8-1-2012

Using the Actor-Partner Interdependence Model to Study the Effects of Group Composition

David A. Kenny
University of Connecticut

Randi L. Garcia
University of Connecticut, rgarcia@smith.edu

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David A. Kenny[1] and Randi L. Garcia[1]

Abstract

We extend the actor–partner interdependence model (APIM), a model originally proposed for the analysis of dyadic data, to the study of groups. We call this extended model the *group actor–partner interdependence model* or *GAPIM*. For individual outcomes (e.g., satisfaction with the group), we propose a group composition model with four effects; for group-level outcomes (e.g., group productivity), we propose a model with two effects; and for dyad-level outcomes (e.g., liking of each of the other members of the group), a model with seven effects. For instance, for an individual outcome with gender as the group composition variable the effects are gender of the actor, gender of the other group members, actor similarity in gender to the others in the group, and the others' similarity in gender. For each of these models, we discuss the ways in which different submodels map onto social-psychological processes. We illustrate the GAPIM with two data sets.

Keywords

climate, dyads, multilevel analysis, satisfaction

[1]University of Connecticut, Storrs, CT, USA

Corresponding Author:
David A. Kenny, University of Connecticut, 406 Babbidge Road, Unit 1020, Storrs,
CT 06269-1020, USA
Email: david.kenny@uconn.edu

The study of group composition is one of the oldest topics in the study of small groups (Haythorn, 1968; Levine & Moreland, 1998; Moreland, 2012). Understanding how a group member thinks, feels, and behaves as a function of who he or she is and who the others are in the group is a central question in group research. There are a multitude of questions that fall under the general rubric of *group composition*. One question is whether one's experience of the group depends on one's own characteristics; another key question is the effect of diversity in group membership (Tsui, Egan, & O'Reilly, 1992). An additional question is the effect of a person's fit into the group or the person's similarity to the other members (Elfenbein & O'Reilly, 2007). Still another question is the effect of being the only member of a certain type in one's group (i.e., a solo; Kanter, 1977; Sekaquaptewa & Thompson, 2002) and the effect of group climate, usually measured by the group's average on the compositional variable. These are just some of the ways that group composition can affect member and group outcomes.

Moreland and Levine (1992) have proposed a general theoretical model for the study of group composition that describes how individual characteristics combine to affect group-level outcomes (e.g., productivity). One important question highlighted by their work is whether group members' characteristics have an additive or interactive composition effect (i.e., whether a group is more than the sum of its parts). The method that we propose in this article offers a straightforward way to answer this question for group-level, individual, and dyadic outcomes. Levine and Moreland (1998) have organized group composition research into three basic categories: composition as a consequence, composition as a context, and composition as a cause. This article focuses on the latter two categories.

Building on these past contributions, we propose a new method for studying many of the effects of group composition on group members. The approach allows us to measure and test if group composition affects group behavior. Moreover, we apply this model when one outcome is obtained for each member of the group (an individual outcome), when there is a single outcome for the entire group (group outcome), and when an outcome is obtained for each person paired with every other member of the group (a dyad outcome).

The most common type of outcome in group research is an individual outcome. We use gender as the group composition variable throughout the article. Technical details and computer setups can be obtained online in the web appendix (davidakenny.net/doc/gapim_tech.pdf).

Individual Outcomes

For an individual outcome, each group member provides a single score, for example, how much he or she identifies with the group. To analyze such data, Gonzalez and Griffin (2001) developed the actor-partner interdependence model (APIM; Kenny, Mannetti, Pierro, Livi, & Kashy, 2002). Currently, the APIM is most often used to study dyads (Kenny, Kashy, & Cook, 2006). In its use as a dyadic model, one dyad member's response depends on his or her own characteristics, the *actor effect* and on the characteristics of the person's interaction partner, the *partner effect*. These two effects can interact, which can sometimes be interpreted as a similarity effect: When an actor is similar to his or her partner, is the actor more or less satisfied in the relationship than when an actor is dissimilar to his or her partner? In this article, we further extend the APIM to study group composition.

For groups, we refer to the individual who provides the data point as the *actor* and the remaining $n-1$ members of the group as the *others*.[1] Consider work teams in a given company that vary in gender composition. In some of the teams, workers are all of the same gender, either all male or all female. In other teams, there is a mixture of males and females. A particular person's feelings of group satisfaction might depend on his or her gender, denoted as X_{ik} (with females coded as -1 and males coded as $+1$), as well as on the average gender of the other $n-1$ members in the group, denoted as X_{ik}'. For example, if the others in the group are all females, then X_{ik}' would be -1, and if they are all males, then the average gender of others would be $+1$. If the others in the group were half of each gender, the average gender of others would equal 0. The effects of these two variables are the main effects of gender and of others' gender on group satisfaction.

There are potentially two interaction variables that may model the effects due to gender composition:

1. the actor by others interaction or I_{ik}, which measures how similar the person's gender is to each of the other $n-1$ members of the group (actor similarity) and
2. the average interaction of all possible pairs of others or I_{ik}' which measures how similar the other $n-1$ members' genders are to each other (others' similarity).

Each of these interaction variables is formed as the mean of product terms of pairs of gender terms. As we use effect coding, these product terms can be interpreted as a measure of similarity.

More formally, we denote the individual outcome as Y_{ik} for person i in group k. The group APIM for individual outcomes or GAPIM-I model is as follows:

$$Y_{ik} = b_{0k} + b_1 X_{ik} + b_2 X_{ik}' + b_3 I_{ik} + b_4 I_{ik}' + e_{ik} \tag{1}$$

For example, the effects of the four variables are defined as follows:

b_1: the effect of a person's own gender, the *actor effect*;

b_2: the effect of the average gender of the other $n - 1$ members of the group, the *others effect*;

b_3: the effect of the average similarity of person i's gender to the gender of the other $n - 1$ members of the group, the *actor similarity effect*; and

b_4: the effect of the average similarity of the genders of all possible pairs of others in the group, the *others' similarity effect*.

The I_{ik} variable, or actor similarity, was called the *actor–partner interaction* in Kenny et al. (2002). The I_{ik}' variable, or *others' similarity*, is the average of the partner–partner product terms, and was not considered in Kenny et al. (2002) or any previous APIM article. Presuming the X variable is effect coded (+1, -1), these I variables equal 1 when there is exact similarity and –1 when there is complete difference. As we discuss later, the dissimilarity of *all* the group's members (the group's level of diversity) is a combination of these two variables. We denote the model in Equation 1 as the *complete model* because later models either contain fewer effects or place constraints on those effects.

As explained in Kenny et al. (2002), the GAPIM does not use the usual multilevel formulation of entering the group mean of X to predict Y. As a person's X is part of the group mean of X (i.e., a person's own gender is part of the group's gender), the two effects are correlated. Furthermore, from our point of view, the key conceptual and psychological contrast in groups is between self and others and not between self and group.[2] We note that all four variables in the GAPIM-I are all at the individual level; however, as shall be seen later, combinations of these variables that can be created (e.g., the group average and group diversity) are at the group level.

Submodels

Kenny and Cook (1999) considered four submodels of the APIM, which parallel models drawn from interdependence theory (Kelley et al., 2003). It
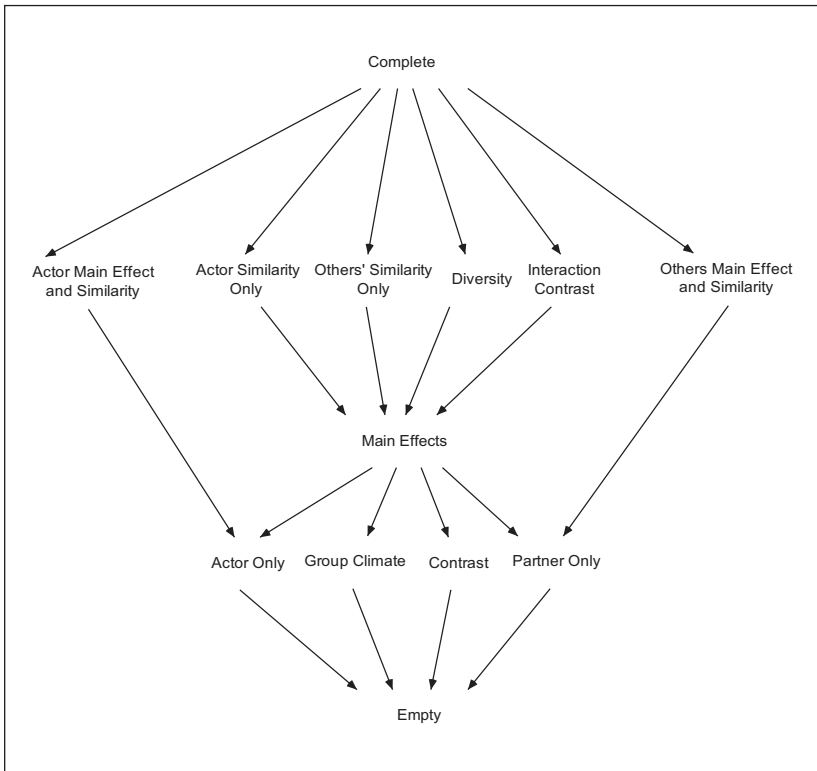
Figure 1. Hierarchy of GAPIM-I submodels with arrows pointing toward the simpler model

is these submodels that evaluate social-psychological theories of group processes. These different submodels help the researcher find a simpler and ideally more conceptually appropriate model than the complete model with all four variables. By estimating and testing the submodels, we can begin to understand the social-psychological processes that affect group members. Each submodel places some sort of constraint on the complete model, either by fixing an effect to zero, setting two or more coefficients equal to each other, or creating a contrast. Figure 1 presents all of the GAPIM-I submodels to be discussed and their relationship to each other.

For the GAPIM-I, we first consider four submodels of a model containing only the actor and others effects, denoted as the main effects model. Using gender as the example of the *X* variable or composition variable and member satisfaction as the *Y* or outcome variable, the four submodels are (a) the *actor*

only model, where only the actor's gender has an effect on the outcome ($b_1 \neq 0$ and $b_2 = 0$ in Equation 1); (b) the *others only model*, where only the average gender of the other $n - 1$ persons in the group has an effect on the outcome ($b_1 = 0$ and $b_2 \neq 0$); (c) the *group model*, in which the mean of the group's genders has an effect on the outcome ($b_1 = b_2 \neq 0$); and (d) the *contrast model*, in which a person's gender is compared with the average gender of the others in the group ($b_1 - b_2 = 0$); that is, the two effects have opposite signs, but equal magnitudes.

In the actor only model, the genders of the others in the group have no effect on the individual's satisfaction, whereas in the others only model, it is only the others who matter. So for instance, in the actor only model, we might find that males are more satisfied with the group than females; in the others only model, people are more satisfied with the group when the others are females. In the group model, it is the overall composition of the group that matters, and the individual's own gender plays no special role in affecting his or her satisfaction. In this model, the equality motive dominates, and there is no boundary between self and other (see Smith & Henry, 1996). However, in the contrast model, there is a sharp boundary between the individual and the others in the group. What matters is how *different* the person is from others, and the direction of the difference matters as well. This effect has been dubbed the *frogpond effect*. For example, Davis (1966) found that college students had higher career aspirations if they were smarter than most of the others students at their college. Hence, it is better to be a big fish (or frog) in a smaller pond than a big fish in a larger pond.

We can also consider three submodels of the complete model involving the two interaction effects, b_3 and b_4 in Equation 1, that also test social-psychological theories. The first is the *diversity model*, which contains the two main effects and a measure of the overall diversity of the group. We can measure group diversity as a weighted average of the two interaction terms. The diversity model implies that $b_3 = b_4 \neq 0$. Several different investigators (Antonio, Chang, Hakuta, Kenny, & Levin, 2004; Harrison & Klein, 2007; Harrison, Price, & Bell, 1998; Jackson et al., 1991; Sommers, 2006) have predicted that group diversity has an effect on individuals, as well as on groups and dyads. For instance, we might expect members of gender-diverse groups to feel less identified with the group (Tsui et al., 1992). Second, the *person-fit model*[3] assumes that what matters is how similar the actor is to the others in the group (i.e., $b_3 \neq 0$ and $b_4 = 0$), and not how similar the other members are to each other. For instance, Elfenbein and O'Reilly (2007) found that if a group member fit into the group, he or she had better performance ratings (see also Wright, Giammarino, & Parad, 1986; Boivin, Dodge,

& Coie, 1995). The third model is the *contrast model of interaction effects*. In this model, actor similarity is measured relative to the similarity of the others in the group. This model implies that the two interaction effects are equal, but of opposite signs: $b_3 - b_4 = 0$. For the *interaction contrast model*, the group members see how different they are from the others in contrast to how different the others are from each other.

The last two submodels have both main effects and interaction effects in the GAPIM-I. First, is the *actor main effect* and *similarity model*, which includes only the actor effect and the actor similarity effect. Second, the others main effect and similarity includes only the others effect and the other similarity effect. Again, the reader might benefit by consulting Figure 1 to see the relationships between the various submodels.

Estimation and Testing

There are two random variables in the model contained in Equation 1:

b_{0k}: the extent to which some groups have more or less satisfaction than other groups, which can be viewed as the group effect and

e_{ik}: error, or the extent to which person i is satisfied with his or her group more than others in the study are satisfied with their group.

Thus, the model in Equation 1 has two levels, and so multilevel modeling estimation must be used. The individual is Level 1 and the group is Level 2, with all of the group composition predictors in Equation 1 at Level 1. Although all of the variables in the complete model of the GAPIM-I are at Level 1, some of the variables in the submodels are at Level 2. Most notably, the group effect in the group model and the diversity effect in the diversity model are at Level 2. There might be additional predictors at Level 1 (e.g., how long someone has been in the group) and at Level 2 (e.g., the type of group). The variance of the intercepts, or b_{0k}, represents the group-level effects, and the variance of e_{ik} represents the combination of error and person variance. Below we used SPSS (syntax provided at davidakenny.net/doc/gapim_tech.pdf), but any multilevel modeling program could have been used. As we are comparing different models with different fixed effects, we used maximum likelihood estimation and not the usual default estimation method (restricted maximum likelihood). As we are computing many models and need to judge which are better fitting, we computed a measure of fit for each model that we estimated. We used the sample-size-adjusted Bayesian information criterion (SABIC), which equals $D + q\ln([N + 2] / 24)$ where D

is the model's deviance, N is the number of groups, q is the number of parameters in the model, and ln is the natural logarithm function. To obtain a baseline value, we estimated the SABIC for an empty model in which all four coefficients were set to zero.

Our model-testing strategy was as follows: First, a main effects model was estimated. The two main effects in that model were tested for statistical significance, and the model's fit was compared with that of the empty model. We then estimated the complete model, the one with all four variables and compared the fit of this model with that of the main effects model. Finally, based on these analyses, we chose the submodel that had better fit than any of the prior models and whose key terms were statistically significant.

Example

We collected group interaction data from 58 groups of four to five University of Connecticut students. Gender composition varied across groups. Six groups were eliminated because one person in the group had missing gender information. The remaining 52 groups had four or five members, for a total of 87 males and 154 females. Participants' ages ranged from 17 to 22 years, with the average age of 18.6 years. The sample included 24 Asian Americans (10.0%), 11 Latino/as (4.6%), 6 African Americans (2.5%), and 195 Whites (80.9%); 5 people indicated Other (2.1%).

After being told that they were participating in a study investigating group composition and interactions, participants completed a short demographic questionnaire. During the group interaction portion of the study, participants were given a picture and asked to write (working individually) a short three to five sentence creative story about this picture. They were given 5 min to complete their stories. Then, they discussed these stories as a group. After composing and discussing their individual stories, together group members worked to compile another story (three to five sentences) about the same picture. Five minutes were given to complete these group stories. Leadership was not assigned, and there were no rules about whose individual ideas should be included in the final story. After the group finished its story, the participants completed a series of outcome measures that included questions asking about their feelings regarding the group and the individual group members. Included in these outcome measures was a 13-item assessment of group identification (Leach et al., 2008), which had a reliability of .915. We effect coded gender, +1 for males and −1 for females.

Table 1. Effect Coefficient Estimates of Gender (*Female* = −1, *Male* = 1) on Individual Identification With the Group

	Main effects		Interactions		Fit
Model	Gender	Others' gender	Actor similarity	Others' similarity	SABIC[b]
Empty	0[a]	0[a]	0[a]	0[a]	675.827
Main effects	−0.071	0.234*	0[a]	0[a]	672.818
Complete	−0.026	0.227*	0.295**	−0.210	665.788
Interaction contrast	−0.034	0.198	0.256***,c	−0.256***,c	665.224

Note: SABIC = Sample-size-adjusted Bayesian information criterion.
[a]Fixed to zero.
[b]Smaller SABIC means a better fitting model.
[c]Fixed to be equal, but opposite sign.
*$p < .10$. **$p < .05$. ***$p < .01$.

Results

As seen in Table 1, the main effects model was tested and the effect of actor's gender was not statistically significant. However, there was a marginally significant effect of others' gender, $b_2 = 0.234$, $p = .054$, indicating a trend that when the others were male and not female people identified more with the group. We next estimated the complete model and found that the fit improved over the main effects model. There was again a marginally significant effect of others' gender ($b_2 = 0.227$, $p = .097$), and a statistically significant effect of actor similarity ($b_3 = 0.295$, $p = .014$). No effects of actor gender or others' similarity were found. The coefficient for others' similarity was close in magnitude to the coefficient for actor similarity, but the two coefficients had opposite signs. This pattern indicates that the interaction contrast model might have been a better fit to the data. The interaction contrast model was thus estimated—the difference between actor similarity and others' similarity was added as one parameter (the two parameters were constrained to be equal in size, but opposite in sign). This proved to be the best-fitting model. As seen in Table 1, there was a statistically significant contrast effect between actor's similarity and others' similarity ($b_4 = 0.256$, $p = .004$). A group member identified least with the group when he or she was different in gender from the other group members who were of the same gender.
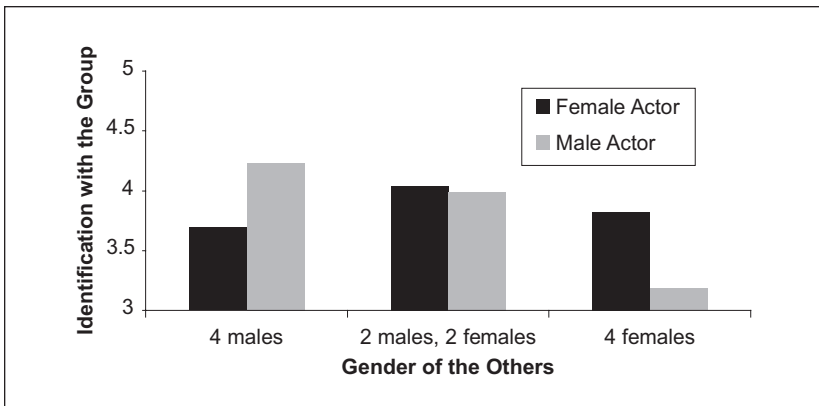
Figure 2. Predicted means of gender composition effects on identification with the group for five-person groups

To help interpret the results, we used the complete model to compute predicted means in Figure 2 for five-person groups where *the others* were either all male, all female, or two males and two females. People identified least with a group when their own gender differed from that of other group members, *and* those other members all had the same gender (i.e., the actor was a solo). Identification was nearly equal between the heterogeneous groups and homogeneous groups. The figure also shows a tendency for greater identification in groups where the others were male rather than female.

Group-Level Outcomes

Researchers are often interested in the impact of group composition on group-level outcomes, such as group productivity. For example, a question of great interest recently has been the effect of group diversity on group productivity (see Moreland, 2012, for an overview of this work). We can adapt the GAPIM to model group outcomes (GAPIM-G). In such a model, there are only group-level predictors:

$$Y_k = b_0 + b_1\overline{X}_k + b_2\overline{I}_k + e_k \tag{2}$$

The variable $\overline{X}_k$ is the average gender of the n members of group k and $\overline{I}_k$ is the average similarity of all $n(n-1)/2$ pairs of members of group k. In this case, the group's productivity is determined by the proportion of males

in the group and the extent to which the group has an equal number of males and females. We note that b_2 captures, in part, the nonadditive effect of group composition, which is sometimes called *chemistry* or *synergy* (i.e., whether the group is more than the sum of its parts). However, as discussed by Moreland (2010), not all group effects can be explained by individual and dyadic effects. Higher order interactions (e.g., triadic) could be added to the model (see the web appendix).

The study that we described earlier in the GAPIM-I section can also be used to investigate the effects of gender composition on a group-level outcome, namely, group output. This variable was the quality of the group stories, as rated by three outside judges. The 52 group stories were transcribed, and then three independent coders rated each story in four categories. The stories were rated on 0 to 10 scales for how funny, creative, and entertaining they were, as well as for their overall quality. We then computed the average of the four ratings, across the three raters, to create a measure of story quality. This measure was reliable across coders ($\alpha = .80$), so all of the ratings were then averaged together. The two all-male groups had a mean story quality score of 5.625, and the 13 all-female groups had a mean story quality score of 5.455. The 37 nonhomogenous groups had a mean quality score of 6.585. With the GAPIM-G, we found that $b_1 = 0.245$ ($p = .463$) and $b_2 = -0.822$ ($p = .034$). Thus, groups with greater gender diversity wrote higher quality stories. We found no effect due to the gender of the group (i.e., the proportion of males). Note that with the GAPIM-G, we estimated the effect of diversity controlling for group gender, something that is not routinely done.

Dyad-Level Outcomes

For most applications of the GAPIM, there is an individual outcome—a single measure for each person. Here, we consider the less frequent, yet still interesting, case of a dyadic outcome. We assume *n*-person groups where there is a measure of some characteristic (e.g., ethnicity, gender, or opinion) for each person. We again denote this characteristic as X_{ik} for person *i* in group *k*. Assume that it is a dichotomy, allowing us to use effect coding (1 and –1). (We later discuss how to handle nondichotomous categorical variables, as well as continuous variables.) If the characteristic were gender, then again we might code males as +1 and females as –1. Now, consider an outcome variable that is dyadic, for example, how persuasive person *i* thinks person *j* is in group *k*, or Y_{ijk}. We refer to *i* as the *actor* and to *j* as the *partner*; subscript *k* refers to group. The main effects model of the GAPIM for dyad data (GAPIM-D) is as follows:

$$Y_{ijk} = b_0 + b_1 X_{ik} + b_2 X_{jk} + b_3 X_{ijk}' + e_{ijk} \qquad (3)$$

where X_{ijk}' is the mean of all Xs in group k besides persons i and j. Thus, if person i is a man, person j is a female, and the other members of the group were all females, then X_{ik} would equal $+1$, X_{jk} would equal -1, and X_{ijk}' would equal -1. We would interpret the coefficients for these three main effect variables a follows:

- b_1: *actor effect*: If positive, then males view others as more persuasive than do females.
- b_2: *partner effect*: If positive, then male partners are viewed as more persuasive than female partners.
- b_3: *others' effect*: If positive, then an actor tends to view his or her partner as persuasive when other group members are male.

These three main effects can also interact in four ways. We model these four interactions by including the following interaction variables:

1. Actor by partner interaction (how similar actor i is to partner j). We refer to this interaction effect as *dyad similarity*. We denote this interaction variable as I_{ijk}, which equals $X_{ik} X_{jk}$. This variable measures whether the actor and partner are the same gender or not; note that it equals 1 when i and j are both males or both females, and -1 when one person is a man and the other a woman.
2. Actor by others interaction (how similar person i is to the average of the other $n - 2$ members of the group). We refer to this as *actor similarity*; note that it equals 1 when the person has the same gender as the other $n - 2$ persons in the group, -1 when the person is of a different gender, and 0 when the others contain an equal number of males and females. We denote this variable as I_{ik}. It measures how similar gender is between the actor and the others.
3. Partner by others interaction (how similar person j is to the other $n - 2$ members of the group). We refer to this as *partner similarity*; note that it equals 1 when the partner has the same gender as the other $n - 2$ persons in the group, and -1 when the partner is of a different gender. We denote this variable as I_{jk}. It measures how similar the partner is to the others.
4. Average interaction of all pairs of the others' (how similar the other $n - 2$ members are to each other, across $[n - 2][n - 3] / 2$ dyads). We call this variable the *others' similarity* and denote it as I_{ijk}'. It measures how similar the others are to each other.
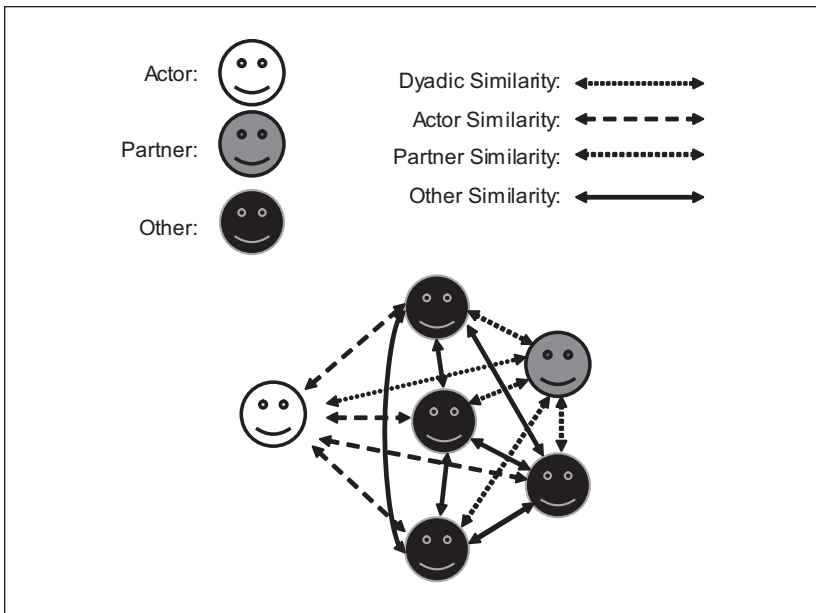
Figure 3. The different ties between members in the GAPIM-D

Figure 3 might aid in understanding these four interaction variables. The figure shows a six-person group. One member is designated as the actor (the white face), one as the partner (the gray face), and four as the others (the black faces). In Figure 3, there are a total of 15 different dyadic ties between members of the group (represented by a line connecting each face). For each of these ties, it can be determined whether the two people are similar or not. The tie would be +1 if the two persons were similar and −1 if they were dissimilar. The 15 ties are allocated to the four interaction variables. One of those ties is between the actor and partner; four between the actor and the others; four between the partner and the others; and six between the four others. These ties represent dyad, actor, partner, and others' similarity, respectively. The complete model with the three main effects and four interactions is as follows:

$$Y_{ijk} = b_0 + b_1 X_{ik} + b_2 X_{jk} + b_3 X_{ijk}{}' + b_4 I_{ijk} + b_5 I_{i.k} + b_6 I_{.jk} + b_7 I_{ijk}{}' + e_{ijk} \quad (4)$$

Submodels

The complete model for the GAPIM-D has seven variables in the model, but usually a much simpler and more theoretically plausible submodel would fit
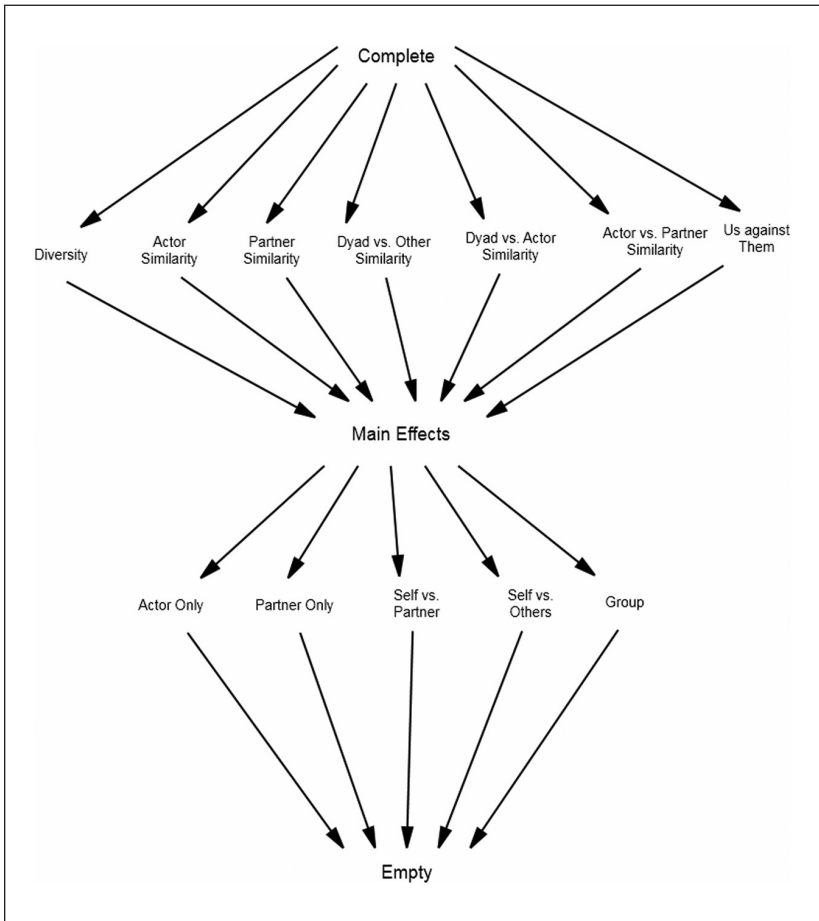
Figure 4. Hierarchy of GAPIM-D submodels with arrows pointing toward the simpler model

better than the complete model. These different submodels help the researcher find a simpler and ideally more conceptually appropriate model than the complete model with all seven effects. By estimating and testing the submodels, we can begin to understand the social-psychological processes that affect group members. Figure 4 presents all the GAPIM-D submodels to be discussed and their relationship to each other. We first consider six submodels of the main effects.

The main effects model includes all three main effects, the actor effect, the partner effect, and the others effect, but no interactions. In the actor only model, there is only an actor effect. In the partner only model, there is only a partner effect; persuasiveness depends only on the gender of the partner. The group model uses the group mean of X (the weighted average of the three main effects); the outcome variable is determined by the average of the group members' characteristics (e.g., gender). The next two main effects submodels can be viewed as contrast models. In the self versus partner model, the actor and partner effects are compared, and so the operative variable is $X_i - X_j$. In the self versus others model, the actor's gender is compared with all the others in the group (including the partner), and this comparison is what affects his or her evaluation of persuasiveness. As we discussed with individual outcomes, this pattern of results is sometimes called a *frogpond effect*.

We can also consider seven submodels of the interaction effects. In the diversity model, all four interaction effects are equal, $b_4 = b_5 = b_6 = b_7$. This model implies that if we aggregated the four interaction variables into a single measure of group diversity, the fit of the model would not suffer. The operative variable is how similar (or different) everyone in the group is. The actor similarity model assumes that the important similarity variables are actor similarity, the effect of the actor's similarity to the others (b_5), and dyad similarity (b_4). Together these variables represent the actor's similarity to everyone else in the group. This model implies that $b_4 = b_5$ and $b_6 = b_7 = 0$ and is comparable with the person-fit model (Elfenbein & O'Reilly, 2007), where person is the actor. Analogously, the most important predictor of how persuasive a partner seems is how similar that *partner* is to the others in the group. If the partner is dissimilar to others in the group, for example, then he or she might seem more persuasive. This model is referred to as the *partner similarity model* and implies that $b_4 = b_6$ and $b_5 = b_7 = 0$.

At least four different contrast models of the interaction effects can be estimated and tested. A contrast model implies that interaction effects have opposite signs, but equal magnitudes. We might test that an actor sees a partner as persuasive if the partner is similar to the actor, but the actor is different from others. In this model, the dyad similarity and actor similarity effects are of opposite signs, and the remaining interaction effects equal zero. Alternatively, what might matter is how similar the partner is to the others in the group, relative to how similar the actor is to the partner. For example, the actor might view the partner as persuasive when the partner is not only similar to the actor but also different from others. We might also examine an actor versus partner contrast model, in which the actor sees the partner as

persuasive if the actor is similar to others and the partner is different from others. In the final contrast model, we test an *us against them* effect: The actor and partner are similar to each other, but both different from the others in the group who are all similar to each other. This variable is most extreme (i.e., equal to 1 or –1), when the actor and partner are the only two persons in the group with the same gender.

Estimating and Testing

The GAPIM-D is a complicated multilevel model with several types of nonindependence. They are the social relations model's (SRM; Kenny & Livi, 2009) variances and covariances (summarized in the web appendix). As the major focus of this article is the effects of group composition, those SRM effects are not discussed here. Nonetheless, we need to compute these variances and covariances to obtain the proper standard errors for the seven fixed effects of group composition in the GAPIM-D. We used the computer package SAS to estimate the model (see Kenny & Livi, 2009 and the web appendix for details, as well as syntax). As we are comparing different models with different fixed effects, we again used maximum likelihood estimation, not restricted maximum likelihood estimation.

Again we used the SABIC to compare the relative fit of the models. To get a baseline value, we estimated the SABIC for a model in which all seven effects of the model were set to zero (an empty model). Our model-testing strategy was as follows: We first estimated a main effects model testing its three main effects for statistical significance, and then compared its fit with the empty model. We then estimated the complete model (the one with all seven variables). The fit of this model was compared with that of the main effects model. Finally, based on these analyses we chose a submodel that had better fit than any of the prior models, and whose effects were mostly significant.

Example

To further test the GAPIM-D, we analyzed data from Culhane, Hosch, and Weaver (2004). Six-person mock juries were assigned to watch one of six videotaped versions of a burglary trial. The trials were videotaped in a local courtroom with a judge, attorneys, and a police officer playing their actual roles. The language and race of the defendant varied across juries, but the victim was always female and the perpetrator was always male. There were 804 participants in 134 mock juries from El Paso County, Texas. The

Table 2. Effect Coefficient Estimates of Gender (*Female = −1, Male = 1*) on Dyadic Perceptions of Persuasiveness

	Main effects			Interactions				Fit
Model	Actor gender	Partner gender	Others' gender	Dyad similarity	Actor similarity	Partner similarity	Others' similarity	SABIC[b]
Empty	0[a]	0[a]	0[a]	0[a]	0[a]	0[a]	0[a]	11,477.79
Main effects	−0.023	0.102***	−0.098	0[a]	0[a]	0[a]	0[a]	11,456.27
Complete model	−0.007	0.086***	−0.092	0.018	0.148**	−0.102*	0.076	11,449.98
Contrast: Actor versus partner	−0.007	0.086***	−0.097	0[a]	0.125***,c	−0.125***,c	0[a]	11,446.90

Note: SABIC = Sample-size-adjusted Bayesian information criterion.
[a]Fixed to zero.
[b]Smaller SABIC means a better fitting model.
[c]Fixed to be equal, but opposite sign.
*$p < .10$. **$p < .05$. ***$p < .01$.

participants' median age was 45 years, ranging from 18 to 89 years. The sample was 54.6% female, 58.5% Hispanic, 31.3% White, 3.9% Black/African American, and 2.2% Asian American or Native American. After viewing the videotaped trial, jurors deliberated for up to 3 hr to reach a unanimous verdict or were declared as hung. After deliberation, each juror made round-robin ratings of persuasiveness of the other five jury members. All ratings were on a 1 to 5 scale, where higher scores indicated greater persuasiveness.

The composition predictor variable was gender. There was only one participant with a missing value for gender, and so we dropped his or her entire group from the analyses, resulting in 133 6-person juries and 798 jurors. Each juror rated the other five members on four variables (persuasiveness, knowledgeable, likeable, and similar), resulting in 3,990 dyadic observations. However, there were two missing cases on the persuasiveness measure and so the resultant sample size was 3,988.

Results

We first estimated the main effects model. In Table 2, we see that the only statistically significant effect was the main effect of partner gender. This effect was positive ($b_2 = 0.102$), indicating that males were seen as more persuasive than females, a result found by Eagly and Carli's (1981) meta-analysis of gender differences in influenceability. The effect of others' gender was nearly as large in absolute value ($b_3 = −0.098$) as the partner gender effect, but was not statistically significant ($p = .118$). There was less power

for the test of the others' gender than there was for the test of partner gender, because the former varied mostly by group and the latter varied mostly by individual within the group. It is interesting to note that these effects were opposite in sign, perhaps indicating a contrast between the partner's gender and the gender of others: A man is seen as more persuasive when the others in the group are females rather than when the others are males.

When we added the four interactions and estimated the complete model, the fit of the model improved. Although the dyad and others' similarity effects were not statistically significant, the actor similarity effect was significant, and the partner similarity effect was marginally significant. Note that the actor similarity effect was positive, whereas the partner similarity effect was negative, suggesting that if the actor was similar to others in gender *and* the partner was different from others then the partner seemed more persuasive. When we considered the submodels, the one that fit the data best was the actor versus partner contrast model. A female seemed more persuasive to a male when the other members of a group were mostly male, and a male seemed more persuasive to a female when the other members of a group were mostly female. These results suggest that persons who are different from others are viewed as more persuasive, a result previously found in other studies (e.g., Antonio et al., 2004).

In Figure 5, we have graphed the predicted means from the complete model for gender of partner, actor similarity, and partner similarity. Note that the bars on the left (homogeneous groups and partner a solo) tend to be higher than those on the right (actor a solo and other dissimilar to actor and partner). This is the effect of actor similarity: When a person is similar to others, the person sees the partner as persuasive. In addition, if we focus on the gender of partner effect, then it is noteworthy that when the others were homogeneous (the other five people in the jury were either all male or all female), there was no effect of gender of partner effect. However, when the partner was different from the other four group members, there was a gender of partner difference. This result might be interpreted as an interaction between partner gender and partner similarity, but that interaction is equivalent to the main effect of others' gender (see Shaffer, 1977).

In summary, the effects in the model can be viewed in terms of contrast effects: A partner seemed more persuasive when his or her gender was different from the gender of others in the group *and* the actor's gender was similar to the gender of others. In addition, a male partner seemed more persuasive when other group members were female. These two main effects were roughly equal, which means that when the partner and others were the same gender, male partners seemed more persuasive than female partners, but
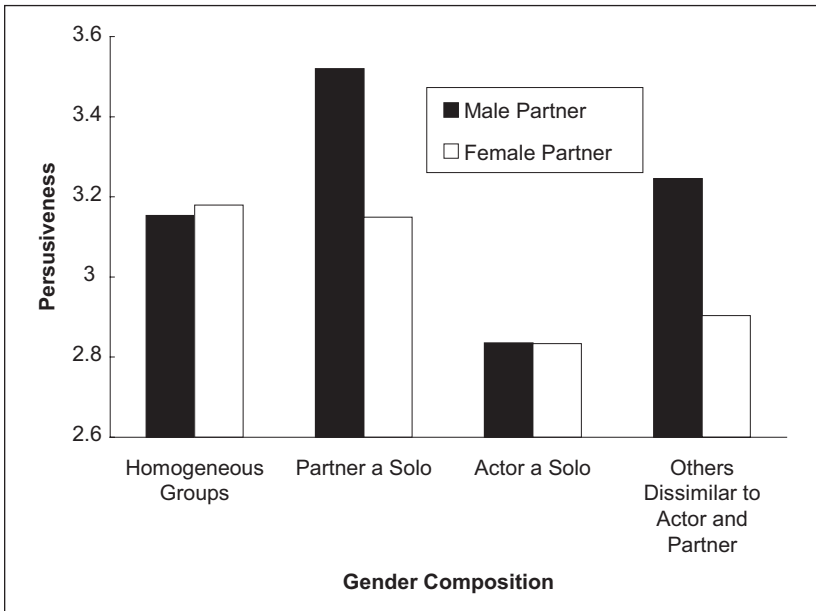
Figure 5. Predicted means for gender composition effects on ratings of persuasiveness

when the partner and others had different genders, there was no effect of partner gender. Certainly, these results require replication, but they do illustrate the potential of the GAPIM.

Extensions

In this section, we discuss aspects of the model that we have thus far ignored. These involve solo status, unequal group sizes, missing data, and continuous variables. Moreover, in the last part of this section, we discuss design issues and consider the important question of how many groups are needed to estimate the model.

Solo Status

Solo members, especially persons from low-status demographic groups (i.e., tokens), may experience the group very differently from the rest of the group (Sekaquaptewa & Thompson, 2002). Much of the research on solo and token status has focused on issues of power, for example measuring participation,

and determining whose ideas are most persuasive (Hewstone et al., 2006; Kanter, 1977; Saenz, 1994).

The GAPIM predicts that solos should see the group very differently from other group members because they have extreme scores on many of the model's variables and not because of a special effect of being a solo. In terms of the GAPIM-I, a solo is someone who differs from everyone else in the group ($I_{ik} = -1$), who are themselves all the same ($I_{ik}' = 1$). For example, if there were a large effect of being solo, then the model would forecast that $b_4 - b_3$ would be large in absolute value. Note that if $b_4 - b_3$ were indeed large, then there would be a contrast effect at the level of the two interaction effects.

Alternatively, it is possible that the reaction of someone who is a solo may be more extreme than predicted by the GAPIM. To extend the GAPIM to allow for a qualitatively different effect of being a solo, we would create an additional variable that would equal one if the person is a solo and zero otherwise. The test of the effect of this variable would evaluate if there were anything special about being a solo, over and above the effect of the GAPIM variables. Moreover, we can have this variable interact with X_{ik} to determine if there are token effects, that is, if being a solo *and* someone of lower social status (e.g., female) has an effect on the outcome.

Unequal Group Sizes

The GAPIM does not require equal group sizes, but unequal group sizes create complications for the analysis that we have developed in this article. Note that several of the variables, both main effects and interactions, are defined in terms of *means* across others or relationships. We would then use the group size for that particular group to compute those means. For the individual model, the computation of others' similarity requires at least three persons in every group because with just two persons there is just one other; for the dyad model, at least four persons in every group are needed to compute others' similarity. Note also that group size can be treated as a covariate in the model (Kenny et al., 2002), as well as a factor in interactions with the GAPIM parameters.

Missing Data

Missing data can be especially problematic for the GAPIM. Even if there were missing data on the outcome variable for a person, ideally there would not be missing data on X for that person so that the score could still be used

to compute the composition variables. For example, if we are studying the effects of gender composition on liking, then we might still have information about the gender of participants who did not provide liking ratings. This is a better scenario than if the converse pattern were present (we have liking scores, but no gender information). Note that if one participant in a group has a missing X_{ik} score (e.g., gender), then the scores on the other three variables of the GAPIM-I are missing for all the other respondents in the group. Moreover, the scores for at least five of the six variables would be missing in the GAPIM-D case. In this situation, the researcher is faced with a choice for how to handle the missing data: Either the entire group is treated as if it was missing or the participant who has a missing gender is ignored, and the group is presumed to contain one less member. Although neither of these solutions is ideal, the latter strategy may be preferable if the group size is fairly large because the variables should not change much. In addition, if the sample contains only a small number of groups, the latter is again preferable, so that there would be a sufficient number of groups.

Nondichotomous Variables

If X, the composition variable, were a continuous variable, like age, and not a dichotomy, like sex, then we might modify the strategy as follows: We would determine the largest score in the sample (X_L) and the smallest score in the sample (X_S). For variables that have upper and lower limits, these limits would be used to determine X_L and X_S. We would then recode X_{ik} as $2(X_{ik} - X_S) / (X_L - X_S) - 1$. This would change the largest score to +1 and the smallest score to −1. In this way, the interaction variables can be interpreted as equaling 1 when people have exactly the same score on X and −1 when they have maximally different scores. A score of zero would indicate a pair of scores that fell halfway between no difference and the largest possible difference in the sample.

Of course, the variable X might be categorical, but not a dichotomy. For instance, X might be ethnicity, with five different ethnicities possible. For the main effect composition variables X_{ik} and X_{ik}', we suggest using multiple dummy variables to code for those ethnicities. That is, if we had five ethnicities, then we would create four dummy variables, using one ethnicity as the standard group. We can retain the same coding for the interaction variables, I_{ik} and I_{ik}'. For example, if I_{ik}' equals 1, this score would imply the others in the group are all members of the same ethnic group. However, if it is equal to −1, then that would imply that the other members all belong to different ethnic groups.

When X_{ik} is a dichotomy, the lower limit of others' similarity in the GAPIM-I (I_{ik}') and the GAPIM-D (I_{ijk}'), is ordinarily not –1. Recall that these variables are scaled such that a value of one means complete similarity and minus one means complete dissimilarity. When a variable takes on only two values (e.g., male and female), the lower limit of this variable is –1 / m if m is odd and –1 / (m – 1) if m is even, where m is the number of others in the group besides the actor (or the actor and partner in the dyadic case). For instance, if m is 10, the lower limit is not −1, but rather −0.111. If, however, X_{ik} can take on as many values as n (e.g., six ethnicities in a group of six), then both I_{ik}' and I_{ijk}' can equal their theoretical lower limit of –1. That is, a person can be completely dissimilar to the others in the group and they can also be completely dissimilar to each other. In this case, diversity would measure *variety*, as defined by Harrison and Klein (2007).

Multiple Xs

We have assumed so far that there is just one X variable. As in the Culhane et al. (2004) data set, however, there may be several different composition variables simultaneously affecting one outcome, and we may wish to combine these variables. For instance, we might be interested in the combined effects of gender and ethnic composition on liking. This problem is closely related to the idea of demographic faultlines—subgroups may form within groups based on differences in group members' characteristics (Lau & Murnighan, 2005). Furthermore, these faultlines increase in strength as subgroup differences based on one characteristic are reinforced by differences on other characteristics. For example, half of the group may be Hispanic and female, whereas the other half may be White and male. Clearly, testing hypotheses about multiple variables is important and deserving of further investigation.

Number and Sizes of Groups

In this section, we discuss the design of a GAPIM study. We first discuss how many groups to study. We then discuss what happens with the model when the X variable is skewed or when there is only one group.

Number of groups. We had 52 groups in the individual example data set and 133 groups in the dyadic example data set. However, how many groups are really needed to perform our analyses? Is it necessary to have 50 groups or more? Although we cannot provide definitive answers to these questions, we can provide some guidance.

If the interest is in estimating the full GAPIM, then the number of groups in a sample cannot be small for at least two reasons. First, as we have emphasized, several different variables of the model (the others and diversity effects) vary primarily at the group level. The effective sample size for such effects is not the total number of persons in the sample, but rather the number of groups. Tests of the effects of these group variables have less power than the individual variables. Second, the variables in the model are not independent and can thus be correlated with one another. This increases standard errors and reduces power. In the next section, we discuss skewed X variables, which can result in very strong correlations between the predictor variables in the model.

It is difficult to give a rule of thumb about the minimum number of groups because it would vary depending on effect sizes and what variables are present in the model. We have actually found effects in a study (not reported here) with only 19 groups. One way of increasing power is to estimate one of the submodels. For instance, if the interaction variables were correlated, then we might estimate the diversity and contrast models, and as these models have fewer variables, colinearity is less of an issue.

Skewed X variables. In some studies, X may be highly skewed. For instance, a company might have 100 working groups of five members (500 workers in all), but only 50 of these workers might be male. By chance, it is thus unlikely that any group would contain mostly male workers. In this case, actor gender and actor similarity, as well as others' gender and others' similarity, become highly correlated. If a male worker is dissimilar to others in the group, and those others are all similar to one another, then the group is almost certain to be mostly female.[4] We suggest that in cases where there are only a few groups in which one type of person is the majority, it might be best to estimate only the main effects model; however, in such an analysis, the effect of X_{ik} is still confounded with I_{ik} and that the effect of X_{ik}' (or the average of X of the others in the group) is confounded with I_{ik}' (the diversity of others in the group).

Single group. What happens to our model when there is just one large group? For instance, we might ask members of a large organization how much they like being in the organization and we seek to compare males' and females' response to that item. Assume that females are a minority in this particular organization. In that case, X_{ik}' and I_{ik}' hardly vary, so they should not be included in the model. Also, note that the effects of X_{ik} and I_{ik} have a perfect negative correlation, making their effects confounded. Echoing Kanter (1977), if we found that females liked being in the organization less than did males, we would not know if that was due to gender (males liked and females disliked the organization), or due to actor similarity (everyone liked

the organization insofar as it contained workers similar to themselves). Typically, such effects are interpreted as an actor effect (e.g., females enjoy working for the organization less than do males), when in fact the effect may actually be one of actor similarity (e.g., people do not like working for an organization when few of their coworkers are similar to themselves).

Conclusion

The variables in the GAPIM involve individuals (the main effects) and dyads (the interaction effects). So, one might ask "Where is the group in the GAPIM?" It is true that the complete models decompose group effects into individual and dyadic group processes. However, if there are group effects (e.g., diversity effects), then a relevant submodel should fit the data better than the complete model. Thus, the GAPIM allows group researchers to show that effects occur that are not at the level of the individual or the dyad, but rather at the group level.

In addition, the reader should not confuse the level of measurement for an outcome measure with the level at which a phenomenon occurs within groups. For instance, we might measure liking dyadicly by asking each member how much he or she likes the other members of the group. Such a measurement process does not imply that the underlying psychological process is dyadic. Using the GAPIM-D, we might find that the phenomenon is at the group level (cohesiveness), the individual level (popularity), or the dyadic level (the match between perceiver and partner). By measuring the phenomenon at the lowest possible level, we can empirically evaluate the level at which the phenomenon operates, which might well be a level higher than the unit of measurement. However, the participant's frame of reference at the lower level may not represent the meaning of what is happening at the higher level and some constructs cannot be measured at a lower level (Moreland, 2010). Finally, although as presented the GAPIM includes only individual and dyadic effects, one could further complicate the GAPIM to allow for interactions at triadic and higher levels. In this way, the concern that groups are more than individuals and dyads can be addressed.

How group composition affects groups, people and relationships is a complex process. We have shown that there is not one effect of group composition, but several. Moreover, these effects occur at multiple levels of analysis (the individual and the group), and effects can be main effects and interactions. These effects can work in combination. Following Brown (1965), there is a fundamental dichotomy of processes in groups. The first is

solidarity. The boundaries between persons break down and the person and the group merge. The second is status. Here, the person sees how he or she is different from the others in the group. With the development of the GAPIM, we can now estimate and test these two processes more carefully.

We focused on the topic of demographic group composition because it interests us, and it has been a classic question in the study of groups (Levine & Moreland, 1998). However, the variable X need not be a demographic compositional variable. For instance, consider the hypothesis that perceptions of fairness lead to feelings of being satisfied in the group. We could perform a GAPIM-I analysis treating perceptions of fairness as the X variable. That is, the group composition variable of interest may be a surface or deep characteristic (Harrison et al., 1998). Perhaps the most classic questions of group composition are the effects of member ability on members' perceptions and group performance (Tziner & Eden, 1985) as well as the effects of newcomers and personnel turnover (Jackson et al., 1991; Levine, Choi, & Moreland, 2003). The GAPIM can be used to address these questions. Alternatively, the X variable might be an experimentally manipulated variable. For instance, the experimenter might manipulate group identification and determine how hard the individual works in the group, or randomly assign participants to artificially created groups, such as a red team or blue team and investigate group cooperation under varying red-blue compositions.

The study of group composition is much more complicated than one might think. There are main effects and interactions, and there are the group, dyad, and individual levels. Moreover, these effects can be combined to form group and contrast models. With individual outcomes, there are 4 fixed effects, 2 random effects, and 11 models that we recommend estimating. With dyadic outcomes, there are 7 fixed effects, many random effects, and 15 models. It is our view that all of these complexities must be considered (at first, anyway) if we are to understand the many different ways that group composition can affect the behavior of people in groups. In one model, we can simultaneously measure individual differences, person fit, climate, diversity, contrast, and solo effects. Only by considering all of these effects simultaneously can the group researcher fully understand the effects of group composition. With the GAPIM, researchers interested in main effects would also have to consider interactions and vice versa; researchers interested in individual-level effects would also have to consider group-level effects and vice versa; and researchers interested in both individual and group effects would also consider contrast effects. Armed with the GAPIM, we anticipate significant advances in the understanding of group and intergroup processes.

Acknowledgments

Notes

1. In Kenny et al. (2002), the term *partners* is used. As in the dyad model, there is a term called *partner*, we use *others* here to reduce confusion.
2. As done in Kenny et al. (2002), it is possible to transform the GAPIM effects into the traditional multilevel effects.
3. A commonly estimated model is the contextual analysis model, where the individual group composition variable, the group mean, and the product of the two variables are entered as predictors (Raudenbush & Bryk, 2002). This model is statistically equivalent to the person-fit model.
4. If we take the Culhane et al. (2004) data and omit those groups in which males are in the majority—in effect creating a minority male sample, and thus a skewed X variable—the correlation between gender and actor similarity is $-.612$ and between others' gender and others' similarity is $-.799$, which is quite a change from $r = -.240$ and $-.143$, respectively, in the full sample. That is, when the group is not diverse, it is almost certainly because most of the other group members are female and not mostly males.

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Bios

David A. Kenny is a board of trustees and alumni distinguished professor at the University of Connecticut, United States. He is the author of six books and has written extensively in the areas of mediational analysis, interpersonal perception, and the analysis of social interaction data.

Randi L. Garcia is a doctoral candidate in the Department of Psychology at the University of Connecticut, United States. Her research interests include small group dynamics, dyadic data analysis, self and other objectification, and group identification. She teaches undergraduate courses in social psychology and psychology research methods.