - 8:45 p.m.	3 hours
	Parents	9 p.m. - 9:30 p.m.	3 hours

Note. Time = at which time or within which time interval the questionnaire was sent, Duration = time to respond to the questionnaire before it expired.

Missing data

If we had followed current standards in mlVAR network estimation, excluding rows containing missing values, this would have had implications for family-structured data. For example, if both the adolescent and mother provided 100% of time points, but the father provided only 20% of time points, only 20% of the time points of the mother and adolescent could have been used for the estimation of the family network, posing a power problem. Of the 60 families that met the inclusion criteria of our study, 22 families completed less than 50% of the time points. On average, adolescents had 27% missing time points, fathers 20%, and mothers 17%. Combined, this would result in 47% missing time points in total, while this would be 20% when looking at the individual level. By a simulation, discussed later in the section *Simulation*, we evaluated the influence that missing data have on the network estimation. To overcome the power problem and avoid the unnecessary exclusion of valid data, we used the Kalman filter for data imputation (Harvey, 1990). The Kalman filter predicts future responses (in our case, missing values) based on the observed responses for time-series data using a state-space model (Durbin & Koopman, 2012). Previous studies have demonstrated the advantages of this method for data imputation for $N = 1$ designs (e.g., Mansueto et al., 2023). A simulation carried out before the preregistration indicated that the correlation between the true and imputed data by the Kalman filter dropped below .5 when there is more than 60% missingness (results of this simulation are presented under *Simulation*). Therefore, we excluded families with a family member who had more than 60% missing time points from the analysis. For the other participants, we applied the *na_kalman* function in R (R Core Team,

2021) from the package *imputeTS* (Moritz & Bartz-Beielstein, 2017). The Kalman filter provides us with continuous data. In the preregistration, we stated that we would round the imputations to one decimal to obtain integer data, similar to the gathered data. However, we later learned that this is not common practice, and therefore, we decided to deviate from the preregistration and use the continuous data instead. To check if this would influence the results, we also performed the analysis using the integer data and compared it to the results based on the continuous data in section *Family Networks based on Integer Data*. In some cases, the variability in time-series data over time of one affect state was too small to apply the Kalman filter. For instance, one participant only reported 1s and missing responses (NA) for a given affect state on nine time points (e.g., 1 1 1 1 NA 1 1 NA 1). In these cases, missing data were replaced by the value of the other responses (e.g., NAs were set to 1, resulting in 1 1 1 1 1 1 1 1 1).

To evaluate the performance of the Kalman filter as an imputation method, we performed a simulation. One of the participants in the EMA study responded to all the questionnaires, meaning that this participant had no missing data. We used these time points and randomly removed time points according to a certain percentage (0 to 90%). Then, for the first simulation, we imputed missing time points by random data sampled from a uniform distribution with a minimum of 1 and a maximum of 7 (corresponding with the possible responses for this data set). For the second simulation, we imputed the missing time points using the Kalman filter. Both imputation methods resulted in new simulated data sets. Finally, we computed the correlation between these simulated data sets and the original data. This process was repeated 1000 times for every percentage of missing data. The results are shown in Figure 3.4. The left panel shows the correlation between the data sets resulting from imputing from random data and the original data, and the right panel shows the correlation between the data sets resulting from imputing using the Kalman filter and the original data. The figure shows that the data sets imputed with the Kalman filter had a higher correlation with the original data compared to data sets imputed with random data. This indicates that the Kalman filter performs better than random data imputation.

Figure 3.4. *Correlation between Observations and Imputations when Varying the Percentage of Missing Observations*

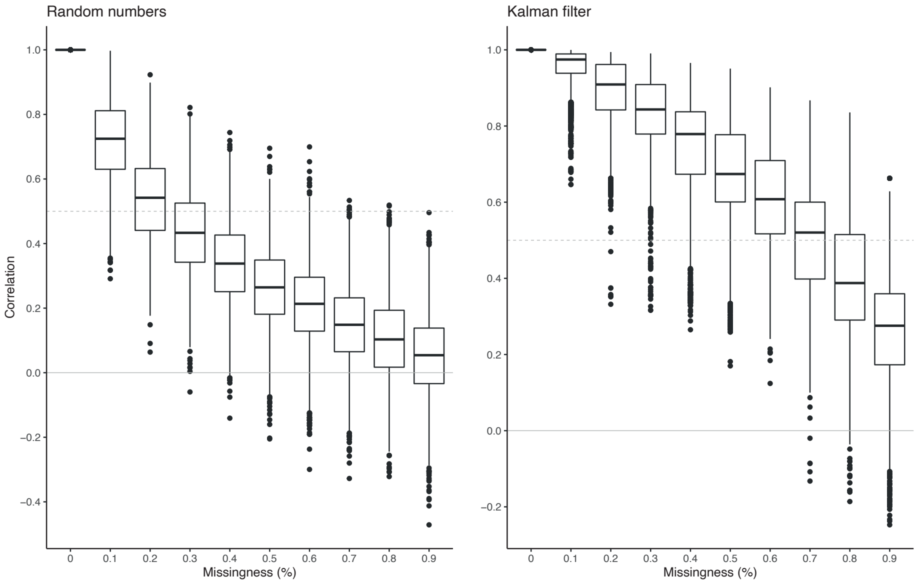


Table 3.4. *Number of Missing Time Points per Family*

Family	Adolescent	Mother	Father	Combined
1	19	2	15	25
2	22	5	24	33
3	8	3	12	20
4	12	6	6	20
5	16	7	14	27
6	13	12	23	35
7	32	5	23	46
8	17	18	3	26
9	27	14	19	45
10	13	9	9	23
11	22	11	1	29

(To be continued)

3

Family	Adolescent	Mother	Father	Combined
12	21	10	15	34
13	13	15	11	28
14	20	5	8	29
15	13	17	15	27
16	19	0	10	27
17	9	9	8	23
18	30	16	12	36
19	7	4	5	13
20	12	16	10	26
21	10	7	19	29
22	13	2	15	24
23	33	13	29	45
24	19	6	5	26
25	20	17	12	37
26	10	3	4	16
27	15	1	1	15
28	13	6	14	24
29	2	1	5	8
30	11	3	6	15
31	4	6	10	17
32	20	7	2	25
33	13	6	15	23
34	15	2	8	21
35	23	12	19	39
36	29	11	33	44
37	6	6	5	10
38	17	13	13	28
39	7	6	3	13
40	6	23	16	30
41	9	8	13	22
42	3	2	14	15
43	33	5	5	36
44	14	15	4	26

(To be continued)

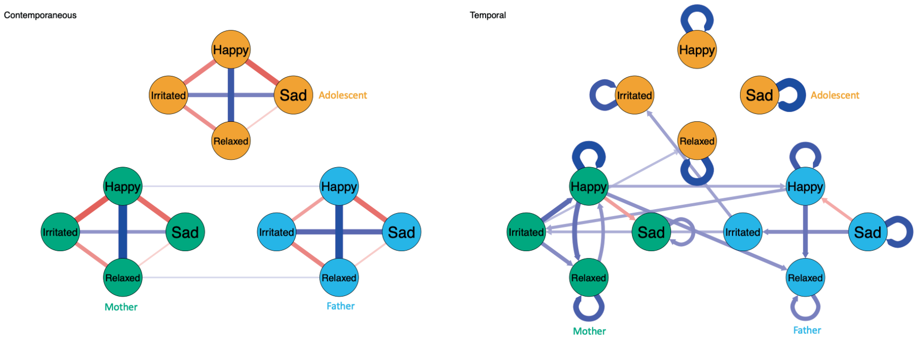
Family	Adolescent	Mother	Father	Combined
45	21	20	22	38
46	3	2	2	7
47	24	7	0	30
48	6	8	3	16
49	8	6	5	14
50	21	10	4	31
51	12	5	12	26
52	12	7	5	18
53	24	30	30	48
54	1	18	9	21
55	21	27	18	41
56	18	23	18	36
57	10	7	13	22
58	9	7	8	15
59	4	10	8	19
60	32	9	9	38

Family networks based on integer data

Figure 3.5 shows the nomothetic networks based on the integer data (rounding the imputed data to one decimal). The idiographic contemporaneous network shows the same intra-individual relations as the nomothetic contemporaneous network shown in Panel A of Figure 3.1, but the inter-individual relations differ: the relation between relaxation of the mother and sadness of the father is missing, while there is an additional relation between happiness of the mother and father. The correlation between the adjacency matrix of the contemporaneous network (this also includes the non-significant edges) with the contemporaneous network of Figure 3.1 is high (r = .999). The absolute difference in edge weights is 0.755.

The nomothetic temporal network differs from the nomothetic temporal network presented in Panel C of Figure 3.1. This temporal network contains fewer edges (24 versus 27). The relations between relaxation of the adolescent and happiness of the mother, irritation of the adolescent on irritation of the mother, and relaxation of the adolescent and irritation of the father are missing. The correlation of the adjacency matrix of this temporal network (this also includes the non-significant edges) with the temporal network of Figure 3.1 is .989 with an absolute difference in edge weights of 0.821.

Figure 3.5. *Nomothetic Networks based on Integer Data*



Note. The networks only contain the significant edges. Red edges indicate negative relations between affect states, and blue edges positive relations. The strength of the relation is represented by the thickness of the edge, with thicker edges indicating stronger relations.

Simulation

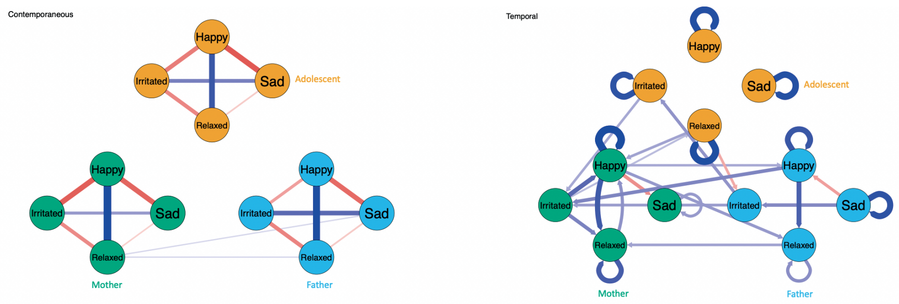
This section contains a figure with the nomothetic contemporaneous and temporal networks based on 59 families that are used for the simulation study, a table with the number of successful repetitions per simulation scenario (i.e., number of families, number of time points and percentage of missing data), and the results of the simulation in the scenarios with 30 and 45 families.

The nomothetic contemporaneous and temporal networks shown in Figure 3.6 are similar to the nomothetic contemporaneous and temporal networks based on 60 families presented in Figure 3.1. They contain the same edges. However, the nomothetic temporal network used for the simulation contains an additional edge from relaxation of the father at time point t to relaxation of the mother at the next time point $t + 1$.

Table 3.5 shows that we should be careful with conclusions based on the scenarios with a small number of families, a small number of time points, and a high percentage of missing data, as in these scenarios, there are only a few successful repetitions.

Figures 3.7 and 3.8 show the results of the simulation in the scenario with 30 and 45, respectively, and are discussed in the results section of the study.

Figure 3.6. *Temporal and Contemporaneous Networks used for Simulation Based on 59 Families*



Note. The figure only shows the significant edges. Blue edges indicate positive relations between affect states, and red edges indicate negative relations. The strength of the relation is represented by the thickness of the edge, with thicker edges indicating stronger relations.

Table 3.5. *Successful Repetitions per Simulation Scenario*

Families	Time points	Missing 0%	10%	25%	50%
30	20	658	436	194	3
	56	989	952	825	213
	100	999	995	972	629
45	20	963	905	662	79
	56	1000	1000	994	734
	100	1000	1000	999	966
59	20	998	985	887	142
	56	1000	1000	1000	935
	100	1000	1000	1000	995

Note. Successful repetitions: simulations in which no errors occurred; families: number of families; time points: number of time points; missing: percentage of missing data; total possible successful repetitions: 1000.

Figure 3.7. *Network Estimation Results of the Simulation with 30 Families for Different Scenarios of Missing Data and Total Time Points.*

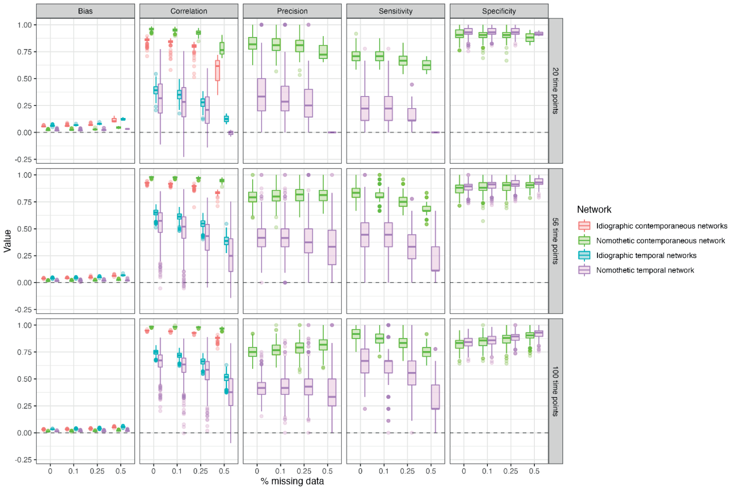
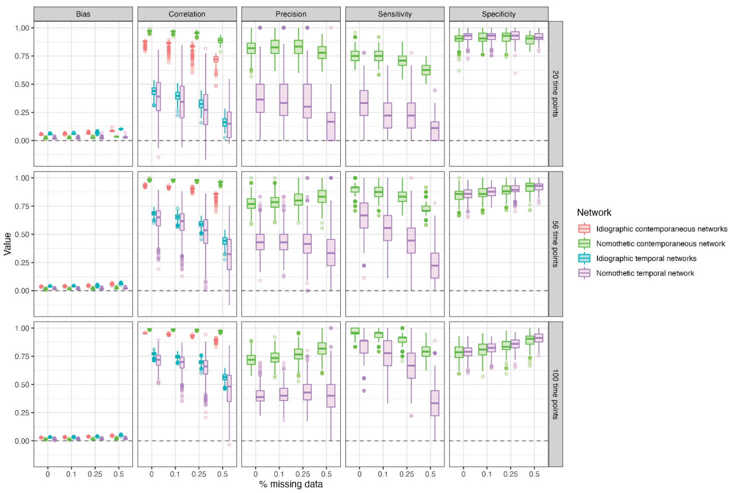


Figure 3.8. *Network Estimation Results of the Simulation with 45 Families for Different Scenarios of Missing Data and Total Time Points.*

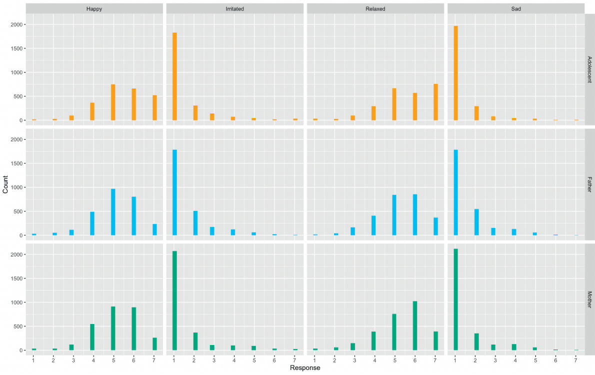


Note. The x-axis represents the percentage of missing data. The boxes on the right y-axis represent the different scenarios for the number of total time points.

Descriptives

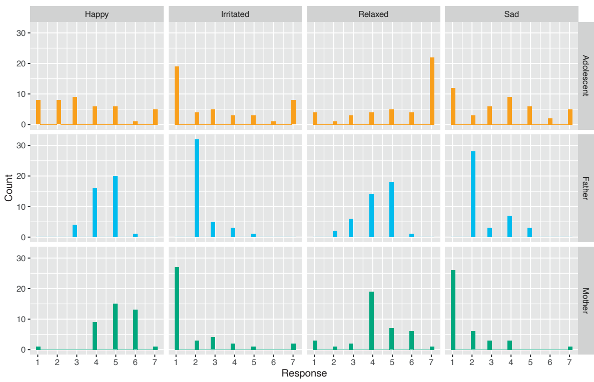
This section shows the distribution of the affect state ratings per family member (all families combined). The figure illustrates that the responses on positive affects (happy and relaxed) are left skewed, while the responses on the negative affects (irritated and sad) are right skewed.

Figure 3.9. *Frequency Affect State Ratings (1: not at all; 7: very) per Family Member.*



The response distribution can be different per family; therefore, we also visualized the frequencies of the responses per family. Figure 3.10 shows the response distribution of one family; the response frequencies for all families are available on the OSF.

Figure 3.10. *Frequency Affect State Ratings (1: not at all; 7: very) of One Family per Family Member.*



Overview edge labels

Table 3.6 contains an overview of the network edges presented in Figure 3.1 of the contemporaneous network, panels A and B, and the temporal network, panels C and D.

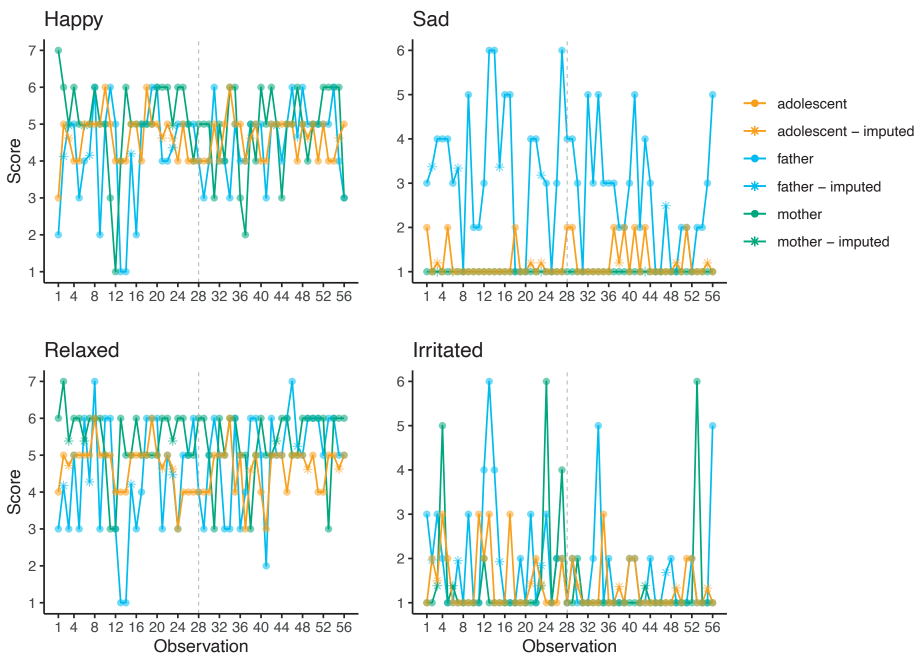
Table 3.6. *Overview edge labels*

Contemporaneous	Temporal
1. Happy-adolescent - sad-adolescent	1. Happy-adolescent → happy-adolescent
2. Happy-adolescent - relaxed-adolescent	2. Sad-adolescent → sad-adolescent
3. Happy-adolescent - irritated-adolescent	3. Relaxed-adolescent → relaxed-adolescent
4. Sad-adolescent - relaxed-adolescent	4. Irritated-mother → relaxed-adolescent
5. Sad-adolescent - Irritated-adolescent	5. Irritated-adolescent → irritated-adolescent
6. Irritated-adolescent - relaxed-adolescent	6. Irritated-father → irritated-adolescent
7. Happy-mother - sad-mother	7. Relaxed-adolescent → happy-mother
8. Happy-mother - relaxed-mother	8. Happy-mother → happy-mother
9. Happy-mother - irritated-mother	9. Relaxed-mother → happy-mother
10. Between sad-mother and relaxed-mother	10. Irritated-mother → happy-mother
11. Between sad-mother and irritated-mother	11. Happy-mother → sad-mother
12. Irritated-mother - relaxed-mother	12. Sad-mother → sad-mother
13. Relaxed-mother - sad-father	13. Happy-mother → relaxed-mother
14. Relaxed-mother - relaxed-father	14. Relaxed-mother → relaxed-mother
15. Happy-father - sad-father	15. Irritated-mother → relaxed-mother
16. Happy-father - relaxed-father	16. Irritated-adolescent → irritated-mother
17. Happy-father - irritated-father	17. Happy-father → irritated-mother
18. Sad-father - relaxed-father	18. Irritated-father → irritated-mother
19. Sad-father - irritated-father	19. Happy-mother → happy-father
20. Irritated-father - relaxed-father	20. Happy-father → happy-father
	21. Sad-father → happy-father
	22. Sad-father → sad-father
	23. Happy-mother → relaxed-father
	24. Happy-father → relaxed-father
	25. Relaxed-father → relaxed-father
	26. Relaxed-adolescent → irritated-father
	27. Sad-father → irritated-father

Family comparison

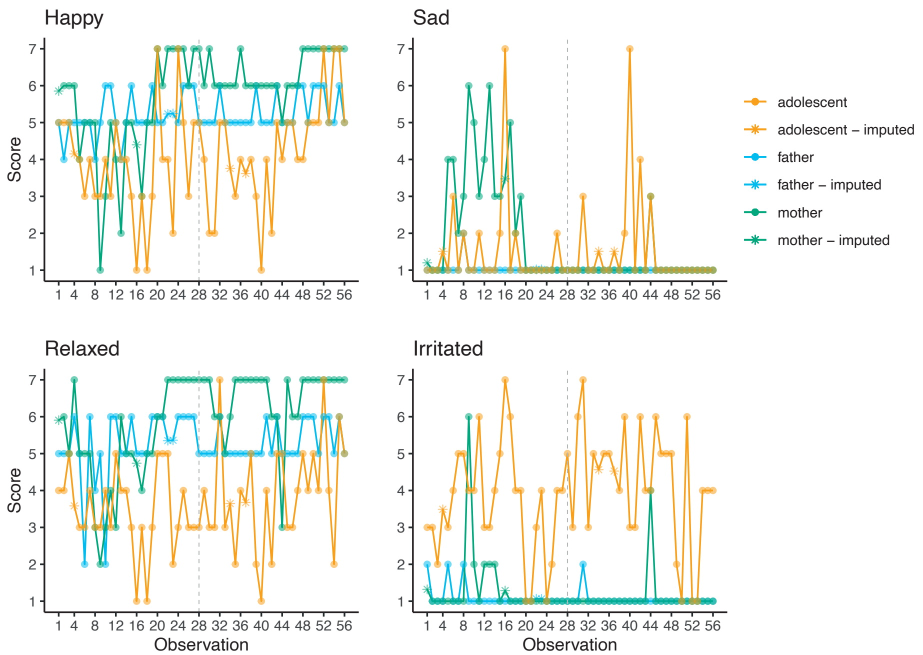
This section shows the affect state trajectories of the adolescent and their parents for families A and B discussed in the family comparison. The family affect state trajectories show differences in responses for each family member, and the variation of the responses. For instance, in family A, the adolescent's ratings of irritation are rather stable, varying between 1 and 3, while the adolescent's ratings of irritation in family B are more variable, ranging from 1 to 7.

Figure 3.11. *Affect State Trajectory of Family A.*



Note. The reported affect states are represented by dots, and the imputed affect states by stars.

Figure 3.12. *Affect State Trajectory of Family B.*



Note. The reported affect states are represented by dots, and the imputed affect states by stars.

Additional networks

In the preregistration, we explained that we would estimate additional family networks based on subsamples of the data. A discussion of these subsamples can be found in the preregistration: *https://osf.io/72c9x/registrations*. The estimated networks based on the subsamples are available online: *https://osf.io/72c9x/*. The sample numbers correspond to the sample numbers discussed in the preregistration.