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Recent Advances in Causal Modeling Methods for Organizational and Management Research

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The purpose of this article is to review recent advanced applications of causal modeling methods in organizational and management research. Developments over the past 10 years involving research on measurement and structural components of causal models will be discussed. Specific topics to be addressed include reflective vs. formative measurement, multidimensional construct assessment, method variance, measurement invariance, latent growth modeling (LGM), moderated structural relationships, and analysis of latent variable means. For each of the areas mentioned above an overview of developments will be presented, and examples from organizational and management research will be provided.
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In most instances, management research involves the evaluation of one or more models that have been developed based on theory. These models typically describe processes presumed to underlie and be responsible for values obtained on variables from the model with sample data, and these processes are also assumed to induce or generate measures of association (e.g., correlation) among the variables in the models. When these models are depicted in graphic form, they are often referred to as path models, since variables that are hypothesized to be related are connected with arrows. Beginning in the early 1980s, organizational and management researchers widely embraced a new latent variable method for model testing. The frequency of use of latent variable techniques increased dramatically in

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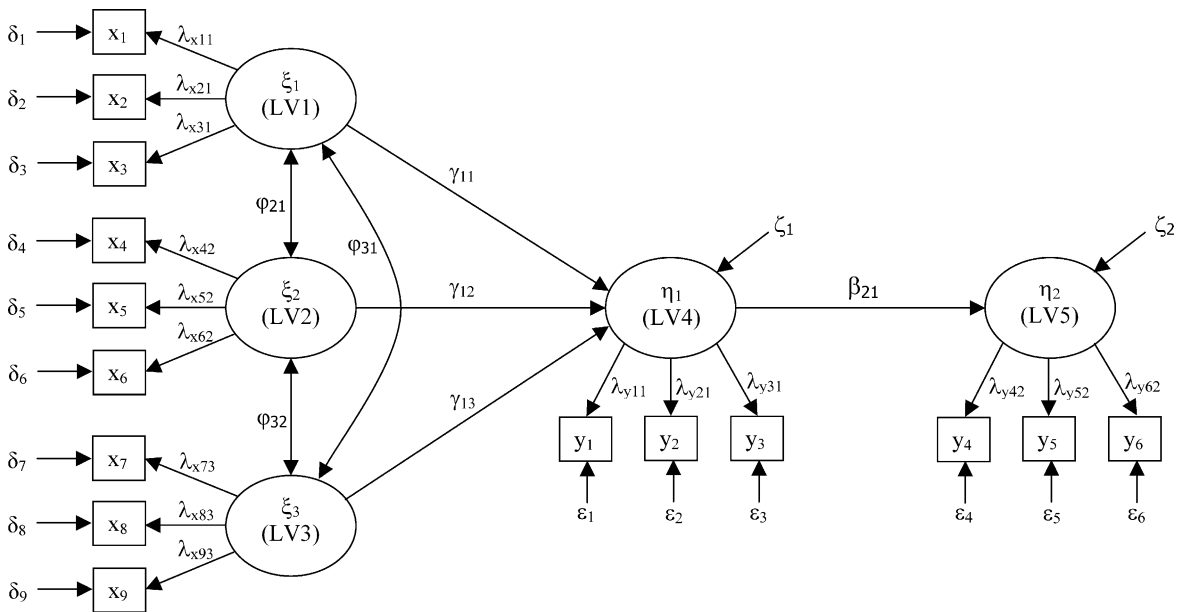
Figure 1. Basic latent variable model.

the next 20 years, as noted in reviews by Scandura and Williams (2000) and Stone-Romero, Weaver and Glenar (1995).

A basic latent variable structural equation model that will be used to introduce advanced applications of this analytical technique is shown in Figure 1. Several aspects of the traditional notation and terminology are illustrated with this figure using the labels associated with the popular LISREL program (Jöreskog & Sörbom, 1996). A circle is used to represent each of the five latent variables, while the boxes represent associated manifest or indicator variables. The relationships between the latent variables and their indicators are often referred to as a "measurement" model, in that it represents or depicts an assumed process in which an underlying construct determines or causes behavior that is reflected in measured indicator variables. Within this context, it is important to note that the arrows go from the circles to the boxes, and this is consistent with the process noted above. Thus, each factor serves as an independent variable in the measurement model, while the indicator variables serve as the dependent variables, and the paths are often referred to as factor loadings. Each indicator is also potentially influenced by a second independent variable in the form of measurement error, and its influence is represented as a cause of the indicator variable through the use of a second arrow leading to each of the indicators. Finally, the model shown in Figure 1 includes correlations (double-headed arrows) among the three exogenous constructs (LV1–LV3), regression-like structural parameters linking exogenous and endogenous constructs (LV4, LV5) and linking endogenous constructs to other endogenous constructs, and the model also acknowledges that there is unexplained variance in the two endogenous latent variables. The part of the overall model that proposes relationships among the latent variables is often referred to as the structural model.

At the same time that management researchers were increasing their use of latent variable techniques for testing models such as the one shown in Figure 1, quantitative methodologists were developing advanced applications that addressed complex research questions and related research designs. The purpose of this paper is to review these applications of latent variable techniques used to address measurement and substantive problems in organizational and management research. For those not familiar with latent variable analysis, a brief overview of terminology and statistical issues appears in the Appendix A. Next, an introduction to seven areas of advanced application will be provided, selected examples will be discussed, and technical guidance for those who may want to apply the technique in the future will be provided.

Advanced Applications of Latent Variable Techniques

Reflective vs. Formative Indicators

One type of advanced application addresses questions related to the direction of relationships between latent variables and their indicators. As noted earlier, Figure 1 specifies latent variables as causes of manifest variables. This specification is based on the premise that the constructs signified by the latent variables produce behavior that is captured by the measures that constitute the manifest variables. Such measures are termed *reflective*, meaning that they are reflections or manifestations of underlying constructs (Edwards & Bagozzi,

2000; Fornell & Bookstein, 1982). Reflective measurement characterizes most applications of structural equation modeling and confirmatory factor analysis in management research.

In some instances, the direction of the relationship between latent and manifest variables is reversed, such that measures are treated as causes of constructs (Bollen & Lennox, 1991; Edwards & Bagozzi, 2000; MacCallum & Browne, 1993). These measures are called *formative*, meaning that the measures form or produce their associated construct (Fornell & Bookstein, 1982). A frequently cited example of formative measurement is socioeconomic status, which is viewed as a composite of social and economic indicators such as occupation, education, and income (Hauser & Goldberger, 1971; Marsden, 1982). In management research, measures consistent with a formative approach include group heterogeneity specified as the sum of differences on race, gender, and occupation (Jarley, Fiorito & Delaney, 1997), job embeddedness as a function of fit, linkages, and sacrifice regarding the organization and community (Mitchell, Holtom, Lee, Sablynski & Erez, 2001), and career success as a function of salary, job level, and number of promotions (Judge & Bretz, 1994).

From a modeling perspective, key distinctions between reflective and formative measures can be seen by comparing Figure 1 with Figure 2, the latter of which respecifies the manifest variables of LV1, LV2, and LV3 as formative. Several points regarding this respecified model are worth noting. First, LV1, LV2, and LV3 are now endogenous rather than exogenous, given that they are each dependent variables with respect to their indicators. Second, the manifest variables themselves do not include measurement errors. Rather, errors in the measurement of LV1, LV2, and LV3 are captured by their residuals, which signifies the part of each latent variable that is not explained by its indicators. Third, the indicators of LV1, LV2, and LV3 are now exogenous, and their covariances with one another are freely estimated. If the model also included latent exogenous variables, then the covariances between these variables and the formative indicators could be modeled by respecifying the formative indicators as latent exogenous variables with single indicators, fixed unit loadings, and no measurement error. Under this specification, the formative indicators would equal their corresponding latent variables, and the covariances of the indicators with one another and with latent exogenous variables would be captured in the Φ matrix.

The use of formative measures in structural equation models introduces several complexities. At the outset, it is necessary to decide whether measures should be considered formative or reflective. In management research, measures are often treated as formative when they describe different facets or aspects of a general concept (e.g., Blau, Merriman, Tatum & Rudmann, 2001; Westphal & Zajac, 2001). However, as implied by the arrows in Figure 2, formative measures are not merely facets of a general construct. Rather, they are viewed as *causes* of the construct, such that variation in the measures produces variation in the construct. Mitchell et al. (2001) addressed the issue of causality regarding their measure of embeddedness, stating that embeddedness does not cause people to attain fit, form linkages, and make sacrifices with their organizations or communities. Instead, they argued that "those activities *cause* the person to become embedded" (Mitchell et al., 2001: 1111 emphasis added).

From a theoretical standpoint, it is often reasonable to view specific constructs as causes of general constructs. For instance, satisfaction with specific job facets may affect satisfaction with the job as a whole. However, this reasoning does not warrant the conclusion that specific measures cause general constructs, because such measures are indicators of specific con-
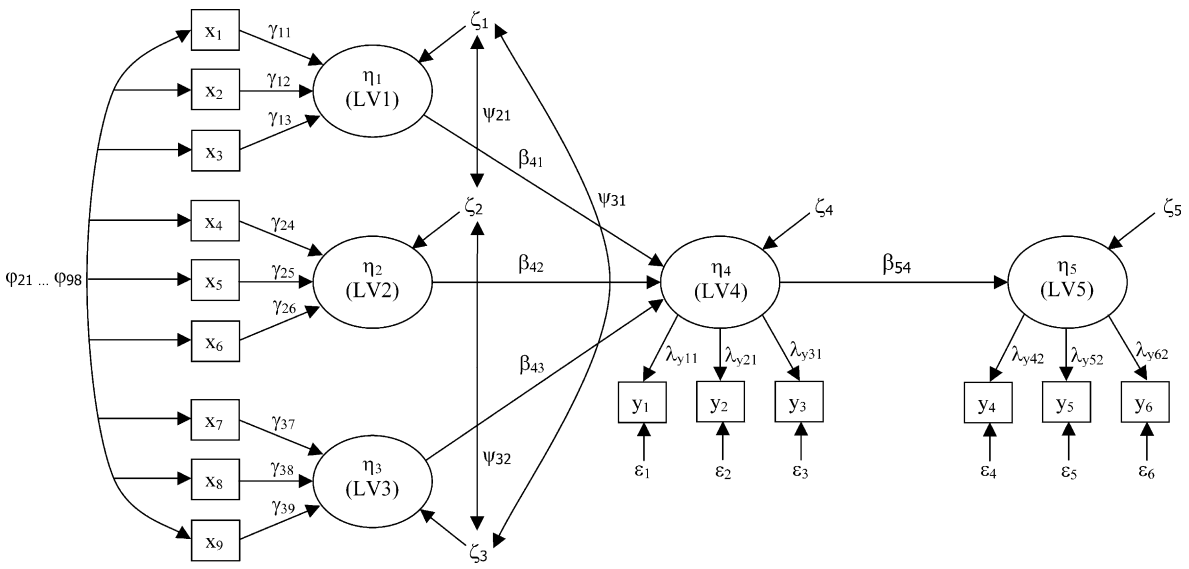
Figure 2. Model with formative indicators.

structs, not the constructs themselves. It is these specific constructs, not their measures, that should be regarded as causes of general constructs. This notion is consistent with arguments advanced by Mitchell et al. (2001), who stated that *activities* represented by measures of fit, linkages, and sacrifice, not the measures *per se*, are causes of embeddedness. To serve as causes of constructs, measures must satisfy conditions for causality analogous to those that apply to causality among constructs (Cook & Campbell, 1979; Edwards & Bagozzi, 2000).

If it is defensible to specify measures as formative, it is then necessary to ensure that the model containing the measures is identified. To identify the paths relating the formative measures to their construct, the following conditions must be met: (a) the construct must be specified as a direct or indirect cause of at least two manifest variables; and (b) the variance of the residual of the construct must be fixed, or at least one of the covariances between the measurement errors of the manifest variables caused by the construct must be fixed (Bollen & Davis, 1994; Edwards, 2001; MacCallum & Browne, 1993). These conditions are met by the model in Figure 2, given that the indicators of LV1, LV2, and LV3 are indirect causes of the six manifest variables assigned to LV4 and LV5, and the covariances among the measurement errors of these manifest variables are fixed to zero. Under these conditions, the variances and covariances of the residuals on LV1, LV2, and LV3 can be freely estimated. The residual variances of LV1, LV2, and LV3 will represent the variance in each construct not explained by its measures and is analogous to measurement error.

Models with formative measures also create interpretational difficulties. Some of these difficulties involve evidence needed to evaluate the construct validity of formative measures. Diamantopoulos and Winklhofer (2001) indicated that formative measures should meet four criterion: (a) the domain of content covered by the measures should be clearly specified; (b) the measures should constitute a census of the content domain, covering all of its facets; (c) the correlations among the measures should be modest to avoid multicollinearity; and (d) the construct associated with the measures should exhibit meaningful relationships with criterion variables. Although the first and second criteria are reasonable, the third and fourth criteria may result in eliminating measures, thereby altering the meaning of the construct.

Other difficulties involve the interpretation of the construct represented by formative measures. Typically, the meaning of a construct is inferred from the paths linking the construct to its measures. However, the paths linking formative measures to their construct are identified entirely by the covariances between the measures and measures of other constructs in the model. For instance, the paths linking x_1, x_2, and x_3 to LV1 are determined not by the covariances among x_1, x_2, and x_3, but instead by the covariances of these variables with the indicators of LV4 and LV5 (i.e., y_1, y_2, y_3, y_4, y_5, and y_6). Hence, the paths linking formative measures to their construct, and thus the interpretation of the construct itself, will vary depending on the other measures that happen to be included in a model. Further ambiguity is created by the residual on the construct (i.e., ζ_1, ζ_2, and ζ_3 in Figure 2). By definition, a residual represents unknown factors excluded from the model. As the variance of the residual increases, the meaning of the construct becomes progressively ambiguous. We have encountered situations where the residual accounts for 90% of the variance of constructs with formative measures. Certainly, the meaning of a construct is elusive when most of its variance is attributable to unknown factors.

Given the complications and drawbacks associated with formative measures, it is reasonable to question whether formative measures should be used at all. At present, we believe that

management researchers should continue to consider formative measures when developing and testing structural equation models. At the same time, we urge researchers to carefully consider the theoretical and philosophical conditions that formative measures must satisfy, and we emphasize that researchers who use formative measures are likely to encounter difficulties regarding model identification and interpretation. However, as noted previously, we have found that formative measures are often better treated as reflective measures of constructs that cause the construct initially represented by the formative measures. Models specified in this manner can be specified and estimated using procedures for handling multidimensional constructs, as described in the following section.

Multidimensional Constructs

A second application of advanced causal modeling methods involves designs where the latent variables include different dimensions of an overarching construct. Latent variables such as those in Figure 1 are often conceived as unidimensional constructs, meaning that each latent variable represents a single conceptual entity and its manifest variables serve as alternative indicators of that entity. For instance, overall job satisfaction is a unidimensional construct when it is conceptualized as a summary affective evaluation of the job and measured by indicators that each describe satisfaction with the job as a whole (Ironson, Smith, Brannick, Gibson & Paul, 1989). Latent variables can also be viewed as multidimensional constructs, which comprise several distinct but related dimensions that are collectively treated as a single theoretical concept (Law, Wong & Mobley, 1998). For example, overall job satisfaction is a multidimensional construct when it is defined as the combination of satisfaction with specific job facets (Smith, Kendall & Hulin, 1969; Warr, Cook & Wall, 1979).

In management research, latent and manifest variables are usually specified as shown in Figure 1 regardless of whether the latent variables refer to unidimensional or multidimensional constructs. When constructs are unidimensional, the specification in Figure 1 is appropriate, provided the indicators of the construct are reflective rather than formative. However, when constructs are multidimensional, the specification in Figure 1 has two shortcomings. First, multidimensional constructs are often conceptualized as composites of their dimensions, such that the paths run from the dimensions to the construct. In such instances, the dimensions of the construct are analogous to formative indicators such as those in Figure 2, as opposed to the reflective indicators in Figure 1. Second, the indicators of a multidimensional construct are not manifest variables, as shown in Figure 1, but instead are specific latent variables that signify the dimensions of the construct. These latent variables require their own manifest variables as indicators, such that the manifest variables and the multidimensional construct are separated by latent variables that constitute the dimensions of the construct. Because multidimensional constructs are not directly linked to manifest variables, models that contain multidimensional constructs introduce complications that are not found in conventional structural equation models.

Edwards (2001) developed a framework for specifying and estimating multidimensional constructs. This framework is organized around two key distinctions. The first is the direction of the relationships between the multidimensional construct and its dimensions. When the relationships flow from the construct to its dimensions, the construct is termed *superordinate*, meaning that the construct is a general entity that is manifested or reflected by the specific

dimensions that serve as its indicators. When the relationships flow from the dimensions to the construct, the construct is called *aggregate*, meaning that the construct is a composite of its dimensions. The second distinction is whether the multidimensional construct is a cause or effect of other constructs within a larger causal model. This distinction has important implications for the specification and estimation of models with multidimensional constructs. These two distinctions combine to yield four prototypical models, as outlined below.

The first model contains a superordinate construct as a cause. This model is illustrated in Figure 3, in which the multidimensional construct is LV4, the dimensions of the construct are LV1, LV2, and LV3, and the effects of the construct are LV5, LV6, and LV7. The distinction between the dimensions and effects of the construct is a matter of interpretation, given that both represent first-order factors relative to the second-order factor (SOF) that signifies the multidimensional construct. However, unlike most second-order factor models, the superordinate cause model may include relationships among the effects of the construct, either through correlated residuals (as in Figure 3) or causal paths between the effects of the construct. In contrast, the model does not include relationships among the dimensions of the multidimensional construct, based on the premise that the construct is the only source of covariation among its dimensions. According to the model, the relationships between the dimensions and effects of the construct are spurious, given that the dimensions and effects both depend on the multidimensional construct. Drawing from management research, the model in Figure 3 is applicable when personality is defined as a multidimensional construct indicated by specific personality facets that causes various aspects of job performance (Barrick & Mount, 1991).

The second model represents an aggregate construct as a cause. This model is shown in Figure 4, which again depicts the multidimensional construct as LV4, the dimensions of the construct as LV1, LV2, and LV3, and the effects of the construct as LV5, LV6, and LV7. In contrast to the superordinate cause model, the aggregate cause model contains paths leading from the dimensions to the construct. The covariances among the dimensions of the construct are freely estimated, based on the principle that associations among exogenous variables arise from forces outside the model. The variance of the residual on the multidimensional construct may be fixed to define the construct as a weighted composite of its dimensions or freed to represent aspects of the construct not captured by its dimensions. The model specifies the relationships between the dimensions and effects of the constructs as indirect, such that the dimensions combine to produce the construct which in turn influences its effects. The aggregate cause model would be relevant for research that conceptualizes total life stress as a composite of stress associated with job and personal life events and uses total life stress to predict psychological distress and withdrawal behavior (Bhagat, McQuaid, Lindholm & Segovis, 1985).

The third model, shown in Figure 5, portrays a superordinate construct as an effect. This model is closely related to the aggregate cause model, in that both models contain paths to and from the multidimensional construct. However, in the superordinate effect model, the paths to the construct emanate from causes of the construct, and the paths from the construct are directed toward the dimensions of the construct. Because the construct is considered the only source of covariation among its dimensions, the covariances of the residuals of the dimensions are fixed to zero. In addition, the variance of the residual of the multidimensional construct must be freed to capture the variance in the construct not
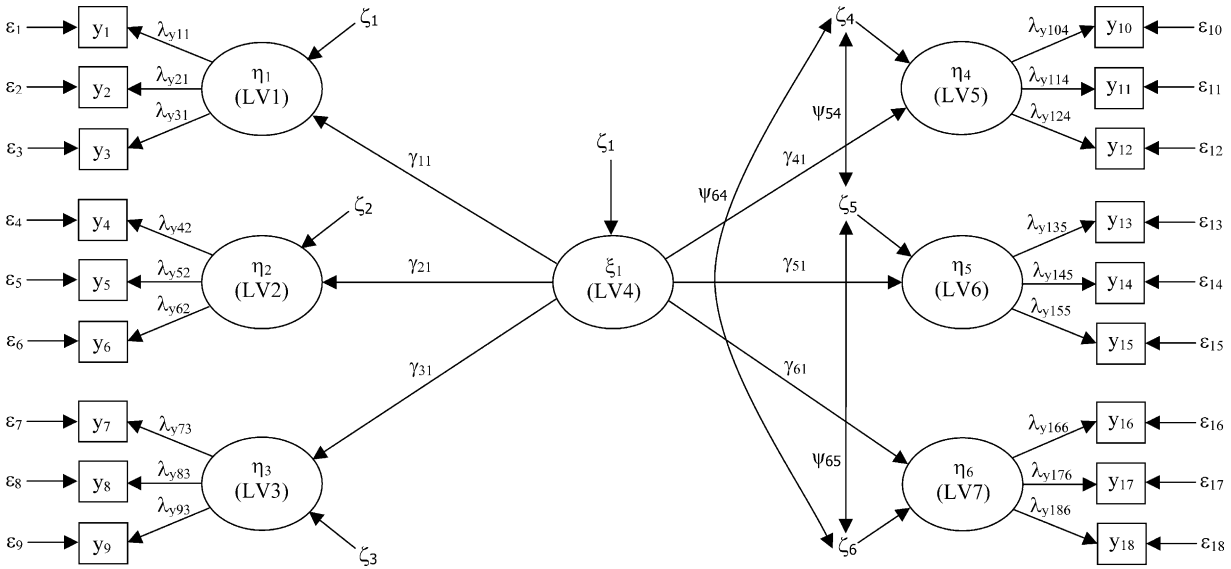
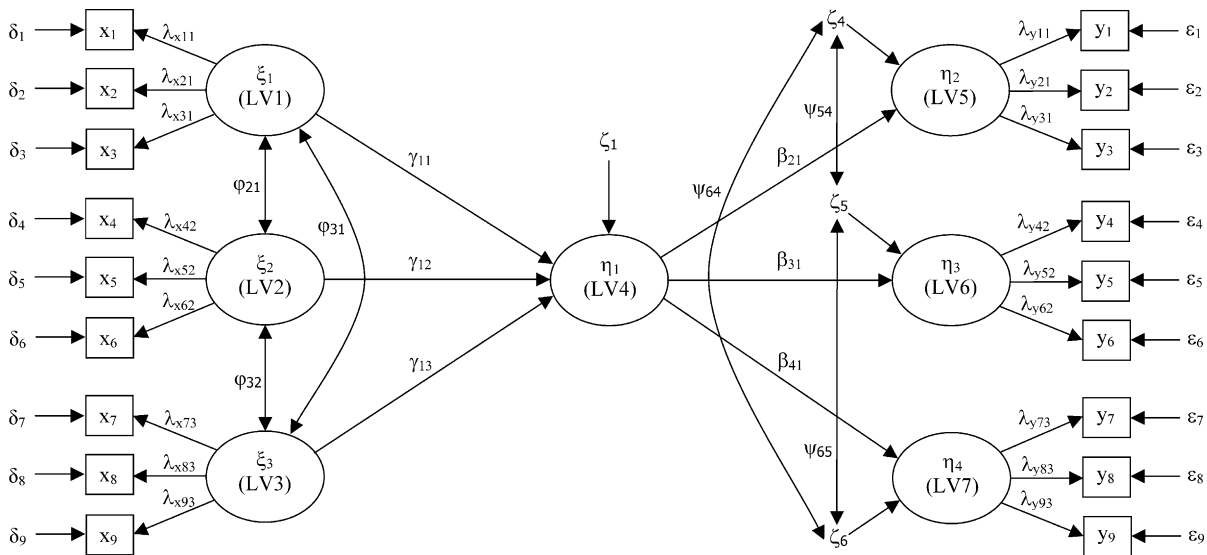Figure 3. Model with superordinate construct as cause.

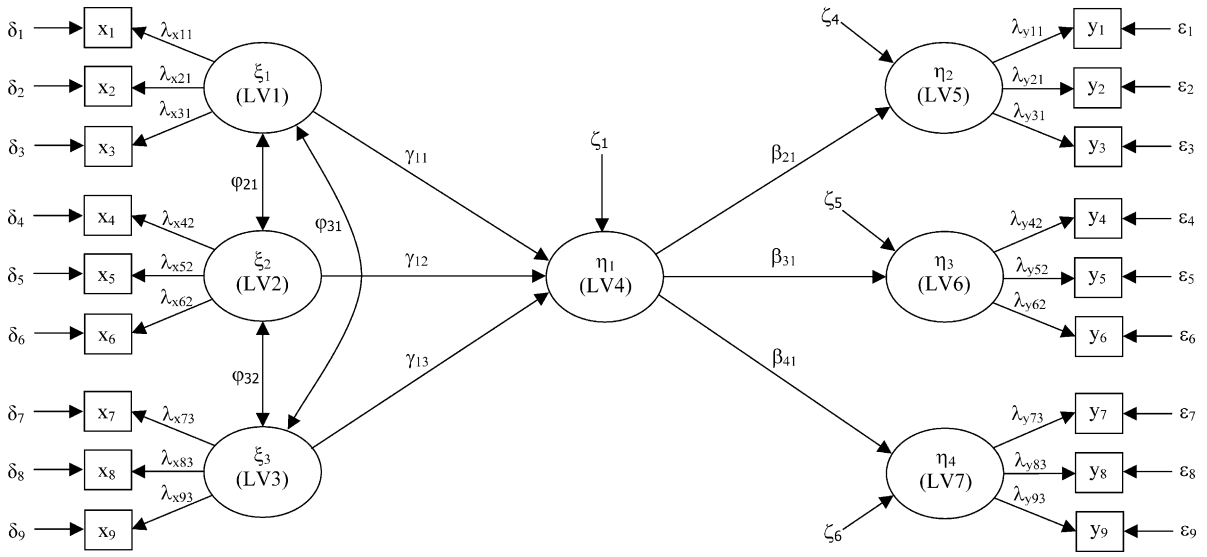Figure 4. Model with aggregate construct as cause.

Figure 5. Model with superordinate construct as an effect.

explained by its causes. The superordinate effect model depicts the relationships between the causes and dimensions of the construct as indirect, whereby the causes influence the construct which in turn produces variation in its dimensions. This model would be applicable in studies that treat influence tactics as specific dimensions of general constructs that signify hard, soft, and rational influence strategies, which are caused by various situational and personal factors (Farmer, Maslyn, Fedor & Goodman, 1997).

Finally, the fourth model specifies an aggregate construct as an effect, as shown in Figure 6. Unlike the preceding models, all paths in the aggregate effect model are directed toward the multidimensional construct. The model includes covariances among the dimensions and among the causes of the construct (as shown in Figure 6) as well as covariances between the dimensions and causes of the construct, given that all of these latent variables are exogenous. Whereas the preceding three models specify the relationships between the dimension and causes or effects of the construct as spurious or indirect effects, the aggregate effect model implicitly specifies the relationships between the dimensions and causes of the constructs as direct effects. These effects are collapsed into the paths relating the causes to the construct, and the magnitudes of these paths depend on the magnitudes of the indirect effects relating the causes to each dimension of the construct. The aggregate effect model would be appropriately applied in research that examines the effects of work experiences on work withdrawal defined as a composite of specific withdrawal behaviors, such as absenteeism, lateness, and escapist drinking (Hanisch, Hulin & Roznowski, 1998).

In summary, the framework developed by Edwards (2001) may be used to compare broad versus specific constructs on a study-by-study basis. If the examples considered by Edwards (2001) are representative, it is likely that models with multidimensional constructs will often be rejected in favor of models that use the dimensions of the construct as a set and omit the multidimensional construct from the model. Future research should investigate these issues in areas beyond the job satisfaction, personality, and work withdrawal domains mentioned in this review.

Method Variance

A third application of advanced causal modeling techniques involves attempts to deal with problems associated with common method variance. As noted previously, the measurement model that describes the relationships between the latent variables and their indicators acknowledges that the indicators contain measurement error, which is represented by the delta/epsilon symbol parameters. This measurement error is comprised of two components, random and systematic. The measurement model portrayed thus far is not capable of distinguishing between these two components. However, under some research designs advanced structural equation models yield estimates of both components, with the values for the systematic components being referred to as representing method variance. In recent years there have been two main streams of research on method variance that utilize S.E.M. techniques, one which investigates method variance associated with variables that can be directly measured, and the other which examines method variance with research designs in which multiple measurement methods are used.

Classic examples of measured method effect variables include social desirability and negative affectivity, each of which can be assessed with paper and pencil measures that can
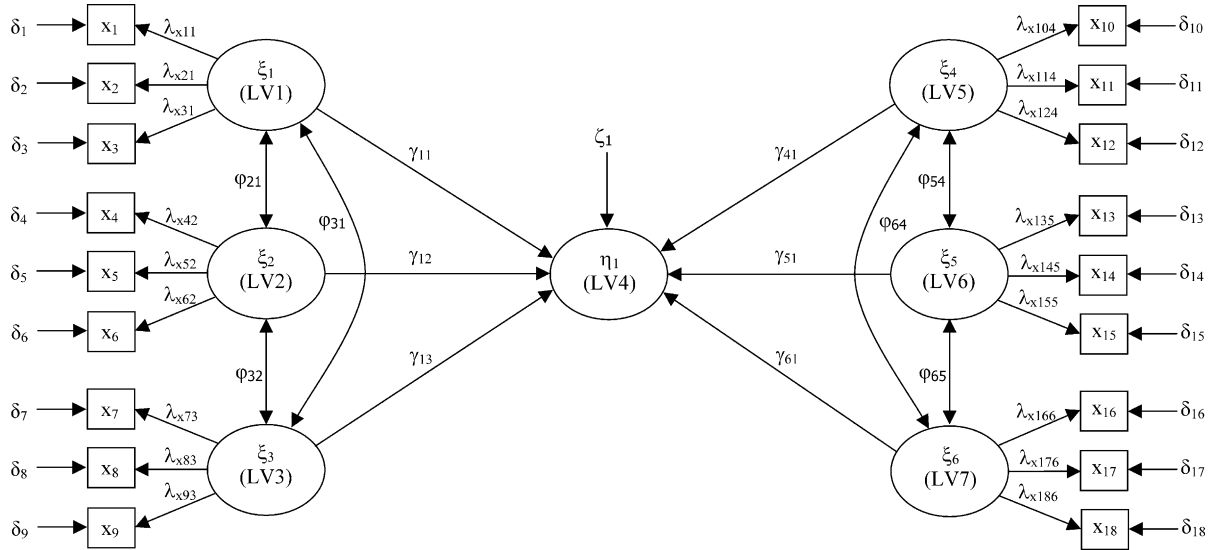
Figure 6. Model with aggregate construct as an effect (covariances relating ξ_1, ξ_2, and ξ_3 to ξ_4, ξ_5, and ξ_6 are omitted from the figure but included in the model).

be included along with substantive variables in the questionnaire. An important advancement linking S.E.M. techniques with this research design was the model specification that allowed a latent variable associated with a method effect variable to be associated with the indicators of substantive latent variables. This type of "complex" measurement model includes factor loadings linking the method effect latent variable to the substantive indicators, and these factor loadings represent the type of measurement contamination process associated with variables such as social desirability and negative affectivity. A confirmatory factor analysis example of such a model is shown in Figure 7a (which incorporates three of the latent variables from models discussed previously).

With this model, the method effect factor is directly associated with its own indicator (x_i), and this factor is assumed to be uncorrelated with the three substantive latent variables. Typically, evidence related to method variance with such a model is obtained in several ways. First, this model is compared with an alternative model that forces all of the method factor loadings to zero via a chi-square difference test. Second, assuming this comparison favors the model with the method factor loadings, the statistical significance of these loadings is examined. Third, if completely standardized estimates are obtained, the squared values of the method factor loadings can be interpreted as the percent of indicator variance that is method based (while the squared loadings linking the substantive latent variables with their indicators interpreted as the percent of substantive variance). Finally, the comparison of estimates of substantive relationships from models with and without method factor loadings shows the potential biasing effects due to method variance.

Early applications of this approach to measured method effect variables investigated negative affectivity with a variety of organizational behavior variables (e.g., Munz, Huelsman, Konold & McKinney, 1996; Williams & Anderson, 1994; Williams, Gavin & Williams, 1996). Moving beyond the focus on affectivity, Schmitt, Pulakos, Nason and Whitney (1996) examined likeability and similarity of raters as a source of method variance associated with predictor-related criterion bias and found there was no effect on estimates of the relationships between the predictors and criteria. Alternatively, Barrick and Mount (1996) examined response distortion associated with self-deception and impression management as sources of method variance and found distorting effects on personality measures of conscientiousness and emotional stability associated with both self-deception and impression management, but their results also indicated that this distortion did not attenuate the predictive validities of either personality construct.

A more recent study extended the investigation of method variance using S.E.M. techniques to the performance appraisal area. Keeping and Levy (2000) focused on the measurement of performance appraisal reactions, including system and session satisfaction, perceived utility and accuracy, and procedural and distributive justice. Both positive and negative affectivity were examined as method effect variables. Following approaches described by Williams et al. (1996), their confirmatory factor analysis results indicated that neither positive or negative affect resulted in method biases in the performance appraisal reaction measures.

Williams, Hartman and Cavazotte (2003) provide a final example of a measured method effect variable as they present an alternative approach to the analysis of marker variables discussed by Lindell and Whitney (2001). A marker variable is measured but assumed to be theoretically unrelated to substantive variables, and Williams et al. describe latent variable
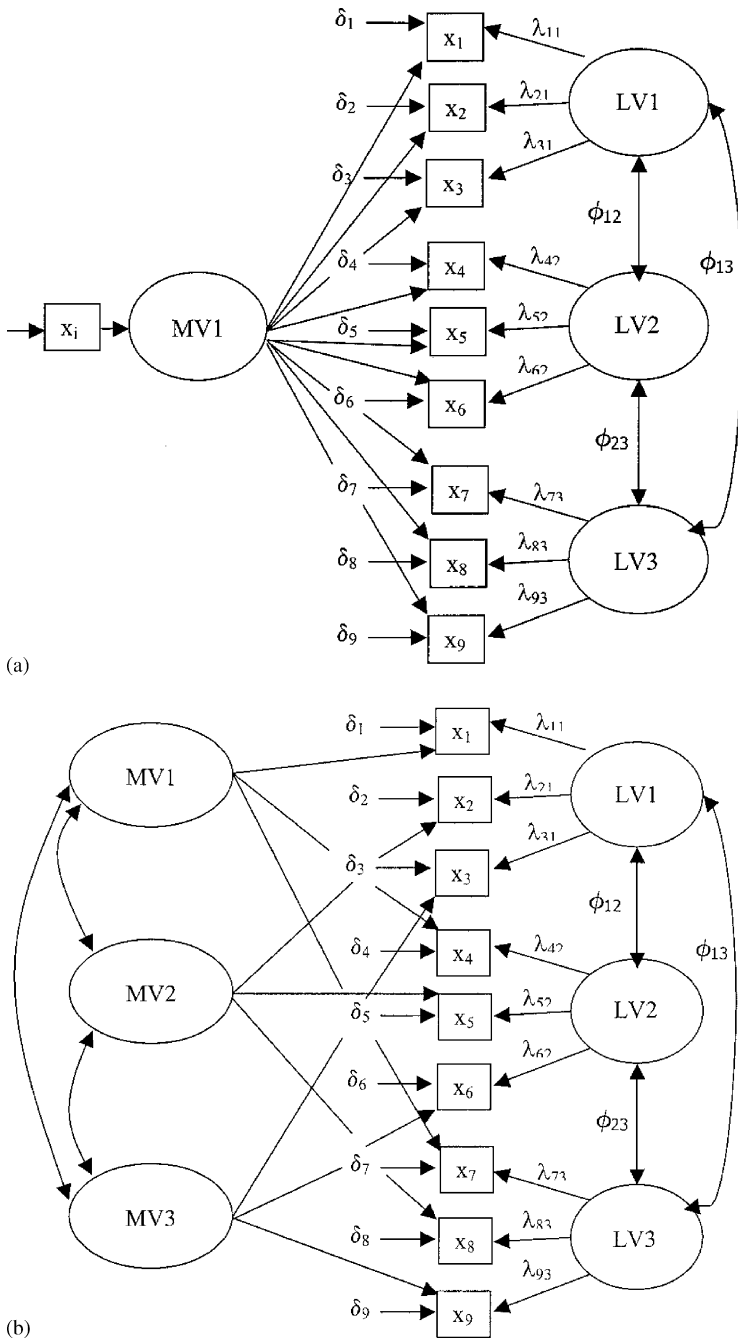
Figure 7. (a) Method measurement model; (b) multi-trait multi-method measurement model.

techniques that have advantages relative to the partial correlation approach presented by Lindell and Whitney (2001). The method effects associated with three substantive variables (leader member exchange, job complexity, role ambiguity) due to a marker variable (benefit administration satisfaction) were examined using latent variable techniques. The results showed that although method variance associated with the marker variable was present, it did not significantly impact the correlations among the three substantive variables.

As mentioned previously, in addition to advanced applications of S.E.M. techniques involving measured method effect variables, another stream of research on method variance has involved designs in which multiple methods of measurement are used. In this literature, the multiple methods involved range from different scaling formats for the same questionnaire items (e.g., semantic differential vs. Likert response formats) to completely different sources of information (e.g., self-report, peer, supervisor ratings). This design is often referred to as multitrait-multimethod, in that early applications were used with multiple measures of personality constructs. A confirmatory factor analysis model for this type of design involving the same three latent variables incorporated in preceding examples, each measured with three indicators based on different methods, is shown in Figure 7b. In this example, indicators x_1, x_4, and x_7 are measured using the same method, x_2, x_5, and x_8 are measured using a second method, and the remaining indicators are measured using the third method.

The model shown in this figure differs from the model for measured method effect variables in two important ways. First, each of the three method factors associated with the three measurement methods is not directly measured (and as such is not linked to its own indicators). Second, each method factor is only associated with one indicator for each substantive latent variable (unlike with the measured method effect factor, which is linked with all substantive indicators). It should also be noted that with this model, the three method factors are themselves correlated, but they are assumed to be uncorrelated with the three substantive latent variables. Evaluation of method variance in analysis of this type of model parallels that of the measured method effect model, in that a model with the method factor loadings is compared to a model without these loadings, the significance of the method factor loadings is examined, and the squared method factor loadings are used to partition the indicator variance into substantive, method, and random error components.

Over the years there have been many applications of this design in organizational research. Recently, Doty and Glick (1998) reanalyzed data from 28 of these studies using the S.E.M. approach. Their results indicated that 46% of the variance in the indicators was accounted for by trait factors, while 32% was accounted for by method factors. They also compared the substantive factor correlations from models with and without the method factors and concluded that the method variance resulted in a 26% bias in observed relationships among the substantive factors. Doty and Glick noted that this bias did not invalidate many of the research findings from these studies.

An alternative model for MTMM designs is referred to as the correlated uniqueness model. This model is different from the one just discussed in that there are no method factors associated with the indicators in the model to account for method variance. Instead, the systematic variance shared by indicators is accounted for by allowing for correlations among the error variance (uniqueness) terms for indicators measured using the same method. Thus, for this model, such correlations would be allowed among the x_1, x_4, and x_7 indicators, among the x_2, x_5, and x_8 indicators, and among the x_3, x_6, and x_9 indicators. However, no

correlations are allowed among error terms of indicators measured using different methods, implying that this model assumes that the methods themselves are uncorrelated. Conway (1996) reviewed studies of multitrait-multimethod matrices involving job performance ratings provided via self-reports and by ratings from sources such as supervisors, peers, and subordinates. They applied the correlated uniqueness model and found the self-ratings had a mean proportion of method variance of .32.

Finally, in efforts aimed at improving understanding of methods for the analysis of this type of data, Conway (1998) presented an averaging method for determining the amount of method variance in indicators used with a correlated uniqueness model. Subsequently, Scullen (1999) provided a different approach that provides a more precise and unbiased estimate of the amount of method variance associated with measurement methods with correlated uniqueness models, while Lance, Noble and Scullen (2002) have provided a critique indicating that the original approach involving method factors may be preferable to the correlated uniqueness approach due to theoretical and substantive shortcomings in the latter approach.

In summary, extensions of the basic measurement model shown in Figure 1 to include efforts at modeling systematic shared variance among indicators due to method of measurement have been popular. Research applying these techniques has yielded evidence about the extent of bias in research findings that could not be obtained using traditional approaches such as partial correlation and multiple regression. Future research should extend these studies by using designs that might allow simultaneous investigation of measurement and substantive processes with variables beyond those previously studied like negative affectivity and social desirability. Other discussion of analysis of method variance via S.E.M. techniques can be found in Conway (2002) and Williams, Ford and Nguyen (2002).

Measurement Equivalence or Invariance

A fourth type of advanced application of advanced causal modeling methods is relevant for designs in which the same measures or indicators are used in multiple samples. In some instances, the conceptual basis of a study requires that the model be tested separately with two (or more) groups (see Figure 8). Assume, for example, that the original model in Figure 1 represents the work adjustment process of individual employees, and Group One in Figure 8 is U.S. employees high in individualism, and Group Two consists of Chinese employees high in collectivism. The model could also represent the linkages between internal quality initiatives and their effects on customer attitudes or behaviors, and one group is a set of teams or organizations that received a quality oriented intervention, and the other, control group of teams or organizations, did not. A final example of this setting includes research that investigates gender or race as moderators, in which the multiple samples are based on gender or race.

Regardless of whether or not structural parameters are being compared to test hypotheses (which will be discussed in a later section), potential concerns of equivalence actually exist within all of the various components of the measurement and structural models in any S.E.M. application. Testing the equivalence of structural parameters without first establishing equivalence at the other levels may indeed result in inaccurate conclusions (Vandenberg & Lance, 2000). For example, evidence showing that the link from LV4 to LV5 (β_{21} from Figure 8) is statistically greater in strength for the individualistic group (Group 1) than for
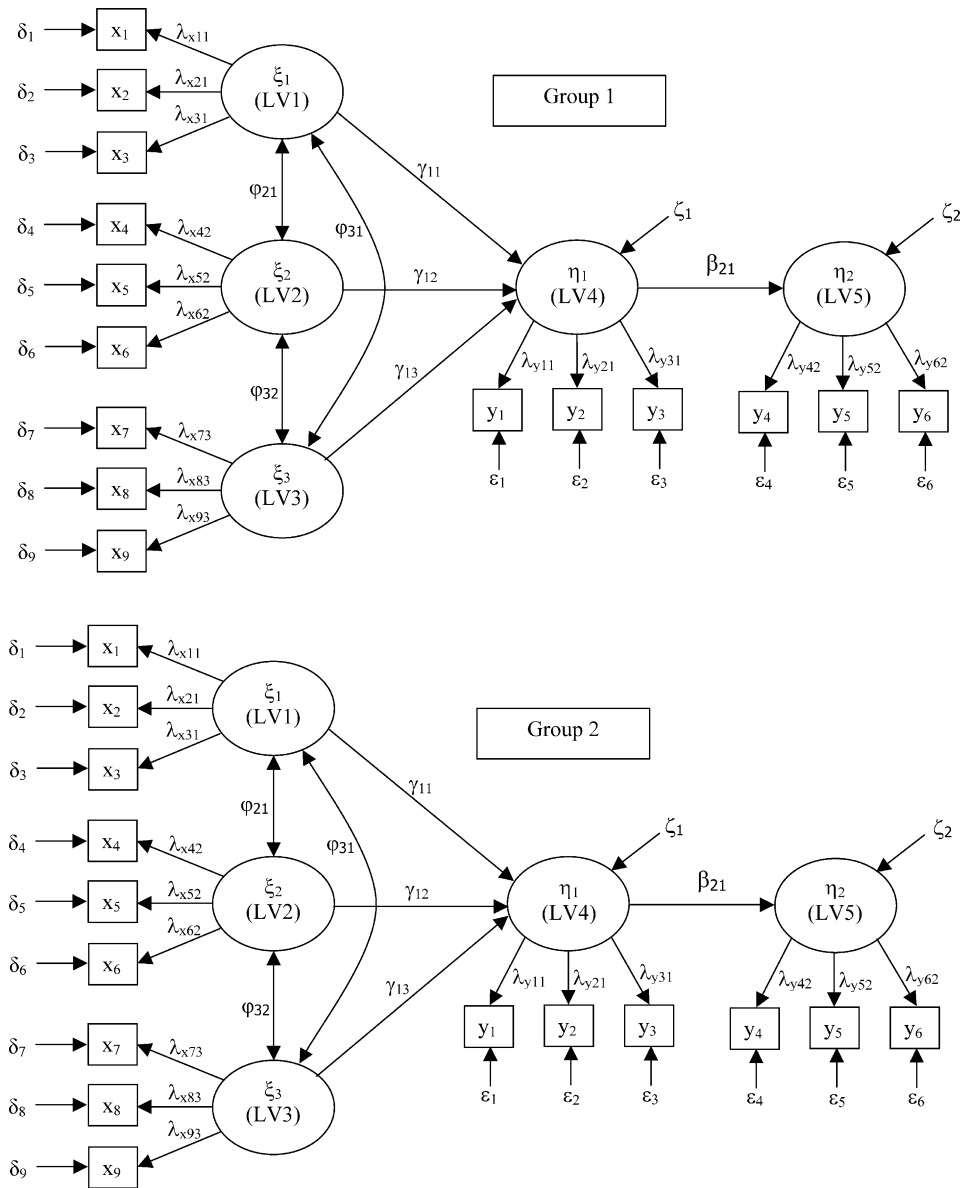
Figure 8. Model for cross-group comparison.

the collectivistic group (Group 2) may be confounded due to the *unaccounted for* differences in factor loadings across the two groups. In other words, the factor loadings of the individualistic group (Λ^g, or $\lambda_{y11}, \lambda_{y21}, \ldots \lambda_{y62}$ from Figure 8) for LV4 and LV5 are much stronger than the factor loadings of the collectivistic group ($\Lambda^{g'}$, or $\lambda_{y11}, \lambda_{y21}, \ldots \lambda_{y62}$ from Figure 8) for LV4 and LV5, and it is this statistical mechanism that causes the difference

between groups on β_{21}, and not some underlying conceptual mechanism. Because the lack of invariance in factor loadings is unaccounted for, the researcher may draw an inaccurate conclusion concerning the difference between groups in the structural parameter.

A thorough technical treatment of all of the measurement equivalence or invariance (hereafter referred to as ME/I) tests may be found in Vandenberg and Lance (2000). Collectively, the crux of all of the research on ME/I is that cross-group comparisons, regardless of whether through testing for mean differences using traditional tests (e.g., ANOVA) or for differences in S.E.M. parameters, *require* (i.e., demand) prerequisite assumptions of invariant measurement operations across the groups being compared.

The example above where metric invariance was found untenable, and therefore, resulted in the wrong conclusion concerning the hypothesized differences between the structural parameter is just one case in point as to how ambiguity may slip into interpreting results about group differences. As another example, consider the most severe case of not supporting configural invariance, with the last scenario in the paragraph above whereby one set of teams underwent some intervention process to improve the linkages between quality delivery mechanisms and quality outcomes, and the control set of teams that did not. For this scenario further assume that LV1–LV3 in Figure 8 are the quality delivery mechanisms and it is the teams' perceptions that are used to operationalize those latent variables. It would be expected that the comparison of the intervention group to the control group would indicate that the relationships among the latent variables (e.g., LV1–LV3 to LV4) were not invariant or equivalent; that is, the strength of associations was indeed stronger for the intervention group than for the control group. However, it could be the case that the very intervention process itself (because of its high impact) caused the teams in the intervention group to form the constructs for the first time (Feldman & Lynch, 1988), or to alter their cognitive frame of reference regarding the quality delivery mechanisms (Golembiewski, Billingsley & Yeager, 1976). In any event, the constructs presumed to drive responses to the items in the intervention group are not the same as the constructs driving responses to the same set of items in the control group. That is, even though the items are identically worded in both groups, they are referencing different conceptual content domains (Lance & Vandenberg, 2001). Therefore, it would be impossible to compare groups. It is for this reason that the test for configural variance precedes the majority of all other ME/I tests. If the configural invariance hypothesis is not supported, then undertaking the remaining tests is moot. It makes no sense to test for metric invariance, for example, when items are loading onto different conceptual or cognitive frames of reference (the latent variable).

A major point of Cheung and Rensvold (1999), and Vandenberg and Lance (2000) among others is that, "(a) knowingly or unknowingly, researchers invoke assumptions about measurement equivalence in conducting tests of substantive hypotheses; (b) although rarely tested, *these assumptions are routinely and straightforwardly testable as extensions to the basic CFA framework*; and (c) if not tested, violations of measurement equivalence assumptions are as threatening to substantive interpretations as is an inability to demonstrate reliability and validity" (Vandenberg & Lance, 2000: 6). The italicized statement in Point b emphasizes that the assumptions of ME/I can be easily tested. Continuing with the configural invariance example, this could be evaluated by not evoking any relationships among the latent variables (i.e., a structural model), and putting all measures regardless of whether they are exogenous or endogenous into one measurement model. That is, the same pattern

of free and fixed factor loadings is invoked in both groups. This test is based on the assumption that the factor structure is the most reasonable empirical map of the underlying conceptual or cognitive frame of reference used to make item responses (Vandenberg & Self, 1993). If the fit indices are strong (i.e., supporting that the measurement model is the same in both groups), then configural invariance is tenable. If, though, model fit is poor, then configural invariance between the groups may not be assumed. Indeed, an exploratory factor analysis may uncover different factor structures between groups (e.g., three factors characterize responses of one group, whereas a different numbers of factors or a different factor pattern configuration characterize the other group).

If configural invariance is supported, then the next test in the sequence is that for metric invariance. The specific test of metric invariance is evoked by fixing the factor loadings of like items to be equivalent or equal between groups. If these equality restrictions don't result in a significant worsening of model fit (relative to fit indices generated by the test of configural invariance above), then metric invariance is tenable. A significant worsening in model fit, however, would indicate that one or more of the items are not truly metrically equivalent, and the researcher may have to engage in a partial metric invariance strategy to identify the aberrant items. The end result will be a model where some item loadings are specified as equivalent between groups, and others are freely estimated within the groups. This metric invariance pattern is held in place as the next test for scalar invariance is undertaken. Again, the test starts with fixing scalar values of like items to be equivalent between groups, and depending on the indices of model fit, either supporting scalar invariance or also having to engage in a partial scalar invariance strategy.

To conclude, as recently highlighted by Vandenberg (2002), ME/I testing procedures have traditionally been viewed as means to detect problems with the quality of the measurement system—the view adopted for purpose of this review as well. They can, however, be used in a hypothesis testing framework. Vandenberg (2002) provides several cases in point to illustrate this application of ME/I test. For example, some interventions purportedly alter recipients' mental models of work. Assuming pre- and post-intervention data are collected, the test for configural invariance could conceivably detect that shift. In this scenario, though, not supporting configural invariance would be a "good" thing. Similarly, there may be cultural or other individual differences that permit a researcher to predict a priori which items on a particular scale are most sensitive to those differences. The metric invariance test could be used to test those predictions where once more not supporting invariance is the desired outcome.

Latent Growth Modeling

The fifth category of advanced application involves designs with longitudinal data collection, in which the same indicators are available from multiple points in time, and where the interest is in change in a latent variable across time but the indicators do not directly address change. The paths between the latent variables in Figure 1 (i.e., the structural model) typify the types of associations evaluated in the majority of S.E.M. applications; that is, associations among or between static levels on the focal variables. While many meaningful advances have come from such tests, a known limitation is the inability to unambiguously address questions concerning actual change along the constructs of interest (Chan, 1998, 2002; Chan & Schmitt, 2000; Collins & Sayer, 2001; Lance, Meade & Williamson, 2000;

Lance, Vandenberg & Self, 2000). Would, for example, the actual change in an independent variable (e.g., an increasing trajectory across time in an individual's organizational commitment) be associated with known outcomes of that variable (e.g., a decreasing trajectory across time in an individual's turnover intention)? The ability to address questions concerning change permits the researcher: (a) to step closer to the causality issue than is the case with tests among static levels of the variable; and (b) to make more accurate judgments about the effectiveness of some purposeful change initiative or about some event (e.g., a massive downsizing) known to bring change (e.g., in employees' feelings of commitment) in some conceptually relevant outcome. This limitation is in part the rationale given for decades justifying longitudinal studies. However, despite the fact that data were collected at different times, change is not being addressed with traditional analyses (Burr & Nesselroade, 1990; Collins & Sayer, 2001; Cronbach & Furby, 1970; Duncan, Duncan, Strycker, Li & Alpert, 1999; Lance, Vandenberg, et al., 2000; Rogosa, 1995).

While certainly not the sole reason, a major hurdle to incorporating actual change in research studies has been the absence of an analytical framework that is assessable to researchers. One such promising framework, however, is latent growth modeling (LGM) also referred to as latent trajectory modeling (Chan & Schmitt, 2000; Lance, Meade, et al., 2000; Lance, Vandenberg, et al., 2000). To illustrate, Figure 1 was modified to look like the model in Figure 9. As exhibited, LV1, LV2 and LV3 now represent the Time 1, Time 2, and Time 3 application of the same measures to the same individuals at three equally spaced intervals in time. Assume that a three-item measure of organizational commitment was given for a 12-month period with Time 2 occurring at the 6-month point and Time 3 at the 12-month point. Thus, and for example, λ_{11} in Figure 9 refers to the factor loading of the first commitment item on the Time 1 (LV1) latent variable in as much as λ_{12} refers to the loading of the same first commitment item but on the Time 2 (LV2) latent variable. Assume further that LV4 represents employee turnover intention at Time 3, and LV5 represents the frequency of turnover for the 6 months following Time 3 data collection. Unlike the LV5 in Figure 1 which was represented by three fictitious indicator variables, LV5 in Figure 9 has one indicator to be consistent with the example here that it represents turnover (0 = stay; 1 = leave).

Technically speaking, Figure 9 is a second-order factor model known in this context as a curve-of-factors model (Chan, 2002; Duncan et al., 1999). There are potentially simpler LGMs of the same hypothetical data underlying the fictional model in Figure 9 (see Duncan et al., 1999), but the SOF approach offers the greatest flexibility when the goal of the research is to examine the antecedents and consequences of change (Chan, 1998, 2002; Lance, Vandenberg, et al., 2000). A fundamental difference between Figures 1 and 9 are the matrices. For reasons provided in this article's section on higher-order models, it is necessary to use an all Y model (in LISREL terminology) to estimate the higher-order constructs, which in this illustration are the exogenous variables. That is, unlike Figure 1 where the arrows emanated from LV1–LV3 to LV4, the current model states that LV4 is a function of the two higher-order latent variables, intercepts and slopes. From this point forward, the intercepts latent variable will be referred to as the initial status latent variable while the slopes latent variable will be called the change latent variable because these names are more befitting of their function in this model. Finally, given that the data are repeated measures, the parameterization of the first-order measurement model for LV1–LV3 would assume, as shown in Figure 9, autoregression between like items across time, and therefore,
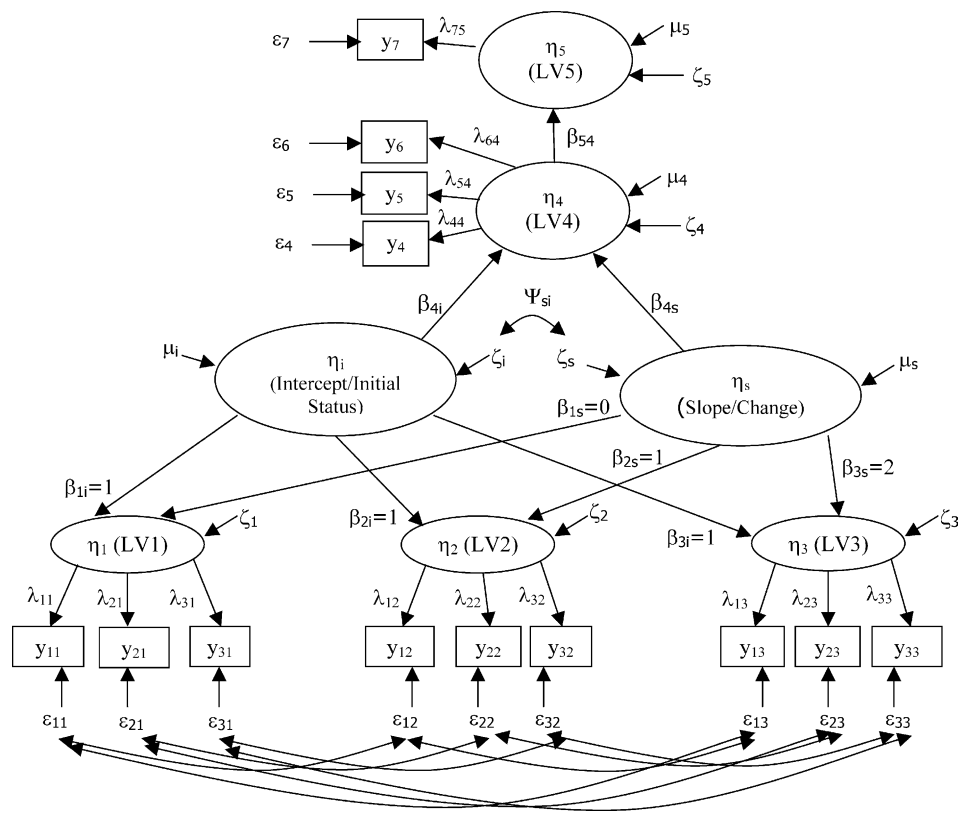
Figure 9. A hypothetical LGM.

would permit their disturbance terms to covary across time (e.g., ε_{11} with ε_{12} with ε_{13}, etc.) to account for any biases that this presents.

Several things are accomplished by fixing the loadings of the second-order initial status latent variable onto the first-order commitment latent variables to 1, and the loadings of the change variable to 0, 1 and 2 (see Figure 9). First, it locates the initial status latent variable at Time 1. Second, the scale of time is captured by or defined through the 0, 1, and 2 values on the loadings of the change latent variable. The latter pattern represents equally spaced intervals, but if for some reason, the Time 3 data collection had occurred 12 months after Time 2 (twice the interval length between Times 1 and 2), the pattern of fixed values would be 0, 1, and 3. Third, and perhaps most importantly, it identifies a trajectory of change for each individual in the database. Four types of potential trajectories have been suggested (see Duncan et al., 1999, pp. 27–28 for more complete descriptions).

The real advantages of LGM, though, are illustrated through an interpretation of the values. Thus, continuing with the parallel stability scenario above, in all likelihood, the covariance between initial status and change (Ψ_{si}) will be small and/or statistically nonsignificant. This means that regardless of a person's initial status on commitment, s/he changed positively in commitment across time. We should also expect a negative parameter estimate for β_{4i}, the path from initial status to LV4 (Time 3 turnover intention). The latter estimate is the typical one in that it is between static levels of the two focal latent variables; that is, between the initial status of the commitment latent variable located at Time 1, and the turnover intention latent variable at Time 3. The question, though, that piques the greatest interest among researchers and practitioners is, "if something were instituted to improve commitment, would there be a payoff in lower turnover intention, and consequently, lower turnover?" Or in "change" terminology, "if the commitment of employees were to change positively over time, would we observe lower turnover within our workforce?" Confidence that the answer is "yes" would be greatly enhanced if β_{4s}, the path from the change variable to LV4 (Time 3 turnover intention) were statistically significant and negative, and β_{54}, the path from LV4 to LV5 (Time 4 turnover), was statistically significant and positive. A negative β_{4s} would indicate that the greater an individual's rate of change on commitment across time (which in this hypothetical case is increasing), the lower his/her turnover intention, and the positive β_{54} means that the greater the intention, the greater the likelihood of actually leaving the organization.

Only a handful of empirical applications of latent growth models appear in the organizational sciences research literature. They clearly illustrate, however, the potential LGM has in making much stronger inferences from our data. Garst, Frese and Molenaar (2000), for one, demonstrated how long-term changes in the stressors impacting individuals (e.g., job insecurity, organizational problems, time pressures, etc.) were associated with increases in those individuals' strains such as depression, somatic stress, and irritation, and the implications these changes have on individual functioning. In another application, Chan and Schmitt (2000) used LGM to operationalize the adaptation process experienced by newcomers during the early organizational socialization period. They found that changes in how newcomers proactively seek out information and build relationships over time had relatively immediate effects upon such factors as task mastery and social integration into the new environment. In yet another study, Ployhart and Hakel (1998) used LGM to create trajectories of individuals' sales performance across a 5-year time period. They noted that performance

follows a classic s-learning curve, but that there were strong intraindividual differences in the change trajectories; that is, the performance of some individuals changed at faster or slower rates than others. Interestingly, though, Ployhart and Hakel (1998) also predicted and supported that the degree to which the individual garners empathy from others predicted both initial status and change in performance, as did the individual's persuasive abilities.

Lance, Vandenberg, et al. (2000) used LGM to operationalize the development (i.e., change) in newcomers' compliance and internalization commitment to the organization. They further predicted and largely supported that the development process (i.e., change) is a function of: (a) initially meeting newcomer expectations, (b) the level of cognitive dissonance experienced at organizational entry, and (c) the types of initial socialization experiences. Additionally, level of turnover intention was largely predicted by the change in internalization. Finally, Bentein, Vandenberg, Vandenberge and Stinglhamber (2003) predicted and supported the notion that the trajectory of individual change in commitment across time would be associated with the trajectory of individual change in turnover intentions; that is, the steeper the rate of an individual's descent in organizational commitment across time, the steeper the rate of individual's ascent in turnover intention. Further, they found that the steeper the rates of increase in turnover intention, the greater the frequency of actual turnover behavior for an extended period of time.

All of the illustrated studies were completed at the individual level. However, that is purely a function of the researchers' own interest. LGM is equally applicable at other units of observation and analysis (i.e., teams, organizations, etc.). Further, in all of the examples, measurement invariance was established first before proceeding with the LGM analyses. Additionally, if model fit indices are poor, it makes little sense to interpret individual parameters. Also, only linear change was considered in this overview. As noted by many others, change may be quite nonlinear, and indeed, the Ployhart and Hakel (1998) study provide an excellent example of just such a case. Further, while Figure 9 illustrated the use of the initial status and change latent variables as antecedents to the fictitious latent variable, LV4, the initial status and change latent variables may themselves be modeled to have antecedents. For example, Bentein et al. (2003) treated the change in the latent organizational commitment construct as an antecedent to the change in the latent turnover intention construct. Additionally, as noted previously Ployhart and Hakel (1998) modeled the change in the latent performance variable as functions of individuals' persuasive abilities and garnering empathy from others. Finally, the current illustration only considered the case with three periods of measurement. However, change may be tracked over many more periods of time than 3.

Moderators and Latent Variable Relationships

Research in organizational behavior and human resources management often investigates moderation, in which the strength of the relationship between an independent variable and a dependent variable depends on the level of a third variable, termed a moderator variable (Cohen, 1978). Early methods for testing moderation involved splitting the sample on the moderator variable and comparing correlations between the independent and dependent variables across the subsamples (Arnold, 1982; Zedeck, 1971). This approach has been supplanted by hierarchical moderated regression in which the independent and moderator variables are entered first followed by their product, and the increment in variance explained

by the product term provides evidence for moderation (Aiken & West, 1991; Cohen, 1978; Stone & Hollenbeck, 1984). Moderated regression avoids the loss of information and statistical power created by splitting samples and can accommodate different combinations of continuous and categorical moderator variables.

In structural equation modeling, methods for testing moderation parallel the subgrouping and moderated regression approaches. In particular, one approach often used for testing moderating in structural equation modeling involves creating subgroups based on a moderator variable and use multi-sample techniques such as those previously discussed in the section on measurement invariance (Rigdon, Schumacker & Wothke, 1998). However, whereas tests of measurement invariance entail the equality of measurement parameters, such as item loadings and error variances, tests of moderation focus on the equality of structural parameters linking latent variables to one another. For example, a researcher could test the equivalence of the five structural parameters (gammas and betas) shown in Figure 8 across two subgroups. Differences in these parameters across groups would constitute evidence for moderation.

Although the subgrouping approach works well for categorical moderator variables (e.g., gender, race), many moderator variables are continuous. To avoid problems with categorizing continuous moderator variables, researchers have developed structural equation modeling procedures that are analogous to moderated regression analysis. These procedures can be traced to the seminal work of Kenny and Judd (1984), who demonstrated how to specify interactive and curvilinear effects in structural equations with latent variables. Jaccard and Wan (1995) showed how these methods could be implemented using nonlinear constraints in LISREL 8 (Jöreskog & Sörbom, 1996). More recently, Jöreskog and Yang (1996) demonstrated that, for proper model specification, analyses must include intercepts in measurement and structural equations and means of observed and latent variables. Additional approaches for testing moderation in structural equation models have been developed by Bollen and Paxton (1998) and Ping (1995, 1996).

As noted in a recent review by Cortina, Chen and Dunlap (2001), moderated structural equation models present several major challenges. One challenge involves choosing indicators to represent the latent product term. Cortina et al. (2001) reviewed and empirically evaluated various recommendations, ranging from using all possible pairwise products of the main effect indicators to using a single product indicator based on one or more of the main effect indicators. Based on their assessment, Cortina et al. (2001) recommend an approach that is relatively simple to implement and easy to understand for researchers trained in classical test theory.

To illustrate this approach, consider the model in Figure 1, but assume that each latent variable has a single indicator that is a scale constructed by summing the items used to measure the latent variable and standardizing the sum. Also, assume that LV3 signifies the product of LV1 and LV2 (i.e., LV1*LV2) and has a single indicator formed by multiplying the standardized indicators of LV1 and LV2. With one indicator for each latent variable, the measurement parameters (i.e., factor loadings and error variances) are not identified and must be fixed to prespecified values. Based on classic measurement theory, these values can be derived from estimates of the measurement error (e.g., coefficient alpha) for each scale. For LV1 and LV2, the factor loading is set equal the square root of the reliability of the scale, and the measurement error variance is set equal to one minus the reliability of the

scale multiplied by the variance of the scale. For LV3, the reliability of the product term can be computed from the correlation between LV1 and LV2 and the reliabilities of their indicators (Bohrnstedt & Marwell, 1978), and this quantity can be used to fix the loading and error variance for the product indicator. Once these measurement parameters have been fixed, the test of the interaction between LV1 and LV2 is conducted by comparing a model that includes a path from the LV3 product latent variable to an endogenous variable (e.g., LV4) to a model that excludes this path using a chi-square difference test.

The form of the interaction between LV1 and LV2 can be determined by applying procedures analogous to those used in moderated regression analysis. For instance, methods for testing simple slopes (Aiken & West, 1991) can be adapted to test the relationship between LV1 and LV4 at specific values of LV2, such as one standard deviation above and below its mean (Edwards & Kim, 2002). Simple slopes can be computed from weighted linear combinations of the parameters linking LV1 and LV3 to LV4 (i.e., γ_{11} and γ_{13}) and tested using the additional parameters feature of LISREL 8. Values of LV2 at which to test the relationship between LV1 and LV4 can be chosen based on the scale for LV2. In practice, it is convenient to standardize both LV1 and LV1, which is accomplished by fixing the measurement parameters as described above and setting the means of LV1 and LV2 to zero, which can be done using the kappa matrix of LISREL. It should be noted that, under this specification, LV3 is *not* standardized, given that the mean and variance of the product of two standardized variables generally differ from zero and one, respectively (Bohrnstedt & Goldberger, 1969).

The use of product terms as indicators in moderated structural equation models violates the assumption of multivariate normality underlying maximum likelihood estimation (Bollen, 1989). When this assumption is violated, parameter estimates remain unbiased, but standard errors are reduced and chi-square statistics are inflated (Chou, Bentler & Satorra, 1991; Curran, West & Finch, 1996; Hu, Bentler & Kano, 1992; Olsson, Foss, Troye & Howell, 2000). These problems can be addressed by using estimation procedures that do not require distributional assumptions such as multivariate normality (Browne, 1984) or by correcting standard errors and chi-square statistics based on the degree of nonnormality (Satorra & Bentler, 1994). Simulation studies indicate that distribution-free estimation procedures yield biased parameter estimates unless samples are very large (Chou et al., 1991; Curran et al., 1996; Hu et al., 1992; Olsson et al., 2000). Thus, maximum likelihood estimation combined with Satorra–Bentler corrections provides a practical approach for handling the nonnormality associated with moderated structural equation models.

Analysis of Latent Variable Means

Thus far, the discussion of the advanced methods has assumed the use of covariances among indicators, and thus, model parameter estimates are similarly assumed to derive from these covariances. There has been considerable recent development, however, involving models that incorporate information from the means of the indicators (the intercepts) and include parameters representing the means of the latent variables. Although discussion of models with latent variable means can be traced back over 20 years, applications of these models have been infrequent. As noted by Hayduk (1987), reasons for this infrequency include the late appearance of procedures for handling means in statistical software, and the fact that social scientists coming out of the path analysis tradition are more comfortable

with equations without intercepts. Fortunately, changes in statistical software programs now accommodate models with latent variable means. There are three types of research designs and questions in particular, for which the inclusion of these means can be an important part of the analysis: (a) within a measurement invariance context; (b) within LGM; and (c) extending S.E.M. to the analysis of experimental data.

While the measurement invariance review presented earlier included a focus on the equality of factor loadings, error variances, and factor covariances across two or more groups, as noted by Vandenberg and Lance (2000), some researchers have also included in the invariance analyses models that test the equality of factor means to test for differences between groups in the level on the construct of interest. Within this context, for example, one could constrain all of the latent variable means as equivalent between groups, and subsequently, compare this model to an alternative, baseline model that allows the means to be freely estimated within each group. If the "equivalent" model results in a significant worsening of fit relative to the baseline model, it may be assumed that the model with equality constraints is untenable, and therefore, differences exist in latent means between the two groups.

Vandenberg and Lance (2000) identified in their review several areas where latent variable means had been examined under a measurement invariance context, including changes in work-related perceptions during organizational entry, newcomer work adjustment, cross-cultural models of advertising, and race and gender differences in personality. They also noted that like traditional ANOVA analyses, the tests typically begin with an omnibus approach per the example presented in the previous paragraph, and if overall differences exist, the researcher may undertake "simple effects" analyses whereby some, but not all, latent means are constrained as equal between groups, and compared to the baseline model. If a constrained model has equivalent fit to the baseline model, then the latent means may be considered equal to one another. As discussed by Vandenberg and Lance, the advantages of this approach, in comparison to traditional approaches, include the ability to test for mean differences while accounting for differences due to a lack of measurement equivalence (either partial or full), and while accounting for effects of measurement error. An example may be found in Vandenberg and Self (1993) who found that the substantive conclusions regarding the development of commitment to an organization differed when testing for latent mean difference with invariance constraints in place versus when testing the same data using a repeated measures ANOVA.

The second design in which the analysis of latent variable means has occurred is within LGM. Chan (1998) has presented an integrative approach for longitudinal designs with data from the same sample of individuals obtained repeatedly over a few time waves. Chan refers to his approach as LMACS-MLGM, with the first component indicating longitudinal mean and covariance structure analysis and the second indicating multiple indicator latent growth modeling. In the first of two phases with LMACS-MLGM, measurement invariance is examined by tests involving factor loadings and error variances. However, the Phase 1 analysis also includes examining the changes in latent variable means over time. This is treated as an exploratory step that informs the specification of the LGM models in Phase 2. That is, it identifies the optimal nature of change, and permits the proper specification of the change in Phase 2 where the estimates of intraindividual changes and systematic interindividual differences in theses changes are obtained.

To illustrate, Chan evaluated data based on four waves of data collection for a single construct. To achieve identification of the model, equality constraints were imposed on the intercepts of one of the indicators across time and the latent factor mean at Time 1 was fixed to zero. Doing so actually means that the estimated factor means at each of the other three time points represents the difference in factor mean value between the first time period and the subsequent time point. The differences in factor means were used to identify the boundaries for possible forms of growth trajectories at the group level. In the example, the differences in factor means across time (0, 1.5, 3.2, 4.7) suggested a systematic positive general linear trend, which was then incorporated in Phase 2 of the analysis (which does not involve the estimation of factor means). Finally, Chan also presented a multi-sample extension of his LMACS-MLGM approach and an example using gender as a grouping variable.

The third area of activity related to latent variable means emphasizes the analysis of experimental data. Ployhart and Oswald (2003) discuss the advantages of analysis of latent variable means relative to traditional approaches involving *t*-tests or ANOVAs on group means, and they also describe a series of models and model comparisons to guide researchers who want to test hypotheses about latent variable means. Their sequence of model comparisons begins with a series of models for tests of invariance, as previously considered in this paper, and then progresses to include tests of equality of item intercepts and then equality of latent means. The latter sequence of tests includes provisions for pairwise comparisons, omnibus tests of overall latent mean differences, and tests that parallel ANOVA with contrasts. Ployhart and Oswald provide examples of latent mean analysis involving data from three independent groups and data from two independent groups with two repeated measures. They also discuss potential problems with latent mean analysis including larger sample size requirements (relative to traditional approaches), the required assumption of multivariate normality, and difficulties when the number of groups increases to greater than five.

Finally, the use of latent variables in experimental contexts with the analysis of multivariate factorial data has been investigated by McDonald, Seifert, Lorenzet, Givens and Jaccard (2002). These researchers used a Monte Carlo simulation approach to compare ANOVA, MANOVA, and multiple indicator latent variable analytical approaches. Their simulation design was based on an experimental model of a 2×2 multivariate factorial design with four dependent variables. These authors recommend that a multiple indicator latent variable approach is best when a covariate accounts for variance in the dependent variables, measures are unreliable, and there is a large sample.

Conclusions

The advancements discussed in this paper involve measurement related issues, which should not be surprising since the inclusion of a measurement model into the model testing process is a major contribution of latent variable techniques. This paper has reviewed approaches for model specification when latent variables cause and are caused by their indicators. At the heart of most organizational research are constructs that are multidimensional, and this has implications for the type of latent variable representation that is used. Issues related to this choice were discussed. Since organizational researchers typically use questionnaire data, techniques for evaluating the amount and effects of method

variance are important; these were discussed. Researchers also are increasingly interested in whether the measures they use behave similarly in different contexts or with different research participants, raising questions related to the invariance of their measures. The analytical approaches for assessing invariance were discussed. Longitudinal applications of latent variable techniques involving improved assessment of change patterns have also become popular, and these were reviewed. Finally, techniques for investigating moderator relationships among latent variables and for examining hypotheses related to latent variable means were presented.

It is hoped that this review will stimulate management researchers who do not currently use latent variable techniques to consider applying them in their theory testing. Those making this transition should be aware of the full range of research questions that can be addressed, given the current state of the technical literature, so they can take best advantage of this methodology. It is also hoped that this paper will prompt researchers who do use structural equation techniques, but have limited themselves to basic models such as the one shown in Figure 1, to consider advanced applications. It should be remembered that the full potential of basic and advanced latent variable techniques will only be realized when the analytical approach is closely aligned with theory. It should also be understood that when properly matched with theory, latent variable techniques provide a powerful tool for advancing organizational theories.

Acknowledgments

Appendix A.

One feature of the model shown in Figure 1 is that three of the latent variables only serve as causes or independent variables, and these are referred to as exogenous latent variables (LV1, LV2, LV3) or ksi (ξ). These exogenous variables are correlated, and the correlations are represented via the curved double-headed arrows. These exogenous latent variables also have variances, but these are typically set at 1.0 to achieve identification (which is necessary for unique parameter estimates to be obtained). The covariances among the three exogenous latent variables are referred to as phi parameters (ϕ), which includes the factor correlations mentioned above (and factor variances if identification is achieved by setting a factor loading at 1.0 rather than the factor variance). The factor loadings for the indicators of exogenous latent variables are referred to as lambda x (λ_x) parameters with LISREL, while the corresponding error variances are referred to as theta delta parameters (θ_δ).

The figure shows that the three exogenous latent variables are related to two dependent variables (LV4, LV5), and these are referred to as endogenous variables or etas (η). These

endogenous latent variables and their indicators are related by lambda y factor loadings, while the measurement errors for these indicators are referred to as theta epsilon parameters (θ_ε). Identification for the latent endogenous variables is typically achieved by setting one factor loading for each at 1.0. The relationships between the exogenous and endogenous latent variables are each represented by a single-headed arrow, the parameters used to estimate these relationships are often called structural parameters, and they are conceptually similar to partial regression coefficients (although they are different in that they are estimated while accounting for the effects of random measurement error). Thus, they represent the influence of one latent variable on another, while holding constant or controlling for the influence of other predictors of the dependent latent variable. In LISREL notation these three paths are referred to as gamma parameters (γ). The model shown in Figure 1 also proposes a relationship between the two endogenous latent variables. Although the parameter representing this relationship is identical in nature to the gamma parameters just mentioned, it is given a different name in LISREL notation as a beta parameter (β). Additionally, the model reflects the fact that there is an error term for each endogenous variable, and these are represented as zeta, while the residual variance in the two latent endogenous variables that is not accounted for by the predictors of each is represented in the psi matrix (Ψ). While it is sometimes possible to allow for a correlation between the two error terms, this is not done in the present model since this parameter would not be identified because of the direct path between the two variables. Finally, the structural part of the model shown in Figure 1 can be represented with two equations, one for each of the endogenous latent variables.

The analysis of this latent variable model is implemented on the covariance matrix for the 15 indicators. Maximum likelihood is the most commonly used technique, and it yields a set of parameter estimates and their standard errors, which can be used to test null hypotheses that each parameter estimate equals zero. In terms of judging the adequacy of the model, a chi-square statistic is obtained, and it is typically supplemented with other measures of model fit (e.g., Comparative Fit Index, Bentler, 1990). One final aspect of evaluating latent variable models that should be addressed is the capability of comparing competing models within a data set. This is most easily accomplished if the two models are nested, where nesting means that one model is a more restricted version of the other model. Two nested models can be compared using a chi-square difference test.

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