

The Study of Congruence in Organizational Behavior Research: Critique and a Proposed Alternative

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Numerous studies in organizational behavior research have examined the congruence (i.e., fit, match, agreement, similarity) between two constructs as a predictor of some outcome. The vast majority of these studies have operationalized congruence by collapsing two or more measures into a single index, such as an algebraic, absolute, or squared difference, or an index of profile similarity (D , D^2 , etc.). Unfortunately, these indices present numerous substantive and methodological problems that severely threaten the interpretability and conclusiveness of the obtained results. This article summarizes problems with congruence indices, presents an alternative approach that overcomes these problems, and illustrates this approach using data from two samples. Recommendations regarding the use and further development of this approach are offered. © 1994 Academic Press, Inc.

For decades, the study of congruence has been widespread in organizational behavior research. Congruence refers to the fit, match, agreement, or similarity between two conceptually distinct constructs. Examples of such constructs include perceived and wanted work attributes (Chatman, 1989; Dawis & Lofquist, 1984; Locke, 1976), job demands and employee abilities (French, Caplan, & Harrison, 1982; McGrath, 1976), supervisor and subordinate values (Kemelgor, 1982; Meglino, Ravlin, & Adkins, 1989, 1991; Posner, Kouzes, & Schmidt, 1985), and rewards received by oneself and a referent other (Adams, 1965; Goodman, 1977; Oldham, Kulik, Ambrose, Stepina, & Brand, 1986). Typically, congruence is considered a predictor of outcomes relevant to the employee or organization, most notably job choice, job satisfaction, and employee well-being (for reviews, see Assouline & Meir, 1987; Edwards, 1991; Michalos, 1986; Spokane, 1985).

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Although studies of congruence have emphasized widely different processes and outcomes, they have consistently operationalized congruence by collapsing two or more component measures into a single index. Common examples of such indices include the algebraic, absolute, or squared difference between two component measures (e.g., Caplan, Cobb, French, Harrison, & Pinneau, 1980; French *et al.*, 1982; Porter & Lawler, 1968) and the similarity between profiles of component measures (e.g., Chatman, 1989, 1991; Meglino *et al.*, 1989, 1991; Rounds, Dawis, & Lofquist, 1987). Although indices such as these present numerous substantive and methodological problems (Cronbach, 1958; Cronbach & Furby, 1970; Edwards & Cooper, 1990; Johns, 1981; Wall & Payne, 1973), their use persists in congruence research (Edwards, 1991), and viable alternatives have been largely overlooked.

The purpose of this article is to summarize problems associated with commonly used congruence indices, offer solutions specific to each index, and propose an alternative approach that avoids these problems altogether. This approach borrows from response surface methodology (Box & Draper, 1987; Myers, 1971) and captures the underlying three-dimensional relationship between paired sets of component measures and the outcome. It will be shown that this approach represents a generalization of most congruence indices currently in use and, as such, can detect relationships represented by these indices as well as other relationships these indices cannot adequately depict.

AN OVERVIEW OF CURRENT CONGRUENCE INDICES

This section summarizes problems with commonly used congruence indices and offers solutions specific to each index. The discussion is divided into two parts, the first dealing with bivariate congruence indices, which collapse a pair of corresponding component measures, and the second concerning profile similarity indices, which combine a series of paired component measures. The indices reviewed are summarized in Table 1.

Bivariate Congruence Indices

The most commonly used bivariate congruence indices are the algebraic difference, absolute difference, and squared difference. These indices are discussed below.

Algebraic difference. Perhaps the most widely used congruence index consists of the algebraic difference between two component measures. This index has been used extensively in job satisfaction research to represent the gap between actual and desired job attributes (Edwards, 1991; Locke, 1976; Porter, 1964). Similarly, studies of participation in decision making have used the algebraic difference between actual and preferred

participation to represent decisional deprivation, equilibrium, and excess (Alutto & Acito, 1974; Alutto & Belasco, 1972; Alutto & Vredenburgh, 1977; Ivancevich, 1979). Goal-setting studies have used the algebraic difference between goals and performance to represent goal-feedback discrepancies (Kernan & Lord, 1990; Vance & Colella, 1990), and studies of the person-environment (P-E) fit approach to stress have used it to represent P-E misfit (Blau, 1981; Caplan *et al.*, 1980; French *et al.*, 1982). Algebraic differences have also been used to represent supervisor-subordinate disagreement regarding authority (Boyd & Jensen, 1972), appropriate task activities (Toffler, 1981), and behavioral expectations (Lawrie, 1966).

Many of the problems with algebraic difference indices can be derived from methodological discussions of difference scores (e.g., Cronbach, 1958; Cronbach & Furby, 1970; Johns, 1981; Wall & Payne, 1973; Werts & Linn, 1970). First, by collapsing conceptually distinct component measures, algebraic difference indices cannot be unambiguously interpreted (Wolins, 1982). On the surface, they may seem to represent equal but opposite contributions of each component. However, this is true only when component measures exhibit the same variance. Otherwise, the resulting difference will primarily represent the component with the larger variance. Unequal component variances are likely when multiple subordinates are compared to the same superior (e.g., Lawrie, 1966; Turban & Jones, 1988) or when preferences for normatively desirable job attributes (e.g., security, esteem) are compared to their availability in different occupations (e.g., Porter, 1964).

Second, algebraic difference indices confound the effects of their components, concealing their relative contribution to the relationship between the index and an outcome. In some cases, this relationship may be attributable to a single component. For example, Wall and Payne (1973) showed that relationships reported by Wanous and Lawler (1972) between job facet satisfaction and the difference between perceived and wanted facet amounts were no longer significant after controlling for perceived facet scores. Because controlling for one component transforms an algebraic difference index into a partialled measure of the remaining component (Wall & Payne, 1973; Werts & Linn, 1970), these findings indicate that the relationships found by Wanous and Lawler (1972) were attributable primarily to perceived facet scores. Similar results were reported by Sweeney, McFarlin, and Inderrieden (1990), who found that the relationship between pay satisfaction and an index representing current minus previous income disappeared after controlling for current income.

Third, algebraic difference indices are often assumed to explain variance beyond that associated with their components (e.g., French, Rogers, & Cobb, 1974; Humphrys, 1981). Although these indices may explain

TABLE I
SUMMARY OF CONGRUENCE INDICES

Index	Mathematical form	Constrained equation	Unconstrained equation	Implied constraints	Total number of constraints
Algebraic difference	$(X - Y)$	$Z = b_0 + b_1(X - Y) + e$ $= b_0 + b_1X - b_1Y + e$	$Z = b_0 + b_1X + b_2Y + e$	$b_1 = -b_2$	1
Absolute difference	$ X - Y $	$Z = b_0 + b_2(1 - 2W)(X - Y) + e$ $= b_0 + b_1X - b_1Y - 2b_1WX + 2b_1WY + e$	$Z = b_0 + b_1X + b_2Y$ $+ b_3W + b_4WX$ $+ b_5WY + e$	$b_1 = -b_2$ $b_4 = -b_5$ $b_4 = -2b_1^a$ $b_3 = 0$	4
Squared difference	$(X - Y)^2$	$Z = b_0 + b_1(X - Y)^2 + e$ $= b_0 + b_1X^2 - 2b_1XY + b_1Y^2 + e$	$Z = b_0 + b_1X + b_2Y$ $+ b_3X^2 + b_4XY$ $+ b_5Y^2 + e$	$b_3 = b_5$ $b_4 = -2b_3^b$ $b_1 = 0$ $b_2 = 0$	4
$ D $	$\sum_{i=1}^k X_i - Y_i $	$Z = b_0 + b_1 \sum_{i=1}^k (1 - 2W_i)(X_i - Y_i) + e$ $= b_0 + b_1X_1 - b_1Y_1 - 2b_1W_1X_1$ $+ 2b_1W_1Y_1 + b_1X_2 - b_1Y_2 - 2b_1W_2X_2$ $+ 2b_1W_2Y_2 + \dots + b_1X_k - b_1Y_k$ $- 2b_1W_kX_k + 2b_1W_kY_k + e$	$Z = b_0 + b_1X_1 + b_2Y_1$ $+ b_3W_1 + b_4W_1X_1$ $+ b_5W_1Y_1 + b_6X_2$ $+ b_7Y_2 + b_8W_2$ $+ b_9W_2X_2 + b_{10}W_2Y_2$ $+ \dots + b_{5k-4}X_k$ $+ b_{5k-3}Y_k + b_{5k-2}W_k$ $+ b_{5k-1}W_kX_k$ $+ b_{5k}W_kY_k + e$	$b_{5i-4} = -b_{5i-3}$ $b_{5i-1} = -b_{5i}$ $b_{5i-1} = -2b_{5i-4}^c$ $b_{5i-2} = 0$ $b_1 = b_6 = \dots$ $= b_{5k-4}^d$	$5k - 1$

D^2	$\sum_{i=1}^k (X_i - Y_i)^2$	$Z = b_0 + b_1 \sum_{i=1}^k (X_i - Y_i)^2 + e$ $= b_0 + b_1 X_1^2 + -2b_1 X_1 Y_1 + b_1 Y_1^2 + b_1 X_2^2 + -2b_1 X_2 Y_2 + b_1 Y_2^2 + \dots + b_1 X_k^2 + -2b_1 X_k Y_k + b_1 Y_k^2 + e$	$Z = b_0 + b_1 X_1 + b_2 Y_1 + b_3 X_1^2 + b_4 X_1 Y_1 + b_5 Y_1^2 + b_6 X_2 + b_7 Y_2 + b_8 X_2^2 + b_9 X_1 Y_2 + b_{10} Y_2^2 + \dots + b_{5k-4} X_k + b_{5k-3} Y_k + b_{5k-2} X_k^2 + b_{5k-1} X_k Y_k + b_{5k} Y_k^2 + e$	$b_{5i-2} = b_{5i}$ $b_{5i-1} = -2b_{5i-2}^f$ $b_{5i-4} = 0$ $b_{5i-3} = 0$ $b_3 = b_8 = \dots$ $= b_{5k-2}^f$	$5k - 1$
D	$\left[\sum_{i=1}^k (X_i - Y_i)^2 \right]^{1/2}$	$Z = b_0 + b_1 \left[\sum_{i=1}^k (X_i - Y_i)^2 \right]^{1/2} + e$	—	—	—
Q^x	$\frac{\sum_{i=1}^k (X_i - \bar{X})(Y_i - \bar{Y})}{\left[\sum_{i=1}^k (X_i - \bar{X})^2 \sum_{i=1}^k (Y_i - \bar{Y})^2 \right]^{1/2}}$	$Z = b_0 + b_1 \left[\frac{\sum_{i=1}^k (X_i - \bar{X})(Y_i - \bar{Y})}{\left[\sum_{i=1}^k (X_i - \bar{X})^2 \sum_{i=1}^k (Y_i - \bar{Y})^2 \right]^{1/2}} \right] + e$	—	—	—

Note. For all indices, X and Y are commensurate component measures and Z is the dependent variable. For the absolute difference index and $|D|$, $W = 0$ when $X \geq Y$ and $W = 1$ when $X < Y$. For $|D|$, D^2 , D , and Q , k represents the number of dimensions combined in the index. For D and Q , unconstrained equations and implied constraints cannot be expressed in terms of the original or transformed component measures.

- ^a Given the first two constraints, this constraint is equivalent to $b_5 = -2b_2$, $b_5 = 2b_1$, or $b_4 = 2b_2$.
- ^b Given the first constraint, this constraint is equivalent to $b_4 = -2b_5$.
- ^c Given the first two constraints, this constraint is equivalent to $b_{5i} = -2b_{5i-3}$, $b_{5i} = 2b_{5i-4}$, or $b_{5i-1} = 2b_{5i-3}$.
- ^d Given the first three constraints, this constraint is equivalent to $b_2 = b_7 = \dots = b_{5k-3}$, $b_4 = b_9 = \dots = b_{5k-1}$, or $b_5 = b_{10} = \dots = b_{5k}$.
- ^e Given the first constraint, this constraint is equivalent to $b_{5i-1} = -2b_{5i}$.
- ^f Given the first two constraints, this constraint is equivalent to $b_4 = b_9 = \dots = b_{5k-1}$ or $b_5 = b_{10} = \dots = b_{5k}$.
- ^g When X and Y are rankings with no ties, Q simplifies to a simple linear transformation of D^2 ; see Cohen and Cohen (1983, p. 40).

more variance than either component taken separately, they *cannot* explain more variance than both components considered *jointly*. This is illustrated by the following regression equations, the first using the algebraic difference between X and Y as a single predictor of Z (e represents a random disturbance term)

$$Z = b_0 + b_1(X - Y) + e. \quad (1)$$

Expanding this equation yields

$$Z = b_0 + b_1X - b_1Y + e. \quad (2)$$

Now consider an equation which simply uses X and Y as separate predictors:

$$Z = b_0 + b_1X + b_2Y + e. \quad (3)$$

Comparing Eqs. 2 and 3 reveals that they are identical, except that the former constrains the coefficients on X and Y to be equal in magnitude but opposite in sign (i.e., $b_1 = -b_2$; see Table 1). Like any constraint, this *cannot* increase explained variance and, in most cases, will decrease it. This obviously calls into question studies attempting to demonstrate the superiority of algebraic difference indices over their components. However, closer examination reveals that these studies have compared an algebraic difference index to either component taken separately (e.g., Blau, 1981) or have transformed the index first, usually by squaring it or taking its absolute value (e.g., Caplan *et al.*, 1980; Hatfield & Huseman, 1982; Tsui & O'Reilly, 1989; Turban & Jones, 1988; White, Crino, & Hatfield, 1985). These comparisons are misleading because they implicitly contrast different underlying models of the relationship between component measures and the outcome. Specifically, an algebraic difference index represents a plane in which both components exhibit equal but opposite linear relationships with the outcome (Fig. 1b). In contrast, a model containing a single component represents a surface sloped with respect to that component but flat with respect to the excluded component (Fig. 1a). Absolute and squared differences are substantively similar, in that both imply a maximum (or minimum) along the diagonal line where both components are equal. However, the former implies constant (i.e., linear) effects on either side of the maximum (Fig. 1c), whereas the latter indicates stronger effects as the distance from the maximum increases (Fig. 1d). Comparisons among these models do not demonstrate some unique aspect of "congruence," but instead represent different approximations of the surface relating the component measures to the outcome. If both components are included and the functional form of the relationship is held constant, it is *impossible* for an algebraic difference index to explain more variance than its components.

Fourth, the analysis of algebraic difference indices usually involves testing whether the relationship between the index and some outcome is significant. This is equivalent to determining whether the coefficient shared by both components in Eq. 2 differs from 0. This approach is incomplete, because support for an algebraic difference index requires not only that the shared coefficient in Eq. 2 differs from 0, *but also that the implied constraint is valid*. Verifying this constraint involves demonstrating that the component coefficients in Eq. 3 have opposite signs but do not differ significantly in absolute magnitude or, equivalently, that the variance explained by Eq. 2 is not significantly lower than that explained by Eq. 3. Failure to examine Eq. 3 not only conceals the constraint implied in Eq. 2, but also prevents the detection of alternative but conceptually consistent forms of congruence, such as those in which components exhibit opposite but unequal effects (e.g., French *et al.*, 1982; Sweeney *et al.*, 1990).

The preceding problems may be avoided by using Eq. 3, which includes both components as separate predictors (Wall & Payne, 1973; Werts & Linn, 1970). If the model implied by the algebraic difference index is tenable, then the increment in variance explained by both coefficients entered simultaneously will be significant, each component will exhibit a significant independent effect, and the coefficients on the components will be opposite in sign and not significantly different in absolute magnitude. The difference between these coefficients may be tested directly (Cohen & Cohen, 1983, pp. 479–480) or, equivalently, by testing the difference between the multiple correlations yielded by Eqs. 2 and 3 (Cohen & Cohen, 1983, p. 145) or the reduction in variance explained by Eq. 3 when the coefficients on *X* and *Y* are constrained to be equal in magnitude but opposite in sign, as in Eq. 2 (Dwyer, 1983, Chap. 8; Wilkinson, 1988, Chap. 23). Of course, these tests presume adequate statistical power to allow true differences between the coefficients to emerge (Cohen, 1988).

Absolute difference. Another common congruence index consists of the absolute difference between two component measures. Numerous studies have used this index to represent the fit between perceived and desired job attributes (e.g., Alutto, Hrebiniak, & Alonson, 1971; Barrett, 1978; French *et al.*, 1982; Hrebiniak & Alutto, 1972; Kaufmann & Beehr, 1989; Meir & Engel, 1986; O'Brien & Dowling, 1980; Phillips, Barrett, & Rush, 1978; Swaney & Prediger, 1985; Toffler, 1981) or job demands and either employee competence (Rosman & Burke, 1980) or employee discretion (Payne & Fletcher, 1983). Absolute difference indices have also been used to represent the discrepancy between personal and assigned goals (Tubbs & Dahl, 1991) and interpersonal similarity or agreement regarding authority (Boyd & Jensen, 1972), attitudes (Zalesny & Kirsch, 1989), and demographics (Turban & Jones, 1988; Zalesny & Kirsch, 1989).

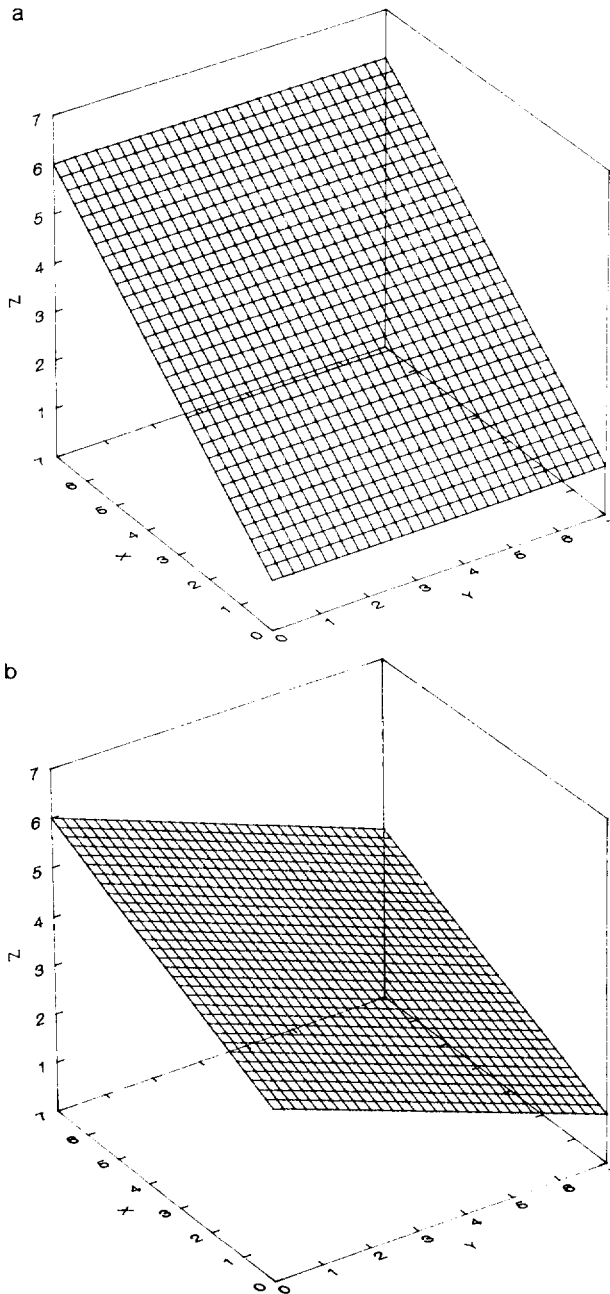


FIG. 1. Surfaces corresponding to congruence indices. (a) Single component; (b) algebraic difference; (c) absolute difference; (d) squared difference.

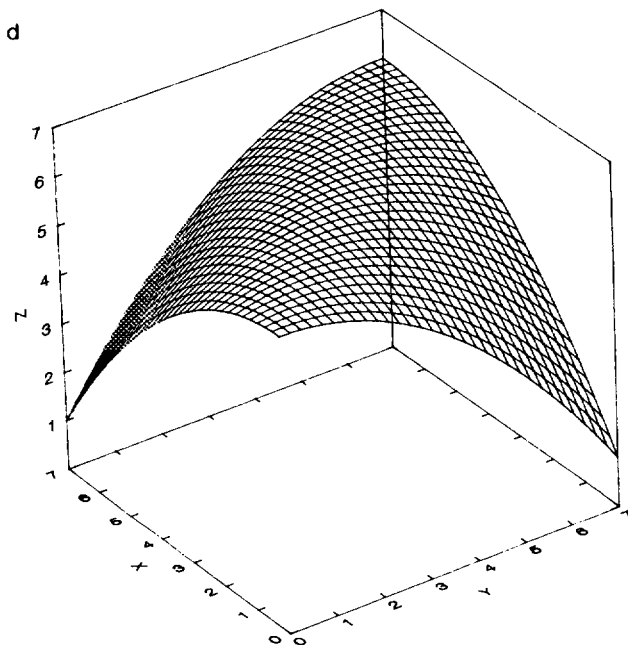
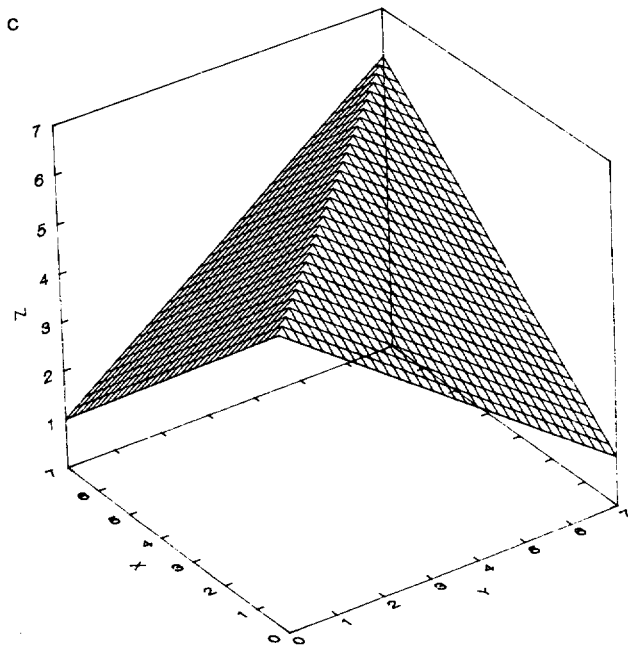


FIG. 1—Continued

Absolute difference indices have also been used to represent role theory constructs (Kahn, Wolfe, Quinn, Snoeck, & Rosenthal, 1964). For example, Dansereau, Graen, and Haga (1975) and Toffler (1981) operationalized role noncompliance as the absolute difference between supervisor's ratings of actual and preferred subordinate behavior. Ford, Walker, and Churchill (1975) operationalized role conflict as the absolute difference between role expectations of subordinates and supervisors, and Dougherty and Pritchard (1985) operationalized role ambiguity regarding specific job products as the absolute difference between the lowest and highest rating one's supervisor might give to the importance of that product.

Because absolute difference indices represent simple transformations of algebraic difference indices, they exhibit similar problems, although these problems are manifested in different ways. First, like algebraic difference indices, absolute difference indices cannot be unambiguously interpreted. Typically, they are considered "directionless" measures of congruence, since they treat positive and negative scores the same. However, this interpretation presumes an equal proportion of positive and negative scores. When scores are highly skewed in either direction (e.g., Alutto & Acito, 1974; Alutto & Vredenburg, 1977; French *et al.*, 1982; Porter, 1964), an absolute difference index effectively reduces to a unidirectional (i.e., algebraic) difference. Furthermore, as with algebraic difference indices, absolute difference indices do not represent component measures equally unless the variances of these measures happen to be equal. Because the distribution and variances of component measures are susceptible to sampling variability, the interpretation of absolute difference indices may vary across studies, even those using the same measures.

Absolute difference indices also confound the effects of their components. However, this confounding does not involve the simple linear effects of the original component measures, but rather their joint piecewise linear effects (Neter, Wasserman, & Kutner, 1989). This is easily seen by considering the following regression equation:

$$Z = b_0 + b_1(1 - 2W)(X - Y) + e \quad (4)$$

where $W = 0$ if $X \geq Y$
 $W = 1$ if $X < Y$.

The term $(1 - 2W)$ reduces to 1 when X is greater than or equal to Y and -1 when X is less than Y . Hence, when the quantity $(X - Y)$ is positive or zero, its sign is unaltered, but when it is negative, its sign is reversed, yielding the same effect as an absolute value transformation. Expanding Eq. 4 yields

$$Z = b_0 + b_1(1 - 2W)X - b_1(1 - 2W)Y + e. \quad (5)$$

This expansion shows that an absolute difference index confounds the piecewise linear effects of its components. It is certainly possible that the relationship obtained for an absolute difference index may be primarily attributable to the piecewise effect of either component rather than the equal but opposite effects depicted in Eq. 5.

Third, absolute difference indices have been used to demonstrate that congruence explains variance beyond that associated with component measures (e.g., Turban & Jones, 1988). This claim is misleading for two reasons. First, as demonstrated by Eq. 5, absolute difference indices do not represent component measures in their original form, but rather as multiplicative composites with $(1 - 2W)$. Hence, the components of an absolute difference index are these composites, not the original component measures. Equation 5 also reveals that an absolute difference index constrains the coefficients on these composites to be equal in magnitude but opposite in sign. Obviously, a model imposing this constraint cannot explain more variance than a model that simply contains both composites as separate predictors. Second, as argued earlier, the surface underlying the relationship between an absolute difference index and an outcome (Fig. 1c) is substantively different from that represented by the joint linear effects of the original component measures (Fig. 1b). Such comparisons suggest different relationships between the components and the outcome rather than the presumed unique explanatory power of congruence.

Fourth, tests of absolute difference indices are incomplete, because they almost invariably examine whether the coefficient associated with the index differs from zero without testing the implied constraints. These constraints become evident by further expanding Eq. 5, which yields

$$Z = b_0 + b_1X - b_1Y - 2b_1WX + 2b_1WY + e. \quad (6)$$

Now consider a general piecewise linear model containing the same terms (W is also included, because it is used as a moderator of X and Y ; see Cohen, 1978; Evans, 1991):

$$Z = b_0 + b_1X + b_2Y + b_3W + b_4WX + b_5WY + e. \quad (7)$$

This equation allows X and Y to independently take on different slopes on either side of the line where $X = Y$, as well as a vertical shift in the surface along this line. This reveals that Eq. 6 imposes the following constraints: (1) the coefficients on X and Y are equal in magnitude but opposite in sign; (2) the coefficients on WX and WY are equal in magnitude but opposite in sign; (3) the coefficient on WX is twice as large as the coefficient on X , but

opposite in sign;¹ and (4) the coefficient on W is zero (see Table 1). Rather than simply imposing these constraints, they should be considered a set of hypotheses that, if supported, imply a surface consistent with an absolute difference index.

The preceding problems can be avoided by using Eq. 7 in place of absolute difference indices. Support for the implied underlying model would require: (1) significant coefficients on X , Y , WX , and WY (both individually and as a set), but not W ; (2) coefficients on X and Y that are opposite in sign and not significantly different in absolute magnitude; (3) coefficients on WX and WY that are opposite in sign and not significantly different in absolute magnitude; and (4) a coefficient on WX that is not significantly different from twice the negative of the coefficient on X .² Differences between individual coefficients may be tested by adapting the formula presented by Cohen and Cohen (1983, pp. 479–480), and all four constraints (i.e., $b_1 = -b_2$, $b_4 = -b_5$, $b_4 = -2b_1$, $b_3 = 0$) may be tested simultaneously by imposing them on Eq. 7 and examining the reduction in explained variance (Dwyer, 1983; Wilkinson, 1988), or by testing the difference between the multiple correlations yielded by Eq. 4 (which is equivalent to using an absolute difference as a single predictor) and Eq. 7.

Four issues should be considered when implementing the preceding procedure. First, constructing W requires that the difference between X and Y accurately represent the degree to which one component exceeds the other, which in turn requires that component scales are equivalent (i.e., share the same origin and interval size). Fortunately, this can be reasonably assumed when the same scale is used for both component measures (Cronbach & Furby, 1970), as in most congruence research. A second issue is whether to set W to zero or one for cases where $X = Y$. Either procedure will yield the same results for the constrained model in Eq. 4, but results will differ for the unconstrained model in Eq. 7, particularly when the number of cases where $X = Y$ is large. A simple but reasonable solution is to randomly set W to 0 or 1 for these cases. Third, this procedure requires tests of coefficients on X , Y , and W , which are scale dependent when WX and WY are included in the equation (Cohen, 1978). This is of little consequence for tests of b_1 and b_2 , because the

¹ Given the first two constraints, this is equivalent to stating that: (1) the coefficient on WY is twice as large as the coefficient on Y , but opposite in sign; (2) the coefficient on WY is twice as large as the coefficient on X ; or (3) the coefficient on WX is twice as large as the coefficient on Y .

² Given the third and fourth constraints, this is equivalent to hypothesizing: (1) a coefficient on WY that is not significantly different from twice the negative of the coefficient on Y ; (2) a coefficient on WX that is not significantly different from twice the coefficient on Y ; or (3) a coefficient on WY that is not significantly different from twice the coefficient on X .

scaling of W (which influences these coefficients) is fixed (i.e., no other scaling yields the desired transformation). However, the scaling of X and Y , which affects tests of b_3 , is often arbitrary. This does not render tests of b_3 meaningless, but simply indicates that the vertical distance between the estimated surfaces on either side of the $X = Y$ line may vary at different points in the X, Y plane (Aiken & West, 1991; Jaccard, Turrisi, & Wan, 1990). For absolute difference indices, the points of primary interest are along the $X = Y$ line, because these indices presume no vertical shift in the surface at all points along this line. Tests of b_3 at the point 0,0 are obtained directly from Eq. 7, and tests at other points along the $X = Y$ line can be conducted using information provided by most regression packages (see Appendix). Support for the model underlying an absolute difference index should be inferred only if b_3 does not differ from zero at all points along the $X = Y$ line, within the range of the obtained data. Fortunately, the scaling of X and Y has no effect when the constraints associated with an absolute difference index are tested as a set, provided the scale equivalence of X and Y is preserved. Finally, Eq. 7 will often exhibit multicollinearity, particularly among W , WX , and WY . This represents "nonessential ill-conditioning" (Marquardt, 1980), which is typically eliminated by centering X and Y (Cronbach, 1987). To maintain the interpretability of b_3 , X and Y should be centered around the same value, such as the midpoint of their shared scale or the point halfway between their means. Note that this rescaling simply changes the point along the $X = Y$ line at which b_3 is estimated and has no effect on other coefficients in Eq. 7, the obtained R^2 , or tests of all four constraints as a set.

Squared difference. A conceptually similar but less common congruence index is the squared difference between two components. Caplan *et al.* (1980) used this index to represent curvilinear effects of person-environment fit regarding workload, responsibility for persons, job complexity, and role ambiguity. Dougherty and Pritchard (1985) operationalized role conflict regarding specific job products as the squared difference between subordinate and perceived supervisor ratings of the importance of a project. Similarly, Tsui and O'Reilly (1989) operationalized relational demography as the squared difference between demographic measures (e.g., age, education, tenure) obtained from superior-subordinate dyads.

Not surprisingly, problems with squared difference indices parallel those associated with algebraic and absolute difference indices. For example, squared difference indices cannot be unambiguously interpreted. Like absolute difference indices, squared difference indices are typically considered directionless measures of congruence (e.g., Caplan *et al.*, 1980). However, this interpretation again requires an approximately equal proportion of scores on either side of the line where component measures are equal. Squared difference indices also do not represent component

measures equally unless their variances are the same. Differences in component measure variances can have pronounced effects, because squaring the difference further exaggerates the measure with the larger variance.

Squared difference indices also confound the effects of their components. However, this confounding does not involve the original component measures, but rather the square of each measure and their product. This can be seen by considering the following regression equation, which contains a squared difference as a single predictor:

$$Z = b_0 + b_1(X - Y)^2 + e. \quad (8)$$

Expanding this expression yields

$$Z = b_0 + b_1X^2 - 2b_1XY + b_1Y^2 + e. \quad (9)$$

This shows that a squared difference index implicitly represents the square of each component and their product (Cronbach, 1958). Hence, relationships obtained for this index simply reflect the combined effects of these three variables, but because they are confounded, it is impossible to determine their relative contribution. Although it may be tempting to conclude that the square of each component and their product are represented equally, since the product is given twice the weight of the squared terms, this conclusion is invalid unless the variance of the product equals the sum of the variances of the squared terms, which cannot be assumed *a priori*.

Squared difference indices have also been used to demonstrate the unique explanatory power of congruence, after controlling for component measures (e.g., Tsui & O'Reilly, 1989). As with absolute difference indices, this interpretation is misleading, because the components of a squared difference index are the square of each component and their product, *not* the original component measures. Furthermore, the model underlying the joint linear effects of the original component measures (Fig. 1b) differs substantially from that implied by their squared difference (Fig. 1d). Comparing these models does not reveal some unique contribution of congruence, but simply indicates different surfaces relating the components to the outcome.

Finally, most tests of squared difference indices are incomplete, because they do not evaluate the implied constraints. These constraints become apparent by comparing Eq. 9 to the following quadratic regression equation (X and Y are included, because they constitute the curvilinear and interactive terms; see Cohen, 1978):

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e. \quad (10)$$

This comparison reveals that a squared difference index imposes the following constraints: (1) the coefficients on X^2 and Y^2 are equal; (2) the

coefficient on XY is twice as large as the coefficient on either X^2 or Y^2 and opposite in sign; and (3) the coefficients on X and Y are zero (see Table 1). As before, these constraints should be tested, not simply imposed on the data.

Problems with squared difference indices may be avoided by using Eq. 10. Results consistent with a squared difference index would include: (1) significant coefficients on X^2 , XY , and Y^2 (both individually and as a set), but not X or Y ; (2) coefficients on X^2 and Y^2 that are not significantly different; and (3) a coefficient on XY that is not significantly different from twice the negative of the coefficient on either X^2 or Y^2 . As before, differences between coefficients can be tested separately, and all four constraints (i.e., $b_3 = b_5$, $b_4 = -2b_3$, $b_1 = 0$, $b_2 = 0$) can be tested as a set by imposing them onto Eq. 10 and examining the reduction in explained variance, or by testing the difference between the multiple correlations yielded by Eq. 8 and Eq. 10.

Implementing the preceding procedure raises two issues. First, the coefficients on X and Y are scale dependent when X^2 , XY , and Y^2 are included in the equation (Cohen, 1978). As before, this simply reflects variation in the slope of X and Y at various points in the X, Y plane (Aiken & West, 1991; Jaccard *et al.*, 1990). For squared difference indices, tests should focus on points along the $X = Y$ line, because the slopes of both X and Y are presumed to be zero at all points along this line. Tests at the point 0,0 are obtained directly from Eq. 10, and tests at other points along the $X = Y$ line are straightforward (see Appendix). If the coefficients on X and Y do not differ from zero at all points along the $X = Y$ line, then the model underlying the squared difference index is supported, provided the remaining conditions are met. Second, including X^2 , XY , and Y^2 in an equation with X and Y will often produce nonessential ill conditioning. Again, this is easily corrected by centering X and Y around some common value close to their respective means.

Profile Similarity Indices

Of the various profile similarity indices proposed (e.g., Cronbach & Gleser, 1953), the most commonly used in congruence research are the sum of absolute differences, the sum of squared differences, the square root of the sum of squared differences, and the correlation between component measure profiles. These indices are discussed below.³

Sum of absolute differences. Numerous investigators have used the sum of absolute differences (hereafter $|D|$) to represent congruence. For

³ It should be noted that this discussion pertains to the use of profile similarity indices as predictors in congruence research. For discussions of similarity indices in cluster analysis, discriminant analysis, and other multivariate procedures, see Dillon and Goldstein (1984) and Harris (1985).

example, Lopez and Greenhaus (1978) operationalized need satisfaction as $|D|$ for preferred and actual ratings of 23 job attributes. Similarly, Healy (1973) used $|D|$ to represent self-occupation congruence, and Pervin (1967) used it to represent self-college similarity. $|D|$ has also been used to represent supervisor-subordinate agreement regarding the effectiveness of conflict resolution strategies (Bernardin & Alvares, 1975) and the importance of job activities (Zalesny & Kirsch, 1989).

$|D|$ has also been used to represent role theory constructs. For instance, Johnson and Graen (1973; see also Graen, Orris, & Johnson, 1973) operationalized role ambiguity and conflict using $|D|$ for measures of preferred involvement in various role activities reported by focal persons and members of their role set. Similarly, Greene and Organ (1973; see also Greene, 1972) operationalized role accuracy as $|D|$ for measures of role expectations obtained from subordinates and supervisors, and role compliance as $|D|$ for measures of supervisor expectations and subordinate activities.

Because the elements constituting $|D|$ are absolute differences, the problems associated with absolute difference indices also pertain to $|D|$ and, hence, will not be repeated here. However, $|D|$ presents some additional problems. For example, $|D|$ not only confounds the piecewise linear effects embedded in each absolute difference, but also the separate effects of the absolute differences constituting the sum. In many cases, these absolute differences are based on conceptually distinct dimensions. For instance, job attributes examined by Johnson and Graen (1973) included task activities, personal fulfillment, and relations with co-workers, and those examined by Lopez and Greenhaus (1978) ranged from challenge, variety, and opportunity for growth, to relations with co-workers and supervisors, to perceptions of the company. These attributes typically exert different effects on outcomes (e.g., French *et al.*, 1982; Wanous & Lawler, 1972), which are necessarily obscured when the attributes are collapsed into a single index (Cronbach, 1958; Joyce & Slocum, 1982). Furthermore, $|D|$ confounds information regarding profile shape and level (i.e., separation), such that profiles with identical shapes but different levels can yield the same $|D|$ value as profiles with different shapes but similar levels.

$|D|$ also imposes additional constraints beyond those associated with simple absolute difference indices. These constraints are illustrated by the following regression equation, which uses $|D|$ for k dimensions as a single predictor:

$$Z = b_0 + b_1 \sum_{i=1}^k (1 - 2W_i)(X_i - Y_i) + e. \quad (11)$$

As before, each W_i is set to zero when the corresponding X_i is greater than or equal to Y_i and one when X_i is less than Y_i . Expanding and distributing b_1 through the expression yields

$$\begin{aligned} Z = & b_0 + b_1X_1 - b_1Y_1 - 2b_1W_1X_1 + 2b_1W_1Y_1 & (12) \\ & + b_1X_2 - b_1Y_2 - 2b_1W_2X_2 + 2b_1W_2Y_2 + \dots \\ & + b_1X_k - b_1Y_k - 2b_1W_kX_k + 2b_1W_kY_k + e. \end{aligned}$$

Equation 12 shows that $|D|$ not only incorporates the pattern of constraints represented in Eq. 6 for each of the k dimensions constituting $|D|$, but also forces the same set of coefficients on each dimension (see Table 1). In other words, for each dimension constituting $|D|$, the surface relating its component measures to the outcome is presumed to be identical, regardless of the conceptual distinctions among the dimensions. This obviously represents a highly restrictive set of assumptions, which are rarely verified empirically.

The preceding problems may be avoided by using an expanded version of Eq. 7, in which separate sets of X , Y , W , WX , and WY are used to represent each dimension constituting $|D|$, and constraints are tested using the procedures described previously. Certainly, this approach can place enormous demands on sample size, in that five independent variables are needed to represent each dimension. However, the additional degrees of freedom seemingly gained by using $|D|$ only result from imposing a set of constraints that are highly restrictive and rarely tested. An alternative approach is to estimate Eq. 7 separately for each dimension. Although this approach will accommodate smaller samples, reduce multicollinearity, and yield more readily interpretable results, it carries the obvious disadvantage of not controlling for component measure correlations across different dimensions (James, 1980).

Sum of squared differences. The sum of squared differences (D^2 ; Cronbach & Gleser, 1953) has also been widely used to represent profile similarity. Greenhaus (1971) used D^2 to operationalize self-occupation congruence, and Tom (1971) used it to represent similarity between oneself and one's most and least preferred organizations. Studies based on the Theory of Work Adjustment (Dawis & Lofquist, 1984; Rounds *et al.*, 1987; Scarpello & Campbell, 1983) have frequently used D^2 to operationalize person-job congruence, based on corresponding scales of the Minnesota Importance Questionnaire (MIQ; Gay, Weiss, Hendel, Dawis, & Lofquist, 1971) and the Minnesota Job Description Questionnaire (MJDQ; Borgen, Weiss, Tinsely, Dawis, & Lofquist, 1968). Analogously, Pfeffer and Salancik (1975) used D^2 to represent the disparity between expected and actual job behaviors.

D^2 has also been used to represent interpersonal agreement. For ex-

ample, several investigators have used D^2 to represent supervisor-subordinate agreement regarding characteristics of good customer service (Parkington & Schneider, 1979), the importance of various behaviors for receiving a pay raise (Turban & Jones, 1988), and the meaning of mutually experienced events (Graen & Schiemann, 1978). Similarly, Sparrow (1989) used D^2 as an index of job similarity based on profiles from the Position Analysis Questionnaire (PAQ; McCormick, 1979).

Role theory constructs have also been operationalized using D^2 . For example, Dougherty and Pritchard (1985) used D^2 to represent overall role conflict, based on subordinate and perceived supervisor ratings of the importance of 27 job products. Similarly, Bernardin (1979) used D^2 to operationalize both role ambiguity and conflict, the former based on 45 effectiveness ratings from sergeants and officers, and the latter based on the same ratings for sergeants and officers' partners.

As with $|D|$, D^2 is prone to the same problems as its constituent elements (i.e., squared difference indices), which will not be repeated here. However, D^2 presents some additional problems that, not surprisingly, closely parallel those associated with $|D|$. For example, D^2 confounds the effects of each squared difference constituting the sum (Cronbach, 1958) as well as information regarding profile shape and level (Cronbach & Gleser, 1953; Nunnally, 1962). Furthermore, like $|D|$, D^2 imposes an additional set of constraints beyond those associated with squared difference indices. These constraints are illustrated by the following regression equation, which uses D^2 as a single predictor:

$$Z = b_0 + b_1 \sum_{i=1}^k (X_i - Y_i)^2 + e. \quad (13)$$

Expanding and distributing b_1 yields

$$\begin{aligned} Z = & b_0 + b_1 X_1^2 - 2b_1 X_1 Y_1 + b_1 Y_1^2 \\ & + b_1 X_2^2 - 2b_1 X_2 Y_2 + b_1 Y_2^2 + \dots \\ & + b_1 X_k^2 - 2b_1 X_k Y_k + b_1 Y_k^2 + e. \end{aligned} \quad (14)$$

Thus, D^2 not only incorporates the constraints represented in Eq. 9 for each of the k dimensions constricting D^2 , but imposes the same set of coefficients for each dimension (see Table 1). Again, this represents a highly restrictive set of assumptions that are rarely tested. Equation 14 also reveals that D^2 contains curvilinear and interactive terms without their corresponding lower-order terms (i.e., the X_i and Y_i), rendering b_1 in Eq. 13 scale dependent (Cohen, 1978; Evans, 1991).

To avoid the preceding problems, D^2 should be replaced with an equation containing X , Y , X^2 , XY , and Y^2 for all k dimensions (Cronbach, 1958;

Nunnally, 1962), with the constraints implied by D^2 tested as described before. Again, as k becomes large, this procedure will require very large samples and may yield results that are difficult to interpret. Alternately, separate equations for each of the k dimensions may be estimated, acknowledging the potential problems introduced by not controlling for component measure correlations across different dimensions (James, 1980).

Square root of sum of squared differences. A variation of D^2 that is often used in congruence research is its square root, or D . This index has been widely used to represent similarity between supervisors and subordinates (Hatfield & Huseman, 1982; Miles, 1964; Senger, 1971; Vancouver & Schmitt, 1991; Wexley, Alexander, Greenwalt, & Couch, 1980, Wexley & Pulakos, 1983; White *et al.*, 1985) and interviewers and interviewees (Frank & Hackman, 1975). D has also been used to measure demographic similarity among group members (Jackson, Brett, Sessa, Cooper, Julin, & Peyronnin, 1991; O'Reilly, Caldwell, & Barnett, 1989; Wagner, Pfeffer, & O'Reilly, 1984; Zenger & Lawrence, 1989) and the correspondence between needs and reinforcer patterns (Betz, 1969, Vandenberg & Scarpello, 1990).

Because D represents a simple transformation of D^2 , it is susceptible to essentially the same problems (Cronbach, 1958; Nunnally, 1962). However, unlike D^2 , an unconstrained regression equation corresponding to D cannot be readily derived, because D cannot be expressed as a linear combination of component measures, either transformed or in their original form. Although Berger-Gross and Kraut (1984) claimed that D could be decomposed into the sum of X_i , the sum of Y_i , and the square root of twice the sum of $X_i Y_i$, this is incorrect. On the other hand, D bears certain similarities to $|D|$. For example, when differences between profile shapes are the same for all pairs of profiles compared, D and $|D|$ are linearly related, and when a single dimension accounts for the entire difference between profiles, D and $|D|$ are equal. However, because these conditions are unlikely to arise in real data, $|D|$ should not be considered a proxy for D .

Problems with D can be avoided by using the procedures recommended as replacements for $|D|$ and D^2 . Although neither of these procedures is mathematically equivalent to D , they can adequately depict the underlying surface implied by D when each of its dimensions is considered separately, as these procedures recommend (cf., Cronbach, 1958; Lykken, 1956; Nunnally, 1963).⁴

⁴ One reviewer suggested Mahalanobis' D^2 as a viable congruence index. Although this index has been occasionally used in congruence research (e.g., Berger-Gross, 1982), it should be avoided. As noted by Cronbach and Gleser (1953), Mahalanobis' D^2 is algebra-

Profile correlation. A final profile similarity index considered here is the correlation between sets of component measures (Q ; Cronbach & Gleser, 1953; Stephenson, 1953). This index has been used to represent fit between employee preferences and characteristics of the job (Betz, 1969; Rounds *et al.*, 1987), organization (Caldwell & O'Reilly, 1990; Chatman, 1989, 1991; O'Reilly, Chatman, & Caldwell, 1991), and occupation (Amerikaner, Elliot, & Swank, 1988). Q has also been used to represent interpersonal similarity regarding values (Meglino *et al.*, 1989, 1991), traits, interests, and preferences (Dalessio & Imada, 1984), leader behavior (London & Wohlers, 1991), the perceived instrumentality of behavior–outcome linkages (Hammer & Dachler, 1975), and the meaning of mutually experienced events (Graen & Schiemann, 1978). Q has also been used to represent the similarity between jobs based on PAQ profiles (Sparrow, 1989).

Many of the problems with $|D|$, D^2 , and D could be inferred from their relationships with simpler congruence indices considered previously. Although Q bears no obvious relationship to these indices, it nonetheless shares many of their shortcomings. For example, the interpretation of Q is ambiguous, because it collapses across components and dimensions that, in most cases, are conceptually distinct. Q also confounds the effects of the component measures constituting each profile, such that relationships observed for Q may represent anything from the effect of a single component to the combined effects of all components. Furthermore, Q implies a very specific surface relating each set of component measures to the outcome, which is rarely compared to more general surfaces. Unfortunately, such comparisons are difficult, because it is impossible to construct an unconstrained regression equation corresponding to Q in terms of the original or transformed component measures. However, as with D , the surface implied by Q can be adequately represented by procedures recommended as replacements for other profile similarity indices, particularly D^2 .

In addition to these problems, Q presents some additional shortcomings not found in $|D|$, D^2 , or D . For example, Q solely represents similarity in profile shape, with no indication of the distance between profiles (Cronbach & Gleser, 1953; Nunnally, 1978). Consequently, profiles with large discrepancies but similar shapes may produce high values of Q , whereas profiles with small discrepancies but minor difference in shape may pro-

ically equivalent to D^2 (i.e., the sum of squared differences) when one first factors the k variables into k orthogonal components, computes scores on these components, and then uses these scores to calculate D^2 . Hence, Mahalanobis' D^2 not only introduces the same problems as D^2 , but also effectively transforms the data into component scores, which further obscures the effects of the original variables.

duce small or even negative values of Q (Kulka, 1979; Osgood & Suci, 1952). Because most studies of congruence are concerned with the distance between profiles rather than similarities in their shape, Q provides information of little apparent utility (Cronbach & Gleser, 1953). Furthermore, the meaning of Q values low in absolute magnitude is unclear, because low profile similarity is completely confounded with random measurement error (Kulka, 1979).

Problems associated with Q can be avoided by using the procedure recommended as a replacement for D^2 , which can represent surfaces compatible with Q when each dimension is considered separately (Cronbach, 1958; Lykken, 1956; Nunnally, 1962). However, it should be noted that this procedure is inappropriate when component measures are based on rankings (Meglino *et al.*, 1989, 1991) or Q -sorts (Caldwell & O'Reilly, 1990; Chatman, 1989, 1991; O'Reilly *et al.*, 1991), for several reasons. First, these measures are ordinal (McKeown & Thomas, 1988; Nunnally, 1978), whereas regression analysis assumes at least interval measurement (Cohen & Cohen, 1983).⁵ Second, these measures are ipsative and, hence, violate the assumptions of standard statistical techniques, including those proposed here (Hicks, 1970; Johnson, Wood, & Blinkhorn, 1988). Third, an important advantage of the proposed procedure is that it preserves information regarding the distance between component measures, which is not contained in rankings or Q -sorts in the first place (Hicks, 1970; Nunnally, 1978). Because this information is essential to the study of congruence, these measures have little apparent value for congruence research, no matter how they are analyzed.

A PROPOSED GENERAL ALTERNATIVE

The foregoing discussion has identified numerous problems with congruence indices currently used in organizational behavior research. Each index is inherently ambiguous, confounds the effects of its constituent components, and implies a set of constraints that are rarely tested. Profile similarity indices present additional problems, such as confounding the effects of each dimension constituting the profile, incorporating a more elaborate set of untested constraints, and obscuring information regarding profile shape and level. Alternative procedures were proposed for each index, but these procedures were intended only to test the particular model underlying each index. As a result, they provide no basis for ruling

⁵ Of course, separate dummy variables could be created to represent $k - 1$ of the rank or Q -sort levels, but the surface estimated by this procedure would be distorted unless the true distance between levels happened to be equal, and the number of variables required to represent even a modest number of levels would become unwieldy, particularly when quadratic and interactive effects are considered.

out higher-order models, such as those containing cubic or quartic terms, and may be insensitive to alternative models yet to be considered in congruence research. What is needed is a single, general approach that not only encompasses the models depicted by the procedures described thus far, but can also detect models these procedures cannot readily represent.

The general procedure proposed here is based on three guiding principles. First, the relationship between congruence and an outcome should be considered in three dimensions, with paired components constituting the two horizontal (i.e., X , Y) axes and the outcome constituting the vertical (i.e., Z) axis. Congruence indices effectively reduce this relationship to two dimensions by collapsing the component measures, thereby introducing the substantive and methodological problems described earlier. Because most component measures comprising congruence indices represent conceptually distinct constructs (e.g., employee preferences and job characteristics) or the same construct from distinct perspectives (e.g., the values of supervisor and subordinate), these distinctions should be retained in data analysis (cf. Cronbach & Furby, 1970).

Second, the relationship between congruence and an outcome should be viewed not as a simple two-dimensional function, but instead as a three-dimensional response surface (Box & Draper, 1987; Myers, 1971). As emphasized throughout the preceding discussion, all congruence indices imply a surface (or series of surfaces) relating component measures to the outcome (see Fig. 1). It is these surfaces, not the two-dimensional functions represented by congruence indices, that should constitute the focus of data analysis and interpretation.

Third, the constraints implied by congruence indices should not be simply imposed on the data, but instead should be considered a set of hypotheses that, if confirmed, lend support to the conceptual model upon which the index is based. Given adequate theory, analysis can focus on testing one or more models developed *a priori*. Otherwise, analysis can proceed in an exploratory fashion, seeking the model that best describes the observed surface. Of course, such models should be considered tentative, pending cross-validation (Box & Draper, 1987; MacCallum, 1986; Piehl, 1974).

The approach proposed here proceeds as follows. First, it is assumed that component measures are commensurate, at least at the interval level, and share the same scale. Commensurate measures express both components in terms of the same content dimension (e.g., the amount of variety wanted and received by the employee; the degree to which both supervisor and subordinate view the company as adaptive) (Caplan, 1987; French *et al.*, 1982; Graham, 1976). This ensures the conceptual relevance of the component measures to one another and is necessary to

meaningfully interpret results in terms of congruence (Edwards, 1991; Rounds *et al.*, 1987). Interval measurement is required for the proposed regression analyses, and component scale equivalence is required for comparisons among coefficient estimates.

Next, one or more conceptual models of congruence is chosen, and the corresponding regression equations are identified. The simple discrepancy model implied by an algebraic difference index would require a linear equation including both component measures in their original form (Eq. 3). The symmetric discrepancy model implied by the absolute difference index and $|D|$ would employ Eq. 7, and the symmetric model associated with the squared difference index and D^2 would employ Eq. 10. D and Q also imply effects that, as argued earlier, can be adequately represented using either Eq. 7 or Eq. 10. In many cases, the choice between these two equations is of little consequence, because both can depict an inflection along the $X = Y$ line, which is usually of central interest in congruence research. However, each presents certain advantages, in that the squared difference equation can represent curvilinearity, whereas the absolute difference equation can depict an abrupt change in slope. A conservative strategy is to use both equations and determine whether they yield the same conclusions.

Once the appropriate equation is identified and estimated, tests required to evaluate the model of interest should be conducted. This involves establishing that: (1) the proportion of variance explained by the overall equation is significant; (2) appropriate coefficients are significant and in the right direction; (3) the implied constraints are valid; and (4) no higher-order terms beyond those indicated by the model are significant. The first condition represents a simple omnibus test, and the second rules out trivial cases (i.e., constraints are satisfied because all coefficients are essentially zero). The third condition evaluates the pattern of coefficients implied by the model of interest, and the fourth ensures that the complexity of the underlying surface has not been underestimated. This fourth test is necessary, because it is possible to obtain coefficient estimates that are significant, in the appropriate direction, and satisfy relevant constraints, but fail to depict higher-order curvatures in the underlying surface. Unless these higher-order models are ruled out, support for the model of interest cannot be inferred (cf. Anderson & Gerbing, 1988). In most cases, these tests need not proceed more than one order higher than the model of interest (quadratic for linear models, cubic for quadratic models, etc.), although exceptions may arise. In any case, analyses will be illuminated considerably by comparing three-dimensional plots of the raw data to the surface estimated by the model of interest.

Some applications may require comparisons of multiple models. When the models are nested, standard procedures for testing restrictions in

multiple regression analysis may be used (Neter *et al.*, 1989). For example, the algebraic difference model may be compared to the squared difference model by testing the coefficients on X^2 , XY , and Y^2 as a set. Similarly, the algebraic difference model may be compared to the absolute difference model by testing WX and WY as a set. In either case, support for the chosen model also requires satisfying the remaining conditions corresponding to that model. When the models are not nested, as when the absolute and squared difference models are compared, there is no accepted statistical criterion for choosing between them. If both models satisfy their respective conditions, then either model may be considered tenable. This is of little concern for comparisons of the absolute and squared difference models, because they yield very similar substantive interpretations (Caplan *et al.*, 1980).

If no specific model is identified *a priori*, analysis may proceed in an exploratory fashion. This involves estimating equations of progressively higher order (linear, quadratic, cubic, quartic, etc.) until the variance explained by the added terms is no longer significant.⁶ To maintain parsimony and reduce the likelihood of Type I error, terms corresponding to each level should be entered as a set, and individual coefficients should be interpreted only if the *F* test for the set of terms is significant. Again, these analyses are greatly facilitated by examining three-dimensional plots of the raw data and estimated surfaces. It should be reemphasized that models derived in this manner are subject to cross-validation and appropriate conceptual scrutiny (for discussions of cross-validation, see Mosier, 1951; Neter *et al.*, 1989; Snee, 1977). It is folly to construct elaborate post hoc interpretations of complex surfaces that are not both generalizable and conceptually meaningful.

AN EMPIRICAL EXAMPLE

The approach proposed here is illustrated using data from 172 entering MBA students and 161 participants in an executive education program. All respondents completed commensurate, scale equivalent component measures of actual and preferred amounts of various job attributes and outcome measures of satisfaction with the same attributes. For the MBA students, these attributes consisted of time spent on various activities in their most recent job, including planning/coordinating, decision-making, processing paperwork, exchanging information, and motivating/rewarding others. For the executives, these attributes included opportu-

⁶ For exploratory analyses, polynomial models of progressively higher order are preferred to piecewise linear models of increasing complexity, because the latter require prior specification of the points of inflection in the surface being estimated. By definition, these points are unknown in exploratory analyses.

nity for growth, input into decisions, rewards received, and workload. Component measures ranged from 0 to 40 for the MBA sample and from 0 to 30 for the executive sample. All component measures were scale centered prior to analysis, such that they represented deviations from their midpoint (20 for the MBA sample, 15 for the executive sample). Consequently, in subsequent regression analyses, coefficients on lower-order terms (i.e., b_3 in the absolute difference equation, b_1 and b_2 in the squared difference equation) represent slopes at the midpoint of the component measure scales (no other results are affected by scale centering). Scale reliabilities ranged from .509 to .924 (median = .730) for the MBA sample and from .616 to .836 (median = .720) for the executive sample. For each job attribute, W (used in testing the absolute difference index and $|D|$) was coded 0 when actual amount was greater than preferred amount, 1 when actual amount was less than preferred amount, and randomly coded 0 or 1 when actual and preferred amount were equal.

For both samples, three sets of analyses were conducted. First, relationships between satisfaction and the congruence indices reviewed earlier (i.e., algebraic, absolute, and squared difference indices, $|D|$, D^2 , D , Q) were examined. These analyses followed traditional (i.e., two-dimensional) procedures and provided a baseline for comparing subsequent results. Next, the general approach was used to conduct confirmatory tests of the models underlying the congruence indices, providing tests of overall variance explained, individual coefficient estimates, implied constraints, and higher-order terms. Finally, the general approach was employed in an exploratory fashion, examining models of progressively higher order until one that adequately described each surface was identified. Because the profile similarity indices collapsed across job attributes, the dependent variable used for their analysis was the average of the attribute satisfaction measures, calculated separately for each sample.

Traditional Tests of Congruence Indices

Correlations between satisfaction and the algebraic, absolute, and squared difference indices are presented in Table 2. With few exceptions, these correlations were significant and consistent with previous research (Edwards, 1991; Michalos, 1986). Results for the profile similarity indices (Table 3) were also significant and in the expected direction. When considered separately (as is usually the case), these results seem to provide rather strong support for the model underlying each index. However, when considered together, these results are ambiguous and somewhat contradictory, because indices representing different underlying models (e.g., algebraic difference vs absolute difference) received approximately equal support.

TABLE 2
TESTS OF BIVARIATE CONGRUENCE INDICES

Index	MBA sample					Executive sample			
	Planning and coordinating	Decision making	Processing paperwork	Exchanging information	Motivating and rewarding	Opportunity for growth	Input into decisions	Rewards received	Workload
Algebraic difference	.373***	.285***	-.148	-.219**	.448***	.324***	.253***	.327***	-.463***
Absolute difference	-.514***	-.369***	-.179*	-.262***	-.502***	-.279***	-.060	-.293***	-.418***
Squared difference	-.535***	-.360***	-.209**	-.256***	-.498***	-.224***	.029	-.245***	-.323***

Note. $N = 172$ for the MBA sample; $N = 161$ for the executive sample. Table entries are product-moment correlations.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

TABLE 3
TESTS OF PROFILE SIMILARITY INDICES

Index	MBA sample	Executive sample
Sum of absolute differences ($ D $)	-.402***	-.293***
Sum of squared differences (D^2)	-.425***	-.232***
Square root of sum of absolute differences (D)	-.407***	-.303***
Profile correlation (Q)	.355***	.338***

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Confirmatory Application of the General Approach

Confirmatory tests of the models underlying the algebraic, absolute, and squared difference indices are presented in Table 4. For each job attribute, X represents the actual job attribute amount and Y represents the preferred amount. To facilitate comparisons with the preceding analyses, multiple correlations (R) are used to express total explanatory power. Constraints implied by each model (see Table 1) were tested by directly imposing them on the model and examining the reduction in explained variance (Dwyer, 1983; Wilkinson, 1988). Tests of higher-order models employed terms one order higher than the model being examined. For the algebraic difference model, these terms corresponded to a quadratic equation, including the square of both component measures and their product. For the absolute difference model, six higher-order terms were used, including the square of both component measures, their product, and the product of these three terms with W . These terms allowed independent curvature and tilt in the surfaces on either side of the line where component measures were equal. For the squared difference model, terms corresponding to a cubic equation were used, consisting of the cube of both component measures and the product of either measure with the square of the other measure. These terms allowed a second inflection in the surface relating the component measures to the outcome, and for variation in the curvature of the surface, depending on the level of either measure. For each model, higher-order terms were entered as a set.⁷

⁷ The interpretation of certain higher-order terms used in these analyses may create some confusion. As with simpler multiplicative terms, these terms indicate a conditional relationship. For example, XY^2 represents change in the magnitude of the XY interaction across levels of Y or, equivalently, change in the magnitude of the curvilinear component of Y (i.e., Y^2) across levels of X . Interpreting terms of higher-order is often cumbersome, but the same logic applies. However, it is difficult to determine what these terms imply for a given surface without considering the other terms included in the equation. In practice, it is often helpful

Results for the algebraic difference model indicated significant multiple correlations for eight of the nine job attributes tested (see Table 4). However, component coefficients were significant and opposite in sign for only two attributes (motivating/rewarding, workload), and coefficients did not significantly differ in absolute magnitude only for workload. Furthermore, significant higher-order terms were found for three attributes (planning/COORDINATING, decision-making, motivating/rewarding), indicating that the underlying surface was more complex than the simple plane implied by the algebraic difference index (see Fig. 1b). Results for the absolute difference model indicated significant multiple correlations for the same eight attributes. However, none of these attributes yielded significant coefficients on X , Y , WX , and WY , and the implied constraints were rejected for all eight attributes. In addition, planning/COORDINATING and motivating/rewarding yielded significant higher-order terms, indicating that the surface was not planar on both sides of the line where component measures were equal. Results for the squared difference model yielded significant multiple correlations for the same eight attributes. However, the implied constraints were rejected for all eight attributes, and significant higher-order terms were found for two attributes (decision-making, opportunity for growth). Hence, of the 27 sets of confirmatory tests conducted, only 1 (the algebraic difference model for workload) supported the hypothesized model.

The poor performance of the models underlying the algebraic, absolute, and squared difference indices can be explained by comparing the surfaces predicted by these indices to the raw data. For illustrative purposes, two attributes are used here, including planning/COORDINATING and rewards received. As Fig. 2 shows, the surface representing the raw data for planning/COORDINATING increases along the line where component measures are approximately equal and decreases on either side of this line. In contrast, the surface predicted by the algebraic difference index represents a plane and, hence, cannot depict the curvature in the underlying data. Surfaces predicted by the absolute and squared difference indices adequately capture the downward slope on either side of the line where component measures are equal, but both presume the same level of satisfaction along this line, which is clearly not the case. The raw data for rewards received (Fig. 3) essentially represent a surface that is positively sloped along the axis representing actual attribute amount (the curvature

to plot surfaces predicted by two equations, one including all relevant terms, and another excluding the term in question. By comparing these two surfaces, the influence of the term in question on the predicted surface can be determined. For further discussion of the interpretation of higher-order terms, see Box and Draper (1987), Cohen and Cohen (1983), and Neter *et al.* (1989).

TABLE 4
CONFIRMATORY TESTS OF BIVARIATE CONGRUENCE INDICES

Index	MBA sample					Executive sample			
	Planning and coordinating	Decision making	Processing paperwork	Exchanging information	Motivating and rewarding	Opportunity for growth	Input into decisions	Rewards received	Workload
Algebraic difference									
X	.413***	.579***	-.140	-.197	.544***	.493***	.491***	.395***	-.329***
Y	-.034	.264**	.259*	.454***	-.188*	.125*	.078	.069	.310***
R	.481***	.653***	.177	.323***	.560***	.651***	.575***	.573***	.463***
Constraint	20.430***	101.793***	1.612	10.619***	27.803***	87.771***	62.803***	52.130***	.116
Higher-order terms	18.420***	5.376***	1.867	2.391	8.305***	1.434	.717	.346	1.417
Absolute difference									
X	-.355	.275	-.266*	-.370**	-.244	.357**	.545***	.349*	-.356***
Y	.583**	.392	.390**	.710***	.592	.195	.050	.120	.368***
W	2.073	.224	-.035 ^a	-3.994	1.206 ^a	-.140 ^a	.660 ^a	-.222 ^a	.865 ^a
WX	1.179***	.585*	.651	.336	.954***	.297	-.018	.034	.285
WY	-.901***	-.375	-.389	-.700	-.932***	-.249	-.016	-.044	-.446
R	.621***	.684***	.221	.408***	.612***	.664***	.576***	.574***	.484***
All constraints	8.274***	25.923***	.743	4.860***	8.163***	25.113***	19.051***	14.111***	3.026*
Higher-order terms	2.226*	1.422	1.311	.691	2.255*	1.132	1.217	1.638	1.836
Squared difference									
X	.083	.709***	.090 ^a	.194 ^a	.155	.763***	.310	.395**	-.415***
Y	.259**	.058	-.095 ^a	.030 ^a	.139	.280	-.150 ^a	-.040 ^a	.253
X ²	-.032***	-.036***	-.012	-.028	-.024***	-.020	.012	.003	.010
XY	.043***	.032*	.042*	.066*	.036***	.008	-.006	-.004	.008
Y ²	-.006	.004	-.034*	-.047*	.000	-.014	.017	.010	.004
R	.651***	.691***	.251	.376***	.635***	.663***	.583***	.577***	.485***
All constraints	9.874**	27.609***	.854	3.662**	10.780***	26.964***	19.861***	15.863***	6.649***
Higher-order terms	2.313	2.473*	1.406	1.502	.746	4.187***	.172	1.249	2.015

Note. N = 172 for the MBA sample; N = 161 for the executive sample. For each job attribute, values corresponding to each independent variable (X, Y, etc.) are unstandardized regression coefficients, R represents the multiple correlation coefficient for the overall model, and values corresponding to constraints and higher-order terms are F ratios.

^a the coefficient for this variable was not significant at all points along the X = Y line.

- * p < .05.
- ** p < .01.
- *** p < .001.

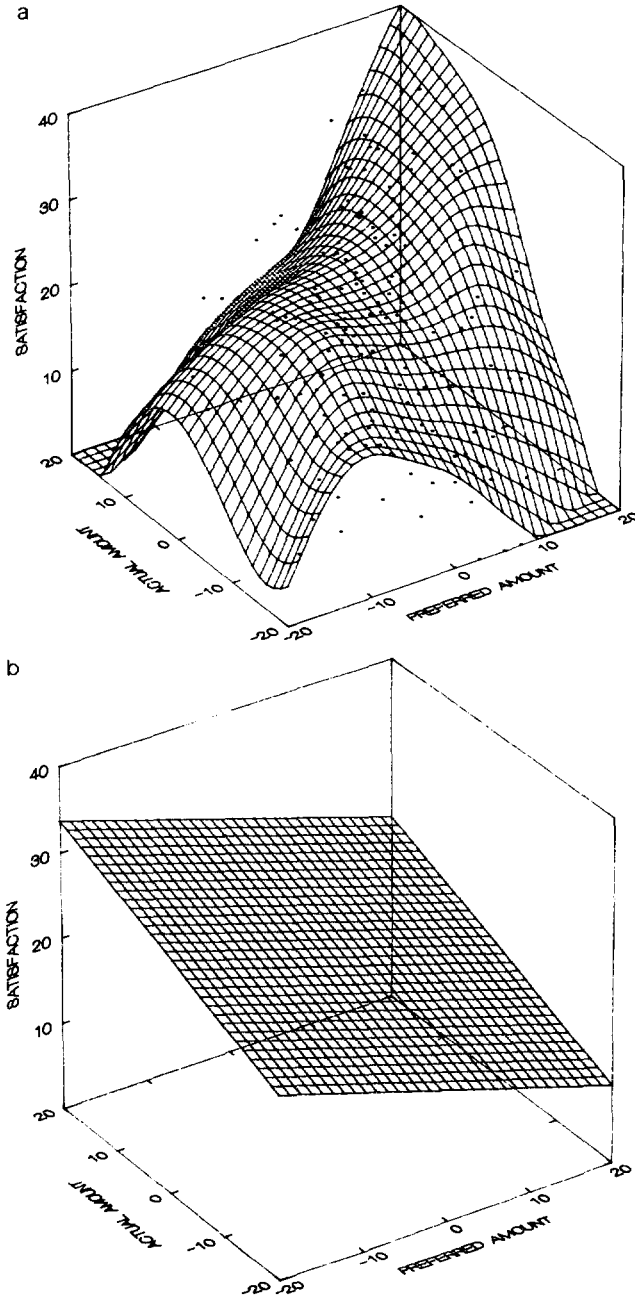


FIG. 2. Actual and estimated surfaces for planning/COORDINATING. (a) Raw data; (b) algebraic difference; (c) absolute difference; (d) squared difference.

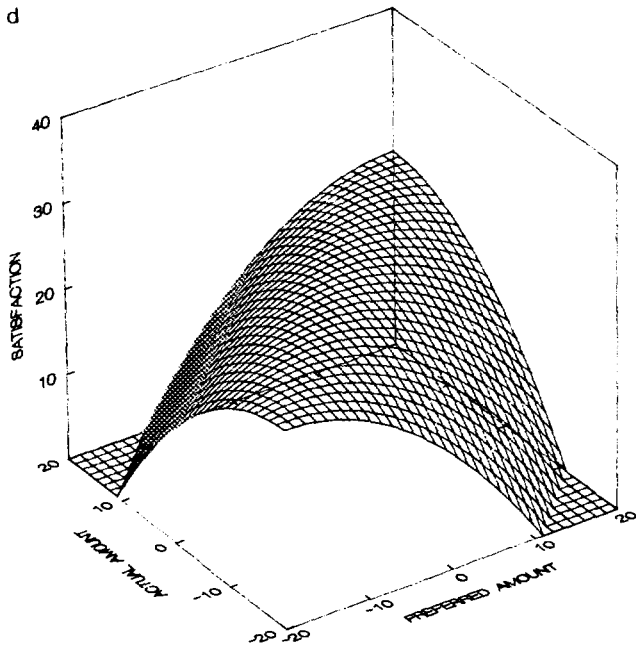
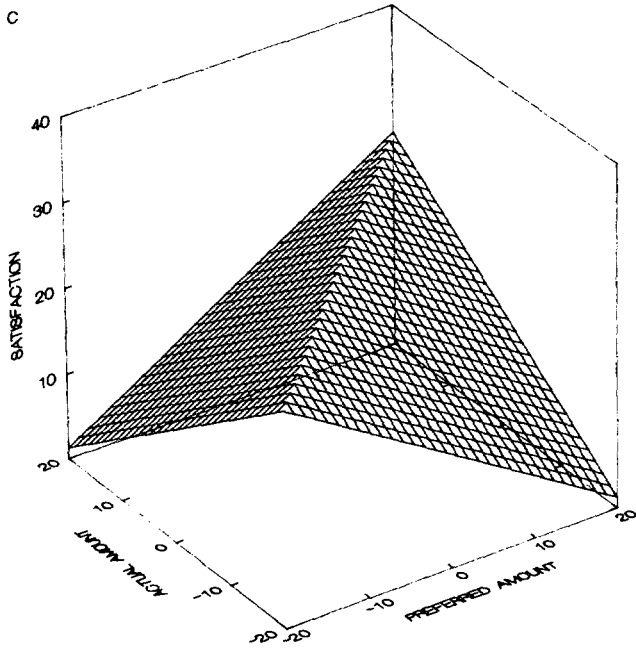


FIG. 2—Continued

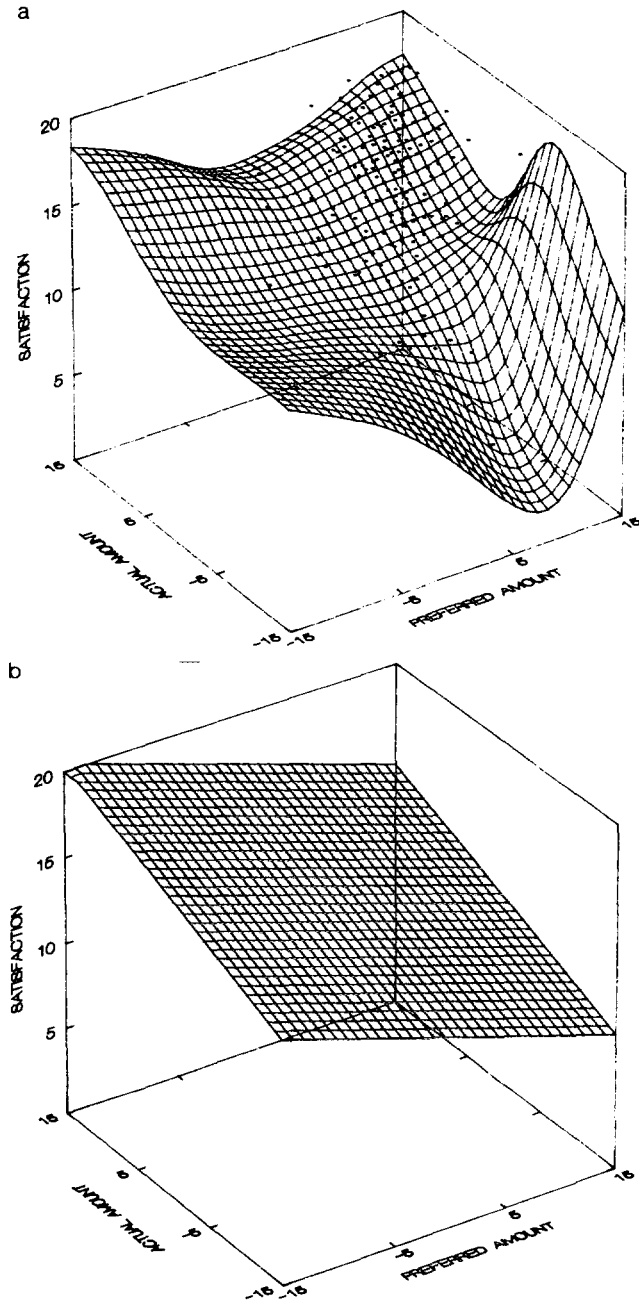


FIG. 3. Actual and estimated surfaces for rewards received. (a) Raw data; (b) algebraic difference; (c) absolute difference; (d) squared difference.

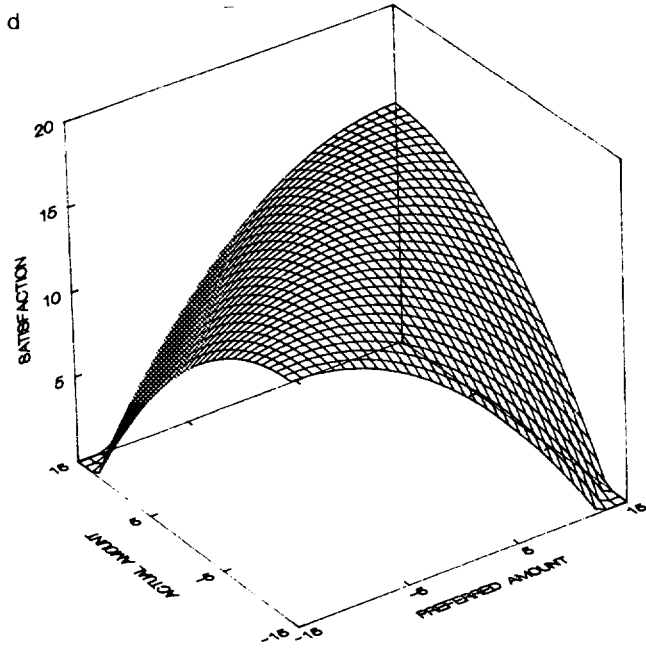
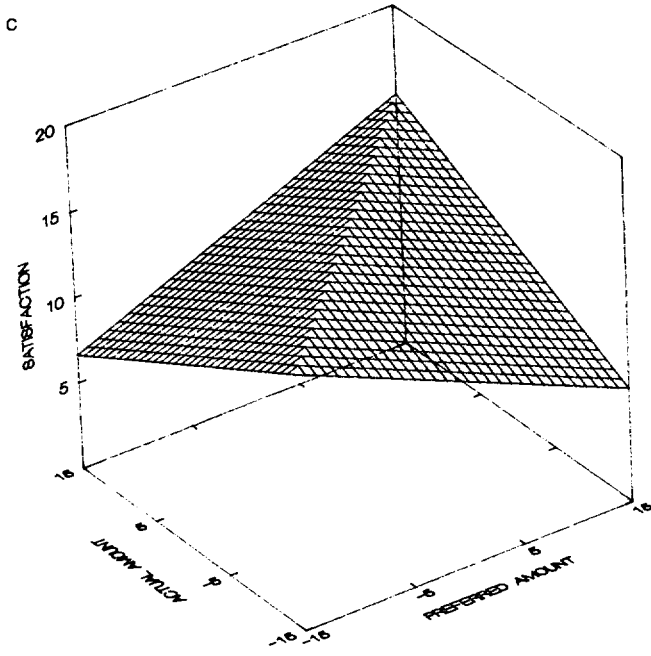


FIG. 3—Continued

in the right-hand portion of the surface was caused by a few isolated cases and did not yield significant higher-order terms; see Table 6). The surface predicted by the algebraic difference index captures this positive slope, but also forces a negative slope along the axis representing preferred attribute amount, which is not evident in the data. Surfaces predicted by the absolute and squared difference indices suggest symmetric curvature, which is clearly not present. Thus, although the algebraic, absolute, and squared difference indices were highly significant for both of these attributes, the surfaces predicted by these indices deviated substantially from the actual data.

Confirmatory tests for $|D|$ and D^2 are presented in Table 5. For both samples, the $|D|$ model yielded a significant multiple correlation, but the set of implied constraints was rejected. This is not surprising, given the substantial variability in the coefficient estimates across the attributes constituting $|D|$ (see Table 5). The D^2 model also yielded significant multiple correlations for both samples, but the implied set of constraints was again rejected, and significant higher-order terms were found for the executive sample.

As previously stated, confirmatory tests of D and Q are difficult to conduct, because unconstrained versions of the models underlying these indices cannot be expressed in terms of the original or transformed X_i and Y_i . However, if the unconstrained models corresponding to $|D|$ and D^2 adequately depict the surfaces implied by D and Q , as argued earlier, then D and Q should explain no additional variance after controlling for the terms constituting either of these models. Results supported this contention for both samples. Furthermore, after controlling for either D or Q , significant additional variance was explained by the set of terms corresponding to either $|D|$ or D^2 , indicating that D and Q did not adequately describe the data.

Exploratory Application of the General Approach

Exploratory analyses of the nine job attributes were conducted by hierarchically testing sets of terms representing models of progressively higher order and stopping when the additional variance explained was no longer significant. Much of the information required for these analyses was provided in Table 4, which reported tests of terms corresponding to linear, quadratic, and cubic models for each attribute. To derive final models, individual terms were retained if they were significant when first entered into the model or were required for meaningful coefficient estimates for higher-order terms (Cohen, 1978).

The final exploratory models are presented in Table 6. For three attributes, the model contained a single predictor, with two (input, rewards received) indicating greater satisfaction with higher actual levels of the

TABLE 5
CONFIRMATORY TESTS OF PROFILE SIMILARITY INDICES

Index	MBA sample					Executive sample		
	Planning and coordinating	Decision making	Processing paperwork	Exchanging information	Motivating and rewarding	Opportunity for growth	Input into decisions	Rewards received
Sum of absolute differences ($ D $)								
<i>X</i>	-.267	.003	.000	-.122	.088	.227*	.217*	.093
<i>Y</i>	.197	.184	.008	.140	.151	-.054	.081	-.012
<i>W</i>	.682 ^a	-2.446 ^a	1.322 ^a	1.794 ^a	1.134 ^a	2.139	.462 ^a	-1.590
<i>WX</i>	.393*	.099	.485	.669	.220	.206	-.083	-.193
<i>WY</i>	-.267	.042	-.254	-.734	-.307	-.321*	.024	.277*
<i>R</i>					.647***			
All constraints					2.695***			
Higher-order terms					.685			
Sum of squared differences (D^2)								
<i>X</i>	-.147	.395*	.143 ^a	-.133 ^a	.253*	.155	.268	.118
<i>Y</i>	.156*	.164 ^a	-.233 ^a	.088 ^a	-.026 ^a	-.201 ^a	-.041 ^a	.152 ^a
<i>X</i> ²	-.015**	-.005	-.005	.000	.003	-.013	.000	.015*
<i>XY</i>	.023**	-.018	.015	.003	.002	.031*	-.009	-.030*
<i>Y</i> ²	.002	.005	-.016	-.001	-.007	-.010	.011	.007
<i>R</i>					.663***			
All constraints					2.818***			
Higher-order terms					.930			

Note. $N = 172$ for the MBA sample; $N = 161$ for the executive sample. For both samples, values corresponding to each independent variable (X) are unstandardized regression coefficients, R represents the multiple correlation coefficient for the overall model, and values corresponding to constraints and higher-order terms are F ratios.

^a The coefficient for this variable was not significant at all points along the $X = Y$ line.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

TABLE 6
EXPLORATORY TESTS OF CONGRUENCE

Independent variable	MBA sample					Executive sample			
	Planning and coordinating	Decision making	Processing paperwork	Exchanging information	Motivating and rewarding	Opportunity for growth	Input into decisions	Rewards received	Workload
X	.089	.047			.154	.514	.518***	.411***	-.329***
Y	.244**	2.654***		.302***	.140	1.860**			.310***
X^2	-.032***	.086*			-.024***	.129*			
XY	.041***	-.021			.036***	-.162*			
Y^2		-.450***				-.106**			
X^3						-.006**			
X^2Y		-.028***							
XY^2		.036***				.010**			
Y^3		.019***							
X^4									
X^3Y									
X^2Y^2		.001**							
XY^3		-.002***							
Y^4									
R	.650***	.741***		.293***	.635***	.696***	.569***	.568***	.463***

Note. $N = 172$ for the MBA sample; $N = 161$ for the executive sample. For each job attribute, values corresponding to each independent variable (X , Y , etc.) are unstandardized regression coefficients, and R represents the multiple correlation coefficient for the overall model. All coefficients are significant ($p < .05$) or involve terms that are required for estimation of coefficients on higher-order terms.

- * $p < .05$.
- ** $p < .01$.
- *** $p < .001$.

attribute, and one (exchanging information) indicating greater satisfaction with higher preferred levels of the attribute. One attribute (workload) yielded results corresponding to an algebraic difference model (see also Table 4), where satisfaction decreased as actual workload exceeded preferred workload. Two attributes (planning/coordinating, motivating/rewarding) yielded results essentially representing a modified squared difference model, in which satisfaction was not only maximized when actual and preferred attribute amounts were approximately equal, but was also higher when both actual and preferred amounts were high than when both were low (cf. Imparato, 1972). One attribute (opportunity for growth) yielded an incomplete cubic model, and another (decision-making) yielded an incomplete quartic model. However, comparing predicted surfaces to the raw data revealed that, for both attributes, the cubic and quartic terms represented minor curvatures in the surface rather than substantively meaningful effects. Because these curvatures were produced by a small number of individual cases, they are unlikely to survive cross-validation. Finally, one attribute (processing paperwork) did not yield significant results. This suggests that the significant relationships for congruence indices calculated for this attribute (see Table 2) were obtained by gaining degrees of freedom through the use of constraints which, when tested, were not supported (see Table 4).

SUMMARY AND DISCUSSION

Advantages of the Proposed General Approach

The general approach to the study of congruence proposed here offers several advantages over congruence indices currently in use. First, it maintains the interpretability of the original component measures, which is lost when these measures are collapsed into a congruence index. Second, it yields separate estimates of the relationships between component measures and the outcome, which are confounded when congruence indices are used. Third, it provides a complete test of models underlying congruence indices, focusing not only on the overall magnitude of the relationship, but also on the significance of individual effects, the validity of implied constraints, and the significance of higher-order terms. These additional tests are critical, because the empirical verification of any model requires not only that adequate variance is explained, but also that the individual relationships constituting the model are supported, and that the pattern of constraints implied by the model is neither too lenient nor too stringent (cf. Anderson & Gerbing, 1988). Finally, the proposed approach may yield considerable increases in explained variance. For example, relaxing the constraints implied by the algebraic, absolute, and squared difference indices yielded average increases in adjusted R^2 values

of .155, .173, and .191, respectively. In most cases, these increases were significant, as indexed by F tests for the set of constraints implied by each model (see Table 4).

Extensions to the Basic Approach

The approach presented here can be readily extended to address additional issues in the study of congruence. One issue concerns the use of product (i.e., interactive) terms to represent congruence. Although several early studies used unpartialled product terms to represent congruence (e.g., Beer, 1966; Sheridan & Slocum, 1975; Wanous & Lawler, 1972), most current studies use the appropriate hierarchical procedure (e.g., Berger-Gross, 1982; Berger-Gross & Kraut, 1984; Butler, 1983; Cherrington & England, 1980; O'Brien & Dowling, 1980; O'Brien & Humphrys, 1982; O'Brien & Stevens, 1981; Rice, McFarlin, & Bennett, 1989; White & Ruh, 1973). Consequently, these studies are free from most of the problems surrounding congruence indices. Nonetheless, the results from such studies may be substantiated by applying the procedure proposed here. For example, when component measures are positively correlated, their product is often highly correlated with the square of either measure. As a result, a significant interaction may actually represent a curvilinear effect for one or both components (Lubinski & Humphreys, 1990). Even if the interaction is not spurious, it may nonetheless be accompanied by significant curvilinear or other higher-order effects, as demonstrated in the preceding example. If these additional terms are ignored, the estimated surface will misrepresent the actual data, and substantive interpretations will be erroneous.

A second issue involves variables that may moderate the effects of congruence. For example, several investigators have argued that the impact of congruence between perceived and valued job attributes on job satisfaction is moderated by value importance (e.g., Locke, 1976; Mobley & Locke, 1970; Porter & Lawler, 1968). This may be represented by hierarchically testing the product of importance and each term in the model of interest, after controlling for value importance and the terms in the original model. For example, if a squared difference model is chosen, this procedure would yield the following regression equation (V represents value importance):

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + b_6V + b_7XV + b_8YV + b_9X^2V + b_{10}XYV + b_{11}Y^2V + e. \quad (15)$$

If the test for the last five terms as a set is significant, then a moderating effect for importance is suggested. If importance intensifies the effects of congruence on satisfaction (Locke, 1976), then the coefficients on these terms will be of the same sign as those obtained for the corresponding

terms with V omitted (b_7 vs b_1 , b_8 vs b_2 , etc.). Again, interpretation will be facilitated substantially by three-dimensional plots of estimated surfaces for various values of V .

Problems with Other Approaches Currently in Use

Some investigators have attempted to avoid problems with congruence indices by adopting approaches other than the one proposed here. Unfortunately, most of these approaches are ineffective, and some actually introduce additional problems. One approach has been to simply substitute one representation of congruence for another. For example, in response to problems with difference scores, O'Brien and Dowling (1980) tested the interaction between component measures, and Kahana, Liang, and Felton (1980) used a squared difference index. These approaches are ineffective, because they simply substitute one model of congruence for another, leaving the original (i.e., algebraic difference) model untested. Furthermore, they presume that substantively different models of congruence are interchangeable, which is clearly not the case (see Fig. 1).

Another approach involves estimating the effects of congruence after controlling for one component. For example, Sheridan and Slocum (1975) regressed performance on need deficiency (i.e., "should be" minus "is now"), after controlling for "is now" scores. Unfortunately, the coefficient for need deficiency yielded by this procedure no longer represents the effect of congruence, but rather the effect of should be, holding is now constant (cf. Wall & Payne, 1973). An analogous approach involves regressing one component measure on the other and using the residuals to predict the outcome (e.g., Vecchio & Sussmann, 1989). Because these residuals simply represent the difference between the component measures, with one measure rescaled by the obtained regression coefficient, this procedure effectively reintroduces difference scores into the analysis. In addition, rescaling one component measure eliminates scale equivalence, which further obscures the interpretation of the obtained score.

A third approach involves "direct" measures of congruence, which are designed to elicit a relative comparison between two components (e.g., the degree to which one component is greater than or less than the other) within a single item (e.g., Cook & Wall, 1980; Crosby, 1982; Dornstein, 1988; Greenberg, 1989; Greenhaus, Seidel, & Marinis, 1983; Hollenbeck, 1989; Lee & Mowday, 1987; McFarlin & Rice, in press; Michalos, 1980, 1983; Posner *et al.*, 1985; Rice *et al.*, 1989; Scholl, Cooper, & McKenna, 1987; Tziner, 1987; Tziner & Falbe, 1990). The presumed advantage of these measures is that they do not require the calculation of difference scores and, hence, are immune to their problems. While these measures do not require the *investigator* to calculate a difference, it is certainly

possible that the *respondent* may implicitly or explicitly calculate a difference in the process of generating a response. If this occurs, then these measures are susceptible to the same problems associated with difference scores, because these problems do not depend upon who calculates the difference. A more fundamental problem is that these measures hopelessly confound the components involved in the comparison, making it impossible to determine their relative contribution to the obtained score. Furthermore, these measures assume symmetric effects of components on the outcome, but provide no means to verify this assumption. As the example presented here illustrated, this assumption may be unwarranted (see also French *et al.*, 1982; Sweeney *et al.*, 1990).

Remaining Problems and Areas for Further Development

Although many of the problems with congruence indices are overcome by the procedure proposed here, several additional problems remain to be solved. One problem concerns the measurement of component variables. As in any application of regression analysis, the procedure proposed here assumes that independent variables are measured without error. When this assumption is violated (as is usually the case), coefficient estimates may be biased upward or downward, depending upon the degree of measurement error and the correlations among the independent variables (Kenny, 1979; Pedhazur, 1982). Furthermore, coefficients on higher-order terms may be biased by nonlinear or multiplicative measurement error, which may either attenuate or exaggerate the obtained estimates (Busemeyer & Jones, 1983). Although structural equations modeling may be used to incorporate the effects of measurement error (Anderson & Gerbing, 1988; Joreskog & Sorbom, 1988; Long, 1983), the estimation of parameters associated with higher-order terms becomes exceedingly complicated as the number of indicators per term and total number of terms increase (Bollen, 1989; Hayduk, 1987; Kenny & Judd, 1984). At present, it seems that the most advisable procedure is to develop measures with high reliabilities prior to data analysis rather than attempt to compensate for measurement error at later stages.

It should be noted that the oft-cited problem of reduced reliability associated with difference scores is not eliminated by the procedure proposed here. As Johns (1981) demonstrates, when component measures are positively correlated, the reliability of their difference is less than the average of the reliabilities of the components. However, this comparison is relevant only if the reliability associated with a model containing both components separately (as opposed to their difference) were represented by the average reliability of the component measures, which is not the case. Instead, the comparison of interest is between the reliabilities yielded by the weighted linear combination of component measures de-

icted by Eq. 2 (which is equivalent to using a difference score) and Eq. 3 (Nunnally, 1978). If the component coefficients obtained in Eq. 3 are equal in magnitude but opposite in sign, then the reliability for both models will obviously be the same. If this constraint does not hold, then the reliability of the model depicted in Eq. 3 will generally be higher, unless component measure reliabilities are drastically different (for further discussion, see Nunnally, 1978, pp. 250-254).

A second limitation of the proposed procedure is its exclusive focus on congruence indices used as independent variables. Many studies have examined congruence indices as dependent variables (e.g., Hall, Schneider, & Nygren, 1970; Sulsky & Balzer, 1988; Wanous & Youtz, 1986; Weiss, 1977) or the relationship between two or more congruence indices (e.g., Alutto & Belasco, 1972; Bernardin & Alvares, 1975). Many of the conceptual and methodological problems surrounding studies using congruence indices as independent variables also apply to these studies, but appropriate alternative procedures are difficult to derive and test, due to the complexity of the associated unconstrained models. Although procedures that avoid problems with algebraic difference indices as dependent variables have been proposed (e.g., Cronbach & Furby, 1970), alternatives for more complex indices await further work.

Finally, the procedure proposed here may meet some resistance among researchers accustomed to congruence indices, because using separate component measures may seem to eliminate any vestige of congruence from data analysis. Although the proposed procedure does not represent congruence in the traditional sense, the preceding discussion has shown that most congruence indices in use are mathematically equivalent to regression equations containing separate component measures, with certain constraints imposed. This mathematical equivalence also implies a logical equivalence, meaning that hypothesizing a relationship for a congruence index is logically equivalent to hypothesizing a pattern of coefficients for its components. For example, predicting a positive relationship for an algebraic difference index is logically equivalent to hypothesizing a positive relationship for the first component in the difference and a negative relationship for the second component. Hence, the proposed procedure does not threaten the concept of congruence, but instead suggests a fundamental shift in how congruence is conceptualized, from a two-dimensional to a three-dimensional view. This shift will allow more complete tests of relationships implied by traditional congruence indices, as well as tests of relationships more complex than these indices can depict.

CONCLUSION

A substantial body of research in organizational behavior has focused

on the effects of congruence on various outcomes. Unfortunately, much of this research has relied on congruence indices and, therefore, has yielded ambiguous and potentially misleading results. The present article has summarized problems with major congruence indices currently in use and proposed an alternative procedure that overcomes these problems. By applying this procedure, future congruence research may avoid the problems reviewed here and obtain results that are more definitive and adequately represent the complexity of the underlying phenomenon.

APPENDIX

For the absolute difference model (see Eq. 7), the vertical shift in the surface estimated at a given point c along the $X = Y$ line is given by the following equation:

$$b_3 \text{ at } c = b_3 + c(b_4 + b_5). \quad (\text{A1})$$

The variance of b_3 at c is given by

$$\begin{aligned} \text{var}(b_3 \text{ at } c) = & \text{var}(b_3) + 2c[\text{cov}(b_3, b_4) + \text{cov}(b_3, b_5)] \\ & + c^2[\text{var}(b_4) + \text{var}(b_5) + 2\text{cov}(b_4, b_5)]. \end{aligned} \quad (\text{A2})$$

Thus, a t test for b_3 at c can be conducted by dividing the value obtained in Eq. A1 by the square root of the value obtained in Eq. A2, with the usual degrees of freedom.

For the squared difference model, the slope of X at a given point along the $X = Y$ line is given by

$$b_1 \text{ at } c = b_1 + c(2b_3 + b_4). \quad (\text{A3})$$

The variance of b_1 at c is given by

$$\begin{aligned} \text{var}(b_1 \text{ at } c) = & \text{var}(b_1) + 2c[2\text{cov}(b_1, b_3) + \text{cov}(b_1, b_4)] \\ & + c^2[4\text{var}(b_3) + 4\text{cov}(b_3, b_4) + \text{var}(b_4)]. \end{aligned} \quad (\text{A4})$$

A t test for b_1 at c is conducted by dividing the value obtained in Eq. A3 by the square root of the value obtained in Eq. A4, with the usual degrees of freedom.

The slope of Y at a given point along the $X = Y$ line is given by

$$b_2 \text{ at } c = b_2 + c(b_4 + 2b_5). \quad (\text{A5})$$

The variance of b_2 at c is given by

$$\begin{aligned} \text{var}(b_2 \text{ at } c) = & \text{var}(b_2) + 2c[\text{cov}(b_2, b_4) + 2\text{cov}(b_2, b_5)] \\ & + c^2[\text{var}(b_4) + 4\text{cov}(b_4, b_5) + 4\text{var}(b_5)]. \end{aligned} \quad (\text{A6})$$

The t test for b_2 at c is conducted by dividing the value obtained in Eq. A5 by the square root of the value obtained in Eq. A6, with the usual degrees of freedom.

REFERENCES

- Adams, J. S. (1965). Inequity in social exchange. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 2, pp. 267-299). New York: Academic Press.
- Aiken, L. A., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Newbury Park, CA: Sage.
- Alutto, J. A., & Acito, F. (1974). Decisional participation and sources of job satisfaction: A study of manufacturing personnel. *Academy of Management Journal*, 17, 160-167.
- Alutto, J. A., & Belasco, J. A. (1972). A typology for participation in organizational decision-making. *Administrative Science Quarterly*, 17, 117-125.
- Alutto, J., Hrebiniak, L., & Alonso, R. (1971). Variation in hospital employment and influence perceptions among nursing personnel. *Journal of Health and Social Behavior*, 12, 30-34.
- Alutto, J. A., & Vredenburg, D. J. (1977). Characteristics of decisional participation by nurses. *Academy of Management Journal*, 20, 341-347.
- Amerikaner, M., Elliot, D., & Swank, P. (1988). Social interest as a predictor of vocational satisfaction. *Individual Psychology*, 44, 316-323.
- Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two step approach. *Psychological Bulletin*, 103, 411-423.
- Arnold, H. J., & Evans, M. G. (1979). Testing multiplicative models does *not* require ratio scales. *Organizational Behavior and Human Performance*, 24, 41-59.
- Assouline, M., & Meir, E. I. (1987). Meta-analysis of the relationship between congruence and well-being measures. *Journal of Vocational Behavior*, 31, 319-332.
- Barrett, G. V. (1978). Task design, individual attributes, work satisfaction, and productivity. In A. Negandhi & B. Wilpert (Eds.), *Work organization research* (pp. 261-278). Kent, OH: Kent State University Press.
- Beer, M. (1966). *Leadership, employee needs, and motivation*. Columbus: Ohio State University, Bureau of Business Research.
- Berger-Gross, V. (1982). Difference score measures of social perceptions revisited: A comparison of alternatives. *Organizational Behavior and Human Performance*, 29, 279-285.
- Berger-Gross, V., & Kraut, A. L. (1984). "Great expectations:" A no-conflict explanation of role conflict. *Journal of Applied Psychology*, 69, 261-271.
- Bernardin, H. J. (1979). The predictability of discrepancy measures of role constructs. *Personnel Psychology*, 32, 139-153.
- Bernardin, H. J., & Alvares, K. M. (1975). The effects of organizational level on perceptions of role conflict resolution strategy. *Organizational Behavior and Human Performance*, 14, 1-9.
- Betz, E. (1969). Need-reinforcer correspondence as a predictor of job satisfaction. *Personnel and Guidance Journal*, 47, 878-883.
- Blau, G. (1981). An empirical investigation of job stress, social support, service length, and job strain. *Organizational Behavior and Human Performance*, 27, 279-302.
- Bollen, K. A. (1989). *Structural equations with latent variables*. New York: Wiley.
- Borgen, F. H., Weiss, D. J., Tinsely, H. E. A., Dawis, R. V., & Lofquist, L. H. (1968). The measurement of occupational reinforcer patterns. *Minnesota Studies in Vocational Rehabilitation*, 25.
- Box, G. E. P., & Draper, N. R. (1987). *Empirical model-building and response surfaces*. New York: Wiley.
- Boyd, B. B., & Jensen, J. M. (1972). Perception of the first-line supervisor's authority: A study in superior-subordinate communication. *Academy of Management Journal*, 15, 331-342.

- Busemeyer, J. R., & Jones, L. E. (1983). Analysis of multiplicative combination rules when the causal variables are measured with error. *Psychological Bulletin*, *93*, 549–562.
- Butler, J. K. (1983). Value importance as a moderator of the value–fulfillment–job satisfaction relationship: Group differences. *Journal of Applied Psychology*, *68*, 420–428.
- Caldwell, D. F., & O'Reilly, C. A. (1990). Measuring person–job fit with a profile comparison process. *Journal of Applied Psychology*, *75*, 648–657.
- Caplan, R. D. (1987). Person–environment fit theory and organizations: Commensurate dimensions, time perspectives, and mechanisms. *Journal of Vocational Behavior*, *31*, 248–267.
- Caplan, R. D., Cobb, S., French, J. R. P., Jr., Harrison, R. V., & Pinneau, S. R. (1980). *Job demands and worker health: Main effects and occupational differences*. Ann Arbor, MI: Institute for Social Research.
- Chatman, J. A. (1989). Improving interactional organizational research: A model of person–organization fit. *Academy of Management Review*, *14*, 333–349.
- Chatman, J. A. (1991). Matching people and organizations: Selection and socialization in public accounting firms. *Administrative Science Quarterly*, *36*, 459–484.
- Cherrington, D. J., & England, J. L. (1980). The desire for an enriched job as a moderator of the enrichment–satisfaction relationship. *Organizational Behavior and Human Performance*, *25*, 139–159.
- Cohen, J. (1978). Partialled products are interactions: Partialled powers are curve components. *Psychological Bulletin*, *85*, 858–866.
- Cohen, J. (1988). *Statistical power analysis for the behavior sciences* (2nd ed.). New York: Academic Press.
- Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.
- Cook, J., & Wall, T. (1980). New work attitude measures of trust, organizational commitment and personal need non-fulfilment. *Journal of Occupational Psychology*, *53*, 39–52.
- Cronbach, L. J. (1958). Proposals leading to analytic treatment of social perception scores. In R. Tagiuri & L. Petrullo (Eds.), *Person perception and interpersonal behavior* (pp. 353–379). Stanford, CA: Stanford University Press.
- Cronbach, L. J. (1987). Statistical tests for moderator variables: Flaws in analyses recently proposed. *Psychological Bulletin*, *102*, 414–417.
- Cronbach, L. J., & Furby, L. (1970). How should we measure “change”—or should we? *Psychological Bulletin*, *74*, 68–80.
- Cronbach, L. J., & Gleser, G. C. (1953). Assessing the similarity between profiles. *Psychological Bulletin*, *50*, 456–473.
- Crosby, F. (1982). *Relative deprivation and working women*. New York: Oxford University Press.
- Dalessio, A., & Imada, A. S. (1984). Relationships between interview selection decisions and perceptions of applicant similarity to an ideal employee and self. *Human Relations*, *37*, 67–80.
- Dansereau, F., Jr., Graen, G., & Haga, W. J. (1975). A vertical dyad linkage approach to leadership within formal organizations: A longitudinal investigation of the role making process. *Organizational Behavior and Human Performance*, *13*, 46–78.
- Dawis, R. V., & Lofquist, L. H. (1984). *A psychological theory of work adjustment*. Minneapolis: University of Minnesota Press.
- Dillon, W. R., & Goldstein, M. (1984). *Multivariate analysis: Methods and applications*. New York: Wiley.
- Dornstein, M. (1988). Wage reference groups and their determinants: A study of blue-collar and white-collar employees in Israel. *Journal of Occupational Psychology*, *61*, 221–235.
- Dougherty, T. W., & Pritchard, R. D. (1985). The measurement of role variables: Explor-

- atory examination of a new approach. *Organizational Behavior and Human Decision Process*, 35, 141–155.
- Dwyer, J. H. (1983). *Statistical models for the social and behavioral sciences*. New York: Oxford University Press.
- Edwards, J. R. (1991). Person–job fit: A conceptual integration, literature review, and methodological critique. In C. L. Cooper & I. T. Robertson (Eds.), *International review of industrial and organizational psychology* (Vol. 6, pp. 283–357). New York: Wiley.
- Edwards, J. R., & Cooper, C. L. (1990). The person–environment fit approach to stress: Recurring problems and some suggested solutions. *Journal of Organizational Behavior*, 10, 293–307.
- Evans, M. G. (1991). The problem of analyzing multiplicative composites: Interactions revisited. *American Psychologist*, 46, 6–15.
- Ford, N. M., Walker, O. C., & Churchill, G. A. (1975). Expectations-specific measures of the intersender conflict and role ambiguity experienced by industrial salesmen. *Journal of Business Research*, 3, 95–112.
- Frank, L. L., & Hackman, J. R. (1975). Effects of interviewer–interviewee similarity on objectivity in college admissions interviews. *Journal of Applied Psychology*, 60, 356–360.
- French, J. R. P., Jr., Caplan, R. D., & Harrison, R. V. (1982). *The mechanisms of job stress and strain*. London: Wiley.
- French, J. R. P., Jr., Rodgers, W. L., & Cobb, S. (1974). Adjustment as person–environment fit. In G. Coelho, D. Hamburg, & J. Adams (Eds.), *Coping and adaptation* (pp. 316–333). New York: Basic Books.
- Gay, E. G., Weiss, D. J., Hendel, D. D., Dawis, R. V., & Lofquist, L. H. (1971). Manual for the Minnesota Importance Questionnaire. *Minnesota Studies in Vocational Rehabilitation*, 28 (Bulletin No. 54).
- Goodman, P. S. (1977). Social comparison processes in organizations. In B. M. Staw & G. R. Salancik (Eds.), *New directions in organizational behavior* (pp. 97–132). Chicago, IL: St. Clair Press.
- Graen, G., Orris, J. B., & Johnson, T. W. (1973). Role assimilation processes in a complex organization. *Journal of Vocational Behavior*, 3, 395–420.
- Graen, G., & Schiemann, W. (1978). Leader–member agreement: A vertical dyad linkage approach. *Journal of Applied Psychology*, 63, 206–212.
- Graham, W. K. (1976). Commensurate characteristics of persons, groups, and organizations: Development of the Trait Ascription Questionnaire (TAQ). *Human Relations*, 29, 607–622.
- Greenberg, J. (1989). Cognitive reevaluation of outcomes in response to underpayment inequity. *Academy of Management Journal*, 32, 174–184.
- Greene, C. N. (1972). Relationships among role accuracy, compliance, performance evaluation, and satisfaction within managerial dyads. *Academy of Management Journal*, 15, 205–215.
- Greene, C. N., & Organ, D. W. (1973). An evaluation of causal models linking the received role with job satisfaction. *Administrative Science Quarterly*, 18, 95–103.
- Greenhaus, J. H. (1971). Self-esteem as an influence on occupational choice and occupational satisfaction. *Journal of Vocational Behavior*, 1, 75–83.
- Greenhaus, J. H., Seidel, C., & Marinis, M. (1983). The impact of expectations and values on job attitudes. *Organizational Behavior and Human Performance*, 31, 394–417.
- Hall, D. T., Schneider, B., & Nygren, H. T. (1970). Personal factors in organizational identification. *Administrative Science Quarterly*, 15, 176–190.
- Hammer, T. H., & Dachler, H. P. (1975). A test of some assumptions underlying the path

- goal model of supervision: Some suggested conceptual modifications. *Organizational Behavior and Human Performance*, **14**, 60-75.
- Harris, R. J. (1985). *A primer of multivariate statistics* (2nd ed.). New York: Academic Press.
- Hatfield, J. D., & Huseman, R. C. (1982). Perceptual congruence about communication as related to satisfaction: Moderating effects of individual characteristics. *Academy of Management Journal*, **25**, 349-358.
- Hayduk, L. A. (1987). *Structural equation modeling with LISREL*. Baltimore, MD: Johns Hopkins University Press.
- Healy, C. C. (1973). The relation of esteem and social class to self-occupation congruence. *Journal of Vocational Behavior*, **3**, 43-51.
- Hicks, L. E. (1970). Some properties of ipsative, normative, and forced-choice normative measures. *Psychological Bulletin*, **74**, 167-184.
- Hollenbeck, J. R. (1989). Control theory and the perception of work environments: The effects of focus of attention on affective and behavioral reactions to work. *Organizational Behavior and Human Decision Process*, **43**, 406-430.
- Hrebiniak, L. G., & Alutto, J. A. (1972). Personal and role-related factors in the development of organizational commitment. *Administrative Science Quarterly*, **17**, 555-573.
- Humphrys, P. (1981). The effect of importance upon the relation between perceived job attributes, desired job attributes, and job satisfaction. *Australian Journal of Psychology*, **33**, 121-133.
- Imparato, N. (1972). Relationship between Porter's Need Satisfaction Questionnaire and the Job Descriptive Index. *Journal of Applied Psychology*, **56**, 397-405.
- Ivancevich, J. M. (1979). An analysis of participation in decision making among project engineers. *Academy of Management Journal*, **22**, 253-269.
- Jaccard, J., Turrisi, R., & Wan, C. K. (1990). *Interaction effects in multiple regression*. Newbury Park, CA: Sage.
- Jackson, S. E., Brett, J. F., Sessa, V. I., Copper, D. M., Julin, J. A., & Peyronnin, K. (1991). Some differences make a difference: Individual dissimilarity and group heterogeneity as correlates of recruitment, promotions, and turnover. *Journal of Applied Psychology*, **76**, 675-689.
- James, L. R. (1980). The unmeasured variable problem in path analysis. *Journal of Applied Psychology*, **65**, 415-421.
- Johns, G. (1981). Difference score measures of organizational behavior variables: A critique. *Organizational Behavior and Human Performance*, **27**, 443-463.
- Johnson, C. E., Wood, R., & Blinkhorn, S. F. (1988). Spuriouser and supriouser: The use of ipsative personality tests. *Journal of Occupational Psychology*, **61**, 153-162.
- Johnson, T. W., & Graen, G. (1973). Organizational assimilation and role rejection. *Organizational Behavior and Human Performance*, **10**, 72-87.
- Joreskog, K. G., & Sorbom, D. (1988). *LISREL VII*. Chicago: SPSS Inc.
- Joyce, W. F., & Slocum, J. W. (1982). Climate discrepancy: Refining the concepts of psychological and organizational climate. *Human Relations*, **35**, 951-972.
- Kahana, E., Liang, J., & Felton, B. J. (1980). Alternative models of person-environment fit: Prediction of morale in three homes for the aged. *Journal of Gerontology*, **35**, 584-595.
- Kahn, R. L., Wolfe, D. M., Quinn, R. P., Snoeck, J. D., & Rosenthal, R. A. (1964). *Organizational stress: Studies in role conflict and ambiguity*. New York: Wiley.
- Kaufmann, G. M., & Beehr, T. A. (1989). Occupational stressors, individual strains, and social supports among police officers. *Human Relations*, **42**, 185-197.
- Kemelgor, B. H. (1982). Job satisfaction as mediated by the value congruity of supervisors and their subordinates. *Journal of Occupational Behavior*, **3**, 147-160.
- Kenny, D. A. (1979). *Correlation and causality*. New York: Wiley.

- Kenny, D. A., & Judd, C. M. (1984). Estimating the nonlinear and interactive effects of latent variables. *Psychological Bulletin*, *96*, 201-210.
- Kernan, M. C., & Lord, R. G. (1990). Effects of valence, expectancies, and goal-performance discrepancies in single and multiple goal environments. *Journal of Applied Psychology*, *75*, 194-203.
- Kulka, R. A. (1979). Interaction as person-environment fit. In L. R. Kahle (Ed.), *New directions for methodology of behavioral science* (pp. 55-71). San Francisco: Jossey-Bass.
- Lawrie, J. W. (1966). Convergent job expectations and ratings of industrial foremen. *Journal of Applied Psychology*, *50*, 97-101.
- Lee, T. W., & Mowday, R. T. (1987). Voluntarily leaving an organization: An empirical investigation of Steers and Mowday's model of turnover. *Academy of Management Journal*, *30*, 721-743.
- Locke, E. A. (1976). The nature and causes of job satisfaction. In M. Dunnette (Ed.), *Handbook of industrial and organizational psychology* (pp. 1297-1350). Chicago: Rand McNally.
- London, M., & Wohlers, A. J. (1991). Agreement between subordinate and self-ratings in upward feedback. *Personnel Psychology*, *44*, 375-390.
- Long, J. S. (1983). *Covariance structure models: An introduction to LISREL*. Beverly Hills: Sage.
- Lopez, E. M., & Greenhaus, J. H. (1978). Self-esteem, race, and job satisfaction. *Journal of Vocational Behavior*, *13*, 75-83.
- Lubinski, D., & Humphreys, L. G. (1990). Assessing spurious "moderator effects" illustrated substantively with the hypothesized ("synergistic") relation between spatial and mathematical ability. *Psychological Bulletin*, *107*, 385-393.
- Lykken, D. T. (1956). A method of actuarial pattern analysis. *Psychological Bulletin*, *53*, 102-107.
- MacCallum, R. (1986). Specification searches in covariance structure modeling. *Psychological Bulletin*, *100*, 107-120.
- Marquardt, D. W. (1980). You should standardize the predictor variables in your regression models. *Journal of the American Statistical Association*, *75*, 87-91.
- McCormick, E. J. (1979). *Job analysis: Methods and applications*. New York: American Management Association.
- McFarlin, D. B., & Rice, R. W. (in press). The role of facet importance as a moderator in job satisfaction processes. *Journal of Organizational Behavior*.
- McGrath, J. E. (1976). Stress and behavior in organizations. In M. Dunnette (Ed.), *Handbook of industrial and organizational psychology* (pp. 1351-1395). Chicago: Rand McNally.
- McKeown, B., & Thomas, D. (1988). *Q methodology*. Newbury Park, CA: Sage.
- Meglino, B. M., Ravlin, E. C., & Adkins, C. L. (1989). A work values approach to corporate culture: A field test of the value congruence process and its relationship to individual outcomes. *Journal of Applied Psychology*, *74*, 424-434.
- Meglino, B. M., Ravlin, E. C., & Adkins, C. L. (1991). Value congruence and satisfaction with a leader: An examination of the role of interaction. *Human Relations*, *44*, 481-495.
- Meir, E. I., & Engel, K. (1986). Interests and specialty choice in medicine. *Social Science and Medicine*, *23*, 527-530.
- Michalos, A. C. (1980). Satisfaction and happiness. *Social Indicators Research*, *8*, 385-422.
- Michalos, A. C. (1983). Satisfaction and happiness in a rural northern resource community. *Social Indicators Research*, *13*, 224-252.
- Michalos, A. C. (1986). Job satisfaction, marital satisfaction, and the quality of life: A

- review and preview. In F. M. Andrews (Ed.), *Research on the quality of life* (pp. 57-83). Ann Arbor: University of Michigan Institute for Social Research.
- Miles, R. E. (1964). Attitudes toward management theory as a factor in managers' relationships with their superiors. *Academy of Management Journal*, 7, 308-314.
- Mobley, W. H., & Locke, E. A. (1970). The relationship of value importance to satisfaction. *Organizational Behavior and Human Performance*, 5, 463-483.
- Mosier, C. I. (1951). Symposium: The need and means of cross-validation. *Educational and Psychological Measurement*, 11, 5-11.
- Myers, R. H. (1971). *Response surface methodology*. Boston: Allyn & Bacon.
- Neter, J., Wasserman, W., & Kutner, M. H. (1989). *Applied linear regression models* (2nd ed.). Homewood, IL: Irwin.
- Nunnally, J. C. (1962). The analysis of profile data. *Psychological Bulletin*, 59, 311-319.
- Nunnally, J. C. (1978). *Psychometric theory*. New York: McGraw-Hill.
- O'Brien, G. E., & Dowling, P. (1980). The effects of congruency between perceived and desired job attributes upon job satisfaction. *Journal of Occupational Psychology*, 53, 121-130.
- O'Brien, G. E., & Humphrys, P. (1982). The effects of congruency between work values and perceived job attributes upon the job satisfaction of pharmacists. *Australian Journal of Psychology*, 34, 91-101.
- O'Brien, G. E., & Stevens, K. (1981). The relationship between perceived influence and job satisfaction among assembly line employees. *Journal of Industrial Relations*, 23, 33-48.
- Oldham, G. R., Kulik, C. T., Ambrose, M. L., Stepina, L. P., & Brand, J. F. (1986). Relations between job facet comparisons and employee reactions. *Organizational Behavior and Human Decision Process*, 38, 27-47.
- O'Reilly, C. A., Caldwell, D., & Barnett, W. (1989). Work group demography, social integration, and turnover. *Administrative Science Quarterly*, 34, 21-37.
- O'Reilly, C. A., Chatman, J. A., & Caldwell, D. F. (1991). People and organizational culture: A profile comparison approach to assessing person-organization fit. *Academy of Management Journal*, 34, 487-516.
- Osgood, C. E., & Suci, G. J. (1952). A measure of relation determined by both mean difference and profile information. *Psychological Bulletin*, 49, 251-262.
- Parkington, J. J., & Schneider, B. (1979). Some correlates of experienced job stress: A boundary role study. *Academy of Management Journal*, 22, 270-281.
- Payne, R., & Fletcher, B. C. (1983). Job demands, supports, and constraints as predictors of psychological strain among schoolteachers. *Journal of Vocational Behavior*, 22, 136-147.
- Pedhazur, E. J. (1982). *Multiple regression in behavioral research*. New York: Holt.
- Pervin, L. A. (1967). A twenty-college study of student \times college interaction using TAPE (Transactional Analysis of Personality and Environment): Rationale, reliability, and validity. *Journal of Educational Psychology*, 58, 290-302.
- Pfeffer, J., & Salancik, G. R. (1975). Determinants of supervisory behavior: A role set analysis. *Human Relations*, 28, 139-154.
- Phillips, J. S., Barrett, G. V., & Rush, M. C. (1978). Job structure and age satisfaction. *Aging & Work*, 1 (2) 109-119.
- Piehl, D. (1974). Nonlinearity and the study of organizations. *Academy of Management Journal*, 17, 760-767.
- Porter, L. W. (1962). Job attitudes in management. I. Perceived deficiencies in need fulfillment as a function of job level. *Journal of Applied Psychology*, 46, 375-384.
- Porter, L. W. (1964). *Organizational patterns of managerial job attitudes*. New York: American Foundation for Management Research.

- Porter, L. W., & Lawler, E. E. (1968). *Managerial attitudes and performance*. Homewood, IL: Dorsey Press.
- Posner, B. Z., Kouzes, J. M., & Schmidt, W. H. (1985). Shared values make a difference: An empirical test of corporate culture. *Human Resource Management, 24*, 293-309.
- Rice, R. W., McFarlin, D. B., & Bennett, D. E. (1989). Standards of comparison and job satisfaction. *Journal of Applied Psychology, 74*, 591-598.
- Rosman, P., & Burke, R. J. (1980). Job satisfaction, self-esteem, and the fit between perceived self and job on valued competencies. *Journal of Psychology, 105*, 259-269.
- Rounds, J. B., Dawis, R. W., & Lofquist, L. H. (1987). Measurement of person-environment fit and prediction of satisfaction in the Theory of Work Adjustment. *Journal of Vocational Behavior, 31*, 297-318.
- Scarpello, V., & Campbell, J. P. (1983). Job satisfaction and the fit between individual needs and organizational rewards. *Journal of Occupational Psychology, 56*, 315-328.
- Scholl, R. W., Cooper, E. A., & McKenna, J. F. (1987). Referent selection in determining equity perceptions: Differential effects on behavioral and attitudinal outcomes. *Personnel Psychology, 40*, 113-123.
- Senger, J. (1971). Managers' perceptions of subordinates' competence as a function of personal value orientations. *Academy of Management Journal, 14*, 415-423.
- Sheridan, J. E., & Slocum, J. W. (1975). The direction of the causal relationship between job satisfaction and job performance. *Organizational Behavior and Human Performance, 14*, 159-172.
- Snee, R. D. (1977). Validation of regression models: Methods and examples. *Technometrics, 19*, 415-428.
- Sparrow, J. A. (1989). The measurement of job profile similarity for the prediction of transfer of learning: A research note. *Journal of Occupational Psychology, 62*, 337-341.
- Spokane, A. R. (1985). A review of research on person-environment congruence in Holland's theory of careers. *Journal of Vocational Behavior, 26*, 306-343.
- Stephenson, W. (1953). *The study of behavior: Q-technique and its methodology*. Chicago: University of Chicago Press.
- Sulsky, L. M., & Balzer, W. K. (1988). Meaning and measurement of performance rating accuracy: Some methodological and theoretical concerns. *Journal of Applied Psychology, 73*, 497-506.
- Swaney, K., & Prediger, D. (1985). The relationship between interest-occupation congruence and job satisfaction. *Journal of Vocational Behavior, 26*, 13-24.
- Sweeney, P. D., McFarlin, D. B., & Inderrieden, E. J. (1990). Using relative deprivation theory to explain satisfaction with income and pay level: A multistudy examination. *Academy of Management Journal, 33*, 423-436.
- Toffler, B. L. (1981). Occupational role development: The changing determinants of outcomes for the individual. *Administrative Science Quarterly, 26*, 396-418.
- Tom, V. R. (1971). The role of personality and organizational images in the recruiting process. *Organizational Behavior and Human Performance, 6*, 573-592.
- Tsui, A. S., & O'Reilly, C. A., III. (1989). Beyond simple demographic effects: The importance of relational demography in superior-subordinate dyads. *Academy of Management Journal, 32*, 402-423.
- Tubbs, M. E., & Dahl, J. G. (1991). An empirical comparison of self-report and discrepancy measures of goal commitment. *Journal of Applied Psychology, 76*, 708-716.
- Turban, D. B., & Jones, A. P. (1988). Supervisor-subordinate similarity: Types, effects, and mechanisms. *Journal of Applied Psychology, 73*, 228-234.
- Tziner, A. (1987). Congruency issues retested using Fineman's achievement climation notion. *Journal of Social Behavior and Personality, 2*, 63-78.
- Tziner, A., & Falbe, C. M. (1990). Actual and preferred climates of achievement orientation

- and their congruency: An investigation of their relationships to work attitudes and performance in two occupational strata. *Journal of Organizational Behavior*, **11**, 159-168.
- Vance, R. J., & Colella, A. (1990). Effects of two types of feedback on goal acceptance and personal goals. *Journal of Applied Psychology*, **75**, 68-76.
- Vancouver, J. B., & Schmitt, N. W. (1991). An exploratory examination of person-organization fit: Organizational goal congruence. *Personnel Psychology*, **44**, 333-352.
- Vecchio, R. P., & Sussmann, M. (1989). Preferences for forms of supervisory social influence. *Journal of Organizational Behavior*, **10**, 135-143.
- Wagner, W. G., Pfeffer, J., & O'Reilly, C. A. (1984). Organizational demography and turnover in top management groups. *Administrative Science Quarterly*, **29**, 74-92.
- Wall, T. D., & Payne, R. (1973). Are deficiency scores deficient? *Journal of Applied Psychology*, **58**, 322-326.
- Wanous, J. P., & Lawler, E. E. (1972). Measurement and meaning of job satisfaction. *Journal of Applied Psychology*, **56**, 95-105.
- Wanous, J. P., & Youtz, M. A. (1986). Solution diversity and the quality of group decisions. *Academy of Management Journal*, **29**, 149-159.
- Weiss, H. M. (1977). Subordinate imitation of supervisor behavior: The role of modeling in organizational socialization. *Organizational Behavior and Human Performance*, **19**, 89-105.
- Werts, C. E., & Linn, R. L. (1970). A general linear model for studying growth. *Psychological Bulletin*, **73**, 17-22.
- Wexley, K. N., Alexander, R. A., Greenwalt, S. P., & Couch, M. A. (1980). Attitudinal congruence and similarity as related to interpersonal evaluations in manager-subordinate dyads. *Academy of Management Journal*, **23**, 320-330.
- Wexley, K. N., & Pulakos, E. D. (1983). The effects of perceptual congruence and sex on subordinates' performance appraisals of their managers. *Academy of Management Journal*, **26**, 666-676.
- White, J. K., & Ruh, R. A. (1973). Effects of personal values on the relationship between participation and job attitudes. *Administrative Science Quarterly*, **18**, 506-514.
- White, M. C., Crino, M. D., & Hatfield, J. D. (1985). An empirical examination of the parsimony of perceptual congruence scores. *Academy of Management Journal*, **28**, 732-737.
- Wilkinson, L. (1988). *SYSTAT: The system for statistics*. Evanston, IL: SYSTAT, Inc.
- Wolins, L. (1982). *Research mistakes in the social and behavioral sciences*. Ames, IA: The Iowa State University Press.
- Zalesny, M. D., & Kirsch, M. P. (1989). The effect of similarity on performance ratings and interrater agreement. *Human Relations*, **42**, 81-96.
- Zenger, T. R., & Lawrence, B. S. (1989). Organizational demography: The differential effects of age and tenure distributions on technical communication. *Academy of Management Journal*, **32**, 353-376.

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