

Using a Random-Effects Model To Test Differing Conceptualizations of Multidimensional Constructs

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Previous work investigating the dimensionality of psychological constructs has assumed a fixed-effects model, in which one true correlation describes the relationship between two given dimensions. We challenge this assumption by showing how a random-effects model may aid in representing individual perceptions of multidimensional constructs. Using the Pay Satisfaction Questionnaire (PSQ), we demonstrate that the relationships that individuals hold between the (purported) dimensions of the PSQ are predictable by cognitive complexity, pay level satisfaction, pay level, and interactions; we also show how between-dimension variation assists in establishing criterion-related validity.

The methodological issues associated with the measurement, and more importantly, the understanding of multidimensional constructs is an issue receiving attention in many domains (Edwards, 2001; Law & Wong, 1999). In the management sciences, researchers have examined such multidimensional constructs as job performance (e.g., Borman, Hanson, & Hedge, 1997; Campbell, 1990; Murphy, 1996; Rotundo & Sackett, 2002; Welbourne, Johnson, & Erez, 1998), job satisfaction (e.g., Kinicki, McKee-Ryan, Schriesheim, & Carson, 2002; Smith, Kendall, & Hulin, 1969), employee silence and voice (Van Dyne, Ang, & Botero, 2003), pay satisfaction (e.g., Heneman & Schwab, 1985; Judge, 1993; Judge & Welbourne, 1994), benefits satisfaction (Williams, Malos, & Palmer, 2002), and personality (e.g., Barrick & Mount, 1991; Digman, 1990), to name but a few. Research involving the conceptualization, prediction, or consequences of multidimensional measures, however, often assumes—without theoretical foundation or empirical verification—that the association between theoretically hypothesized dimensions varies systematically across individuals (Carraher & Buckley, 1996). The purpose of this article is to challenge (and perhaps falsify) this assumption and to present a methodology that can be used to examine multidimensional measures and estimate the extent to which individuals differentiate between hypothesized dimensions.

The methodology we introduce uses a random-effects approach to modeling the relationship between the facets of a multidimensional scale. This article seeks to take the preliminary steps of

determining if the association between theoretically hypothesized dimensions indeed does vary systematically across individuals, and if this variance exists, (a) demonstrating with a specific case that this variance can be predicted and (b) showing that this variance can be used to predict outcomes in applied research. Note that it is beyond the scope of this article to develop a general random-effects modeling approach to factor analysis. Such methodological developments may be fruitful but only if one can verify that such random effects exist. Furthermore, our approach does not yield an estimate of the number of dimensions conceived by any specific individual; rather, we focus on the level of similarity between facets. Nonetheless, our article takes an important step by testing a generally unquestioned assumption, and based on our theory and findings, it presents a number of directions for future research.

Why Examine Multidimensional Constructs Using a Random-Effects Approach? Questioning the Underlying Methodological Assumption

When considering multidimensional constructs, statistical methods have sought a single underlying factor structure with loadings that may vary across dimensions but are consistent across individuals (Edwards, 2001). Tests of the dimensionality of multidimensional constructs thus have relied on exploratory and/or confirmatory factor analyses derived from information in correlation or covariance matrices (Bobko, 1991; Bollen, 1989). Consequently, such techniques implicitly assume that the relationship between any two dimensions of a multidimensional construct is constant and that any variance in observed correlations across studies occurs because of random sampling error within each study. This can be expressed mathematically, as follows:

$$E(\text{Dimension}_A) = \rho_{AB} \times \text{Dimension}_B + \varepsilon_i \varepsilon_i \sim N(0, \sigma^2)$$

where $E(\text{Dimension}_A)$ is the expected (standardized) value of one dimension of a multidimensional construct, Dimension_B is another (standardized) dimension of a multidimensional construct, ρ_{AB} is the relationship (correlation) between the two dimensions, and ε_i is random (within-person) error. After factor analyses are performed, based on eigenvalues or some goodness-of-fit statistics, a judgment is made regarding the number of dimensions captured by a focal construct.

Depending on the specific domain, however, there actually may be little evidence to support the idea that individuals perceive cues in the same way to form identical multidimensional conceptualizations. We argue that the assumption of uniform multidimensional structures is tenuous and merits explicit testing. The strength of the relationship between dimensions may be a function of individual characteristics or unique individual perceptions. Essentially, this view is that of a random-

effects model (Bryk & Raudenbush, 1992): each individual potentially perceives a different relationship between any two dimensions. Relaxing the assumption that there exists a single, true correlation between any two dimensions, Equation 1 expands as follows:

$$E(\text{Dimension}_A) = \rho_{AB(i)} \times \text{Dimension}_B + \varepsilon_{ij} \quad \varepsilon_{ij} \sim N(0, \sigma^2)$$

where $\rho_{AB(i)}$ is the relationship between any two dimensions for person i .

In this random-effects model, the relationship between Dimension A and Dimension B is not a constant but is specific to each individual (hence, the subscript i for the term ρ_{AB}). Thus, Equation 2 represents a model of the relationships between items for Dimension A and Dimension B within each individual (to be referred to as the within-person level of analysis). These items then are nested within individuals; that is, for each individual, there are a number of items that represent Dimension A and a number of items that represent Dimension B. The term $\rho_{AB(i)}$ represents the relationship (referred to here as the within-person relationship) between these items for each individual. As each individual has a specific relationship between two focal dimensions, we then also can consider what predicts this relationship. In other words, we can try to estimate what individual-level characteristics predict each person's $\rho_{AB(i)}$. This can be expressed as follows:

$$\rho_{AB(i)} = \beta_0 + \beta_1 (x_{i1}) + \beta_2 (x_{i2}) + \dots + \delta_i \quad \delta_i \sim N(0, \theta^2)$$

where x is an individual characteristic, β that the individual i 's characteristics have on $\rho_{AB(i)}$, and δ_i is random across-person error.

Thus, Equation 3 is using individual-level characteristics to predict each individual's relationship between Dimension A and Dimension B. In other words, Equation 2 is modeling within-person variance, whereas Equation 3 is modeling across-person variance.

In this article, we are challenging the fixed-effects approach to factor analysis. We will consider how to capture and model the strength of the relationships between dimensions in proposed multidimensional constructs. Note, however, that we are focusing on the strength of any given relationship, not on the number of dimensions perceived by any given individual. Although the issues of strength of relationships and number of dimensions are related, this article represents a first attempt to determine if such variance even exists. Furthermore, it may not even make sense to discuss the number of dimensions captured by a construct, as we are arguing there is no single number. Instead, the number of dimensions represents a maximum number of potential dimensions, and the strength of the relationships across dimensions potentially varies across individuals.

Methodological Implications of Considering Variable Conceptualizations

Although relaxing the fixed-effects assumption and the derivation of Equations 2 and 3 may be logical, the implications of this logic need to be made clear. A major concern is that methods assuming a fixed-effects approach may support a multifactor solution for a construct when the dimensionality of the structure is multidimensional for only a portion of the sample.

To help consider the implications of falsely accepting the fixed-effects assumption, we generated a data set, using the DataSim computer program (Sturman, 2004) with two constructs, each captured by four variables that have a coefficient alpha of 0.90, and with 300 observations. We made the correlation between the two constructs random: set to 0.00 for half of the sample and 1.00 for the other half. This simulation represented a situation in which half of the population perceived a single construct, and the other half saw the two constructs as distinct. Using confirmatory factor analysis (CFA), we compared a one-factor to a two-factor solution. The one-factor solution had poor fit, whereas the two-factor solution had nearly perfect fit ($RMSEA < 0.01$; $GFI, NFI, NNFI, CFI, \text{ and } AGFI \geq 0.99$).

This example illustrates how the paradigm of a consistent factor structure is confirmed by CFA, even though we “know” from setting up the simulation that this assumption is false. This exemplifies Kuhn’s (1970) argument that “often the paradigm theory is implicated directly in the design of apparatus able to solve the problem” (p. 27). Therefore, even though CFA provides a useful tool for understanding and representing multidimensional structures, there may be value to investigating specifically whether people conceptualize constructs in different ways.

Note that we are not suggesting that a random-effects approach replace fixed-effects approaches. In fact, it is absolutely necessary (at least, with the current state of methodologies) to use the fixed-effects approaches as one must know the maximum number of potential dimensions in a multidimensional measure. The aforementioned simulation supports this, as even with variable dimensionality present, the CFA did identify the maximum number of dimensions correctly. Furthermore, to implement the random-effects approach that we propose, the researcher must have a priori hypotheses about a dimensional structure to be able to test if the relationship between potential dimensions indeed does vary. Thus, the random-effects approach that we are proposing should be seen in the context of a tool designed to augment (and not supplant) current approaches to factor analysis.

The idea of using a random-effects approach in factor analysis is not entirely new. Previous research has introduced techniques for using a random-effects approach when considering multiple groups (e.g., Muthen, 1984, 1989, 1994). This research shows the value of random-effects modeling for factor analysis but is limited in its applicability because it only considers how a factor structure may vary

with group membership (i.e., a categorical moderator; Muthen, 1989). In this article, we are questioning whether individuals, even within the same group, conceptualize multidimensional constructs in the same way.

Criterion Validity Implications of Considering Variable Conceptualizations

So far, we have provided only theoretical and technical rationalizations for the use of a random-effects approach. Granted, a better understanding of how individuals perceive constructs is of scientific value; however, in applied settings, the greater complexity associated with a new methodological technique must be justified by potentially different conclusions that have implications for theory or practice. That is, before presenting our methodology, it is critical to consider the value of a random-effects approach being added to the existing set of factor analysis–related tools.

The utility of variable dimensionality depends first on how a construct is conceptualized. If one considers a multidimensional measure to an aggregate—that is, as combining specific dimensions into a single concept (Edwards, 2001)—then the potential variable relationships between component dimensions is unimportant because the sum of the dimensions is unaffected. If a construct is subordinate—that is, it is manifested by specific dimensions and each of these dimensions is important at least in part unto itself (Edwards, 2001)—then the effect of dimensionality can be very important when considering the construct validity of the multidimensional measure. To illustrate why, we again will turn to our simple simulation.

Consider again the situation in which there is a potentially multidimensional construct conceived as a single construct by half of a population and as two constructs by the other half. We added to the preceding simulation three outcomes variables with strong ($p = .50$), medium ($p = .30$), and weak ($p = .10$) relationships with the two posited constructs. Again, all constructs were captured with four items, each with a reliability of 0.90, and sample size was 300. We ran regressions predicting each outcome with the two constructs (recall from our previous simulation that CFA confirmed the existence of two constructs, and thus, using both constructs in a regression would be a likely use of the multidimensional measure in a criterion-validation study). In all three cases, the effect size of the second construct (the construct perceived by only half the population) was roughly half of that found for the first construct and roughly half the true effect size. Furthermore, the second construct was statistically significant only when the effect size was strong; when the effect size was medium, the second construct was nonsignificant, whereas the first was significant; when the effect size was weak, both constructs

were nonsignificant when entered into the regression simultaneously, although the first one was still significant when entered by itself.

The implication of these simulations is that a variable's dimensionality can have effects that alter the interpretation of a construct's criterion validity. Specific facets of a multidimensional construct may have relationships with outcomes, but these effects may be missed (or at least underestimated) because portions of a population do not perceive the two facets as distinct. Granted, for half the population, the second construct would have no effect, but the effects could be very meaningful for those who do perceive the second dimension.

We are not concluding that the theoretical and substantive problems that can emerge with variable dimensionality exist in all cases, nor do we think it necessarily has caused inappropriate conclusions in previous research involving multidimensional constructs; nonetheless, the combination of the theoretical rationale for potentially variable dimensionality, combined with the possible effects on substantive outcomes associated with specific dimensions, suggests that the issue of variable dimensionality is important to consider. Again, we are challenging the assumption that the relationship between facets of a proposed multidimensional construct always is represented by a constant (and thus, only needs to be modeled using a fixed-effects approach). Thus, we turn to presenting an in-depth example in which we can test this assumption explicitly. Through this example, we wish to test the fixed-effects assumption by illustrating (a) that theoretical justification can be developed in a specific circumstance to predict variable dimensionality, (b) that variable dimensionality can be predicted, and (c) that variable dimensionality can be useful for predicting important dependent variables. Although this will be but a single example, the successful falsification of the fixed-effects assumption would suggest the need for further consideration and research into the random-effects approach to factor analysis.

An Illustration: Pay Satisfaction and Its Dimensionality

To examine the potential to find and predict variable dimensionality, to challenge the assumption of a purely fixed-effects approach, and to illustrate the random-effects approach for examining differentiation between facets of a multidimensional construct, we turn to the literature on the dimensionality of pay satisfaction. Although some have suggested there be a moratorium on research exploring the dimensionality of pay satisfaction (Heneman & Judge, 2000), the primary focus of this article is on the application of the random-effects technique rather than specifically on the dimensionality of pay satisfaction. In fact, the number of articles addressing the idea of pay

dimensionality, in conjunction with the long-running debate about its dimensionality (for a review, see Heneman & Judge, 2000), makes this context a useful illustration for comparing fixed-effects and random-effects approaches. We also recognize that work on pay-satisfaction dimensionality should address more than just the form of the construct; thus, we also will demonstrate how variable dimensionality can help enhance the criterion-related validity of the measure. Furthermore, any research concerned with multidimensional structures may benefit from the methodological technique introduced and illustrated in this article. More generally, the falsification of the fixed-effects assumption, even if in a single context, is sufficient evidence from a philosophy-of-science perspective to suggest the need for research into random-effects approaches to factor analysis.

The Pay Satisfaction Questionnaire (PSQ; Heneman & Schwab, 1985) is the most prevalent measure of multidimensional pay satisfaction (Heneman & Judge, 2000). Exploratory factor analyses of the PSQ have suggested variously that pay satisfaction is composed of one (Orpen & Bonnici, 1987), three (Carragher, S.M., 1991; Scarpello, Huber, & Vandenberg, 1988), four (Heneman, Greenberger, & Strasser, 1988; Heneman & Schwab, 1985; Scarpello et al., 1988), and five (Mulvey, Miceli, & Near, 1992) dimensions. Confirmatory factor analyses suggested that the traditional PSQ captures four dimensions (Judge, 1993; Judge & Welbourne, 1994; Sturman & Short, 2000). Judge (1993) and Judge and Welbourne (1994) argued that the data-driven nature of exploratory factor analyses led to this diversity of results; others have argued that differences across companies (Scarpello et al., 1988) and across individuals (Carragher & Buckley, 1996; Carragher, Mulvey, Scarpello, & Ash, 2004) cause employees to conceptualize pay satisfaction differently.

The vast majority of empirical evidence supports the idea of the PSQ's multidimensionality. The results of the CFAs (see Judge, 1993; Judge & Welbourne, 1994) has presented (within the context of a fixed-effects approach) the most compelling evidence that the PSQ is described best by its hypothesized four-factor solution (i.e., pay-level satisfaction, benefits satisfaction, raise satisfaction, pay-structure/administration satisfaction). Furthermore, even if some individuals do not differentiate between a number of these dimensions, our earlier discussion (and simulation) suggests that the four-factor solution generally would be confirmed when using factor analysis. Thus, with any data set using the PSQ and testing the factor structure with CFA and consistent with the supported hypotheses of Judge (1993) and that in Judge and Welbourne (1994), we expect that items from the PSQ will load on their hypothesized dimensions and that the dimensions of the PSQ will be empirically distinct.

Yet, whereas we expect data analyzed with a fixed-effects perspective to confirm existing research findings, the hypothesized existence of a four-factor structure does not disprove the idea of

variable dimensionality because it only suggests that enough variance exists across individuals' scores to make one certain model generalize better than other models. There are also theoretical reasons to question that the number of dimensions captured by pay satisfaction measures is constant.

The two theories most often used to predict and explain pay satisfaction—equity theory and discrepancy theory (Heneman & Judge, 2000)—support the assertion that individuals form perceptions of pay satisfaction differently. Equity theory suggests that pay satisfaction is a relative, not an absolute, phenomenon (Heneman & Schwab, 1979; Jaques, 1961). The theory implies that even if two people receive equal compensation, they may have different levels of pay satisfaction because of different expectations or external comparisons. They also may conceptualize their pay packages differently. Some individuals may make external comparisons about their pay plan as a whole, whereas others may form opinions about each of the components of a pay plan. Similarly, discrepancy theory posits that satisfaction is a function of the difference between what an individual expects and what is received (Locke, 1983). This theory, too, suggests that individuals with the same compensation may have different satisfaction levels, thus implying that individuals may form perceptions of their pay in different ways (Shaw, Duffy, Jenkins, & Gupta, 1999). Therefore, if we are considering the strength of the relationship that exists between two dimensions of pay satisfaction, existing theory actually suggests that the strength of the relationship may vary across individuals because of the different cognitive processes driving the conceptualizations of pay satisfaction.

In sum, we expect that the strength of a relationship between proposed pay-satisfaction dimensions potentially should vary across individuals. Whereas we present this evidence specifically for the content domain of pay satisfaction, we argue that similar cases could be made for many other multidimensional constructs. Nonetheless, most tests of the dimensionality of such constructs have sought a single factor structure to describe a group of employees. Although the fixed-effects approach may identify the overarching number of potential dimensions in a given sample, it may be useful to look into the strength of relationships that exist between given dimensions.

Using a random-effects approach, we potentially can (a) estimate these relationships and (b) predict them with individual characteristics (Bryk & Raudenbush, 1992). Applied to the context of pay satisfaction, we expect that the random-effects model describes the relationships between satisfaction measures of different components of pay (e.g., pay level, benefits) as varying across individuals. Therefore, we hypothesize

Hypothesis 1: There will be significant across-person variance of individuals' relationships between the dimensions of pay satisfaction.

Whereas the presence of this phenomenon is interesting, it also would be valuable to understand what predicts such differentiation. As part of our illustration, we consider individuals' ability and motivation to make such differentiations. For ability, we build on prior research on cognitive complexity (Bieri et al., 1966; Kelly, 1955). As we will explain below, this work should be applicable to any research on potentially multidimensional constructs. The motivation to differentiate between dimensions, however, is driven by context-specific factors. Thus, our arguments for individuals' motivation to differentiate between dimensions will be based on the pay-satisfaction literature. Although not generalizable to other measures, this demonstration should help reveal how such arguments could be developed in other domains.

The Ability To Differentiate: Cognitive Complexity

Kelly's (1955) theory of personality posits that each individual has the ability to form a certain number of personal constructs for "cognizing" and perceiving events. Thus, an individual's cognitive complexity provides the capacity to structure cues in a multidimensional way (Bieri et al., 1966). The greater one's cognitive complexity, the more one can form a differentiated system of constructs for perceiving events (Carragher & Buckley, 1996; Carragher et al., 2004). Furthermore, not only do highly cognitively complex people have the ability to perceive more constructs, but they often actually do perceive more constructs than those with low cognitive complexity (Bieri et al., 1966).

The theory behind the predictions for cognitive complexity should be relevant to any multidimensional construct. Furthermore, representation of cognitive complexity's effects fits well into the random-effects approach proposed in this article. Applying this theory to the pay-satisfaction domain, Carragher and Buckley (1996) hypothesized that cognitive complexity positively relates to the number of pay-satisfaction dimensions perceived by individuals. Therefore, we expect that cognitive complexity will explain some of the across-person variance predicted in Hypothesis 1. Specifically, as we expect that greater cognitive complexity leads to greater differentiation (i.e., a lower correlation) between dimensions of a multidimensional construct, we hypothesize:

Hypothesis 2: The relationships between the dimensions of pay satisfaction will be (negatively) moderated by the individuals' levels of cognitive complexity.

The Motivation To Differentiate: Pay-Level Satisfaction and Pay Level

According to Kelly's (1955) theory and related work by Bieri et al. (1966), cognitive complexity serves as a limit on individual dimensionality. Whereas individuals higher in cognitive complexity often do perceive constructs in more dimensions (Bieri et al., 1966), possession of high cognitive complexity

does not guarantee that an individual will differentiate between the facets of a hypothesized multidimensional measure. Cognitive complexity essentially provides individuals with the ability to differentiate, but it does not provide the motivation to differentiate. Thus, we turn our attention to examining some factors that may provide such motivation.

Pay-level satisfaction. Scarpello et al. (1988) argued that contextual factors from a compensation plan may affect PSQ item intercorrelations, and hence, the resulting number of dimensions perceived by individuals. Because raises and pay structure/administration ultimately influence pay level (Judge, 1993), individuals may conceptualize them as part of pay-level satisfaction (Scarpello et al., 1988). Moreover, pay-level satisfaction includes items about individuals' total pay, which individuals may perceive as including raises and structure (Miceli & Lane, 1991). The argument that individuals may be influenced by an overall feeling of pay-level satisfaction when forming perceptions of compensation satisfaction is supported by the finding that perceptions of distributive justice relate to person-level evaluations (Sweeney & McFarlin, 1993), and more generally, by studies that have shown that measures of satisfaction related to pay are an outcome of procedural and distributive justice (Brockner & Wiesenfeld, 1996; Colquitt, Conlon, Wesson, Porter, & Ng, 2001).

This previous research suggests that those satisfied with the ultimate distribution of their pay (i.e., those who possess high pay-level satisfaction) may be similarly satisfied with related evaluations of pay and pay policy (i.e., the raises causing their current pay level and the fairness of the system leading to the organization's pay decisions). This should increase the relationship between pay-level satisfaction and the dimensions of raise satisfaction and pay-structure/ administration satisfaction and between the dimensions of raise and pay-structure/administration satisfaction. Benefits, however, are more conceptually distinct from pay level (Judge & Welbourne, 1994; Scarpello et al., 1988). Thus, pay-level satisfaction should be associated with less differentiation (i.e., a stronger relationship) between pay level, raises, and structure but should not be related to differentiation (or lack thereof) with benefit satisfaction.

Recall, however, that we hypothesized that cognitive complexity provides individuals with the ability to differentiate between dimensions of pay satisfaction, whereas low pay-level satisfaction provides a motivation for such differentiation. Considering these two phenomena simultaneously suggests an interaction. That is, the motivating effect of pay-level satisfaction for differentiating between the pay-level, raise, and structure/administration satisfaction facets depends on the individual possessing the cognitive complexity to make such a differentiation. Thus, we expect that low pay-level satisfaction will have a negative effect at high cognitive complexity.

On the other hand, if an individual has no desire to differentiate between the dimensions of pay satisfaction, then high cognitive complexity will not necessarily lead to such differentiation. That is, because of a high level of satisfaction with one's pay level, one may be inclined to rate all dimensions of pay satisfaction similarly high.

Note that we are considering pay satisfaction from a hierarchical perspective. We predict that the level-two characteristics of motivation (low pay-level satisfaction) and ability (high cognitive complexity) predict the relationship between dimensions of satisfaction estimated through the level-one model (i.e., $p_{AB(i)}$). Thus, we predict

Hypothesis 3a: Cognitive complexity and pay-level satisfaction (positively) interact to affect the within-person relationship between pay-level satisfaction and raise satisfaction, such that the within-person relationship between pay-level satisfaction and raise satisfaction increases as pay-level satisfaction increases.

Hypothesis 3b: Cognitive complexity and pay-level satisfaction (positively) interact to affect the within-person relationship between pay-level satisfaction and structure/administration satisfaction, such that the within-person relationship between pay-level satisfaction and structure/administration satisfaction increases as pay-level satisfaction increases.

Hypothesis 3c: Cognitive complexity and pay-level satisfaction (positively) interact to affect the within-person relationship between raise satisfaction and pay structure/administration satisfaction, such that the within-person relationship between raise satisfaction and pay-structure/administration satisfaction increases as pay-level satisfaction increases.

Pay level. Although pay-level satisfaction and pay level may be correlated (e.g., Dreher, Ash, & Bretz, 1988; Judge, 1993; Lawler, 1971), they are not equivalent. Perceptions of fairness, deserved payments, and obtained payments affect pay-level satisfaction (Heneman & Schwab, 1979; Locke, 1983). Thus, there remains substantial variance between the two (Heneman & Judge, 2000). We expect these two variables to have different effects on individuals' conceptualizations of pay satisfaction.

If a benefits package is less than ultimately desired, a high pay level may compensate for such a package by allowing the individual to obtain other desired benefits or offset the costs of a less-than-desired package (Hart & Carragher, 1995). Thus, beyond any effect of pay-level satisfaction, salary level can compensate for deficient benefits. This may decrease the salience of benefits, which should make benefits satisfaction correspond more strongly to the other dimensions of pay satisfaction.

Although pay level may provide a motivator for differentiating between the benefits satisfaction dimension and the other dimensions, making such a differentiation requires the individual to possess sufficient cognitive complexity. Thus, cognitive complexity and pay level should interact when predicting the differentiation between benefits satisfaction and the other facets of pay satisfaction. Again, we are hypothesizing that the level-one coefficient representing the relationship an individual holds between two (potential) dimensions of pay satisfaction (i.e., $p_{AB(i)}$) is a function of individual characteristics (motivation, here approximated by pay level, and ability, here represented by cognitive complexity). We predict that the level-two characteristics predict the relationship between dimensions of satisfaction estimated through the level-one model.

Hypothesis 4a: Cognitive complexity and pay level (positively) interact to affect the within-person relationship between pay-level satisfaction and benefits satisfaction, such that the within-person relationship between pay-level satisfaction and benefits satisfaction increases as pay level increases.

Hypothesis 4b: Cognitive complexity and pay level (positively) interact to affect the within-person relationship between raise satisfaction and benefits satisfaction, such that the within-person relationship between raise satisfaction and benefits satisfaction increases as pay level increases.

Hypothesis 4c: Cognitive complexity and pay level (positively) interact to affect the within-person relationship between pay structure/administration satisfaction and benefits satisfaction, such that the within-person relationship between pay structure/administration satisfaction and benefits satisfaction increases as pay level increases.

Note that because pay-level satisfaction mediates the effect of pay level (Sturman & Short, 2000), we do not expect pay level to affect the other relationships between pay-satisfaction dimensions.

The Substantive Impact of the Method

As mentioned in our literature review, whereas there is value in having a better theoretical understanding of multidimensional constructs (or in falsifying the fixed-effects assumption), a methodological technique also must have a substantive impact on applied research to merit its use. Through our hypotheses above, we focused on detecting and explaining variance in the strength of relationships between various facets of pay satisfaction. If these hypotheses hold, then we would expect that when examining the substantive impact of various facets of pay satisfaction, the differentiation could affect criterion-related validity.

Sturman and Short (2000) performed a study that provides an opportunity to illustrate this point. They performed a construct validation study on a new facet of pay satisfaction: bonus satisfaction. As part of their study, they sought to demonstrate that bonus satisfaction, beyond being construct valid, has a substantive impact on important research outcomes. Specifically, they showed that bonus satisfaction—after controlling for pay information, common attitude variables, and the other facets of pay satisfaction—helped predict organizational commitment and intent to turnover. The ideas we introduce in this article, though, suggest that not everyone in Sturman and Short’s sample may have perceived bonus satisfaction as a separate dimension, even though the five-factor structure was supported through a confirmatory factor analysis, and criterion-related validity for the bonus-satisfaction dimension was found. Considering the idea of variable dimensionality may help better reveal bonus satisfaction’s effect.

Our previous hypotheses focused on the variability of strengths in the relationships between pay-satisfaction dimensions and how these level-one relationships are affected (i.e., moderated) by the level-two interaction of cognitive complexity with either pay level (for relationships with benefits satisfaction) or pay-level satisfaction (for all other relationships). Extending this logic to the introduction of bonus satisfaction, we can consider the level of differentiation between (a) bonus satisfaction and pay-level satisfaction and (b) bonus satisfaction and benefits satisfaction. Note that we are not concerned with modeling why these may be conceptualized similarly; rather, we wish to examine if the variable conceptualization affects substantive outcomes. Furthermore, although we could have considered any number of within-person relationships, our goal here is to illustrate how our approach can provide meaningful additional information. Thus, we sought to demonstrate our approach as it should have been implemented, had it been considered as the next logical step in the analyses described by Sturman and Short (2000).

As Sturman and Short (2000) did predict (and showed on average) that bonus satisfaction does predict organization commitment and intent to turnover, we predict that specifically examining the effect of bonuses for those who perceive them as different from pay level and benefits satisfaction should reveal a stronger effect. For organizational commitment, Sturman and Short found (as hypothesized) a positive effect. Thus, we expect here

Hypothesis 5: The relationship between bonus satisfaction and pay-level satisfaction will (positively) moderate the relationship between bonus satisfaction and organizational commitment.

Hypothesis 6: The relationship between bonus satisfaction and benefits satisfaction will (positively) moderate the relationship between bonus satisfaction and organizational commitment.

For intent to turnover, although Sturman and Short (2000) predicted a negative relationship, their results showed a positive relationship. The methods we describe in this article suggest that more directly considering the effect of bonus satisfaction and looking at its effects for those who perceive it separately from pay-level and benefits satisfaction should enhance again whatever main effect already was observed. Thus, given that Sturman and Short already found a positive relationship, we expect that the within-person relationships associated with bonus satisfaction will be similarly positive. Thus, we hypothesize

Hypothesis 7: The relationship between bonus satisfaction and pay-level satisfaction will (positively) moderate the relationship between bonus satisfaction and intent to turnover.

Hypothesis 8: The relationship between bonus satisfaction and benefits satisfaction will (positively) moderate the relationship between bonus satisfaction and intent to turnover.

Study 1

The purpose of Study 1 is to illustrate our technique, demonstrate our approach, falsify the fixed-effects assumption, and test the first four hypotheses. To accomplish this, we collected data from two groups: one of certified teachers and another of financial-services personnel. All the data were collected by an author of this study. Participants were assured that the data would be kept confidential. These data have not been used in any other study.

Method

Samples and Setting

The teachers were employed in five districts in a Southwestern state. Participation was voluntary, but it was encouraged by superintendents and the state teachers union. Surveys were provided to teachers, who completed them during a 2-week period. Usable results were obtained for 402 teachers for a response rate of 69%.

The financial-services personnel completed a survey at a training seminar. Participating employees included financial analysts, bank tellers, representatives who handle telephone calls, and financial-services support personnel. Again, participation in the survey was voluntary, but it was encouraged strongly by supervisors at the seminar. Usable results were obtained for a total of 435

financial-services personnel for a response rate of 89%. The two samples of employees are analyzed together to increase the diversity of individual characteristics and circumstances.

Measures

The multidimensional measure: Pay satisfaction. Continuing the example used throughout this article, we used Heneman and Schwab's (1985) multidimensional measure of pay satisfaction: the Pay Satisfaction Questionnaire. The 18-item measure is supposed to capture: (a) satisfaction with pay level [four items], (b) satisfaction with benefits [four items], (c) satisfaction with raises [four items], and (d) satisfaction with pay structure/administration [six items]. The items were measured on a 5-point scale, with 5 connoting *high satisfaction*. The reliabilities of the four facets of pay satisfaction were .96, .95, .74, and .82, respectively.

Cognitive complexity. Subjects were asked to complete the Rep Test of cognitive complexity (Bieri et al., 1966). The Rep Test consists of a 10 × 10 matrix. Each of the columns is identified by a different person from the respondent's social environment (e.g., self, person you dislike, mother, father, boss). The 10 rows contain bipolar constructs related to personality constructs (e.g., outgoing-shy, adjusted-maladjusted). Cognitive complexity is measured by comparing each rating in a particular row with the rating directly below it (e.g., for the same person—self, mother, etc.) in the other rows in the matrix. In comparing any two responses, a score of 1 is given for an exact agreement for rating from one person. The matching process is carried out for all 45 possible comparisons, and the scores for each comparison then are added to give one total score. Scores can range from 40 (very high cognitive complexity) to 450 (very low cognitive complexity). The mean level of cognitive complexity for our sample was 171 (standard deviation = 51; mean = 169, standard deviation = 52 for the sample of teachers; mean = 173, standard deviation = 59 for the sample of financial-services employees), which is comparable to means and standard deviations of the measure reported elsewhere (e.g., Carraher & Buckley, 1996).

Because the scoring process involves counting rather than raw scores, internal consistency measures of reliability are inappropriate for the Rep Test and cannot be calculated (Bieri et al., 1966). Past research has shown the Rep Test to have high 1-week test-retest reliability (Tripodi & Bieri, 1963, 1964). Others have reviewed the literature on cognitive complexity and have concluded that it has high construct validity (Goldstein & Blackman, 1978; Menasco & Curry, 1978; Streufert & Swezey, 1986). To facilitate interpretation, the measure was reverse scored so that a higher number connoted higher

cognitive complexity (specifically, the value was set equal to 490 – the level of cognitive complexity; this is equal to the [maximum possible score – (observed score – minimum possible score)]).

Other variables. Respondents also were asked to provide some demographic and personal information. Data on employee salary, age, and sex (1 = female, 0 = male) were gathered. A dummy variable also was created, coded as 0 for those from the teacher sample and 1 for the financial-services personnel.

Modeling the Within-Individual Relationships

We hypothesized that (a) the relationships among the pay-satisfaction dimensions vary across individuals and (b) this variance is in part a function of an individual's cognitive complexity, pay-level satisfaction, and pay level. We wished to approximate the six relationships between the dimensions for each individual. We examined the relationships between: (a) pay-level satisfaction and benefit satisfaction, (b) pay-level satisfaction and raise satisfaction, (c) pay-level satisfaction and structure/administration satisfaction, (d) benefit satisfaction and raise satisfaction, (e) benefit satisfaction and structure/administration satisfaction, and (f) raise satisfaction and structure/administration satisfaction.

The traditional approach for comparing the PSQ dimensions has been to examine the correlations between the averages of each facet. This method, however, assumes that all individuals differentiate between the dimensions in the same way (i.e., a fixed-effects model) and does not permit the modeling of the relationship between the facets. Thus, we wanted to base our analyses on the items, although we ultimately will be discussing the implications of our results based on assessment of the relationships individuals hold between the measures.

For each individual, we had scores on 18 satisfaction items: 4 for pay level satisfaction, 4 for benefit satisfaction, 4 for raise satisfaction, and 6 for structure/administration satisfaction. The PSQ is designed so that each dimension of pay satisfaction is measured by highly similar items, as evidenced by a history of high reliability estimates (as noted earlier, reliability levels in our sample were .96, .95, .74, and .82; examples of similar levels are reported in Heneman & Schwab, 1985; Judge, 1993; Judge & Welbourne, 1994; Scarpello et al., 1988). Therefore, we assumed that for each individual, there existed a single metric of the relationship between any two of the PSQ's (purported) dimensions that could be approximated by the relationships between each combination of dimension items. Thus, depending on the dimensions being compared, we had either 16 comparisons (4 items × 4 items) or 24 comparisons (4

items × the 6 items for structure/administration satisfaction). An example of how the data actually are set up is shown in Table 1.

Table 1
Setting up the Data

Level-One Variables							
Person ID	Construct A	Construct B					
1	Pay level satisfaction Item 1	Benefits satisfaction Item 1					
1	Pay level satisfaction Item 1	Benefits satisfaction Item 2					
1	Pay level satisfaction Item 1	Benefits satisfaction Item 3					
1	Pay level satisfaction Item 1	Benefits satisfaction Item 4					
1	Pay level satisfaction Item 2	Benefits satisfaction Item 1					
1	Pay level satisfaction Item 2	Benefits satisfaction Item 2					
1	Pay level satisfaction Item 2	Benefits satisfaction Item 3					
1	Pay level satisfaction Item 2	Benefits satisfaction Item 4					
1	Pay level satisfaction Item 3	Benefits satisfaction Item 1					
1	Pay level satisfaction Item 3	Benefits satisfaction Item 2					
1	Pay level satisfaction Item 3	Benefits satisfaction Item 3					
1	Pay level satisfaction Item 3	Benefits satisfaction Item 4					
1	Pay level satisfaction Item 4	Benefits satisfaction Item 1					
1	Pay level satisfaction Item 4	Benefits satisfaction Item 2					
1	Pay level satisfaction Item 4	Benefits satisfaction Item 3					
1	Pay level satisfaction Item 4	Benefits satisfaction Item 4					
2	Pay level satisfaction Item 1	Benefits satisfaction Item 1					
2	Pay level satisfaction Item 1	Benefits satisfaction Item 3					
2	Pay level satisfaction Item 1	Benefits satisfaction Item 4					
2	Pay level satisfaction Item 2	Benefits satisfaction Item 1					
.							
.							
.							
837	Pay level satisfaction Item 3	Benefits satisfaction Item 4					
837	Pay level satisfaction Item 4	Benefits satisfaction Item 1					
837	Pay level satisfaction Item 4	Benefits satisfaction Item 2					
837	Pay level satisfaction Item 4	Benefits satisfaction Item 3					
837	Pay level satisfaction Item 4	Benefits satisfaction Item 4					
Level 2 Variable Setup:							
Person ID	Job	Age	Cognitive Complexity	Mean Pay Satisfaction	Salary	Pay Satisfaction × Cognitive Complexity	Salary × Cognitive Complexity
1							
2							
.							
.							
.							
837							

Analyses were performed using the HLM statistical package (Bryk, Raudenbush, Cheong, & Congdon, 2000). In HLM with two levels, each level is modeled through its own equation. In this two-level analysis, an individual’s pay-satisfaction scores are nested within the individual. The level-one

model portrayed each individual's relationship between two satisfaction-facet measures (e.g., as shown in Table 1: pay satisfaction and benefits satisfaction).

We transformed the satisfaction measures into z scores and thus did not model an intercept in our level-one model. This transformation had a number of advantages. First, it made the interpretation of the beta-coefficient comparable (although not exactly equal to) a correlation coefficient. That is, because the expected value of $Z_y = r_{xy} \times Z_x$, by transforming both the X and Y variables in the simple level-one model, the beta-coefficient being modeled became comparable to a correlation coefficient. Second, by standardizing the measures, we were able to not model an intercept. This allowed us to have a simpler, more interpretable level-two model because we could focus exclusively on what affected the relationship between X and Y, as the intercept (once the variables were standardized) should be 0. It also should be noted that standardizing the variables only changes the units. The 5-point scale for measuring pay satisfaction is not meaningful per se and thus expressing the same information in z scores does not lose any information.

The level-one (within-person) model is as follows:

$$Y_{ij} = B_i X_{ij} + r_{ij} \text{ (level 1)}$$

where Y_{ij} is the value of measure j of person i for the first dimension; X_{ij} is the value of measure j of person i for the second dimension; B_i represents the relationship between dimensions A and B for person i ; and r_{ij} is the residual at level one with a mean of 0 and a variance of σ^2 .

The test of the first hypothesis is that B_i varies across individuals. HLM can test this explicitly by modeling the following level-two model:

$$B_i = y_{00} + u_j \text{ (level 2)}$$

where u_j is the level-two residual with a mean of 0 and a variance of τ , and y_{00} represents the average intercept across individuals. In this pair of equations (Equations 4 and 5), the level-one model captures the relationship between pay satisfaction dimensions and the level-two model captures the extent to which that relationship varies across individuals. HLM also provides a chi-square test to determine if the variance of u_j (i.e., τ) is significantly greater than zero. That is, the null hypothesis, $\sigma^2(B_i) = 0$, states that there is no variance in the relationship across individuals. Rejection of this null hypothesis would support Hypothesis 1.

If the null hypothesis is rejected (and thus, Hypothesis 1 is supported), then we can move to the next step, accounting for variation in this relationship across individuals by adding individual-level

variables as specified in the level-two equation below, in which the relationship β_i (determined from the level-one model) is the dependent variable in the level-two model:

$$B_i = y_{00} + y_{01}W_{1i} + y_{02}W_{2i} + \dots + u_j$$

where u_j is the level-two residual with a mean of 0 and a variance of τ , y_{00} represents the average intercept across individuals, and y_{01} , y_{02} , and so on are the level-two regression weights for the variables W_1 , W_2 , and so on. In this article, the level-two model will include the following independent variables: sex, age, job, cognitive complexity, salary, mean pay-level satisfaction, Cognitive Complexity \times Salary, and Cognitive Complexity \times Mean Pay- Level Satisfaction. Note that in this level-two model, mean pay-level satisfaction is the average of the four pay-level satisfaction items for a given person. Thus, the level-two analyses reveal the way in which the individual's characteristics relate to the individual's estimated relationship between Dimension A and Dimension B.

Note also that although the HLM method requires us to specify one dimension as a dependent variable and another dimension as an independent variable, the cross-sectional analysis and theoretical rationale do not imply causality. We simply are trying to represent the relationship between two dimensions, not suggesting that one dimension causes the other. For that reason, all of the analyses were replicated switching the dependent and independent variables. These results are available from the lead author on request, but significance levels are not substantively different from those reported below, and there is no change in the overall evidence with regard to the support of the hypotheses.

It also should be clear that we are modeling only a single relationship at a time. Conceivably, it would be possible to represent all possible relationships in a single three-level model in which all possible combinations of items were examined; however, as our intent is to consider individual relationships and falsify the fixed-effects assumption given a priori hypothesized facets of a multidimensional measure, the separate tests were easier to interpret and allowed us to consider the fixed-effects-versus-random-effects question for each relationship separately.

Results

The descriptive statistics and correlation matrix for the variables used in this study (analyzed at the individual level and measure level) are reported in Table 2. The satisfaction measures reported in Table 2 are calculated as the mean of individual constituent items, as is typical of research using the PSQ. Item correlations between the satisfaction measures and the reliability estimates are similar to results of other studies using the PSQ. All satisfaction measures ranged from 1 to 5; age ranged from 20 to 61; the measure of cognitive complexity ranged from 69 to 397.

Before describing the results of our hypothesis tests, we wanted to show that our data are not atypical of data used in other studies on the dimensionality of pay satisfaction. Thus, we used CFA to replicate previous findings of the PSQ's dimensionality. We expected that, when grouping our data through a covariance matrix, factor analyses will suggest that the four-factor solution hypothesized by Heneman and Schwab (1985) and replicated by Judge (1993) and Judge and Welbourne (1994) best fits the data. Consistent with these three previous studies, we compared the hypothesized four-factor model to a number of reasonable, or previously hypothesized, alternatives. This included a null model (a model in which all 18 PSQ items were not allowed to load on the factors, and the four PSQ dimensions were not allowed to correlate with each other), an orthogonal model (in which the correlation between the four dimensions was set to 0), and a single-factor model (in which all the 18 items load onto a single factor). We also compared the four-factor solution to a number of models with fewer factors. Because pay level, raise, and structure/administration satisfaction are the most correlated factors, like previous research (Judge, 1993; Judge & Welbourne, 1994), we considered a two-factor solution in which benefits satisfaction was separate from a second factor consisting of all the other items. Additionally, because of the high relationships between pay level, raise, and structure satisfaction, we considered the three-factor solutions that combined any two of these factors (thus, one model combining pay-level and raise satisfaction, a second combining pay-level and structure satisfaction, and a third combining raise and structure satisfaction).

Table 2
Summary Statistics and Correlations

	Mean	Standard Deviation	1	2	3	4	5	6	7	8	9
1. Sex	0.79	0.41	—								
2. Job	0.48	0.50	.05	—							
3. Age	38	9.63	.15	.19	—						
4. Cognitive complexity	171	51	-.03	.04	-.13	—					
5. Salary	27,749	9,626	-.09	-.40	.49	-.08	—				
6. Pay-level satisfaction	2.2	0.90	-.06	-.15	-.21	-.10	-.12	(.96)			
7. Benefits satisfaction	2.5	1.00	.00	-.09	-.11	.01	-.06	.44	(.95)		
8. Raise satisfaction	2.5	0.78	-.03	-.12	-.26	-.01	-.12	.69	.47	(.74)	
9. Structure/administration satisfaction	2.7	0.69	-.08	-.09	-.14	.05	-.03	.55	.40	.64	(.82)

Note: $N = 837$. Coefficient alphas are reported in parentheses on the main diagonal. For sex, 0 = male, 1 = female; cognitive complexity is recoded so that high scores mean high cognitive complexity. Coefficients greater than .07 are significant at $p < .05$.

The CFA performed on our combined sample supports the hypothesized four-factor structure. The factor loadings (available from the lead author on request) were all relatively strong (average loading = 0.77) and highly significant ($p < .01$), thus supporting our assertion that the items from the PSQ will load on their hypothesized dimensions. As shown in Table 3, the CFA supported the hypothesized four-factor model. Specifically, the four-factor model had significantly better fit than any of the other models we compared it against (all at $p < .0001$), and the fit statistics for the four-factor model (GFI, NNFI, CFI, and RMSEA) were all better in the four-factor model than in all other models. This finding confirms our expectation that, when considering the entire sample from a fixed-effects perspective, the dimensions of the PSQ are empirically distinct. Thus, although we still predict that a random-effects model is more appropriate than a fixed-effects model, our data are similar to those of other studies and therefore show how a fixed-effects approach may suggest this four-dimensional structure.

We began our hypothesis testing by examining fixed effects and the basic random-effects model (i.e., Equations 4 and 5) for each of the six relationships between the dimensions of the PSQ. Table 4 shows the models predicting these relationships. First, we used correlations (i.e., a fixed-effects approach) to model the relationship between the aggregated measures of the pay-satisfaction dimensions (e.g., the correlation between the average of the pay-satisfaction dimensions and the benefits-satisfaction dimensions). As mentioned above, the correlations of the aggregated measures are typical of other studies using the PSQ. We also estimated relationships based on all the interitem relationships (which do not become larger because of aggregating over the random item-level errors); these correlations are notably smaller in magnitude. This suggests that there is a significant amount of random within-person error.

Table 3
Fit Statistics for Group-Level Analysis of Predicted and Alternative Models

Model	χ^2	<i>df</i>	GFI	NNFI	CFI	RMSEA
Null model	23,940.08	153	—	—	—	—
Orthogonal model	1993.03	135	.79	.92	.93	.13
Single-factor	5851.46	135	.56	.80	.82	.23
Two-factor: Combining level, raise, structure, and administration	2568.99	134	.75	.93	.94	.15
Three-factor: Combining pay level and structure/administration	2222.85	132	.77	.93	.94	.14
Three-factor: Combining pay level and raise	1000.11	132	.88	.96	.97	.09
Three-factor: Combining raise and structure/administration	956.20	132	.89	.96	.97	.09
Four-factor (hypothesized)*	630.50	129	.92	.98	.98	.06

Note: The four-factor model is significantly better fitting than all other models ($p < .0001$).

We used HLM to estimate the basic random-effects model and test if significant across-person variance existed. This test indicates whether the residual variance is statistically significantly different from zero (Bryk & Raudenbush, 1992; Hofmann, 1997). For all six models, the HLM analyses yield very large chi-square values (such that $p < .0001$ for all comparisons). Thus, the random-effects model demonstrates the presence of across-person variance and provides support for Hypothesis 1.

Because significant across-person variance was discovered, we could continue our hypothesis tests by attempting to predict this variance (Hofmann, 1997). We used HLM to test the more complex random-effects model (which provides an estimate of Equations 4 and 6 described above). Results of these analyses are shown in Table 5. Values in the table are coefficients from the individual level (the more macro-level in our case) of analysis that estimate the effect of the variables on the relationship between the corresponding components of pay satisfaction. To facilitate interpretation, all of the continuous independent variables were transformed into z scores (i.e., standardized). This facilitates interpretation of our results, as the intercept represents the average relationship between the dimensions; the dichotomous independent variables (i.e., job and sex) were left as zeros and ones.

The results support the second hypothesis. Specifically, the coefficient for cognitive complexity is significantly negative in all cases ($p < .001$). This means that greater cognitive complexity is related to less similarity (or greater differentiation) between the components of pay satisfaction.

Table 4
Predicting the Relationships Between the PSQ Dimensions

Level-One Model: (Construct Y) = $\beta \times$ (Construct X) + error						
Construct Y Construct X	Pay Benefits	Raise Benefits	Structure Benefits	Raise Pay	Structure Pay	Structure Raise
Fixed-effects estimate (r)						
Group level (means of measures)	0.44***	0.47***	0.40***	0.69***	0.55***	0.64***
Item level	0.38***	0.31***	0.26***	0.47***	0.37***	0.32***
Mean random-effects estimate	0.34***	0.29***	0.21***	0.41***	0.34***	0.30***
Level-One variance component (sigma squared)	0.265	0.617	0.613	0.612	0.593	0.722
Level-Two variance component (tau)	1.131	0.511	0.525	0.640	1.566	0.178
Percentage of variance caused by within-person differences	19%	55%	54%	49%	27%	80%
Percentage of variance caused by between-person differences	81%	45%	46%	51%	73%	20%
Reliability of level-one coefficient	0.966	0.855	0.898	0.747	0.889	0.784
Chi-square	30587***	7221***	11500***	5231***	10315***	5742***

Note: For group-level fixed-effects model, correlation coefficients are based on $N = 837$. For item-level analyses, including both fixed-effects and random-effects, $N = 20,088$ when pay-structure/administration satisfaction is one of the variables; otherwise, $N = 13,392$. For all chi-square tests, degrees of freedom = 836. The dependent and independent variables both were standardized before analysis. No intercept was modeled in the analyses.
* $p < .05$. ** $p < .01$. *** $p < .001$.

The results also demonstrate support for the third and fourth hypotheses. We predicted that the interaction of cognitive complexity and mean pay-level satisfaction would be related positively to the relationships between: (a) pay-level and raise satisfaction, (b) pay-level and structure/administration satisfaction, and (c) raise and structure/administration satisfaction. All three relationships are significant at $p < .05$ or better. We also predicted that the interaction of cognitive complexity and salary would be positively related to the relationships between benefits satisfaction and: (a) pay-level satisfaction, (b) raise satisfaction, and (c) structure/ administration satisfaction. All three of these relationships are supported at $p < .01$ or better.

Discussion

The results of this study directly challenge the assumption that individuals differentiate between the components of their pay package in the same way. Although we replicated previous findings of the hypothesized dimensionality of the PSQ using CFA (Judge, 1993; Judge & Welbourne, 1994), this study shows that systematic across-person variance exists, thus indicating that people differentiate between the dimensions of pay satisfaction to different degrees. Our results suggest that a random-effects conceptualization of constructs may be a useful complement to fixed-effects analyses.

Table 5
Predicting the Relationships Between the PSQ Dimensions

Level-One Model: (Construct Y) = $\beta \times$ (Construct X) + error						
Construct Y Construct X	Pay Benefits	Raise Benefits	Structure Benefits	Raise Pay	Structure Pay	Structure Raise
Predictors of β (level-two model)						
Intercept	0.42***	0.24***	0.21***	0.41***	0.47***	0.31***
Sex	-0.03	0.07	-0.01	-0.01	-0.16	0.00
Job	-0.12	0.04	0.06	0.05	0.13	-0.08
Age	0.11*	0.01	0.08**	0.08**	0.15*	-0.01
Cognitive complexity	-0.19***	-0.25***	-0.25***	-0.24***	-0.44***	-0.22***
Mean pay satisfaction	0.10**	0.04	0.03	0.01	0.00	0.08***
Salary	-0.12*	-0.04	-0.03	-0.03	-0.05	-0.01
Pay satisfaction*	-0.07*	0.08	-0.05	0.12**	0.19*	0.07*
Cognitive complexity Salary*	0.11***	0.07**	0.09***	0.03	0.09*	-0.01
Cognitive complexity						
Percent variance of β explained	15%	20%	19%	27%	29%	16%
Percentage points of variance explained of β attributable to interactions	2%	3%	4%	4%	2%	1%

Note: For item-level analyses, $N = 20,088$ when pay-structure/administration satisfaction is one of the variables; otherwise, $N = 13,392$. All continuous coefficients were standardized before analysis. For sex, 0 = male and 1 = female. For job, 0 = teachers and 1 = financial-services personnel.

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

This study also shows that individual-level variables can predict the relationships between a multidimensional measure's facets. Whereas other studies have made similar hypotheses and drawn the same conclusion for the cognitive-complexity construct (e.g., Carraher & Buckley, 1996), ours is the first study (a) to keep both the hypotheses and analyses at the individual level and (b) to demonstrate statistical tests of the significance of these individual-level relationships. We agree with Carraher and Buckley that researchers need to recognize that mean-level differences between samples may influence findings of dimensionality as expressed through factor analyses, but we also assert that even when factor analyses provide support for the hypothesized dimensionality, there may be effects occurring within the sample that reflect different behaviors or outcomes than observed through the aggregated data.

The results of Study 1 support the first four hypotheses. More generally, and perhaps most importantly, the results challenge the methodological assumption that the relationship between any two dimensions of a multidimensional construct is best represented by a constant. There are limitations of this study, however, that should be highlighted. First, whereas we provide technical support for the random-effects approach, we have not supported the conceptual advantage of this methodology yet. That is, does using a random-effects approach help explain outcomes better than a fixed-effects approach (and thus, is the technique worth using)?

Second, it is possible that the burdensome nature of the cognitive-complexity measure could affect our results. Given the amount of time that a subject must devote to completing a survey with the cognitive-complexity measure, it is possible that we are capturing the respondents' attention to detail or motivation when completing the survey. If so, others using the PSQ (or other multidimensional measures) may not observe the same variable relationships between dimensions that we did here. Therefore, we used a second data set to (a) demonstrate the substantive value of the random-effects approach and (b) show that the random-effects phenomenon occurs even when we do not use the Rep Test.

Study 2

Whereas the first study used new data to demonstrate the idea that variable dimensionality exists, is systematic, and can be predicted, this second study is intended to demonstrate the substantive value of our approach. To do so, we rely on data previously examined by Sturman and Short (2000). We rely on this existing data because the Sturman and Short article provides a good example of using the PSQ under the assumption of fixed dimensionality. We will continue where this previous work left off

and use our technique to show the additional value that would be gained by considering variable dimensionality.

Method

As the data for Study 2 already have been used in previous research, we refer readers to the original study for complete detail on the method (see Sturman & Short, 2000); however, we will review the information pertinent to our analyses in this article. Sturman and Short used a sample of 416 employees in five organizations. The purpose of the study was to design and validate a measure of lump sum–bonus satisfaction. Data were collected on the employees' pay satisfaction (using the PSQ; alphas of .96, .94, .90, and .90), bonus satisfaction (with a measure designed in the study, $\alpha = .93$), job satisfaction (a 3-item measure, $\alpha = .80$), organizational commitment (9 items, $\alpha = .88$), and intent to turnover (5 items, $\alpha = .91$). Data also were collected on each individual's base pay and bonus. The hypothesized dimensionality of the PSQ was confirmed using CFA.

We chose to reexamine this study for a number of reasons. First, Sturman and Short (2000) examined pay satisfaction, the question of dimensionality, and the substantive impact of a new dimension (bonus satisfaction); however, their analyses implicitly assumed that bonus satisfaction was perceived as its own dimension by all subjects, a finding that they supported through the use of a CFA. Learning from what we have studied in this article, we should expect that people may conceive of this new dimension differently, and considering this conceptualization should allow us to detect the effect of the new dimension for those who do perceive it as more separate from the other dimensions of pay satisfaction.

In their study, Sturman and Short predicted organizational commitment and intent to turnover. Through a series of steps in hierarchical regressions, they showed that the dimension of bonus satisfaction explained variance in the dependent measures after controlling for (a) base pay and bonus, (b) job satisfaction, (c) the other pay-satisfaction dimensions, and (d) organizational commitment when predicting intent to turnover. We will continue where this previous study ended and use the technique introduced in this article to predict these outcomes.

First, we will determine if the relationships of bonus satisfaction with pay-level satisfaction and benefits satisfaction are represented better as variable or constant. Using HLM, we will use a chi-square test to determine if there is significant across-person variance for each of these relationships. This will be performed using the same approach of modeling Equations 4 and 5 from Study 1.

Second, if the results from this initial test suggest that a random-effects approach is warranted, we will use the associations of bonus satisfaction with (a) pay-level satisfaction and (b) independent variables in the prediction of organizational commitment and intent to turnover. Using the method described earlier and used in Study 1, we used HLM to estimate the within-person relationships between (a) pay-level satisfaction and bonus satisfaction and (b) benefits satisfaction and bonus satisfaction. The resultant level-one coefficients representing the relationship for each individual were saved and used below as independent variables. In other words, we obtained the individualized estimates of the within-person relationships for these two pay satisfaction–dimension comparisons.

These two independent variables were added as a main effect; we also performed another step in which we consider the interaction of these deviance scores with bonus satisfaction. If, indeed, people separate in their minds the constructs of pay satisfaction and bonus satisfaction (and benefits satisfaction and bonus satisfaction), then we should see that the effect of bonus satisfaction is more pronounced the more people conceptualize the facet separately.

Results

As with Study 1, we first used HLM to estimate the basic random-effects model and test if significant across-person variance existed. If this chi-square test indicates that significant across-person variance exists, we can continue with our analyses. For (a) the relationship between bonus satisfaction and pay-level satisfaction ($df = 418$; chi-square = 8526) and (b) the relationship between bonus satisfaction and benefits satisfaction ($df = 418$; chi-square = 7726), the chi-square tests indicated that there is significant across-person variance (for both tests, $p < .0001$). Thus, once again, the random-effects model demonstrates that significant across-person variance exists and provides support for Hypothesis 1.

With support for the random-effects approach, we continued with our analyses to test our hypotheses related to these variable relationships and the dependent variables of organizational commitment and intent to turnover. Table 6 shows our examination of the substantive impact of our method, applied to the example originally described by Sturman and Short (2000). The results support the overarching hypothesis of this article: that examining the level of differentiation between dimensions can have substantive effects. When the amount of deviation between bonus satisfaction and pay-level satisfaction was related to either organizational commitment or intent to turnover, it added no explanatory power. However, when the amount of deviation was interacted with the level of bonus satisfaction, the effect (as hypothesized) was significant (at $p < .05$ or better) and added explanatory

power to the regression (for both dependent variables, change in $R_2 = .02$; $p < .05$). It also should be noted that this increase in R_2 was in a very conservative test in which an already high portion of variance was explained. Our finding of statistical significance and additional variance explained provides some validation for our view that considering multidimensional variables in this way can be of use to applied research. Furthermore, we feel that this technique may be more valuable in other contexts in which the nature of dependent variables is far less well known.

Table 6
Effect of Differentiation on Substantive Outcomes:
Illustration from Sturman and Short (2000)

Independent Variables	Dependent Variable					
	Organizational Commitment			Intent to Turnover		
	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3
Base pay	0.06	0.05	0.05	0.02	0.01	0.02
Logarithm bonus award	0.08*	0.09*	0.09**	-0.08*	-0.08*	-0.08*
Job satisfaction	0.49**	0.53**	0.52**	-0.35**	-0.36**	-0.36**
Pay-level satisfaction	-0.15**	-0.11**	-0.17**	-0.17**	-0.16**	-0.10
Benefits satisfaction	0.13**	0.12**	0.14**	-0.03	-0.03	-0.03
Raise satisfaction	-0.01	0.00	0.00	-0.04	-0.05	-0.06
Structure/administration satisfaction	0.20**	0.12*	0.12*	0.06	0.06	0.05
Lump sum–bonus satisfaction	0.18**	0.17**	0.24**	0.11*	0.15**	0.07
Organizational commitment	—	—	—	-0.36**	-0.36**	-0.35**
Deviation (pay satisfaction and bonus satisfaction)		0.01	0.22*		0.07	-0.10
Deviation (benefits satisfaction and bonus satisfaction)		0.06	0.00		0.03	0.02
Deviation (pay satisfaction and bonus satisfaction) × bonus satisfaction			0.23**			0.19*
Deviation (benefits satisfaction and bonus satisfaction) × bonus satisfaction			0.06			0.01
Adjusted R -squared	.50	.50	.52	.48	.48	.50
Change in adjusted R -squared		.00	.02*		.00	.02*

Note: $N = 419$. For each dependent variable, step 1 represents the last step for each set of comparisons, as reported by Sturman & Short (2000), Table 5 (p. 693) for predicting organizational commitment and Table 6 (p. 695) for predicting intent to turnover.

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

Discussion

By reanalyzing the Sturman and Short (2000) study, we show that the technique introduced in this article can be used to help make conceptual contributions in areas that use a multidimensional measure. The study provided support for Hypotheses 5 and 7, that the level of differentiation between bonus satisfaction and pay-level satisfaction is related to organizational commitment and intent to turnover. Hypotheses 6 and 8 were not supported: the level of differentiation between bonus satisfaction and benefits satisfaction was not related to these dependent variables. We also show that

the measurement of cognitive complexity is not driving our results, as the measure was not used in the Sturman and Short (2000) study.

More generally, this study demonstrates how the random-effects methodology can be applied to addressing questions of theoretical and practical value. For research on bonuses, our findings suggest that understanding how and why people differentiate between bonuses and pay level is an important consideration in the design of bonus plans. By showing that using the extent to which individuals differentiate between subscales can be related to important outcomes, we present evidence that our approach is more than simply a methodological nicety. It may be important to consider how individuals differentiate between facets of a multidimensional measure to truly understand the theoretical role of various constructs.

Conclusion

The main purpose of this article was to demonstrate a random-effects measurement technique appropriate for investigations of multidimensional constructs. Using the methods described above, it is possible to estimate the level of individual association between facets of a purportedly multidimensional measure. The technique allows both a specific test that determines if a random-effects model is more appropriate than a fixed-effects model, and if appropriate, a means to model this individual variation. The technique also fosters the estimation of a measure of this association that then can be used in studies examining the consequences of facets of the multidimensional measure.

There are notable implications of these findings for future research on pay satisfaction, specifically, and measurement in general. For any study examining the consequences of a multidimensional measure, our results suggest that a blind correlational approach examining relationships between the various facets of a multidimensional measure and various outcomes could miss critical aspects about how individuals are conceptualizing the construct in question. Investigations into the consequences of the different dimensions of a construct need to pay attention to the specific dimensions of the construct that each individual conceptualizes. Otherwise, effects may be obscured. Although Sturman and Short (2000) showed that bonus satisfaction was related to organizational commitment and intent to turnover, our results here demonstrate that it has more effects than originally shown. The true effect of bonus satisfaction is more notable when an individual conceptualizes it as a separate and distinct component of pay satisfaction. CFA shows that people do, on average, conceptualize it as a separate dimension; however, those who differentiate it more from pay-level

satisfaction have stronger relationships of bonus satisfaction with organizational commitment and intent to turnover.

This article ultimately adds to the extensive literature about construct creation and the methods used to identify the dimensions of multidimensional measures. We challenge the fixed-effects approach to considering factors, an approach that has been used to date essentially without question. The primary implication of this article is that it reveals the need for a new type of research on multidimensional constructs: investigations into the antecedents and consequences of variable dimensionality. Yet, we once again want to point out that we are not suggesting an end to fixed-effects approaches to factor analysis. The random-effects approach we describe is a useful complement to EFA and CFA. The fixed-effects approaches are necessary to test the maximum number of dimensions that a multidimensional construct captures and to confirm a priori hypotheses about the potential dimensions that exist, the relationships between which may vary across individuals. In short, applied research considering implementing the random-effects approach we discussed (or an advancement to this method) should use such an approach after proper theoretical grounding and appropriately tested hypotheses with CFA.

This article is limited, though, in that we only begin down this path with a demonstration of a methodology to detect differing conceptualizations. Much of the purpose of this article was to falsify the fixed-effects assumption, and indeed, our findings achieve this result. However, this method introduced here is only a first step toward developing methods to represent the factor structure of multidimensional constructs better. One limitation of our approach is that we only analyzed the relationship between two dimensions at a single time, whereas CFA and EFA consider multiple dimensions simultaneously. Furthermore, by only looking at relationships between two dimensions at a time, our methodology is limited in that it cannot provide an estimate of the number of dimensions perceived by any given individual. It is also worth noting that our methodology cannot detect a situation in which an individual truly does conceptualize two dimensions as distinct but has the same level of satisfaction with each dimension. It is not clear if this sort of information can be detected with any sort of random-effects approach or quantitative analysis in general. Issues such as this might be served best by complementary qualitative analysis specifically on how individuals conceptualize potentially multidimensional measures. Nonetheless, as our goal here was to reveal the need to begin research considering multidimensional constructs using a random-effects framework, this limitation provides a fruitful opportunity for future research.

It is also worth noting that whereas we have framed our entire discussion within the context of multidimensional construct, the theory behind cognitive complexity—and more generally, our discussion of individuals' ability and motivation to differentiate between constructs—is equally applicable to understanding how individuals potentially distinguish between other constructs. For example, an individual with low cognitive complexity may not distinguish between constructs such as perceived organizational support, organizational commitment, and job satisfaction. Thus, our method may be useful when considering issues such as convergent and discriminate validity of constructs.

Our method also may be useful when considering the potential causes and consequences of common method variance. A lack of ability (e.g., cognitive complexity) and motivation may cause individuals to yield inflated relationships between measures on a survey. Our evidence from the fixed-effects approaches shows that this variability, although present, may not be detected through factor analyses. It may be valuable for future research on common method variance to consider that individuals may distinguish between items collected within the same method differently, and this too may be an issue better considered from a random-effects rather than a fixed-effects framework.

Another significant implication of the current study is that we may need to be aware of characteristics that give people the ability and motivation to differentiate between potentially multidimensional measures. In research, we often develop tunnel vision in our areas of study and believe that we know how a population should perceive variables of interest. For instance, suppose that a survey asks subjects to rate the usefulness of anthraquinone-glycidyl methacrylates, phenolsulfonphthalein, acrylated azo, poly (2-vinylanthoquinones), chromorange GR, coumaric acid, fluorescein, erythrosine B, and vinyl malachite green (copolymerized with N-vinylcarbazol) as polydyes. Whereas individuals in industrialized societies deal with polydyes nearly every day of their lives (e.g., dyes in clothing, paint on cars, in computer mouse pads), it is unlikely that most populations of interest would see this survey as containing three clear dimensions (see Carraher, C. E., 1990). A researcher deeply involved in this context might expect that respondents should see clearly that the first three items are all good for use as polydyes, the second three make just moderate polydyes, and the last three are poor polydyes. Furthermore, the researcher may expect that this survey should have perfect test-retest reliability, as the properties of these polymers will not change through time. However, the terminology used in this questionnaire is unfamiliar to most nonpolymer chemists and therefore the reliabilities, validities, and number of observed dimensions captured through the questionnaire likely will change from sample to sample. When developing or applying any measure, researchers need to seek to understand how various populations of interest naturally perceive the constructs being

considered rather than impose the researchers' belief of how subjects should conceptualize constructs in those areas.

It is our expectation that the more closely related the facets of a construct, the more ability and/or motivation a subject will need to differentiate between those dimensions. Thus, it would be useful for researchers to examine the tendency of instruments to have consistent dimensionalities. The results of this work further suggest that additional basic research should be performed to facilitate the development of new theories about the interplay between individuals' conceptualization processes and instrumentation. This better understanding, or at least the recognition of potential variable dimensionality, also should help reveal the associations that exist between important theoretical and practical outcomes and the various subscales.

In summary, this article provides evidence falsifying a purely fixed-effects approach for conceptualizing dimensions of a multidimensional measure. The implication of this is that we demonstrate a need for theory and methods to consider how and why individuals perceive multidimensional constructs in different ways and how to measure this variable dimensionality. This study opens the door to a number of potentially important methodological issues, such as how to produce a general random-effects approach to factor analysis, and to conceptual issues depending on the specific context of the measurement situation. It also suggests that there are opportunities to understand better how individuals perceive various multidimensional constructs.

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