PROBLEMS WITH THE USE OF PROFILE SIMILARITY INDICES IN THE STUDY OF CONGRUENCE IN ORGANIZATIONAL RESEARCH

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Profile similarity indices (PSIs) have become widely used in studies of congruence (i.e., fit, matching, similarity, agreement) in organizational research. PSIs combine two sets of measures, or profiles, from corresponding entities (e.g., the person and organization, supervisor and subordinate, organization and environment) into a single score intended to represent their overall congruence. Unfortunately, PSIs are conceptually ambiguous, discard information essential to testing congruence hypotheses, conceal the source of the difference between entities, and impose a highly restrictive set of constraints on the coefficients relating the measures comprising the PSI to the outcome. This article shows how polynomial regression analysis may be used to avoid problems with PSIs while capturing the underlying relationships PSIs are intended to represent. Limitations and extensions to the procedure are discussed.

Profile similarity indices (PSIs) have become widely used in the study of congruence (i.e., fit, matching, similarity, or agreement) in organizational research (e.g., Chatman, 1991; Dougherty & Pritchard, 1985; Drazin & Van de Ven, 1985; Rounds, Dawis, & Lofquist, 1987; Venkatraman & Prescott, 1990). PSIs combine two sets of measures, or profiles, representing corresponding entities (e.g., the person and organization, supervisor and subordinate, organizational strategy and environment) into a single score intended to represent their overall congruence (Cronbach & Gleser, 1953).

Despite their widespread use, PSIs are prone to numerous methodological problems (Cronbach, 1958; Cronbach & Gleser, 1953; Edwards, in press; Johns, 1981; Lykken, 1956; Nunnally, 1962). Unfortunately, these problems have been overlooked in recent congruence research, which has relied heavily on PSIs and, in some cases, explicitly advocated their use (Caldwell & O'Reilly, 1990; Drazin & Van de Ven, 1985; Smith & Tisak, in press). Furthermore, procedures that may overcome these problems, such as polynomial regression analysis (Cronbach, 1958;

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Edwards, in press), have not been fully developed or become widely adopted. As a result, studies of congruence continue to rely on PSIs, yielding results that are methodologically flawed and potentially invalid.

This article discusses problems with PSIs used in the study of congruence in organizational research and describes alternative procedures that overcome these problems. The contribution of this article is twofold. First, it integrates the literature concerning problems with the use of PSIs, which has spanned 40 years and tended to address problems in a piecemeal fashion (Cronbach, 1958; Cronbach & Gleser, 1953; Edwards, in press; Johns, 1981; Lykken, 1956; Nunnally, 1962). Second, it extends Cronbach (1958) and Edwards (in press) by describing and illustrating procedures for testing key assumptions underlying various PSIs, as well as analyses that apply when these assumptions are not met. As will be shown, these procedures avoid problems with PSIs but nonetheless permit comprehensive tests of hypotheses derived from congruence research.

The following discussion focuses specifically on problems resulting from the use of PSIs as predictors in congruence research. As will become evident, these problems arise whether PSIs represent individual, group, or organizational constructs; rely on single or multiple methods; or use data from single or multiple sources. This discussion does not address the use of PSIs as indices of interrater agreement (Jones, Johnson, Bulter, & Main, 1983; Tinsley & Weiss, 1975) or as dependent variables, as in studies of performance rating accuracy (Sulsky & Balzer, 1988) or decision quality (Wanous & Youtz, 1986). Nonetheless, using PSIs for these purposes introduces many of the problems discussed here, and the procedures presented here may be adapted to overcome these problems. These issues are considered in greater detail later in this article.

Profile Similarity Indices Used in Congruence Research

Sum of Differences Between Profile Elements

With few exceptions, PSIs used in congruence research can be placed into one of two broad categories (see Table 1). One category consists of indices derived from the sum of differences between profile elements. For example, D^2 represents the sum of squared differences between profile elements (e.g., Miller, 1991; Rounds et al., 1987; Turban & Jones, 1988; Venkatraman & Prescott, 1990). Because it squares each difference, D^2 is nondirectional (i.e., treats positive and negative differences the same) and assigns greater weight to differences of larger magnitude. D, or the square root of D^2 (e.g., Drazin & Van de Ven, 1985; Govindarajan, 1989; Gresov, 1989; Sparrow, 1989; Vancouver & Schmitt, 1991;

TABLE 1

Profile Similarity Indices Used in Organizational Research

Index	Formula	Index	Formula
D^2	$\sum(X_i-Y_i)^2$	Q	$\dfrac{k\sum X_iY_i-\sum X_i\sum Y_i}{\sqrt{[k\sum X_i^2-(\sum X_i)^2][k\sum Y_i^2-(\sum Y_i)^2]}}$
D	$\sqrt{\sum(X_i-Y_i)^2}$		
$|D|$	$\sum|X_i-Y_i|$	Q_q	$1+\dfrac{k\sum(X_i-Y_i)^2}{2[(\sum X_i)^2-k\sum X_i^2]}$
D^1	$\sum(X_i-Y_i)$		
		Q_r	$1-\dfrac{6\sum(X_i-Y_i)^2}{k(k^2-1)}$
M's D	$\sqrt{(X_i-Y_i)'S^{-1}(X_i-Y_i)}$		

Note: M's D = Mahalanobis' D

X_i and Y_i represent measures of profile elements, and k represents the number of elements comprising each profile. Summations are over all k measures. For Q_q, ΣX_i and ΣX_i^2 are constants determined by the prescribed distribution of the Q-sort. For Mahalanobis' D, S represents the pooled within-entity variance-covariance matrix of the k element measures.

Vandenberg & Scarpello, 1990; Wexley & Pulakos, 1983; White, Crino, & Hatfield, 1985) is also nondirectional but, unlike D^2, yields a geometric interpretation, representing the Euclidean distance between the two entities in k-dimensional space, where k represents the number of elements involved. $|D|$ represents the sum of absolute differences between profile elements (e.g., Dougherty & Pritchard, 1985; Meglino, Ravlin, & Adkins, 1992; Zalesny & Kirsch, 1989). $|D|$ is nondirectional but, unlike D^2, assigns equal weight to differences of increasing magnitude (e.g., a difference of three units on one element is equivalent to a difference of one unit on three elements). $|D|$ also yields a geometric interpretation, indicating the cumulative distance between two entities measured along the k orthogonal axes corresponding to the profile elements.

Two indices based on the sum of differences between profile elements have been used less frequently than D^2, D, or $|D|$. D^1, which represents the sum of algebraic differences (e.g., Sparrow, 1989; Tannenbaum, Mathieu, Salas, & Cannon-Bowers, 1991; Wohlers & London, 1989) is analogous to $|D|$ but distinguishes between positive and negative differences, indicating the net difference between two entities across all k elements. Mahalanobis' D (Berger-Gross, 1982) may be calculated using the formula shown in Table 1 or by factoring the pooled within-entity variance-covariance matrix into k orthogonal components, using the resulting component loadings divided by their respective eigenvalues as weights to calculate component scores, and then using these scores to compute D (Cronbach & Gleser, 1953). Thus, Mahalanobis' D represents the Euclidean distance between the two entities in k-dimensional

space, where each dimension is a weighted linear composite of the original elements.

Correlation Between Profiles

A second category of PSIs consists of indices representing the correlation between two profiles. These indices share a common interpretation, indicating similarity in the rank ordering of the elements within each profile. However, these indices may be distinguished according to the type of measure constituting each profile. Q represents the correlation between two sets of interval measures (e.g., Dalessio & Imada, 1984; London & Wohlers, 1991; Rounds et al., 1987; Sparrow, 1989; Wohlers & London, 1989). Q_q represents the correlation between two Q-sorts (e.g., Caldwell & O'Reilly, 1990; Chatman, 1991; O'Reilly, Chatman, & Caldwell, 1991), and Q_r represents the correlation between two rankings (e.g., Amerikaner, Elliot, & Swank, 1988; Meglino, Ravlin, & Adkins, 1989; Meglino et al., 1992; Rounds et al., 1987). Although Q_q and Q_r can be calculated using the formula for Q, the distributional properties of Q-sorts and rankings simplify computation and, furthermore, show that Q_q and Q_r are linear transformations of D^2, given that all terms in the formulas for Q_q and Q_r other than $\Sigma(X_i - Y_i)^2$ are constants (see Table 1).

Problems With the Use of Profile Similarity Indices in Congruence Research

Conceptual Ambiguity

As used here, the term conceptual ambiguity refers to the inability to clearly identify the construct underlying a measure. By construction, PSIs present two forms of conceptual ambiguity. One form results from combining measures of conceptually distinct elements into a single profile (Cronbach, 1955, 1958; Lykken, 1956). For example, O'Reilly et al. (1991) constructed profiles using measures of 54 different values, such as autonomy, pay for performance, and social responsibility. Similarly, Drazin and Van de Ven (1985) combined measures of 11 organizational characteristics such as personnel expertise, unit specialization, and methods of conflict resolution. Indices that combine conceptually heterogeneous elements such as these into a single score defy clear interpretation, because they conceal the contribution of each element to the overall score (Cronbach, 1958; Gerbing & Anderson, 1988; Hattie, 1985; Wolins, 1982). It may seem that the elements contribute equally, given that each is implicitly assigned the same weight (i.e., unity) when the index is constructed. However, the contribution of each element is

determined not by these weights, but by the variances and covariances of the element measures. This information is rarely reported and, furthermore, is sample dependent, such that a PSI based on a single set of measures may yield different interpretations across studies.

A second form of conceptual ambiguity results from combining profiles from two entities (Cronbach, 1958; Nunnally, 1962). With few exceptions, these entities are conceptually distinct, either because they represent different constructs (e.g., actual vs. ideal job or organizational attributes) or are drawn from different sources (e.g., supervisor and subordinate). Furthermore, the relative contributions of the entities to the PSI should not be considered equal, given that they depend upon the variances and covariances of the entity measures. In extreme cases, scores for one entity are constants, as when multiple employees are compared to a single job profile (Caldwell & O'Reilly, 1990) or several firms are compared to an "ideal" firm profile (Govindarajan, 1989; Venkatraman & Prescott, 1990). In these cases, PSIs simply represent variance attributable to one entity and, hence, should not be interpreted as measures of congruence.

Discarded Information

In studies of congruence, hypotheses are typically framed in terms of the magnitude of the difference between two entities, based on the premise that some outcome is minimized or maximized when the entities are equal (e.g., Chatman, 1991; Drazin & Van de Ven, 1985; Meglino et al., 1989; 1992; O'Reilly et al., 1991; Vancouver & Schmitt, 1991; Venkatraman & Prescott, 1990; Zalesny & Kirsch, 1989). Hypotheses framed in these terms embody two fundamental assumptions. One assumption is that the function relating the difference between the two entities to the outcome is symmetric, meaning that the effects of positive and negative differences are the same. The second assumption is that the outcome is constant at all points where the two entities are equal, regardless of the absolute level of the entities.

To verify these assumptions, it is obviously necessary to consider information regarding the absolute level of both entities and the direction of their difference. Unfortunately, this information is lost when PSIs are used. This is illustrated by the profiles shown in Figure 1 and the corresponding PSIs in Table 2. For example, when D^2, D, $|D|$, or D^1 is used, information regarding the absolute level of both entities is lost. This is seen by comparing the difference between profiles B and C to the difference between profiles D and E. Note that both pairs of profiles differ by one unit across all seven elements, but that scores for profiles B and C
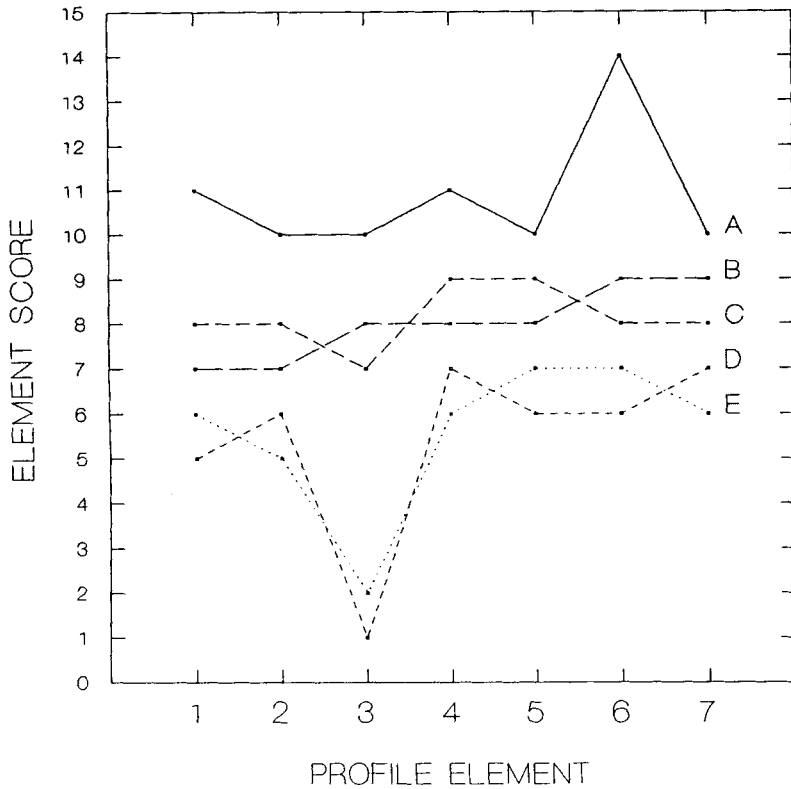
Figure 1: **Five Hypothetical Profiles**

are greater than those for profiles D and E. However, both comparisons yield identical values of D^2, D, $|D|$, and D^1.

D^2, D, and $|D|$ also discard information regarding the direction of the difference between entities. This is seen by comparing profile C with profiles A and D. Note that scores for profile A are greater than those for profile C, whereas scores for profile D are less than those for profile C. Nonetheless, both comparisons yield the same values of D^2, D, and $|D|$.[1]

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[1] Based on Table 2, it may seem that D^1 also discards information regarding the direction of the difference between entities, because the comparison of profiles A and C yielded the same value of D^1 as the comparison of profiles C and D. This is because D^1 was calculated by subtracting profiles with smaller scores from those with larger scores. In empirical applications, one profile would serve as the referent to compare other profiles, such that profile C would be subtracted from profiles A and D, yielding scores of 19 and -19, respectively. Thus, D^1 does, in fact, preserve information regarding the direction of the difference between entities, representing the net difference across all k elements.

TABLE 2

Profile Similarity Indices Comparing Profiles Shown in Figure 1

Index	A,B	A,C	A,D	A,E	B,C	B,D	B,E	C,D	C,E	D,E
D^2	68.00	67.00	238.00	213.00	7.00	72.00	59.00	67.00	56.00	7.00
D	8.25	8.19	15.43	14.59	2.65	8.49	7.68	8.19	7.48	2.65
$|D|$	20.00	19.00	38.00	37.00	7.00	18.00	17.00	19.00	18.00	7.00
D^1	20.00	19.00	38.00	37.00	−1.00	18.00	17.00	19.00	18.00	−1.00
M's D	8.21	7.99	15.24	14.41	2.71	8.32	7.43	8.11	7.41	2.64
Q	0.42	0.02	0.19	0.44	0.00	0.20	0.24	0.77	0.76	0.86

Note: M's D = Mahalanobis' D. The two letters at the top of each column indicate the pair of profiles for which the indices were calculated (e.g., A,B indicates that the indices were calculated for profiles A and B). D^2 represents the sum of squared differences between profile elements, D represents the square root of D^2, $|D|$ represents the sum of absolute differences between profile elements, D^1 represents the sum of algebraic differences between profile elements, and Q represents the correlation between the two profiles (because interval measurement was assumed, Q_q and Q_r were not calculated). Mahalanobis' D was calculated by assuming that each profile in Figure 1 was drawn from a sample of 100 cases with means for each element measure equal to the reported profile and standard deviations equal to unity.

Mahalanobis' D also discards information regarding the absolute level of both entities and the direction of their difference. However, the discarded information pertains not to the original element measures, but rather to scores on the k orthogonal components derived from the pooled within-entity variance-covariance matrix. Of course, because these scores are weighted composites of the original element measures, they contain information regarding the level and direction of the difference between the two entities, although this information is not expressed in terms of the original elements. Nonetheless, this information is lost when Mahalanobis' D is calculated, because component scores for the two entities are subtracted and squared, as in the calculation of D.

Like D^2, D, $|D|$, and Mahalanobis' D, Q discards level and directional information. This occurs because Q effectively standardizes element measures within each profile, resulting in a mean of zero for both profiles. However, by standardizing both profiles, Q also discards information regarding the magnitude of the difference between entities (Cronbach & Gleser, 1953). This is shown by comparing profile C with profiles B and D. Although profiles C and D are separated by 1 to 6 units, they are quite similar in shape, yielding a Q of .77. In contrast, profiles B and C differ by no more than 1 unit but yield a Q of zero. Given that the magnitude of the difference between entities is central to congruence hypotheses, it is difficult to imagine a situation in which profiles D and C should be considered more alike than profiles B and C. Unfortunately, this phenomenon occurs whenever Q is used. Although Q_q and Q_r do not standardize measures within each profile, they nonetheless fail to reflect the magnitude of the difference between entities, because Q-sorts

and rankings do not contain this information in the first place (Hicks, 1970; Nunnally, 1978).

Insensitivity to the Sources of Profile Differences

By construction, PSIs fail to reflect which elements contribute to the difference between two entities (Johns, 1981). This is illustrated by comparing profile B with profiles A and D. Note that both comparisons yield similar values on all six indices. However, Figure 1 shows that the difference between profiles A and B is primarily due to element 6, whereas the difference between profiles B and D is primarily due to element 3. In general, different sources of incongruence should not be considered the same, given that they typically refer to conceptually distinct dimensions (e.g., Drazin & Van de Ven, 1983; O'Reilly et al., 1991), represent different psychological experiences for the respondent, and predict different outcomes (Cronbach, 1958; Johns, 1981; Lykken, 1956). Unfortunately, PSIs necessarily obscure these distinctions.

Overly Restrictive Constraints

Although rarely recognized, using a PSI as a predictor imposes a highly restrictive set of constraints on the coefficients relating the measures composing the PSI to the outcome (Cronbach, 1958; Edwards, in press). These constraints may be identified by writing a regression equation containing the PSI, expanding the equation and distributing the coefficient preceding the PSI, and comparing this equation to an equation containing the measures comprising the PSI as predictors. For example, using D^1 as a predictor is represented by the following equation:

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

In this equation, X_i and Y_i are corresponding element measures, k represents the number of elements, Z is the outcome, and e is a random disturbance term. Expanding this equation and distributing b_1 yields:

$$Z = b_0 + b_1 X_1 - b_1 Y_1 + b_1 X_2 - b_1 Y_2 + \cdots b_1 X_k - b_1 Y_k + e \qquad (2)$$

Now consider the following equation, which uses the X_i and Y_i as predictors:

$$Z = b_0 + b_1 X_1 + b_2 Y_1 + b_3 X_2 + b_4 Y_2 + \cdots + b_{2k-1} X_k + b_{2k} Y_k + e \qquad (3)$$

Comparing Equations 2 and 3 shows that D^1 imposes the following constraints: (a) The coefficients on all paired X_i and Y_i are equal in magnitude but opposite in sign; and (b) the coefficients on the X_i and Y_i are equal across the k elements. In essence, these constraints imply that the X_i and Y_i exhibit equal but opposite effects, and that these effects are of the same magnitude across all elements. Obviously, such a restrictive set of constraints should be tested empirically, not simply imposed on the data (Cronbach, 1958; Edwards, in press). Constraints for $|D|$ and D^2 may be derived in a similar manner (see Edwards, in press).

Summary

As the preceding discussion has shown, the use of PSIs as predictors in congruence research introduces numerous methodological problems. First, by combining measures of conceptually distinct elements and entities into a single score, PSIs are conceptually ambiguous. Second, PSIs discard information regarding the absolute level of both entities and, with the exception of D^1, the direction of their difference. Profile correlations also discard information regarding the magnitude of the difference between entities, although with Q_q and Q_r, this information is lost when the Q-sorts and rankings are initially collected. Third, PSIs fail to reflect which elements are responsible for the difference between two entities. Finally, PSIs impose a highly restrictive set of constraints on the coefficients relating the measures comprising the PSI to the outcome. Given these problems, it seems evident that PSIs should no longer be used in congruence research.

Recommendations

Problems with the use of PSIs as predictors in congruence research can be avoided by following five general guidelines. First, hypotheses regarding the effects of congruence should be stated not in general terms, but rather in reference to specific, conceptually distinct dimensions (Cronbach, 1958; Lykken, 1956). As argued by Cronbach and Gleser (1953), *"similarity is not a general quality. It is possible to discuss similarity only with respect to specified dimensions"* [italics in original] (p. 457). Obviously, two entities can be similar on some dimensions and different on others, and the meaning and effects of similarity are likely to differ across dimensions. These differences are ignored when hypotheses are stated in terms of general congruence between two entities. Although framing hypotheses in general terms may seem to provide conceptual parsimony, this parsimony is more apparent than real,

given the numerous alternative interpretations that may apply to a general congruence hypothesis (Cronbach, 1958). Moreover, any ostensible gains in parsimony are more than offset by the numerous methodological problems described here.

Second, given that congruence hypotheses should be stated in terms of specific dimensions, measurement should focus not on entire profiles, but rather on conceptually distinct dimensions contained within profiles. When profiles comprise a few distinct elements (e.g., Govindarajan, 1989; Gresov, 1989; Meglino et al., 1989, 1992; Miller, 1991), these elements may adequately represent the dimensions of interest. However, when profiles contain numerous highly specific elements (e.g., Caldwell & O'Reilly, 1990; Chatman, 1991; Dougherty & Pritchard, 1985; London & Wohlers, 1991; O'Reilly et al., 1991; Rounds et al., 1987; Sparrow, 1989), it may be impractical or undesirable to use separate measures of each element. In these situations, factor analysis may be used to assign the original elements to subscales representing conceptually distinct dimensions. However, if the original elements are highly specific, these subscales may maximize specific-item variance at the expense of common-item variance, resulting in low reliability (Lord & Novick, 1968). This may be avoided by developing new measures using a domain sampling procedure (Nunnally, 1978) and phrasing items at a level of specificity that corresponds to the dimension of interest. In either case, the resulting measures should be evaluated using confirmatory factor analysis to verify their reliability, validity, and unidimensionality (Anderson & Gerbing, 1988; Gerbing & Anderson, 1988; Hattie, 1985).

Third, single-item measures of profile elements should be abandoned in favor of multi-item measures. Arguments for multi-item measures are certainly not new (Nunnally, 1978), nor are they restricted to congruence research. However, they have often been overlooked in studies using PSIs (Johns, 1981). Although PSIs themselves consist of multiple items, these items typically represent different content domains and, in combination, yield a measure that is ambiguous and, hence, of questionable validity. When PSIs combine numerous elements, it may be impractical to administer multi-item measures of each element. However, it seems more advisable to collect valid data on fewer elements than data of questionable validity on numerous elements. Furthermore, when measures of highly specific elements are replaced by measures of broader conceptual dimensions, the use of multi-item measures becomes much more feasible.

Fourth, entities should be measured using normative rather than ipsative measures, most notably Q-sorts (Caldwell & O'Reilly, 1990; Chatman, 1991; O'Reilly et al., 1991) and rankings (Amerikaner et al., 1988; Meglino et al., 1989, 1992). Ipsative measures are scaled separately

within each entity and, hence, provide no information regarding the magnitude of the difference between entities. As emphasized earlier, this information is central to the study of congruence, and measures that cannot provide this information are of little use. As noted by Nunnally (1978), the primary advantage of Q-sorts and rankings is that they can provide large amounts of comparative information. However, this information is useful only for comparing scores on different elements within entities, which is largely irrelevant to congruence research.

Some investigators have advocated the use of ipsative measures, claiming that they account for difference in the salience of elements across entities (Caldwell & O'Reilly, 1990; O'Reilly et al., 1991). However, because ipsative measures are scaled separately for each entity, they effectively discard all information regarding differences between entities, including information necessary to assess congruence. A more direct approach is to explicitly measure the salience of each element for both entities and then use these measures as covariates or, when theoretically justified, as moderators of the effects of congruence (Edwards, 1992; Locke, 1976; Rice, McFarlin, Hunt, & Near, 1985).

Finally, the effects of congruence should be analyzed using polynomial regression equations containing separate measures of both entities, supplemented by higher-order terms (e.g., the squares of both entity measures and their product) required to depict the shape of the hypothesized relationship (Edwards, in press; Edwards & Parry, in press). By doing this, problems due to combining entity measures into a single score may be avoided, and the underlying three-dimensional relationship between paired entities and the outcome is preserved. Furthermore, theoretically meaningful relationships that cannot be depicted using PSIs can be examined, such as slope along the line where paired entities are equal and rotations or lateral shifts in the overall orientation of the surface (Edwards & Parry, in press). In general, measures of entities across all relevant dimensions should be analyzed within a single equation, particularly when congruence on each dimension is hypothesized to influence the same outcome, or when dimensions are correlated and, hence, may result in biased coefficient estimates if analyzed separately (James, 1980). The interpretation of these equations is greatly facilitated by using the obtained coefficients to test various features of the surfaces relating the paired entities on each dimension to the outcome (Edwards & Parry, in press).

It has been argued that examining the effects of congruence on separate dimensions is reductionistic and, hence, cannot capture holistic effects presumably represented by PSIs (e.g., Drazin & Van de Ven, 1985; Gresov, 1989; Venkatraman & Prescott, 1990). However, this argument

applies only when PSIs are compared to separate analyses of each dimension. When multiple dimensions are analyzed within a single regression equation, as advocated here, their combined effects are captured by the overall R^2 for the equation. Furthermore, these equations can reveal differences in the functional forms relating congruence on each dimension to the outcome, which are concealed when PSIs are used. Thus, the regression approach provides holistic as well as dimension-specific information regarding the effects of congruence.

Some investigators have attempted to capture variation in the effects of congruence across dimensions by weighting the k bivariate difference scores comprising a PSI (e.g., Sparrow, 1989; Tannenbaum et al., 1991; Venkatraman & Prescott, 1990). Unfortunately, this procedure does not determine whether the effects of the *weighted* differences are, in fact, equal. Furthermore, when the differences are weighted by a third variable (Sparrow, 1989; Tannenbaum et al., 1991), this variable and the original bivariate differences must be statistically controlled in order to obtain a meaningful coefficient on the weighted PSI (Evans, 1991). Unfortunately, these variables are rarely controlled in studies using weighted PSIs.

An Illustration of the Polynomial Regression Procedure

The use of polynomial regression as an alternative to PSIs was initially described by Cronbach (1958). Edwards (in press) formally elaborated this procedure by deriving and testing constraints imposed by $|D|$ and D^2. This section extends Edwards in three ways. First, it includes tests of constraints imposed by D^1. Second, it derives and tests intermediate sets of constraints for D^1, $|D|$, and D^2. Finally, it demonstrates procedures that apply when constraints imposed by these indices are rejected.

Data for the following analyses were drawn from 165 graduating MBA students, who completed four-item measures of actual and desired amounts of seven job attributes (e.g., compensation, independence, relations with coworkers) in reference to the job each student would begin upon graduation. Reliabilities for these measures were acceptable (median = .805), and correlations among the measures were not excessive (median = .164). These measures were used to calculate D^1, $|D|$, and D^2 using the formulas shown in the first column of Table 3, with actual and desired amounts constituting the two entities and the seven job attributes constituting the elements. Satisfaction with each attribute was also assessed using a four-item measure and, for this illustration, overall job satisfaction was calculated as the sum of these measures. Items

TABLE 3

Constrained and Unconstrained Equations for D^1, $|D|$, and D^2

Index	All constraints	Within-Element constraints	Between-Element constraints	No constraints
D^1	$Z=b_0+b_1\Sigma(X_i-Y_i)+e$ $=b_0+b_1X_1-b_1Y_1$ $+b_1X_2-b_1Y_2+\cdots$ $+b_1X_k-b_1Y_k+e$	$Z=b_0+\Sigma b_i(X_i-Y_i)+e$ $=b_0+b_1X_1-b_1Y_1$ $+b_2X_2-b_2Y_2+\cdots$ $+b_kX_k-b_kY_k+e$	$Z=b_0+b_1\Sigma X_i+b_2\Sigma Y_i+e$ $=b_0+b_1X_1+b_2Y_1$ $+b_1X_2+b_2Y_2+\cdots$ $+b_1X_k+b_2Y_k+e$	$Z=b_0+b_1X_1+b_2Y_1$ $+b_3X_2+b_4Y_2+\cdots$ $+b_{2k-1}X_k+b_{2k}Y_k+e$
$|D|$	$Z=b_0+b_1\Sigma(1-2W_i)(X_i-Y_i)+e$ $=b_0+b_1X_1-b_1Y_1-2b_1W_1X_1$ $+2b_1W_1Y_1+b_1X_2-b_1Y_2$ $-2b_1W_2X_2+2b_1W_2Y_2+\cdots$ $+b_1X_k-b_1Y_k-2b_1W_kX_k$ $+2b_1W_kY_k+e$	$Z=b_0+\Sigma b_i(1-2W_i)(X_i-Y_i)+e$ $=b_0+b_1X_1-b_1Y_1-2b_1W_1X_1$ $+2b_1W_1Y_1+b_2X_2-b_2Y_2$ $-2b_2W_2X_2+2b_2W_2Y_2+\cdots$ $+b_kX_k-b_kY_k-2b_kW_kX_k$ $+2b_kW_kY_k+e$	$Z=b_0+b_1\Sigma X_i+b_2\Sigma Y_i+b_3\Sigma W_i+b_4\Sigma W_iX_i$ $+b_5\Sigma W_iY_i+e$ $=b_0+b_1X_1+b_2Y_1+b_3W_1+b_4W_1X_1$ $+b_5W_1Y_1+b_1X_2+b_2Y_2+b_3W_2$ $+b_4W_2X_2+b_5W_2Y_2+\cdots+b_1X_k$ $+b_2Y_k+b_3W_k+b_4W_kX_k+b_5W_kY_k+e$	$Z=b_0+b_1X_1+b_2Y_1+b_3W_1+b_4W_1X_1$ $+b_5W_1Y_1+b_6X_2+b_7Y_2+b_8W_2$ $+b_9W_2X_2+b_{10}W_2Y_2+\cdots$ $+b_{5k-4}X_k+b_{5k-3}Y_k+b_{5k-2}W_k$ $+b_{5k-1}W_kX_k+b_{5k}W_kY_k+e$
D^2	$Z=b_0+b_1\Sigma(X_i-Y_i)^2+e$ $=b_0+b_1X_1^2-2b_1X_1Y_1+b_1Y_1^2$ $+b_1X_2^2-2b_1X_2Y_2+b_1Y_2^2+\cdots$ $+b_1X_k^2-2b_1X_kY_k+b_1Y_k^2+e$	$Z=b_0+\Sigma b_i(X_i-Y_i)^2+e$ $=b_0+b_1X_1^2-2b_1X_1Y_1+b_1Y_1^2$ $+b_2X_2^2-2b_2X_2Y_2+b_2Y_2^2+\cdots$ $+b_kX_k^2-2b_kX_kY_k+b_kY_k^2+e$	$Z=b_0+b_1\Sigma X_i+b_2\Sigma Y_i+b_3\Sigma X_i^2+b_4\Sigma X_iY_i$ $+b_5\Sigma Y_i^2+e$ $=b_0+b_1X_1+b_2Y_1+b_3X_1^2+b_4X_1Y_1+b_5Y_1^2$ $+b_1X_2+b_2Y_2+b_3X_2^2+b_4X_2Y_2+b_5Y_2^2+\cdots$ $+b_1X_k+b_2Y_k+b_3X_k^2+b_4X_kY_k+b_5Y_k^2+e$	$Z=b_0+b_1X_1+b_2Y_1+b_3X_1^2+b_4X_1Y_1$ $+b_5Y_1^2+b_6X_1+b_7Y_1+b_8X_1^2$ $+b_9X_1Y_1+b_{10}Y_1^2+\cdots+b_{5k-4}X_k$ $+b_{5k-3}Y_k+b_{5k-2}X_k^2+b_{5k-1}X_kY_k$ $+b_{5k}Y_k^2+e$

Note: Summations are over all k elements. In the equations for $|D|$, W_i is a dummy variable that equals 0 when $X_i > Y_i$, 1 when $X_i < Y_i$, and is randomly set to 0 or 1 when $X_i = Y_i$.

for each attribute were drawn from the Work Aspect Preference Scale (Pryor, 1983).

Correlations between overall job satisfaction and both $|D|$ and D^2 were negative ($r = -.263$ and $r = -.229$, respectively, both $p < .01$), whereas the correlation between satisfaction and D^1 was positive but not significant ($r = .137$, $p > .05$). Based on these results, it would seem that satisfaction decreased as actual attribute amount deviated from desired amount in either direction. However, this conclusion assumes that the constraints imposed by $|D|$ and D^2 are tenable, meaning that the coefficients on the measures comprising these indices follow the pattern shown in the first column of Table 3, and that the constraints imposed by D^1 did not conceal relationships that would have otherwise been significant.

To test these assumptions, the constraints imposed by D^1, $|D|$, and D^2 were tested by estimating the unconstrained equations shown in the last column of Table 3 and testing the increment in R^2 over the constrained equations, which used each index as a single predictor. As shown in Table 4, the coefficients yielded by the unconstrained equations deviated from the patterns corresponding to D^1, $|D|$, and D^2. For example, recall that D^1 constrains the coefficients on the X_i and Y_i to be equal in magnitude but opposite in sign. In contrast, the coefficients shown in Table 4 varied in absolute magnitude and were often of the same sign. Deviations from the constraints imposed by $|D|$ and D^2 can also be seen by comparing the coefficients reported in Table 4 to the patterns shown in the first column of Table 3. The R^2 for each unconstrained equation was also significantly higher than that for the corresponding constrained equation (see Table 5), indicating that the constraints imposed by each index were rejected. On average, the adjusted R^2 was .311 higher for the unconstrained equations than for the constrained equations, representing more than a sevenfold increase.

In some situations, it may be useful to test constraints less restrictive than those imposed by D^1, $|D|$, or D^2. For example, when the constraints imposed by D^1 are rejected, it is nonetheless possible that the coefficients *within* each element (i.e., on each paired X_i and Y_i) are equal in magnitude but opposite in sign. Equations that impose within-element constraints for D^1, $|D|$, and D^2 are shown in the second column of Table 3. Note that these equations are equivalent to using the k bivariate differences comprising each index (i.e., the algebraic, absolute, and squared differences for D^1, $|D|$, and D^2, respectively) as predictors. Alternately, it may be useful to test whether the relationship between paired entities and the outcome is constant *between* elements, even though the precise form of this relationship is not specified in advance. Equations that impose between-element constraints for D^1, $|D|$,

TABLE 4

Unconstrained Regression Equations for D^1, $|D|$, and D^2 Predicting Overall Job Satisfaction

	D^1			$|D|$						D^2					
	X_i	Y_i	R^2	X_i	Y_i	W_i	W_iX_i	W_iY_i	R^2	X_i	Y_i	X_i^2	X_iY_i	Y_i^2	R^2
Compensation	0.293	−0.018		−0.758	0.400	−1.876	1.514	−0.169		−0.061	0.034	−0.267	0.503	−0.212	
Creativity	0.196	0.697		−0.051	0.621	0.863	1.677	−0.846		−0.185	1.051	−0.422	1.090*	−0.536	
Independence	0.400	−0.777		0.366	−0.989	−1.823	−1.082	1.215		0.832	−2.443**	0.497	−0.893	1.203**	
Job security	0.281	0.410		0.411	−0.431	−0.973	−0.964	2.259*		0.336	0.281	0.002	−0.053	0.437**	
Life style	0.968**	0.559		−0.368	1.568	0.145	1.970	−1.582		0.244	0.540	−0.332	0.646	0.046	
Relations with coworkers	0.178	0.540		0.576	1.159	3.265	0.253	−2.068		−0.188	1.075	0.440	−0.205	−0.397	
Self-development	0.712	−0.025	.352**	1.206	−0.812	0.789	−0.513	0.966	.481**	1.855*	1.576	−0.097	−0.851	0.130	.545**

Note: $N = 165$. Table entries are unstandardized regression coefficients. X_i represents actual attribute amount, Y_i represents desired attribute amount, and W_i represents a dummy variable that equals 0 if $X_i > Y_i$ and 1 if $X_i < Y_i$ (if $X_i = Y_i$, W_i is randomly set to 0 or 1). All X_i and Y_i were centered at their scale midpoint (i.e., 4 on a 7-point scale).

*$p < .05$; **$p < .01$

TABLE 5

Squared Multiple Correlations from Constrained and Unconstrained
Regression Equations for D^1, $|D|$, and D^2 Predicting Overall Job Satisfaction

	All constraints	Within-element constraints	Between-element constraints	No constraints
D^1	$.018_b$	$.067_b$	$.294_a$**	$.352_a$**
	(.012)	(.025)	(.285)	(.292)
$|D|$	$.069_b$**	$.098_b$*	$.329_a$**	$.481_a$**
	(.063)	(.057)	(.308)	(.341)
D^2	$.052_b$**	$.101_b$*	$.353_{a,b}$**	$.545_a$**
	(.046)	(.061)	(.332)	(.421)

Note: $N = 165$. Table entries are squared multiple correlations (adjusted squared multiple correlations are shown in parenthesis). For the first column, each R^2 is from an equation using the PSI as a single predictor. For the second column, each R^2 is from an equation using the seven separate difference scores as predictors (algebraic, absolute, or squared differences for D^1, $|D|$, or D^2, respectively). For the third column, each R^2 is from an equation using sums of variables across elements as predictors (i.e., ΣX_i and ΣY_i for D^1; ΣX_i, ΣY_i, ΣW_i, $\Sigma W_i X_i$, and $\Sigma W_i Y_i$ for $|D|$; ΣX_i, ΣY_i, ΣX_i^2, $\Sigma X_i Y_i$, and ΣY_i^2 for D^2). For the fourth column, each R^2 is from the fully unconstrained equation for D^1, $|D|$, and D^2 (see last column of Table 3).

[a] The R^2 for this equation was significantly greater than that from the equation with all constraints imposed ($p<.05$).

[b] The R^2 for this equation was significantly less than that from the fully unconstrained equation ($p<.05$).

*$p<.05$;   **$p<.01$.

and D^2 are shown in the third column of Table 3. These equations are equivalent to summing each variable from the unconstrained equations across the k elements and using these sums as predictors, yielding two predictors for D^1 and five predictors for $|D|$ and D^2.

The within- and between-element constraints described above were tested by comparing the variance explained by the equations in the second and third columns of Table 3 to that explained by the corresponding unconstrained equations in the last column of Table 3. In all three cases, the within-element constraints were rejected (see Table 5), indicating that the coefficients from the unconstrained equations did not follow the pattern corresponding to the bivariate difference scores embedded in D^1, $|D|$, or D^2, even when the elements were considered separately. In contrast, the between-element constraints were not rejected for D^1 or $|D|$, indicating that the coefficients from the unconstrained equations for these indices did not differ across elements. In contrast, the between-element constraints were rejected for D^2, indicating that, when the X_i, Y_i, X_i^2, $X_i Y_i$, and Y_i^2 were used as predictors, the obtained coefficients differed across elements.

One potential explanation for these conflicting results is that, by omitting the X_i^2, $X_i Y_i$, and Y_i^2, the unconstrained equations for D^1 and

$|D|$ were insensitive to between-element differences in curvilinearity detected by the unconstrained equation for D^2. However, this presumes that the X_i^2, X_iY_i, and Y_i^2 captured variation that was not already accounted for by the unconstrained equations for D^1 or $|D|$. To examine this, the increment in R^2 yielded by adding the X_i^2, X_iY_i, and Y_i^2 to these equations was tested. The increment in R^2 was .193 for the unconstrained equation for D^1 ($F(21, 129) = 2.60$, $p < .001$) and .205 for the unconstrained equation for $|D|$ ($F(21, 108) = 3.37$, $p < .001$). Further analyses showed that the variance explained by the set of cubic terms formed from the X_i and Y_i (i.e., X_i^3, $X_i^2Y_i$, $X_iY_i^2$, and Y_i^3) was not significant after controlling for the terms in the unconstrained equation for D^2 ($F(28, 101) = 1.47$, $p > .05$). Taken together, these results indicate that the X_i^2, X_iY_i, and Y_i^2 in the unconstrained equation for D^2 indeed represented between-element variation in curvilinearity that was not detected by the unconstrained equations for D^1 or $|D|$, and that the unconstrained equation for D^2 was sufficient to describe the relationship between the paired entity measures and the outcome.

The preceding results suggest that substantive interpretation should focus on the unconstrained equation for D^2. Unfortunately, this equation is difficult to interpret, given that 30 of the 35 coefficients estimated were not significant (see Table 4). When unconstrained equations for PSIs yield results such as these (cf. Edwards, in press), it is useful to identify a smaller number of predictors that are primarily responsible for the variance explained by the equation. This may be accomplished using three sequential analyses. The first should verify that the elements in the equation actually represent k distinct dimensions. When multiple indicators for each measure are available, as in the data used here, the distinctions among the k elements may be examined by using confirmatory factor analysis to estimate a k-factor measurement model for each entity and test whether the correlations among the element factors are less than unity (Singh, 1991). When applied to the present data, these analyses indicated that, for both entities, the correlations among the factors corresponding to the seven elements were significantly less than unity (all $p < .001$). This is not surprising, given that the element measures were originally designed to represent distinct dimensions and yielded fairly high reliabilities and modest intercorrelations.

The second set of analyses should determine whether the elements are empirically redundant, meaning that the paired entities for a given element explain little variance after controlling for the remaining elements. This may be examined by testing the increment in variance explained by the set of terms corresponding to each element (e.g., the X_i,

TABLE 6

Reduced Unconstrained Equation for D² Predicting Overall Job Satisfaction

	X	Y	X^2	XY	Y^2	R^2
Creativity	−0.300	1.134	−0.354	1.096**	−0.634*	
Independence	0.750	−2.245**	0.478	−0.709	1.168**	
Job security	0.377	0.385	−0.089	−0.034	0.455**	
Life style	0.908**	0.455				
Self-development	1.006*	0.374				.477**

Note: $N = 165$. Table entries are unstandardized regression coefficients. X represents actual attribute amount, and Y represents desired attribute amount; X and Y measures were centered at their scale midpoint (Edwards, in press).
*$p<.05$; **$p<.01$

Y_i, X_i^2, X_iY_i, and Y_i^2 in the unconstrained equation for D^2). When applied to the present data, these tests indicated that the terms for compensation and relations with coworkers were not significant ($F(5, 129)$ = 0.83 and $F(5, 129) = 0.80$, respectively, both, $p > .05$). Consequently, these terms were dropped from the equation.

The third set of analyses should determine whether the higher-order terms in the equation (i.e., the X_i^2, X_iY_i, and Y_i^2 in the unconstrained equation for D^2) are significant for each element. For the present data, higher-order terms for life style and self-development were not significant ($F(3, 139) = 1.61$ and $F(3, 139) = 2.51$, respectively, both, $p > .05$) and, hence, were dropped. Omitting these 6 terms along with the 10 terms dropped previously reduced the overall R^2 by .068, which was not significant ($F(16, 129) = 1.20, p > .05$).

The reduced equation resulting from this procedure is reported in Table 6. Three-dimensional plots using coefficients from this equation indicated three basic functional forms relating each pair of elements to job satisfaction. For life style and self-development, satisfaction was simply a positive linear function of actual attribute amount. For independence and job security, satisfaction increased as desired attribute amount deviated from its scale midpoint. Because relationships for these four attributes represent the influence of only one entity (i.e., either actual or desired amount), they provide no evidence for congruence. Finally, for creativity, satisfaction was greatest along the line where actual and desired amounts were approximately equal and decreased in either direction. Further analyses revealed that, for creativity, the within-element constraints for D^2 were not rejected ($F(4, 145) = 1.58, p > .05$), indicating that the functional form relating the difference between actual and desired creativity to satisfaction was a symmetric inverted-U.

Limitations of the Polynomial Regression Procedure

As the preceding example has illustrated, the polynomial regression procedure avoids problems with PSIs but nonetheless provides holistic and dimension-specific information regarding the relationship between paired entities and the outcome. Despite these advantages, the procedure also has several limitations. First, it cannot be used to test constraints imposed by D, Mahalanobis' D, or Q, because equations for these indices cannot be algebraically expanded (see Table 1). Equations for Q_q and Q_r are linear transformation of D^2 and, hence, can be expanded, but the regression procedure should not be used for Q-sorts and rankings, given that these measures are ipsative (Hicks, 1970; Johnson, Wood, & Blinkhorn, 1988).

Second, as the number of elements increases, the residual degrees of freedom for the unconstrained equations will rapidly decrease and, in some cases, may be entirely exhausted. Obviously, this problem can be avoided with large samples, but the required sample sizes may quickly surpass the resources of most researchers, particularly when statistical power is considered. When this occurs, the constraints imposed by PSIs may be partially tested by comparing the fully constrained equations to various less constrained equations, such as those that impose within- and between-element constraints (see Table 3). Alternately, conceptually homogenous groups of elements may be assigned to subscales, which would reduce the number of predictors in the unconstrained equations. Of course, the factor structure of these subscales should be confirmed prior to analysis, as described earlier (Anderson & Gerbing, 1988).

Third, the order in which variables were dropped from the unconstrained equation was somewhat arbitrary, and other orderings could produce different results. For example, one could first drop nonsignificant higher-order terms and then drop nonsignificant entity measures for each element. When applied to the present data, this ordering resulted in the same reduced equation, but different results may be obtained with other data. Alternately, paired entity measures and higher-order terms could be entered using a forward stepwise procedure, as opposed to the backward elimination procedure employed here. To reduce the likelihood that the obtained equation is an artifact of the procedure used, several forward stepwise and backward elimination procedures could be used, with the final equation consisting of terms that emerge across procedures.

Fourth, the procedure used to derive the reduced equation is exploratory and therefore risks capitalizing on chance variation. This may be diminished by cross-validating the equation and basing substantive conclusions on terms common to both samples (Mosier, 1951; Snee,

1977). Fortunately, as results accumulate across samples, hypotheses regarding the functional form relating paired entities to the outcome may be derived and tested using confirmatory procedures, making it unnecessary to rely exclusively on exploratory analyses.

Fifth, the regression procedure requires numerous tests of significance, which may inflate Type I error rates. This may be controlled with error correction procedures, such as the Bonferroni (Holland & Copenhaver, 1988). For example, to test the contribution of the set of terms corresponding to each element, the nominal probability level (e.g., .05) could be divided by the number of elements, thereby maintaining alpha for the entire set of tests below the nominal level. Type I error may also be reduced by focusing interpretation on equations that survive cross-validation, as described earlier.

Finally, equations yielded by the regression procedure are likely to contain coefficients on curvilinear and interactive terms that are difficult to interpret. Coefficients for the reduced equation reported in Table 6 were fairly easy to interpret, given that they represented the influence of only one entity for four elements and followed the pattern corresponding to a squared difference for the fifth element. However, other applications of the regression procedure have yielded coefficient patterns that are notably more complex (Edwards, in press). When this occurs, the framework developed by Edwards and Parry (in press) may be used to test basic features of the surface relating paired entity measures to the outcome, such as the overall orientation of the surface and its slope along various lines of interest, such as the line along which both entities are equal. Interpretation is also greatly facilitated by using the regression coefficients to plot surfaces relating each pair of entities to the outcome.

Extensions and Further Developments

The preceding discussion has focused specifically on problems that occur when PSIs are used as predictors in congruence research. However, many of these problems also arise when PSIs are used for other purposes. For example, the assessment of interrater agreement has often relied on PSIs, including Q (e.g., Harvey & Hayes, 1986; Jones et al., 1983; Sanchez & Levine, 1989; Tsui & Barry, 1986), $|D|$ (e.g., Jako & Murphy, 1990; Zalesny & Kirsch, 1989), and various indices not reviewed here, such as the intraclass correlation coefficient (e.g., Jako & Murphy, 1990; Jones et al., 1983; Sanchez & Fraser, 1992) and r_{WG} (e.g., James, Demaree, & Wolf, 1984). These indices collapse across multiple raters, multiple rating dimensions, or both, thereby concealing whether agreement is uniform across raters and dimensions or limited to some subset of raters or dimensions. These ambiguities may be resolved by

following up the assessment of overall interrater agreement with an assessment of agreement between pairs of raters on specific dimensions (Borman, 1978; Cronbach, 1955). If scores from j raters on k dimensions are organized into a $j \times k$ ANOVA (Bartko, 1976), the uniformity of agreement across raters can be assessed using *post hoc* contrasts among the j levels of the rater factor. The uniformity of agreement across dimensions is depicted by the Rater × Dimension interaction, which indicates whether the dispersion of scores among raters is the same for each dimension. In either case, a nonsignificant effect would indicate that agreement was uniform. Of course, testing the Rater × Dimension interaction would require multiple observations for each rater on each dimension, which may be difficult to obtain as the number of raters and dimensions increases.

Studies of performance rating accuracy have used various PSIs to compare observer and expert ratings, collapsing across ratees and rating dimensions (Sulsky & Balzer, 1988). These indices have included Q (e.g., Becker & Cardy, 1986; McIntyre, Smith, & Hassett, 1984; Pulakos, 1984), D^1 (e.g., McIntyre et al., 1984; Pulakos, 1984), $|D|$ (e.g., Bernardin, Cardy, & Carlyle, 1982; Heneman & Wexley, 1983; McIntire et al., 1984), and components of D^2 derived by Cronbach (1955) (e.g., Becker & Cardy, 1986; Bernardin et al., 1982; Murphy & Balzer, 1986; Pulakos, 1986). Again, these indices conceal whether accuracy is general or specific to certain ratees or dimensions. As Cronbach (1955) emphasized, "any index combining results from heterogeneous items presents serious difficulties of interpretation," and scores from these indices "should be replaced or extended by separate analyses of J's [the rater's] ability to predict different qualities of O [the ratee]" (p. 178).

Finally, numerous studies have used PSIs as dependent variables (e.g., Bretz, Milkovich, & Read, 1992; Heneman, Wexley, & Moore, 1987; Smith, 1986; Wanous & Youtz, 1986). Although this introduces essentially the same problems as when PSIs are used as independent variables, these problems are not amenable to the polynomial regression procedure, which only applies when congruence is viewed as a predictor. Instead, a multivariate approach may be used, in which the measures comprising the PSI are treated as a vector of dependent variables, and constraints imposed by the index are analyzed using multivariate hypothesis testing procedures (Dwyer, 1983).

Conclusion

Although PSIs are widely used as predictors in congruence research, they are prone to numerous methodological problems. Taken together,

these problems render the results of studies using PSIs largely incon-
clusive. Fortunately, these problems can be avoided by following the
guidelines described in this article, which advocate the use of multi-item,
normative measures of paired entities, supplemented by selected higher-
order terms, as predictors in polynomial regression equations. These
equations permit direct tests of the hypothesized relationships underly-
ing PSIs as well as theoretically meaningful relationships that are sub-
stantially more complex than PSIs can represent (Edwards & Parry, in
press). By following these guidelines, future studies may obtain more
comprehensive and valid information regarding the nature and effects
of congruence, while avoiding problems with PSIs that have plagued this
area of investigation for decades.

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