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Individual differences in adjustment to spousal loss: A nonlinear mixed model analysis

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The study of within-person change lies at the core of developmental research. Theory and empirical data suggest that many of these developmental processes are not linear. We describe a broad class of multilevel models that allows for nonlinear change – nonlinear mixed models. To demonstrate the utility of these models, we present a nonlinear mixed model analysis of adjustment to conjugal loss. Coming from a perspective of the individual as a regulatory system, our model predicts a faster rate of adjustment immediately following the loss and diminished adjustment as time since the loss increases, approaching an equilibrium level of well-being. This model allows us to estimate various aspects of the adjustment trajectory and individual differences in these trajectories, including multiple ways that pre- and post-loss factors can explain variability in the adjustment process. The model provides new insights into an important phenomenon that cannot be gleaned from linear models and other methods of trajectory analysis. We discuss the strengths and limitations of this type of analysis relative to other methods.

Keywords: loss; mixed model analysis; nonlinear mixed models

One of the central aims of developmental research is to understand the processes of change occurring within individuals over time. To realize this aim, researchers must collect longitudinal data, and then choose an analytic technique that can distinguish within-person changes from between-person variability in those changes (Baltes, Reese, & Nesselroade, 1988). There are many such techniques available, ranging from simple paired *t* tests to sophisticated structural equation models, and each model has its strengths and limitations. In many instances, the most appropriate model is determined by properties of the design and sample. How many participants are available in the sample? How many waves of data are there, and how are they spaced? How much data is missing at various time points? When the number of repeated observations is small and the number of participants is relatively large, linear models are often recommended because they can parsimoniously account for basic covariation with a minimal number of parameters.

The choice of models may also be driven by theoretical considerations. In particular, when theory predicts nonlinear patterns of change over time, models that assume linearity may not be acceptable. Many biological, psychological, and social processes do not conform to a simple linear form. For example, models of physical stature must take into account at least two growth spurts, as well as the ultimate attainment of mature height. A variety of nonlinear models has been proposed to fit stature data, and some of these have both descriptive and predictive power (Bock, 1991). Nonlinear trajectories that can be fit by mathematical functions using relatively few parameters can be productively applied to data sets for which there are a limited number of longitudinal observations. Below, we apply this approach to examine the time course of adjustment to the loss of a loved one.

Adjustment to loss

When considering human development across the lifespan, the loss of a loved one is an event that nearly everyone experiences at least once. Perhaps not surprisingly, then, it is a topic that has received much attention across a variety of literatures that span the breadth of the social sciences (for reviews, see Palgi & Abramovitch, 1984; Riley, 1983). Within psychology, the study of adjustment to bereavement and associated grief reactions has traditionally fallen into the realm of clinical psychology. As such, much of the initial focus of this work was on distinguishing adaptive versus maladaptive ways of coping with loss and prescribing a series of steps or stages that constitute normal recovery (Bowlby, 1980). Much of the literature in this tradition was theoretical and based on informal reflections on bereavement experiences or on individual case studies.

Because there were few studies based on rigorous empirical information about post-bereavement adjustment trajectories, it was unclear how much credence to give to the pictures of normative and counter-normative ways of adjusting that were emerging in the field. This uncertainty was captured in a classic article by Wortman and Silver (1989), which laid out a series of unsubstantiated "myths" held by both clinicians and laity about the way grieving should work, and presented at least preliminary evidence to the contrary, motivating the need for more careful examinations. These myths included the notion

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that experiencing distress or depression is both inevitable and necessary when coping with loss, that individuals need to 'work through' the loss, and that individuals should be completely recovered from the loss within a year or two of the loss, reaching a state of resolution in doing so. In a follow-up (Wortman & Silver, 2001), they reviewed additional research suggesting that, by and large, these assumptions about the nature of adjustment to loss were unsupported.

Of particular relevance to this study is the assumption that bereaved individuals reach a state of recovery within a relatively short period following the loss. This assumption is founded on a view of loss as an acute event that arises, is addressed, and is left in the past. From this perspective, recovery would be indicated by, for instance, a bereaved individual reaching a point where thoughts of the lost loved one *never* invoke feelings of sadness or anger. An alternative viewpoint is that the loss of a loved one marks a qualitative psychological shift, such that the typical bereaved person is forever changed by the experience of the loss. Over time, he or she may employ coping techniques, gradually adapting to life without the deceased, but adjustment may be more a matter of reaching homeostasis than achieving complete resolution per se. That is, upsetting reactions to thoughts about the loved one may decline over time, but they may not ever disappear completely. Rather, they may level off at some equilibrium level determined by a combination of psychological (e.g., coping efficacy) and environmental (e.g., the presence of a supportive social network) factors.

Carnelley, Wortman, Bolger, and Burke (2006) recently reported evidence that many grief-related outcomes may follow a nonlinear trajectory over time. Consistent with other research (Bisconti, Bergeman, & Boker, 2004), they hypothesized that the loss of a spouse could be compared with a regulatory system being knocked into a state of disequilibrium. According to this perspective, the influence of regulatory factors (e.g., coping and social support) is proportional to the discrepancy between the current state and the equilibrium state (Carver & Scheier, 1982). As a result, adjustment should happen more rapidly at first, when the individual is furthest from equilibrium, and should slow over time as the individual nears his or her equilibrium level of adjustment. Looking at a number of grief process-related outcomes (e.g., the frequency of thoughts about the lost spouse, the intensity of anniversary reactions), Carnelley et al. found evidence that this nonlinear model of adjustment tended to fit the data better than a comparable linear model. One of the strengths of this study was the large, representative sample of nearly 800 respondents who had experienced spousal loss anywhere from a few months to 64 years prior to the interview. However, inferences about individual grief trajectories were precluded by the cross-sectional nature of the data. In the present study, we use a longitudinal data set and a series of nonlinear mixed models to gain further insight into the way different individuals adjust to loss, as well as the factors associated with differences in adjustment patterns. Before we describe these formal nonlinear models, however, we briefly review some of the other statistical approaches that have been used to describe developmental trajectories.

Alternative methods for treating nonlinearity

Until fairly recently, fitting nonlinear mixed models was technically challenging, and researchers needed to consider alternatives to modeling the nonlinearity directly. Perhaps the simplest way to manage nonlinear trajectories is to assume that the process is approximately linear in its parameters[1] within the range of the data. With this assumption, the data can be fit by more familiar linear models, which includes a class of polynomial growth models. In recent years, these linear mixed models (i.e., hierarchical linear models; Raudenbush & Bryk, 2002) have become increasingly popular for modeling change trajectories, and they have provided a great deal of insight about developmental phenomena.

The linear approximation gives an overall idea about who is improving, who is getting progressively worse and who is staying about the same following bereavement. However, it does not address the questions raised above about the difference between early and later adjustment. A polynomial model can detect some curvature, but it may imply nonsensical patterns beyond the range of the data. For instance, a quadratic function used to model the leveling-off of physical stature in adolescence actually implies that growth will begin to reverse just after reaching this peak height. Moreover, because these models are only approximations of the intended trajectories, one needs to be cautious about the interpretation of sampling variability and formal tests of significance that are obtained from them. One way to improve upon a simple linear model is to take into account different phases of the trajectories. Cudeck and Klebe (2002), for example, describe sophisticated ways to fit different linear trends to different phases so that the overall pattern is nonlinear. To our knowledge, these multiphase methods have not yet been applied to bereavement data, although they could be informative. Because of space limitations, we do not consider this generalization of the linear model further in this article.

Another way to manage nonlinear trajectories is to classify individuals by their "type" of trajectory. With this strategy, researchers typically identify categories of people within the population and place individuals from the sample into the appropriate group. These categories can be constructed based on prior theory, or they can be derived empirically (Burchinal & Appelbaum, 1991). With each person's trajectory classified, the researcher is then able to look at the relationships between the classification and other substantive predictors using analysis of variance (ANOVA) or discriminant function techniques. This method may be useful when the differences between the proposed groups are truly qualitative rather than quantitative, as indicated by theory or prior research. Low within-group variability is an indication that the group differences are qualitative rather than quantitative. In this case, variability existing within groups may be less interesting than the comparisons between groups highlighted by this analysis. Within the bereavement literature, these methods have been applied by Bonanno and colleagues (Bonanno et al., 2002; Bonanno, Wortman, & Nesse, 2004) and Levy, Martinkowski, and Derby (1994).

The primary limitation of this analysis strategy arises when differences between persons are actually more quantitative than qualitative. In this case, the use of categories can result in the loss of useful information. In terms of the understanding

[1] The literature on nonlinear modeling distinguishes between inherently nonlinear models and models linear in their parameters. For example, although a quadratic function does not look 'linear', it is linear in its parameters and can be estimated by any linear regression software. See Singer and Willett (2003) for a discussion of this distinction.

of the process of interest, there may be important within-group variability that gets ignored in a categorical analysis. In terms of purely methodological issues, creating categorical distinctions from continuous distributions may decrease power and bias estimates of effects (MacCallum, Zhang, Preacher, & Rucker, 2002). A further complication of this strategy is that missing data at any time-point can make classification of a given trajectory impossible and can result in the loss of the whole individual from the analysis.

Nonlinear mixed modeling

The estimation of quantitative models of nonlinear trajectories has been made easier by both the availability of flexible software for fitting these models and affordable computing power for running this software. As we discuss in more detail below, fitting nonlinear models usually requires iterative programs that work with rough estimates of parameters (i.e., starting values) and refine them through specialized numerical algorithms. This is true whether or not individual differences in the nonlinear models are explicitly taken into account.

The idea behind nonlinear regression techniques is essentially the same as that of linear regression techniques in that a model is specified that attempts to describe the sequence of data points, and the model is customized to the data by finding parameter estimates that maximize fit or minimize discrepancies. As long as the hypothesized trajectory can be written as an equation, nonlinear regression methods can, in principle, be used to model it. For example, developmental models of skill acquisition or other phase transitions can be estimated with a logistic or sigmoid function, including processes with estimated rather than fixed upper and lower bounds. Patterns of oscillation over time can be modeled with a sine wave (Boker, 2001). Singer and Willett (2003) describe several additional functions that can be useful for describing nonlinear biological processes.

For the purpose of describing recovery following bereavement, we focus in this article on variations of exponential decay (i.e., negative exponential) models, an example of which is shown as the solid line in Figure 1. This simple prototype depends on only two constants, an acceleration/decay parameter (b_1) and an initial level parameter (b_0). The functional form is $Y = b_0 e^{-b_1 t}$, where b_1 is chosen to be a positive number. To give the reader more intuition about this function, when t = 0, $e^{-b_1 t} = 1$, and $Y = b_0$. As t gets large, $e^{-b_1 t}$ (and therefore Y) approaches 0. The value of b_1 determines how steeply the curve drops off over time. It is worth noting the similarity between this simple nonlinear model and a typical linear model (shown as the dashed line in Figure 1): each uses two parameters – one representing an initial value and one representing the process of change – to describe the pattern of Y as a function of t. A quick glance at Figure 1, however, shows that these two models can predict very different patterns of change over time. We build on this simple nonlinear form to account for other aspects of the bereavement process, including the possibility that Y approaches a value other than zero over time.

Just as linear longitudinal models can be viewed in a multilevel context (Raudenbush & Bryk, 2002) with level 1 models describing individual trajectories and level 2 models describing individual differences across persons, so can nonlinear longitudinal models account for within-person change and between-person variability in change. The nonlinear mixed models we employ can consider parameters such as b_0 and b_1 discussed above to vary across persons, making them so-called random effects. We assume that the random effects in the bereavement example have a multivariate normal distribution, and this allows estimation of the between-person variances of (and covariances between) these effects, as well as significance tests on these estimates. In addition, we generate examples of different fitted trajectories to illustrate how people differ in their bereavement experiences.

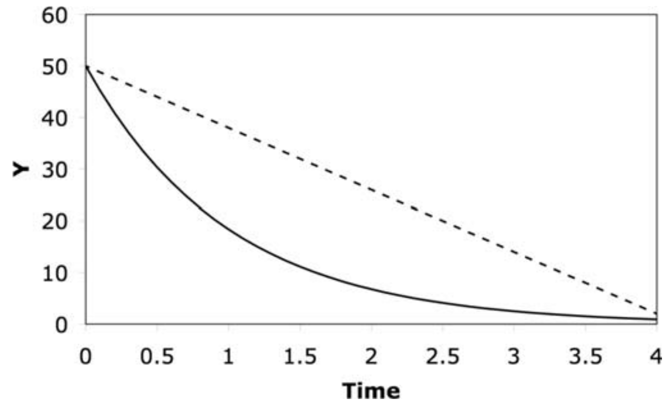

Figure 1. An example of the exponential decay (i.e., negative exponential) function (solid line) compared to a typical linear function (dashed line).

Method

Participants

The data for this analysis come from the Changing Lives of Older Couples (CLOC) study – a prospective study of conjugal loss with four waves of interviews, including a baseline (pre-loss) interview and follow-up interviews at 6, 18, and 48 months post loss. The sample is described in detail by Carr et al. (2000). In brief, the bereaved sample consists of 250 respondents at the baseline and 6-month interview, with attrition resulting in samples of 205 and 150 for the 18- and 48-month interviews, respectively.

Measures

The primary measure of adjustment used in the present study was a short form of the Center for Epidemiologic Studies Depression scale (CES-D; Radloff, 1977) developed by Kohout, Berkman, Evans, and Cornoni-Huntley (1993). Participants responded to 11 items on a scale from 1 (hardly ever) to 3 (most of the time). An example item is, “I felt that everything I did was an effort.” Responses to these items were summed (α = .81), with two positively phrased items first being reverse-coded. These scale scores were then transformed to a 0 to 60 scale for ease of comparison to other studies using the standard CES-D (Radloff, 1977).

To explain between-person variability in adjustment, we used a measure of the respondent’s perceived coping efficacy and a measure of marital quality, both assessed in the pre-loss interview. Coping efficacy was measured by four items (e.g., “I can handle myself pretty well in a crisis”; α = .56). These were the same four items used by Bonanno et al. (2002) to assess coping efficacy. Marital quality was measured by 10 items (e.g., "How much does your (husband/wife) make you feel loved and cared for?"; $\alpha = .88$). The marital quality scale combined the positive and negative marital quality scales reported by Bonanno et al. (2002). Both coping efficacy and marital quality were centered at their grand means before being entered into the regression analyses.

Modeling the nonlinear trajectories

All analyses were conducted using the NLMIXED procedure of SAS software (SAS Institute, 2004). This procedure allows the user to specify any functional relationship between a set of independent variables and model parameters and a dependent variable as the analytic model. In a linear model, these parameters would represent the intercept and slopes, but in nonlinear models they represent other aspects of the trajectory (e.g., an asymptote). In principle, NLMIXED allows any of these parameters to be specified as random effects, which means that they are expected to vary across persons. In most cases these random effects are represented as normally distributed individual difference, and in the case of multiple random effects, the assumption is multivariate normality.[2] Annotated SAS syntax for the analyses reported below can be obtained at the following website: http://www.psych.nyu.edu/couples/bereave_nlmixed.sas.

The model used by Carnelley et al. (2006) was a cross-sectional model that implied the following within-person (i.e., level 1; Raudenbush & Bryk, 2002) process:[3]

$$\text{Level 1:} \quad Y_{ij} = F_i + (L_i - F_i)e^{-S \cdot t_{ij}} + \varepsilon_{ij} \qquad (1)$$

Here, Y_{ij} represents the outcome – level of depressive symptoms in the current study – for person i on measurement occasion j, L_i represents the predicted level of depressive symptoms at the time of the loss (what we refer to as the *at-loss* level of depressive symptoms) for person i, F_i represents the level of depressive symptoms long after the loss (what we refer to as the *final* level of depressive symptoms) for person i, e is a mathematical constant, S represents the rate of adjustment (i.e., how slowly or quickly the discrepancy between L_i and F_i is traversed), and t_{ij} represents time in years since loss for person i, wave j. Finally, ε_{ij} represents the unexplained within-person residual at each assessment. The ε terms are assumed to be normally distributed with a mean of zero, be uncorrelated with other variables in the model, and have equal variance over time and across persons.[4]

It is worth noting the similarities and differences between Equation 1 and the general form of the negative exponential function presented in the Introduction. The S parameter in Equation 1 directly maps onto the b_1 parameter in the general form. The difference in appearance between the two equations arises because Equation 1 allows the outcome to approach a nonzero value over time. When $t_{ij} = 0$, $e^{-S \cdot t_{ij}} = 1$, and the expected value of Y is $F_i + L_i - F_i = L_i$, just as b_0 represented the initial value of the general form. As t_{ij} gets large, $e^{-S \cdot t_{ij}}$ approaches 0, and the expected value of Y approaches F_i, rather than 0, as it did in the general form.

The subscript i on the F and L parameters in Equation 1 suggests that these parameters are allowed to vary between persons. In principle, the rate of decay parameter S in Equation 1 might also vary between persons. However, we were restricted in the number of random effects we could estimate because of the number of within-person data points. Attempting to estimate this additional random effect would have resulted in a saturated model, thus preventing statistical inference. Preliminary analyses suggested that the inter-individual variability in S was relatively small compared to that of the other model parameters, so we assumed it to be constant within the bereaved population. One additional post-loss time point would have made the estimation of between-person variability in S possible, which would be of great interest to bereavement researchers.

To describe the between-person variability in at-loss and final depression, the level 2 (between-person) equations are:

$$\text{Level 2:} \quad \begin{aligned} L_i &= \gamma_L + \zeta_{Li} \\ F_i &= \gamma_F + \zeta_{Fi} \end{aligned} \qquad (2)$$

Here, the γ_L and γ_F terms are the mean levels of at-loss and final depression, respectively, within the population of bereaved individuals (i.e., the fixed effects), and ζ_{Li} and ζ_{Fi} represent multivariate-normally distributed person-level random variables (i.e., random effects) with means equal to zero, variances σ_L^2 and σ_F^2, and covariance σ_{LF}

$$\begin{bmatrix} \zeta_{Li} \\ \zeta_{Fi} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_L^2 & \sigma_{LF} \\ \sigma_{LF} & \sigma_F^2 \end{bmatrix} \right) \qquad (3)$$

Significance tests of these variance and covariance parameters indicate whether there is reliable between-person variability in these parameters within the population.[5]

The analysis by Carnelley et al. (2006) and Equation 1 only account for patterns of depression following the loss. Bonanno et al. (2002, 2004) have shown that pre-loss levels of depression are meaningfully related to patterns of adjustment following bereavement. Equation 4 is a refinement of Equation 1, taking into account pre-loss levels of depression:

$$\text{Level 1:} \quad Y_{ij} = (d_{ij}) \cdot [B_i] + (1 - d_{ij}) \cdot [F_i + (L_i - F_i)e^{-S \cdot t_{ij}}] + \varepsilon_{ij} \qquad (4)$$

$$\text{Level 2:} \quad \begin{aligned} B_i &= \gamma_B + \zeta_{Bi} \\ L_i &= \gamma_L + \zeta_{Li} \\ F_i &= \gamma_F + \zeta_{Fi} \end{aligned} \qquad (5)$$

Here, d_{ij} is a binary indicator, equal to 1 for baseline (i.e., pre-loss) assessments and 0 for post-loss assessments. Thus, for a pre-loss observation, $d_{ij} = 1$ and $1 - d_{ij} = 0$, so the model selects the first term in Equation 4 (B_i) but not the second ($[F_i + (L_i - F_i)e^{-S \cdot t_{ij}}]$); likewise, for a post-loss observation, $d_{ij} = 0$ and $1 - d_{ij} = 1$, so the model selects the second term in Equation 4 but not the first. This technique is useful for specifying

[2] NLMIXED does not offer options for the distribution of random effects other than normal (and multivariate normal), but other more technical software such as WinBUGS (Spiegelhalter, Thomas, Best, & Lunn, 2003) do allow users to assume other distributional forms.

[3] Equation 1 involves a reparameterization of the model used by Carnelley et al. (2006), where the L parameter in Equation 1 is equal to $f - d$ in Equation 3 of Carnelley et al.

[4] We make the assumption that the level 1 residuals are independent and identically distributed because the NLMIXED procedure of SAS does not currently accommodate other forms. However, this form may be too restrictive in circumstances where heteroscedasticity or correlated residuals are expected. See Cudeck and Harring (2007) for a discussion of possible covariance structures in nonlinear mixed models.

[5] Note that if we had been able to allow between-person variability in S, there would have been a level 2 equation for S_i analogous to Equation 2, including an additional random effect ζ_{Si} with variance σ_S^2 and covariances σ_{LS} and σ_{FS}.

different functional forms on opposite sides of a developmental transition point (see Cudeck & Klebe, 2002 and Singer & Willett, 2003 for more details). γ_B represents the average level of baseline depression (assumed to be constant during the pre-loss period), and ζ_B is a random person variable with mean 0 and variance $\sigma_B{}^2$ representing individual differences in baseline depression. The person-level random variables in Equation 5 are multivariate-normally distributed as follows:

$$\begin{bmatrix} \zeta_{Bi} \\ \zeta_{Li} \\ \zeta_{Fi} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_B^2 & \sigma_{BL} & \sigma_{BF} \\ \sigma_{BL} & \sigma_L^2 & \sigma_{LF} \\ \sigma_{BF} & \sigma_{LF} & \sigma_F^2 \end{bmatrix} \right) \tag{6}$$

To illustrate the types of patterns that this model estimates, Figure 2 shows sample trajectories based on Equation 4. This figure contains four panels in which the *B*, *L*, *F*, and *S* parameters are systematically varied.

Explaining individual differences in the nonlinear trajectories

The variance and covariance parameters in Equation 6 indicate the amount of unexplained between-person variability in adjustment trajectories. In this section, we consider two alternative models for explaining this variability. One model explains stable between-person differences in level of depressive symptoms, whereas the other model focuses on individual differences in the shape of the trajectories over time.

To be explicit, this first model describes a process whereby a pre-existing individual difference or contextual variable, *M*, has a constant relationship to level of depressive symptoms. The level 1 equation of this model is still represented by Equation 4, but the level 2 equations have an additional term added reflecting this relationship:

$$\text{Level 2:} \quad \begin{aligned} B_i &= \gamma_B + b_M \cdot M_i + \zeta_{Bi} \\ L_i &= \gamma_L + b_M \cdot M_i + \zeta_{Li} \\ F_i &= \gamma_F + b_M \cdot M_i + \zeta_{Fi} \end{aligned} \tag{7}$$

Here, b_M represents the strength of the linear relationship between variable *M* and pre-loss, at-loss, and final levels of depression. Note that this relationship is assumed to be the same for all three levels (i.e., at all times relative to the loss).

The second model describes a process whereby a pre-existing variable, *M*, can have different relationships to the *B*, *L*, and *F* parameters of the model – that is, it explains variability in the shapes of people's trajectories. Here again, this *M* variable is assumed not to vary within an individual over time, but its relationship to depressive symptoms *is* allowed to vary. The level 1 equation for this model is represented by Equation 4, and the level 2 equations are:

$$\text{Level 2:} \quad \begin{aligned} B_i &= \gamma_B + b_B \cdot M_i + \zeta_{Bi} \\ L_i &= \gamma_L + b_L \cdot M_i + \zeta_{Li} \\ F_i &= \gamma_F + b_F \cdot M_i + \zeta_{Fi} \end{aligned} \tag{8}$$

Here, b_B, b_L, and b_F represent the linear relationship between this explanatory variable and pre-loss, at-loss, and final levels of depressive symptoms, respectively. This model allows these relationships to be similar to each other, but they can also differ. For example, a variable may be positively related to pre-loss depression, unrelated to at-loss depression, and negatively related to final depression, whereas the model described by Equation 4 and 7 would hold this relationship constant across the three levels.

As with linear models, there is still value in parsimony with

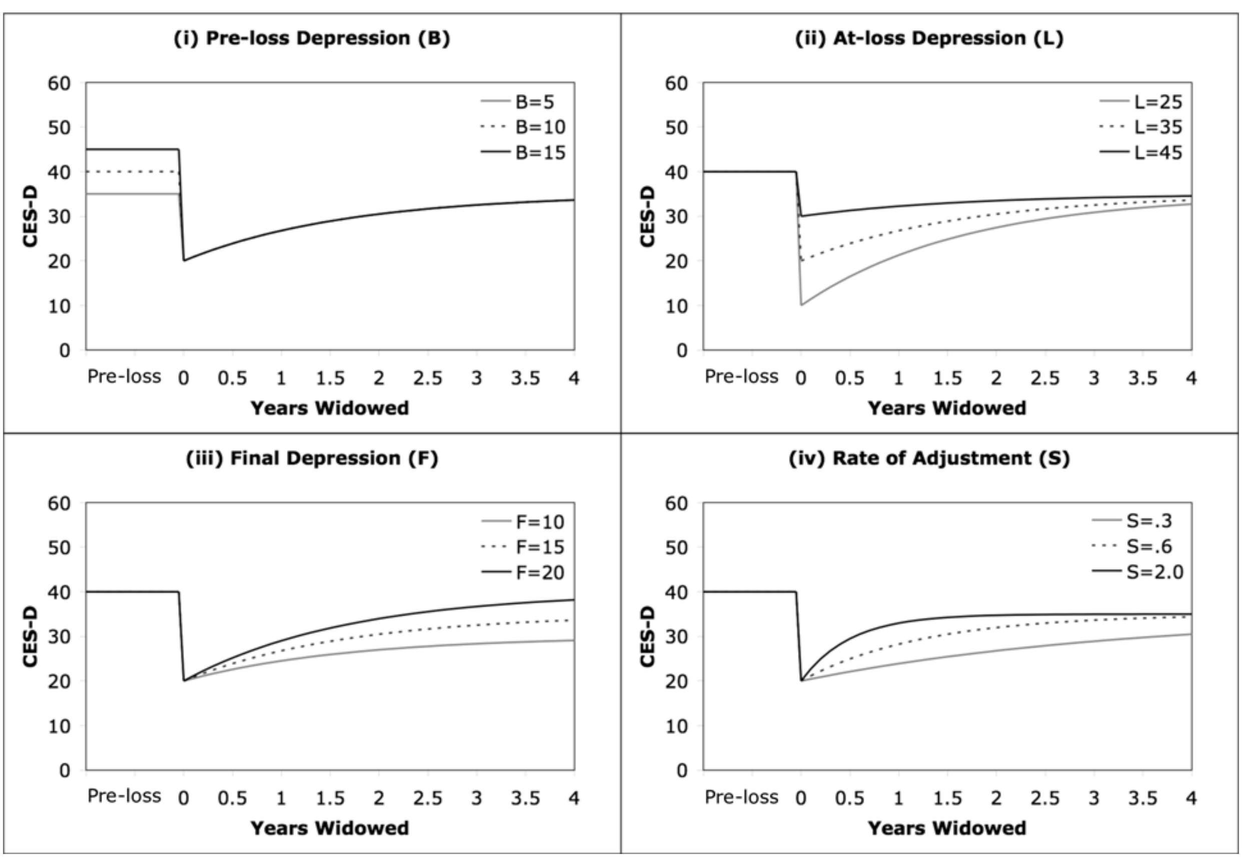

Figure 2. Sample trajectories formed by systematic variation of the (1) *B*, (2) *L*, (3) *F*, and (4) *S* parameters in equation (4).

nonlinear models. Therefore, the fit of a more complicated model should be compared with the fit of a less complicated model, taking into consideration the number of additional parameters being estimated, in order to justify the added complexity. Many available fit statistics, such as the Akaike information criterion (AIC; Akaike, 1974), adjust the log likelihood for the complexity of the model. In general, models with lower values of these fit statistics fit the data better and should be preferred over models with higher values. In the present analysis, this means that the models described by Equations 4 and 7, and Equations 4 and 8 should only be preferred over the model described by Equations 4 and 5 if they improve a fit statistic like the AIC. In addition, because the model described by Equations 4 and 8 represents a less parsimonious account of between-person variability than the model described by Equations 4 and 7 does, the model described by Equations 4 and 8 should only be preferred if it improves the fit relative to model described by Equations 4 and 7.

Results

Describing the nonlinear trajectories

Table 1 shows the parameter estimates for each of the fixed effects in Equations 4 and 5, and Figure 3 plots the predicted trajectory of depressive symptoms before and after spousal loss

Table 1
Estimates of fixed and random effects from equations (4) and (5)

Parameter	*Estimate (SE)*	*Correlation*	*t(247)*	p
γ_B	11.08 (.61)	—	18.24	< .001
γ_L	15.18 (1.05)	—	14.48	< .001
γ_F	7.77 (2.59)	—	3.00	.003
S	.39 (.27)	—	1.45	.149
σ^2_B	60.1 (9.1)	—	6.64	< .001
σ^2_L	117.3 (22.7)	—	5.16	< .001
σ^2_F	70.9 (24.9)	—	2.84	.005
σ_{BL}	29.0 (8.2)	.35	3.52	< .001
σ_{BF}	36.6 (10.1)	.56	3.61	< .001
σ_{LF}	35.0 (24.4)	.38	1.44	.152

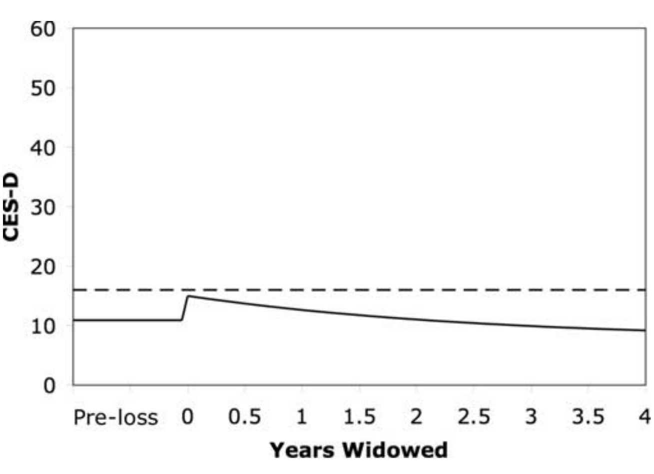

Figure 3. Predicted depression trajectory from baseline to 4 years post loss for the average person based on equation (4). The dotted line represents the conventional clinical cut-off point of 16.

for the average person. These results suggest that the average person does experience an increase in depressive symptoms as a result of spousal loss, though this increased level does not exceed the conventional cut-off point for clinical depression (i.e., 16 on the 0 to 60 scale). Figure 3 also shows the nonlinear decrease in depressive symptoms over time, with levels of depression predicted to ultimately drop below pre-loss levels.

If one only considered the fixed effects, it would seem from Figure 3 that people are not affected much by the loss of a spouse in terms of depressive symptoms. However, these results do not depict any between-person variability. Looking at Figure 3, it may be that everybody has a trajectory that looks like the line shown. It may also be the case, however, that individuals vary greatly in their trajectories, and that this "average" trajectory fails to describe anyone's path of adjustment. The variance and covariance estimates of the random person effects from Equation 5 (found in Table 1) show which interpretation is borne out in the data. These results demonstrate that there is reliable (not to mention substantial) interindividual variability in levels of pre-loss, at-loss, and final depression. Interestingly, the results indicate that the variance in depressive symptoms is much larger at the time of the loss (117.3, *SD* = 10.8) than it is before the loss (60.1, *SD* = 7.8) or finally (70.9, *SD* = 8.4). This may suggest that the typical distribution of depression scores is disrupted by the loss, with individuals reacting in many different ways, and that the variability in depressive symptoms returns to pre-loss levels over time.

Table 1 also shows the covariances among the random person effects (correlations are also presented for easier interpretation). The first thing to note in these results is that all of the correlations are positive (ranging from .35 to .56), suggesting that there is a tendency for individuals to more or less maintain their rank within the distribution of depression scores over time. Second, the correlation between pre-loss depression and at-loss depression (.35), although still statistically significant, is much smaller than the correlation between pre-loss depression and final depression (.56), while the correlation between at-loss depression and final depression (.38) does not even reach statistical significance. These results are consistent with the above interpretation of the variances, suggesting that individuals react in a variety of ways to the loss, but that people generally return to a level of depression comparable with pre-loss levels.

Explaining variability with respondent's pre-loss coping efficacy

Next, we examine the relationship of pre-loss coping efficacy to depression trajectories in the context of our nonlinear mixed model to see if and in what way coping efficacy explains the variability in depression trajectories described above. We estimated two models, one using Equations 4 and 7 that specifies a constant relationship between pre-loss coping efficacy and depression over time, and one using Equations 4 and 8 that allows the relationship between pre-loss coping efficacy and depression to vary over time relative to the loss, where pre-loss coping efficacy is the *M* variable in both sets of equations. We used the AIC fit statistic to decide whether incorporating information about coping efficacy improved the fit and to determine which of these ways of modeling coping efficacy was most appropriate. The AICs of the three models were 5846.7, 5818.1, and 5821.8 for Equations 4 and 5, 4 and 7, and 4 and 8, respectively. Thus, both ways of incorporating coping efficacy improved the fit, but the simpler model using Equations 4 and 7 seems to fit the data better than the more complex model using Equations 4 and 8.

These results suggest that coping efficacy is related to lower levels of depressive symptoms irrespective of time relative to the loss. The unstandardized estimate of the effect of coping efficacy on depression is $b_M = -4.76$ ($t(247) = 5.70$, $p < .001$), indicating that each unit increase in pre-loss coping efficacy (measured on a 3-point scale) was associated with a 4.8-point drop in depressive symptoms on the 60-point CES-D scale. Table 2 shows the implications of accounting for this relationship on fixed effects, and on the variance–covariance matrix of the random effects, quantifying differences in terms of percent change. The unexplained variance in pre-loss depression decreased from 60.1 to 52.9, the unexplained variance in at-loss depression decreased from 117.3 to 109.0, and the unexplained variance in final depression decreased from 70.9 to 62.1. Accounting for the effect of coping efficacy also reduced the relationships among the random effects, with the correlations now ranging from .29 to .52, as indicated in Table 2.

Explaining variability with respondent's pre-loss marital quality

In the next analysis, we examine whether including information about pre-loss marital quality in the model can help explain the random effects reported in Table 1, and determine whether the relationship between marital quality and depressive symptoms could be explained best by the model described by Equations 4 and 7 or 4 and 8. Here again, the model described by Equations 4 and 7 stipulates a constant relationship between marital quality and depressive symptoms over time, while the model described by Equations 4 and 8 allows marital quality to relate differently to depressive symptoms at different points in time relative to the loss. In this case, the AIC fit statistics indicated that the relationship between marital quality and depressive symptoms does depend on time relative to the loss (AIC = 5813.5, versus 5846.7 for Equations 4 and 5, and 5823.8 for Equations 4 and 7).

Table 3 presents the estimates of the fixed effects for this analysis. Perhaps not surprisingly, higher levels of pre-loss marital quality are associated with lower levels of pre-loss depression, $b_B = -4.52$, $t(247) = 6.34$, $p < .001$. There was also a trend suggesting that higher levels of pre-loss marital quality are associated with fewer depressive symptoms finally, $b_F = -3.27$, $t(247) = 1.62$, $p = .106$. However, marital quality seems to be unrelated to at-loss level of depressive symptoms, $b_L = -.48$, $t(247) = .47$, $p = .639$. Table 3 also shows the reductions in variance and covariance after accounting for marital quality. The unexplained variance in pre-loss depression decreased the most, from 60.1 to 47.1. The unexplained variance in at-loss and final depression showed more modest decreases, from 117.3 to 113.2 and from 70.9 to 70.7, respectively. Marital quality also explained some of the apparent relationships among the effects. The correlation between pre-loss and final depression decreased from .56 to .52, and the correlation between at-loss depression and final depression fell to .31 from .38. The relationship between pre-loss and at-loss depression remained essentially unchanged at .37.

Discussion

Our goal in this article was to outline a method for directly modeling nonlinear change over time via the nonlinear mixed model. By modeling nonlinearity directly, this model makes fewer assumptions than do other approaches to modeling nonlinear change. These other approaches include: (1) assuming that the trajectories are locally linear, and (2) assuming that individuals can be categorized according to a limited set of trajectory types. Although these methods can provide useful insight into the general nature of change and interindividual variability in change, nonlinear mixed models allow users the flexibility to specify the form of the change based on theoretical grounds, estimate an average trajectory, and describe the variability of individual trajectories about this average.

We implemented a nonlinear mixed model to examine how individuals vary in the way they adjust to the passing of a spouse. Recent research with a cross-sectional sample

Table 2
Estimates of fixed and random effects from equations (4) and (7) after incorporating coping efficacy

Parameter	*Estimate (SE)*	*% Change*[a]	*Correlation*	*t(247)*	p
γ_B	10.92 (.59)	—	—	18.66	< .001
γ_L	14.88 (1.02)	—	—	14.55	< .001
γ_F	7.22 (3.20)	—	—	2.26	.025
S	.34 (.27)	—	—	1.27	.205
b_M	–4.76 (.84)	—	—	5.70	< .001
σ_B^2	52.9 (8.5)	–12	—	6.22	< .001
σ_L^2	109.0 (21.0)	–8	—	5.20	< .001
σ_F^2	62.1 (30.4)	–11	—	2.04	.042
σ_{BL}	22.7 (7.6)	–22	.30	2.98	.003
σ_{BF}	29.5 (10.0)	–18	.52	2.96	.003
σ_{LF}	23.5 (31.8)	–34	.29	.74	.461

[a] Percent change is computed as the difference between the new parameter estimate and the estimate presented in Table 1, divided by the estimate presented in Table 1, multiplied by 100.

Table 3
Estimates of fixed and random effects from equations (4) and (8) after incorporating marital quality

Parameter	*Estimate (SE)*	*% Change*[a]	*Correlation*	*t(247)*	p
γ_B	10.99 (.56)	—	—	19.51	< .001
γ_L	15.02 (1.04)	—	—	14.48	< .001
γ_F	6.91 (3.81)	—	—	1.81	.071
S	.32 (.27)	—	—	1.17	.244
b_B	–4.52 (.71)	—	—	6.34	< .001
b_L	–.49 (1.04)	—	—	.47	.639
b_F	–3.27 (2.01)	—	—	1.62	.106
σ_B^2	47.1 (8.0)	–23	—	5.87	< .001
σ_L^2	113.2 (21.6)	–4	—	5.25	< .001
σ_F^2	70.7 (36.2)	–2	—	1.95	.052
σ_{BL}	27.3 (7.5)	–8	.37	3.66	< .001
σ_{BF}	29.8 (9.4)	–21	.52	3.17	.002
σ_{LF}	27.8 (34.6)	–23	.31	.80	.422

[a] Percent change is computed as the difference between the new parameter estimate and the estimate presented in Table 1, divided by the estimate presented in Table 1, multiplied by 100.

(Carnelley et al., 2006) found evidence suggesting that various dimensions of adjustment to loss tend to change rapidly immediately following the loss and slow over time as they approach some ultimate equilibrium level, rather than changing linearly. Using a nonlinear mixed model with a longitudinal sample, we were able to not only rule out cohort effects in these previous findings, but also to model and explain individual differences in these grief reactions.

Our analysis revealed that the average person experiences a modest increase in depressive symptoms at the time of the loss relative to pre-loss levels, and that the level of depressive symptoms decreases over a time, approaching a level comparable with pre-loss levels. Both pre-loss and final levels of depressive symptoms fall well below the common clinical cut-off point for the CES-D of 16 on average. Interestingly, the average level of depression immediately following the loss also fails to exceed the cut-off point (Figure 3). However, we also found substantial between-person variability in depressive symptoms before the loss, immediately following the loss, and ultimately, suggesting that this 'average' pattern should not be over-interpreted. Although all three of these levels showed significant variability (Table 1), the variance in at-loss depression was greater than that of pre-loss and final levels of depression. This finding suggests that individuals vary more in their reactions to the loss than in their pre-loss or final levels of depression. This relationship was corroborated by the correlations between these effects, which showed that individuals' pre-loss and equilibrium levels were more highly correlated than either of these effects was with level immediately following the loss.

Taken together, these individual differences offer support for the regulatory account of adjustment to bereavement described earlier. That is, individuals operate near their equilibrium levels of depression before the loss, experience a disruption in normal functioning at the time of the loss, and eventually return to equilibrium again. Depending on the individual, this post-loss equilibrium may or may not be similar to the pre-loss equilibrium, and individuals may vary greatly in the magnitude (and direction) of the disruption created by the loss.[6]

In an attempt to explain some of the individual differences described above, we looked at how individuals' pre-loss coping efficacy and marital quality related to these trajectories. We found that pre-loss coping efficacy was negatively related to depressive symptoms at all times. An examination of the distribution of the coping efficacy variable shows a negative skew, with most people toward the ceiling of the scale. This suggests that those low in coping efficacy were driving this effect. That is, individuals who lack confidence in their ability to cope with life's stressors have reliably higher levels of depressive symptoms overall than individuals those who feel capable in the face of adversity.

We found a somewhat more complex relationship between marital quality and depression trajectories. As with coping efficacy, marital quality was negatively related to the pre-loss and final levels of depression, but it did not predict level of depression immediately following the loss. The marital quality variable also shows a negative skew, with most people clustered around the ceiling, suggesting that respondents in poor marriages had elevated levels of depression before the loss and higher levels of depression in the long run compared with those with more satisfactory marriages.[7]

[6] Note that Equation 4 can be reparameterized by replacing B_i with $L_i - \Delta_i$ where Δ_i represents the change in depressive symptoms from pre loss to at loss. The model would then provide an estimate of the average level and amount of interindividual variability in this quantity. Bonanno et al. (2002, 2004) show that many individuals do not experience strong, negative reactions to the loss.

[7] Given the literature on depression, one might expect that two person-level variables – sex and age – might explain a lot of the variability in depression observed here. However, including age at 6 months post loss (a time-invariant form of age) and sex in the model – either via Equations 4 and 7 or 4 and 8 – failed to improve the fit of the model according to the AIC, and none of the regression estimates reached significance. For clarity, we presented the results of the analyses without sex and age, but the results remain virtually unchanged when sex and age are included.

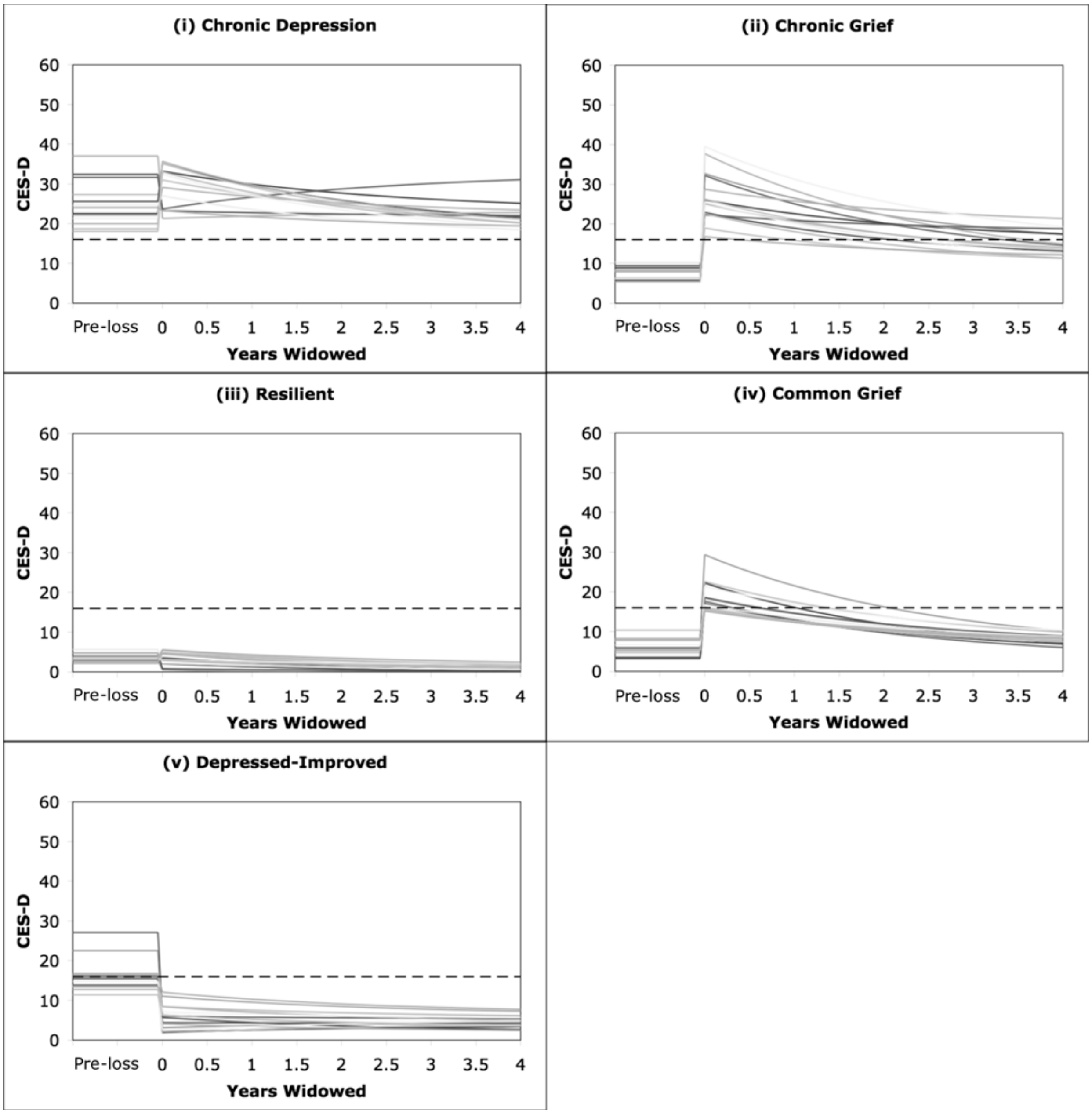

Figure 4. Predicted trajectories for sub-samples of participants representing each of the grief trajectories described by Bonanno et al. (2002, 2004).

Comparisons with other methods

An important question with respect to these results is how well they fit with the existing bereavement literature. Bonanno et al. (2002, 2004) have also analyzed depression trajectories with the CLOC data by classifying individuals into categories based on how their level of depressive symptoms varied across time. They found five primary ways that individuals grieve the loss of a loved one, each of which was supported by past bereavement research, and they related these categories to a variety of pre- and post-loss factors. These categories include: (1) chronic depression (high pre-loss depression that remains high over time); (2) chronic grief (low pre-loss depression that becomes elevated and remains so following the loss); (3) common grief (low pre-loss depression that becomes elevated following the loss but soon returns to normal); (4) depressed–improved (high pre-loss depression that decreases substantially following the loss); and (5) resilient (low pre-loss depression that remains low over time).

Figure 4 shows predicted trajectories of individuals generated by our nonlinear mixed model who seem to represent each of the categories identified by Bonanno et al. (2002, 2004), suggesting that our model is sensitive to the types reactions identified within the grief literature. Indeed, when we ran a model adjusting for these categories, we found that they accounted for much of the variability in depression trajectories uncovered by the nonlinear mixed model. Importantly, however, even after adjusting for the categories, there remained substantial and reliable between-person variability in these parameters over and above that explained by the grief categories. This variability represents the within-group variability that was lost in creating categories of grief reactions from the continuous depression scale. This variability is particularly apparent in the curves associated with chronic depression group in Figure 4, with some individuals showing large decreases in depression at the time of the loss and others showing large increases.[8]

The relationships we described between the grief trajectories and pre-loss coping efficacy and marital quality were also consistent with this past research. Bonanno et al. (2002) reported that chronically depressed individuals had significantly lower coping efficacy than those in the other categories. Likewise, we found a stable negative relationship between coping efficacy and depressive symptoms via a model represented by Equations 4 and 7. As most individuals were high in coping efficacy, this effect would have been driven primarily by those low in coping efficacy, consistent with the relationship described by Bonanno et al. (2002). With respect to marital quality, these researchers found that depressed–improved individuals were significantly lower in marital quality than those in the chronic grief, common grief, or resilient groups, but they did not differ from chronically depressed individuals. The model represented by Equations 4 and 8 in this study showed that marital quality was negatively related to pre-loss depression, consistent with their finding that those high in depression prior to the loss have poorer marriages. The marginal negative relationship with final depression may not have reached significance because, as suggested by the results of Bonanno et al. (2002), some of these individuals remained depressed, whereas others showed relief reactions to the loss.

Comparison with the results of Bonanno et al. (2002) does raise an interesting question about the nature of individual differences in grief processes. Our model assumes that level of depressive symptoms in the population of bereaved individuals is normally distributed prior to the loss, at the time of the loss, and long after the loss. These normal distributions are free to have different means (i.e., fixed effects), variances, and covariances. Our model does not allow for the existence of distinct categories of grievers, as suggested by Bonanno et al. (2002). It may be that there are distinct types of grief reactions, with between-person variability around some prototypic pattern for each group. Emerging methods such as mixture modeling could potentially be used to examine this possibility, although this has not yet been done to our knowledge.

Strengths of the nonlinear mixed model

Our aim in this article was to demonstrate that the nonlinear mixed model is a viable alternative to other methods of modeling nonlinear trajectories. In using this method, the researcher avoids having to make simplifying assumptions (e.g., local linearity of the trajectories or categorical differences among individuals) in order to analyze the data. The primary assumption (other than the typical assumptions of a mixed model) is that the data conform to one's hypothesized curve. That is, can the researcher justify using this more specific model over a simpler linear model? This assumption can be checked by comparing the fit of the nonlinear mixed model to that of a comparable linear mixed model.[9]

When the nonlinear model is more appropriate than a linear model, it should increase the researcher's power to detect relationships between other variables and these trajectories and provide a more flexible means of examining these relationships. In principle, any parameter in the model that is based on repeated observation can be allowed to vary between persons. As shown above, potential explanatory variables can be constrained to have the same effect on each parameter (e.g., the model described by Equations 4 and 7) or to have different relationships to each parameter (e.g., the model described by Equations 4 and 8). Here again, fit statistics can indicate the justifiability of a more complex pattern of relationships.

Finally, the nonlinear mixed model shares the strengths of other mixed models. As a mixed model, the nonlinear mixed model estimates the distribution of effects within the population, thereby allowing the researcher to make inferences that generalize beyond the sample at hand to anybody in the population. It is also not as sensitive to missing data as other methods such as latent growth curve modeling or the categorization technique described above. For example, an analysis using all four waves of the CLOC data that required respondents to have complete data would only make use of 60% of the original sample. In contrast, with a mixed model, as long as a person has any data at all, he or she is included in the analysis. The more data a person has, the more influence he or she has over the parameter estimates and the less influenced his or her trajectory is by information from the rest of the sample. Mixed models do assume that any missing data are missing at random (MAR; Little & Rubin, 1987), meaning that systematic missingness can be explained by observed subject characteristics. With the CLOC data, we might be concerned if, for instance, missing data were due to severe depression in some respondents, however there is no evidence for this explanation in the data.

Limitations and complications of the nonlinear mixed model

Although the nonlinear mixed model can be very useful for modeling these nonlinear trajectories, it is not the best choice in all circumstances. First, the complexity of the model is limited by the number of observations per person. With only three time points, for instance, it would be difficult to estimate a complex pattern of oscillation. In cases where the number of time points is limited, one might consider a multiphase model, discussed by Cudeck and Klebe (2002). The number of random effects, or parameters allowed to vary between persons, is also limited in mixed models at one fewer than the number of observations per person. Thus, with four observations, as we had in this study, we were able to estimate up to

[8] The individual trajectory curves in Figure 4 were created by outputting estimated random effects for each person (i.e., ζ_{Bi}, ζ_{Li}, and ζ_{Fi}) from the NLMIXED analysis using the 'out=' option in the RANDOM statement (see the syntax at http://www.psych.nyu.edu/couples/bereave_nlmixed.sas). This option creates a new SAS dataset with the random effects estimates for each person. This dataset can be exported from SAS to other programs more conducive to generating graphs (e.g., MS Excel), where these estimates can be combined with the fixed effects estimates (i.e., γ_B, γ_L, γ_F, and S) via Equations 4 and 5 to create the individualized trajectories. We identified the individuals depicted in the different panels of Figure 4 by sorting the sample according to the sizes of their random effects.

[9] In the case of the present analyses, the model represented by Equations 4 and 5 and the comparable linear model had nearly identical AIC fit indices, with the nonlinear model fitting slightly better.

three random effects. In principle, the *S* parameter in Equation 4 could also have been allowed to vary between persons, but this would have led to a saturated model, so we were forced to keep it fixed for everyone in the population.

Even with many observations per person, computational factors can limit the number of estimable random effects. Estimating more than three or four random effects is not currently recommended because of the computational resources that it demands. The primary consequences of increasing the number of random effects are exceedingly long running times and failure to converge. Providing good starting values for the model parameters can help in both of these respects, so starting values become more important with more complex models. We recommend first running a fixed effects model (i.e., one with no random effects) to obtain reasonable starting values for the more complex random effects models, as fixed effects models will be less sensitive to initial conditions and will converge more readily. However, finding meaningful starting values may still be difficult with models that have multiple random effects, and estimating these models can prove to be a test of one's patience.

Conclusion

In sum, nonlinear mixed models add versatility and precision to a developmental researcher's statistical toolbox. By modeling nonlinear trajectories directly rather than making simplifying assumptions, they describe meaningful properties of developmental change while avoiding the complications that accompany missing data in other approaches. In addition, they provide estimates of the variances and covariances of these properties in the population, serving as a basis for prediction and explanation. Coupled with other longitudinal modeling techniques, this method can give the researcher a more complete picture of the way developmental processes unfold over time.

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