Journal of Modern Applied Statistical Methods

Volume 12 | Issue 1 Article 23

5-1-2013

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Cover Page Footnote
The authors are grateful to Al Ozonoff for helpful discussions of the problem and review of the article. This research was supported by a grant from the Aerosmith Endowment Fund, Boston Children's Hospital, Boston, MA.

Journal of Modern Applied Statistical Methods
May 2013, Vol. 12, No. 1, 207-219

1538 – 9472/13/$95.00

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A method is described for estimating and testing predictors for influence on the variance of momentary behaviors in dyadic ecological momentary assessment data. Results show that the method allows intraclass correlations of momentary observations from two members of the same couple to vary by observation-level, individual-level and couple-level predictors.

Key words: Dyadic data, intra-class correlation coefficient, ecological momentary assessment.

Introduction

Human emotions and behaviors are difficult to measure and can vary greatly with time, company and context. Testing hypotheses about variable relationship dynamics often requires collecting data in a manner that accounts for this variability and records information about the many factors that can influence it, such as, social context, individual-level and dyad-level characteristics. Ecological momentary assessment (EMA) is a technique that permits data to be collected in-the-moment on emotion, behavior and other related factors at several points over the time during which the measured emotion or behavior is expected to vary.

When studying people in close relationships, such as romantic partnerships, one of the factors that has the most potential to influence an individual's emotion is that of the partner. Thus, when studying characteristics of a partnership, such as sexual behavior or individual mood, collecting data on both members of a couple is important (Bolger, Davis & Rafaeli, 2003; Harvey, et al., 2004). Data collected in this way are often referred to as dyadic data. Momentary information from both members of a dyad is likely to be associated, but there are certain factors that may influence the dyad-level intra-class correlation (ICC) or degree of association of these momentary measures (Newsom, 2002). This study focuses on research questions related to factors associated with the dyad-level ICC.

Ecological Momentary Assessment

Ecological momentary assessment (EMA) is a data collection technique in which research study participants complete questionnaires via a handheld computer signaled repeatedly throughout a day. This method allows many behavioral research questions to be answered (Schwatz & Stone, 2007). As opposed to only obtaining one or a few datapoints from each individual in a study, as in traditional cross-sectional or longitudinal studies, several datapoints are collected per day, thus, each participant typically provides many datapoints; this permits a researcher to gain near real-time assessment of behavioral measures of interest. EMA is particularly useful in behavioral studies because it reduces recall bias associated with self-report data (Stone & Shiffman, 2002). In addition, the amount of data collected from each

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individual allows a researcher to study not only the mean of the desired outcome, but also how an individual's response changes over time and in response to momentary influences. This provides a level of data not previously available – even from long-term longitudinal studies. The most commonly used method for analysis of these data is a mixed effects model (Laird & Ware, 1982), which provides a flexible approach to account for correlation due to multiple observations from the same individual, while not requiring each individual to have the same number of observations.

Dyadic Data

The study of behavior and emotion naturally benefits from gathering information about the most influential factors. For many individuals, characteristics of their close relationships may extensively influence their behavior and affect (Burleson, Trevathan & Todd, 2007; Widman, Welsh, McNulty & Little, 2006). For this reason, it is desirable to study couples or dyads together. Methodologically, these data are more complete in terms of potentially influential factors, because interactions between partners (such as disagreements or sexual intercourse), couple-level characteristics (such as relationship duration) and individual-level characteristics (such as age) may all play a role in determining behavior and mood (Burleson, et al., 2007; Fortenberry, et al., 2005). Dyadic data, therefore, can answer complex questions about behavior and mood.

Analytically, dyadic data presents challenges when compared with data from independent individuals. Several methods have been proposed for analyzing dyadic data (Kenny, Kashy & Cook, 2006), among them are methods based on mixed effects or multi-level models and structural equation models (Laurenceau & Bolger, 2005). Many of these methods, however, require each observation to have a measure from one member of the dyad paired with a measure from the other member of the dyad so that the data consists of multiple paired observations; this is not always the case depending on how data is collected. Laurenceau and Bolger (2005) emphasized that predicting causes of variability among dyads and covariability between members of a dyad are of distinct interest. A method proposed by Raudenbush, Brennan and Barnett (1995) for distinguishable dyads does not require observations to be paired and proposes a multi-level approach to analyzing dyadic data; their model fits a two-intercept model (one for males, one for females) and individual-level random effects for each partner. The covariance between partners is captured as the covariance of the male and female random effect.

Dyadic EMA Data

EMA can be used in observational behavioral studies of dyads where information is collected from both members of a dyad electronically on a momentary basis. This technique provides rich data that allow the study of both mean and variability within and between individuals as well as within and between dyads, thus providing the advantages of both EMA data and dyadic data. Data collection is aimed at providing a random sample of moments throughout the day for every individual, each of whom may have differing schedules. Individuals in the dyad are therefore not signaled at exactly the same time.

These data, however, increase the complexity of the analysis; there is a more complicated correlation structure than in typical EMA data and more repeated measures than a usual dyadic diary data. Unlike diary dyadic data, the measurements for each member of a dyad are not distinctly paired to an observation from the other member (because each individual is signaled randomly within a day); therefore, methods specific to dyadic diary data (Laurenceau & Bolger, 2005) cannot always be applied. The Raudenbush, et al. (1995) method can be applied to dyadic EMA data with distinguishable dyads.

A mixed effect regression model with a random individual intercept to account for the correlation of repeated observations from the same individual and a random dyad intercept to account for the correlation of repeated observations from the same dyad. The model can incorporate momentary observation-level predictors, individual-level predictors and couple-level predictors. In addition to modeling means based on all levels of predictors, variance components can also be modeled on multiple levels of predictors.

Hedeker and Mermelstein (2007) described methods for estimating heterogeneous variances determined by subject-level characteristics in individual EMA data and note the importance of characterizing individual-level variability. The method of estimating heterogeneous variances is presently applied to estimate heterogeneous variances at the levels of the dyad, the observation and the individual and the way in which heterogeneous variances determined by dyad-level predictors contribute to heterogeneous dyad-level ICCs is illustrated herein. Thus, by estimating heterogeneous dyad-level ICCs, questions about differences in within-couple similarity of responses for different types of couples can be answered.

The multi-level model proposed is most similar to that introduced by Raudenbush, et al. (1995), but does not require distinguishable dyads and does not fit separate fixed and random intercepts for each member of the couple. The proposed model fits a single individual-level random effect in addition to a dyad-level random effect, which allows for testing dyad-level variance heterogeneity. The variance of the individual-level random effects is thus the same for both members of the couple, not specific to gender. The proposed model also does not fit separate effects of individual-level predictors for each member of the couple, although such effects could be estimated in the current model by adding interaction terms with gender.

It is of interest whether momentary observations from the two members of a dyad in one group are closely related while observations from the two members of a dyad in another group tend to be more disparate. Specifically, do dyads with a given dyad-level characteristic tend to have individual momentary responses that are similar to one another more often (high covariance, large dyad-level ICC) than dyads with a different value of that couple-level characteristic? The advantage of having data that is both dyadic and EMA in nature is that these types of research questions can be answered. The way in which couple-level predictors affect both mean level of momentary individual outcomes as well as the interplay between the members of the couple can be determined.

Young Adult Couples Study

Shrier and colleagues performed a study designed to assess affective states, emotional intimacy, relationship qualities and sexual behaviors in heterosexual young adult couples (Sunner et al. 2012). Primary research questions of this study included exploring affective patterns and affective concordance and discordance within a couple related to intimacy, communication and behaviors during the daily course of a relationship. Secondary research questions investigated whether couple-level characteristics influenced the degree to which momentary measures from a couple were related. For example, do couples who have been in a relationship for longer periods of time tend to have momentary measures of affect that are more similar while couples with shorter relationship duration tend to have momentary measures of affect that are more dissimilar? When the male partner of a heterosexual couple rates relationship conflict higher than the female, does that couple tend to have more similar momentary affect measures than couples in which the female rates relationship conflict higher? To assess these research questions, analytic techniques are needed to test for couple-level heterogeneity in the association of momentary measures.

Methodology

Dyadic EMA data were collected from both members of a dyad over time. Data from each member is not necessarily collected at the same moment and each member of the dyad is not required to have the same number of observations. However, observations from different members of the same dyad should be assumed to be correlated, as should the repeated observations from each individual. Dyadic EMA data can be represented with a mixed effects regression model, with a random effect of the couple, a random effect of the individual and an observation-level error term. The model can also include fixed effects at the observation, individual, or couple level. The model is:

$$Y_{ipj} = \beta_0 + \beta_1 x_{ipj} + \beta_2 x_{ip} + \beta_3 x_p + v_{ip} + v_p + \varepsilon_{ipj} \tag{1}$$

where i (i = 1, …, N) indexes the individual, p = 1, …, P indexes the dyad and j (j =1, …, J_i) indexes the observation. Observation, individual and couple-level predictors are represented by x_{ipj}, x_{ip}, and x_p, respectively. Conditional on the random individual and random dyad effects, the observations are assumed independent from each other and errors are assumed to be normally distributed; therefore the covariance matrix for ε is $\sigma_\varepsilon^2 I$. If the individual and dyad random effects (v_{ip} and v_p, respectively) are assumed to be independent, then the covariance matrix of the random effects is:

$$\begin{bmatrix} \sigma_{ip}^2 & 0 \\ 0 & \sigma_p^2 \end{bmatrix}.$$

The resulting variance-covariance matrix of all observations is block diagonal with observations from different dyads being independent and observations from the same dyad having the following variance-covariance block matrix (see Figure 1). The upper left and lower right sections of this matrix give the within-person covariance matrix for each member of the dyad and the lower left and upper right blocks give the between-person covariance matrix between the members of the dyad. The variance of a given observation Y_{ipj} is $\sigma^2_{ip}+\sigma^2_p + \sigma^2_\varepsilon$. This quantity is made up of the variance in individuals (σ^2_{ip}), the variance in dyads (σ^2_p) and the degree of residual variability in an observation (σ^2_ε). The covariance between two observations from the same individual at different times is $\sigma^2_{ip}+\sigma^2_p$, and the covariance between two observations from different individuals is σ^2_p.

In dyadic data, several research questions focus on the similarity of momentary responses among members of the same dyad. Because the observations from each member of the dyad are collected randomly throughout the day, each datapoint from one member does not match up to the time and date of a datapoint from the other member. The correlation between paired observations from the same dyad can therefore not be computed (which is possible with non-EMA dyadic data): the ICC of a dyad must be computed to evaluate this phenomenon. This is accomplished by examining the covariance between any given observation from one member of the dyad and any given observation from the other member of the dyad. The variance-covariance matrix (Figure 1) from one dyad shows that this quantity is expressed as σ^2_p and, when scaled to the total variance of all observations, represents the dyad-level ICC. A dyad-level ICC is generally defined as the variance of a dyad divided by the total variance and this quantity represents the degree of association among observations from the same pair (Newsom, 2002). With this model specification, the dyad-level ICC is the ratio of the dyad-level variance to the total variance of an observation:

Figure 1: Block Diagonal Variance-Covariance Matrix of All Observations

$$\begin{bmatrix}
\sigma_{ip}^2+\sigma_p^2+\sigma_\varepsilon^2 & \sigma_{ip}^2+\sigma_p^2 & \cdots & \sigma_{ip}^2+\sigma_p^2 & \sigma_p^2 & \sigma_p^2 & \cdots & \sigma_p^2 \\
\vdots & \sigma_{ip}^2+\sigma_p^2+\sigma_\varepsilon^2 & & \sigma_{ip}^2+\sigma_p^2 & \sigma_p^2 & \sigma_p^2 & \cdots & \sigma_p^2 \\
\vdots & & \ddots & \sigma_{ip}^2+\sigma_p^2 & \vdots & \vdots & & \vdots \\
\sigma_{ip}^2+\sigma_p^2 & & & \sigma_{ip}^2+\sigma_p^2+\sigma_\varepsilon^2 & \sigma_p^2 & \sigma_p^2 & \cdots & \sigma_p^2 \\
\sigma_p^2 & \sigma_p^2 & \cdots & \sigma_p^2 & \sigma_{ip}^2+\sigma_p^2+\sigma_\varepsilon^2 & \sigma_{ip}^2+\sigma_p^2 & \cdots & \sigma_{ip}^2+\sigma_p^2 \\
\sigma_p^2 & \sigma_p^2 & \cdots & \sigma_p^2 & \sigma_{ip}^2+\sigma_p^2 & \sigma_{ip}^2+\sigma_p^2+\sigma_\varepsilon^2 & & \sigma_{ip}^2+\sigma_p^2 \\
\vdots & & & \vdots & \vdots & & \ddots & \sigma_{ip}^2+\sigma_p^2 \\
\sigma_p^2 & \cdots & \cdots & \sigma_p^2 & \sigma_{ip}^2+\sigma_p^2 & & & \sigma_{ip}^2+\sigma_p^2+\sigma_\varepsilon^2
\end{bmatrix}$$

$$\frac{\sigma_p^2}{\sigma_{ip}^2 + \sigma_p^2 + \sigma_\varepsilon^2}.$$

This result is highlighted because, if heterogeneous variance components for the dyad-level random effect are estimated, heterogeneous covariance between two observations from the same dyad (σ^2_p) and therefore heterogeneous dyad-level ICCs will be modeled. However, heterogeneous dyad-level ICCs can also result from heterogeneity in σ^2_{ip} and/or σ^2_ε, because these terms appear in the denominator of the ICC. The dyad-level ICC is of interest in describing EMA data from a couple because it represents the degree of association between momentary responses of the two members of a dyad. Although in some longitudinal studies, correlation between observations are sometimes considered a nuisance rather than an object of study, in individual EMA studies, Hedeker and Mermelstein (2007) have shown the variances and covariances of observations can themselves be informative. This is particularly true with dyadic EMA data where there is interest in the degree of association of momentary response from dyad members.

Suppose there is a couple-level characteristic such as relationship duration that is believed influences the dyad-level ICC. A model of heterogeneous dyad-level random effects can be described where one dyad-level variance is specified for the dyads with short relationship duration and another dyad-level variance is specified for the dyads with a longer relationship duration:

Short Duration Group

$$Y_{ipj} = \beta_0 + \beta_1 x_{ipj} + \beta_2 x_{ip} + \beta_3 x_p + v_{ip} + v_{p*} + \varepsilon_{ipj} \tag{2}$$

Long Duration Group

$$Y_{ipj} = \beta_0 + \beta_1 x_{ipj} + \beta_2 x_{ip} + \beta_3 x_p + v_{ip} + v_{p'} + \varepsilon_{ipj} \tag{3}$$

The dyad-level ICC for dyads in the short relationship duration group is

$$\frac{\sigma_{p*}^2}{\sigma_{ip}^2 + \sigma_{p*}^2 + \sigma_\varepsilon^2}.$$

Similarly, the dyad-level ICC for dyads with longer relationship duration is

$$\frac{\sigma_{p'}^2}{\sigma_{ip}^2 + \sigma_{p'}^2 + \sigma_\varepsilon^2}.$$

Heterogenous variance models can be estimated using the GROUP option in SAS PROC MIXED RANDOM and REPEATED statements (see Appendix A for example SAS code).

In addition to fitting this model, the hypothesis that there is a difference in dyad-level variance can be tested, similar to the tests on the individual-level variance performed by Hedeker and Mermelstein (2007) in individual EMA data. If all other aspects of the model remain the same, a model with homogeneous dyad-level variance is nested within a model with heterogeneous variance at this level, thus, differences in deviances (−2 log likelihood) between the two models can be computed and compared to a Chi-square critical value with 1 degree of freedom.

Because the dyad-level ICC is composed of several variance components, however, heterogeneity in dyad-level ICC due to a dyad-level characteristic is possible in several ways. If, for example, the observation-level variance differs between dyads with a longer versus shorter relationship durations, but all other variance components are homogeneous, the dyad-level ICC will still differ by relationship duration. Specifically, the dyad-level ICC in the long duration group would be:

$$\frac{\sigma_p^2}{\sigma_{ip}^2 + \sigma_p^2 + \sigma_{\varepsilon'}^2}$$

and the dyad-level ICC in the short duration group would be:

$$\frac{\sigma_p^2}{\sigma_{ip}^2 + \sigma_p^2 + \sigma_{\varepsilon*}^2}.$$

This heterogeneity can be modeled and tested. With dyadic data, there are three levels of variability, each of which could be affected by a dyad-level characteristic. Table 1 shows all combinations of homogeneous and heterogeneous variance in a dyadic multilevel model. If no level of variance differs by a dyad-level characteristic then Model (1) is appropriate. If there is variance heterogeneity only at the dyad-level then Model (2) is appropriate. If there is variance heterogeneity at all levels of variance then Model (8) is appropriate. Appropriate variance models can be selected by comparing −2 log likelihood values for nested models or comparing AIC and BIC for non-nested models (Hedeker & Mermelstein, 2007). After the appropriate model is selected, heterogeneity in dyad-level ICC ($\hat{\rho}$) can be estimated and tested.

Using the delta method (Casella & Berger, 2002) the variance of each ICC can be estimated and these variances can be used to create confidence intervals and to construct a test of differences in ICCs between dyad groups. The delta-method variance of an ICC estimate is:

$$var(\hat{\rho}) = \left[\hat{\rho}(1-\hat{\rho})\right]^2 \left[\frac{var(\hat{\sigma}_p^2)}{(\hat{\sigma}_p^2)^2} + \frac{var(\hat{\sigma}_{ip}^2)}{(\hat{\sigma}_{ip}^2+\sigma_\varepsilon^2)^2} + \frac{var(\hat{\sigma}_\varepsilon^2)}{(\hat{\sigma}_{ip}^2+\sigma_\varepsilon^2)^2} \right] - 2\frac{\left[\hat{\rho}(1-\hat{\rho})\right]^2}{\hat{\sigma}_{ip}^2+\sigma_\varepsilon^2} \left[\frac{cov(\hat{\sigma}_p^2,\hat{\sigma}_{ip}^2)}{\hat{\sigma}_p^2} + \frac{cov(\hat{\sigma}_p^2,\hat{\sigma}_\varepsilon^2)}{\hat{\sigma}_p^2} - \frac{cov(\hat{\sigma}_{ip}^2,\hat{\sigma}_\varepsilon^2)}{\hat{\sigma}_p^2+\hat{\sigma}_\varepsilon^2} \right] \quad (4)$$

which leads to confidence intervals of the form $\hat{\rho} \pm z_{\alpha/2}\sqrt{\mathrm{var}(\hat{\rho})}$ and a test statistic for comparing two dyad-level ICCs, $\frac{\hat{\rho}_1-\hat{\rho}_2}{\sqrt{\mathrm{var}(\hat{\rho}_1-\hat{\rho}_2)}}$, with a standard normal distribution.

Young Adult Couples Study

The technique of selecting the appropriate model and testing for heterogeneity in dyad-level ICC is illustrated using data collected in the Young Adult Couples Study conducted by Shrier, et al. (Sunner et al. 2012). A total of 2,089 observations were obtained from 36 participants (18 heterosexual couples) aged 18-25 years. To be eligible for the study, couples had to have been in a relationship for at least 3 weeks. Ecological momentary assessment data was gathered from participants, with each individual contributing between 15 and 107 observations. Each member of the couple was asked several baseline questions regarding demographics, relationship duration and quality, emotional and physical intimacy, sexual behavior and substance use. Each individual was given a handheld computer and was randomly signaled several times within a day to complete questionnaires on affect, disagreements, sexual behavior and substance use. Individuals carried the handheld computer for up to two weeks.

Momentary affective states were measured using an abbreviated version of the Positive and Negative Affect Scale (PANAS; Watson, Clark & Tellegen, 1988) consisting of 5-point Likert scale ratings for 6 positive and 6 negative affective states. A composite positive score and a composite negative score were computed by summing item ratings for each type. Baseline measures included: relationship duration was dichotomized to shorter duration, defined as <3 months, and longer duration, defined as ≥3 months and Quality of Relationship Inventory (QRI; Pierce, Sarason & Sarason, 1991) measuring relationship quality. The QRI included a depth subscale (6 items, Cronbach's α = 0.77), a conflict subscale (12 items, Cronbach's α = 0.89) and a social support subscale (7 items, Cronbach's α = 0.66). Dyadic data from 18 of 20 couples were available.

To explore methods for secondary research questions specific to the effect of dyad-level predictors on the dyad-level ICC in EMA data, two example hypotheses were examined. These analyses represent a range of possible applications of the heterogeneous ICC technique in dyadic EMA data. Whether couples in longer-term relationships tended to have momentary affect measures that were more similar to their

Table 1: Dyadic Data Models of Variance Heterogeneity

Model	Dyad Variance	Individual Variance	Observation Variance	Variance Parameter Estimates
(1)	Homogeneous	Homogeneous	Homogeneous	3
(2)	**Heterogeneous**	Homogeneous	Homogeneous	4
(3)	Homogeneous	**Heterogeneous**	Homogeneous	4
(4)	Homogeneous	Homogeneous	**Heterogeneous**	4
(5)	**Heterogeneous**	**Heterogeneous**	Homogeneous	5
(6)	**Heterogeneous**	Homogeneous	**Heterogeneous**	5
(7)	Homogeneous	**Heterogeneous**	**Heterogeneous**	5
(8)	**Heterogeneous**	**Heterogeneous**	**Heterogeneous**	6

Table 2: Fit statistics From Models of Relationship Duration Associated with Momentary Negative Affect

Model	Dyad Variance	Individual Variance	Observation Variance	−2LL[1]	AIC[2]	BIC[3]
(1)	Homogeneous	Homogeneous	Homogeneous	9950.6	9956.6	9959.2
(2)	**Heterogeneous**	Homogeneous	Homogeneous	9941.9	9949.9	9953.5
(3)	Homogeneous	**Heterogeneous**	Homogeneous	9941.7	9949.7	9953.3
(4)	Homogeneous	Homogeneous	**Heterogeneous**	9807.9	9815.9	9819.5
(5)	**Heterogeneous**	**Heterogeneous**	Homogeneous	9934.5	9944.5	9948.9
(6)	**Heterogeneous**	Homogeneous	**Heterogeneous**	9799.3	9808.3	9813.8
(7)	Homogeneous	**Heterogeneous**	**Heterogeneous**	9799.5	9809.5	9813.9
(8)	**Heterogeneous**	**Heterogeneous**	**Heterogeneous**	9792.2	9804.2	9809.6

1: −2 log-likelihood
2: Akaike information criterion
3: Bayesian information criterion

partner versus couples who had not been in a relationship for as long was examined first. Next, because the study of young adult couples consisted only of heterosexual couples, the members of the dyads are distinguishable by gender. This distinguishability can therefore be used to create directional couple-level variables. As an example, a couple-level characteristic indicating whether the male rated the relationship conflict higher than the female is created. In the second research question, this directional couple-level predictor is used to test whether those couples in which males rated the relationship conflict higher than the female tended to have more or less similar momentary negative affect. In all models, fixed effects of dyad-level predictors are included in the models to test whether the dyad-level predictors affects the mean outcome in addition to the variability.

Results

Relationship Duration and Negative Affect

In the Young Adult Couples Study data, two hypotheses related to heterogeneous ICCs were tested. The first was related to the effect of relationship duration on similarity in negative affect within a couple. A first step in testing this hypothesis was determining whether heterogeneity exists at the dyad-level, individual-level or observation-level. Therefore, all possible models allowing for heterogeneity of variance component were fit. The fit statistics from these models are provided in Table 2.

First, the fit statistics from each of Model (2), Model (3) and Model (4) respectively, were compared to Model (1), the completely homogeneous model. The homogeneous model is nested within each of these models with only one degree of freedom difference and a Chi-square likelihood ratio test was performed. To test dyad-level variance heterogeneity, Model (2), with a −2 log likelihood value of 9941.9, was compared to Model (1), with a −2 log likelihood of 9950.6. The difference between these likelihoods is 8.7 indicating significant dyad-level heterogeneity (X^2 (1) = 8.7, p = 0.003). Likewise, a comparison of likelihoods from Model (3) to (1) (9950.5-9941.7 = 8.9) shows significant individual-level heterogeneity ($X^2(1) = 8.9$, p = 0.003). Finally, a comparison of Models (4) and (1) indicates heterogeneity at the observation level as well ($X^2(1) = 142.7$, $p < 0.001$). Because there is evidence of heterogeneity at all three levels of variance, the full Model (8) was considered. Nesting Models (5), (6) and (7) within Model (8) and conducting likelihood ratio tests confirmed that all three levels of heterogeneity were statistically significant within the full model. Model (8), therefore, appears to be the best model; this model has the lowest AIC and BIC values (9804.2 and 9809.6) indicating best fit. Model (8) was fit to the data and the dyad-level ICCs for short and long duration were computed. Model (8)'s fit to the adolescent couples study is displayed in Table 3.

Examining the effects of relationship duration, a shorter relationship duration was associated with more similarity in momentary negative affect. Couples with a shorter relationship duration (n = 9) had a dyad-level ICC (95% CI) of 0.49 (0.20, 0.77); dyad-level ICC in the group of couples with longer relationship duration was 0.19 (0.01, 0.38). To test whether this difference in similarity within couple was significant, a significance test based on the delta-method was performed. The value of the test statistic was 1.71 (p-value = 0.09). Despite the significant variability at all levels of variance, the heterogeneity in the dyad-level ICC's for short and longer duration couples was not statistically significant.

Relationship Conflict and Negative Affect

Working with distinguishable dyads, directional differences in dyad-level characteristics can also be examined. This is illustrated by categorizing couples by which partner rated level of relationship conflict higher, the male or the female, and whether this influenced the similarity of within-couple momentary negative affect was explored. First, it is necessary to determine if heterogeneity in variance components occurs at any of the three levels. To do this, likelihood values for Models (2), (3) and (4) were compared to Model (1), the homogeneous model. Fit statistics from Models (1) through (8) are shown in Table 4. Comparing Model (2) to (1), shows significant heterogeneity at the dyad-level ($X^2(1) = 8.9$, p = 0.003); comparing Model (3) to (1) and Model (4) to (1).

Table 3: Model of Relationship Duration Affecting Momentary Negative Affect Allowing Heterogeneity of Variance at All Levels (Model (8))

	Estimate	(SE)
Fixed Effect		
Short duration	9.4024	(1.1706)
Long duration	78.542	(0.3780)
p-value	.23	
Random Dyad Effect		
Short duration	11.0387	(6.2010)
Long duration	1.0992	(0.6490)
Individual Effect		
Short duration	2.4066	(1.2202)
Long duration	0.2765	(0.1708)
Observation Effect		
Short duration	9.1568	(0.4093)
Long duration	4.3069	(0.1891)
Dyad-level Intra-class Correlation Coefficient (ICC)		
Short duration	0.4884	(0.1455)
Long duration	0.1934	(0.0933)
Test of Heterogeneity of Dyad-level ICC		
p-value	.09	

Table 4: Fit Statistics from Models of Ratings of Relationship Conflict Affecting Momentary Negative Affect

Model	Dyad Variance	Individual Variance	Observation Variance	−2LL[1]	AIC[2]	BIC[3]
(1)	Homogeneous	Homogeneous	Homogeneous	9949.9	9955.9	9958.6
(2)	**Heterogeneous**	Homogeneous	Homogeneous	9941.0	9949.0	9952.6
(3)	Homogeneous	**Heterogeneous**	Homogeneous	9949.6	9957.6	9961.2
(4)	Homogeneous	Homogeneous	**Heterogeneous**	9949.8	9957.8	9961.4
(5)	**Heterogeneous**	**Heterogeneous**	Homogeneous	9940.9	9950.9	9955.3
(6)	**Heterogeneous**	Homogeneous	**Heterogeneous**	9940.9	9950.9	9955.4
(7)	Homogeneous	**Heterogeneous**	**Heterogeneous**	9949.5	9959.5	9964.0
(8)	**Heterogeneous**	**Heterogeneous**	**Heterogeneous**	9940.8	9952.8	9958.1

1: −2 log-likelihood
2: Akaike information criterion
3: Bayesian information criterion

show that no significant heterogeneity occurs at the individual-level ($X^2(1) = 0.3$, $p = 0.58$) or the observation-level ($X^2(1) = 0.1$, $p = 0.75$). Model (2) appears to be the appropriate model for these data; fitting this model allowed estimation of the heterogeneity of the dyad-level ICC. Results from Model (2) are displayed in Table 5.

In dyads where females reported higher relationship conflict, momentary negative affect was more similar between members of the dyad compared to dyads in which males reported higher relationship conflict (dyad-level ICC, 95% CI, where females reported higher relationship conflict than males was 0.75 (0.44, 1.1) versus 0.18 (0.01, 0.35)). Testing whether these two ICC's were statistically different, yields a test statistic of 3.16 (p-value = 0.002) indicating that these values differ significantly. This significant heterogeneity in dyad-level ICC is observed despite no significant effect of relationship conflict measures on mean negative affect.

Conclusion

It was demonstrated that the use of heterogeneous variance terms in a mixed effect model of dyadic EMA data effectively estimates and allows for testing of heterogeneous dyad-level ICCs, which are often the focus of dyadic data research questions. Thus, this technique fills a methodologic void in dyadic EMA data analysis.

Many techniques available for dyadic data are not applicable to unpaired EMA data and require paired observations from members of a dyad. Analyzing unpaired EMA data with these techniques requires aggregation to obtain paired observations from members of a dyad (Laurenceau & Bolger, 2005). Although aggregating these data across a period of time allows questions to be asked regarding the influence of one dyad member's response on the other dyad member's response, it also results in a loss of the momentary aspect of this data so the EMA data are not used to their fullest extent.

Table 5: Model of Ratings of Relationship Conflict Associated With Momentary Negative Affect Allowing Heterogeneity of Variance at the Dyad-Level (Model (2))

	Estimate	(SE)
Fixed Effect		
Male ≥ Female	8.1837	(0.4227)
Male < Female	10.1931	(2.4936)
p-value	.44	
Random Dyad Effect		
Male ≥ Female	1.7594	(1.0050)
Male < Female	24.1525	(20.3225)
Individual Effect		
	1.3316	(0.4889)
Observation Effect		
	6.6898	(0.2096)
Dyad-level Intra-class Correlation Coefficient (ICC)		
Male ≥ Female	0.1799	(0.0869)
Male < Female	0.7507	(0.1581)
Test of Heterogeneity of Dyad-level ICC		
p-value	.002	

Answering research questions using mixed effect models of momentary data capitalizes on EMA data benefits, such as reduction of recall bias and in-the-moment information about behavior and emotions, while also being able to answer questions that take the dyadic nature of the data into account.

With dyadic EMA data, research questions often focus on the degree to which momentary responses of individuals in a dyad are related (as measured by a dyad-level ICC). To answer such questions, the application of a technique for estimating heterogeneous variance components to the random effects in EMA data was proposed with the result of actually estimating heterogeneous dyad-level ICCs. With this method dyad-level characteristics can be tested for their influence on dyad-level ICCs.

Data from the Young Adult Couples Study was used to demonstrate that couple-level characteristics can influence the dyad-level ICC despite not directly influencing the mean of the measure itself. For example, the variability at the observation, individual and dyad-level was significant by relationship duration, however, the associated effect on the dyad-level ICC was tested and no significant difference was found. With the gender-distinguishable dyads the direction – not only the degree – of the discrepancy between couples was related to the magnitude of the dyad-level ICC. For example, when couples rated a difference in relationship conflict, momentary affect measures were more similar when the female rated the relationship conflict higher than the male. Together these results show the possible research questions that can be answered by applying this technique to dyadic EMA data.

One limitation of this study was the small sample size available to demonstrate this methodology. Although data from only 36 participants (18 couples) was used, a large amount of data within participant was available providing adequate data for evaluating momentary measures. Additionally, this study was limited to a basic application of heterogeneous variance estimation technique to dyadic EMA data. The relationship between dyad-level predictor and degree of association between momentary assessments of members of the dyad was limited to categorical dyad-level predictors. Hedeker, et al. (2008) proposed more complex log-linear models estimated via non-linear mixed effects models for individual-level EMA data that can incorporate continuous predictors as well as categorical predictors into the variance models. These models, however, have not been extended to dyadic data or used for computing heterogeneous ICCs. More complex associations between dyad-level characteristics and momentary measures may require more complex variance models. Finally, the model proposed does not account for time between measurements. For a dyadic EMA analysis, it is possible to incorporate random slope terms in addition to random intercept terms, however, this will make the estimation of dyad-level ICC much more complex and dependent on time. The model proposed examines, over the course of the study, the similarity in measurements between members of a couple.

The proposed analysis technique allows for testing the influence of dyad-level characteristics on degree of association among momentary responses of members of a dyad. The set of analyses performed on the Young Adult Couples Study illustrates that important insights about behavior and affect of dyads can be gained by testing such hypotheses. By examining the influences on the couple's emotion and behavior, as measured by ICC, in addition to the individual's behavior, as measured by mean and variance, it is possible to study the couple as a unit as opposed to solely as two individuals.

Acknowledgements

The authors are grateful to Al Ozonoff for helpful discussions of the problem and review of the article. This research was supported by a grant from the Aerosmith Endowment Fund, Boston Children's Hospital, Boston, MA.

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Appendix A: SAS Code for Estimating Heterogeneity at All Levels of Variance

This code is based on the negative affect model (`na`) examining the effect of relationship duration (`longduration`).

```
PROC MIXED DATA=couples COVTEST ASYCOV;
CLASS subid pairid longduration;
MODEL na = longduration / SOLUTION;
RANDOM intercept / SUBJECT=pairid GROUP=longduration;
RANDOM intercept / SUBJECT=subid(pairid) GROUP=longduration;
REPEATED / SUBJECT=subid(pairid) GROUP=longduration;
TITLE 'Model 8';
RUN;
```

A RANDOM statement is given to specify heterogeneity at each of: the random effect at the dyad level (`pairid`) and the random effect at the individual level (`subid(pairid)`).

A REPEATED statement is given to specify heterogeneity in the residual error.

The ASYCOV option is used to output the covariance components of the covariance parameter estimates needed for calculation of the delta-method variance.