

## Alternatives to Difference Scores as Dependent Variables in the Study of Congruence in Organizational Research

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**In organizational research, difference scores and profile similarity indices are often used as dependent variables in studies predicting the congruence (i.e., fit, match, similarity, agreement) between two constructs. Unfortunately, this practice introduces serious conceptual and methodological problems that render results ambiguous and potentially misleading. This article proposes an alternative procedure that avoids these problems but fully captures the effects of one or more independent variables on the congruence between two dependent variables. This procedure is illustrated by reanalyzing data from a study of feedback seeking and rating accuracy (Ashford & Tsui, 1991), and the results of this study are reinterpreted in light of these analyses. Limitations and areas for further development of the procedure are discussed.** © 1995 Academic Press, Inc.

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The concept of congruence (i.e., fit, match, similarity, agreement) between two constructs is fundamental to organizational research. In some situations, congruence is considered an independent variable, as when person-job fit is used to predict job satisfaction (Assouline & Meir, 1987; Edwards, 1991) or the match between ideal and actual organizational structure is used to predict firm performance (Venkatraman, 1990; Venkatraman & Prescott, 1990). In other situations, congruence is viewed as a dependent variable, as when training is used to enhance performance rating accuracy (Hedge & Kavanagh, 1988; McIntyre, Smith, & Hassett, 1984; Pulakos, 1986; Smith, 1986) or demographic variables are used to predict supervisor-

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subordinate agreement (Evans, 1972; Ferris, Yates, Gilmore, & Rowland, 1985; London & Wohlers, 1991; Shore & Bleicken, 1991; Wohlers, Hall, & London, 1993). These situations are merged when congruence mediates the relationship between two constructs (Ashford & Tsui, 1991; Shanley & Correa, 1992) or the relationship between two forms of congruence is examined (Fox, Ben-Nahum, & Yinon, 1989; Mount & Thompson, 1987; Phillips & Bedeian, 1994; Sutcliffe, 1994; Wanous & Youtz, 1986; Zalesny & Kirsch, 1989).

In most studies, congruence has been operationalized as the algebraic, absolute, or squared difference between two component measures, or as an index representing the similarity between profiles of component measures (e.g.,  $D^2$ ,  $D$ ,  $|D|$ , or  $Q$ ; see Cronbach & Gleser, 1953; Edwards, 1993). As is widely known, difference scores suffer from numerous substantive and methodological problems (Cronbach, 1958, 1992; Cronbach & Furby, 1970; Edwards, 1994; Johns, 1981; Wall & Payne, 1973; Werts & Linn, 1970). Fortunately, procedures that overcome these problems have been recently developed (Edwards, 1993, 1994; Edwards & Parry, 1993), but these procedures are appropriate only when congruence is viewed as an independent variable. Procedures that apply when congruence is considered a dependent variable have yet to be fully developed.

This article presents a procedure for analyzing congruence as a dependent variable. As will be shown, this procedure avoids problems with the use of difference scores and profile similarity indices (PSIs) but nonetheless captures the relationships these measures are intended to represent. First, problems that arise when difference scores and PSIs are used as dependent variables are briefly reviewed. Next, an alternative procedure that avoids these problems is developed and illustrated, using data from a study of feedback seeking and rating accuracy conducted by Ashford and Tsui (1991). The article concludes by discussing the advantages and limitations of the proposed procedure, comparing it to other multivariate methods, and outlining areas for its further development.

The procedure developed here is intended for situations in which the two variables comprising the congruence measures are both endogenous, meaning that they are logically dependent on the predictors under examination. This may occur when, for example, subordinate demographics influence reports from both subordinates and supervisors, which are then combined into a measure of agreement (e.g., Evans, 1972; Ferris *et al.*, 1985; London & Wohlers, 1991; Shore & Bleicken, 1991). These situations may be distinguished from those in which one variable is exogenous or predetermined, as in studies of performance rating accuracy (Bretz, Milkovich, & Read, 1992; Ilgen, Barnes-Farrell, & McKellin, 1993; Murphy & Balzer, 1989). These studies typically focus on interventions such as training or rating context that influence the agreement between novice scores and "expert" ratings. Because expert ratings are not influenced by these interventions, they should be considered exogenous. Likewise, studies of change in one variable over time often examine predictors that occur after the first measurement of the variable but before the second measurement (Allison, 1990; Cronbach & Furby, 1970; Werts & Linn, 1970). Given this temporal ordering, the first measurement of the variable should be considered exogenous. The adaptation of the procedure presented here to situations in which only one variable is endogenous is discussed later in this article.

#### PROBLEMS WITH THE USE OF DIFFERENCE SCORES AND PROFILE SIMILARITY INDICES AS DEPENDENT VARIABLES

As mentioned previously, the use of difference scores and PSIs as dependent variables introduces numerous substantive and methodological problems. Because many of these problems have been discussed in the literature concerning the general use of difference scores (e.g., Cronbach, 1958; Cronbach & Furby, 1970; Edwards, 1994; Johns, 1981; Wall & Payne, 1973; Werts & Linn, 1970) and PSIs (Cronbach, 1958; Edwards, 1993; Lykken, 1956; Nunnally, 1962), they are only briefly summarized here, with particular emphasis on their relevance to difference scores and PSIs as dependent variables.

The use of difference scores and PSIs as dependent variables creates four general problems. First, when component measures are positively correlated (as is often the case), difference scores are generally less reliable than their component measures (Johns, 1981; Zimmerman, Brotohusodo, & Williams, 1981). Although this does not mean that difference scores are necessarily unreliable in an absolute sense (Smith & Tisak, 1993), reliability will generally be higher when the components of the difference are used as separate

dependent variables. As the reliability of the difference score decreases, the standard error of estimate increases and statistical power decreases, although coefficient estimates for the predictors of the difference score will remain unbiased (Pedhazur, 1982).

Unlike difference scores, PSIs often yield reliabilities that are higher than their component measures (Smith & Tisak, 1993). However, this occurs because PSIs usually comprise numerous dimensions, and even small correlations among these dimensions can yield reliability estimates that meet conventional standards (Green, Lissitz, & Mulaik, 1977). Moreover, reliability estimates derived from classical test theory are based on the assumption that the items constituting a measure represent a single (i.e., unidimensional) construct (Cronbach, 1951; Lord & Novick, 1968; Nunnally, 1978). This assumption is untenable for most PSIs, which usually collapse across conceptually distinct dimensions (Cronbach, 1958; Edwards, 1993; Lykken, 1956). For these reasons, reliability estimates reported for PSIs should generally be considered suspect.

Second, difference scores and PSIs are conceptually ambiguous, because they conceal the relative contribution of the component measures to variance in the composite score (Edwards, 1994). Although it may seem that the components contribute equally, given that they are implicitly assigned the same weight (i.e., unity) when the score is calculated, the variance of a difference score or PSI is a function of the variances and covariances of its component measures. Because these quantities are sample dependent, the interpretation of a difference score or PSI based on a given set of measures is likely to vary across studies. In some cases, one component is a constant (e.g., Jenkins & Maslach, 1994; Wanous & Youtz, 1986), such that the composite score simply represents a rescaled version of the other component.

Third, difference scores and PSIs confound the effects of the independent variables on the components of the difference, yielding results that are ambiguous and potentially misleading. This is shown by the following regression equation, which uses an algebraic difference as a dependent variable (e.g., Dockery & Steiner, 1990; Evans, 1972; Ferris *et al.*, 1985; Hall, Schneider, & Nygren, 1970; Phillips & Bedeian, 1994):

$$Y_1 - Y_2 = b_0 + b_1X + e. \quad (1)$$

In Eq. (1),  $Y_1$  and  $Y_2$  are measures of two endogenous variables,  $X$  is an independent variable,  $b_1$  is an unstandardized regression coefficient, and  $e$  is a random disturbance term (for simplicity, we will consider a single independent variable, but the following reasoning can be readily generalized to equations using multiple independent variables). Equation (1) can be rewritten

as two equations, using  $Y_1$  and  $Y_2$  as separate dependent variables:

$$Y_1 = b_{10} + b_{11}X + e_1 \quad (2)$$

$$Y_2 = b_{20} + b_{21}X + e_2. \quad (3)$$

In these equations,  $b_{11}$  and  $b_{21}$  are unstandardized regression coefficients and  $e_1$  and  $e_2$  are random disturbance terms for equations predicting  $Y_1$  and  $Y_2$ , respectively. By subtracting Eq. (3) from Eq. (2), we can recover an equation with  $Y_1 - Y_2$  as a dependent variable that retains the coefficients relating  $X$  separately to  $Y_1$  and  $Y_2$  (i.e.,  $b_{11}$  and  $b_{21}$ ):

$$Y_1 - Y_2 = (b_{10} - b_{20}) + (b_{11} - b_{21})X + (e_1 - e_2). \quad (4)$$

Equation (4) reveals that the coefficient relating  $X$  to  $Y_1 - Y_2$  equals the difference between the coefficients relating  $X$  to  $Y_1$  and  $Y_2$  as separate dependent variables (i.e.,  $b_1 = b_{11} - b_{21}$ ). Thus, by estimating Eqs. (2) and (3),  $b_1$  can be readily recovered. However, estimating Eq. (1) provides no indication as to the signs or magnitudes of  $b_{11}$  and  $b_{21}$ , other than that their difference equals  $b_1$ . Thus,  $b_1$  could represent equal but opposite effects of  $X$  on  $Y_1$  and  $Y_2$  (i.e.,  $b_{11} = -b_{21}$ ), an effect on  $Y_1$  but not  $Y_2$  (i.e.,  $b_{11} = b_1$ ,  $b_{21} = 0$ ), an effect on  $Y_2$  but not  $Y_1$  (i.e.,  $b_{11} = 0$ ,  $b_{21} = -b_1$ ), or any other combination of  $b_{11}$  and  $b_{21}$  that maintains their difference at  $b_1$ . Different values of  $b_{11}$  and  $b_{21}$  may yield drastically different substantive interpretations of the process linking  $X$  to  $Y_1$  and  $Y_2$ , but these interpretations cannot be disentangled by simply estimating Eq. (1).

A somewhat more complicated example is provided by an equation using the absolute difference between  $Y_1$  and  $Y_2$  as a dependent variable (e.g., Fox *et al.*, 1989; Notz & Starke, 1978; Shore & Bleicken, 1991; Sutcliffe, 1994):

$$|Y_1 - Y_2| = b_0 + b_1X + e. \quad (5)$$

Like Eq. (1), Eq. (5) confounds the effects of  $X$  on  $Y_1$  and  $Y_2$ . However, these effects cannot be isolated in the same manner as for Eq. 1, because  $|Y_1 - Y_2|$  cannot be rewritten as a linear function of  $Y_1$  and  $Y_2$ . This problem can be resolved by replacing Eq. (5) with the following equation

$$Y_1 - Y_2 = b_0(1 - 2W) + b_1(1 - 2W)X + e. \quad (6)$$

In Eq. (6),  $W$  is a dummy variable that equals 0 when  $Y_1 > Y_2$  and equals 1 when  $Y_1 < Y_2$ . Thus,  $W$  simply changes the signs on  $b_0$  and  $b_1$ , depending on whether  $Y_1 - Y_2$  is positive or negative. Specifically, if  $Y_1 - Y_2$  is positive, the signs on  $b_0$  and  $b_1$  are unaltered, and Eq. (6) reduces to Eq. (1), whereas if  $Y_1 - Y_2$  is negative, the

signs on  $b_0$  and  $b_1$  are reversed. Thus, the equation relating  $X$  to  $Y_1 - Y_2$  is  $b_0 + b_1X$  when  $Y_1 - Y_2$  is positive but switches to  $-b_0 - b_1X$  when  $Y_1 - Y_2$  is negative, yielding the same effect as using  $|Y_1 - Y_2|$  as a dependent variable in Eq. (5).

As shown above, Eq. (6) provides no means for testing whether the intercept and slope where  $Y_1 > Y_2$  are, in fact, equal in magnitude but opposite in sign when compared to the intercept and slope where  $Y_1 < Y_2$ . Rather, Eq. (6) imposes these constraints by construction. The exact form of these constraints can be seen by expanding and rearranging terms in Eq. (6):

$$Y_1 - Y_2 = b_0 + b_1X - 2b_0W - 2b_1WX + e. \quad (7)$$

This shows that Eq. (6) imposes two constraints: (1) the coefficient on  $W$  is twice as large as the intercept but opposite in sign; and (2) the coefficient on  $WX$  is twice as large as the coefficient on  $X$  but opposite in sign. Testing these constraints requires an unconstrained version of Eq. (6) that uses  $X$ ,  $W$ , and  $WX$  as separate predictors:

$$Y_1 - Y_2 = b_0 + b_1X + b_2W + b_3WX + e. \quad (8)$$

The constraints imposed by Eq. 6 can be tested by determining whether the coefficients in Eq. 8 satisfy the conditions  $b_2 = -2b_0$  and  $b_3 = -2b_1$  (or, equivalently, whether the  $R^2$  from Eq. (8) is significantly larger than that from Eq. (6)), using a standard  $F$  test.

Although Eq. (8) permits explicit tests of the constraints imposed by Eq. (6), it uses  $Y_1 - Y_2$  as a dependent variable. Therefore, the effects of  $X$  on  $Y_1$  and  $Y_2$  remain confounded, and no information is provided regarding the coefficients relating  $X$ ,  $W$ , and  $WX$  to  $Y_1$  and  $Y_2$ , other than that the differences between these coefficients equal  $b_1$ ,  $b_2$ , and  $b_3$ , respectively. This ambiguity can be resolved by using  $Y_1$  and  $Y_2$  as separate dependent variables, analogous to Eqs. (2) and (3).

$$Y_1 = b_{10} + b_{11}X + b_{12}W + b_{13}WX + e_1 \quad (9)$$

$$Y_2 = b_{20} + b_{21}X + b_{22}W + b_{23}WX + e_2. \quad (10)$$

Coefficients from these equations can be used to examine the effects of  $X$  on  $Y_1$  and  $Y_2$  for cases where  $Y_1 > Y_2$  versus  $Y_1 < Y_2$ . Specifically, when  $Y_1 > Y_2$ , the effects of  $X$  on  $Y_1$  and  $Y_2$  are represented by  $b_{11}$  and  $b_{21}$ , respectively, whereas when  $Y_1 < Y_2$ , the effects of  $X$  on  $Y_1$  and  $Y_2$  are represented by the sums  $(b_{11} + b_{13})$  and  $(b_{21} + b_{23})$ . Standard errors for these sums can be calculated using the usual formula for the variance of a sum of random variables (e.g., DeGroot, 1975).

It should be noted that using  $|Y_1 - Y_2|$  as a dependent variable does *not* imply a specific pattern of coef-

ficients in Eqs. 9 and 10. This can be seen by subtracting Eq. 10 from Eq. 9, which yields:

$$Y_1 - Y_2 = (b_{10} - b_{20}) + (b_{11} - b_{21})X + (b_{12} - b_{22})W + (b_{13} - b_{23})WX + (e_1 - e_2). \quad (11)$$

Comparing Eq. (8) to Eq. (11) shows that  $b_0 = b_{10} - b_{20}$ ,  $b_1 = b_{11} - b_{21}$ ,  $b_2 = b_{12} - b_{22}$ , and  $b_3 = b_{13} - b_{23}$ . Substituting these equalities into the expressions for the constraints for  $|Y_1 - Y_2|$  (i.e.,  $b_2 = -2b_0$ ,  $b_3 = -2b_1$ ) yields  $b_{21} - b_{22} = -2(b_{10} - b_{20})$  and  $b_{13} - b_{23} = -2(b_{11} - b_{21})$ . Thus,  $|Y_1 - Y_2|$  imposes constraints on *linear combinations* of the coefficients from Eqs. (9) and (10) but does *not* constrain the signs or magnitudes of these coefficients, either individually or across equations. For example, the constraint  $b_{13} - b_{23} = -2(b_{11} - b_{21})$  can be satisfied by an infinite range of  $b_{11}$ ,  $b_{13}$ ,  $b_{21}$ , and  $b_{23}$ , provided that  $b_{13} - b_{23}$  is twice as large as  $b_{11} - b_{21}$  but opposite in sign (although less obvious, this ambiguity also underlies tests of the  $|Y_1 - Y_2|$  constraints using Eq. (8)). Consequently, any test of the constraints imposed by  $|Y_1 - Y_2|$  should be accompanied by tests of magnitudes and directions of the coefficients from Eqs. (9) and (10) to clarify the nature of the relationships of  $X$  with  $Y_1$  and  $Y_2$ .

Finally, using a difference score or PSI as a dependent variable transforms an inherently multivariate model into a univariate model. This is seen by again comparing Eqs. (2) and (3) to Eq. (1). By jointly estimating Eqs. (2) and (3), the effects of  $X$  on  $Y_1$  and  $Y_2$  can be directly assessed, correlations between residuals (i.e.,  $e_1$  and  $e_2$ ) can be analyzed, multivariate tests of significance can be conducted for the joint effects of  $X$  on  $Y_1$  and  $Y_2$  (e.g., Dwyer, 1983), and the model can be readily adapted to include a causal relation between  $Y_1$  and  $Y_2$ . These features are unavailable in a univariate model, as represented by Eq. (1).

#### AN ALTERNATIVE PROCEDURE

The procedure proposed here is based on three general principles. First, given that component measures used in difference scores and PSIs typically represent conceptually distinct constructs (e.g., actual and desired job attributes, supervisor and subordinate perceptions), they should remain distinct in data analysis. Second, models predicting congruence should be tested using multivariate analyses that treat the dependent component measures jointly, thereby providing estimates of the effects of each predictor on each component measure along with multivariate tests of the association between the predictors and component measures as a set. Third, hypotheses regarding the prediction of congruence should be stated in terms of

the joint prediction of the component measures, supplemented by constraints that represent the effects of interest. For example, if the hypothesis underlying Eq. (1) is that an increase in  $X$  simultaneously increases  $Y_1$  and decreases  $Y_2$ , then one should predict that  $b_{11}$  is positive and  $b_{21}$  is negative, as opposed to simply predicting that  $b_1$  is positive (which, as noted earlier, is ambiguous as to the separate effects of  $X$  on  $Y_1$  and  $Y_2$ ). If one further hypothesizes that the effects of  $X$  on  $Y_1$  and  $Y_2$  are equal in absolute magnitude, then the constraint  $b_{11} = -b_{21}$  should be explicitly tested. Hypotheses regarding the differential effects of  $X$  for cases where  $Y_1 > Y_2$  versus  $Y_1 < Y_2$  can be similarly derived and tested.

The following discussion is organized in terms of two basic distinctions regarding the prediction of congruence. The first is whether congruence is assessed along a single dimension or multiple dimensions. Studies that assess congruence on a single dimension have typically used algebraic, absolute, or squared difference scores (e.g., Dockery & Steiner, 1990; Evans, 1972; Ferris *et al.*, 1985; Fox *et al.*, 1989; Hall *et al.*, 1970; Notz & Starke, 1978; Phillips & Bedeian, 1994; Shore & Bleicken, 1991; Sutcliffe, 1994; Weiss, 1978; Wood, 1973). Studies of congruence on multiple dimensions have used PSIs such as  $D^2$ ,  $D$ ,  $|D|$ , or  $Q$  (e.g., Ashford & Tsui, 1991; Jako & Murphy, 1990; London & Wohlers, 1991; Mount & Thompson, 1987; Shanley & Correa, 1992; Tannenbaum & Wesley, 1993; Weiss, 1977; Wohlers *et al.*, 1993; Zalesny & Kirsch, 1989).

The second distinction is whether the effects of the independent variables on congruence are considered directional or nondirectional. Studies examining directional effects have used an algebraic difference (e.g., Dockery & Steiner, 1990; Evans, 1972; Ferris *et al.*, 1985; Hall *et al.*, 1970; Phillips & Bedeian, 1994; Wood, 1973) or the sum of algebraic differences across multiple dimensions, here labeled  $D^1$  (e.g., Mount & Thompson, 1987; Wohlers *et al.*, 1993). Studies examining nondirectional effects have used scores that discard directional information, such as an absolute difference (e.g., Fox *et al.*, 1989; Notz & Starke, 1978; Shore & Bleicken, 1991; Sutcliffe, 1994), squared difference (e.g., Weiss, 1978), or a PSI such as  $D^2$ ,  $D$ ,  $|D|$ , or  $Q$  (e.g., Ashford & Tsui, 1991; Graen & Schiemann, 1978; Jako & Murphy, 1990; London & Wohlers, 1991; Morrison, 1993; Mount & Thompson, 1987; Shanley & Correa, 1992; Tannenbaum & Wesley, 1993; Tsui & Ohlott, 1988; Weiss, 1977, 1978; Wohlers *et al.*, 1993; Zalesny & Kirsch, 1989). Table 1 combines these distinctions into a two-way classification scheme, yielding a set of basic equations for predicting directional and nondirectional effects along single and multiple dimensions.

TABLE 1

Equations for Predicting Directional and Nondirectional Effects on Congruence along Single and Multiple Dimensions

Directional effects	Nondirectional effects
Single dimension	
$Y_1 = b_{10} + b_{11}X_1 + \dots + b_{1q}X_q + e_1$	$Y_1 = b_{10} + b_{11}X_1 + \dots + b_{1q}X_q + b_{1(q+1)}W + b_{1(q+2)}WX_1 + \dots + b_{1(2q+1)}WX_q + e_1$
$Y_2 = b_{20} + b_{21}X_1 + \dots + b_{2q}X_q + e_2$	$Y_2 = b_{20} + b_{21}X_1 + \dots + b_{2q}X_q + b_{2(q+1)}W + b_{2(q+2)}WX_1 + \dots + b_{2(2q+1)}WX_q + e_2$
Multiple dimensions	
$Y_{11} = b_{101} + b_{111}X_1 \dots + b_{1q1}X_q + e_{11}$	$Y_{11} = b_{101} + b_{111}X_1 + \dots + b_{1q1}X_q + b_{1(q+1)1}W_1 + b_{1(q+2)1}W_1X_1 + \dots + b_{1(2q+1)1}W_1X_q + e_{11}$
$Y_{21} = b_{201} + b_{211}X_1 \dots + b_{2q1}X_q + e_{21}$	$Y_{21} = b_{201} + b_{211}X_1 + \dots + b_{2q1}X_q + b_{2(q+1)1}W_1 + b_{2(q+2)1}W_1X_1 + \dots + b_{2(2q+1)1}W_1X_q + e_{21}$
⋮	⋮
$Y_{1r} = b_{10r} + b_{11r}X_1 \dots + b_{1qr}X_q + e_{1r}$	$Y_{1r} = b_{10r} + b_{11r}X_1 + \dots + b_{1qr}X_q + b_{1(q+1)r}W_r + b_{1(q+2)r}W_rX_1 + \dots + b_{1(2q+1)r}W_rX_q + e_{1r}$
$Y_{2r} = b_{20r} + b_{21r}X_1 \dots + b_{2qr}X_q + e_{2r}$	$Y_{2r} = b_{20r} + b_{21r}X_1 + \dots + b_{2qr}X_q + b_{2(q+1)r}W_r + b_{2(q+2)r}W_rX_1 + \dots + b_{2(2q+1)r}W_rX_q + e_{2r}$

Note. In the equations for a single dimension,  $Y_1$  and  $Y_2$  are the component dependent variables, the  $b_{ij}$  are unstandardized coefficients for the regression of  $Y_i$  on  $X_j$ , and  $W$  is a dummy variable that equals 0 when  $Y_1 > Y_2$  and equals 1 when  $Y_1 < Y_2$ . In the equations for multiple dimensions,  $Y_{1k}$  and  $Y_{2k}$  are the component dependent variables measured on the  $k$ th dimension, the  $b_{ijk}$  are unstandardized coefficients for the regression of  $Y_{ik}$  on  $X_j$  for the  $k$ th dimension, and  $W_k$  is a dummy variable that equals 0 when  $Y_{1k} > Y_{2k}$  and equals 1 when  $Y_{1k} < Y_{2k}$ . Note that  $i$  ranges from 1 to  $p$  (which, for these equations, equals 2),  $j$  ranges from 1 to  $q$  (representing the number of  $X$  variables), and  $k$  ranges from 1 to  $r$  (representing the number of dimensions).

Directional Effects on a Single Dimension

As Table 1 shows, predicting directional effects on a single dimension requires the use of generalized versions of Eqs. (2) and (3). These equations permit explicit tests of the relative effects of the  $X_j$  on  $Y_1$  and  $Y_2$ . For example, to determine whether the effects of the  $X_j$  on  $Y_1$  and  $Y_2$  are equal in magnitude but opposite in sign, the coefficients on each  $X_j$  across the two equations may be constrained to sum to zero (i.e.,  $b_{11} + b_{21} = 0$ ,  $b_{12} + b_{22} = 0$ , . . . ,  $b_{1q} + b_{2q} = 0$ ). These constraints can be tested with multivariate regression analysis (Dwyer, 1983; Wilkinson, 1990), using Wilks'  $\Lambda$  and its associated approximate  $F$  test (Rao, 1959). If this test is not significant, then the hypothesis that the  $X_j$  have equal but opposite effects on  $Y_1$  and  $Y_2$  may be considered tenable (assuming the sample is sufficiently large to yield adequate statistical power; see Cohen, 1988). If the test is significant, follow-up analyses may be conducted to determine which of the  $X_j$  yields coefficients that deviate from the imposed constraint. Alternately, if *a priori* hypotheses state that some subset of the  $b_{1j}$  and  $b_{2j}$  sum to zero, then tests may focus specifically on those coefficients. Of course, these analyses should also take into consideration whether the  $b_{1j}$  and  $b_{2j}$  themselves differ from zero, given that failure to reject the null hypothesis that  $b_{1j} + b_{2j} = 0$  may simply indicate that neither  $b_{1j}$  nor  $b_{2j}$  differs from zero.

Nondirectional Effects on a Single Dimension

Nondirectional effects on a single dimension require generalized versions of Eqs. 9 and 10, as shown in Table 1. Coefficients on the  $X_j$ ,  $W$ , and  $WX_j$  for  $Y_1$  and  $Y_2$  can be compared across equations, analogous to the

procedure described above. Differences in the effects of the  $X_j$  for cases where  $Y_1 > Y_2$  versus  $Y_1 < Y_2$  can be examined by testing whether the coefficients on the  $WX_j$  differ from zero. A significant coefficient on  $WX_j$  indicates that the effect of the associated  $X_j$  differs depending on whether  $Y_1$  is greater than or less than  $Y_2$ . A multivariate omnibus test may be conducted for the coefficients on the  $WX_j$  for both equations jointly, using follow-up tests to determine which  $WX_j$  yields significant coefficients. Alternately, tests may focus on any subset of the  $WX_j$  hypothesized to yield significant coefficients. As before, analyses should also determine whether coefficients on the  $X_j$  for  $Y_1 > Y_2$  and  $Y_1 < Y_2$  are significant to avoid trivial cases in which both coefficients do not differ from zero. These equations can also be used to test the constraints imposed by using  $|Y_1 - Y_2|$  as a dependent variable, i.e.,  $b_{1(q+1)} - b_{2(q+1)} = -2(b_{10} - b_{20})$ ,  $b_{1(q+2)} - b_{2(q+2)} = -2(b_{11} - b_{21})$ , . . . ,  $b_{1(2q+1)} - b_{2(2q+1)} = -2(b_{1q} - b_{2q})$ . As noted previously, these tests should be accompanied by tests of the magnitudes and directions of the individual  $b_{1j}$  and  $b_{2j}$  to clarify the relationships of the  $X_j$  with  $Y_1$  and  $Y_2$ .

Directional Effects on Multiple Dimensions

Estimating directional effects on multiple dimensions (here labeled  $k$ , where  $k$  ranges from 1 to  $r$ ) requires replicating the equations used for a single dimension  $r$  times, yielding a total of  $2r$  equations (see Table 1). The effects of the  $X_j$  across dimensions can be compared by testing the differences between the coefficients on the  $X_j$  in predicting  $Y_{1k}$ ,  $Y_{2k}$ , or both. For example, to determine whether the effects of  $X_1$  on  $Y_1$  are the same across all  $r$  dimensions, one would test

the constraint  $b_{111} = b_{112} = \dots = b_{11r}$  (or, equivalently, that the difference between  $b_{111}$  and each of the remaining  $b_{11k}$  equals zero). These tests may be combined with tests comparing coefficients on the  $X_j$  predicting each pair of  $Y_{1k}$  and  $Y_{2k}$ . For instance, by combining tests that the  $b_{1jk}$  are equal across dimensions with tests that all paired  $b_{1jk}$  and  $b_{2jk}$  sum to zero, one may evaluate the constraints implied when  $D^1$  is used as a dependent variable and symmetric effects for each  $X_j$  on each paired  $Y_{1k}$  and  $Y_{2k}$  are assumed.

### *Nondirectional Effects on Multiple Dimensions*

Finally, predicting nondirectional effects across  $k$  dimensions also involves replicating the equations used for a single dimension  $r$  times, again yielding  $2r$  equations. As before, the effects of the  $X_j$  on the  $Y_{1k}$  and  $Y_{2k}$  may be compared by testing whether the coefficients for the  $X_j$  are equal across the  $r$  dimensions. These tests may be combined with tests of the constraints imposed by  $|Y_1 - Y_2|$ , repeated for all  $r$  dimensions (i.e.,  $b_{1(q+1)k} - b_{2(q+1)k} = -2(b_{10k} - b_{20k})$ ,  $b_{1(q+2)k} - b_{2(q+2)k} = -2(b_{11k} - b_{21k})$ ,  $\dots$ ,  $b_{1(2q+1)k} - b_{2(2q+1)k} = -2(b_{1qk} - b_{2qk})$ ) to evaluate the constraints implied when  $|D|$  (i.e., the sum of absolute differences) is used as a dependent variable.

### *Estimation*

As noted previously, the equations shown in Table 1 may be estimated using multivariate regression analysis (Dwyer, 1983; Wilkinson, 1990). Several points regarding the application of multivariate regression to these equations should be noted. First, although multivariate regression yields the same coefficient estimates as a series of univariate regressions, it also permits multivariate tests of the variance explained by all equations jointly as well as tests of the relative magnitudes of coefficients across equations. These tests are based on Wilks'  $\Lambda$ , which is calculated as the ratio of the determinants of the covariance matrices of residuals from two sets of equations, one that imposes constraints on the coefficient estimates (e.g., all  $b_{ij}$  are zero) and another that relaxes these constraints. Thus, multivariate regression takes into account not only the relationships among the independent variables, but also the relationships among the dependent variables, including that portion of these relationships explained by common predictors (i.e., the  $X_j$ ) and the unexplained portion represented by the covariance among the residuals. This classifies multivariate regression as a truly multivariate procedure and distinguishes it from a series of univariate regression analyses (Dwyer, 1983).

Second, for equations depicting nondirectional effects using the  $WX_j$ , the coefficients on the  $X_j$  and  $W$

terms are scale-dependent (Cohen, 1978). Specifically, adding an arbitrary constant to any of the  $X_j$  will influence the intercepts (i.e.,  $b_{10}$ ,  $b_{20}$ ) and the coefficients on  $W$  (i.e.,  $b_{1(q+1)}$ ,  $b_{2(q+1)}$ ). However, inspection of the nondirectional equations in Table 1 shows that, for cases where  $Y_1 > Y_2$ ,  $b_{10}$  and  $b_{20}$  represent the values of  $Y_1$  and  $Y_2$  where all  $X_j = 0$ , whereas for cases where  $Y_1 < Y_2$ ,  $(b_{10} + b_{1(q+1)})$  and  $(b_{20} + b_{2(q+1)})$  represent the values of  $Y_1$  and  $Y_2$  where all  $X_j = 0$ . Rescaling the  $X_j$  merely changes the point in the  $q$ -dimensional space defined by the  $X_j$  at which the values of  $Y_1$  and  $Y_2$  are estimated. For example, when  $q = 2$  and  $X_1$  and  $X_2$  are centered at their respective means, values for  $Y_1$  and  $Y_2$  are estimated at the overall mean of the  $X_1$ ,  $X_2$  distribution. It can be shown that rescaling the  $X_j$  has no effect on tests of constraints associated with using  $|Y_1 - Y_2|$  as a dependent variable, provided these constraints are tested simultaneously. Likewise, assigning values other than 0 and 1 to  $W$  will influence the coefficients on the  $X_j$ . However, this would also change the pattern of constraints associated with using  $|Y_1 - Y_2|$  as a dependent variable (see Eq. 7), and tests of these constraints would yield the same result.

Third, when specifying equations for nondirectional effects, a decision must be made regarding the coding of  $W$  for cases where  $Y_1 = Y_2$ . Dropping these cases is perhaps the simplest strategy but discards information and statistical power. Setting  $W$  to 0 or 1 for all cases where  $Y_1 = Y_2$  should generally be avoided without a compelling rationale for equating these cases with those for which  $Y_1 > Y_2$  or  $Y_1 < Y_2$ . However, if these two coding options yield the same substantive conclusions,  $W$  may be randomly set to 0 or 1 for cases where  $Y_1 = Y_2$  (cf. Edwards, 1994). If these two options yield different conclusions, a second dummy variable may be coded to identify the  $Y_1 = Y_2$  cases. This variable and its products with the  $X_j$  would then be used as covariates in the equations shown in Table 1. This procedure yields unbiased coefficient estimates for the  $X_j$  and  $WX_j$  and reduces the loss of statistical power associated with dropping the  $Y_1 = Y_2$  cases (assuming the number of these cases exceeds  $q$ , the number of  $X_j$ ). (For an application of this procedure to the treatment of missing data, see Cohen and Cohen, 1983, pp. 284–289.)

Finally, when nondirectional effects are estimated across multiple dimensions, the coding of the  $W_k$  will likely vary across dimensions (i.e., cases for which  $Y_1 > Y_2$  versus  $Y_1 < Y_2$  will differ for each dimension). Consequently, a total of  $r$  multivariate regression analyses must be conducted, one for each paired  $Y_{1k}$  and  $Y_{2k}$  for each dimension. Although this approach allows multivariate tests of significance within each dimension, it does not permit multivariate tests across dimensions. Therefore, Type I error rate for multivariate tests involving each of the  $2r$  equations should be controlled.

using the Bonferroni procedure, such that the probability levels obtained for these tests are multiplied by  $r$  (Harris, 1985). Tests of differences between coefficients across dimensions may be conducted using jackknife or bootstrap procedures (Efron & Gong, 1983), with probability levels corrected according to the number of tests performed. Note that when directional effects are of interest,  $W$  is omitted, and the  $2r$  equations may be estimated in a single multivariate regression analysis.

### AN EMPIRICAL EXAMPLE

To illustrate the procedure developed here, data from a study by Ashford and Tsui (1991) on feedback seeking and rating accuracy were reanalyzed. This study was chosen because it involved the analysis of nondirectional effects across multiple dimensions and, hence, represented the most general case depicted in Table 1. The data consisted of reports from 387 managers and their peers, supervisors, and subordinates regarding the managers' effectiveness in various role behaviors and methods used by the managers to seek evaluative feedback.

For illustration, we will focus on the relationships of five feedback-seeking variables with the degree to which managers were able to accurately estimate their supervisors' ratings of the managers' effectiveness. Two of the feedback-seeking variables represented feedback type, i.e., *negative feedback*, or seeking criticism, and *positive feedback*, or seeking praise and approval. The other three variables represented feedback-seeking strategy, i.e., *inquiry*, or directly asking for feedback, *direct cue monitoring*, or attending to cues with explicit evaluative content, and *indirect cue monitoring*, or attending to cues with implicit evaluative content.

Accuracy was operationalized using  $D^2$ , representing the sum of squared differences between supervisors' ratings of each managers' effectiveness and managers' estimates of their supervisors' ratings, both assessed in reference to 10 managerial roles (e.g., representing the company, managing subordinates) identified by Mintzberg (1973). This index was reverse scored, such that higher values indicated greater accuracy. Regression analyses using this index as a dependent variable yielded a positive coefficient on seeking negative feedback and nonsignificant coefficients on the remaining feedback-seeking variables, suggesting that seeking negative feedback was positively related to managers' accuracy in estimating their effectiveness as rated by their supervisors.

To provide continuity with Ashford and Tsui (1991), reanalyses began by using  $|D|$  as a dependent variable.  $|D|$  was used rather than  $D^2$  because the equations in Table 1 assume that the effects of the  $X_j$  are

linear for cases where  $Y_1 > Y_2$  and  $Y_1 < Y_2$  (comparing analyses using  $|D|$  with those using  $D^2$  showed that both indices yielded substantively equivalent results). Also,  $|D|$  was used in its raw form, such that higher values indicated greater inaccuracy (as will be seen, this clarifies the correspondence between results using  $|D|$  and those using the equations shown in Table 1). Subsequent analyses progressively decomposed  $|D|$  into separate dimensions (i.e., managerial roles), separate scores for cases where  $Y_1 > Y_2$  (i.e., managers who overestimated their effectiveness) and  $Y_1 < Y_2$  (i.e., managers who underestimated their effectiveness), and separate scores for managers and supervisors. These analyses permitted sequential tests of the assumptions embodied in  $|D|$  (and  $D^2$ ), i.e., relationships for feedback-seeking are the same across all managerial roles and are symmetric, with equal but opposite relationships for overestimators (i.e., cases where  $Y_1 > Y_2$ ) and underestimators (i.e., cases where  $Y_1 < Y_2$ ). These analyses also clarified whether feedback-seeking was related to managers' estimates, supervisors' ratings, or both. All analyses were conducted using the multivariate general linear hypothesis (MGLH) module of SYSTAT (Wilkinson, 1990). Results of these analyses are reported in Table 2.

As Table 2 shows, using  $|D|$  as a dependent variable yielded results consistent with those reported by Ashford and Tsui (1991), i.e., inaccuracy is negatively related to seeking negative feedback and is unrelated to other feedback-seeking variables. Next, analyses were conducted to determine whether these results were consistent across the 10 managerial roles. Instead of treating each role as a separate dimension, roles were clustered into conceptually homogeneous subsets. This avoided the use of single-item measures as dependent variables and reduced redundancy across equations, given that many roles were conceptually similar. According to Mintzberg (1973), the 10 roles may be grouped into three clusters, representing interpersonal, informational, and decisional roles. To test this, a six-factor measurement model corresponding to these three clusters for managers and supervisors was tested using confirmatory factor analyses (Joreskog & Sorbom, 1993). The  $\chi^2$  test and Bentler's (1990) comparative fit index (CFI) indicated that this model yielded moderate fit to the data ( $\chi^2(155) = 524.54, p < .001$ , CFI = .867), but several factor correlations did not differ significantly from one, indicating poor discriminant validity. Moreover, reliabilities for scales corresponding to these factors were adequate for supervisors (ranging from .703 to .833) but were unacceptably low for managers (ranging from .510 to .695). Given these results, the 10 roles were reassembled based on item content into two clusters representing internal and external roles. The four-factor model corresponding to these

TABLE 2

Regressions of Difference Scores, Supervisors' Evaluations, and Managers' Estimates on Feedback-Seeking Variables

Dependent variables	Independent variables						$R^2$	$R_g^2$	$\Delta R_g^2$
	Constant	Seeking negative feedback	Seeking positive feedback	Inquiry	Direct cue monitoring	Indirect cue monitoring			
$ D $	1.569**	-0.143**	0.055	-0.010	-0.043	0.024	.069**		
Absolute difference									
Internal role	1.322**	-0.217**	0.194**	-0.041	-0.051	-0.038	.136**		
External role	1.296**	-0.089	-0.017	0.016	-0.022	-0.025	.010		
Algebraic difference, internal role									
$Y_1 > Y_2$	1.643**	-0.301** <sub>a</sub>	0.276** <sub>a</sub>	0.015	-0.186*	0.009	.705**	.223**	.064**
$Y_1 < Y_2$	-0.607	-0.079	0.010	0.053	-0.077	0.098		.033	.003
Algebraic difference, external role									
$Y_1 > Y_2$	1.953**	-0.296**	0.028	0.057	-0.114	0.003	.697**	.116**	.022**
$Y_1 < Y_2$	-0.279	-0.255**	0.086	0.061	-0.068	0.014		.081*	.012*
Managers' estimates, internal role <sup>b</sup>									
$Y_1 > Y_2$	5.269**	0.061	-0.036	0.189**	-0.036	0.033	.141**	.084**	.043**
$Y_1 < Y_2$	5.750**	0.002	-0.046	0.030	-0.039	-0.152		.031	.011
Supervisors' ratings, internal role									
$Y_1 > Y_2$	3.625**	0.361** <sub>a</sub>	-0.312** <sub>a</sub>	0.174* <sub>a</sub>	0.151	0.023 <sub>a</sub>	.515**	.234**	.112**
$Y_1 < Y_2$	6.357**	0.080	-0.056	-0.023	0.039	-0.251*		.100*	.011
Managers' estimates, external role <sup>c</sup>									
$Y_1 > Y_2$	4.538**	0.162*	0.045	0.113	0.035	-0.130	.186**	.073*	.033*
$Y_1 < Y_2$	4.615**	0.102	-0.026	-0.005	0.031	-0.148		.031	.012
Supervisors' ratings, external role									
$Y_1 > Y_2$	2.585**	0.458**	0.016	0.056	0.149	-0.133	.518**	.194**	.076**
$Y_1 < Y_2$	4.893**	0.357**	-0.113	-0.067	0.099	-0.162		.179**	.034**

Note.  $N = 333$ .  $Y_1$  = managers' estimates;  $Y_2$  = supervisors' ratings. For internal role effectiveness,  $N = 185$  for  $Y_1 > Y_2$  (i.e., overestimators) and  $N = 120$  for  $Y_1 < Y_2$  (i.e., underestimators); for external role effectiveness,  $N = 163$  for  $Y_1 > Y_2$  and  $N = 147$  for  $Y_1 < Y_2$ . Table entries in the first six columns are unstandardized regression coefficients (constants are shown to indicate the vertical position of the regression line). For rows labeled  $Y_1 > Y_2$ , coefficients for the  $X_j$  (where  $j = 1$  to 5, representing the five feedback-seeking variables) were obtained directly from the estimated equation; for rows labeled  $Y_1 < Y_2$ , coefficients were calculated by adding the coefficients on the  $WX_j$  product terms to those on the corresponding  $X_j$  (Cohen & Cohen, 1983, p. 315). For the remaining columns,  $R^2$  = squared multiple correlation for the overall equation using the full sample,  $R_g^2 = R^2$  from separate subgroup analyses of cases where  $Y_1 > Y_2$  or  $Y_1 < Y_2$  (as indicated by the row of the table), and  $\Delta R_g^2$  = increment in  $R^2$  associated with coefficients for either group (for cases where  $Y_1 > Y_2$ , these are the coefficients on the five  $X_j$ ; for cases where  $Y_1 < Y_2$ , these are the five sums of coefficients on the corresponding  $X_j$  and  $WX_j$ ).

<sup>a</sup> The coefficient on this variable was significantly different for cases where  $Y_1 > Y_2$  versus  $Y_1 < Y_2$ ,  $p < .05$  (to control Type I error, these tests were conducted only when the coefficients for all five feedback seeking variables differed as a set,  $p_c < .05$ ; this test omitted intercepts, which were expected to differ by construction).

<sup>b</sup> The multivariate test for the equations for managers' estimates and supervisors' ratings of internal role effectiveness was significant overall ( $\Lambda = .267$ ,  $F(34,628) = 17.287$ ,  $p_c < .001$ ) and for overestimators ( $\Lambda = .759$ ,  $F(10,628) = 9.307$ ,  $p_c < .001$ ), but not for underestimators ( $\Lambda = .975$ ,  $F(10,628) = 0.808$ ,  $p_c > .05$ ).

<sup>c</sup> The multivariate test for the equations for managers' estimates and supervisors' ratings of external role effectiveness was significant overall ( $\Lambda = .261$ ,  $F(34,628) = 17.652$ ,  $p_c < .001$ ) and for both overestimators ( $\Lambda = .850$ ,  $F(10,628) = 5.325$ ,  $p_c < .001$ ) and underestimators ( $\Lambda = .924$ ,  $F(10,628) = 2.517$ ,  $p_c < .05$ ).

\*  $p < .05$ .

\*\*  $p < .01$ .

clusters yielded an adequate fit to the data ( $\chi^2(164) = 404.65$ ,  $p < .001$ , CFI = .913), and all factor correlations were significantly less than one. Reliabilities for these scales ranged from .723 to .879 and, hence, were considered adequate.

Based on these results, separate scales for internal and external role effectiveness for managers and supervisors were created by averaging the respective items, and the absolute difference between manager and supervisor scores were used as dependent vari-

ables in a multivariate regression analysis. Although a significant multivariate effect was found ( $\Lambda = .848$ ,  $F(10,652) = 5.587$ ,  $p < .001$ ), only the internal role effectiveness equation yielded a significant  $R^2$ . This equation indicated that seeking negative feedback was negatively related to inaccuracy, but also revealed that seeking positive feedback was positively related to inaccuracy. This additional relationship was concealed when internal and external role effectiveness items were collapsed into a single score.

The preceding analyses maintained the assumption that feedback seeking exhibited equal but opposite relationships for managers who overestimated their ratings and managers who underestimated their ratings. This assumption was evaluated by testing whether coefficients for overestimators and underestimators conformed to the constraints shown in Eq. (7), based on regression equations using the algebraic difference between managers' estimates and supervisors' ratings as dependent variables for internal and external role effectiveness. Cases where  $Y_1 > Y_2$  versus  $Y_1 < Y_2$  differed for internal and external roles, which required coding  $W$  independently for the two roles. Consequently, separate regression analyses were conducted for internal and external roles, and the Bonferroni correction was applied by multiplying the obtained probability levels for omnibus tests for both equations by 2 (these corrected probability levels are hereafter labeled  $p_c$ ). Preliminary analyses indicated that results differed somewhat depending on whether  $W$  was coded 0 or 1 for cases where  $Y_1 = Y_2$  (28 and 23 out of 333 cases for internal and external roles, respectively). Therefore, a separate dummy variable was coded for these cases, and this variable and its product with the  $X_j$  were used as covariates in all subsequent analyses.

Results from these equations indicated that the constraints imposed by the absolute difference were rejected for internal and external role effectiveness (both  $p_c < .001$ ). Follow-up analyses indicated that the coefficients on the feedback-seeking variables differed for overestimators and underestimators for internal role effectiveness ( $F(5,315) = 3.152, p_c < .05$ ) but not for external role effectiveness ( $F(5,315) = 0.147, p_c > .05$ ). Further analyses of the internal role effectiveness equation showed that the coefficients for overestimators and underestimators differed for seeking negative and positive feedback (both  $p < .05$ ). Tests of significance of the slopes for overestimators and underestimators suggested that, for overestimators, inaccuracy was negatively related to seeking negative feedback and positively related to seeking positive feedback, whereas for underestimators, neither form of feedback seeking was related to inaccuracy. In addition, direct cue monitoring was negatively related to inaccuracy for overestimators but not for underestimators, although the difference between the coefficient on this variable for overestimators and underestimators was not significant.

Given that the external role effectiveness equations did not differ for overestimators and underestimators, both dummy variables and their products with the  $X_j$  were dropped. The resulting equation yielded a  $R^2$  of .225 ( $p_c < .001$ ), a significant negative coefficient on seeking negative feedback, and significant positive

coefficients on seeking positive feedback and inquiry. Plots revealed that managers who sought little negative feedback overestimated their effectiveness, whereas managers who sought large amounts of negative feedback underestimated their effectiveness. In contrast, as inquiry and seeking positive feedback increased, managers increasingly overestimated their effectiveness.

The preceding analyses suggest that feedback seeking is related to accuracy for overestimators in the evaluation of internal role effectiveness and for both overestimators and underestimators in the evaluation of external role effectiveness. However, these analyses do not reveal whether feedback seeking is related to managers' estimates, supervisors' ratings, or both. For example, the negative coefficient on seeking negative feedback represents one of five possibilities: (1) managers' estimates decrease and supervisors' ratings increase; (2) managers' estimates decrease but supervisors' ratings remain constant; (3) managers' estimates remain constant but supervisors' ratings increase; (4) managers' estimates and supervisors' ratings both increase, with supervisors' ratings increasing to a greater extent; or (5) managers' estimates and supervisors' ratings both decrease, with managers' estimates decreasing to a greater extent. In each case, the difference between the coefficients relating negative feedback seeking to managers' estimates and supervisors' ratings would remain negative, although the coefficients themselves may be positive, negative, or non-significant (i.e., essentially zero).

To resolve this ambiguity, scores for managers' estimates and supervisors' ratings were treated as separate dependent variables in multivariate regression analyses. The equations for internal role effectiveness were jointly significant ( $\Lambda = .267, F(34,628) = 17.287, p_c < .001$ ), as was the multivariate test of the difference in coefficients for overestimators and underestimators ( $\Lambda = .916, F(10,628) = 2.814, p_c < .01$ ). Further analyses showed that the coefficients relating the feedback-seeking variables to managers' estimates and supervisors' ratings were jointly significant for overestimators ( $\Lambda = .759, F(10,628) = 9.307, p_c < .001$ ) but not for underestimators ( $\Lambda = .975, F(10,628) = 0.808, p_c > .05$ ). The equations for overestimators revealed that seeking negative feedback was positively related to supervisors' ratings but was unrelated to managers' estimates. Thus, seeking negative feedback was negatively related to inaccuracy not because managers' estimates decreased toward supervisors' ratings, but because supervisors' ratings increased toward managers' estimates. Analogously, seeking positive feedback was positively related to inaccuracy because supervisors' ratings decreased while managers' estimates remained

essentially constant. Furthermore, although inquiry was unrelated to accuracy in previous analyses, the equations for overestimators showed that it was positively related to both supervisors' ratings and managers' estimates.

Multivariate analyses verified that the external role effectiveness equations did not differ for underestimators and overestimators ( $\Lambda = .982$ ,  $F(10,628) = 0.568$ ,  $p_c > .05$ ). Therefore, both dummy variables and their products with the  $X_j$  were dropped, and the equations were reestimated. The multivariate test of the two equations was significant ( $\Lambda = .687$ ,  $F(10,652) = 13.488$ ,  $p_c < .001$ ), but only the equation for supervisors' ratings yielded a significant  $R^2$ . This equation indicated a positive relationship for seeking negative feedback, such that supervisors' ratings increased toward and then exceeded managers' estimates (which remained essentially constant). Seeking positive feedback and indirect cue monitoring also exhibited slight negative relationships with supervisors' ratings, although coefficients on these variables were only marginally significant ( $p = .059$  and  $p = .060$ , respectively).

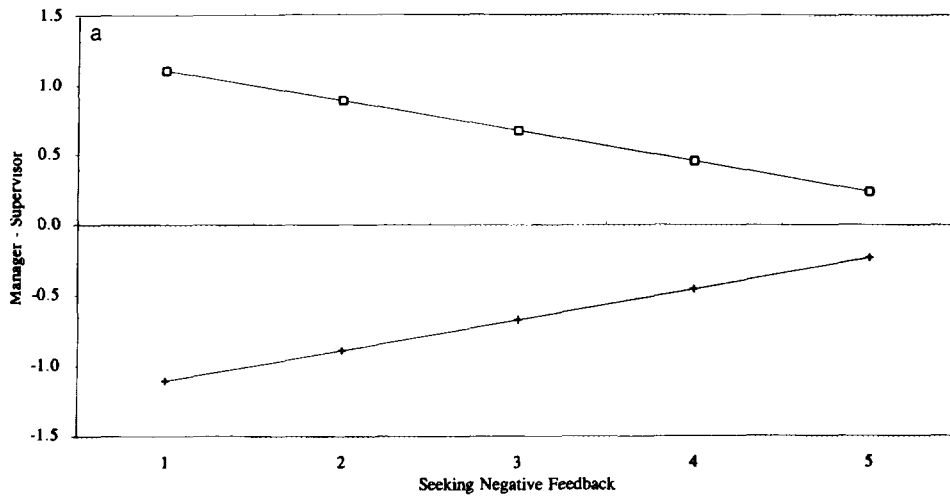
Figure 1 depicts how the preceding reanalyses alter the interpretation of the relationship between feedback seeking and accuracy. For illustration, we will consider the relationship between seeking negative feedback and accuracy regarding internal role effectiveness. Figure 1a shows that, when an absolute difference is used as the dependent variable (thereby imposing the constraints shown in Eq. (6)), seeking negative feedback is related to decreased positive errors for overestimators and decreased negative errors for underestimators. However, the symmetry of these relationships is an artifact of the constraints imposed by the absolute difference. Relaxing these constraints shows that seeking negative feedback is related to decreased errors for overestimators only (Fig. 1b). However, these results are ambiguous, because they do not show whether seeking negative feedback is related to managers' estimates, supervisors' ratings, or both. This ambiguity is resolved by using manager and supervisor scores as separate dependent variables, which reveals that seeking negative feedback is positively related to supervisors' ratings for overestimators but is unrelated to supervisors' ratings for underestimators or managers' estimates for either overestimators or underestimators (Figure 1c).

Ashford and Tsui (1991) also examined the relationship between feedback seeking and accuracy regarding managers' estimates of their evaluations by peers and subordinates. For peers, Ashford and Tsui (1991) re-

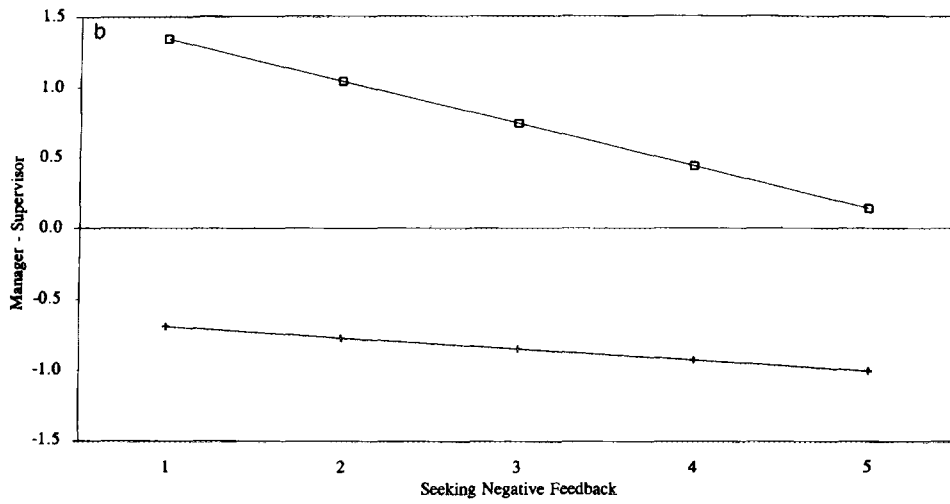
ported that seeking negative feedback was positively related to accuracy. These data were reanalyzed using managers' estimates and peers' ratings of internal and external role effectiveness as dependent variables. Because results differed somewhat when  $W$  was coded 0 or 1 for cases where  $Y_1 = Y_2$  (12 and 15 out of 381 cases for internal and external roles, respectively), a separate dummy variable was coded for these cases, and this variable and its product with the  $X_j$  were used as covariates. These results indicated that the relationships of feedback seeking with managers' estimates and peers' ratings did not differ for overestimators or underestimators (all  $p_c > .05$ ). Therefore, all dummy variables and their products with the  $X_j$  were dropped, and the four equations were reestimated in a single multivariate regression analysis (see Table 3). The multivariate test for all four equations was significant ( $\Lambda = .601$ ,  $F(20,1234) = 10.258$ ,  $p < .001$ ). Further analyses showed that seeking negative feedback was positively related to peers' ratings but was unrelated to managers' estimates. Plots indicated that, as negative feedback seeking increased, peers' ratings increased toward and then exceeded managers' estimates. In addition, peers' ratings of internal role effectiveness were negatively related to inquiry, whereas their ratings of external role effectiveness were positively related to direct cue monitoring (for both of these relationships, peers' ratings remained below managers' estimates).

For subordinates, Ashford and Tsui (1991) indicated that accuracy was positively related to seeking negative feedback and inquiry but was negatively related to seeking positive feedback. Results using managers' estimates and subordinates' ratings of internal and external role effectiveness as dependent variables again differed slightly depending on whether  $W$  was coded 0 or 1 for cases where  $Y_1 = Y_2$  (18 and 12 out of 382 cases for internal and external roles, respectively). Therefore, a dummy variable was coded for these cases, and this variable and its product with the  $X_j$  were used as covariates. Results of these analyses showed that, for both internal and external role effectiveness, seeking negative feedback was positively related to managers' estimates and subordinates' ratings, although these relationships were stronger for subordinates' ratings of overestimators than for their ratings of underestimators (see Table 4). Further analyses showed that, for overestimators, the relationship for negative feedback seeking was larger for subordinates' ratings than for managers' estimates ( $F(1,364) = 27.933$ ,  $p < .001$  for internal role effectiveness;  $F(1,364) = 18.763$ ,  $p < .001$  for external role effectiveness), indicating that the ap-

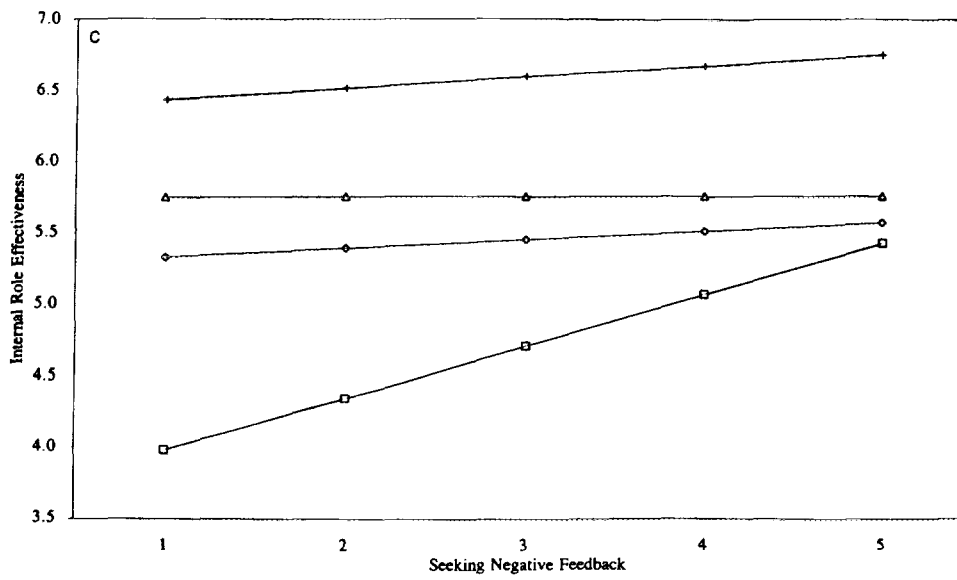
**FIG. 1.** Relationship of seeking negative feedback with managers' estimates and supervisors' ratings of internal role effectiveness using constrained absolute difference, unconstrained absolute difference, and separate manager and supervisor scores as dependent variables. (a) Constrained absolute difference; (b) unconstrained absolute difference; (c) separate manager and supervisor scores.



□ Overestimators + Underestimators



□ Overestimators + Underestimators



□ Overestimators, Supervisors      + Underestimators, Supervisors  
 ◆ Overestimators, Managers      ▲ Underestimators, Managers

**TABLE 3**  
**Regressions of Peers' Evaluations and Managers' Estimates on Feedback-Seeking Variables**

Dependent variables	Constant	Independent variables					R <sup>2</sup>
		Seeking negative feedback	Seeking positive feedback	Inquiry	Direct cue monitoring	Indirect cue monitoring	
Separate scores, internal role							
Managers	5.106**	-0.012	-0.015	-0.036	0.002	0.173*	.016
Peers	3.176**	0.675**	-0.125	-0.160*	0.152	-0.025	.227**
Separate scores, external role							
Managers	4.630**	-0.081	-0.053	0.062	0.129	0.100	.026
Peers	2.076**	0.703**	0.031	-0.049	0.235**	-0.067	.335**

Note. N = 381. For all columns except those labeled R<sup>2</sup>, table entries are unstandardized regression coefficients (constants are included to indicate the vertical position of the regression line).

\* p < .05.

\*\* p < .01.

parent increase in accuracy from seeking negative feedback actually involved an increase in managers' estimates combined with a larger increase in subordinates' ratings.

Table 4 also shows that, for internal role effectiveness, seeking positive feedback was negatively related to managers' estimates for underestimators and subordinates' ratings of both overestimators and underes-

**TABLE 4**  
**Regressions of Difference Scores, Subordinates' Evaluations, and Managers' Estimates on Feedback-Seeking Variables**

Dependent variables	Constant	Independent variables					R <sup>2</sup>	R <sub>g</sub> <sup>2</sup>	ΔR <sub>g</sub> <sup>2</sup>
		Seeking negative feedback	Seeking positive feedback	Inquiry	Direct cue monitoring	Indirect cue monitoring			
Managers' estimates, internal role <sup>b</sup>									
Y <sub>1</sub> > Y <sub>2</sub>	4.843**	0.218**	0.017 <sub>a</sub>	-0.049	0.011	0.155*	.281**	.067*	.027*
Y <sub>1</sub> < Y <sub>2</sub>	4.120**	0.387**	-0.273*	0.047	0.137	0.000	.149**	.149**	.060**
Subordinates' ratings, internal role									
Y <sub>1</sub> > Y <sub>2</sub>	3.088**	0.617**	-0.319**	0.075	0.035	0.304**	.485**	.312**	.174**
Y <sub>1</sub> < Y <sub>2</sub>	5.180**	0.332**	-0.266*	0.028	0.061	0.027	.169**	.169**	.026**
Managers' estimates, external role <sup>c</sup>									
Y <sub>1</sub> > Y <sub>2</sub>	4.539**	0.181*	-0.052	-0.075	0.137	0.160*	.315**	.109**	.042**
Y <sub>1</sub> < Y <sub>2</sub>	4.156**	0.136	-0.144	0.129	0.095	0.033	.065*	.065*	.024*
Subordinates' ratings, external role									
Y <sub>1</sub> > Y <sub>2</sub>	2.777**	0.524**	-0.208**	-0.010	0.163	0.246**	.493**	.351**	.118**
Y <sub>1</sub> < Y <sub>2</sub>	4.817**	0.181*	-0.147	0.045	0.123	0.017	.110*	.110*	.019*

Note. N = 382. Y<sub>1</sub> = managers' estimates; Y<sub>2</sub> = subordinates' ratings. For internal role effectiveness, N = 216 for Y<sub>1</sub> > Y<sub>2</sub> (i.e., overestimators) and N = 148 for Y<sub>1</sub> < Y<sub>2</sub> (i.e., underestimators); for external role effectiveness, N = 200 for Y<sub>1</sub> > Y<sub>2</sub> and N = 170 for Y<sub>1</sub> < Y<sub>2</sub>. Table entries in the first six columns are unstandardized regression coefficients (constants are shown to indicate the vertical position of the regression line). For rows labeled Y<sub>1</sub> > Y<sub>2</sub>, coefficients for the X<sub>j</sub> (where j = 1 to 5, representing the five feedback-seeking variables) were obtained directly from the estimated equation; for rows labeled Y<sub>1</sub> < Y<sub>2</sub>, coefficients were calculated by adding the coefficients on the WX<sub>j</sub> product terms to those on the corresponding X<sub>j</sub> (Cohen & Cohen, 1983, p. 315). For the remaining columns, R<sup>2</sup> = squared multiple correlation for the overall equation using the full sample, R<sub>g</sub><sup>2</sup> = R<sup>2</sup> from separate subgroup analyses of cases where Y<sub>1</sub> > Y<sub>2</sub> or Y<sub>1</sub> < Y<sub>2</sub> (as indicated by the row of the table), and ΔR<sub>g</sub><sup>2</sup> = increment in R<sup>2</sup> associated with coefficients for either group (for cases where Y<sub>1</sub> > Y<sub>2</sub>, these are the coefficients on the five X<sub>j</sub>; for cases where Y<sub>1</sub> < Y<sub>2</sub>, these are the five sums of coefficients on the corresponding X<sub>j</sub> and WX<sub>j</sub>).

<sup>a</sup> The coefficient on this variable was significantly different for cases where Y<sub>1</sub> > Y<sub>2</sub> versus Y<sub>1</sub> < Y<sub>2</sub>, p < .05 (to control Type I error, these tests were conducted only when the coefficients for all five feedback seeking variables differed as a set, p<sub>c</sub> < .05; this test omitted intercepts, which were expected to differ by construction).

<sup>b</sup> The multivariate test for the equations for managers' estimates and subordinates' ratings of internal role effectiveness was significant overall (Λ = .260, F(34,726) = 20.501, p<sub>c</sub> < .001) and for both overestimators (Λ = .714, F(10,726) = 13.345, p<sub>c</sub> < .001) and underestimators (Λ = .918, F(10,726) = 3.177, p<sub>c</sub> < .01).

<sup>c</sup> The multivariate test for the equations for managers' estimates and subordinates' ratings of external role effectiveness was significant overall (Λ = .259, F(34,726) = 20.605, p<sub>c</sub> < .001) and for overestimators (Λ = .716, F(10,726) = 13.214, p<sub>c</sub> < .001), but not for underestimators (Λ = .952, F(10,726) = 1.805, p<sub>c</sub> > .05).

\* p < .05.

\*\* p < .01.

timators. Moreover, for overestimators, the negative relationship was larger for subordinates' ratings than for managers' estimates ( $F(1,364) = 20.404, p < .001$ ), indicating that the decrease in accuracy for seeking positive feedback involved a decrease in subordinates' ratings combined with no relationship for managers' estimates (relationships did not differ for underestimators,  $F(1,364) = 0.005, p > .05$ ). Similar results were obtained for external role effectiveness, although the relationships for underestimators failed to reach significance (both  $p > .05$ ).

Finally, for both internal and external role effectiveness, indirect cue monitoring was positively related to subordinates' ratings and managers' estimates for overestimators but not for underestimators. In addition, the relationship for subordinates' ratings was larger than that for managers' estimates for internal role effectiveness ( $F(1,364) = 5.167, p < .05$ ) but not for external role effectiveness ( $F(1,364) = 1.866, p > .05$ ). These findings were not evident in the results reported by Ashford and Tsui (1991).

## DISCUSSION

The procedure developed here provides several advantages over the use of difference scores as dependent variables. First, it maintains the conceptual distinctions between the component measures constituting the difference. Second, it reveals the directions and relative magnitudes of the relationships between the independent variables and the components of the difference. This resolves ambiguities inherent in the use of difference scores as dependent variables, such as whether independent variables are related to one or both component measures, whether relationships differ for positive versus negative differences, and for profile similarity indices, whether relationships are equivalent across all dimensions subsumed by the index. Third, it yields multivariate tests of the relationships between each independent variable and the component measures along with omnibus tests of these relationships as a set. This provides a flexible, comprehensive method for determining whether these relationships conform to hypotheses that typically underlie the use of difference scores as dependent variables in congruence research.

The importance of these advantages was demonstrated by reanalyzing data from a study by Ashford and Tsui (1991) of feedback seeking and rating accuracy. As noted previously, this study operationalized accuracy using  $D^2$ , representing the sum of squared differences between managers' estimates of their ratings by various constituencies (i.e., supervisors, peers, subordinates) and the actual ratings reported by these constituencies. Regression analyses using  $D^2$  as a dependent variable indicated that accuracy was posi-

tively related to seeking negative feedback. These findings suggest that seeking negative feedback provided managers with information that helped them correctly estimate how others evaluated them. As Ashford and Tsui (1991) concluded, "if the self-regulatory objective of managers is to gain accurate knowledge of how constituents view their work, the managers should focus on seeking negative, rather than positive, feedback" (p. 272). Analyses reported by Ashford and Tsui (1991) also indicated that, for subordinates' ratings, accuracy was positively related to inquiry and negatively related to seeking positive feedback. Again, these results imply that these forms of feedback seeking are related to the estimates held by managers.

The procedure employed here indicates that these conclusions should be modified in several respects. First, accuracy should not be interpreted in global terms, but rather in terms of internal versus external role behaviors, at least for the measures used in this study. This reinforces early admonitions by Cronbach (1955), Lykken (1956), and Nunnally (1962) that similarity should not be viewed in a general sense, but rather with respect to specific dimensions of comparison. As Cronbach (1955) forcefully argues, "any index combining results from heterogeneous items presents serious difficulties of interpretation . . . an accuracy score based on heterogeneous items is only an exploratory procedure; where possible it should be replaced or extended by separate analyses of [the rater's] ability to predict different qualities of [the ratee]" (p. 178). Certainly, internal and external role behaviors may be further distinguished, but this was not feasible with the measures used in this study. To examine accuracy regarding more specific roles, multiple items for each role may be developed and used in multivariate analyses analogous to those used here.

Second, feedback seeking did not yield equal but opposite relationships for overestimators and underestimators, as presumed by the use of nondirectional indices such as  $D^2$  or  $|D|$ . Instead, relationships were usually in the same direction for both groups, although they often differed in magnitude. For example, seeking negative feedback exhibited a stronger positive relationship with subordinates' ratings of overestimators, suggesting that subordinates were more impressed when negative feedback was sought by managers with inflated views of themselves than when it was sought by managers with understated views of themselves. Similar results were obtained for indirect cue monitoring, such that attempts by managers to read cues with little overt evaluative content were positively related to subordinates' ratings of overestimators but not underestimators. In contrast, supervisors' ratings were negatively related to indirect cue monitoring by underestimators but not by overestimators, implying that attempts by managers to read indirect cues were det-

rimental only for managers with understated views of themselves. On the other hand, supervisors' ratings of overestimators were negatively related to seeking positive feedback but were positively related to seeking negative feedback and inquiry. Perhaps these supervisors were impressed when managers with inflated views of themselves solicited criticism but reacted harshly when these managers sought praise, which might further inflate their self appraisals. Results for peers did not differ for overestimators and underestimators, indicating instead that peers' ratings of all managers were positively related to seeking negative feedback and, to a lesser extent, were positively related to direct cue monitoring and negatively related to inquiry. Note that *none* of these findings represents a decrease in positive errors for overestimators along with a decrease in negative errors for underestimators, as implied by the use of  $D^2$  or  $|D|$ .

Third, feedback seeking was primarily related to constituencies' ratings of managers. In general, seeking negative feedback was positively related to constituencies' ratings, whereas seeking positive feedback was negatively related to these ratings, particularly those held by subordinates. Other forms of feedback seeking exhibited differential relationships with constituencies' ratings, as summarized in the preceding discussion. In contrast to these findings, feedback seeking exhibited few relationships with managers' estimates of their constituencies' ratings. Some evidence was obtained for positive relationships between managers' estimates and both seeking negative feedback and indirect cue monitoring, but these relationships varied across constituencies and differed for overestimators and underestimators. Thus, it appears that feedback seeking was related to evaluations of managers held by their constituencies, but had little relationship with managers' estimates of these evaluations.

In summary, these results indicate that feedback seeking plays a larger role in impression management than in providing managers with information that relates to their estimates of how their effectiveness is evaluated by others. Moreover, it appears that managers are largely unaware of the relationship between feedback seeking and how they are evaluated by others, given that several feedback seeking variables were significantly related to constituencies' rating but were unrelated to the managers' estimates of those ratings. An alternative explanation for these null results is that feedback seeking exhibited opposite relationships with managers' estimates that canceled each other out. For example, seeking negative feedback may be negatively related to managers' estimates of their effectiveness due to the critical information obtained and, at the same time, may be positively related to their estimates due to the presumed impression management benefits

of seeking negative feedback. Future studies may attempt to disentangle these effects by asking managers and their constituencies to rate hard performance outcomes and impression management criteria separately. Pending these studies, the present results suggest that feedback seeking bears little relationship with managers' estimates of how others evaluate their effectiveness.

It should be noted that these results are consistent with other findings described by Ashford and Tsui (1991). For example, a separate set of regression analyses reported in the original study used global measures of each manager's effectiveness as rated by each constituent as dependent variables. Although these measures did not separate effectiveness into internal and external dimensions, they indicated that effectiveness was positively related to seeking negative feedback and negatively related to seeking positive feedback. These findings are consistent with the results reported here.

#### THE VIABILITY OF OTHER MULTIVARIATE PROCEDURES

This article has demonstrated the utility of multivariate regression as an alternative to difference scores as dependent variables. Given that other multivariate procedures can accommodate multiple dependent variables, it is reasonable to ask whether these procedures are viable alternatives to difference scores as dependent variables. One such procedure is canonical correlation analysis, which yields coefficient estimates on both the  $X_j$  and  $Y_i$  variables and is symmetric, producing the same results when the independent and dependent variables are switched. Based on this, it might seem appropriate to simply reverse the roles of the independent and dependent variables, conduct a canonical correlation analysis, and apply methods developed as alternatives to difference scores as independent variables (Edwards, 1993, 1994; Edwards & Parry, 1993).

Unfortunately, the use of canonical correlation analysis in this manner has several serious limitations. First, canonical correlation analysis transforms the original  $X_j$  and  $Y_i$  variables into weighted linear composites, or canonical variates (Thompson, 1984), thereby shifting interpretation from the original variables to the canonical variates. If the original variables represent conceptually distinct constructs, then the canonical variates are inherently multidimensional, and their interpretation is problematic. Although the loadings obtained from a canonical analysis indicate the correlation of the original variables with each variate, the variate itself remains an amalgam of several constructs that are conceptually confounded. This problem

is analogous to that created when conceptually distinct items are collapsed into a single scale (Gerbing & Anderson, 1988; Hattie, 1985; Wolins, 1982) and is a general case of the interpretational problems with algebraic difference scores, in which the weights on the original variables are preassigned to +1 and -1. Put simply, collapsing conceptually distinct variables into a single score creates problems of interpretation, regardless of whether that score represents a scale, a difference score, or a canonical variate.

Second, the correlations between the  $X$  and  $Y$  variates yielded by canonical correlation analysis confound the relationships between the original  $X_j$  and  $Y_i$  variables. Although a redundancy analysis can reveal the relationships of the original variables in one set with the canonical variates from the other set (van den Wollenberg, 1977), relationships among the original  $X_j$  and  $Y_i$  variables remain confounded. This problem is particularly relevant in congruence research, where the relative effects of the  $X_j$  on  $Y_1$  and  $Y_2$  are of central interest. These effects cannot be teased apart in canonical correlation analysis.

Third, canonical correlation analysis yields as many pairs of canonical variates as the number of variables in the smaller of the two sets (i.e.,  $\min(p, q)$ , where  $p$  = number of  $Y$  variables and  $q$  = number of  $X$  variables). Because of this, one cannot extract a single, unambiguous estimate of the effects of the  $X_j$  on the  $Y_i$ , but instead must infer these effects from multiple pairs of variates (Cohen, 1982). The consequences of this ambiguity for congruence research are severe, because tests of constraints on the  $X_j$  and  $Y_i$  coefficients will generally yield different results, depending on which pair of variates is considered.

Fourth, although canonical correlation analysis can produce predicted values for the opposite variate, it does not yield unique predicted values for the variables constituting the variate. This is because a given variate score can represent an infinite set of values of its constituent variables, provided the weighted linear combination of the variables yields the same variate score. For example, suppose the raw canonical weights on  $Y_1$  and  $Y_2$  for a  $Y$  variate are .2 and .4, and a set of scores for the  $X_j$  variables yields a predicted  $Y$  variate score of 3. This value may represent  $Y_1$  and  $Y_2$  scores of 3 and 6, 5 and 5, 7 and 4, or any other combination that conforms to the equality  $.2Y_1 + .4Y_2 = 3$ . Note that the possible scores for  $Y_1$  and  $Y_2$  include cases where  $Y_1 > Y_2$ ,  $Y_1 = Y_2$ , and  $Y_1 < Y_2$ . This ambiguity is particularly troublesome in congruence research, where the relation of  $Y_1$  to  $Y_2$  is of central interest. This ambiguity is compounded when the  $Y$  variables are quadratic (i.e.,  $Y_1, Y_2, Y_1^2, Y_1Y_2, Y_2^2$ ) or piecewise linear (i.e.,  $Y_1, Y_2, W, WY_1, WY_2$ ; see Edwards, 1994), because a  $Y$  variate score can be produced by an even wider set of values of

the original  $Y_1$  and  $Y_2$  variables. When predicted  $Y$  scores for several variate pairs are considered, the ambiguity is multiplied.

Fifth, canonical correlation analysis does not yield tests of the increment in variance explained by adding variables to either set, because adding new variables to one set produces new weighted linear combinations of variables in the other set (Harris, 1985). Because tests of increments in explained variance are mathematically identical to tests of constraints imposed by difference scores (Edwards, 1994), it follows that canonical correlation analysis cannot be used to test difference score constraints. This is a fundamental flaw, given that tests of constraints are central to procedures for analyzing relationships of interest in congruence research (e.g., Edwards, 1994; Edwards & Harrison, 1993).

Finally, when higher-order terms are used, as in analyses of quadratic response surfaces using  $Y_1, Y_2, Y_1^2, Y_1Y_2, Y_2^2$  (cf. Edwards & Parry, 1993), results from canonical correlation analysis are scale-dependent. Although the scaling of  $Y_1$  and  $Y_2$  does not affect the sizes of the canonical correlations, the raw and standardized canonical weights and the structure and redundancy coefficients are affected. Given that the scaling of variables in congruence research is often arbitrary, it follows that results from canonical correlation analyses using higher-order terms cannot be meaningfully interpreted. This is a serious shortcoming, given that higher-order terms are the basis for testing most effects of interest in congruence research (Edwards, 1994; Edwards & Parry, 1993).

Other multivariate procedures may also be considered as alternatives to difference scores as dependent variables. For example, redundancy analysis has been advocated as a possible substitute for multivariate regression and canonical correlation analysis (Lambert, Wildt, & Durand, 1988; Muller, 1981). However, like canonical correlation analysis, redundancy analysis yields multiple representations of the relationships between the  $X_j$  and  $Y_i$  variables, making it impossible to identify a unique predicted value of  $Y_1$  or  $Y_2$  for given values of the  $X_j$  or to obtain an unambiguous test of the constraints on the coefficients relating the  $X_j$  to  $Y_1$  or  $Y_2$ . Set correlation has also been suggested as an alternative to canonical correlation analysis (Cohen, 1982). However, the primary advantage of set correlation is that it yields a single measure of association between the  $X_j$  and  $Y_i$  variables (i.e.,  $1 - \Lambda$ ). Beyond this, the relationships among the original  $X_j$  and  $Y_i$  variables are represented as a set of multivariate regression equations. Given that  $\Lambda$  may also be obtained from a multivariate regression analysis, it appears that set correlation offers no substantial advantage over multivariate regression for studies of congruence.

### LIMITATIONS AND AREAS FOR FURTHER DEVELOPMENT

Although the procedure proposed here has several advantages over the use of difference scores as dependent variables, it also contains certain drawbacks. First, as with any application of regression analysis, it assumes that variables are measured without error (Pedhazur, 1982). Fortunately, this assumption can be easily relaxed by using procedures that incorporate measurement error, such as structural equations modeling (Bollen, 1989). Constraints on coefficients within and between structural equations can be readily imposed using LISREL 8 (Joreskog & Sorbom, 1993), and separate structural equations for cases where  $Y_1 < Y_2$  and  $Y_1 > Y_2$  may be estimated using a multiple groups analysis.

Second, as presented here, the procedure assumes that all relationships are linear. Although this assumption is consistent with the use of difference scores such as an algebraic difference, absolute difference,  $D^1$ , and  $|D|$ , the use of a squared difference or  $D^2$  implies that the effects of the predictors on the difference diminish as the difference becomes smaller. Fortunately, this can be tested by adding higher-order terms to the equations used to depict nondirectional effects. For example, Eqs. (9) and (10) may be modified to incorporate diminishing effects as follows:

$$Y_1 = b_{10} + b_{11}X + b_{12}X^2 + b_{13}W + b_{14}WX + b_{15}WX^2 + e_1 \quad (12)$$

$$Y_2 = b_{20} + b_{21}X + b_{22}X^2 + b_{23}W + b_{24}WX + b_{25}WX^2 + e_2 \quad (13)$$

A diminishing effect of  $X$  on  $Y_1$  for cases where  $Y_1 > Y_2$  would yield a negative value for  $b_{11}$  and a positive value for  $b_{12}$ . A symmetric effect for cases where  $Y_1 < Y_2$  would yield a positive value for  $b_{14}$  and a negative value for  $b_{15}$ , with the constraint that the absolute magnitudes of these coefficients are twice as large as those for  $b_{11}$  and  $b_{12}$ , respectively. Equal but opposite effects on  $Y_2$  would yield coefficients for Eq. (13) that are equal in magnitude but opposite in sign from those obtained from Eq. (12). Each of these effects can be readily tested by adapting the procedures described here. However, it seems likely that most studies using a squared difference or  $D^2$  simply intend to capture symmetric effects of  $X$  on the  $Y_1 - Y_2$  difference, and that diminishing effects are not of interest. For these purposes, the equations reported in Table 1 will suffice.

Third, the procedure requires the researcher to specify *a priori* the values of  $Y_1$  and  $Y_2$  at which relationships for the independent variables are likely to differ. For studies of congruence, relationships are generally

assumed to change where  $Y_1 = Y_2$ , and this assumption served as the basis for coding  $W$  in the preceding analyses. However, the proposed procedure provides no mechanism for directly testing this assumption. It is possible that relationships may change where  $Y_1$  and  $Y_2$  differ by a constant, or that the values of  $Y_1$  and  $Y_2$  at which relationships change vary according to the levels of  $Y_1$  and  $Y_2$ . To explore these possibilities, researchers may systematically select several values of  $Y_1$  and  $Y_2$  to code  $W$  and compare the obtained results.

Finally, the procedure proposed here assumes that  $Y_1$  and  $Y_2$  are both endogenous and do not exert a causal influence on one another. As previously noted, in studies of performance rating accuracy and change, it is often reasonable to assume that either  $Y_1$  or  $Y_2$  is exogenous. If this is the case, then it makes little sense to cast both  $Y_1$  and  $Y_2$  as dependent variables. One alternative is to use the exogenous  $Y_i$  as a covariate, such that all analyses control for the level of the exogenous  $Y_i$  when estimating the endogenous  $Y_i$ . Although this approach has been recommended in the study of change (e.g., Cronbach & Furby, 1970; Werts & Linn, 1970), it has recently been criticized (Allison, 1990). Moreover, the implications of this approach in situations other than the study of change have not been fully resolved. It seems likely that this approach may be combined with the procedure described here to permit tests of effects on both  $Y_1$  and  $Y_2$  as well as causal relationships between both  $Y_1$  and  $Y_2$ , along with tests of constraints relevant to the study of agreement, similarity, and accuracy. Future research should focus on these important developments.

### CONCLUSION

Difference scores and PSIs are widely used as dependent variables in studies predicting the congruence (i.e., fit, matching, similarity, or agreement) between two constructs. As this article has shown, the use of difference scores and PSIs for this purpose presents serious conceptual and methodological problems. The alternative procedure developed here avoids these problems but permits explicit tests of the relationships difference scores and PSIs are intended to represent. By employing this procedure, future research may clarify relationships traditionally examined by using difference scores and PSIs as dependent variables, thereby determining whether these relationships represent congruence effects or other potentially meaningful processes.

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