



# “Ghost Chasing”: Demystifying Latent Variables and SEM

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# Topics

- “Ghost Chasing” and Latent Variables
- What is SEM?
- SEM elements and Jargon
- Example Latent Variables
- SEM Limitations



# “Ghost Chasing”

- Psychologists are in the business of Chasing “Ghosts”
  - Measuring “Ghosts”
  - “Ghost” diagnoses
  - Exchanging one “Ghost” for another “Ghost”
- Latent (AKA “Ghost”) Variables
  - Anything we can’t measure directly
  - We must rely on measurable indicators



# What is a Latent Variable?

- ➔ An operationalization of data as an abstract construct
  - A data reduction method that uses “regression like” equations
  - Take many variables and explain them with a one or more “factors”
  - Correlated variables are grouped together and separated from other variables with low or no correlation



# Establishing Latent Variables

## ➤ Exploratory Factor Analysis

- Summarizing data by grouping correlated variables
- Investigating sets of measured variables for underlying constructs
- Often done near the onset of research and/or scale construction



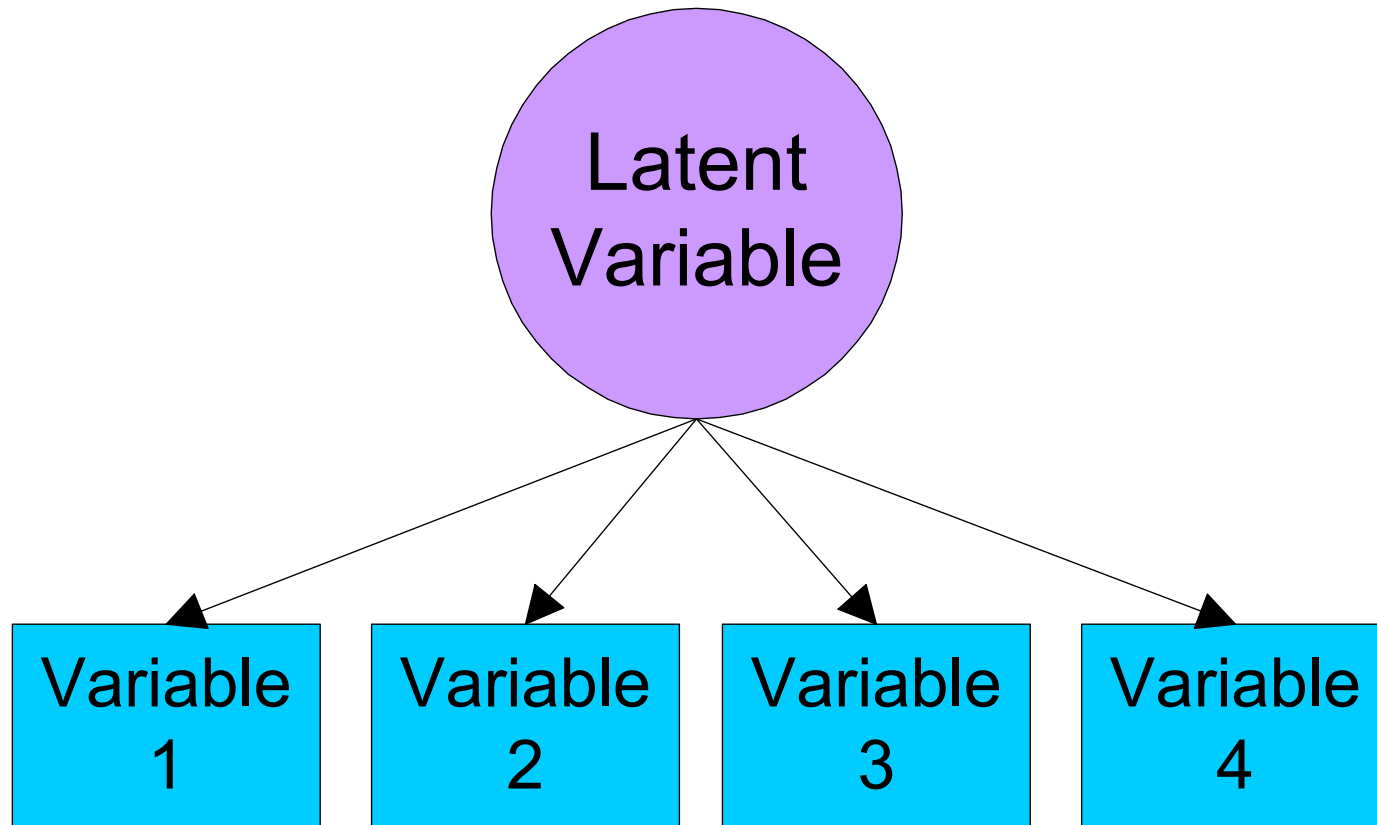
# Establishing Latent Variables

## ➤ Confirmatory Factor Analysis

- Testing whether proposed constructs influence measured variables
- When factor structure is known or at least theorized
- Often done when relationships among variables are known



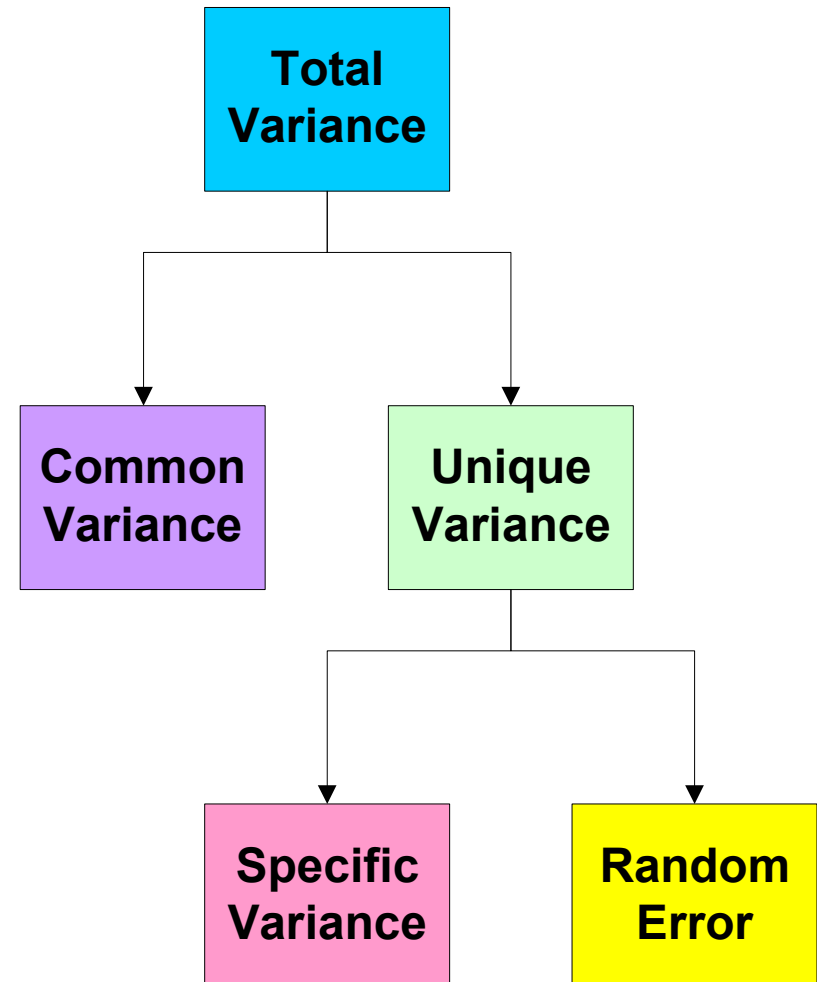
# Conceptualizing Latent Variables





# Conceptualizing Latent Variables

- Latent variables – representation of the variance shared among the variables
  - common variance without error or specific variance







# What is SEM?

➔ SEM – Structural Equation Modeling

➔ Also Known As

- CSA – Covariance Structure Analysis
- Causal Models
- Simultaneous Equations
- Path Analysis
- Confirmatory Factor Analysis
- Latent Variable Modeling



# SEM in a nutshell

- Combination of factor analysis and regression
  - Tests relationships variables
  - Specify models that explain data with few parameters
  - Flexible - Works with continuous and discrete variables
  - Significance testing and model fit



# Goals in SEM

- Hypothesize a model that:
  - Has a number of parameters less than the number of unique Variance/Covariance entries (i.e.  $(p*(p+1))/2$ )
  - Has an implied covariance matrix that is not significantly different from the sample covariance matrix
  - Allows us to estimate population parameters that make the sample data the most likely



# Important Matrices

## → $\mathbf{s}$ matrix

- Sample Covariances
- The data

	Item <sub>1</sub>	Item <sub>2</sub>	Item <sub>3</sub>	Item <sub>4</sub>
Item <sub>1</sub>	$\mathbf{s}_{11}^2$	$\mathbf{s}_{12}^2$	$\mathbf{s}_{13}^2$	$\mathbf{s}_{14}^2$
Item <sub>2</sub>	$\mathbf{s}_{21}^2$	$\mathbf{s}_{22}^2$	$\mathbf{s}_{23}^2$	$\mathbf{s}_{24}^2$
Item <sub>3</sub>	$\mathbf{s}_{31}^2$	$\mathbf{s}_{32}^2$	$\mathbf{s}_{33}^2$	$\mathbf{s}_{34}^2$
Item <sub>4</sub>	$\mathbf{s}_{41}^2$	$\mathbf{s}_{42}^2$	$\mathbf{s}_{43}^2$	$\mathbf{s}_{44}^2$

## → $\sigma(\theta)$ matrix

- Model Implied Covariances

	Item <sub>1</sub>	Item <sub>2</sub>	Item <sub>3</sub>	Item <sub>4</sub>
Item <sub>1</sub>	$\sigma_{11}^2$	$\sigma_{12}^2$	$\sigma_{13}^2$	$\sigma_{14}^2$
Item <sub>2</sub>	$\sigma_{21}^2$	$\sigma_{22}^2$	$\sigma_{23}^2$	$\sigma_{24}^2$
Item <sub>3</sub>	$\sigma_{31}^2$	$\sigma_{32}^2$	$\sigma_{33}^2$	$\sigma_{34}^2$
Item <sub>4</sub>	$\sigma_{41}^2$	$\sigma_{42}^2$	$\sigma_{43}^2$	$\sigma_{44}^2$

## → Residual Covariance Matrix



# SEM Jargon

## ➤ Measurement

- The part of the model that relates measured variables to latent factors
- The measurement model is the factor analytic part of SEM

## ➤ Structure

- This is the part of the model that relates variable or factors to one another (prediction)
- If no factors are in the model then only path model exists between measured variables



# SEM Jargon

## ➤ Model Specification

- Creating a hypothesized model that you think explains the relationships among multiple variables
- Converting the model to multiple equations

## ➤ Model Estimation

- Technique used to calculate parameters
- E.G. - Ordinary Least Squares (OLS), Maximum Likelihood (ML), etc.



# SEM Jargon

## ➤ Model Identification

- Rules for whether a model can be estimated
- For example, For a single factor:
  - ◆ At least 3 indicators with non-zero loadings
  - ◆ no correlated errors
  - ◆ Fix either the Factor Variance or one of the Factor Loadings to 1



# SEM Jargon

## ➤ Model Evaluation

- Testing how well a model fits the data
- Just like with other analyses (e.g. ANOVA) we look at squared differences
  - ◆ SEM looks at the squared difference between the  $s$  and  $\sigma(\theta)$  matrices
  - ◆ While weighting the squared difference depending on the estimation method (e.g. OLS, ML, etc.)

$$\text{pick a } \sigma(\theta) \xrightarrow{\min} Q = (s - \sigma(\theta))' W (s - \sigma(\theta))$$





# SEM Jargon

## ➤ Model Evaluation

- Even with well fitting model you need to test significance of predictors
  - ◆ Each parameter is divided by its SE to get a Z-score which can be evaluated
  - ◆ SE values are calculated as part of the estimation procedure



# Conventional SEM diagrams

- ▣ = measured variable
- = latent variable
- ⇒ = regression weight or factor loading
- ↔ = covariance



# Sample Variance/Covariance Matrix

	X1	X2	X3
X1	1.8782	1.0824	1.1080
X2	1.0824	2.3414	1.3409
X3	1.1080	1.3409	2.6023



# Basic Tracing Rules for a Latent Variable

- Once parameters are estimated
- Calculating the Implied Covariance Matrix
- Rules for Implied Variance
  - Common Variance – trace a path from a variable back to itself, multiplying parameters
  - Add to it the unique variance of that DV
- Rules for covariance between variables
  - Trace path from any variable to another, multiplying parameters



# Implied Covariance Matrix

## Variances

$$\sigma_{X_1}^2 = .9457(1)(.9457) = .8944 + .9838 = 1.8782$$

$$\sigma_{X_2}^2 = 1.1445(1)(1.1445) = 1.3099 + 1.0314 = 2.3413$$

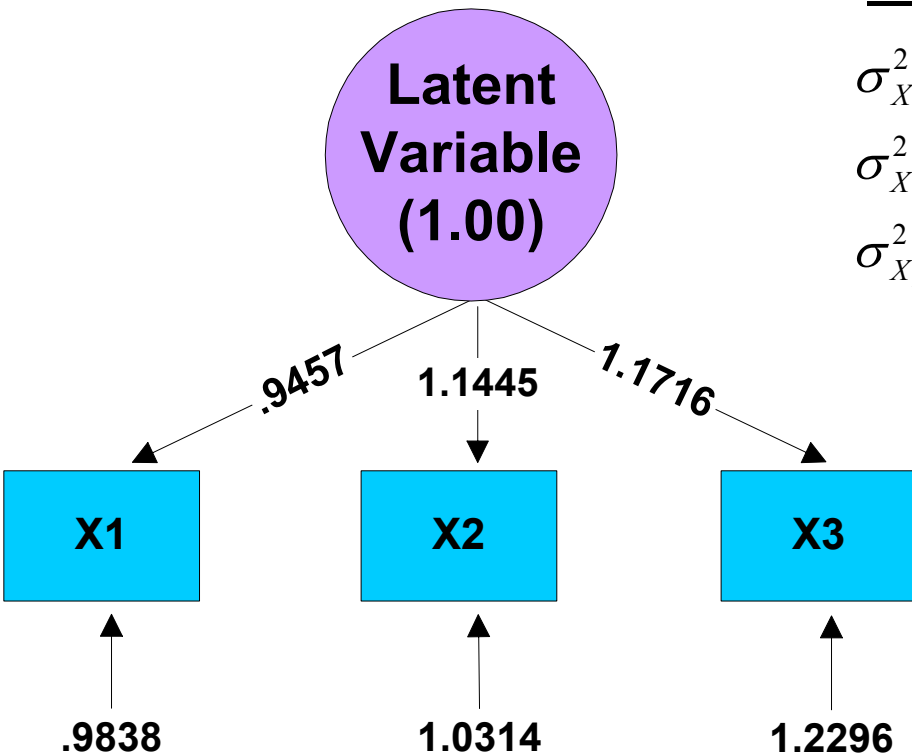
$$\sigma_{X_3}^2 = 1.1716(1)(1.1716) = 1.3726 + 1.2296 = 2.6022$$

## Covariances

$$\sigma_{X_1X_2} = .9457(1)(1.1445) = 1.0824$$

$$\sigma_{X_1X_3} = .9457(1)(1.1716) = 1.1080$$

$$\sigma_{X_2X_3} = 1.1445(1)(1.1716) = 1.3409$$



	X1	X2	X3
X1	1.8782	1.0824	1.1080
X2	1.0824	2.3413	1.3409
X3	1.1080	1.3409	2.6022



# Residual Matrix

$$\begin{array}{ccc|c} \left| \begin{array}{ccc} 1.8782 & 1.0824 & 1.1080 \\ 1.0824 & 2.3414 & 1.3409 \\ 1.1080 & 1.3409 & 2.6023 \end{array} \right| & - & \left| \begin{array}{ccc} 1.8782 & 1.0824 & 1.1080 \\ 1.0824 & 2.3413 & 1.3409 \\ 1.1080 & 1.3409 & 2.6022 \end{array} \right| & = & \left| \begin{array}{ccc} 0 & 0 & 0 \\ 0 & .0001 & 0 \\ 0 & 0 & .0001 \end{array} \right| \\ \begin{array}{ccc} s & & \end{array} & & \begin{array}{ccc} \sigma(\theta) & & \end{array} & & \begin{array}{ccc} residual & & \end{array} \end{array}$$

# Function Min and Chi-Square

$$Q = (s - \sigma(\theta))' W (s - \sigma(\theta)) =$$

$$Q = \begin{bmatrix} \left[ \begin{array}{ccc|ccc} 1.8782 & 1.0824 & 1.1080 & 1.8782 & 1.0824 & 1.1080 \\ 1.0824 & 2.3414 & 1.3409 & 1.0824 & 2.3413 & 1.3409 \\ 1.1080 & 1.3409 & 2.6023 & 1.1080 & 1.3409 & 2.6022 \end{array} \right] & * & \left[ \begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array} \right] \\ \begin{array}{ccc} s & & \\ & & \sigma(\theta) \end{array} & & W \end{bmatrix}$$

$$* \begin{bmatrix} \left[ \begin{array}{ccc|ccc} 1.8782 & 1.0824 & 1.1080 & 1.8782 & 1.0824 & 1.1080 \\ 1.0824 & 2.3414 & 1.3409 & 1.0824 & 2.3413 & 1.3409 \\ 1.1080 & 1.3409 & 2.6023 & 1.1080 & 1.3409 & 2.6022 \end{array} \right] & = & \\ \begin{array}{ccc} s & & \\ & & \sigma(\theta) \end{array} \end{bmatrix}$$

$$Q = .000000008$$

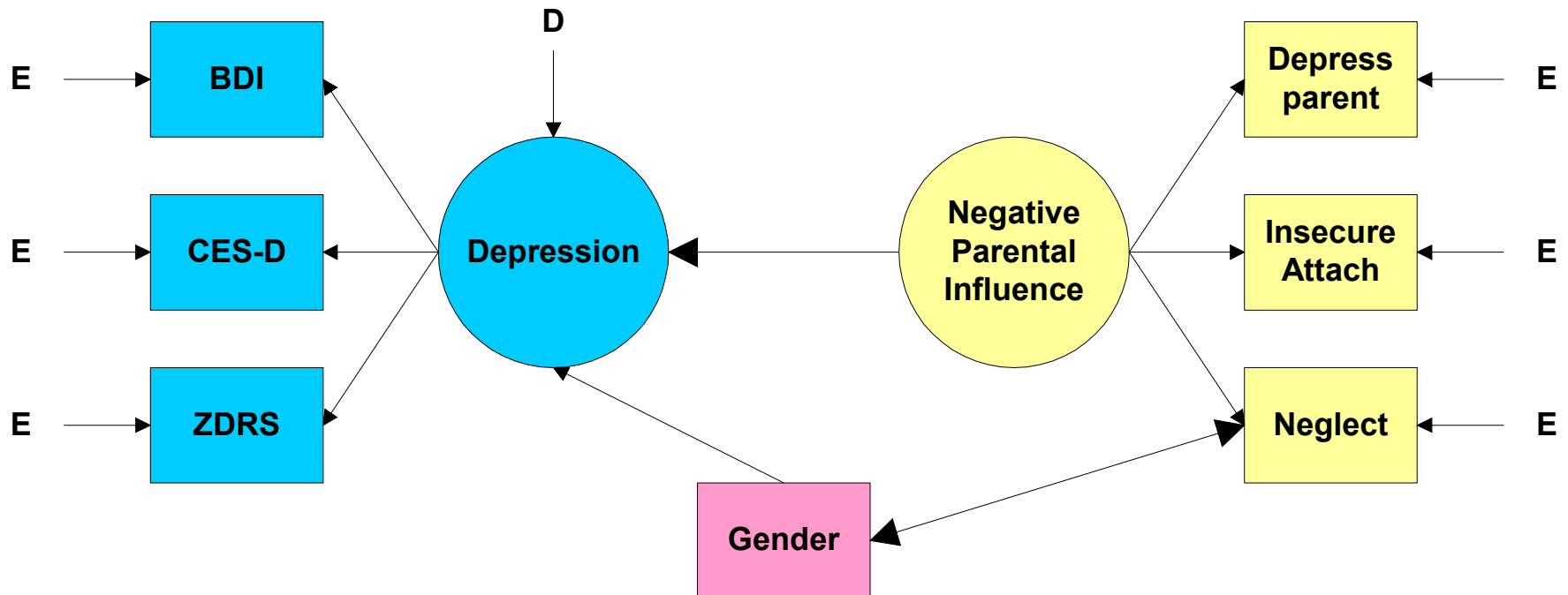
$$\chi^2 (?) = Q * (492 - 1) = .000000008 * 491 = .000000982$$

$$df_{\chi^2} = (\# \text{unique VC elements}) - (\# \text{ of estimated parameters})$$

$$df_{\chi^2} = 6 - 6 = 0$$



# Full Measurement Diagram







# SEM limitations

- SEM is a confirmatory approach
  - You need to have established theory about the relationships
  - Exploratory methods (e.g. model modification) can be used on top of the original theory
  - SEM is not causal; experimental design = cause



# SEM limitations

- SEM  $\Rightarrow$  correlational but, can be used with experimental data
  - Mediation and manipulation can be tested
- SEM  $\Rightarrow$  very fancy technique but it does not make up for a bad methods



# SEM limitations

- Biggest limitation is sample size
  - It needs to be large to get stable estimates of the covariances/correlations
  - @ 200 subjects for small to medium sized model
  - A minimum of 10 subjects per estimated parameter
  - Also affected by effect size and power



# Take Home Messages

- You're a "Ghost Chaser" and didn't know it
- Latent Variables are "Ghosts"
- SEM – method for getting closer to studying the "ghosts" directly
- SEM is complicated but it is accessible to you if you need to use it

Thank You!!



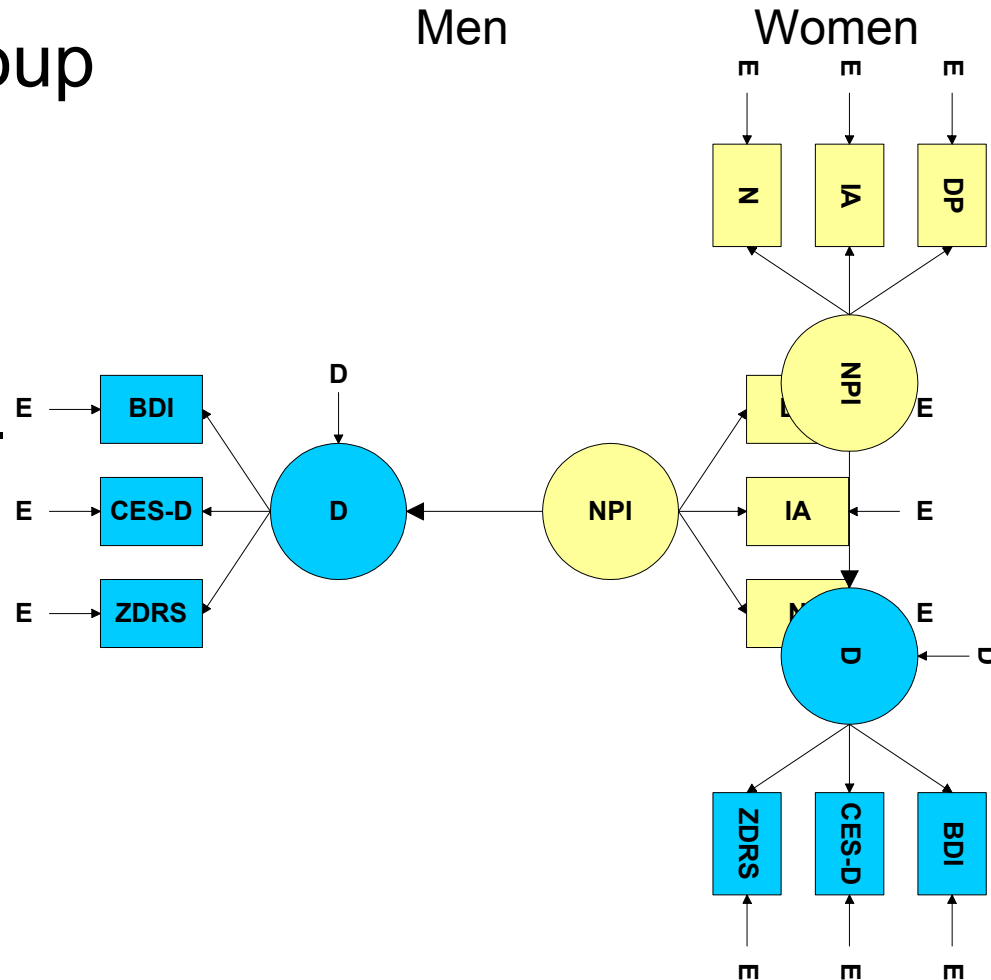
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# Some SEM advanced questions

➔ Are there group differences?

- Multigroup models
- e.g. Men vs. Women





# Some SEM advanced questions

- Can change in responses be tracked over time?
  - Latent Growth Curve Analysis

# Latent Growth Model

