International Journal of Behavioral Development
2005, 29 (2), 101–109
http://www.tandf.co.uk/journals/pp/01650244.html

Psychology Press
Taylor & Francis Group

DOI: 10.1080/01650250444000405

The Actor–Partner Interdependence Model: A model of bidirectional effects in developmental studies

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The actor–partner interdependence model (APIM) is a model of dyadic relationships that integrates a conceptual view of interdependence with the appropriate statistical techniques for measuring and testing it. In this article we present the APIM as a general, longitudinal model for measuring bidirectional effects in interpersonal relationships. We also present three different approaches to testing the model. The statistical analysis of the APIM is illustrated using longitudinal data on relationship specific attachment security from 203 mother–adolescent dyads. The results support the view that interpersonal influence on attachment security is bidirectional. Moreover, consistent with a hypothesis from attachment theory, the degree to which a child's attachment security is influenced by his or her primary caregiver is found to diminish with age.

The Actor–Partner Interdependence Model (APIM: Kashy & Kenny, 1999; Kenny, 1996a) is a model of dyadic relationships that integrates a conceptual view of interdependence in two-person relationships with the appropriate statistical techniques for measuring and testing it. The APIM is being increasingly used in the social sciences; for example, in studies of emotion (Butler, Egloff, Wilhelm, Smith, Erickson, & Gross, 2003), health (Butterfield, 2001), leisure activities (Berg, Trost, Schneider, & Allison, 2001), communication competence (Lakey & Canary, 2002), personality (Robins, Caspi, & Moffitt, 2000), and attachment style (Campbell, Simpson, Kashy, & Rholes, 2001). Additionally, the model has been recommended in the area of the study of families (Rayens & Svavardottir, 2003), close relationships (Campbell & Kashy, 2002), small groups (Bonito, 2002), and as a framework for evaluating treatment outcomes in couple therapy (Cook, 1998; Cook & Snyder, in press). The purpose of this article is to describe the APIM and discuss one key use of the model: to assess bidirectional effects within longitudinal designs. We begin with an explication of interdependence in relationships from conceptual and statistical perspectives. This necessarily involves a discussion of measurement issues in relationship research. Next we use a path diagram to elucidate the components of APIM. Three different statistical approaches for testing the parameters of this path diagram are provided and the advantages and disadvantages of each are discussed. We then illustrate the application of the APIM by investigating processes of interpersonal influence in the attachment security of mothers and their adolescent children.

Interdependence and the assumption of independent observations

As the name suggests, the APIM is designed to measure interdependence within interpersonal relationships. There is interdependence in a relationship when one person's emotion, cognition, or behaviour affects the emotion, cognition, or behaviour of a partner (Kelley & Thibaut, 1978; Kelley, Holmes, Kerr, Reis, Rusbult, & Van Lange, 2003). A consequence of interdependence is that observations of two individuals are linked or correlated such that knowledge of one person's score provides information about the other person's score. For example, the marital satisfaction scores of husbands and wives tend to be positively correlated. This linkage of scores is more generally referred to as *nonindependence of observations*. Other processes by which nonindependent observations may arise in dyad scores are discussed elsewhere (Cook, 1998; Kenny, 1996a; Kenny & Cook, 1999). Commonly used statistical procedures (e.g., ANOVA and multiple regression) assume independent (uncorrelated) observations in the dependent variable. Consequently, the scores of two "linked" individuals would be treated as if they were completely independent observations, when in fact the correlation would indicate that they are not independent observations. When the assumption of independence is violated, the test statistic (e.g., t or F) and the degrees of freedom for the test statistic are inaccurate, and its statistical significance (i.e., the p value) is biased (Kenny, 1995; Kenny & Judd, 1986; Kenny, Kashy, & Bolger, 1998). Thus, whenever there are nonindependent observations, it is necessary to treat the dyad (or group) rather than the individual as the unit of analysis (see Kenny, 1995; Kenny & Judd, 1986).

The presence of nonindependence is determined by measuring the association between the scores of the dyad members. Different measures are used depending on the type of dyad. For dyads with distinguishable members (e.g., husbands and wives or older and younger siblings), nonindependence can be measured with the Pearson product–moment correlation. For indistinguishable dyad members (e.g., identical twins or same-sex couples), nonindependence is measured with the intraclass correlation (Kenny, 1995). According to

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The research was supported in part by a grant from the National Science Foundation (DBS-9307949).

Myers (1979), a liberal test (p = .20, two-tailed) should be used in testing whether there is nonindependence because the failure to detect nonindependence could lead to bias in significance tests. If the independence of observations is supported statistically, then one could, in principal, treat the individual rather than the dyad as the unit of analysis. The larger N would generally result in greater power for testing hypotheses. Additional information on the measurement of nonindependence as well as the effects on power of using the dyad rather than the individual as the unit of analysis can be found in Kenny et al. (1998) and Gonzalez and Griffin (2001).

Measurement and the meaning of interdependence

What does it mean to treat the dyad rather than the individual as the unit of analysis? It means that the sample size for the analysis is based on the number of pairs of participants (parent–child, siblings, or married couples), rather than the number of individuals. This requirement begs another question. How can the scores of two individuals be analysed as if they are one? One of the early solutions to this problem was to take the sum or the average of the two individual scores and treat it as a "dyad score" in the analysis. This solution had some appeal because it seemed, on the surface at least, to imply that a "higher-order" phenomenon was being measured, something truly "dyadic". Baucom (1983) recognised that there are conceptual problems with such measures when he criticised the practice of summing husband and wife scores on marital satisfaction measures to create a dyad-level variable. Christensen and Arrington (1987) have re-articulated this complaint:

> For instance, a summing (or averaging) procedure could produce results that would equate a couple in which one spouse is very satisfied and the other unsatisfied with a couple in which both partners are moderately satisfied (the average marital satisfaction score would be the same). Most clinicians and researchers would conceptualize these two cases in very different ways, and the unit resulting from an averaging procedure would not capture these distinctions (pp. 268–269).

Thus, regardless of the type of dyad (e.g., husband–wife, father–child, brother–sister), summed or averaged scores may well create a *mis*-measure of the dyad. This may also be the case when ratings are made of dyadic or group characteristics such as cohesion (Cook & Kenny, 2004).

The actor–partner interdependence model

As an alternative to combining the scores of dyad members to manage nonindependent observations, a generally more informative approach is to retain the individual unit measures but treat them as being nested within the dyad. As will be seen, this approach allows for the estimation of both individual and dyadic factors. For purposes of illustration, suppose we are interested in the development of relationship-specific attachment security in mother–adolescent relationships (Cook, 2000). By relationship-specific attachment security, we mean how secure each person feels in relationship to the other and not the more global measure of attachment style. For brevity, these measures are referred to as *attachment security*. A unidirectional, social-mould theory would predict that the

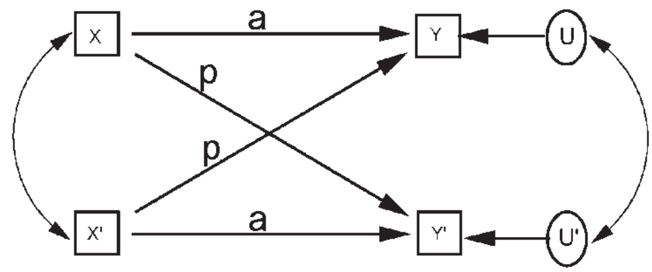

Figure 1. The actor–partner interdependence model (APIM). X = data for person A, Time 1; X' data for person B, Time 1; Y = data for person A, Time 2; Y' = data for person B, Time 2; U = residual (unexplained) portion of person A's Time 2 score; U' = residual for person B's Time 2 score. Single-headed arrows indicate causal or predictive paths. Double-headed arrows indicate correlated variables. Paths labelled as a indicate actor effects and paths labelled as p indicate partner effects.

adolescent's attachment security would be predicted by characteristics of the mother. A more contemporary, bidirectional view would predict that each person influences the other (Kobak & Hazan, 1991; Lollis & Kuczinski, 1997; Kuczinski, 2003).

Figure 1 presents the path diagram for the essential version of the APIM. There are four variables in this model. The two dependent or outcome variables are labelled Y and Y' and stand for the outcomes for persons A (e.g., mother's attachment security or Y) and B (e.g., child's attachment security or Y'), respectively. The X and X' variables are the measures of Person A and Person B, respectively, that are expected to predict Y and Y'. In the most basic longitudinal model, the model of focus in this article, they would be based on the same measurement instrument as the Y variables but measured at some earlier point in time. For example, earlier measures of the mother's attachment security (X) and the child's attachment security (X') are expected to predict mother's (Y) and child's (Y') attachment security at a later point in time.

The two most central components of the APIM are the actor effects and the partner effects. In longitudinal terms, an *actor effect* measures how much a person's current behaviour is predicted by his or her own past behaviour. In Figure 1, the actor effects are represented by the two paths labelled a. The actor effect is a measure of the *stability* of mother's attachment security in relationship to the child (X to Y) and the *stability* of the child's attachment security in relationship to the mother (X' to Y'). Developmental researchers have long understood that the prediction of development (i.e., change) must occur within the context of having statistically controlled for the stability of the outcome variable. Thus, the inclusion of actor effects in longitudinal models has a long history, although these stability effects have not been typically labelled as actor effects until recently (Cook, 1998). What may not be as well understood is that actor effects, to be measured accurately, should be estimated while controlling for partner effects. *Partner effects* measure how much one person is influenced by a partner and are represented in Figure 1 by the diagonal paths labelled p.[1] For example, the path from X to Y' might measure the mother to adolescent partner effect (how much her prior attachment security predicts her child's later attachment security) and the path from X' to Y would measure the

[1] Although we use the term *influence*, an actor or partner path in the model may simply indicate a predictive relation, not necessarily a causal one.

adolescent to mother partner effect (i.e., how much the child's prior attachment security predicts his or her mother's later attachment security). Partner effects measure a form of interdependence. Consequently, they cannot be measured within individuals; they are by definition dyadic. Because the APIM is not limited to longitudinal designs, actor effects can more generally be defined as the effects of a person's own characteristics on his or her own outcomes, and partner effects are defined as the effects of a partner's characteristics on a person's outcome.

There are two additional features of the APIM to consider, correlations between the independent variables and correlations between residual variables: The correlation between the independent variables is indicated by the curved, double-headed arrow between X and X'. There is an important statistical role for this correlation. It ensures that if either of the X variables predicts a Y variable, it is done while controlling for the other X variable. Thus, actor effects are estimated controlling for partner effects, and partner effects are estimated controlling for actor effects.

It is unlikely that the X variables explain all the variance in the dependent variables. The extent to which the Y variables are not explained by either of the X variables is represented in Figure 1 by U and U'; the residual or error terms for Y and Y', respectively. If the actor and partner effects are the only reason for the correlation between Y and Y' (i.e., the only source of nonindependence), when the variance in Y and Y' due to partner effects is removed, Y and Y' should no longer be correlated. However, there may be other reasons for the correlation between Y and Y'. For example, if the two individuals come from the same family, a family-level factor may cause their scores to covary. The curved, double-headed arrow connecting U and U' indicates that the unexplained variance in the dependent variables is correlated, even after the covariance due to partner effects has been removed. Specification of a correlation between the residuals controls for additional sources of nonindependence such as family effects.

It should be clear from Figure 1 that when one tests for bidirectionality, one is not testing a single hypothesis but rather two hypotheses. Bidirectionality is supported only if X predicts Y' *and* X' predicts Y (i.e., both partner effects are statistically significant). Typically, theory would suggest the inclusion of additional variables into the model. If the added variables measure characteristics of the individuals in the dyad, their effects on the dependent variables would also be either actor or partner effects. For example, in Figure 2 child age and gender have been added to the model for mother's and child's attachment security. If child age or child gender predicts the child's own attachment security, it is a child actor effect. If child age or child gender predicts the mother's security in relationship to the child, it is a partner effect. Note that there would be bidirectional effects if mothers feel more secure in relationship to older children (a child partner effect for age) and if children feel more secure if they have been raised by secure mothers (a partner effect for mother's attachment security). Thus, the two partner effects do not have to be defined over the same variable to conclude that there is bidirectional influence.

Interaction effects

In the language of the analysis of variance (ANOVA), actor and partner effects are main effects, i.e., the direct effects of the independent variables on the dependent variables. The standard ANOVA model also tests whether *combinations* of

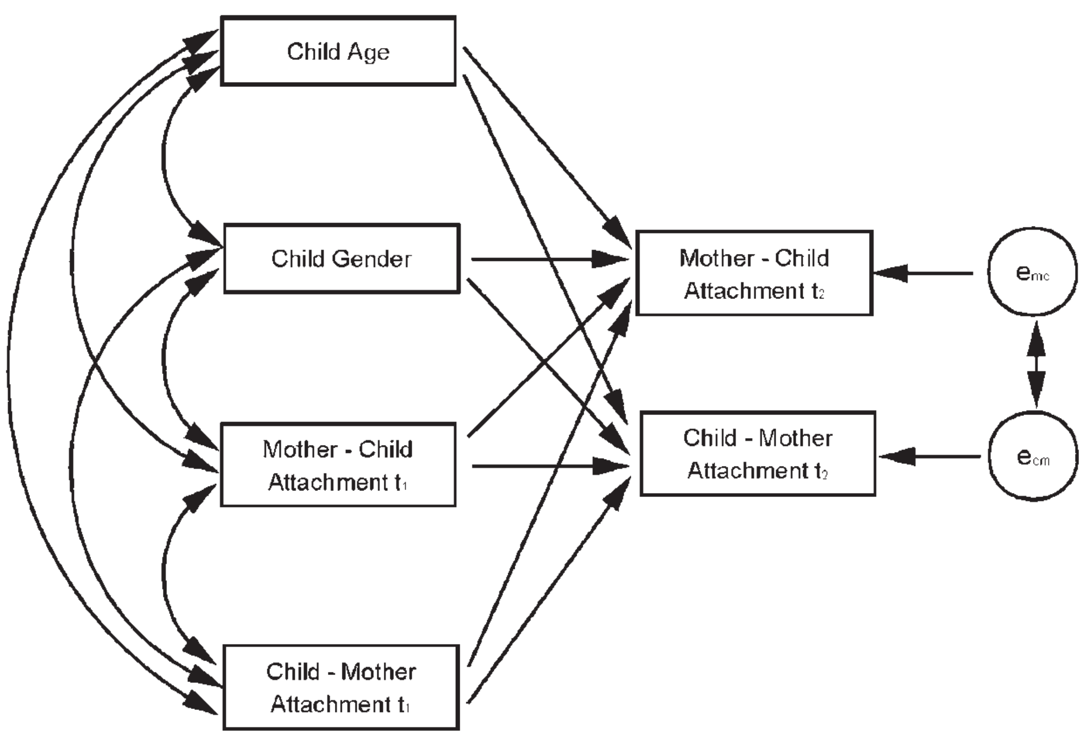

Figure 2. The actor–partner interdependence model including child age and gender variables. Child age, child gender, security of child's attachment to mother, and security of mother's attachment to child at time t_1 predict security in child's attachment to mother and security in the mother's attachment to child at time t_2. Single-headed arrows indicate causal or predictive paths. Double-headed arrows indicate correlated variables.

the independent variables have an effect on the outcome, interaction effects. In terms of parent–child relationships, interaction effects can be important determinants of child outcomes. Sameroff (1975; Sameroff & Chandler, 1975) coined the term *interactional model* to describe the investigation of child outcomes that are affected by the crossing of parent and child characteristics. The interactional model has also been referred to as the ‘‘goodness of fit’’ model because it assumes that developmental outcomes depend on the extent to which parent and child characteristics match or fit together (Lerner, 1993; Thomas & Chess, 1977).

In an interactional model, one of the independent variables, called the *moderator* variable, affects the size of the effect of another independent variable on the outcome variable. Of particular importance are partner characteristics that moderate the effect of actor characteristics, or actor–partner interactions. As an example of actor–partner interaction, suppose that temperamentally easy children are relatively compliant to low power-oriented parental demands and temperamentally difficult children are relatively compliant to high power-oriented parental demands. In this case, the main effects (parental power orientation and child temperament) would not be predictive of child compliance. Rather, it is the combination or goodness-of-fit of parent and child characteristics that determines child compliance. The interaction of actor and partner characteristics can also be used to model synergy or reciprocity. If reciprocity of negativity is characteristic of their relationship, the product of parent and child negativity scores at one point in time would be predictive of their negativity scores at a later point in time, independent of the main effects (i.e., actor or partner effects). That there is often conceptual overlap in the nature of the data (i.e., *interpersonal* interactions) and analytic terminology (i.e., *statistical* interaction) no doubt has led to confusion in the use of the term *interactional* in research studies.

Sometimes the size of an actor or partner effect can be different depending on the value of a third variable. For example, if a parent has been very responsive to the child, the probability that the child will comply with a subsequent parental request (a partner effect) may be greater than in parent–child relationships of unresponsive parents (Parpal & Maccoby, 1985). This would constitute a *partner-moderated partner effect* because parental responsiveness (a partner characteristic) moderates a partner effect (i.e., the probability that the child will comply with a parental request). If we look for a more proximal cause, we may find that children in a positive mood or who, more generally, have warm feelings for their parents, are more compliant (see Lay, Waters, & Park, 1989). This would constitute an *actor-moderated partner effect* because the child's attitude toward the parent (a child characteristic) moderates the probability of his or her being compliant with a parental request (a partner effect). An interaction like this is what is meant when it is said that relationships are contexts for interaction (Hinde & Stevenson-Hinde, 1987; Lollis & Kuczinski, 1997). The relationship as constituted by the enduring attitudes and expectations of one person toward another (e.g., the child's positive attitude toward the parent) moderates how that person responds to the other at any given moment.

Age as a moderator of actor and partner effects. In the previous example, relationships (and attitudes toward others) were proposed as moderators of interpersonal processes affecting child compliance. Given the importance of parent–child relationships to child development, developmental researchers are naturally interested in the development of relationships. In this regard, we do not simply mean the processes of influence that unfold over time, but how the age and development of the participants affects these processes (Hartup & Laursen, 1999). Stated differently, the interest is in how development may affect actor and partner effects.

As noted earlier, one type of actor effect is that the person's past score on a variable will predict his or her future score on the same variable. For example, a child's attachment security at age 15 would tend to be a strong predictor of his or her attachment security at age 16. According to attachment theory (Bowlby, 1973), the strength of this relationship should change over time. As the child ages, working models of relationships (i.e., over-learned expectations or schemas) should become increasingly stable and influential psychological factors. Consequently, the degree to which an 11-year-old's attachment security predicts his or her attachment security at age 12 should not be as strong as the degree to which a 17-year-old's attachment security predicts his or her attachment security at age 18. In other words, the child's age moderates the child's actor effect, revealing that the stability of internal working models of relationships is developmental. Such would constitute an *actor-moderated actor effect*.

The child's age might also moderate the parent partner effect in this example. It could be that the more the child's expectations are predicted by intrapersonal processes (i.e., by internal working models), the less they would be predicted by interpersonal processes (i.e., the parent's actual behaviour). If true, we may find that the older the child, the less the influence of the parent's attachment security on the child's attachment security. Such would constitute an *actor-moderated partner effect*.

The statistical analysis of the APIM

In this section, we provide general guidance for the analysis of the APIM using three statistical techniques: ordinary regression analysis, structural equation modelling (SEM), and multilevel modelling (MLM). The methods presented here apply to dyads in which two persons are distinguishable by their role (e.g., mother and child) or some other characteristic (e.g., birth order of siblings). The methods for the analysis of dyads in which the members are indistinguishable (e.g., identical twins, gay couples) are detailed elsewhere (Griffin & Gonzalez, 1995; Kenny 1996a; Kenny, Kashy, & Cook, in press).

Ordinary regression analysis

The simplest, but least general approach to the assessment of bidirectional influence in longitudinal research with dyads is via a pair of separate multiple regression analyses, one each for predicting the outcome of the two partners. In one analysis, the mother outcome variable (i.e., the variable measured at time t_2) would be regressed on the child and mother predictor variables measured at time t_1. In the other analysis, the child outcome variable would be regressed on the child and mother predictor variables measured at time t_1. (The order of these two analyses does not matter.) Couple is the unit of analysis (i.e., the N being the number of dyads, not the number of individuals), so the independence assumption is not violated. The interests are the magnitude of actor and partner effects in each analysis and their statistical significance. The actor effect estimating the stability of the variable over time would almost always be present, but other actor effects (e.g., age or other measures of actor characteristics) may not be. If any of the partner effects are present, the inference can be that there is interpersonal influence or interdependence. A partner effect for each partner must be statistically significant to support the hypothesis that influence is bidirectional. Additionally, the model may also include contextual variables or other factors that are not personal characteristics of either partner.

There are drawbacks to this ordinary least squares approach. First, this method of analysis does not allow a test of differences between the two actor effects or between the two partner effects of the dyad members. So if a researcher were interested, for example, in whether children influence their mothers more than mothers influence their children, this approach cannot address the question. Second, it cannot address the question of whether for either individual the actor or partner effect is the larger effect. Third, it also does not allow one to pool effects across dyad members. For example, it may be that the partner effect for neither mothers nor children is statistically significant when evaluated separately, but when the two partner effects are pooled, the combined partner effect is significantly different from zero. Thus, one would conclude that there is interdependence, but it is not role-specific. Tests of pooled effects generally have more power than do tests of separate effects (Kenny & Cook, 1999).

Structural equation modelling (SEM)

The SEM approach has several advantages over the ordinary regression analysis approach to testing the APIM. With respect to the APIM, key features of SEM are (1) that more than one equation can be estimated and tested simultaneously and (2) the relations between parameters in different equations can be specified. This allows a direct translation of the model in Figure 1 into one model to be estimated and tested using a *SEM* statistical program (e.g., LISREL, EQS, AMOS). The dyad is the unit of analysis (i.e., the *N* is equal to the number of dyads) and the model is estimated from the covariance matrix of all the independent and dependent variables. Unless latent variables are used, the sample size requirements are no different than for ordinary regression analysis (Kenny & Cook, 1999).

Different SEM software programs have different languages and procedures for estimating the components in the model, but all require the same general specifications. In the basic model, there are two equations, one for each of the dependent variables. So for an analysis of mother–child dyads, there would be one equation written for the mother outcome at time t_2 and another for the child outcome at t_2. The mother and child variables at time t_1 would be the predictor variables in this equation. The regression coefficient for the mother's time t_1 variable would estimate the actor effect for mothers and the regression coefficient for the child's time t_1 variable would estimate the partner effect for the child on the mother. The child outcome at time t_2 would be the dependent variable in the second equation and, again, the predictor variables would be the mother and child variables measured at time t_1. In this case, the regression coefficient for the mother variable would estimate the partner effect of the mother on the child and the regression coefficient for the child variable would estimate the child actor effect. There is a residual variance for each equation, representing the effect of all the other predictor variables that have not been included in the equation plus errors of measurement. The residual effects from the mother and child equations would be allowed to correlate, as noted earlier, to control for other sources of nonindependence. The independent variables (mother's and child's scores at time t_1) would also be allowed to correlate so that partner effects would be estimated while controlling for actor effects and vice versa. Some software programs now have graphical interface tools that can be used to draw a path model like that of Figure 1. The software translates the drawing into the corresponding specifications.

A powerful feature of SEM is that it is possible to compare and statistically evaluate the size of parameters within the model, something that cannot be done within least squares. For example, one can test whether the mother partner effect is equal to the child partner effect, which answers the question of who has more influence in the relationship. One can test whether actor effects, partner effects, and residual variances are equal across time, thus testing whether the data have stationarity. Finally, one can compare parameters within a given role (e.g., just the mothers); for example, whether the actor effect for mothers is equal to the partner effect for mothers. To compare the size of two parameters, one compares the chi-square goodness-of-fit value for a model with the two parameters forced to be equal to the chi-square goodness-of-fit value for the same model but without the parameters set to be equal. If the difference between the two chi-square values is statistically significant, then forcing the parameters to be equal has significantly worsened the fit of the model. Thus, it is inferred that the parameters are not equal. This procedure, referred to as the chi-square difference test, is described in any text or manual for structural equation modelling.

Multilevel modelling (MLM)

The analysis of the APIM using multilevel modelling procedures, compared to SEM methods, requires a considerable shift in thinking about the organisation of data and the estimation of effects. Whereas there are two equations in the SEM version of the APIM, one for each member of the dyad, MLM estimates all the parameters of the model within a single equation and so implies a very different data structure. Table 1 presents an example of the data for three dyads organised for a MLM analysis. There are several ways to model dyadic processes within MLM. We illustrate what is called the "two-intercept" approach that was introduced by Raudenbush, Brennan, and Barnett (1995).

The first two variables in Table 1 are dyad ID and the person number. Note that for every dyad there is a record for person 1 (e.g., mother) and a record for person 2 (e.g., child) and always in that order (or always in the order of child followed by the mother). This ordering reflects the nested structure of the data; person nested within dyad. The data must be organised according to the appropriate nesting structure for most MLM programs. The next variable in Table 1 is the dependent variable (DV) or outcome score. The value of the dependent variable is typically different for each member of the dyad. That each person occupies a separate record gives the appearance that the individual is the unit of analysis, but

Table 1
Organisation of data for multilevel modelling

ID	*Person*	*DV*	*M_dum*	*C_dum*	*M_act*	*C_act*	*M_prt*	*C_prt*
3	1	3.8	1	0	5.0	0	0	3.5
3	2	3.7	0	1	0	3.5	5.0	0
5	1	4.4	1	0	3.7	0	0	3.5
5	2	3.4	0	1	0	3.5	3.7	0
6	1	4.7	1	0	4.3	0	0	2.8
6	2	3.0	0	1	0	2.8	4.3	0

DV = dependent variable; *M_dum* = dummy code identifying records where mother is the actor; *C_dum* = dummy code identifying records where child is the actor; *M_act* = mother actor variable; *C_act* = child actor variable; *M_prt* = mother partner variable; and *C_prt* = child partner variable.

this is not the case. MLM programs take into account the nesting of individuals within dyads and the concomitant nonindependence of observations this entails.

As in any regression analysis, the predictor variables must be on the same record as the outcome variable. This introduces a complexity into the data organisation, because the identity of the actor and the identity of the partner shift with each record. For record 1, the actor is mother (her outcome is the *Y* variable) and the partner is child. For record 2, the actor is the child (his or her outcome is the *Y* variable) and the partner is mother. To ensure that the appropriate actor and partner variables are used in predicting a particular outcome, the following procedure can be used.

First, in the two-intercept approach, two dummy variables are created to identify whose outcome the *Y* variable refers to for that particular record. The mother dummy variable, labelled *M_dum* in Table 1, is scored as 1 for records in which mother's outcome is the *Y* variable and 0 if the child's outcome is the *Y* variable. The child dummy variable, labelled *C_dum* in Table 1, is scored as 1 for records in which the child's outcome is the *Y* variable and 0 if the mother's outcome is the *Y* variable. These dummy codes are used to create the predictor variables that measure and test for actor and partner effects. Recall that the original predictor variables are the mother and child scores at time t_1. These two scores are multiplied by the two dummy variables, as if to create moderator variables. Multiplying the mother dummy variable by the mother time t_1 variable reproduces the mother's time t_1 variable for records where the mother's outcome is the *Y* variable and she is the actor, but it produces a zero for records where the child's outcome is the Y variable. This new variable is the mother actor variable (*M_act*). Multiplying the mother dummy variable by the child's time t_1 variable reproduces the child's time t_1 score for records where the mother's outcome is the *Y* variable (and so the child is the partner) and a zero otherwise. This new variable is therefore the child partner variable (*C_part*). Now, for all the records in which the mother's outcome is the *Y* variable, the mother's time t_1 score is the mother actor variable and the child's time t_1 score is the child's partner variable. Otherwise, these variables are scored with zeros.

Creation of the child actor variable and the mother partner variable uses the same procedure as above, but now the predictor variables are multiplied by the child dummy variable. When the child dummy variable is multiplied by the child's time t_1 score, this creates the child actor variable (*C_act*), which will be the child's time t_1 score for records where the child's outcome is the *Y* variable and the child is the actor. When the child dummy variable is multiplied by the mother's time t_1 score, it reproduces the mother's time t_1 score on records where the child's outcome is the *Y* variable and the mother is in the partner role (*M_prt*). In summary, four variables are created; a mother actor variable, a mother partner variable, a child actor variable and a child partner variable. These variables have values for every record, but they have non-zero values only for those records where the appropriate dyad member's outcome is the *Y* variable. Thus, they are predictor variables only for the outcomes that they are supposed to predict.

Specifications

After the data file has been created and read into the multilevel modelling program, the details of the analysis must be specified. It is necessary to indicate number of levels (of nesting) in the data. For the APIM, the outcome variable (e.g., attachment security at time t_2) has two levels; dyad and individual. The dyadic level is identified by the ID variable, and the individual level is identified by the person variable. Next, one specifies the independent variables, indicating for each whether it has fixed and/or random components, and if it has a random component, at what level (individual or dyadic) it varies. There are a total of six independent variables in the simplest version of the APIM. The model has no ordinary error term. Rather *M_dum* and *C_dum* variables are used as intercept variables for mother and child, respectively, instead of the usual common intercept. The intercept variables will each have a fixed component, which is the intercept, and a random component. The correlation between random components for *M_dum* and *C_dum* models the residual covariance in Figure 1. Not all MLM programs (e.g., SAS and SPSS[2]) allow for the multiple intercepts and zero error variance needed to replicate precisely the SEM approach, but several programs do (e.g., HLM and MLwiN).

The other four variables in the model are the two actor variables and the two partner variables. Estimation of these coefficients is the primary goal of the analysis. Most multilevel modelling programs also allow for the comparison of effects (e.g., whether mother or child has the larger partner effect) using a procedure comparable to the chi-square difference test. Thus, it shares an important advantage with SEM.

[2] SPSS and SAS can be used to estimate a version of the two-intercept model but space precludes a complete description of these models.

Illustration

Returning to the example of attachment security in mother–adolescent dyads, we said that the bidirectional view would predict that each person influences the other. We can test this using the APIM. Our outcome variables are mother's comfort depending on the adolescent (Y) and the adolescent's comfort depending on the mother (Y'), both obtained at time t_2. Our predictor variables are mother's comfort depending on the adolescent (X) and the adolescent's comfort depending on mother (X')at time t_1, approximately a year earlier. These data are from a larger study of attachment security in family relationships (Cook, 2000). That study investigated the interdependence of attachment security using the social relations model (SRM: Cook, 1994; Kenny & La Voie, 1984). The SRM analysis (Cook, 2000) was cross-sectional, but provided information on whether one person's attachment security in relationship to another family member was due to family, actor, partner, or unique relationship effects.[3] We will focus here only on the variable "relationship specific comfort depending on others", which we refer to as *attachment security*.

Participants

The data involve 203 mother–adolescent pairs who provided data at both of two waves of sampling, approximately 1 year apart. The average age at time 1 of the mothers was 46 years (SD = 3.36), and the average age of the adolescent was 16 years (SD = 2.15). There were 96 boys and 106 girls in the adolescent sample.

Analysis and results

We first examine the APIM with only main effects included, which corresponds to the path diagram presented in Figure 2. We also test for the equality of the actor and partner effects within each role; that is, whether a person's actor effect is equal to his or her own partner effect. The purpose of this test is primarily to illustrate the technique of testing equality constraints. Finally, we test whether age of the adolescent moderates the actor or partner effects of the mothers and adolescents. We performed all tests using the SEM approach because for distinguishable dyads it offers the simplest and most direct way to perform the analysis. The EQS program is used for all SEM analyses.

Actor effects. The question of whether characteristics of the person predict his or her own outcome over time is measured and tested by the actor effects. The results are presented in the first four rows of Table 2. For both mothers and adolescents, the actor effects for attachment security are large, positive, and statistically significant, indicating that there is reliable stability in the degree to which they feel comfortable depending on each other. We do note that as predicted, the actor effect for the mother is more stable than it is for the child. Two additional actor effects were tested for the child; whether the child's gender and age predict changes in the child's attachment security. Neither of these actor effects was statistically significant.

Table 2
APIM of mother–child dynamics (N = 203 dyads)

APIM parameters	*Estimate*	*Z*
Actor effects		
$C_1 \rightarrow C_2$	.663*	11.40
$M_1 \rightarrow M_2$	.789*	16.18
Child age$_1 \rightarrow C_2$	.037	1.86
Child gender$_1 \rightarrow C_2$	–.045	–0.51
Partner effects		
$C_1 \rightarrow M_2$	.155*	3.07
$M_1 \rightarrow C_2$	.127*	2.26
Child age$_1 \rightarrow M_2$	.013	0.77
Child gender$_1 \rightarrow M_2$	.139+	1.82
Interaction effects		
Child age*$M_1 \rightarrow M_2$	–.017	–0.827
Child age*$C_1 \rightarrow C_2$	.056+	1.891
Child age*$M_1 \rightarrow C_2$	–.052*	–2.167
Child age*$C_1 \rightarrow M_2$	–.027	–1.043

The estimates are unstandardised regression coefficients. M_1 = mother's attachment security, time t_1; C_1 = child's attachment security, time t_1; M_2 = mother's attachment security, time t_2; C_2 = child's attachment security, time t_2. An asterisk between two variables indicates an interaction effect. Interaction effects were tested within a model that included all the main effects.
* $p < .05$; + $p < .10$.

Partner effects. The question of whether characteristics of the mother or the child predict each other's attachment security is measured and tested by the partner effects. The results are presented in the middle section of Table 2. Both of the partner effects for attachment security are positive and statistically significant. These results indicate that the mother's prior level of attachment security influences the child's later level of attachment security, and that the child's prior level of attachment security influences the mother's later level of attachment security. In other words, the influence process is bidirectional.

In many cases an interesting question might be: Who has more influence on whom? As seen in Table 2, the effect of child on the mother is slightly larger than the effect of the mother on the child, but the difference is very small and not very meaningful theoretically. For these data, a more interesting comparison is between the actor and the partner effects predicting a given person's outcomes. For the adolescent the comparison is between the adolescent actor effect (an intrapsychic variable) and the mother partner effect (an interpersonal variable). For mother outcomes, this comparison is between the mother actor effect and the adolescent partner effect. These comparisons are made using the chi-square difference test, which was described earlier. Because the basic APIM is a saturated model and so has zero degrees of freedom, the chi-square for goodness of fit for the model is zero. If we constrain the adolescent's actor effect (b = .663) and the mother partner effect (b = .127) to be equal, we gain a degree of freedom and the chi-square will be non-zero. If the chi-square were statistically significant, we would reject the null hypothesis that the two covariances are equal. For this test, we find χ^2 (N = 203, df = 1) = 33.23, $p < .001$, indicating that

[3] The actor and partner effects of the APIM should not be confused with similarly named effects from the social relations model (Kenny & La Voie, 1984). In the social relations model analysis, actor and partner effects are components in a measurement model (i.e., latent variables or factors) rather than causal variables. In the APIM the actor and partner effects reflect causal or predictive effects.

the two effects cannot be treated as equal without seriously worsening the fit of the model. The adolescent's outcome is affected more by his or her own prior level of attachment security than by the mother's influence over the course of a year. The comparison of the predictors of mother's outcomes yields a similar result. The mother actor effect ($b = .789$) is significantly larger than the child partner effect ($b = .155$), χ^2 (1, $N = 203$) = 58.27, $p < .001$.

Interaction effects. Lastly we tested whether child age moderated the actor and partner effects for attachment security in mother–adolescent dyads. This involved creating two interaction variables; (1) the product of mother's attachment security by child age, and (2) the product of child's attachment security by child age. Prior to performing these multiplications, we centred each of the variables (Aiken & West, 1991). Centring involves subtracting out the mean of each variable in the interaction. It has the important role of reducing multicollinearity due to high correlations between interaction terms and the independent variables from which they are created, and it increases the interpretability of the main effects. In the case of dyadic measures, the centring variable (or mean) that is subtracted out should be the mean of the partners' scores taken together (Kenny & Cook, 1999; Kenny et al., in press). In other words, one does not subtract the mean for mothers from the mother score and the mean for adolescents from the adolescent score; rather, one subtracts the mean of their combined score from both of their scores.

The interaction terms were included as independent variables, along with the actor and partner main effects, in a new model predicting mother and child attachment security (time t_2) outcomes. The results of this analysis are presented in the bottom third of Table 2. The first two rows of the table present the effects of child's age as a moderator of the actor effects. Age does not moderate the mother actor effect or the child actor effect at conventionally accepted levels of statistical significance. The last two rows in Table 2 present the effects of child's age as a moderator of the partner effects. The results indicate that the child's age moderates the mother partner effect, but not the child partner effect. The attachment security of younger adolescents is affected more by their mothers than that of older adolescents, $b = -.052$, $Z = -2.167$, $p < .05$. This result is consistent with the hypothesis from attachment theory that the internal working models of younger adolescents, compared to older adolescents, are affected more by recent relationships with significant others (Bowlby, 1973). It also demonstrates how the APIM can be used to test hypotheses on the development of relationships.[4]

Conclusion

This article has presented and illustrated the APIM as a means of conceptualising and measuring interdependence in close relationships, with a special focus on the assessment of bidirectional effects. Interdependence is measured by the APIM partner effect, the extent to which one person's thoughts, feelings, or behaviour influence the thoughts, feelings, or behaviour of another person. Bidirectional effects are present when the partner effects for both members of a dyad are present and statistically significant. Although the APIM has often been presented within the context of cross-sectional data analysis (Berg et al., 2001; Butler et al., 2003; Butterfield, 2001; Campbell et al., 2001; Lakey & Canary, 2002), we hope we have demonstrated that it is equally applicable to longitudinal data analysis.

There are other models of dyadic relationships that correspond to other forms of dyadic nonindependence. These include the common fate model, in which group effects (or couple effects) are distinguished from individual effects, and the dyadic feedback or mutual influence model, in which each person's outcomes affect the other's outcomes (Cook, 1998; Kenny, 1996a). Of all these models, the APIM has been—and is likely to continue to be—favoured by researchers. As we hope this article has shown, the APIM corresponds to patterns of interpersonal processes that are of considerable interest to family and developmental researchers.

As a conceptual model of interdependence, the APIM is applicable to a variety of analytic situations. For example, in time-series analyses of dyadic interaction such as sequential analysis and cross-lagged regression analysis, the conceptualisation of actor–partner interdependence is the same as presented in Figure 1. The only difference is that the unit of analysis is time (or event) rather than dyad. In this context, the autocontingency or autocorrelation effects are actor effects and the measures of reciprocity (i.e., cross-lagged contingencies) are partner effects (Cook, 2002). The APIM has also been used in complex analyses of growth in relationships. For instance, Raudenbush et al. (1995) tested whether growth (or decline) in a partner's job-role quality predicted growth (or decline) in own or partner's marital satisfaction. Kurdek (1998) has also published analyses that integrate the APIM with growth curve modelling. He found that growth in a person's depressive symptoms was associated with decline in own marital satisfaction (an actor effect) but was not associated with decline in partner's marital satisfaction.

In summary, the APIM is a method of estimating interdependence in naturalistic studies of close relationships. It is particularly well-suited to developmental research in areas where experimentation is not appropriate. Finally, the APIM is not a model that is in competition with other methods of analysis such as sequential analysis or growth curve analysis. Rather, it is a general model that is complementary to these other methods. The integration of the APIM with other analytic methods has the potential to address important and complex questions about human development.

[4] We also tested whether child gender moderated the actor and partner effects in this model, and it did not.

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