
A Guide for the Estimation of Gender and Sexual Orientation Effects in Dyadic Data: An Actor-Partner Interdependence Model Approach

Tessa V. West

Center for Mental Health Services & Criminal Justice Research

Danielle Popp

Florida Atlantic University

David A. Kenny

University of Connecticut

The study of gender differences is a pervasive topic in relationship science. However, there are several neglected issues in this area that require special care and attention. First, there is not just one gender effect but rather three gender effects: gender of the respondent, gender of the partner, and the gender of respondent by gender of the partner interaction. To separate these three effects, the dyadic research design should ideally have three different types of dyads: male-female, male-male, and female-female. Second, the analysis of gender differences in relational studies could benefit from the application of recent advances in the analysis of dyadic data, most notably the Actor-Partner Interdependence Model. Third, relationship researchers need to consider the confounding, mediating, and moderating effects of demographic variables. We use the American Couples (Blumstein & Schwartz, 1983) data set to illustrate these points.

Keywords: *gender differences; Actor-Partner Interdependence Model; American Couples; dyadic analysis; sexual orientation*

Researchers, ranging from evolutionary psychologists to feminist scholars, have been interested in the differences and similarities between women and men in relationships. Although the study of gender effects in relationship research is ubiquitous, there has not been a careful examination of design and analysis strategies

employed in the area of relationships. We argue that the analysis of gender effects is both conceptually and methodologically complicated and that researchers must consider these complications when examining gender effects. The goal of this article is to present three difficulties and their solutions in this area. The first difficulty is the conceptualization and testing of gender effects; the second is the statistical analysis of dyadic data with men and women; and the third is the inclusion of demographic variables and how such variables can be conceptualized as confounds, mediators, and moderators and how to test the effects of each.

Our goal is to provide a statistical approach that allows researchers to more completely test theories within the field of relationships that focus on gender similarities and differences. Through a series of illustrative analyses, we demonstrate the difficulties of examining gender in dyadic data and their solutions using Blumstein and Schwartz's (1983) *American Couples* data set and SPSS. Although we use dyadic data from romantic partners, the method that we illustrate is appropriate for a wide variety of dyadic relationships including friendships, family and work relationships, and strangers.

Authors' Note: Address correspondence to Tessa V. West, Department of Psychology, 406 Babbidge Road, U-20, University of Connecticut, Storrs, CT 06269-1020; email: tessa.west@uconn.edu.

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THE CONCEPTUALIZATION OF GENDER IN RELATIONSHIPS

Historically, close-relationships researchers have focused on the interdependent nature of relational outcomes, demonstrating that an individual's outcome is not simply the result of his or her own predictors but of his or her partner's predictors as well (Kelley et al., 2003; Kelley & Thibaut, 1978; Thibaut & Kelley, 1959). In fact, recent research has illustrated that variables measured for one partner often affect the outcomes of the other partner (Bradbury & Fincham, 1990; Campbell, Simpson, Kashy, & Rholes, 2001; Kenny & Acitelli, 2001; Murray, Holmes, & Griffin, 1996).

Using past work on the interdependence of relationship partners as a methodological framework, we argue that it is equally important to consider partner-level as well as respondent-level predictors for dyadic studies. We specifically consider the role of partner gender in dyadic analysis. Although the predictive ability of partner variables on outcomes has been studied in a variety of contexts, relationship researchers often study gender only in terms of the gender of the respondent and ignore the potential predictive power of the partner's gender. For instance, research on division of household labor has consistently demonstrated that women engage in comparatively more housework than do men (Sayer, 2005). However, much of the research that examines gender differences in the division of labor considers the gender of only one of the relationship partners, the respondent. There are two additional gender variables that often should be considered. The second gender variable is gender of the respondent's partner. A researcher may hypothesize that individuals with male partners engage in comparatively more household labor than do those with female partners. The Actor-Partner Interdependence Model (APIM; Kashy & Kenny, 2000) has enabled researchers to directly test the path from partner gender to respondent outcome (Burk & Laursen, 2005; Campbell et al., 2001; Cillessen, Jiang, West, & Lazkowski, 2005; Cook & Kenny, 2005; Oriña, Wood, & Simpson, 2002).

A third and final gender variable that often should be considered is the interaction between gender of the respondent and gender of the respondent's partner, which can be conceptualized as same-gendered versus mixed-gendered dyads, what we refer to as *dyad gender*. For romantic couples, dyad gender is sexual orientation. To return to our division of labor example, it may be the case that inequitable division of household labor occurs more in mixed-gendered (i.e., heterosexual) than same-gendered (i.e., gay and lesbian) couples. To test this possibility, researchers should consider all three gender variables: respondent gender, partner gender, and sexual orientation in one analysis. Using the appropriate

analytic method, researchers can examine each of these three effects while controlling for the effects of the other two. Such a procedure allows for a detailed estimation and test of the gender effects.

A researcher may be interested in only one of the three gender effects, for example, the gender of respondent effect. The researcher still needs to consider partner gender and sexual orientation because they may be correlated or even confounded with the gender effect of interest. To illustrate this point, consider the gender difference among dating couples for positive illusions in romantic relationships: Women are more likely to idealize their partners relative to their partners' self-perceptions than are men (Murray et al., 1996). Research on this topic has consistently used heterosexual couples to study positive illusions and their effect on relationship outcomes. When data from only heterosexual couples are measured, researchers do not know whether the gender difference in bias is because of women idealizing their partners more than men do or whether individuals idealize men more than women do. To be able to determine whether the bias is because of gender of the respondent or gender of the partner, researchers need to also include same-gendered couples. Thus, even if the researcher is not interested in how positive illusions differ by sexual orientation, the researcher would need to consider both men and women with male and female partners. If they find the same gender difference between lesbians and gay men and no sexual orientation effect (i.e., women idealize their partners more than do men, and this effect does not interact with gender of the partner), then we can be confident that the gender effect was due to the gender of the respondent and not to gender of the partner or their interaction.

To examine all three gender effects in dyadic data, the design must be one that includes male-female, female-female, and male-male dyads. Although historically most studies that examine gender differences in relationships include only male-female dyads, there is a growing body of research that includes all three sexual orientation groups (e.g., Bailey, Kim, Hills, & Linsenmeier, 1997; Cohen & Tannenbaum, 2001; Gonzales & Meyers, 1993; Kenrick, Keefe, Bryan, Barr, & Brown, 1995; Kurdek, 1997; Kurdek & Schmitt, 1986a, 1986b; Regan, Medina, & Joshi, 2001). In the majority of studies that contained all three sexual orientation groups, researchers examined the effect of a categorical variable with three levels of sexual orientation (gay, lesbian, and heterosexual) on an outcome. With this method, the independent variable has three levels and, therefore, has two degrees of freedom. We refer to this strategy as the *Three-Group method*. One limitation of the Three-Group method is that it does not examine differences between heterosexual men and women.

An Alternative Method for Studying Gender Effects in a Complete Design

As an alternative to the Three-Group method, we describe a relatively unused method, termed the *factorial method*, for analyzing gender and sexual orientation effects in dyadic data. Imagine a study that measures both members of a couple and uses all three types of couples. There are four types of individuals: gay men, lesbians, heterosexual men, and heterosexual women. For the factorial method, we view the variation in the four cells as due to three main effects: Respondent Gender, Partner Gender, and Dyad Gender (i.e., the difference between same-gendered and different-gendered respondents). Whereas the Three-Group method emphasizes a test of sexual orientation effects, the factorial method emphasizes a test of three gender effects and examines how each effect is moderated by the other two. If we treat any two of the three main effects as factors in a 2×2 design, the third main effect can be viewed as the interaction of the other two (Schaffer, 1977). For example, if we estimate the two main effects of Respondent Gender and Partner Gender, then the interaction of Respondent Gender by Partner Gender becomes Dyad Gender, or in this context the sexual orientation main effect (i.e., gays and lesbians versus heterosexuals; Kenny & Cook, 1999; Kraemer & Jacklin, 1979; Kurdek, 1997). Alternatively, we can consider the two main effects of Respondent Gender and Dyad Gender. With these two main effects, the interaction of Respondent Gender and Dyad Gender becomes the Partner Gender main effect. The key point is that there are three main effects in the 2×2 design and any one of the main effects can be viewed as the interaction of the other two.

We next illustrate a pattern of results that we interpret using both the Three-Group method and the factorial method. Table 1 presents five different hypothetical patterns of results. For Pattern A, using the Three-Group method, we see that the three groups differ such that gay men score the highest, lesbians the lowest, and heterosexuals in the middle. For the factorial method, there is only one effect: Male and female respondents, regardless of dyad gender, differ. Men score higher than women do. Thus, Pattern A is one of a universal Respondent Gender difference. This simple pattern is overlooked using the Three-Group method because it ignores the difference between heterosexuals.

For Pattern B, the Three-Group method reveals no gender effects. However, further examination of the means for heterosexual men and women reveals a gender difference but only for heterosexuals. The factorial method demonstrates that heterosexual men score higher than heterosexual women do and that there is no difference between gay men and lesbians. This result implies a main effect of respondent gender (i.e., on average

TABLE 1: Hypothetical Patterns of Results

Group	Pattern				
	A ^a	B ^b	C ^c	D ^d	E ^e
Gay men	6.0	5.5	6.0	6.0	6.0
Lesbians	5.0	5.5	6.0	5.0	6.0
Heterosexuals ^f	5.5	5.5	5.0	5.0	5.5
Men	6.0	6.0	5.0	5.0	6.0
Women	5.0	5.0	5.0	5.0	5.0

a. Universal gender difference.

b. No gender difference only in heterosexuals.

c. Sexual orientation difference.

d. Unusual group, gay men.

e. Unusual group, heterosexual women.

f. Average across heterosexual men and women.

men score higher than women do), which is moderated by dyad gender (i.e., the gender difference is found only among heterosexuals).

Pattern C shows a clear pattern of results regardless of analysis strategy. Gay and lesbian couples score higher than heterosexual couples do. Both the factorial and Three-Group methods reveal the same result but the factorial method tests it more powerfully than the Three-Group method does because the former method is test with one degree of freedom.

Finally, Patterns D and E show a difference between one group and the other three groups, termed the *unusual group* effect. That unusual group is gay men for Pattern D in Table 1: Gay men score the highest and lesbians, heterosexual men, and heterosexual women score the same. Note that for Pattern D the results using the Three-Group method and the factorial method both show a large difference between one group and the other three. However, if the unusual group is heterosexual men or women, an analysis using the Three-Group method results in a main effect of dyad gender. As seen in Pattern E, there appears to be a main effect of dyad gender such that gay men and lesbians do not differ from each other but they score higher than heterosexuals do. The factorial method shows that one group, heterosexual women, stands out from the other three. Thus, heterosexual women are the unusual group.

Example

We have discussed five hypothetical outcomes in the analysis of couple data. We demonstrate these effects using real rather than hypothetical data. The *American Couples* data set contains data from 6,045 couples: 969 gay couples, 4,292 heterosexual couples, and 784 lesbian couples. We removed all individuals who had missing data on any of the demographics or outcome variables, resulting in a data set with no missing data. A total of

TABLE 2: Means for Gender Groups

Group	Variable				
	Attractiveness ^a	Social Value ^{b,c}	Confide Feelings ^d	Sexual Fidelity ^e	Relationship Stability ^b
Gay men	5.07	4.67	8.02	4.76	7.11
Lesbians	4.40	4.72	8.16	7.08	7.00
Heterosexuals ^f	4.78	5.23	7.87	7.52	7.39
Men	5.16	4.76	7.80	7.29	7.22
Women	4.40	5.79	7.94	7.60	7.56

a. Universal gender difference.

b. Gender difference only in heterosexuals.

c. Unusual group, heterosexual women.

d. Dyad gender difference.

e. Unusual group, gay men.

f. Average across heterosexual men and women.

7.8% of cases were excluded. The remaining sample included 11,148 individuals: 5,514 couples and 120 solos (complete data from just one of two people). We have 1,790 gay men (22 solos), 1,440 lesbians (12), 3,948 heterosexual men (33), and 3,970 heterosexual women (53). The *American Couples* data set is used for all methodological demonstrations in this article.

We chose a subset of the ideal partner variables in the original Blumstein and Schwartz (1983) data set. For all items, the respondent indicated how important each of the following variables is in an ideal relationship partner. For illustrative purposes, four composite variables were created: Relationship Stability, Social Value, Attractiveness, and Sexual Fidelity. The Relationship Stability composite contained two items: "Our relationship is permanent" and "I have someone to grow old with." Social Value contained the following four items: "My partner is well liked by my friends," "I am well liked by my partner's friends," "My partner provides me with financial security," and "We both have the same social class background." The Attractive composite contained three items: "My partner is sexy looking," "My partner is 'movie star' good looking," and "My partner is athletic." Sexual Fidelity contained two items: "I am sexually faithful to my partner" and "My partner is sexually faithful to me." In addition, we examine one single-item variable, Confide Feelings: "We can confide all of our personal feelings to each other." All items were measured on a 1 (*not at all*) to 9 (*very much*) scale.

Table 2 presents the means for the four groups for each of the five variables from the *American Couples* study. We consider in the next section statistically meaningful differences between these means. The focus here is on the patterns of means. We discuss these patterns using the Three-Group and the factorial methods.

Pattern A. The first variable presented in Table 2 is Attractiveness, which measures how important it is to

the respondent that her or his partner is physically attractive. When data are analyzed using the Three-Group method, there is a difference between the three types of dyads. Gay men score the highest, followed by the heterosexuals, followed by the lesbians. However, when the data are analyzed using the factorial method, a pattern of universal Respondent Gender difference emerges (Pattern A). As seen in Table 2, men value attractiveness more than women do. This effect does not appear to interact with Dyad Gender.

Pattern B. Next we examine Social Value. This variable measures how important it is to an individual that his or her partner is valuable both financially and has a good social network. Using the Three-Group method, we see that there is a negligible difference between gay men and lesbians but a large difference between sexual orientation groups such that heterosexuals score higher on Social Value than do gays and lesbians.

Using the factorial method, the results are more complex. As seen in Table 2, a universal Respondent Gender difference between men and women emerges. Gay men and heterosexual men score lower than do heterosexual women and lesbians. Second, there is a gender difference between heterosexuals such that heterosexual women score higher than do heterosexual men, and this effect is not replicated for gays and lesbians. Gay men score slightly lower than lesbians do but the effect is much smaller than the gender difference between heterosexuals. Results from this analysis indicate a main effect of Respondent Gender that is moderated by Dyad Gender. This result is closest to Pattern B, although it can be conceptualized as a combination of Patterns A and B.

Results for Relationship Stability show a similar pattern of results. For the Three-Group method, there is marginal difference between gay men and lesbians such that lesbians score lower than gay men do, and a more substantial difference between homosexuals and heterosexuals indicates

that heterosexuals score higher than do gays and lesbians. However, using the factorial method, there is a universal Respondent Gender difference (i.e., women score higher than men do) that is moderated by Dyad Gender. Among heterosexuals, women score higher than men do; among gays and lesbians, men score higher than women do.

Pattern C. To illustrate Pattern C, we examine the variable Confide Feelings, or how important it is to respondents that they confide feelings in each other. As seen in Table 2, results for the Three-Group method indicate that gay men and lesbians value confiding feelings more than heterosexual men and women do, with lesbians' valuing it slightly more than gay men do. Results from the factorial analysis indicate the same sexual orientation difference between heterosexuals and the other two groups. Note that in using the factorial method, we can see that the difference between gay men and lesbians is the same magnitude and is in the same direction as the difference between heterosexual women and men, indicating a main effect of Respondent Gender such that women, regardless of sexual orientation, value confiding feelings more than men do. Thus, the Respondent Gender effect found for heterosexuals is replicated for gays and lesbians. This result indicates a main effect of Dyad Gender that is not moderated by Respondent Gender, which is consistent across both the factorial and Three-Group methods.

Pattern D. We next examine the variable Sexual Fidelity to illustrate Pattern D, the unusual group effect in which the unusual group is either gay men or lesbians. Results for both the Three-Group and factorial methods indicate that gay men score much lower than heterosexuals and lesbians do on how important it is for partners to be sexually faithful in a relationship (see Table 2).

Pattern E. Next, we re-examine the variable Social Value to illustrate the unusual group effect in Pattern E. In this pattern, the unusual group is either heterosexual men or women. Using the Three-Group method to analyze Social Value, it appears that heterosexuals score higher on Social Value than do gays and lesbians (see Table 2). However, the factorial method elaborates the result. Heterosexual women are the unusual group, scoring higher than both gay men and heterosexual men, and lesbian women who score only slightly higher than men, both gay and heterosexual.

In sum, an unusual group effect may or may not appear using the Three-Group method, depending on which group is unusual. No matter who the unusual group is, the factorial method would reveal it.

Thus far, we have provided a theoretical rationale for the inclusion of both mixed-gendered and same-gendered dyads in relationship research and argued their inclusion as necessary for a complete test of gender effects regardless of research question. Furthermore, we have illustrated how results can vary using two methods of analysis: the Three-Group method and the factorial method. In doing so, we have presented five possible patterns of results and demonstrated with data how they differ depending on analysis strategy when all three sexual orientation groups are analyzed. These illustrations reveal how theoretical conclusions about gender differences can be influenced by the analysis strategy. In the remainder of the article, we focus on a detailed examination of how to analyze dyadic data using the factorial method via multilevel modeling.

THE STATISTICAL ANALYSIS OF GENDER DIFFERENCES: APIM

For studies that include all three gender combinations, gay men, lesbians, and heterosexual couples, gender varies both between and within dyads. That is, some dyads contain a male and a female partner, some contain two male partners, and some contain two female partners. Gender is called a mixed variable (Kenny, Kashy, & Cook, 2006). When examining the effects of mixed variables, the APIM (Campbell & Kashy, 2002; Griffin & Gonzalez, 1995; Kashy & Kenny, 2000; Kenny & Cook, 1999; Kenny et al., 2006) is a data-analytic approach that allows the simultaneous estimation of the effect that a respondent's predictor has on his or her own outcome score (actor effect) and the effect of the respondent's partner's predictor on the respondent's outcome score (partner effect). The path from respondent gender to the outcome is the actor path, and the path from partner gender to the respondent's outcome is the partner path. Additionally, we test the path from the interaction between the actor and partner gender variables (i.e., sexual orientation) to the outcome.

Historically, several different methods of analysis have been proposed for the APIM (e.g., Kraemer & Jacklin, 1979). Recently, Kenny et al. (2006) have detailed a series of analysis alternatives for the APIM. When members are distinguishable, as is the case for heterosexual couples, the APIM model can be most easily estimated and tested via structural equation modeling (e.g., Kenny & Acitelli, 2001). However, when members are indistinguishable, multilevel modeling (Campbell & Kashy, 2002) is the most direct method to estimate the APIM. Although it is possible to apply a structural equation modeling method when dyad members are

TABLE 3: Example Pairwise Data Set With Four Persons and Two Dyads

PID	DyadID	Partnum	GenderR	XR	YR	GenderP	XP	YP
10	1	1	1	44	12	-1	56	15
11	1	2	-1	56	15	1	44	12
20	2	1	-1	33	16	-1	22	24
21	2	2	-1	22	24	-1	33	16

NOTE: PID = separate identification number given to each participant; DyadID = dyad number for each dyad; Partnum = arbitrary distinction for person 1 and person 2; GenderR = gender of the respondent; XR = respondent's predictor; YR = respondent's outcome; GenderP = gender of the partner; XP = partner's predictor; YP = partner's outcome.

indistinguishable (Olsen & Kenny, 2006; Woody & Sadler, 2005), these methods are relatively complex.

Data Preparation

The first step in undertaking a multilevel modeling analysis of the APIM is to create a pairwise data set. In this data set, there is one record or line for each individual in the sample (i.e., two lines per dyad). However, a pairwise data set is not an individual data set. As shown in the example data set in Table 3, the record includes not only the respondent's data but also the respondent's partner's data. For instance, we see that there is a gender variable for both the respondent (GenderR) and the partner (GenderP). Note that a person's data appears twice in the file, once for respondent and once for partner. Each record also contains a dyad identification variable (DyadID) and as well as a partner number (Partnum). Note that the first two lines of data are from a mixed-gendered dyad and the third and fourth lines of data are from a same-gendered dyad. It is generally advisable, although not always necessary, to sort the data by the dyad identification variable and to include dummy records if only one member of the dyad is measured.

ASSESSING NONINDEPENDENCE

The first step in conducting an analysis of dyadic data is to examine the degree of nonindependence. Analyses using the individual as the unit of analysis, ignoring the couple, still occur in couples' research (e.g., Howard, Blumstein, & Schwartz, 1987; Metz, Rosser, & Strapko, 1994; Sternberg & Barnes, 1985). However, failing to account for nonindependence of couple data can lead to inaccurate estimates of standard errors, which can lead to both Type I and II errors (Griffin & Gonzalez, 1995; Kenny & Judd, 1986; Kenny, Kashy, & Bolger, 1998), improper effect sizes, and incorrect degrees of freedom. It is important to realize that considering the couple in the analysis can sometimes increase the power of statistical tests.

Because our dyads are indistinguishable, nonindependence is assessed by computing the intraclass correlation

(Kenny et al., 2006). We can use the following SPSS syntax to estimate the degree of nonindependence:

MIXED

```
YR
/PRINT = SOLUTION TESTCOV
/REPEATED = Partnum | SUBJECT(DyadID)
COVTYPE(CS).
```

Note that YR refers to the respondent's outcome variable. From the output, the intraclass correlation equals $CS_{cov} / (CS_{cov} + CS_{diag})$. The intraclass correlations for each of the variables in the *American Couples* data set are all positive and small to moderate in size, ranging from .17 to .45 with the average being .22. Given these nonzero correlations, the data are nonindependent, and dyad must be included in the analysis.

Building the APIM Model

In building an APIM model, we allow for both respondent and partner characteristics to predict a respondent's response. To model nonindependence, we allow for a correlation between the two errors of the respondent and partner's responses. For all of our sample analyses, data were analyzed using the MIXED procedure in SPSS. Recall that in the factorial approach we analyze three gender variables: Respondent Gender, Partner Gender, and the interaction between Respondent Gender and Partner Gender (Dyad Gender). The SPSS syntax¹ is as follows:

MIXED

```
YR WITH GenderR GenderP
/FIXED = GenderR GenderP GenderR × GenderP
/PRINT = SOLUTION TESTCOV
/REPEATED = Partnum | SUBJECT(DyadID)
COVTYPE(CS).
```

For the APIM analysis, YR refers to the respondent outcome variable. GenderR and GenderP are the predictor variables Respondent Gender and Partner Gender, respectively. We prefer to effect code the gender variables and not to treat them as factors within SPSS. Men are coded as 1, and women are coded as -1. The “Fixed” statement in the model contains the main effects of GenderR and GenderP and the Dyad Gender effect, which is captured by the GenderR \times GenderP interaction. The “Repeated” statement specifies that each individual within the dyad can be distinguished by Partnum, which arbitrarily distinguishes members of the dyad as person 1 and the other as person 2. The “Subject” for SPSS is DyadID. The CS option forces the two error variances to be equal and allows the two errors to be correlated to model the non-independence in the dyad. We note that results would be essentially the same with any (e.g., HLM or MLwiN) multilevel modeling software (Kenney et al., 2006).

American Couples Example

For Attractiveness, we see that the factorial method gives a straightforward account of the results. Table 4 provides SPSS output for the outcome variable Attractiveness. Recalling that men are coded +1 and women -1, we see that men value attractiveness regardless of sexual orientation, as indicated by the positive and statistically significant effect estimate for GenderR under Fixed Effects. There is a negative effect of GenderP, indicating that respondents with female partners value attractiveness more than those with male partners. There is also a negative effect of GenderR \times GenderP, indicating that heterosexuals value attractiveness more than do gays and lesbians. However, note that the GenderP and GenderR \times GenderP effects are not statistically significant.

The actor, partner, and interactions effect estimates for the remaining variables are presented in Table 5. We see that, in addition to Respondent Gender and Dyad Gender effects, there are effects of Partner Gender. Results for four of the five variables demonstrate interactions between the gender variables. So far we have presented a very simple APIM model, one with the three gender variables. In the next section, we examine the role of adding control variables to the model. In particular, we examine the inclusion of demographic variables in the study of gender effects.

DEMOGRAPHIC VARIABLES IN STUDIES OF GENDER

We have considered the conceptualization of gender and the statistical analysis of gender effects with dyadic data, and we have illustrated how these effects are interpreted using the factorial method. We now consider the

importance of demographic variables and how the factorial method enables the estimation of demographic effects at the respondent, partner, and relationship levels.

We begin with the pervasive finding that gender is very often correlated with demographic variables (Jacklin, 1981). For instance, if men are older than women are in heterosexual relationships, then the demographic variable age is correlated with gender. In relationship research, controls for demographic variables are infrequent, with some important exceptions (e.g., Gangestad, 1993; Kurdek, 1997). Even when demographic variables are controlled, it is rare that researchers also control for the demographics of the relationship partner. As we have advocated throughout this article, it is critically important to also consider the effect of the respondent's predictors and partner's predictors on respondent's outcomes. For example, if we were to ask respondents and their partners to rate their life satisfaction, it may be the case that people are more satisfied the fewer health problems their partners have. Thus, partner health would predict respondent life satisfaction.

There is not a universal set of variables that should be included in analyses. Specific demographic variables, like other predictor variables, are determined by the research question. For instance, income would be an important demographic to include in the study of job satisfaction among couples because there would likely be pre-existing differences between men and women on income (Deckard, 1983; Hyde, 1996), but in studies of transactive memory (Wegner, Erber, & Raymond, 1991) age would likely be a more relevant demographic variable than income. We use the term *demographic variable* very broadly to include any important variable that is likely related to gender and the outcome variable and, thus, needs to be included in the analysis.

For the *American Couples* data set, we examine two demographics variables for illustrative purposes: Income and Age of both the respondent and the partner. Couple demographics, such as relationship length, can be examined using the same analytic steps that we present for testing respondent and partner level demographics. Age and Income are continuous variables whose units are years and dollars, respectively. For each variable we subtracted the overall sample mean (i.e., grand mean centering).

The different ways in which a demographic variable may alter the effect of gender on an outcome variable are illustrated in Figure 1. As seen in Figure 1A, the demographic variable is a confounding variable, in 1B the demographic variable is a mediator, and in 1C the demographic variable is a moderator. We consider each in turn.

TABLE 4: SPSS Output for the Factorial Model With Attractive as the Outcome (Dependent Variable: Attractive)

		Model Dimension				
		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects.
<i>Mixed Model Analysis</i>						
Fixed effects	Intercept	1	1			
	GenderR	1		1		
	GenderP	1		1		
	GenderR × GenderP	1		1		
Repeated effects	Partnum	2	Compound symmetry	2	DyadID	6048
Total		6		6		
<i>Information Criteria^a</i>						
–2 restricted log likelihood	45495.975					
Akaike's Information Criterion	45499.975					
Hurvich and Tsai's Criterion	45499.976					
Bozdogan's Criterion	45516.770					
Schwarz's Bayesian Criterion	45514.770					
<i>Fixed Effects</i>						
<i>Type III Tests of Fixed Effects</i>						
<i>Source</i>		<i>Numerator df</i>	<i>Demonimator df</i>	<i>F</i>	<i>Sig.</i>	
Intercept		1	6032.574	65683.853	.000	
GenderR		1	8630.500	425.427	.000	
GenderP		1	8630.500	1.975	.160	
GenderR × GenderP		1	6032.574	1.370	.242	
<i>Estimates of Fixed Effects</i>						
						<i>95% Confidence Interval</i>
<i>Parameter</i>	<i>Estimate</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>Sig.</i>	<i>Lower Bound Upper Bound</i>
Intercept	4.7551336	0.0185538	6032.574	256.289	.000	4.7187615 4.7915057
GenderR	0.3574518	0.0173303	8630.500	20.626	.000	0.3234804 0.3914233
GenderP	–0.0243556	0.0173303	8630.500	–1.405	.160	–0.0583270 0.0096159
GenderR × GenderP	–0.0217174	0.0185538	6032.574	–1.171	–0.0580895	0.0146547
<i>Covariance Parameters</i>						
<i>95% Confidence Interval</i>						
<i>Parameter</i>	<i>Estimate</i>	<i>SE</i>	<i>Wald Z</i>	<i>Sig.</i>	<i>Lower Bound</i>	<i>Upper Bound</i>
Repeated measures	CS diagonal offset	1.8958271	0.0345839	54.818	.000	1.8292412
1.9648367	CS covariance	0.7532666	0.0355462	21.191	.000	0.6835974
0.8229358						

a. Displayed in smaller-is-better forms.

Demographic Variables as Confounding Variables

We first consider how gender effects found for relationship data may not be due to gender per se but rather due to demographic differences between men and women. For a demographic variable to be a confounding variable, there are three defining conditions. First, the confounding variable must cause but not be caused

by the outcome variable. Second, the confounding variable must be correlated with the gender variable.

The third and most complicated point concerns the source of the correlation between the confounding variable and gender. There are two possible explanations of why a variable is correlated with gender: The first is non-random sampling, and the second is a causal relationship between gender and the confounding variable. If the

TABLE 5: *Effect Estimates for the Gender Effects for the Factorial Method*

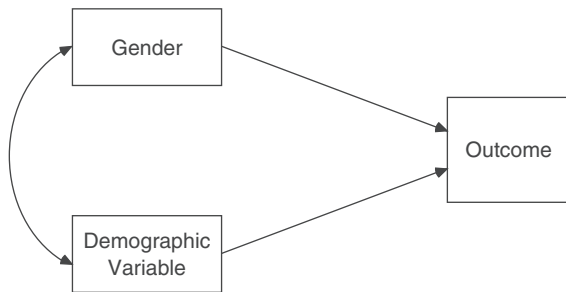
	GenderR ^a	GenderP ^b	GenderR × GenderP ^c
Attractiveness	.357*	-.024	-.022
Social value	-.293**	.267**	-.267**
Confide feelings	-.071**	.001	.107**
Sexual fidelity	-.697**	-.460**	-.800**
Relationship stability	-.053*	.112*	-.167**

a. Male respondents coded +1, females -1.

b. Male partners coded +1, females -1.

c. Gay men and lesbians coded +1, heterosexuals -1.

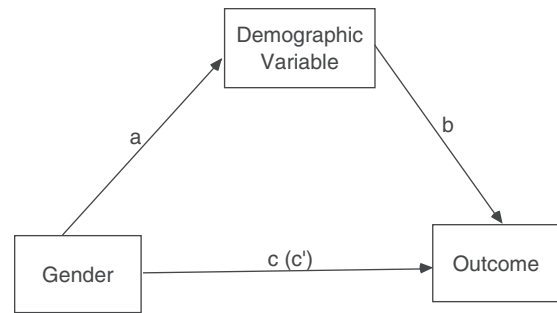
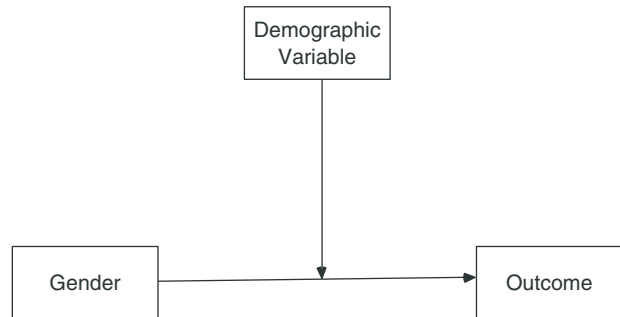
* $p < .05$. ** $p < .001$.

A**Figure 1A** Model in which demographic variable Z confounds the relationship between gender on outcome Y.

sampling procedure creates an artificial difference between men and women on a variable that in turn causes the outcome, there is a clear case of confounding. Consider the finding among elderly couples that men have more health problems than women do. If men on average are older than women are in elderly couples, then age explains some of the gender difference in health problems. Age confounds the effect of gender on health status.

In addition to nonrandom sampling, gender variables correlate with confounding variables when gender causes the confounder. Technically, in this case, the variable is not a confounding variable per se but a mediator (see next section). However, a mediator is sometimes treated as a confounder (i.e., when a researcher wants to know the effect of gender on the outcome controlling for a variable, even if that variable is caused by the gender variable). We note that although including confounding variables in an analysis of gender effects on an outcome typically weakens gender effects it sometimes strengthens and even reverses the signs of effects.

To control for the effect of a confounding variable, the researcher includes that variable in the analysis. For successful controlling for the confounding variable, it needs

B**Figure 1B** Model in which demographic variable Z mediates the relationship between gender on outcome Y.**C****Figure 1C** Model in which demographic variable Z moderates the relationship between gender on outcome Y.

to be measured reliably (i.e., have high reliability) and its functional form (e.g., linearity) must be properly specified.

Example: APIM and Age

We use the demographic variables Respondent Age and Partner Age to illustrate how gender effects change once confounds are controlled. Recall that for a variable to be a confound it must correlate with gender and cause the outcome. Gender is correlated with Respondent Age (and Partner Age) because men in the *American Couples* sample are older than women are by 2.78 years. In addition, sexual orientation is related to age: Heterosexuals are 3.76 years older than are gays and lesbians. Respondent Age and Partner Age also cause the outcome variables. Respondent Age significantly predicted all of the five ideal relationship variables, and Partner Age significantly predicted all of the ideal relationship variables with the exception of Sexual Fidelity.

To examine how controlling for the confounds of Respondent Age and Partner Age affect gender effects, we expanded the factorial model by including the main effects of Respondent Age and Partner Age in each model. The SPSS syntax for the example outcome variable Attractiveness is as follows:

MIXED

Attractive WITH GenderR GenderP RAge PAge
 /FIXED = GenderR GenderP GenderR × GenderP
 RAge PAge
 /PRINT = SOLUTION TESTCOV
 /REPEATED = Partnum | SUBJECT(DyadID)
 COVTYPE(CS).

The syntax expands on that presented for the factorial model with the addition of two fixed effects, RAge (Respondent Age) and PAge (Partner Age). We next examine how the gender effects change once RAge and PAge are included in the model. The effect estimates for Respondent Gender, Partner Gender, and Dyad Gender when the age variables are controlled for are presented in Table 6. Earlier, in Table 5, we presented the effects of the gender variables, ignoring age. When we compare the effects after controlling for age, we see that there are both increases and decreases in the gender effects for four of the five variables, the one exception being Sexual Fidelity. For example, for Attractiveness, the Dyad Gender effect, which was not statistically significant in the original APIM, becomes statistically significant when Respondent Age and Partner Age are controlled. When we control for the age variables, we find that heterosexuals place more value on Attractiveness than do gays and lesbians. This change occurs because in the sample gays and lesbians are younger than heterosexuals are and because younger people value attractiveness more than older people do. Thus, controlling for a confound strengthens, not weakens, the Dyad Gender effect.

Demographic Variables as Mediators

As previously discussed, the distinction between a confounding variable and a mediator is that a confounding variable only correlates with gender and causes the outcome variable, whereas a mediating variable is caused by gender and causes the outcome variable (Baron & Kenny, 1986). Note that it is assumed that the outcome variable does not cause the mediator. For example, an individual's gender created a difference on a respondent-level demographic variable (e.g., being a man leads to more health problems), and the demographic variable in turn causes the outcome (e.g., having more health problems leads to less relationship satisfaction).

When the demographic variable is not included in the analysis, the path from the gender effect (i.e., Respondent Gender, Partner Gender, Dyad Gender) to the outcome is called the *total effect* (Baron & Kenny, 1986; Path c in Figure 1B). When we add the main effect of the demographic variable to the model, the effect of

TABLE 6: Effect Estimates for the Gender Effects Controlling for the Demographic Variables Respondent Age and Partner Age

	GenderR ^a	GenderP ^b	GenderR × GenderP ^c
Attractiveness	.391**	-.003	-.092**
Social value	-.311**	.233**	-.210**
Confide feelings	-.060**	.010	.080**
Sexual fidelity	-.721**	-.465**	-.764**
Relationship stability	-.094**	.090**	-.095**

a. Male respondents coded +1, females -1.

b. Male partners coded +1, females -1.

c. Gay men and lesbians coded +1, heterosexuals -1.

***p* < .001.

gender on the outcome variable is called the *direct effect* (Path c' in Figure 1B). The difference between the total effect and the direct effect measures what is called the *indirect effect*, or the effect of the demographic variable on the outcome. The total effect or c is the sum of the direct effect (c' in Figure 1B) and the indirect effect (ab in Figure 1B). To demonstrate that a variable is a mediating variable, we need to show that gender affects the mediator (Step 2 in Baron & Kenny, 1986) and that the mediator affects the outcome controlling for gender (Step 3). Alternatively, we can test the indirect effect or ab in Figure 1B by using the Sobel (1982) test.

Mediators are tested within the APIM by including them in the model. Note that if the mediator is measured for each member of the dyad, there would be two mediators: the mediator for the respondent and the mediator for the partner.

Example: Income Mediating the Gender Effects on Social Value

To illustrate the necessary steps of mediation, we test whether Respondent and Partner Income mediate the effects of Respondent Gender, Partner Gender, and Dyad Gender on Social Value.

Mediation in the APIM is more complex than is shown in Figure 1B because there are three gender variables (Respondent Gender, Partner Gender, and Dyad Gender) and two potential mediators (Respondent and Partner Income). There are, then, three effects that could be mediated and two different variables that can serve as mediators, resulting in six possible mediating or indirect effects. There are several steps (Baron & Kenny, 1986) that a researcher must conduct to test for mediation of respondent and partner level mediators using multilevel modeling. The results for each step are presented in Table 7.

In Step 1, we test whether Respondent Gender, Partner Gender, and Dyad Gender predict Social Value, or the total effect (Path c in Figure 1B). The Step 1 model

TABLE 7: Baron and Kenny (1986) Steps in Testing the Mediation of Gender Effects on Social Value by Income

Predictor	Social Value	R Income	P Income
Step 1			
R Gender	-.293 (.0167)		
P Gender	.267 (.0167)		
R Gender × P Gender	-.267 (.0177)		
Step 2			
R Gender		5.770 (0.149)	-3.388 (0.149)
P Gender		-3.388 (0.149)	5.770 (0.149)
R Gender × P Gender		-1.278 (0.153)	-1.278 (0.153)
Step 3			
R Income	.00326 (.000975)		
P Income	.01503 (.000975)		
Step 4			
R Gender	-.243 (.0177)		
P Gender	.182 (.0177)		
R Gender × P Gender	-.248 (.0177)		

NOTE: Standard errors are in parentheses. R = respondent; P = partner.

is the same as the factorial model, with the three gender variables simultaneously predicting the outcome, Social Value. As seen in Table 7 (and previously in Table 5), all three effects are present. There is an effect of Respondent Gender (women place more emphasis on Social Value than do men), an effect due to Partner Gender (people with male partners value Social Value), and an effect due to Dyad Gender (heterosexuals see Social Value as more important than do gays and lesbians).

In Step 2, we test the paths from Respondent Gender, Partner Gender, and Dyad Gender to the mediators, Respondent Income (RIncome) and Partner Income (PIncome). These paths correspond to Path a in Figure 1B. When RIncome is treated as the outcome, the path from GenderR to RIncome is the same as the path from GenderP to PIncome (if PIncome is treated as the outcome). In addition, the path from GenderP to RIncome is the same as the path from GenderR to PIncome (see Table 7). The path from GenderR × GenderP to RIncome is the same as the path from GenderR × GenderP to PIncome. Thus, we need use only RIncome as the outcome, as an analysis of PIncome would be redundant. The SPSS syntax for Step 2 using RIncome as the outcome is as follows:

MIXED

```
RIncome WITH GenderR GenderP
/FIXED = GenderR GenderP GenderR × GenderP
/PRINT = SOLUTION TESTCOV
/REPEATED = Partnum | SUBJECT(DyadID)
COVTYPE(CS).
```

As can be seen in Table 7, men earn significantly more money than do women, individuals with female partners earn more money than do those with male partners, and heterosexuals earn more money than do gays and lesbians.

In Step 3, we test the paths from Respondent Income and Partner Income to the outcome, Social Value (Path b in Figure 1B), controlling for the gender variables and their effects. The syntax is the same as that used in Step 4, where we examine the effects of the gender variables controlling for the income variables. The syntax for Steps 3 and 4 is as follows:

MIXED

```
SocialValue WITH RIncome PIncome GenderR
GenderP
/FIXED = RIncome PIncome GenderR GenderP
GenderR × GenderP
/PRINT = SOLUTION TESTCOV
/REPEATED = Partnum | SUBJECT(DyadID)
COVTYPE(CS).
```

The effects of both Respondent and Partner Income on Social Value are both positive: The more money either partner earns, the more the respondent desires a socially valuable partner. Note that the effect for Partner Income is somewhat stronger than that of Respondent Income.

In Step 4, we examine the effects of the gender variables controlling for the mediators using the same syntax as Step 3. Step 4 estimates and tests the direct effect of the gender variables on Social Value. To establish that Respondent and Partner Income completely mediate the relationship between the gender variables and Social Value, the effects of the gender variables on Social Value should be small and not significantly different from zero when Respondent and Partner Income are controlled.

As can be seen in Table 7, the gender effects decrease in magnitude, but remain statistically significant once RIncome and PIncome are added to the model, a result consistent with partial mediation.

Table 7 presents the six possible ways in which income mediates the effect of gender on Social Value. Recall that mediation implies the combination of two paths: a path from gender to the mediator (Path a in Figure 1B) and a path from the mediator to the outcome (Path b). Because there are two mediators, Respondent Income and Partner Income, each gender effect has two indirect effects.

Consider first Respondent Gender. In one set of paths, Respondent Gender is mediated by Respondent

TABLE 8: Tests of the Six Mediated Effects

<i>Effect</i>	<i>Indirect Effect</i>	<i>Sobel Z (p)</i>
Respondent gender		
Actor-Actor	(5.770)(.00326) = .0188	3.33 (.001)
Partner-Partner	(-3.388)(.01503) = -.0509	3.31 (.001)
Total	-.0321	
Partner gender		
Actor-Partner	(5.770)(.01503) = .0867	14.32 (.001)
Partner-Actor	(-3.388)(.00326) = -.0110	12.76 (.001)
Total	.0757	
R Gender × P Gender		
Actor	(-1.278)(.01503) = -.0042	3.10 (.002)
Partner	(-1.278)(.00326) = -.0192	7.34 (.001)
Total	-.0234	

Income. We call this indirect effect *Actor-Actor* (see Table 8) because the effect of Respondent Gender on Respondent Income is an actor effect and the effect of Respondent Income on Social Value is also an actor effect. Respondent Gender is mediated by Partner Income, which is referred to as *Partner-Partner* because the effect of Respondent Gender on Partner Income is a partner effect, and the effect of Partner Income on Social Value is also a partner effect. As seen in Table 7, these two effects are of opposite sign.

There are also two indirect effects of the Partner Gender effect, an Actor-Partner and a Partner-Actor effect. The Actor-Partner indirect effect is the effect of Partner Gender on Partner Income and the effect of Partner Income on Social Value. The Partner-Actor indirect effect is the effect of Partner Gender on Respondent Income and the effect of Respondent Income on Social Value. As seen in Table 7, these two effects are in the opposite direction but the Actor-Partner effect is much larger than the Partner-Actor effect.

There are two indirect effects of the Dyad Gender effect. Note there is only one effect of Dyad Gender on the mediators, Respondent and Partner Income. However, there are two effects of income on Social Value, Respondent Income to Social Value (i.e., actor effect) and Partner Income to Social Value (i.e., partner effect). Both of these indirect effects are negative and so both explain the overall negative effect of this variable on Social Value. Table 8 also presents the results for the Sobel test of each of the six indirect effects. All six of the indirect effects are statistically significant.

In the results that we present, all of the paths from the predictors to the mediators and the mediators to the outcomes were statistically significant. Very often, this may not be the case. For example, one of the gender effects may not significantly predict one of the mediators, or one of the mediators may not significantly predict the outcome. Nonetheless, we still recommend that,

when this is the case, researchers keep all variables in the models (i.e., do not trim out nonsignificant effects) and report the effects that were mediated and those that were not. We make this suggestion because if the researcher were to selectively trim from the model the nonsignificant effects, sampling errors would likely obscure the basic pattern of the results.

Demographic Variables as Moderators

Thus far we have discussed how demographics may confound or mediate gender effects. There is a third possibility: Demographic variables may also moderate effects of gender. In this case, the effect of gender on the outcome differs as a function of the demographic variable (Baron & Kenny, 1986).

When researchers conduct moderator analyses, they assign roles to the variables: predictor variable, outcome variable, and moderator. However, the roles of predictor and moderator can be reversed. With gender and demographic variables, moderation can be conceptualized in one of two ways: A demographic variable can moderate the relationship between gender and an outcome or a gender variable can moderate the relationship between a demographic variable and an outcome. Typically, when relationship researchers examine moderation, they treat gender (or sexual orientation) as the moderator and the demographic variable as the predictor. For example, a researcher is interested in whether the effect of relationship length on relationship satisfaction differs as a function of gender; that is, gender moderates the effect of relationship length on satisfaction. In our illustration, we treat demographic variables as moderators and gender variables as predictors.

Within the APIM, we can test moderator effects that refer to the respondent, the partner, and relationship by including interaction terms between the gender variables and these moderator variables. For example, we can test if respondent ethnicity and partner ethnicity moderate the effect of Respondent Gender on an outcome. Both of these possibilities are tested in one analysis.

Example: Age Moderating the Effect of Gender on Relationship Stability

We test whether Respondent Age and Partner Age moderate the effect of Respondent Gender, Partner Gender, and Dyad Gender on Relationship Stability. Respondent Age and Partner Age were previously tested as confounds; we emphasize that whether a variable is treated as a confounding variable or a moderator depends on the researcher's interest.

Recall that in tests of moderation we include interactions between the gender variables and the moderators. Unlike mediation, we test moderation in a single step. To

test Respondent and Partner Age as moderators of the effects of Respondent Gender, Partner Gender, and Dyad Gender on Relationship Stability, we create a model with six possible moderator effects. First, we allow the three gender variables to interact with Respondent Age. In addition, the three gender variables interact with Partner Age. We also include the main effects of the three gender variables, Respondent Age, and Partner Age. The syntax for the tests of moderation is as follows:

MIXED

```
Relationship_Stability WITH GenderR GenderP
RAge PAge
/FIXED = GenderR GenderP RAge PAge GenderR ×
GenderP GenderR × RAge GenderP × RAge
GenderP × GenderR × RAge GenderR × PAge
GenderP × PAge GenderR × GenderP × PAge
/PRINT = SOLUTION TESTCOV
/REPEATED = Partnum | SUBJECT(DyadID)
COVTYPE(CS).
```

Effect estimates and their *p* values for all parameters in the moderation example are presented in Table 9. Results for Relationship Stability indicate that only one of the six interactions is statistically reliable: The interaction between Respondent Gender and Partner Age. Recall that women value Relationship Stability more than men do (as indicated by the negative effect estimate for GenderR). This effect is moderated by Partner Age such that the effect is weaker as respondents' partners get older. This example demonstrates how a partner-level demographic can moderate the effect of a respondent-level predictor on a respondent's outcome.

FINAL COMMENTS

We have discussed three key considerations in the study of gender in relationships. First, we argued that gender should be treated not as one variable but as three variables: gender of respondent, gender of partner, and dyad gender. Second, we described the estimation of the APIM using multilevel modeling. Third, we illustrated three ways in which demographic variables can be tested in the analysis of dyadic data: confounders, mediators, and moderators. In this final section, we consider some additional methodological and theoretical issues.

Expansions and Complications

There are numerous ways in which the models that we illustrated can be elaborated. We discuss three types

TABLE 9: Effect Estimates for Age Moderating the Effect of Gender on Relationship Stability

<i>Parameter</i>	<i>Effect (p)</i>
GenderR	-.106 (.001)
GenderP	.082 (.001)
GenderR × GenderP	-.089 (.001)
RAge	.031 (.001)
PAge	.024 (.001)
GenderR × RAge	-.005 (.08)
GenderP × RAge	.004 (.16)
GenderR × GenderP × RAge	.004 (.14)
GenderR × PAge	.005 (.05)
GenderP × PAge	-.003 (.18)
GenderR × GenderP × PAge	.005 (.06)

of complications: additional variables, over-time analyses, and nominal and ordinal outcomes.

For confounding, mediation, and moderation, we have illustrated the most elementary case. In practice, there may be multiple confounding variables, mediators, and moderators. For example, the moderation model can be expanded by estimating the effects of multiple moderators in the same model. For instance, we can test how the effects of the gender variables on an outcome are moderated by respondent age, partner age, relationship length, and respondent and partner commitment. When tests of moderation are conducted simultaneously, researchers can examine the effect of one moderating effect while controlling for the effects of the others. This same approach can be applied to tests of confounding variables and mediators. We recommend that when researchers estimate several parameters in one model, family-wise error is taken into account, perhaps by applying a Bonferroni correction.

In addition to adding more variables to the models, the APIM model can be expanded to over-time analyses. With this expansion, however, there are additional complications. Kenny et al. (2006) detail a series of dyadic over-time analyses that can be integrated with the factorial approach. For instance, it is possible to measure over-time partner effects: How one person was in the past influences his or her partner in the future. This effect might be moderated by the gender of each person or the gender of the dyad.

Finally, we have limited our consideration of the APIM to variables measured at the interval level measurement. Many important outcomes, especially behavioral ones, are measured at the nominal and ordinal levels of measurement. The APIM can be extended to estimate such models; however, currently SPSS does not allow for outcome variables of this type. Other multi-level computer programs (e.g., HLM) do allow for such variables.

How Can the Factorial Model Inform Relationships Theories?

Although our primary focus has been on the illustration of a statistical approach, we wish to emphasize that the factorial approach to studying gender is a methodological tool that enables researchers to test and expand close relationship theories. Ironically, many relationship researchers who study gender look at gender much like a personality or biological variable and not as a potentially relational variable. Consider the study of gender differences in partner preferences, a topic that has sparked much debate between evolutionary and sociocultural theorists. Historically, the focus on gender differences in partner preferences (and mate selection in general) has been on gender of the respondent. For example, numerous empirical studies of mate preference regardless of theoretical orientation have found that men value physical attractiveness more than do women, whereas women value social status more than do men (e.g., Berscheid & Walster, 1974; Buss, 1989; Buss & Barnes, 1986). However, as we have illustrated along with others (e.g., Kenrick et al., 1995; Regan et al., 2001), mate preferences depend on more than respondent gender. Moreover, gender of the respondent examined without the inclusion of gender of the partner and sexual orientation provides a relatively limited picture of the role of gender in partner preferences. Although we need to be cautious in generalizing our particular findings given that our analyses were limited to illustration, we have demonstrated how our analysis strategy can be used to build upon the existing literature, with the important caveat that issues such as direction of causation are carefully considered.

Moving beyond partner preferences, the factorial approach can be used to examine a number of relationship topics, such as gender differences and similarities in sexual jealousy and infidelity (e.g., Harris, 2003), which focuses largely on heterosexual relationships, and studies of domestic violence, where much of the focus has been on heterosexual women as victims (e.g., Schechter, 1982), with an emphasis on the psychological and social processes related to respondent gender that contribute to partner violence (e.g., Cano & Vivian, 2001). The factorial model can allow researchers to examine gender of the perpetrator as well as gender of the victim in relationships where domestic violence takes place and to consider how interactions between gender variables influence partner violence.

More broadly, research that examines communication patterns in relationships (e.g., approach and avoidance) can benefit from the factorial approach. Recent work in the field has begun to study how communication processes differ by sexual orientation (Julien, Chartrand, Simard,

Bouthillier, & Bégin, 2003); the factorial approach can help tease apart effects due to gender and sexual orientation and take into account mediators and moderators at the actor, partner, and relationship levels.

We have addressed a subset of relationship theories that may benefit from the factorial approach; we acknowledge there are a plethora of relationship theories that address how men and women, gay men, lesbians, and heterosexuals are different and are similar. The analysis strategy we demonstrated can help build on relationship theories by taking into account variables at the actor, partner, and relationship levels, which enables researchers to more completely examine truly dyadic processes in relationships.

The approach that we have developed leads to a reconceptualization of use of gay men and lesbians in close relationship research. All too often, these groups are included in the research to determine if they are different (i.e., deviant) from heterosexuals. However, our view is that without including gay men and lesbians in research one can never understand how gender operates in relationships. The inclusion of gay men and lesbians is required not so much for reasons of external validity but rather for reasons of the construct validity of gender.

More Than Gender

Lastly, we have emphasized that our method can be applied to the study of gender for a number of dyad types including friendship, stranger, and family relationships. The factorial method can be applied to the study of dyads for any variable used to distinguish people from one another. For example, within the study of intergroup relations, minority and majority status can be used to compare intergroup (i.e., same status) to intragroup (i.e., different status) dyadic interactions. Additionally, within the area of HIV prevention, HIV status (positive or negative) of relationship partners can also be treated as we have treated gender in this article. Any time there is a factor that dyad members can be either the same or different on, the basic analysis approach that we have proposed can be employed.

Conclusion

The study of dyadic processes is becoming increasingly prevalent in the field of social psychology and, as such, new methodological tools are needed. The factorial approach is a user-friendly methodological strategy that will enable researchers to truly test dyadic processes as they are related to gender and to other distinguishing factors that vary between and within dyads.

NOTE

1. The SAS syntax is as follows:

PROC MIXED;

```
CLASS Dyad;
MODEL YR = GenderR GenderP GenderR ×
GenderP / SOLUTION DDFM = SATTERTH;
REPEATED = / SUBJECT(DyadID) COV-
TYPE(CS).
```

Note that in the output the error variance equals CS + RESIDUAL and the partial intraclass correlation equals C / (CS + RESIDUAL).

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