Multivariate Data Analysis

(MGT513, BAT531, TIM711)

Lecture 10

Structural Equation Models 2

References

1. LCG: Ch.10 Structural Equation Models with Latent Variables
2. SEM Exercise 1 – AMOS

   Structural Equation Modeling (Bowen and Guo)

   https://global.oup.com/us/companion.websites/9780195367621/examples/

Ch.10 Structural Equation Models with Latent Variables

Intuition

- Interdependence: The measurement equations relate the observed measures **X** and **Y** to the unobserved factors
- Dependence: The structural equations describe the dependence relationships among the unobserved factors
- **Example**: Measuring the impact of self-esteem on salesperson job satisfaction

TABLE 10.2 Correlations among two measures of job satisfaction (Y_1 and Y_2) and two measures of self-esteem (X_1 and X_2).($n = 106$)

	Y_1	Y_2	X_1	X_2
Y_1	1.000			
Y_2	0.647	1.000		
X_1	0.297	0.288	1.000	
X_2	0.254	0.284	0.548	1.000
Std Dev	3.43	2.81	2.16	2.06

Bagozzi and Aaker (1979)

Measurement Equations (Latent Variables)

- Self-esteem of the salesperson: independent (exogenous) latent variable(ξ) which is not directly observable

$$X_1 = \lambda_{x1}\xi + \delta_1$$
$$X_2 = \lambda_{x2}\xi + \delta_2$$

where a subscript x denotes the factor loadings for the independent variable.

- In matrix notation,

$$\mathbf{X} = \boldsymbol{\Xi}\boldsymbol{\Lambda}_x^{\mathrm{T}} + \boldsymbol{\Delta}$$

$$\boldsymbol{\Xi} = [\xi]$$

$$\mathrm{cov}(\xi) = \Phi$$

$$\mathrm{cov}(\delta) = \Theta_\delta$$

where matrix Θ_δ is generally assumed to be *diagonal*

Measurement Equations (Latent Variables)

- Salesperson satisfaction: dependent (endogenous) latent variable (η) which is not directly observable

$$Y_1 = \lambda_{y1}\eta + \varepsilon_1$$
$$Y_2 = \lambda_{y2}\eta + \varepsilon_2$$

where a subscript y denotes the factor loadings for the independent variable.

- In matrix notation,

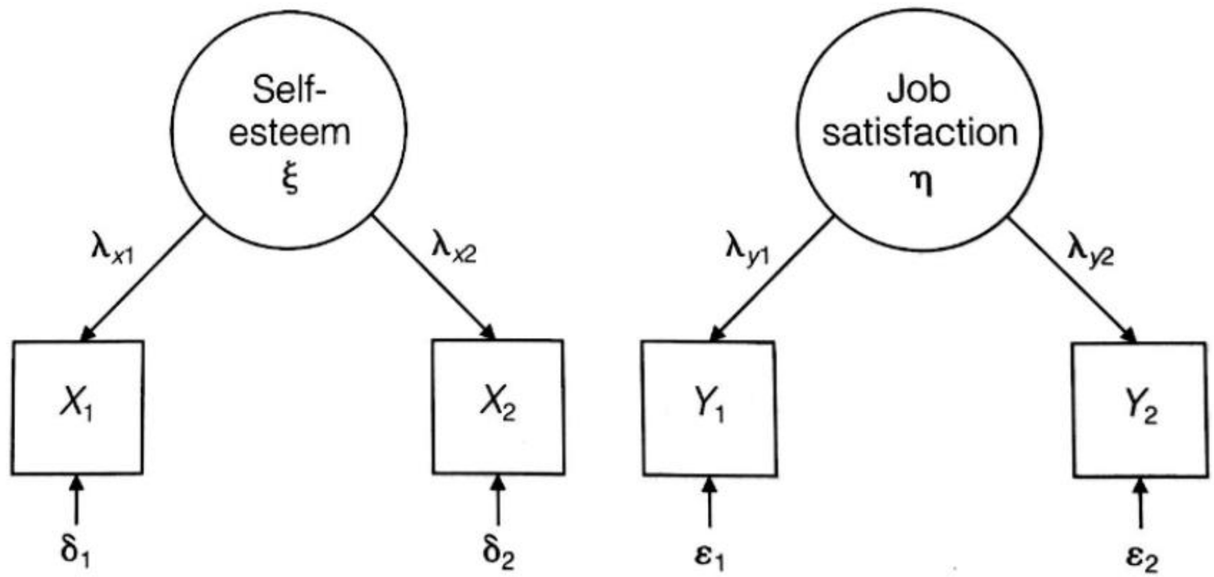
$$\mathbf{Y} = \mathbf{H}\mathbf{\Lambda}_y^{\mathrm{T}} + \mathbf{E}$$

$$\mathbf{H} = [\eta]$$

$$\mathrm{cov}(\varepsilon) = \Theta_\varepsilon$$

Measurement Equations (Latent Variables)

FIGURE 10.2
Measurement models for self-esteem and job satisfaction



- Note: Neither the measurement model for ”self-esteem” nor the model ”satisfaction” is identified on its own

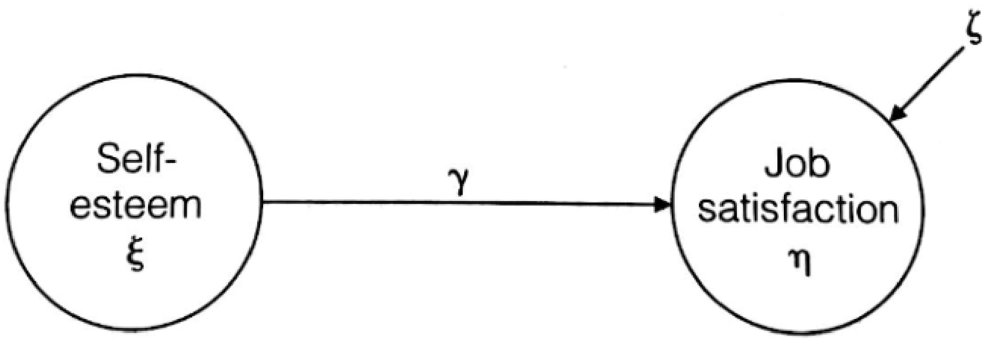
Structural Equations

- Description of the dependence relationships between the dependent latent variable η and the independent latent variable ξ

$$\eta = \gamma\xi + \varsigma$$

- which is a simple linear regression without intercept and $\mathrm{cov}(\varsigma) = \mathbf{\Psi}$

FIGURE 10.3
Structural equation relating job satisfaction to self-esteem



Structural Equations with Latent Variables

- Measurement equations:

$$\mathbf{X} = \xi \mathbf{\Lambda}_x^{\mathrm{T}} + \mathbf{\Delta}$$

where

$$\mathbf{\Lambda}_x = \begin{bmatrix} \lambda_{x1} \\ \lambda_{x2} \end{bmatrix}, \qquad \mathbf{\Theta}_\delta = \begin{bmatrix} \theta_{\delta 11}^2 & 0 \\ 0 & \theta_{\delta 22}^2 \end{bmatrix}, \qquad \mathbf{\Phi} = [1]$$

and also

$$\mathbf{Y} = \eta \mathbf{\Lambda}_y^{\mathrm{T}} + \mathbf{E}$$

where

$$\mathbf{\Lambda}_y = \begin{bmatrix} \lambda_{y1} \\ \lambda_{y2} \end{bmatrix}, \qquad \mathbf{\Theta}_\varepsilon = \begin{bmatrix} \theta_{\varepsilon 11}^2 & 0 \\ 0 & \theta_{\varepsilon 22}^2 \end{bmatrix}$$

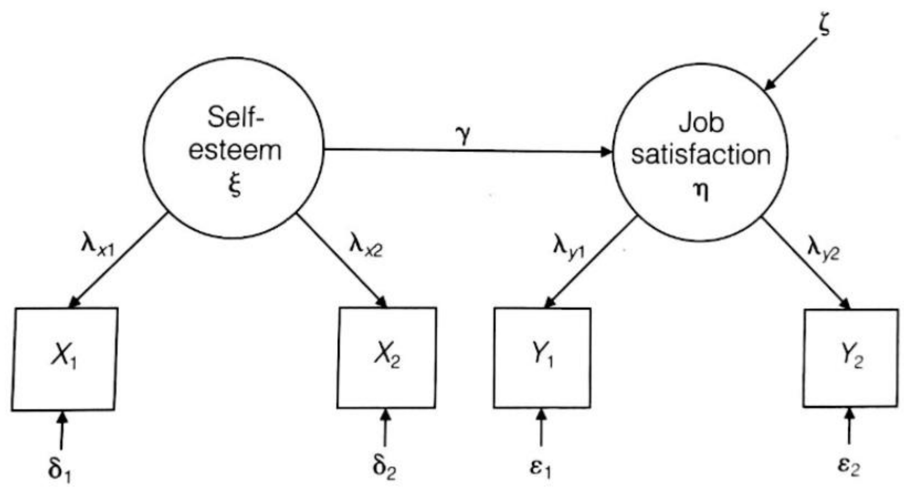
Structural Equations with Latent Variables

- Structural equations:

$$\eta = \gamma\xi + \varsigma$$

$$\mathrm{cov}(\varsigma) = \mathbf{\Psi} = [\psi]$$

FIGURE 10.4
Path diagram showing structural equation model with latent variables



Structural Equations with Latent Variables

- To estimate the parameters for the measurement equation, we need to set $\mathrm{var}(\xi) = 1$ or to set one of the coefficients λ_x equal to 1
- For the measurement of self-esteem, $\underline{\text{set } \mathrm{cov}(\xi) = \boldsymbol{\Phi} = 1}$

$$\mathrm{var}(\eta) = E[(\xi\gamma + \varsigma)^{\mathrm{T}}(\xi\gamma + \varsigma)] = \gamma E[\xi^{\mathrm{T}}\xi]\gamma + 2E[\xi^{\mathrm{T}}\xi]\gamma + E[\zeta^{\mathrm{T}}\zeta]$$
$$= \gamma^2 + \psi$$

- Let's $\underline{\text{set } \lambda_{y1} = 1}$. Then nine parameters must be estimated:

$$\lambda_{x1}, \lambda_{x2}, \theta^2_{\delta 11}, \theta^2_{\delta 12}, \lambda_{y2}, \theta^2_{\varepsilon 11}, \theta^2_{\varepsilon 22}, \gamma, \text{and } \psi$$

- The number of observed variances and covariances is

$$\frac{1}{2}(p+q)(p+q+1)$$

where the model is over-identified with one additional degrees of freedom

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Structural Equations with Latent Variables

$$\mathrm{cov}(X_1, X_2) = \mathrm{cov}(\lambda_{x1}\xi + \delta_1, \lambda_{x2}\xi + \delta_2) = \lambda_{x1}\lambda_{x2} = 0.548$$

$$\mathrm{cov}(X_1, Y_1) = \mathrm{cov}\big(\lambda_{x1}\xi + \delta_1, (\xi\gamma + \varsigma)\lambda_{y1} + \varepsilon_1\big) = \lambda_{x1}\gamma\lambda_{y1} = 0.297$$

$$\mathrm{cov}(X_1, Y_2) = \mathrm{cov}\big(\lambda_{x1}\xi + \delta_1, (\xi\gamma + \varsigma)\lambda_{y2} + \varepsilon_2\big) = \lambda_{x1}\gamma\lambda_{y2} = 0.288$$

$$\mathrm{cov}(X_2, Y_1) = \mathrm{cov}\big(\lambda_{x2}\xi + \delta_2, (\xi\gamma + \varsigma)\lambda_{y1} + \varepsilon_1\big) = \lambda_{x2}\gamma\lambda_{y1} = 0.254$$

$$\mathrm{cov}(X_2, Y_2) = \mathrm{cov}\big(\lambda_{x2}\xi + \delta_2, (\xi\gamma + \varsigma)\lambda_{y2} + \varepsilon_2\big) = \lambda_{x2}\gamma\lambda_{y2} = 0.284$$

$$\begin{aligned}\mathrm{cov}(Y_1, Y_2) &= \mathrm{cov}\big((\xi\gamma + \varsigma)\lambda_{y1} + \varepsilon_1, (\xi\gamma + \varsigma)\lambda_{y2} + \varepsilon_2\big) \\ &= \lambda_{y1}(\gamma^2 + \psi)\lambda_{y2} = 0.647\end{aligned}$$

- Letting $\lambda_{y1} = 1$, five parameters $\lambda_{x1}, \lambda_{x2}, \lambda_{y2}, \gamma, and\ \psi$ are to be estimated by the above six equations. The remaining parameters of the error variances $\theta^2_{\delta 11}, \theta^2_{\delta 12}, \theta^2_{\varepsilon 11}, \theta^2_{\varepsilon 22}$ can be chosen to fit the diagonal elements of the observed covariance matrix

Structural Equations: Extended Model

Example

- In example of attitude, intention and the usage of coupon; one exogenous variable(attitude ξ) and two endogenous variables(intention and behavior, η_1 and η_2)

$$\eta_1 = \gamma_{11}\xi + \varsigma_1$$
$$\eta_2 = \gamma_{21}\xi + \beta_{21}\eta_1 + \varsigma_2$$

- Rearranging the terms gives

$$\eta_1 = \gamma_{11}\xi + \varsigma_1$$
$$-\beta_{21}\eta_1 + \eta_2 = \gamma_{21}\xi + \varsigma_2$$

Structural Equations: Extended Model

- In a matrix form

$$\mathbf{HB} = \mathbf{\Xi\Gamma} + \boldsymbol{Z}$$

where

$$\mathbf{H} = [\eta_1 \;\; \eta_2]$$

$$\mathbf{B} = \begin{bmatrix} 1 & -\beta_{21} \\ 0 & 1 \end{bmatrix}$$

$$\mathbf{\Xi} = [\xi]$$

$$\mathbf{\Gamma} = \begin{bmatrix} \gamma_{11} \\ \gamma_{21} \end{bmatrix}$$

$$\mathbf{Z} = [\varsigma_1 \;\; \varsigma_2]$$

Mechanics

Let $\mathbf{S}$ = the observed covariance matrix between $\mathbf{X}$ and $\mathbf{Y}$

$$\mathbf{S} = \begin{bmatrix} \mathbf{S}_{YY} & \mathbf{S}_{YX} \\ \mathbf{S}_{XY} & \mathbf{S}_{XX} \end{bmatrix}$$

which is an estimate of the population covariance matrix between $\mathbf{X}$ and $\mathbf{Y}$

$$\boldsymbol{\Sigma} = \begin{bmatrix} E(\mathbf{Y}^{\mathrm{T}}\mathbf{Y}) & E(\mathbf{Y}^{\mathrm{T}}\mathbf{X}) \\ E(\mathbf{X}^{\mathrm{T}}\mathbf{Y}) & E(\mathbf{X}^{\mathrm{T}}\mathbf{X}) \end{bmatrix}$$

Since $\mathbf{Y} = \mathbf{H}\boldsymbol{\Lambda}_y^{\mathrm{T}} + \mathbf{E}$

$$E\left(\mathbf{Y}^{\mathrm{T}}\mathbf{Y}\right) = E\left[\left(\mathbf{H}\boldsymbol{\Lambda}_y^{\mathrm{T}} + \mathbf{E}\right)^{\mathrm{T}}\left(\mathbf{H}\boldsymbol{\Lambda}_y^{\mathrm{T}} + \mathbf{E}\right)\right] = \boldsymbol{\Lambda}_y \mathrm{var}(\mathbf{H})\boldsymbol{\Lambda}_y^{\mathrm{T}} + \boldsymbol{\Theta}_\varepsilon$$

Thus

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Lambda}_y \mathrm{var}(\mathbf{H})\boldsymbol{\Lambda}_y^{\mathrm{T}} + \boldsymbol{\Theta}_\varepsilon & \boldsymbol{\Lambda}_y \mathrm{cov}(\mathbf{H}, \boldsymbol{\Xi})\boldsymbol{\Lambda}_x^{\mathrm{T}} \\ \boldsymbol{\Lambda}_x \mathrm{cov}(\mathbf{H}, \boldsymbol{\Xi})\boldsymbol{\Lambda}_y^{\mathrm{T}} & \boldsymbol{\Lambda}_x \mathrm{var}(\boldsymbol{\Xi})\boldsymbol{\Lambda}_x^{\mathrm{T}} + \boldsymbol{\Theta}_\delta \end{bmatrix}$$

Mechanics

The covariance matrix of exogenous and endogenous factors $\boldsymbol{\Xi}$ and $\mathbf{H}$ is given by

$$\boldsymbol{\Sigma}_{\eta\xi} = \begin{bmatrix} \mathrm{var}(\mathbf{H}) & \mathrm{cov}(\mathbf{H}, \boldsymbol{\Xi}) \\ \mathrm{cov}(\mathbf{H}, \boldsymbol{\Xi}) & \mathrm{var}(\boldsymbol{\Xi}) \end{bmatrix}$$

Since $\mathbf{HB} = \boldsymbol{\Xi}\boldsymbol{\Gamma} + \boldsymbol{Z}$

$$\begin{aligned} \mathrm{var}(\mathbf{H}) &= E[\mathbf{B}^{-1}(\boldsymbol{\Xi}\boldsymbol{\Gamma} + \mathbf{Z})^{\mathrm{T}}(\boldsymbol{\Xi}\boldsymbol{\Gamma} + \mathbf{Z})\mathbf{B}^{-\mathrm{T}}] \\ &= \mathbf{B}^{-1}(\boldsymbol{\Gamma}\boldsymbol{\Phi}\boldsymbol{\Gamma}^{\mathrm{T}} + \boldsymbol{\Psi})\mathbf{B}^{-\mathrm{T}} \end{aligned}$$

Therefore

$$\boldsymbol{\Sigma}_{\eta\xi} = \begin{bmatrix} \mathbf{B}^{-1}(\boldsymbol{\Gamma}\boldsymbol{\Phi}\boldsymbol{\Gamma}^{\mathrm{T}} + \boldsymbol{\Psi})\mathbf{B}^{-\mathrm{T}} & \mathbf{B}^{-1}\boldsymbol{\Gamma}\boldsymbol{\Phi} \\ \boldsymbol{\Phi}\boldsymbol{\Gamma}^{\mathrm{T}}\mathbf{B}^{-\mathrm{T}} & \boldsymbol{\Phi} \end{bmatrix}$$

Mechanics

Finally

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Lambda}_y \mathbf{B}^{-1}(\boldsymbol{\Gamma}\boldsymbol{\Phi}\boldsymbol{\Gamma}^{\mathrm{T}} + \boldsymbol{\Psi})\mathbf{B}^{-\mathrm{T}}\boldsymbol{\Lambda}_y^{\mathrm{T}} + \boldsymbol{\Theta}_\varepsilon & \boldsymbol{\Lambda}_y \mathbf{B}^{-1}\boldsymbol{\Gamma}\boldsymbol{\Phi}\boldsymbol{\Lambda}_x^{\mathrm{T}} \\ \boldsymbol{\Lambda}_x \boldsymbol{\Phi}\boldsymbol{\Gamma}^{\mathrm{T}}\mathbf{B}^{-\mathrm{T}}\boldsymbol{\Lambda}_y^{\mathrm{T}} & \boldsymbol{\Lambda}_x \boldsymbol{\Phi}\boldsymbol{\Lambda}_x^{\mathrm{T}} + \boldsymbol{\Theta}_\delta \end{bmatrix}$$

- The maximum likelihood estimation procedure provides estimates of the asymptotic standard error of each model parameter, which can be used to perform *t*-tests of significance.
- The chi-square tests of model fit and goodness-of-fit indices described in Chapter 6 (on confirmatory factor analysis) can be used to assess structural equation models with latent variables.

Sample problem:
Modelling the adoption of Innovation

- Forecasting the adoption of a new technology product
- Two dependent (endogenous) variables: Measures of intended early adoption (ADOPT), Y_1 and Y_2
- Three independent (exogenous) variables: Measures of the value (VALUE) of the innovation (all on five-point Likert scale), X_1 , X_2 and X_3
- Three independent (exogenous) variables: Measures of leading-edge usage (all on five-point Likert scale), X_4 , X_5 and X_6

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Sample problem: Modelling the adoption of Innovation

- Measures of intended early adoption (ADOPT):
  - Y_1: "Suppose that Stateflow® were available to you today. What are the chances (out of 100) that you would adopt Stateflow® within the next month?"
  - Y_2: "If you discovered that (only) 10 percent of Simulink® users would be adopting Stateflow® over the next six months, what would be your chances (out of 100) of adopting Stateflow® during the same period?"
- Measures of the value (VALUE) of the innovation (all on five-point Likert scale):
  - X_1: "Stateflow® will enhance my ability to deal with complex simulation problems."
  - X_2: "Stateflow® will be suitable for dealing with problems in my application area."
  - X_3: "Stateflow® will increase my capability for dealing with discrete logic systems "

Sample problem: Modelling the adoption of Innovation

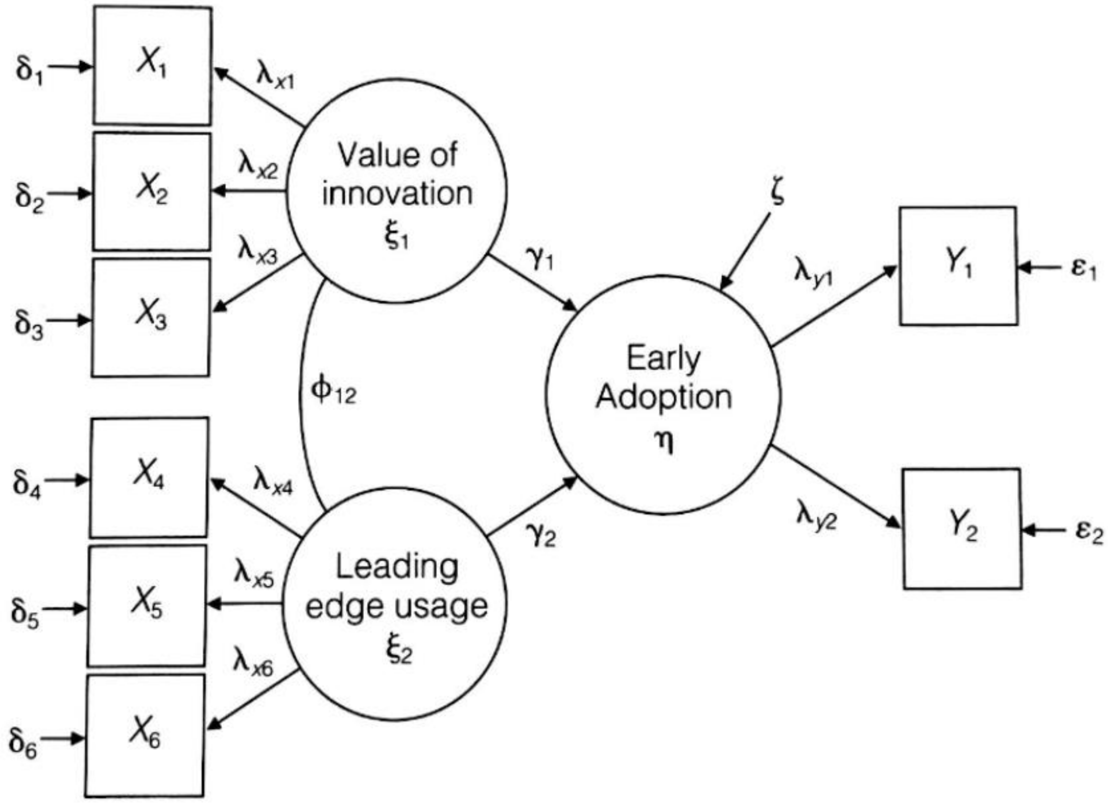
- Measures of leading-edge usage (all on five-point Likert scale):
  - X_4: "We are quick to take advantage of new technical opportunities."
  - X_5: "We are willing to take risks in the adoption of new software."
  - X_6: "We are usually ahead of others in recognizing and planning solutions to problems."

TABLE10.5 Correlation matrix for data collected by Lattin and Roberts (n = 188)

	Y_1	Y_2	X_1	X_2	X_3	X_4	X_5	X_6
Y_1	1.000							
Y_2	0.599	1.000						
X_1	0.478	0.571	1.000					
X_2	0.464	0.580	0.763	1.000				
X_3	0.360	0.481	0.628	0.720	1.000			
X_4	0.263	0.110	0.187	0.208	0.122	1.000		
X_5	0.248	0.156	0.124	0.139	0.051	0.437	1.000	
X_6	0.222	0.104	0.155	0.191	0.054	0.542	0.421	1.000

Sample problem: Modelling the adoption of Innovation

FIGURE 10.6 Path diagram for model describing impact of innovation and leading-edge usage on adoption



Sample problem: Modelling the adoption of Innovation

- Measurement equations:

$$Y_1 = 1.0\eta + \varepsilon_1$$
$$Y_2 = \lambda_{y2}\eta + \varepsilon_2$$
$$X_1 = \lambda_{x11}\xi_1 + \delta_1$$
$$X_2 = \lambda_{x21}\xi_1 + \delta_2$$
$$X_3 = \lambda_{x31}\xi_1 + \delta_3$$
$$X_4 = \lambda_{x42}\xi_2 + \delta_4$$
$$X_5 = \lambda_{x52}\xi_2 + \delta_5$$
$$X_6 = \lambda_{x62}\xi_2 + \delta_6$$

$$\mathbf{\Phi} = \begin{bmatrix} 1 & \phi_{12} \\ \phi_{21} & 1 \end{bmatrix}$$

- Structural equations:

$$\eta = \xi_1\gamma_1 + \xi_2\gamma_2 + \varsigma$$

$$\mathbf{\Psi} = [\psi]$$

Sample problem:
Modelling the adoption of Innovation

TABLE 10.6 Parameter estimates for structural equation model of Lattin and Roberts data

Goodness-of-fit index (GFI)		0.9759
GFI adjusted for degrees of freedom (AGFI)		0.9489
Root mean square residual (RMR)		0.0363
$\chi^2 = 16.4009$	$df = 17$	$p = 0.4956$
Null model chi-square:	$df = 28$	541.8123

Model Coefficient	Parameter Estimate	Standard Error	Standardized Solution
λ_{y1}	1.0000	***	0.6927
λ_{y2}	1.2446	(0.1601)	0.8621
λ_{x1}	0.8443	(0.0656)	0.8433
λ_{x2}	0.9138	(0.0629)	0.9138
λ_{x3}	0.7695	(0.0682)	0.7695
λ_{x4}	0.7514	(0.0910)	0.7514
λ_{x5}	0.5618	(0.0868)	0.5618
λ_{x6}	0.6660	(0.0888)	0.6660
γ_1	0.5120	(0.0765)	0.7392
γ_2	0.0520	(0.0585)	0.0751
ϕ_{12}	0.2836	(0.0912)	0.2836

*** Parameter value fixed to 1.0
Estimates of error variances not shown

Model diagnostics

- Failure to Converge
  - Occasionally, an indication of an ill-conditioned or inappropriately specified model
  - Remedy: Use different starting value / respecify the model
- Infeasible Estimates(e.g., Negative Variances)
  - If estimates of some variance parameters are negative, then the estimates are infeasible
  - Remedy: Use different starting value
  - Constraining the estimate to a feasible range often simply masks the problem rather than dealing with it

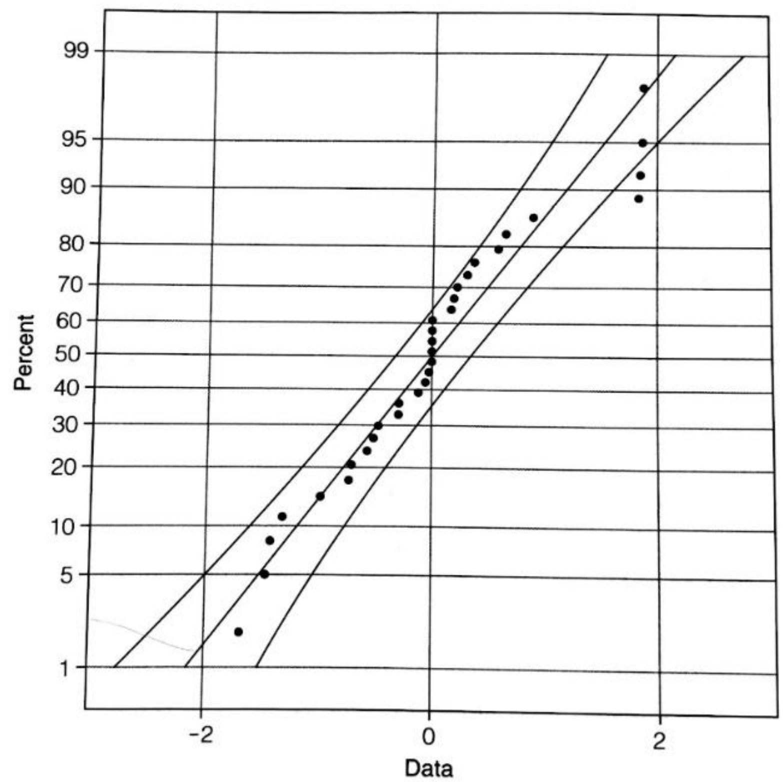
Model diagnostics

- Pattern of Residuals
  - Residuals: differences between the observed
  - covariances and the covariances values as fitted by the model
  - Residuals capture ”outliers” or ”model adequacy”
  - Use a probability plot of the normalized residuals: Roughly speaking, two-thirds of the observations should fall within one standard deviation of zero, and only 5 percent of the observations should fall outside two standard deviations

Model diagnostics

- Pattern of Residuals

FIGURE 10.7
Distribution of standardized residuals from Lattin and Roberts model



Model diagnostics

- Modification Indices
  - Modification indices help us answer 'what if?' questions about whether freeing parameter constraints or adding paths to our models would help improve it.
  - The modification index is the χ^2 value, with 1 degree of freedom, by which model fit would improve if a particular path was added or constraint freed.
  - Values bigger than 3.84 indicate that the model would be 'improved', and the *p*-value for the added parameter would be < .05, and values larger 10.83 than indicate the parameter would have a *p*-value < .001.
  - It can be an aid to improving the model, in combination with domain or theoretical knowledge.

Source: https://benwhalley.github.io/just-enough-r/modification-indices.html

Structural Equation Modeling
(Exercise 1 - AMOS)

The Stages in Conducting SEM

1. Defining Individual Constructs
2. Developing the Overall Measurement Model
3. Designing a Study to Produce Empirical Results
4. Assessing the Measurement Model Validity
5. Specifying the Structural Model
6. Assessing Structural Model Validity

Stage 4 and Stage 6 : Model fits

Measure	Name	Description	Cut-off for good fit
X^2	Model Chi-Square	Assess overall fit and the discrepancy between the sample and fitted covariance matrices. Sensitive to sample size. H_0: The model fits perfectly.	p-value> 0.05
(A)GFI	(Adjusted) Goodness of Fit	GFI is the proportion of variance accounted for by the estimated population covariance. Analogous to R^2. AGFI favors parsimony.	GFI ≥ 0.95 AGFI ≥0.90
(N)NFI TLI	(Non) Normed-Fit Index Tucker Lewis index	An NFI of .95, indicates the model of interest improves the fit by 95% relative to the null model. NNFI is preferable for smaller samples. Sometimes the NNFI is called the Tucker Lewis index (TLI)	NFI ≥ 0.95 NNFI ≥ 0.95
CFI	Comparative Fit Index	A revised form of NFI. Not very sensitive to sample size. Compares the fit of a target model to the fit of an independent, or null, model.	CFI ≥.90
RMSEA	Root Mean Square Error of Approximation	A parsimony-adjusted index. Values closer to 0 represent a good fit.	RMSEA < 0.08
(S)RMR	(Standardized) Root Mean Square Residual	The square-root of the difference between the residuals of the sample covariance matrix and the hypothesized model. If items vary in range (i.e. some items are 1-5, others 1-7) then RMR is hard to interpret, better to use SRMR.	SRMR <0.08
AVE (CFA only)	Average Value Explained	The average of the R^2s for items within a factor	AVE >.5

Source:
https://www.cscu.cornell.edu/news/Handouts/SEM_fit.pdf

Model fit indices

Fit statistic	Cut off point
Chi-square	Non-significant
RMSEA	.08 or below
CFI	.95 or above
SRMR	.08 or below
GFI	0.95 or above

AMOS Examples

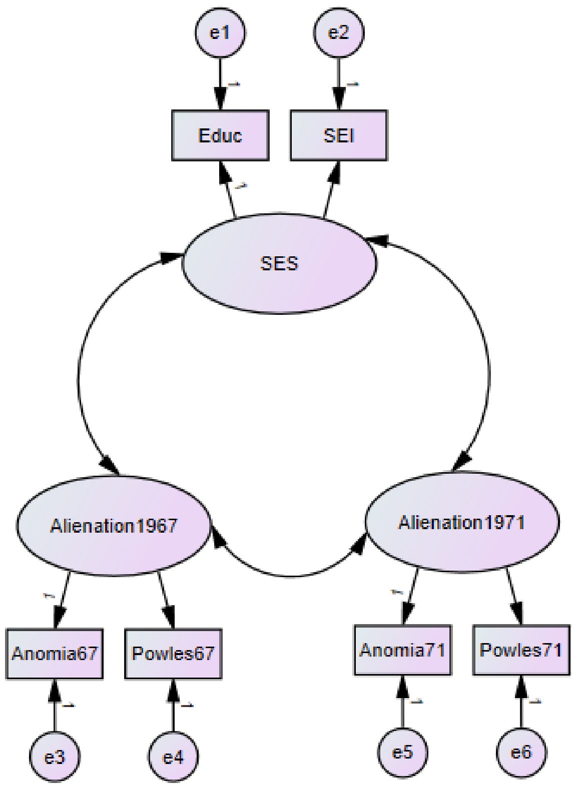
1. Wheaton, Muthen, Alwin, and Summers (1977), “Assessing reliability and stability in panel models”
2. Bollen (1989), “A panel model of political democracy and industrialization for developing countries”
3. Bagozzi, R. (1980), “Performance and satisfaction in an industrial sales force: An examination of their antecedents and simultaneity”

Example 1

- Testing a model of the stability of alienation over time, as measured by anomia and powerlessness feelings at two measurement occasions, 1967 and 1971, as well as education level and a socioeconomic index.

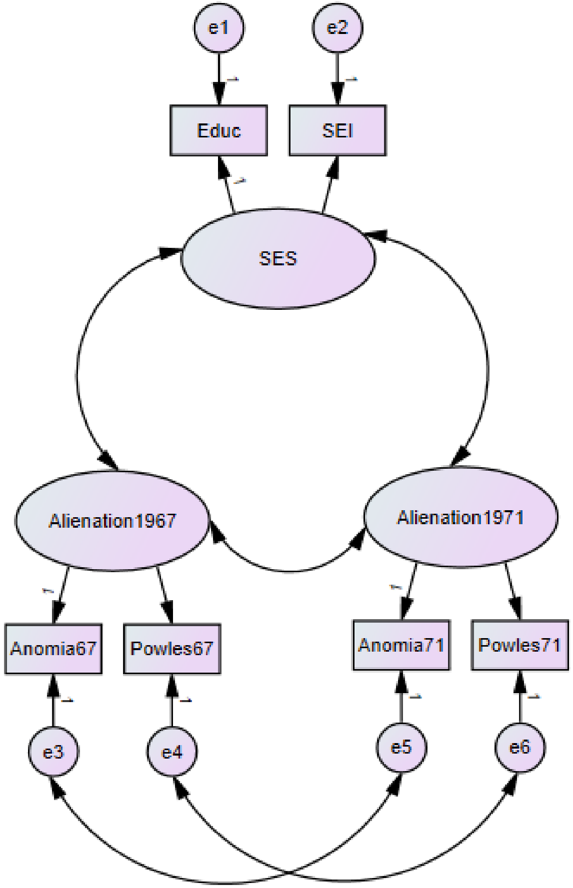
Source: Structural Equation Modeling Using AMOS (https://stat.utexas.edu/images/SSC/Site/AMOS_Tutorial.pdf)

Example 1: CFA 1



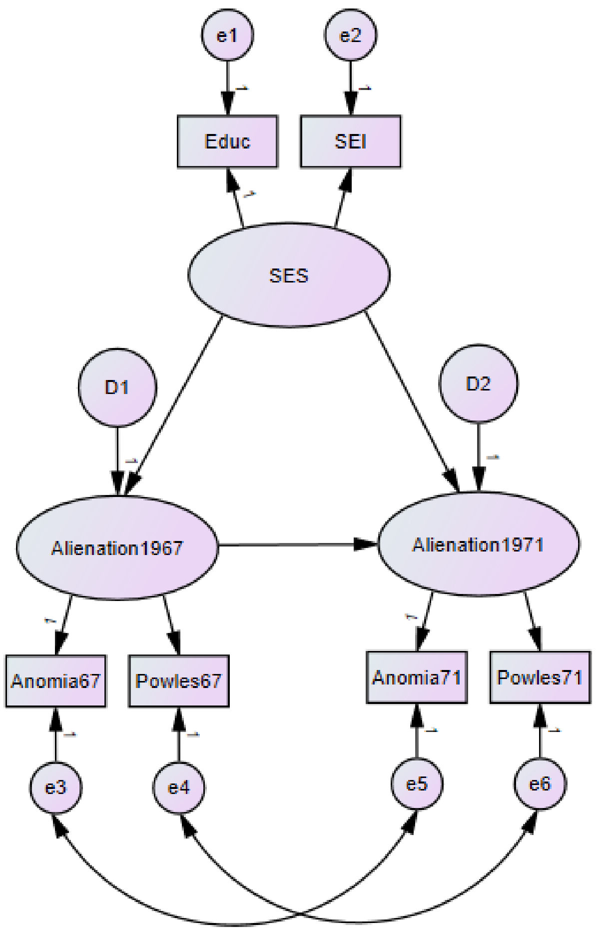
W1: CFA 1

Example 1: CFA 2



W2: CFA 2

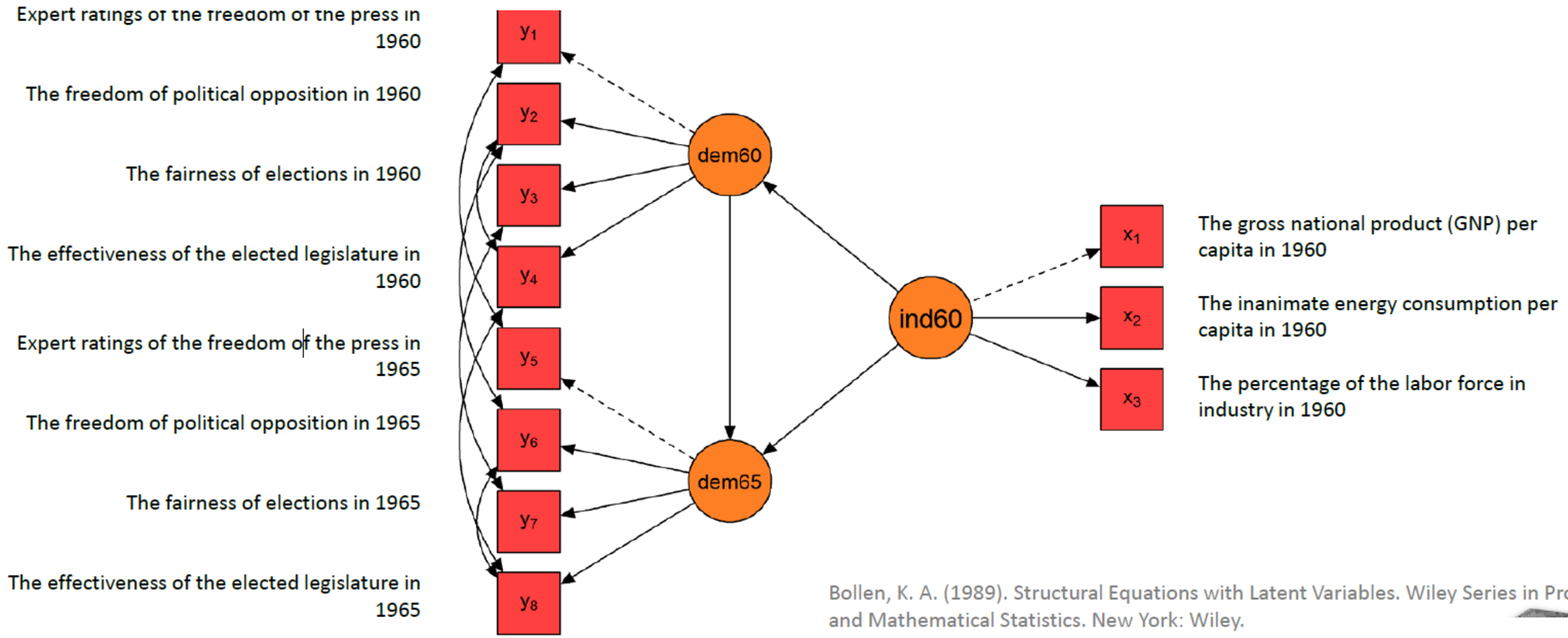
Example 1: Structural model



W3: Structural Model

Example 2

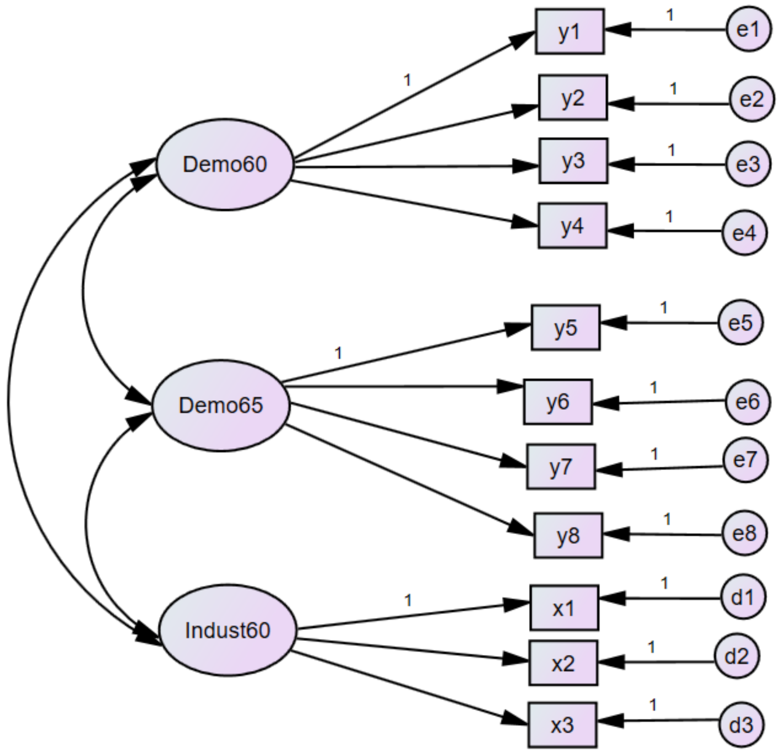
- Influence of industrialization ('60) on political democracy ('60 and '65)



Bollen, K. A. (1989). Structural Equations with Latent Variables. Wiley Series in Probability and Mathematical Statistics. New York: Wiley.

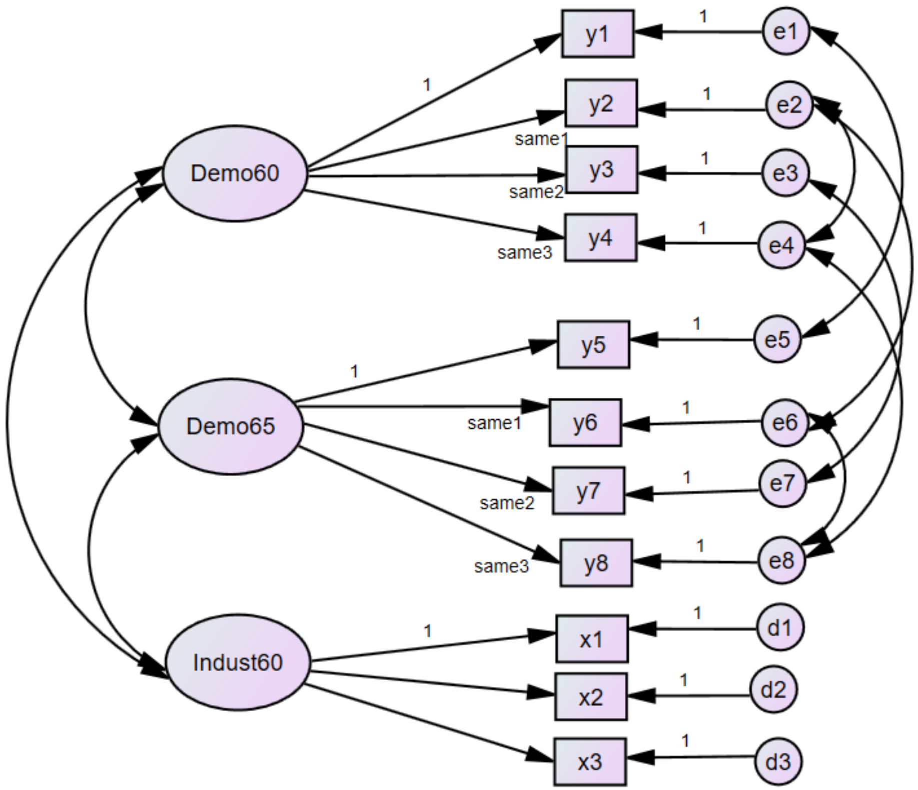
Source: Structural Equation Modeling by Bowen and Guo
(https://global.oup.com/us/companion.websites/9780195367621/examples/)

Example 2: CFA 1



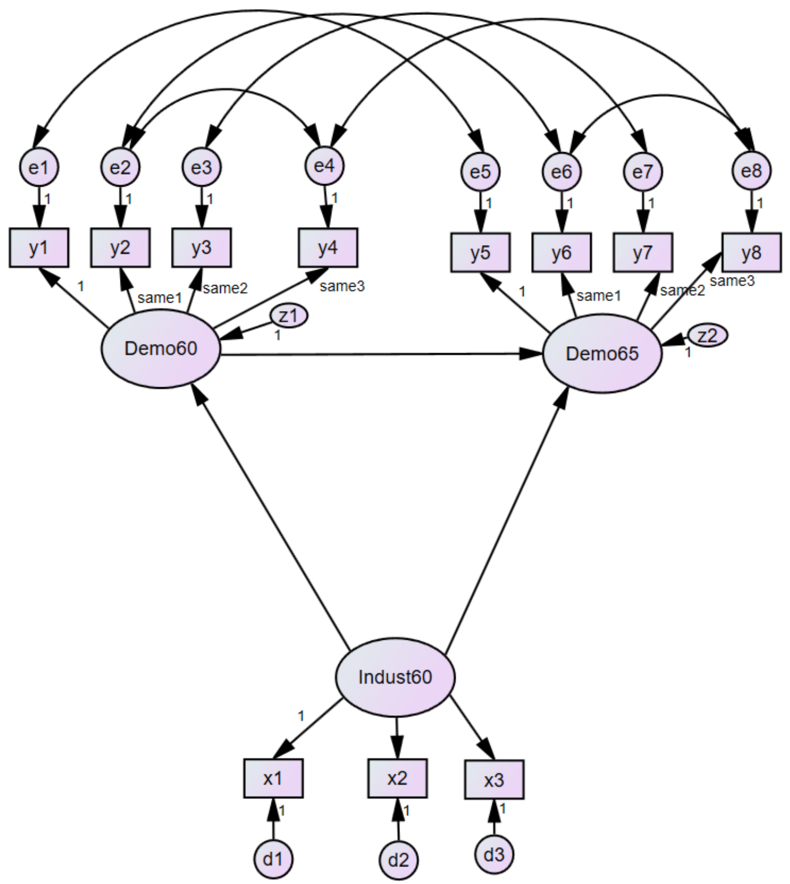
BM1: CFA 1 of Bollen Mode(1989) p.324

Example 2: CFA 2



BM2: CFA 2 of Bollen Mode(1989) p.324 - Respedification

Example 2: Structural model



BM3: Structural Regression Model (A Panel Model) Bollen (1989) p.324

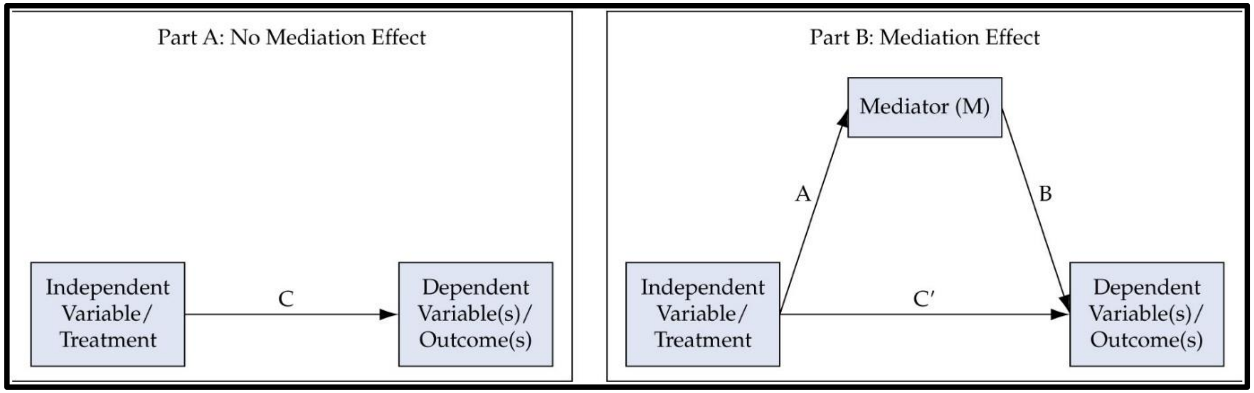
Example 2

- Direct effect and Indirect effect of industrialization (’60) on political democracy (‘65)
- Calculating confidence intervals & p-values via bootstrapping

Mediation

Involves two additional relationships (A and B) which create the indirect effect (A x B)

- Introducing this indirect effect into the analysis allows for an “alternative” effect to supplant the direct effect (C).
- The result is **two** types of mediation:
  - Full (Complete) mediation -- C’ becomes non-significant
  - Partial mediation – C’ is still significant while the indirect effect is also significant



- Statistical significance of the indirect effect tested by *Sobel test* or *bootstrapping*

Example 3

Relationship between performance and job satisfaction

Research questions:

1. Controlling for exogenous factors (i.e., achievement motivation, task-specific self esteem, and verbal intelligence), is the relationship between performance and job satisfaction myth or reality?
2. Controlling for exogenous factors (i.e., achievement motivation, task-specific self esteem, and verbal intelligence), does performance influence satisfaction, or does satisfaction influence performance?

Source: Structural Equation Modeling by Bowen and Guo
(https://global.oup.com/us/companion.websites/9780195367621/examples/)

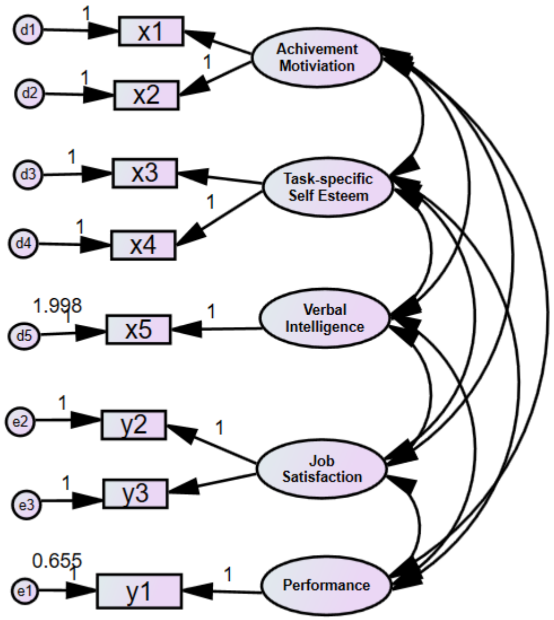
Example 3

Four hypotheses:

1. H1: the correlation is spurious; the two latent variables are correlated, because they are both determined by common causes of k1 (Achievement Motivation), k2 (Task-specific Self Esteem), and k3 (Verbal Intelligence).
2. H2: n2 (job satisfaction) influences n1 (performance).
3. H3: n1 (performance) influences n2 (job satisfaction).
4. H4: n1 (performance) and n2 (job satisfaction) influence each other reciprocally.

Source: Structural Equation Modeling by Bowen and Guo
(https://global.oup.com/us/companion.websites/9780195367621/examples/)

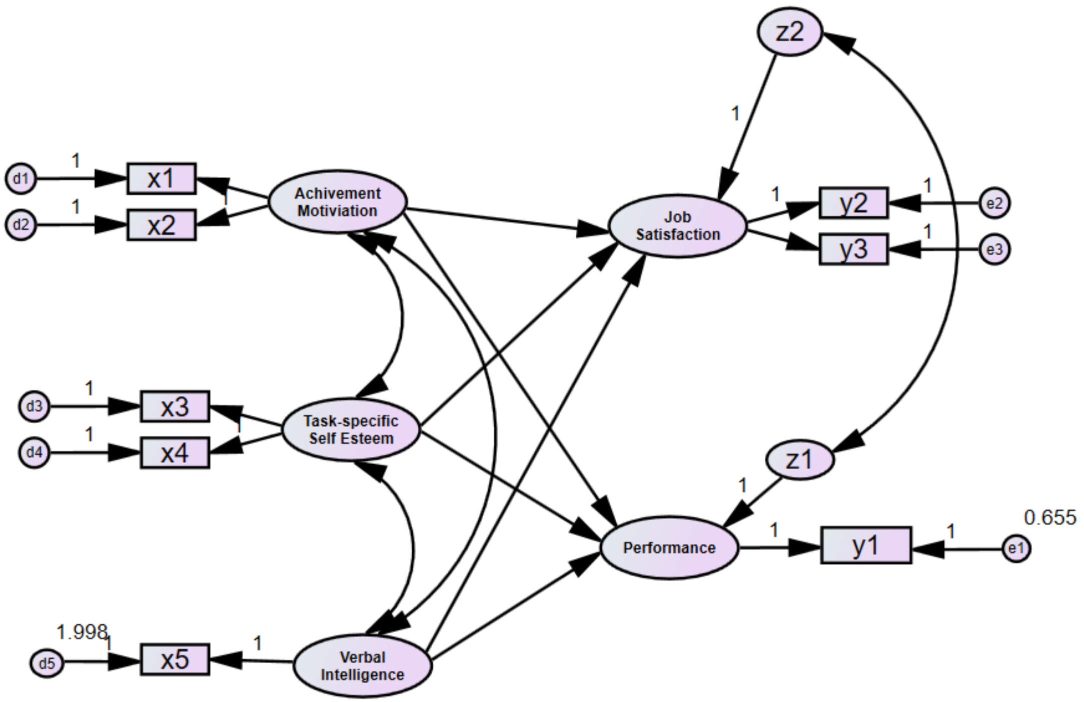
Example 3: CFA



Job1: CFA Measurement model about
job satisfaction and performance (Bagozzi, 1980)

Example 3: H1

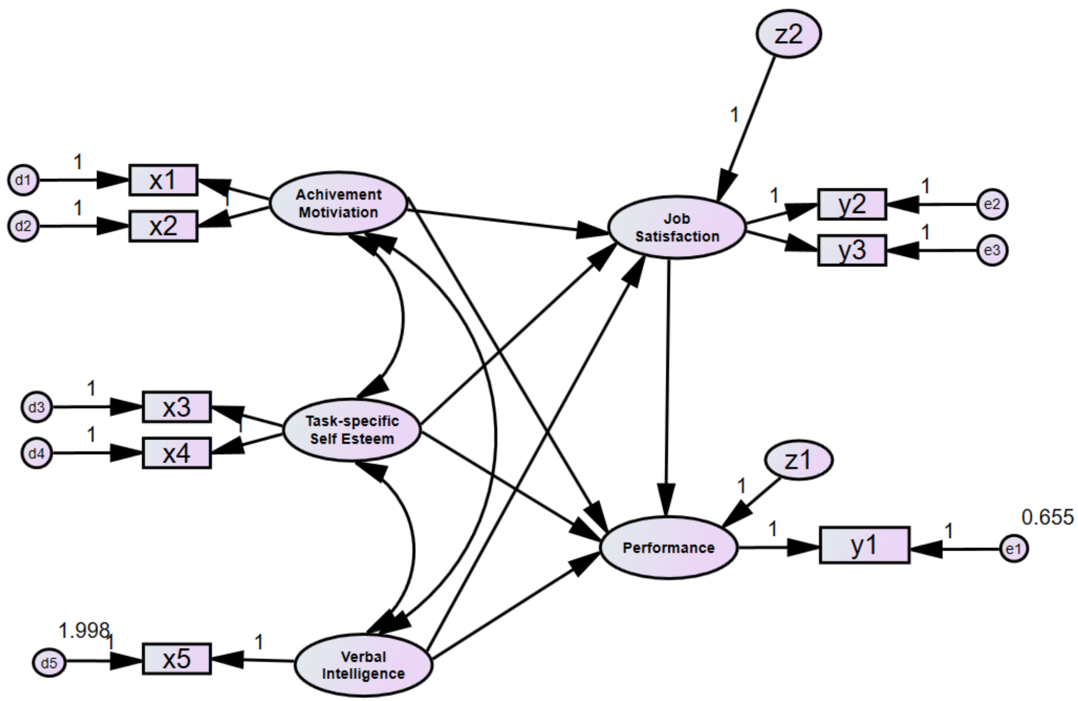
- H1: Spurious correlation of job satisfaction and performance



Job 2: (Bagozzi, 1980) Test "H1: Spurious correlation of job satisfaction & performance"
- They have the three exogenous factors as common causes

Example 3: H2

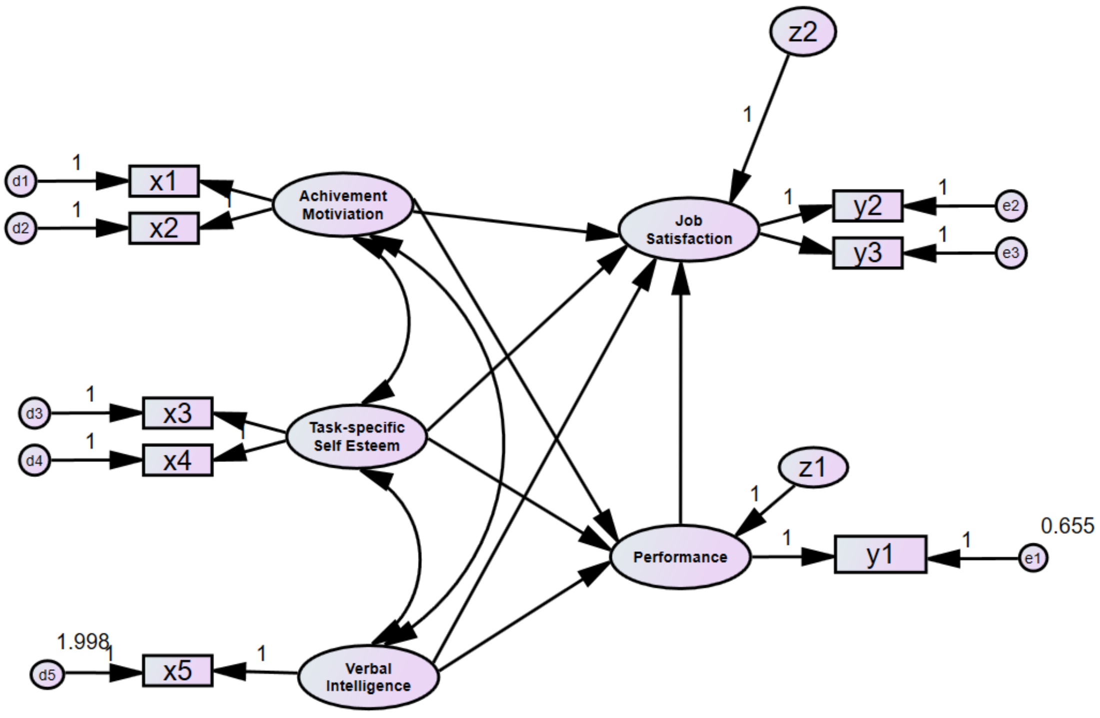
- H2: Job satisfaction influences performance



Job 3: (Bagozzi, 1980) Test "H2: job satisfaction influences performance"

Example 3: H3

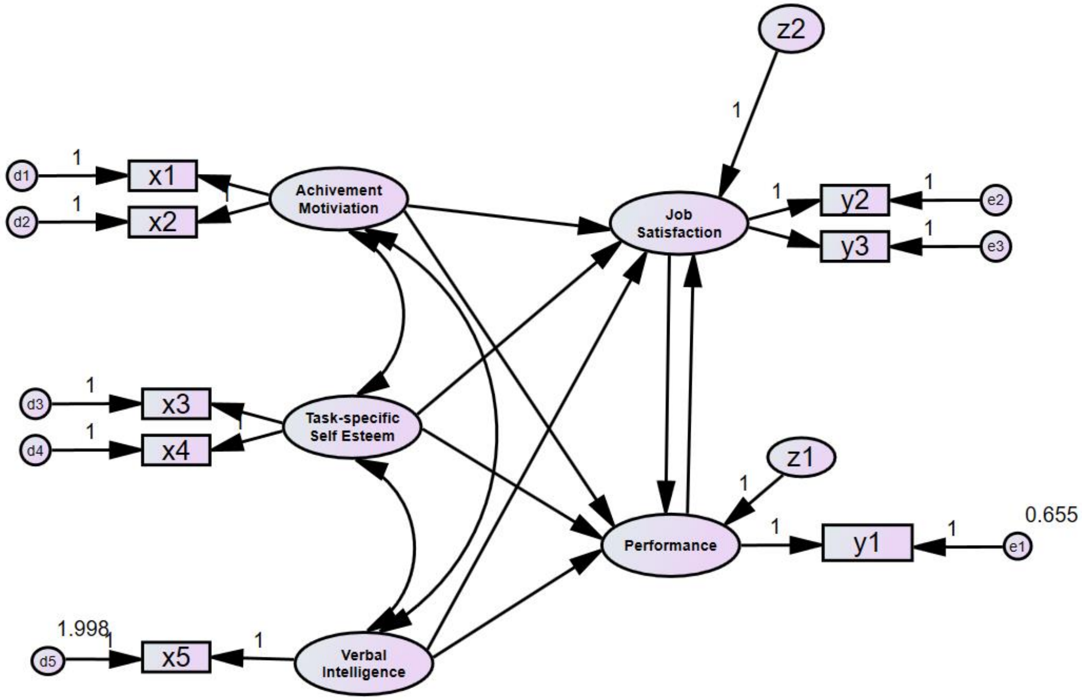
- H3: Performance influences Job satisfaction



Job 4: (Bagozzi, 1980) Test "H3 performance influences job satisfaction"

Example 3: H4

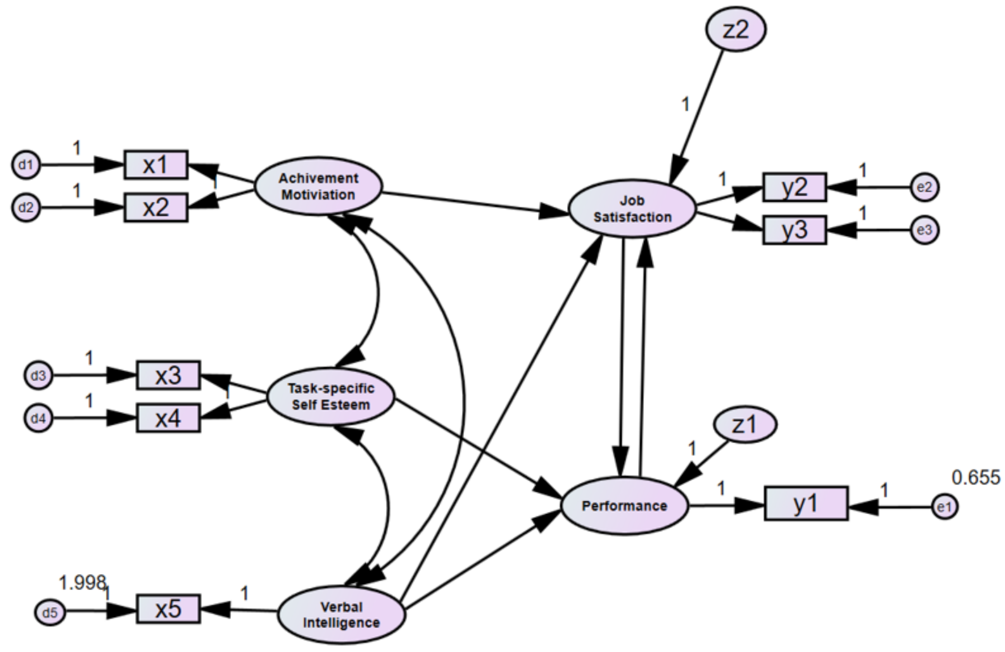
- H4: Non-recursive relation



Job 5: (Bagozzi, 1980) Test "H4: nonrecursive relation"

Example 3

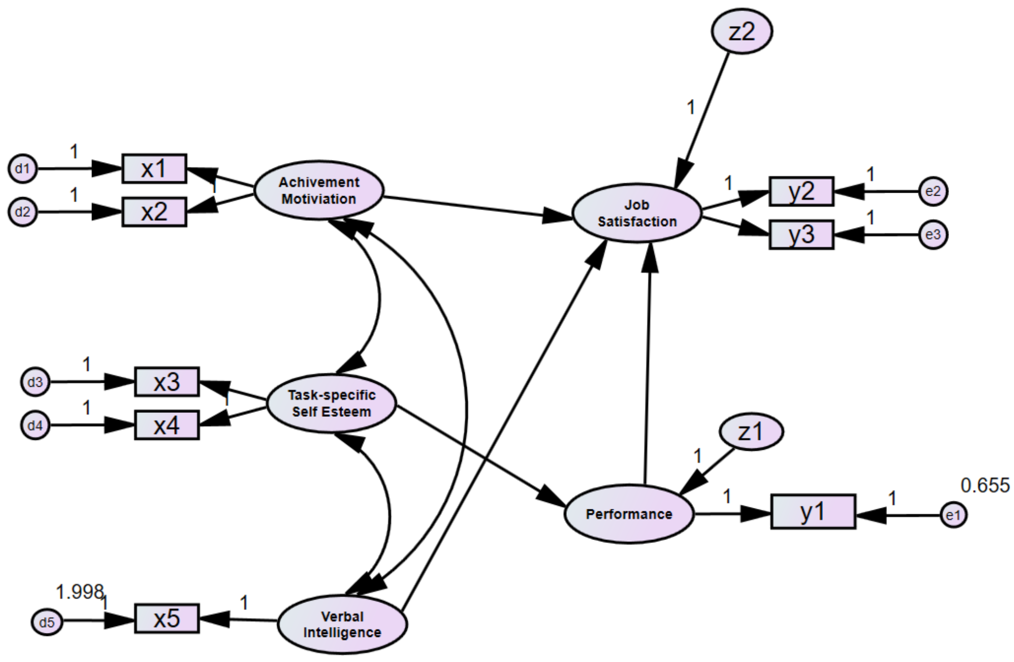
- Delete two non-significant paths to make the model identified



Job 6: (Bagozzi, 1980) Test "H4: nonrecursive relation",
Delete two nonsignificant paths to make
the model identified

Example 3: Final Model

- Delete non-significant paths of the previous model: Recursive model



Job 7: (Bagozzi, 1980) Final Model:
Delete nonsignificant paths of JOB6
Recursive Model