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ABSTRACT

This paper provides an introduction to basic issues concerning structural equation modeling (SEM), a research methodology increasingly being used in social science research. First, seven key issues that must be considered in any SEM analysis are explained. These include matrix of associations to analyze, model identification, parameter estimation theory, multivariate normality, model misspecification and specification searches, sample size, and measurement model adequacy. Second, heuristic SEM analyses involving structural models are presented to demonstrate how SEM takes score measurement reliability into account and how SEM may shed light on causal issues. Finally, ten commandments for proper SEM use are presented, among which are the following: (1) never conclude that a model has been definitely proven; (2) for specification searches that require larger samples, test the re-specified model with a "hold-out" or independent sample and never change a specification without a theoretical justification; (3) test multiple plausible rival models; and (4) don't use SEM with small samples. Appendices provide five examples of statistical analyses using SEM. (Contains 66 references.) (DB)

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The Ten Commandments of Good Structural Equation Modeling Behavior:

A User-friendly, Introductory Primer on SEM

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Abstract

The present paper provides a user-friendly introduction to and guidance regarding some of the basic issues that must be resolved to conduct structural equation modeling (SEM). The paper incorporates many of the latest findings regarding covariance structure analysis, and presumes no SEM background on the part of the reader. First, *seven key issues* that must be considered in any SEM analysis are explained. Second, *heuristic SEM analyses* involving structural models are presented to make clear in a concrete fashion (a) how SEM takes score measurement reliability into account and (b) how SEM may shed some limited light on causal issues. Third, *10 commandments* for proper SEM behavior are presented.

Structural equation modeling (SEM; also variously called covariance structure analysis and, somewhat speciously, causal modeling) is being increasingly used within the social science literature. Indeed, it would be difficult to locate recent issues of social science journals in which some SEM applications were not reported. And one new journal--Structural Equation Modeling: A Multidisciplinary Journal--has been created that is exclusively devoted to SEM reports and issues. SEM has been termed "the single most important contribution of statistics to the social and behavioral sciences during the past twenty years" (Lomax, 1989, p. 171). Similarly, Stevens (1996) argued that SEM techniques "have been touted as one of the most important advances in quantitative methodology in many years" (p. 415). Many would regard this as an understatement, though it is also clear that SEM is sometimes used when much simpler methods would suffice.

It is also clear that SEM is sometimes not correctly used. Of course, some misuses and errors are to be expected with a method that is relatively new, that is still undergoing refinement at a seemingly exponential rate, and that many social scientists are still learning.

SEM has historical roots in two major classical traditions. First, SEM always invokes a ***"measurement model"*** specifying that the *measured/observed* variables reflect underlying *latent/synthetic* variables, and sometimes is even used exclusively to investigate measurement issues (i.e., "confirmatory factor analysis"); this aspect of structural modeling dates back to factor analysis theory articulated by Spearman (1904). Second, sometimes a regression structure among the latent/synthetic variables defined by the measurement model(s), called a ***"structural model"***, is also specified and tested; this aspect of SEM can be traced back to path analysis methods (cf. Wright, 1921, 1934).

However, the modern roots of SEM can be traced especially to the theoretical developments formulated by Karl Jöreskog (cf. 1967, 1969, 1970, 1971, 1978), and to the computer program, LISREL (i.e., analysis of LInear Structural RELationships) developed by Jöreskog and his colleagues (e.g., Jöreskog & Sörbom, 1989). Today, modern SEM software is extremely user-friendly, and allows users of microcomputers to declare models to be tested using software-aided drawings and point-and-click menus. Particularly respected today for both their technical accuracy and their user-friendliness are the two microcomputer software packages, EQS (Bentler, 1992a) and AMOS (Arbuckle, 1997).

Accessible short treatments of SEM have been provided by Baldwin (1989), Mueller (1997), and Lomax (1989). Extraordinarily good longer treatments, which include numerous examples and focus on EQS and LISREL, are the various works by Barbara Byrne (cf. 1994, 1998; also see Long (1983a, 1983b)).

The purpose of the present paper is to provide a user-friendly introduction to and guidance regarding some of the basic issues that must be resolved to conduct structural equation modeling. First, *seven key issues* that must be considered in any SEM analysis are explained. Second, *heuristic SEM analyses* involving structural models are presented to make clear in a concrete fashion (a) how SEM takes score measurement reliability into account and (b) how SEM may shed some limited light on causal issues. Third, *10 commandments* for proper SEM behavior are proffered.

Seven Key Decisions in SEM Analysis

1. Matrix of Associations to Analyze

Most researchers today (hopefully) realize that all parametric statistical analyses are special cases within a single general linear model (GLM) family. In one of his innumerable seminal contributions, the late Jacob "Jack" Cohen (1968) demonstrated that multiple regression subsumes all the univariate parametric methods (e.g., *t*-test, ANOVA, ANCOVA) as special cases. Subsequently, Knapp (1978) presented mathematical theory showing that canonical correlation analysis subsumes all the parametric analyses, both univariate and multivariate, as special cases. Fan (1996a) and Thompson (1984, 1991) present concrete demonstrations of these relationships.

However, structural equation modeling (SEM) is an even bigger conceptual tent subsuming narrower special cases (Bagozzi, Fornell & Larcker, 1981), including both canonical correlation analysis and multiple regression. Illustrations of these relationships have been offered by Fan (1997) and by Thompson (1998a).

The general linear model is a powerful heuristic device that can help researchers see three important commonalities that exist across various analytic methods. First, all these methods use weights (e.g., regression beta weights, standardized canonical function coefficients) to optimize explained variance and minimize model error variance. Second, all the methods focus on the latent synthetic variables (e.g., the regression $\hat{Y}$ variable, factor scores) created by applying the weights (e.g., beta weights) to scores on measured/observed variables (e.g., regression predictor variables); we take these latent/synthetic variables as measures of our constructs. Third, all analytic methods are correlational (Knapp, 1978; Thompson, 1998a) and yield variance-accounted-for effect sizes analogous to $\underline{r}^2$ (e.g., R^2, η^2, ω^2).

The commonality that all parametric methods apply weights to the measured/observed variables to compute latent/synthetic variables is obscured by the inherently confusing language of traditional statistics. As I have noted elsewhere, the weights in different analyses

> ...are all analogous, but are given different names in different analyses (e.g., beta weights in regression, pattern coefficients in factor analysis, discriminant function coefficients in discriminant analysis, and canonical function coefficients in canonical correlation analysis), mainly to obfuscate the commonalities of [all] parametric methods, and to confuse graduate students. (Thompson, 1992, pp. 906-907)

Indeed, both the weight systems (e.g., regression equation, factor, canonical function) and the synthetic variables (e.g., the regression $\hat{Y}$ variable, factor scores, discriminant function scores) are also arbitrarily given different names across the analyses, again mainly so as to confuse the graduate students.

The first step of GLM analyses often involves the computation of a matrix of associations (e.g., Pearson product-moment correlation matrix, variance/covariance matrix) among the measured/observed variables. In fact, with only this matrix (as will be seen momentarily) many GLM analyses can be replicated.

SEM analyses can be based on numerous matrices of association (e.g., product-moment correlation, polychoric correlation). Some researchers prefer to analyze Pearson correlation coefficients. These association coefficients are "scale-free," because the standard deviations of a given pair of variables have been removed from the covariance of the two variables by division (i.e., $r_{XY} = COV_{XY} / [SD_X * SD_Y]$). Thus, the weights derived from these correlations are themselves "scale-free," and can be more readily interpreted in relation to each other because all the measured variables have been effectively "standardized" by this process.

However, most SEM theory was developed for application with the matrix of associations among the measured/observed variables being a variance/covariance matrix (i.e., variances on the diagonal, covariances off the diagonal). And it has been established that while using the product-moment correlation matrix may be appropriate with some models, for other models some SEM statistics will be incorrect unless the variance/covariance matrix is employed (Cudeck, 1989).

It is also very important that the level of scale of the measured variables (e.g., categorical/nominal, ordinal/ranked, continuous/interval) is honored when selecting a given matrix of associations to be computed and analyzed. Of course, to some degree judgments about measurement scale are subjective, and researchers may reasonably disagree regarding some of these decisions. However, data might be analyzed using a variety of plausible matrices of association, to confirm that results are not artifacts of methods choices.

2. Model Identification

When we conduct analyses, we are fitting a model to our data and estimating the weights and other parameters (e.g., latent variable variances and/or covariances) associated with that model. A critically important issue in this process involves determining whether the model is ***"identified"***. A model is identified if, given the model and the data, a single set of weights and other model parameters can be computed. If infinitely many sets of weights and other parameters are plausible, the parameters are mathematically indeterminate, and the model is not identified (i.e., "under-identified"). As Byrne (1998) noted, "statistical identification is a complex topic that is difficult to explain in nontechnical terms" (p. 28; see Mueller (1997, pp. 358-359) for a fairly accessible summary of the conditions sufficient for model identification).

One key issue as regards identification involves degrees of freedom. The notion of identification can be partially explored in the context of classical statistics (e.g., product-moment correlation, multiple regression). The degrees of freedom total in classical univariate analyses equals n-1. If we have scores of only two people on only two variables, the model degrees of freedom is 1 and the degrees of freedom error is 0; here, no matter what the scores on the two variables, the r^2 value can only be 1.0. This result can be computed, although the computation is a waste of time, because only one result is plausible when a model is "just-identified". Similarly, scores of three people on one criterion variable and two predictor variables would yield a degrees of freedom error of 0, and an inescapable R^2 value of 1.0.

In SEM degrees of freedom total is a function of the number of nonredundant pieces of information present in the matrix of associations being analyzed (and <u>not</u> of the number of people). For example, with eight measured variables, there would be eight variances and 28 nonredundant (either below or above the diagonal) covariances ([8 * (8-1)] / 2 = [8 * 7] / 2 = 56 / 2 = 28). This would result in 36 (8 + 28 = 36 = [8 * (8+1)] / 2 = 72 / 2) degrees of freedom being available for any SEM model being fit to these data.

In SEM each parameter (e.g., weight, path coefficient, variance of or covariance among latent/synthetic variables) that we estimate takes one degree of freedom. Thus, for the problem involving eight measured variables, if we specify a model involving the estimation of 36 model parameters, the model will be just-identified. These parameters can be estimated (i.e., the parameters are mathematically determined, with only one plausible set of estimates). However, the results from a just-identified SEM model are just as interesting as were the results from an r^2 analysis involving scores of two people on two measured/observed variables (i.e., interest in the results for a model with zero degrees of freedom equals that degrees of freedom), because such models will always exactly reproduce the analyzed matrix of associations.

We are scientifically most interested in SEM models that spend fewer degrees of freedom (i.e., estimate fewer model parameters), and are thus more parsimonious. When models have more degrees of freedom (i.e., there are a lot more degrees of freedom total than the number of estimated parameters), but still do reasonably well at reproducing the matrix of associations, there are more ways in which the models are potentially falsifiable, and so such models represent more rigorous and persuasive tests of our conceptions of latent constructs (Mulaik, 1987, 1988; Mulaik, James, van Alstine, Bennett, Lind & Stilwell, 1989). In other words, we prefer models that are considerably "over-identified."

Having more than zero degrees of freedom is a necessary-but-not-sufficient condition for model identification. That is, we simply cannot estimate the parameters for any "under-identified" model.

SEM computer programs tend to run diagnostics that indicate when models have not been identified. When this occurs, some parameters for which estimates were initially requested (i.e., "freed" to be estimated) must be "fixed" as not being estimated (e.g., a weight or the latent/synthetic variable's variance is "fixed" to equal 1.0, or the error variance of a measured/observed variable is "fixed" to equal .0).

3. Parameter Estimation Theory

Classical univariate and multivariate parametric analyses (e.g., *t*-tests, ANOVA, descriptive discriminant analysis) invoke a statistical theory of parameter estimation called ***"ordinary least squares"***. There are, in fact, numerous other statistical theories that can be invoked to estimate freed model parameters. Among these various alternatives are ***"maximum likelihood"*** (ML), ***"generalized least squares"*** (GLS), and ***"asymptotically distribution-free"*** (ADF; Browne, 1984) estimation theories. The various estimation theories differ as regards both their assumptions and their theoretical properties.

For example, as regards assumptions both maximum likelihood and generalized least squares estimations presume that the data have a multivariate normal distribution. Of course, this distributional assumption also invokes issues involving the measurement scale of the measured/observed variables, because, for example, dichotomous variables cannot be even univariate normally distributed, even if the dichotomous variable scores are symmetrical. ADF estimation, on the other, does not require the assumption of multivariate normal distribution. West, Finch and Curran (1995) review some relevant issues and choices regarding distributional assumptions.

In most SEM computer programs ML estimation is the default. Perhaps for this reason maximum likelihood estimation is used with considerable frequency. ML estimates seek to estimate parameters that best reproduce the estimated *population* variance/covariance matrix. Of course, this may be another reason for the frequent use of this estimation method, since accurate estimates of population parameters in theory should result in result replicability.

4. Multivariate Normality

A necessary but not sufficient condition for multivariate normality is bivariate normality of all pairwise combinations of the measured/observed variables. In turn, a necessary but not sufficient condition for bivariate normality is univariate normality of all the measured/observed variables.

However, even just univariate normality is a more elusive concept than most researchers realize (Bump, 1991). There are infinitely many univariate normal data distributions, each differing in appearance. [Some researchers have been lulled into the misconception that all univariate normal distributions have a single classic "bell shape," because almost all textbooks only present graphs of the normal distributions of z-scores. However, for data not in z-score form, there are infinitely many plausible symmetrical distributions that are normal, but that differ markedly in appearance.]

There is no definitely superior method by which to establish that the multivariate normal distribution assumption has been met, so that certain estimation theories can then be employed. Ashcraft (1998) reviews some of the available choices.

One user-friendly method for evaluating multivariate normality invokes a graphical procedure. Thompson (1990) describes this method in more detail. Appendix A presents an SPSS for Windows version of this program. Fan (1996b) has made available a SAS version of this program.

5. Model Misspecification and Specification Searches

All over-identified models portray the relationships among measured and latent variables. The goal is to specify these relationships for the population, so that future samples from the same population will yield comparable findings. The model is over-identified partly so that the model is falsifiable, but also because we seek simplifications of reality that remain useful but make our understandings of reality more manageable. As Mueller (1997) noted,

> A structural equation model is nothing more than an oversimplified approximation of reality, no matter how carefully conceptualized. A good model can be characterized as featuring an appropriate balance between efforts to represent a complex phenomenon in the simplest [most parsimonious] way and to retain enough complexity that [still] leads to the most meaningful [and true] interpretations possible. (p. 365)

A perfectly "specified" over-identified model would perfectly reproduce the associations among the measured/observed variables. However, because the model is over-identified, the model will never perfectly reproduce data in either the sample or the population. Thus, we must somehow evaluate whether the model is sufficiently adequate to remain both reasonably manageable and reasonably correct.

Model Misspecification. If the model is deemed to not be correct, the model is deemed ***"mispecified"***. Making this judgment is critical, because the SEM parameter (e.g., weights, variances, covariances) estimation processes

> all fail to provide correct sample estimates, standard errors, and data-model fit chi-square statistics... if the model under consideration is misspecified and does not reflect at least a very close approximation to the true structure in the population. (Mueller, 1997, p. 359)

Of course, since a simplified model of reality is always at least partially misspecified, making the judgment as to when a model is misspecified can be challenging.

Through the years myriad fit statistics have been developed to aid in making these judgments. Byrne (1998, pp. 109-119) reviews some of the fit statistics provided by the SEM computer programs. Arbuckle (1997, pp. 551-572) summarizes some of the relevant formulae used to compute these statistics, and summarizes a bit of the literature on rules of thumb for interpreting these values.

However, the stark, harsh reality is that we still have much to learn regarding both how these SEM fit statistics operate under different conditions and what should be the cutoffs for declaring reasonable model fit. Indeed, until recently too much of the Monte Carlo simulation work on these issues failed to use misspecified models, meaning that the results did not directly bear upon the real-world situation in which the model is at least partially misspecified and the researcher does not know for certain which or how many features of the model specification are correct (Fan, Thompson & Wang, in press; Fan, Wang & Thompson, 1997).

A very important consideration in evaluating the fit of a given model involves the modeling context of this judgment. The most persuasive case that a model has been correctly specified is created when a researcher finds differentially better fit of a given model against the fit of numerous other defensible, thoughtfully-formulated, rival plausible models. Thus, multiple models should usually be evaluated in any SEM project.

It is also critical to remember that even such findings do not conclusively establish that a single given model is definitively correct. Infinitely many models can fit a given data set. Thus, the fit of a single tested model is always an artifact of having not tested all possible models.

In any case, also remember that we are defining an over-identified model to simplify reality. We seek a simplification that we subjectively judge to be inherently somewhat inaccurate but still reasonably useful and more manageable. We are not seeking a single truth in the context of a simplification that inherently distorts some features of reality. We use model fit statistics to assist us in making these judgments, but the judgment we make is inherently subjective. We then must accept the responsibility for the construct definitions we formulate (Mulaik, 1994).

Model Fit Statistics. Given space limitations, only a few of the myriad model fit statistics can be reviewed here (Bentler, 1994). A χ^2 *goodness-of-fit test statistic* can be computed to test the null hypothesis that the variance/covariance matrix reproduced by the freed model parameter estimates equals the variance/covariance matrix (i.e., that the model exactly reproduces all observed relationships). This statistic is printed by all the SEM computer programs. Note that here, as against in traditional statistical significance testing, the researcher hopes to not reject this null hypothesis, so that the model can be taken as fitting the data.

Even though this application of statistical testing is a variant on usual practice, one of the numerous criticisms of classical statistical significance testing applies here also: the result is partially an artifact of sample size (cf. Cohen, 1994; Thompson, 1996, 1998b, in press-a, in press-b, in press-c). As Bentler and Bonett (1980) made very clear,

> [I]n very large samples virtually all models that one might consider would have to be rejected as statistically untenable... This procedure cannot be justified, since the chi-square variate v can be made small by simply reducing sample size. (p. 591)

However, the chi-square statistic can be of some use in comparing the fits of models for a given data set with a single sample size, particularly if the models are "nested" within each other (cf. Jöreskog & Sörbom, 1989, pp. 230-233).

The ***Goodness-of-Fit Index*** (GFI) and the ***Adjusted Goodness-of-Fit Index*** (AGFI) (Jöreskog & Sörbom, 1984) essentially compare the ability of a model to reproduce the variance/covariance matrix to the ability of no model at all to do so. The AGFI adjusts the GFI for the number of degrees of freedom expended in estimating the model parameters. Indices less than zero are treated as zero, and range up to one, with one indicating perfect model fit. Most researchers expect these values to be greater than .9 or .95 for correctly specified models.

The ***Root Mean-square Residual*** (RMR) evaluates the average residual value for the variance/covariance matrix reproduced by the model parameters and the actual variance/covariance matrix. The RMR can range down to zero, which would indicate perfect model fit. A well-fitting model will have values of "say, .05 or less" (Byrne, 1998, p. 115).

Bentler and Bonett (1980) proposed a ***Normed Fit Index*** (NFI), which compares model fit to that of a model for the same data presuming independence of the measured/observed variables. NFI ranges between zero and one, with higher values indicating better fit. Usually values greater than .9 or .95 are considered as reflecting adequate fit.

The Bentler and Bonett article has been one of the most widely cited articles in the psychological literature (see Bentler (1992b)). However, NFI has been shown to be an underestimate when small samples are used. Consequently, Bentler (1990) proposed an adjustment to the NFI, the ***Comparative Fit Index*** (CFI), which takes sample size into account. Some have suggested that the CFI should be a fit statistic of choice in SEM research (Byrne, 1998).

Various ***parsimony-weighted fit indices*** have been proposed (see Mulaik et al. (1989), but also Marsh and Hu (1998)). These fit statistic weights, which range up to one and down to zero for just-identified models, are multiplied times indices such as the NFI, to take model complexity into account and reward models that estimate fewer parameters.

Some fit indices focus on estimated population fit. Steiger and Lind (1980) proposed a ***Root Mean Square Error of Approximation*** (RMSEA). As Byrne (1998) noted, RMSEA "has only recently been recognized as one of the most informative criteria in covariance structure modeling" (p. 112). Values approaching zero are desired, and "a value of .08 or less for RMSEA would indicate a reasonable error of approximation" (Browne & Cudeck, 1993).

The various fit indices provide a constellation of information about the competing models being considered in an SEM analysis. Because some of the different fit indices evaluate different aspects of fit, it is important to evaluate fit based on multiple fit statistics, so that judgments will not be an artifact of analytic choice. Furthermore, as Byrne (1998) so correctly emphasized, "[A]ssessment of model adequacy must be based on multiple criteria that take into account theoretical, statistical, and practical considerations" (p. 119).

<u>Specification Search</u>. In addition to providing fit indices for a given model, SEM analyses also provide important information

regarding exactly where potential model specification errors may have occurred. There are two possible types of errors, and different information is used to evaluate each of the possibilities.

First, model misspecification may involve having "freed" a parameter to be estimated when, if fact, the parameter is not very useful in reproducing relationships, and should instead have been "fixed" (e.g., two latent/synthetic variables should have been constrained to be uncorrelated in the model, or the measurement error variance of a measured/observed variable should have been constrained to be zero). In classical statistics, the ratio of a mean to the standard error of the mean can be computed, and is called the calculated test statistic, $\underline{t}$. For most sample sizes, a $\underline{t}_{CALCULATED}$ greater than two in absolute value is statistically significant at approximately the α=.05 level.

In SEM ***t* statistics** (sometimes also called Wold statistics) can be computed by dividing any given parameter estimate by its standard error. Any ratio less than $|2|$ suggests a possible model specification error in the form of "freeing" a parameter than instead might have been "fixed."

Second, model misspecification may involve having "fixed" a parameter to not be estimated when, if fact, the parameter might be very useful in reproducing relationships, and should instead have been "freed." SEM computer programs upon request will provide ***modification indices*** for each "fixed" model parameter; these modification indices indicate approximately how much smaller (i.e., better) the model chi-square statistic would get if a given "fixed" parameter was instead "freed." Large values for these indices may indicate that freeing a given fixed parameter should be considered.

The process of modifying an *a priori* model based on such results is called a ***specification search***. This practice is considerably controversial (see Mueller (1997)), unless the model is changed based on statistical results for one sample, and then the re-specified model is evaluated in an independent sample. Clearly, the more model features that are altered based on sample results, the greater is the likelihood that sampling error variance (i.e., the variability reflecting the idiosyncratic and non-replicable features of a given sample) is being capitalized on, leading then to non-replicable model fit.

Furthermore, model specification should never be based on blind dust-bowl empiricism. Models should only be re-specified in those cases where the researcher can articulate a persuasive rationale as to why the modification is theoretically and practically defensible.

6. Sample Size

Structural equation modeling is inherently a **large-sample** technique. At least four cases in which especially even larger samples are needed can be noted. First, even larger samples are needed as more measured/observed variables are employed. Second, even larger samples are required as more complex models are evaluated. Third, even larger samples are needed when more elegant parameter estimation theories (e.g., asymptotically distribution-free estimation) are employed. Fourth, even larger samples are needed if the researcher is going to do any model search specification.

Some have suggested that sample size should be at least 200 (Baldwin, 1989). Similarly, Lomax (1989) suggested "a sample size of at least 100 (if not 200)" (p. 189). Furthermore, it has been suggested that the ratio of the number of people to the number of measured/observed variables should be at least 10:1 (Mueller, 1998), if not 15:1 or 20:1. Thus, in even the most straightforward SEM applications, sample size should probably be the minimum of (a) 100 to 200 people, or (b) an n:v ratio of at least 10:1 or 15:1. MacCallum, Browne and Sugawara (1996) have provided some statistical methods for more precisely estimating the sample size necessary for a given SEM problem.

7. Measurement Model Adequacy

As noted previously, SEM structural models incorporate several measurement models in which measured/observed variables are taken as reflecting underlying latent constructs in the form of latent/synthetic variables, and the regression path models of some of these latent/synthetic variables with each other are then estimated. Researchers have increasingly recognized that the measurement models within SEM structural models have often been the weak links in past SEM analyses.

Put simply, if the specified measurement models do not fit the measured variables, then knowing the relationships among the latent/synthetic variables defined by these measurement models is essentially useless. Thus, some researchers (cf. Anderson & Gerbing, 1988) have recommended that SEM structural analyses should be approached as a two-step hierarchical process: first confirm that the specified measurement models all fit their respective data, and only then explore the structural relationships among the latent/synthetic variables.

It has been generally agreed that it is useful to explore the measurement models embedded within structural models prior to evaluating the structural models. However, some have argued that measurement models may also be reasonably re-evaluated and perhaps respecified within the subsequent structural model analyses (see Hayduk, 1996).

But it is quite clear that bad measurement models make the related structural models uninteresting. And some researchers have paid inadequate attention to the fit of the measurement models they have specified within their structural models.

Heuristic SEM Application

To make this discussion concrete, heuristic SEM analyses involving the data reported by Bagozzi (1980) will be summarized (also see Jöreskog & Sörbom (1989, pp. 151-156)). The study investigated the job satisfaction and job performance of 122 workers. The relevant data are presented in Table 1.

INSERT TABLE 1 ABOUT HERE.

Here only selected models are evaluated to illustrate previously made ideas and to emphasize some new concepts as well. Given space considerations, all relevant analyses are not reported.

For example, here measurement model adequacy is not initially evaluated prior to structural equation modeling.

Here the primary model of interest is portrayed in Figure 1. This model will be referenced as Model A. In Model A, as is conventional, (a) measured/observed variables are designated within boxes, (b) latent/synthetic variables are represented within circles or ovals, and (c) correlations or covariances are represented by two-headed arrows.

INSERT FIGURE 1 ABOUT HERE.

Also as is conventional, measured/observed variables are taken as being the joint function of measurement error plus the underlying construct (thus the arrows proceed from the latent variables to the relevant measured variables, and not vice versa). This model asserts (a) that job satisfaction is a function of both achievement motivation and verbal intelligence, (b) that job performance is solely a function of task-specific self esteem, and that (c) job performance predicts job satisfaction, and not vice versa.

The relevant maximum-likelihood parameter estimates for this structural model are also presented in Table 2. Table 3 presents some fit statistics for this model (and others) for these data.

INSERT TABLES 2 AND 3 ABOUT HERE.

Variations on this model test are explored here to emphasize two major ideas. First, the integral and unique role of ***measurement error variance*** within structural equation modeling is explained and explored. Second, the mechanisms and nature of SEM ***causal modeling*** are illustrated.

Role of Measurement Error Variance Within SEM

Too few researchers understand either what reliability is, or how reliability impacts statistical analyses. For example, some researchers persist in erroneously referring to the "reliability of the test" (see Reinhardt (1996), Thompson (1994), and especially Vacha-Haase (1998)).

In classical statistical analyses (e.g., ANOVA, regression, canonical correlation analysis), measurement error impacts parameter estimates and attenuates detected effect sizes (Thompson, 1994). But in classical analyses these measurement effects are not directly explored and evaluated. The primary distinguishing feature of structural equation modeling is that score reliability (i.e., [1 - measurement error variance] / total score variance) is directly considered (Stevens, 1996, p. 415).

In the present model, some of the measurement error variances (i.e., [1 - the score reliability coefficients] * the score variances) were "freed" to be estimated. For example, as reported in both Figure 1 and Table 2, the measurement error variance of the measured variable "Achievement Motivation measure #1" was estimated to be δ_1=2.571. Since the variance of this measured variable, reported in Table 1, was 3.802, the reliability coefficient for this measured/observed variable was poor (i.e., [1 - 2.571] / 3.802 = .324).

Also in Model A some measured variables were presumed to be measured with perfect reliability (i.e., ϵ_1=0 for the measured job performance variable). But the measurement error variance for the measured "Verbal Intelligence Variable," although also "fixed" (i.e., not estimated), was not constrained to equal zero. Instead, a score reliability coefficient of .85 was presumed, based on previous reliability generalization research (Vacha-Haase, 1998) or some theoretical expectation. Therefore, the measurement error variance was "fixed" as 1.998 (i.e., [1 - .85] * the measured score variance of 13.323 reported in Table 1 = .15 * 13.323 = 1.998).

For heuristic purposes, a second model (Model B) was fit to the Table 1 data. The only difference in Model A and Model B was that score reliability for the measured variable, "Verbal Intelligence Variable," was "fixed" to zero in Model B (i.e., perfect score reliability on this measured variable was assumed). Table 2 also presents the parameter estimates for Model B.

Compare the Table 2 parameters estimated for these two models. Notice how changing just slightly the error variance for just one measured variables changes (at least slightly) the parameter estimates throughout the entire model.

Classical statistical analyses (e.g., ANOVA, canonical correlation analyses) presume no measurement error variance for any of the measured variables, while SEM models are usually specified to estimate and to take into account measurement error variance for all or most of the measured/observed variables. Think how different the parameter estimates even for the same data may therefore be across SEM as against non-SEM analyses, since usually all or none, respectively, of the score reliability coefficients are taken into account in making parameter estimates! Which analytic model best honors a reality where measured/observed variables are not measured with perfect reliability?

SEM as "Causal Modeling"

As noted at the outset, historically some have referred to structural equation modeling as "causal modeling." Here the mechanisms for this thinking are illustrated. But some strong cautions are also noted.

Model A specified that the latent/synthetic variable "Job Performance" predicts "Job Satisfaction," and not vice versa. Model C was identical to Model A except that "Job Performance" and "Job Satisfaction" were presumed to reciprocally predict each other. Finally, Model D specified that "Job Satisfaction" predicts "Job Performance," and not vice versa.

The maximum-likelihood parameters estimates for these three models are all presented in Table 2. Table 3 presents various fit and other statistics for these three rival models. The tabled results indicate that Model D ("Job Satisfaction" predicts "Job Performance," and not vice versa) is less satisfactory than the other two models. For example, the chi-square and the chi-square-to-df ratio (1.556) is considerably inferior (i.e., larger) for Model D.

As regards the judgment between Model A and Model C, the critical issue involves the Wold or t statistics for the freed parameters. As reported in Table 3, the t value for estimating "Job

Satisfaction" predicted by "Job Performance" was 4.239 (.594 / .140). In Model C the same _t_ value was 3.887 (.816 / 3.887). However, in Model C the _t_ statistic for estimating "Job Performance" predicted by "Job Satisfaction" was ¦1.362¦ (¦-.220¦ / .161). These results suggest that Model A may be more correctly specified.

But does this suggest that Model A is a superior "causal model"? Certainly some insight regarding causality might be inferred from the comparisons made here.

However, making such inferences would be extremely controversial. The view here is that definitive causal evidence can only be extrapolated from thoughtfully designed true experiments. Given a non-experimental design, such as yielded the present data, correlational analysis of such data yield inherently ambiguous causal results.

The argument can be framed as regards the context-specificity of all GLM weights (see Thompson (1998)). If we added or subtracted a single measured/observed variable, all the parameters might change quite dramatically. This is one aspect of model specification (i.e., are the exactly correct and only the exactly correct measured variables present?).

If we were certain that we had exactly (and only) the correct measured variables, then SEM might bear more powerfully on issues of causality. But as Pedhazur (1982) has noted, "The rub, however, is that the true model is seldom, if ever, known" (p. 229). And as Duncan (1975) has noted, "Indeed it would require no elaborate sophistry to show that we will never have the 'right' model in any absolute sense" (p. 101).

The Ten Commandments for Good SEM Behavior

Huberty and Morris (1998) have observed that, "As in all of statistical inference, subjective judgment cannot be avoided. Neither can reasonableness!" (p. 573). This is true throughout the panorama of statistical methods. But judgment and reasonableness are especially the *sine qua non* of structural equation modeling.

Here some basic precepts and principles have been laid out to guide the novice modeler is exercising this judgment. Some of the principles can be summarized in the form of the following *10 Commandments for Good SEM Behavior*:

10. Don't use SEM with small samples.
9. Carefully consider the levels of scale and distributions of measured/observed variables when selecting the matrix of associations to be analyzed.
8. All things equal, prefer well-fitting more parsimonious models, since their fit is least an artifact of the model being nearly just-identified.
7. When using estimation theories requiring multivariate normality, use measured/observed variables that can be normally distributed, and empirically evaluate whether the distributional assumption is met.
6. Use multiple fit statistics, because several fit statistics consider different aspects or conceptions of fit, so that a judgment of correct specification will not be an artifact of analytic choice, and because we still have much to learn about the behavior of these statistics.
5. In evaluating model specification, in addition to considering statistical evidence, "assessment of model adequacy must be based on multiple criteria that [also] take into account theoretical... and practical considerations" (Byrne, 1998, p. 119) [i.e., remember that we define the constructs we use, and are responsible for making and defending these decisions].

4. Individually evaluate the measurement models prior to evaluating a structural equation model [but consider reformulating measurement models if structural modeling then suggests this may be appropriate].

3. Test multiple plausible rival models, so that stronger evidence supporting the correct specification of a model can be adduced.

2. Regarding specification searches, require larger samples, test the re-specified model with a "hold-out" or independent sample, and never change a specification unless you can offer a theoretical justification for the changes to the *a priori* model.

1. Never conclude that a model has been definitively proven, because infinitely many models can fit any given data set [thus, the fit of a single tested model is always an artifact of having tested too few models].

References

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

Arbuckle, J.A. (1997). Amos users' guide: Version 3.6. Chicago: Smallwaters.

Ashcraft, A.S. (1998, April). Ways to evaluate the assumption of multivariate normality. Paper presented at the annual meeting of the Southwestern Psychological Association, New Orleans. (ERIC Document Reproduction Service No. ED forthcoming)

Bagozzi, R.P. (1980). Performance and satisfaction in an industrial sales force: An examination of their antecedents and simultaneity. Journal of Marketing, 44, 65-77.

Bagozzi, R.P., Fornell, C., & Larcker, D.F. (1981). Canonical correlation analysis as a special case of a structural relations model. Multivariate Behavioral Research, 16, 437-454.

Baldwin, B. (1989). A primer in the use and interpretation of structural equation models. Measurement and Evaluation in Counseling and Development, 22, 100-112.

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

Bentler, P.M. (1992a). EQS: Structural equations program manual. Los Angeles, CA: BMDP Statistical Software.

Bentler, P.M. (1992b). On the fit of models to covariances and methodology to the *Bulletin*. Psychological Bulletin, 112, 400-404.

Bentler, P.M. (1994). On the quality of test statistics in covariance structure analysis: Caveat emptor. In C.R. Reynolds (Ed.), Cognitive assessment: An multidisciplinary perspective (pp. 237-260). New York: Plenum Press.

Bentler, P.M., & Bonett, D.G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88, 588-606.

Browne, M.W. (1984). Asymptotically distribution-free methods for the analysis of covariance structures. British Journal of Mathematical and Statistical Psychology, 37, 62-83.

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

Bump, W. (1991, January). The normal curve takes many forms: A review of skewness and kurtosis. Paper presented at the annual meeting of the Southwest Educational Research Association, San Antonio. (ERIC Document Reproduction Service No. ED 342 790)

Byrne, B.M. (1994). Structural equation modeling with EQS and EQS/Windows: Basic Concepts, applications, and programming. Thousand Oaks, CA: Sage.

Byrne, B.M. (1998). Structural equation modeling with LISREL, PRELIS, and SIMPLIS: Basic concepts, applications, and programming. Mahwah, NJ: Erlbaum.

Cohen, J. (1968). Multiple regression as a general data-analytic system. Psychological Bulletin, 70, 426-443.

Cohen, J. (1994). The earth is round (p < .05). American Psychologist, 49, 997-1003.
Cudeck, R. (1989). The analysis of correlation matrices using covariance structure models. Psychological Bulletin, 105, 317-327.
Duncan, O.D. (1975). Introduction to structural equation models. New York: Academic Press.
Fan, X. (1996a). Canonical correlation analysis as a general analytic model. In B. Thompson (Ed.), Advances in social science methodology (Vol. 4, pp. 71-94). Greenwich, CT: JAI Press.
Fan, X. (1996b). A SAS program for assessing multivariate normality. Educational and Psychological Measurement, 56, 668-674.
Fan, X. (1997). Canonical correlation analysis and structural equation modeling: What do they have in common? Structural Equation Modeling, 4, 65-79.
Fan, X., Thompson, B., & Wang, L. (in press). The effects of sample size, estimation methods, and model specification on SEM fit indices. Structural Equation Modeling.
Fan, X., Wang, L., & Thompson, B. (1997, March). Effects of data nonnormality on fit indices and parameter estimates for true and misspecified SEM models. Paper presented at the annual meeting of the American Educational Research Association, Chicago. (ERIC Document Reproduction Service No. ED 408 299)
Fish, L.J. (1988). Why multivariate methods are usually vital. Measurement and Evaluation in Counseling and Development, 21, 130-137.
Hayduk, L.A. (1996). LISREL issues, debates, and strategies. Baltimore, MD: Johns Hopkins University Press.
Huberty, C.J, & Morris, J.D. (1988). A single contrast test procedure. Educational and Psychological Measurement, 48, 567-578.
Jöreskog, K.G. (1967). Some contributions to maximum likelihood factor analysis. Psychometrika, 32, 443-482.
Jöreskog, K.G. (1969). A general approach to confirmatory maximum likelihood factor analysis. Psychometrika, 34, 183-220.
Jöreskog, K.G. (1970). A general method for analysis of covariance structures. Biometrika, 57, 239-251.
Jöreskog, K.G. (1971). Simultaneous factor analysis in several populations. Psychometrika, 36, 409-426.
Jöreskog, K.G. (1978). Structural analysis of covariance and correlation matrices. Psychometrika, 43, 443-477.
Jöreskog, K.G., & Sörbom, D. (1984). LISREL VI user's guide (3rd ed.). Mooresville, IN: Scientific Software.
Jöreskog, K.G., & Sörbom, D. (1989). LISREL 7: A guide to the program and applications (2nd ed.). Chicago: SPSS.
Knapp, T. R. (1978). Canonical correlation analysis: A general parametric significance testing system. Psychological Bulletin, 85, 410-416.
Lomax, R. (1989). Covariance structure analysis: Extensions and developments. In B. Thompson (Ed.), Advances in social science

methodology (Vol. 1, pp. 171-204). Greenwich, CT: JAI Press.
Long, J.S. (1983a). Confirmatory factor analysis: A preface to LISREL. Thousand Oaks, CA: Sage.
Long, J.S. (1983b). Covariance structure models: An introduction to LISREL. Thousand Oaks, CA: Sage.
MacCallum, R.C., Browne, M.W., & Sugawara, H.M. (1996). Power analysis and determination of sample size for covariance structural modeling. Psychological Methods, 1, 130-149.
Marsh, H.W., & Hu, K. (1998). Is parsimony always desirable? Journal of Experimental Education, 66, 274-285.
Mueller, R.O. (1997). Structural equation modeling: Back to basics. Structural Equation Modeling, 4, 353-369.
Mulaik, S.A. (1987). A brief history of the philosophical foundations of exploratory factor analysis. Multivariate Behavioral Research, 22, 267-305.
Mulaik, S.A. (1988). Confirmatory factor analysis. In R.B. Cattell & J.R. Nesselroade (Eds.), Handbook of multivariate experimental psychology. New York: Plenum.
Mulaik, S.A. (1994). The critique of pure statistics: Artifact and objectivity in multivariate statistics. In B. Thompson (Ed.), Advances in social science methodology (Vol. 3, pp. 247-296). Greenwich, CT: JAI Press.
Mulaik, S.A., James, L.R., van Alstine, J., Bennett, N., Lind, S., & Stilwell, C.D. (1989). Evaluation of goodness-of-fit indices for structural equation models. Psychological Bulletin, 105, 430-445.
Pedhazur, E.J. (1982). Multiple regression in behavioral research: Explanation and prediction (2nd ed.). New York: Holt, Rinehart and Winston.
Reinhardt, B. (1996). Factors affecting coefficient alpha: A mini Monte Carlo study. In B. Thompson (Ed.), Advances in social science methodology (Vol. 4, pp. 3-20). Greenwich, CT: JAI Press.
Spearman, C. (1904). The proof and measurement of association between two things. Journal of Psychology, 15, 72-101.
Steiger, J.H., & Lind, J.C. (1980, June). Statistically based tests for the number of common factors. Paper presented at the annual meeting of the Psychonomic Society, Iowa City, IA.
Stevens, J. (1996). Applied multivariate statistics for the social sciences (3rd ed.). Mahwah, NJ: Erlbaum.
Thompson, B. (1984). Canonical correlation analysis: Uses and interpretation. Thousand Oaks, CA: Sage.
Thompson, B. (1990). MULTINOR: A FORTRAN program that assists in evaluating multivariate normality. Educational and Psychological Measurement, 50, 845-848.
Thompson, B. (1991). A primer on the logic and use of canonical correlation analysis. Measurement and Evaluation in Counseling and Development, 24, 80-95.
Thompson, B. (1992). DISCSTRA: A computer program that computes bootstrap resampling estimates of descriptive discriminant analysis function and structure coefficients and group centroids. Educational and Psychological Measurement, 52,

905-911.
Thompson, B. (1994). Guidelines for authors. Educational and Psychological Measurement, 54(4), 837-847.
Thompson, B. (1996). AERA editorial policies regarding statistical significance testing: Three suggested reforms. Educational Researcher, 25(2), 26-30.
Thompson, B. (1998a, April). Five methodology errors in educational research: The pantheon of statistical significance and other faux pas. Invited address presented at the annual meeting of the American Educational Research Association, San Diego. (ERIC Document Reproduction Service No. ED forthcoming)
Thompson, B. (1998b). Review of *What if there were no significance tests?* by L. Harlow, S. Mulaik & J. Steiger (Eds.). Educational and Psychological Measurement, 58, 332-344.
Thompson, B. (in press-a). If statistical significance tests are broken/misused, what practices should supplement or replace them?. Theory & Psychology.
Thompson, B. (in press-b). Journal editorial policies regarding statistical significance tests: Heat is to fire as p is to importance. Educational Psychology Review.
Thompson, B. (in press-c). Statistical significance tests, effect size reporting, and the vain pursuit of pseudo-objectivity. Theory & Psychology.
Vacha-Haase, T. (1998). Reliability generalization: Exploring variance in measurement error affecting score reliability across studies. Educational and Psychological Measurement, 58, 6-20.
West, S.G., Finch, J.F., & Curran, P.J. (1995). Structural equation models with nonnormal data. In R.H. Hoyle (Ed.), Structural equation modeling (pp. 56-75). Thousand Oaks, CA: Sage.
Wright, S. (1921). Correlation and causality. Journal of Agricultural Research, 20, 557-585.
Wright, S. (1934). The method of path coefficients. Annals of Mathematical Statistics, 5, 161-215.

Table 1
Pearson Correlation Coefficients, Standard Deviations,
and Variances/Covariances of the 8 Measured/Observed Variables

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	y1	y2	y3	x1	x2	x3	x4	x5
SD	2.09	3.43	2.81	1.95	2.06	2.16	2.06	3.65
y1	1.000[a]							
	2.090[b]							
	2.090[c]							
	4.368[d]							
y2	0.418	1.000						
	2.090	3.430						
	3.430	3.430						
	2.997	11.765						
y3	0.394	0.627	1.000					
	2.090	3.430	2.810					
	2.810	2.810	2.810					
	2.314	6.043	7.896					
x1	0.129	0.202	0.266	1.000				
	2.090	3.430	2.810	1.950				
	1.950	1.950	1.950	1.950				
	0.526	1.351	1.458	3.802				
x2	0.189	0.284	0.208	0.365	1.000			
	2.090	3.430	2.810	1.950	2.060			
	2.060	2.060	2.060	2.060	2.060			
	0.814	2.007	1.204	1.466	4.244			
x3	0.544	0.281	0.324	0.201	0.161	1.000		
	2.090	3.430	2.810	1.950	2.060	2.160		
	2.160	2.160	2.160	2.160	2.160	2.160		
	2.456	2.082	1.967	0.847	0.716	4.666		
x4	0.507	0.225	0.314	0.172	0.174	0.546	1.000	
	2.090	3.430	2.810	1.950	2.060	2.160	2.060	
	2.060	2.060	2.060	2.060	2.060	2.060	2.060	
	2.183	1.590	1.818	0.691	0.738	2.429	4.244	
x5	-0.357	-0.156	-0.038	-0.199	-0.277	-0.294	-0.174	1.000
	2.090	3.430	2.810	1.950	2.060	2.160	2.060	3.650
	3.650	3.650	3.650	3.650	3.650	3.650	3.650	3.650
	-2.723	-1.953	-0.390	-1.416	-2.083	-2.318	-1.308	13.323

Note. "y1" = Performance measure; "y2" = Job Satisfaction measure #1; "y3" = Job Satisfaction measure #2; "x1" = Achievement Motivation measure #1; "x2" = Achievement Motivation measure #2; "x3" = Task-specific Self Esteem measure #1; "x4" = Task-specific Self Esteem measure #2; "x5" = Verbal Intelligence measure.

[a]Pearson *r* between two measured/observed variables ($r_{XY} = COV_{XY} / (SD_X \times SD_Y)$)

[b]Standard deviation of one measured/observed variable in a given variable pair

[c]Standard deviation of the other measured/observed variable in a given variable pair

[d]Variance of a given measured/observed variable, if on the diagonal, or the covariance between two measured/observed variables ($COV_{XY} = r_{XY}\ (SD_X)\ (SD_Y)$), if off-diagonal

Table 2
Parameter Estimates for 4 Model Variations

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Figure 1 Model (Performance Predicts Job Satisfaction; *Reliability of Verbal Intelligence (X_5) Scores Fixed as .85*) [see Appendix B for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=2.571	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.751	$\gamma_{2,1}$=1.228
δ_2=2.566	$\lambda_{2,1}$=1.168	$\phi_{3,1}$=-1.627	$\gamma_{2,3}$=0.213
(δ_5=1.998)	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.303	$\gamma_{1,2}$=0.923
δ_3=1.931	($\lambda_{3,2}$=1)		
δ_4=2.213	$\lambda_{4,2}$=0.862		

Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
$\beta_{2,1}$=0.594	ζ_2=3.865	($\lambda_{2,2}$=1)	ϵ_2=4.492
	ζ_1=2.038	$\lambda_{3,2}$=0.831	ϵ_3=2.875
		($\lambda_{1,1}$=1)	[ϵ_1=0]

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Model that Performance Predicts Job Satisfaction with *Reliability of Verbal Intelligence Scores (X_5) Fixed as 1.0* [see Appendix C for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=2.571	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.747	$\gamma_{2,1}$=1.179
δ_2=2.562	$\lambda_{2,1}$=1.169	$\phi_{3,1}$=-1.628	$\gamma_{2,3}$=0.175
==> [δ_5=0]	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.316	$\gamma_{1,2}$=0.923
δ_3=1.930	($\lambda_{3,2}$=1)		
δ_4=2.215	$\lambda_{4,2}$=0.861		

Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
$\beta_{2,1}$=0.583	ζ_2=3.925	($\lambda_{2,2}$=1)	ϵ_2=4.517
	ζ_1=2.038	$\lambda_{3,2}$=0.834	ϵ_3=2.858
		($\lambda_{1,1}$=1)	[ϵ_1=0]

Table 2 (cont.)

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Model that *Performance and Job Satisfaction Reciprocally Predict Each Other* with Reliability of Verbal Intelligence Scores (X_5) Fixed as .85 [see Appendix D for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=2.506	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.773	$\gamma_{2,1}$=1.057
δ_2=2.566	$\lambda_{2,1}$=1.138	$\phi_{3,1}$=-1.648	$\gamma_{2,3}$=0.265
[δ_5=1.998]	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.235	$\gamma_{1,2}$=1.111
δ_3=1.955	($\lambda_{3,2}$=1)		
δ_4=2.212	$\lambda_{4,2}$=0.866		

	Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
	$\beta_{2,1}$=0.816	ζ_2=3.904	($\lambda_{2,2}$=1)	ϵ_2=4.921
=========>	**$\beta_{1,2}$=-.220**	ζ_1=2.573	$\lambda_{3,2}$=0.881	ϵ_3=2.578
			($\lambda_{1,1}$=1)	[ϵ_1=0]

Maximum-Likelihood Freed/Estimated and the Fixed, Non-zero (in Parentheses) Parameters for the Model that *Job Satisfaction Predicts Performance* with Reliability of Verbal Intelligence (X_5) Scores Fixed as .85 [see Appendix E for the LISREL commands and results]

Predictor Measurement Error Variances	Predictor Measurement Parameters	Predictor Synthetic Covariances	Predictor Construct Path Coefficients
δ_1=3.123	($\lambda_{1,1}$=1)	$\phi_{2,1}$=0.870	$\gamma_{2,1}$=3.208
δ_2=3.293	$\lambda_{2,1}$=1.184	$\phi_{3,1}$=-1.629	$\gamma_{2,3}$=0.348
[δ_5=1.998]	($\lambda_{5,3}$=1)	$\phi_{3,2}$=-2.296	$\gamma_{1,2}$=0.801
δ_3=1.911	($\lambda_{3,2}$=1)		
δ_4=2.214	$\lambda_{4,2}$=0.858		

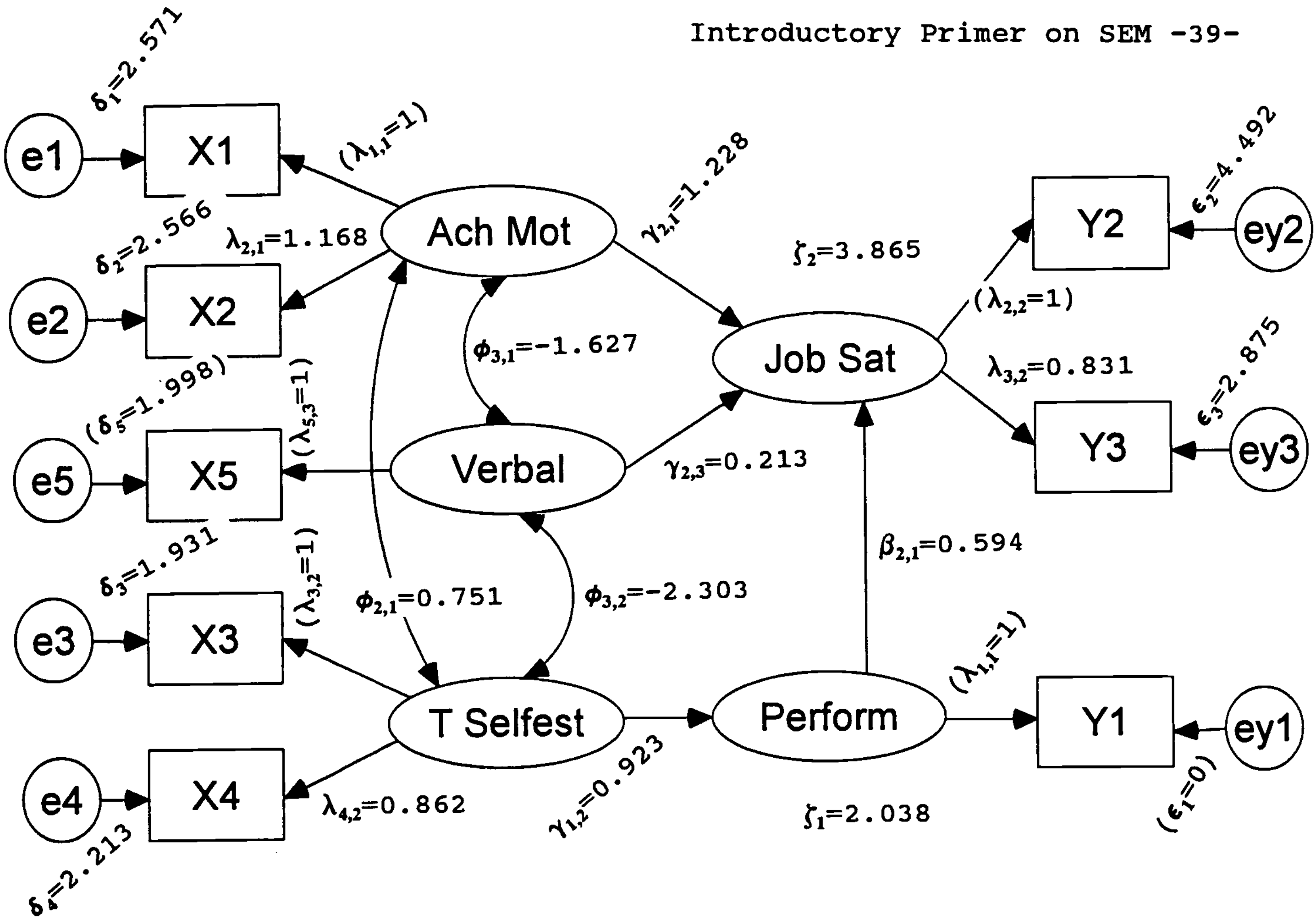
	Criterion Synthetic Path Coefficients	Criterion Synthetic Error Variances	Criterion Measurement Parameters	Criterion Measurement Error Variances
=========>	**$\beta_{1,2}$=0.150**	ζ_2=4.475	($\lambda_{2,2}$=1)	ϵ_2=4.475
	[$\beta_{2,1}$=0]	ζ_1=2.822	$\lambda_{3,2}$=0.834	ϵ_3=2.822
			($\lambda_{1,1}$=1)	[ϵ_1=0]

Table 3
A Few Fit Statistics for the Three
Substantively Competitive Models (A, C, D)

sem_osep.wk1 7/9/98

	Model		
Statistic	A	C	D
chi square	14.19	12.12	23.34
n of parameter estimates	21	22	21
df	15	14	15
chi square to df ratio	0.946	0.866	1.556
goodness of fit index (GFI)	0.969	0.974	0.953
adjusted goodness of fit index (AGFI)	0.926	0.932	0.886
root mean-square residual (RMR)	0.285	0.287	0.304
coef of determination for 5 X variables	0.974	0.974	0.961
coef of determination for structural equations	0.663	0.547	0.797
$\beta_{(2,1)}$	0.594	0.816	--
SE $\beta_{(2,1)}$	0.140	0.210	--
$\beta_{(2,1)}$ / SE	4.239	3.887	--
$\beta_{(1,2)}$	--	-0.220	0.150
SE $\beta_{(1,2)}$	--	0.161	0.078
$\beta_{(1,2)}$ / SE	--	-1.362	1.928

Note. With 8 observed variables, available degrees of freedom equal 36 ([8 * 9] / 2). If, for example, 21 parameters are estimated, the model's degrees of freedom equal 15 (36 - 21).



Declaration of Freed/Estimated (**in Greek letters**) and Fixed (**numbers**) Model Parameters

Theta Delta

$$\begin{bmatrix} \delta_1 \\ \delta_2 \\ 1.998_5 \\ \delta_3 \\ \delta_4 \end{bmatrix}$$

Lambda X

$$\begin{bmatrix} 1_{1,1} & 0_{1,2} & 0_{1,3} \\ \lambda_{2,1} & 0_{2,2} & 0_{2,3} \\ 0_{5,1} & 0_{5,2} & 1_{5,3} \\ 0_{3,1} & 1_{3,2} & 0_{3,3} \\ 0_{4,1} & \lambda_{4,2} & 0_{4,3} \end{bmatrix}$$

Phi

$$\begin{bmatrix} \phi_{1,1} & & \\ \phi_{2,1} & \phi_{2,2} & \\ \phi_{3,1} & \phi_{3,2} & \phi_{3,3} \end{bmatrix}$$

Gamma

$$\begin{bmatrix} 0_{1,1} & \gamma_{1,2} & 0_{1,3} \\ \gamma_{2,1} & 0_{2,2} & \gamma_{2,3} \end{bmatrix}$$

Beta

$$\begin{bmatrix} 0_{1,1} & 0_{1,2} \\ \beta_{2,1} & 0_{2,2} \end{bmatrix}$$

Psi

$$\begin{bmatrix} \zeta_1 & \zeta_2 \end{bmatrix}$$

Lambda Y

$$\begin{bmatrix} 1_{1,1} & 0_{1,2} \\ 0_{2,1} & 1_{2,2} \\ 0_{3,1} & \lambda_{3,2} \end{bmatrix}$$

Theta Epsilon

$$\begin{bmatrix} 0_1 \\ \epsilon_2 \\ \epsilon_3 \end{bmatrix}$$

N.B. Given the reliability of the Verbal Intelligence scores was fixed (constrained) as equaling .85, the fixed error variance for this variable in this model equals the variance of this measured variable (13.323 from Table 1) times (1 - .85) [(1 - .85) 13.323 = (.15) 13.323 = 1.998].

Figure 1
Performance Predicts Job Satisfaction;
Reliability of Verbal Intelligence Scores Fixed as .85

Appendix A
SPSS for Windows Version of Program MULTINOR to Evaluate Multivariate Normality

multino2.aer 10/11/97

multinor.sps

```
SET BLANKS=SYSMIS UNDEFINED=WARN printback=list.
TITLE 'MULTINOR.SPS   tests multivar normality graphically****'.
COMMENT *****************************************************.
COMMENT The original MULTINOR computer program was presented,
COMMENT with examples, in:
COMMENT     Thompson, B. (1990). MULTINOR: A FORTRAN program that
COMMENT     assists in evaluating multivariate normality.
COMMENT     _Educational and Psychological Measurement_, 50,
COMMENT     845-848.
COMMENT
COMMENT The logic and the data source for the example are from:
COMMENT     Stevens, J. (1986). _Applied multivariate statistics
COMMENT     for the social sciences_. Hillsdale, NJ: Erlbaum.
COMMENT     (pp. 207-212)
COMMENT *********************************************************.
COMMENT  Here there are 3 variables for which multivariate
COMMENT  normality is being confirmed.
COMMENT       Note. The number of cases in actual practice should be
COMMENT  at least 25-30 for the graphical procedure to function
COMMENT  effectively.
DATA LIST
  FILE='c:\spsswin\multinor.dat' FIXED RECORDS=1 TABLE
  /1 x1 1-3 (1) x2 5-7 (1) x3 9-11 (1).
list variables=all/cases=9999/format=numbered .
COMMENT  'y' is a variable automatically created by the program, and
COMMENT  does not have to modified for different data sets.
compute y=$casenum .
print formats y(F5) .
regression variables=y x1 to x3/
  descriptive=mean stddev corr/
  dependent=y/enter x1 to x3/
  save=mahal(mahal) .
sort cases by mahal(a) .
execute .
list variables=y x1 to x3 mahal/cases=9999/format=numbered .
COMMENT  In the next TWO lines, for a given data set put the actual n
COMMENT  in place of the number '12' used for the example data set.
loop #i=1 to 12 .
COMMENT  In the next line, change '3' to whatever is the number
COMMENT  of variables.
COMMENT       The p critical value of chi square for a given case
COMMENT  is set as [the case number (after sorting) - .5] / the
COMMENT  sample size].
compute p=($casenum - .5) / 12. .
compute chisq=idf.chisq(p,3) .
end loop .
print formats p chisq (F8.5) .
list variables=y p mahal chisq/cases=9999/format=numbered .
plot
  vertical='chi square'/
  horizontal='Mahalabis distance'/
  plot=chisq with mahal .
```

multinor.dat

```
2.4 2.1 2.4
3.5 1.8 3.9
6.7 3.6 5.9
5.3 3.3 6.1
5.2 4.1 6.4
3.2 2.7 4.0
4.5 4.9 5.7
3.9 4.7 4.7
4.0 3.6 2.9
5.7 5.5 6.2
2.4 2.9 3.2
2.7 2.6 4.1
```

multinor.lst

```
-> SET BLANKS=SYSMIS UNDEFINED=WARN printback=list.

-> TITLE 'MULTINOR.SPS   tests multivar normality graphically****'.

-> COMMENT ******************************************************.
-> COMMENT The original MULTINOR computer program was presented,
-> COMMENT with examples, in:
-> COMMENT     Thompson, B. (1990). MULTINOR: A FORTRAN program that
-> COMMENT     assists in evaluating multivariate normality.
-> COMMENT     _Educational and Psychological Measurement_, 50,
-> COMMENT     845-848.
-> COMMENT
-> COMMENT The logic and the data source for the example are from:
-> COMMENT     Stevens, J. (1986). _Applied multivariate statistics
-> COMMENT     for the social sciences_. Hillsdale, NJ: Erlbaum.
-> COMMENT     (pp. 207-212)
-> COMMENT *********************************************************.

-> COMMENT  Here there are 3 variables for which multivariate
-> COMMENT  normality is being confirmed.

-> DATA LIST
->   FILE='c:\spsswin\multinor.dat' FIXED RECORDS=1 TABLE
->   /1 x1 1-3 (1) x2 5-7 (1) x3 9-11 (1).

-> list variables=all/cases=9999/format=numbered .

        X1   X2   X3
    1  2.4  2.1  2.4
    2  3.5  1.8  3.9
    3  6.7  3.6  5.9
    4  5.3  3.3  6.1
    5  5.2  4.1  6.4
    6  3.2  2.7  4.0
    7  4.5  4.9  5.7
    8  3.9  4.7  4.7
    9  4.0  3.6  2.9
   10  5.7  5.5  6.2
   11  2.4  2.9  3.2
   12  2.7  2.6  4.1

Number of cases read:  12    Number of cases listed:  12

-> COMMENT  'y' is a variable automatically created by the program, and
-> COMMENT  does not have to modified for different data sets.

-> compute y=$casenum .
```

```
-> print formats y(F5) .

-> regression variables=y x1 to x3/
->   descriptive=mean stddev corr/
->   dependent=y/enter x1 to x3/
->   save=mahal(mahal) .

           * * * *  M U L T I P L E   R E G R E S S I O N   * * * *
Listwise Deletion of Missing Data
           Mean  Std Dev  Label
Y          6.500    3.606
X1         4.125    1.384
X2         3.483    1.147
X3         4.625    1.406

N of Cases =    12

Correlation:
                  Y          X1          X2          X3
Y             1.000       -.207        .376       -.044
X1            -.207       1.000        .606        .845
X2             .376        .606       1.000        .656
X3            -.044        .845        .656       1.000

           * * * *  M U L T I P L E   R E G R E S S I O N   * * * *

Equation Number 1    Dependent Variable..   Y
  Descriptive Statistics are printed on Page   83

Block Number  1.  Method:  Enter      X1       X2       X3

Variable(s) Entered on Step Number
   1..    X3
   2..    X2
   3..    X1

Multiple R           .66417
R Square             .44112
Adjusted R Square    .23154
Standard Error      3.16069

Analysis of Variance
                    DF      Sum of Squares      Mean Square
Regression           3            63.08053         21.02684
Residual             8            79.91947          9.98993

F =       2.10480       Signif F =  .1780

------------------ Variables in the Equation ------------------

Variable                B        SE B       Beta         T  Sig T

X1              -1.909097    1.296480   -.733029    -1.473  .1791
X2               2.445453    1.110369    .778083     2.202  .0588
X3                .165296    1.345478    .064454      .123  .9053
(Constant)       5.092203    3.454771                1.474  .1787

End Block Number   1   All requested variables entered.

           * * * *  M U L T I P L E   R E G R E S S I O N   * * * *
Equation Number 1    Dependent Variable..   Y

Residuals Statistics:
```

```
            Min       Max      Mean   Std Dev    N
*PRED      2.0801    9.9172   6.5000   2.3947   12
*ZPRED    -1.8457    1.4270    .0000   1.0000   12
*SEPRED    1.2118    2.4798   1.7932    .3534   12
*ADJPRED    .6074   10.6661   6.2406   2.9511   12
*RESID    -5.0425    5.0265    .0000   2.6954   12
*ZRESID   -1.5954    1.5903    .0000    .8528   12
*SRESID   -1.9334    1.8781    .0291   1.0420   12
*DRESID   -7.4057    7.0104    .2594   4.0901   12
*SDRESID  -2.4778    2.3496    .0287   1.2152   12
*MAHAL      .7004    5.8543   2.7500   1.5070   12
*COOK D     .0000     .4543    .1364    .1713   12
*LEVER      .0637     .5322    .2500    .1370   12

Total Cases =       12


          * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
From Equation   1:   1 new variables have been created.

  Name        Contents
  ----        --------
  MAHAL        Mahalanobis' Distance

-> sort cases by mahal(a) .
-> execute .

-> list variables=x1 to x3 mahal/cases=9999/format=numbered .

         X1   X2   X3       MAHAL
     1  3.2  2.7  4.0      .70038
     2  2.4  2.9  3.2     1.65042
     3  5.2  4.1  6.4     1.98854
     4  3.9  4.7  4.7     2.17303
     5  2.7  2.6  4.1     2.19634
     6  4.5  4.9  5.7     2.22174
     7  5.3  3.3  6.1     2.37118
     8  3.5  1.8  3.9     2.53196
     9  2.4  2.1  2.4     2.59346
    10  5.7  5.5  6.2     3.12622
    11  4.0  3.6  2.9     5.59246
    12  6.7  3.6  5.9     5.85428

Number of cases read:  12    Number of cases listed:  12

-> COMMENT  In the next TWO lines, for a given data set put the actual
-> COMMENT  in place of the number '12' used for the example data set.

-> loop #i=1 to 12 .

-> COMMENT  In the next line, change '3' to whatever is the number
-> COMMENT  of variables.
-> COMMENT       The p critical value of chi square for a given case
-> COMMENT  is set as [the case number (after sorting) - .5] / the
-> COMMENT  sample size].

-> compute p=($casenum - .5) / 12. .

-> compute chisq=idf.chisq(p,3) .

-> end loop .

-> print formats p chisq (F8.5) .
```

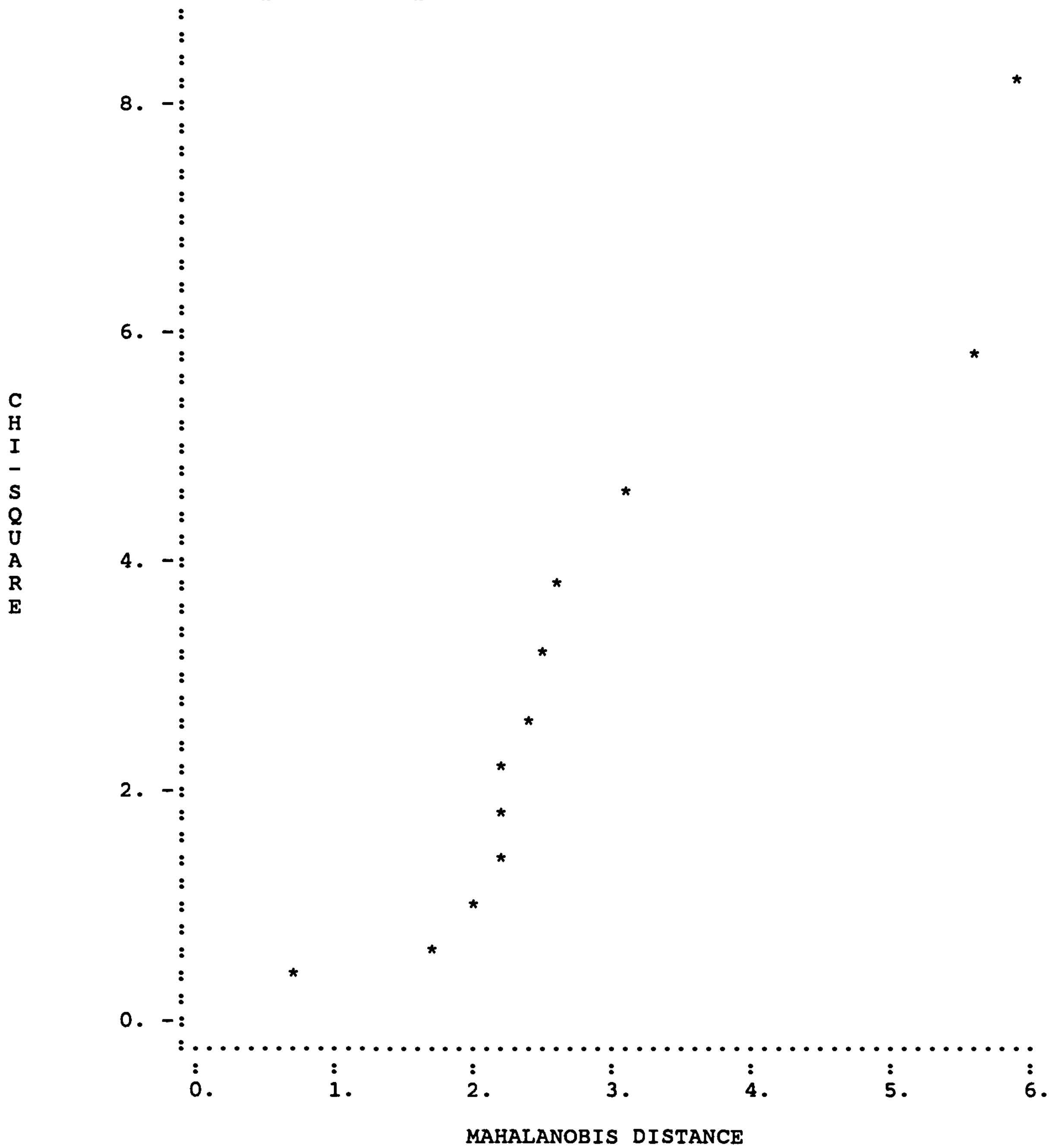
```
-> list variables=y p mahal chisq/cases=9999/format=numbered .
          Y         P       MAHAL     CHISQ
     1    6    .04167      .70038    .30897
     2   11    .12500     1.65042    .69236
     3    5    .20833     1.98854   1.03962
     4    8    .29167     2.17303   1.38807
     5   12    .37500     2.19634   1.75398
     6    7    .45833     2.22174   2.15099
     7    4    .54167     2.37118   2.59519
     8    2    .62500     2.53196   3.10983
     9    1    .70833     2.59346   3.73392
    10   10    .79167     3.12622   4.54475
    11    9    .87500     5.59246   5.73941
    12    3    .95833     5.85428   8.22056

Number of cases read:  12    Number of cases listed:  12


-> plot
->   vertical='chi square'/
->   horizontal='Mahalabis distance'/
->   plot=chisq with mahal .

Hi-Res Chart  # 6:Plot of chisq with mahal
```

SCATTERPLOT OF D SQ AND CHI SQUARE FOR GROUP #2



Note. For data sets involving at least 25-30 data points, the graph will define a straight line for multivariate normal data.

Appendix B
Maximum-Likelihood Analysis for the Figure 1 Model
(Performance Predicts Job Satisfaction;
Reliability of Verbal Intelligence (X_5) Scores Fixed as .85)

lisr152a.lst 7/9/98

```
08-Jul-98   SPSS RELEASE 4.1 FOR IBM OS/MVS                                                   Page   1
15:44:29    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS        License Number 1267
This software is functional through August 31, 1998.

    0  title 'LISR152a.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
    0  data list file=abc records=3 table/1 id 1-4
    0    /2 /3
This command will read 3 records from 'E100BT.ARTHUR.DAT'
Variable   Rec   Start     End        Format

ID           1       1       4        F4.0

    0  lisrel
    0    /"Joreskog/Sorbom pp. 155-156 Model ****"
    0    /DA NI=8 NO=122 MA=CM
    0    /LA
    0    /'PERFORMM' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
    0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
    0    /KM SY
    0    /(8F8.3)
    0    /   4.368
    0    /   2.997  11.765
    0    /   2.314   6.043   7.896
    0    /   0.526   1.351   1.458   3.802
    0    /   0.814   2.007   1.204   1.466   4.244
    0    /   2.456   2.082   1.967   0.847   0.716   4.666
    0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
    0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
    0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
    0    /LE
    0    /'PERFORMN' 'JOBSATIS'
    0    /LK
    0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
    0    /FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
    0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
    0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
    0    /VA 1.998 TD(5,5)
    0    /OU SE SS SC TV MI ND=3
There are 3,033,288 bytes of memory available.
The largest contiguous area has 3,026,960 bytes.



                 LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
                         PROGRAM VERSION 7.16        DISTRIBUTED BY

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                         (317) 831-6336


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```

MVS - L I S R E L 7.16
BY
KARL G JORESKOG AND DAG SORBOM

THE FOLLOWING LISREL CONTROL LINES HAVE BEEN READ :

```
Joreskog/Sorbom pp. 155-156 Model ****
DA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
VA 1.998 TD(5,5)
OU SE SS SC TV MI ND=3
```

Joreskog/Sorbom pp. 155-156 Model ****

NUMBER OF INPUT VARIABLES 8
NUMBER OF Y - VARIABLES 3
NUMBER OF X - VARIABLES 5
NUMBER OF ETA - VARIABLES 2
NUMBER OF KSI - VARIABLES 3
NUMBER OF OBSERVATIONS 122

Joreskog/Sorbom pp. 155-156 Model ****

COVARIANCE MATRIX TO BE ANALYZED

	PERFORMM	JBSATIS1	JBSATIS2	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
PERFORMM	4.368							
JBSATIS1	2.997	11.765						
JBSATIS2	2.314	6.043	7.896					
ACHIMOT1	0.526	1.351	1.458	3.802				
ACHIMOT2	0.814	2.007	1.204	1.466	4.244			
TASKSEL1	2.456	2.082	1.967	0.847	0.716	4.666		
TASKSEL2	2.183	1.590	1.818	0.691	0.738	2.429	4.244	
VERBALIQ	-2.723	-1.953	-0.390	-1.416	-2.083	-2.318	-1.308	13.323

Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0	0
JBSATIS1	0	0
JBSATIS2	0	1

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0	0	0
ACHIMOT2	2	0	0
TASKSEL1	0	0	0
TASKSEL2	0	3	0
VERBALIQ	0	0	0

BETA

	PERFORMN	JOBSATIS
PERFORMN	0	0
JOBSATIS	4	0

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0	5	0
JOBSATIS	6	0	7

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	8		
TASKSELF	9	10	
VERBINTL	11	12	13

PSI

PERFORMN	JOBSATIS
14	15

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0	16	17

THETA OELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
18	19	20	21	0

Joreskog/Sorbom pp. 155-156 Model ****
INITIAL ESTIMATES (TSLS)

LAMBOA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.797

LAMBOA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	0.877	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.939	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.707	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.926	0.000
JOBSATIS	0.989	0.000	0.208

COVARIANCE MATRIX OF ETA ANO KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.368				
JOBSATIS	3.478	8.316			
AMOTIVAT	0.759	1.810	1.671		
TASKSELF	2.395	2.114	0.820	2.587	
VERBINTL	-1.744	-0.692	-1.833	-1.885	11.325

PSI

PERFORMN	JOBSATIS
2.151	4.209

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.181	3.081

THETA OELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.131	2.958	2.079	1.963	1.998

SQUAREO MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM JBSATIS1 JBSATIS2

1.000	0.665	0.632

SQUAREO MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.440	0.303	0.554	0.537	0.850

TOTAL COEFFICIENT OF OETERMINATION FOR X - VARIABLES IS 0.976

SQUAREO MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN	JOBSATIS
0.507	0.494

TOTAL COEFFICIENT OF OETERMINATION FOR STRUCTURAL EQUATIONS IS 0.626

Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)

LAMBOA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.831

LAMBOA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	1.168	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.862	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.594	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.923	0.000
JOBSATIS	1.228	0.000	0.213

COVARIANCE MATRIX OF ETA ANO KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.368				
JOBSATIS	2.995	7.401			
AMOTIVAT	0.694	1.577	1.231		
TASKSELF	2.524	1.932	0.751	2.735	
VERBINTL	-2.125	-0.845	-1.627	-2.303	11.327

PSI

PERFORMN	JOBSATIS
2.038	3.865

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.492	2.875

THETA OELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.571	2.566	1.931	2.213	1.998

SQUAREO MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2
1.000	0.622	0.640

SQUAREO MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.324	0.395	0.586	0.479	0.850

TOTAL COEFFICIENT OF OETERMINATION FOR X - VARIABLES IS 0.974

SQUAREO MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN JOBSATIS

```
          0.533     0.478
      TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.663
W_A_R_N_I_N_G : THETA EPS is not positive definite


       CHI-SQUARE WITH  15 DEGREES OF FREEDOM =    14.19 (P = .511)
                    GOODNESS OF FIT INDEX =0.969
           ADJUSTED GOODNESS OF FIT INDEX =0.926
                ROOT MEAN SQUARE RESIDUAL =     0.285

Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =   -1.108
  MEDIAN FITTED RESIDUAL =    0.000
 LARGEST FITTED RESIDUAL =    0.676
STEMLEAF PLOT
-10|1
- 8|
- 6|0
- 4|
- 2|33
- 0|8776319772200000000
  0|13470557
  2|116
  4|3
  6|8
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL =   -2.053
  MEDIAN STANDARDIZED RESIDUAL =    0.000
 LARGEST STANDARDIZED RESIDUAL =    1.825
STEMLEAF PLOT
- 2|1
- 1|8
- 1|3322
- 0|87777
- 0|222110000000
  0|1234
  0|55778
  1|012
  1|8
Joreskog/Sorbom pp. 155-156 Model ****

STANDARD ERRORS
        LAMBDA Y
           PERFORMN   JOBSATIS

PERFORMM      0.000      0.000
JBSATIS1      0.000      0.000
JBSATIS2      0.000      0.134
        LAMBDA X
           AMOTIVAT   TASKSELF   VERBINTL

ACHIMOT1      0.000      0.000      0.000
ACHIMOT2      0.336      0.000      0.000
TASKSEL1      0.000      0.000      0.000
TASKSEL2      0.000      0.138      0.000
VERBALIQ      0.000      0.000      0.000
        BETA
           PERFORMN   JOBSATIS

PERFORMN      0.000      0.000
JOBSATIS      0.140      0.000
        GAMMA
           AMOTIVAT   TASKSELF   VERBINTL

PERFORMN      0.000      0.144      0.000
JOBSATIS      0.477      0.000      0.107
        PHI
           AMOTIVAT   TASKSELF   VERBINTL
```

AMOTIVAT	0.500		
TASKSELF	0.298	0.646	
VERBINTL	0.592	0.683	1.713

PSI

PERFORMN	JOBSATIS
0.396	1.222

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	1.177	0.799

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.479	0.574	0.425	0.388	0.000

Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	6.195

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	3.474	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	6.254	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	4.239	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	6.395	0.000
JOBSATIS	2.572	0.000	2.000

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	2.464		
TASKSELF	2.520	4.236	
VERBINTL	-2.749	-3.373	6.612

PSI

PERFORMN	JOBSATIS
5.145	3.163

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	3.816	3.599

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
5.371	4.468	4.549	5.702	0.000

Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	2.090	0.000
JBSATIS1	0.000	2.720
JBSATIS2	0.000	2.260

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.109	0.000	0.000
ACHIMOT2	1.296	0.000	0.000
TASKSEL1	0.000	1.654	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.366

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.457	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.501	0.000	0.264

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.527	1.000			
AMOTIVAT	0.299	0.522	1.000		
TASKSELF	0.730	0.429	0.410	1.000	
VERBINTL	-0.302	-0.092	-0.436	-0.414	1.000

PSI

PERFORMN	JOBSATIS
0.467	0.522

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.501	0.333	0.264

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	0.789
JBSATIS2	0.000	0.800

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.569	0.000	0.000
ACHIMOT2	0.629	0.000	0.000
TASKSEL1	0.000	0.766	0.000
TASKSEL2	0.000	0.692	0.000
VERBALIQ	0.000	0.000	0.922

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.457	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.501	0.000	0.264

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.527	1.000			
AMOTIVAT	0.299	0.522	1.000		
TASKSELF	0.730	0.429	0.410	1.000	
VERBINTL	-0.302	-0.092	-0.436	-0.414	1.000

PSI

PERFORMN	JOBSATIS
0.467	0.522

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	0.378	0.360

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.676	0.605	0.414	0.521	0.150

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.501	0.333	0.264

Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE

MODIFICATION INDICES FOR LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	1.647
JBSATIS1	0.570	0.000
JBSATIS2	0.570	0.000

ESTIMATED CHANGE FOR LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	-0.153
JBSATIS1	0.192	0.000
JBSATIS2	-0.160	0.000

MODIFICATION INDICES FOR LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.009	0.480
ACHIMOT2	0.000	0.169	0.480
TASKSEL1	0.044	0.000	0.000
TASKSEL2	0.030	0.000	3.328
VERBALIQ	0.000	0.704	0.000

ESTIMATED CHANGE FOR LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	-0.016	0.059
ACHIMOT2	0.000	-0.080	-0.068
TASKSEL1	0.049	0.000	0.001
TASKSEL2	-0.038	0.000	0.109
VERBALIQ	0.000	-1.329	0.000

MODIFICATION INDICES FOR BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	1.647
JOBSATIS	0.000	0.000

ESTIMATED CHANGE FOR BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.153
JOBSATIS	0.000	0.000

MODIFICATION INDICES FOR GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.003	0.000	3.068
JOBSATIS	0.000	0.704	0.000

ESTIMATED CHANGE FOR GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	-0.012	0.000	-0.107
JOBSATIS	0.000	0.284	0.000

NO NON-ZERO MODIFICATION INDICES FOR PHI
NO NON-ZERO MODIFICATION INDICES FOR PSI

```
      MODIFICATION INDICES FOR THETA EPS
         PERFORMM   JBSATIS1   JBSATIS2
         --------   --------   --------
            0.704      0.000      0.000
      ESTIMATED CHANGE FOR THETA EPS
         PERFORMM   JBSATIS1   JBSATIS2
         --------   --------   --------
            1.054      0.000      0.000
      MODIFICATION INDICES FOR THETA DELTA
         ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
         --------   --------   --------   --------   --------
            0.000      0.000      0.000      0.000      0.704
      ESTIMATED CHANGE FOR THETA DELTA
         ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
         --------   --------   --------   --------   --------
            0.000      0.000      0.000      0.000    -19.467
     MAXIMUM MODIFICATION INDEX IS    3.33 FOR ELEMENT ( 4, 3) OF LAMBDA X
      THE PROBLEM USED     8736 BYTES (=  0.3% OF AVAILABLE WORKSPACE)
                       TIME USED :    0.00 SECONDS

08-Jul-98   LISR152a.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156                Page  2
15:44:41    TEXAS A&M UNIVERSITY: CIS     IBM 3090-400J    MVS/ESA/JES3

Preceding task required .40 seconds CPU time;  7.99 seconds elapsed.

  30  0
    29 command lines read.
     0 errors detected.
     0 warnings issued.
     1 seconds CPU time.
    13 seconds elapsed time.
       End of job.
```

Appendix C
Maximum-Likelihood Analysis for the Model that Performance Predicts Job Satisfaction
(*Reliability of Verbal Intelligence (X_5) Scores Fixed as 1.0*)

lisr152b.lst 7/9/98

```
08-Jul-98    SPSS RELEASE 4.1 FOR IBM OS/MVS                                         Page   1
15:45:47     TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS        License Number 1267
This software is functional through August 31, 1998.

   1  0  title 'LISR152b.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
   2  0  data list file=abc records=3 table/1 id 1-4
   3  0    /2 /3
This command will read 3 records from 'E100BT.ARTHUR.OAT'
Variable    Rec   Start     End        Format

IO           1       1       4         F4.0

   4  0  lisrel
   5  0    /"Joreskog/Sorbom pp. 155-156 Model *****"
   6  0    /OA NI=8 NO=122 MA=CM
   7  0    /LA
   8  0    /'PERFORMM' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
   9  0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
  10  0    /KM SY
  11  0    /(8F8.3)
  12  0    /   4.368
  13  0    /   2.997  11.765
  14  0    /   2.314   6.043   7.896
  15  0    /   0.526   1.351   1.458   3.802
  16  0    /   0.814   2.007   1.204   1.466   4.244
  17  0    /   2.456   2.082   1.967   0.847   0.716   4.666
  18  0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
  19  0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
  20  0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=OI,FR
  21  0    /LE
  22  0    /'PERFORMN' 'JOBSATIS'
  23  0    /LK
  24  0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
  25  0    /FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
  26  0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TO(5,5)
  27  0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
  28  0    /OU SE SS SC TV MI NO=3
There are 3,033,680 bytes of memory available.
The largest contiguous area has 3,027,384 bytes.


                    LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
                           PROGRAM VERSION 7.16        OISTRIBUTEO BY

                           SCIENTIFIC SOFTWARE, INC.
                           1369 NEITZEL ROAO
                           MOORESVILLE, INOIANA 46158
                           (317) 831-6336


                     THIS COPY AUTHORIZEO FOR USE IN SPSS-X
                PROGRAM COPYRIGHT 1977-89 BY SCIENTIFIC SOFTWARE, INC.,
```

MVS - L I S R E L 7.16
BY
KARL G JORESKOG ANO OAG SORBOM

THE FOLLOWING LISREL CONTROL LINES HAVE BEEN REAO :

```
Joreskog/Sorbom pp. 155-156 Model ****
OA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=OI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(2,1)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TO(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
OU SE SS SC TV MI NO=3
Joreskog/Sorbom pp. 155-156 Model ****
```

NUMBER OF INPUT VARIABLES 8
NUMBER OF Y - VARIABLES 3
NUMBER OF X - VARIABLES 5
NUMBER OF ETA - VARIABLES 2
NUMBER OF KSI - VARIABLES 3
NUMBER OF OBSERVATIONS 122

Joreskog/Sorbom pp. 155-156 Model ****

COVARIANCE MATRIX TO BE ANALYZEO

	PERFORMM	JBSATIS1	JBSATIS2	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
PERFORMM	4.368							
JBSATIS1	2.997	11.765						
JBSATIS2	2.314	6.043	7.896					
ACHIMOT1	0.526	1.351	1.458	3.802				
ACHIMOT2	0.814	2.007	1.204	1.466	4.244			
TASKSEL1	2.456	2.082	1.967	0.847	0.716	4.666		
TASKSEL2	2.183	1.590	1.818	0.691	0.738	2.429	4.244	
VERBALIQ	-2.723	-1.953	-0.390	-1.416	-2.083	-2.318	-1.308	13.323

Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS

LAMBOA Y

	PERFORMN	JOBSATIS
PERFORMM	0	0
JBSATIS1	0	0
JBSATIS2	0	1

LAMBOA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0	0	0
ACHIMOT2	2	0	0
TASKSEL1	0	0	0
TASKSEL2	0	3	0
VERBALIQ	0	0	0

BETA

	PERFORMN	JOBSATIS
PERFORMN	0	0
JOBSATIS	4	0

GAMMA

AMOTIVAT	TASKSELF	VERBINTL

PERFORMN	0	5	0
JOBSATIS	6	0	7

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	8		
TASKSELF	9	10	
VERBINTL	11	12	13

PSI

PERFORMN	JOBSATIS
14	15

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0	16	17

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
18	19	20	21	0

Joreskog/Sorbom pp. 155-156 Model ****
INITIAL ESTIMATES (TSLS)

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.797

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	0.877	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.939	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.688	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.926	0.000
JOBSATIS	0.954	0.000	0.168

COVARIANCE MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.368				
JOBSATIS	3.437	8.239			
AMOTIVAT	0.759	1.808	1.671		
TASKSELF	2.395	2.114	0.820	2.587	
VERBINTL	-1.744	-0.711	-1.833	-1.885	13.323

PSI

PERFORMN	JOBSATIS
2.151	4.269

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.181	3.081

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.131	2.958	2.079	1.963	0.000

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2
1.000	0.663	0.629

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.440	0.303	0.554	0.537	1.000

SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN	JOBSATIS
0.507	0.482

TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS IS 0.620

Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.834

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	1.169	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.861	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.583	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.923	0.000
JOBSATIS	1.179	0.000	0.175

COVARIANCE MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.368				
JOBSATIS	2.987	7.371			
AMOTIVAT	0.689	1.569	1.231		
TASKSELF	2.525	1.948	0.747	2.736	
VERBINTL	-2.136	-0.833	-1.628	-2.316	13.323

PSI

PERFORMN	JOBSATIS
2.038	3.925

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.517	2.858

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.571	2.562	1.930	2.215	0.000

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2
1.000	0.620	0.642

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.324	0.396	0.586	0.478	1.000

SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN	JOBSATIS
0.533	0.468

TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS IS 0.656

W_A_R_N_I_N_G : THETA EPS is not positive definite

```
W_A_R_N_I_N_G : THETA DELTA is not positive definite


         CHI-SQUARE WITH  15 DEGREES OF FREEDOM =    14.08 (P = .519)
                     GOODNESS OF FIT INDEX =0.970
            ADJUSTED GOODNESS OF FIT INDEX =0.927
                ROOT MEAN SQUARE RESIDUAL =     0.284
Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =   -1.120
  MEDIAN FITTED RESIDUAL =    0.000
 LARGEST FITTED RESIDUAL =    0.686
STEMLEAF PLOT
-10|2
- 8|
- 6|
- 4|9
- 2|22
- 0|88662099710000000
  0|1113570357
  2|104
  4|2
  6|9
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL =   -2.302
  MEDIAN STANDARDIZED RESIDUAL =    0.000
 LARGEST STANDARDIZED RESIDUAL =    1.854
STEMLEAF PLOT
- 2|31
- 1|8
- 1|3322
- 0|7766
- 0|22100000000
  0|11234
  0|557789
  1|12
  1|9
Joreskog/Sorbom pp. 155-156 Model ****
```

STANDARD ERRORS

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	0.135

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	0.337	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	0.138	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.139	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.144	0.000
JOBSATIS	0.454	0.000	0.085

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	0.500		
TASKSELF	0.298	0.646	
VERBINTL	0.592	0.683	1.713

PSI

PERFORMN	JOBSATIS
0.396	1.204

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	1.175	0.799

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.479	0.575	0.424	0.388	0.000

Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	6.196

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	3.469	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	6.256	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	4.205	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	6.399	0.000
JOBSATIS	2.598	0.000	2.056

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	2.463		
TASKSELF	2.506	4.238	
VERBINTL	-2.750	-3.388	7.778

PSI

PERFORMN	JOBSATIS
5.146	3.259

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	3.844	3.575

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
5.366	4.454	4.547	5.708	0.000

Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	2.090	0.000
JBSATIS1	0.000	2.715
JBSATIS2	0.000	2.264

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.110	0.000	0.000

ACHIMOT2	1.297	0.000	0.000
TASKSEL1	0.000	1.654	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.650

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.449	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.482	0.000	0.235

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.526	1.000			
AMOTIVAT	0.297	0.521	1.000		
TASKSELF	0.730	0.434	0.407	1.000	
VERBINTL	-0.280	-0.084	-0.402	-0.383	1.000

PSI

PERFORMN	JOBSATIS
0.467	0.532

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.482	0.328	0.235

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	0.787
JBSATIS2	0.000	0.801

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.569	0.000	0.000
ACHIMOT2	0.630	0.000	0.000
TASKSEL1	0.000	0.766	0.000
TASKSEL2	0.000	0.691	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	0.449	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.482	0.000	0.235

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.526	1.000			
AMOTIVAT	0.297	0.521	1.000		
TASKSELF	0.730	0.434	0.407	1.000	
VERBINTL	-0.280	-0.084	-0.402	-0.383	1.000

PSI

PERFORMN	JOBSATIS
0.467	0.532

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	0.380	0.358

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.676	0.604	0.414	0.522	0.000

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.730	0.000
JOBSATIS	0.482	0.328	0.235

Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE

MODIFICATION INDICES FOR LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	1.536
JBSATIS1	0.620	0.000
JBSATIS2	0.620	0.000

ESTIMATED CHANGE FOR LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	-0.148
JBSATIS1	0.200	0.000
JBSATIS2	-0.167	0.000

MODIFICATION INDICES FOR LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.005	0.498
ACHIMOT2	0.000	0.147	0.498
TASKSEL1	0.038	0.000	0.000
TASKSEL2	0.032	0.000	3.436
VERBALIQ	0.000	0.591	0.000

ESTIMATED CHANGE FOR LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	-0.012	0.050
ACHIMOT2	0.000	-0.075	-0.058
TASKSEL1	0.046	0.000	0.000
TASKSEL2	-0.039	0.000	0.092
VERBALIQ	0.000	-1.465	0.000

MODIFICATION INDICES FOR BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	1.536
JOBSATIS	0.000	0.000

ESTIMATED CHANGE FOR BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.148
JOBSATIS	0.000	0.000

MODIFICATION INDICES FOR GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.001	0.000	3.082
JOBSATIS	0.000	0.591	0.000

ESTIMATED CHANGE FOR GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	-0.008	0.000	-0.089
JOBSATIS	0.000	0.256	0.000

NO NON-ZERO MODIFICATION INDICES FOR PHI

NO NON-ZERO MODIFICATION INDICES FOR PSI

MODIFICATION INDICES FOR THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.591	0.000	0.000

```
      ESTIMATED CHANGE FOR THETA EPS
         PERFORMM   JBSATIS1   JBSATIS2
         ________   ________   ________
            0.971      0.000      0.000
      MODIFICATION INDICES FOR THETA DELTA
         ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
         ________   ________   ________   ________   ________
            0.000      0.000      0.000      0.000      0.592
      ESTIMATED CHANGE FOR THETA DELTA
         ACHIMOT1   ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
         ________   ________   ________   ________   ________
            0.000      0.000      0.000      0.000    -26.192
     MAXIMUM MODIFICATION INDEX IS    3.44 FOR ELEMENT ( 4, 3) OF LAMBDA X
      THE PROBLEM USED     8736 BYTES (=   0.3% OF AVAILABLE WORKSPACE)
                        TIME USED :    0.00 SECONDS
08-Jul-98   LISR152b.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156              Page  2
15:46:05    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

Preceding task required .41 seconds CPU time;  12.51 seconds elapsed.

  29  0
    28 command lines read.
     0 errors detected.
     0 warnings issued.
     1 seconds CPU time.
    18 seconds elapsed time.
       End of job.
```

Appendix D
Performance and Job Satisfaction *Reciprocally* Predict Each Other

lisr152c.lst 7/9/98

```
08-Jul-98   SPSS RELEASE 4.1 FOR IBM OS/MVS                                    Page   1
16:03:13    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS         License Number 1267
This software is functional through August 31, 1998.

   1  0  title 'LISR152c.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
   2  0  data list file=abc records=3 table/1 id 1-4
   3  0    /2 /3
This command will read 3 records from 'E100BT.ARTHUR.OAT'
Variable   Rec   Start    End       Format

IO           1      1       4       F4.0

   4  0  lisrel
   5  0    /"Joreskog/Sorbom pp. 155-156 Model ****"
   6  0    /OA NI=8 NO=122 MA=CM
   7  0    /LA
   8  0    /'PERFORMM' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
   9  0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
  10  0    /KM SY
  11  0    /(8F8.3)
  12  0    /   4.368
  13  0    /   2.997  11.765
  14  0    /   2.314   6.043   7.896
  15  0    /   0.526   1.351   1.458   3.802
  16  0    /   0.814   2.007   1.204   1.466   4.244
  17  0    /   2.456   2.082   1.967   0.847   0.716   4.666
  18  0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
  19  0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
  20  0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=OI,FR
  21  0    /LE
  22  0    /'PERFORMN' 'JOBSATIS'
  23  0    /LK
  24  0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
  25  0    /FR LY(3,2) LX(2,1) LX(4,2) BE(2,1) BE(1,2)
  26  0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TO(5,5)
  27  0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
  28  0    /VA 1.998 TO(5,5)
  29  0    /OU SE SS SC TV MI NO=3
There are 3,033,048 bytes of memory available.
The largest contiguous area has 3,026,720 bytes.



                    LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
                           PROGRAM VERSION 7.16       OISTRIBUTEO BY

                           SCIENTIFIC SOFTWARE, INC.
                           1369 NEITZEL ROAO
                           MOORESVILLE, INOIANA 46158
                           (317) 831-6336


                  THIS COPY AUTHORIZEO FOR USE IN SPSS-X
             PROGRAM COPYRIGHT 1977-89 BY SCIENTIFIC SOFTWARE, INC.,
                           (A MICHIGAN CORPORATION).
```

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                    MVS - L I S R E L  7.16
                              BY
                  KARL G JORESKOG AND DAG SORBOM

THE FOLLOWING LISREL CONTROL LINES HAVE BEEN READ :

Joreskog/Sorbom pp. 155-156 Model ****
DA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(2,1) BE(1,2)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
VA 1.998 TD(5,5)
OU SE SS SC TV MI ND=3
Joreskog/Sorbom pp. 155-156 Model ****
                          NUMBER OF INPUT VARIABLES  8
                          NUMBER OF Y - VARIABLES    3
                          NUMBER OF X - VARIABLES    5
                          NUMBER OF ETA - VARIABLES  2
                          NUMBER OF KSI - VARIABLES  3
                          NUMBER OF OBSERVATIONS   122
Joreskog/Sorbom pp. 155-156 Model ****
```

COVARIANCE MATRIX TO BE ANALYZED

	PERFORMM	JBSATIS1	JBSATIS2	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
PERFORMM	4.368							
JBSATIS1	2.997	11.765						
JBSATIS2	2.314	6.043	7.896					
ACHIMOT1	0.526	1.351	1.458	3.802				
ACHIMOT2	0.814	2.007	1.204	1.466	4.244			
TASKSEL1	2.456	2.082	1.967	0.847	0.716	4.666		
TASKSEL2	2.183	1.590	1.818	0.691	0.738	2.429	4.244	
VERBALIQ	-2.723	-1.953	-0.390	-1.416	-2.083	-2.318	-1.308	13.323

Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0	0
JBSATIS1	0	0
JBSATIS2	0	1

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0	0	0
ACHIMOT2	2	0	0
TASKSEL1	0	0	0
TASKSEL2	0	3	0
VERBALIQ	0	0	0

BETA

	PERFORMN	JOBSATIS
PERFORMN	0	4
JOBSATIS	5	0

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL

```
PERFORMN         0         6         0
JOBSATIS         7         0         8
        PHI
           AMOTIVAT  TASKSELF  VERBINTL
           --------  --------  --------
AMOTIVAT         9
TASKSELF        10        11
VERBINTL        12        13        14
        PSI
           PERFORMN  JOBSATIS
           --------  --------
                15        16
        THETA EPS
           PERFORMM  JBSATIS1  JBSATIS2
           --------  --------  --------
                 0        17        18
        THETA DELTA
           ACHIMOT1  ACHIMOT2  TASKSEL1  TASKSEL2  VERBALIQ
           --------  --------  --------  --------  --------
                19        20        21        22         0
Joreskog/Sorbom pp. 155-156 Model ****
INITIAL ESTIMATES (TSLS)
        LAMBDA Y
           PERFORMN  JOBSATIS
           --------  --------
PERFORMM     1.000     0.000
JBSATIS1     0.000     1.000
JBSATIS2     0.000     0.797
        LAMBDA X
           AMOTIVAT  TASKSELF  VERBINTL
           --------  --------  --------
ACHIMOT1     1.000     0.000     0.000
ACHIMOT2     0.877     0.000     0.000
TASKSEL1     0.000     1.000     0.000
TASKSEL2     0.000     0.939     0.000
VERBALIQ     0.000     0.000     1.000
        BETA
           PERFORMN  JOBSATIS
           --------  --------
PERFORMN     0.000    -0.176
JOBSATIS     0.707     0.000
        GAMMA
           AMOTIVAT  TASKSELF  VERBINTL
           --------  --------  --------
PERFORMN     0.000     1.070     0.000
JOBSATIS     0.989     0.000     0.208
        COVARIANCE MATRIX OF ETA AND KSI
           PERFORMN  JOBSATIS  AMOTIVAT  TASKSELF  VERBINTL
           --------  --------  --------  --------  --------
PERFORMN     4.476
JOBSATIS     2.691     7.149
AMOTIVAT     0.581     1.683     1.671
TASKSELF     2.395     2.114     0.820     2.587
VERBINTL    -1.877    -0.786    -1.833    -1.885    11.325
        PSI
           PERFORMN  JOBSATIS
           --------  --------
             2.687     4.209
        THETA EPS
           PERFORMM  JBSATIS1  JBSATIS2
           --------  --------  --------
             0.000     4.181     3.081
        THETA DELTA
           ACHIMOT1  ACHIMOT2  TASKSEL1  TASKSEL2  VERBALIQ
           --------  --------  --------  --------  --------
             2.131     2.958     2.079     1.963     1.998
        SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES
           PERFORMM  JBSATIS1  JBSATIS2
           --------  --------  --------
             1.000     0.631     0.596
```

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.440	0.303	0.554	0.537	0.850

TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS 0.976

SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN	JOBSATIS
0.400	0.411

TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS IS 0.543

Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.881

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	1.138	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.866	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS	
PERFORMN	0.000	**-0.220**	**<==========**
JOBSATIS	0.816	0.000	

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	1.111	0.000
JOBSATIS	1.057	0.000	0.265

COVARIANCE MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.358				
JOBSATIS	2.793	6.881			
AMOTIVAT	0.554	1.386	1.296		
TASKSELF	2.512	2.274	0.773	2.711	
VERBINTL	-2.339	-0.654	-1.648	-2.235	11.324

PSI

PERFORMN	JOBSATIS
2.573	3.904

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.921	2.578

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.506	2.566	1.955	2.212	1.998

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2
1.000	0.583	0.675

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.341	0.395	0.581	0.479	0.850

TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS 0.974

SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN	JOBSATIS
0.410	0.433

```
       TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS  IS  0.547
W_A_R_N_I_N_G : THETA EPS is not positive definite


        CHI-SQUARE WITH  14 DEGREES OF FREEDOM =     12.12 (P = .597)
                     GOODNESS OF FIT INDEX =0.974
            ADJUSTED GOODNESS OF FIT INDEX =0.932
                ROOT MEAN SQUARE RESIDUAL =      0.287
Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =   -1.299
  MEDIAN FITTED RESIDUAL =   -0.004
 LARGEST FITTED RESIDUAL =    0.627
STEMLEAF PLOT
-12¦0
-10¦
- 8¦
- 6¦
- 4¦
- 2¦881
- 0¦9965864443322100000
  0¦11278889
  2¦034
  4¦3
  6¦3
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL =   -2.041
  MEDIAN STANDARDIZED RESIDUAL =   -0.036
 LARGEST STANDARDIZED RESIDUAL =    1.682
STEMLEAF PLOT
- 2¦0
- 1¦
- 1¦440
- 0¦9877655
- 0¦31111110000
  0¦11334
  0¦55889
  1¦123
  1¦7
Joreskog/Sorbom pp. 155-156 Model ****
```

STANDARD ERRORS

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	0.144

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	0.335	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	0.137	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS	
PERFORMN	0.000	**0.161**	<==========
JOBSATIS	0.210	0.000	

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.222	0.000
JOBSATIS	0.437	0.000	0.105

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	0.523		

TASKSELF	0.304	0.640	
VERBINTL	0.600	0.678	1.713

PSI

PERFORMN	JOBSATIS
0.751	1.243

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	1.152	0.817

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.493	0.584	0.419	0.385	0.000

Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	6.131

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	3.393	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	6.323	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS	
PERFORMN	0.000	**-1.362**	**<==========**
JOBSATIS	3.887	0.000	

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	4.998	0.000
JOBSATIS	2.418	0.000	2.522

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	2.476		
TASKSELF	2.545	4.238	
VERBINTL	-2.744	-3.295	6.612

PSI

PERFORMN	JOBSATIS
3.428	3.141

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.272	3.154

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
5.087	4.393	4.664	5.749	0.000

Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	2.088	0.000
JBSATIS1	0.000	2.623
JBSATIS2	0.000	2.312

LAMBDA X

AMOTIVAT	TASKSELF	VERBINTL

ACHIMOT1	1.138	0.000	0.000
ACHIMOT2	1.295	0.000	0.000
TASKSEL1	0.000	1.646	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.365

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.276
JOBSATIS	0.649	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.876	0.000
JOBSATIS	0.459	0.000	0.339

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.510	1.000			
AMOTIVAT	0.233	0.464	1.000		
TASKSELF	0.731	0.527	0.412	1.000	
VERBINTL	-0.333	-0.074	-0.430	-0.403	1.000

PSI

PERFORMN	JOBSATIS
0.590	0.567

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	-0.107	0.743	-0.079
JOBSATIS	0.389	0.482	0.288

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	0.764
JBSATIS2	0.000	0.821

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.584	0.000	0.000
ACHIMOT2	0.629	0.000	0.000
TASKSEL1	0.000	0.762	0.000
TASKSEL2	0.000	0.692	0.000
VERBALIQ	0.000	0.000	0.922

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.276
JOBSATIS	0.649	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.876	0.000
JOBSATIS	0.459	0.000	0.339

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.510	1.000			
AMOTIVAT	0.233	0.464	1.000		
TASKSELF	0.731	0.527	0.412	1.000	
VERBINTL	-0.333	-0.074	-0.430	-0.403	1.000

PSI

PERFORMN	JOBSATIS

```
         0.590     0.567
THETA EPS
     PERFORMM  JBSATIS1  JBSATIS2
     --------  --------  --------
        0.000     0.417     0.325
THETA DELTA
     ACHIMOT1  ACHIMOT2  TASKSEL1  TASKSEL2  VERBALIQ
     --------  --------  --------  --------  --------
        0.659     0.605     0.419     0.521     0.150
REGRESSION MATRIX ETA ON KSI (STANDARDIZED)
     AMOTIVAT  TASKSELF  VERBINTL
     --------  --------  --------
PERFORMN   -0.107     0.743    -0.079
JOBSATIS    0.389     0.482     0.288
Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE
MODIFICATION INDICES FOR LAMBDA Y
     PERFORMN  JOBSATIS
     --------  --------
PERFORMM    0.000     0.000
JBSATIS1    1.551     0.000
JBSATIS2    1.551     0.000
ESTIMATED CHANGE FOR LAMBDA Y
     PERFORMN  JOBSATIS
     --------  --------
PERFORMM    0.000     0.000
JBSATIS1    0.284     0.000
JBSATIS2   -0.250     0.000
MODIFICATION INDICES FOR LAMBDA X
     AMOTIVAT  TASKSELF  VERBINTL
     --------  --------  --------
ACHIMOT1    0.000     0.023     0.661
ACHIMOT2    0.000     0.000     0.661
TASKSEL1    0.078     0.000     0.066
TASKSEL2    0.308     0.000     2.700
VERBALIQ    0.000     0.263     0.000
ESTIMATED CHANGE FOR LAMBDA X
     AMOTIVAT  TASKSELF  VERBINTL
     --------  --------  --------
ACHIMOT1    0.000     0.027     0.070
ACHIMOT2    0.000     0.003    -0.080
TASKSEL1   -0.066     0.000    -0.017
TASKSEL2   -0.120     0.000     0.098
VERBALIQ    0.000     1.132     0.000
NO NON-ZERO MODIFICATION INDICES FOR BETA
MODIFICATION INDICES FOR GAMMA
     AMOTIVAT  TASKSELF  VERBINTL
     --------  --------  --------
PERFORMN    0.843     0.000     1.845
JOBSATIS    0.000     0.263     0.000
ESTIMATED CHANGE FOR GAMMA
     AMOTIVAT  TASKSELF  VERBINTL
     --------  --------  --------
PERFORMN    0.275     0.000    -0.103
JOBSATIS    0.000    -0.299     0.000
NO NON-ZERO MODIFICATION INDICES FOR PHI
NO NON-ZERO MODIFICATION INDICES FOR PSI
MODIFICATION INDICES FOR THETA EPS
     PERFORMM  JBSATIS1  JBSATIS2
     --------  --------  --------
        0.263     0.000     0.000
ESTIMATED CHANGE FOR THETA EPS
     PERFORMM  JBSATIS1  JBSATIS2
     --------  --------  --------
       -0.850     0.000     0.000
MODIFICATION INDICES FOR THETA DELTA
     ACHIMOT1  ACHIMOT2  TASKSEL1  TASKSEL2  VERBALIQ
     --------  --------  --------  --------  --------
```

```
        0.000     0.000     0.000     0.000     0.263
  ESTIMATED CHANGE FOR THETA DELTA
     ACHIMOT1  ACHIMOT2  TASKSEL1  TASKSEL2  VERBALIQ
     --------  --------  --------  --------  --------
        0.000     0.000     0.000     0.000    17.352
 MAXIMUM MODIFICATION INDEX IS    2.70 FOR ELEMENT ( 4, 3) OF LAMBDA X
  THE PROBLEM USED     8960 BYTES (=   0.3% OF AVAILABLE WORKSPACE)
                    TIME USED :    0.00 SECONDS
08-Jul-98   LISR152c.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156                Page  2
16:03:22    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

Preceding task required .41 seconds CPU time;  6.65 seconds elapsed.

  30  0
    29 command lines read.
     0 errors detected.
     0 warnings issued.
     1 seconds CPU time.
     8 seconds elapsed time.
       End of job.
```

Appendix E
Job Satisfaction Predicts Performance

lisr152d.lst 7/9/98

```
08-Jul-98   SPSS RELEASE 4.1 FOR IBM OS/MVS                                          Page   1
15:51:04    TEXAS A&M UNIVERSITY: CIS      IBM 3090-400J    MVS/ESA/JES3

For MVS/ESA/JES3        TEXAS A&M UNIVERSITY: CIS         License Number 1267
This software is functional through August 31, 1998.

   1  0  title 'LISR152d.SPS  Bagozzi (1980) / J&S, 1989, pp. 151-156'
   2  0  data list file=abc records=3 table/1 id 1-4
   3  0    /2 /3
This command will read 3 records from 'E100BT.ARTHUR.DAT'
Variable    Rec   Start     End        Format

ID           1      1        4         F4.0

   4  0  lisrel
   5  0    /"Joreskog/Sorbom pp. 155-156 Model ****"
   6  0    /DA NI=8 NO=122 MA=CM
   7  0    /LA
   8  0    /'PERFORMM' 'JBSATIS1' 'JBSATIS2' 'ACHIMOT1'
   9  0    /'ACHIMOT2' 'TASKSEL1' 'TASKSEL2' 'VERBALIQ'
  10  0    /KM SY
  11  0    /(8F8.3)
  12  0    /   4.368
  13  0    /   2.997  11.765
  14  0    /   2.314   6.043   7.896
  15  0    /   0.526   1.351   1.458   3.802
  16  0    /   0.814   2.007   1.204   1.466   4.244
  17  0    /   2.456   2.082   1.967   0.847   0.716   4.666
  18  0    /   2.183   1.590   1.818   0.691   0.738   2.429   4.244
  19  0    /  -2.723  -1.953  -0.390  -1.416  -2.083  -2.318  -1.308  13.323
  20  0    /MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
  21  0    /LE
  22  0    /'PERFORMN' 'JOBSATIS'
  23  0    /LK
  24  0    /'AMOTIVAT' 'TASKSELF' 'VERBINTL'
  25  0    /FR LY(3,2) LX(2,1) LX(4,2) BE(1,2)
  26  0    /FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
  27  0    /VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
  28  0    /VA 1.998 TD(5,5)
  29  0    /OU SE SS SC TV MI ND=3 AD=OFF
There are 3,033,168 bytes of memory available.
The largest contiguous area has 3,026,840 bytes.



                   LISREL 7:  ESTIMATION OF LINEAR STRUCTURAL EQUATION SYSTEMS
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```

```
                         MVS - L I S R E L  7.16
                                    BY
                      KARL G JORESKOG AND DAG SORBOM


THE FOLLOWING LISREL CONTROL LINES HAVE BEEN READ :


Joreskog/Sorbom pp. 155-156 Model ****
DA NI=8 NO=122 MA=CM
LA
PERFORMM   JBSATIS1   JBSATIS2   ACHIMOT1
ACHIMOT2   TASKSEL1   TASKSEL2   VERBALIQ
KM SY
(8F8.3)
MO NY=3 NX=5 NE=2 NK=3 BE=FU,FI PS=DI,FR
LE
PERFORMN   JOBSATIS
LK
AMOTIVAT   TASKSELF   VERBINTL
FR LY(3,2) LX(2,1) LX(4,2) BE(1,2)
FI GA(1,1) GA(2,2) GA(1,3) TE(1,1) TD(5,5)
VA 1 LY(1,1) LY(2,2) LX(1,1) LX(3,2) LX(5,3)
VA 1.998 TD(5,5)
OU SE SS SC TV MI ND=3 AD=OFF
Joreskog/Sorbom pp. 155-156 Model ****
                          NUMBER OF INPUT VARIABLES  8
                          NUMBER OF Y - VARIABLES    3
                          NUMBER OF X - VARIABLES    5
                          NUMBER OF ETA - VARIABLES  2
                          NUMBER OF KSI - VARIABLES  3
                          NUMBER OF OBSERVATIONS   122
Joreskog/Sorbom pp. 155-156 Model ****
```

COVARIANCE MATRIX TO BE ANALYZED

	PERFORMM	JBSATIS1	JBSATIS2	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
PERFORMM	4.368							
JBSATIS1	2.997	11.765						
JBSATIS2	2.314	6.043	7.896					
ACHIMOT1	0.526	1.351	1.458	3.802				
ACHIMOT2	0.814	2.007	1.204	1.466	4.244			
TASKSEL1	2.456	2.082	1.967	0.847	0.716	4.666		
TASKSEL2	2.183	1.590	1.818	0.691	0.738	2.429	4.244	
VERBALIQ	-2.723	-1.953	-0.390	-1.416	-2.083	-2.318	-1.308	13.323

Joreskog/Sorbom pp. 155-156 Model ****

PARAMETER SPECIFICATIONS

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0	0
JBSATIS1	0	0
JBSATIS2	0	1

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0	0	0
ACHIMOT2	2	0	0
TASKSEL1	0	0	0
TASKSEL2	0	3	0
VERBALIQ	0	0	0

BETA

	PERFORMN	JOBSATIS
PERFORMN	0	4
JOBSATIS	0	0

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0	5	0

JOBSATIS	6	0	7

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	8		
TASKSELF	9	10	
VERBINTL	11	12	13

PSI

PERFORMN	JOBSATIS
14	15

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0	16	17

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
18	19	20	21	0

Joreskog/Sorbom pp. 155-156 Model ****

INITIAL ESTIMATES (TSLS)

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.797

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	0.877	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.939	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	-0.176
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	1.070	0.000
JOBSATIS	1.123	0.000	0.060

COVARIANCE MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	5.577				
JOBSATIS	-0.471	7.584			
AMOTIVAT	0.566	1.768	1.671		
TASKSELF	2.624	0.809	0.820	2.587	
VERBINTL	-1.772	-1.385	-1.833	-1.885	11.325

PSI

PERFORMN	JOBSATIS
2.687	5.681

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.181	3.081

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
2.131	2.958	2.079	1.963	1.998

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2
1.000	0.645	0.610

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.440	0.303	0.554	0.537	0.850

TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS 0.976

SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN	JOBSATIS
0.518	0.251

TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS IS 0.637

Joreskog/Sorbom pp. 155-156 Model ****

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	1.000
JBSATIS2	0.000	0.834

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	1.000	0.000	0.000
ACHIMOT2	1.184	0.000	0.000
TASKSEL1	0.000	1.000	0.000
TASKSEL2	0.000	0.858	0.000
VERBALIQ	0.000	0.000	1.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.150
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.801	0.000
JOBSATIS	3.208	0.000	0.348

COVARIANCE MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	4.348				
JOBSATIS	2.689	7.290			
AMOTIVAT	0.938	1.611	0.679		
TASKSELF	2.506	1.991	0.870	2.755	
VERBINTL	-2.033	-1.289	-1.629	-2.296	11.327

PSI

PERFORMN	JOBSATIS
1.937	2.569

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	4.475	2.822

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
3.123	3.293	1.911	2.214	1.998

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

PERFORMM	JBSATIS1	JBSATIS2
1.000	0.620	0.643

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.179	0.224	0.590	0.478	0.850

TOTAL COEFFICIENT OF DETERMINATION FOR X - VARIABLES IS 0.961

SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

PERFORMN	JOBSATIS
0.554	0.648

TOTAL COEFFICIENT OF DETERMINATION FOR STRUCTURAL EQUATIONS IS 0.797

```
W_A_R_N_I_N_G : THETA EPS is not positive definite


         CHI-SQUARE WITH  15 OEGREES OF FREEOOM =    23.34 (P = .077)
                      GOODNESS OF FIT INOEX =0.953
             AOJUSTEO GOOONESS OF FIT INOEX =0.886
                  ROOT MEAN SQUARE RESIOUAL =     0.304
Joreskog/Sorbom pp. 155-156 Model ****
SUMMARY STATISTICS FOR FITTEO RESIOUALS
SMALLEST FITTEO RESIOUAL =   -0.690
  MEOIAN FITTEO RESIOUAL =    0.000
 LARGEST FITTEO RESIOUAL =    0.686
STEMLEAF PLOT
- 6|96
- 4|1
- 2|9106
- 0|552654220000000
  0|2367901
  2|1119
  4|
  6|669
SUMMARY STATISTICS FOR STANOAROIZEO RESIOUALS
SMALLEST STANOAROIZEO RESIOUAL =   -2.781
  MEOIAN STANOAROIZEO RESIOUAL =    0.000
 LARGEST STANOAROIZEO RESIOUAL =    2.784
STEMLEAF PLOT
- 2|821
- 1|75332
- 0|98653211000000
  0|334466
  1|223889
  2|88
LARGEST NEGATIVE STANOAROIZEO RESIOUALS
RESIOUAL FOR VERBALIQ ANO VERBALIQ =  -2.781
LARGEST POSITIVE STANOAROIZEO RESIOUALS
RESIOUAL FOR PERFORMM ANO PERFORMM =   2.784
RESIOUAL FOR ACHIMOT2 AND ACHIMOT1 =   2.784
Joreskog/Sorbom pp. 155-156 Model ****
```

STANOARD ERRORS

LAMBOA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	0.145

LAMBOA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	0.369	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	0.137	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.078
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.154	0.000
JOBSATIS	1.328	0.000	0.221

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	0.339		
TASKSELF	0.298	0.649	
VERBINTL	0.573	0.687	1.713

PSI

	PERFORMN	JOBSATIS
	0.354	1.887

THETA EPS

	PERFORMM	JBSATIS1	JBSATIS2
	0.000	1.257	0.858

THETA DELTA

	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
	0.445	0.491	0.427	0.388	0.000

Joreskog/Sorbom pp. 155-156 Model ****

T-VALUES

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.000	0.000
JBSATIS2	0.000	5.741

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.000	0.000
ACHIMOT2	3.207	0.000	0.000
TASKSEL1	0.000	0.000	0.000
TASKSEL2	0.000	6.261	0.000
VERBALIQ	0.000	0.000	0.000

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	1.928
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	5.211	0.000
JOBSATIS	2.416	0.000	1.574

PHI

	AMOTIVAT	TASKSELF	VERBINTL
AMOTIVAT	2.004		
TASKSELF	2.915	4.245	
VERBINTL	-2.844	-3.342	6.612

PSI

	PERFORMN	JOBSATIS
	5.471	1.361

THETA EPS

	PERFORMM	JBSATIS1	JBSATIS2
	0.000	3.561	3.289

THETA DELTA

	ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
	7.014	6.700	4.479	5.706	0.000

Joreskog/Sorbom pp. 155-156 Model ****

STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	2.085	0.000
JBSATIS1	0.000	2.700
JBSATIS2	0.000	2.253

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.824	0.000	0.000

ACHIMOT2	0.975	0.000	0.000
TASKSEL1	0.000	1.660	0.000
TASKSEL2	0.000	1.425	0.000
VERBALIQ	0.000	0.000	3.365

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.194
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.638	0.000
JOBSATIS	0.979	0.000	0.433

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.478	1.000			
AMOTIVAT	0.546	0.724	1.000		
TASKSELF	0.724	0.444	0.636	1.000	
VERBINTL	-0.290	-0.142	-0.588	-0.411	1.000

PSI

PERFORMN	JOBSATIS
0.446	0.352

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.190	0.638	0.084
JOBSATIS	0.979	0.000	0.433

Joreskog/Sorbom pp. 155-156 Model ****

COMPLETELY STANDARDIZED SOLUTION

LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	1.000	0.000
JBSATIS1	0.000	0.787
JBSATIS2	0.000	0.802

LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.423	0.000	0.000
ACHIMOT2	0.473	0.000	0.000
TASKSEL1	0.000	0.768	0.000
TASKSEL2	0.000	0.692	0.000
VERBALIQ	0.000	0.000	0.922

BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.194
JOBSATIS	0.000	0.000

GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.000	0.638	0.000
JOBSATIS	0.979	0.000	0.433

CORRELATION MATRIX OF ETA AND KSI

	PERFORMN	JOBSATIS	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	1.000				
JOBSATIS	0.478	1.000			
AMOTIVAT	0.546	0.724	1.000		
TASKSELF	0.724	0.444	0.636	1.000	
VERBINTL	-0.290	-0.142	-0.588	-0.411	1.000

PSI

PERFORMN	JOBSATIS
0.446	0.352

THETA EPS

PERFORMM	JBSATIS1	JBSATIS2
0.000	0.380	0.357

THETA DELTA

ACHIMOT1	ACHIMOT2	TASKSEL1	TASKSEL2	VERBALIQ
0.821	0.776	0.410	0.522	0.150

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.190	0.638	0.084
JOBSATIS	0.979	0.000	0.433

Joreskog/Sorbom pp. 155-156 Model ****

MODIFICATION INDICES AND ESTIMATED CHANGE

MODIFICATION INDICES FOR LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	2.282	0.000
JBSATIS2	0.017	0.000

ESTIMATED CHANGE FOR LAMBDA Y

	PERFORMN	JOBSATIS
PERFORMM	0.000	0.000
JBSATIS1	0.348	0.000
JBSATIS2	0.025	0.000

MODIFICATION INDICES FOR LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	0.861	0.308
ACHIMOT2	0.000	2.674	0.308
TASKSEL1	0.023	0.000	0.000
TASKSEL2	0.805	0.000	3.376
VERBALIQ	0.000	7.752	0.000

ESTIMATED CHANGE FOR LAMBDA X

	AMOTIVAT	TASKSELF	VERBINTL
ACHIMOT1	0.000	-0.196	0.052
ACHIMOT2	0.000	-0.394	-0.062
TASKSEL1	0.073	0.000	0.001
TASKSEL2	-0.376	0.000	0.111
VERBALIQ	0.000	-5.752	0.000

MODIFICATION INDICES FOR BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	9.411	0.000

ESTIMATED CHANGE FOR BETA

	PERFORMN	JOBSATIS
PERFORMN	0.000	0.000
JOBSATIS	1.321	0.000

MODIFICATION INDICES FOR GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.973	0.000	3.641
JOBSATIS	0.000	7.752	0.000

ESTIMATED CHANGE FOR GAMMA

	AMOTIVAT	TASKSELF	VERBINTL
PERFORMN	0.513	0.000	-0.111
JOBSATIS	0.000	2.000	0.000

NO NON-ZERO MODIFICATION INDICES FOR PHI
NO NON-ZERO MODIFICATION INDICES FOR PSI
NO NON-ZERO MODIFICATION INDICES FOR THETA EPS
NO NON-ZERO MODIFICATION INDICES FOR THETA DELTA

MAXIMUM MODIFICATION INDEX IS 9.41 FOR ELEMENT (2, 1) OF BETA

EC 306528

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