

Actor–Partner Interdependence Model

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The actor–partner interdependence model (APIM) was developed as a conceptual framework for collecting and analyzing dyadic data, primarily by stressing the importance of considering the interdependence that exists between dyad members (e.g., romantic partners, friends, parents and children, clients and therapists). Specifically, the APIM approach allows researchers to estimate, simultaneously and independently, the effect that a person's independent variable score has on both his or her *own* dependent variable score (known as the *actor effect*) and on his or her *partner's* dependent variable score (known as the *partner effect*). Interactions between actor and partner effects can also be tested to determine if particular combinations of characteristics from each dyad member uniquely predict relationship outcomes. This model can be used for dyads that have distinguishable members (e.g., married or dating heterosexual couples) or for dyads that have nondistinguishable members (e.g., same-sex friends or same-sex romantic couples). In statistical models used to estimate actor and partner effects, the dyad, and not the individual, serves as the unit of analysis.

The APIM Conceptually

Berscheid (1999) observed that relationships between individuals are like great forces of nature, such as gravity, electricity, and the four winds, in that they are powerful but ultimately invisible; it is only by observing their effects that we can obtain knowledge of their character and qualities. Berscheid suggested it is therefore necessary to observe how two individuals influence each other, preferably over time and

across contexts, to gather information about the nature and quality of their relationship. Consistent with this perspective, Kelley et al. (1983) defined a close relationship as “one of strong, frequent, and diverse interdependence that lasts over a considerable period of time” (p. 38). According to this perspective, a quintessential feature of close relationships is the existence of connections between the thoughts, feelings, and behaviors of one partner with the thoughts, feelings and behaviors of the other partner (i.e., interdependence). In the language of the APIM, this interdependence between partners is referred to as a partner effect.

The APIM Analytically

Standard statistical methods such as multiple regression and analysis of variance (ANOVA) are not sufficient for estimating actor and partner effects in data obtained from both relationship partners because these approaches require independence between observations. The interdependence that defines close relationships is likely to result in significant correlations between the responses of both partners, resulting in biased tests of significance when this interdependence is ignored. Analyzing dyadic data therefore requires special analytic approaches that can properly account for the statistical interdependence between partners' data points. Fortunately for researchers investigating dyadic processes, a number of excellent resources are available that provide guidance on analyzing dyadic data, including Kenny, Kashy, and Cook's (2006) book that provides the most comprehensive review of how to analyze dyadic data guided by the APIM. In what follows we provide a brief overview of the types of variables in dyadic data, as well as how to estimate actor and partner effects using structural equation modeling and multilevel modeling.

Types of Variables in Dyadic Research

There are three types of predictor variables in dyadic research: between-dyads variables, within-dyads variables, and mixed variables. A between-dyads variable is one for which scores are the same for both members of a given dyad, but they differ from dyad to dyad. For example, in a study where the behavior between a parent and young child was observed in either a room with many interesting toys for the child to play with or a room with only a table and chair, type of room would be a between-dyads variable. A naturally occurring between-subjects variable could be length of marriage, or length of friendship when studying friendship dyads. A within-dyads variable, on the other hand, is one for which the scores for partners within each dyad are different, but the average score is the same for all dyads. In research involving heterosexual couples, gender is an example of a within-dyads variable (e.g., if women were coded as 1 and men as -1 , within dyad the codes are different but across dyads the average of these codes is the same or 0). The percent of household chores performed by each partner is another type of within-dyads variable (assuming that percentages add to 1.0 across the couple members). With mixed predictor variables there is variation both within dyads and between dyads. Self-esteem, extraversion, yearly income, self-regulatory ability, and attachment anxiety are all examples of mixed variables because some people score higher or lower than others on each variable, and the average level of each variable within a dyad differs across dyads.

Interactions

Actor and partner effects can be directly estimated for mixed predictor variables but not for between- or within-dyad variables. Instead, interactions of between- and within-dyad variables with the actor and partner effects of mixed variables can be estimated to determine, for example, if women are less satisfied with a more anxiously attached partner than are men

(i.e., an interaction between gender and the partner effect of anxious attachment). Similarly, differences in actor and partner effects across experimental conditions can be tested.

In addition to interactions between actor effects or partner effects on mixed variables and between- or within-dyads variables, interactions between actor and partner effects on the mixed variables can be tested. For example, a more anxiously attached individual may report relatively high relationship satisfaction when in a romantic relationship with a less avoidantly attached partner, but report much lower levels of satisfaction when in a relationship with a partner scoring high on avoidant attachment.

There are also instances where only one partner's score can serve as the interaction term. For instance, sometimes only one person in a relationship needs to have a certain skill or deficit for differences between couples to emerge. For example, a couple with one highly depressed member is likely to evidence lower levels of satisfaction than a couple in which neither partner is depressed. Additionally, a couple with one member that is ill (e.g., cancer) or disabled could potentially differ in important ways compared to couples with two normal healthy adults.

Estimation Using Structural Equation Modeling

One popular approach for estimating actor and partner effects is structural equation modeling (SEM). An advantage of SEM is that multiple equations can be estimated simultaneously, allowing for actor and partner effects to be estimated for more than one independent and/or dependent variable in the same model. Also, researchers have the option of deriving latent variables, assuming a large enough sample size is collected, in order to estimate actor and partner effects that are free of measurement error. It is also possible to estimate growth curve models with longitudinal data in SEM, thus allowing researchers to determine how dyad members influence each others' outcomes over time.

Lastly, in SEM it is possible to statistically test the difference between the size of two parameters in the same model (even if the two parameters come from different equations), allowing, for example, direct tests of gender differences of actor and partner effects, or for comparisons between the size of actor and partner effects of a predictor variable on the same outcome.

Estimation using Multilevel Modeling

The use of multilevel modeling (MLM), also known as hierarchical linear modeling (HLM), to analyze dyadic data has been growing at a steady rate the past decade. One reason for its widespread use in the relationship sciences is that MLM is very flexible in terms of its ability to accommodate the wide variety of data structures that typically occur in relationship research (see Kenny et al., 2006). Additionally, it allows researchers to simultaneously estimate effects at different levels of analysis (e.g., individual level, dyadic level, group level), as well as assess these effects over time in longitudinal data sets. A number of popular data analytic software packages are also capable of estimating MLM (e.g., HLM, R, PROC MIXED in SAS, SPSS).

As the name implies, MLM is used with data sets that have a multilevel, or nested, data structure. Data collected from both members of a dyad has a multilevel structure because the two individuals are nested within a dyad. Therefore, with dyadic data, individuals are the lower level units and dyad is the upper level unit. Outcomes at the lower, or person, level can be predicted by lower level variables (e.g., attachment anxiety), upper level variables (e.g., household income), as well as interactions between lower and upper level variables (e.g., interaction between attachment anxiety and household income).

Consider a hypothetical example where a researcher wants to determine if individuals with lower self-esteem behave less positively toward a romantic partner (an actor effect), and have partners that behave less positively

toward them (a partner effect), when discussing a major versus minor relationship problem. Couples were randomly assigned to discuss a major or minor relationship problem (a between-dyads variable), and independent raters coded how positively each partner behaved during the interaction. Observed positive behavior is the outcome variable that is measured once for each lower level unit. Self-esteem is a predictor variable that varies across the two partners within a dyad (i.e., a mixed predictor variable), and is a lower level predictor variable. Experimental condition is a predictor variable that varies between dyads (so that both members of any given dyad have the same score but members of two different dyads may differ) and is an upper level variable. In this example experimental condition should be effect coded (1, -1), and self-esteem scores should be centered around the grand mean so that interactions with other variables can be estimated if desired (see Aiken & West, 1991).

In the simplest sense, estimation in MLM has two steps. In the first step, an analysis is computed for each upper level unit, which in the current example is couple. That is, an analysis would be computed for each couple examining the relations between self-esteem and experimental condition on observed behaviors. In the second step, the results of the first step analysis are aggregated across the upper level units (couples). Significance testing is typically conducted at the highest level in the data structure, which is the level where independence between units exists.

Below we provide prototype equations for both steps outlined above, using standard HLM notation (Raudenbush & Bryk, 2002), for testing hypotheses in this hypothetical example. The Level 1 equation denotes the relation between the lower level variables:

$$Y = \beta_0 + \beta_1 \text{ (actor self - esteem)} \\ + \beta_2 \text{ (partner self - esteem)} + d + e$$

This equation predicts the observed positive interaction behaviors (Y) for an individual within a couple from an average level term

(β_0 , the intercept); the individual's self-esteem score (β_1); the individual's partner's self-esteem score (β_2); an error term (d) that reflects variation across couples (i.e., a random intercept); and error (e).

The Level 2 models, using HLM notation, are:

$$\beta_0 = \gamma_{00} + a_{01}(\text{condition}) + u_0$$

$$\beta_1 = \gamma_{10} + a_{11}(\text{condition})$$

$$\beta_2 = \gamma_{20} + a_{21}(\text{condition})$$

In the first model, the intercept for the dyad is a function of two fixed components (γ_{00} and a_{01}) and a random (u_0) component. The first fixed component provides an estimate of observed positive interaction behaviors averaged across couples when all other predictor variables equal zero, and the second component provides an estimate of mean differences in observed positive interaction behaviors between experimental conditions. The random component estimates the degree to which observed positive interaction behaviors varies from dyad to dyad after controlling for the effects of the other predictor variables. The first fixed effect in the second and third models provide an estimate of the main effect association between actor and partner self-esteem on observed positive interaction behavior, whereas the second fixed effect in each model provides an estimate of the interaction between actor and partner self-esteem with experimental condition on observed positive interaction behavior. There is no random component in these two models because of the fact that each dyad involves only two individuals, meaning there is not enough information in the data to estimate a variance in the slopes (see Kenny et al., 2006).

The above example, where outcomes are assessed at one time from both dyad members, is typical of a lot of extant dyadic research. More and more research, however, collects multiple measures from both partners over time. For example, researchers have used daily diary

studies across multiple days, typically between 14 and 28 consecutive days, to assess relationship experiences over short periods of time (e.g., Campbell, Simpson, Boldry, & Rubin, 2010). Researchers have also tracked newlywed couples a few times a year over several years to assess experiences during the early years of marriage. With these types of data sets, the lower level variable is now day of measurement, not individual. When dyad members provide data for the same repeated measures (e.g., they both make ratings on the same variables at the end of each day), the level of repeated measure is the same for both members of the dyad, and repeated measure and person are crossed, not nested, resulting in a two-level crossed structure (repeated measure and individual are crossed, with individual nested within dyad). Kenny et al. (2006) provide specific suggestions for how to alter the basic statistical model discussed above to accommodate repeated measures obtained from both partners to assess actor and partner effects.

Applications of the APIM

The APIM has already been applied in the areas of social and personality psychology, helping expand theory in new and novel directions. In recent years the APIM has also begun to inform research in clinical and counseling psychology. For the latter two fields, the APIM may be particularly useful in examining dyadic processes in therapy, including but not limited to short- and long-term program effectiveness, alliance patterns, and more. In the following section, we present examples of application of the APIM in four major areas of research: romantic relationships, friendships, parent-child relationships, and client-therapist relationships.

Romantic Relationships

Perhaps the most generative application of the APIM in psychology to date has been in the field of romantic relationships. For example, in one study 47 couples were videotaped while discussing a self-improvement goal, after which

they completed follow-up interviews regarding relationship quality and self-improvement goal attainment at three-month intervals for the next year (Overall, Fletcher, & Simpson, 2010, Study 2). Objective raters observed partners' behavior during the initial videotaped discussion, coding for nurturant support (e.g., emotional support), action-facilitating support (e.g., tangible support), and negative support behaviors (e.g., criticizing/blaming). The authors used SEM to estimate actor and partner effects in their longitudinal data set, and found that when Partner A exhibited greater nurturant and action-facilitating support behaviors, Partner B perceived those behaviors as more helpful and consequently achieved greater self-improvement success and experienced better relationship quality over the following 12 months and vice versa. The opposite pattern emerged for negative support behaviors. This research demonstrates the value of modeling how partner's behaviors influence each other in romantic relationships over time.

Research guided by the APIM has also tapped relationship processes associated with sexual frequency and satisfaction. Over the course of a 21-day diary study, Rubin and Campbell (2012) had 67 couples complete daily measures of intimacy (i.e., the extent to which they engaged in mutual self-disclosures, felt close to their partner, and communicated affection), passion, and sexual occurrence and satisfaction (if the couple had engaged in sexual intercourse on a given day). Dyadic data were analyzed with MLM, and results revealed that daily increases in intimacy predicted a higher probability of engaging in sexual intercourse, as well as greater passion and sexual satisfaction. Moreover, partner effects emerged such that relationship outcomes for Partner A were associated not only with their own personal daily experience of intimacy, but also with Partner B's daily experience of intimacy.

These two examples of how the APIM has been applied in research on romantic relationship processes are by no means exhaustive. Studies utilizing the APIM have also examined how forgiveness of transgressions

can influence both victims and perpetrators, which communication strategies are effective for resolving relationship conflicts both immediately and over time, how individual differences in adult attachment orientations influence relationship dynamics in neutral, benign, and stressful situations, the psychological consequences of divorce and custody disputes, parental coping following the loss of a child, and alliance patterns in couple therapy. Thus, there seems to be great potential for the APIM to inform romantic relationship research in clinical and counseling psychology by providing perspectives from both members of a couple that can meaningfully predict outcomes immediately and over time.

Friendships

The APIM is not limited to the study of romantic relationships, however; the model can apply to any group comprising two people, including friends. To investigate how well friends know each other and how specific knowledge of each other can positively influence their friendship, Friesen and Kammrath (2011) asked 82 pairs of friends to complete the *if-then trigger profile questionnaire* (TPQ), a descriptive list of 72 behaviors that may or may not trigger immediate negative emotions (e.g., if a person feels anxious when others are mistrustful, suspicion is more of a "trigger" for that person). Participants provided reports of their own trigger profile (i.e., the extent to which they feel a given behavior is a trigger for themselves), as well as their perceptions of their friend's trigger profile (i.e., the extent to which they feel a given behavior is a trigger for their friend), and then completed a measure of friendship quality. Estimating the APIM parameters with MLM, Friesen and Kammrath found that friends were moderately accurate in their knowledge of each other's triggers (accuracy was greater in deeper friendships), and that greater knowledge was associated with less conflict in the friendship for both individuals.

Other researchers have applied the APIM to investigate how the development and stability

of aggression is influenced by friendships. One study had 6th-grade students provide reports of aggression in an initial session and again six months later (Adams, Bukowski, & Bagwell, 2005). In the initial session, adolescents also provided a ranked list of the top three same-sex students they considered their best friends, after which they were coded as reciprocated (i.e., if their first or second friend choice also picked them) or unreciprocated (i.e., if their first or second friend choice did not pick them) friendships. The researchers used HLM to analyze their data and found, overall, that adolescents remained relatively stable in their aggression. However, this stability varied as a function of friendship type (reciprocated vs. unreciprocated) and their friend aggression such that adolescents initially low in aggression were not as influenced by those factors, whereas adolescents initially high in aggression were particularly influenced by unreciprocated friends who were high in aggression as well. Additional studies of friendship using the APIM have explored general predictors of friendship quality such as closeness and security and how friends can influence each other's drinking behavior, but there is great potential to extend this literature.

Parent–Child Relationships

Researchers have also used the APIM to expand knowledge of how parents and their children interact and influence each other. For instance, to examine perceptions of alliance and therapy progress, one study utilized an archival sample of 20 families (parents and adolescents) and examined data from measures of alliance (i.e., engagement in the therapeutic process, emotional connection with the therapist, safety within the therapeutic system, and shared family sense of purpose), session depth (i.e., value) and therapy progress at Sessions 3, 6, and 9 of a 10-session therapy program (Friedlander, Kivlighan, & Shaffer, 2012). Using HLM to analyze their data, the authors found actor effects such that adolescents' alliance predicted therapy session progress but not session depth.

For parents, greater alliance was associated with session depth but not therapy progress (the latter effect was marginal). Furthermore, partner effects emerged such that parents felt good about therapy session progress, and reported greater session depth, when their adolescents experienced greater alliance. The extant literature on parent–child relationships seems to focus on family therapy; however, APIM research on such relationships is still open to new empirical possibilities both in and out of therapeutic contexts.

Client–Therapist Relationships

Finally, a current area of literature with the potential to blossom involves using the APIM to lend insight into client–therapist relationships. One group of researchers asked 68 exercise clients and their therapists to report their self-efficacy (i.e., confidence in their own capability) and other-efficacy (i.e., confidence in the other person's capability) beliefs, their perceptions of the other person's beliefs, and professional relationship quality (Jackson, Dimmock, Taylor, & Hagger, 2012, Study 2). Results, analyzed with MLM, revealed actor effects such that when confident in their own and the other person's capability, or when perceiving that the other person was confident in their ability, both clients and therapists experienced better professional relationship quality. Additionally, a partner effect emerged such that when clients and therapists were confident in the other person's capability, that person experienced better relationship quality as well. This partner effect was stronger for clients than for therapists, presumably because clients, as more dependent members of the dyad, may have a greater propensity to be influenced by their therapist's interpersonal behaviors.

In another study examining client–therapist relationships, Kivlighan (2007) recruited 53 dyads whose members completed measures of working alliance (defined similarly to Friedlander et al., 2012; e.g., goal congruence between client and therapist), session depth, and session smoothness immediately after their third

therapy session. The results of the study's HLM analysis revealed actor effects such that a client or therapist's working alliance was associated with session smoothness (no partner effects emerged for session smoothness). For session depth, Kivlighan found both actor and partner effects. Specifically, a client or therapist's working alliance was associated with their own reports of session depth; moreover, a client's working alliance was related to his or her therapist's session depth ratings, and vice versa. Consistent with Jackson et al. (2012) discussed above, the partner effect was stronger for clients compared to therapists such that clients' perceptions of session depth were influenced by their therapists' working alliance ratings. These studies have interesting implications for individuals in therapy. At present, as with parent-child relationships research, there are very few studies that empirically investigate client-therapist relationships using the APIM.

SEE ALSO: Correlational Designs; Intraclass Correlation Coefficients; Multitrait-Multimethod Analysis; Structural Equation Modeling

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