SEM Model

- A theory serves as a conceptual foundation for developing a model and all relationships must be specified before the estimation of SEM model.

STRUCTURAL EQUATION MODELING (SEM)

- Measurement model
- Structural model

Measurement Model

- It depicts how the observed (measured, manifest, indicators) variables represent constructs.
- Permits the assessment of construct validity.
- No single indicator can completely represent a construct (*at least three helps in model identification*).
- Uses the technique of Confirmatory Factor Analysis (CFA)
  - It seeks to confirm if the number of factors (or constructs) and the loadings of observed (indicator) variables on them conform the expectations of theory.
  - Tests the hypothesis on relationships b/w observed variables and their underlying latent constructs.

Structural Model

- It shows how the constructs are interrelated to each other, often with multiple dependence relationships.
- It specifies whether a relationship exists or does not exist.
- If a relationship is hypothesized by the theory, then an arrow is drawn
- Measurement theory specifies how the constructs are represented; structural theory posits how the constructs are interrelated

Model Constructing

- One of the most well known covariance structure models is called LISREL (**LI**near **S**tructural **REL**ationships) or Jöreskog-Keesling-Wiley –model.
- LISREL is also a name of the software (Jöreskog et al., 1979), which is later demonstrated in this presentation to analyze a latent variable model.
- The other approach in this study field is Bentler-Weeks -model (Bentler et al., 1980) and EQS –software (Bentler, 1995).

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Model Constructing

- The latest software release attempting to implement SEM is graphical and intuitive AMOS (Arbuckle, 1997).
- AMOS has since 2000 taken LISREL's place as a module of a well-known statistical software package SPSS (**S**tatistical **P**ackage for **S**ocial **S**ciences).
- Also other high quality SEM programs exist, such as Mplus (Muthén & Muthén, 2000).
  - MPlus is targeted for professional users, it has only text input mode.

Conducting SEM

Define the individual constructs
↓
Develop and specify the Measurement model
↓
Assess Measurement Model validity
↓
Measurement model valid?
If no refine measures and design a new study
↓
Specify the Structural model
↓
Assess Structural Model validity
↓
Structural Model Valid?
If no refine model and test with new data
↓
Draw conclusions and make recommendations

Define the Individual constructs

- Specific constructs, how each construct will be defined and measured, and the interrelationships among constructs must all be specified based on theory

Constructs (e.g.)

Variable Description

	Item	Summary variable	Sample statement
Supportive Management	X1	**Participative Leadership**	It is easy to be touch with the leader of the training programme.
	X2	**Elaborative Leadership**	This organization improves it's members professional development.
	X3	**Encouraging Leadership**	My superior appreciates my work.
Functional Group	X4	**Collaborative Activities**	My teacher colleagues give me help when I need it.
	X5	**Teacher – Student Connections**	Atmosphere on my lectures is pleasant and spontaneous.
	X6	**Group Spirit**	The whole working community co-operates effectively.

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Sample of data

	Variables					
	Supportive Management			Functional Group		
Teachers	Participative Leadership (x1)	Elaborative Leadership (x2)	Encouraging Leadership (x3)	Collaborative Activities (x4)	Teacher-student Connections (x5)	Group Spirit (x6)
1.	2.75	3.25	4.00	2.60	3.00	2.00
2.	3.25	3.75	5.00	3.40	4.00	3.00
3.	3.50	3.75	4.00	3.60	4.75	3.00
. . .						
319	5.00	1.00	3.00	3.00	3.00	5.00

Covariance Matrix

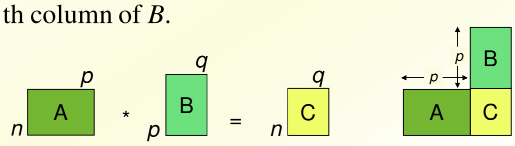
	Covariance Matrix					
	Supportive Management			Functional Group		
	X1	X2	X3	X4	X5	X6
X1	.734	.343	.438	.220	.104	.275
X2	.343	.668	.467	.234	.037	.307
X3	.438	.467	.938	.306	.165	.391
X4	.220	.234	.306	.459	.182	.308
X5	.104	.037	.165	.182	.387	.114
X6	.275	.307	.391	.308	.114	.552

What is Covariance matrix?

- Scatter, covariance, and correlation matrix form the basis of a multivariate method.
- The correlation and the covariance matrix are also often used for a first inspection of relationships among the variables of a multivariate data set.
- All of these matrices are calculated using the matrix multiplication (A · B).
- The only difference between them is how the data is scaled before the matrix multiplication is executed:
  - scatter: no scaling
  - covariance: mean of each variable is subtracted before multiplication
  - correlation: each variable is standardized (mean subtracted, then divided by standard deviation)

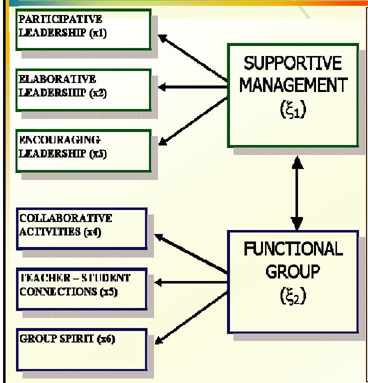
Matrix Multiplication?

- Let (a_{rs}), (b_{rs}), and (c_{rs}) be three matrices of order $m_x n$ $n_x p$ and $p_x q$ respectively. Each element c_{rs} of the matrix *C*, the result of the *matrix product* **A•B,** is then calculated by the inner product of the *s* th row of *A* with the *r* th column of *B*.



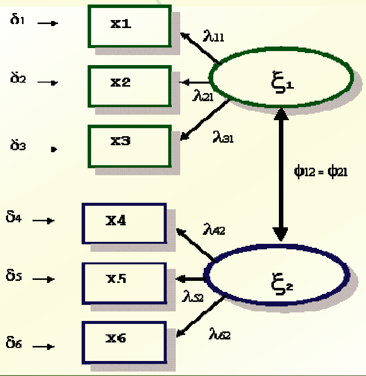
Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Hypothesized Model



- Two main hypotheses of interest are:
  - Does a two-factor model fit the data?
  - Is there a significant covariance between the supportive and functional factors?

Model Specification (stage to Measurement Model)



Model Specification

- The relationships for this part of the measurement model can now be specified in a set of *factor equations* in a scalar form:

$x_1 = \lambda_{11}\xi_1 + \delta_1$ $\quad x_2 = \lambda_{21}\xi_1 + \delta_2$

$x_3 = \lambda_{31}\xi_1 + \delta_3$ $\quad x_4 = \lambda_{42}\xi_2 + \delta_4$

$x_5 = \lambda_{52}\xi_2 + \delta_5$ $\quad x_6 = \lambda_{62}\xi_2 + \delta_6$

  - δ_i is the residual variable (error) which is the unique factor affecting x_i.
  - λ_{ij} is the loading of the observed (measured) variables x_i on the latent factor ξ_j .
  - Φ is the correlation between constructs

Model Specification

- In the earlier case, total of 13 parameters need to be estimated
  - Six loading estimates, Six error estimates and One constructs correlation

Note: For each relation that is not specified, the parameter is fixed and set at zero.

We should set the scale of latent construct (as it is not observed directly) using the following options:

1. One of the factor loadings can be fixed, generally equal to one
2. The construct variance can be fixed, generally to one.

2. Model Specification

- Most of the calculations are performed as matrix computations because SEM is based on covariance matrices.
  - To translate equation into a more matrix friendly form,

$x_1 = \lambda_{11}\xi_1 + 0\xi_2 + \delta_1$
$x_2 = \lambda_{21}\xi_1 + 0\xi_2 + \delta_2$
$x_3 = \lambda_{31}\xi_1 + 0\xi_2 + \delta_3$
$x_4 = 0\xi_1 + \lambda_{42}\xi_2 + \delta_4$
$x_5 = 0\xi_1 + \lambda_{52}\xi_2 + \delta_5$
$x_6 = 0\xi_2 + \lambda_{62}\xi_2 + \delta_6$

Equivalent to $x = \Lambda_x\xi + \delta$

Model Specification

$x = \Lambda_x\xi + \delta$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ 0 & \lambda_{42} \\ 0 & \lambda_{52} \\ 0 & \lambda_{62} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \end{bmatrix}$$

Model Specification

- The covariances between factors are represented with arrows connecting ξ_1 and ξ_2.
  - This covariance is labeled $\phi_{12} = \phi_{21}$ in Φ.

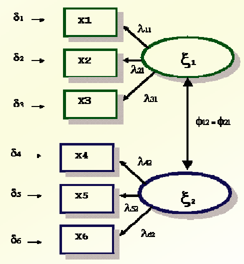
$$\Phi = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$$

The diagonal elements of Φ are the variances of the common factors.

Model Specification

- In this model, error variances are assumed to be uncorrelated:

$$\Theta = \begin{bmatrix} \theta_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & \theta_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & \theta_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & \theta_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & \theta_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & \theta_{66} \end{bmatrix}$$



Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Model Specification

- Because the factor equations cannot be directly estimated, the covariance structure of the model is examined.
- Matrix Σ contains the structure of covariances among the observed variables after multiplying equation by its transpose

  $\Sigma = E(xx')$

  and taking expectations

  $\Sigma = E[(\Lambda\xi+\delta)(\Lambda\xi+\delta)'] = E[(\Lambda\xi+\delta)(\xi'\Lambda'+\delta')]$

  $= E[\Lambda\xi\xi'\Lambda' + \Lambda\xi\delta' + \delta\xi'\Lambda' + \delta\delta']$

  $\Sigma = E[\Lambda\xi\xi'\Lambda'] + E[\Lambda\xi\delta'] + E[\delta\xi'\Lambda'] + E[\delta\delta']$

  $\Sigma = \Lambda E[\xi\xi']\Lambda' + \Lambda E[\xi\delta'] + E[\delta\xi']\Lambda' + E[\delta\delta']$ Since the values of the parameters in matrix Λ are constant

Model Specification

- Since $E[\xi\xi'] = \Phi$, $E[\delta\delta'] = \Theta$, and δ and ξ are uncorrelated, previous equation can be simplified to *covariance equation*:

  $\Sigma = \Lambda\Phi\Lambda' + \Theta$
- The left side of the equation contains the number of unique elements $q(q+1)/2$ in matrix Σ.
  - q denotes the no. of observed & 's' no. of latent variables
- The right side contains $qs + s(s+1)/2 + q(q+1)/2$ *or* **$(s+q)(s+q+1)/2$** unknown parameters from the matrices Λ, Φ, and Θ.
- Unknown parameters have been tied to the population variances and covariances among the observed variables which can be directly estimated with sample data.

Model Identification

- Identification is a theoretical property of a model, which depends neither on data or estimation.
  - When our model is identified we obtain unique estimates of the parameters.
- "Attempts to estimate models that are not identified result in arbitrary estimates of the parameters." (Long, 1983, p. 35.)

Model Identification

- A model is identified if it is possible to solve the covariance equation $\Sigma = \Lambda\Phi\Lambda' + \Theta$ for the parameters in Λ, Φ and Θ.
  - Estimation assumes that model is identified.
- There are three conditions for identification:
  - *necessary conditions*, which are essential but not sufficient,
  - *sufficient conditions*, which if met imply that model is identified but if not met do not imply opposite (unidentified),
  - *necessary and sufficient conditions.*

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Model Identification

- Necessary condition is simple to test since it relates the number of independent covariance equations to the number of independent parameters.
- Covariance equation contains q(q+1)/2 independent equations and qs + s(s+1)/2 + q(q+1)/2 *or* **(s+q)(s+q+1)/2)** possible independent parameters in Λ, Φ and Θ.
  - Number of independent, unconstrained parameters of the model must be less than or equal to q(q+1)/2.
  - *Note that this number is the sum of all the unique covariance* q(q-1)/2 *and all the variances 'q'*

Model Identification

- We have six observed variables and, thus, 6(6+1)/2 = 21 distinct variances and co-variances in Σ.
  - There are 15 independent parameters:

$$\Lambda=\begin{bmatrix}1 & 0\\ 2 & 0\\ 3 & 0\\ 0 & 4\\ 0 & 5\\ 0 & 6\end{bmatrix} \qquad \Phi=\begin{bmatrix}7 & 8\\ 8 & 9\end{bmatrix} \qquad \Theta=\begin{bmatrix}10 & 0 & 0 & 0 & 0 & 0\\ 0 & 11 & 0 & 0 & 0 & 0\\ 0 & 0 & 12 & 0 & 0 & 0\\ 0 & 0 & 0 & 13 & 0 & 0\\ 0 & 0 & 0 & 0 & 14 & 0\\ 0 & 0 & 0 & 0 & 0 & 15\end{bmatrix}$$

Model Identification

- Since the number of independent parameters is smaller than the independent covariance equations (15<21), the necessary condition for identification is satisfied.

Levels of Identification

Identification – degree to which there are a positive dof. And there is a sufficient number of equations to 'solve for' each of the coefficients (unknowns) to be estimated**.**

Three possible levels:

- **Under-identified** – negative dof. (model cannot be fit)
- **Just-Identified** – zero dof. (no. of equations = no. of estimated coefficients)
- **Over-identified** – positive dof. (more equations than no. of estimated coefficients)

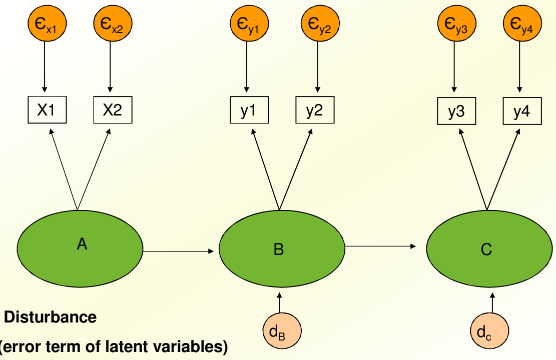
Objective: *achieve acceptable fit with largest number of dof.*

Formula to compute (dof) – (Hair, page 608)

df = (s+q)(s+q+1)/2 – no. of estimated coefficients

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Model Identification (E.g.)



d= Disturbance

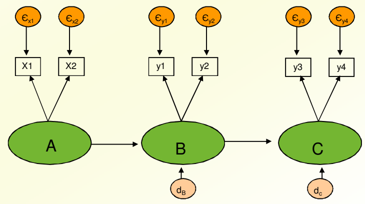
(error term of latent variables)

Steps

1. Calculate the observed variables formula (v(v+1)/2):

= (6(6+1)/2)

= 21

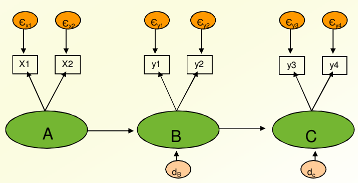


2. Now the limits are known, using the # of parameters from the example we can calculate:

a) total # of variances (exogenous variables): 1
- Ex: A = 1

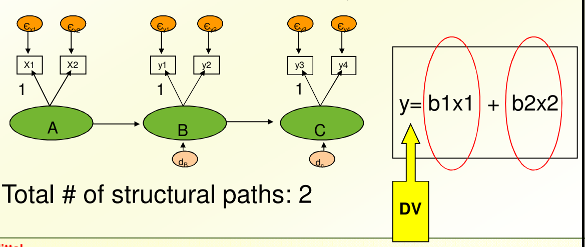
b) total # of d : 2

c) total # of Є: 6



d) Total # of paths: 3

Rule of thumb: Set one path per each set of observed variables to "1" (hence, no longer a free parameter, so no estimation needed since it is now fixed).



e) Total # of structural paths: 2

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

3. Now we must add up all the values:
   1+2+6+3+2= 14

- Please note that our task is much eased since AMOS will tell you if you have the correct number of parameters.
  - It will give you an error, or not run at all if it is under-identified.
  - NB: if your model is based on theory, identification should not be an encountered problem.

Prabhat Mittal
profmittal@yahoo.co.in

Model Identification

- The most effective way to demonstrate that a model is identified is to show that each of the parameters can be solved in terms of the population variances and covariances of the observed variables.
  - Solving covariance equations is time-consuming and there are other 'recipe-like' solutions.

Prabhat Mittal
profmittal@yahoo.co.in

Model Identification

- We gain constantly an identified model if
  - each observed variable in the model measures only one latent factor and
  - factor scale is fixed (Figure 6) or one observed variable per factor is fixed (Figure 7). (Jöreskog et al., 1979, pp. 196-197; 1984.)

Prabhat Mittal
profmittal@yahoo.co.in

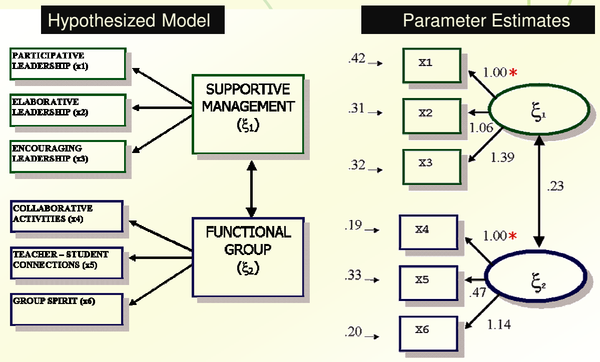
Model Estimation

- When identification is approved, estimation can proceed.
- If the observed variables are normal and linear and there are more than 200 observations, Maximum Likelihood estimation is applicable.
- Large samples are required when the communalities (variance of a measured variable that is explained by the construct on which it loads) become smaller than 0.5.
- *Note:* SEM models Constructs <= 5, each with indicators > 3, and communalities >0.5 preferably Sample size >200.
- SEM models Constructs <= 5, each with indicators <= 3, and communalities <0.5 preferably Sample size >300.

Prabhat Mittal
profmittal@yahoo.co.in

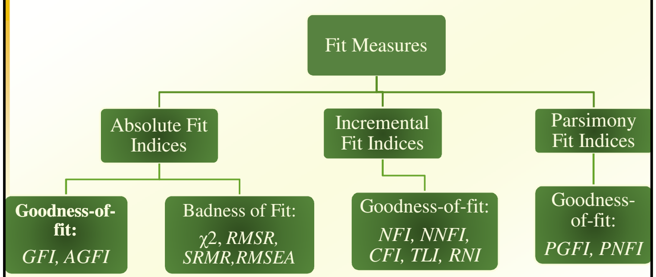
Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Model Estimation



Assess Measurement Model Fit

Fit measures



Fit measures

- Absolute fit Indices each model is evaluated independently of other possible models. These indices directly measure how well the specified model reproduces the observed or sample data.
  - ***Goodness-of- fit*** indices indicate how well the specified model fits the observed or sample data, and so higher values are desired.
  - ***Badness-of -fit*** indices measure error or deviation in some form and so lower values on these indices are desirable.
- Incremental fit indices evaluate how well the specified model fits the sample data relative to some alternative model related to a baseline model.
- Parsimony fit indices are designed to assess fit in relation to model complexity and are useful in comparing models. (*ratio of df used by the model to the total df*)

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Absolute Fit Indices (**Goodness-of-fit**)

Fit Measure	Acceptable Fit
1. Goodness-of-fit: $GFI = 1 - \frac{F_k}{F_0}$	
2. Adjusted goodness-of-fit: $AGFI = 1 - \left(\frac{p(p+1)}{2df}\right)(1 - GFI)$	**higher values >0.9**

Where:
Df : degrees of freedom of the model
P : total number of observed variables
$\mathbf{F_k}$: minimum fit function of the estimated model
$\mathbf{F_0}$: fit function of the baseline model

Prabhat Mittal
profmittal@yahoo.co.in

Absolute Fit Indices (**Badness-of-fit**)

Fit Measure	Acceptable Fit
1. Chi-square (χ^2):(statistical test of significance) $\chi^2 = (n-1)(S - \sum_k)$ $df = \frac{1}{2p(p+1)} - k$	**Lower value of chi-square (Insignificant)**
2. Root mean square residual (RMSR): square root of mean of the squared residuals	
3. Standardized root **mean square residual (SRMR):** to compare the RMSR of two models	**SRMR <=0.08**
4. **Root mean square error of approximation (RMSEA):** $RMSEA = \sqrt{\frac{\frac{\chi^2}{df} - 1}{n-1}}$	**RMSEA <=0.08**

n : sample size **p:** total number of observed variables
K: number of estimated parameters
S : observed sample covariance matrix
Σk: estimated covariance matrix

Prabhat Mittal
profmittal@yahoo.co.in

Incremental Fit Indices (**Goodness-of-fit**)

Fit Measure	Acceptable Fit
1. Normed fit Index: $NFI = \frac{(x^2_{null} - x^2_{prop})}{x^2_{null}}$	
2. Non-normed fit Index or Tucker Lewis Coeff. (TLI): $NNFI = \frac{\left(\frac{x^2_{null}}{df_{null}} - \frac{x^2_{prop}}{df_{prop}}\right)}{\frac{x^2_{null}}{df_{null}}}$	**≥ 0.9**
3. Comparative Fit Index: $CFI = 1 - \frac{(x^2_{prop} - df_{prop})}{(x^2_{null} \quad df_{null})}$	

***null*:** null model
***prop* :** proposed model
As the chi-square value of the *prop* model tends to zero, NFI tens to perfect fit of 1.
NFI does not reflect parsimony; the more parameters in the model, the larger the NFI, hence NNFI is preferred.

Prabhat Mittal
profmittal@yahoo.co.in

Parsimony Fit Indices (**Goodness-of-fit**)

Fit Measure	Acceptable Fit
1. Parsimony GFI: Parsimony ratio calculated as the ratio of *df* used by the model to the total *df* available.	**models with higher values of PGFI & PNFI are preferred**
2. Parsimony NFI: Parsimony ratio * NFI	

Prabhat Mittal
profmittal@yahoo.co.in

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Conclusions

- ***CFI*** and ***RMSEA*** are among the measures least affected by sample size and quite popular in use.
- It is a good practice to always report chi-square value with the associated *df*.
- It is a good practice to use at least one from each i.e. goodness-of –fit, one absolute badness-of-fit and one incremental fit measure.
- If models of different complexities are taken, it is good to use one measure from parsimony fit index.

Measurement Model Reliability, validity and modification

Fit measures

- **Composite Reliability (CR)**
- CR ≥ 0.7 are considered good

$$CR = \frac{\left(\sum_{i=1}^{p} \lambda_i\right)^2}{\left(\sum_{i=1}^{p} \lambda_i\right)^2 + \left(\sum_{i=1}^{p} \delta_i\right)}$$

Completely standardized factor loading
Error variance
No. of indicators or observed variables

- **Convergent Validity:** it measures the extent to which the scale correlates positively with other measures of the same construct. Size of the factor loadings determine CV. High factor loadings should be significant and higher than 0.7.

AVE Average Variance Extracted

Variance explained by latent construct

$$AVE = \frac{\sum_{i=1}^{p} \lambda_i^2}{\sum_{i=1}^{p} \lambda_i^2 + \sum_{i=1}^{p} \delta_i}$$

AVE should be ≥ 0.50

Lack of Validity: Diagnosing Problems

- Path estimates or loadings.
  - ***Standardized loadings should be in range -1 to 1***.
  - Loadings on the indicators should be statistically significant preferably above 0.7. A non-significant can be dropped
  - Sign of the loadings should be in the direction hypothesized by the theory.
- Standardized residuals: ***observed covariance on the sample data – estimated covariance terms divided by the standard error.***
  - Absolute values of SR > 4 are problematic
- Specification approach ***empirical approach to find a better-fitting model.***
  - *Generally not recommended.*
  - *Note that all adjustments/modifications in upto 10% of the observed variables is permissible. Else you must modify the measurement theory and specify a new measurement model.*

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

Model Modification

- If indices indicate a poor fit, you can do post-hoc modifications to see if it is possible to achieve fit.
  - Omission of variables,
  - Dropping non-significant paths,
  - Adding significant paths.
- Caveat: SEM is a knowledge based testing statistical tool. Therefore, applying a post-hoc modification can be a poor practice in theory.

Model Modification-II

- Must remember that it is unreasonable to expect a structural model to fit perfectly.
  - A structural model with linear relations is only an approximation and the world is unlikely to be linear.
  - So instead of asking "Does the model fit perfectly?", you must ask "Does it fit well enough to be a useful approximation of reality and a reasonable explanation of the trends in the data?".

Model Modification-III

- Simply because a model fits well, it does not prove that the model is correct.
  - Fit indicates the that you are on the right track, however you must acknowledge the possibility that it could also be wrong, or that another could be even better.
  - ***Therefore, it is a fallacy to affirm proof.***

Relationship of SEM to Other Multivariate Techniques

- SEM is a dependence technique similar to other multivariate dependence techniques such as Multiple Regression. The endogenous construct is the dependent variable and the constructs with arrows pointing to the endogenous construct are the independent variables. However
  - Dependent in one relationship may become the independent in another relationship unlike Multiple regression.
  - All equations are estimated simultaneously unlike multiple regression.
  - Similar to MANOVA if categorical variables are used in SEM.

- Measurement model of SEM is similar to factor analysis.
- Concepts of correlation and covariance are common in both techniques.
- SEM requires the specification of the measurement model. The loadings are estimated only for the specified relationships and all other loadings are assumed to be zero. Thus SEM is a confirmatory technique.
- In contrast, factor analysis is an explanatory technique EFA. It identifies factors that explain the correlations among a set of variables. Every variable has a loading on every factor extracted which are contained in the factor matrix.

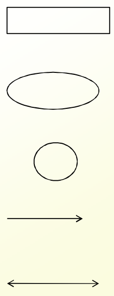
Application of SEM with AMOS

Technology Acceptance Model: TAM

- To predict individuals' reactions to an information technology.
  - A structural model with linear relations is only an approximation and the world is unlikely to be linear.
  - So instead of asking "Does the model fit perfectly?", you must ask "Does it fit well enough to be a useful approximation of reality and a reasonable explanation of the trends in the data?".

Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in

SEM Graphical Vocabulary



Observed Variable

Latent variable estimated from observed variable

Error/ residual in predicting a variable

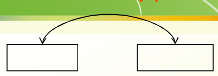
Predictive/ relationship

Association/ Correlation

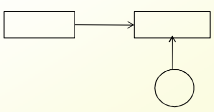
About the variables

- Exogenous variables have causes that are assumed to be external to the model. Exogenous variables can only have double headed arrows (i.e., correlation) going into them.
- Endogenous variables are predicted by other variables in the model. Endogenous variables will have a directed arrow entering into them (i.e., prediction) both from the substantive predictors and a residual term that represents the variance not explained by the predictors.
- Latent variables are not measured directly in a study. They are assumed to bring about the observed responses.
- Observed variables are directly measured in a study.

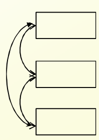
Prototypical Path Diagrams



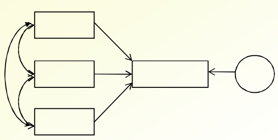
Correlation of two observed variables



Simple regression one predictor

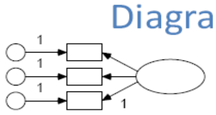


Correlation: between 3 observed variables



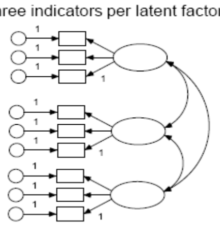
Multiple regression

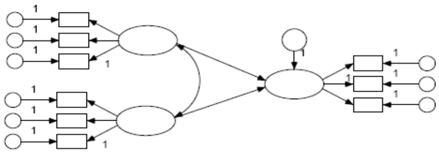
Prototypical Path Diagrams



Latent factor with three indicator variables

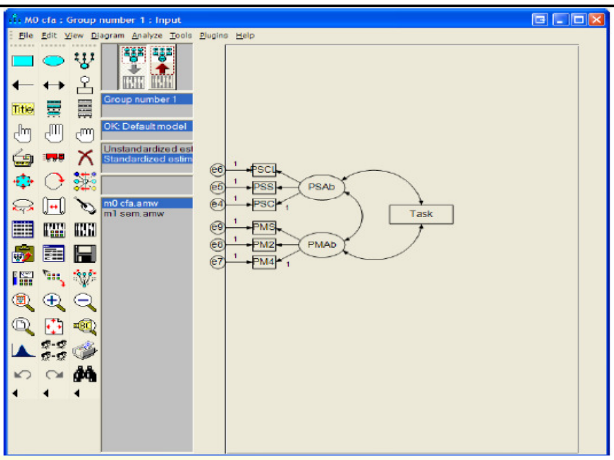
Confirmatory factor analysis with three correlated latent factors and three indicators per latent factor





Structural equation model: One latent variable predicted by two latent predictor variables each latent variable has three indicators each

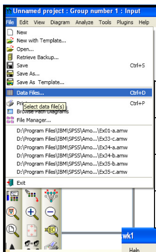
Instructor: **Dr. Prabhat Mittal** M. Sc., M.Phil, Ph.D. (FMS, DU)
Post-doctoral, University of Minnesota, USA
E-mail Id: profmittal@yahoo.co.in



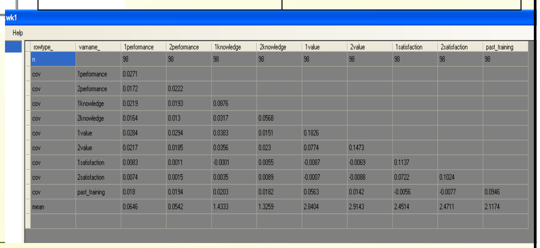
Amos Tools

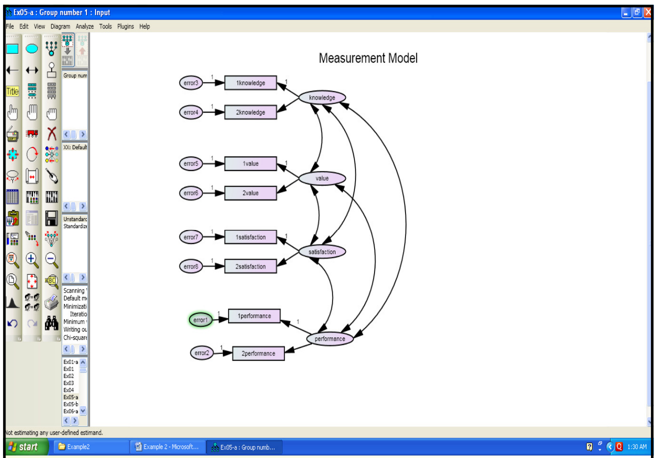
- Draw an observed variable; a latent variable or a latent variable with indicators and error terms
- Draw residual
- Draw regression line or correlation line between two variables
- Select/deselect particular objects; select all; select none
- Move object or selection of objects
- Copy object or selection of objects
- Set analysis properties including method of estimation, output options, and bootstrapping options
- Run the model
- Left downward arrow: model specification mode
  Right upward arrow: output mode
- View tabular output

Case Study



1performance & 2 performance	subtest of Role Performance
1knowledge & 2 knowledge	subtest of Knowledge
1value & 2value	subtest of Value Orientation
1satisfaction & 2satisfiaction	subtest of Role Satisfaction





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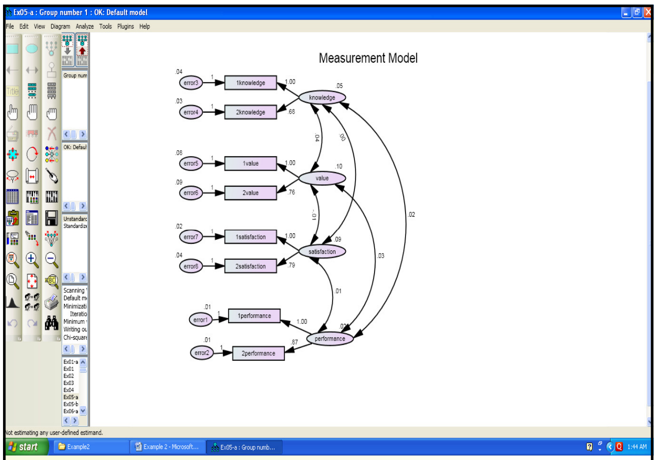
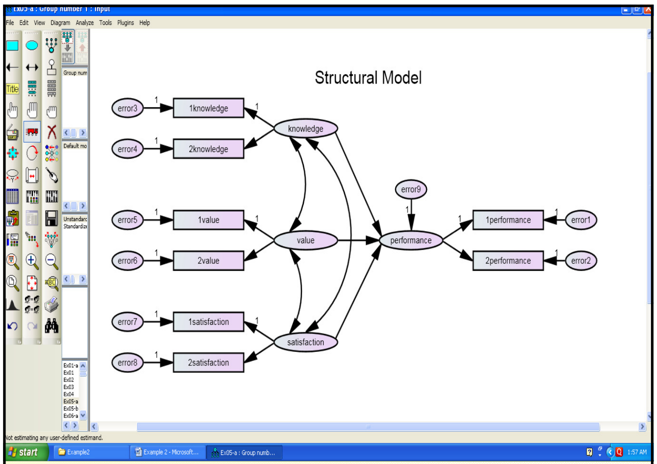
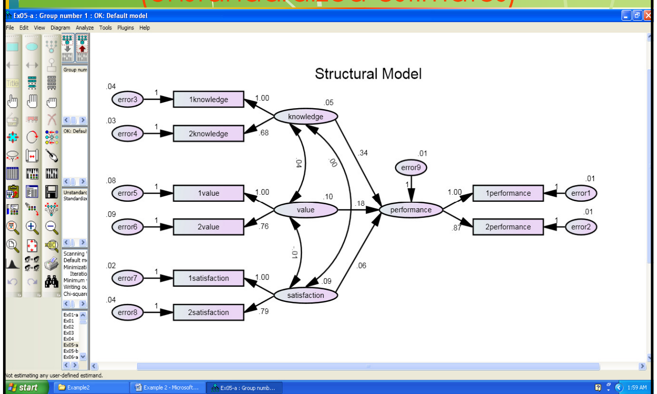
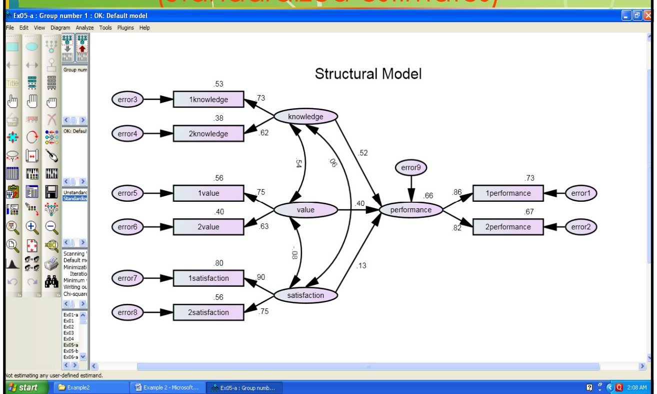




Graphics output (Unstandardized estimates)



Graphics output (Standardized estimates)



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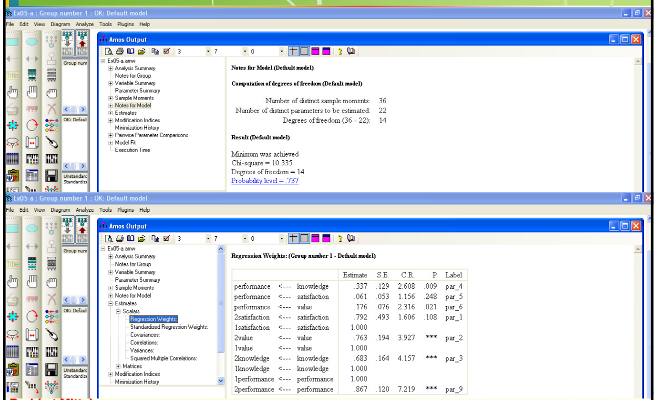
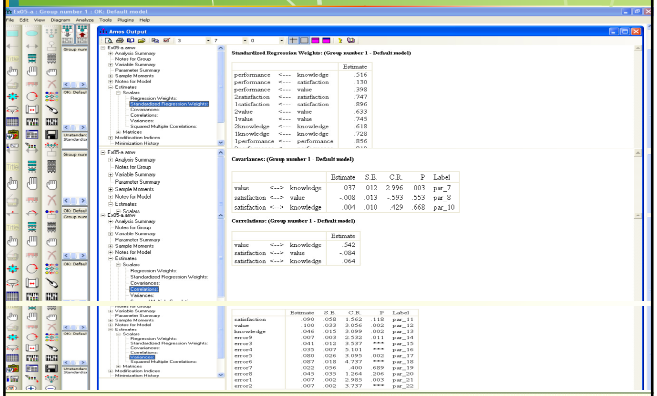
Text Output



Text Output



Advantages of SEM

- Software is very user friendly.
- Allows models with latent variables.
- Studies complex multivariate relationships that are closer to reality (vs. exploratory methods).
- Compensates for lack of perfect reliability in measurement scales (therefore reveals true relationship between variables).
- Due to necessary a priori hypothesis, yielded model provides stronger evidence.

Limitations of SEM

- If there is not enough theoretical background, the model WILL suffer.
- The model is only as good as the validated tests used in the experiment to measure the observed variables.

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