Handbook of Dynamics in Parent-Child Relations

Quantitative Methods for Deductive (Theory-Testing) Research on Parent-Child Dynamics

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Book Title: Handbook of Dynamics in Parent-Child Relations
Chapter Title: "Quantitative Methods for Deductive (Theory-Testing) Research on Parent-Child Dynamics"
Pub. Date: 2003
Access Date: October 15, 2013
Publishing Company: SAGE Publications, Inc.

City: Thousand Oaks
Print ISBN: 9780761923640
Online ISBN: 9781452229645
DOI: http://dx.doi.org/10.4135/9781452229645.n17
Print pages: 347-373

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http://dx.doi.org/10.4135/9781452229645.n17
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Chapter 17: Quantitative Methods for Deductive (Theory-Testing) Research on Parent-Child Dynamics

William L. Cook, ed.

As the substantive chapters in this book reveal, the dynamic processes of parent-child interaction are believed to be fairly complex. In some cases, our ability to test these beliefs empirically may not be up to the task. It may also be that the process of specifying these complex processes in a manner consistent with a quantitative analysis will show that the problems, although complex, are not as complex as imagined. Since the 1980s, a much-expanded repertoire of quantitative techniques has developed for the study of close personal relationships, including, but not limited to, parent-child relationships. These methods, when combined with clear thinking about the nature of the data and the relations between variables, allow us to test many hypotheses for which traditional statistical analyses have been found inadequate. This chapter will introduce these ideas and methods in a stepwise fashion, building from the most rudimentary issues concerning the nature of the data to relatively complex models for the analysis of interpersonal interactions. It has been my experience that the best way to deal with complexity is to start with simple steps. This seems to me to be inherent in the scientific value placed on parsimony—the idea that if two theories account for the data equally well, the simpler of the two theories is to be preferred. In other words, complexity is not valued for its own sake, but only because it promotes the scientific understanding of some phenomenon. This phenomenon generally is called the *dependent variable* and is the focus of research. The dependent variable in studies of parent-child dynamics might be a child outcome, a parent outcome, or a process occurring in the parent-child relationship. Regardless, in order to proceed in a scientific and logical fashion, the researcher must begin by identifying one or more dependent variables on which a study will focus.

The role of *theory* is to guide the researcher in determining how to describe, predict, explain, and understand the dependent variable(s). Some theories guide the researcher in the selection of **[p. 348 ↓]** the independent variables that are relevant to the study of the dependent variable, including *contextual variables* (or *moderators*) that explain the strength of the relation between the dependent and independent variables. These are called *substantive theories*. Other theories focus on how the independent variables and dependent variables should be operationalized or measured. These are called *measurement theories*. Still other theories focus on the rules of evidence for determining the validity of a systematic association between the dependent and independent variables and how that association should be understood (e.g., is it causal or spurious?). This last type of theory could be called *causal modeling theory*. It generally is the domain of the quantitative methodologist and, at a higher level of abstraction, the philosopher of science.

Substantive theories at times can become too far removed from the data or overly speculative. One of the roles of the quantitative methodologist is to ground the substantive theorist—to hold his or her feet to the fire, so to speak, by requiring that the theory consist of constructs that can be operationalized as measurable variables and that can be related to each other by well-articulated processes. Hypotheses about interpersonal processes, like any other scientific hypotheses, are evaluated by testing the relationship between variables. A causal hypothesis (e.g., person A influences person B) must meet three criteria to be supported (Kenny, 1979). The first is that change in the independent variable must temporally precede change in the dependent variable: Causal processes do not move backward in time. The second criterion is that a reliable association exist between the independent variable and the dependent variable. We are often cautioned that correlation does not imply causality but seldom reminded that causality *does* imply correlation. Assuming that the variables are adequately measured (i.e., the measures are reliable and valid) and sufficient observations have been obtained (i.e., there is sufficient power), then if person A influences person B, there will be a reliable association between the independent variable (something measured on person A) and the dependent variable (something measured on person B). The third criterion for inferring a causal (influence) process is that the relation between the independent and dependent variables is not spurious; it is not caused by some other variable that was not statistically or experimentally controlled.

Perhaps part of the reason that I emphasize the importance of simplicity, staying close to the data, and clearly articulating the hypothesized relationship among variables is that my own research on families has tended toward the complex, sometimes leading to confusion and a loss of focus. When studying the system of relationships in families, no one person's outcome provides the sole rationale for the study. Identification of processes such as *bidirectional influence* and *reciprocity* necessarily involves the outcomes for two people, and family effects (factors affecting all members of the family) involve the outcomes for several people. A focus on such processes therefore tends to draw one's attention away from any particular individual's outcome. Take, for example, the following statement.

> Within a reciprocal and interacting system such as the family, individuals produce by their actions the environmental conditions that affect their own as well as others' behavior. One person's behavior is simultaneously a response to environmental stimuli and a stimulus to others' responses within the interactive system of social exchange. (Baumrind, 1980, p. 640)

In my opinion, this statement captures in a clear and eloquent manner much of what is meant by the notion that the family is a system. Note that this statement does not limit itself to child outcomes, or parental outcomes, or marital outcomes, or sibling outcomes—the description incorporates the outcomes for all family members. The challenge of empirically describing, predicting, and explaining the outcomes of such complex family processes has been a key motivation in my work. Sometimes it is helpful to be reminded that the ultimate goal is the understanding of individual outcomes and that the purpose of focusing on complex processes occurring between individuals is to contextualize, and therefore elaborate, understanding of how these individual outcomes come to be. It is the goal of analysis to identify the simplest elements of such processes. This should be viewed in contrast to the goal of integrative thinking, **[p. 349 ↓]** which is to reintegrate the simple elements into a coherent whole. Both are necessary to the process of doing science.

Although the family is an open system, such that the behaviors of family members toward each other often are influenced by forces coming from outside the set of nuclear family relationships (Bronfenbrenner, 1979), it is the presence of *feedback loops* among the behaviors of interacting family members that is the source of the family's self-organizing features. Baumrind's (1980) description highlights this aspect of family interaction. In my view, it is the self-organizing nature of family relationships that gives them “systemness.” There are two kinds of feedback loop: positive and negative. Both are defined in relation to the system when it is in a state of dynamic equilibrium; that is, when the processes of interaction are relatively constant or stable (not to be confused with “at rest”). Positive feedback loops, sometimes referred to as deviation-amplifying processes, involve factors that move the system away from this state of equilibrium. Interpersonal negativity is considered a deviation-amplifying factor because it is so often reciprocated by the person who receives it. The reciprocated negativity is then re-reciprocated, and the potential exists for each person to become increasingly negative until the system moves so far from equilibrium that the system itself goes through a transformation (i.e., *a state-transition)*. In the place of a system characterized by the exchange of verbal behavior (i.e., negative words), a system characterized by the exchange of physically violent behaviors may emerge. State-transitions also can be a result of normal development; for example, a child leaves home for college, marries, or has his or her own children. Each of these events changes the pattern of relationships within the family system, such that the dynamic equilibrium of the system is based on either a larger, a smaller, or a fundamentally different set of relationships.

Negative feedback loops are characterized by factors that pull the system back toward the state of equilibrium or maintain it within some preset range of deviation. The most familiar example is the homeostat that regulates the air-conditioning in a house. As the temperature rises, a set-point is reached that turns on the cool air, thus keeping the room within a preset range of temperatures. Bell's (Bell, 1968; Bell & Chapman, 1986; Bell & Harper, 1977) use of control theory to describe parent-child interaction emphasizes negative feedback processes. When one person's behavior reaches the tolerance level of another person, that other person acts to modulate that behavior and return it to a tolerable level. Of course, inappropriate attempts of one person to control the behavior of another can lead to reciprocal acts of coercion, a deviation-amplifying, positive feedback process (Patterson, 1982).

One of the challenges that theorists have posed for those of us interested in the quantitative analysis of parent-child interactions is how to deal with circular causal processes such as those found in positive and negative feedback loops. The argument put forward is this: As soon as you punctuate the circular process by defining one person's outcome as the dependent variable and the other person's behavior as the independent variable, you distort the very nature of the process. This is so because when one observes the stream of the people's behaviors over time, at any give moment, one person's behavior will appear to be the independent variable (preceding the other's outcome), but at the very next moment what was perceived as the outcome variable can be seen as the independent variable predicting the first person's subsequent behavior. Thus, it is argued that the very first act of scientific inquiry, that of specifying a dependent (outcome) variable and one or more independent (predictor) variables, necessarily will lead to a misunderstanding of the process.

It is true that to study scientifically the processes of parent-child interaction, one must punctuate the circular process by identifying a dependent variable and one or more independent variables hypothesized to predict it. As stated earlier, scientific thinking works best when proceeding from the simple to the complex, and the selection of a dependent variable is the first simplifying step in this process. But studying the same variables (e.g., father and child aggressiveness) at multiple points in time avoids the problem of punctuating the sequence arbitrarily. Some of the methods described below can be applied to the analysis of sequences. Moreover, the use of quantitative methods in no way restricts the researcher from studying both persons' outcomes, treating each person's behavior as an antecedent of the **[p. 350 ↓]** other's outcomes. With respect to parent-child interactions, one simply specifies one model for predicting the parent's behavior, including the child's behaviors among the independent variables, and another model for predicting the child's behaviors, including the parent's behaviors among the independent variables. The conjunction of these models represents the more elaborate notion that there is bidirectional influence (i.e., the child influences the parent *and* the parent influences the child).

As noted by Kuczynski (Chapter 1, this volume), bidirectionality is just one of the processes proposed to describe parent-child dynamics. Several other terms also are used to describe the interdependence of parent and child outcomes (e.g., transactional, interactional, synchronous, and reciprocal models of influence). Just as the theoretical constructs in a model of parent-child relationships require operational definitions in order to be measured and evaluated, the nature of the process also should be operationalized. In this chapter, I will use path diagrams to operationalize some of those processes. It is my position that unless a particular process of parent-child interdependence can be specified in a path diagram consisting of operationally defined constructs and processes, the thinking of the theorist has not developed to the point of providing testable hypotheses. In this case, the barrier to research is not in the domain of quantitative methods but in the conceptual work that must precede the application of such methods. The simple models of interdependence presented below can be thought of as starting points for the evaluation and elaboration of more complex models. Even more fundamental than the specification of the processes that create interdependence in parent-child relationships is the specification of what, exactly, we mean by the term “relationship.” The next section addresses this question.

Measurement and the Meaning of “Relationship”

One of the most confusing aspects of research on relationships—whether parent-child, marital, or sibling—is a lack of clarity about what we mean by the term “relationship.” Take, for example, the following simple hypothesis: “A distressed marital relationship will negatively affect maternal responsiveness to the child.” We might all think we know what is being hypothesized by this statement, but when we get to the level of operationalizing variables, we find a fundamental problem. Do we mean by “distressed marital relationship” the husband's relationship to the wife, the wife's relationship to the husband, or some characteristic of the “husband-wife dyad” (e.g., mutual distress)? The reference to *the* marital relationship implies that there is one relationship between two people, what I call reifying the relationship. The tendency for researchers and theorists to speak in terms of a single relationship between two people has long been criticized (e.g., Bernard, 1972) and has come under increasing criticism more recently (Christensen & Arrington, 1987; Cook, 1998; Dakof, 1996).

The most frequent manifestation of reifying the relationship is found in the practice of combining two people's scores on some measure in an attempt to create a dyadic-level variable; for example, taking the average of husband and wife marital satisfaction scores to create a measure of satisfaction “in the marriage” (Christensen & Arrington, 1987). In fact, there are three sources of systematic variance in such measures:

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variance resulting from the husband's unique relationship to the wife, variance resulting from the wife's unique relationship to the husband, and variance that is common to both spouses (i.e., mutual satisfaction). Other attempts to create dyadic-level variables from the scores of individuals might include taking the sum, the difference, the product, or the ratio of the two scores.

Most researchers are aware that when they use the product of two independent variables in a statistical analysis, they have created an interaction term. It is generally understood that when testing the influence of an interaction effect in the prediction of a dependent variable, one must control for the main effects (i.e., the original raw scores). The interaction effect is important only to the extent that it explains variance that is not explained by the main effects. What is realized less frequently is that other methods of combining two scores (the average, the difference, **[p. 351 ↓]** the ratio, etc.) also produce interaction terms; they too contain three potential sources of systematic variance. Consequently, when using any such indexes in statistical analysis, one should control for the individual components that make up the index (for a discussion of dyadic indexes, see Kenny & Cook, 1999). Just as important, the researcher should be aware that each of these methods of combining the two variables operationalizes a different dyadic construct, and the interpretation of this construct should be consistent with the hypothesis being tested. For example, the product of the two scores might reflect synergistic effects of dyadic interaction, as when negativity is reciprocated and escalates, whereas the average of two scores usually operationalizes agreement or mutuality. Thus, one would use the product term to test whether synergistic effects of partners predict an individual's outcome, and one would use the sum of the partners' scores to test whether mutuality predicts an individual's outcome. In either case, the original scores from each person (i.e., those that were multiplied or summed) must be included (as “main effects”) in the prediction equation.

Combining two people's scores to create a dyadic variable clearly has it problems, but some constructs are fundamentally measures of the dyad. Kenny (1988) has called these “purely dyadic variables.” A purely dyadic variable reflects characteristics of the pair, not one individual's orientation to another. Purely dyadic variables are easily recognized because each person in the pair has the same score. For example, the number of arguments a parent and child have over some specified period of time will be the same for the parent as for the child.

Over the course of those arguments, however, the parent and child are expressing negative affect toward each other, and the number of negative statements the parent makes to the child usually will not be the same as the number of negative statements the child makes to the parent. Kenny (1988) calls these “directed relationship variables” because it is usually clear from which direction the action proceeds, who is the actor and who is the partner. Measures of coercion, responsiveness, and marital satisfaction are other examples of directed relationship variables. Directed relationships data reflect the “two-sided” nature of interpersonal relationships.

Another quite common approach to the measurement of relationships involves the attempt to measure the emergent properties of dyadic and family systems using the ratings of individual family members. This practice is ubiquitous in the clinical literature, where family systems-oriented researchers have created assessment instruments intended to capture features of “the system as a whole.” Examples include the Family Environment Scale (Moos & Moos, 1981), the Family Assessment Measure (Skinner, Steinhauer, & Santa-Barbara, 1983), and the Family Cohesion and Adaptability Scales (Olson, Portner, & Lavee, 1985). An example of an item intended to measure cohesion in the family is “Members of our family look out for each other.” Recognition that cohesion might be different in different subsystems of the family has led some researchers to rewrite items to reflect subsystem-level measures; for example, cohesion in the mother-father, mother-child, and father-child dyads (Cole & Jordan, 1989; Jacob & Windle, 1999). Rather than rating the family as a whole, a son might be asked to rate the level of cohesion in the mother-son relationship using the revised item “My mother and I look out for each other.” As the form of the item suggests, cohesion is conceptualized as a purely dyadic variable; there is one relationship (mother-son), and the son is rating this relationship. From a psychometric point of view, such measures are called “double-barreled items” (Judd, Smith, & Kidder, 1991). A double-barreled item is problematic because it has two or more possible answers. In responding to the item, the son might report on how much mother looks out after him, he might report on how much he looks out after his mother (i.e., the directed relationships), or he might report on what he perceives to be the level of mutual “looking-out-for” in the dyad. In any case, such items are seriously flawed psychometrically because one does not know which component of *the* relationship is being rated (him, her, or them). In fact, Kenny (1996a) has shown that such ratings are influenced more by the characteristics of the rater and the individual-level characteristics of the dyad members than by the features of the dyad as a unit (see also Cook & **[p. 352 ↓]** Goldstein, 1993). In effect, these measures are subject to the same criticisms that were presented earlier in discussing the combining of two people's scores to create dyadic indexes. The relationship of each person to the other should be measured and controlled when attempting to measure higher order, emergent characteristics of relationship systems. If there are emergent properties, generally they should be observed via the measurement of the components from which they emerge. Assuming the presence of emergent properties and attempting to measure them directly generally will conceal more than it reveals about interpersonal dynamics. In dynamic models of parenting, both “sides” of the relationship must be measured to determine the influence of the child on the parent and the influence of the parent on the child. Consequently, the remainder of this chapter will focus on directed relationship measures.

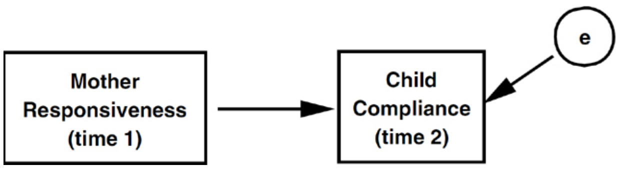
Models of Interdependence in Parent-Child Relationships

Much of the recent progress in the analysis of relationship dynamics can be attributed to the work of David A. Kenny and his colleagues (Cook, 1994, 1998; Kashy & Snyder, 1995; Kenny, 1988, 1996a, 1996b; Kenny & Cook, 1999; Kenny & Kashy, 1991; Kenny, Kashy, & Bolger, 1997). These psychologists have focused on a variety of close personal relationships, including dating relationships, marital relationships, and parent-child relationships. The information presented here will refer specifically to parent-child relationships, but it should be understood that the models are more general than that.

Partner Effect Models

Implicit in any hypothesis about parent-child dynamics is a model of how each is affecting the other. Such models are easily represented by path diagrams. Take, for instance, the hypothesis that maternal responsiveness produces child compliance (Parpal & Maccoby, 1985). In its simplest form, this hypothesis consists of two constructs, the mother's responsiveness and the child's compliance. The mother's responsiveness is operationalized by a directed relationship measure. That is, it is her responsiveness to the child that is measured, not her responsiveness to her husband or to the child's older sibling or her general level of responsiveness. The child's compliance is also operationalized by a relationship specific measure, specifically the child's compliance to mother. The path diagram for this hypothesis is illustrated in Figure 17.1.

Figure 17.1 A Partner Effect Model



This diagram represents what generally can be referred to as a “partner effect model” (Kenny, 1996b). The child's outcome is determined by the antecedent behavior of a partner, in this case the mother's responsiveness. The arrow indicates that maternal responsiveness precedes child compliance temporally and generally is understood to imply a causal relationship. The error term (e) indicates that there are sources of variance in child compliance that are not accounted for by maternal responsiveness; in other words, there is residual variance.

The effect of maternal responsiveness on child compliance was tested elegantly in a laboratory study using an experimental design (Parpal & Maccoby, 1985). The study met all three criteria for inferring a causal relationship.

[p. 353 ↓] Maternal responsiveness was the independent variable. It was experimentally manipulated prior to making observations of child compliance, thus meeting the criteria of temporal precedence. The possibility of a spurious outcome was controlled by randomly assigning mother-child pairs to experimental conditions. Thus, the finding that more responsive mothers had more compliant children (the association of the dependent variable to the independent variable) was reasonably concluded to be due to the experimental manipulation (i.e., maternal responsiveness).

Given a convincing experimental demonstration such as the Parpal and Maccoby study, it is reasonable to ask whether this finding can be generalized to naturally occurring

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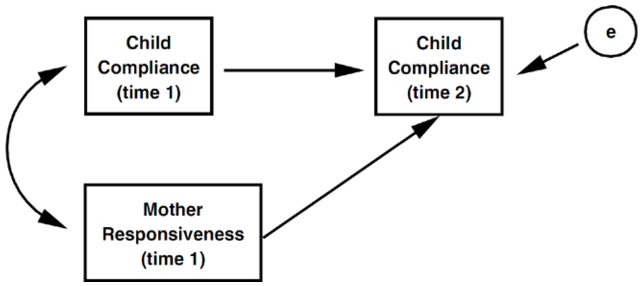
parent-child interactions. Thus, one might propose the use of a longitudinal design in which maternal compliance was the independent variable and child compliance was the dependent variable. For present purposes, assume that maternal and child behaviors have been measured on a reasonably large sample of mother-child dyads (e.g., *N* = 30), that the observations were made at two points in time, that mother's behavior was measured at time t1 and child's was measured at time t2, and that the interval between these measurements was the same for each dyad. For statistical reasons to be discussed below, the model in Figure 17.1 would *not* provide an accurate test of maternal responsiveness on child compliance.

Actor Effect Models

Statistically, one cannot accurately estimate the effect of an independent variable on a dependent variable without controlling for other variables that are correlated with the independent variable and that might be the true cause of change in the dependent variable. Without such controls, the results might be spurious. Within true experimental designs, control is achieved by means of random assignment to groups. In longitudinal designs, it is achieved by measuring the potentially confounding variables and controlling for them in the statistical analysis (Kenny, 1979). The child's prior level of compliance is extremely likely to be such a confounding variable. In general, the best predictor of a person's future behavior is his or her own past behavior. This hypothesis is tested by the statistical relationship between child compliance at time t1 and child compliance at time t2, which measures stability in the child's level of compliance. If child compliance is also caused by maternal responsiveness, then they should be correlated at time t1; as mentioned earlier, causality *does* imply correlation. If both maternal responsiveness at time t1 and child compliance at time t1 are true causes of child compliance at time t2, then the estimation of the effect of either, estimated in isolation from the other, will be biased. Thus, child compliance must be included as a control variable in the model predicting the effect of maternal responsiveness. Figure 17.2 presents the path model expanded to include child compliance at time t1 as a variable.

Figure 17.2 A Model With Actor and Partner Effects

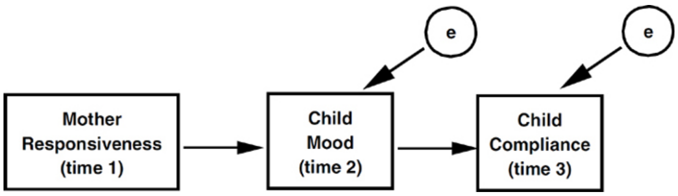


In this model, the effect of child compliance at time t1 on child compliance at time t2 is called an “actor effect” (Kenny, 1996b). There is an actor effect whenever one of a person's own characteristics predicts his or her own outcome. Thus, if we added child temperament at time t1 to the model and it was found to be a significant predictor of child compliance at time t2, this would also represent an actor effect. It is just as necessary to control for partner effects when estimating actor effects as it is to control for actor effects when estimating partner effects. Thus, the model in Figure 17.2 has greater validity for testing either kind of effect than would either an actor effect or partner effect model tested in isolation. Both actor effects and partner effects are included in Sameroff's characterization of “main effects models” (Sameroff, 1975; Sameroff & Chandler, 1975).

Models with Mediator Variables

One of the explanations for the finding that maternal responsiveness increases child compliance was that the mother's responsiveness induced a positive mood in the child, and that the child's positive mood, in turn, predisposed the child to be compliant (Parpal & Maccoby, 1985). This elaboration of the causal process is an example of a *mediator model*, and it was subsequently tested in a study by Lay, Waters, and Park (1989). Figure 17.3 illustrates the **[p. 354 ↓]** relationship among the variables in a simple mediator model.

Figure 17.3 A Mediator Model



The child's mood is a mediator variable in this model. It comes *between*, or mediates, the relationship between maternal responsiveness and child compliance. In everyday language, the model specifies that maternal responsiveness creates in the child a positive mood, and a positive mood predisposes the child to be compliant. Thus, the child's mood is a dependent variable with respect to maternal responsiveness and an independent variable with respect to child compliance. The child's mood might also be referred to as the *proximal cause* of child compliance, because it is temporally “closer” to child compliance within the causal chain of events. Lay et al. (1989) did, in fact, find that positive mood induction predisposed the child toward compliance. As with the Parpal and Maccoby results (1985), this finding was the product of a laboratory experiment. To test whether the finding generalizes to the naturalistic setting (e.g., mother and child interacting at home), a longitudinal design would be required. In this case, child compliance at time t1 would need to be added to the model to control for the child actor effect. It was excluded from Figure 17.3 so that the figure clearly illustrated the nature of the mediator variable. Because mood can be a rather transient state, a more global measure of the child's positive regard for the mother might be a better mediator variable if the time between observations (i.e., time t1 to time t2) is long.

Models with Moderator Variables

We may raise the level of complexity in our analysis by taking into account the mixture **[p. 355 ↓]** or crossing of parent and child characteristics, a model that Sameroff (Sameroff, 1975; Sameroff & Chandler, 1975) has referred to as the *interactional model*. For example, a child with a difficult temperament may be more compliant with a relatively firm versus a relatively responsive mother. In other words, the effect of maternal responsiveness on the child's compliance may be moderated by characteristics of the child. The interactional model also has been referred to as the

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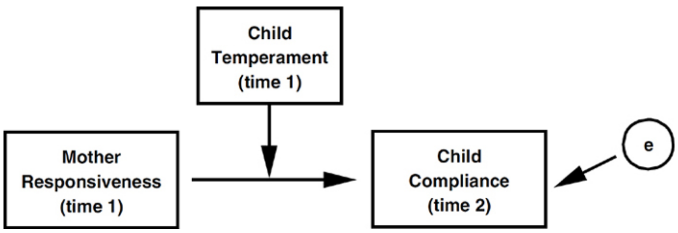
"goodness-of-fit" model because it assumes that developmental outcomes depend on the way that parent and child characteristics "fit" together (Lerner, 1993; Thomas & Chess, 1977). The path diagram for an interactional model is presented in Figure 17.4.

Figure 17.4 An Interactional Model



An essential feature of this model is the partner effect, the path from maternal responsiveness to child compliance. This interactional model specifies that the path between maternal responsiveness and child compliance is affected by the child's temperament. For example, we might be predicting that for temperamentally "easy" children, maternal responsiveness has a greater effect on child compliance than it does for temperamentally "difficult" children.

Another way of expressing this is to say that the effect of maternal responsiveness on child compliance is *moderated* by child temperament. Note how the path diagram for the interactional model differs from the path model for the mediator model (Figure 17.3). A moderator variable affects the strength of the relationship between two other variables, which is why the arrow from child temperament points to the line between maternal responsiveness and child compliance. The child's relationship to the mother (e.g., positive regard) is another possible moderator of the mother's influence on the child. A child who feels positively toward his or her mother will probably be more cooperative with maternal requests than will a child who feels negatively toward his or her mother. Contextual variables are often moderators of actor and partner effects. For example, the history of the parent-child relationship may create interpersonal expectations and affective states that will increase or decrease the effect of the parent on the child, the child on the parent, or the temporal stability of either's behavior (Lollis & Kuczynski, 1997). Some expectations may even function as self-fulfilling prophecies. The adolescent who expects his or her parent to say "No" to a request may introduce the request in a coercive manner, thus priming the parent to say “No.” The expectation moderates the relationship between the adolescent's request and the parent's response. For more information on testing mediator and moderator variables, see Baron and Kenny (1986).

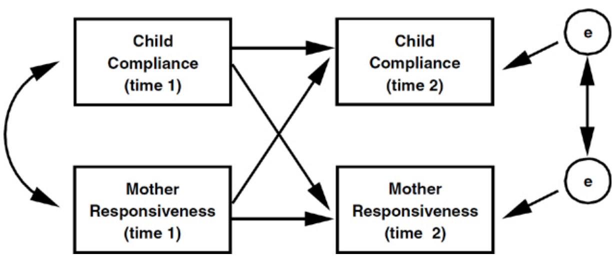
The diagram in Figure 17.4 provides a conceptual perspective on what is meant by an interactional model. It does not, however, present the specifics of analysis. Assume, for example, that one multiplied the measures of maternal responsiveness by the measures of child temperament to produce the moderator or interactional variable. The actual analysis would require the inclusion of all four independent variables —maternal responsiveness at time t1, **[p. 356 ↓]** child compliance at time tl, child temperament at time tl, and the product (moderator) term obtained by multiplying maternal responsiveness at time tl by child temperament at time tl—as predictors of child compliance at time t2. As mentioned earlier, the effect of the moderator variable is valid only if the “main effects” are included in the analysis, and this is true however the moderator variable is constructed (i.e., the sum, the difference, the product, or the ratio of the mother and child measures; see Kenny & Cook, 1999).

The analysis of interactional or goodness-of-fit models requires some additional steps in terms of data preparation. One step is to compute the moderator variable by summing, differencing, dividing, or multiplying the two variables that are believed to interact. Prior to creating a moderator variable, it is a good idea to “center” the independent variables that are combined to create the moderator variable (Aiken & West, 1991). Centering involves removing the sample mean from each of the independent variable scores from which the moderator or interaction term is created. The reason for this is that the moderator variable, because it is a composite of the other two independent variables, will tend to be very highly correlated with these variables. Very high correlations among independent variables causes *multicollinearity*, which seriously confounds the results of the analysis. Centering the variables is an effective means of removing multi-collinearity from the data. Thus, in the example above, the analysis would actually consist of a centered measure of maternal responsiveness at time tl, a centered version of child temperament at time tl, and the product of these two centered variables, which would serve as the moderator variable. Child compliance at time tl and the dependent variable, child compliance at time t2, would not need to be centered.

Bidirectional Effects

Figure 17.2 is a path diagram depicting the hypothesis that maternal responsiveness increases child compliance. The child's outcome is likely affected by both his or her own prior behavior and maternal behavior, so child compliance at time t1 (the actor effect) was included in the model. In bidirectional models, however, each person in the dyad influences the other. This represents a rather large jump in complexity, at least statistically, because we now have two dependent variables rather than one. Child compliance at time t2 is still one of the dependent variables, but now we have parental responsiveness at time t2 as a second dependent variable. In this example, the hypothesis of bidirectional effects implies not only that maternal responsiveness causes child compliance but also that child compliance causes maternal responsiveness. The path diagram for the bidirectional effects model is presented in Figure 17.5.

Figure 17.5 Bidirectional Effects and the Actor-Partner Interdependence Model



This model is called the *actor-partner independence model* (Kashy & Kenny, 2000; Kenny, 1996b). The model has been presented as a means of analyzing both cross-sectional **[p. 357 ↓]** data (Kenny, 1996b) and longitudinal data (Cook, 1998). The longitudinal version of the model is presented here. In this, the most simple version of the model, there are four variables. Each person contributes an independent variable, and each person contributes a dependent variable. There are two actor effects, measured by the path from each person's time t1 variable to his or her own time t2 variable, and there are two partner effects, measured by the path from the partner's time t1 variable to the individual's time t2 variable. The characteristic that distinguishes this as a bidirectional model is the specification that each person affects the behavior of the other—the two partner effects. If either of the partner effects is nonsignificant, the hypothesis of bidirectional effects between child compliance and maternal responsiveness would be rejected. Thus, the test of bidirectionality is actually a test of two hypotheses, not one.

Because there are two dependent variables, the statistical analysis of this model will be multivariate. This will, of course, require greater statistical expertise. It is reasonable, though not the optimal method of analysis, to separate this model into two simpler univariate models like those in Figure 17.2 and conduct the analysis using ordinary regression procedures. One model would have child compliance at time t2 as the dependent variable, with child compliance and maternal responsiveness measured at time t1 as independent variables, as in Figure 17.2. The other model would have maternal responsiveness at time t2 as the dependent variable, with child compliance and maternal responsiveness measured at time t1 as the independent variables. Once again, there would be support of bidirectionality only if the partner effect in both models was significant. An extensive discussion of the analysis of partner effects is provided by Kenny and Cook (1999).

There are advantages, however, to testing the model as a whole rather than two submodels. Using structural equation modeling programs such as LISREL (Jöreskog & Sörbom, 1989) and EQS (Bentler, 1989) to evaluate all the parameters of the model simultaneously, one can glean important additional information from the data. Specifically, one can test whether the child's influence on the parent is equal to the parent's influence on the child. This is achieved by using “equality constraints.” Equality constraints are program options that allow one to force any two paths in the model to be equal. If the test of how well the model accounts for the data (i.e., the statistical goodness-of-fit test) is significantly worsened in the constrained model in comparison with the model without the constraint, one can reject the equality of the two paths. Thus, even if there is bidirectionality of influence, it may turn out that child compliance influences maternal responsiveness more than maternal responsiveness influences child compliance, or vice versa.

A second advantage of using a structural equations modeling approach is that one can allow the residuals (the “e” terms in Figure 17.5) for the two dependent variables to correlate. This specification implies that there is interdependence in the two partners'

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behavior above and beyond that accounted for by the partner effects. For example, it could be that there is similarity in the cooperativeness of all family members within the same family (e.g., based on a shared family value) and that this affects both maternal responsiveness and child compliance. Thus, mother's responsiveness and child's compliance would be correlated in part because the mother and child come from the same family, a factor not included in the analysis. On the other hand, if the mother and child behaviors were measured using the same questionnaire, or if they were rated by the same observer, mother and child outcomes might be correlated because of shared method variance. The correlation of the residuals takes such additional sources of interdependence into account.

An important consideration with regard to all the models discussed in this chapter is the effect of the reliability of measurements on the results. The correlation between two variables is diminished by unreliability, or “noise,” in the measurements. Even if the true relation between two variables is perfect (i.e., a correlation of 1.0), noise in measurements will result in a measured correlation less than 1.0. In general, the more noise in the measurements, the lower the observed correlation will be. This is called *attenuation due to errors of measurement* (Judd & Kenny, 1981). Now suppose that the measurement of child compliance is less reliably measured than the measurement of maternal **[p. 358 ↓]** responsiveness. This will cause the correlation between child compliance at time t1 and time t2 to be attenuated more than the correlation between maternal responsiveness at time t1 and child compliance at time t2. In other words, the child actor effect will be underestimated. Importantly, if one of the paths in the model is underestimated, then the paths that are estimated while controlling for this underestimated path might be biased. For example, if the child actor effect is underestimated, the mother partner effect might be overestimated.

This should not be taken, however, as a suggestion that ordinary regression procedures should not be used to test the actor-partner interdependence model. First, if the reliabilities of the independent variables are roughly equivalent, then the differential effects of attenuation due to errors of measurement should not be serious. Second, there are methods to correct for the effects of attenuation due to errors of measurement (Judd & Kenny, 1986, p. 186). If attenuation due to errors of measurement has biased the actor or partner effects, these corrections will reveal that. Third, the study could be done using latent-variable measures of the independent variables (Cook &

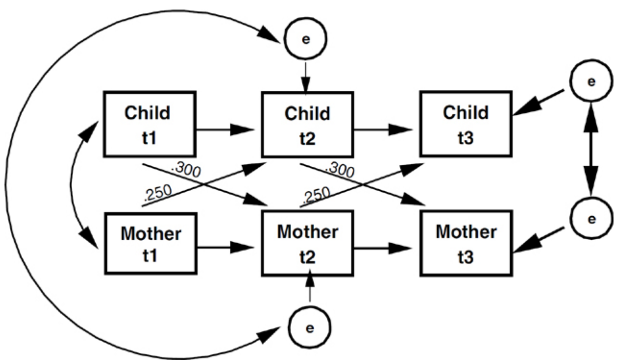
Goldstein, 1993; Rogosa, 1980). Latent variables (i.e., factors) are, in principle, perfectly measured. Thus, attenuation due to errors of measurement can be eliminated. Use of latent variables, however, requires a much larger sample size. Findings from a preliminary analysis using the observed variables could serve to justify the time and expense of conducting a larger, latent variables study.

Differences in the validity of measures can also affect estimates of interpersonal influence. For example, the *Strange Situation* produces valid measures of attachment security for infants, but the same procedure would not provide valid measures for older children. If one used an invalid measure of attachment security for older children, one would expect to find a weaker relationship between maternal responsiveness during infancy and attachment security in childhood than would be found using developmentally appropriate measures. Because the validity of measures changes over the developmental life course, it is important to establish the measurement equivalence of study variables both across time and across individuals who are at different developmental stages. A rudimentary example of the attempt to establish measurement equivalence across a variety of family relationships can be found in Cook (1993), but for a more sophisticated development, the reader should consult Loehlin (1992, pp. 88–95).

Transactional Effects

In the models presented above, actor and partner effects were operationalized as effects occurring over the time frame t1 to t2, what is sometimes called a two-wave panel design. No specification was made regarding the length of time between t1 and t2, though it was required that this duration be approximately the same for all the dyads in the sample. From such data, the actor-partner interdependence model can be tested, thus providing information about the presence of child effects on parent outcomes and parent effects on child outcomes. Assuming that we have controlled for other important causal variables (i.e., ruled out spuriousness), we can conclude that there are bidirectional effects if both of the partner effects are significant. We are limited, however, in our ability to conclude from such data that the process of influence is circular, or *transactional*. A transaction process is one in which a person's prior behavior affects the environment (e.g., another person) in a way that influences the person's subsequent behavior (Sameroff, 1975; Sameroff & Chandler, 1975). For example, we may know that the child behavior at time t1 affects the parent behavior at time t2, but to demonstrate feedback, we would need to show, additionally, that parent behavior at time t2 has a subsequent effect on child behavior at time t3. Thus, transactional models require a minimum of three waves of data (i.e., observations at three points in time). Figure 17.6 presents a path diagram illustrating such a process.

Figure 17.6 A Transactional Model



Note that the model in Figure 17.6 has the same paths as the actor-partner independence model, only they each occur twice. There are actor effects (representing temporal stability) for mother and child spanning time t1 to time t2, and again spanning time t2 to time t3. There are also partner effects (representing interpersonal influence) for mother and child spanning time t1 to time t2 and again spanning time t2 to time t3.

[p. 359 ↓] Assume that the mother partner effect from time t1 to time t2 is .250 and the child partner effect from time t2 to time t3 is .300, and that these regression coefficients are statistically significant. The parent affects the child, who subsequently affects the parent, thus indicating a transactional process of influence with respect to parental behavior. Assume also that the child effect on the parent from time t1 to time t2 is .300 and the parent effect on the child from time t2 to time t3 is .250, and that these effects are also significant. Thus, the child affects the parent, who subsequently affects the child, indicating a transactional process with respect to child behavior.

An important feature of this model is that the processes of interpersonal influence have been presented as stable over time. For instance, the size of the child partner effect from time tl to time t2 is the same size as the child partner effect from time t2 to time t3 (i.e., .300). If the effects from time t1 to time t2 are the same size as the effects from time t2 to time t3, we say that the process has *stationarity*. It does not mean that the individual behaviors are not changing over time, but rather that the process of change (e.g., the size of regression coefficients and whether they have a positive or negative sign) is constant over time. Normally, we expect there to be stationarity for both the actor and the partner effects. This is an important assumption, because it allows us to simplify the model (and the data collection process) by excluding the third wave of data. In other words, if we can reasonably assume stationarity, then it is reasonable to infer a transactional process from the presence of bidirectional effects estimated from just two waves of data. That is, if processes occurring from time t2 to time t3 are redundant with those from time tl to time t2, they are superfluous. On the other hand, if there are changes in the size of the effects (e.g., as a result of maturation or changes in interpersonal expectations), then we must estimate the full model.

Reciprocal Effects

Narrowly defined, *reciprocity* means that one person contingently returns the same behavior enacted by a partner (Cairns, 1979). If some friends invite you over to dinner, you might reciprocate by inviting them over to dinner at some later time. On the other hand, you might reciprocate by doing something else, for example, giving them tickets to a show or sending them flowers. Thus, within a broader definition, the essential feature of reciprocity is that one person's behavior is temporally contingent upon **[p. 360 ↓]** the others. This requires more than simply showing, for example, that the rate of a mother's behavior correlates with the rate of a child's behavior. These correlations should not be mistaken for “reciprocity correlations.” Gottman (1979) discussed two ways reciprocity has been operationalized in the literature, the rate matching and probability change definitions:

> The two definitions are not equivalent. … A husband may eat or type at a rate similar to his wife's without any contingency between these two activities; they may, for example, have similar physical tempos. In this case, we would merely report that eating or typing took place at similar rates, not that they were reciprocal. If a mother smiles at a rate similar

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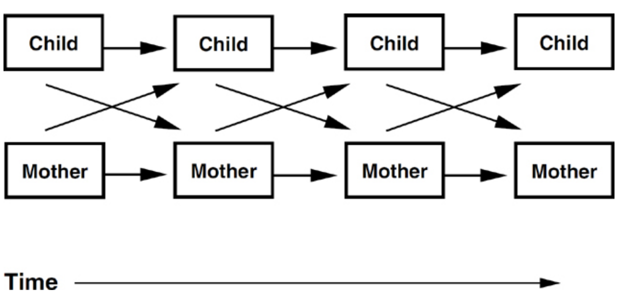
> to her infant, their interaction may, nonetheless, be totally unconnected and noncontingent; the mother's smiling and her infant's smiling would be considered reciprocal only if they were somehow connected in the probability change sense. (p. 65)

Consequently, Gottman correctly argued that correlations of behavior rates or ratings across couples or families, because they may reflect similarity rather than contingency, cannot provide valid tests of reciprocity.

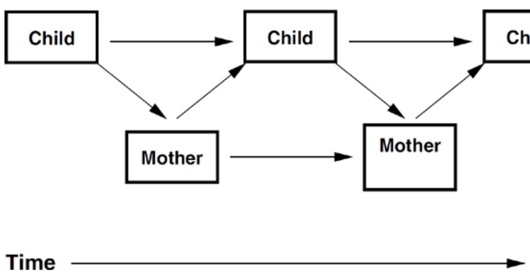
The most valid means of measuring reciprocity in interpersonal relationships is to observe the behavior of two people over time, have trained observers rate or code each person's behavior at each point of observation, and then perform a cross-lagged time series analysis on their behaviors (e.g., sequential analysis or cross-lagged regression analysis). Such analyses provide information on the degree to which each person's prior response affects the partner's subsequent response, averaged over the stream of behavior. The data that are used in these analyses generally take one of two forms. Data may be based on observations that are made at specific intervals of time, say every 5 seconds, or may be based on codings for the onset and termination of particular events. These may be referred to as *time-sampling* and *event-sampling* designs, respectively. Time-sampling designs produce two parallel streams of behavior, as illustrated in Figure 17.7.

Figure 17.7 Illustration of Time-Sampled Data



Some types of observations don't fit this pattern. Conversational data is an example. In conversations, there is a general tendency for one person to speak at a time, a form of turn-taking (e.g., Cook, Strachan, Goldstein, & Miklowitz, 1989). Although time is still a key factor in this design, the duration of each coded event may vary. For example, the child might speak for 20 seconds, followed by the mother speaking for 15 seconds, followed by the child speaking for 5 seconds, followed by the mother speaking for 8 seconds, and so on. Although in principle two events can co-occur (e.g., both persons speaking at the same time), the overall pattern is one of alternation. Thus, the stream of behavior would resemble Figure 17.8.

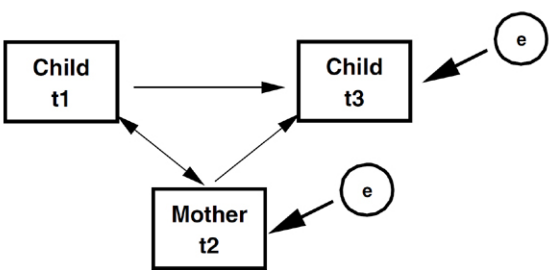
Figure 17.8 Illustration of Event-Sampled Data



[p. 361 ↓] Figure 17.7 and Figure 17.8 are illustrations of the form of the data collected within time-sampling and event-sampling designs, not the analytic model that is actually tested. The analytic model (i.e., path diagram) for the time-sampled data is exactly the same as that presented in Figure 17.2, and the path diagram for the analysis of event-series data is only slightly different. Both can be viewed as versions of the actor-partner interdependence model, but there are some important differences that should be understood. First, in discussing the models presented earlier, it was assumed that the data were collected from a reasonably large sample of dyads, say 30 or more parent-child pairs. Thus, the actor and partner effects reflected the amount of influence one would find in the *average* parent-child pair. When applying the model to time-series or sequential data, however, one estimates the components of the actor-partner interdependence model for a particular dyad. In this case, the sample size for the statistical tests corresponds to the number of observations sampled from that specific dyad. Thus, having a sample size of 30 would mean that one had 30 observations of the mother's and child's behavior as their interaction unfolds over time. The estimate for the actor effect will now reflect the degree, on average, that the actor's immediately prior behavior predicts his or her subsequent behavior. The partner effect will reflect the degree, averaged over the stream of behavior, that the partner's immediately prior behavior predicts the actor's subsequent behavior. Thus, the actor effect is still a measure of temporal stability, and the partner effect is a still measure of interpersonal influence. In the context of time-series data, however, the partner effect usually is not interpreted as the influence of the partner on the actor. Rather, it is interpreted as the actor's reciprocity; that is, the extent to which the actor responds contingently to the partner's prior behavior. This subtle but important difference in interpretation will be discussed further below.

As illustrated by Figure 17.8, when an event-sampling design is used, an event rarely or never follows itself in the stream of behavior. Rather, the stream of behavior is punctuated by the onset of a new event, and with each new event, the identity of the person observed switches (e.g., mother, child, mother, child, mother, child, and so on). Thus, in contrast to Figure 17.2, the analytic model will not consist of independent variables reflecting the behavior of the actor and partner's behavior at time t1 and a dependent variable reflecting the partner's behavior at time t2. Instead, time t1 might contain the child's behavior and time t2 the parent's behavior, and it is time t3 before the child's behavior is coded again. The path model for the event sampling design is presented in Figure 17.9.

Figure 17.9 A Model for Event-Sampled Data



This model illustrates the case in which the child's behavior at time t3 is being predicted from his or her own behavior at time t1 and the mother's behavior at time t2. The child's reciprocity is measured by the path from the mother's time t2 behavior to the child's time t3 behavior (i.e., the partner effect). One might be **[p. 362 ↓]** tempted to interpret the path from child's time t1 behavior to mother's time t2 behavior as the mother's reciprocity; however, this path has not been estimated with controls for the mother's temporal stability (i.e., the mother actor effect). Consequently, it is not a valid estimate of the mother's reciprocity (Allison & Liker, 1982). Consequently, a double-headed arrow connects these variables, indicating correlation rather than causality. Measurement of the mother's reciprocity would be obtained by analyzing a second model, otherwise identical to Figure 17.9 but including the mother's time t1 behavior and the child's time t2 behavior as the independent variables predicting the mother's time t3 behavior. A separate model also would be used to test each partner's reciprocity when time-sampled data are used.

The data from which reciprocity is estimated typically are measured on a nominal scale (i.e., categorically). For example, mother and child verbalizations might be coded as either “warm” or “cold,” or gaze behavior may be coded for whether a person is looking at the partner or away. Consequently, the statistics used for estimating the parameters of the model in Figure 17.9 should be appropriate for categorical data. Loglinear analysis (or logit-linear analysis) is recommended for the analysis of categorical time series data of dyadic interactions because one can estimate the effect of one person's influence on the other (the partner effect) while controlling for the temporal stability of the actor's behavior (the actor effect). Allison and Liker (1982) provide an excellent discussion of the analysis of sequential data, and a more in-depth explanation of log-linear analysis applied to sequential analysis can be found in Gottman and Roy (1990). Prior to investigating the specifics of data analysis, one should consult Bakeman and Gottman (1986) for an excellent presentation of the methods of collecting and coding sequential interaction data. Unfortunately, the methods of statistical analysis of sequential interaction data presented in this book are outdated.

As mentioned earlier, most statistical methods are limited by the assumption of stationarty; that is, the process of change is constant over the time frame during which observations are being analyzed. Suppose, however, that you suspect that the dynamics between parent and child change over time; for example, across developmental phases or distinct phases in an interaction task. One way to analyze such data is to limit one's analysis to observations occurring between any two specific phases, first analyzing the interpersonal dynamics occurring between phases A and B, then separately analyzing the dynamics between phases B and C. The assumption of stationarity is not violated because one has not extended either analysis to observations occurring beyond the point where the causal process has changed. Gottman (1979) used this approach to understand the processes underlying different phases in problem-solving interactions of married couples.

[p. 363 ↓]

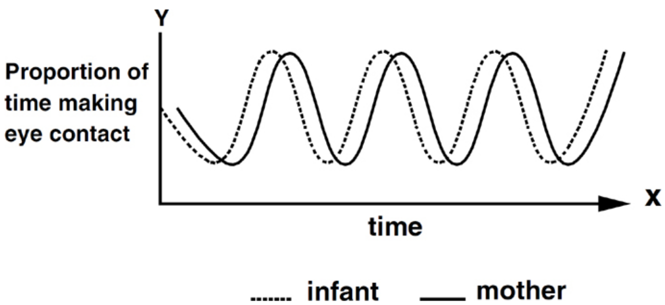
Synchrony

In sequential analysis and cross-lagged regression analysis, the role of time is only to establish temporal precedence. In fact, when event-sampled data are collected, one ignores how long it took for one event to follow the other, preserving only the order of the events. Sometimes, however, the role of time is much more important to the analysis. For instance, a mother's attention to an infant may for a while capture the infant's attention to the mother, but as the infant tires or becomes overstimulated, her attention might begin to have a negative effect (Brazelton, Koslowski, & Main, 1974). This might seem to represent a violation of the stationarity assumption because the process of influence changes over time, but coded over time for the proportion of time spent making eye contact with the mother, the stream of behavior for the infant might resemble a constant series of waves. There are periods of attention that persist for some time and then transition into periods of inattention, and the same pattern repeats over the stream of observations. As long as the manner in which this change of influence occurs is constant over time, there is stationarity. The pattern therefore can be modeled by a mathematical function and included in the analysis.

When analyzing data that cycles, a sine or cosine function is used to model the pattern of change in an individual's behavior. Cycles are like actor effects for autocontingency in sequential analysis. That is, just as it is necessary to control for the actor effect before estimating the influence of a partner in a sequential analysis, it is necessary to control for cycles in the actor's behavior when estimating the influence of a partner in time series analysis. This is done by including an independent variable in the model that describes the cycle (e.g., the cosine of the amount of time the interaction has been going on). Including this variable removes from the dependent variable the variability that results from cyclicity, thus allowing an unbiased estimate of the partner's influence.

In the example of the mother and the infant, the behavior of both people might have been cyclical. It might be that the mother, being sensitive to the infant's signals, reduces her attention to the infant as she becomes aware that the infant is overstimulated. If one is interested in whether the mother's and infant's behaviors are coordinated or coupled, it will be necessary to measure the degree to which the two sets of waves rise and fall together. Figure 17.10 illustrates such a process.

Figure 17.10 An Illustration of Synchrony in Mother-Infant Interactions



The measure of phasic correspondence between two sets of waves is called *coherence*. When there is high coherence between the two sets of waves (i.e., they are “in-phase” with each other), we say their behavior exhibits *synchrony* (Bakeman & Gottman, 1986). This is often of **[p. 364 ↓]** interest in its own right, independently of questions of who influenced whom. It is also possible to estimate the extent to which one person's waves systematically lead or follow those of the partner, suggesting a process of interpersonal influence. If the amount of time the mother makes eye contact with her infant begins to decrease after she notices that the infant has begun to avoid eye contact with her, the cycles describing her behavior would lag slightly behind those of her infant. As can be seen in Figure 17.10, the infant's behavior changes first, followed shortly by a change in the mother's behavior. Lag-lead relationships between sets of cyclical data are analyzed using cross-spectral analysis. Warner (1998) has provided a clear and comprehensive introduction to these methods. Although statistical analysis is complicated by the presence of cycles in the data, the dynamics of interpersonal influence still can be conceptualized in terms of the actor-partner interdependence model.

Although in some cases the researcher may be interested in the dynamics of a particular dyad, in most cases the goal will be to generalize to a particular group or population. For example, one might want to compare the parent-child dynamics of families at high risk of having a disturbed child to families where the risk is low (e.g., Cook, Strachan, et al., 1989). In this case, one simply uses the parameter estimates for the actor and partner effects obtained from a log-linear, time series, or cross-spectral analysis of individual dyads as the dependent variables in a more conventional analysis (e.g., a *t* test or an ANOVA). For example, using the results of sequential analysis, one could test whether fathers in high-risk families are more likely to reciprocate their child's negativity than fathers in low-risk families. Because father's reciprocity is measured by the child's partner effect (alternatively, how much the child influences the father), the *average* child partner effect for high-risk families should be larger than the average child partner effect in low-risk families.

The Source versus the Direction of Influence

In a typical longitudinal design, there may be 6 months, a year, or longer between observations. For example, one may test whether parental use of coercive influence tactics when the child is 10 years old predicts the child's level of aggression when the child is 11. A positive finding would be consistent with the hypothesis that parental coerciveness causes child aggressiveness. It is a separate question whether the aggressiveness of a 10-year-old child will cause the parent to be coercive when the child is 11. If both hypotheses are supported, we probably would conclude that there is bidirectional influence. In both cases, we would tend to view the characteristics of the partner as having some kind of causal influence. But suppose we had taken observations of these same behaviors over the course of one day in the family's home, and we used sequential analysis to measure the actor and partner effects. In terms of the model predicting the parent's behavior from the child's behavior, would we still conclude that the child aggressiveness *causes* parental coerciveness, or would we conclude instead that some parents use coercive tactics to manage child aggressiveness? In terms of the model predicting the child's behavior from parental behavior, would we still conclude that the parental coerciveness causes child aggressiveness, or would we conclude that the child tries to stop the parent from being coercive by responding aggressively? In either case, we know the direction of effects; that is, whose behavior is the antecedent and whose is the consequence. We do not know, however, whose characteristics are driving the interaction. This is a fundamental problem in understanding the results of sequential analysis, cross-lagged regression analysis, and cross-spectral analysis, in particular, and processes of interpersonal influence in general. The source of the effects and the direction of effects are not equivalent. This problem was identified quite some time ago. In the context of describing mother-infant interaction, Maccoby and Martin (1983) put it this way:

> There are some surprising complexities in arriving at an answer concerning who is “driving” the interaction. Mothers can facilitate interaction in several ways: They can initiate it, by emitting signals that capture the infant's attention when the infant is quiescent; they can convert infants' nonsocial behavior into social behavior by joining **[p. 365 ↓]** in when the infant has begun a sequence of behaviors that probably were not initially social (such as babbling); and they can sustain an interactive sequence once begun, by responding in attention-maintaining ways to behavior initiated by the infant. Maternal responsiveness of the latter two kinds could be considered as merely another term for infant control. (p. 30)

Thus, knowledge of the temporal direction of effects (i.e., whose behavior leads and whose follows contingently) leaves unanswered the question of who is actually controlling the interaction. Such questions can be addressed using the Social Relations Model (SRM) (Kenny & La Voie, 1984).

The SRM: An Integrative Model of Family Relationships

Few researchers would minimize the value of understanding parent and child behaviors within the broader context of the family system. The child's behavior toward the parent may reflect the way the child behaves toward other family members in general, which would suggest that the behavior is traitlike. On the other hand, the child's behavior may be unique to the parent-child relationship. Similarly, the parent's behavior toward the child might reflect a trait of the parent, as indicated by the way the parent behaves toward other family members in general, or it might reflect something about the child, as indicated by the fact that the child seems to elicit the same behavior from other family members. In short, we can understand parent-child dynamics better if we know about other relationships in the family. Consequently, analyzing the family as a system of relationships is a worthy goal. The SRM has been applied to family relationships data with this goal in mind. In this section, I will describe how the SRM can be used to test for actor, partner, and relationship effects; bidirectionality; and reciprocity in family relationships.

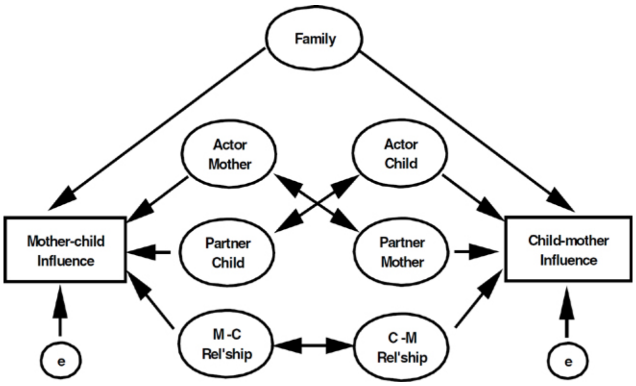
The SRM can be applied to either observational data or self-report data. What matters is that the data are collected according to a round-robin design or one of its close relatives (e.g., a block design). A round-robin design is one in which each person interacts with each other person in the group. In this design, a person is an actor with respect to observations of how he or she thinks, feels, or behaves toward others, and a partner with respect to being the target of the thoughts, feelings, or behavior of others. In families, each person is both an actor and a partner in relationship to other members of the family, so data on family relationships constitute a round-robin design. If one is interested only in parent-child relationships, and if one's sample consists of two-parent, two-child families, one could exclude measures of the husband's and wife's relationships to each other and the sibling's relationships to each other. This would constitute a block design (i.e., it is “blocked” on intergenerational relationships). Because fewer relationships are measured, the block design may be less burdensome for the respondents. The tradeoff is that potentially important relationships are excluded from the analysis.

Suppose one had used sequential analysis to determine the extent to which each person in the family had “influenced” each of the other family members (i.e., the sequential analysis partner effects). In a two-parent, two-child round-robin design, we would have 12 directed relationship measures, one reflecting how each of four persons affected each of three partners. In a sample of families, we would find that the mother's influence on one of the children (e.g., child 1) varies across families. In some families, the mother has more influence than in other families. Likewise, we would find variance in the father's influence on child 1, the father's influence on child 2, the father's influence on the mother, the mother's influence on the father, and so on. However, we would not know for any of these measures of interpersonal influence why there was more influence in some families than in others—we would not know whose characteristics were *driving* the influence process. For example, variance in mother's influence on child could be due to characteristics of the mothers, the children, the unique mother-child relationships, or the nature of the families in which their relationships were embedded. The SRM provides estimates of these sources of variability in family relationships data.

Because of its complexity, the SRM is not easily presented as a single path diagram. As an **[p. 366 ↓]** alternative, a path diagram for just one dyad, the mother-child relationship, will be presented. It will be important to keep in mind that the mother-child dyad is just one of the dyads found in the round-robin family design and that one of the other dyads (e.g., father-child, father-mother, older sibling-younger sibling) could have been used for purposes of illustration. Estimation of the components of the family SRM requires the simultaneous analysis of all the dyads included in the design. Minimally, a sample of three-person family groups is needed to conduct an SRM analysis.

According to the family version of the SRM (Cook, 1994; Kashy & Kenny, 1990), person A's thoughts, feelings, or behavior in relation to person B will be a function of four factors: (a) person A's actor effect, (b) person B's partner effect, (c) the unique relationship of person A to person B (i.e., a relationship effect), and (d) a family effect. Figure 17.11 presents a path diagram that reflects the sources of variance affecting mother's relationship to the child (mother-child influence) and the child's relationship to the mother (child-mother influence). Although interpersonal influence is the variable being discussed in this example, other measures of directed relationships (e.g., negativity, perceived control, coerciveness, attachment security) observed within a family round-robin design have been analyzed with this model (see Cook, 1993, 1994, 2000; Cook, Kenny, & Goldstein, 1991).

Figure 17.11 The Social Relations Model



In this figure, the observed measures of mother-child influence and child-mother influence are represented by the rectangles. On the left side of the figure, it is seen that a mother's influence on her child will be a function of four systematic sources of variance—the family effect, the actor effect for the mother, the partner effect for the child, and the mother-child relationship effect. This is indicated by the single-headed arrows pointing from the SRM effects (represented by ovals) to the observed measure. In the terminology of latent variables analysis (also called factor analysis), the observed measure *loads on*—or serves as an indictor for—each of the four SRM factors. The "e" factor represents variance in the observed measure that is not explained by these factors. It is the residual variance. On the right side of the figure are the components accounting for the observed measure of the child's influence on the mother. Child-mother influence will be a function of the family effect, the child actor effect, the mother partner effect, the child-mother **[p. 367 ↓]** relationship effect, and residual variance (i.e., errors of measurement). The actor, partner, relationship, and family effects are represented by ovals to indicate that they are not directly measured but are instead latent variables. The double-headed arrows indicate reciprocity correlations. Reciprocity is measured at the individual level of analysis, as indicated by the correlation between an individual's actor and partner effects, and at the dyadic level, as indicated by the correlation between the relationship effects. Each of these effects will be described in more detail below.

SRM Actor Effects. Actor effects reflect characteristics of a person that influence all of his or her relationships, a kind of cross-situational consistency. An actor effect therefore is an index of individual differences or traits. With respect to interpersonal influence, the actor effect indicates that a person has a consistent degree of influence across a variety of relationships. Consequently, one must measure the person's influence with at least two partners (e.g., mother's relationship to both father and a child) to determine if his or her level of influence is consistent. An advantage of the family round-robin design is that there are multiple partners in a family group. Significant variance in the mother actor effect would indicate that in some families, the mother has more influence than in others. For example, women who use inductive control techniques (e.g., reasoning, explaining) may be more influential in all their family relationships than are women who use power-assertive control techniques (e.g., physical punishment, restriction of privileges). If this is so, the actor effect for mothers will account for significant variance in mother-child influence. The actor effects for mother and father correspond to the "parental trait" aspect of Sameroff's main effects model (Sameroff, 1975; Sameroff & Chandler, 1975); that is, the extent to which parental characteristics determine their influence on the child. In the SRM, however, actor effects are estimated for all family members: mother, father, and child. Thus, the estimation of SRM actor effects for interpersonal influence will address not only the question "Do parental traits determine parent-child influence?" but also whether the traits of children affect their influence in relationship to their parents, or in relationship to each other. It is therefore possible to draw more general conclusions regarding the role of individual differences of "actors" in determining interpersonal influence.

SRM Partner Effects. Partner effects reflect consistency in the behavior a person elicits from or affords to others. For example, Baumrind's (1967) proposal that authoritative parents produced more competent children than did authoritarian (i.e., power-assertive) parents did not take into account that different children may elicit different styles of parenting (Lewis, 1981). Some children may be more compliant than other children. This would be reflected in the SRM partner effect for the child. Partner effects, like actor effects, correspond to the notion of a "main effect" in Sameroff's (Sameroff, 1975; Sameroff & Chandler, 1975) model of developmental processes. Like the actor effect, it represents stability across multiple relationships, in this case, multiple relationships in which the individual is the partner. Thus, consistency in mother's and father's influence over the child (i.e., either both have high influence or both have low influence) suggests the presence of a child partner effect. Viewed across families, significant variance in the child partner effect would indicate that in some families the child is more easily influenced than in other families. As with actor effects, SRM analysis produces estimates of partner effects for each participating family member. Thus, the analysis addresses not only the question “Is parental influence determined by child influenceability?” but also the corresponding question for all the relationships in the family. In marital relationships, for example, is the wife's influence determined by the husband's influenceability? SRM analysis makes it possible to draw more general conclusions about the role of the partner in determining interpersonal influence in families.

SRM Relationship Effects. Relationship effects indicate the unique adjustment one person makes to another. For example, the degree of influence a mother has on a child may reflect the way the parent and child “fit” together (Lerner, 1993; **[p. 368 ↓]** Thomas & Chess, 1977) rather than general characteristics of either the mother or the child. It might be that mothers who use inductive disciplinary techniques will have more influence than power-assertive mothers in relation to easy children, but power-assertive disciplinary techniques may be more effective with difficult children. Thus, neither the mother or child characteristics, taken alone, can explain the outcome. Estimating the variance in mother-child relationship effects can address the question “Is the mother's influence on the child unique to that relationship?”

SRM relationship effects correspond to Sameroff's interactional model (Sameroff, 1975; Sameroff & Chandler, 1975). Relationship effects differ from the statistical notion of an interaction effect because they are directional; that is, the mother-child relationship effect is not equivalent to the child-mother relationship effect. In the SRM, separate relationship effects are estimated for both sides of “the relationship” (i.e., mother-to-child and child-to-mother). Thus, in a family with two parents and two children, there will be 12 relationship effects because each of four family members has a relationship with 3 other people. Estimation of all 12 relationship variances provides the opportunity to determine whether the importance of the “fit” between partners in determining interpersonal influence generalizes across multiple types of family relationships (i.e., marital, parent-child, and sibling relationships).

To estimate the 12 relationship effects as independent factors, it is necessary to have two measures of each relationship (e.g., two measures of mother's influence on the child). The reason for this is that a latent variable requires, at a minimum, two indicators in order to be identified. Identification of latent variables is a complex topic for which the reader might wish to consult a text on structural equations modeling (e.g., Kenny, 1979; Kline, 1998; Loehlin, 1992). The estimation of relationship effects adds to the complexity of the analysis insofar as the number of observed variables doubles. For instance, round-robin designs involving four people will involve 24 relationship measures, each of which must be specified to load on the appropriate actor, partner, and relationship factors, as well as the family factor.

SRM Family Effects. A family effect is a group effect. Family effects are a function of factors that make family members similar (e.g., socioeconomic status, culture, and family norms). In the present case, a significant family effect would indicate that members of the same family are similar to each other in their ability to influence each other. Significant variance in the family effect would indicate that in some families, everyone's influence is greater than in other families. For example, some families may create a “culture of responsiveness,” whereas others create a “culture of resistance.” Thus, a mother's ability to influence her child could depend on whether she is a member of a responsive or a resistive family. Family effects should not be confused with the notion that the family is a system. This idea is better captured by estimates of reciprocity in family relationships.

SRM Reciprocity Correlations. Social relations analysis provides estimates of reciprocity at both the individual and dyadic levels of analysis. At the dyadic level of analysis, reciprocity is measured by the correlation of relationship effects between the two persons composing a dyad. This is illustrated in Figure 17.11 by the correlational arrow connecting the mother-child relationship effect with the child-mother relationship effect. If the dyadic reciprocity correlation is positive and significant, it would indicate that mothers have more influence with children by whom they are influenced more (i.e., that influence is mutual within the dyad).

At the individual level of analysis, reciprocity is measured by the correlation between the actor and partner effect for the same individual. In the present context, this correlation tests whether individuals who have influence across all their relationships are correspondingly influenced by all their partners. This is indicated in Figure 17.11 by the correlational arrow connecting mother's actor effect with mother's partner effect, and again by the correlational arrow connecting child's actor effect with his or her partner effect. SRM analysis of four-person families (two parents and two children) provide four individual-level (actor-partner) reciprocity correlations (one each for mother, father, child 1, and child 2) along with six dyadic reciprocity correlations (i.e., mother-father, mother-child 1, **[p. 369 ↓]** mother-child 2, father-mother, father-child 1, father-child 2, and child 1-child 2). Thus, the SRM analysis not only estimates the extent of reciprocal influence in mother-child dyads but also tests whether this pattern generalizes to other types of familial relationships, and it tests for this pattern at both the individual and dyadic levels of analysis.

SRM reciprocity correlations correspond to the pattern Sameroff (Sameroff, 1975; Sameroff & Chandler, 1975) has referred to as the transactional model. One nice feature of the SRM is that the logic of the model helps to clarify the distinction between bidirectional influence and reciprocal (or transactional) influence. Recall that bidirectional influence is indicated when each person in the dyad influences the other. In terms of the SRM, bidirectional influence would be indicated if the variances for both the mother and the child partner effects were significant (indicating bidirectional influence at the individual level of analysis) or if the variances for both the mother-child relationship effects and the child-mother relationship effects were significant (indicating bidirectional influence at the dyadic level of analysis). The important word is “and,” because both conditions must be met to infer bidirectional influence. Once again, a test of bidirectionality is actually a test of two distinct unidirectional effects. Bidirectionality does not imply that each person's influence in relation to the other is coordinated or co-regulated. SRM reciprocity correlations capture the dynamics of co-regulation or reciprocal influence. If mother's influence on the child (the mother-child relationship effect) is correlated with the child's influence on the mother (the child-mother relationship effect), it means that the more one influences the other, the more that person is influenced by the other. Similarly, at the individual level of analysis, if a person's influence over others in general (based on the person's actor effect) is correlated with how much that person is influenced in general (based on the same person's partner effect), then we would infer reciprocal influence.

I recently completed a study in which I analyzed round-robin measures of interpersonal influence in 208 two-parent, two-child families (Cook, 2001). The measures were not based on direct observations, but rather relied on the consensus of parent and child perspectives. Evidence was found to support several potentially competing models of influence in family relationships. The proposition that child effects determine the level of parental control (Lewis, 1981) was supported by significant partner factors for the two children. The partner factors for mother and father also were significant. Thus, the importance of the partner in determining interpersonal influence was extended to include all nuclear family relationships. Some people are more influenceable than others. The actor factor for fathers, which corresponds to the parental-trait model of parental influence, also was significant. Some fathers have more influence than others, but there was no evidence that mothers differ in this regard. The actor-partner reciprocity correlation for fathers also was significant, but negative, indicating that the more influence the father has, the less influenceable he is. The “goodness-of-fit” hypothesis (Lerner, 1993; Thomas & Chess, 1977) was supported by findings that interpersonal influence is largely determined by relationship-specific factors. All the relationship factors were significant. Relationship effects correspond to Sameroff's (Sameroff, 1975; Sameroff & Chandler, 1975) “interactional model” of influence. The proposition that influence—or, more exactly, responsiveness—is reciprocal (Parpal & Maccoby, 1985) was supported for dyads involving mothers and their young adult children, dyads involving fathers and both their adolescent and young adult children, and sibling dyads. These findings are consistent with Sameroff's (Sameroff, 1975; Sameroff & Chandler, 1975) “transactional” model of interpersonal influence. Reciprocal influence was not found, however, in every dyad. Consequently, this level of complexity should be suspected but not assumed. The results revealed no variance in these measures that was due to the family as a group. Taken together, the results of this study provided some support for all three models proposed by Sameroff (Sameroff, 1975; Sameroff & Chandler, 1975). This suggests that the inclination to make assumptions about which of these models is the “one true model” would be unwise.

[p. 370 ↓]

Summary and Conclusions

Currently, there is inconsistency among theorists in the use of terms to describe processes of interpersonal influence in parent-child relationships. In this chapter, I have provided conceptual models of interpersonal influence and interdependence, hoping to facilitate creation of a common terminology and understanding about the nature of these processes. Actor effects have been described as the effect of a person's own characteristics on their own outcomes. Partner effects have been described as the effect of partner characteristics on the actor's outcome. Mediator and moderator models have been presented to illustrate how these simple models might be elaborated by the addition of other key factors. In addition, bidirectional effects, transactional effects, and reciprocal effects have been described, and the differences between them have been clarified. Within the context of time series analysis, synchrony has been defined as the degree of correspondence between the cycles in two people's behavior. Finally, the Social Relations Model has been described, demonstrating in the process how it integrates family, actor, partner, relationship, and reciprocity effects within a comprehensive analysis of the family system. I have intentionally avoided in-depth discussion of the statistical procedures involved in these analyses so that the conceptual issues might be clearly presented. Although the analyses of these models can be complicated, there are ample applications in the substantive literature and explications in the methodological literature to guide the prospective researcher. Even though these models can be complex, the simplest model that can account for the data should be the model of choice.

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