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Partitioning the variability of daily emotion dynamics in dyadic interactions with a mixed-effects location scale model

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We examine the daily exchanges in affect and emotional experiences of individuals in dyads using a mixed-effects location scale model. We argue that this method is useful to characterize the daily fluctuations in emotions for each individual as well as their interrelations over time. Furthermore, we illustrate how to consider the potential effect of factors external to the dyads' emotion dynamics, an aspect often ignored in emotion research. In particular, we show how daily weather may influence within-person variability of affect toward one's relationship, beyond the influence of one's and the partner's affect. We interpret our findings in the context of emotion research and methodology for dyadic interactions.

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Dyadic interactions change over time and involve time-lagged sequences. To examine such dynamics, two features are necessary: (a) an intense set of measurements that reflects the dyad's fluctuations over time and the time dependency of those fluctuations, and (b) models that can accurately and reliably capture such kinetics. One design suited to identify these features is the intra-individual variability design. In this design, a person is measured at multiple occasions and multiple variables, allowing researchers to study processes, as they unfold over time.

A number of modeling techniques are available that use the intensive measurements of the intra-individual variability design. One of such techniques is dynamic factor analysis (DFA; [1,2]). DFA combines factor analysis with time series, and allows the identification of the factorial structure of the data as well as its time-related signature [1,3]. DFA has been used to examine the ups and downs of daily emotions in couples [4,5]. DFA is particularly useful to address questions related to emotion dynamics, such as the number and nature of factors underlying affect (*e.g.*, positive and negative affect) together with possible influences between the individuals' emotions over time (*e.g.*, from one person to the other across days).

Increasingly popular in the social and behavioral sciences are differential equation models (DEM). DEM are useful for modeling data that are continuous, such as time series of physiological signals or fMRI. In dyadic interactions, DEM have been used as heuristics to develop theoretical models [6,7]. In addition, they have been implemented to model empirical data on the emotional interaction between spouses and subsequent break-up [8], daily intimacy and disclosure in married couples [9], and the dynamics of emotional experiences between individuals in close relationships [10–15,16•].

Arguably the most popular technique for analyzing data of dyadic interactions is multilevel modeling (MLM). MLM takes into account clustering in the data (*e.g.*, repeated observations within individuals, individuals within couples) and partitions the variance accordingly. In research with dyads, MLM has been used to distinguish among actor, partner, and interaction effects [17,18], investigate the quality of marital roles in married couples [19], characterize the interrelations of affect between romantic partners [20], model daily intimacy and disclosure in married couples [21,22], and to capture emotional contagion between couple members undergoing a stressful event [23].

MLM is a framework particularly useful to consider hierarchical structure in the data and to incorporate potential influences from covariates (both time-varying and invariant). Some of its limitations include the difficulty to capture the factorial structure in multivariate data, quantify temporal dynamics, handle small samples – or single-case studies –, or identify unique idiosyncrasy across the units in the data [15,24].

In addition to the drawbacks specific to each approach, one limitation shared by all these modeling frameworks is the lack of information about the residuals. Generally speaking, residuals represent the part that is unexplained by the model. In most approaches, such residuals (*e.g.*, random shocks, innovations) represent external influences that are not being considered by the model and that are not part of the data. MLM can accommodate various residual structures, but it is often hard to invoke a theory that dictates these residuals. Moreover, a general criticism of most models for dyadic interactions is that they represent closed systems, without information about external sources that that may permeate the dyad over time.

One relatively recent technique suited to overcome this criticism about residuals is the mixed-effects location scale model (LSM; [25–28]; see also Ref. [29•]). LSM allows partitioning the residuals in systematic ways. In particular, this modeling approach is useful to separate within- and between-subjects variability [30•], and to characterize the mean structure and variability of the response, allowing explanatory variables to account for such variation.

In social science research, LSM has been used in only a handful of occasions. For example, it was used to examine dispersion in school achievement as a function of socioeconomic status [31•], or to examine variability in adolescents' mood following a smoking event [26]. More recently, LSM was used to model the fluctuations in individuals' affect during one week [28]. In that study, individual differences in within-person variability of negative and positive affect were accounted for by perceived stress. With regard to dyadic interactions, to the best of our knowledge, LSM has yet to be used. Here, we briefly describe this modeling approach (see Ref. [32]) and illustrate its implementation using affect data from dyads.

Assume a response variable Y, measured on individual i at occasion j. A standard linear mixed-effect model can be written as

$$\mathbf{y}_{\mathrm{i}} = \mathbf{X}'_{\mathrm{i}}\,\beta + \mathbf{Z}'_{\mathrm{i}}\,\mathbf{b}_{\mathrm{i}} + \boldsymbol{\varepsilon}_{\mathrm{i}}, \tag{1}$$

where $\mathbf{y_i}$ is the response vector containing observations for individual i. $\mathbf{X}_{\mathrm{i}}$ is the design matrix for the fixed effects, β represents the fixed effects parameters, $\mathbf{Z}_{\mathrm{i}}$ is the matrix of random effects, $\mathbf{b}_{\mathrm{i}}$ is the vector with the random effects coefficients, and $\boldsymbol{\varepsilon}_{\mathrm{i}}$ denotes the residuals. In a standard linear mixed-effect model, the random effects are commonly assumed to follow a normal distribution with $\mathbf{0}$ mean and $\boldsymbol{\Phi}$ covariance matrix of random effects, including variances $\sigma^2{}_b$ and covariances $\sigma_{bb'}$. Similarly, the residuals $\boldsymbol{\varepsilon}_{\mathrm{i}}$ are assumed to be normally distributed with mean $\mathbf{0}$ and covariance of $\sigma^2{}_{\boldsymbol{\varepsilon}}\boldsymbol{\Psi}_i$.

Typically, a standard linear mixed-effect model assumes that the within-person variance $\sigma^2{}_{\boldsymbol{\varepsilon}}$ is fixed. In LSM, however, this restriction is relaxed and $\sigma^2{}_{\varepsilon i}$ is allowed to vary at the individual level and across time. The residual variance is now a function of a set of explanatory variables such as

$$\sigma^2{}_{\varepsilon ij} = \exp\left(\mathbf{W}'{}_{ij}\boldsymbol{\tau} + \mathbf{V}'{}_{ij}\mathbf{t}_i\right) \tag{2}$$

where $\mathbf{W}_{ij}$ and $\mathbf{V}_{ij}$ denote time varying covariates (for the fixed and random effects) that affect the within-person variance, $\boldsymbol{\tau}$ is a vector of regression coefficients, and $\mathbf{t}_i$ represents random effects, which are assumed to be normally distributed with mean 0 and variance $\sigma^2{}_t$. Because of the time-varying influences, the within-person variance $\sigma^2{}_{\varepsilon ij}$ is allowed to vary both across individuals and across time. Finally, the exponential function is used to ensure the variance is positive (see Refs. [26–28]).

This LSM specification can be extended to the dyad level by including an additional nested level k, as

$$\mathbf{y}_{\mathrm{ik}}\sum_{k=1}^{m} d_k(\mathbf{X}'_{\mathrm{ik}}\ \beta + \mathbf{Z}'_{\mathrm{ik}}\ \mathbf{b}_{\mathrm{ik}} + \boldsymbol{\varepsilon}_{\mathrm{ik}}), \tag{3}$$

where $k = 1, \ldots, m$, represents the number of units in the level (two in our case). Here we define $m = 2$ dummy variables, one for each partner in the dyad, where $d_k = 1$ if a given measure is y_k and $d_k = 0$ otherwise.[1] The elements in d_k are then mutually exclusive and ensure that the model is estimated either for one partner or the other partner in the dyad. The remaining components of the model are extended in a similar way.

Most of the LSMs have been estimated using Bayesian procedures (*e.g.*, MCMC; [28]), or a combination of maximum likelihood for the fixed effects and empirical Bayes methods for the random effects [41]. Here, we use maximum likelihood with dual quasi-Newton optimization, as implemented in SAS PROC NLMixed [33], a flexible program that allows constraints such as ensuring predicted values remain in bounds.[2]

Empirical example

We use data from 165 heterosexual couples recruited as part of a study of dyadic interactions [15,5]. Participants include couples involved in a romantic relationship who completed a daily questionnaire about their affect for up to 90 consecutive days. They ranged in age from 17 to

[1] This is a general expression but the specific coding scheme may vary depending on the statistical program. For example, in SAS PROC NlMixed, only one dummy variable (0,1) is necessary.

[2] Input code from SAS proc NLMixed is available from the authors via email.