Multivariate Data Analysis

(MGT513, BAT531, TIM711)

Lecture 11

Structural Equation Models 3

1. SEM in R (Example 2 and 3)
2. Latent Growth Curve Model in AMOS and R

"Lavaan" Package in *R*

lavaan

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ugent.be
https://lavaan.ugent.be

The lavaan Project

The **lavaan** package is developed to provide useRs, researchers and teachers a free open-source, but commercial-quality package for latent variable modeling. You ...
You visited this page on 5/15/23.

A SEM example
lavaan latent variable analysis.

Tutorial.pdf
Abstract. If you are new to lavaan, this is the place to ...

Tutorial
A CFA example - Multilevel SEM - Multiple groups - Installation

Getting started
Install R. lavaan is implemented as an R package.

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Python alternatives

Lavaan is a popular package for structural equation modeling (SEM) in R programming language. It provides a comprehensive set of functions for estimating, analyzing, and visualizing SEM models. However, if you're specifically looking for a Python alternative to lavaan, there are a few options available.

1. `semopy`: semopy is a Python package that offers similar functionality to lavaan. It allows you to specify and estimate structural equation models using maximum likelihood estimation. It supports various SEM techniques such as confirmatory factor analysis (CFA), path analysis, and latent growth modeling. You can find more information and examples in the official documentation: https://semopy.com/
2. `statsmodels`: statsmodels is a comprehensive statistical modeling package in Python that includes some functionality for SEM. It provides classes for fitting linear models, including multivariate regression models, which can be used to perform some basic SEM analyses. While statsmodels may not have all the advanced features of lavaan, it can be a good starting point for simpler SEM tasks. You can find more information and examples in the official documentation: https://www.statsmodels.org/stable/index.html
3. `PySEM`: PySEM is another Python package specifically designed for structural equation modeling. It provides a user-friendly interface for specifying and estimating SEM models using the maximum likelihood estimation method. PySEM supports various types of models, including path models, factor models, and latent growth curve models. You can find more information and examples in the official documentation: https://pypi.org/project/pypath/

It's worth noting that these Python alternatives may not offer the exact same functionality and syntax as lavaan. However, they provide similar capabilities for performing SEM analyses within the Python programming environment.

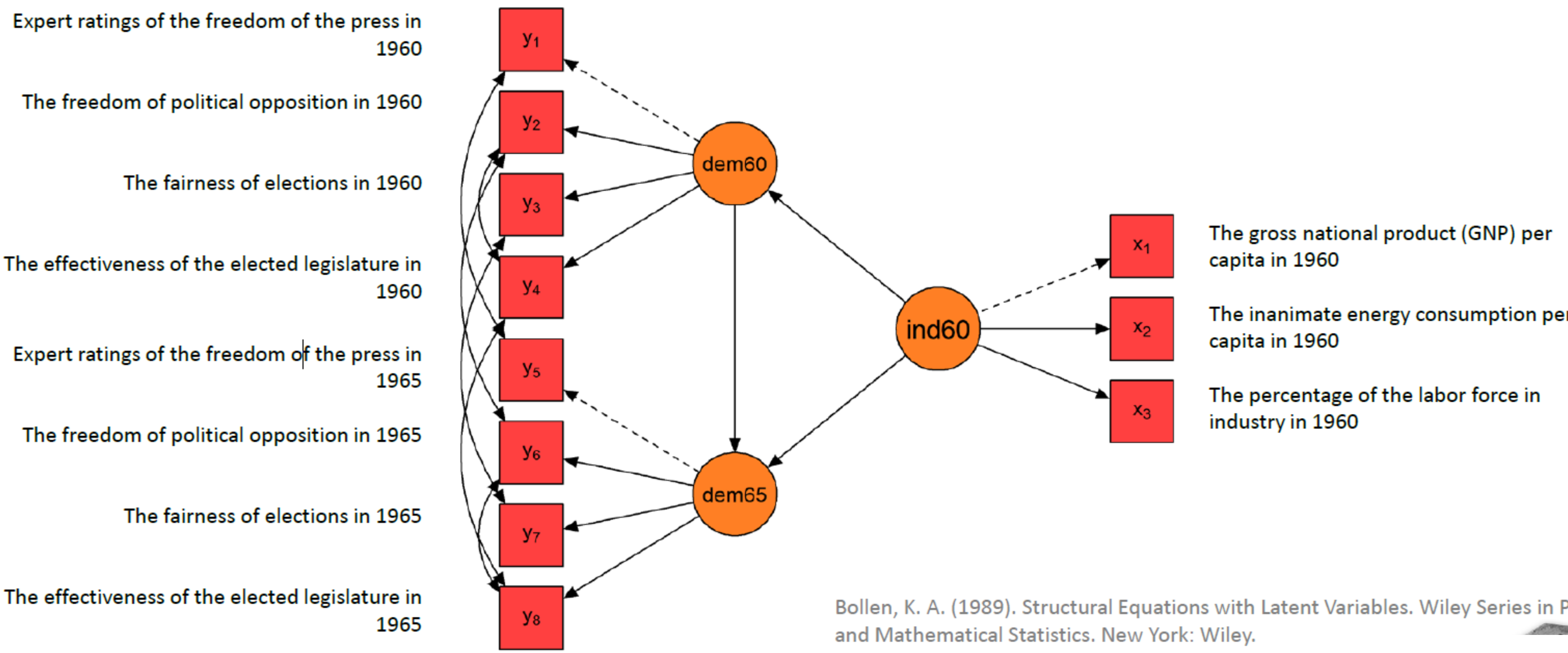
1. SEM in R (Example 2 and 3)

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

Example 2

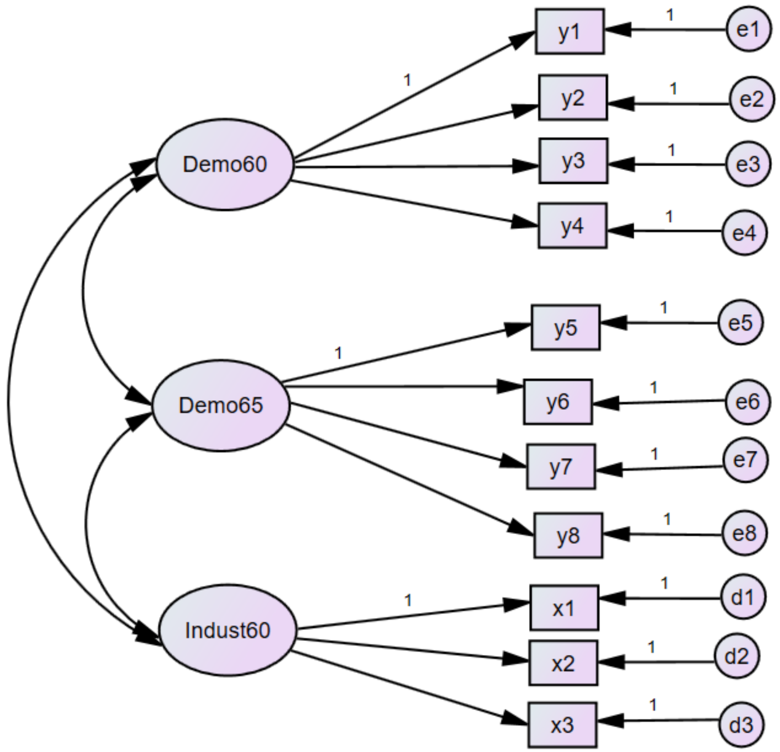
- Influence of industrialization ('60) on political democracy ('60 and '65)



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

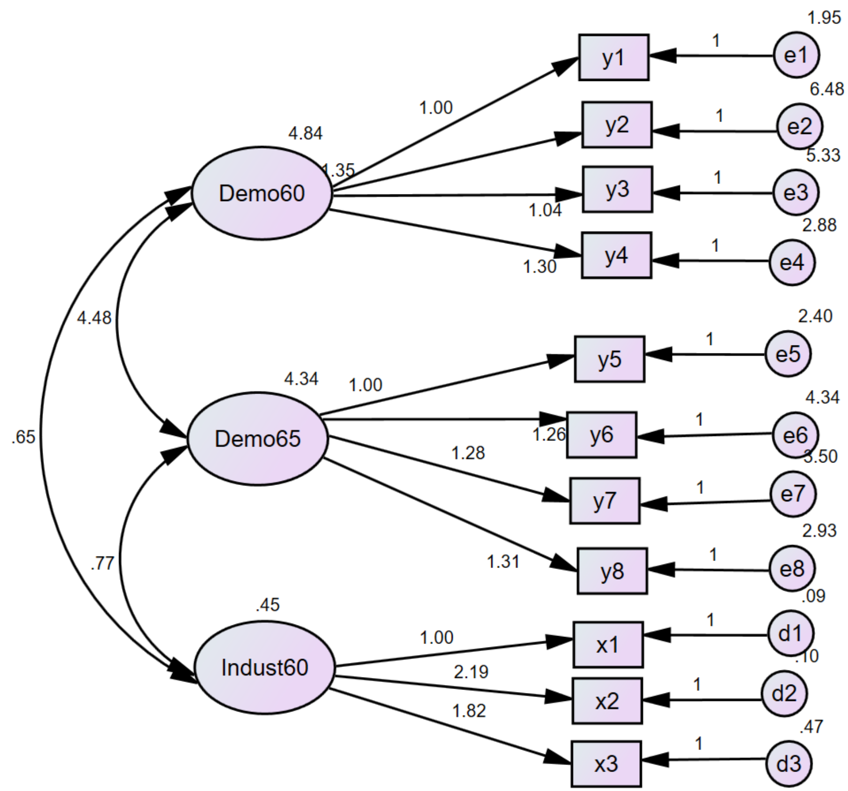
Source: Structural Equation Modeling by Bowen and Guo (https://global.oup.com/us/companion.websites/9780195367621/examples/)

Example 2: CFA 1



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

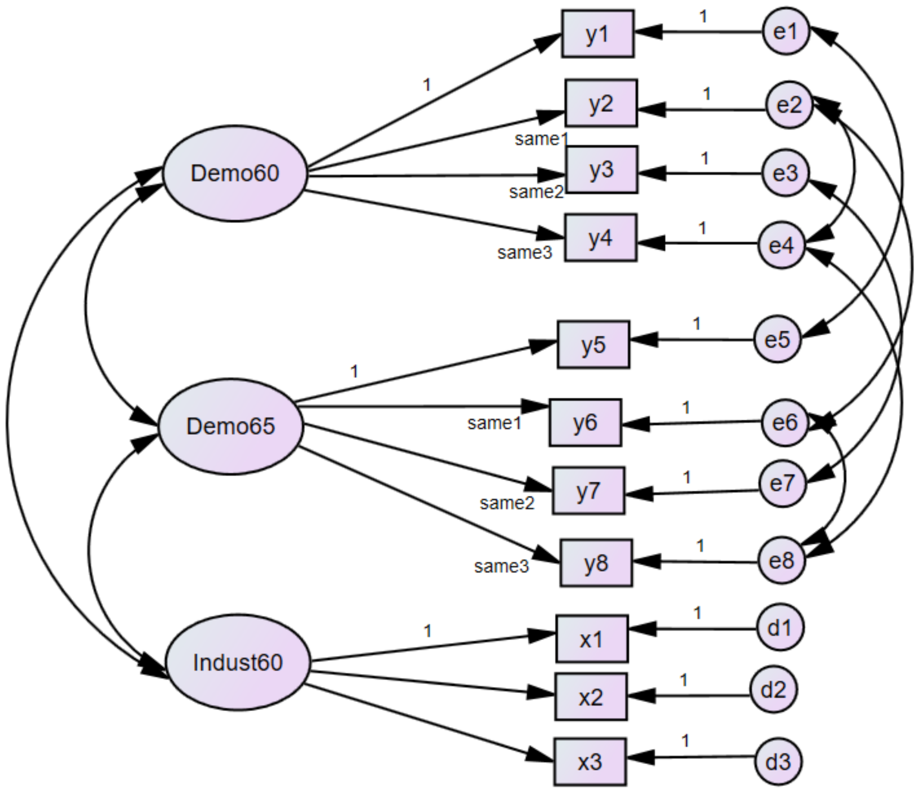
Example 2: CFA 1



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

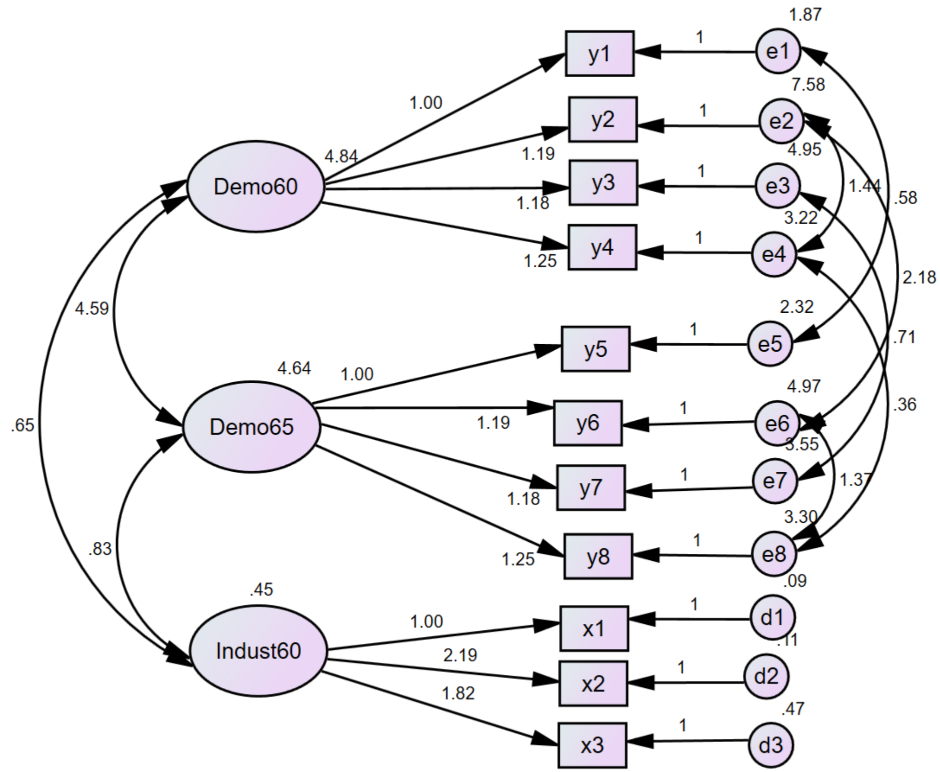
Chi-square = 70.575 (41 df), p=.003
RMSEA=.099
GFI=.856, CFI=.955

Example 2: CFA 2



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

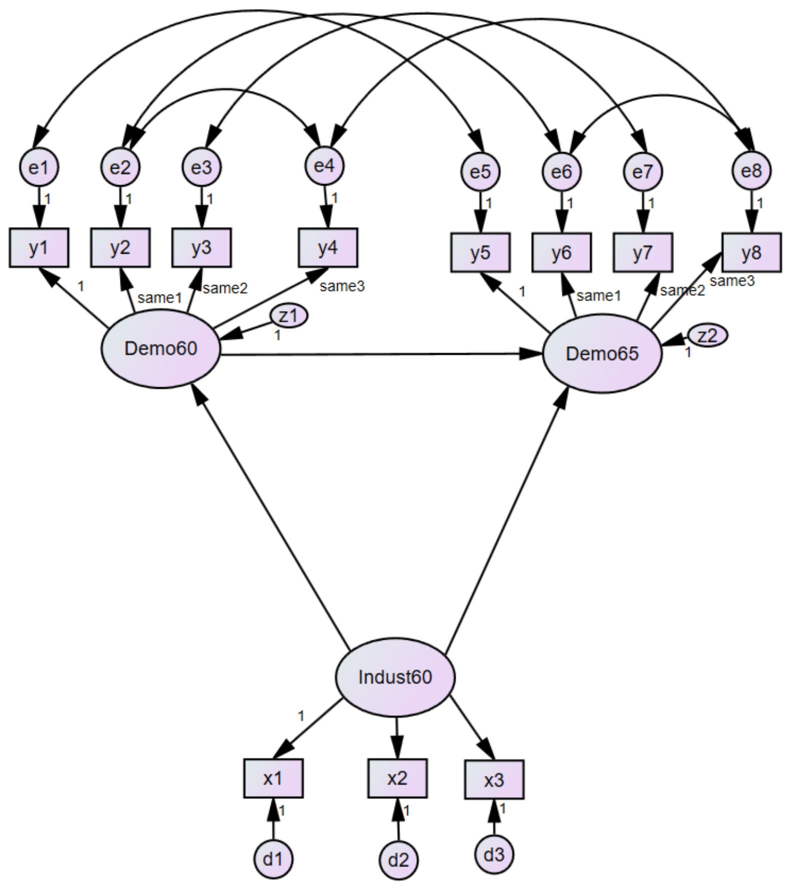
Example 2: CFA 2



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

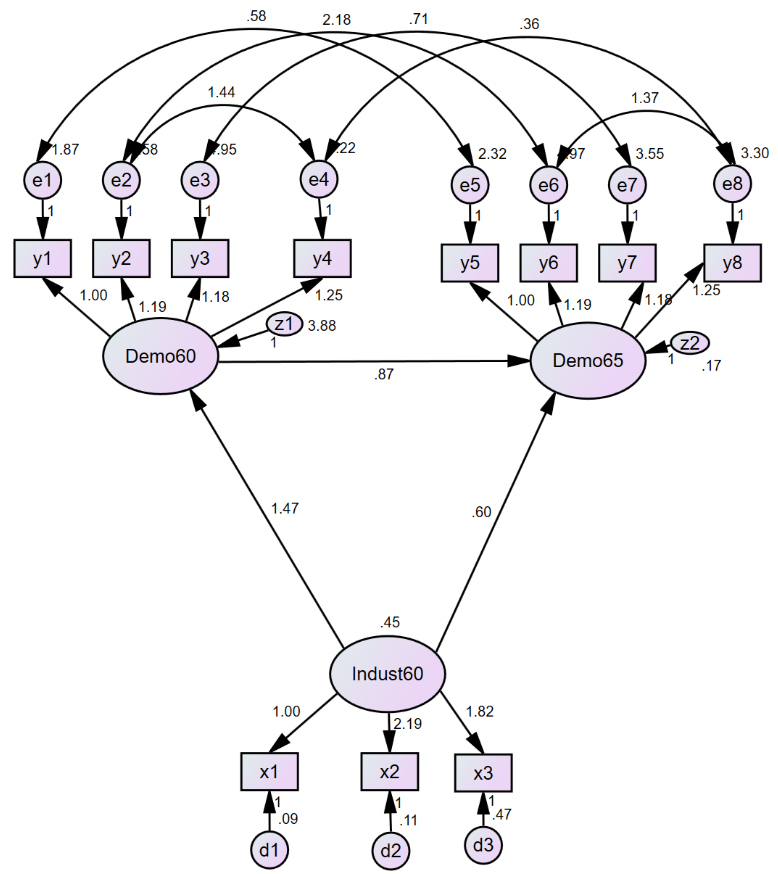
Chi-square = 38.767 (38 df), p=.435
RMSEA=.017
GFI=.921, CFI=.999

Example 2: Structural model



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

Example 2: Structural model



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

Chi-square = 38.767 (38 df), p=.435
RMSEA=.017
GFI=.921, CFI=.999

Example 3

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/)

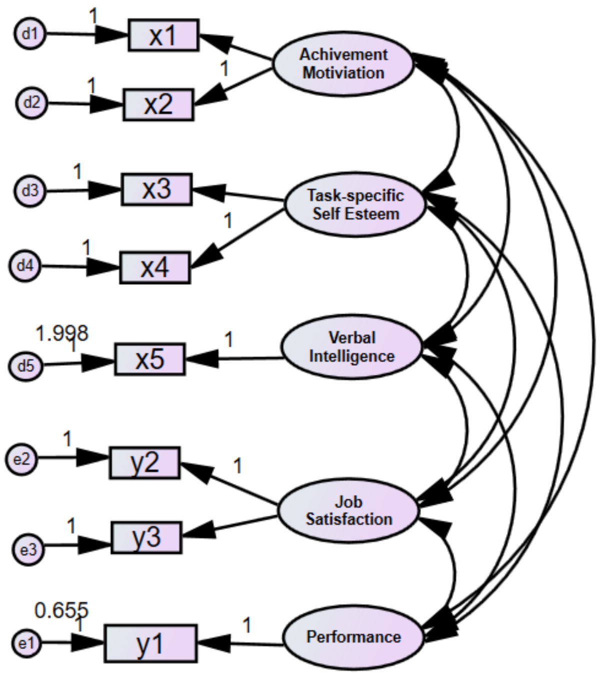
Example 3

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/)

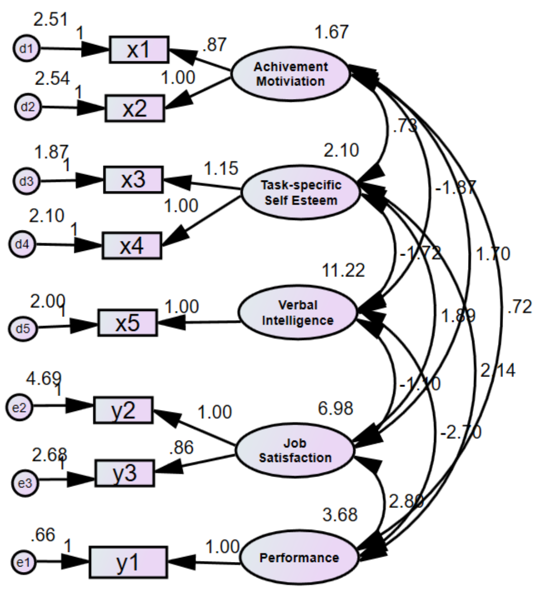
Example 3: CFA



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

Example 3: CFA

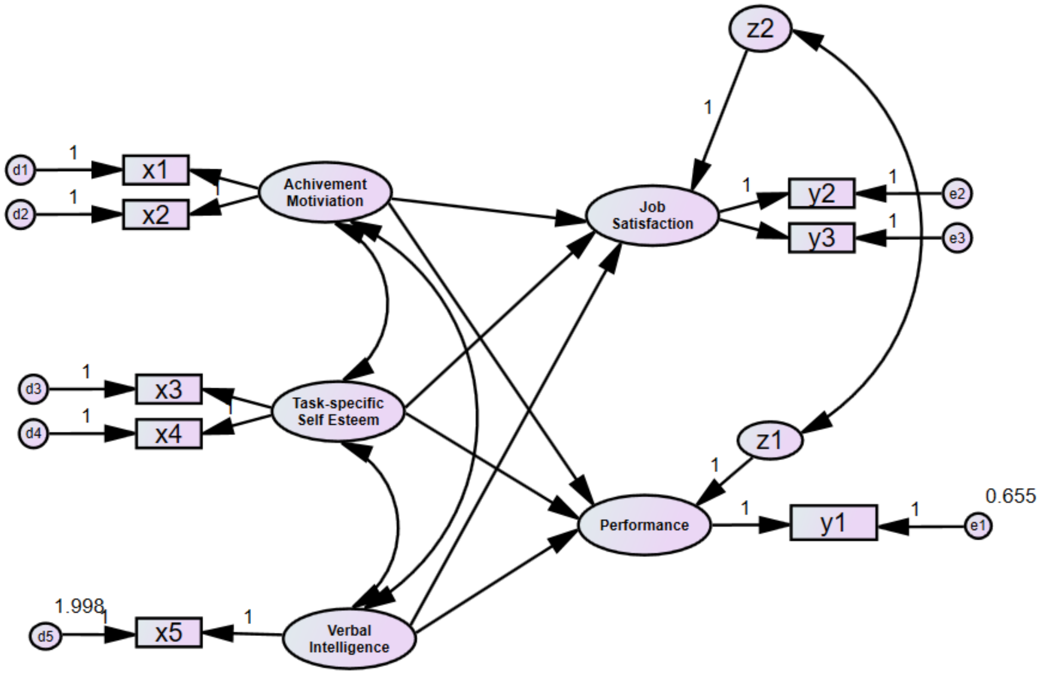
Chi-square = 10.309 (12 df), p=.589
RMSEA=.000
GFI=.978, CFI=1.000



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

Example 3: Job 2(H1)

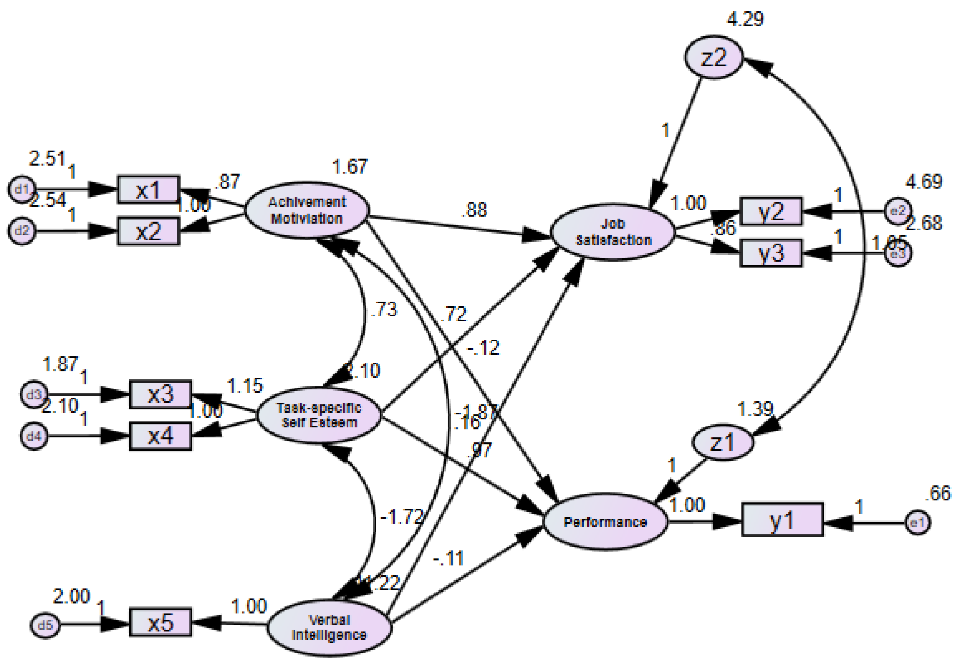
- H1: Spurious correlation of job satisfaction and performance



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

Example 3: Job 2(H1)

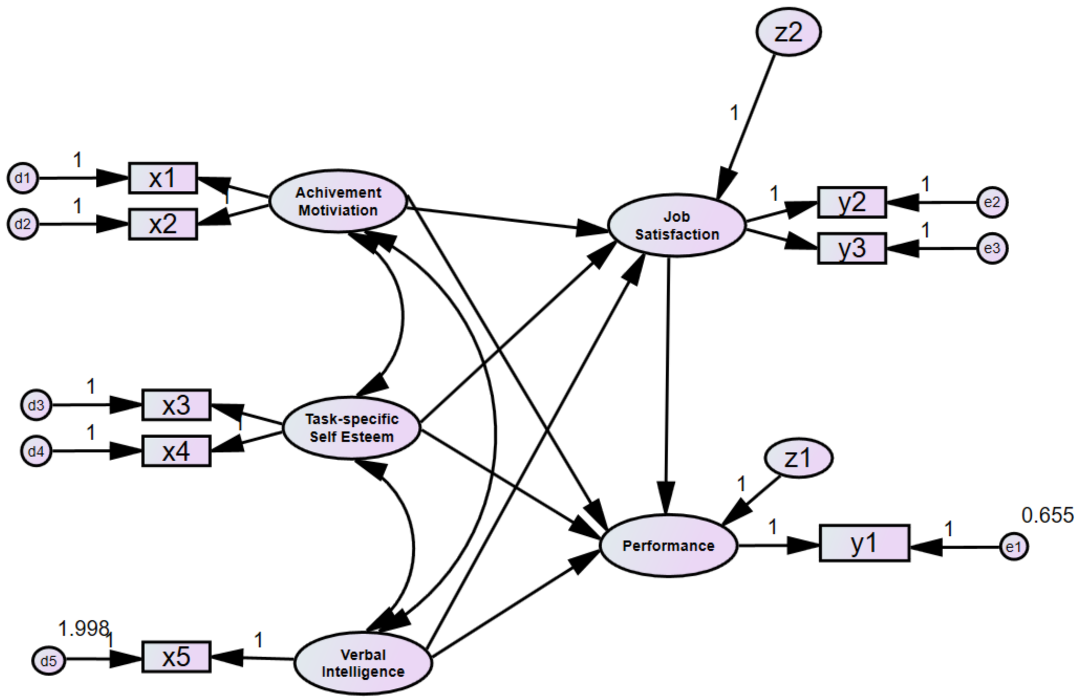
Chi-square = 10.309 (12 df), p=.589
RMSEA=.000
GFI=.978, CFI=1.000



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

Example 3: Job 3(H2)

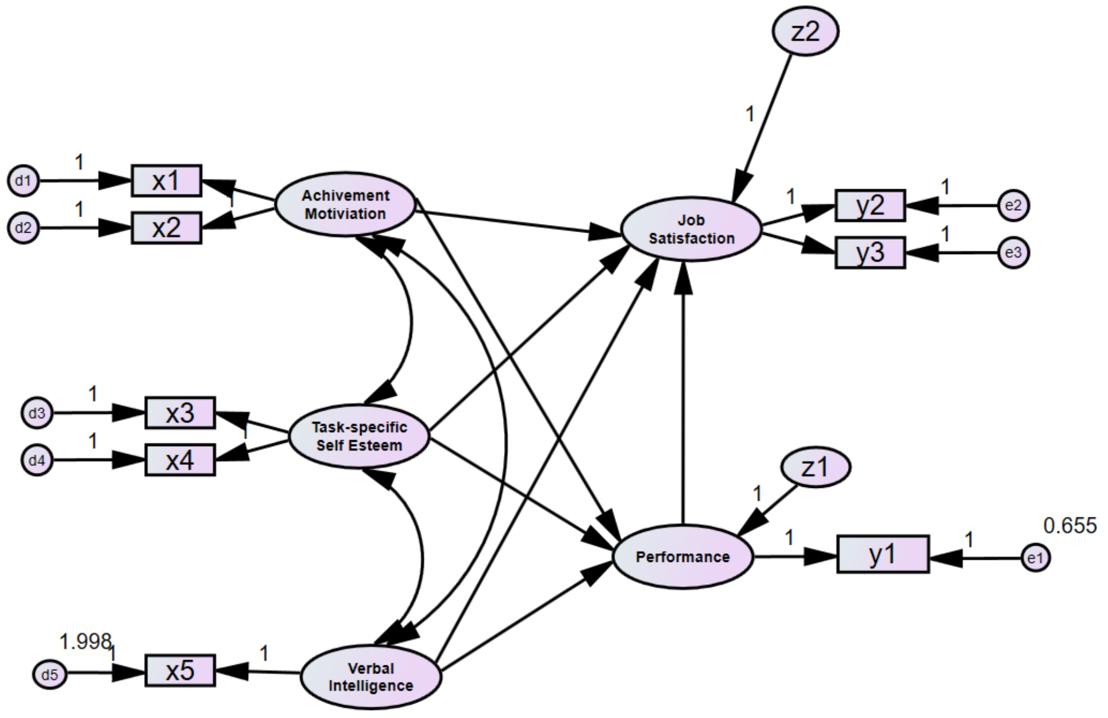
- H2: Job satisfaction influences performance



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

Example 3: Job 4(H3)

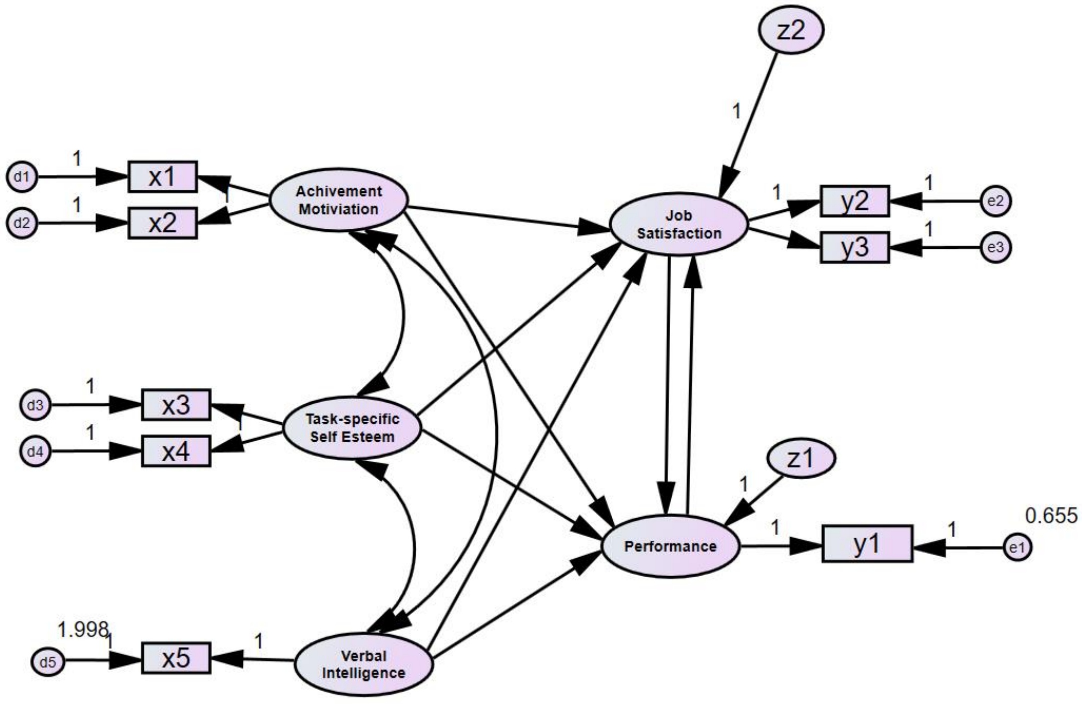
- H3: Performance influences Job satisfaction



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

Example 3: Job 5(H4)

- H4: Non-recursive relation



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

Example 3: Job 5(H4)

- AMOS output: Model unidentified!

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

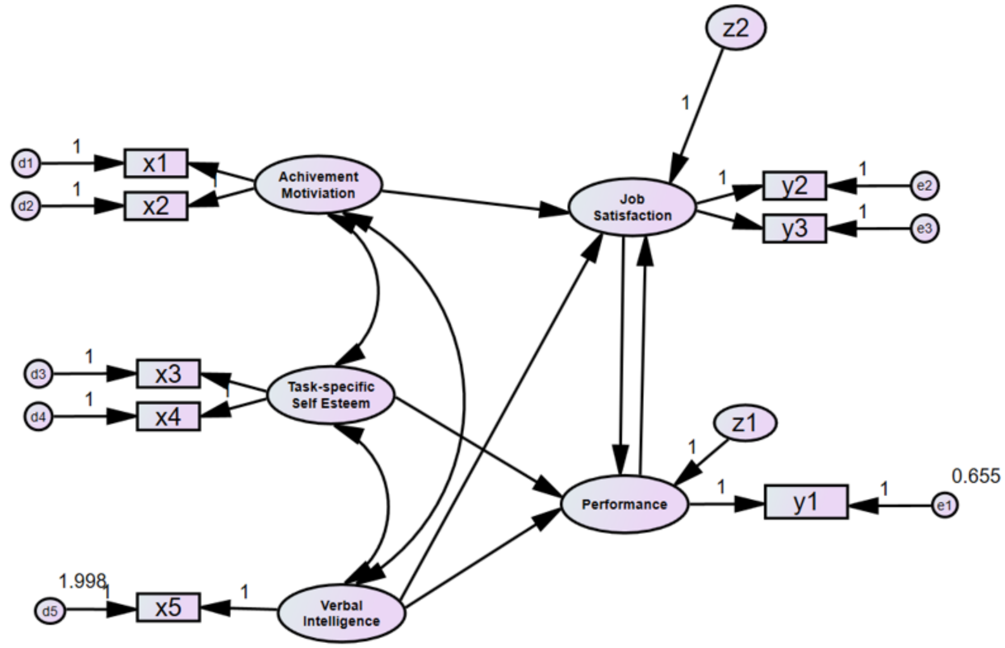
Number of distinct sample moments:	36
Number of distinct parameters to be estimated:	25
Degrees of freedom (36 - 25):	11

Result (Default model)

The model is probably unidentified. In order to achieve identifiability, it will probably be necessary to impose 1 additional constraint.

Example 3: Job 6 (H4)

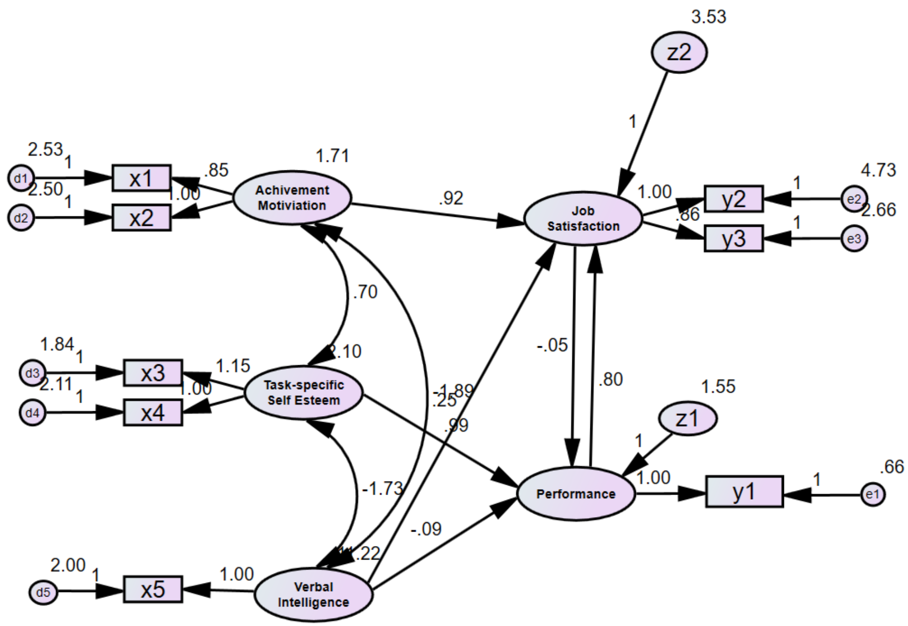
- Delete two non-significant paths to make the model identified



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

Example 3: Job 6 (H4)

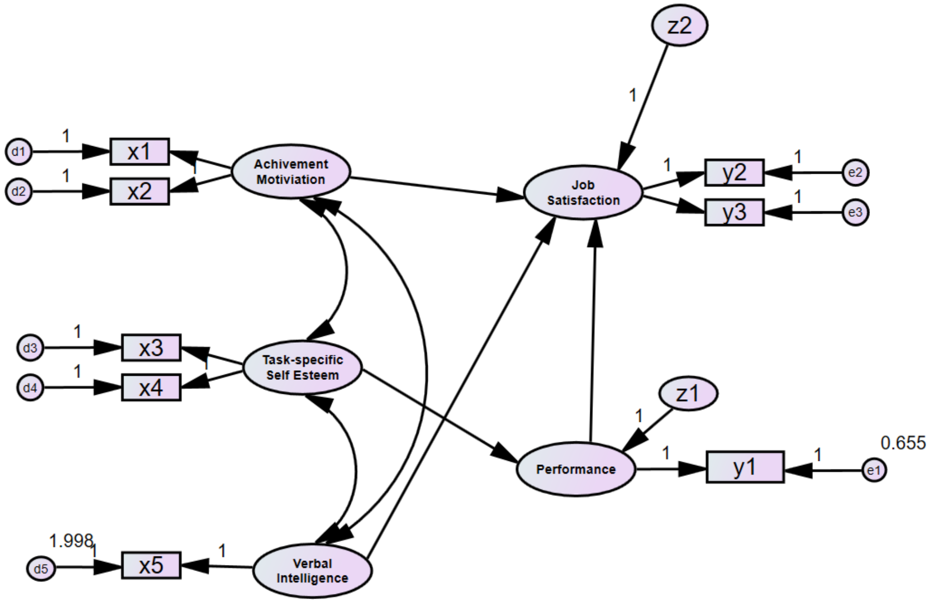
Chi-square = 10.474 (13 df), p=.655
RMSEA=.000
GFI=.978, CFI=1.000



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

Example 3: Job 7 (Final Model)

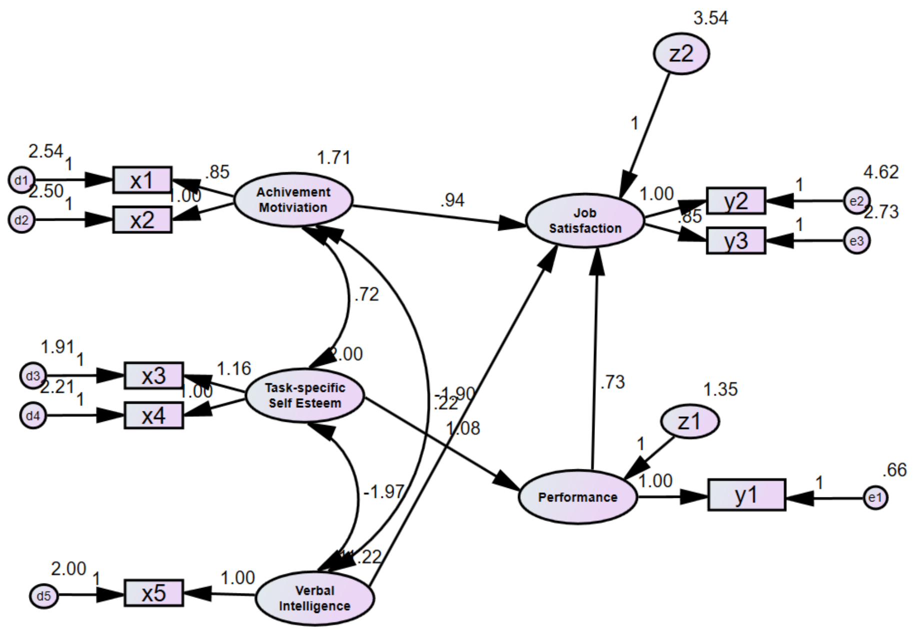
- Delete non-significant paths of the previous model: Recursive model



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

Example 3: Job 7 (Final Model)

Chi-square = 13.508 (15 df), p=.563
RMSEA=.000
GFI=.971, CFI=1.000



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

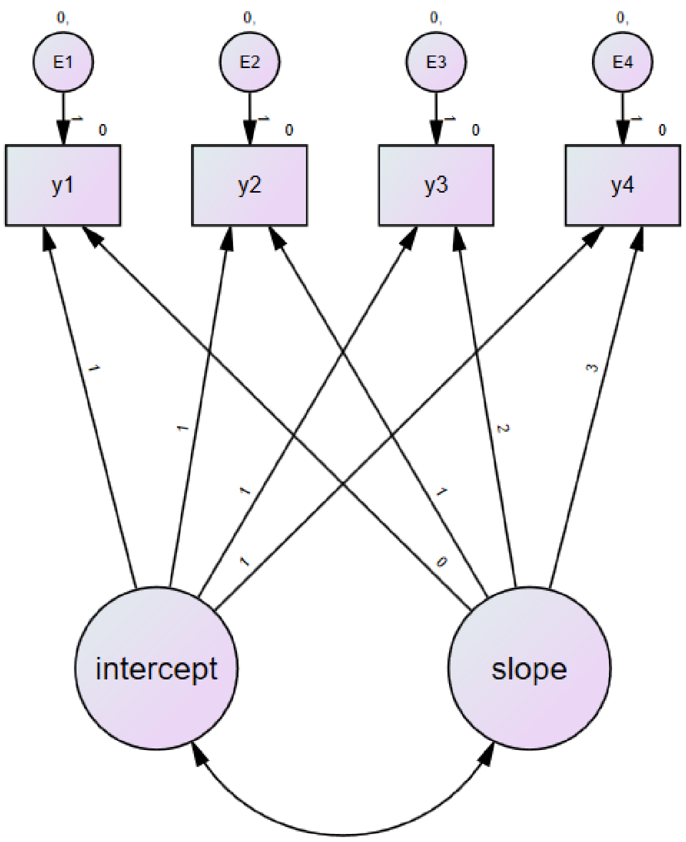
2. Latent Growth Curve Model in AMOS and R

Latent Growth Curve Model

- Longitudinal analysis technique to estimate growth over a period of time
- Considers change over time in terms of an underlying, latent, unobserved process
- Very flexible
- Incorporates time-specific measurement error
- Allows for covariance among the variance for slope and the variance for the intercept
- Allows researchers to model and test longitudinal associations among several outcome variables measured repeatedly over time

Latent Growth Curve Model

- Customers' satisfaction data over four time periods
- No covariate



Latent Growth Curve Model

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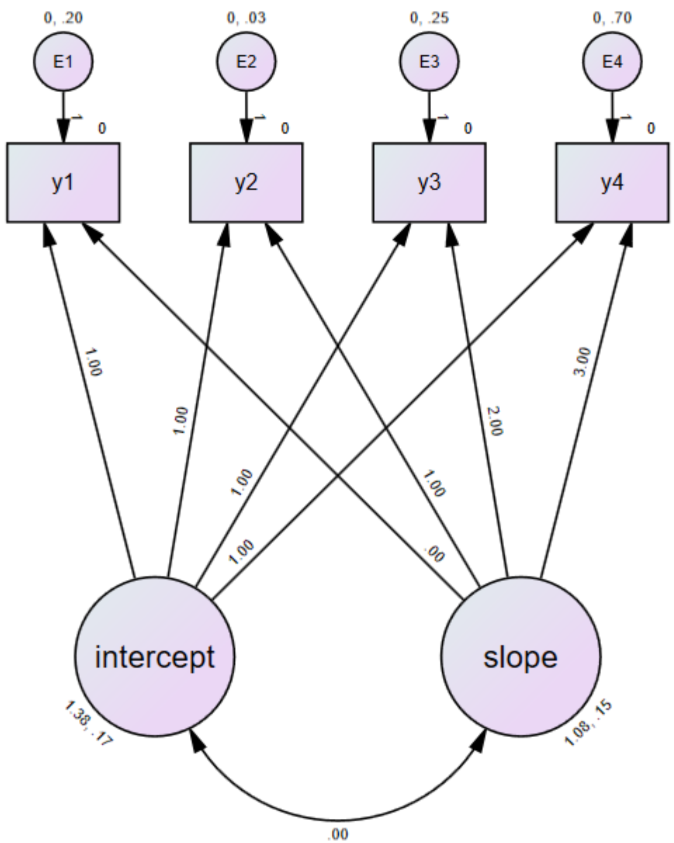
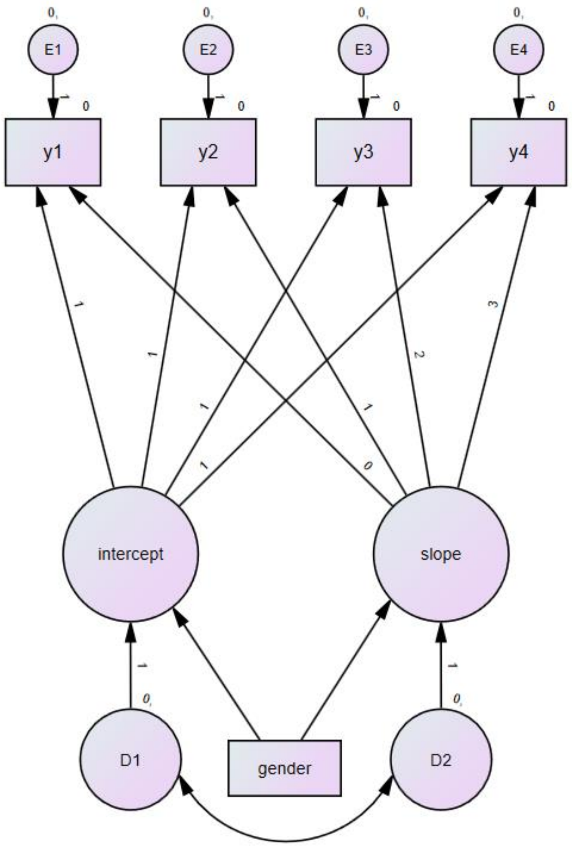


Latent Growth Curve Model

- Customers' satisfaction data over four time periods
- Gender (Male: 0, Female: 1)



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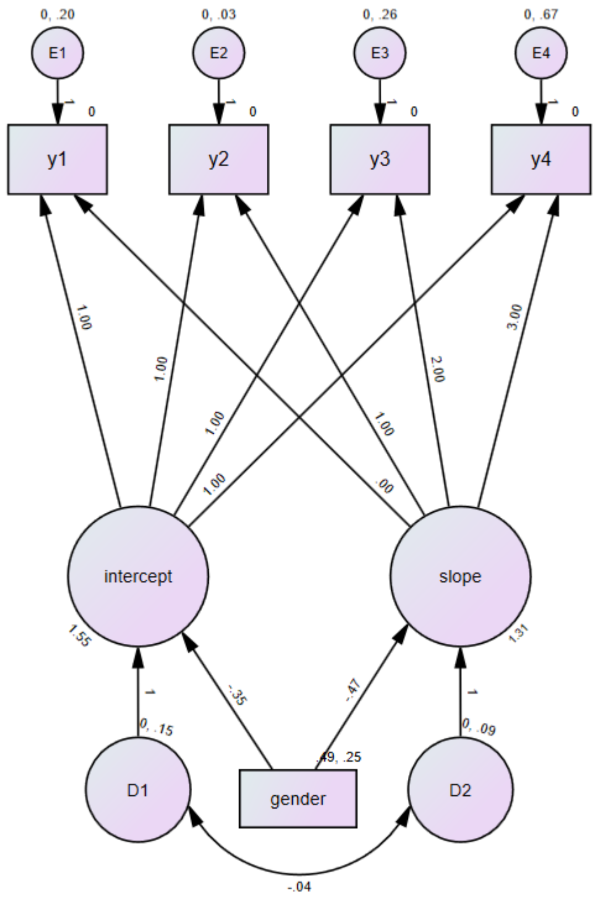

Latent Growth Curve Model

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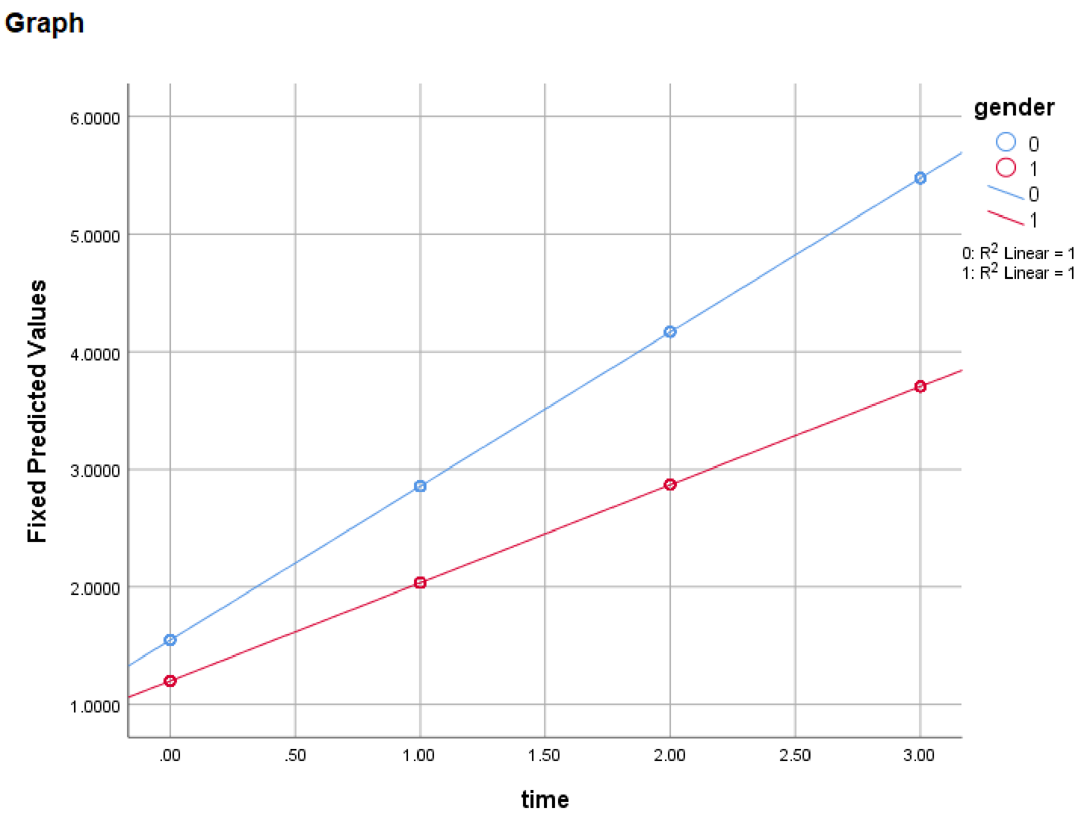

Source: Mike Crowson