

A Structural Equation modelling Approach

To the Impact of Re-engineering on the Staff of a Large Teaching Hospital

A STRUCTURAL EQUATION MODELLING APPROACH

To the Impact of Re-engineering on the Staff of a Large Teaching Hospital

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Abstract

In this project we used structural equation method to analyze the data collected during the period of re-engineering in hospitals in Ontario 1995 to 1997. We want to understand how organizational change affect the well being of the staff of large teaching hospital. Two main models were considered in this project: cross-sectional models and longitudinal models for the data collected in 1995 and 1997. We tested six models for each year's data in cross-sectional model, effect-indicator, cause-indicator and mixed-indicator were used in both standard and non-standard models. We explored standard model with effect-indicators in our longitudinal case. The study was carried by SAS software program.

We demonstrated an important association of job stressors with psychological outcomes of hospital staff directly and indirectly via interference. Decision-making capacity was associated with psychological outcomes in the opposite direction. Similar results were concluded from longitudinal model. The limitation was discussed.

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Table of Contents

ABSTRACT.....	III
ACKNOWLEDGEMENTS	IV
LIST OF FIGURES	VIII
LIST OF TABLES	X
1 INTRODUCTION TO SEM.....	1
1.1 BUILDING BLOCKS FOR SEMS	1
1.2 GENERAL CHARACTERISTICS FOR SEMS	6
Manifest (Observed) versus latent variables	6
Composite versus latent variable	6
Cause versus effect indicator	6
Endogenous versus exogenous variable.....	7
Recursive versus nonrecursive model.....	7
Standard versus Non-standard model	8
1.3 IDENTIFICATION AND PARAMETER ESTIMATION	11
2 BACKGROUND TO THIS STUDY	15
2.1 RE-ENGINEERING WAS INTRODUCED IN HOSPITALS.....	15
2.2 HOSPITAL SETTING AND SCALES IN THE ANALYSIS.....	16
3 DATA EXPLORATION	19

3.1	THE INITIAL EXAMINATION OF DATA	19
3.2	REPORTS OF PREVIOUS ANALYSIS	20
4	METHOD OF ANALYSIS	22
4.1	EXPLORATORY FACTOR ANALYSIS	22
4.2	DESCRIPTIVE CRITERIA OF MODEL FITS	25
4.3	HOW PROGRAMS ESTIMATE PARAMETERS	31
4.4	DIFFERENT MODELS PROPOSED	33
4.4.1	<i>First, we propose the cross-sectional models in 1995 and 1997.</i>	33
4.4.2	<i>We describe our hypothesized longitudinal model in Figure 14.</i>	36
5	INTERPRETING THE RESULTS OF THE ANALYSIS	38
5.1	OUTLINE OF MODELS	40
5.2	1995 CROSS-SECTIONAL MODELS	42
5.2.1	<i>Standard models (data95).</i>	42
5.2.2	<i>Nonstandard model (data95).</i>	50
5.3	1997 CROSS-SECTIONAL MODELS	54
5.3.1	<i>Standard models (data97).</i>	54
5.3.2	<i>Nonstandard models (data97)</i>	56
5.3.3	<i>Comparison of 1995, 1997 results.</i>	57
5.4	LONGITUDINAL MODEL (95—97)	62
6	DISCUSSION	66

6.1 REVIEW OF RESULTS.....	66
6.2 WHAT SEM HAS ADDED TO PREVIOUS ANALYSES?.....	67
6.3 LIMITATION..	68
APPENDIX 1.....	72
APPENDIX 2(A)	81
APPENDIX 2(B).....	84
APPENDIX 3(A)	87
APPENDIX 3(B).....	88
APPENDIX 4(A)	89
APPENDIX 4(B).....	90
APPENDIX 4(C)	91
APPENDIX 4(D)	92
APPENDIX 4(E).....	93
APPENDIX 4(F).....	94
APPENDIX 4(G)	95
REFERENCES.....	96

List of Figures

Figure 1 Path model types. (a) Correlated path model (b) Mediated path model (c) Independent path model.....	3
Figure 2 Single-Factor analysis model.....	4
Figure 3 standard model with effect indicators (95) (initial model): Unstandardized (bracketed value) and standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-Headed Arrows; Arrows for Error terms.	47
Figure 4 standard model with effect indicators (95) (modified model): Unstandardized (bracketed value) and standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-Headed Arrows; Arrows for Error terms.	48
Figure 5 standard model with effect indicators (95) (final model): standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-Headed Arrows; Arrows for Error terms.	60
Figure 6 standard model with effect indicators (97) (final model): standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-Headed Arrows; Arrows for Error terms.	61
Figure 7 Longitudinal model (95-97): Standardized path coefficients appeared on Single-Headed Arrows; correlations appeared on Curved Double-Headed Arrows.	65
Figure 8 Standard Model with effect indicators.....	74
Figure 9 Nonstandard Model with effect indicators	75
Figure 10 Standard model with cause indicators	76

Figure 11 Nonstandard model with cause indicators	77
Figure 12 Standard model with mixed indicators	78
Figure 13 Nonstandard model with mixed indicators.....	79
Figure 14 Longitudinal model (95—97).....	80
Figure 15 Histograms of some of the variables	82
Figure 16 Histograms of some of the variables	83

List of Tables

Table 1 cross-sectional models and longitudinal models.....	42
Table 2 Goodness of Fit Indices for Standard model (data 95) with effect indicators	45
Table 3 Sums of Standardized Path coefficients to “Psyout”	45
Table 4 Sums of Standardized Path coefficients to “Psyout”	45
Table 5 Unstandardized and Standardized loadings for effect indicators	45
Table 6 Unstandardized and Standardized loadings for effect indicators	46
Table 7 Goodness-of-fit indices for model 2 (data95).....	50
Table 8 Standardized Path coefficients to “Psyout”	51
Table 9 Goodness-of-fit indices for Model 6.....	52
Table 10 Unstandardized and Standardized factor loadings for cause indicator	53
Table 11 Unstandardized and Standardized loadings for effect indicators.....	53
Table 12 Sums of Standardized Path coefficients to “Psyout”	54
Table 13 Goodness-of-fit indices for Model 6.....	54
Table 14 Sums of Standardized Path coefficients to “Psyout”	55
Table 15 Unstandardized and Standardized loadings for effect indicators.....	55
Table 16 Goodness-of-fit indices for Model 5.....	55
Table 17 Unstandardized and Standardized factor loadings for cause indicators.....	56
Table 18 Unstandardized and Standardized loadings for effect indicators.....	56
Table 19 Sums of Standardized Path coefficients to “Psyout”	56
Table 20 Summary table of the results of our model fits.....	58

Table 21 Goodness of fit indices for Model 7	62
Table 22 Goodness of fit indices for Model 8	63
Table 23 Standardized estimates for path coefficients (model 8).....	63
Table 24 Descriptive statistics	81
Table 25 Pearson Correlations among Variables in 1995 and 1997	84
Table 26 Exploratory Factor analysis of data95.....	85
Table 27 Exploratory Factor analysis of data97.....	86
Table 28 GOF Criteria and Acceptable Fit Interpretation.....	88
Table 29 Goodness of Fit Indices for Standard model with cause indicators.....	89
Table 30 Sums of Standardized Path coefficients to “Psyout”	89
Table 31 Unstandardized and Standardized loadings for cause indicators	89
Table 32 Unstandardized and Standardized loadings for effect indicator	89
Table 33 Goodness of Fit Indices for Standard model with mixed indicators.....	90
Table 34 Sums of Standardized Path coefficients to “Psyout”	90
Table 35 Unstandardized and Standardized loadings for cause indicators	90
Table 36 Unstandardized and Standardized loadings for effect indicators.....	90
Table 37 Goodness of Fit Indices for nonstandard model with cause indicators.....	91
Table 38 Standardized Path coefficient estimates.....	91
Table 39 Unstandardized and Standardized loadings for cause indicators	91
Table 40 Unstandardized and Standardized loadings for effect indicators.....	91
Table 41 Goodness of Fit Indices for Standard model with cause indicators.....	92
Table 42 Sums of Standardized Path coefficients to “Psyout”	92

Table 43 Unstandardized and Standardized loadings for cause indicators	92
Table 44 Unstandardized and Standardized loadings for effect indicators.....	92
Table 45 Goodness of Fit Indices for nonstandard model with effect indicators	93
Table 46 Sums of Standardized Path coefficients to “Psyout”	93
Table 47 Goodness of Fit Indices for nonstandard model with cause indicators.....	94
Table 48 Standardized Path coefficient estimates.....	94
Table 49 Unstandardized and Standardized loadings for cause indicators	94
Table 50 Unstandardized and Standardized loadings for effect indicators.....	94
Table 51 Goodness of Fit Indices for nonstandard model with cause indicators.....	95
Table 52 Unstandardized and Standardized factor loadings for cause indicators.....	95
Table 53 Unstandardized and Standardized loadings for effect indicator	95
Table 54 Sums of Standardized Path coefficients to “Psyout”	95

1 Introduction to SEM

Structural equation models (SEMs) represent a comprehensive, flexible approach to research design and data analysis. They are sets of linear equations used to specify phenomena in terms of their presumed cause-and-effect variables. SEMs with latent variables include simultaneous equations with numerous exogenous and endogenous variables, along with measurement error models. Thus, Structural equation models are particularly helpful in the social and behavioral sciences and have been used to study the relationship between social status and achievement, the determinants of firm profitability, discrimination in employment, the efficacy of social action programs and other interesting mechanisms ([3], [4], [5], [6], [7]).

In this project, we apply structural equation modeling methods to analyze the impact of re-engineering on staff at Chedoke-McMaster Hospitals. SAS program software will be employed to perform the analysis here ([8] and [9]).

We give a brief description of the structural equation modeling method; further detail can be found in standard books of the subject, for example, in [5], [7] and [10].

1.1 Building blocks For SEMs

SEMs are also referred to as covariance structure models, latent variable models, linear structural relations models, and causal models with unmeasured variables. They are most frequently referred to as “LISREL-type” models, as many people associate them with the LISREL program (for Linear Structural Relations). LISREL was the first widely available software that made possible the analysis of causal models with latent

variables [7].

The structural equation models generalize some earlier statistical approaches. SEMs build on multiple regression, factor analysis and path analysis methods by incorporating a confirmatory factor analysis approach into theoretical relationships among the latent variables. Thus, structural equation modeling can be used to test hypotheses that are difficult or important to address with multiple regression, factor analysis and other techniques.

The procedures emphasize covariances rather than cases. The fundamental hypothesis for these structural equation procedures is that the covariance matrix of the observed variables is a function of a set of parameters. If we assume that the model is correct and the parameters are known, then the population covariance matrix would be exactly reproduced by SEM (except for sampling variation).

Multiple regression is used to identify and estimate the amount of variance in a single dependent variable attributed to one or more independent variables. This method basically determines the overall contribution of a set of observed variables to prediction, tests full and restricted models for the significant contribution of a variable in a model, or delineates the best subset of multiple independent predictors. However, it is not robust to measurement error and model misspecification. Therefore, we need path analysis.

Path analysis can identify relationships among a set of variables. It has distinct advantages over multiple regression. It can be used to test theoretical models that specify causal relationships among a set of variables. It determines whether the theoretical model successfully accounts for the actual relationships observed in the sample data. And path analysis does more. It allows for more complex relationships, e.g., $A \rightarrow B \rightarrow C$ rather than $A \rightarrow B$ and $A \rightarrow C$. Path models are analyzed by simultaneously conducting several multiple regression analyses. For illustration, we include **Figure 1** path model types [7]: (a) Correlated path model (b) Mediated path model and (c) Independent path model, which indicate three different ways a path model could be depicted, depending on whether there is a correlated causal effect, an indirect (mediate) causal effect, or a direct effect respectively.

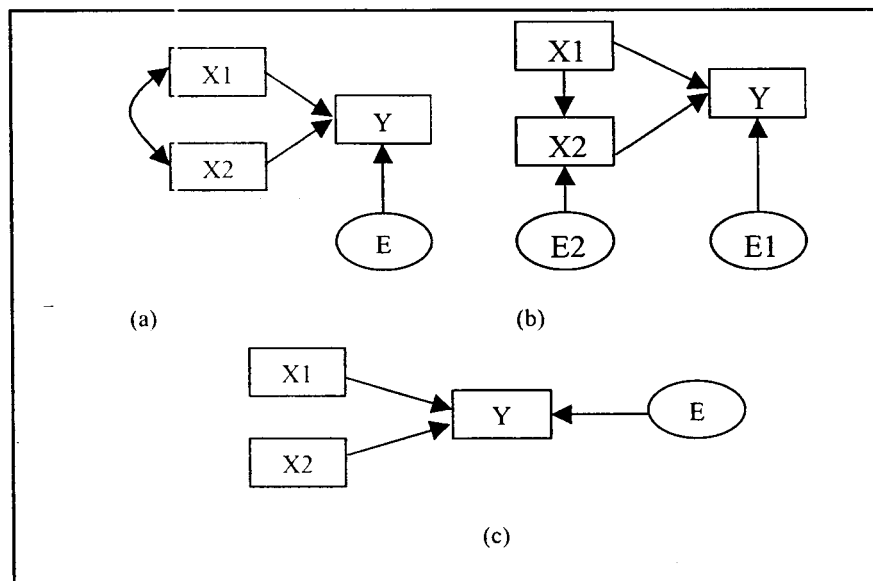


Figure 1 Path model types. (a) Correlated path model (b) Mediated path model (c) Independent path model

Path analysis also has certain limitations. For example, many path models do not include interaction effects, and the observed variables are assumed to be perfectly measured [7].

Factor analysis methods generally attempt to determine which sets of observed variables sharing common variance–covariance characteristics define constructs. In practice, we use factor analytic techniques to either explore how variables relate to factors (exploratory factor analysis) or confirm that a set of variables defines a construct (confirmatory factor analysis). In SEMs, confirmatory factor analysis is used to test specific hypotheses regarding which variables correlate with which constructs (in a measurement model). Covariances between indicators are explained by postulated factors. Because of the imperfect measurement of a construct by indicators, there are errors in indicator variables. Figure 2 shows an example of a single-factor model.

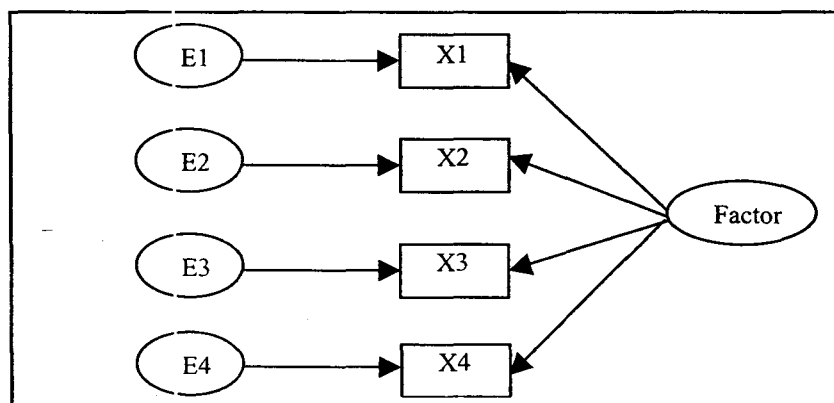


Figure 2 Single-Factor analysis model

Path diagram permits representation of the relationships among factors, while also displaying that observed (measured) variables define which factors. The variance of each

observed variable is made up of the proportion of variance determined by the common factor (F) and the proportion determined by the unique factor (E_i), which together equal the total variance of each observed variable. The factor loadings (variable weights) can be interpreted as standardized partial regression weights in standard-score form. In our single unidimensional factor, the weights indicate the correlation between the observed variables and the single factor. If the variables' factor loadings are squared, summed, and divided by the number of variables, they indicate the total factor variance defined. This is traditionally known as an eigenvalue, or communality in factor analysis.

The general structural equation model typically consists of two parts: the measurement model, and the structural equation model. The measurement model specifies how latent variables or hypothetical constructs are measured in terms of observed variables and describe the measurement properties (reliability and validity). The structural equation model specifies structural relations among the latent hypothetical constructs. The measurement model does not specify any causal relationships between the latent constructs, while the structural equation model does. In establishing latent variable relationships, structural equation models differ from path models, which use only observed variables.

Therefore SEM methods incorporate the strengths of multiple regression analysis, factor analysis, and path analysis simultaneously. Moreover, they permit directional predictions among a set of independent or a set of dependent variables, and permit

modeling of indirect effects. The SEM methods constitute a comprehensive, flexible approach to modeling relations among variables.

1.2 General characteristics for SEMs

We list some important terms in SEMs here:

Manifest (Observed) versus latent variables

A manifest variable (indicator) is one that is directly measured or observed in the course of an investigation, while a latent variable is a hypothetical construct that is not directly measured or observed. For example, in **Figure 8** (in **Appendix 1**) **ANX** (see **Appendix 1** for description of variables) is treated as a manifest variable; it is possible to directly determine exactly where each subject stands on this variable. On the other hand, **Psyout** is as a latent variable; it is a construct that is presumed to exist, although it cannot be directly observed. By convention, observed variables are enclosed by rectangles or squares, latent variables are enclosed by ovals or circles.

Composite versus latent variable

In conventional representations of covariance structure models, latent variables influence measured variables. In an alternative representation, constructs can be defined as linear functions of their indicators, i.e. constructs are influenced by measured variables. Such constructs are not latent variables but composite variables.

Cause versus effect indicator

Cause indicators [14] are observed variables that are assumed to “cause” a latent variable. Indicators depend on the latent variable, i.e. the latent variable determines its indicators. Most researchers in the social sciences assume that indicators are effect

indicators, since it's not easy to distinguish them sometimes. In **Figure 10 (Appendix 1)** **SAD, ANX, EXH** are effect indicators influenced by latent variable **Psyout**. While **TEAM, COWORK, and SUPWK** are cause indicators, which determine the latent variable **Workrelation** in **Figure 10**.

Endogenous versus exogenous variable

An endogenous variable is one whose variability is predicted to be causally affected by other variables in the model. Any variable that has a straight, single-headed arrow pointing at it is thus an endogenous variable (straight lines, i.e., with an arrow at only one end, show causal relationships, while curved lines with arrows at both ends show correlations). In **Figure 9**, **PSYOUT** is an endogenous variable, as it is directly influenced by **FAMINT** and **JOBINT** and others. Exogenous (independent) variables are constructs that are influenced only by variables that lie outside of the causal model. Thus, they do not have any straight, single-headed arrows pointing at them. For example, **decision-making capacity** and **work relationships** are exogenous variables in **Figure 9**. These two variables are connected by curved arrows (indicating that they may covary).

Recursive versus nonrecursive model

A recursive model is one in which causation flows in only one direction. This means that none of the variables that constitute the structural portion of the models will be involved in feedback loops or reciprocal causation. In a nonrecursive model, causation may flow in more than one direction, and a variable may have a direct or indirect effect on another variable that preceded it in the causal chain.

Standard versus Non-standard model

With standard models, all constructs that constitute the structural portion of the model are presented as latent variables with multiple manifest indicators. With a nonstandard model, at least one of the constructs that constitute the structural portion of the model is represented as a single manifest variable.

General characteristics of SEMs include the following:

- In a standard model, all substantive variables of interest are latent. While in nonstandard model, at least one of the constructs is a manifest variable.
- In a measurement model, observed variables can be effect or cause indicators.
- In SEMs, the amount of influence is determined by direct, indirect and total “effects” among variables.
- Measurement equations specify how observed variables depend on latent variables.
- There are errors in equations and errors in effect indicators.

The **structural model** is written in the following matrix equation:

$$\eta \equiv B\eta + \Gamma\xi + \zeta \quad (1)$$

Here,

ξ is n-vector of latent exogenous variables.

ζ is m-vector of latent residual variables.

η is m-vector of latent endogenous variables.

$\Phi \equiv \text{Cov}(\xi)$, a $n \times n$ -covariance matrix of ξ -variables.

$\psi \equiv \text{Cov}(\zeta)$, a $m \times m$ -covariance matrix of ζ -variables.

B is a $m \times m$ -matrix of path coefficients between η -variables.

Γ is a $m \times n$ -matrix of path coefficients between ξ - and η - variables.

$\text{Cov}(\zeta, \xi) = 0$.

B has zeros on diagonal, and $I - B$ is nonsingular.

As described in Joreskog and Sorbom (1993), the **measurement models** can be written in the following set of matrix equations, for exogenous variables:

$$X = \Lambda_X \xi + \delta \quad (2)$$

Here,

X is q -vector of manifest indicator variables for ξ -variables.

δ is q -vector of latent error variables.

Λ_X is a $q \times n$ matrix of factor loadings of X on ξ .

Θ_δ is a $q \times q$ covariance matrix of measurement errors for X .

For endogenous variables, the equation is of the following form,

$$Y = \Lambda_Y \eta + \varepsilon \quad (3)$$

Here,

Y is p -vector of manifest indicator variables for η -variables.

ε is p -vector of latent error variables.

Λ_Y is a $p \times m$ matrix of factor loading of Y on η .

Θ_ε is a $p \times p$ covariance matrix of the measurement errors for Y .

According to Bollen's statement (in [5]), the basic hypothesis of the general structural equation model is:

$$\Sigma = \Sigma(\theta)$$

Where Σ is the population covariance matrix of y and x and $\Sigma(\theta)$ is the covariance matrix written as a function of the free model parameters in Σ . As population covariance Σ matrix is not known, in practice, it is replaced by sample covariance matrix S . On average, the sample covariance matrix S equals the population covariance matrix Σ . Thus our hypothesis becomes: $S = \hat{\Sigma}$.

The matrix $\hat{\Sigma}$ can be determined by the eight different matrices, B , Γ , Λ_x , Λ_y , Φ , Ψ , Θ_ε , Θ_δ defined above. It is composed of four submatrices as follows:

$$\hat{\Sigma} = \begin{bmatrix} \Sigma_{yy} & \Sigma_{yx} \\ \Sigma_{xy} & \Sigma_{xx} \end{bmatrix}.$$

The submatrices are defined mathematically by the eight matrices we mentioned above. For example, in our model Σ_{yy} deals with the covariances among Y variables:

$$\Sigma_{yy} = \Lambda_y [(I - B)^{-1} (\Gamma \Phi \Gamma' + \Psi) (I - B')^{-1}] \Lambda_y' + \Theta_\varepsilon$$

Σ_{xx} deals with the covariances among X variables:

$$\Sigma_{xx} = \Lambda_x \Phi \Lambda_x' + \Theta_\delta$$

And Σ_{xy} deals with the covariances between X variables and Y variables:

$$\Sigma_{xy} = \Lambda_x \Phi \Gamma' (I - B')^{-1} \Lambda_y'$$

Finally, the matrix Σ_{yx} is the transpose of Σ_{xy} .

The relation of S to $\hat{\Sigma}$ is basic to an understanding of identification, estimation, and assessments of model fit. In summary, once model is specified, the variances and covariances are functions of the model parameters. Attempts to establish that unique values can be found for these parameters introduces the issue of identification.

Note: All manifest variables are endogenous, and ε , δ , ζ and ξ are mutually uncorrelated. In measurement model, only effect indicator is discussed here.

The SEMs discussed in this project will demonstrate only unidirectional causal flow, i.e., recursive model.

1.3 Identification and parameter estimation

In SEMs, it is very important that we resolve the identification problem prior to the estimation of parameters. They depend on the amount of information in the sample covariance matrix, S , necessary for uniquely estimating the parameters in the model. Identification is demonstrated by showing that the unknown parameters are functions only of the identified parameters and these functions lead to unique solutions. If this can be done, the unknown parameters are identified; otherwise, one or more parameters are unidentified. Thus the goal is to solve for the unknown parameters in terms of the unknown-to-be-identified parameters. A model is said to be under-identified if one or more parameters may not be uniquely determined because there is not enough information in the matrix S . On the other hand, a model is said to be overidentified when there is more than one way of estimating a parameter.

The known-to-be-identified parameters are the elements of S . The parameters whose identification status is unknown are in θ , where θ contains the t free and constrained parameters of B , Γ , Φ , and Ψ . The equation relating S to θ is the covariance structure hypothesis, $S = \hat{\Sigma}$. Bollen presented the general principle [5]: "If an unknown parameter in θ can be written as a function of one or more elements of S , that parameter is identified. If all unknown parameters in θ are identified, then the model is identified."

A necessary, but insufficient condition for identification is the order condition (i.e. t -rule). The t -rule for identification is that the number of free parameters (a free estimator is a parameter that is unknown and thus is one that we wish to estimate) to be estimated must be less than or equal to the number of distinct values in the matrix S [5], i.e.

$$t \leq (1/2)(p + q)(p + q + 1)$$

where $p + q$ is the number of observed variables and t is the number of free parameters in matrix S . However, this is only a necessary condition, it does not mean that the model is identified.

We want to obtain estimates for each of parameters specified in the model that produce the covariance matrix $\hat{\Sigma}$ such that the parameter values are as close as possible to those in sample covariance S . This estimation process involves the use of a particular fitting function to minimize the difference between the produced covariance matrix $\hat{\Sigma}$ and sample covariance S . There are several methods including unweighted or ordinary least squares (ULS or OLS), generalized least squares (GLS), and maximum likelihood

(ML) procedures that are currently available. In this project, all analyses were conducted using the SAS system's **CALIS** procedure. These analyses used the maximum likelihood method of parameter estimation. ML estimation methods need assumptions of large sample size and multivariate normality of the observed variables. Running the sample covariance matrix with the specified model, we will obtain parameter estimates and fit statistics. We then determine from the parameter estimate and fit information whether the model needed to be modified as it did in our data set. We further discuss several indices of model fit in Chapter 4.

We will compare the relative size of standardized path coefficient estimates to determine which independent variable has the largest effect on the dependent variable, since unstandardized path coefficients depend on the units in which the variables are scaled. Often observed variables have different scales. This makes the assessment of relative direct influences difficult. The standardized path coefficient is the expected shift in standard deviation units of the dependent variable that is due to a one standard deviation shift in the dependent variable when the other variables are held constant. Thus we can compare the shift in standard deviation units of the dependent variable that accompanies shifts of one standard deviation in the observed variables as a means to assess relative effects.

Standardized coefficients can be useful in assessing relative effects of different explanatory variables. For example, the standardized path coefficient from exogenous latent variable to endogenous latent variable was defined as in [5]:

$$\hat{\gamma}_{ij}^s = \hat{\gamma}_{ij} \left(\frac{\hat{\sigma}_{jj}}{\hat{\sigma}_{ii}} \right)^{1/2}$$

and the standardized factor loading in measurement model was defined as [5]:

$$\hat{\lambda}_{ij}^s = \hat{\lambda}_{ij} \left(\frac{\hat{\sigma}_{jj}}{\hat{\sigma}_{ii}} \right)^{1/2}$$

where the superscript s represent a standardized coefficient, i is the dependent variable, j is the independent variable, and $\hat{\sigma}_{ii}$ and $\hat{\sigma}_{jj}$ are the model-predicted variances of the ith and jth variables, and γ_{ij} (λ_{ij}) represents the path from j to i.

2 Background to this study

2.1 Re-engineering was introduced in hospitals

Now we describe the historical background of the hospital re-engineering program, which was introduced in 1995 by the hospital in response to funding cuts. Re-engineering was first used in industry, now is getting widely used in hospitals.

“In 1995, the Ontario government announced an 18% (1.3 billion) reduction in hospital operating budgets over the next three years” [13]. Due to fiscal constraints, hospitals in the province were forced by the government to make organizational changes. To meet the challenges, hospitals took action to downsize, re-engineering and restructure service delivery. During the period, hospital workers were faced with job changes, losses and increased competition for limited numbers of positions. Workers confronted repeated threats to job control, loss of job security, fear of job obsolescence, and early retirement which were hypothesized to contribute to stress, burnout, depression, and poor physical health (see [1] for further references). A research initiative was undertaken by a research team led by Dr. C.A. Woodward of McMaster University. They have contributed valuable information about the impact of the changes occurring in CMH.

Study questions:

This project explores the impact on the staff of Chedoke-McMaster hospitals (CMH) of their re-engineering efforts. Our study will model the interplay between work life quality, psychological adjustment and family relationship. The data gathered

longitudinally at the three points will be examined via structural equation modeling to determine the paths via which changes in **decision making capacity, work relationships, and job stressors** contribute to **psychological outcomes** mediated by **family and job interference**. The approach to this research design and data analysis will help us to find out how these factors lead to positive or negative health outcomes.

2.2 Hospital setting and scales in the analysis

This study took place in a large teaching hospital with 2 separate campuses -- Chedoke-McMaster hospitals (CMH). Three surveys have been completed on three occasions (1995-1997) separately at CMH. A sample of 900 staff was randomly selected from the personnel files at CMH, which represented about 21 percent of the employees and was drawn from all segments and job categories. All staff members who were employed by the hospital at the time of the study were eligible. Questionnaires were mailed to the random sample of hospital employees in May of each year at their hospital address. Thank you reminder cards were sent one week later, and two subsequent mails were sent to non-respondents. However, not everyone replied. Six hundred and fifty-four, five hundred and twenty-eight, and four hundred usable responses were obtained in 1995, 1996, and 1997, respectively. Three hundred and forty-six staff replied in all 3 years.

The survey used scales taken from the literature to measure key constructs of interest. Scale reliability was assessed by calculating coefficient alpha. We have administered a multiple-item to a group of subjects and want to determine the internal consistency (reliability) of the scale. The internal consistency of scales was checked using

Cronbach's coefficient [15]. Coefficient alphas for key constructs are very good as indicated in [1]. The scales used in the analysis are described as follows:

- (1). Self-Efficacy: a 5-item measure (alpha = 0.71) of confidence in the competitiveness and transferability of one's skills, job prospects and ability to cope with job change.
- (2). Readiness for change: a 6-item (alpha = 0.63) adaptation of the readiness-for-change scales developed by Prochaska and colleagues.
- (3). Active coping style: a 5-item measure (alpha = 0.75) of an active problem solving style.
- (4). Job influence: 10-items (alpha = 0.84) reflecting the amount of influence employees feel they have over a wide range of job-related dimensions.
- (5). Skill discretion: a 6-item scale (alpha = 0.82) reflects the breadth of skills workers could use.
- (6). Decision authority: a 3-item scale (alpha = 0.82) reflects the decision-making authority on their jobs.
- (7). Teamwork: a 6-item factor (alpha = 0.86) reflecting the extent to which one's work unit co-ordinates, solves problems and works effectively together.
- (8). Co-worker support: a 7-item measure (alpha = 0.86) of the extent to which co-workers are competent, understanding and supportive of an individual employee.
- (9). Supervisor support: a 3-item factor (alpha = 0.88) reflecting the extent to which supervisors are helpful, concerned with the welfare of employees and able to facilitate effective interaction among employees.

- (10). Lack of role clarity: this 4-item scale ($\alpha = 0.65$) with responses categories was developed by Brosnan and Johnston to examine the extent to which job responsibilities and expectations are unclear and there is difficulty with conflicting priorities and job demands.
- (11). Psychological job demands: a 6-item scale ($\alpha = 0.69$) reflects the psychological and physical demands of one's work.
- (12). Family interference: the 4-item scale ($\alpha = 0.77$) reflects the potentially adverse effects of family demands on work performance.
- (13). Job interference: the 4-item scale ($\alpha = 0.64$) measures the adverse effects of job on family life.
- (14). Anxiety: a 10-item scale ($\alpha = 0.89$) version of the State Anxiety Scale, which asks how much anxiety (as reflected in feeling jittery, nervous, rattled, etc.) the person experiences now.
- (15). Emotional exhaustion: the 7-item ($\alpha = 0.91$) emotional exhaustion scale of the Maslach Burnout Inventory measured using 7 response categories.
- (16). Depression: a 10-item version of the centre for the Epidemiological Study of Depression Scale ($\alpha = 0.78$) which is used to measure depression in the general population using 4 response categories.

3 Data Exploration

3.1 The initial examination of data

There are 701 subjects and 328 variables from the raw data in SPSS file. After converting the file into SAS file, the questionnaire data is input in the form of raw data in SAS program. We determine the sample size will be 346, which comes from those who replied to the questionnaires in all three years. We will study 1995 and 1997 data. As for the variables, we use scores on the 32 scales (actually 2 groups of them, 16 scales in 1995 and 1997 each) to assess constructs constituting our hypothesized model. (The terms scale, indicator and variable will be used interchangeably, on the basis of reviewing the relevant research literature and theoretical beliefs and ideas.)

Sample Size:

In structural equation modeling, the researchers often require a much larger sample size (than multiple regression) to maintain the accuracy of estimates and to ensure representativeness. The need for larger sample sizes is due in part to the program requirements and the multiple observed indicator variables used to define latent variables (degrees of freedom in a measurement model). One rule-of-thumb suggests reasonable results can be attained when the number of subjects (responses) is at least five times the number of parameter [9]. The total number of parameters is the sum of the path coefficients, variances, and covariances to be estimated. Large samples are always preferable. For our project, we have different hypothesized models. The number of parameters to be estimated is different in various models. We have 327 observations

(there are missing values on 19 subjects) for data95, 323 observations (there are 23 missing values) for data97, and 308 observations (there are 38 missing values) for the longitudinal model in Figure 5 (see Appendix 1). The largest number of parameters is in the longitudinal model (80 parameters), so the sample size is strictly speaking not big enough. The parameters in other models are 40 or 38, which means the sample size is big enough. Overall, the sample size (except for the longitudinal model) is moderately good.

Data were first analyzed descriptively using SPSS and SAS software. The means, variances, standard deviations, the ranges, missing values and more information on the variables are shown in the table in **Appendix 2**. We also found that not all the variables fit normal distributions. From the histograms (see **Appendix 2**) we could see that most of the variables fit well. There also exist some outliers for the data in our tests. Even so we can still make the assumption that our data are distributed as normal distributions approximately. With this assumption, we now move to correlation analysis. The correlation matrix is also presented in the table in **Appendix 2**.

In it, the correlations above the diagonal are for 1995 data, below diagonal for 1997 data. Sample sizes range between 327 and 346. We also note that correlations range (in absolute value) from 0.00 – 0.64. None of them are very high, which indicates that there are likely no redundant variables to remove, and that they measure different things.

3.2 Reports of previous analysis

We will integrate the results of our analysis with those that were previously obtained by other methods. Reports of the impact of the changes in Ontario hospitals to

date are limited. There are research studies of re-engineering effects on hospital staff examining different aspects of the same data set we will use [11,12].

J. A. Brown et al [12] reported that workers at different supervisory levels in the hospital experience job stresses and job satisfaction differently. Increased job demands were related to increased stress for all levels of workers. For those with supervisory positions, the limited ability to make decisions was related to increased stress. Co-worker support and teamwork were important for job satisfaction for all levels of workers.

A longitudinal study of the impact on the hospital staff of the re-engineering [11] concluded along with the rapid change there was increased emotional distress among staff and deterioration in their relationship with their employer. Significant increases in depression, anxiety, emotional exhaustion, and job insecurity were seen among employees, particularly during the first year of the change process. By the end of the second year, deterioration appeared in teamwork, increased unclarity of role, and increased use of distraction to cope. Job demands increased throughout the period whereas little change occurred in the employee's job influence or decision latitude. Meanwhile a significant decline in perceptions of patient care, attention to quality improvement, and overall quality of care was seen after the first year.

4 Method of analysis

4.1 Exploratory factor analysis

We first perform an exploratory factor analysis to identify the factor structure underlying the data. We need to discover the number of relevant factors assessed, how the factors intercorrelate, and how the variables load on the factors. From reviewing a previous study on the same data set and the research literature in SEM and other area, we divided our 16 scales into three levels (or groups) of constructs, which are:

- (1) Job related scales: **AUTH, PSY, EFF, READY, TEAM, ROLE, COPACT, JOBINF, DISC, COWORK, SUPWK** (Please refer these notations to **Appendix 1**).
- (2) Interference scales: **JOBINT, FAMINT**.
- (3) Psychological outcome: **ANX, SAD, and EXH**.

We hypothesize that job related scales cause the psychological outcomes through interference (job-family). The problem is that we don't know how this group (job related scales) might be separated into different factors. Thus, exploratory factor analysis is used to find out the underlying pattern in this group.

Responses to the 11 scales in group 1 were included in an exploratory factor analysis. The principal factor method was used to extract the factors, and this was followed by rotations. We provide some explanation of the method.

In exploratory factor analysis we do not begin with a specific model, only rather general specifications about what kind of a model we are looking for. We must then find the model as well as estimate the values of its paths and correlations. In general there are many possible path models that can reproduce any given set of intercorrelations. We are looking for the simplest factor model that will do a reasonable job of explaining the observed intercorrelations. What does a simple model mean? Loehlin described two-step definition [10]: (1) a model that requires the smallest number of latent variables (factors); (2) given this number of factors, the model with the smallest number of non-zero paths in its pattern matrix. Application of these two steps corresponds to the two main divisions of an exploratory factor analysis, factor *extraction* and *rotation*. The factor extraction method is employed to yield models having the smallest number of factors that will do a reasonable job of explaining the correlations. In the factor extraction step, the SAS program "Proc Factor" can carry out a simple principal factor analysis of a correlation matrix.

Then, in the rotation step, models are transformed to retain the same number of factors, but improve them with respect to the second criterion of non-zero paths. After factor extraction, if more than one factor has been retained, an unrotated factor pattern is usually difficult to interpret. To make interpretation easier, the next is to transform such solutions to simplify them in another way: to minimize the number of paths appearing in the path diagram. This rotation process consists of transformations as rotations of coordinate axes. Uncorrelated factors are called *orthogonal*, the correlated factors are called *oblique*. The *orthogonal transformation* is to achieve the goal that after the

transformation the factors remain independent, but they are simpler in the sense of having more zeros or near-zero paths. The SAS program Varimax is a procedure for this purpose. After orthogonal transformations, the second step is *oblique transformation*, which deals with correlated factors. Promax in SAS program is a procedure, which retains the general robustness of the orthogonal methods while arriving at an oblique factor solution [16].

In interpreting the rotated factor pattern, we identify the variables that demonstrate high loadings for a given component, and determine what these variables have in common. A scale was said to load on a given factor if the factor loading was 0.35 or greater for that factor, and was less than 0.35 for the other. The result of the SAS output for 1995 data suggests that 10 scales measure three factors. **EFF95, READY95, COPACT95, JOBINF95** and **AUTH95** were found to load on the first factor, which was labelled **decision-making capacity**. **TEAM95, COWORK95, SUPWK95** loaded on the second factor, which was labeled **work relationships**. **ROLE95** and **PSY95** loaded on the third factor, which was labeled **job stressors**. The scale **DISC95** was omitted since this scale loads on all of the three factors (the loadings for three factors were between 0.30-0.39, thus we omit this variable). Corresponding factor loadings from the rotated factor pattern matrix and factor structure matrix are presented in **Appendix 2**. We also list the correlations between **JOBINT95, FAMINT95** and the estimated factor scores: Factor 1, Factor 2 and Factor3 in **Appendix 2**. We find that **JOBINT95** correlated with Factor 1 and Factor 2 negatively, but positively with Factor 3. That makes sense for our hypothesized model.

A similar method was used for the 1997 data. A different set of scales ends up in the factors. We found that the 10 variables located on the three factors. **EFF97** and **COPACT97** loaded on factor 1. **JOBINF97**, **AUTH97**, **TEAM97**, **COWORK97** and **SUPWK97** loaded on factor 2. **ROLE97** and **PSY97** still loaded on factor 3. Corresponding factor loadings from rotated factor pattern matrix and factor structure matrix are presented in **Appendix**.

This gives us a problem. Since we want to use data95 and data97 to perform longitudinal analysis, we need the same measurement models. There was only a fairly small difference between the constructs (factor 1) for data95 and data97. Thus we choose to keep the same constructs in data97 as in data95 for our analysis.

Although re-engineering affected hospital staff as shown in previous analyses by researchers, there were no SEM studies examining the relationships among **decision-making capacity, work relationships, job stressors and psychological outcomes**.

4.2 Descriptive criteria of model fits

The determination of model fit in SEMs is not as straightforward as it is in the other statistical approaches in multivariable procedures such as multiple regression. There is no single statistical test of significance that identifies the correct model given the sample data. None of the goodness of fit criteria, except χ^2 , have an associated statistical test of significance.

Model fit criteria in SEMs commonly used are chi-square (χ^2), goodness-fit-index (GFI), adjusted goodness-of-fit index (AGFI), the comparative fit index (CFI) and the normed fit index (NFI), non-normed fit index (NNFI), parsimonious fit index (PFI),

and Akaike information criterion (AIC) (We only discuss the indices produced by the CALIS procedure). What complicates the matter is that several GOF criteria will be used to assess and interpret SEMs under differing model-building assumptions. Schumacker and Lomax [7] suggested that the various GOF criteria should be used in combination to assess *model fit, model comparison, and model parsimony*. Overall, the fit indices fall into the category of either model fit, model comparison, or model parsimony fit indices. No one index serves as a definite criterion for testing a hypothesized SEM. Each index provides somewhat different information. A single “ideal” does not exist, since an “ideal” fit index should be one that is independent of sample size, accurately reflects differences in fit, imposes a penalty for inclusion of additional parameters, and supports the choice of a true model when it is known. We briefly describe different criteria for model fit, model comparison, and model parsimony.

(1) Model fit

Model fit criteria commonly used are chi-square (χ^2), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI). These criteria are based on differences between the observed (original, S) and model-implied (reproduced, Σ) correlation or covariance matrix.

A significant χ^2 value relative to the degrees of freedom indicates that the observed and estimated matrices differ. Thus the p-value associated with the model chi-square test should exceed 0.05, the closer to 1.00, the better. The level of statistical significance indicates the probability that this difference is due to sampling variation. A

nonsignificant χ^2 value indicates that two matrices are not statistically significantly different. Although the χ^2 GOF criterion is a statistical test procedure, it has limitations as a descriptive index of model fit. For example, χ^2 is sensitive to sample size and also sensitive to departures from the normality assumption.

Three approaches are commonly used to calculate χ^2 : maximum likelihood (ML) generalized least squares (GLS), and ordinary least squares (OLS). Each approach estimates a best-fitting solution and evaluates the model fit. The most widely used fitting function is the ML function. The χ^2 statistic is $\chi^2 = (n-1) F$ (in Appendix 3, we will show that under null hypothesis, $(n-1) F$ is asymptotically distributed as a Chi-square variate [5]), where:

$$F_{ML} = \text{tr}(S\Sigma^{-1}) - (p + q) + \ln|\Sigma| - \ln|S| \quad (4)$$

$$F_{GLS} = 0.5\text{tr}[(S - \Sigma)S^{-1}]^2 \quad (5)$$

$$F_{OLS} = 0.5\text{tr}[(S - \Sigma)^2] \quad (6)$$

$$df = 0.5 (p+q) (p+q+1) - t$$

t = total number of independent parameters estimated

n = number of observations

(p+q) = number of observed variables analyzed and where *tr* indicate the trace.

The GFI is based on a ratio of the sum of the squared differences between the observed and reproduced matrices to the observed variances, thus allowing for scale. The GFI index can be computed for ML, GLS, or OLS estimates too. The AGFI adjusts GFI by a ratio of the degrees of freedom of the restricted to the null matrix. For example, the

goodness-of-fit index (GFI) using the unweighted least squares approach (ULS) cited by Schumacker and Lomax in [7] is:

$$GFI = 1 - 0.5(S - \Sigma)^2 \quad (7)$$

The AGFI index is computed as $1 - [(k/df)(1 - GFI)]$, where k = the number of unique values in S , or $(p+q)(p+q+1)/2$, and df = the number of degrees of freedom in the model.

(2) Model comparison

The NFI is a measure that rescales chi-square into a 0 (no fit) to 1.0 (perfect fit) range [7]. It is used to compare a restricted model with a full model using a baseline null model as follows

$$(\chi^2_{\text{null}} - \chi^2_{\text{model}}) / \chi^2_{\text{null}} \quad (8)$$

This index may be viewed “as the percentage of observed-measure covariation explained by a given measurement or structural model”. Although the NFI has the advantage of being easily interpreted, it has the disadvantage of sometimes underestimating goodness of fit in small samples. A variation on the NFI is the non-normed fit index (NNFI). The NNFI [10] has been shown to better reflect model fit at all sample sizes. The comparative fit index developed by Bentler (1995), like the NNFI, overcomes the deficiencies in NFI for nested models. It provides an accurate assessment of fit regardless of sample size. In addition, the CFI tends to be more precise than the NNFI in describing comparative model fit. The rationale for assessment of comparative fit in the nested model approach involved a series of models that ranged from least restrictive to saturated. Corresponding to the sequence of nested models is a sequence of

GOF test statistics with associated degrees of freedom. The CFI measures the improvement in noncentrality in going from a restrictive model to a saturated model and uses the noncentral χ^2 distribution with noncentrality parameter to define comparative fit.

(3) Model parsimony

Parsimony refers to the number of estimated coefficients required to achieve a specific level of fit. The AGFI measure also provides an index of model parsimonious goodness of fit. Other indices are parsimonious fit index (PFI), and Akaike information criterion (AIC) etc [7]. The AIC measure will always be positive. A minimum value (close to zero) represents an optimum fit.

Many of the goodness of fit (GOF) criteria (e.g. GFI, AGFI, CFI, NFI, and NNFI) range in value from 0 (no fit) to 1 (perfect fit) and are assessed as to what is an acceptable model fit. There is no unambiguous answer to how large the GOF must be to indicate an “adequate” fit. Bentler and Bonett (1980) suggest that for NFI and TLI: “In our experience models with overall fit indices of less than 0.9 can usually be improved substantially”[5]. A structural equation model with a GOF value of close to 0.90 or higher is acceptable [7]. Although this provides a rough guideline, several factors (e.g., sample size, the choice of baseline) can affect the GOF criteria that may lead to other cutoffs. We discuss some GOF criteria outputted by the SAS program (see **Table 28** in **Appendix 3**). We note that a model does not necessarily have to display all these characteristics to be considered acceptable. So we will use GFI, AGFI, CFI, NFI, and NNFI for our overall fit indices in our project. Hatcher suggested that values over 0.9 on the NNFI and CFI indicate an acceptable fit. In particular, he mentioned that “a nonsignificant chi-square

value is normally not essential, as long as the value of chi-square is not very large in relation to the degrees of freedom” [8].

Assessing the adequacy of a path model is not a simple thing. Besides considering goodness of fit indices, individual parameter estimates in a model must be consulted. We should examine whether parameter estimates have the expected sign (either plus or minus) and are within an expected reasonable range of values. If the absolute t value of the statistics for a path coefficient exceed 1.96, then the path coefficient is significant at the $p < 0.05$ level. In other words, this path coefficient may be viewed as being significantly different from zero. And the standardized path coefficient should be nontrivial in magnitude (i.e., absolute values should exceed 0.05). Moreover, the “ideal” fit model requires the absolute values of entries in the normalized residual matrix to be small (preferably less than 2.00), the R-square value (the squared multiple correlation coefficient indicates the amount of variance in the dependent variable explained, predicted, or accounted for by the set of independent variables) for each endogenous variable should be relatively large.

Since it is rare that an initial theoretical model demonstrates a good fit, we need to modify the model to get a better fit. The **MODIFICATION** option included in the **PROC CALIS** statement requests that two modification indices be computed. The first index is the **WALD test**, which identifies parameters that might be dropped from the model. The second modification index is the **Lagrange multiplier**, which identifies parameters that could be added.

4.3 How programs estimate parameters

The **PROC CALIS** program that analyzes a structural equation model is longer than most **SAS** programs, but it is not especially complicated. The **CALIS** procedure can perform a variety of structural equation analyses. The basic program input consists of **CALIS**, **LINEQS**, **STD**, and **VAR** statements. There are some options followed by **CALIS**, such as **COVARIANCE**, **CORR**, **RESIDUAL**, **MODIFICATION** etc.

The **CALIS** procedure estimates four different types of parameters:

- Factor loadings, which represent the relationships between observed variables and latent variables.
- Path coefficient, which represents the amount of change in a dependent variable that is associated with a one-unit change in the relevant independent variable, while holding constant the remaining independent variables.
- Variances, which represent the variability in exogenous variables.
- Covariances, which represent the covariation between pairs of exogenous variables.

All four types of parameters may be either estimated, fixed, or constrained.

For linear equations input, the **LINEQS** statement (analysis-model-in-equations-notation) is used to identify the variables that have direct effects on the endogenous variables. It serves two functions in a path analysis: it indicates which factor loading is to be estimated or fixed, and it specifies the causal relations between variables in the structural model.

For example, with $Y=V1$, $\Lambda_y = LV1F1$, $\xi = F1$ and $\varepsilon = E1$, the **LINEQS** statement for formula (3) $Y = \Lambda_y \xi + \varepsilon$ (in chapter 1.2) is:

$$V1 = LV1F1 F1 + E1,$$

Accordingly, if $F1 = \eta$ is a scalar vector variable (so $B = 0$ in this case), $(F2, F3) = \xi$, $(PF1F2, PF1F3) = \Gamma$, $D1 = \zeta$, the **LINEQS** statement for formula (1) $\eta = B\eta + \Gamma\xi + \zeta$ (in chapter 1.2) is:

$$F1 = PF1F2 F2 + PF1F3 F3 + D1,$$

Where V = manifest endogenous variable

$F1$ = latent endogenous variable

$(F2, F3)$ = latent exogenous variable

L = factor loadings

P = path coefficients

E = residual (or disturbance) term for corresponding manifest variables

$D1$ = residual term for corresponding latent variables

The factor loadings are represented with coefficient names that begin with the “L” prefix, and the path coefficients are represented with coefficient names that begin with the “P” prefix.

The **STD** statement (variances) is to identify the variables whose variances are to be estimated in the analysis. The **COV** statement (covariances) is used to identify pairs of variables that are expected to covary (to be correlated). The **VAR** statement (variables) identifies the manifest variables to be analyzed in the path analysis.

4.4 Different models proposed

We illustrate the analysis with two possible types of models: **cross-sectional** model and **longitudinal** model.

4.4.1 *First, we propose the cross-sectional models in 1995 and 1997.*

We show the hypothesized model in **Figure 8 – 13**. There are six different diagrams (see **Appendix 1**) that are:

Figure 8: **Model 1** – Standard model with effect manifest indicators.

Figure 9: **Model 2** – Non-standard model with effect indicators.

Figure 10: **Model 3** – Standard model with cause indicators.

Figure 11: **Model 4** – Non-standard model with cause indicators.

Figure 12: **Model 5** – Standard model with both effect and cause indicators located on a latent variable.

Figure 13: **Model 6** – Non-standard model with mixed indicators.

We opt for **non-standard** models in Figure 9, 11, and 13 in which two of the constructs that constitute the structural portion of the model are each represented as a single manifest variable (i.e., **family interference** construct is measured by just one manifest variable, as is **job interference**, they are both scales actually).

In our hypothesized model 2 in Figure 9, there are four latent variables. Among them, there are three latent independent variables: **Decmakcap** (Please refer to the descriptions of notations in **Appendix 1**), **Workrelation**, and **Jobstress**, one latent dependent variable **Psyout**. And there are two constructs, directly measured by manifest variables **FAMINT** and **JOBINT**.

For our **standard model** in Figure 8, 10, and 12, none of the constructs of interest are observed variables. There are five constructs. Among them, there are three latent independent variables, as in the non-standard model. But there are two latent dependent variables, which are **INT** and **Psyout**. We should note that **INT** is also an independent variable in predicting **Psyout**.

In both model 1 and model 2, indicators are defined as linear functions of latent variables, plus error. An indicator under this representation can be thought of as an effect of a latent variable, and is called effect indicator. For example, **Decmakcap** is hypothesized to be a latent variable that influences the performance of the effect indicators: **EFF, READY, COPACT, JOBINF** and **AUTH** in **model 1** and **model 2**. In an alternative representation, indicators could be viewed as causing rather than being caused by the latent variable measured by the indicators. Constructs can be defined as linear functions of their indicators, called cause indicators, plus an error term. Such constructs are not latent variables but composite variables, and they have no indicators in the conventional sense. In our **model 3** and **model 4**, **decmakcap, workrelation** and **jobstress** were hypothesized to be composite variables, which were influenced by their indicators respectively. In some cases, it may be reasonable to define a set of indicators for a latent variable as including both effect indicators and cause indicators. In **model 5**, **decmakcap** was hypothesized both to be influenced by cause indicators – **JOBINF**, and **AUTH** – and to influence effect indicators – **EFF, READY** and **COPACT**. We will analyze and compare those different models in order to get a reasonable model for our

data set. Now we discuss the two models that make up structural equation modeling: the measurement model and the structural model.

As previously mentioned, the measurement model allows for certain relationships between the latent (or composite) variables and the observed variables. Therefore, an example of the equations for the measurement model is illustrated by the equations for model 1 (please see **Figure 8** in **appendix 1**):

SAD = function of Psyout (*)	+ error
ANX = function of Psyout	+ error
EXH = function of Psyout	+ error
FAMINT = function of INT (*)	+ error
JOBINT = function of INT	+ error
EFF = function of Decmakcap (*)	+ error
READY = function of Decmakcap	+ error
CAPACT = function of Decmakcap	+ error
JOBINF = function of Decmakcap	+ error
AUTH = function of Decmakcap	+ error
TEAM = function of Workrelation (*)	+ error
COWORK = function of Workrelation	+ error
SUPWK = function of Workrelation	+ error
ROLE = function of Jobstress (*)	+ error
PSY = function of Jobstress	+ error

The structural models allow for certain relationships among the latent variables depicted by direct lines or arrows. One of the examples of the equations for our structural

models is illustrated by the equations for model 1 (please see **Figure 8 in appendix 1** also):

$$\text{Psyout} = \text{INT} + \text{Decmakcap} + \text{Workrelation} + \text{Jobstress} + \text{error}$$

$$\text{INT} = \text{Decmakcap} + \text{Workrelation} + \text{Jobstress} + \text{error}$$

The asterisk signifies that a factor loading was fixed to 1. Thus, for each latent or composite variable, one factor loading has been fixed to 1 to identify the model, and the program uses that variable's scale for the latent or composite variables.

It seems reasonable to consider both effect and cause indicators embedded in our models. For each latent variable, we could consider whether the indicators would most reasonably be defined as cause or effect indicators. Then the model would be constructed accordingly and fitted to the data. But the presence of composite variables in a model can, in some situations, result in an iteration problem, which lead to nonconvergence. We will further discuss this topic.

4.4.2 We describe our hypothesized longitudinal model in Figure 14.

Latent variable casual models are often used to analyze situations in which variables are measured over a period of time. We can test the hypothesis that **Psyout** in 1995 would have effect on **Psyout** in 1997.

This design will help us to check the effect of pre-re-engineering (95) to post-re-engineering (97) over time. That is, we want to examine if **Psyout** in 1997 was affected by **Psyout** in 1995 and other variables (see Figure in Appendix 1). **Psyout** in 1997 is partly predictable by **Decmakcap**'s, **Workrelation**'s, **Jobstress**'s, and **INT**'s in 1995 and 1997. The general degree of **Psyout** in any year is reflected in **SAD**, **ANX** and **EXH**.

It is assumed that the measurement models are the same on both occasions of measurements.

5 Interpreting the Results of the analysis

When the SAS program for estimating the theoretical model has been executed, we review the SAS log file and output file to verify that the program ran correctly. For example, we verify that the LINEQS statements were written correctly, and that the model is overidentified. The output reveals the number of data points associated with the analysis (the amount of independent information in the data matrix). We verify that the number of data points in the analysis is larger than the number of parameters to be estimated, which is the t-rule in Chapter 1 (1.3). When this is not the case, the model is not identified. We also check that the estimation algorithm converges.

Then, reviewing the substantive results of our analysis (e.g., the goodness of fit indices, the factor loadings, etc.), we begin our assessment of the fit between model and data as follows according to Hatcher's suggestion [7]:

Step 1. Reviewing the chi-square test. When the proper assumptions are met, the chi-square test provides a statistical test of the null hypothesis that the model fits the data. However, with large samples and real-world data, the chi-square statistic will very frequently be significant even if the model provides a good fit. So it has been recommended that it be treated as a general goodness of fit index, but not as a statistical test in the strictest sense. That is to say, these indices may reveal a relatively good fit even when the chi-square test suggests rejection of the model. Some of the additional fit indices are list in step 2

- Step 2.** Reviewing the goodness of fit index (GFI), GFI adjusted for degrees of freedom (AGFI), comparative fit index (CFI), normed index (NFI), and non-normed index (NNFI). As noted earlier these indices have been proposed as alternatives to the chi-square test. Values on these indices may range from 0 to 1, with values over 0.9 (especially for CFI and NNFI) indicative of an acceptable fit of the model to the data.
- Step 3.** Reviewing significance tests for factor loadings and path coefficients. Before interpreting the t tests, the corresponding standard error should be reviewed to determine if any of them are excessively small (i.e., close to zero). This sometimes reflects an estimation problem that results when one parameter is linearly dependent on other parameters, and can result in invalid tests. We should check whether all of the factor loadings and path coefficients are of the expected magnitude and direction. Then we check the t tests; if the t values are greater than 1.96 the coefficients are significantly different from zero at the 5% level.
- Step 4.** Reviewing R-square values for latent endogenous variables. These R-square values indicate the percent of variance in the endogenous variables that is accounted by their direct antecedents. As in multiple regression, R-square values range from 0 to 1 with larger values indicating a great percent of variance accounted for.
- Step 5.** Reviewing the residual matrix and normalized residual matrix. When the original covariance matrix is analyzed, it is possible to use the resulting path coefficients to create a reproduced covariance matrix. If the theoretical model successfully

accounts for the actual causal relationships between the variables, this reproduced covariance matrix should be identical to the original covariance matrix. When the path analysis is performed on a covariance matrix, the elements of the residual matrix are not standardized in any meaningful way, making it difficult to determine how large a residual should be to be considered too large.

Schumacker and Lomax recommend that a model does not necessarily have to display all of these characteristics to be considered acceptable [7]; in fact, the literature contains studies reporting acceptable models that fail to demonstrate one or more of the preceding traits. Therefore we will examine our hypothesized models and analyze them cautiously according to above procedures.

For our hypothesized models, we will discuss the output for each respectively.

5.1 Outline of models

First, we describe the hypothesized models we want to analyze in Table 1. We explain some models in detail, and for completeness show others in Appendix 4.

The cross-sectional models were analyzed first. Lomax recommends that each latent variable be assessed with at least three indicators to avoid problems with identification and convergence [7]. Thus we applied both standard and non-standard models to our data. In our non-standard models, there were two constructs **FAMINT** and **JOBINT** in the structural portion of the model that are represented as a single manifest variable each.

For some of the latent variables, we consider whether the indicators would most reasonably be defined as cause or effect indicators. In 4.4.1 (Chapter 4), model 3 and

model 4 are respecified on the basis of the argument that certain indicators should be considered as cause indicators, thus requiring a reversal of paths between those indicators and their corresponding latent variables. In the standard model with cause indicators (model 3), cause indicators seemed relevant to three of the latent variables. **Decmakcap95** could be thought of as a composite variable determined by **EFF95**, **READY95**, **COPACT95**, **JOBINT95**, and **AUTH95**. Also, **Workrelation95** could be viewed as a composite variable determined by **TEAM95**, **COWORK95**, and **SUPWK95**. **Jobstress95** could be viewed as a composite variable determined by **ROLE95** and **PSY95**.

Sometimes, it may be reasonable to define a set of indicators for a latent variable as including both effect indicators and cause indicators. The latent variable **Decmakcap95**, which is, influenced by indicator variables **JOBINF95** and **AUTH95**, meanwhile it influence **EFF95**, **READY95**, and **COPACT95**, which are thus effect indicators. So five indicators both influence and are influenced by one latent variable at the same time. The other latent variable **Psyout95** is considered as before, and **Workrelation95** and **Jobstress95** were still treated as composite variables (for the above descriptions, see **Figure 8 -13** in **appendix 1**).

We only deal with the standard model with effect indicators for longitudinal models. The other cases may be considered as a future topic. As well, the main text shows only some of the models examined. The results for the others are described in the Appendices.

Table 1 cross-sectional models and longitudinal models

Year	Standard/Nonstandard	Type of Indicators	Tables
1995	standard	effect	5.2.1
1995	standard	cause	Appendix 4(a)
1995	standard	mixed	Appendix 4(b)
1995	nonstandard	effect	5.2.2
1995	nonstandard	cause	Appendix 4(c)
1995	nonstandard	mixed	5.2.2
1997	standard	effect	5.3.1
1997	standard	cause	Appendix 4(d)
1997	standard	mixed	5.3.1
1997	nonstandard	effect	Appendix 4(e)
1997	nonstandard	cause	Appendix 4(f)
1997	nonstandard	mixed	Appendix 4(g)
95-97	Standard (model 7)	effect (30 variables)	5.4
95-97	Standard (model 8)	Effect (28 variables)	5.4

5.2 1995 cross-sectional models

5.2.1 *Standard models (data95)*

(1) Standard model with effect indicators (Model 1)

The program was executed as expected. The output shows that the analysis was based on 327 observations and 15 variables. The data points were 120 and the parameters were 40. The necessary (but not sufficient) condition for model identification has been met. The iteration history indicated that the convergence criterion was satisfied.

The goodness-of fit index showed that model 1 chi-square was 266.4 with 80 degree of freedom. Although a nonsignificant chi-square would have shown support for

our model, this significant chi-square does not necessarily indicate a bad fit. Other fit indices showed that the GFI was 0.9, AGFI was 0.85, CFI was 0.87, NFI was 0.82, and NNFI was 0.83 (Please see Table 2 GOF indices). These indices provide mixed signals concerning our model's fit. Only GFI reached 0.90, the others were close to 0.90. Though most of these indices cannot reach 0.90 higher for data95, we still can say these indices didn't show of poor fit

We look for the factor loadings and path coefficients, first checking the signs. All of these coefficients look reasonable based on our prior expectations. All of the estimated factor loadings showed positive values. And there were no near-zero standard errors for the factor loadings and path coefficients, which could have indicated estimation problems. Also all of the estimated t values for factor loadings were significantly different from zero. Of great interest in this analysis, are the path coefficients for the causal paths that constitute the structural portion of the model. The path coefficients for the path Decmakcap95 to Psyout95, Jobstress95 to Psyout95, and Jobstress95 to INT95 were significant. The path from INT95 to Psyout95, Workrelation95 to Psyout95, Decmakcap95 to INT95, and Workrelation95 to INT95 were nonsignificant. But, the path for INT95 to Psyout95 is 1.70 (t-value), which is nonsignificant at the 5% level, but very close to 1.96 (Figure 3 displayed unstandardized and standardized path coefficients for initial model 1). We will keep this path in the model when we decide to modify our model. And the t value for Workrelation95 to Psyout95 was 1.28, which was not significant, but we want to keep this for the moment, since we don't want to make many modifications at this stage.

The R-square value for the endogenous variables shows that the independent F variables accounted for 71% of the variance in **Psyout95** and 41% of the variance in **INT95**.

Reviewing the residual matrix and normalized residual matrix: unfortunately, the table of normalized residuals from the output did not show strict symmetry and centering around zero for both data sets.

Although some overall fit indices are in the acceptable range, our initial theoretical model does not provide a fully acceptable fit to the data. So we try to modify the model to produce a better fit.

Models may be modified in several ways: they are most frequently modified by either fixing causal paths at zero (e.g., eliminating a nonsignificant path from the model), or freeing causal paths to be estimated (i.e., adding new paths to the model). In our case, eliminating a nonsignificant path is necessary. The first parameter listed is the one that would result in the least change in chi-square if deleted; the second parameter listed would result in the second-least change, and so forth. From the result of the Wald test, the first parameter listed in the result is VarE5, and the last entry is CF3F5 (covariance between **Decmakcap95** and **Jobstress95**), the covariance between F3 (**Decmakcap95**) and F5 (**Jobstress95**). The error terms and covariances are generally estimated in an analysis. So we will disregard the Wald test results for VarE5 and CF3F5 for the moment. The others are F2F4 (the path from **Workrelation95** to **INT95**), F2F3 (the path from **Decmakcap95** to **INT95**), and F1F4 (the path from **Workrelation95** to **Psyout95**). We should be cautious to make only a few modifications initially, and the safest approach to

modifying models is to change just one parameter at a time. We choose F2F4 to be eliminated, which would result in the least change in chi-square compare to F2F3 and F1F4. The Wald test suggests that model chi-square will only change 0.12 (a nonsignificant amount) if this path was deleted, i.e., it was possible to delete the path from **Workrelation95** to **INT95** without a significant increase in model chi-square.

We therefore re-estimate our model with PF2F4 fixed at zero, and then review the results to see if this gets a better fit. Once again, overall goodness of fit indices for the modified model was acceptable. Tables 2, 3, 4, 5, and 6 show the goodness of fit indices, estimates of path coefficients and factor loading coefficients, respectively.

Table 2 Goodness of Fit Indices for Standard model (data 95) with effect indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
Initial model 1(95)	266.4(80)	0.899	0.849	0.868	0.82	0.826
Modified model 1(95)	266.6(81)	0.896	0.85	0.868	0.82	0.829

Table 3 Sums of Standardized Path coefficients to "Psyout"

Initial model 1 (data95)					
	TO INT95	INT95 TO PSYOUT	INDIRECT	DIRECT	TOTAL
		0.20			
Decmakcap95	0.05		0.01	-0.22	-0.21
Workrelation95	0.035		0.007	0.13	0.137
Jobstress95	0.66		0.132	0.70	0.832

Table 4 Sums of Standardized Path coefficients to "Psyout"

Modified model 1 (data95)					
	TO INT95	INT95 TO PSYOUT	INDIRECT	DIRECT	TOTAL
		0.21			
Decmakcap95	0.07		0.014	-0.21	-0.196
Workrelation95	NA		NA	0.12	0.12
Jobstress95	0.64		0.134	0.68	0.814

Table 5 Unstandardized and Standardized loadings for effect indicators (initial model 1)

From Decmakcap95 to			From Workrelation95 to			From Jobstress95 to		
EFF95	5.35	0.42	TEAM95	1.00*	0.79	ROLE95	1.00*	0.70
READY95	1.00*	0.44	COWORK95	9.39	0.66	PSY95	7.82	0.54
COPACT95	6.19	0.55	SUPWK95	8.61	0.58			
AUTH95	7.00	0.77						
JOBINF95	6.81	0.69						

Table 6 Unstandardized and Standardized loadings for effect indicators (initial model 1)

From Psyout95 to			From INT95 to		
SAD95	9.87	0.64	FAMINT95	4.85	0.40
ANX95	1.00*	0.65	JOBINT95	1.00*	1.02
EXH95	11.93	0.89			

Note: NA shows path is deleted; Set to 1.00* for one variable in each of latent variables in order to obtain identification in the model.

In table 3, the total effect on psyout95 was calculated as the sum of direct and indirect effect. For example, the total effect from Decmakcap95 on Psyout95 was calculated as:

$$\text{Total effect} = \text{Direct effect} + \text{Indirect effect} = (-0.22) + 0.05 \times 0.20 = -0.21$$

We list standardized path coefficients in table 3 and 4 in order to compare the effects in our models, since unstandardized path coefficients depend on the units which the variables are scaled. For example, the total of standardized path coefficients for **Decmakcap95** to **Psyout95** was -0.21 and for **Workrelation95** to **Psyout95** was 0.137 in the initial model. The total of standardized path coefficients for **Jobstress95** to **Psyout95** was 0.832 . This indicated a larger average change in standard deviation units of **Psyout95** for a one standard deviation difference in **Jobstress95** than for a one standard deviation difference in **Workrelation95** (or **Decmakcap95**) net of the other variables. The greater relative influence of **Jobstress95** is evident.

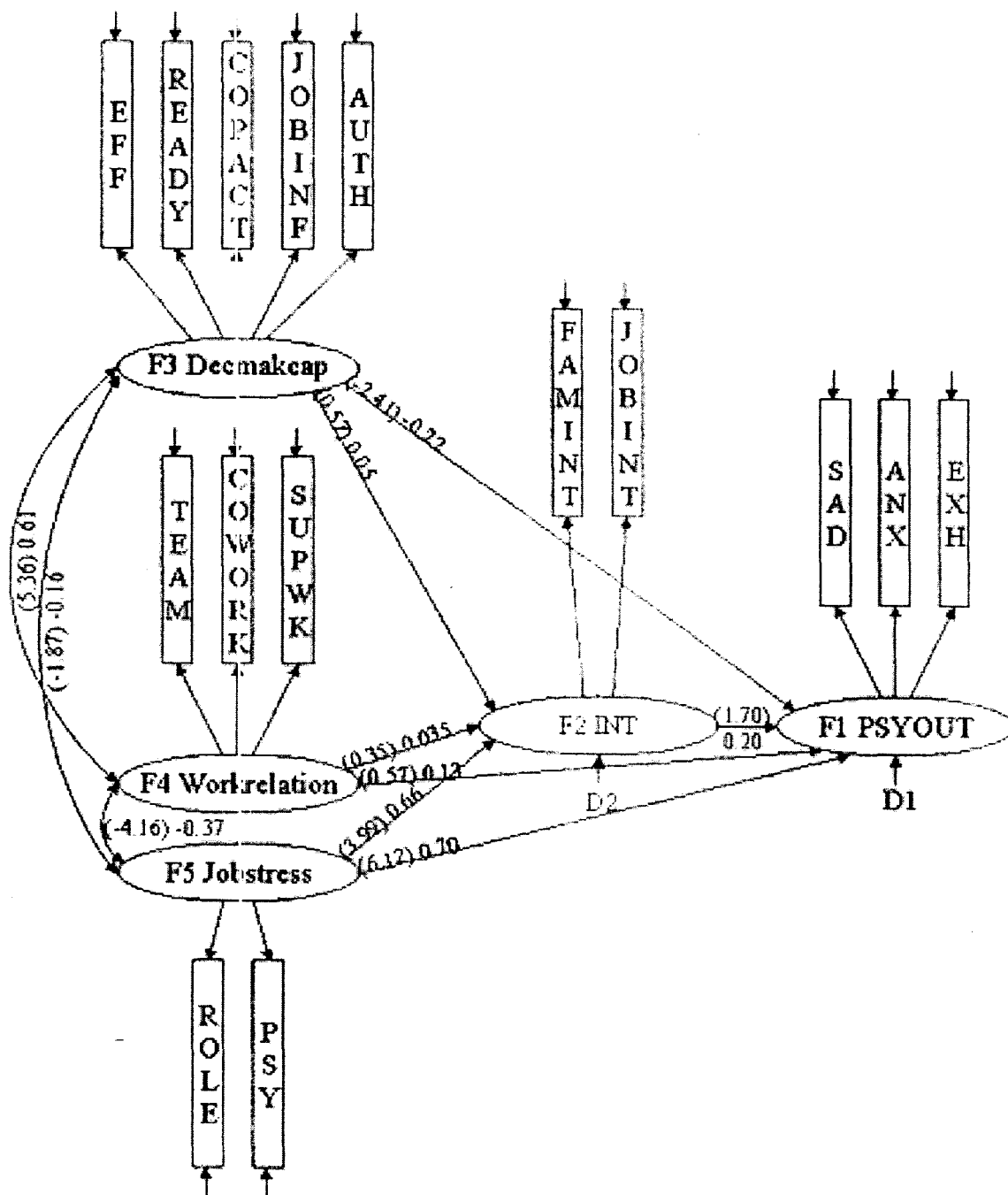


Figure 3 standard model with effect indicators (95) (initial model): Unstandardized (bracketed value) and standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-Headed Arrows; Arrows for Error terms.

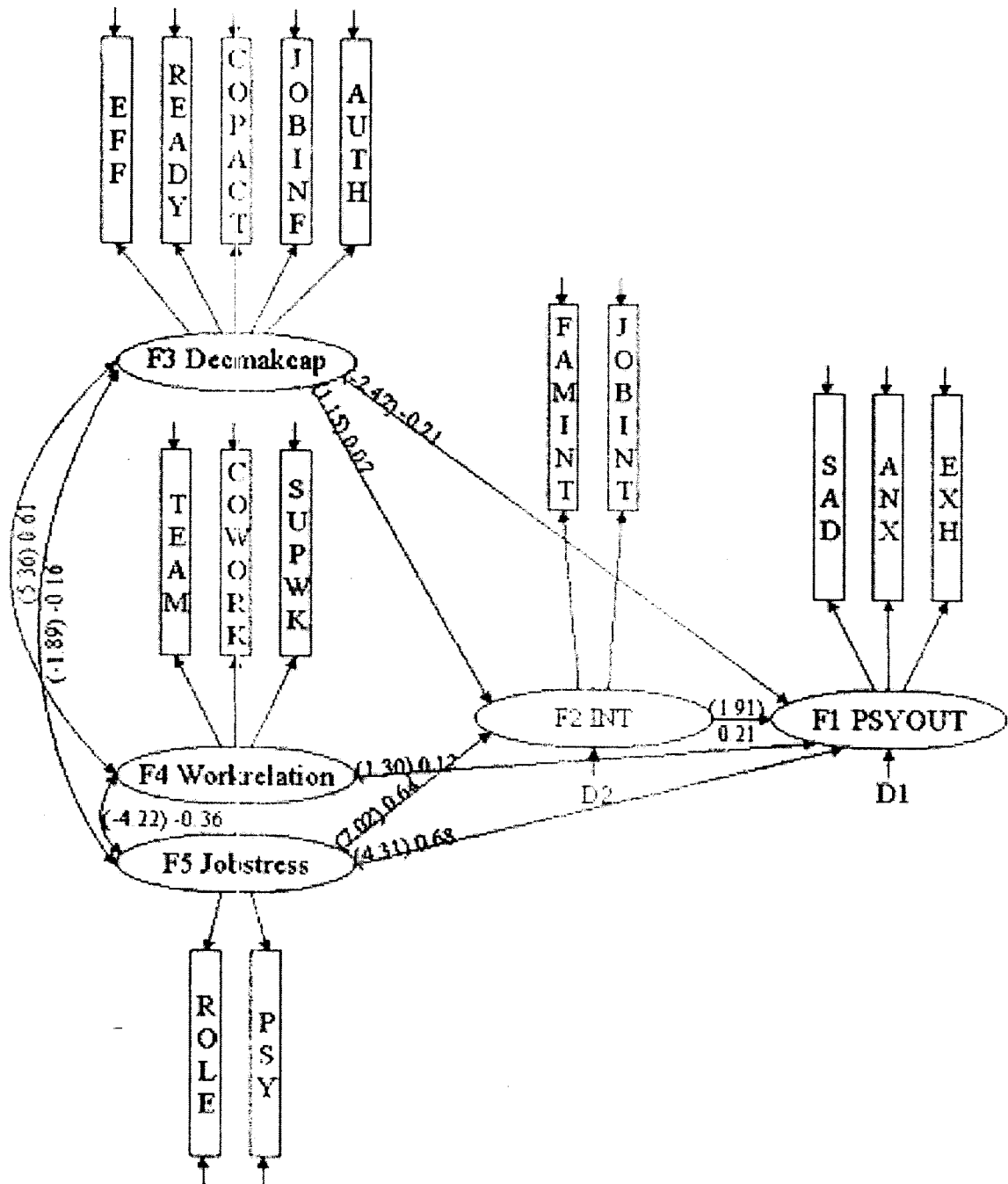


Figure 4 standard model with effect indicators (95) (modified model): Unstandardized (bracketed value) and standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-Headed Arrows; Arrows for Error terms.

From above tables, we noted that the goodness-of-fit indices did not improve much. We then conclude that there are not big difference between our initial model and modified model. Thus we suggest keeping initial model as our desired model. We have diagrams for initial model and modified model as above.

(2) Standard models with cause indicators (model 3)

In the fitting of this standard model with cause indicators (data95), convergence problems arose. Indeed, the convergence criterion was not satisfied; that is, the fitting algorithm did not converge. The fitting functions generally require iterative numerical procedures to obtain solutions. When the values for the unknown parameters in two consecutive steps differ by less than some preset criterion, the iterative process stops. Nonconvergence occurs if the values are insufficiently close after repeated iterations. Bollen noted that whether estimates converge or not depends on several factors [5]. We will discuss this topic in next chapter. Thus estimates from nonconvergent runs should be considered very cautiously, since they might not be used to give substantive interpretations.

There were near-zero standard errors for some of our factor loadings (e.g., the estimated factor loading for cause indicator EFF95 to Decmakcap95 was 0.000147). This indicated that an estimation problem occurred in this model.

Overall, we reject the standard model with cause indicators. We put some tables that were relative to the outputs for model 3 (data95) in **appendix 4 (a)**.

(3) Standard model with mixed indicators (model 5).

We explored this mixture case here and situation becomes more complicated.

The first troublesome issue was the iteration problem, as in model 3. And the second was that there existed near-zero standard errors for some of the estimated factor loadings. Therefore this model was not reliable either. Similarly we have some tables presented for this model in **appendix 4 (b)**.

5.2.2 Nonstandard model (data95)

(1) Nonstandard model with effect indicators (model 2)

Before we looked at the model fitness, both SAS log file and output files were checked, and there were no errors in both files. The information from the output showed that the analysis was based on 327 observations and 15 variables. The number of data points associated with the analysis was 120, which is much greater than the number of parameters to be estimated, since there were 42 parameters to be estimated. We also noted that the convergence criterion is satisfied.

Then we assess the fit between the model and data. The chi-square test for the present analysis was 280.8 with 78 degrees of freedom, which was highly significant. Since the chi-square test is sensitive to sample size, normality distribution, etc, we do not rely on this test only. Some of the other fit indices will be considered. The overall fit indices did not show a very bad fit. The table lists these indices as follows:

Table 7 Goodness-of-fit indices for model 2 (data95)

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 2 (95)	280.8 (78)	0.896	0.840	0.856	0.814	0.806

We look at the factor loadings and path coefficients. All factor loadings that were tested have t value greater than 1.96, significantly different from zero. Of great interest in

our analysis, are the path coefficients for the causal path that constitute the structural portion of the model. We noticed that the both causal paths from **FAMINT95** to **Psyout95** and from **JOBINT95** to **Psyout95** showed negative values and the t-tests were nonsignificant. But we expect these two paths to have positive signs, and show **FAMINT95** and **JOBINT95** affect **Psyout95** significantly. This is very important finding because the model we want to test should at least make sense. Basically we tend to reject this non-standard model with effect indicators.

We list the standardized path coefficients for Model 2 in Table 8.

Table 8 Standardized Path coefficients to “Psyout”

	TO FAMINT	TO JOBINT	FAMINT TO PSYOUT	JOBINT TO PSYOUT	INDIRECT	DIRECT
			-0.15	-0.26		
Decmakcap95	-0.08	-0.10			0.038	-0.63
Workrelation95	0.31	0.43			0.158	1.69
Jobstress95	0.51	1.07			-0.355	4.10

(2) Non-standard models with cause indicators (model 4)

We explored the non-standard model with effect indicators, and we found that the model did not fit well. To determine the causes of the poor fit, we considered the possibility that the definition of all indicators as effect indicators might be inappropriate. Just like standard models, for some of the latent variables, we consider whether cause indicators are relevant to three of the latent variables. **Decmakcap95** could be thought of as a composite variable determined by **EFF95**, **READY95**, **COPACT95**, **JOBINF95**, and **AUTH95**. Also, **Workrelation95** could be viewed as a composite variable

determined by **TEAM95**, **COWORK95**, and **SUPWK95**. **Jobstress95** could be a composite variable determined by **ROLE95** and **PSY95**.

However, we again had an iteration problem. The goodness-of-fit indices, and path and factor loading coefficient estimates are presented in tables in **appendix 4 (c)**.

(3) Nonstandard model with mixed indicators (model 6)

Model 6 include one latent variable (Decmakcap95) with both cause and effect indicators loaded on it, as happened for the standard model with mixed indicators case (model 5). See figure 4(f) in appendix 1 for more information. But unlike model 5, there was no iteration problem and other errors involved in this model. The program's convergence criterion was satisfied.

The goodness-of-fit indices are discussed first. Overall, the indices did not show very good fit. The GFI was close to 0.89, and the CFI was almost 0.84, but NNFI was near 0.72, which is rather poor (see Table 9 Goodness-of-fit indices for model 6 for these relative indices).

Table 9 Goodness-of-fit indices for Model 6

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 6 (95)	302.8 (63)	0.888	0.786	0.829	0.800	0.716

Looking at the estimated factor loadings, we found that not all of them were significant different from zero. The t values of factor loading estimates for SAD95, ANX95, and EXH95 (they are effect indicators) were all significant. Meanwhile the t values of factor loading estimates for ROLE95 and PSY95 (both of them are cause indicators) were significant also. As for the indicators loaded on Decmakcap95, only one

showed a significant t value, though all values were positive. The same problem occurred in the composite variable Workrelation95. Even worse, there were negative values for two of them, which was incompatible with the measurement model.

The estimates of path coefficient showed the expected sign and had fairly high magnitude as we hypothesized. Decmakcap95 showed negative significant effect on Psyout95, while JOBINT and Jobstress95 showed positive significant effects on Psyout95. The factor loading and path coefficient estimates were presented in Table 10, Table 11, and Table 12 respectively.

Overall, this nonstandard model performs fairly well, although the results (some estimates of factor loading) did not seem very reasonable. Thus there was not strong, consistent support for this model fit to the data. We can mark this model as a questionable model.

Table 10 Unstandardized and Standardized factor loadings for cause indicator

To Decmakcap95			To Workrelation95			To Jobstress95		
JOBINF95	2.49	0.80	TEAM95	-1.10	-0.36	ROLE95	4.36	0.70
AUTH95	1.00*	0.30	COWORK95	1.00*	0.84	PSY95	1.00*	0.50
			SUPWK95	-1.91	-0.83			

Table 11 Unstandardized and Standardized loadings for effect indicators

FROM DECMACAP95 TO	EFF95	2.8	0.31
	READY95	2.9	0.34
	COPACT95	3.0	0.41
From Psyout95 to	SAD97	9.78	0.64
	ANX97	1.00*	0.65
	EXH97	11.8	0.89

Table 12 Sums of Standardized Path coefficients to "Psyout"

	TO FAMINT	TO JOBINT	FAMINT TO PSYOUT	JOBINT TO PSYOUT	INDIRECT	DIRECT	TOTAL
			0.08	0.43			
Decmakcap95	0.04	0.05			0.025	-0.16	-0.135
Workrelation95	0.10	0.14			0.068	-0.05	0.013
Jobstress95	0.12	0.50			0.225	0.38	0.605

5.3 1997 cross-sectional models

5.3.1 Standard models (data97)

(1) Standard model with effect indicators (Model 1)

Now we discuss model 1 for the 1997 data. We got very similar results in model 1 for both 1995 and 1997 data. The program executed well. There were 323 observations and 15 variables, with 40 parameters to be estimated in this analysis.

The goodness-of-fit indices (in table 13) indicated a relatively good overall fit as well. Significance tests for path coefficients appeared in table 14. The signs of these coefficients were as expected, i.e., **interference**, **job stressors** were positively related to **psychology outcomes**, and **decision-making capacity** was negatively related. We found that **work relationships** did not show a significant effect on **interference** and **psychological outcomes**. The very small positive values indicated a small effect on **interference** and **psychological outcomes**. The estimated factor loadings were all significant (see table 15 for details).

Table 13 Goodness-of-fit indices for Model 6

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 1 (97)	288.5 (80)	0.891	0.837	0.876	0.838	0.837

Table 14. Sums of Standardized Path coefficients to “Psyout”

	TO INT97	INT97 TO PSYOUT	INDIRECT	DIRECT	TOTAL
		0.30			
Decmakcap97	-0.09		-0.027	-0.21	-0.237
Workrelation97	0.07		0.021	0.10	0.121
Jobstress97	0.65		0.195	0.68	0.875

Table 15 Unstandardized and Standardized loadings for effect indicators

From Decmakcap97 to			From Workrelation97 to			From Jobstress97 to		
EFF97	4.43	0.47	TEAM97	1.00*	0.83	ROLE97	1.00*	0.69
READY97	1.00*	0.31	COWORK97	11.43	0.83	PSY97	8.96	0.62
COPACT97	4.52	0.50	SUPWK97	9.02	0.73			
AUTH97	4.92	0.71						
JOBINF97	4.98	0.80						

From Psyout97 to			From INT97 to		
SAD97	11.98	0.73	FAMINT97	6.22	0.45
ANX97	1.00*	0.70	JOBINT97	1.00*	1.02
EXH97	13.83	0.87			

Note: Set to 1.00* for one variable in each of latent variables in order to obtain identification in the model.

(2) Standard model with cause indicators (model 3)

There was the same iteration problem with 1997 data, as for the equivalent model for data95. The relevant tables were attached in **appendix 4(d)**.

(3) Standard model with mixed case (model 5)

Unlike model 5 for data95, the program for this model with 1997 data runs well. There was no error in either log or output files. The convergence criterion was satisfied. That was an interesting finding: with the same hypothesized models, different data may lead to two different results. We present some results of our analysis in tables 16-19:

Table 16 Goodness-of-fit indices for Model 5

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 5 (97)	289.9 (65)	0.89	0.80	0.87	0.84	0.78

Table 17 Unstandardized and Standardized factor loadings for cause indicators

To Decmakcap97			To Workrelation97			To Jobstress97		
EFF97	1.15	0.35	TEAM97	0.80	0.42	ROLE97	4.33	0.62
READY97	1.13	0.24	COWORK97	1.00*	0.80	PSY97	1.00*	0.57
COPACT97	1.15	0.34	SUPWK97	-1.33	-0.53			
JOBINF97	1.05	0.91						
AUTH97	1.00*	0.14						

Table 18 Unstandardized and Standardized loadings for effect indicators

From Psyout97 to			From INT97 to		
SAD97	11.88	0.73	FAMINT97	6.29	0.45
ANX97	1.00*	0.70	JOBINT97	1.00*	1.01
EXH97	13.71	0.88			

Table 19 Sums of Standardized Path coefficients to “Psyout”

	TO INT95	INT95 TO PSYOUT	INDIRECT	DIRECT	TOTAL
		0.522			
Decmakcap95	-0.085		-0.044	-0.075	-0.119
Workrelation95	-0.034		-0.018	-0.130	-0.148
Jobstress95	0.480		0.251	0.377	0.628

From the table 16, we found that those fit indices looked not bad, most of them were close to 0.90, although NNFI was only 0.78. However, the estimates of factor loadings for some cause indicators had negative values, e.g., the t value SUPWK97 to Workrelation97 was -1.33. That contradicted our prediction that the coefficients of SUPWK97 should be positive. Therefore, we question this hypothesized model.

5.3.2 Nonstandard models (data97)

(1) Nonstandard models with effect indicators. (Model 2)

This model had similar flaws as did model 2 for data95. Though the program ran well, some path coefficients didn't have the expected sign, e.g., the path from

FAMINT97 and JOBINT97 to Psyout97 showed negative sign, which indicated that FAMINT and JOBINT negatively associated with Psyout97. That did not make sense and contradicted our hypothesis and previous study. So we tend to reject this model for data97. See tables in **appendix 4 (e)** for details.

(2) Nonstandard model with cause indicators (model 4)

The program for this model did not perform well: the iteration problem arose. We reject this model as well. The relevant tables are in **appendix 4 (f)**.

(3) Nonstandard model with mixed indicators (model 6)

The program for nonstandard model with mixture indicators did not produce an iteration problem or other errors. However, some estimated loadings were not significant and did not show the expected signs. We might not reject this model, but say this model is questionable. See tables in **appendix 4 (g)** for model 6 (data97).

5.3.3 Comparison of 1995, 1997 results

Combined, we discuss our results for cross-sectional data. In summary, we have explored six different models for each year (1995 and 1997). In order to get a clear picture for all of the models tested, we present a table summarizing the results of these model fits.

Table 20 Summary table of the results of our model fits

MODEL	CONVERGENCE	GOODNESS-OF-FIT	PREDICTED DIRECTION	OVERALL ASSESSMENT
Model 1(95)	Yes	not bad	make sense	acceptable
Model 2(95)	Yes	not bad	conflict(path coeff.)	unacceptable
Model 3(95)	Nc	good	conflict(loadings)	unacceptable
Model 4(95)	Nc	good	conflict(loadings)	unacceptable
Model 5(95)	Nc	poor	conflict(loadings)	unacceptable
Model 6(95)	Yes	poor	conflict(loadings)	questionable
Model 1(97)	Yes	not bad	make sense	acceptable
Model 2(97)	Yes	not bad	conflict(path coeff.)	unacceptable
Model 3(97)	No	good	conflict(loadings)	unacceptable
Model 4(97)	No	good	conflict(loadings)	unacceptable
Model 5(97)	Yes	poor	conflict(loadings)	questionable
Model 6(97)	Yes	poor	conflict(loadings)	questionable

The nonstandard models with effect indicators for both dat95 and data97 were not reliable, since the magnitudes of effects did not conform to previous research, and the estimated path coefficients showed signs in the “wrong” direction. There existed iteration problems among some of the rest of the models, which are standard and non-standard models with cause indicators (data95 and data97), standard model with mixture case (data95). Thus we reject those models. The models with cause indicators and mixed indicators also had some nonsignificant factor loadings, and some of them showed negative signs, opposite to those expected. These problematic issues prevent us choosing them as our reliable models. Somehow, unstandard model with mixed indicators (data95) and both unstandard and standard models with mixed indicators (data97) did not involve

in the iteration problems. They had some negative value factor loadings. We tend to leave them as questionable models.

Therefore, the suitable model we will take is the standard model with effect indicators for data95 and data97. We concluded that data95 and data97 have very similar results (see diagrams on the following pages).

The goodness of fit indices showed they all in acceptable ranges, though the χ^2 -square values for both models were statistically significant. Technically, when the proper assumptions are met, the chi-square statistic may be used to test the null hypothesis that the model fits the data. In practice, however, the statistic is very sensitive to sample size and departures from multivariate normality, and will very often result in the rejection of a well-fitting model. For this reason, it has been recommended that the model chi-square statistic be used as a goodness of fit index, with smaller chi-square values (relative to the degrees of freedom) indicative of a better model fit [9]. In our standard models for data95 and data97, the chi-square values relative to degrees of freedom were 266.4/80 (i.e., 3.3), and 288.5/80 (i.e., 3.5) respectively. Those values were not very big.

It was seen that all coefficients for both models were in predicted directions. R-square values also substantial. However, a review of the model's residuals showed asymmetry for both models. Some of the normalized residuals were relatively large. We can remedy them by either modifying our initial theoretical models or our measurement models.

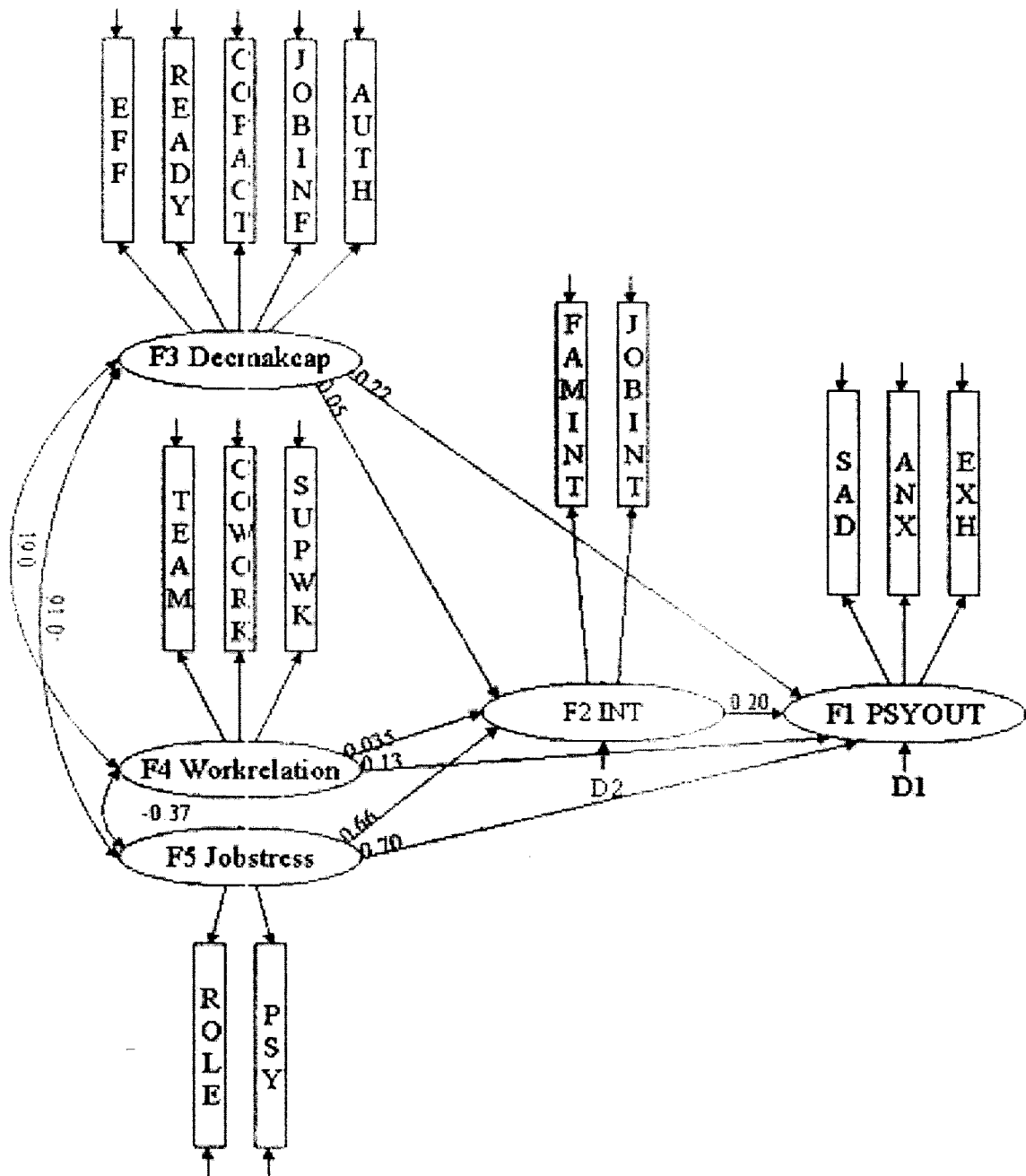


Figure 5 standard model with effect indicators (95) (final model): standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-headed Arrows; Arrows for Error terms.

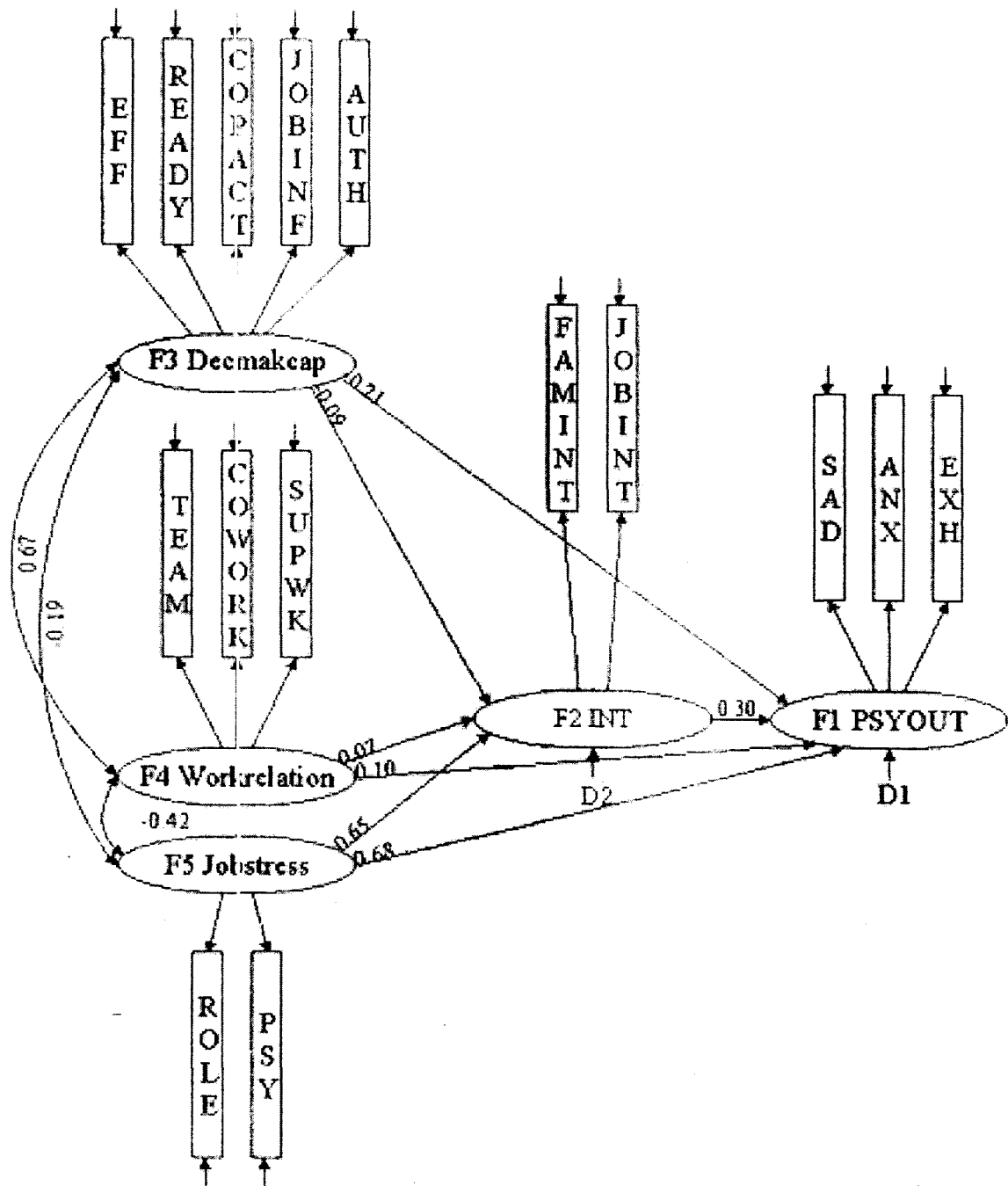


Figure 6 standard model with effect indicators (97) (final model): standardized path coefficients appeared on Single-headed Arrows; correlations appeared on Curved Double-headed Arrows; Arrows for Error terms.

5.4 Longitudinal Model (95—97)

Now we discuss the result for our longitudinal model. Figure 14 (see Appendix 1) shows all the paths that were tested. We used effect indicators for all the latent variables. Only the standard model was employed. Unfortunately there was an iteration error again, so the results of the output were not reliable. We still show the goodness-of-fit table for this longitudinal model (model 7). The overall fit indices showed poor fit to the data: none of them reached 0.72.

Table 21 Goodness of fit indices for Model 7

	Chi-square(DF)	GFI	AGFI	CFI	NFI	NNFI
Model 7	2567.6 (383)	0.71	0.65	0.47	0.43	0.40

Since the analysis was based on 308 observations and 30 variables, and the number of parameters to be estimated was 80, the sample size was not big compared to the number of parameters to be estimated. On the other hand, in the exploratory factor analysis stage, we noticed that there was a minor difference between the factor constructs. **READY95** was loaded on **Decmakcap95** (the standardized factor loading was 0.58, which is highly significant). But **READY97** loaded on two of the factors; this variable should therefore not be used in interpreting the factors. Thus in order to respecify our longitudinal model, we analyze another hypothesized model (model 8) including all the variables for 95 and 97 except for **READY95** and **READY97**.

This time, the convergence criterion was satisfied. There were no errors in the SAS log file and output file. Attached are some tables for Model 8.

Table 22 Goodness of fit indices for Model 8

	Chi-Square(DF)	GFI	AGFI	CFI	NFI	NNFI
Model 8	1292.5 (328)	0.757	0.700	0.750	0.695	0.712

Table 23 Standardized estimates for path coefficients (model 8)

	To F2	To F1	To F7	To F8	To F9	To F10	To F6
F3	0.056	-0.227		0.812			
F4	-0.0032	0.103			0.659		
F5	0.652	0.550				0.732	
F8			-0.086				-0.087
F9			-0.064				-0.062
F10			0.347				0.409
F2		0.300	0.447				
F1							0.278
F7							0.346

Note: F1 (Psyout95), F2 (INT95), F3 (Decmakcap95), F4 (Workrelation95), F5 (Jobstress95), F6 (Psyout97), F7 (INT97), F8 (Deacmakcap97), F9 (Workrelation97), F10 (Jobstress97).

In our longitudinal model from data95 to data97 (model 8), we noted that the estimation of this model, as presented in Figure 14, revealed a significant model chi-square value (chi-square is 1292.5 with 328 degrees of freedom), and values of GFI, AGFI, CFI, NFI, and NNFI were 0.76, 0.70, and 0.75, 0.69, and 0.71 respectively, indicating that the fit between model and data is still not good. The overall fit indices didn't show a good fit. But compared with model 7, this model is much better.

The factor loadings were reviewed first. The t-values for all factor loadings proved to be significant. Most of the path coefficients were significant also, and all of them were of reasonable magnitude. The results were consistent with our cross-sectional models, which is important for this longitudinal model. The t-values for F3 (Decmakcap95) to F2 (INT95), F4 (Workrelation95) to F2 (INT95), F4 (Workrelation95) to F1 (Psyout95), F8 (Decmakcap97) to F7 (INT97), F9 (Workrelation97) to F7 (INT97),

and F9 (Workrelation97) to F6 (Psyout97) were nonsignificant. The others were all significant. The diagram (Figure 7) of this longitudinal model is presented as follows.

It was very clear that job stressors contributed the greatest effects on psychological outcomes. Higher decision-making capacity and better work relationships are related to better psychological outcomes. Decision-making capacity, work relationships, and job stressors in 1995 affect their values in 1997. Interference in 1995 and psychological outcomes in 1995 also predict their values in 1997. The results for longitudinal model were thus consistent with those of cross-sectional models.

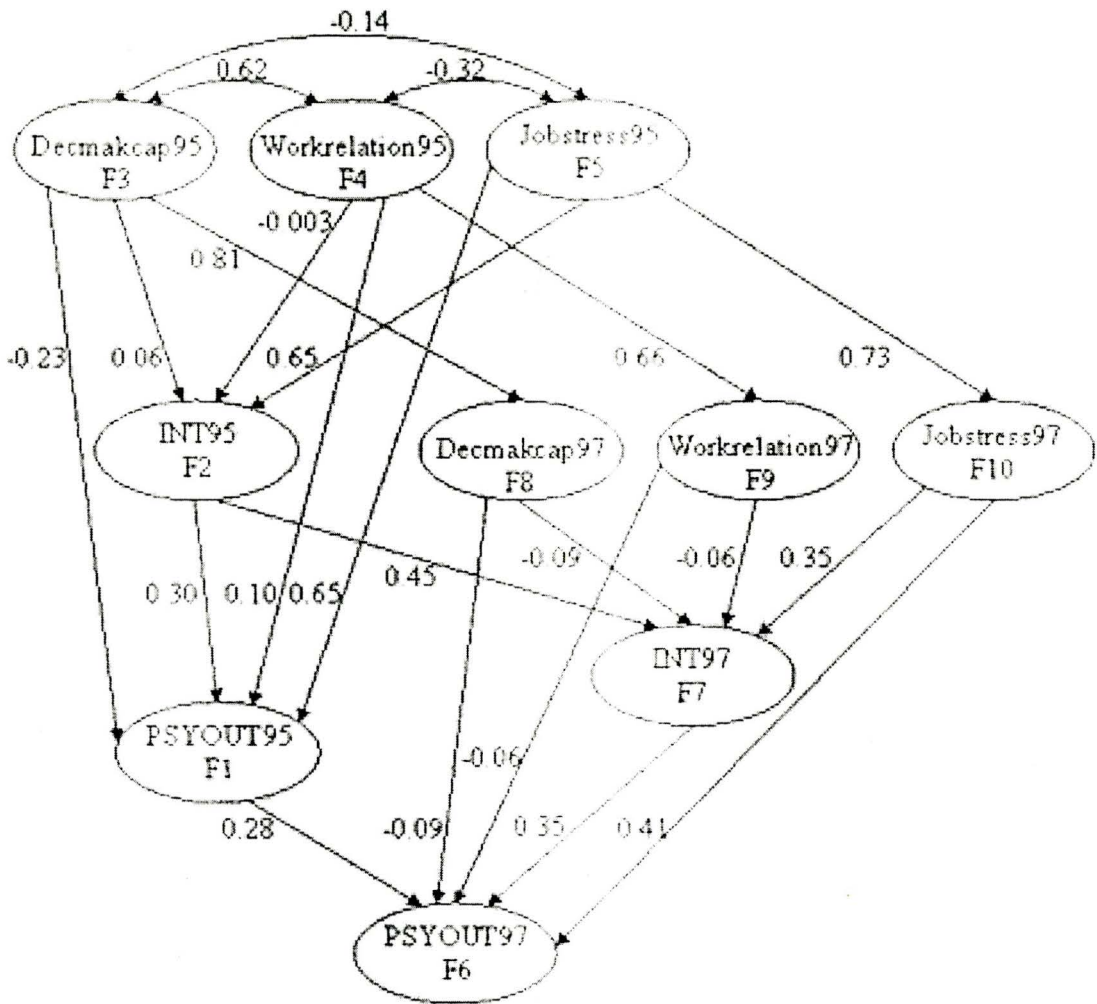


Figure 7 Longitudinal model (95-97): Standardized path coefficients appeared on Single-Headed Arrows; correlations appeared on Curved Double-Headed Arrows.

6 Discussion

6.1 Review of results

Data were analyzed using the SAS System's CALIS procedure. These analyses used the maximum likelihood method of parameter estimation, and all analyses were performed on the variance-covariance matrix.

We constructed cross-sectional and longitudinal studies for our analysis. For cross-sectional models, we choose model 1 (standard model with effect indicators) as our final model. The following conclusions are valid both for 1995 data and 1997 data:

- ◆ Job stressors are a very important predictor of interference (which measured the effect of family life on work performance and effect of job on family life) and psychological outcomes (a latent construct mapping onto measures of anxiety, depression and emotional exhaustion). And they also predict interference and psychological outcomes. The total effect to Psyout95 and Psyout97 are 0.832 and 0.875, respectively. In comparison with decision-making capacity and work relationships, the stronger relative influence of job stressors to psychological outcomes is evident.

- ◆ The total effect of work relationships on psychological outcomes are 0.137 (1995) and 0.121 (1997). The unstandardized path coefficients showed that work relationships did not affect interference and psychological outcomes significantly in both years (for example, there were non-significant t-values 0.35 and 0.57, respectively, in the 1995 model). This indicated work relationships didn't play an important role.

◆ Decision-making capacity is associated in with psychological outcomes in the opposite direction. The total effects from decision-making capacity to psychological outcomes are -0.21 (1995) and -0.237 (1997). The need for decision-making capacity becomes important for hospital staff to face the big challenges of their jobs.

◆ For our longitudinal model, we have similar results in direct and indirect effect on psychological outcomes with the cross-sectional models. As expected, the psychological outcomes in 1997 were not only influenced by decision-making capacity, work relationships and job stressors directly or indirectly via interference in 1997, but also influenced by these factors in 1995. For example, psychological outcomes in 1995 have effect on psychological outcomes in 1997 (the standard path coefficient is 0.278). And interference in 1995 predicts interference in 1997 (the standard coefficient is 0.44).

6.2 What SEM has added to previous analyses?

In our standard models for data95, and data97, we found that decision-making capacity and job stressors, impact on psychological outcomes both directly and indirectly via interference. Higher levels of decision-making capacity are associated with decreased psychological outcomes. Job stressors such as lack of role clarity and job demands are closely related to increased psychological outcomes. All those conclusions are consistent with previous analyses.

In our cross-sectional study, we find that there is some minor difference between model 95 and model 97 regarding the role of decision-making capacity. In the first year when re-engineering started, decision making capacity did not show a significant effect on interference. But we notice that in 1995 the t-values are both positive for the path

from decision-making capacity to interference and from work relationships to interference, while in 1997 the corresponding t-values for decision-making capacity are negative (but quite small). This may indicate some subtle changes in their effect over time. We remark that the higher levels of decision-making capacity are associated lower interference in 1997.

We have the similar conclusions from the longitudinal model (95-97). Decision-making capacity in 1995 showed a positive direct effect on interference in 1995, but decision-making capacity in 1997 appeared to have a negative effect on interference in 1997. We emphasize that the longitudinal study has the advantage of analyzing the cross-sectional and longitudinal relationships among our model constructs.

In our models, work relationships does not display a significant effect on psychological outcomes. This is a contrast to some previous studies, although power in our study may be limited.

6.3 Limitation

SEM requires a sound theoretical perspective. A good design guided by a substantive theory and prior research is required to get a better-fit model. Thus a comprehensive effort to identify relevant variables and their relationships is highly recommended. This will help to determine valid and reliable indicator variables of latent variables, provide a theoretical perspective for our model, and help us to establish latent variable relationships grounded in prior research studies. A well-fitting model is not necessarily unique, there are probably other reasonable models for the same data. We may have different model designs and therefore get different explanations.

Convergence failures involved in some of our models. Nonconvergence occurs if the values are insufficiently close after repeated iteration [5]. Whether estimates converge or not depends on several factors. First, the criterion itself affects convergence. It defines what is “insufficiently close”. This value can be altered. But we should be aware that the smaller the number, the more iterations are typically required. Second, convergence is affected by the number of iterations allowed. A third factor making nonconvergent solutions more or less likely are the starting values for the unknown parameters. The closer these values are to the final estimates, the fewer steps are needed to converge. Other causes of nonconvergence include poorly specified models and sampling fluctuations in the variance and covariances of the observed variables. These occurred quite frequently with small samples and few choices (only two variables) per factor. We have two latent variables (four for the longitudinal model) that have only two indicators: job stressors and interference. That might be the reason for nonconvergence.

We now discuss issue of the names of latent variables. This may depend on whether the measured variables (scales) are considered to be effect or cause indicators. We may not correctly describe which latent variables are related to the indicators. Is the named and defined latent variable truly related to the indicator, or is it some other latent variable linked to the measure? Often the concept that the latent variable represents is not clearly defined and not enough attention is given to tests of measurement validity. For example, the latent variable “decision-making capacity” may be better considered a composite variable, which is influenced by “**EFF, READY, COPACT, JOBINF** and

AUTH” as indicators. In fact, “decision-making capacity” in our final model is treated as a latent variable. A different naming might be possible here.

Goodness of fit measures are sensitive to sample size, method of estimation, and model misspecification. It should be noted that the chi-square criterion for model fit has a number of weaknesses, and should be used only with caution. Our data are not strictly normal distributed, and outliers might exist. This might be one reason that make our cross-sectional models not fit very well. The sample size for the longitudinal model is not big enough, so the longitudinal model didn't fit data well.

In order to improve our models, we might first consider measurement. Some of the results of the factor analysis solution may not be accurate. For example, some of the constructs are less than satisfactory in the sense that their factors displayed meaningful loadings for less than three variables. The more variables that are used to assess the construct, the more reliable the model will be. Adding new items or new scales to the questionnaire would be a suitable way to get a better measurement model. But this may need a new large sample. If we have very large sample size, it will be possible to generalize to other samples.

Another way to improve our model for a better fit is to respecify the model. In our study, we have tried different models embedding cause indicators. Although some problems arise (for example, problems of non-convergence), we emphasize that we are not taking the position that one should not use cause indicators in models. On the contrary, one should evaluate whatever model is most appropriate and useful in practice. The theory of the cause indicator model is currently not as complete as the theory of the

effect indicator model. This is one of the main reasons behind some of the problems associated with cause indicators' models. We leave this for future research.

Appendix 1

We explain some notations we use. The ovals are for latent variables, and the rectangles are for observed variables in the diagrams (in Figures).

Decision-making capacity (Decmakcap),

Work relationships (Workrelation),

Job stressor (Jobstress),

Psychological Outcomes (Psyout),

Readiness for change (READY),

Active coping style (COPACT),

Job self-efficacy (EFF),

Skill discretion (DISC),

Decision authority (AUTH),

Psychologically, job demands (PSY),

Role un-clarity (ROLE),

Job influence (JOBINF),

Team work (TEAM),

Co-workers' support (COWORK),

Supervisor support (SUPWT),

Depression (SAD),

Anxiety (ANX),

Emotional exhaustion (EXH),

Family Interference (FAMINT),
Job Interference (JOBINT).

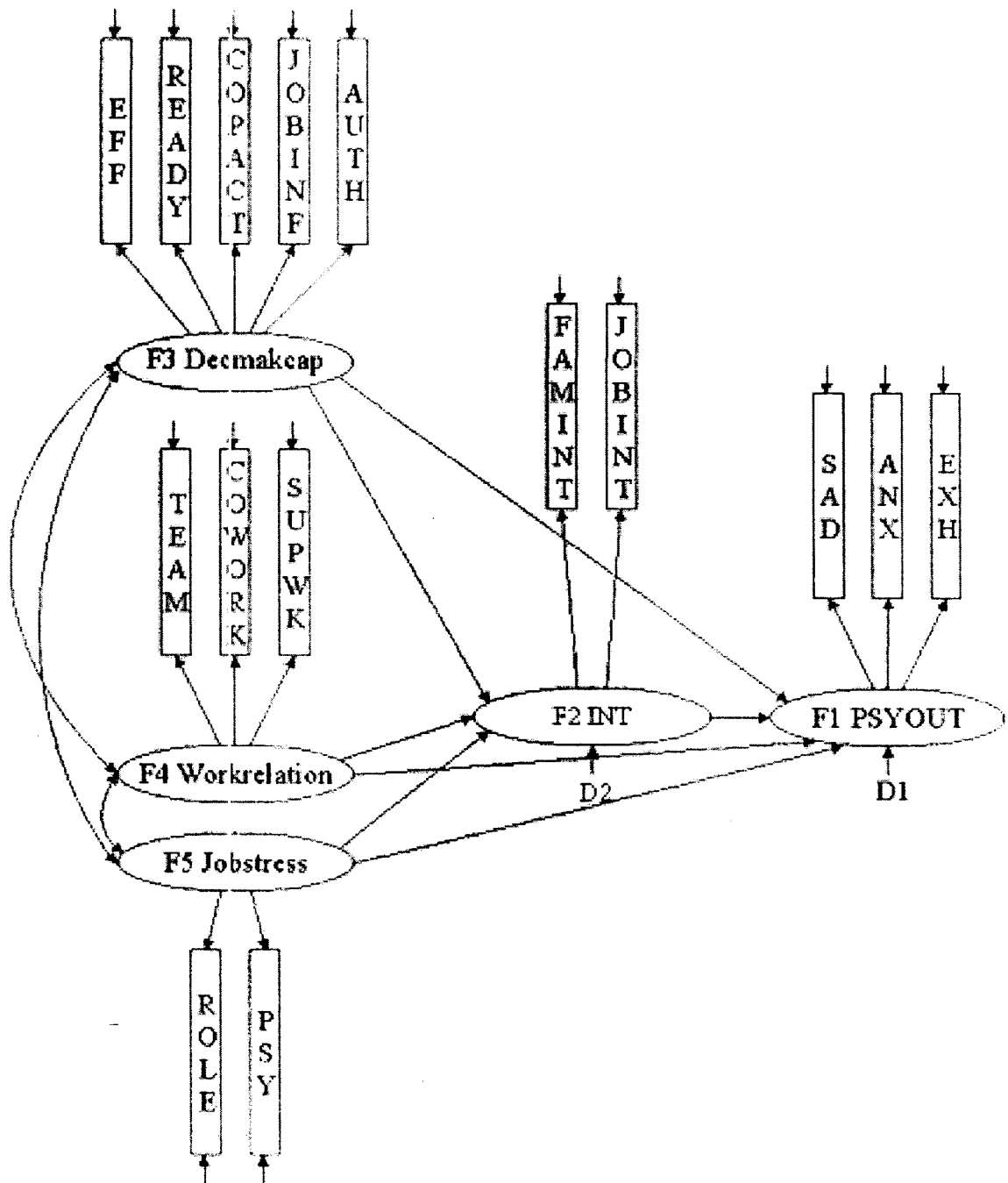


Figure 8 Standard Model with effect indicators (model 1)

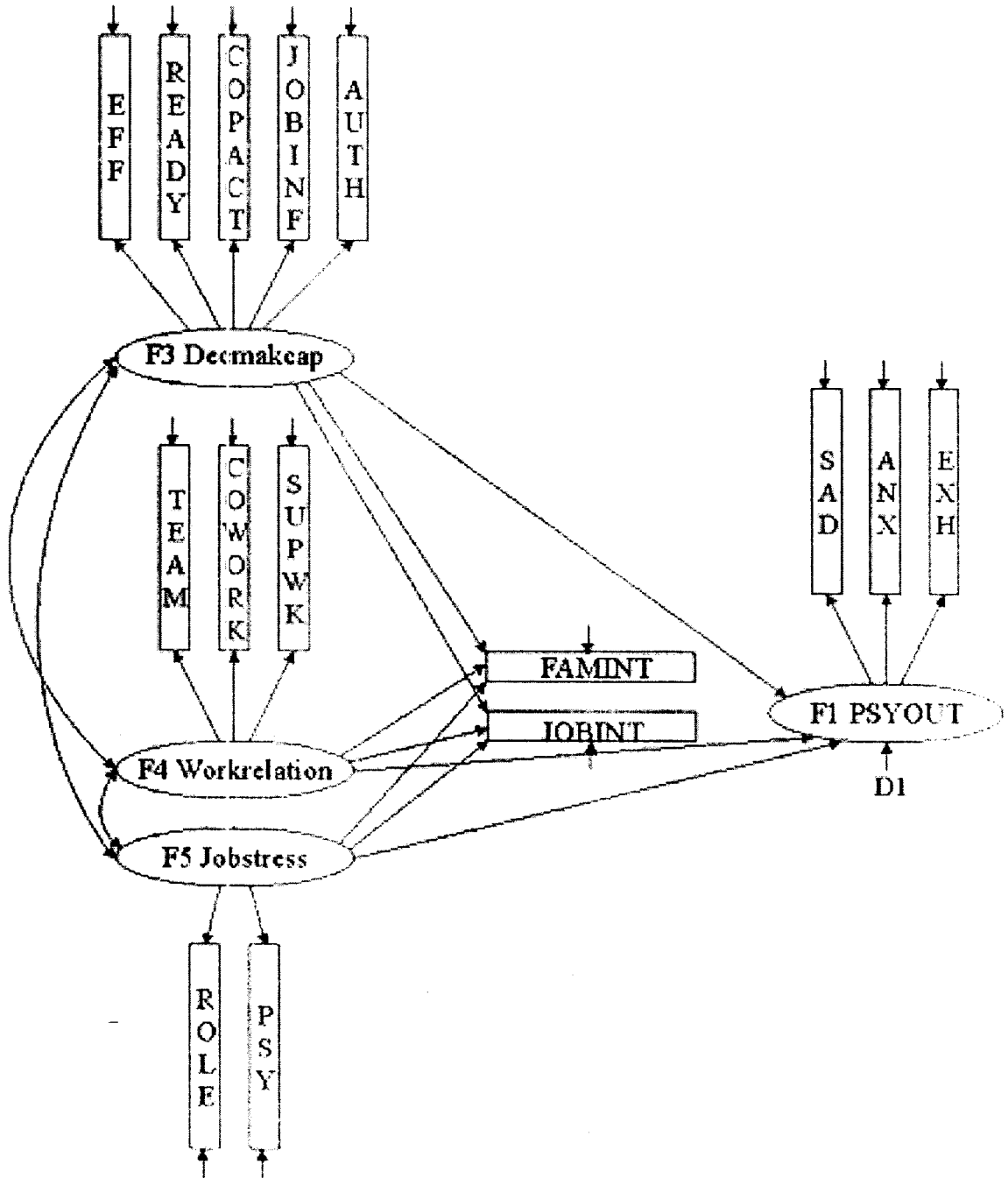


Figure 9 Nonstandard Model with effect indicators (model 2)

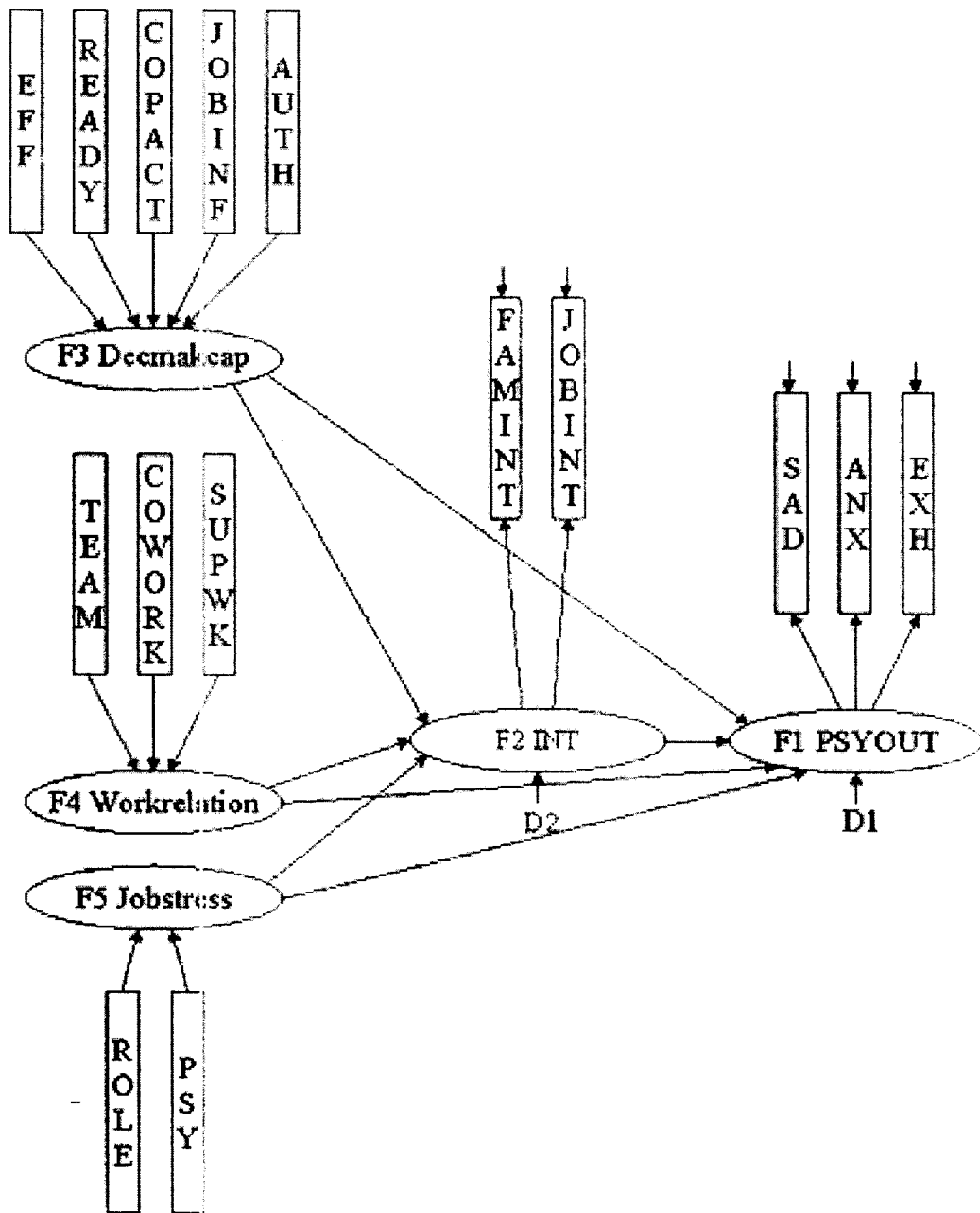


Figure 10 Standard model with cause indicators (model 3)

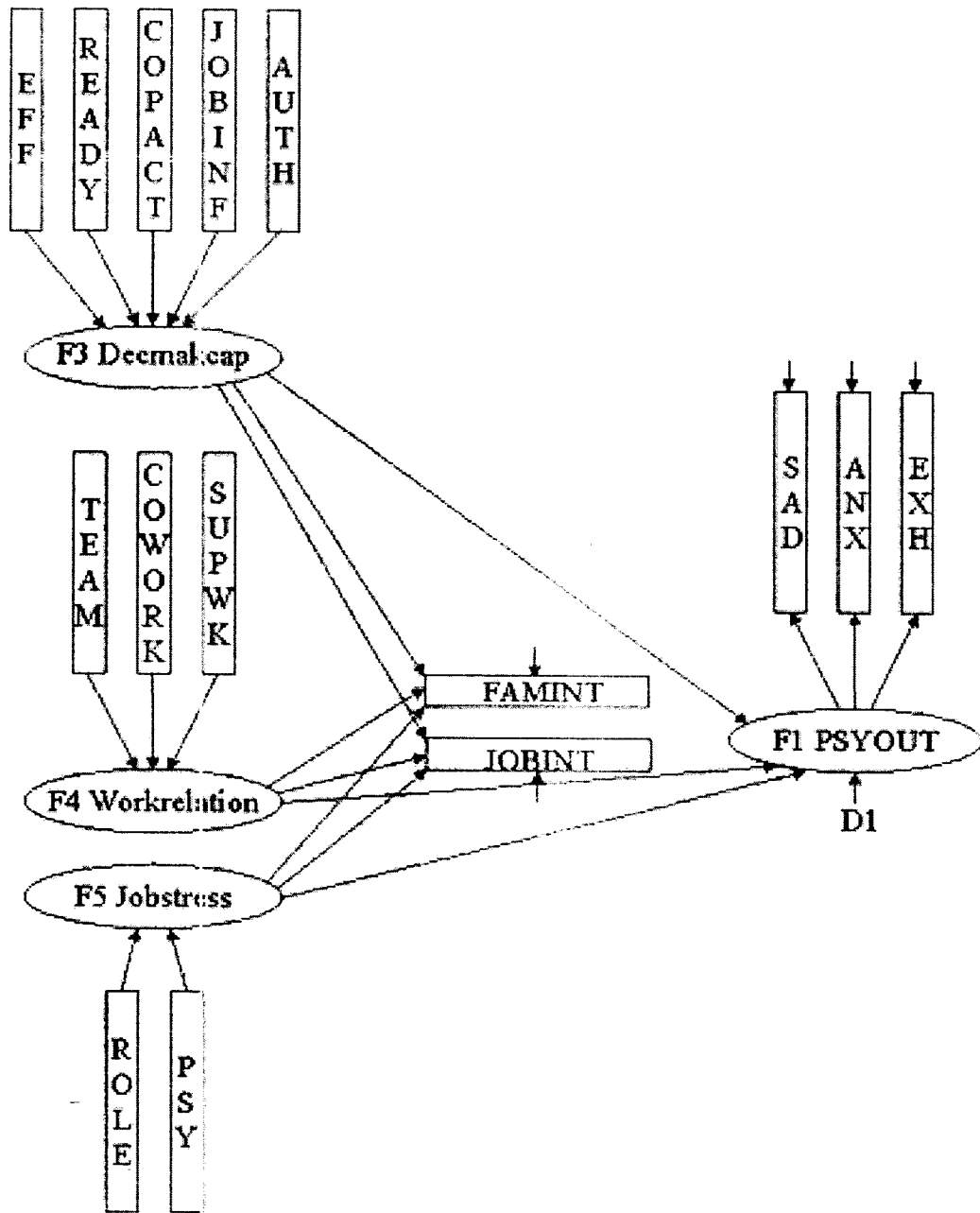


Figure 11 Nonstandard model with cause indicators (model 4)

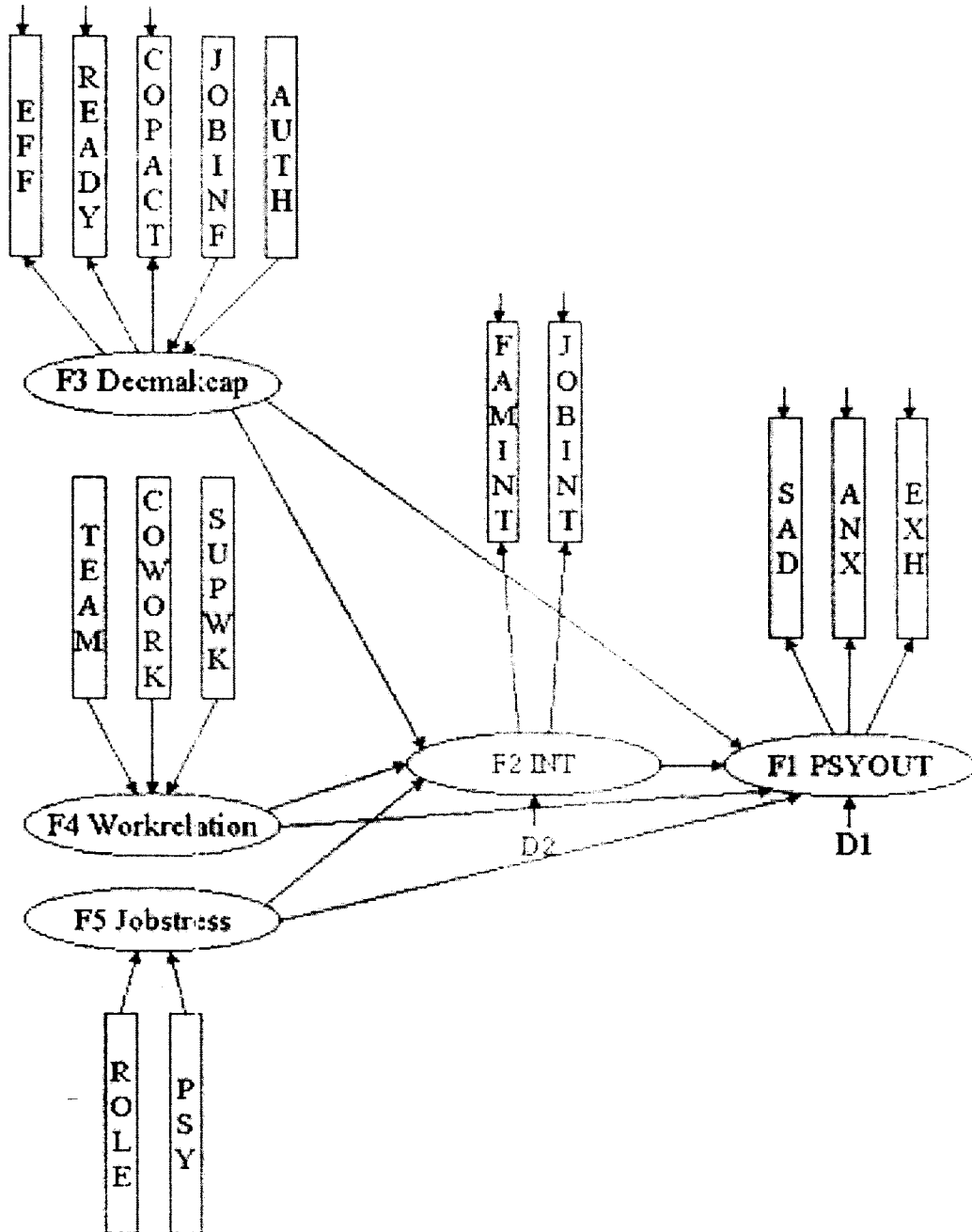


Figure 12 Standard model with mixed indicators (model 5)

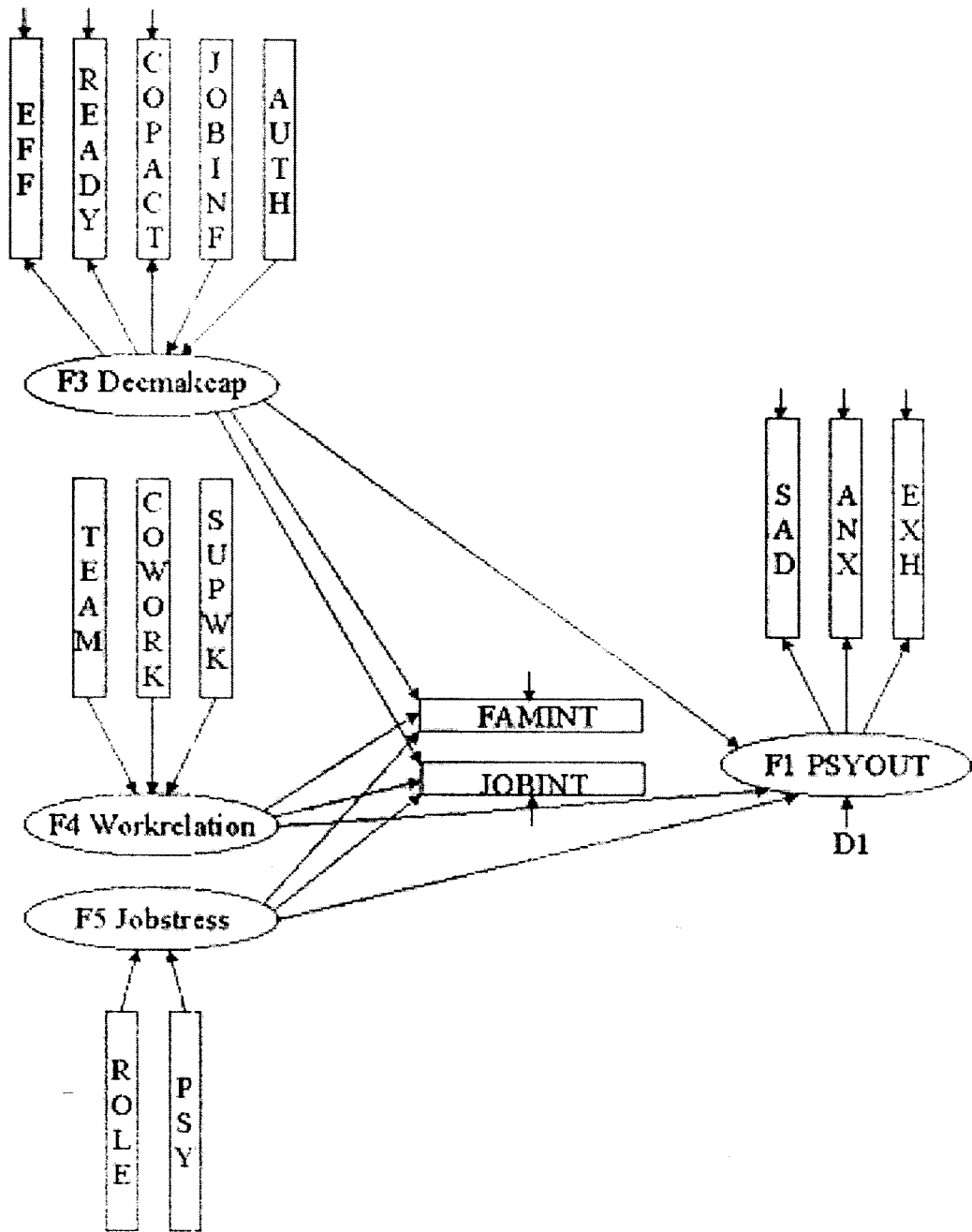


Figure 13 Nonstandard model with mixed indicators (model 6)

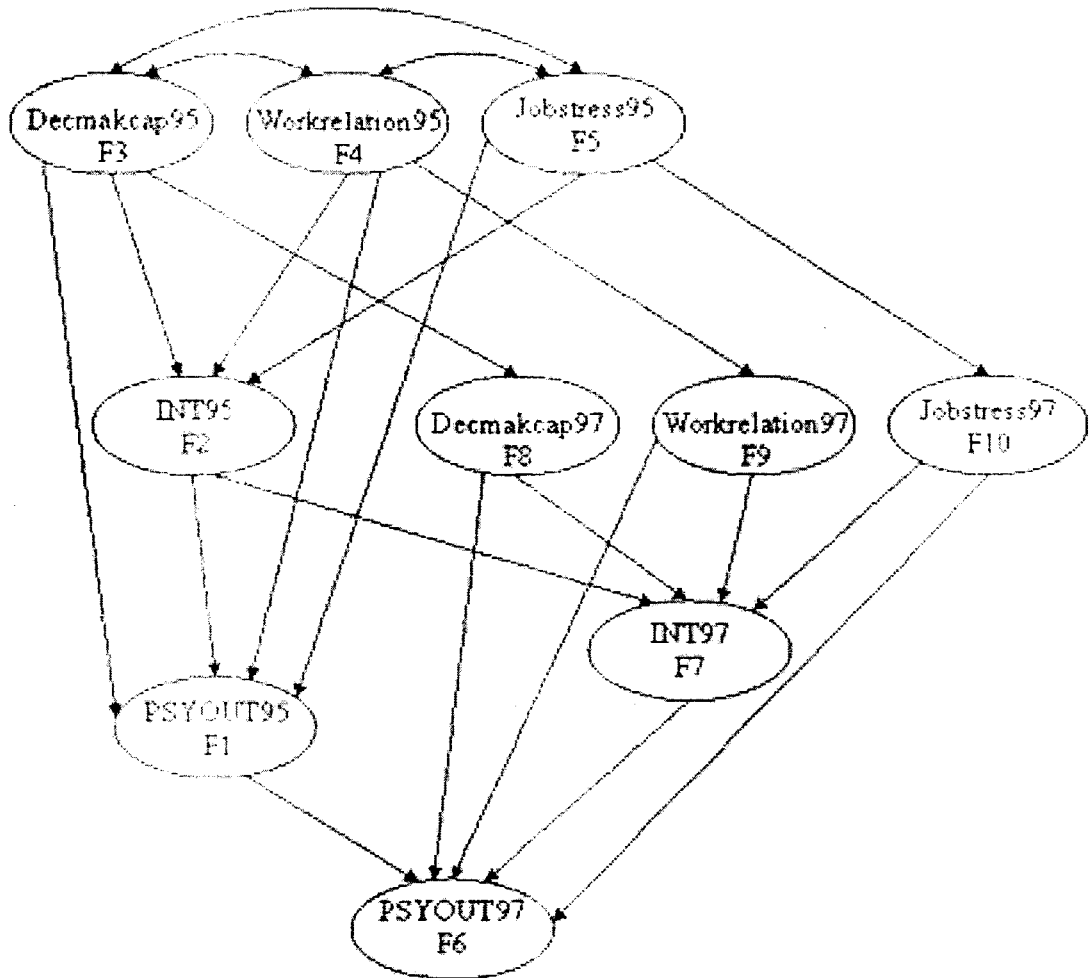


Figure 14 Longitudinal model (95—97) (model 7 & 8)

Appendix 2(a)

Variable	Mean	Std Dev	Miss	Range	Variance	Skewness	Kurtosis
EFF95	3.58	0.76	0	3.60	0.58	-0.18	-0.49
READY95	3.50	0.60	0	3.67	0.36	-0.15	-0.05
TEAM95	3.79	0.74	3	3.83	0.55	-0.50	0.18
ROLE95	2.36	0.76	1	4.00	0.58	0.40	0.39
COPACT95	3.52	0.65	2	3.80	0.42	-0.39	0.21
ANX95	1.46	0.52	1	3.00	0.27	1.92	4.75
FAMINT95	1.42	0.45	8	2.00	0.21	1.22	1.11
JOBINT95	1.80	0.53	4	2.00	0.28	0.33	-0.49
DISC95	3.73	0.69	0	4.00	0.47	-0.76	0.60
AUTH95	3.53	0.81	0	4.00	0.66	-0.32	-0.21
PSY95	3.52	0.66	0	4.00	0.44	-0.32	0.50
COWORK95	3.86	0.63	1	3.29	0.40	-0.46	0.15
SUPWK95	3.35	1.02	3	4.00	1.04	-0.37	-0.44
EFF97	3.57	0.73	0	3.80	0.54	-0.18	-0.20
READY97	3.52	0.58	1	2.83	0.33	0.10	-0.59
TEAM97	3.61	0.81	0	4.00	0.65	-0.43	-0.12
ROLE97	2.53	0.81	0	4.00	0.66	0.20	-0.20
COPACT97	3.48	0.61	2	3.20	0.37	-0.32	0.24
ANX97	1.68	0.60	5	3.00	0.36	1.20	1.34
FAMINT97	1.50	0.47	7	2.00	0.22	0.71	-0.28
JOBINT97	1.94	0.54	5	2.00	0.29	0.06	-0.65
SAD97	1.72	0.52	5	2.40	0.27	0.92	0.49
EXH97	2.57	1.53	1	6.00	2.34	0.24	-1.02
JOBINF97	2.78	0.73	0	3.80	0.54	0.24	0.05
DISC97	3.77	0.62	1	3.67	0.39	-0.67	0.68
AUTH97	3.51	0.80	1	4.00	0.63	-0.43	0.08
PSY97	3.75	0.65	2	3.80	0.42	-0.21	0.33
COWORK97	3.69	0.64	0	3.57	0.41	-0.55	0.54
SUPWK97	3.00	1.08	6	4.00	1.17	-0.08	-0.73

Table 24 Descriptive statistics

Figure 15 Histograms of some of the variables

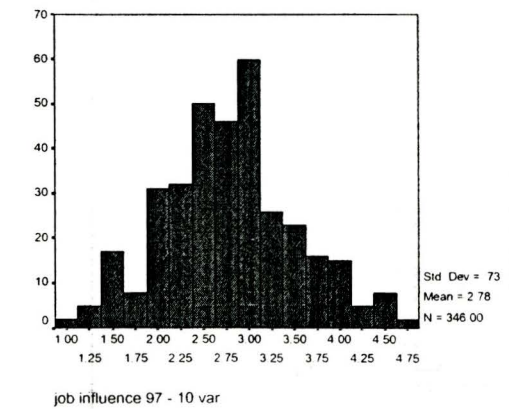
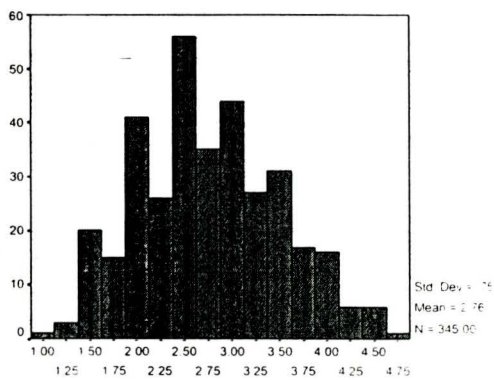
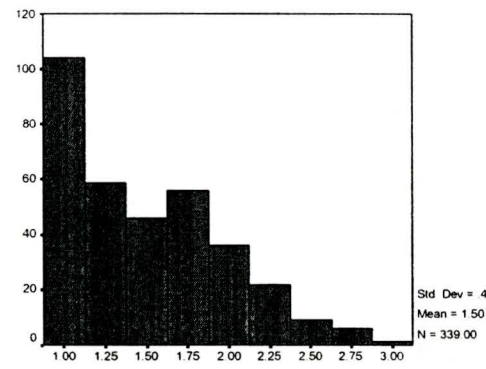
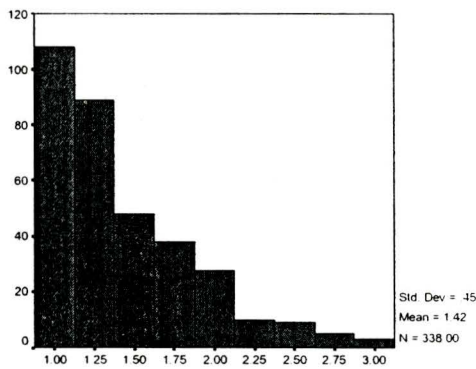
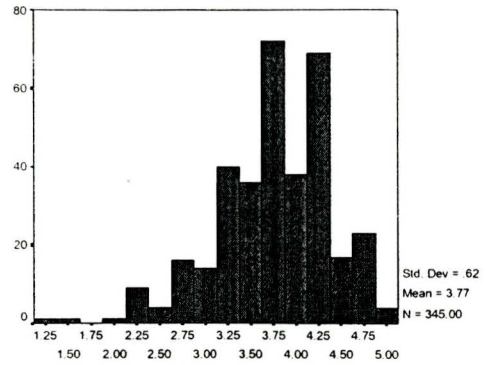
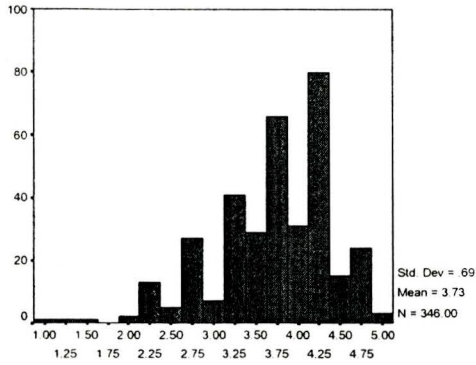
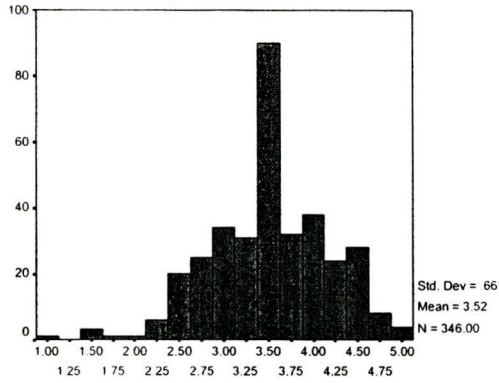
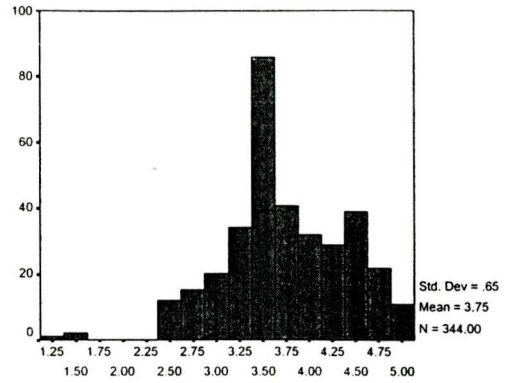


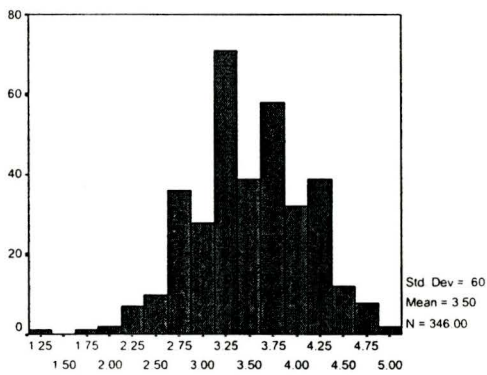
Figure 16 Histograms of some of the variables



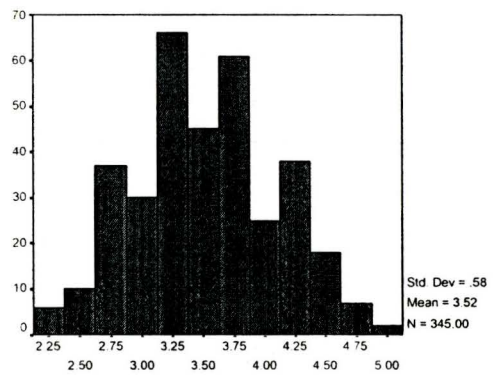
physch job demands 95 - 5 var



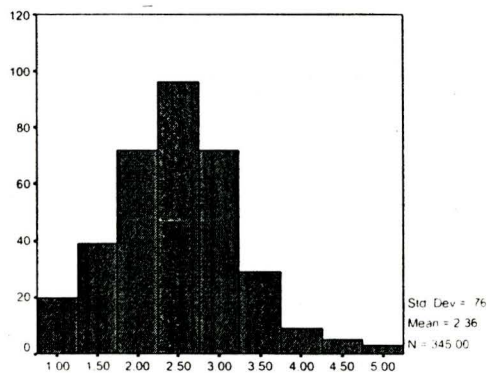
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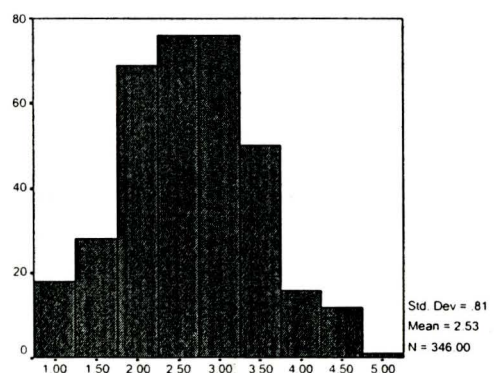
ready for change 95 - 6 var



ready for change 97 - 6 var



role unclarity 95 - 4 var



role unclarity 97 - 4 var

Appendix 2 (b)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. EFF	0.58	0.25	0.16	-0.18	0.28	-0.23	-0.10	-0.08	-0.25	-0.17	0.28	0.22	0.25	0.08	0.15	0.18
2. READY	0.19	0.56	0.08	0.08	0.33	-0.02	0.06	0.14	-0.07	0.06	0.32	0.34	0.26	0.25	0.12	0.14
3. TEAM	0.26	0.08	0.49	-0.33	0.33	-0.17	-0.03	-0.18	-0.13	-0.21	0.31	0.28	0.36	-0.02	0.53	0.47
4. ROLE	-0.16	0.22	-0.30	0.53	-0.22	0.34	0.12	0.43	0.32	0.53	-0.13	0.09	-0.07	0.38	-0.22	-0.15
5. COPAC	0.37	0.42	0.34	-0.17	0.53	-0.21	-0.04	-0.15	-0.25	-0.23	0.41	0.25	0.31	-0.05	0.24	0.29
6. ANX	-0.31	0.06	-0.24	0.37	-0.18	0.42	0.18	0.32	0.64	0.53	-0.16	-0.04	-0.09	0.19	-0.17	-0.11
7. FAMINT	-0.10	0.11	-0.08	0.11	-0.01	0.28	0.62	0.40	0.30	0.21	-0.02	0.02	0.07	0.07	0.05	-0.07
8. JOBINT	-0.16	0.21	-0.22	0.43	-0.06	0.50	0.46	0.59	0.34	0.62	-0.01	0.06	0.01	0.40	-0.07	-0.18
9. SAD	-0.34	0.03	-0.20	0.36	-0.24	0.65	0.33	0.51	0.48	0.57	-0.15	-0.04	-0.07	0.18	-0.14	-0.14
10. EXH	-0.25	0.18	-0.30	0.54	-0.14	0.59	0.28	0.67	0.58	0.59	-0.15	0.02	-0.06	0.43	-0.19	-0.15
11. JOBINF	0.33	0.26	0.41	-0.14	0.35	-0.20	-0.07	-0.15	-0.22	-0.18	0.60	0.38	0.58	0.00	0.28	0.29
12. DISC	0.27	0.37	0.25	0.17	0.26	0.01	0.11	0.13	0.00	0.09	0.36	0.63	0.55	0.24	0.36	0.19
13. AUTH	0.27	0.14	0.38	-0.09	0.26	-0.13	0.01	-0.10	-0.17	-0.12	0.62	0.48	0.53	0.06	0.32	0.29
14. PSY	-0.06	0.30	-0.15	0.43	0.00	0.34	0.13	0.41	0.32	0.51	-0.08	0.22	-0.02	0.51	-0.07	-0.03
15. COWORK	0.20	0.10	0.62	-0.23	0.28	-0.25	-0.02	-0.19	-0.20	-0.28	0.34	0.23	0.37	-0.14	0.43	0.35
16. SUPWK	0.20	0.09	0.45	-0.13	0.25	-0.07	-0.02	-0.19	-0.14	-0.17	0.36	0.13	0.29	-0.17	0.39	0.36

Table 25 Pearson Correlations among Variables in 1995 and 1997

Note: Correlations above the diagonal are for 1995 data, below diagonal for 1997 data, on diagonal are between 1995 and 1997 values; Sample sizes range from 327 to 346.

Rotated Factor Pattern (Standardized Regression Coefficients)					
	Factor 1	Factor 2	Factor 3		
EFF95	0.51	-0.06	-0.09		
READY95	0.58	-0.12	0.19		
TEAM95	-0.05	0.74	-0.11		
ROLE95	-0.15	-0.16	0.58		
COPACT95	0.58	0.03	-0.20		
JOBINF95	0.62	0.11	-0.07		
DISC95	0.29	0.33	0.39		
AUTH95	0.46	0.28	0.12		
PSY95	0.04	-0.02	0.55		
COWORK95	-0.06	0.69	0.003		
SUPWK95	0.08	0.48	-0.08		

Factor Structure (Correlations)

	Factor 1	Factor 2	Factor 3		
EFF95	0.46	0.27	0.004		
READY95	0.53	0.23	0.30		
TEAM95	0.40	0.72	-0.17		
ROLE95	-0.15	-0.30	0.56		
COPACT95	0.56	0.41	-0.10		
JOBINF95	0.68	0.50	0.03		
DISC95	0.57	0.48	0.41		
AUTH95	0.66	0.56	0.18		
PSY95	0.12	-0.04	0.56		
COWORK95	0.38	0.66	-0.06		
SUPWK95	0.37	0.54	-0.10		

Pearson correlation coefficients

	JOBINT95	FAMINT95	Factor 1	Factor 2	Factor 3
JOBINT95	1.00	0.40	-0.03	-0.16	0.46
FAMINT95	0.40	1.00	0.002	-0.004	0.13
Factor 1	-0.03	0.002	1.00	0.78	0.21
Factor 2	-0.16	-0.004	0.78	1.00	-0.09
Factor 3	0.46	0.13	0.21	-0.09	1.00

Table 26 Exploratory Factor analysis of data95

Rotated Factor Pattern (Standardized Regression Coefficients)					
	Factor 1	Factor 2	Factor 3		
EFF97	0.16	-0.05	0.37		
READY97	-0.009	0.43	0.55		
TEAM97	0.48	-0.32	0.20		
ROLE97	-0.02	0.60	-0.11		
COPACT97	0.04	-0.02	0.65		
JOBINF97	0.66	0.03	0.09		
DISC97	0.52	0.41	0.11		
AUTH97	0.84	0.10	-0.14		
PSY97	-0.04	0.58	0.09		
COWORK97	0.48	-0.25	0.13		
SUPWK97	0.38	-0.23	0.13		

Factor Structure (Correlations)

	Factor 1	Factor 2	Factor 3		
EFF97	0.39	-0.09	0.47		
READY97	0.25	0.41	0.53		
TEAM97	0.64	-0.39	0.50		
ROLE97	-0.17	0.61	-0.14		
COPACT97	0.42	-0.04	0.67		
JOBINF97	0.71	-0.06	0.48		
DISC97	0.53	0.33	0.40		
AUTH97	0.75	-0.004	0.35		
PSY97	-0.06	0.58	0.05		
COWORK97	0.60	-0.32	0.43		
SUPWK97	0.48	-0.28	0.36		

Pearson Correlation Coefficients

	JOEINT97	FAMINT97	Factor 1	Factor 2	Factor 3
JOEINT97	1.00	0.46	-0.18	0.50	-0.09
FAMINT97	0.46	1.00	-0.02	0.16	-0.01
Factor 1	-0.18	-0.02	1.00	-0.18	0.76
Factor 2	0.50	0.16	-0.18	1.00	-0.04
Factor 3	-0.09	-0.01	0.76	-0.04	1.00

Table 27 Exploratory Factor analysis of data97

Appendix 3 (a)

In the following, we will show that the asymptotic distribution of $(N-1) F$ is χ^2 distribution under the null hypothesis, $H_0: S = \hat{\Sigma}$. Where θ is the unknown vector contains the model parameters to be estimated, $\hat{\Sigma}$ is the covariance matrix written as a function of θ . Here we will only deal with F_{ML} ; the other two can be proved in a similar way. Selecting H_1 so that $\hat{\Sigma} = S$ provides a standard of perfect fit against which to compare H_0 . The H_1 could be any exact identified model since $\hat{\Sigma}$ equals S in this case. Based on H_0 , the best we can hope is that $\hat{\Sigma} = \hat{\Lambda}_Y \hat{\Phi} \hat{\Lambda}_Y + \hat{\Theta}_\delta$ exactly reproduces S . Since H_1 sets $\hat{\Sigma}$ to S , comparing $\log L_1$ to $\log L_0$ evaluates H_0 vs. H_1 . The natural logarithm of the likelihood ratio, $\log(L_0/L_1)$, when multiplied by -2 is distributed as chi-square variate when H_0 is true and $(N-1)$ is large. In this case,

$$\begin{aligned} 2\log(L_0/L_1) &= 2\log L_1 - 2\log L_0 \\ &= (N-1)[\log|\hat{\Sigma}| + \text{tr}(\hat{\Sigma}^{-1} S)] - (N-1)(\log|S| + q) \\ &= (N-1)(\log|\hat{\Sigma}| + \text{tr}(\hat{\Sigma}^{-1} S) - \log|S| - q) \end{aligned}$$

The quantity within parentheses in the last line of the above formula is exactly the fitting function F_{ML} evaluated at S and $\hat{\Sigma}$. Thus, it shows that $(N-1)F_{ML}$ evaluated at $\hat{\theta}$ is approximately distributed as a chi-square variate.

Appendix 3 (b)

GFO Criterion	Acceptable Level	Interpretation
Chi-square	Tabled Chi-square value	Compare obtained chi-square value for given df
Goodness-of-fit (GFI)	0 (no fit) to 1 (perfect fit)	Values close to 0.90 reflects a good fit
Adjusted GFI (AGFI)	0 (no fit) to 1 (perfect fit)	Values adjusted for df, with 0.90 a good model fit
Root mean Square Residual (RMR)	Researcher defines level	Indicates the closeness of Σ to S matrix
Comparative Fit Index (CFI)	0 (no fit) to 1 (perfect fit)	Very close to 0.90 reflects a good model fit
Normed fit index (NFI)	0 (no fit) to 1 (perfect fit)	Very close to 0.90 reflects a good model fit
Non-normed fit index (NNFI)	0 (no fit) to 1 (perfect fit)	Very close to 0.90 reflects a good model fit
Akaike information criterion	0 (perfect fit) to positive value (poor fit)	Compares values in alternative models

Table 28 GOF Criteria and Acceptable Fit Interpretation

Appendix 4 (a)

(a) Standard model with cause indicators (data95)

Table 29 Goodness of Fit Indices for Standard model with cause indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 3 (95)	133.6 (41)	0.945	0.838	0.934	0.912	0.832

Table 30 Sums of Standardized Path coefficients to "Psyout"

	TO INT95	INT95 TO PSYOUT	INDIRECT	DIRECT	TOTAL
		0.432			
Decmakcap95	-0.032		-0.014	-0.232	-0.246
Workrelation95	-0.127		-0.054	0.064	0.010
Jobstress95	0.485		0.210	0.362	0.572

Table 31 Unstandardized and Standardized loadings for cause indicators

	To Decmakcap95		To Workrelation95			To Jobstress95		
	U	S		U	S		U	S
EFF95	1565522	0.57	TEAM95	0.69	0.33	ROLE95	4.23	0.65
READY95	-83523	-0.002	COWORK95	-1.68	-0.89	PSY95	1.00*	0.55
COPACT95	1115799	0.423	SUPWK95	1.00*	0.81			
AUTH95	701512	0.377						
JOBINF95	1.00*	0.003						

Table 32 Unstandardized and Standardized loadings for effect indicator

	From Psyout95 to		From INT95 to		
	U	S		U	S
SAD95	9.99	0.64	FAMINT95	4.92	0.40
ANX95	1.00*	0.66	JOBINT95	1.00*	1.02
EXH95	12.10	0.89			

Note: U represents for unstandardized loading

S represents for standardized loading

Appendix 4 (b)

(b) Standard model with mixed indicators (data95)

Table 33 Goodness of Fit Indices for Standard model with mixed indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 5 (95)	257.6 (65)	0.898	0.811	0.863	0.830	0.779

Table 34 Sums of Standardized Path coefficients to "Psyout"

	TO INT95	INT95 TO PSYOUT	INDIRECT	DIRECT	TOTAL
		0.432			
Decmakcap95	0.078			-0.145	-0.111
Workrelation95	-0.132			-0.011	-0.068
Jobstress95	0.474			0.390	0.595

Table 35 Unstandardized and Standardized loadings for cause indicators

	To Decmakcap95		To Workrelation95		To Jobstress95			
	U	S		U	S	U	S	
JOBINF95	2.42	0.804	TEAM95	3354808	0.169	ROLE95	4.23	0.65
AUTH95	1.00*	0.292	COWORK95	1.00*	0.0009	PSY95	1.00*	0.55
			SUPWK95	49231949	0.910			

Table 36 Unstandardized and Standardized loadings for effect indicators

	From Psyout95 to		From Decmakcap95 to		
	U	S	U	S	
SAD95	9.99	0.64	EFF95	2.75	0.31
ANX95	1.00*	0.66	READY95	2.80	0.34
EXH95	12.10	0.89	COPACT95	2.90	0.41

Appendix 4 (c)

(c) Nonstandard model with cause indicators (data95)

Table 37 Goodness of Fit Indices for nonstandard model with cause indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
Model 4 (95)	178.70 (39)	0.935	0.799	0.901	0.882	0.733

Table 38 Standardized Path coefficient estimates

	TO FAMINT95	TO JOBINT95	FAMINT95 TO PSYOUT95	JOBINT95 TO PSYOUT95	TO PSYOUT95
			0.067	0.413	
Decmakcap95	0.133	0.07			0.209
Workrelation95	-0.10	-0.12			0.084
Jobstress95	0.10	0.49			0.358

Table 39 Unstandardized and Standardized loadings for cause indicators

	To Decmakcap95		To Workrelation95		To Jobstress95		U	S
	U	S	U	S	U	S		
EFF95	-1.19	-0.70	TEAM95	0.55	0.23	ROLE95	4.22	0.66
READY95	0.639	0.18	COWORK95	-1.74	-1.07	PSY95	1.00*	0.54
COPACT95	-1.11	-0.46	SUPWK95	1.00*	0.63			
JOBINF95	-1.34	-0.38						
AUTH95	1.00*	0.28						

Table 40 Unstandardized and Standardized loadings for effect indicators

	From Psyout95 to		From Decmakcap95 to		
	U	S	U	S	
SAD95	10.01	0.65	EFF95	2.75	0.31
ANX95	1.00*	0.66	READY95	2.80	0.34
EXH95	12.01	0.88	COPACT95	2.90	0.41

Appendix 4 (d)

(d) Standard model with cause indicators (data97)

Table 41 Goodness of Fit Indices for Standard model with cause indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 4 (95)	96.3 (41)	0.959	0.880	0.967	0.946	0.916

Table 42 Sums of Standardized Path coefficients to "Psyout"

	TO INT97	INT97 TO PSYOUT	INDIRECT	DIRECT	TOTAL
		0.507			
Decmakcap97	-0.119		-0.060	-0.232	-0.292
Workrelation97	0.010		0.005	0.116	0.121
Jobstress97	0.476		0.024	0.357	0.381

Table 43 Unstandardized and Standardized loadings for cause indicators

	To Decmakcap97		To Workrelation97		To Jobstress97			
	U	S	U	S	U	S		
EFF97	0.018	0.85	TEAM97	-0.463	-0.204	ROLE97	4.248	0.600
READY97	-0.018	-0.12	COWORK97	-1.579	-0.875	PSY97	1.00*	0.584
COPACT97	0.018	0.19	SUPWK97	1.00*	0.809			
AUTH97	1.00*	0.004						
JOBINF97	0.018	0.18						

Table 44 Unstandardized and Standardized loadings for effect indicators

	From Psyout97 to		From INT97 to		
	U	S	U	S	
SAD97	12.42	0.74	FAMINT97	6.33	0.45
ANX97	1.00*	0.71	JOBINT97	1.00*	1.01
EXH97	14.09	0.86			

Appendix 4 (e)

(e) Nonstandard model with effect indicators

Table 45 Goodness of Fit Indices for nonstandard model with effect indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
model 3 (97)	305.5 (78)	0.886	0.825	0.865	0.829	0.818

Table 46 Sums of Standardized Path coefficients to "Psyout"

	TO FAMINT	TO JOBINT	FAMINT TO PSYOUT	JOBINT TO PSYOUT	INDIRECT	DIRECT
			-0.22	-3.62		
Decmakcap97	-0.36	-0.45				-2.34
Workrelation97	0.62	0.76				3.80
Jobstress97	0.66	1.21				6.02

Appendix 4 (f)

(f) Nonstandard model with cause indicators (data97)

Table 47 Goodness of Fit Indices for nonstandard model with cause indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
Model 4 (97)	160.9 (39)	0.941	0.819	0.927	0.910	0.804

Table 48 Standardized Path coefficient estimates

	TO FAMINT97	TO JOBINT97	FAMINT97 TO PSYOUT	JOBINT97 TO PSYOUT	TO PSYOUT97
			0.06	0.489	
Decmakcap97	0.106	0.128			0.22
Workrelation97	-0.02	0.02			0.12
Jobstress97	0.114	0.473			0.35

Table 49 Unstandardized and Standardized loadings for cause indicators

	To Decmakcap97		To Workrelation97			To Jobstress97		
	U	S		U	S		U	S
EFF97	-0.16	-0.86	TEAM97	-0.37	-0.16	ROLE97	4.25	0.60
READY97	0.16	0.22	COWORK97	-1.52	-0.97	PSY97	1.00*	0.58
COPACT97	-0.16	-0.17	SUPWK97	1.00*	0.65			
JOBINF97	-0.17	-0.22						
AUTH97	1.00*	0.03						

Table 50 Unstandardized and Standardized loadings for effect indicators

From Psyout97 to		
SAD97	12.3	0.74
ANX97	1.00*	0.71
EXH97	13.9	0.85

Appendix 4 (g)

(g) Nonstandard model with mixed indicators (data97)

Table 51 Goodness of Fit Indices for nonstandard model with cause indicators

	Chi-Square (DF)	GFI	AGFI	CFI	NFI	NNFI
Model 6 (97)	356.8(63)	0.87	0.76	0.83	0.80	0.71

Table 52 Unstandardized and Standardized factor loadings for cause indicators

To Decmakcap97			To Workrelation97			To Jobstress97		
	U	S		U	S		U	S
JOBINF97	0.97	0.92	TEAM97	0.71	0.33	ROLE97	4.41	0.62
AUTH97	1.00*	0.13	COWORK97	1.00*	0.87	PSY97	1.00*	0.57
			SUPWK957	-1.18	-0.42			

Table 53 Unstandardized and Standardized loadings for effect indicator

		U	S
From Decmakcap97 to	EFF97	1.05	0.35
	READY97	1.04	0.24
	COPACT97	1.05	0.34
From Psyout97 to	SAD97	11.83	0.73
	ANX97	1.00*	0.70
	EXH97	13.59	0.87

Table 54 Sums of Standardized Path coefficients to "Psyout"

	TO FAMINT	TO JOBINT	FAMINT TO PSYOUT	JOBINT TO PSYOUT	INDIRECT	DIRECT	TOTAL
			0.066	0.507			
Decmakcap97	-0.06	-0.08				-0.071	-0.116
Workrelation97	0.026	-0.042				-0.134	-0.136
Jobstress97	0.13	0.48				0.377	0.629

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