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Multilevel Modeling of Social Interactions and Mood in Lonely and Socially Connected Individuals

The MacArthur Social Neuroscience Studies

Louise C. Hawkley, Kristopher J. Preacher, and John T. Cacioppo

For all the intellectual sophistication and ingenuity of the human species, it is our rudimentary need to belong (Baumeister & Leary, 1995) that motivates much of our behavior and shapes our thoughts and feelings about others. We engage in strategies that facilitate being accepted by others; we cultivate friendships and partnerships; we strive to overcome obstacles that threaten our social bonds; and we suffer when our social relationships are hurting or broken. Ultimately, the success we experience in achieving, negotiating, and maintaining our social relationships helps determine our overall satisfaction with life (Myers, 2000; Myers & Diener, 1995).

Social relationships take shape and substance in social interactions, and the quality of interactions therefore contributes to the impact of social relationships on mood and well-being. In cross-sectional studies, correlations are often observed between mood and interaction type or quality. Moreover, experimental evidence has indicated a bidirectional causal relationship between social interactions and mood. Although experimental manipulations establish the temporal precedence required to infer causality, manipulations of social exchanges or mood are typically low in ecological validity. Experimental constraints on participant choice of interaction partner or setting, for example, are not trivial when we are interested in generalizing reciprocal influences to everyday life. A preferable test of the causal relationship between mood and social exchanges is to examine their reciprocal influence in everyday contexts.

Importantly, permitting individuals to choose when, where, and with whom they interact also allows a realistic evaluation of individual differences in estimates of the relationship between interaction quality and mood. We know that some individuals report dissatisfaction with their social relationships and a feeling of isolation or lack of relational or collective connectedness with friends or groups (Hawkley, Browne, & Cacioppo, 2005). We have begun to learn that potentially adverse health consequences may ensue from these feelings of loneliness and isolation (e.g., Cacioppo et al., 2002; Hawkley, Burleson, Berntson, & Cacioppo, 2003). In marked contrast, very little research has examined how those who are low in feelings of loneliness are protected from these consequences. Studying these socially connected individuals—their cognitions, motives, and interactions—could help us understand what it means to be a successful social being.

In prior research (Hawkley et al., 2003), we found that socially connected individuals reported less negativity and more positivity in feelings about their interaction partners than did their lonely counterparts. Socially connected individuals also reported lower negative affect and higher positive affect over the course of the week than did their less connected counterparts. Several explanations could contribute to these differences in affect and interaction quality. First, the social interactions of socially connected individuals could be objectively different than those of lonely individuals. For example, socially connected individuals may attract or choose the kind of interaction partners that facilitate positive social exchanges, and this could subsequently contribute to higher positive affect and lower negative affect among socially connected than lonely individuals. Second, comparable social interactions may be perceived more positively by socially connected than by lonely individuals. The same perceptual bias may contribute to reported mood differences between socially connected and lonely individuals. Third, socially connected individuals may experience a larger or longer-lasting boost in mood following positive social interactions, or a smaller or shorter-lasting decrement in mood following negative social interactions. This could help to explain why, across a typical week, average positive affect was higher and average negative affect was lower among socially connected than lonely individuals. For each of these explanations, the underlying assumption is that affective aspects of everyday life may contribute to downstream health effects, and more interaction positivity or less negativity could put socially connected individuals at a distinct advantage.

Theoretical Background

Numerous studies have examined the relationship between social interactions and mood, and results suggest a reciprocal causal relationship. For example, in a series of experimental studies, Cunningham (1988a, 1988b) induced mood states and found that a positive mood, relative to a negative mood, stimulated greater interest in social interactions and increased conversation quantity and quality (i.e., self-disclosure). The reverse causal direction has also garnered support, however. In a series of experimental studies, McIntyre and colleagues found that either spontaneous or arranged social interactions increased positive affect relative to affect during a neutral control setting (McIntyre, Watson, Clark, & Cross, 1991; McIntyre, Watson, & Cunningham, 1990). Similarly, when a diary methodology was employed, state positive affect was higher when individuals were socializing (Watson, Clark, McIntyre, & Hamaker, 1992), engaging in physically active social events (Clark & Watson, 1988), interacting with familiar as opposed to relatively unfamiliar partners (Vittengl & Holt, 1998a), and experiencing fun or necessary social interactions (Vittengl & Holt, 1998b). Conversely, negative affect was elevated during arguments and confrontations (Clark & Watson, 1988; Vittengl & Holt, 1998b), interactions marked by the receipt of social support (Vittengl & Holt, 1998b), and interactions with poor communication quality (Vittengl & Holt, 1998a).

Positive and negative affect are largely independent dimensions of mood (Watson, Clark, & Tellegen, 1988) and may be differentially affected by positive and negative qualities of social interactions. In cross-sectional analyses, Rook (2001) found that number of daily positive social exchanges was related to greater daily positive mood but was unrelated to negative mood, whereas number of negative social exchanges was related to dampened positive mood and increased negative mood. Similarly, Finch, Okun, Barrera, Zautra, and Reich (1989) showed that number of positive social ties was associated with well-being, whereas number of negative ties was associated with well-being and psychological distress. More recently, Newsom, Nishishiba, Morgan, and Rook (2003) reported significant correlations between positive and negative social exchanges and both positive and negative affect in both cross-sectional and longitudinal analyses. However, independent of each other, concurrent effects of positive and negative social exchanges were valence-specific. That is, frequency of negative exchanges predicted negative affect and not positive affect when positive exchanges were held constant, and frequency of positive exchanges predicted positive affect and not negative affect when negative exchanges were held constant. On the other hand, longitudinal analyses revealed independent crossover effects: When positive exchanges were held constant, frequency of negative exchanges at baseline predicted both positive and negative affect at follow-up, whereas positive exchanges, independent of negative exchanges, did not predict either positive or negative affect at follow-up.

The foregoing results suggest that inconsistencies in the valence specificity of the effects of social interactions may reflect, at least in part, differing temporal dynamics of positive versus negative exchanges. Vittengl and Holt (1998b) examined these temporal kinetics using time-series analyses of concurrent and time-lagged associations between positive or negative affect and time spent in various types of social interactions. Data consisted of diary reports obtained three times daily for 4 weeks. Positive and negative affect were concurrently associated with qualitatively distinct types of social interactions, but there was no evidence of time-lagged associations within days, possibly because fleeting affective states and infrequent diaries hindered the ability to detect time-lagged associations. On the other hand, the results of longitudinal analyses reported by Newsom et al. (2003) suggest that negative aspects of interactions have an impact on subsequent negative affect, and that these effects may be more long-lasting than the effects of positive aspects of interactions on positive affect.

Our interest is in examining whether degree of loneliness moderates any of these effects linking interaction quality and affect. Prior research indicates that individuals differ in their abilities to benefit from social sources of emotion regulation (reviewed by Mikulincer, Shaver, & Pereg, 2003). Extraverted individuals, for example, are not only more likely to find a willing interaction partner but are also more likely than are shy or introverted individuals to perceive their interactions as positive events (Barrett & Pietromonaco, 1997; Watson et al., 1992). Socially anxious individuals, on the other hand, not only perceive interactions in the natural environment as poorer in quality but also of greater impact on their mood than do individuals low in social anxiety (Vittengl & Holt, 1998a). Similarly, individuals with less social support show a greater impact of events on next-day mood (Affleck, Tennen, Urrows, & Higgins, 1994).

In our research, we have observed that socially connected individuals perceive their interactions more positively than do less connected individuals (Hawkley et al., 2003). This may dispose them to experience a greater reduction of negative mood or enhancement of positive mood following social interactions than would be true for less connected individuals. Even when interactions have negative aspects, socially connected individuals perceive them less negatively than do less connected individuals (Hawkley et al., 2003), so negative aspects of interactions may have less of an impact on mood in individuals high versus low in social connectedness. In addition, the reciprocal nature of the relationship between affect and interaction quality suggests that the greater positive affect reported by socially connected individuals (Hawkley et al., 2003) may foster better-quality social interactions, thereby perpetuating a cycle of positivity that may be quite resistant to assault in the form of negative interactions. Thus, interaction negativity may have shorter-lasting effects among individuals high versus low in social connectedness.

The Quantitative Approach: Summary of Expectations

A nested repeated-measures design provides a rich source of data permitting the examination of complex questions. We instantiated this design in an experience-sampling study of social isolation and connectedness in young adults (Cacioppo et al., 2000), in which we acquired approximately nine diary entries every day for a week from individuals differing in degree of loneliness. The resulting data structure can be considered hierarchical: Diaries are nested within days, which in turn are nested within individuals. Multilevel modeling (MLM; Goldstein, 1995; Hox, 2002; Kreft & de Leeuw, 1998; Raudenbush & Bryk, 2002; Snijders & Bosker, 1999), also known as hierarchical linear modeling, mixed-effects modeling, and random coefficients modeling, is a technique designed to analyze hierarchically structured data such as these and is the approach we use in this study.

One of the advantages of MLM is that missing data typically do not pose a serious problem; individuals can be measured for different numbers of days, and different days can involve as few or as many measurement occasions as necessary.

In this chapter, we illustrate how MLM has made it possible to examine the following kinds of theoretical questions in incomplete time-series data such as that obtained using an experience-sampling methodology (ESM). For didactic clarity, subsequent MLM analyses will address these questions in the sequence enumerated here.

First, MLM can be used to evaluate the proportion of total variation in a given outcome variable (e.g., affect) that is attributable to variation at a given level of the data hierarchy (e.g., diary, day, or person). Predictors (e.g., loneliness) can then be introduced to explain variation at some of these levels. We expect considerable variability in affect and interaction quality at each level (diary, day, person). Based on our prior work (Hawkley et al., 2003), we hypothesize that loneliness will predict lower levels of positivity and higher levels of negativity in affect and interaction quality.

Second, MLM permits examination of the concurrent relationship between affect and interaction quality in a way that avoids the bias that would result if ordinary linear regression were employed without regard to the hierarchical structure of the data. Based on prior research (Cunningham, 1988a, 1988b; McIntyre et al., 1990, 1991), we expect to find a reciprocal and valence-specific relationship between social interaction quality and affect (i.e., positive interaction quality and positive affect will be mutually predictive, as will negative interaction quality and negative affect). Concurrent interaction quality and affect may also exhibit crossover effects (e.g., Newsom et al., 2003), but prior research has been mixed in this regard.

Third, MLM makes it possible to study intra- and interindividual variability in the concurrent relationship between lower-level variables. Specifically, multilevel modeling permits regression parameters (e.g., slopes) at lower levels to be modeled as dependent variables in regression equations at higher levels. Such effects are termed *cross-level interactions* because they involve variables at higher levels predicting slopes at lower levels. In our case, we study the effects of individual differences in loneliness on the association between interaction quality and affect. We expect that individuals low in loneliness (i.e., socially connected individuals) may exhibit more robust positive affect such that negative interaction quality may not have as great an impact on concurrent positive affect as it does among those high in loneliness.

Fourth, MLM can be employed to examine the temporal relationship between variables. Typically, time-series analyses are used to examine time-lagged effects. We introduce a novel alternative means of assessing temporal relationships by testing lagged effects within the context of MLM. Specifically, we use multilevel modeling to examine the lagged effects linking interaction quality and affect. Moreover, by varying the lag between predictor and criterion, we can use the MLM approach to test the duration of the effects of social interaction quality on affect—that is, we can examine the duration as well as the causal direction of effects.

Prior experimental research has shown reciprocal causal effects relating interaction quality and affect (Cunningham, 1988a, 1988b; McIntyre et al., 1990, 1991), and we expect that lagged effects will support this causal structure. Namely, we hypothesize that mood will influence subsequent interaction quality and vice versa. In general, negative exchanges have a greater impact on psychological outcomes than do positive exchanges (a negativity effect; Rook, 1990). The potency of negative exchanges may therefore lengthen the duration of their influence on affect. If this is the case, we expect that negative interaction quality will continue to influence affect when the temporal lag is extended.

Fifth, adding yet another level of complexity, MLM makes it possible to study intra- and interindividual variability in the lagged relationships between lower-level variables. A temporal lag between lower-level variables allows us to ask whether the causal structure linking interpersonal interactions and affect is the same for individuals regardless of degree of loneliness. In addition, we can examine whether loneliness moderates the duration of the effects of interaction quality and affect on each other. If social connectedness facilitates effective emotional regulation, then a given degree of positivity in a social interaction may elicit greater or longer-lasting increases in subsequent positive affect with or without greater or shorter-lasting decreases in subsequent negative affect among individuals low versus high in loneliness. In addition, reciprocal reinforcement between positive interactions and positive affect may lead to more effective buffering of the effects of negative interactions among individuals low as opposed to high in loneliness. Thus, socially connected individuals may recover from negative interactions more quickly than do their lonely counterparts.

Sample and Methods

Over 2,000 students were screened and recruited to represent the lower (total score ≤ 28), middle (total score ≥ 33 and <39), and upper (total score ≥ 46) quintile of scores on the R-UCLA Loneliness Scale (Russell, Peplau, & Cutrona, 1980). The R-UCLA Loneliness Scale consists of 20 items that were originally selected to represent experiences that best distinguished lonely from nonlonely individuals. Examples of these items are "I feel isolated from others"; "I lack companionship"; and "There are people I can turn to." Notably, none of the items refer to the terms *lonely* or *loneliness*. Nevertheless, scores on the R-UCLA Loneliness Scale are highly positively correlated with self-reports of loneliness and inversely correlated with objective measures of social experiences (e.g., amount of time spent alone each day, number of close friends; Russell et al., 1980). Conversely, low scores on the R-UCLA Loneliness Scale represent a high degree of subjective social embeddedness and objective social engagement.

Participants were 135 undergraduate students (83% Caucasian; 7% African American; 7% Asian, Asian American, or Pacific Islander; 3% other or undeclared), equally distributed among the loneliness groups, and males and females were equally represented within each group. Exclusionary criteria have been reported elsewhere (Hawkley et al., 2003). At the time of recruitment, students' mean age was 19.2 ($SD = 1.0$) and they had completed at least one and, on average, 3.2 ($SD = 2.8$) academic quarters; 52% were freshmen, 32% were sophomores, 8% were juniors, and the remaining 8% were seniors or fifth-year students.

We employed ESM (Larson & Csikszentmihalyi, 1983) to collect information about psychosocial and behavioral states. Participants completed diaries for a total of 7 consecutive days. A programmable watch provided to participants was programmed to beep at nine random times between 9:30 a.m. and 12:00 midnight each day, subject to the constraint that the interbeep interval was between 45 and 120 minutes. The 134 participants who completed the 7-day diary study provided 6,772 of a possible 8,442 diaries, representing an 80% return rate. An analysis of covariance revealed that the rate of diary returns did not differ as a function of loneliness, $F(1, 131) = 2.512$, $p = .115$, or gender, $F(1, 131) = 0.539$, $p = .464$.

Diary format consisted primarily of closed-ended questions (multiple options) requiring participants to check the appropriate response. If participants were interacting with someone when they were beeped, they were asked to respond to 16 adjectives, 8 positive and 8 negative (scaled from 1 = *not at all* to 5 = *very*), to rate the social interaction. Responses to positive aspects of interactions (i.e., comfortable, intimate, involved, sharing, uninhibited, supported, affectionate, understood) were averaged to create an interaction positivity score (Cronbach's alpha = 0.867), and responses to negative aspects of interactions (i.e., cautious, disconnected, conflicted, closed off, distant, phony, dishonest, distrustful) were averaged to create an interaction negativity score (Cronbach's alpha = 0.886). Positive and negative affect were calculated by summing responses to the 10 positive and 10 negative items of the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988).

Data Analytic Strategy

In this study, we employed multilevel modeling to capitalize on the hierarchical structure of our repeated measures diary data. As we alluded to earlier, some of the advantages associated with MLM include the fact that lower-level coefficients can be modeled as dependent variables, and missing data typically do not pose a serious problem. In addition, analysis of hierarchical data by MLM avoids problems of (a) severe parameter bias encountered when data are analyzed without regard to nested structure, as with ordinary linear regression; and (b) unclear interpretation and low power attendant upon unnecessarily aggregating Level 1 data to higher levels (Goldstein, 1995). The assumptions necessary for the use of MLM are largely the same as those necessary for ordinary least squares: normality and independence of residuals and random effects, within-unit residual homoscedasticity, and linearity (see Snijders & Bosker, 1999, for a discussion of methods to check these assumptions). Given the nature of the hypotheses and the hierarchical structure of the present data set, MLM was chosen as the most appropriate analytical tool.

Three-Level Models

In MLM, the lowest level of the hierarchy (here the diary level) is commonly denoted Level 1, the next highest as Level 2, and so on. Most applications of MLM involve only two levels, for example, students nested within schools or repeated measures nested within individuals. There is theoretically no limit to the number of levels a multilevel model can contain, but there are often practical and software-related limitations, and few sources discuss MLM with more than two levels. Our data could be organized into the three-level hierarchy depicted in figure 39.1.

The three-level, fully unconditional multilevel model can be represented in terms of Level 1, Level 2, and Level 3 submodels. The Level 1 (diary level) submodel is:

$$Y_{ijk} = \pi_{0jk} + e_{ijk} \qquad e_{ijk} \sim N(0, \sigma^2) \qquad (1)$$

where Y_{ijk} represents the response at diary i on day j for individual k, π_{0jk} represents the mean response on day j for individual k, and e_{ijk} represents the deviation of Y_{ijk} from π_{0jk}.[1] The Level 2 (day-level) model is:

$$\pi_{0jk} = \beta_{00k} + r_{0jk} \qquad r_{0jk} \sim N(0, \tau_\pi) \qquad (2)$$

where β_{00k} represents the mean response for individual k and r_{0jk} represents the deviation of π_{0jk} from β_{00k}, or the random effect for day j. The Level 3 (person-level) model is:

$$\beta_{00k} = \gamma_{000} + u_{00k} \qquad u_{00k} \sim N(0, \tau_\beta) \qquad (3)$$

where γ_{000} represents the grand mean and u_{00k} represents the deviation of β_{00k} from γ_{000}. Combining Equations 1, 2, and 3 yields the following composite model:

$$Y_{ijk} = \gamma_{000} + u_{00k} + r_{0jk} + e_{ijk} \qquad (4)$$

which explicitly models Y_{ijk} as the sum of the grand mean and deviations at Level 3, Level 2, and Level 1, respectively.

Predictor variables may be entered at any level in order to explain variability in random effects at lower levels. For example, if a day-level variable is entered to explain variation in the Level 1 intercept, Equation 2 becomes:

$$\pi_{0jk} = \beta_{00k} + \beta_{01k}(w_{jk}) + r_{0jk} \qquad (5)$$

In this equation, the predictor w is hypothesized to predict intraindividual (intraday or interdiary) variability in the outcome. The slope parameter describing the expected increase in π_{0jk} given a unit change in w is here specified as a *fixed effect*, meaning that it is not permitted to vary across individuals or days. Consequently,

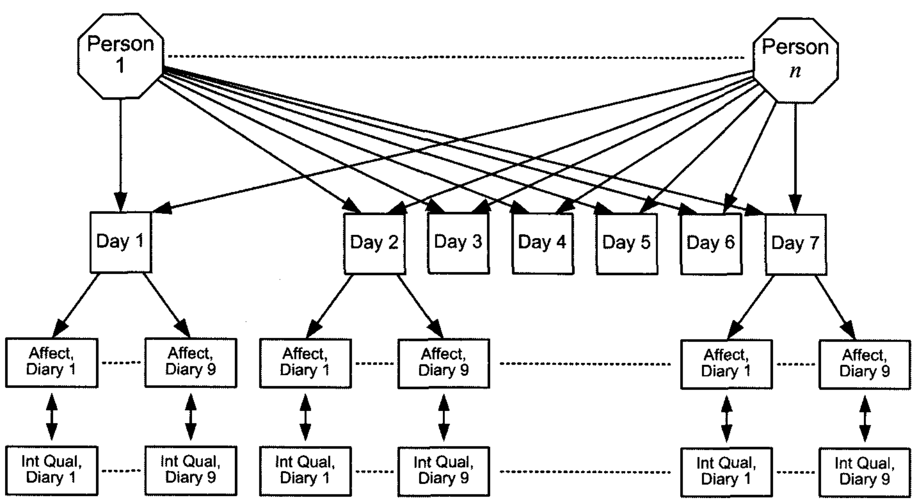

Figure 39.1 Three-level data structure. Data used in this study could be organized into a three-level hierarchy. Level 1 (diary level) consists of repeated measures of affect (positive and negative) and interaction quality (positive and negative) nested within days (Level 2), which in turn are nested within individuals (Level 3).

the equation for β_{01k} may be represented as:

$$\beta_{01k} = \gamma_{010} \tag{6}$$

The full, conditional, three-level model would now be:

$$Y_{ijk} = \gamma_{000} + \gamma_{010}(w_{jk}) + u_{00k} + r_{0jk} + e_{ijk} \tag{7}$$

Models such as that in Equation 7 represent only the tip of the iceberg in terms of the potential of MLM to test complex hypotheses about the magnitude and direction of effects in hierarchically structured data sets with more than two levels. Multilevel models may be extended to include nonlinear effects, more than three levels, and multivariate outcomes. Covariates can be entered into the model at any level, and complex error distributions and covariance structures may be specified. In addition, predictors may sometimes be centered (i.e., recast as deviations from their means) in order to improve the stability of estimation and enhance interpretability.[2] For more involved discussions of the possibilities and limitations of MLM, see chapter 30, this volume or any introductory text on the subject (e.g., Hox, 2002; Kreft & de Leeuw, 1998; Raudenbush & Bryk, 2002; Snijders & Bosker, 1999).

Software

Facilities for specifying and estimating multilevel models are included in several statistical software packages, including newer versions of LISREL (8.54) and SPSS (12.0) and dedicated MLM packages such as HLM (Bryk, Raudenbush, Cheong, & Congdon, 2000) and MLwiN (Rasbash et al., 2000). We chose LISREL 8.54 (Jöreskog & Sörbom, 1996) for its speed and ease of use. Complex multilevel models may be easily specified in newer versions of LISREL using PRELIS syntax (du Toit & du Toit, 2001; Jöreskog, Sörbom, du Toit, & du Toit, 1999), examples of which we include in the appendix.

Results and Discussion

Null Models and Other Preliminaries

As a first step, it is often useful to estimate a *null model*. A null model, like Equation 4 above, models the response variable as a function of an intercept and random effects at each level:

$$Y_{ijk} = \gamma_{000} + u_{00k} + r_{0jk} + e_{ijk} \tag{8}$$

Estimation of a null model allows the partitioning of variance into components at Levels 1, 2, and 3. We estimated a series of null models treating diary-level positive and negative affect (hereafter abbreviated posaff and negaff) and positive and negative interaction quality (hereafter abbreviated posint and negint) as the outcomes of interest. The equation corresponding to the first of these models is:

$$posaff_{ijk} = \gamma_{000} + u_{00k} + r_{0jk} + e_{ijk} \tag{9}$$

The null model equations for negaff, posint, and negint have identical forms. LISREL provides maximum likelihood point estimates, standard errors, t values, and p values for the random intercept term (γ_{000}) and the Level 1, Level 2, and Level 3 variances (σ^2, τ_π, and τ_β, respectively).[3] Null model results are reported in table 39.1, with LISREL syntax for the posaff model in the appendix. Here and following, values for positive and negative interaction quality were multiplied by 10 to render similar scaling of the affect and interaction quality values. This increased the number of decimal places we could display in parameter estimates involving the

TABLE 39.1 Parameter Estimates for Null Models

	Dependent Variable			
	posaff	negaff	posint*	negint*
$\hat{\gamma}_{000}$	14.284 (0.511)	3.765 (0.307)	30.531 (0.503)	13.821 (0.323)
$\hat{\sigma}^2$	43.829 (0.813)	14.844 (0.276)	54.542 (1.528)	19.225 (0.539)
$\hat{\tau}_\pi$	7.581 (0.705)	3.014 (0.262)	11.486 (1.437)	3.316 (0.465)
$\hat{\tau}_\beta$	32.524 (4.265)	11.729 (1.541)	29.158 (4.147)	12.349 (1.702)

Note: Numbers in parentheses are standard errors.

*Values for positive and negative interaction quality were multiplied by 10, so in original measurement units, the grand mean for posint is 3.053 and the grand mean for negint is 1.382.

interaction quality variables, but does not alter the statistical significance of any reported effects.

In the null model, the point estimate of the intercept is an unconditional estimate of the sample mean, which in all four cases is significantly different from zero ($p < .00001$). The fact that the Level 1, Level 2, and Level 3 variances also are all significantly different from zero implies that there exists variation to be potentially explained in all four outcome variables by adding predictor variables to the model. Variation is additive across levels, such that the variation which exists at a given level in a given outcome variable can be expressed as a proportion of the total variation by the intraclass correlation. For example, the proportions of variability in negaff that exist at the diary, day, and person levels are, respectively:

$$\rho_{diary} = \frac{\sigma^2}{\sigma^2 + \tau_\pi + \tau_\beta} = \frac{14.844}{14.844 + 3.014 + 11.729} = 0.502 \quad (10)$$

$$\rho_{day} = \frac{\tau_\pi}{\sigma^2 + \tau_\pi + \tau_\beta} = \frac{3.014}{14.844 + 3.014 + 11.729} = 0.102 \quad (11)$$

$$\rho_{person} = \frac{\tau_\beta}{\sigma^2 + \tau_\pi + \tau_\beta} = \frac{11.729}{14.844 + 3.014 + 11.729} = 0.396 \quad (12)$$

Most of the explainable variation in all four outcome variables occurs at Level 1, or across diaries (within days and persons).

After specifying null models, the next step in a multilevel analysis is usually to introduce predictor variables. Of primary interest to us was the ability of loneliness to predict variability in affect and interaction quality. Loneliness was measured only once per individual, making it a Level 3 predictor. The success of loneliness in predicting affect and interaction quality can be gauged by noting the magnitude of the regression coefficient associated with loneliness, its significance, and any reduction in Level 1, Level 2, or Level 3 variation when compared to the null model. A typical equation for this type of model is:

$$posaff_{ijk} = \gamma_{000} + \gamma_{001}(loneliness_k) + u_{00k} + r_{0jk} + e_{ijk} \quad (13)$$

Results of fitting this model to data for all four outcome measures are reported in table 39.2. The γ_{001} coefficient in each case represents the slope of the dependent variable regressed on loneliness.

Individual differences in loneliness explain variability in all four outcome variables, but comparison of the variance estimates in tables 39.1 and 39.2 reveals that the explanation occurred mostly at Level 3 (the person level). This means that loneliness does not tend to account for fluctuations in affect or interaction quality observed across diaries or across days within persons. In line with expectations, however, loneliness predicted decreased positivity and increased negativity in affect and interaction quality. Referring to the coefficients in table 39.2, a one-unit increase in loneliness produced an increase in negative affect of 0.120 and a decrease in positive affect of 0.130. Values for posint and negint were multiplied by 10 before analysis, so we can say that a 10-unit increase in loneliness produced a 0.151 increase in interaction negativity and a 0.140 decrease in interaction positivity.

Conversely, in mood and social interactions, experiential domains that arguably are the primary determinants of overall well-being, social connectedness provides a distinct advantage. Specifically, social connectedness predicts higher positive and lower negative affect, and more positive and less negative qualities in social interactions. Not surprisingly, life is

TABLE 39.2 Parameter Estimates for Models With Loneliness as a Predictor

	Dependent Variable			
	posaff	negaff	posint	negint
$\hat{\gamma}_{001}$	−0.130 (0.050)	0.120 (0.029)	−0.140 (0.049)	0.151(0.029)
$\hat{\sigma}^2$	43.828 (0.813)	14.845 (0.276)	54.527 (1.528)	19.219 (0.539)
$\hat{\tau}_\pi$	7.581 (0.705)	3.015 (0.262)	11.515 (1.438)	3.349 (0.467)
$\hat{\tau}_\beta$	30.868 (4.062)	10.272 (1.362)	27.251 (3.913)	9.918 (1.404)

Note: Numbers in parentheses are standard errors.

experienced more positively by socially connected individuals.

Concurrent Effects

As has been noted in prior research (Vittengl & Holt, 1998a, 1998b; Watson et al., 1992), a second key question involves whether affect and interaction quality are concurrently related. In other words, does positive or negative affect predict the positivity or negativity of the current interaction (or vice versa)? To examine this possibility, we specified a series of eight models with posint and negint serving as Level 1 predictors of concurrent affect and posaff and negaff serving as Level 1 predictors of interaction quality. The general form of the equation is:

$$\begin{aligned} posaff_{ijk} &= \pi_{0jk} + \pi_{1jk}(posint_{ijk}) + e_{ijk} \\ \pi_{0jk} &= \beta_{00k} + r_{0jk} \\ \beta_{00k} &= \gamma_{000} + u_{00k} \\ \pi_{1jk} &= \beta_{10k} \\ \beta_{10k} &= \gamma_{100} \end{aligned} \tag{14}$$

The combined equation is thus:

$$posaff_{ijk} = \gamma_{000} + \gamma_{100}(posint_{ijk}) + u_{00k} + r_{0jk} + e_{ijk} \tag{15}$$

Code for this model can be found in the appendix. Results are reported in table 39.3, with point estimates, standard errors, and p values associated with $\hat{\gamma}_{100}$.

In every case, there is a strong concurrent relationship between affect and interaction quality. The direction of these effects was as expected: positive interaction quality predicted higher positive and lower negative affect; negative interaction quality predicted lower positive and higher negative affect. The fact that these concurrent relationships were not valence specific is consistent with valence crossover effects also reported by Newsom et al. (2003). Moreover, we found reciprocal crossover effects: positive affect predicted higher positive and lower negative interaction quality; negative affect predicted lower positive and higher negative interaction quality.

Intra- and Interindividual Variability in Concurrent Relationships

A complex question that MLM allows us to ask is if the Level 1 slopes relating concurrent affect and interaction quality vary at the day level (within persons) or the person level (across persons). If significant variability is observed at either or both levels, then a case can be made for attempting to predict that variability with Level 2 or Level 3 predictor variables. We adopted the strategy of specifying random effects at both the day and person levels, followed by constraining nonsignificant random effects. The Level 2 variance of the random effect associated with the slope of the predictor will be represented by τ_2 and the Level 3 variance by τ_3. First, we allowed the Level 1 slopes to vary freely across both days and persons. The general form of the equation is:

$$\begin{aligned} posaff_{ijk} &= \pi_{0jk} + \pi_{1jk}(posint_{ijk}) + e_{ijk} \\ \pi_{0jk} &= \beta_{00k} + r_{0jk} \\ \beta_{00k} &= \gamma_{000} + u_{00k} \\ \pi_{1jk} &= \beta_{10k} + r_{1jk} \\ \beta_{10k} &= \gamma_{100} + u_{10k} \end{aligned} \tag{16}$$

The combined equation is:

$$posaff_{ijk} = \gamma_{000} + (\gamma_{100} + r_{1jk} + u_{10k})posint_{ijk} + u_{00k} + r_{0jk} + e_{ijk} \tag{17}$$

Code for this model can be found in the appendix. Results are reported in table 39.4, with point estimates, standard errors, and p values.

TABLE 39.3 Parameter Estimates for Concurrent Fixed-Effects Models

Outcome	Predictor	Effect
posaff	posint	$\hat{\gamma}_{100} = 0.284\ (0.014)\ p < .00001$
posaff	negint	$\hat{\gamma}_{100} = -0.134\ (0.025)\ p < .00001$
negaff	posint	$\hat{\gamma}_{100} = -0.072\ (0.009)\ p < .00001$
negaff	negint	$\hat{\gamma}_{100} = 0.316\ (0.015)\ p < .00001$
posint	posaff	$\hat{\gamma}_{100} = 0.391\ (0.019)\ p < .00001$
posint	negaff	$\hat{\gamma}_{100} = -0.244\ (0.032)\ p < .00001$
negint	posaff	$\hat{\gamma}_{100} = -0.062\ (0.012)\ p < .00001$
negint	negaff	$\hat{\gamma}_{100} = 0.375\ (0.018)\ p < .00001$

TABLE 39.4 Parameter Estimates for Concurrent Random Effects at the Day and Person Levels

Outcome	Predictor	Effect
posaff	posint	$\hat{\tau}_2 = 0.022$ (0.008) $p = .004$ $\hat{\tau}_3 = 0.022$ (0.007) $p = .001$
posaff	negint	$\hat{\tau}_2 = 0.014$ (0.014) $p = .324$ $\hat{\tau}_3 = 0.041$ (0.016) $p = .010$
negaff	posint	$\hat{\tau}_2 = 0.014$ (0.004) $p < .0001$ $\hat{\tau}_3 = 0.011$ (0.003) $p = .001$
negaff	negint	$\hat{\tau}_2 = 0.062$ (0.013) $p < .00001$ $\hat{\tau}_3 = 0.016$ (0.009) $p = .084$
posint	posaff	$\hat{\tau}_2 = 0.058$ (0.014) $p < .0001$ $\hat{\tau}_3 = 0.011$ (0.009) $p = .221$
posint	negaff	$\hat{\tau}_2 = 0.103$ (0.036) $p = .004$ $\hat{\tau}_3 = 0.175$ (0.048) $p < .001$
negint	posaff	$\hat{\tau}_2 = 0.010$ (0.004) $p = .015$ $\hat{\tau}_3 = 0.007$ (0.003) $p = .040$
negint	negaff	$\hat{\tau}_2 = 0.146$ (0.028) $p < .00001$ $\hat{\tau}_3 = 0.049$ (0.021) $p = .020$

For every pairing of predictor and outcome reported in table 39.4, slopes vary randomly at either the day level or the person level, sometimes both. But do interindividual differences in loneliness explain some of these intra- and interindividual differences in slopes? To address this question, we introduced loneliness as a Level 3 predictor of slopes. Loneliness was not centered because grand-mean centering would not alter the effect of interest, and it is unclear how group-mean centering should be approached or how the results should be interpreted. The full three-level combined equation incorporating a cross-level interaction is (e.g.):

$$\begin{aligned} posaff_{ijk} = {} & \gamma_{000} + (\gamma_{100} + r_{1jk} + u_{10k})(posint_{ijk}) \\ & + \gamma_{001}(loneliness_{jk}) \\ & + \gamma_{101}(loneliness_{jk} \times posint_{ijk}) \\ & + u_{00k} + r_{0jk} + e_{ijk} \end{aligned} \tag{18}$$

Code for this model can be found in the appendix. However, no cross-level interaction effects were found to be significant. That is, the strength of the relationship between affect and concurrent interaction quality did not differ as a function of degree of social connectedness.

Lagged Effects

The results reported thus far do not address the temporal separation (lag) required for establishing causality. Here we depart from assessing purely concurrent effects, and instead focus on examining the relationship between affect and interaction quality when these measures are separated in time. Lagging predictor variables permits us to investigate whether, for example, negative interaction quality at diary $t-1$ influences affect at time t. Using lagged predictors also allows us to make stronger claims about causality than have heretofore been possible. Granted, the lag intervals are not constant, but diaries tended to be around 92.5 ($SD = 9.5$) minutes apart. The general form of the combined equation is, for example:

$$\begin{aligned} posaff_{ijk,t} = {} & \gamma_{000} + u_{00k} + r_{0jk} \\ & + \gamma_{100}(posint_{ijk,t-1}) + e_{ijk} \end{aligned} \tag{19}$$

The LISREL syntax for this model is the same as for the concurrent fixed-effects model; the data are lagged within-day before submitting them to analysis in LISREL. Results are reported in table 39.5, with point estimates, standard errors, and p values associated with $\hat{\gamma}_{100}$.

In virtually every case, there is a strong lagged relationship between affect and interaction quality. These effects were in the expected direction and were not valence-specific. Positive interaction quality at time $t-1$ positively predicted positive affect and negatively predicted negative affect at the subsequent time point (i.e., about 90 minutes later), and negative interaction quality at time $t-1$ positively predicted negative affect and negatively predicted positive affect at the subsequent time point. These results suggest that the crossover effects of interaction quality on positive and negative aspects of mood are not limited to concurrent effects, but extend to influence mood as much as 90 minutes later.

The reverse causal direction linking affect and interaction quality was also supported, with only one exception. Negative affect at time $t-1$ predicted less positivity and more negativity in interactions at the subsequent time point, and positive affect at one time point predicted more positivity (but not less negativity) in interactions at the subsequent time point. Thus, in general, mood had relatively persistent effects on interaction quality.

The strong lagged effects relating interaction quality and affect suggest that their reciprocal influence may last even longer than 90 minutes. We investigated the duration of these effects by lengthening the temporal separation between predictor and outcome. We specified eight

TABLE 39.5 Parameter Estimates for Lag 1 Fixed-Effects Models

Outcome	Predictor	Effect
$posaff_t$	$posint_{t-1}$	$\hat{\gamma}_{100} = 0.079$ (0.017) $p < .00001$
$posaff_t$	$negint_{t-1}$	$\hat{\gamma}_{100} = -0.058$ (0.028) $p = .042$
$negaff_t$	$posint_{t-1}$	$\hat{\gamma}_{100} = -0.029$ (0.010) $p = .003$
$negaff_t$	$negint_{t-1}$	$\hat{\gamma}_{100} = 0.110$ (0.017) $p < .00001$
$posint_t$	$posaff_{t-1}$	$\hat{\gamma}_{100} = 0.108$ (0.020) $p < .00001$
$posint_t$	$negaff_{t-1}$	$\hat{\gamma}_{100} = -0.066$ (0.035) $p = .058$
$negint_t$	$posaff_{t-1}$	$\hat{\gamma}_{100} = 0.002$ (0.012) $p = .880$
$negint_t$	$negaff_{t-1}$	$\hat{\gamma}_{100} = 0.104$ (0.020) $p < .00001$

models similar to those above, but employed a lag of two diaries. Results are reported in table 39.6, with point estimates, standard errors, and p values associated with $\hat{\gamma}_{100}$.

These results indicate that some effects are still in evidence even after three diary sessions. For example, negative interaction quality continued to precipitate negative affect even two lags later. Positive interaction quality failed to exhibit effects of comparable duration, in keeping with prior research documenting the greater potency of negative interaction quality in influencing affect (Rook, 1990; see also Newsom et al., 2003). Notably, mood exhibited significant enduring valence-specific effects on interaction quality even two time points later. That is, positive affect enhanced interaction positivity, and negative affect exacerbated interaction negativity during interactions about 3 hours later.

Predicting Intra- and Interindividual Differences in Lagged Effects

Of primary interest to us was the possibility that intra- or interindividual differences in the slopes relating lagged predictors to outcome variables might be functionally related to loneliness. First, we investigated whether the Lag 1 slopes varied significantly across days or persons. Results are reported in table 39.7.

Note that two of the Level 2 slope variances (for the effects of $negint_{t-1}$ on $posaff_t$ and $posaff_{t-1}$ on $negint_t$) and one Level 3 slope variance (for the effect of $posint_{t-1}$ on negaff) were estimated to have negative values. Such solutions are inadmissible and are usually the result of sampling error. In these cases the variances were not significantly different from zero.

The effect of negative interaction quality at time $t-1$ on negative affect at time t varied significantly across days. We investigated the ability of loneliness to predict this random effect. The combined three-level equation is:

$$\begin{aligned} &negaff_{ijk,t} \\ &\quad = \gamma_{000} + (\gamma_{100} + r_{1jk} + u_{10k})(negint_{ijk,t-1}) \\ &\qquad + \gamma_{001}(loneliness_{jk}) \\ &\qquad + \gamma_{101}(loneliness_k \times negint_{ijk,t-1}) \\ &\qquad + u_{00k} + r_{0jk} + e_{ijk} \end{aligned} \tag{20}$$

Intraindividual variability in slopes was not significantly predicted by individual differences in loneliness, $\hat{\gamma}_{101} = -0.001$ (0.004), $p = .891$.

TABLE 39.6 Parameter Estimates for Lag 2 Fixed-Effects Models

Outcome	Predictor	Effect
$posaff_t$	$posint_{t-2}$	$\hat{\gamma}_{100} = 0.019$ (0.019) $p = .321$
$posaff_t$	$negint_{t-2}$	$\hat{\gamma}_{100} = -0.051$ (0.031) $p = .104$
$negaff_t$	$posint_{t-2}$	$\hat{\gamma}_{100} = 0.001$ (0.011) $p = .924$
$negaff_t$	$negint_{t-2}$	$\hat{\gamma}_{100} = 0.054$ (0.019) $p = .004$
$posint_t$	$posaff_{t-2}$	$\hat{\gamma}_{100} = 0.089$ (0.021) $p < .0001$
$posint_t$	$negaff_{t-2}$	$\hat{\gamma}_{100} = -0.019$ (0.036) $p = .606$
$negint_t$	$posaff_{t-2}$	$\hat{\gamma}_{100} = -0.008$ (0.013) $p = .534$
$negint_t$	$negaff_{t-2}$	$\hat{\gamma}_{100} = 0.056$ (0.021) $p = .008$

TABLE 39.7 Parameter Estimates for Lag 1 Random Effects at the Day and Person Levels

Outcome	Predictor	Effect
posaff	posint_{t-1}	$\hat{\tau}_2 =$ 0.008 (0.009) $p = .378$ $\hat{\tau}_3 =$ 0.004 (0.005) $p = .483$
posaff	negint_{t-1}	$\hat{\tau}_2 = -0.011$ (0.017) $p = .509$ $\hat{\tau}_3 =$ 0.029 (0.017) $p = .083$
negaff	posint_{t-1}	$\hat{\tau}_2 =$ 0.005 (0.003) $p = .136$ $\hat{\tau}_3 = -0.003$ (0.002) $p = .154$
negaff	negint_{t-1}	$\hat{\tau}_2 =$ 0.035 (0.016) $p = .024$ $\hat{\tau}_3 =$ 0.001 (0.015) $p = .934$
posint	posaff_{t-1}	$\hat{\tau}_2 =$ 0.007 (0.010) $p = .466$ $\hat{\tau}_3 =$ 0.004 (0.006) $p = .568$
posint	negaff_{t-1}	$\hat{\tau}_2 =$ 0.010 (0.024) $p = .669$ $\hat{\tau}_3 =$ 0.072 (0.028) $p = .011$
negint	posaff_{t-1}	$\hat{\tau}_2 = -0.001$ (0.004) $p = .725$ $\hat{\tau}_3 =$ 0.002 (0.003) $p = .334$
negint	negaff_{t-1}	$\hat{\tau}_2 =$ 0.007 (0.032) $p = .817$ $\hat{\tau}_3 =$ 0.014 (0.018) $p = .435$

In addition, the effect of negative affect at time $t-1$ on positive interaction quality at time t varied significantly across people. We investigated the ability of loneliness to predict this random effect. The combined three-level equation is:

$$\begin{aligned}
&posint_{ijk,t} \\
&\quad = \gamma_{000} + (\gamma_{100} + r_{1jk} + u_{10k})(negaff_{ijk,t-1}) \\
&\quad\quad + \gamma_{001}(loneliness_{jk}) \\
&\quad\quad + \gamma_{101}(loneliness_k \times negaff_{ijk,t-1}) \\
&\quad\quad + u_{00k} + r_{0jk} + e_{ijk} \qquad (21)
\end{aligned}$$

Intraindividual variability in slopes was not significantly predicted by loneliness, $\hat{\gamma}_{101} = 0.0004$ (0.004), $p = .927$.

Given that there was some evidence for Lag 2 effects (see table 39.6), we were curious to discover whether there existed significant intraindividual variability in day-level or person-level slopes for Lag 2 effects and, if so, whether this variability could be predicted by interindividual differences in loneliness. We examined day-level and person-level random effects of Lag 2 predictors. None of these slopes exhibited significant variance at either the day or person level.

Concluding Remarks

In this study, MLM afforded theoretical tests and insights that would not have been visible from other perspectives. Had we taken an ordinary least squares regression approach, for example, we would not have seen that variance in affect and interaction quality was evident not only across diaries, but also across days and across persons. Specifically, variability in mood and interaction quality associated with momentary circumstances exceeded day-to-day and person-to-person variability in mood and interaction quality. Moreover, MLM enabled us to see that loneliness/social connectedness was more powerful in explaining interindividual variance than momentary or daily variance. This finding provides a first clue that loneliness/social connectedness is characterized to a greater extent by a pervasive enduring influence over the affective experience of everyday circumstances (including social interactions) than by a transitory influence on the experience of momentary circumstances.

Second, we saw that concurrent affect and interaction quality were reciprocally related across valence domains, as has been suggested by prior research (Cunningham, 1988a, 1988b; McIntyre et al., 1990, 1991; Newsom et al., 2003). Importantly, lag analyses revealed potentially causal relationships linking interaction quality and affect: These relationships appeared reciprocal, were in the expected directions, and acted across valence domains. In addition, negative aspects of social interactions had a particularly long-lasting influence on negative affect, consistent with the "negativity effect" reported by other researchers (Rook, 1990; see also Newsom et al., 2003).

What distinguishes these findings from prior research is that we acquired online assessments of the co-occurring positive and negative features of social interactions. This is a significant departure from typical, and frequently retrospective, assessments of the number of individuals with whom participants have generally positive or negative exchanges (e.g., Finch et al., 1989; Rook, 2001), or the frequency with which social exchanges are generally positive or negative (Newsom et al., 2003). Our assessments of interaction quality and affect share method variance, and this may have contributed to the associations we observed among the positive and negative aspects of interaction quality and affect. However, this did not prevent us from evaluating possible explanations for social connectedness/loneliness differences in these outcome variables and their interrelationship.

What might account for generally higher positivity and lower negativity in affect and interaction quality among socially connected individuals? Our data support the notion that socially connected individuals differ from lonely individuals in their perceptions of everyday social experiences, with social connectedness characterized by persistently enhanced perceptions of positivity and reduced perceptions of negativity in interaction quality and affect. The results of our lagged analyses indicate that socially connected individuals do not experience longer-lasting effects of positive interactions on mood, or of positive affect on interaction quality, than do lonely individuals, so this explanation does not account for social connectedness/loneliness differences in overall degree of positivity and negativity in these domains. In addition, we know from past research (Hawkley et al., 2003) that these same individuals did not exhibit social connectedness/loneliness differences in time spent with others, ruling out frequency of social opportunities as an explanation for affect differences. On the other hand, we cannot rule out the possibility that socially connected individuals have greater access to better interaction partners, partners that may be similarly inclined toward greater positivity in affect and interaction quality and thereby help foster and maintain positivity in the socially connected individual.

In sum, our data suggest that the combination of greater perceived positivity among socially connected individuals and the tendency for positivity to be self-reinforcing across the domains of affect and interaction quality fosters the recurrent positive interactions and persistently enhanced mood that are characteristic of social connectedness. Unfortunately, the converse is also true: Initially greater negativity and the tendency of negativity to be self-reinforcing fosters greater negativity in interactions and affect among lonely individuals. The advantage of social connectedness may be not only that it triggers upward spirals of positivity (e.g., better coping strategies) that result from the maintenance of positive emotions (Fredrickson & Joiner, 2002), but that it prevents the downward spiraling of negative affect that leads to dysphoria, clinical depression, and anxiety disorders. So what can we learn from socially connected individuals that might help us understand how to be a successful social being? The data presented here suggest that altering perceptions in either domain—interactions or affect—may help to break the cycle of negativity that so profoundly influences well-being and engage the spiral of positivity that moves individuals into the realm of successful social functioning.

Methodological Remarks

In addition to examining the theoretical tests and insights that MLM provides when dealing with complex data sets, we sought to provide a tutorial on some advanced uses of MLM. Tutorials on MLM usually stop at two levels and illustrate how MLM can be used to examine growth or trajectory over time. Our theoretical questions were more complex and required a three-level MLM with tests of lagged effects. Accordingly, the tutorial explained a three-level MLM with instructions. Although rarely used, three-level MLMs can be applied in many settings (e.g., any setting with two levels of nesting plus repeated measures). Our detailed description of how such models can be specified can serve as a useful guide to others who encounter data that are organized according to a hierarchy with at least three levels.

MLM provides an appropriate method for analyzing repeated-measures data that preserves within-person (and in our case within-day) trends that might otherwise become obscured by collapsing across diaries, days, or individuals. Furthermore, whenever researchers encounter data that are organized hierarchically, they run the risk of suffering low power or biased parameter estimates if the nested structure is not modeled. Thus, we structured our model as repeated measures nested within other repeated measures and addressed important theoretical questions that could not otherwise be addressed. For instance, the relationship between variables can be studied within nesting units (e.g., days, people), which allows us to ask questions about both interindividual variability and intraindividual variability.

We further demonstrated that longitudinal designs need not focus on time as a variable or even on trends. The capability of testing lagged effects is very useful, and is an interesting alternative to incorporating time as a predictor (which is how most researchers study trends). We were not interested in trends over time (i.e., growth curves), but rather concurrent and lagged effects of other relevant variables. Our study was characterized by repeated measurements of the same individuals, yet our predictions and hypotheses had little to do with examining growth or trajectory over time.

Finally, in psychological research, there is an unfortunate tendency to address longitudinal hypotheses using cross-sectional data. Temporal separation is a necessary, but not sufficient, condition for causality (Gollob & Reichardt, 1987). To address causality, we used lagged prediction in MLM of longitudinal data. The examination of lagged effects as illustrated in this chapter should be undertaken more often because this modeling strategy recognizes explicitly that independent variables require time to exert effects on dependent variables. Modeling lagged responses in MLM is a novel but powerful statistical approach that overcomes these limitations in traditional longitudinal analyses.

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Appendix: Selected LISREL Code

PRELIS Code for Null Model

```
OPTIONS OLS=YES CONVERGE=0.001 MAXITER=100 OUTPUT=STANDARD ;
  ! OLS=YES=Use OLS estimates as start values
  ! CONVERGE=0.001=Convergence criterion=.001
  ! MAXITER=100=Maximum of 100 iterations
TITLE=Null Model; ! Title of analysis
MISSING_DAT=-999.000000; ! Missing data code=-999
SY='C:\data\data1.PSF'; ! Location of data, in PRELIS data format
ID1=BEEPNUM; ! Level-1 unit identifier =diary number
ID2=STUDYDAY; ! Level-2 unit identifier=day of study
ID3=SUBNUM; ! Level-3 unit identifier=subject number
RESPONSE=POSAFF; ! Dependent variable=PANAS positive
FIXED=CONS; ! Requests point estimate of fixed effect
RANDOM1=CONS; ! Diary-level intercept is random
RANDOM2=CONS; ! Day-level intercept is random
RANDOM3=CONS; ! Person-level intercept is random
COV1PAT=DIAG; ! Diary-level covariance matrix is diagonal
COV2PAT=DIAG; ! Day-level covariance matrix is diagonal
COV3PAT=DIAG; ! Person-level covariance matrix is diagonal
```

PRELIS Code for Concurrent Fixed-Effects Model

```
OPTIONS OLS=YES CONVERGE=0.001 MAXITER=100 OUTPUT=STANDARD ;
TITLE=Concurrent Fixed Effects;
MISSING_DAT=-999.000000;
SY='C:\data\data1.PSF';
ID1=BEEPNUM;
ID2=STUDYDAY;
ID3=SUBNUM;
RESPONSE=POSAFF;
FIXED=CONS POSINT; ! Requests point estimates of intercept and slope
```

```
RANDOM1=CONS;
RANDOM2=CONS;
RANDOM3=CONS;
COV1PAT=DIAG;
COV2PAT=DIAG;
COV3PAT=DIAG;
```

PRELIS Code for Concurrent Random-Effects Model

```
OPTIONS OLS=YES CONVERGE=0.001 MAXITER=100 OUTPUT=STANDARD ;
TITLE=Concurrent Random Effects;
MISSING_DAT =-999.000000;
SY='C:\data\data1.PSF';
ID1=BEEPNUM;
ID2=STUDYDAY;
ID3=SUBNUM;
RESPONSE=POSAFF;
FIXED=CONS POSINT;
RANDOM1=CONS;
RANDOM2=CONS POSINT; ! Sets slope of POSINT random at level-2
RANDOM3=CONS POSINT; ! Sets slope of POSINT random at level-3
COV1PAT=DIAG;
COV2PAT=1 ! Requests symmetric covariance matrix at level-2
 2 3;
COV3PAT=1 ! Requests symmetric covariance matrix at level-3
 2 3;
```

PRELIS Code for Predicting Concurrent Random Effects With Loneliness

```
OPTIONS OLS=YES CONVERGE=0.001 MAXITER=100 OUTPUT=STANDARD ;
TITLE=Cross-Level Interaction;
MISSING_DAT =-999.000000;
SY='C:\data\data1.PSF';
ID1=BEEPNUM;
ID2=STUDYDAY;
ID3=SUBNUM;
RESPONSE=POSAFF;
FIXED=CONS POSINT UCPOSINT; ! Fixed effects for POSINT and interac-
  tion term
RANDOM1=CONS;
RANDOM2=CONS POSINT;
RANDOM3=CONS POSINT;
COV1PAT=DIAG;
COV2PAT=1
        2 3;
COV3PAT=1
        2 3;
```

Notes

1. The subscript notation employed for coefficients in MLM can be confusing. The notation convention becomes even more confusing when a third level is added, and is further complicated by the fact that different authors tend to use different subscripting strategies. For purposes of this chapter, we adopt a variation of the notation employed by Raudenbush and Bryk (2002) and Snijders and Bosker (1999), in which i, j, and k denote, respectively, diary, day, and person. When one of these subscripts is replaced by an integer, the integer represents the position of the coefficient in the Level 1, Level 2, and Level 3 equations. In Equation 6, for example, the first 0 in γ_{010} represents the fact

that this Level 3 fixed effect is ultimately related to the intercept in the Level 1 equation; the 1 represents the fact that it is related to the first slope coefficient in the Level 2 equation; and the final 0 represents the fact that γ_{010} is the first (intercept) coefficient in the Level 3 equation.

2. Centering sometimes improves the stability of estimation by reducing collinearity with other predictors, and often renders uninterpretable parameter estimates interpretable. For example, the intercept in traditional regression is interpretable as the value of the dependent variable when all predictors equal zero. If a predictor variable has no meaningful zero point, then mean centering allows the intercept to be interpretable as the predicted value of the dependent variable at the mean of the predictor. In two- and three-level models, centering is more complicated (see Kreft & de Leeuw, 1998; Kreft, de Leeuw, & Aiken, 1995; Raudenbush & Bryk, 2002, for general guidance on centering). In this chapter, we limit analyses to uncentered data because the effects of greatest interest are not altered by the most widely employed kind of centering.

3. For the sake of brevity, only those results directly relevant to the question at hand are reported. More details are available from the authors upon request.

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