Multidimensional Constructs in Organizational Behavior Research: An Integrative Analytical Framework

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Multidimensional constructs are widely used to represent several distinct dimensions as a single theoretical concept. The utility of multidimensional constructs relative to their dimensions has generated considerable debate, and this debate creates a dilemma for researchers who want the breadth and comprehensiveness of multidimensional constructs and the precision and clarity of their dimensions. To address this dilemma, this article presents an integrative analytical framework that incorporates multidimensional constructs and their dimensions, using structural equation modeling with latent variables. This framework permits the study of broad questions regarding multidimensional constructs along with specific questions concerning the dimensions of these constructs. The framework also provides tests of issues underlying the multidimensional construct debate, thereby allowing researchers to address these issues on a study-by-study basis. The framework is illustrated using data from studies of the effects of personality on responses to conflict and the effects of work attitudes on employee adaptation.

Multidimensional constructs are pervasive in organizational behavior (OB) research. A construct is multidimensional when it refers to several distinct but related dimensions treated as a single theoretical concept (Law, Wong, & Mobley, 1998). Examples of multidimensional constructs include overall job satisfaction conceptualized as satisfaction with multiple job facets (Smith, Kendall, & Hulin, 1969; Warr, Cook, & Wall, 1979), overall job performance viewed as the aggregation of performance on various job criteria (Murphy & Shiarella, 1997), and broad personality traits that comprise specific personality dimensions (Digman, 1990; McCrae & Costa, 1992). Multidimensional constructs may be distinguished from unidimensional constructs, which refer to a single theoretical concept (Hattie, 1985), and from multiple dimensions regarded as distinct but related concepts rather than a single overall concept.

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The utility of multidimensional constructs has generated considerable debate in the OB literature. Advocates of multidimensional constructs argue that such constructs provide holistic representations of complex phenomena, allow researchers to match broad predictors with broad outcomes, and increase explained variance (Hanisch, Hulin, & Roznowski, 1998; Hulin, 1991; Ones & Viswesvaran, 1996; Roznowski & Hanisch, 1990). Critics contend that multidimensional constructs are conceptually ambiguous, explain less variance than explained by their dimensions taken collectively, and confound relationships between their dimensions and other constructs (Gerbing & Anderson, 1988; Hattie, 1985; Johns, 1998; Paunonen, Rothstein, & Jackson, 1999; Schneider, Hough, & Dunnette, 1996). This debate has been ongoing for decades (e.g., Cattell & Tsujioka, 1964; Humphreys, 1962; Schmidt & Kaplan, 1971) and shows little sign of abating.

The multidimensional construct debate presents a dilemma for OB researchers who want the breadth and comprehensiveness of multidimensional constructs and the clarity and precision of the dimensions that constitute the construct. These apparently conflicting objectives cannot be achieved if a researcher adopts one side of the debate. Moreover, criticisms underlying the debate are often characterized as necessary evils, but many are matters of degree that can be assessed empirically. For example, the degree to which a multidimensional construct captures variance in its dimensions can be assessed empirically, and the variance explained by a multidimensional construct can be statistically compared with that explained by its dimensions. Unfortunately, methods that allow these comparisons have received little attention in the multidimensional construct debate.

This article presents an integrative analytical framework for assessing the utility of multidimensional constructs in OB research. The framework is integrative in that it combines multidimensional constructs and their dimensions within a single analytical approach. The framework incorporates different types of multidimensional constructs and allows researchers to directly assess a range of assumptions regarding the relationships between a multidimensional construct and its dimensions, causes, and effects. The framework is illustrated using data from studies concerning the effects of personality on responses to conflict (Moberg, 1998) and the effects of work attitudes on employee adaptation (Hanisch & Hulin, 1991).

Types of Multidimensional Constructs

Multidimensional constructs can be distinguished in various ways. Perhaps the most basic distinction concerns the direction of the relationship between the construct and its dimensions (Law & Wong, 1999; Ones & Viswesvaran, 1996; Schneider et al., 1996). If the relationships flow from the construct to its dimensions, the construct may be termed *superordinate* because it represents a general concept that is manifested by specific dimensions. If the relationships flow from the dimensions to the construct, the construct may be termed *aggregate* because it combines or aggregates specific dimensions into a general concept. The following discussion elaborates this basic distinction, discusses different ways in which superordinate and aggregate constructs may be operationalized, and provides examples from OB research.

Before proceeding, it is important to clarify the nature of the relationships between a multidimensional construct and its dimensions. Because a multidimensional construct is conceptualized in terms of its dimensions, it does not exist separately from its dimensions. Therefore, the relationships between a multidimensional construct and its dimensions are not causal forces linking separate conceptual entities, but instead represent associations between a general concept and the dimensions that represent or constitute the construct (Law et al., 1998). If a multidimensional construct were replaced by a conceptually analogous construct conceived as distinct from its dimensions, then relationships between this construct and the dimensions may be causal. For example, if overall job satisfaction were defined as a general affective orientation toward the job rather than a composite of satisfaction with job facets (Ironson, Smith, Brannick, Gibson, & Paul, 1989), then it would be meaningful to examine causal relationships between overall job satisfaction and satisfaction with job facets.

Superordinate Construct

As noted previously, a superordinate construct is a general concept that is manifested by its dimensions. The dimensions of a superordinate construct are analogous to reflective measures, which are observed variables that serve as manifest indicators of an underlying construct (Bollen & Lennox, 1991; Edwards & Bagozzi, 2000). However, whereas reflective measures are observed variables, the dimensions of a superordinate construct are themselves constructs that function as specific manifestations of a more general construct.

Superordinate constructs are common in research on personality. For example, the five-factor model of personality (Digman, 1990) comprises five broad personality traits manifested by 30 specific personality facets (McCrae & Costa, 1992). Some investigators further cast these five traits as indicators of two broader personality dispositions, one manifested by agreeableness, conscientiousness, and emotional stability and the other by extraversion and intellect (Digman, 1997). Other examples of superordinate constructs include general work values manifested by preferences for specific aspects of work (Bolton, 1980; Pryor, 1987); leader-member exchange reflected by affect, loyalty, contribution, and professional respect (Liden & Maslyn, 1998); work withdrawal manifested by absenteeism, lateness, leaving early, and escapist drinking (Hanisch et al., 1998); and psychological climate indicated by job characteristics, leader attributes, role stress, and work group relationships (L. A. James & James, 1989).

Superordinate constructs are often operationalized by summing scores on their dimensions. Although this approach is widespread, it disregards measurement error and fails to capture differences in the relationships between the construct and its dimensions. These problems are avoided when a superordinate construct is specified as a first-order factor and dimension scores are treated as observed variables (Hanisch & Hulin, 1991). However, this approach confounds random measurement error with dimension specificity (i.e., systematic variance in each dimension not captured by the superordinate construct) and ignores the relationships between each dimension and its measures. These limitations are overcome by second-order factor models that treat the superordinate construct as a second-order factor, its dimensions as first-order factors, and measures of the dimensions as observed variables (Bagozzi & Edwards, 1998; Hull, Lehn, & Tedlie, 1991; Hunter & Gerbing, 1982; Rindskopf & Rose, 1988). Given these advantages, the framework presented in this article operationalizes superordinate constructs using second-order factor models.

Aggregate Construct

Unlike a superordinate construct, an aggregate construct is a composite of its dimensions, meaning the dimensions combine to produce the construct (Law et al., 1998). The dimensions of an aggregate construct are analogous to formative measures, which form or induce a construct (Bollen & Lennox, 1991; Edwards & Bagozzi, 2000). However, whereas formative measures are observed variables, the dimensions of an aggregate construct are themselves constructs conceived as specific components of the general construct they collectively constitute.

Aggregate constructs are widespread in OB research. For example, overall job satisfaction has been conceptualized as a composite of satisfaction with specific job facets, such as pay, promotions, supervision, coworkers, and the work itself (Locke, 1976; Smith et al., 1969; Warr et al., 1979). Similarly, job performance has been viewed as the combination of performance on specific tasks (Murphy & Shiarella, 1997). Other examples of aggregate constructs include role stress conceived as the combination of role ambiguity, role conflict, and role overload (Bedeian, Burke, & Moffett, 1988; Parasuraman, Greenhaus, & Granrose, 1992); organizational commitment treated as the aggregation of commitment to the work group, supervisor, and top management (Hunt & Morgan, 1994); and job perceptions as a composite of job challenge, job autonomy, and job importance (James & Tetrick, 1986).

Aggregate constructs are typically operationalized by summing scores on their dimensions, such that the dimensions are assigned equal weight. Occasionally, dimensions are assigned empirically derived weights obtained from principal components analysis or factor analysis, which calculate weights based on correlations among the dimensions (Kim & Mueller, 1978). In some instances, dimension weights are estimated by specifying the dimensions as formative indicators of the construct in a structural equation model (Bollen & Lennox, 1991; MacCallum & Browne, 1993). To identify the weights, the construct must be specified as a direct or indirect cause of at least two observed variables (MacCallum & Browne, 1993). Hence, the dimension weights are influenced not only by the correlations among the dimensions, but also by the relationships between the dimensions and the variables caused by the construct. A residual term may be added to the model, such that the construct becomes a weighted composite of its dimensions plus random error and other unspecified variables (Bollen & Lennox, 1991; Heise, 1972; MacCallum & Browne, 1993). Each of these approaches treats the dimensions of the aggregate construct as observed variables, thereby disregarding error in the dimension measures. This limitation can be overcome by specifying the dimensions as latent variables and their measures as manifest variables, as demonstrated later in this article.

Other Types of Multidimensional Constructs

Although most multidimensional constructs are either superordinate or aggregate, other types of multidimensional constructs may be considered. Some of these constructs combine features of superordinate and aggregate constructs. For example, a multidimensional construct may have reflective and formative dimensions, analogous to multiple indicator/multiple cause (MIMIC) models in structural equation modeling (Jöreskog & Goldberger, 1975). This type of construct is illustrated by organizational commitment defined by dimensions that include facets of commitment (e.g., acceptance of organizational goals and values) and manifestations of commitment (e.g., desire to maintain membership in the organization; Mowday, Steers, & Porter, 1979). Other multidimensional constructs have relationships with their dimensions that are more complex than the simple linear relationships linking superordinate and aggregate constructs to their dimensions. For instance, person-organization fit has been defined as the absolute or squared difference between person and organization dimensions (Edwards, 1991; Kristof-Brown, 1996), and the motivating potential of jobs has been defined as a multiplicative composite of core job dimensions (Hackman & Oldham, 1980). Likewise, personality dimensions have been ranked to define personality profiles (Holland, 1985) or dichotomized and cross-classified to define personality typologies (Myers & McCaulley, 1985). The present article focuses on superordinate and aggregate constructs because they are prevalent in OB research (Law & Wong, 1999) and provide a foundation for understanding other multidimensional constructs that relate to their dimensions in more complex ways.

The Multidimensional Construct Debate

As noted previously, the utility of multidimensional constructs has been debated for decades. Although this debate covers a wide range of issues, these issues can be distilled into five key points. This section summarizes and integrates these points, with emphasis on the recent OB literature.

Theoretical Utility

Advocates of multidimensional constructs have argued that such constructs are more theoretically useful than their dimensions. This argument stipulates that theories should be general and that general theories require general constructs that combine specific dimensions (Hanisch et al., 1998). For instance, Roznowski and Hanisch (1990) disparaged specific behaviors as "theoretically sterile" (p. 361) and argued that only aggregates of heterogeneous behaviors provide a complete understanding of behavior in organizations. Likewise, Ones and Viswesvaran (1996) contended that broad personality constructs (i.e., the Big Five) are more basic than specific personality dimensions and are therefore more useful for theory development. Humphreys (1962) advocated a hierarchical model of human abilities in which broad abilities are superordinate constructs, and specific abilities are subordinate constructs located lower in the hierarchy "in the relatively unimportant position that their size and generality warrant" (p. 482).

Critics have questioned the theoretical utility of multidimensional constructs on the grounds that such constructs are conceptually ambiguous (Cronbach, Gleser, Nanda, & Rajaratnam, 1972; Hattie, 1985; Hunter & Gerbing, 1982; McIver & Carmines, 1981). This ambiguity occurs because variation in a multidimensional construct may imply variation in any or all of its dimensions. Consequently, theories that explain the relationship between a multidimensional construct and other variables are difficult to develop, because different explanations may apply to different dimensions of the construct (Johns, 1998). As an alternative, critics advocate theoretical models that relate each dimension of the construct to other variables within a general nomological network (Paunonen et al., 1999; Schneider et al., 1996). Such models accommodate differences in relationships involving the dimensions of the construct, which critics consider important for theory development and refinement (Johns, 1998; Paunonen et al., 1999; Schneider et al., 1996).

The foregoing debate partly reflects ideological differences regarding the value of theories that are broad versus specific. Both of these properties are desirable (Weick, 1979), yet the debate frames them as antithetical. This dilemma may be ameliorated by developing theories that incorporate multidimensional constructs along with their dimensions. Such theories can be used to explain how the construct and its dimensions relate to one another and to other relevant variables, thereby addressing questions that are broad and specific. Alternately, theories may treat conceptually related dimensions as a set, such that they collectively represent a general concept. For example, job performance may be conceived not as a multidimensional construct, but rather as a set of performance dimensions. Such theories would allow researchers to investigate specific questions for each dimension individually along with general questions for the dimensions collectively. These approaches for modeling multidimensional constructs and their dimensions are illustrated later in this article.

Matching Levels of Abstraction

Multidimensional constructs have been recommended for matching general predictors with general outcomes. For example, researchers have asserted that many important outcomes in OB research (e.g., job performance) are factorially complex and therefore require predictors that are also factorially complex (Hogan & Roberts, 1996; Ones & Viswesvaran, 1996). Similarly, researchers have argued that general attitudes should be matched with general behavioral outcomes that combine specific behaviors, as when work withdrawal is represented by lateness, absenteeism, and other unfavorable job behaviors (Hanisch & Hulin, 1990, 1991; Roznowski & Hanisch, 1990).

Critics of multidimensional constructs have argued that general predictors and outcomes should be matched not by combining specific dimensions into a single construct, but instead by treating dimensions collectively as a set. For instance, Schneider et al. (1996) and Paunonen et al. (1999) asserted that the relationship between personality and overall job performance should be examined by linking multiple personality dimensions to multiple performance dimensions. This approach echoes Nunnally's (1978) advice that "instead of building factorial complexity into a particular test, it is far better to meet the factorial complexity by combining tests in a battery by multiple regression, in which case tests would be selected to measure different factors that are thought to be important" (p. 268).

Advocates and critics of multidimensional constructs agree that predictors and outcomes should be at the same level of abstraction (Fisher, 1980; Schmidt & Kaplan, 1971). At issue is whether general constructs should be represented by combining multiple dimensions into a single concept or by treating dimensions as a set. An apparent advantage of combining dimensions is that the association between two general constructs can be indexed by a single quantity (e.g., a correlation coefficient). However, a single index of association can also be obtained for sets of dimensions using set correlation (Cohen, 1982) or multivariate regression (Dwyer, 1983). Moreover, most methods for combining dimensions are special cases of methods that treat dimensions as sets, such that the former can be statistically compared with the latter. These points are elaborated within the framework presented in this article.

Reliability

Another source of debate concerns the internal consistency reliability of measures of multidimensional constructs created by summing dimension scores. Critics note that the dimensions of a multidimensional construct are necessarily heterogeneous because they represent different facets or manifestations of the construct. As dimension heterogeneity increases, correlations among the dimensions decrease, which in turn reduces the reliability of summed dimension scores. When sums of dimension scores exhibit adequate reliabilities in practice, critics point out that these sums often contain numerous items and therefore can attain high reliabilities in spite of dimension heterogeneity (Mershon & Gorsuch, 1988; Paunonen et al., 1999). Some critics have further argued that reliability estimation applies only to measures that are unidimensional (Gerbing & Anderson, 1988; Hunter & Gerbing, 1982), thereby raising fundamental questions regarding the meaning and assessment of reliability for measures of multidimensional constructs.

Advocates acknowledge that the dimensions of multidimensional constructs are often heterogeneous (Roznowski & Hanisch, 1990). However, rather than lamenting the effects of dimension heterogeneity on reliability, advocates have argued that reliability estimates based on internal consistency are irrelevant for measures of multidimensional constructs (Hanisch et al., 1998). As an alternative, some researchers (e.g., Ones & Viswesvaran, 1996) have applied formulas for estimating the reliability of linear composites (Nunnally, 1978), which incorporate the reliabilities of dimension measures and can produce acceptable composite reliabilities even when dimensions are uncorrelated (Aston, 1998).

Ultimately, reliability is an empirical matter that varies across studies. When a multidimensional construct is operationalized by summing dimension scores, reliability may be estimated using formulas appropriate for linear composites (Nunnally, 1978) or latent variables (Jöreskog, 1971), depending on whether the construct is aggregate or superordinate, respectively. However, as explained earlier, multidimensional constructs and their dimensions are better treated as latent variables in structural equation models. This approach corrects for measurement error in the construct and its dimensions, which effectively renders the reliability debate moot. However, just as it is important to assess the strength of the relationship between a construct and its measures, it is important to assess the strength of the relationship between a multidimensional construct and its dimensions. Procedures for assessing these relationships are demonstrated later in this article.

Construct Validity

Advocates of multidimensional constructs have criticized the construct validity of dimension measures, arguing that such measures are dominated by specific variance that should be considered invalid. For example, Ones and Viswesvaran (1996) contended that measures of personality dimensions are “construct deficient” (p. 622) because they contain excessive specific dimension variance that should be regarded as measurement error. Likewise, Humphreys (1970) argued that variance specific to dimensions represents noise and that only variance common to all dimensions is valid. To reduce the effects of specific dimension variance, advocates of multidimensional constructs have recommended summing numerous heterogeneous dimension measures (Humphreys, 1970; Roznowski & Hanisch, 1990) or using dimensions as indicators of a general factor (Hanisch et al., 1998; Hulin, 1991). Both of these approaches emphasize variance common to the dimensions and treat specific dimension variance and random error variance as measurement error (Humphreys, 1970).

Critics of multidimensional constructs have defended the construct validity of dimension measures. For instance, Schneider et al. (1996) challenged claims by Ones and Viswesvaran (1996) that dimension specificity should be treated as measurement error, arguing instead that specificity is valid precisely because it is not measurement error. Accordingly, high specificity should be interpreted not as invalid construct variance, but instead as valid dimension variance that is not captured by the multidimensional construct. A similar argument was advanced by Blau (1998), who criticized superordinate work withdrawal and job withdrawal constructs (Hanisch & Hulin, 1991) on the grounds that these constructs explained little variance in their dimensions, thereby failing to capture dimension specificity.

The evaluation of construct validity begins by identifying the construct of interest (Nunnally, 1978; Schwab, 1980). For advocates of multidimensional constructs, the construct of interest is general, and any variance specific to its dimensions is therefore invalid. For critics, the dimensions themselves are of interest, and the multidimensional construct serves primarily as an organizing category or label for the dimensions. This difference in perspective underlies the interpretation of dimension specificity as invalid or valid. An integrative perspective would treat multidimensional constructs and their dimensions as theoretical constructs, each with its own claim to validity. Evidence for the validity of the multidimensional construct would include the strength of its relationships with its dimensions and the degree to which it captures relationships between its dimensions and other theoretically relevant constructs. Evidence for the construct validity of the dimensions would include the strength of their relationships with their measures and the degree to which each dimension exhibits relationships with other constructs not captured by the multidimensional construct. Methods for assessing these aspects of construct validity are illustrated later in this article.

Criterion-Related Validity

Finally, advocates of multidimensional constructs have argued that such constructs have higher criterion-related validity than their dimensions. In most cases, these arguments pertain to multidimensional constructs as predictors. For example, Ones and Viswesvaran (1996) reported that, across a range of criteria, broad personality traits exhibited higher predictive validity than their dimensions. Less frequently, these arguments are applied to multidimensional constructs as criteria. For instance, in a study of the effects of attitudes on employee adaptation, Roznowski and Hanisch (1990) found that attitudes correlated more highly with a sum of adaptive behaviors than with the individual behaviors constituting the sum.

Critics have countered that, although multidimensional constructs often have higher criterion-related validity than most of their dimensions, they frequently have lower criterion-related validity than at least one dimension (Aston, 1998; Paunonen et al., 1999; Schneider et al., 1996). Critics have further pointed out that a multidimensional construct cannot have higher criterion-related validity than an optimally weighted linear combination of its dimensions, as when the dimensions are used as predictors in multiple regression analysis (Goldberg, 1993; Moberg, 1998; Paunonen et al., 1999; Schneider et al., 1996). At a more fundamental level, some critics have questioned the value of maximizing criterion-related validity as an end unto itself, arguing instead that the goal of empirical research is to obtain parameter estimates that are accurate, regardless of their magnitude (Johns, 1998).

The debate over criterion-related validity has two important limitations. First, although many studies have compared multidimensional constructs with their dimensions taken individually, such comparisons are irrelevant because critics recommend using the dimensions collectively. Therefore, comparisons of criterion-related validity should pit the multidimensional construct against its dimensions as a set. Some researchers have argued that such comparisons are pointless because the construct cannot explain more variance than that explained by its dimensions taken jointly (Paunonen, 1998; Schneider et al., 1996). However, the relevant question is whether the increase in explained variance is worth the degrees of freedom consumed by replacing a multidimensional construct with its dimensions, a question that has received little attention in the criterion-related validity debate. Second, comparisons between multidimensional constructs and their dimensions taken collectively have been limited to aggregate constructs as predictors, perhaps due to the simplicity of comparing the bivariate correlation for an aggregate construct with the multiple correlation for its dimensions. Alternative procedures are required for aggregate constructs as outcomes and for superordinate constructs as predictors or outcomes. These procedures are demonstrated later in this article.

Summary and Implications of the Debate

In sum, the multidimensional construct debate has raised issues of theoretical utility, levels of abstraction, reliability, construct validity, and criterion-related validity. Advocates of multidimensional constructs endorse generality, breadth, and simplicity, whereas critics promote specificity, precision, and accuracy. Given that both sets of objectives are laudable, researchers would be better served by an integrative approach than by admonitions to adopt one side of the debate. Moreover, many issues underlying the debate refer to empirical matters that vary across studies, but methods for quantifying these issues have received little attention. The following section presents an integrative framework that incorporates multidimensional constructs along with their dimensions, quantifies issues that underlie the multidimensional construct debate, and seeks to serve the interests of advocates and critics of multidimensional constructs.

An Integrative Analytical Framework

The framework developed here is based on four principles. First, multidimensional constructs and their dimensions should be included in the same model. Doing so allows tests of broad questions associated with multidimensional constructs along with specific questions concerning the dimensions of the construct. Second, models should incorporate assumptions regarding the direction of the relationships between the construct and its dimensions, thereby capturing the distinction between superordinate and aggregate constructs. Third, analyses should examine the strength and variability of the relationships between the multidimensional construct and its dimensions. These analyses have important implications regarding the interpretation of the construct, given that its meaning arises from its relationships with its dimensions. Fourth, analyses should quantify issues underlying the multidimensional construct debate, such that the relative merits of multidimensional constructs and their dimensions can be assessed on a study-by-study basis. Model specification differs depending on whether the multidimensional construct is superordinate or aggregate and whether the construct is a cause or an effect of constructs other than its dimensions. Combining these distinctions yields the four types of models that are discussed below. All models use standard notation from the structural equation modeling literature (e.g., Jöreskog & Sörbom, 1996).

Superordinate Construct as a Cause

As explained earlier, a superordinate construct is best viewed as a second-order factor with its dimensions as first-order factors. Three second-order factor models are considered here, representing different degrees of variability in the relationships between the construct and its dimensions. The most restrictive model treats the dimensions as parallel, meaning they have equal loadings and equal residual variances. This model embodies two assumptions: (a) each dimension manifests the superordinate construct to the same degree, such that a unit change in the construct leads to the same degree of change in each dimension; and (b) the quality of each dimension as an indicator of the superordinate construct is the same. These assumptions reflect the premise that distinctions among the dimensions can be disregarded, as implied by procedures that collapse the dimensions of a superordinate construct into a single score. An equation that captures this model is

$$\eta_i = \gamma\xi^* + \zeta. \tag{1}$$

In this equation, ξ^* is the superordinate construct, and the η_i are its dimensions (a superscript asterisk is used to differentiate a multidimensional construct from constructs treated as its dimensions, causes, and effects). Note that each η_i has the same loading on ξ^* (i.e., γ) and the same residual (ζ), which in turn implies that the residual variances for the η_i are equal.

A less restrictive model treats the dimensions as tau equivalent, such that the dimensions have equal loadings but different residual variances. This model captures the assumption that a unit change in the construct leads to the same change in each dimension, but the construct explains different amounts of variance in each dimension. This assumption implies that each dimension represents the superordinate construct to the same degree, although some dimensions may do so with greater precision, as indicated by lower residual variance. An equation for this model is

$$\eta_i = \gamma\xi^* + \zeta_i. \tag{2}$$

Note that the relationship of ξ^* with each of its dimensions is represented by a single loading (i.e., γ) but a different residual (i.e., the ζ_i).

Finally, the least restrictive model considered here treats the dimensions as congeneric, meaning that their loadings and residual variances are free to vary. An equation for this model is

$$\eta_i = \gamma_i\xi^* + \zeta_i. \tag{3}$$

Here, the relationship between ξ^* and each of its dimensions is represented by a different loading (i.e., the γ_i) and residual (i.e., the ζ_i). This equation corresponds to a standard second-order factor model (Rindskopf & Rose, 1988).

Constructs caused by the superordinate construct are specified as additional η_i, and incorporating these effects into the preceding models adds equations that follow Equation 3. As such, distinctions between the η_i as dimensions versus effects of the superordinate construct are strictly matters of interpretation. However, comparisons among the parallel, tau equivalent, and congeneric models pertain only to the η_i treated as dimensions of the construct. The effects of ξ^* on the η_i as effects should be unrestricted, such that each η_i has a unique coefficient and residual. Moreover, causal paths and correlated residuals may be included for the η_i as effects but not the η_i as dimensions of ξ^*, given that the superordinate construct is considered the only source of covariation among its dimensions.[1]

As noted earlier, the framework presented here provides tests of relationships for multidimensional constructs and their dimensions simultaneously. For a superordinate construct as a cause, relationships between the construct and its effects are represented by the γ_i in Equation 3, whereas relationships between the dimensions and effects of the construct are captured by the pairwise products of the γ_i for the dimensions and effects, each multiplied by the variance of the construct. For example, if the construct is standardized and has three dimensions, the relationship between the first dimension of the construct (i.e., η_1) and the first effect of the construct (labeled η_4, given that η_1, η_2, and η_3 are dimensions of the construct) is represented by the loading for η_1 times the coefficient for η_4, or $\gamma_1\gamma_4$ (when the construct is standardized, its variance is unity and can be disregarded). Other relationships between the dimensions and effects of the construct can be similarly derived. Thus, using a superordinate construct as a cause treats the relationships between the dimensions and effects of the construct as spurious, due to the common cause ξ^*.

Aggregate Construct as a Cause

As explained earlier, an aggregate construct is best viewed as a function of latent variables representing its dimensions. Here we consider four models that incorporate different degrees of variability in the relationships between the construct and its dimensions. The most restrictive of these models treats the aggregate construct as a simple sum of its dimensions. The corresponding equation is

$$\eta^* = \Sigma\xi_i. \tag{4}$$

Here, the aggregate construct is represented by η^*, its dimensions are represented by the ξ_i, and the summation is over all dimensions of the construct.

A somewhat less restrictive model uses weights specified by the researcher. For example, the correlations among the ξ_i may be entered into a principal components analysis to obtain weights that maximize the variance of η^*, subject to the restriction that sum of the squared weights equals unity (Kim & Mueller, 1978). Alternately, weights may be derived rationally to represent the judged importance of the dimensions (Murphy & Shiarella, 1997; Schneider et al., 1996). An equation containing such weights is

$$\eta^* = \Sigma w_i \xi_i. \tag{5}$$

In this equation, the dimension weights are represented by the w_i, each of which is assigned to a particular dimension.

Neither of the preceding models estimates dimension weights within the model itself. A model that directly estimates dimension weights is captured by the following equation:

$$\eta^* = \Sigma \gamma_i \xi_i. \tag{6}$$

In this model, the dimension weights are represented by the γ_i. These weights are analogous to those derived from principal components analysis, except that the criterion for deriving the γ_i is not to maximize the variance of the aggregate construct, but instead to reproduce the covariances among the dimensions and effects of the construct. Because the model in Equation 6 includes weights as free parameters, it is less restrictive than the models in Equations 4 and 5.

The three preceding models treat the aggregate construct as an exact linear combination of its dimensions. A less restrictive model introduces a residual for the aggregate construct:

$$\eta^* = \Sigma \gamma_i \xi_i + \zeta^*. \tag{7}$$

In Equation 7, ζ^* represents aspects of η^* not captured by its dimensions. Thus, Equation 7 allows the relationships between the dimensions and the construct to vary empirically (as in Equation 6) and further stipulates that the variance of η^* is no longer solely a function of the variance of the linear combination $\Sigma \gamma_i \xi_i$.

Relationships between the aggregate construct and its effects are captured by equations of the following form:

$$\eta_j = \beta_j \eta^* + \zeta_j. \tag{8}$$

In Equation 8, the η_j represent the effects of the aggregate construct η^*, and the ζ_j are residuals for each η_j.

Like a superordinate construct, an aggregate construct represents the relationships between its dimensions and effects as pairwise products of the dimension loadings with the coefficients relating the construct to its effects. These products can be obtained by substituting the equation for the appropriate aggregate construct into Equation 8. Specifically, the relationships between the dimensions and effects of the construct are represented by $\gamma_i\beta_j$ for Equations 6 and 7, $w_i\beta_j$ for Equation 5, and β_j for Equation 4 due to the implied loading of unity on each dimension. These products show that using an aggregate construct as a cause treats the relationships between the dimensions and effects of the construct as indirect, mediated by the construct η^*.

Superordinate Construct as an Effect

We now turn to models that treat a multidimensional construct as an effect, starting with a superordinate construct. As before, the superordinate construct is specified as a second-order factor with its dimensions as first-order factors. Three second-order factor models are again considered, corresponding to the parallel, tau equivalent, and congeneric models discussed previously. To reiterate, the parallel model is the most restrictive of the three models because it specifies that each dimension represents the construct to the same degree and with the same precision. For a superordinate construct as an effect, the parallel model is represented by

$$\eta_j = \beta\eta^* + \zeta. \tag{9}$$

In Equation 9, η^* is the superordinate construct and the η_j are its dimensions. Note that each η_j has the same loading on η^* (i.e., β) and the same residual (ζ), which in turn implies that the residual variances are equal.

The less restrictive tau equivalent model is captured by the following equation:

$$\eta_j = \beta\eta^* + \zeta_j. \tag{10}$$

Here, the relationship of η^* with each of its dimensions is represented by a single loading (i.e., β) and a different residual (i.e., the ζ_j).

Finally, the congeneric model is depicted by the following equation:

$$\eta_j = \beta_j\eta^* + \zeta_j. \tag{11}$$

In this equation, the relationship of η^* with each of its dimensions is captured by a different loading (i.e., the β_j) and residual (i.e., the ζ_j). This equation corresponds to a standard second-order factor model but specifies the second-order factor as endogenous (i.e., η^*) rather than its usual specification as exogenous (i.e., ξ^*).

Adding the causes of the superordinate constructs to the preceding models introduces a set of equations that treat η^* as dependent on one or more ξ_i and a residual:

$$\eta^* = \Sigma\gamma_i\xi_i + \zeta^*. \tag{12}$$

Note that Equation 12 is identical to Equation 7 for an aggregate construct as a cause. However, whereas the ξ_i are interpreted as dimensions of an aggregate construct η^* in Equation 7, they are viewed as causes of the superordinate construct η^* in Equation 12. Moreover, the constraints applied to Equation 7 to obtain the restricted aggregate cause models in Equations 4, 5, and 6 should not be imposed on Equation 12, which instead should freely estimate the parameters linking the superordinate construct to its causes and the residual not explained by these causes.

As with aggregate cause models, superordinate effect models represent the relationships between the causes and dimensions of the construct as the pairwise products of the coefficients on the causes with the loadings on the dimensions, or $\gamma_i\beta_j$. Thus, using a superordinate construct as an effect treats the relationships between the causes and dimensions of the construct as indirect, mediated by the construct η^*.

Aggregate Construct as an Effect

Finally, we turn to models that specify an aggregate construct as an effect. For these models, the dimensions and causes of the aggregate construct are exogenous variables, and their variances and covariances should be freely estimated (MacCallum & Browne, 1993). However, doing so renders the parameters linking the construct to its dimensions and causes unidentified. Nonetheless, if the parameters linking the construct to its dimensions are fixed to a priori values (e.g., unit weights or principal component weights), the parameters linking the construct to its causes become functions of the variances and covariances of the causes and dimensions of the construct. For illustration, consider a model in which an aggregate construct is a sum of three dimensions (ξ_1, ξ_2, and ξ_3) and has one cause (ξ_4). An equation relating the construct to its cause is

$$\eta^* = \gamma_4\xi_4 + \zeta^*. \tag{13}$$

Assuming ξ_4 and ζ^* are independent, covariance algebra yields the following solution for γ_4:

$$\gamma_4 = C(\eta^*, \xi_4)/\phi_{44}, \tag{14}$$

where $C(.)$ is a covariance operator, and ϕ_{44} is the variance of ξ_4. By substituting the sum $\xi_1 + \xi_2 + \xi_3$ for η^* and applying covariance algebra, Equation 14 may be rewritten as

$$\gamma_4 = \phi_{14}/\phi_{44} + \phi_{24}/\phi_{44} + \phi_{34}/\phi_{44}. \tag{15}$$

Equation 15 shows that γ_4 is a function of the variance of ξ_4 and its covariances with ξ_1, ξ_2, and ξ_3. Hence, γ_4 may be constrained to the expression in Equation 15. Next, the variance of ζ^* (i.e., ψ^*) may be written by solving Equation 13 for ζ^* and taking variances:

$$\psi^* = V(\eta^* - \gamma_4\xi_4), \tag{16}$$

where $V(.)$ is a variance operator. Substituting Equation 15 for γ_4 and $\xi_1 + \xi_2 + \xi_3$ for η^* and applying covariance algebra yields

$$\psi^* = \phi_{11} + \phi_{22} + \phi_{33} + 2\phi_{12} + 2\phi_{13} + 2\phi_{23} \\ - (\phi_{14}^2 + \phi_{24}^2 + \phi_{34}^2 + 2\phi_{14}\phi_{24} + 2\phi_{14}\phi_{34} + 2\phi_{24}\phi_{34}) / \phi_{44}. \tag{17}$$

Thus, ψ^* is a function of the variances and covariances of ξ_1, ξ_2, ξ_3, and ξ_4 and therefore may be constrained to the expression shown in Equation 17.[2]

If η^* is specified as a weighted sum of the ξ_i (e.g., $w_1\xi_1 + w_2\xi_2 + w_3\xi_3$), the foregoing approach should be adapted to incorporate rules for calculating variances and covariances of weighted sums of random variables. Doing so yields the following solutions for γ_4 and $V(\zeta^*)$:

$$\gamma_4 = w_1\phi_{14}/\phi_{44} + w_2\phi_{24}/\phi_{44} + w_3\phi_{34}/\phi_{44}, \tag{18}$$

$$\psi^* = w_1^2\phi_{11} + w_2^2\phi_{22} + w_3^2\phi_{33} + 2w_1w_2\phi_{12} + 2w_1w_3\phi_{13} + 2w_2w_3\phi_{23} \\ - (w_1^2\phi_{14}^2 + w_2^2\phi_{24}^2 + w_3^2\phi_{34}^2 + 2w_1w_2\phi_{14}\phi_{24} + 2w_1w_3\phi_{14}\phi_{34} + 2w_2w_3\phi_{24}\phi_{34}) / \phi_{44}. \tag{19}$$

Hence, if η^* is a weighted sum, γ_4 and ψ^* should be constrained to the expressions shown in Equations 18 and 19.

The procedure described above becomes exceedingly complicated as more causes are added to the model. Fortunately, the same results may be obtained by respecifying the dimensions of the construct as endogenous variables. This approach may be illustrated by first substituting the sum $\xi_1 + \xi_2 + \xi_3$ for η^* in Equation 13, which yields

$$\xi_1 + \xi_2 + \xi_3 = \gamma_4\xi_4 + \zeta^*. \tag{20}$$

Because ξ_1, ξ_2, and ξ_3 are now endogenous, they are rewritten as η_1, η_2, and η_3, which yields

$$\eta_1 + \eta_2 + \eta_3 = \gamma_4\xi_4 + \zeta^*. \tag{21}$$

Equation 21 may be expanded into a set of three equations representing a multivariate structural model, as follows:

$$\eta_1 = \gamma_1\xi_4 + \zeta_1$$

$$\eta_2 = \gamma_2\xi_4 + \zeta_2$$

$$\eta_3 = \gamma_3\xi_4 + \zeta_3. \tag{22}$$

In this model, the γ_i and the variances and covariances of the ζ_i are freely estimated. The correspondence between Equations 21 and 22 can be seen by summing the equations in Equation 22, which yields

$$\eta_1 + \eta_2 + \eta_3 = (\gamma_1 + \gamma_2 + \gamma_3)\xi_4 + \zeta_1 + \zeta_2 + \zeta_3. \quad (23)$$

Hence, γ_4 and ζ^* in Equation 21 equal $\gamma_1 + \gamma_2 + \gamma_3$ and $\zeta_1 + \zeta_2 + \zeta_3$ in Equation 22, respectively, and the variance of ζ^* equals the variance of the sum $\zeta_1 + \zeta_2 + \zeta_3$. It can be shown that these expressions for γ_4 and the variance of ζ^* are algebraically equivalent to Equations 15 and 17, respectively. An estimate of γ_4 can be obtained by estimating the model represented by the combination of Equations 13 and 22 (i.e., ξ_4 as a cause of η_1, η_2, η_3, and η^*) and constraining γ_4 to $\gamma_1 + \gamma_2 + \gamma_3$. Estimates of the variance of ζ^* and its covariances with the ζ_i may be obtained by constraining these parameters to values indicated by rules for calculating variances and covariances of linear combinations of random variables. For the present example, the variance of ζ^* equals the sum of the variances of ζ_1, ζ_2, and ζ_3 plus twice their covariances (i.e., $\psi_{11} + \psi_{22} + \psi_{33} + 2\psi_{12} + 2\psi_{13} + 2\psi_{23}$), and the covariances of ζ^* with each ζ_i equal the variance of that ζ_i plus its covariances with the other two ζ_i (e.g., the covariance of ζ^* with ζ_1 equals $\psi_{11} + \psi_{21} + \psi_{31}$).

The procedure shown above may also be applied when the dimensions constituting η^* are assigned different weights. Again assuming η^* has three dimensions, a differentially weighted aggregate construct may be written as

$$\eta^* = w_1\xi_1 + w_2\xi_2 + w_3\xi_3. \quad (24)$$

The weights in Equation 24 may be incorporated into Equation 22 by multiplying both sides of each equation by the appropriate weight, which yields

$$\begin{aligned} w_1\eta_1 &= w_1\gamma_1\xi_4 + w_1\zeta_1 \\ w_2\eta_2 &= w_2\gamma_2\xi_4 + w_2\zeta_2 \\ w_3\eta_3 &= w_3\gamma_3\xi_4 + w_3\zeta_3. \end{aligned} \quad (25)$$

Thus, the effect of ξ_4 on the aggregate construct η^* in Equation 24 equals $w_1\gamma_1 + w_2\gamma_2 + w_3\gamma_3$, and the variance of ζ^* equals the variance of the weighted sum $w_1\zeta_1 + w_2\zeta_2 + w_3\zeta_3$. As before, estimates of these quantities may be obtained by incorporating η^* and ζ^* into the model, constraining γ_4 to $w_1\gamma_1 + w_2\gamma_2 + w_3\gamma_3$, and constraining the variance ζ^* and its covariances with the ζ_i to values indicated by rules for calculating variances and covariances of weighted linear combinations of random variables. Again, this approach yields results that are identical to those provided by the more complicated procedure corresponding to Equations 18 and 19.

Next, we consider how using an aggregate construct as an effect represents the relationships between the causes and dimensions of the construct. If the dimensions are modeled as exogenous variables, then their relationships with the causes of the construct are represented as covariances in the ϕ matrix. If the dimensions are recast as endogenous variables, then their relationships with the causes are represented as direct effects, corresponding to the γ_i in Equation 22. In either case, the relationships between the causes and dimensions of the construct are direct effects that bypass the construct itself. Thus, whereas other multidimensional construct models constrain relationships between the dimensions of the construct and its causes or effects, an aggregate effect model conceals the relationships between the causes and dimensions of the construct. These relationships are concealed because they are effectively summed into composites such as γ_4 in Equation 21. These composites provide no information regarding the individual relationships between the causes and dimensions of the construct, because a given value of a composite can be produced by an infinite number of combinations of the γ_i.

Model Estimation and Evaluation

To apply the preceding framework, various matters of model estimation and evaluation must be addressed. Regarding model estimation, it is necessary to establish that the model is identified and to properly specify the relationships between the multidimensional construct and its dimensions. Regarding model evaluation, it is important to assess model fit, the direction and magnitude of relationships between constructs, and issues underlying the multidimensional construct debate. Issues of theoretical utility and level of abstraction are conceptual rather than statistical and therefore should be addressed as part of the substantive interpretation of the model. Reliability is not an issue of debate when a multidimensional construct and its dimensions are treated as latent variables that contain no measurement error. However, an analogous issue concerns the strength of the relationships between the construct and its dimensions, as these relationships indicate how well a superordinate construct is represented by its dimensions and, likewise, how well an aggregate construct captures variance in its dimensions. Issues of construct validity underlying the debate focus on the utility of dimension specificities, which can be assessed by estimating relationships between the dimensions of the construct and its causes and effects after taking the construct into account (Hull et al., 1991). Finally, issues of criterion-related validity can be addressed by comparing the explained variance associated with the construct with that associated with its dimensions. Procedures for addressing these matters of model estimation and evaluation are discussed below.

Model Estimation

Identification. Prior to estimation, it is necessary to establish that all parameters in a model are identified. The following discussion focuses on identification issues particular to multidimensional construct models. For this discussion, it is assumed that a scale has been set for each dimension, cause, and effect of the construct, and that the parameters of the measurement model for these variables (i.e., item loadings and measurement error variances) are identified. All identification rules set forth in this discussion were verified using procedures outlined by Bekker, Merckens, and Wansbeek (1994).

First, it is necessary to set a scale for the multidimensional construct. This may be accomplished by fixing a path leading to or from the construct to unity or by fixing the variance of the construct to unity, thereby standardizing the construct.[3] To conduct statistical tests involving the multidimensional construct, it is useful to obtain standard errors for paths leading to and from the construct, and these standard errors are not available for fixed paths. Therefore, it is usually preferable to set the scale of the construct by fixing its variance. If the construct is endogenous (i.e., a superordinate construct as an effect or an aggregate construct as a cause or effect), the variance of the construct can be fixed directly in some structural equation modeling programs (e.g., RAMONA; Browne & Mels, 1992), whereas in LISREL (Jöreskog & Sörbom, 1996) it is necessary to write an equation for the variance of the construct, set that equation to unity, solve for one parameter in the equation, and constrain that parameter to the expression indicated by the equation.

Second, it is necessary to ensure that parameters in the model are identified. For superordinate cause models, all parameters are identified if no causal paths are included among the η_i and the residuals for the η_i (i.e., the ζ_i) are uncorrelated, as is customary for second-order factor models (Rindskopf & Rose, 1988). These restrictions make substantive sense for the dimensions of the construct, because presumably the construct is the only systematic source of covariance among the dimensions. However, these restrictions make less sense for the effects of the construct, which may covary for reasons other than sharing the superordinate construct as a cause (e.g., effects may influence one another, omitted variables embodied in residuals may correlate or influence more than one effect). Fortunately, the model remains identified if, for each pair of effects, (a) the residuals are allowed to correlate or (b) a causal path is included between the effects, provided the relationships among the effects as a set remain recursive.

Aggregate cause models and superordinate effect models have the same basic structure and therefore raise similar identification issues. For both types of models, the construct must have paths leading to at least two endogenous variables (Bollen & Davis, 1994; MacCallum & Browne, 1993). This criterion is satisfied if a superordinate effect has at least two dimensions or an aggregate cause has at least two effects. The model remains identified if the residual variances are freed for all endogenous variables (including the superordinate or aggregate construct), the covariances among all residuals are fixed, and the model contains no causal relationships among endogenous variables other than those emanating from the multidimensional construct. This specification makes sense for a superordinate construct as an effect because the construct is considered the only systematic source of covariation among its dimensions, and a residual for the construct must be estimated to capture the variance in the construct not explained by its causes. However, for an aggregate construct as a cause, it may be desirable to estimate causal paths among the effects of the construct or correlations among the residuals of the effects. These parameters are identified if the residual for the aggregate construct is fixed (i.e., the construct is an exact linear combination of its dimensions, as in Equations 4, 5, and 6) and, for each pair of effects, (a) the residuals are allowed to correlate or (b) a causal path is included between the effects and the relationships among the effects as a set remain recursive. If the residual for the aggregate construct is freed, as in Equation 7, then at least one path or covariance among the effect residuals must be constrained to achieve identification.

For an aggregate effect model, estimating the variances and covariances of the dimensions and causes of the construct renders the parameters linking the construct to its dimensions and causes unidentified. As noted previously, this dilemma can be overcome by specifying a priori weights linking the construct to its dimensions, respecifying the dimensions as endogenous variables, and imposing constraints on the paths from the causes to the construct and on the variance and covariances of the residual of the construct. Structural models of this type are saturated and are therefore just identified. If effects of the construct are added to the model, then the parameters linking the construct to its dimensions may be estimated, provided the model conforms to rules for identification of models with an aggregate construct as a cause.

Specifying relationships between the multidimensional construct and its dimensions. As noted previously, the proposed framework provides tests of the variability of the relationships between a multidimensional construct and its dimensions. For superordinate constructs, these tests are performed by imposing constraints analogous to those used to compare congeneric, tau equivalent, and parallel measurement models (Jöreskog & Sörbom, 1996). For congeneric models, no constraints are imposed on the dimension loadings or residual variances. For tau equivalent models, the dimension loadings are set equal to one another. For parallel models, the dimension loadings are set equal to one another, and the residual variances are set equal to one another. These models are nested and can be compared using chi-square difference tests.

Constraints for aggregate constructs represent different approaches to combine dimensions to form the construct. Summing the dimensions is tantamount to assigning them equal weight. To incorporate unit weights, one weight should be set to unity, the remaining weights should be set equal to that weight, and the variance of the construct should be freed. If the construct is standardized by fixing its variance to unity, then the dimension weights may be set equal to one another without fixing any of the weights to a particular value. In either case, the substantive meaning of the construct is the same. For principal component weights, covariances among the dimensions should be obtained from a confirmatory factor analysis and submitted to a principal components analysis from which one component is extracted. The resulting component weights can be used to impose proportional constraints on the paths from the dimensions to the construct. For example, if the principal component weights for three dimensions are .5, .6, and .7, the second path should be constrained to 1.2 times the first, and the third path should be constrained to 1.4 times the first. If the scale for the aggregate construct is set by fixing the first path to the obtained principal component weight, then these constraints will reproduce the full set of component weights (with this approach, the variance of the aggregate construct should be freed, and the resulting estimate will equal the eigenvalue for the principal component). If the aggregate construct is scaled by fixing its variance to unity, then one path should be freed, and the remaining paths should be constrained proportionally to that path. For models with equal weights or principal component weights, the residual for the aggregate construct should be fixed to zero, as implied by Equations 4 and 5. If the aggregate construct is a cause, then all paths from the dimensions to the construct may be freed (as in Equations 6 and 7), and the resulting model may be compared with models with equal or principal component weights using chi-square difference tests.

Model Evaluation

Model fit. Model fit should be assessed using indices recommended in the structural equation modeling literature (Gerbing & Anderson, 1993), such as the comparative fit index (CFI; Bentler, 1990) and the root mean squared error of approximation (RMSEA; Steiger, 1990). The CFI represents the increase in fit of the target model over a null model in which all variables are uncorrelated (Bentler, 1990). The CFI has an expected value of 1.00 when the estimated model is true in the population, and values of .95 or higher indicate adequate fit (Hu & Bentler, 1999). The RMSEA estimates the discrepancy per degree of freedom between the original and reproduced covariance matrices in the population. Values up to .05 indicate close fit, and values up to .08 represent reasonable errors of approximation in the population (Browne & Cudeck, 1993). Point estimates of the RMSEA may be supplemented by confidence intervals to obtain tests of close fit, as indicated by whether the confidence interval includes .05 (MacCallum, Browne, & Sugawara, 1996).

Assessments of model fit should be supplemented by comparisons with alternative models (Anderson & Gerbing, 1988; MacCallum, Roznowski, & Necowitz, 1992). For a superordinate construct, the parallel, tau equivalent, and congeneric models may be compared with one another. For an aggregate construct, models with equal or principal component dimension loadings may be compared with models that freely estimate these loadings. In addition, models that include a multidimensional construct should be compared with models that treat the construct as a set of related dimensions, thereby yielding information directly relevant to the multidimensional construct debate. Sets of dimensions should be modeled using multivariate structural models that differ according to whether the multidimensional construct is a cause or effect. If the construct is a cause, its dimensions are treated as exogenous variables, its effects are treated as endogenous variables, and each dimension is specified as a direct cause of each effect. If the construct is an effect, its dimensions are treated as endogenous variables, its causes are treated as exogenous variables, and a direct effect is included linking each cause to each dimension. For both models, correlations should be included among the exogenous variables and among residuals for the endogenous variables, with the exception of endogenous variables connected by causal paths.

Relationships between the multidimensional construct and its dimensions. Procedures for assessing the overall relationship between a multidimensional construct and its dimensions differ according to whether the construct is aggregate or superordinate. For an aggregate construct, the relationship can be assessed with the adequacy coefficient (R_a^2), which is used in canonical correlation analysis to assess the relationship between a set of variables and their associated canonical variate (Thompson, 1984).[4] R_a^2 is calculated by summing the squared correlations between the construct and its dimensions and dividing by the number of dimensions. The relationship between a superordinate construct and its dimensions can be assessed with the total coefficient of determination or multivariate R^2 (here labeled R_m^2), which represents the proportion of generalized variance in a set of dependent variables explained by one or more independent variables (Bollen, 1989; Cohen, 1982; Jöreskog & Sörbom, 1996). R_m^2 is calculated by taking the determinant of the covariance matrix of the multidimensional construct and its dimensions, dividing this quantity by the variance of the multidimensional construct times the determinant of the covariance matrix of the dimensions, and subtracting the resulting quantity from unity.

Relationships for dimension specificities. Relationships between dimension specificities and the causes and effects of the construct can be assessed by incorporating specificities as latent variables in the model. This approach is straightforward for a superordinate construct but is quite complicated for an aggregate construct for which dimension specificities are represented by creating variables that equal the portion of each dimension that is independent of the construct. A simpler approach that yields equivalent results is to treat relationships for dimension specificities as direct effects for the dimensions after taking into account the multidimensional construct. When the construct is a cause, these direct effects represent the incremental variance explained by each dimension after controlling for the construct. When the construct is an effect, direct effects to the dimensions indicate whether the causes in the model relate to aspects of the dimensions that are distinct from the construct. Individual direct effects can be tested using modification indices (Jöreskog & Sörbom, 1996), which follow a chi-square distribution with 1 degree of freedom and indicate the expected improvement in model fit if a constrained parameter is freed.[5] Alternately, a direct effect can be tested by adding it to the model and testing whether it differs from zero (or, analogously, whether the chi-square for the model is reduced). Multiple direct effects can be tested by adding them to the model and conducting chi-square difference tests, provided the augmented model is identified.

The foregoing tests do not apply to aggregate effect models, because these models already include direct effects from the causes to the dimensions of the construct. Instead, dimension specificities may be assessed by comparing the R^2 for the aggregate construct to the R_m^2 for its dimensions, and a confidence interval for the difference between R^2 and R_m^2 can be obtained using the bootstrap (Efron & Tibshirani, 1993). Alternately, dimension specificity can be reframed as information provided by the dimensions beyond that obtained from the aggregate construct. Using an aggregate construct as an effect implies that a single coefficient adequately represents the effect of each cause on all dimensions of the construct. If the coefficients relating each cause to the dimensions are indeed equal, then no information is lost by using the aggregate construct. However, if the coefficients differ from one another such that the effects of each cause vary across dimensions, then the aggregate construct is concealing potentially useful information. This issue may be examined by imposing equality constraints on the coefficients from each cause to the dimensions and testing the increase in chi-square.

Comparing criterion-related validity for the construct and its dimensions. Differences in criterion-related validity for a multidimensional construct and its dimensions can be assessed using R_m^2. When the multidimensional construct is a cause, the R_m^2 from the model with the construct may be compared with the R_m^2 from a multivariate structural model using the dimensions as correlated causes. Because the former model is nested in the latter, the difference in R_m^2 for these models can be assessed using a chi-square difference test. When the multidimensional construct is an effect, the R^2 for the model with the construct can be compared with the R_m^2 for a multivariate structural model using the dimensions as effects with correlated residuals. If the construct is superordinate, the former model is nested in the latter, and the difference in R_m^2 for the two models model can be assessed using a chi-square difference test. If the construct is aggregate, the R^2 for the aggregate construct may be compared with the R_m^2 for its dimensions as a set, as explained earlier. It should be noted that the foregoing tests are equivalent to omnibus tests for all dimension specificities, given that any increase in criterion-related validity for the dimensions is attributable to aspects of the dimensions not shared with the construct.

Empirical Illustrations

The proposed framework is illustrated using data from two studies: one that examined personality as a multidimensional cause of responses to conflict (Moberg, 1998) and another that examined employee adaptation as a multidimensional effect of job dissatisfaction (Hanisch & Hulin, 1991). For both studies, superordinate and aggregate construct models were examined. Analyses were based on covariance matrices for measures of the dimensions of the construct and its causes or effects, derived from information reported in published articles. To facilitate interpretation, covariances for each study were based on measures converted to a common metric, and all superordinate constructs were scaled by fixing their variances to unity.[6] Measurement error was incorporated by using each measure as a single indicator of a latent variable with its loading set to unity and the variance of its measurement error set to one minus the reported reliability of the measure multiplied by the variance of the measure. Because a single indicator measurement model was used, fit indices refer specifically to the structural model relating the multidimensional construct to its dimensions and causes or effects. Models were estimated using LISREL 8.30 (Jöreskog & Sörbom, 1996) and RAMONA (Browne & Mels, 1992).

Multidimensional Construct as a Cause

Moberg (1998) collected data from 249 managers and supervisors who completed the 240-item NEO-PI-R (Costa & McCrae, 1992) and the 30-item Organizational Communication and Conflict Instrument (OCCI; Putnam & Wilson, 1982). The NEO-PI-R contains 48 items for each of the Big Five personality traits, and items for each trait can be scored on six dimensions, each measured with eight items. The OCCI measures four responses to interpersonal conflict, using 5 to 12 items for each response. The present analyses focused on extraversion as a cause of avoidance, seeking resolution, and exerting control in conflict situations (correlations among residuals of these outcomes were included in all models). Data used for these analyses are reported in Table 1.

Superordinate cause models. Results for extraversion as a superordinate cause are reported in Figure 1 and Table 2. The parallel, tau equivalent, and congeneric models did not fit the data well, as evidenced by CFI values ranging from .584 to .681 and RMSEA values ranging from .150 to .155 (for each model, the 90% confidence interval for the RMSEA was well above .05, thereby rejecting the hypothesis of close fit; MacCallum et al., 1996). Chi-square difference tests indicated that the congeneric model fit better than the tau equivalent model ($\Delta\chi^2(5) = 28.171, p < .001$), which in turn

Table 1
Means, Standard Deviations, Reliabilities, and Correlations for Measures of Extraversion and Responses to Conflict (*N* = 249)

	M	SD	α	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
Extraversion dimensions												
1. Warmth	2.888	0.500	.750	*0.250*	*0.182*	*0.062*	*0.077*	*0.070*	*0.172*	*–0.018*	*0.054*	*–0.045*
2. Gregariousness	2.100	0.688	.810	.530	*0.473*	*0.122*	*0.098*	*0.188*	*0.159*	*–0.039*	*–0.004*	*–0.033*
3. Assertiveness	2.225	0.538	.750	.230	.330	*0.289*	*0.124*	*0.072*	*0.076*	*–0.116*	*0.078*	*0.147*
4. Activity	2.438	0.550	.700	.280	.260	.420	*0.303*	*0.070*	*0.133*	*–0.079*	*0.087*	*–0.004*
5. Excitement seeking	2.125	0.638	.670	.220	.430	.210	.200	*0.406*	*0.100*	*–0.014*	*–0.004*	*0.039*
6. Positive emotions	2.600	0.563	.750	.610	.410	.250	.430	.280	*0.316*	*–0.044*	*0.068*	*–0.015*
Responses to conflict												
7. Avoidance	4.717	0.717	.870	–.050	–.080	–.300	–.200	–.030	–.110	*0.514*	*–0.113*	*–0.079*
8. Resolution	2.800	0.633	.810	.170	–.010	.230	.250	–.010	.190	–.250	*0.401*	*0.048*
9. Control	4.300	0.686	.740	–.130	–.070	.400	–.010	.090	–.040	–.160	.110	*0.470*

Source. Adapted from Moberg (1998).

Note. Table entries labeled α are Cronbach's alpha. Table entries below the diagonal are correlations, and those on and above the diagonal (in italics) are variances and covariances used for analysis. Correlations greater than .124 in absolute magnitude are significantly different from zero ($p < .05$).

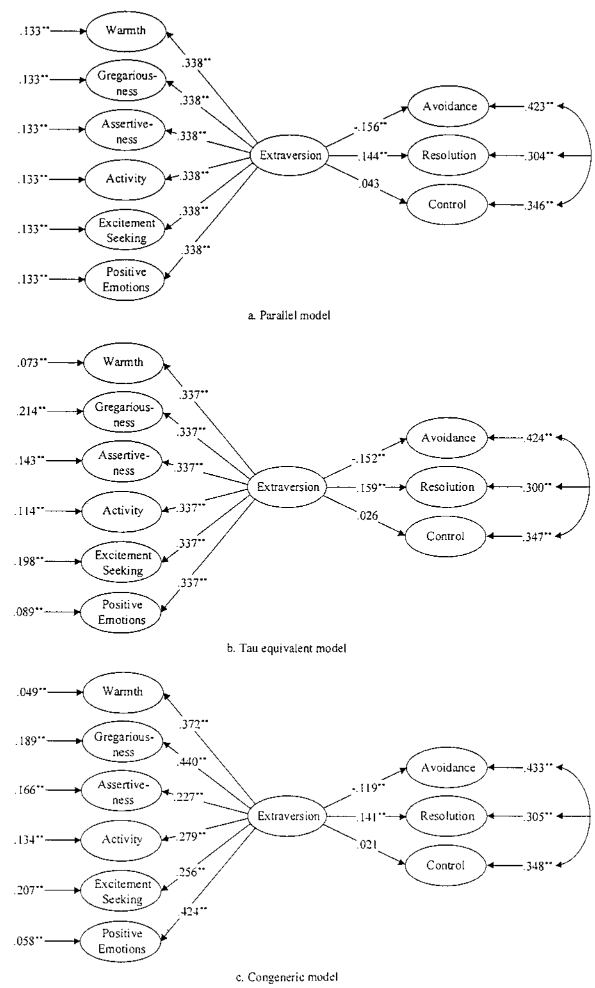

Figure 1: Superordinate Cause Models
$^{**}p < .01$.

fit better than the parallel model ($\Delta\chi^2(5) = 29.198$, $p < .001$). Thus, the congeneric model provided the best fit of the three models, although none of the models fit well in an absolute sense.

For the parallel, tau equivalent, and congeneric models, extraversion exhibited strong multivariate relationships with its dimensions, with R^2_m values of .840, .849, and .891, respectively. For the parallel model, the R^2 linking extraversion to each dimension was .462 (by construction, this value was the same for all dimensions). For the tau equivalent model, dimension R^2 values ranged from .347 for gregariousness to .608 for warmth, whereas for the congeneric model, dimension R^2 values ranged from .236 for assertiveness to .757 for positive emotions.[7] Thus, the congeneric model indicated that the tau equivalent and parallel models concealed considerable variability in the relationships between extraversion and its dimensions. Omnibus significance tests of this

Table 2
Superordinate Cause Models for Extraversion ($N = 249$)

Responses to Conflict	*Warmth*	*Gregariousness*	*Assertiveness*	*Activity*	*Excitement Seeking*	*Positive Emotions*	R^2_m	χ^2	df	*CFI*	*RMSEA*
	Extraversion Dimensions										
Parallel model											
Avoidance	–0.053**	–0.053**	–0.053**	–0.053**	–0.053**	–0.053**	.046				
Resolution	0.049**	0.049**	0.049**	0.049**	0.049**	0.049**	.054				
Control	0.015	0.015	0.015	0.015	0.015	0.015	.004	236.144**	34	.584	.150
Tau equivalent model											
Avoidance	–0.051**	–0.051**	–0.051**	–0.051**	–0.051**	–0.051**	.044				
Resolution	0.054**	0.054**	0.054**	0.054**	0.054**	0.054**	.066				
Control	0.009	0.009	0.009	0.009	0.009	0.009	.002	206.946**	29	.633	.153
Congeneric model											
Avoidance	–0.044*	–0.052*	–0.027*	–0.033*	–0.030*	–0.050*	.028				
Resolution	0.052**	0.062**	0.032**	0.039**	0.036**	0.060**	.055				
Control	–0.008	–0.009	–0.005	–0.006	–0.005	–0.009	.001	178.775**	24	.681	.155

Note. CFI = comparative fit index, RMSEA = root mean squared error of approximation. For the extraversion dimensions, table entries are unstandardized spurious relationships between the extraversion dimensions and responses to conflict, calculated as the product of each dimension loading on extraversion with the path from extraversion to each response to conflict.
**p* < .05. ***p* < .01.

variability are provided by the chi-square difference tests reported earlier, which indicate that the loadings and residuals for the extraversion dimensions differed significantly from one another.

All three models indicated that extraversion was negatively related to avoidance, positively related to resolution, and unrelated to control. R_m^2 values linking extraversion to its outcomes were .092, .101, and .081, respectively, for the parallel, tau equivalent, and congeneric models. The three models produced R^2 values for individual outcomes ranging from .032 to .055 for avoidance, .061 to .078 for resolution, and .001 to .005 for control. Relationships between individual dimensions and outcomes (see Table 2) were necessarily constant across dimensions for the parallel and tau equivalent models, whereas the congeneric model indicated that the relationships with outcomes were strongest for gregariousness, followed by positive emotions and warmth.

Relationships for dimension specificities were examined using modification indices for parameters directly linking the extraversion dimensions to the outcomes. To control for Type I error, the nominal p value of .05 was divided by the number of modification indices examined (i.e., 18), yielding a critical p value of .00278 and corresponding chi-square of 8.498. For all three models, this criterion indicated a negative effect of the gregariousness specificity on resolution, a negative effect of the warmth specificity on control, and a positive effect of the assertiveness specificity on control.

Aggregate cause models. Results for extraversion as an aggregate cause are reported in Figure 2 and Table 3. Models with equal loadings and principal component loadings did not fit the data well, with CFI values of .812 and .805 and RMSEA values of .145 and .148, respectively (for both models, 90% confidence intervals for the RMSEA excluded .05). In contrast, the model that freely estimated the dimension loadings fit the data reasonably well, producing a CFI of .945 and a RMSEA of .099 (the lower bound of the 90% confidence interval was .064, falling between the .05 criterion of close fit and the .08 value indicating reasonable errors of approximation; Browne & Cudeck, 1993). Chi-square difference tests confirmed that this model fit better than the models with equal loadings ($\Delta\chi^2(5) = 69.940$, $p < .001$) or principal component loadings ($\Delta\chi^2(5) = 73.033$, $p < .001$). The same fit was produced by a model that freed the residual on extraversion, as would be expected given that freeing this residual required fixing one of the residual covariances for the responses to conflict. However, the estimated variance of the extraversion residual was negative, indicating an inadmissible solution. Therefore, the model was reestimated using RAMONA, which ensures that all estimated variances are nonnegative. The resulting estimate of the extraversion residual was zero, which essentially rendered this model equivalent to the model in which the extraversion residual was fixed to zero. Therefore, the model that freed the extraversion residual was excluded from further consideration.

For the models with equal loadings and principal component loadings, relationships between extraversion and its dimensions were moderate, as evidenced by R_a^2 values of .552 and .548, respectively. Squared correlations between extraversion and its dimensions (which are analogous to squared structure coefficients in canonical correlation analysis; Thompson, 1984) ranged from .429 for assertiveness to .677 for gregariousness for the equal loadings model and from .368 for assertiveness to .759 for gregariousness for the principal components loadings model. Relationships between

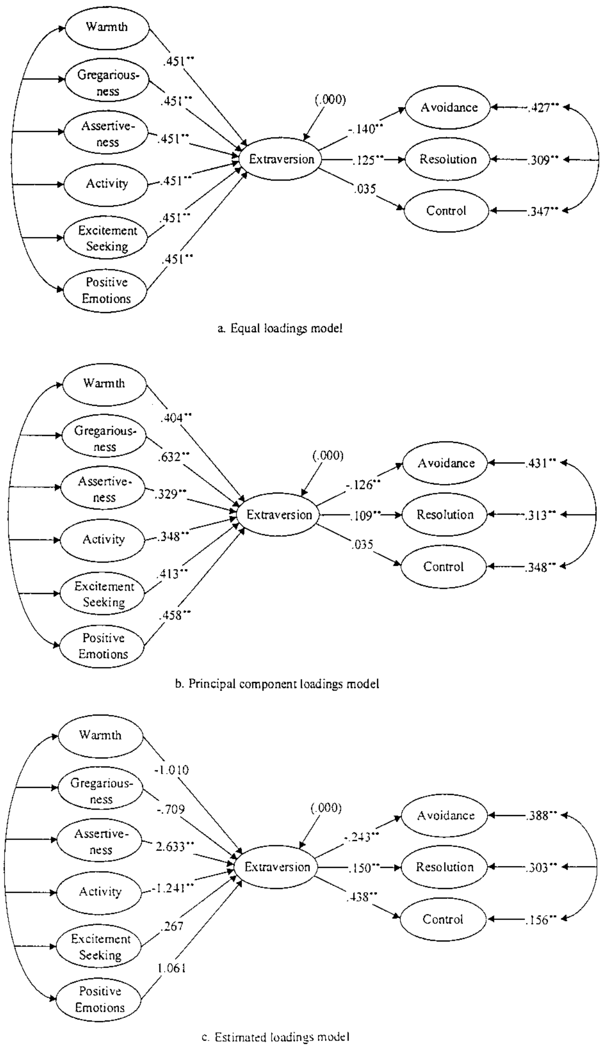

Figure 2: Aggregate Cause Models
$^{**}p < .01$.

extraversion and its dimensions were lower and more varied for the model that estimated the dimension loadings, as indicated by an R_a^2 value of .116, a squared correlation of .626 for assertiveness, and squared correlations smaller than .028 for the other five dimensions. Chi-square difference tests comparing this model with the models with equal or principal component loadings indicated that, although the latter models produced higher R_a^2 values, they concealed substantial variability in the dimension loadings. On the other hand, the model that estimated the dimension loadings transformed extraversion into a construct that was dominated by assertiveness and captured little of the remaining five dimensions.

The models with equal loadings and principal component loadings indicated that extraversion was negatively related to avoidance, positively related to resolution, and

Table 3
Aggregate Cause Models for Extraversion (*N* = 249)

Responses to Conflict	Extraversion Dimensions: *Warmth*	*Gregariousness*	*Assertiveness*	*Activity*	*Excitement Seeking*	*Positive Emotions*	R^2_m	χ^2	df	*CFI*	*RMSEA*
Equal loadings model											
Avoidance	–0.063**	–0.063**	–0.063**	–0.063**	–0.063**	–0.063**	.044				
Resolution	0.056**	0.056**	0.056**	0.056**	0.056**	0.056**	.048				
Control	0.016	0.016	0.016	0.016	0.016	0.016	.004	106.414**	15	.812	.145
Principal component loadings model											
Avoidance	–0.051**	–0.080**	–0.041**	–0.044**	–0.052**	–0.058**	.035				
Resolution	0.044**	0.069**	0.036**	0.038**	0.045**	0.050**	.037				
Control	0.007	0.011	0.006	0.006	0.007	0.008	.001	109.507**	15	.805	.148
Estimated loadings model											
Avoidance	0.245	0.172	–0.640**	0.302*	–0.065	–0.258	.132				
Resolution	–0.152	–0.106	0.395**	–0.186	0.040	0.159	.069				
Control	–0.442	–0.311	1.153**	–0.544*	0.117	0.465	.550	36.474**	10	.945	.099
Estimated loadings model with residual											
Avoidance	0.245	0.172	–0.640**	0.302*	–0.065	–0.258	.132				
Resolution	–0.152	–0.106	0.395**	–0.186	0.040	0.159	.069				
Control	–0.442	–0.311	1.153**	–0.544*	0.117	0.465	.550	36.474**	10	.945	.099

Note. CFI = comparative fit index, RMSEA = root mean squared error of approximation. For the extraversion dimensions, table entries are unstandardized indirect effects of the extraversion dimensions on the responses to conflict, calculated as the product of each dimension loading on extraversion with the path from extraversion to each response to conflict.
*$p < .05$. **$p < .01$.

unrelated to control. R_m^2 values for the two models were .071 and .056, respectively, and the models produced R^2 values for individual outcomes of .044 and .035 for avoidance, .048 and .037 for resolution, and .004 and .001 for control. In contrast, the model that estimated the dimension loadings produced an R_m^2 of .609 and R^2 values of .132, .069, and .550 for avoidance, resolution, and control, respectively. Relationships between dimensions and outcomes (see Table 3) were similar for the models with equal loadings and principal component loadings, indicating that all dimensions were negatively related to avoidance and positively related to resolution. A markedly different pattern emerged for the models that estimated dimension loadings, indicating that assertiveness was negatively related to avoidance and positively related to resolution and control, and that activity was positively related to avoidance and negatively related to control.

Relationships for dimension specificities were examined using modification indices for parameters directly linking the extraversion dimensions to the outcomes, again using a critical chi-square value of 8.498. For the models with equal loadings and principal component loadings, this criterion indicated a positive effect of the assertiveness specificity on control and negative effects of the warmth specificity on control and the gregariousness specificity on resolution. For the model with estimated loadings, modification indices pointed to positive effects of the activity and positive emotions specificities on resolution, a positive effect of the assertiveness specificity on control, and negative effects of the warmth, activity, and positive emotions specificities on control.[8]

Multivariate structural model. Results for the multivariate structural model are reported in Table 4. Because single indicators were used for all latent variables, the model was saturated and therefore fit the data perfectly. The fit of this model relative to the superordinate and aggregate cause models can be tested using the chi-square statistics for those models, which are compared with a value of zero (i.e., the chi-square for the multivariate structural model).[9] These tests indicate that the multivariate structural model fit the data better than any of the superordinate cause and aggregate cause models.

The multivariate structural model yielded an R_m^2 of .731 for the relationships between the extraversion dimensions and outcomes. This value is substantially higher than values for all models except the aggregate cause model with estimated dimension loadings, which produced an R_m^2 of .609. R^2 values linking the extraversion dimensions to avoidance, resolution, and control for the multivariate structural model were .158, .224, and .622, respectively. These values were notably higher than corresponding values from the superordinate and aggregate cause models.

The multivariate structural model indicated that three of the six extraversion dimensions were related to the responses to conflict. In particular, gregariousness was negatively related to resolution, activity was negatively related to control, and assertiveness was negatively related to avoidance and positively related to resolution and control. These results indicate that the relationships for warmth, excitement seeking, and positive emotions found for the superordinate and aggregate cause models were artifacts of the constraints imposed by these models on the loadings of the extraversion dimensions. These differences between the multivariate structural model and the superordinate and aggregate cause models were foreshadowed by the analyses of dimension specificities reported earlier, which indicated that the superordinate and

Table 4
Multivariate Structural Model for Extraversion ($N = 249$)

Responses to Conflict	Warmth	Gregariousness	Assertiveness	Activity	Excitement Seeking	Positive Emotions	R^2_m	χ^2	df	CFI	RMSEA
	Extraversion Dimensions										
Avoidance	0.302	–0.025	–0.539**	–0.045	0.133	–0.246	.158				
Resolution	0.566	–0.406*	0.300*	0.284	0.008	–0.110	.224				
Control	–0.577	–0.314	1.207**	–0.764**	0.192	0.527	.622	0.000	0	1.000	.000

Note. CFI = comparative fit index, RMSEA = root mean squared error of approximation. For the extraversion dimensions, table entries are unstandardized coefficients linking each extraversion dimension to each response to conflict.
*$p < .05$. **$p < .01$.

aggregate cause models overestimated some relationships and underestimated other relationships between the extraversion dimensions and responses to conflict.

Summary. The preceding results provide little support for extraversion as a superordinate construct. Although extraversion exhibited moderate to strong relationships with its dimensions, it distorted the relationships between the extraversion dimensions and outcomes, exaggerating relationships with avoidance and resolution and concealing relationships with control. In addition, the criterion-related validity of the extraversion construct was much lower than its dimensions as a set. Moreover, relationships revealed by treating the extraversion dimensions as a set were theoretically meaningful, as exemplified by the positive relationship between assertiveness and control. Given that relationships with outcomes varied across the extraversion dimensions, it appears that the level of abstraction embodied by the extraversion construct was too broad. Thus, on the grounds of theoretical utility, level of abstraction, dimension specificity, and criterion-related validity, extraversion as a cause of responses to conflict is better viewed as a set of related dimensions than as a superordinate construct.

Results also do not support extraversion as an aggregate construct with dimension loadings that are equal or proportional to principal component weights. For these models, relationships between extraversion and its dimensions were reasonably strong but criterion-related validities were low, particularly for control as an outcome. These models also concealed considerable variability in the effects of the extraversion dimensions, suggesting that the extraversion construct was too broad relative to its outcomes. Models that freely estimated dimension loadings produced higher criterion-related validities and better represented the effects of the extraversion dimensions on the outcomes. However, these models effectively reduced the extraversion construct to assertiveness, indicating that the construct was too broad and had little theoretical utility beyond the assertiveness dimension taken separately. Thus, the aggregate cause models were inferior to the multivariate structural model, although the particular shortcomings of the aggregate cause models differed depending on how the relationships between the aggregate construct and its dimensions were specified.

Multidimensional Construct as an Effect

Hanisch and Hulin (1991) obtained data from 348 university staff members who completed measures of work, pay, and coworker satisfaction from the Job Descriptive Index (Smith et al., 1969), a measure of health satisfaction from the Retirement Descriptive Index (Smith et al., 1969), and measures of five dimensions of employee adaptation, including unfavorable job behavior, lateness, absenteeism, turnover intent, and desire to retire (Roznowski & Hanisch, 1990). Satisfaction measures contained 9 to 19 items, and adaptation measures contained three to seven items. The present analyses examined health, work, coworker, and pay satisfaction as causes of adaptation. Descriptive statistics and correlations for the measures analyzed are reported in Table 5.

Superordinate effect models. Results for adaptation as a superordinate effect are reported in Figure 3 and Table 6. The parallel, tau equivalent, and congeneric models did not fit the data well, with CFI values from .342 to .793 and RMSEA values from .106 to .153 (for all three models, 90% confidence intervals for the RMSEA excluded

Table 5

Means, Standard Deviations, Reliabilities, and Correlations for Measures of Satisfaction and Adaptation (*N* = 348)

	M	SD	α	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
Satisfaction												
1. Health satisfaction	5.620	1.349	.800	*1.820*	*0.348*	*0.283*	*0.149*	*–0.083*	*–0.027*	*–0.122*	*–0.157*	*–0.180*
2. Work satisfaction	5.951	1.033	.850	.250	*1.068*	*0.612*	*0.408*	*0.048*	*–0.072*	*–0.075*	*–0.326*	*–0.322*
3. Coworker satisfaction	5.812	1.234	.900	.170	.480	*1.522*	*0.663*	*–0.038*	*–0.012*	*–0.037*	*–0.403*	*–0.275*
4. Pay satisfaction	4.298	1.580	.820	.070	.250	.340	*2.496*	*0.061*	*–0.284*	*–0.076*	*–0.313*	*0.000*
Adaptation dimensions												
5. Unfavorable job behaviors	2.760	0.770	.620	–.080	.060	–.040	.050	*0.593*	*0.146*	*0.121*	*0.099*	*0.009*
6. Lateness	2.075	0.998	.510	–.020	–.070	–.010	–.180	.190	*0.995*	*0.266*	*0.163*	*0.044*
7. Absenteeism	1.758	0.605	.530	–.150	–.120	–.050	–.080	.260	.440	*0.366*	*0.162*	*0.088*
8. Turnover intentions	2.143	1.167	.540	–.100	–.270	–.280	–.170	.110	.140	.230	*1.361*	*0.325*
9. Desire to retire	4.423	1.114	.820	–.120	–.280	–.200	.000	.010	.040	.130	.250	*1.242*

Source. Adapted from Hanisch and Hulin (1991).

Note. Table entries labeled α are Cronbach's alpha. Table entries below the diagonal are correlations, and those on or above the diagonal (in italics) are variances and covariances used for analysis. Correlations greater than .105 in absolute magnitude are significantly different from zero ($p < .05$).

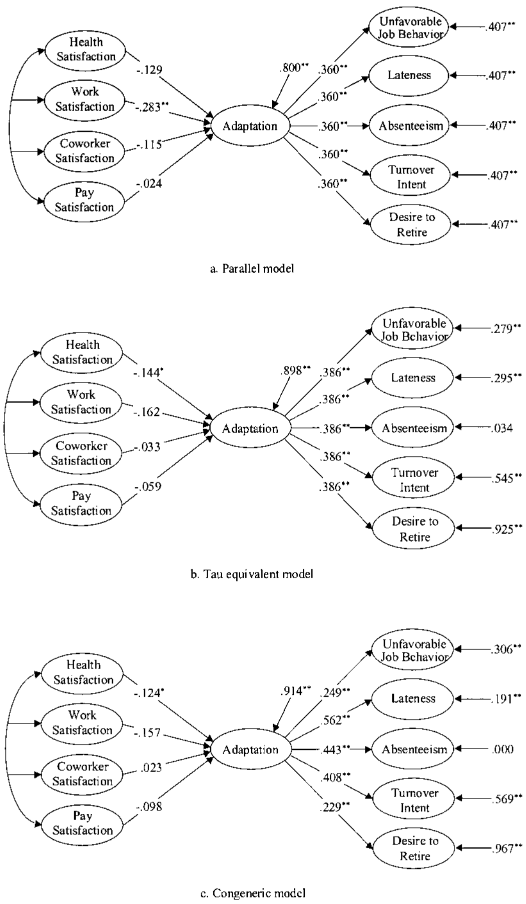

Figure 3. Superordinate Effect Models
$^{**}p < .01$.

.05). In addition, the congeneric model produced a small negative error variance for absenteeism, although this estimate did not differ significantly from zero. Therefore, this model was reestimated using RAMONA, which produced an estimate of zero for the absenteeism error variance and little change in the other parameter estimates. Chi-square difference tests indicated that the congeneric model fit better than the tau equivalent model ($\Delta\chi^2(4) = 20.569, p < .001$), which in turn fit substantially better than the parallel model ($\Delta\chi^2(4) = 152.262, p < .001$). Thus, although the congeneric model produced the best fit of the three models, none of the models fit the data well.

For the parallel, tau equivalent, and congeneric models, R^2_m values relating adaptation to its dimensions were .615, .852, and 1.000, respectively. The R^2_m value of 1.000 for the congeneric model was attributable to the relationship between adaptation and absenteeism, for which the residual variance of zero implied a univariate R^2 of 1.000. The congeneric model also produced an R^2 of .624 for lateness and R^2 values of less than .230 for the remaining adaptation dimensions. For the tau equivalent model, dimension R^2 values ranged from .139 for desire to retire to .813 for absenteeism,

Table 6
Superordinate Effect Models for Adaptation (N = 348)

	Satisfaction								
Adaptation Dimensions	*Health*	*Work*	*Coworker*	*Pay*	R^2	χ^2	df	*CFI*	*RMSEA*
Parallel model									
Unfavorable job behaviors	–0.046	–0.102*	–0.041	–0.009	.048				
Lateness	–0.046	–0.102*	–0.041	–0.009	.048				
Absenteeism	–0.046	–0.102*	–0.041	–0.009	.048				
Turnover intentions	–0.046	–0.102*	–0.041	–0.009	.048				
Desire to retire	–0.046	–0.102*	–0.041	–0.009	.048	270.038**	29	.342	.153
Tau equivalent model									
Unfavorable job behaviors	–0.056*	–0.063	–0.013	–0.023	.035				
Lateness	–0.056*	–0.063	–0.013	–0.023	.034				
Absenteeism	–0.056*	–0.063	–0.013	–0.023	.083				
Turnover intentions	–0.056*	–0.063	–0.013	–0.023	.022				
Desire to retire	–0.056*	–0.063	–0.013	–0.023	.014	117.776**	25	.747	.107
Congeneric model									
Unfavorable job behaviors	–0.031	–0.039	–0.006	–0.024	.014				
Lateness	–0.070	–0.088	–0.013	–0.055	.053				
Absenteeism	–0.055*	–0.070	–0.010	–0.043	.086				
Turnover intentions	–0.051	–0.064	–0.009	–0.040	.019				
Desire to retire	–0.028	–0.036	–0.005	–0.022	.004	97.207**	21	.793	.102

Note. CFI = comparative fit index, RMSEA = root mean squared error of approximation. For the satisfaction facets, table entries are unstandardized indirect effects of the satisfaction facets on the dimensions of adaptation, calculated as the product of the path from each satisfaction facet to adaptation with the loading of each dimension on adaptation.
*$p < .05$. **$p < .01$.

whereas for the parallel model the R^2 for each adaptation dimension was .242. Hence, as parameters relating adaptation to its dimensions were relaxed, these relationships because increasingly variable to the point that adaptation became isomorphic with absenteeism.

The parallel model indicated that adaptation was negatively related to work satisfaction, whereas the tau equivalent and congeneric models indicated that adaptation was negatively related to health satisfaction. R^2 values for adaptation produced by the three models were .200, .102, and .081, respectively. Relationships between satisfaction and the adaptation dimensions (see Table 6) were necessarily constant for the parallel and tau equivalent models, with the former model indicating that all dimensions were negatively related to work satisfaction and the latter model indicating that all dimensions were negatively related to health satisfaction. In contrast, the congeneric model yielded a single negative relationship between health satisfaction and absenteeism, suggesting that the negative relationships for the other four dimensions in the tau equivalent model were artifacts of the equality constraint imposed across the five dimensions.

For the three superordinate effect models, relationships for dimension specificities were examined using modification indices for parameters directly linking satisfaction to the adaptation dimensions. The nominal p value of .05 was divided by the number of modification indices examined (i.e., 20), yielding a critical p value of .0025 and corresponding chi-square of 9.140. For the parallel model, this criterion indicated a positive effect of work satisfaction on the unfavorable job behavior specificity, negative effects of work satisfaction on the turnover intent and desire to retire specificities, a negative effect of coworker satisfaction on the turnover intent and desire to retire specificities, and a negative effect of pay satisfaction on the turnover intent specificity. Similar results were obtained for the tau equivalent model, although modification indices did not reach significance for the effect of coworker satisfaction on the desire to retire specificity or the effect of pay satisfaction on the turnover intent specificity. For the congeneric model, work satisfaction and pay satisfaction were negatively related to the specificities for turnover intent and desire to retire. Thus, although the results of the specificity analyses differed somewhat for the three models, each model indicated that dissatisfaction with work and pay may relate aspects of turnover intent and desire to retire not captured by the adaptation construct.

Aggregate effect models. Results from analyses using adaptation as an aggregate effect are shown in Figure 4 and Table 7. Because aggregate effect models do not impose constraints on the relationships between the adaptation dimensions and outcomes, they yield equivalent fit to the data and therefore cannot be compared using fit statistics or chi-square difference tests. Nonetheless, these models can be evaluated using criteria relevant to the multidimensional construct debate, as discussed below.

Overall, the aggregate effect models yielded modest relationships between adaptation and its dimensions, with R_a^2 values of .449 and .365 for the equal loadings and principal component loadings models, respectively. The equal loadings model yielded squared correlations between adaptation and its dimensions ranging from .264 for unfavorable job behavior to .627 for absenteeism. Squared dimension correlations for the principal component loadings model ranged from .064 for unfavorable job behavior to .704 for desire to retire. The increased variability in dimension correlations for

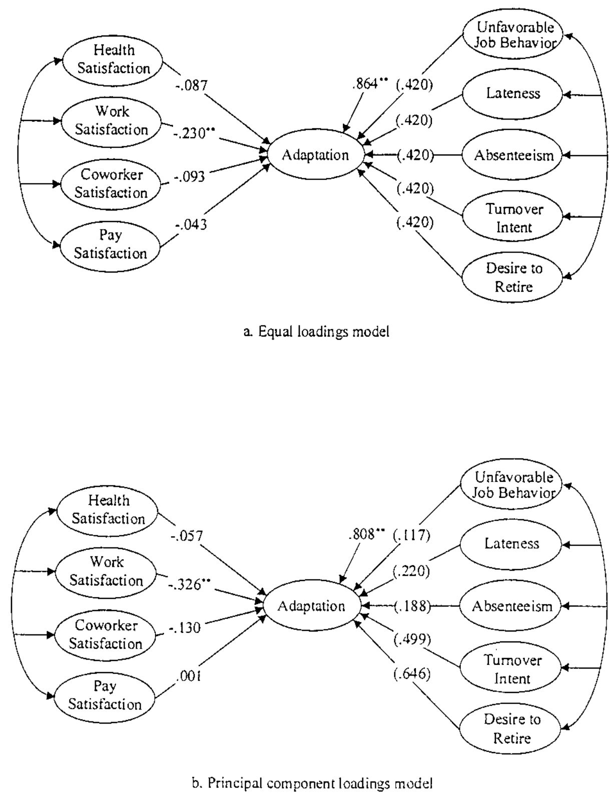

Figure 4. Aggregate Effect Models
$^{**}p < .01$.

the principal component loadings model paralleled the differential weights assigned to the adaptation dimensions, as shown in Figure 4.

The aggregate effects models indicated that adaptation was negatively related to work satisfaction and unrelated to health, coworker, and pay satisfaction. R^2 values were .134 and .193, respectively, for the equal loadings model and principal component loadings model. Relationships between satisfaction and the adaptation dimensions (see Table 7) differed for the two models due to scaling differences produced by the dimension weights used to derive the adaptation construct (e.g., for the equal loadings model, the five coefficients linking health satisfaction to the adaptation dimensions in Table 7 sum to –.087, which equals the coefficient linking health satisfaction to adaptation in Figure 4).

Relationships for dimension specificities were examined by comparing the R^2 for adaptation with the R_m^2 for its dimensions. Whereas the equal loadings and principal component loading models produced R^2 values of .134 and .193, the R_m^2 for the adaptation dimensions was .535. Information provided by the dimensions beyond that yielded by the adaptation construct was further assessed by imposing equality constraints on the coefficients linking each satisfaction facet to the five adaptation dimen-

Table 7
Aggregate Effect Models for Adaptation (*N* = 348)

	Satisfaction								
Adaptation Dimensions	*Health*	*Work*	*Coworker*	*Pay*	R^2	χ^2	df	*CFI*	*RMSEA*
Equal loadings model									
Unfavorable job behaviors	–0.031	0.051*	–0.036	0.016	.048				
Lateness	–0.002	–0.032	0.043	–0.066**	.096				
Absenteeism	–0.030*	–0.026	0.012	–0.012	.075				
Turnover intentions	–0.008	–0.090*	–0.071*	–0.023	.214				
Desire to retire	–0.016	–0.133**	–0.041	0.041*	.134	0.000	0	1.000	.000
Principal component loadings model									
Unfavorable job behaviors	–0.009	0.014*	–0.010	0.005	.048				
Lateness	–0.001	–0.017	0.022	–0.034**	.096				
Absenteeism	–0.013*	–0.012	0.006	–0.005	.075				
Turnover intentions	–0.009	–0.107*	–0.084*	–0.027	.214				
Desire to retire	–0.025	–0.205**	–0.063	0.063*	.134	0.000	0	1.000	.000

Note. CFI = comparative fit index, RMSEA = root mean squared error of approximation. For the satisfaction facets, table entries are weighted direct effects of the satisfaction facets on the dimensions of adaptation (these effects differ from one another and from the multivariate structural model only due to scaling differences).
*$p < .05$. **$p < .01$.

sions. As explained earlier, if the adaptation construct adequately represents the effects of satisfaction on the adaptation dimensions, then a single coefficient should adequately summarize the effects of each satisfaction facet on all five adaptation dimensions. Imposing these constraints significantly worsened the fit of the model ($\Delta\chi^2(16) = 73.262$, $p < .001$). Modification indices were examined to identify which satisfaction facets were most severely affected by the equality constraints, again using a critical chi-square of 9.140. Results indicated that the equality constraints concealed the greatest degree of variability in the effects of work satisfaction and coworker satisfaction, followed by pay satisfaction. Thus, using adaptation as an aggregate construct may have concealed meaningful variability in the effects of these three facets of satisfaction on the adaptation dimensions.

Multivariate structural model. Results for the multivariate structural model are reported in Table 8. Given that single indicators were used for all latent variables, the model was saturated and fit the data perfectly. Consequently, the fit of the model is necessarily the same as that of the aggregate effect models. However, the fit of the multivariate structural model can be compared with that of the superordinate effect models using the chi-square statistics for those models (see Table 6). These tests indicate that the multivariate structural model fit the data better than the superordinate effect models.

The multivariate structural model produced an R_m^2 of .535 for the effects of the satisfaction facets on the five adaptation dimensions as a set. This value is markedly higher than R^2 values for adaptation produced by the superordinate and aggregate effect models. R^2 values for the individual adaptation dimensions ranged from .048 for unfavorable job behavior to .214 for turnover intent. It is worth noting that the R^2 for turnover intent as a single dimension was higher than the R^2 for the adaptation construct produced by any of the superordinate or aggregate cause models.

The multivariate structural model indicated that all five adaptation dimensions were related to various facets of satisfaction. In particular, unfavorable job behavior was positively related to work satisfaction, lateness was negatively related to pay satisfaction, absenteeism was negatively related to health satisfaction, turnover intent was negatively related to work satisfaction and coworker satisfaction, and desire to retire was negatively related to work satisfaction and positively related to pay satisfaction. This pattern of relationships is consistent with the analyses of dimension specificities for the superordinate and aggregate effect models, which indicated that the relationships between the satisfaction facets and adaptation dimensions were more variable than implied by the adaptation construct itself.

Summary. The preceding analyses indicate that adaptation is better viewed as a set of related dimensions than as a superordinate effect. Adaptation was strongly related to its dimensions, but this was primarily due to a relationship with absenteeism that reached unity for the congeneric model. Criterion-related validities for adaptation produced by the superordinate effect models were much smaller than the criterion-related validity yielded by the multivariate structural model. In addition, the superordinate effect models oversimplified the effects of the satisfaction facets on the adaptation dimensions, as suggested by the dimension specificities and confirmed by the multivariate structural model. The variable effects on the adaptation dimensions, combined with the higher criterion-related validity of the multivariate structural model,

Table 8

Multivariate Structural Model for Adaptation (N = 348)

	Satisfaction								
Adaptation Dimensions	*Health*	*Work*	*Coworker*	*Pay*	R^2	χ^2	df	*CFI*	*RMSEA*
Unfavorable job behaviors	–0.073	0.121*	–0.085	0.039	.048				
Lateness	–0.004	–0.076	0.102	–0.156**	.096				
Absenteeism	–0.072*	–0.062	0.030	–0.029	.075				
Turnover intentions	–0.018	–0.214*	–0.168*	–0.054	.214				
Desire to retire	–0.039	–0.318**	–0.098	0.098*	.134	0.000	0	1.000	.000

Note. CFI = comparative fit index, RMSEA = root mean squared error of approximation. For the satisfaction facets, table entries are unstandardized coefficients linking each satisfaction facet to each dimension of adaptation.

*p < .05. **p < .01.

indicate that the level of abstraction represented by the adaptation construct was too broad. Finally, the theoretical utility of adaptation as a superordinate effect is dubious, given that relaxing the constraints on the dimension loadings effectively reduced adaptation to absenteeism, and differences among the effects on the adaptation dimensions were conceptually meaningful (e.g., the negative effect of work satisfaction on desire to retire implies that people want to cease work they dislike, whereas the positive effect of pay satisfaction on desire to retire suggests that people with greater financial security are more likely to stop working). Thus, the superordinate effect models fell short of the multivariate structural model in terms of theoretical utility, level of abstraction, dimension specificity, and criterion-related validity.

The foregoing analyses also provide little support for adaptation as an aggregate effect. Relationships between adaptation and its dimensions were modest for the aggregate effect models, although some dimensions exhibited much stronger relationships than others, even when the dimensions were assigned equal weight. The aggregate effect models also produced much smaller criterion-related validities than the multivariate structural model and concealed substantial variability in the effects of the satisfaction facets on the adaptation dimensions. In conjunction, these results indicate that the level of abstraction for adaptation as an aggregate effect is too broad. The theoretical utility of adaptation as an aggregate construct is also suspect, given that it concealed meaningful variability in the effects of satisfaction facets on adaptation dimensions. Although this variability was embedded within the aggregate effect models, it was evident only when the coefficients for the individual adaptation dimensions were examined, thereby revealing what the aggregate construct had concealed. Hence, the aggregate effect models were inferior to the multivariate structural model on all points underlying the multidimensional construct debate.

Discussion

The framework presented in this article incorporates multidimensional constructs and their dimensions into a single analytical approach. This framework permits the investigation of broad questions regarding multidimensional constructs along with specific questions pertaining to the dimensions of these constructs. The framework also provides tests relevant to issues underlying the ongoing debate over the utility of multidimensional constructs, thereby allowing researchers to address these issues on a study-by-study basis. Thus, the framework provides a holistic approach for research on multidimensional constructs and their dimensions, causes, and effects.

Applications of the Framework

Results of the illustrative applications of the framework are summarized in Table 9, which evaluates each model analyzed on criteria pertaining to the multidimensional construct debate. Overall, the models fared reasonably well regarding the strength of the relationships between the multidimensional construct and its dimensions. However, on issues of theoretical utility, level of abstraction, construct validity, and criterion-related validity, the multidimensional construct models were inferior to multivariate structural models that used the dimensions as a set. Hence, for each of the examples considered here, a multidimensional construct was better represented as a set of related dimensions than as a single latent variable.

Table 9

Summary of Model Comparisons on Issues Underlying the Multidimensional Construct Debate

Model	*Theoretical Utility*	*Matching Levels of Abstraction*	*Relationships Between Construct and Dimensions*	*Construct Validity*	*Criterion Validity*
Superordinate cause	Construct concealed meaningful differences in effects of dimensions	Construct too broad for outcomes, as indicated by variable effects of dimensions on outcomes	Strong relationships between the construct and dimensions for all models; relationships varied across dimensions	Specificities indicated that construct distorted effects of dimensions on outcomes	Construct explained much less variance than its dimensions as a set
Aggregate cause	Information unique to dimensions concealed by models with constrained loadings; models with estimated loadings reduced construct to a single dimension	Construct too broad for outcomes for models with constrained loadings; construct narrowed to match outcomes for models with estimated loadings	Relationships between construct and dimensions were moderate for models with constrained loadings but weak and variable for models with estimated loadings	Specificities indicated that construct distorted effects of dimensions on outcomes, particularly for models with constrained loadings	For models with constrained loadings, construct explained little variance; for models with estimated loadings, construct explained moderate variance but not as much as that explained by its dimensions as a set
Superordinate effect	Information unique to dimensions concealed by all models; models with free residual variances reduced the construct to a single dimension	Construct too broad for causes; for models with free residual varainces, construct narrowed to capture relationship between one cause and one dimension	Relationships between construct and dimensions modest for parallel model but strong for tau equivalent and congeneric models, due to large relationship with absenteeism	Specificities indicated that construct distorted or concealed effects of satisfaction on several dimensions	Much less variance explained in the construct than in its dimensions as a set
Aggregate effect	Construct concealed meaningful differences in effects on dimensions	Construct too broad for causes, as indicated by variable effects of causes on dimensions	Relationships between construct and dimensions were moderate but variable	Substantial variation in effects on the dimensions concealed by using the construct	Much less variance explained in the construct than in its dimensions as a set

Although the results reported here did not support the use of multidimensional constructs, other studies may produce different results. Indeed, a central premise of the proposed framework is that the merits of multidimensional constructs and their dimensions should be compared on a study-by-study basis. Nonetheless, these results exemplify those from other applications of the framework to personality traits, work withdrawal, and other multidimensional constructs. Taken together, these results suggest that support for multidimensional constructs will be the exception rather than the rule.

There are several reasons why multidimensional constructs are likely to perform worse than their dimensions. First, a multidimensional construct comprises dimensions that are necessarily distinct from one another. If the dimensions were not distinct, then the construct would be unidimensional rather than multidimensional. Presumably, the distinctions between the dimensions are conceptually meaningful, such that the dimensions represent different aspects of a general concept or are expected to relate differently to other variables. Consequently, the mere act of defining a multidimensional construct prompts researchers to identify distinct dimensions that contain more information than can be captured by single latent variable.

Second, most multidimensional construct models are more constrained than multivariate structural models that treat the dimensions as a set. In general, constrained models are inferior to unconstrained models in terms of model fit, explained variance, and information regarding relationships among variables. However, constrained models are superior to unconstrained models in terms of parsimony. Thus, the advantages of using models that treat dimensions as a set should be weighed against the loss of parsimony inherent in such models. This tradeoff is built into statistical tests that incorporate differences in degrees of freedom between constrained and unconstrained models. Although experience to date suggests that the benefits of parsimony provided by multidimensional construct models are not worth the costs, the relative magnitudes of these benefits and costs will vary across studies.

Third, as constructs in the field of OB are refined, distinctions that were previously overlooked often become increasingly clear and compelling. This tendency is exemplified by research on job characteristics (Hackman & Oldham, 1980; Hulin & Blood, 1968; Turner & Lawrence, 1965), job stress (Beehr & Newman, 1978; Cooper & Marshall, 1976; Edwards, 1992; Schuler, 1980), and organizational commitment (Allen & Meyer, 1990; Meyer, Allen, & Smith, 1993; Mowday et al., 1979; O'Reilly & Chatman, 1986), each of which has drawn progressively finer distinctions within constructs once treated as unidimensional. As constructs become more differentiated, information specific to construct dimensions becomes increasingly relevant, and multidimensional construct models become less useful than multivariate structural models that treat construct dimension as a set.

The use of multivariate structural models to represent multidimensional constructs may generate resistance among OB researchers, given that these models contain no direct vestige of the construct itself. Consequently, using these models may seem tantamount to abandoning the study of multidimensional constructs. This is not the case. Rather, a multivariate structural model represents a multidimensional construct as a set of dimensions, and hypotheses regarding the causes and effects of the construct can be tested using multivariate procedures, as illustrated earlier. Thus, a multidimensional construct can be represented directly using a multidimensional construct model or indirectly using a multivariate structural model. In either case, questions involving the meaning, causes, and effects of the multidimensional construct can be investigated.

Extensions to the Framework

Although the framework presented in this article applies to multidimensional constructs commonly used in OB research, several extensions to the framework may be considered. First, multidimensional construct models may be elaborated to include direct relationships between the dimensions of the construct and its causes and effects. These relationships may correspond to a priori hypotheses regarding relationships involving the dimensions that are independent of the construct itself. Alternately, these relationships may be added in response to tests of dimension specificities using modification indices. However, such models are exploratory, and their results should be considered tentative, pending cross-validation. Models that add relationships for the dimensions of the construct raise additional issues of identification, and general rules that apply to these models are as follows. For a superordinate cause model, (a) no effect may be caused by all dimensions, and (b) the total number of effects added must not exceed $[p^2 - 2q + p(2q - 3)]/2$, where p is the number of dimensions, and q is the number of effects. For an aggregate cause model, (a) no dimension may cause all effects, (b) no effect may be caused by all dimensions, and (c) the total number of effects added must not exceed $(p - 1)(q - 1)$, where p is the number of dimensions, and q is the number of effects. For both of these models, it is assumed that each effect is connected to each other effect through a correlated residual or causal path, provided the relationship among the effects remains recursive. For a superordinate effect model, (a) no cause may affect all dimensions, and (b) the total number of effects added must not exceed $p(q - 1) + q(q - 3)/2$, where p is the number of causes, and q is the number of dimensions. No identification rules are provided for aggregate effect models because these models already include all direct effects from the causes to the dimensions of the construct.

Second, models may be tested in which multidimensional constructs are causes and effects of other constructs. These models may be derived by starting with a model considered in this article and adding paths connecting the multidimensional construct to additional causes and effects. Most of these models will follow the form of an aggregate cause or superordinate effect model, although some of the latent variables these models depict as construct dimensions will be recast as causes or effects. Models may also be derived in which multidimensional constructs are causes and effects of one another. Again, these models may be derived from those considered here by respecifying a cause or effect as a superordinate or aggregate construct.

Third, multidimensional constructs may be compared with unidimensional constructs at the same level of abstraction (Rushton, Brainerd, & Pressley, 1983). These comparisons can be used to assess whether the dimensions of the multidimensional construct adequately capture the general concept of interest. For example, overall job satisfaction as a multidimensional construct may be compared with a unidimensional construct measured with items that describe general affective reactions to the job (e.g., "Overall, I am satisfied with my job"). The relationship between the multidimensional and unidimensional job satisfaction constructs would indicate how well the dimensions of the multidimensional construct capture the range of job facets that produce feelings of overall job satisfaction (Ferratt, 1981; Ironson et al., 1989; Scarpello & Campbell, 1983). In addition, relationships between the satisfaction dimensions and the unidimensional satisfaction construct may be used to examine the effects of job facet satisfaction on overall job satisfaction.

Finally, the framework may be used to rigorously evaluate measures formed by summing heterogeneous items. These measures are widespread in OB research, yet the methodological issues raised by these measures are rarely discussed. Typically, these measures combine items intended to capture different aspects of a general concept. Measures constructed in this manner are special cases of the aggregate construct model in which the dimensions are represented by single indicators, error in the measurement of the dimensions is disregarded, the dimensions are assigned equal weights, and the residual of the construct is fixed to zero. This model is highly restrictive, and the assumptions embedded in the model may not withstand empirical scrutiny, as demonstrated in this article. Indeed, the prevalence of such measures is curious, given that most researchers staunchly reject individual items that are heterogeneous (e.g., the classic double-barreled item). Even when such items are avoided, problems of item heterogeneity emerge when items that describe different aspects of a concept are combined into a measure, because such measures simply move problems of heterogeneity from the item level to the scale level. The implications of using such measures may be investigated using aggregate construct models that test the constraints implied by summing heterogeneous items. Moreover, these models may be elaborated by using multiple indicators of each dimension and treating the dimensions and the aggregate construct as latent variables. Indeed, if the dimensions represented by heterogeneous items are meaningful and worthwhile, then perhaps each dimension should be measured with multiple items rather than a single item.

Conclusion

Multidimensional constructs are widespread in OB research, yet there is little consensus regarding the merits of these constructs relative to their dimensions. This lack of consensus presents a dilemma for OB researchers who want the breadth and generality of multidimensional constructs along with the clarity and precision provided by the dimensions of such constructs. This article has presented an integrative analytical framework that combines multidimensional constructs and their dimensions and provides tests of issues underlying the multidimensional construct debate. By applying this framework, researchers may obtain a better understanding of the complexities underlying multidimensional constructs and draw firmer conclusions regarding questions that motivate the use of such constructs.

Notes

1. If two η_i as effects are not connected by a causal path, then allowing their residuals to correlate admits the possibility that causes of the η_i excluded from the model may be correlated with one another. If two η_i as effects are connected by a causal path (i.e., one η_i is a cause of the other), then the residuals for the two η_i should not be allowed to correlate, because doing so introduces a correlation between one η_i and the residual for the other η_i, and the parameters in the equations for the two η_i are no longer identified.

2. If the estimated model includes fixed paths of unity from ξ_1, ξ_2, and ξ_3 to η^*, the variance of η^* will be overestimated by $\phi_{11} + \phi_{22} + \phi_{33} + 2(\phi_{12} + \phi_{13} + \phi_{23}) + 2\gamma_4(\phi_{14} + \phi_{24} + \phi_{34})$, and the R^2 reported for η^* will be incorrect. This problem can be solved by constraining the paths from ξ_1, ξ_2, and ξ_3 to η^* to zero. Although doing so may seem inconsistent with the definition of η^* as $\xi_1 + \xi_2 + \xi_3$, this definition is incorporated through the constraints placed on γ_4 and ψ^*.

3. Throughout this discussion, parameters are fixed to values that facilitate model interpretation. The models discussed here will remain identified if parameters are fixed to other values.

4. It may seem reasonable to assess the relationship between an aggregate construct and its dimensions by regressing the construct on its dimensions. However, this approach necessarily yields an R^2 of 1.00 for models that specify the construct as an exact linear combination of its dimensions, regardless of the dimension weights. In contrast, R_a^2 assesses the degree to which the construct captures the total variance of its dimensions. Therefore, R_a^2 is more appropriate in the present context.

5. Modification indices are used here not to guide specification searches (MacCallum, Roznowski, & Necowitz, 1992), but instead to identify sources of misfit due to the omission of direct effects for dimension specificities. This use of modification indices is consistent with the framework presented in this article, which emphasizes comparing multiple a priori models, not deriving models empirically.

6. In the Moberg (1998) study, all items used 5-point response scales, but measures were formed by summing different numbers of items, producing measures with different metrics. By dividing each measure by its number of items (i.e., transforming the measures from item sums to item averages), all measures were returned to a common 5-point scale. A somewhat more complicated procedure was required for the Hanisch and Hulin (1991) data because the satisfaction and unfavorable job behavior items used 4-point scales, whereas the lateness, absenteeism, turnover intentions, and desire to retire items used 7-point scales. Therefore, after each measure was divided by its number of items, the 4-point scales were converted to 7-point scales based on the formula $X7 = (X4 - 1)*2 + 1$, where X4 represents a 1-4 scale and X7 represents a 1-7 scale. Because adding and subtracting constants has no affect on variances and covariances, this transformation amounted to doubling the standard deviations of the 4-point scales.

7. Dimension R^2 values may be calculated from information reported in Figure 1 by dividing the variance explained in each dimension by the total variance for the dimension. The former quantity may be obtained by squaring the dimension loading, and the latter quantity may be obtained by adding the squared dimension loading to the residual variance for the dimension. To illustrate using results for positive emotions from the congeneric model, the squared loading is $.424^2 = .180$, and the total variance is $.180 + .058 = .238$. Dividing .180 by .238 yields .757, which equals the reported R^2 for positive emotions.

8. Although the expected parameter change statistic was negative for the effect of the assertiveness specificity on control, this parameter was positive when added to the model.

9. If multiple indicators had been used for the dimensions or effects in the model, the chi-square for the first-order factor model would have been nonzero, and chi-square difference tests comparing this model with the other three models would be conducted in the usual manner.

References

Allen, N. J., & Meyer, J. P. (1990). The measurement and antecedents of affective, continuance, and normative commitment to the organization. *Journal of Occupational Psychology*, *63*, 1-18.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two step approach. *Psychological Bulletin*, *103*, 411-423.

Aston, M. C. (1998). Personality and job performance: The importance of narrow traits. *Journal of Organizational Behavior*, *19*, 289-303.

Bagozzi, R. P., & Edwards, J. R. (1998). A general approach to construct validation in organizational research: Application to the measurement of work values. *Organizational Research Methods*, *1*, 45-87.

Bedeian, A. G., Burke, B. G., & Moffett, R. G. (1988). Outcomes of work-family conflict among married male and female professionals. *Journal of Management*, *14*, 475-491.

Beehr, T. A., & Newman, J. E. (1978). Job stress, employee health, and organizational effectiveness: A facet analysis, model and literature review. *Personnel Psychology*, *31*, 665-699.

Bekker, P. A., Merckens, A., & Wansbeek, T. J. (1994). *Identification, equivalent models and computer algebra*. New York: Academic Press.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*, 238-246.

Blau, G. (1998). On the aggregation of individual withdrawal behaviors into larger multi-item constructs. *Journal of Organizational Behavior*, *19*, 437-451.

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, *110*, 305-314.

Bollen, K. A. (1989). *Structural equations with latent variables*. New York: Wiley.

Bollen, K. A., & Davis, W. R. (1994). *Causal indicator models: Identification, estimation, and testing*. Paper presented at the American Sociological Association Convention, Miami, FL.

Bolton, B. (1980). Second-order dimensions of the Work Values Inventory (WVI). *Journal of Vocational Behavior*, *17*, 33-40.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Newbury Park, CA: Sage.

Browne, M. W., & Mels, G. (1992). *RAMONA user's guide*. Columbus: Department of Psychology, Ohio State University.

Cattell, R. B., & Tsujioka, B. (1964). The importance of factor-trueness and validity, versus homogeneity and orthogonality, in test scales. *Educational and Psychological Measurement*, *24*, 3-30.

Cohen, J. (1982). Set correlation as a general multivariate data-analytic method. *Multivariate Behavioral Research*, *17*, 301-341.

Cooper, C. L., & Marshall, J. (1976). Occupational sources of stress: Review of literature relating to coronary heart disease and mental ill health. *Journal of Occupational Psychology*, *49*, 11-28.

Costa, P. T., Jr., & McCrae, R. R. (1992). *Manual for the Revised NEO Personality Inventory (NEO-PIR) and the NEO Five-Factor Inventory (NEO-FFI)*. Odessa, FL: Psychological Assessment Resources.

Cronbach, L. J., Gleser, G., Nanda, H., & Rajaratnam, N. (1972). *The dependability of behavioral measurements: Theory of generalizability for scores and profiles*. New York: Wiley.

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology*, *41*, 417-440.

Digman, J. M. (1997). Higher-order factors of the Big Five. *Journal of Personality and Social Psychology*, *73*, 1246-1256.

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. (1992). A cybernetic theory of stress, coping, and well-being in organizations. *Academy of Management Review*, *17*, 238-274.

Edwards, J. R., & Bagozzi, R. P. (2000). On the nature and direction of the relationship between constructs and measures. *Psychological Methods*, *5*, 155-174.

Efron, B., & Tibshirani, R. (1993). *An introduction to the bootstrap*. New York: Chapman & Hall.

Ferratt, T. W. (1981). Overall job satisfaction: Is it a linear function of facet satisfaction? *Human Relations*, *34*, 463-473.

Fisher, C. D. (1980). On the dubious wisdom of expecting job satisfaction to correlate with performance. *Academy of Management Review*, *5*, 607-612.

Gerbing, D. W., & Anderson, J. C. (1988). An updated paradigm for scale development incorporating unidimensionality and its assessment. *Journal of Marketing Research*, *25*, 186-192.

Gerbing, D. W., & Anderson, J. C. (1993). Monte Carlo evaluations of goodness of fit indices for structural equation models. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 40-65). Newbury Park, CA: Sage.

Goldberg, L. R. (1993). The structure of personality traits: Vertical and horizontal aspects. In D. C. Funder, R. D. Parke, C. Tomlinson-Keasey, & K. Widaman (Eds.), *Studying lives through time: Personality and development* (pp. 169-188). Washington, DC: American Psychological Association.

Hackman, J. R., & Oldham, G. R. (1980). *Work redesign*. Reading, MA: Addison-Wesley.

Hanisch, K. A., & Hulin, C. L. (1990). Job attitudes and organizational withdrawal: An examination of retirement and other voluntary withdrawal behaviors. *Journal of Vocational Behavior*, *37*, 60-78.

Hanisch, K. A., & Hulin, C. L. (1991). General attitudes and organizational withdrawal: An evaluation of a causal model. *Journal of Vocational Behavior*, *39*, 110-128.

Hanisch, K. A., Hulin, C. L., & Roznowski, M. (1998). The importance of individuals' repertoires of behaviors: The scientific appropriateness of studying multiple behaviors and general attitudes. *Journal of Organizational Behavior*, *19*, 463-480.

Hattie, J. (1985). Methodology review: Assessing unidimensionality of tests and items. *Applied Psychological Measurement*, *9*, 139-164.

Heise, D. R. (1972). Employing nominal variables, induced variables, and block variables in path analysis. *Sociological Methods and Research*, *1*, 147-173.

Hogan, J., & Roberts, B. W. (1996). Issues and non-issues in the fidelity-bandwidth trade-off. *Journal of Organizational Behavior*, *17*, 627-637.

Holland, J. L. (1985). *Making vocational choices* (2nd ed.). Englewood Cliffs, NJ: Prentice Hall.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1-55.

Hulin, C. L. (1991). Adaptation, persistence, and commitment in organizations. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (2nd ed., pp. 445-505). Palo Alto, CA: Consulting Psychologists Press.

Hulin, C. L., & Blood, M. R. (1968). Job enlargement, individual differences, and worker responses. *Psychological Bulletin*, *69*, 41-55.

Hull, J. G., Lehn, D. A., & Tedlie, J. C. (1991). A general approach to testing multifaceted personality constructs. *Journal of Personality and Social Psychology*, *61*, 932-945.

Humphreys, L. G. (1962). The organization of human abilities. *American Psychologist*, *17*, 475-483.

Humphreys, L. G. (1970). A skeptical look at the pure factor test. In C. E. Lunneborg (Ed.), *Current problems and techniques in multivariate psychology: Proceedings of a conference honoring professor Paul Horst* (pp. 23-32). Seattle: University of Washington.

Hunt, S. D., & Morgan, R. M. (1994). Organizational commitment: One of many commitments or key mediating construct? *Academy of Management Journal*, *37*, 1568-1587.

Hunter, J. E., & Gerbing, D. W. (1982). Unidimensional measurement, second order factor analysis, and causal models. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (pp. 267-320). Greenwich, CT: JAI Press.

Ironson, G. H., Smith, P. C., Brannick, M. T., Gibson, W. M., & Paul, K. B. (1989). Construction of a job in general scale: A comparison of global, composite, and specific measures. *Journal of Applied Psychology*, *74*, 193-200.

James, L. A., & James, L. R. (1989). Integrating work environment perceptions: Explorations into the measurement of meaning. *Journal of Applied Psychology*, *74*, 739-751.

James, L. R., & Tetrick, L. E. (1986). Confirmatory analytic tests of three causal models relating job perceptions to job satisfaction. *Journal of Applied Psychology*, *71*, 77-82.

Johns, G. (1998). Aggregation or aggravation? The relative merits of a broad withdrawal construct. *Journal of Organizational Behavior*, *19*, 453-462.

Jöreskog, K. G. (1971). Statistical analysis of sets of congeneric tests. *Psychometrika*, *36*, 109-133.

Jöreskog, K. G., & Goldberger, A. S. (1975). Estimation of a model with multiple indicators and multiple causes of a single latent variable. *Journal of the American Statistical Association*, *10*, 631-639.

Jöreskog, K. G., & Sörbom, D. (1996). *LISREL 8: User's reference guide*. Chicago: Scientific Software International.

Kim, J. O., & Mueller, C. W. (1978). *Factor analysis*. Beverly Hills, CA: Sage.

Kristof-Brown, A. L. (1996). Person-organization fit: An integrative review of its conceptualization, measurement, and implications. *Personnel Psychology*, *49*, 1-49.

Law, K. S., & Wong, C. S. (1999). Multidimensional constructs in structural equation analysis: An illustration using the job perception and job satisfaction constructs. *Journal of Management*, *25*, 143-160.

Law, K. S., Wong, C. S., & Mobley, W. H. (1998). Toward a taxonomy of multidimensional constructs. *Academy of Management Review*, *23*, 741-755.

Liden, R. C., & Maslyn, J. M. (1998). Multidimensionality of leader-member exchange: An empirical assessment through scale development. *Journal of Management*, *24*, 43-72.

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.

MacCallum, R., & Browne, M. W. (1993). The use of causal indicators in covariance structure models: Some practical issues. *Psychological Bulletin*, *114*, 533-541.

MacCallum, R., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*, 130-149.

MacCallum, R., Roznowski, M., & Necowitz, L. B. (1992). Model modification in covariance structure analysis: The problem of capitalization on chance. *Psychological Bulletin*, *111*, 490-504.

McCrae, R. R., & Costa, P. T., Jr. (1992). Discriminant validity of the NEO-PIR facet scales. *Educational and Psychological Measurement*, *52*, 229-237.

McIver, J. P., & Carmines, E. G. (1981). *Unidimensional scaling*. Beverly Hills, CA: Sage.

Mershon, B., & Gorsuch, R. L. (1988). Number of factors in the personality sphere: Does increase in factors increase predictability of real-life criteria? *Journal of Personality and Social Psychology*, *55*, 675-680.

Meyer, J. P., Allen, N. J., & Smith, C. A. (1993). Commitment to organizations and occupations: Extension and test of a three-component conceptualization. *Journal of Applied Psychology*, *78*, 538-551.

Moberg, P. J. (1998). Predicting conflict strategy with personality traits: Incremental validity and the five factor model. *International Journal of Conflict Management*, *9*, 258-285.

Mowday, R. T., Steers, R. M., & Porter, L. W. (1979). The measurement of organizational commitment. *Journal of Vocational Behavior*, *14*, 224-247.

Murphy, K. R., & Shiarella, A. H. (1997). Implications of the multidimensional nature of job performance for the validity of selection tests: Multivariate frameworks for studying test validity. *Personnel Psychology*, *50*, 823-854.

Myers, I. B., & McCaulley, M. (1985). *Manual: A guide to the development and use of the Myers-Briggs Type Indicator.* Palo Alto, CA: Consulting Psychologists Press.

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). New York: McGraw-Hill.

Ones, D. S., & Viswesvaran, C. (1996). Bandwidth-fidelity dilemma in personality measurement for personnel selection. *Journal of Organizational Behavior*, *17*, 609-626.

O'Reilly, C., III, & Chatman, J. (1986). Organizational commitment and psychological attachment: The effects of compliance, identification, and internalization on prosocial behavior. *Journal of Applied Psychology*, *71*, 492-499.

Parasuraman, S., Greenhaus, J. H., & Granrose, C. S. (1992). Role stressors, social support, and well-being among two-career couples. *Journal of Organizational Behavior*, *13*, 339-356.

Paunonen, S. V. (1998). Hierarchical organization of personality and prediction of behavior. *Journal of Personality and Social Psychology*, *74*, 538-556.

Paunonen, S. V., Rothstein, M. G., & Jackson, D. N. (1999). Narrow reasoning about the use of broad personality measures for personnel selection. *Journal of Organizational Behavior*, *20*, 389-405.

Pryor, R.G.L. (1987). Differences among differences: In search of general work preference dimensions. *Journal of Applied Psychology*, *72*, 426-433.

Putnam, L. L., & Wilson, C. (1982). Communicative strategies in organizational conflict: Reliability and validity of a measurement scale. In M. Burgoon (Ed.), *Communication yearbook* (Vol. 6, pp. 629-652). Newbury Park, CA: Sage.

Rindskopf, D., & Rose, T. (1988). Some theory and applications of confirmatory second-order factor analysis. *Multivariate Behavioral Research*, *23*, 51-67.

Roznowski, M., & Hanisch, K. A. (1990). Building systematic heterogeneity into work attitudes and behavior measures. *Journal of Vocational Behavior*, *36*, 361-375.

Rushton, J. P., Brainerd, C. J., & Pressley, M. (1983). Behavioral development and construct validity: The principle of aggregation. *Psychological Bulletin*, *94*, 18-38.

Scarpello, V., & Campbell, J. P. (1983). Job satisfaction: Are all the parts there? *Personnel Psychology*, *36*, 577-600.

Schmidt, F. L., & Kaplan, L. B. (1971). Composite vs. multiple criteria: A review and resolution of the controversy. *Personnel Psychology*, *24*, 419-434.

Schneider, R. J., Hough, L. M., & Dunnette, M. D. (1996). Broadsided by broad traits: How to sink science in five dimensions or less. *Journal of Organizational Behavior*, *17*, 639-655.

Schuler, R. S. (1980). Definition and conceptualization of stress in organizations. *Organizational Behavior and Human Performance*, *25*, 184-215.

Schwab, D. P. (1980). Construct validity in organizational behavior. In L. L. Cummings & B. M. Staw (Eds.), *Research in organizational behavior* (Vol. 2, pp. 3-43). Greenwich, CT.: JAI Press.

Smith, P. C., Kendall, L., & Hulin, C. L. (1969). *The measurement of satisfaction in work and retirement*. Chicago: Rand McNally.

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research*, *25*, 173-180.

Thompson, B. (1984). *Canonical correlation analysis: Uses and interpretation*. Newbury Park, CA: Sage.

Turner, A. N., & Lawrence, P. R. (1965). *Industrial jobs and the worker: An investigation of responses to task attributes*. Boston: Harvard University Press.

Warr, P. B., Cook, J. D., & Wall, T. D. (1979). Scales for the measurement of some work attitudes and aspects of psychological well-being. *Journal of Occupational Psychology*, *52*, 129-148.

Weick, K. E. (1979). *The social psychology of organizing*. New York: McGraw-Hill.

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