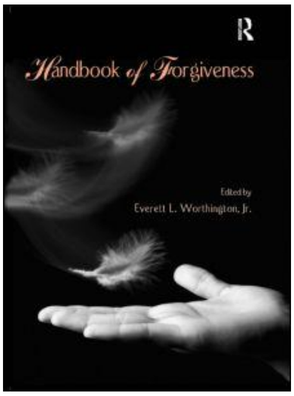

Handbook of Forgiveness

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Forgiveness as Change

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Part Two

METHODS OF STUDYING FORGIVENESS

Chapter Seven

Forgiveness as Change

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Imagine for a moment that instead of being interested in forgiveness, you are interested in the athletic performance of mountain climbers. One morning, five climbers are dropped by helicopter at random points between 1,000 and 5,000 feet above sea level. They climb for the next 12 hours. Your climbers are carrying altimeters that record their altitude at the beginning and at the end of the 12-hour period. At the end of the observation period, you want to figure out how much each of your climbers progressed. What would you do with the available data to get an answer?

People are quite accustomed to this sort of problem so most probably would not consider the assumptions involved in solving it. First, one usually assumes that we know each climber's altitude when the 12-hour period begins and ends, which is only possible if the stopwatch and the altimeter readings are somehow coordinated. One usually assumes that the altimeters measure with perfect reliability, but if these altitude measurements were accurate only to ± 500 feet, one would have to doubt an apparent 500-foot gain in altitude. Fortunately, measurement error in altimeters is small, relative to the gains that our hikers are likely to be making, so we are probably safe to assume that measurement error is only trivially different from zero.

We must also remember that our five climbers start out at different altitudes on the mountain; therefore, we cannot use their final altitudes as a proxy for progress up the mountain. Therefore, we must subtract their starting altitudes from their final altitudes. In fact, when we plot a straight line between each climber's starting and ending altitudes, as in Figure 7.1, we can easily see why this is important. Three climbers appeared to make some progress; the climber who began at the highest altitude seemed to make no progress whatsoever during the 12-hour period; and the climber with the lowest altitude at the end of the 12-hour period actually appeared to be climbing in the wrong direction!

So imagine that we decide to ignore their differing starting points and instead use their final altitudes as proxies for progress. This would give us a greatly distorted impression of each hiker's progress. We might begin correlating traits such as their body weights, physical fitness, prior food intake, or other characteristics with their final altitudes, but these correlations would tell us nothing about the traits associated with

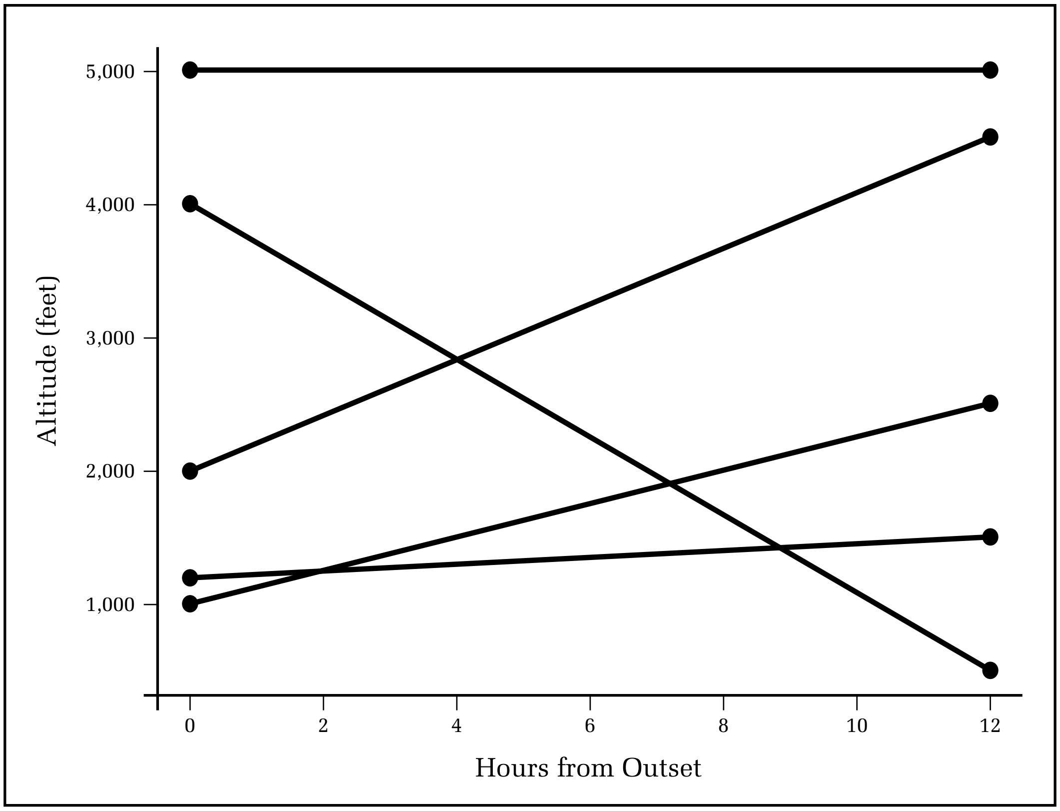

FIGURE 7.1. Altitudes of five climbers at the beginning and end of a 12-hour observation period.

our climbers' progress. To study change in altitude or correlates of change in altitude, we need to know where each individual started on the mountain.

Researchers who study forgiveness and helping professionals are in similar positions to those of the researchers or professionals who wish to study or improve the five climbers' performance. Just as performance researchers and professionals cannot determine how much altitude our climbers gained by simply consulting the altimeter readings at the end of the 12-hour period, researchers and professionals interested in forgiveness cannot learn how much an individual has forgiven a transgressor by simply measuring how the individual feels toward a transgressor at any given time. Yet much of forgiveness research to date has interpreted cross-sectional differences in the forgiveness equivalent of "altitude" as "changes in altitude."

This chapter was written to introduce readers to modern methods for studying change with longitudinal data collected on multiple individuals (sometimes called *panel data*) that permit explicit models of forgiveness as change.

PERSONAL ASSUMPTIONS ABOUT FORGIVENESS

Researchers have defined forgiveness in different ways. For example, Enright, Gassin, and Wu (1992) defined *forgiveness* as "the overcoming of negative affect and judgment toward the offender, not by denying ourselves the right to such affect and judgment, but by endeavoring to view the offender with compassion, benevolence, and love" (p. 101). Exline and Baumeister (2000) defined *forgiveness* as the "cancellation of a debt" by "the person who has been hurt or wronged" (p. 133). Finally, McCullough, Worthington, and Rachal (1997) defined *forgiveness* as "the set of motivational changes whereby one becomes (a) decreasingly motivated to retaliate against an offending relationship partner; (b) decreasingly motivated to maintain estrangement from the offender; and (c) increasingly motivated by conciliation and goodwill for the offender, despite the offender's hurtful actions" (pp. 321–322).

Despite the obvious differences among such definitions, they are all based on the assumption that forgiveness involves prosocial change regarding a transgressor on the part of the transgression recipient. Most theorists concur that when people forgive, their responses (i.e., thoughts, feelings, behavioral inclinations, or actual behaviors) toward a transgressor become more positive and/or less negative. This point of consensus led McCullough, Pargament, and Thoresen (2000) to propose that *intraindividual prosocial change toward a transgressor* is a foundational and uncontroversial feature of forgiveness. We assume this to be true as well.

REVIEW OF THE THEORETICAL AND EMPIRICAL LITERATURE

Several models for studying forgiveness as change are available. Change is a longstanding problem in social sciences research, and tremendous progress has been made in the methods used to study change in human systems. We will review some of what we have learned from some of these approaches and describe some of their strengths and weaknesses. We will also address some common practical questions about using these methods. We close by introducing two models for studying change that may be useful for future work on forgiveness.

Cross-Sectional Approach to Studying Change

Research on forgiveness of specific transgressors received a big push forward with the development of several self-report questionnaires (e.g., McCullough et al., 1998; Subkoviak, Enright, Wu, & Gassin, 1995; Wade, 1990). Such measures prompt respondents to think of a single transgressor who has hurt them in the past, then to answer questions that assess their current thoughts and feelings about the transgressor (e.g., "I want to get even with him/her" vs. "I have overcome my resentment toward him/her"). Researchers often aggregate participants' responses to these items and interpret the scores as measures of how much the individuals have forgiven their various transgressors. These individual differences can then be correlated with characteristics that might influence forgiveness or outcomes that forgiveness might influence.

This approach is problematic. Using a single measurement to assess forgiveness is analogous to using our climbers' altitudes at the end of the 12 hours to determine their progress. This is because some individuals are more deeply wounded and, thus, have more to forgive. Like our climbers, people who have been harmed begin the climb at different places. A few years ago, our group began looking for research approaches that could better depict forgiveness as change.

Two-Wave Panel Model

The simplest model that permits one to observe change is a two-wave panel design in which people complete measures of their thoughts, feelings, emotions, or behaviors regarding a transgressor (i.e., measures traditionally conceptualized as "forgiveness" scales) on two different occasions. Each individual's Time 1 score can be subtracted from or covaried out of his or her Time 2 score to create a value representing the individual's net change between the two time points. This method statistically equates individuals by removing between-persons differences at Time 1. This is the approach one would likely use to ascertain the progress of our five climbers. Our climbers did not begin at the same altitude, but by subtracting or statistically controlling for initial differences, we can pretend that they did. McCullough and colleagues (McCullough, Bellah, Kilpatrick, & Johnson, 2001) used a two-wave panel model to examine vengefulness and rumination as correlates of forgiving. By computing change scores for individuals who completed measures of forgiveness on two occasions, the researchers found that people with high scores on a self-report measure of their vengeful behaviors and their attitudes regarding revenge experienced less reduction in their revenge motivation in the months after an interpersonal transgression than did people with lower scores. They also found that people who experienced reduced avoidance and revenge motivations regarding a transgressor also tended to experience reduced ruminative cognition and reduced effort to suppress those cognitions.

Researchers often use two-wave panel designs to evaluate forgiveness interventions to improve statistical power, but apparently not because they believe it is a better representation of forgiveness. Two-wave panel designs are certainly better than using cross-sectional individual differences to measure forgiveness, but they still have drawbacks. First, researchers using a two-wave design would typically measure people who had been hurt at some point in the past twice (possibly with random assignment to an experimental condition between the two measurements) and compute change scores. In such a design, the only values of time attached to the two scores are values representing their placement in the research design, not values that have psychological meaning (i.e., the amount of time that had passed since the transgression occurred).

Second, by using pre- and post-differences to approximate forgiveness, one necessarily assumes that any given individual changes at a constant rate: Like cannon balls fired into the sky at different angles on a planet with no gravity, the two-wave design assumes that an individual's rate of change stays the same forever and, therefore, can be estimated with fidelity from any two given points in his trajectory. One might not want to assume this, but it is impossible to do otherwise because the most rational trajectory between two points is a straight line.

A third problem with the two-wave design is that true change cannot be separated from measurement error. With our five climbers, this probably is not a problem because our altimeters have low measurement error; however, when using self-reports, one is not so fortunate.

Multilevel Linear Growth Models

The limitations of the two-wave panel model can be addressed with methods called *multilevel linear growth models* (also called *hierarchical linear models*, *mixed models*, or *random coefficient models*). These models are called *multilevel*, *hierarchical*, or *mixed* because they accommodate a nested data structure—for example, the data structure that arises when multiple measurements are obtained from each of several individuals. These models can be tested with various software packages, including SPSS, SAS, HLM, MLWin, and R, as well as various programs for structural equation modeling, but our focus is on the models themselves and what they can teach us about forgiveness. For a fuller examination of mixed models for analyzing longitudinal data, see Bryk and Raudenbush (2002) and Nezlek (2001).

We can use these models if we change our plan for data collection in two ways: We need to measure participants on three occasions or more; and with each measurement, we must record how much time has passed since each person's transgression occurred. Suppose we have three measures of how vengeful an individual feels toward a transgressor (e.g., the values 3.5, 2.0, and 2.1) from three different occasions (e.g., 2, 10, and 15 days after a transgression). We can write:

$$Revenge_{ij} = \beta_{0j} + \beta_{1j}(Time_{ij}) + r_{ij} \tag{1}$$

In Equation (1), the revenge score of person *j* (let's call him Jim) at time *i* is modeled as a function of an intercept β_{0j}, which represents Jim's expected revenge motivation when *Time* = 0 (i.e., just after the transgression) and a rate of change β_{1j}, which represents the rate at which Jim's revenge scores change as a linear function of time. The residual r_{ij} is the deviation of Jim's revenge score at time *i* from what would be expected, based on his initial revenge status (that is, the revenge score that would be expected when time since the transgression = 0, or β_{0j}) and the rate of linear change in his revenge scores (or β_{1j}). For forgiveness research, this equation does three important things. First, Jim's change in revenge motivation (called *trend forgiveness* for reasons we will describe shortly) is separated from his initial level of revenge motivation. We have separated progress up the mountain from initial altitude. Second, by attaching the amounts of time that elapsed between the transgression and each individual measurement to the revenge scores, time is expressed in a psychologically meaningful metric—the amount of time since Jim was harmed. Third, true change is separated from measurement error. Equation (1) is identified with three data points, and we can estimate the two β parameters (i.e., initial status and rate of change).

If we measure Jim's revenge motivation on a fourth occasion, we can identify a linear model that allows for more complex forms of change:

$$Revenge_{ij} = \beta_{0j} + \beta_{1j}(Time_{ij}) + \beta_{2j}(Time^2_{ij}) + r_{ij} \tag{2}$$

In Equation (2), Jim's revenge score on occasion i results from three parameters: (a) his expected revenge score immediately after the transgression (β_{0j}), (b) the rate of linear change in his revenge scores over the measured interval (β_{1j}), and (c) the rate of quadratic change (also called *curvature*) in his revenge scores over the measured interval (β_{2j}). As in Equation (1), r_{ij} is the deviation of Jim's revenge score at time i from what would be expected, based on his initial revenge status and his rates of linear and quadratic change in revenge scores over the measured interval. By including the coefficient for quadratic change, β_{2j}, Jim's trajectory can possess curvature. If, from this regression, we find that Jim's value for β_{0j} is 3.10, for example, we can conclude that when $Time = 0$ (that is, immediately after the transgression) Jim's revenge motivation score was 3.10. If we find that β_{1j} is, for example, −0.04, we can conclude that Jim's revenge motivation went down, on average, 0.04 scale score units per day. If Jim's value for β_{2j} is positive—say, +0.002—then we conclude that Jim's trajectory was "concave upward," and that the declines in Jim's revenge motivation slowed down, on average, 0.002 scale score units per day. In other words, the rate at which Jim was shedding his revenge motivations decreased over time.

Fixed Effects, Random Effects, and Interindividual Differences in Forgiveness

Equations such as (1) and (2) are called *Level 1* or *within-person* equations because they parameterize the observations at the first level in a multilevel design (i.e., in this example, they explain where the variation among the repeated measures of revenge motivation comes from). Recall that these research designs are called *multilevel designs* because several observations are obtained for each of several individuals. Now suppose that we have five people who have been harmed in the last few days by a transgressor. For each of these individuals, we might estimate Level 1 linear equations of the form of Equation (2), which would yield different estimates for their initial status, linear change, and quadratic change parameters. How should we conceptualize the interindividual variation in these parameter estimates? The simplest way is to model the parameters as the result of expected parameter estimates for the entire sample and person-specific deviations from the expected values. In the language of multilevel models, the expected values of the parameters for the sample are called *fixed effects*, and the person-specific deviations from the expected values are called *random effects*. Person-specific variations in linear change in revenge, for example, can be decomposed according to the following between-persons, or Level 2 model:

$$\beta_{1j} = \gamma_{10} + u_{1j} \tag{3}$$

In Equation (3), we have expressed Jim's rate of linear change in revenge motivation (β_{1j}) as a function of a fixed effect and a random effect. The fixed effect γ_{10} (often called the *grand mean*) is the expected linear change for the sample, and the random effect u_{1j} is the deviation of Jim's parameter estimate for linear change β_{1j} from the fixed effect γ_{10}. Note that the γ coefficient has two subscripts, the first of which corresponds to the numerical subscript on the β from the Level 1 equation in which it was used. The fixed effect answers the question, "What is the typical degree of linear change that an individual from our sample can be expected to experience?" To answer the question, "To what extent does Jim's degree of forgiveness differ from the 'average' person in the sample?" we simply interpret Jim's random effect u_{1j}. When we consider our sample of individuals as a whole, the variation in random effects is a variance component that can be predicted based on other variables. If we want to know whether a personality trait or some characteristic of the transgression itself is associated with linear reductions in revenge, for example, we can evaluate whether a personality trait or transgression characteristic explains some of the variation among the person-specific estimates for the β_1 parameters. This is equivalent to correlating the trait or transgression characteristic with the random effects because the fixed effect is a constant that does not contribute to between-persons variance. We can write:

$$\beta_{1j} = \gamma_{10} + \gamma_{11}Neuroticism_j + u_{1j} \tag{4}$$

This decomposes Jim's parameter estimate for linear change into (a) the fixed effect γ_{10}, (b) Jim's score on a self-report measure of *Neuroticism* (which we have centered around the sample mean) multiplied by a parameter γ_{11} that relates *Neuroticism* scores to individual differences in linear change, and (c) a random effect u_{1j}, which now represents variation that cannot be explained by the fixed effect and between-persons differences in *Neuroticism*. If γ_{11} is statistically significant, we can conclude that *Neuroticism* is a significant predictor of individual differences in linear change. If we wish to examine whether a forgiveness intervention is effective, we can create a dummy variable *ForgInt*, for which we assign zero to participants in a control group and 1 to participants in a forgiveness intervention. Then we can write:

$$\beta_{1j} = \gamma_{10} + \gamma_{11}ForgInt_j + u_{1j} \tag{5}$$

where $ForgInt_j$ = Jim's score on the dummy variable. To examine whether the intervention is particularly efficacious for people low in *Neuroticism*, we can create a product variable *Neur*Int* representing the interaction of *Neuroticism* and the treatment effect, and write:

$$\beta_{1j} = \gamma_{10} + \gamma_{11}ForgInt_j + \gamma_{12}Neuroticism_j + \gamma_{13}Neur{*}Int_j + u_{1j} \qquad (6)$$

If γ_{13} is statistically significant, we can conclude that the effects of the forgiveness intervention are moderated by *Neuroticism*. As the random effects variance becomes smaller with successive models, we are doing a better job of accounting for interindividual differences in forgiveness.

Our research group has written several papers that used multilevel linear growth models to study forgiveness (Bono & McCullough, 2004; McCullough & Bono, 2004; McCullough, Fincham, & Tsang, 2003). The studies described in those papers involved longitudinal data from undergraduates who had suffered transgressions in the recent past and whom we measured repeatedly for several months. We obtained up to five measurements per person.

The first question we asked was whether the typical person tended to forgive in the months following their transgressions. By examining the fixed effects obtained from running multilevel models as in Equation (1) on repeated measures of people's avoidance, revenge, and benevolence motivations toward their transgressors, we found that the expected rate of reduction in participants' avoidance and revenge motivations was statistically significant. The typical person became less avoidant and vengeful toward his or her transgressor. However, this was not true of benevolence motivations: The fixed effect for linear change in benevolence was not significantly different from zero. This indicates that we can expect undergraduates to become less avoidant and vengeful toward their transgressors as time passes after a transgression but that we cannot expect them to become more benevolent. This difference suggests that it might be worthwhile to maintain a conceptual distinction between the decay of negative motivations and the restoration of positive ones as components of forgiveness (McCullough et al., 2003), because some of these changes can be expected of the typical individual, whereas others cannot.

In the same paper, we examined the extent to which appraisals of transgression severity, empathy for a transgressor, and responsibility attributions influenced interindividual differences in the linear change of avoidance, revenge, and benevolence motivations (McCullough et al., 2003). We were somewhat surprised to find that initial appraisals of how severe transgressions were and participants' feelings of empathy toward their transgressors were not correlated with individual differences in the rates at which avoidance, revenge, and benevolence motivations changed. However, we did find evidence that people who initially made stronger attributions of responsibility experienced steeper increases in benevolence motivations over time. This latter finding implies that attributing responsibility to one's transgressor may set psychological or social processes in motion that facilitate the return of benevolent motivations.

In a more recent paper (McCullough & Bono, 2004), we were more successful in accounting for individual differences in forgiveness using multilevel linear growth models. By adapting a method for modeling longitudinal change in two variables concurrently (Raudenbush, Brennan, & Barnett, 1995), we examined a question that we had addressed earlier using a two-wave panel design (McCullough et al., 2001): To what extent are reductions in avoidance and revenge motivations associated with reductions in rumination about the transgression? In a first study, we found that the correlations of linear changes in avoidance motivation and revenge motivation with longitudinal changes in rumination were *r*s = .65 and .19, respectively. The revenge-rumination correlation was likely attenuated by a lack of random effects variance for linear change in revenge motivation (i.e., people did not vary much in how much linear change they experienced in revenge motivation). However, we performed the same analyses on a second data set in which there was significant random effects variance for linear changes in revenge, and the correlations of linear change in avoidance motivation and revenge motivation with linear change in rumination were surprisingly strong, *r*s = .87 and .87, respectively (McCullough & Bono, 2004).

To this point in the chapter, we have described how multilevel linear growth models offer a way to model forgiveness as a process of continuous change that is produced by one or more latent growth parameters (e.g., linear and curvilinear change). Because the trajectories produced by this formulation are continuous trends that operate across the entire measured interval on which they are based, we have called this type of forgiveness *trend forgiveness*. However, the multilevel linear growth model can shed light on another aspect of forgiveness that we have called *temporary forgiveness* (McCullough et al., 2003).

Temporary Forgiveness. Notice that the Level 1 (or within-persons) equations (Eqs. 1 and 2) that we specified for our multilevel models include a residual term r_{ij}. Jim's residual *r* at time *i* is the degree to which his instantaneous TRIM value deviates from what we would expect for Jim at that point in time following the transgression, *given what we know about Jim's initial level of revenge motivation and the way in which his revenge motivation changed continuously* (due to a constant growth rate and a degree of acceleration or deceleration imposed on that growth rate) across the measured interval. These deviations r_{ij} from the expected values, based on Jim's Level 1 parameters, are inevitable because of measurement error and occasion-specific error. However, some of the residual variance in Jim's revenge motivations might reflect meaningful, substantive variations in his motivations regarding his transgressor. That is, Jim might feel more vengeful on one day than on another (even after taking his growth trajectory into account) because he is in a particularly good (or bad) mood that day, has had a particularly good (or bad) interaction with his transgressor, or experiences some other transient change. Such transient changes would likely exert real, though fleeting, effects on Jim's revenge motivations. On days when Jim's measured revenge motivations fall below his regression line, we might say that Jim became *temporarily* less vengeful toward his transgressor, or alternatively, temporarily more forgiving.

In contrast, on days when Jim has more revenge motivation than would be expected based on his parameters for initial status and change, we might say that he has become *temporarily* less forgiving. Thus, the fluctuations of Jim's revenge motivation scores around his trajectory might be thought to reflect, in part, a sort of *temporary forgiveness*—a transient and reversible change in his thoughts, feelings, motivations, or behaviors regarding his transgressor that might also tell us something important about the factors that promote or deter forgiveness.

If we add to our data set a measure of Jim's state negative affect (or NA) for each occasion when we also measured his revenge motivations, we can center each of the NA measures around Jim's mean NA value and write:

$$Revenge_{ij} = \beta_{0j} + \beta_{1j}(Time_{ij}) + \beta_{2j}(Time^2_{ij}) + \beta_{3j}(NA_{ij}) + r_{ij} \quad (7)$$

In (7), the coefficient β_{3j} expresses the strength of the relationship of (a) fluctuations in Jim's *NA* scores around the values that would be expected based on his initial status, rate of linear change, and curvature with (b) fluctuations in Jim's *Revenge* scores around the values that would be expected on the basis of his initial status, rate of linear change, and curvature. We now have a total of four parameters in our Level 1 model. To identify this model, we must measure Jim on at least five occasions (to identify a Level 1 model, the number of observations per person must exceed the number of Level 1 parameters). Also, note that *temporary forgiveness* is entirely independent of *trend forgiveness*. Trend forgiveness is an attribute of persons in transgression situations (that is, some people demonstrate trend forgiveness vis-à-vis a given transgression, whereas others do not, making it a *between-persons* phenomenon) but temporary forgiveness is an attribute of individuals on certain occasions but not on others (i.e., a within-persons phenomenon). There is no parameter for temporary forgiveness—it is an unobservable entity that we detect by accounting for fluctuations of people's scores around their growth trajectories.

Our research group has used this method for modeling temporary forgiveness to investigate several substantive questions. First, we used repeated measures of the degree to which individuals experienced ruminative thoughts about a transgression they had recently incurred to examine whether within-persons variation in rumination was associated with within-persons variation in avoidance and revenge motivations. This was the case, which is consistent with the hypothesis that rumination deters temporary forgiveness (McCullough & Bono, 2004). Moreover, through multilevel mediational analyses (Krull & MacKinnon, 2001), we found that rumination deters temporary forgiveness by making people angrier toward (but not more fearful of) their transgressors. We have used similar methods to shed light on the relationship between temporary forgiveness and psychological well-being (Bono & McCullough, 2004).

The multilevel linear growth model provides several different perspectives from which to ask questions about forgiveness as a process of change. In the following few paragraphs, we address some frequently asked practical questions about using these models to study forgiveness.

How Do Multilevel Models Handle Missing and Unbalanced Data? A virtue of the multilevel approach to conceptualizing forgiveness is that the analytic tools that are available for conceptualizing forgiveness this way are themselves quite forgiving of imperfect data. In traditional repeated measures analysis of variance, if a participant is missing any single datum that is named in the model, the participant's data are deleted listwise. In studies with even modest attrition between any two waves of data collection, listwise deletion can lead to a substantial loss of data. Most multilevel programs use estimation procedures that allow missing data on the outcome variables, compensating for this missingness by relying more heavily on the fixed effects to estimate a given individual's parameters. However, few if any of these software programs can accommodate missing data at the highest level (in this case, Level 2, or the between-persons level). If an individual is missing a score on *Neuroticism* per Equation (4) above, his or her data are still deleted listwise.

Another virtue of multilevel models from a design perspective is that the data need not be balanced (i.e., individuals' observations need not be obtained according to a fixed measurement schedule). If Jim's measurements were taken 2, 10, and 15 days after a transgression, and Julie's were obtained 3, 12, and 20 days following a transgression, most multilevel programs can take these differences into account.

How Many Measurements per Participant Do I Need? This is an important consideration for multilevel models. One should measure participants on at least three occasions. Otherwise, it is not possible to estimate the two growth parameters (initial status and linear change), which seem to us to be the minimum for conceptualizing forgiveness as change. Once this "three-minimum" criterion has been met, our quick answer to the question is "as often as possible for as long as possible," but there are two caveats to add to this quick answer. The first caveat is that oversampling participants may cause fatigue that leads them to stop taking the questions seriously. In our published work, we have endeavored to sample once every 2 weeks, but surely one could sample more frequently than that. We are currently analyzing data from a study in which we measured participants each day for 21 days following a transgression, and we expect to learn some important lessons about sampling rates from that study.

The second caveat is that at some point, people's feelings, thoughts, and motivations toward their transgressors must surely stop changing. Theoretically, one could sample an individual for the rest of his or her life, but at some point, presumably that individual's feelings toward his or her transgressor would stabilize around an asymptote. However, how long this takes is currently unknown. We return to this point below in our discussion of nonlinear models.

How Many Participants Do I Need? Judgments of sample size should be based on considerations of statistical power. The power of these models has been studied extensively (Snijders & Bosker, 1993), and software is available for estimating power (Bosker, Snijders, & Guldemond, 2003). Unfortunately for many research areas, including the forgiveness area, the statistical power for multilevel models is hard to estimate because some of the necessary parameters (including the means, variances, and covariances of the random effects) are unknown, and it would be hard to arrive at a reasonable guess. Precise power calculations notwithstanding, to some extent the lack of power that comes from small N can be offset by collecting a large number of observations for each individual and vice versa, but adding Level 1 observations boosts power only insofar as it assists researchers in developing more precise estimates of each individual's growth parameters. At some point, precision cannot be increased substantially by adding more Level 1 units, and adding participants is the best way to boost power.

When Should I Try to Get Participants Into My Study? As quickly as possible after the transgression. We have had good success at locating undergraduates within a few days of incurring significant interpersonal transgressions by repeatedly visiting their classes. This is, no doubt, considerably more difficult when working with samples of individuals who have been harmed in extraordinary ways. Nevertheless, taking time seriously is an important, even indispensable, prerequisite for using multilevel analyses to model forgiveness, so researchers should begin measuring participants as soon after their transgressions as possible. When it is not possible to begin data collection relatively quickly after the transgressions occur, researchers should try to obtain highly accurate information about when people's transgressions occurred.

NEW RESEARCH DIRECTIONS NEEDED IN THE AREA

There are two other multilevel methods for modeling longitudinal data that might be useful complements to multilevel linear growth models that we have discussed here. These methods are called *growth mixture models* and *multilevel nonlinear growth models*.

Growth Mixture Models

The multilevel linear growth model rests on the assumption that there is only one type of trajectory for describing every person's pattern of longitudinal change (Muthén, 2001), although there is variation among people's values on the growth parameters. In other words, even if people's forgiveness trajectories do not conform to the same general shape, the (single-class) multilevel linear growth model assumes that they do. Thus, interindividual differences can be discussed only as parametric differences, not qualitative ones.

One can appreciate the tenuousness of this assumption by considering differences in the TRIM trajectories of three hypothetical individuals, all of whom were harmed on Day 0 (see Figure 7.2). Following the transgression, Person A experiences a very high level of revenge motivation regarding the transgressor and maintains this level for the next month. Person B experiences a very low level of revenge motivation

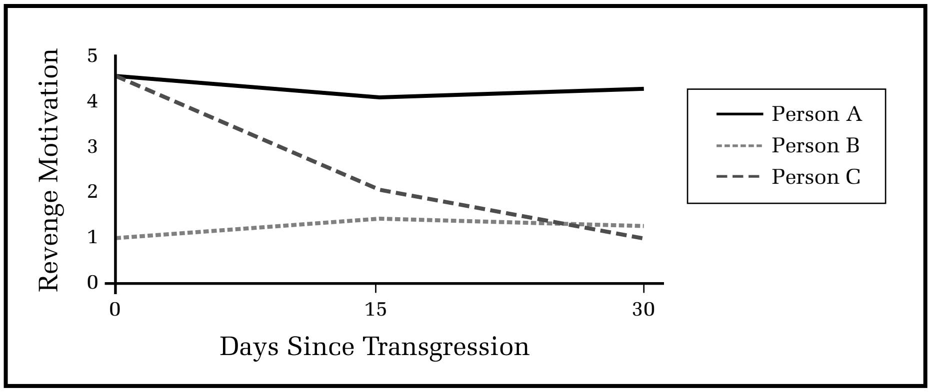

FIGURE 7.2. Three patterns of longitudinal change in revenge motivation.

and maintains this low level for the next month. Person C, however, begins with a very high level of revenge motivation—as high as that of person A—but over the next month, this level decreases until it is as low as that of Person B.

If we fit linear equations to data points of Persons A, B, and C, we would find that Person A's initial revenge parameter estimate was relatively high, but the parameter estimate for his rate of change over time was negligible (i.e., he changed at the rate of approximately zero units per week). For Person B, we would find a very low initial revenge value, but like person A, those values changed at a rate of approximately zero units per week. One can see that the meaning of lack of decay in one's revenge motivations means something very different if one was not very vengeful at the outset (like Person B) from what it means if one was extremely vengeful at the outset (like Person A). Moreover, only Person C demonstrated initially high levels of revenge motivation that decayed over time; therefore, only the Person C could be said to have forgiven.

This example shows that the reduction in Person C's revenge motivations is meaningful only in light of the fact that he was highly vengeful at the outset. In other words, the significance of Person C's longitudinal trajectory comes from treating his initial status and rate of change in tandem, not by considering them individually. This interpretation is not possible in multilevel linear models that do not examine the overall *shape* of a trajectory, instead using decontextualized estimates of linear change without considering initial values.

In (single-class) multilevel linear models for studying forgiveness, estimates of initial status and linear change are almost always negatively correlated—in many cases considerably so. This is because people with very little revenge or avoidance motivation directly following a transgression have very little negative motivation to dissipate, whereas people with the highest initial levels of revenge and avoidance motivations are precisely the people who have the most to forgive and, therefore, are the ones who can experience steep linear reductions in those motivations over time. This dependence between initial status and linear change makes the predictors and consequences of forgiveness difficult to isolate because variables that are associated positively with forgiveness tend to be correlated negatively with initial status. In other words, decomposing people's TRIMs into initial status and slope estimates that are interpreted independently of each other makes it difficult to know whether a predictor or outcome of change in people's TRIMs is caused by its relationship with initial status, forgiveness, or both.

It would be more informative to conceptualize longitudinal change in terms of a set of qualitatively discrete classes of trajectories (Muthén, 2001). We can imagine one trajectory class that is characterized by initially high levels of revenge motivation and no change over time (we might call this trajectory *chronic unforgiveness*, depicted by Person A in Figure 7.2); a second class that is characterized by low levels of revenge initially with no change over time (we might call this trajectory *chronic forbearance*, depicted by Person B in Figure 7.2); and a third class characterized by high levels of revenge that decrease at a steady rate over time (we might call this trajectory *forgiveness*, as depicted by Person C in Figure 7.2).

Using growth mixture modeling (Muthén, 2001, 2003; Muthén et al., 2002), we can develop an efficient taxonomy of such trajectory classes, then use class memberships as a set of variables to be predicted on the basis of background variables or used as predictors of other (e.g., psychological, physiological, or behavioral) outcomes. Growth mixture models have been used to study several problems related to interindividual differences in intraindividual change, including the developmental pathways in cigarette smoking and alcohol use from adolescence to early adulthood (Tucker, Orlando, & Ellickson, 2003), the development of aggression among at-risk adolescents (Muthén et al., 2002), and even the developmental pathways of religious development from the postcollege years to late adulthood (McCullough, Enders, Brion, & Jain, in press). With these models, it is the entire shape of a trajectory—expressed as a discrete, categorical variable—rather than the growth components of a single trajectory that become variables to be predicted on the basis of background variables and to be used as predictors of distal outcomes. Thus, these models lead to novel interpretations of how forgiveness relates to other variables.

We know of only two statistical programs that can be used for growth mixture models—Mplus (Muthén & Muthén, 1998–2004) and the "Traj" procedure developed for SAS (Jones, Nagin, & Roeder, 2001). In our experience, growth mixture models are more difficult to specify and are more sensitive to start values than are (single-class) multilevel linear growth models, but we think they hold considerable promise for forgiveness research, nonetheless.

Multilevel Nonlinear Growth Models

Linear growth models are "linear" not because they force growth to be modeled as a straight-line function of time but because they express the outcome variable as a linear function of the parameters. In reality, however, many things change in a nonlinear way. Washing out of a drug from the blood stream and radioactive decay both involve nonlinear change, even though a linear equation might provide a good fit to observed data over a bounded interval. In such instances, the linear approximations are approximations nonetheless, and it is difficult to give their parameters meaningful interpretations (e.g., knowing that something decays in a linear fashion over a bounded interval does not explain the mechanism that produces the change).

For this reason, it might be useful in the future for researchers to explore equations for forgiveness in which the outcome variable is expressed as a nonlinear function of time. Multilevel nonlinear growth models such as these can be tested with Proc NLMixed in the SAS system or with nlme in S, S-PLUS, and R (Pinheiro & Bates, 1998). In our limited experience, nlme is more flexible and is less picky about start values than is Proc NLMixed, although SAS is considerably more user-friendly and probably more familiar to most forgiveness researchers.

RELEVANCE FOR CLINICAL AND APPLIED INTERVENTIONS

For the practicing clinician, the take-home message is that forgiveness is a change process and that one should not confuse initial status with change when evaluating where clients are. People who come to professionals with help in forgiving by definition are starting with fairly low levels of forgiveness, so even small amounts of progress should be seen as genuine progress.

PERSONAL THEORETICAL PERSPECTIVES ON THE FIELD AND CONCLUSIONS

Scientific progress often is characterized by a transition from static to dynamic views of phenomena (Boker & Nesselroade, 2002), perhaps because thinking about how systems change allows scientists to develop models that predict larger proportions of a system's possible states. Many scientists are expanding the theoretical reach of the social sciences by explicitly considering how we can model change in human systems, just as physical scientists have broadened the reach of the natural sciences by focusing on changes such as motion, growth, decline, and transitions between discrete states. We think that forgiveness is a concept that is ripe for the kind of theorizing that takes seriously the proposition that forgiveness is a dynamic psychological process that unfolds over time rather than a static property of individuals. Modern methods for the analysis of change that allow scientists to take time seriously in how forgiveness is modeled and measured will aid them in advancing theory and, ultimately, providing the world with tools that people can use to experience forgiveness in their own lives.

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