Emperical Methods for Marketing Research and Analytics Using R

Prof. Dr. Martin Wetzels
Maastricht University

Maastricht University

About Me

- Name: Prof. Dr. Martin Wetzels
  Professor in Marketing and Supply Chain Research

- Address: Maastricht University
  School of Business and Economics
  Department of Marketing and SCM
  P.O. Box 616, 6200 MD Maastricht
  Tongersestraat 53, F1.05
  T: +31 43 388 3250/3839
  F: +31 43 388 4918
  E: m.wetzels@maastrichtuniversity.nl
  W: https://www.maastrichtuniversity.nl/m.wetzels

Using R for SEM and PLS Path Modeling

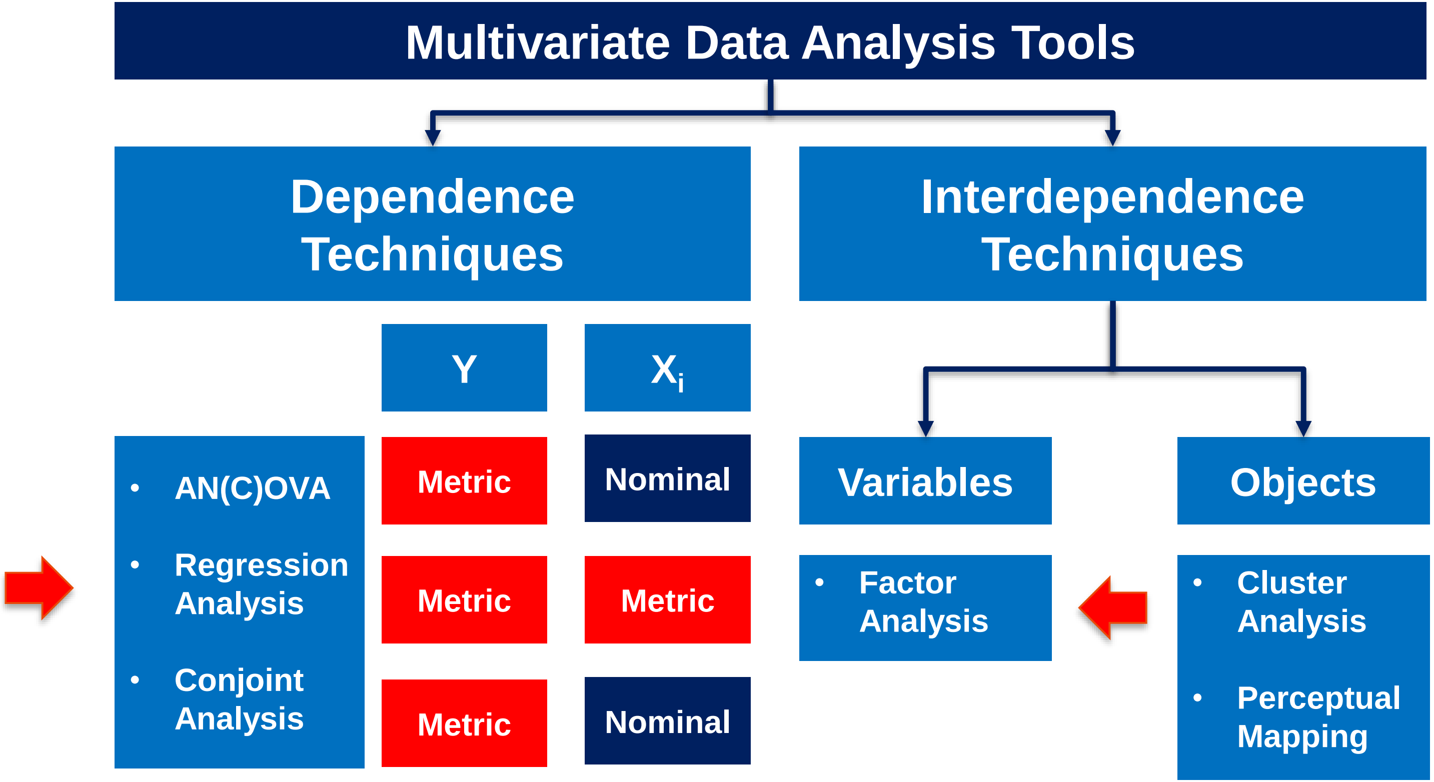
Prof. Dr. Martin Wetzels
Maastricht University

Course Outline

Session:	TOPIC:
DAY 1	
Session 1	INTRODUCING MULTIVARIATE ANALYSIS AND R
Session 2	USING R FOR BASIC ANALYSIS
DAY 2	
Session 3	USING R FOR AN(C)OVA
Session 4	USING R FOR REGRESSION ANALYSIS
DAY 3	
Session 5	USING R FOR SCALING AND FACTOR ANALYSIS
Session 6	USING R FOR SEM and PLS PATH MODELING

Positioning SEM and PLS Path Modeling

Hair et al. (2018); Malhotra (2010); Pallant (2016)



Correlation Analysis

Hair et al. (2018); Malhotra (2010)

- The **(Pearson) product moment correlation, ρ,** summarizes the strength of association between two **metric** (at least **interval**) variables [-1, 1].

- Assumptions
  - **Metric** (at least **interval**) variables
  - Independent, random sample
  - Linearity
  - (Bivariate) Normal distribution
  - Homoscedasticity
  - No causality!
  - Outliers!

Correlation Analysis

Hair et al. (2018); Malhotra (2010)

- Covariance [-∞, + ∞]

$$COV_{XY} = \sum_{i=1}^{n} \frac{(X_i - M_X) * (Y_i - M_Y)}{n-1}$$

- (Pearson Product-Moment) Correlation Coefficient [-1, 1]

$$r_{XY} = \frac{COV_{XY}}{S_X S_Y}$$

Correlation Analysis

Hair et al. (2018); Malhotra (2010)

- Hypotheses
  - H_0: correlation coefficient (ρ) = 0
  - H_1: correlation coefficient (ρ) ≠ 0

- Test statistic

$$t = r * \sqrt{\frac{n-2}{1-r^2}}$$

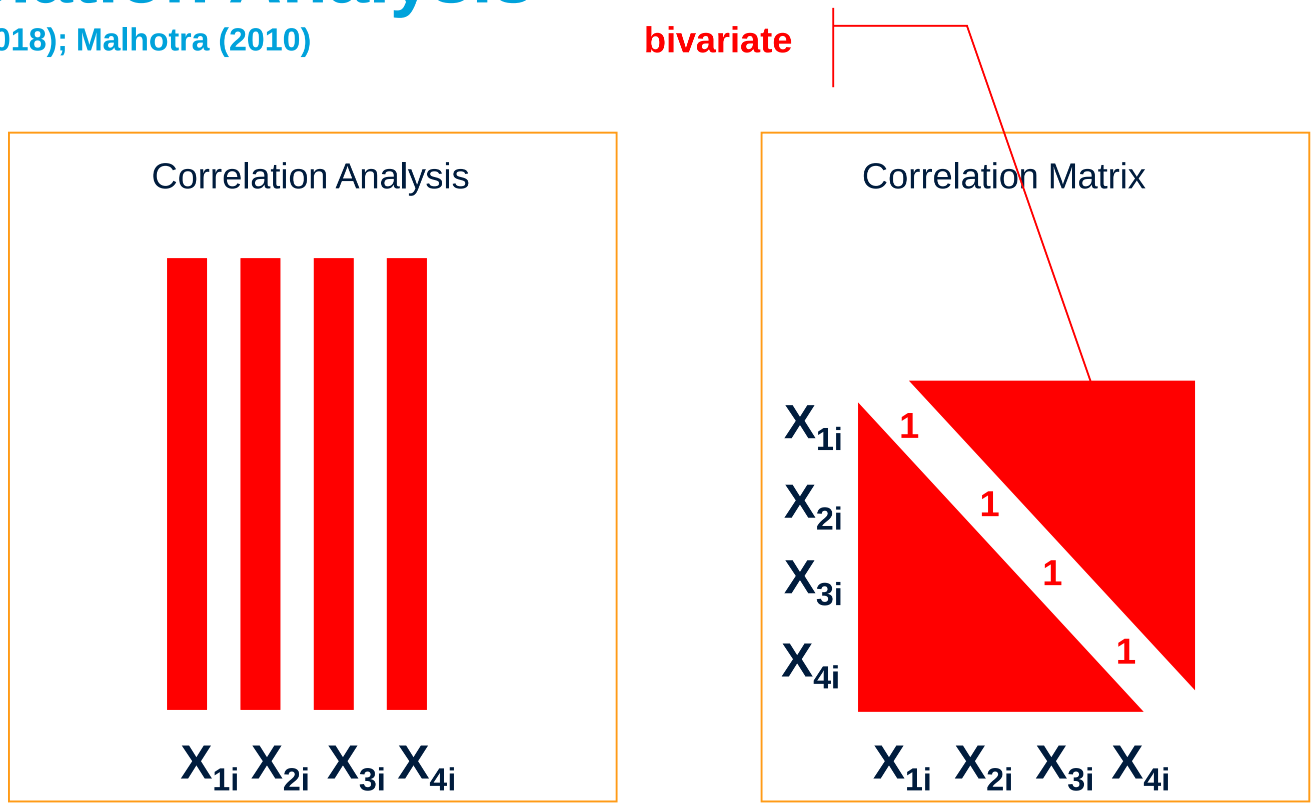
$$df = n-2$$

- Effect Size (r) / Effect Size (R^2)

Effect Size (r)	Effect Size (R^2)	
0.10	0.02	small
0.30	0.13	medium
0.50	0.26	large

Correlation Analysis

Hair et al. (2018); Malhotra (2010)



SPSS Application
TAM Data

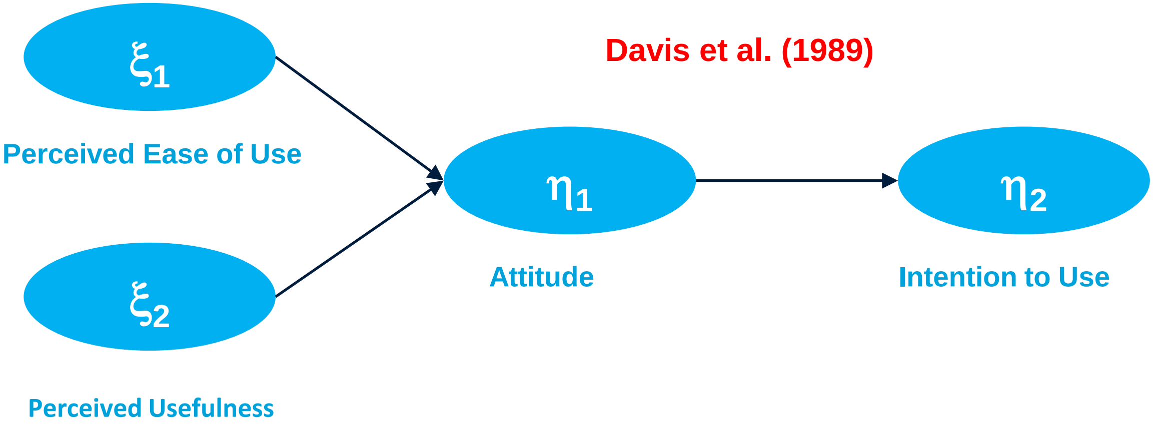
- Data Set *Data-01.sav* (n=439)

- Constructs and Items
  - Perceived Ease of Use (PEU, Q1-Q3)
  - Perceived Usefulness (PU, Q4-Q6)
  - Attitude (ATT, Q7-Q9)
  - Intention (INT, Q10-Q12)

- Reliability Analysis (Coefficient α)
  - PEU 0.93
  - PU 0.92
  - ATT 0.92
  - INT 0.87

SPSS Application

TAM Data



Construct	Items
PEU	Q1, Q2, Q3
PU	Q4, Q5, Q6
ATT	Q7, Q8, Q9
INT	Q10, Q11, Q12

Structural Equation Modeling
Introduction

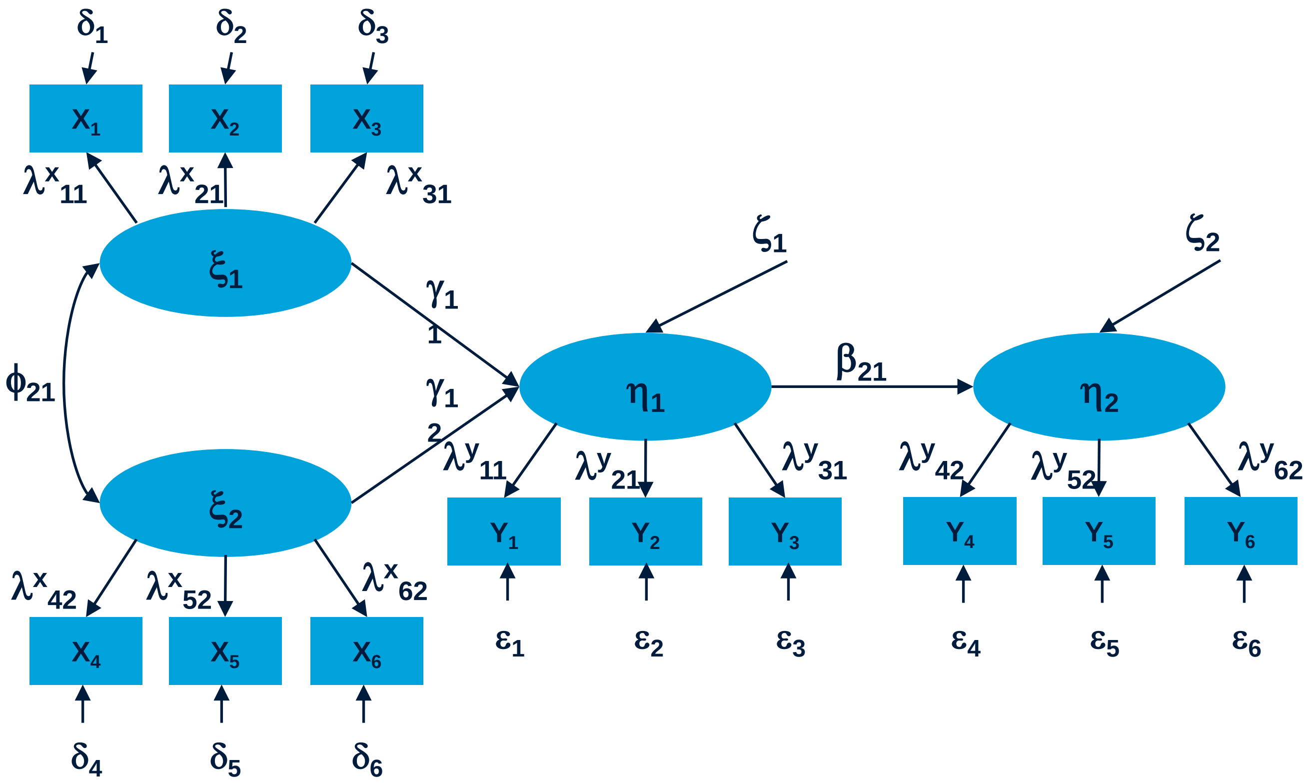
- Hair et al. (2010, 635) provide the following definition of Structural Equation Modeling (SEM):

  "Structural equation modeling (SEM) is a family of statistical models that seek to explain the relationships among multiple variables."

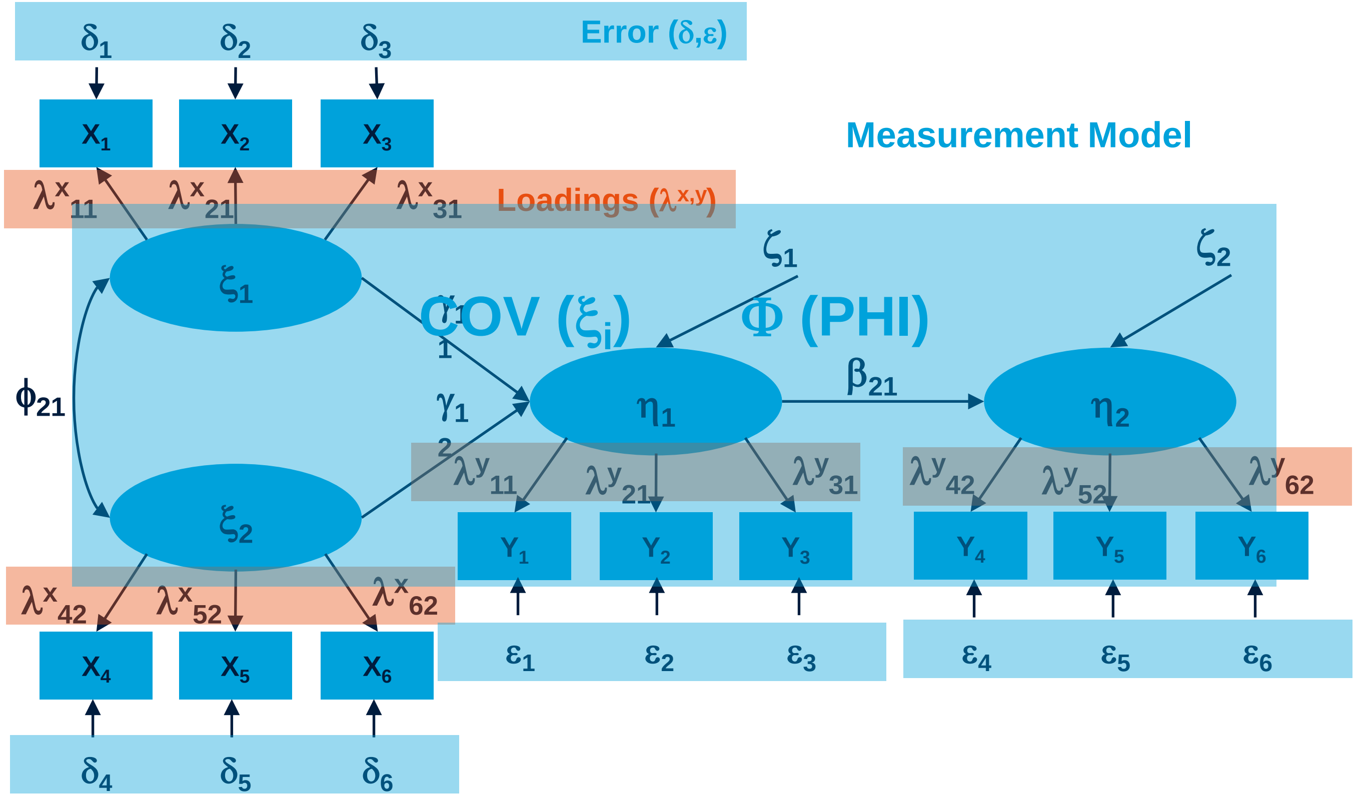
  "… SEM's foundation lies in two familiar multivariate techniques: factor analysis and multiple regression analysis"

- Three characteristics underlie all SEM techniques:
  - Estimation of multiple and interrelated dependence relationships (Structural Model)
  - The ability to represent unobserved concepts in these relationships and account for measurement error in the estimation process (Measurement Model; CFA Model)
  - Defining the model to explain the entire set of relationships (Theorectical Foundation)

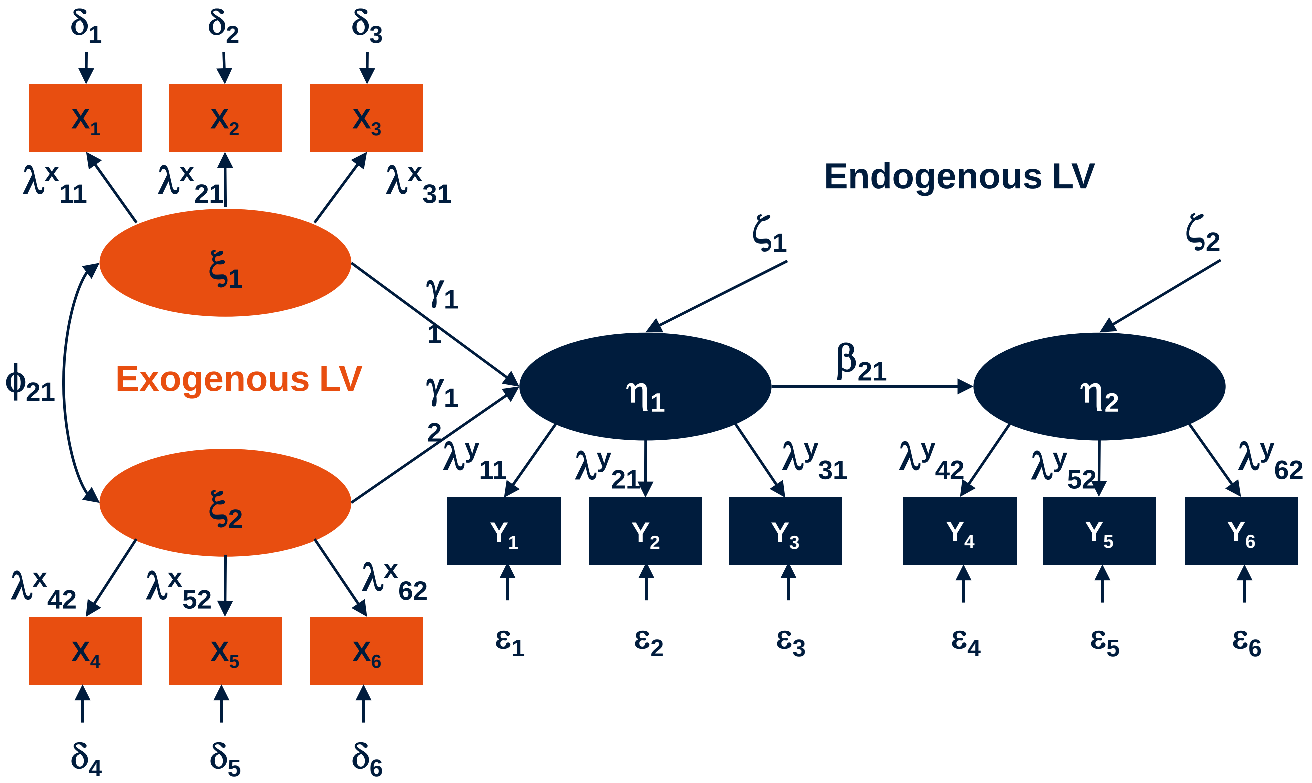
Introducing the “LISREL” Model



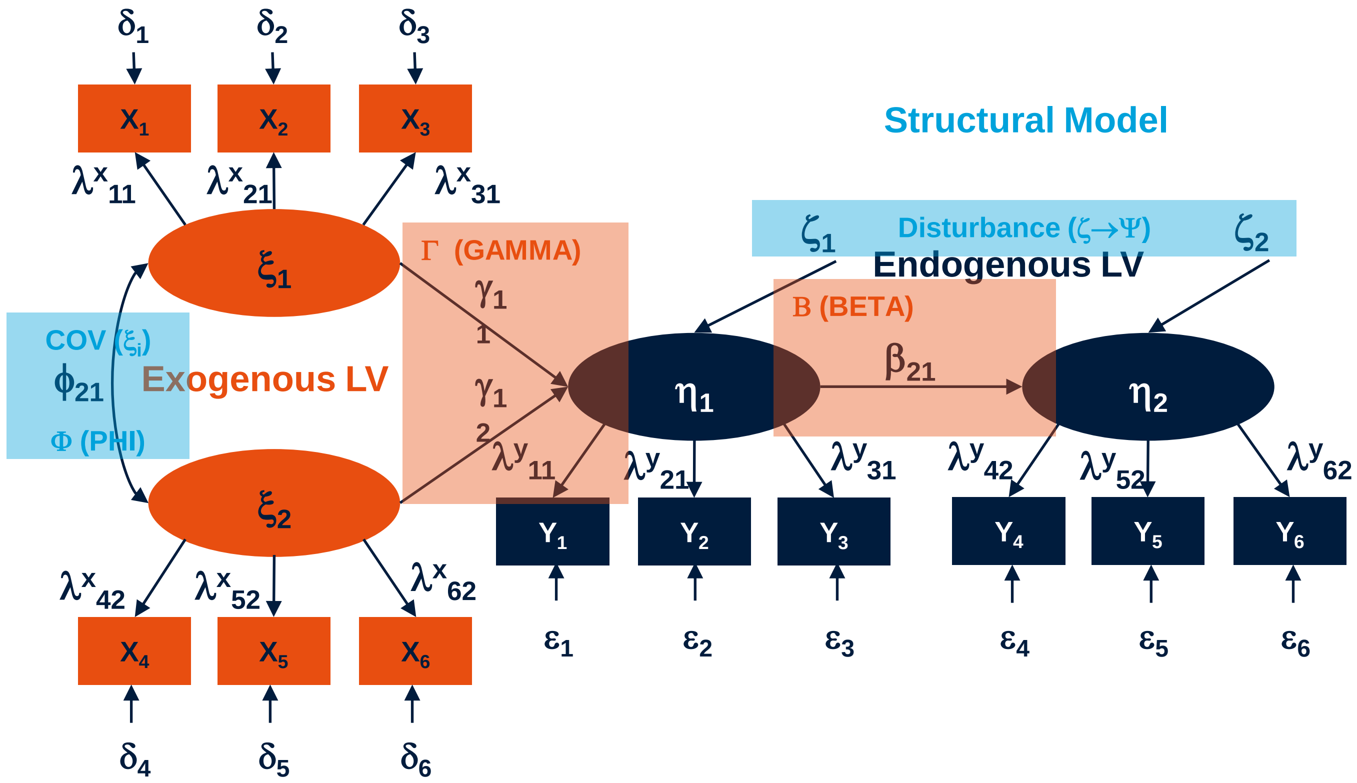
Introducing the “LISREL” Model



Introducing the "LISREL" Model



Introducing the "LISREL" Model



Introduction to Structural Equation Modeling
Analysis Approach (Hair et al., 2018; Malhotra, 2010)

1. Defining the Individual Constructs
2. Develop and Specify the Measurement Model
3. Design an Empirical Study/Collect Data
4. Assessing Measurement Model Validity

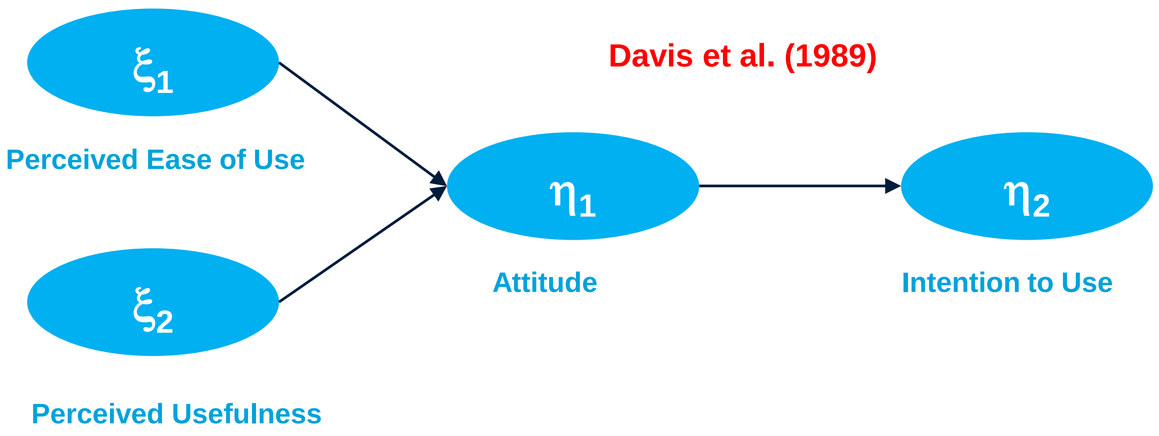
Revise?

Introduction to Structural Equation Modeling
Analysis Approach (Hair et al., 2018; Malhotra, 2010)

5	Specify Structural Model
6	Assess Structural Model validity

Revise?

1. Defining the Individual Constructs



Davis et al. (1989)

MANAGEMENT SCIENCE
Vol. 35, No. 8, August 1989
Printed in U.S.A.

USER ACCEPTANCE OF COMPUTER TECHNOLOGY: A COMPARISON OF TWO THEORETICAL MODELS*

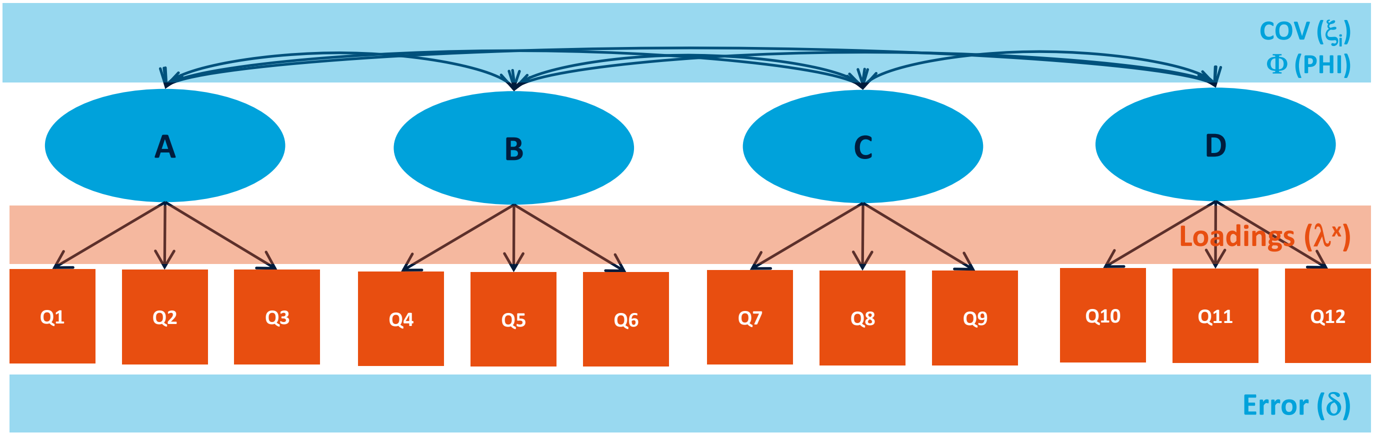
FRED D. DAVIS, RICHARD P. BAGOZZI AND PAUL R. WARSHAW
School of Business Administration, University of Michigan, Ann Arbor, Michigan 48109-1234
School of Business Administration, University of Michigan, Ann Arbor, Michigan 48109-1234
School of Business Administration, California Polytechnic State University, San Luis Obispa, California 93407

Computer systems cannot improve organizational performance if they aren't used. Unfortunately, resistance to end-user systems by managers and professionals is a widespread problem. To better predict, explain, and increase user acceptance, we need to better understand why people accept or reject computers. This research addresses the ability to predict peoples' computer acceptance from a measure of their intentions, and the ability to explain their intentions in terms of their attitudes, subjective norms, perceived usefulness, perceived ease of use, and related variables. In a longitudinal study of 107 users, intentions to use a specific system, measured after a one-hour introduction to the system, were correlated 0.35 with system use 14 weeks later. The intention-usage correlation was 0.63 at the end of this time period. Perceived usefulness strongly influenced peoples' intentions, explaining more than half of the variance in intentions at the end of 14 weeks. Perceived ease of use had a small but significant effect on intentions as well, although this effect subsided over time. Attitudes only partially mediated the effects of these beliefs on intentions. Subjective norms had no effect on intentions. These results suggest the possibility of simple but powerful models of the determinants of user acceptance, with practical value for evaluating systems and guiding managerial interventions aimed at reducing the problem of underutilized computer technology.
(INFORMATION TECHNOLOGY; USER ACCEPTANCE; INTENTION MODELS)

2. Develop and Specify Measurement Model

Construct	Items
A (PEU)	Q1, Q2, Q3
B (PU)	Q4, Q5, Q6
C (ATT)	Q7, Q8, Q9
D (INT)	Q10, Q11, Q12

Develop and Specify Measurement Model
Confirmatory Factor Analysis (CFA)



3. Design an Emperical Study

- Questionnaire (n=439)
- Employees

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
q1	439	1	6	3.39	.944
q2	439	1	6	3.65	.956
q3	439	1	6	3.52	1.009
q4	439	1	6	3.35	.965
q5	439	1	6	3.59	1.010
q6	439	1	7	4.15	.997
q7	439	2	7	4.22	.975
q8	439	1	7	3.24	.947
q9	439	1	7	3.85	.970
q10	439	1	7	4.14	1.239
q11	439	1	6	3.49	.931
q12	439	1	7	3.83	.959
Valid N (listwise)	439				

4. Assessing Measurement Model Validity

- **Reliability**
- **Convergent Validity**
  - Model Fit
  - Factor Loadings (t test)
  - Langrange Multiplier Test (Modification Index)
  - Standardized Residuals
- **Discriminant Validity**
  - χ^2 Difference Test Approach (single degree of freedom tests)
  - Confidence Interval Approach
  - Variance Extracted Approach
  - Nested Model Approach

Model Fit

Hair et al. (2010)

	Cut-Off n>250 m>30	n↓ m↓
ABSOLUTE FIT		
χ^2 statistic (df, *p*)	sig(!)	ns
RMSEA	0.08	0.06
SRMR	0.08	0.06
INCREMENTAL FIT		
TLI (NNFI)	0.90	0.95
CFI	0.90	0.95

Model Fit: ML Estimation

(Hair et al., 2018)

n=number of observations

$$\chi^2 = (n-1)F_{ML}$$

(p+q)=number of MV   Σ =Model-Implied Matrix

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

S=Sample Matrix

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

t=number of estimated parameters

Model Fit: ML Estimation

(Hair et al., 2018)

A Perfect Fit?

$$S = \Sigma$$

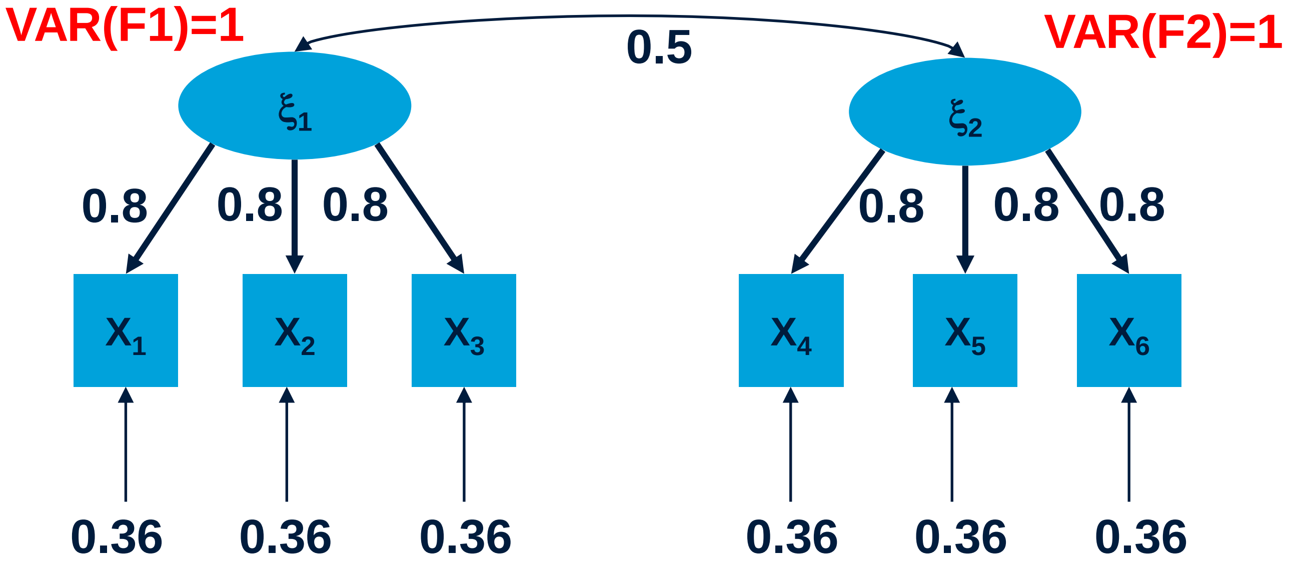
$$F_{ML} = tr(SS^{-1}) – (p+q) + ln|S| - ln|S|$$

$$F_{ML} = tr(I) – (p+q) + ln|S| - ln|S| = 0$$

$$\chi^2 = (n-1)*0 = 0$$

Model Fit: Analysis Approach

(Hair et al., 2018)



Model Fit: Analysis Approach

(Hair et al., 2018)

COVARIANCE MATRIX

1.0000					
0.6400	1.0000				
0.6400	0.6400	1.0000			
0.3200	0.3200	0.3200	1.0000		
0.3200	0.3200	0.3200	0.6400	1.0000	
0.3200	0.3200	0.3200	0.6400	0.6400	1.0000

LISREL EXAMPLE
SIMPLIS LANGUAGE

```
Creating A POPULATION Matrix

OBSERVED VARIABLES:
x1-x6

COVARIANCE MATRIX
1
0 1
0 0 1
0 0 0 1
0 0 0 0 1
0 0 0 0 0 1


SAMPLE SIZE:
10000000

LATENT VARIABLES:
F1 F2
```

```
RELATIONSHIPS
x1 = 0.8*F1
x2 = 0.8*F1
x3 = 0.8*F1
x4 = 0.8*F2
x5 = 0.8*F2
x6 = 0.8*F2

SET THE ERROR VARIANCES of x1-x6
to 0.36

SET THE VARIANCE OF F1-F2 to 1

SET THE COVARIANCE OF F1-F2 to 0.5

LISREL OUTPUT: ALL ND=4 SI=IMP.COV

PATH DIAGRAM

END OF PROBLEM
```

Introduction to Structural Equation Modeling
LISREL

- SEMNET
  - To join SEMNET, send the command:
    SUB SEMNET *first-name last-name* (in *body section* of e-mail)

    to LISTSERV@BAMA.UA.EDU

  - Archives
    http://bama.ua.edu/archives/semnet.html

Introduction to Structural Equation Modeling
LISREL

- LInear Structural RELationships
- Modules
  - LISREL
  - PRELIS (Preprocessor for LISREL)
- Available Command Languages
  - LISREL Command Language
  - SIMPLIS Command Language
  - Interactive Mode
  - Path Diagrams
  - Wizard-Like Approach for LISREL and SIMPLIS (Project)
  - PRELIS

Getting LISREL…

SSI SCIENTIFIC SOFTWARE INTERNATIONAL

- About
- LISREL
- HLM
- IRT
- SuperMix
- Ordering
- Workshops
- Other Products
- FAQs
- Contact Information

S Student edition of LISREL for Windows

Note that SSI, Inc. does not provide technical support for users of the student edition of LISREL for Windows.

Restrictions:

Compared with the full edition, the student edition of LISREL for Windows is restricted as follows.

- Basic statistical analyses and data manipulation is restricted to a maximum of 20 variables.
- Structural equation modeling is restricted to a maximum of 16 observed variables.
- Multilevel modeling is restricted a maximum of 15 variables.
- Generalized Linear Modeling is restricted to a maximum of 20 variables.
- The **Export Data** option on the **File** menu is restricted to ASCII, tab-delimited and comma-delimited data files.
- It can only import ASCII, tab-delimited and comma-delimited and **SOME (NOT ALL)** SPSS for Windows (SAV) data files by using the **Import Data** option on the **File** menu.

SSI, Inc. highly appreciates your comments on the student edition via email (lisrel@ssicentral.com).

Software

The current student edition of LISREL for Windows can be installed using the installation application LISREL92StudentSetup.exe.

Instructions:

- Download LISREL92StudentSetup.exe to a temporary location.
- Open the location above in Windows Explorer or Computer.
- Ensure that the saved file is approximately **61,878 KB** in size. If not, please save it again.
- Click on the Run as Administrator option on the right-click menu for LISREL92StudentSetup.exe.
- Delete LISREL92StudentSetup.exe from the temporary location above.

Download the student edition of LISREL for Windows **(61,878 KB)**

Copyright © 2005-2016, Scientific Software International, Inc., All rights reserved.
P.O. Box 4728, Skokie, IL 60076-4728

Getting LISREL…

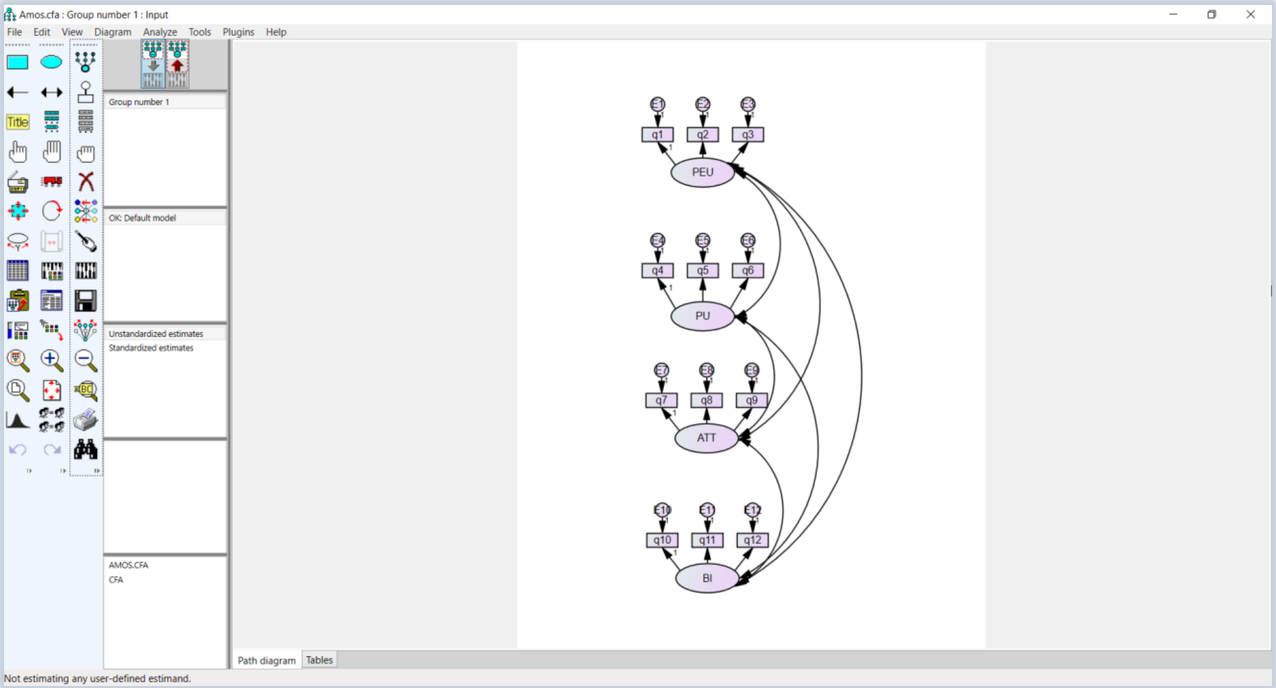
http://www.ssicentral.com/lisrel/techdocs/SIMPLISSyntax.pdf

Introduction to Structural Equation Modeling
Alternatives

- Alternative Software Packages:
  - EQS Version 6.3 (www.mvsoft.com)
  - IBM AMOS Version 25 (http://www-03.ibm.com/software/products/en/spss-amos)
  - Mplus Version 8 (www.statmodel.com)
  - STATA15 (www.stata.com)
  - Proc CALIS in SAS Release 9 (www.sas.com)
  - R (package sem; package lavaan)

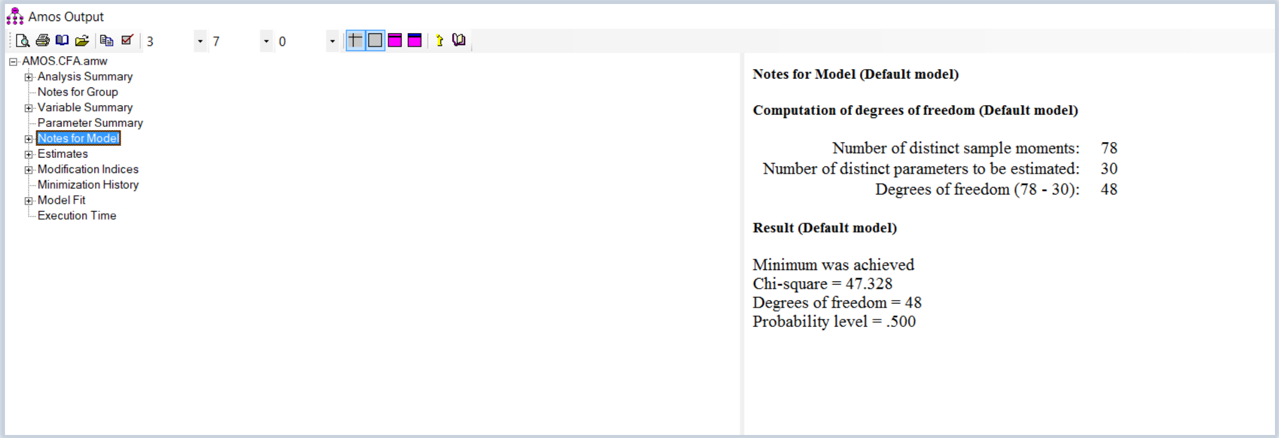
IBM SPSS AMOS 25

https://www.ibm.com/us-en/marketplace/structural-equation-modeling-sem

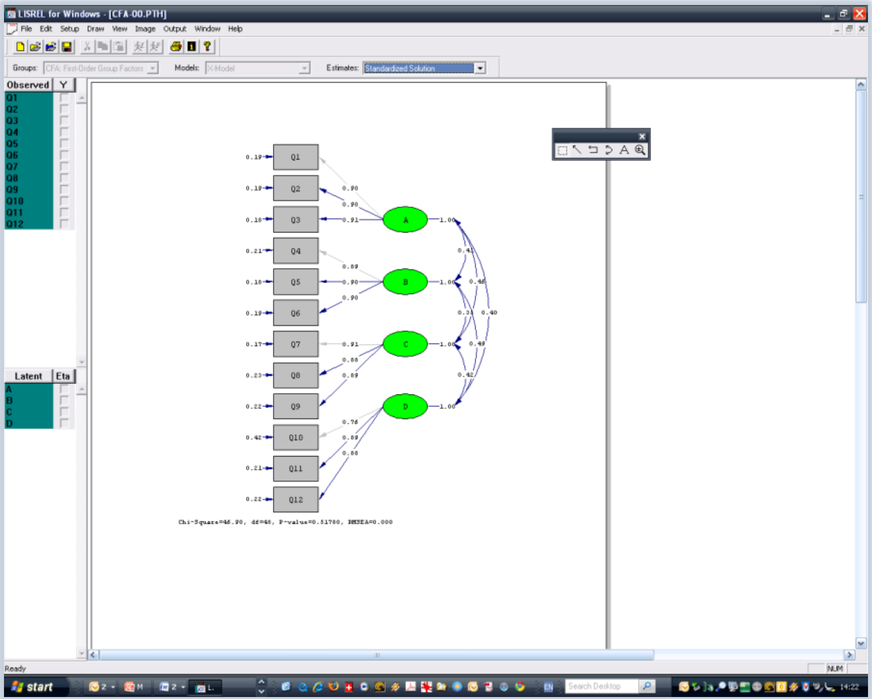


IBM SPSS AMOS 25

https://www.ibm.com/us-en/marketplace/structural-equation-modeling-sem



LISREL EXAMPLE



LISREL EXAMPLE
LISREL LANGUAGE

```
CFA: First-Order Group Factor Model
SP=Data-01.sav
DA MA=CM
MO NX=12 NK=4 LX=FU TD=DI PH=FU
LA
Q1 Q2 Q3 Q4 Q5 Q6 Q7 Q8 Q9 Q10 Q11 Q12
SE
Q1 Q2 Q3 Q4 Q5 Q6 Q7 Q8 Q9 Q10 Q11 Q12
LE
A B C D
PA LX
0 0 0 0
1 0 0 0
1 0 0 0
0 0 0 0
0 1 0 0
0 1 0 0
0 0 0 0
0 0 1 0
0 0 1 0
0 0 0 0
0 0 0 1
0 0 0 1
FI LX 1 1 LX 4 2 LX 7 3 LX 10 4
VA 1 LX 1 1 LX 4 2 LX 7 3 LX 10 4
PATH DIAGRAM
OU ND=2 SE TV RS SC SS MI
```

LISREL EXAMPLE
SIMPLIS LANGUAGE

```
CFA: First-Order Group Factor Model

SPSS-Data from file: Data-01.sav
! Raw Data from File: Data-01.psf

LATENT VARIABLES:
A B C D

EQUATIONS:

Q1 = 1*A
Q2 = A
Q3 = A

Q4 = 1*B
Q5 = B
Q6 = B
```

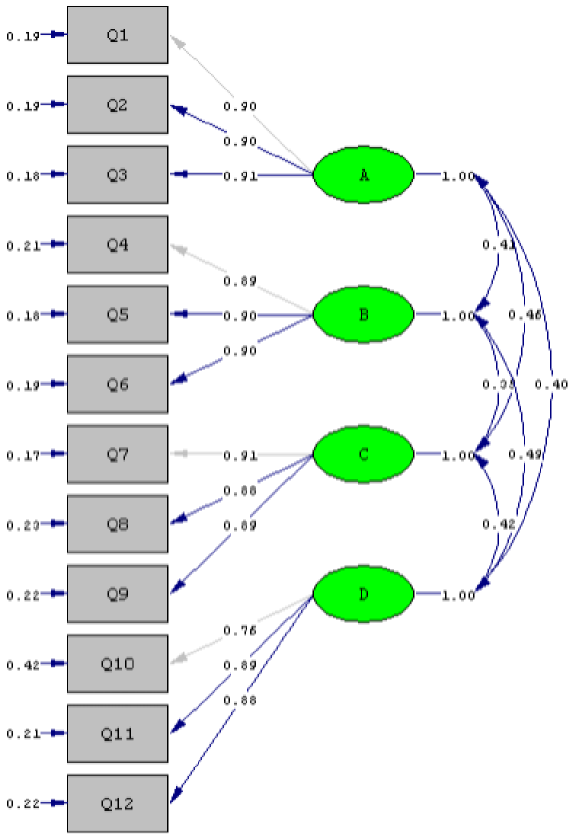
```
Q7 = 1*C
Q8 = C
Q9 = C

Q10 = 1*D
Q11 = D
Q12 = D

OPTIONS:
Number of decimals = 3

LISREL OUTPUT: SS SC MI RS

PATH DIAGRAM

END OF PROBLEM
```

LISREL EXAMPLE
SIMPLIS LANGUAGE - ALTERNATIVE

```
CFA: First-Order Group Factors

SPSS-Data from File: Data-01.sav
!Raw Data from File: Data-01.psf

LATENT VARIABLES:
A B C D

EQUATIONS:

Q1 = A
Q2 = A
Q3 = A

Q4 = B
Q5 = B
Q6 = B

Q7 = C
Q8 = C
Q9 = C
```

```
Q10 = D
Q11 = D
Q12 = D

Set the Variance of A to 1
Set the Variance of B to 1
Set the Variance of C to 1
Set the Variance of D to 1

OPTIONS:
Number of decimals = 3

LISREL OUTPUT: SS SC MI RS

PATH DIAGRAM

END OF PROBLEM
```

LISREL EXAMPLE
Path Diagram



Chi-Square=46.90, df=48, P-value=0.51780, RMSEA=0.000

LISREL EXAMPLE
Model Fit

```
Goodness of Fit Statistics

                           Degrees of Freedom = 48
             Minimum Fit Function Chi-Square = 47.33 (P = 0.50)
     Normal Theory Weighted Least Squares Chi-Square = 46.90 (P = 0.52)
                Estimated Non-centrality Parameter (NCP) = 0.0
            90 Percent Confidence Interval for NCP = (0.0 ; 19.00)

                      Minimum Fit Function Value = 0.11
               Population Discrepancy Function Value (F0) = 0.0
            90 Percent Confidence Interval for F0 = (0.0 ; 0.043)
            Root Mean Square Error of Approximation (RMSEA) = 0.0
           90 Percent Confidence Interval for RMSEA = (0.0 ; 0.030)
             P-Value for Test of Close Fit (RMSEA < 0.05) = 1.00

                Expected Cross-Validation Index (ECVI) = 0.25
           90 Percent Confidence Interval for ECVI = (0.25 ; 0.29)
                       ECVI for Saturated Model = 0.36
                     ECVI for Independence Model = 13.23
```

LISREL EXAMPLE
Model Fit

```
Chi-Square for Independence Model with 66 Degrees of Freedom = 5768.85
Independence AIC = 5792.85
Model AIC = 106.90
Saturated AIC = 156.00
Independence CAIC = 5853.86
Model CAIC = 259.44
Saturated CAIC = 552.59

Normed Fit Index (NFI) = 0.99
Non-Normed Fit Index (NNFI) = 1.00
Parsimony Normed Fit Index (PNFI) = 0.72
Comparative Fit Index (CFI) = 1.00
Incremental Fit Index (IFI) = 1.00
Relative Fit Index (RFI) = 0.99

Critical N (CN) = 682.91

Root Mean Square Residual (RMR) = 0.018
Standardized RMR = 0.018
Goodness of Fit Index (GFI) = 0.98
Adjusted Goodness of Fit Index (AGFI) = 0.97
Parsimony Goodness of Fit Index (PGFI) = 0.60
```

EQS EXAMPLE

```
GOODNESS OF FIT SUMMARY FOR METHOD = ML

INDEPENDENCE MODEL CHI-SQUARE        =    4122.418 ON    66 DEGREES OF FREEDOM

INDEPENDENCE AIC =    3990.418   INDEPENDENCE CAIC =    3654.841
       MODEL AIC =     -48.672          MODEL CAIC =    -292.728

CHI-SQUARE =       47.328 BASED ON      48 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      0.50030

THE NORMAL THEORY RLS CHI-SQUARE FOR THIS ML SOLUTION IS        46.904.

FIT INDICES
-----------
BENTLER-BONETT     NORMED FIT INDEX =     0.989
BENTLER-BONETT NON-NORMED FIT INDEX =     1.000
COMPARATIVE FIT INDEX (CFI)         =     1.000
BOLLEN'S          (IFI) FIT INDEX   =     1.000
MCDONALD'S        (MFI) FIT INDEX   =     1.001
JORESKOG-SORBOM'S  GFI  FIT INDEX   =     0.982
JORESKOG-SORBOM'S AGFI  FIT INDEX   =     0.972
ROOT MEAN-SQUARE RESIDUAL (RMR)     =     0.018
STANDARDIZED RMR                    =     0.018
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      0.000
90% CONFIDENCE INTERVAL OF RMSEA  (       0.000,          0.030)
```

Mplus

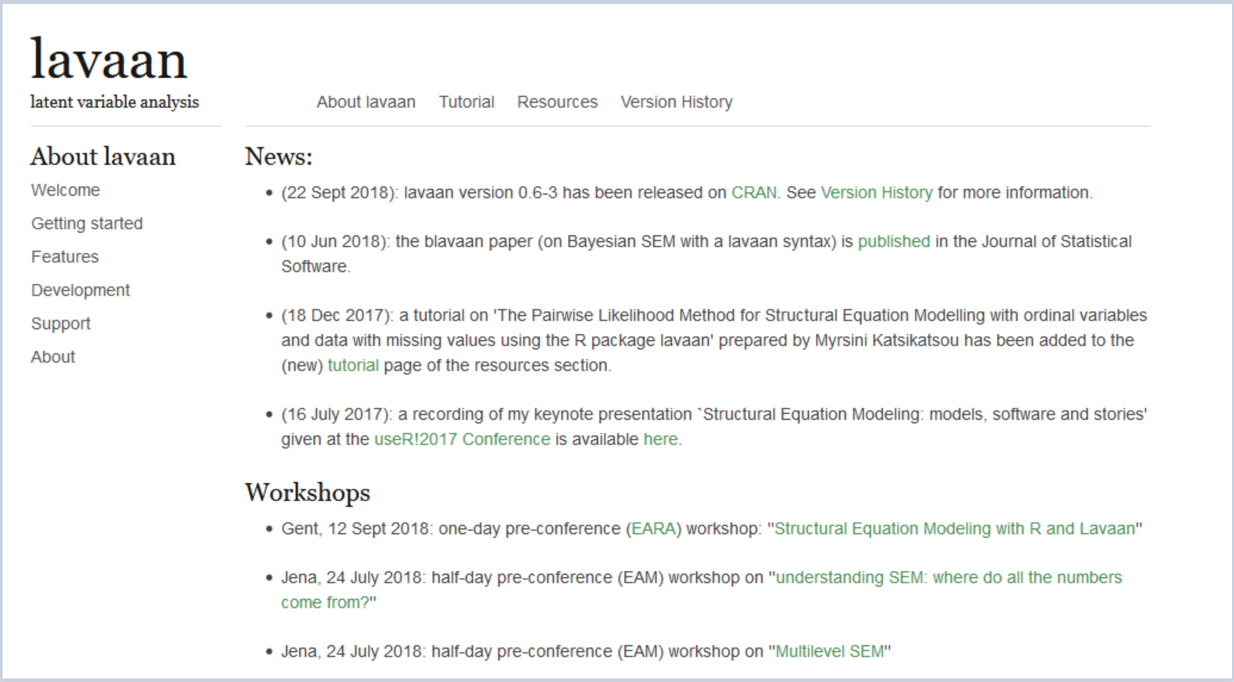
https://www.statmodel.com

Mplus

```
Chi-Square Test of Model Fit

          Value                            47.436
          Degrees of Freedom                   48
          P-Value                          0.4959

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                          0.000
          90 Percent C.I.                   0.000  0.031
          Probability RMSEA <= .05          1.000

CFI/TLI

          CFI                               1.000
          TLI                               1.000

Chi-Square Test of Model Fit for the Baseline Model

          Value                          4131.830
          Degrees of Freedom                   66
          P-Value                          0.0000

SRMR (Standardized Root Mean Square Residual)

          Value                             0.017
```

R LAVAAN

http://lavaan.ugent.be


lavaan
latent variable analysis

About lavaan   Tutorial   Resources   Version History

About lavaan

- Welcome
- Getting started
- Features
- Development
- Support
- About

News:

- (22 Sept 2018): lavaan version 0.6-3 has been released on CRAN. See Version History for more information.
- (10 Jun 2018): the blavaan paper (on Bayesian SEM with a lavaan syntax) is published in the Journal of Statistical Software.
- (18 Dec 2017): a tutorial on 'The Pairwise Likelihood Method for Structural Equation Modelling with ordinal variables and data with missing values using the R package lavaan' prepared by Myrsini Katsikatsou has been added to the (new) tutorial page of the resources section.
- (16 July 2017): a recording of my keynote presentation `Structural Equation Modeling: models, software and stories' given at the useR!2017 Conference is available here.

Workshops

- Gent, 12 Sept 2018: one-day pre-conference (EARA) workshop: "Structural Equation Modeling with R and Lavaan"
- Jena, 24 July 2018: half-day pre-conference (EAM) workshop on "understanding SEM: where do all the numbers come from?"
- Jena, 24 July 2018: half-day pre-conference (EAM) workshop on "Multilevel SEM"

R LAVAAN

Editor

```r
CFA.Model.01<-'
A =~ q1 + q2 + q3
B =~ q4 + q5 + q6
C =~ q7 + q8 + q9
D =~ q10 + q11 + q12
'

FIT01<-cfa(CFA.Model.01, data=Data.01.PPT, mimic="EQS")
#estimator: "MLM"

summary(FIT01, standardized=TRUE, fit.measures=TRUE)
```

R LAVAAN

Console

```
lavaan (0.5-20) converged normally after  39 iterations

  Number of observations                           439

  Estimator                                         ML
  Minimum Function Test Statistic               47.328
  Degrees of freedom                                48
  P-value (Chi-square)                           0.500

Model test baseline model:

  Minimum Function Test Statistic             4122.418
  Degrees of freedom                                66
  P-value                                        0.000

User model versus baseline model:

  Comparative Fit Index (CFI)                    1.000
  Tucker-Lewis Index (TLI)                       1.000
```

```
Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -5374.246
  Loglikelihood unrestricted model (H1)      -5350.528

  Number of free parameters                         30
  Akaike (AIC)                               10808.492
  Bayesian (BIC)                             10930.958
  Sample-size adjusted Bayesian (BIC)        10835.753

Root Mean Square Error of Approximation:

  RMSEA                                          0.000
  90 Percent Confidence Interval          0.000  0.031
  P-value RMSEA <= 0.05                          1.000

Standardized Root Mean Square Residual:

  SRMR                                           0.018
```

R LAVAAN

Console

```
Latent Variables:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv  Std.all
  A =~
    q1                1.000                               0.849    0.899
    q2                1.013    0.036   27.822    0.000    0.860    0.900
    q3                1.077    0.038   28.204    0.000    0.914    0.907
  B =~
    q4                1.000                               0.857    0.888
    q5                1.064    0.039   26.930    0.000    0.912    0.903
    q6                1.045    0.039   26.694    0.000    0.895    0.898
  C =~
    q7                1.000                               0.890    0.913
    q8                0.931    0.035   26.339    0.000    0.828    0.875
    q9                0.965    0.036   26.877    0.000    0.859    0.885
  D =~
    q10               1.000                               0.943    0.761
    q11               0.880    0.046   18.951    0.000    0.829    0.891
    q12               0.899    0.048   18.871    0.000    0.848    0.884

Covariances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv  Std.all
  A ~~
    B                 0.299    0.041    7.268    0.000    0.412    0.412
    C                 0.345    0.043    7.950    0.000    0.457    0.457
    D                 0.317    0.047    6.771    0.000    0.396    0.396
  B ~~
    C                 0.263    0.042    6.251    0.000    0.345    0.345
    D                 0.393    0.050    7.888    0.000    0.486    0.486
  C ~~
    D                 0.349    0.050    7.037    0.000    0.416    0.416
```

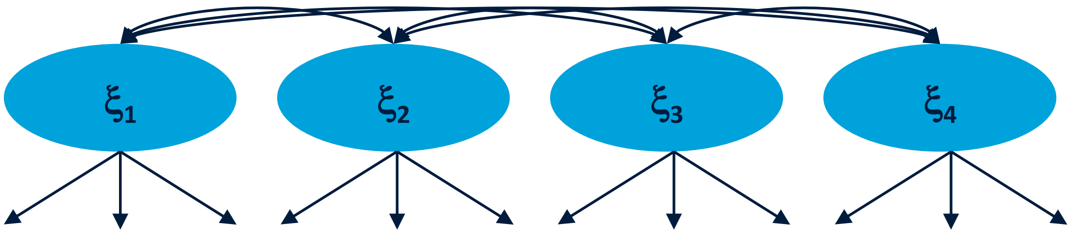
R LAVAAN

Console

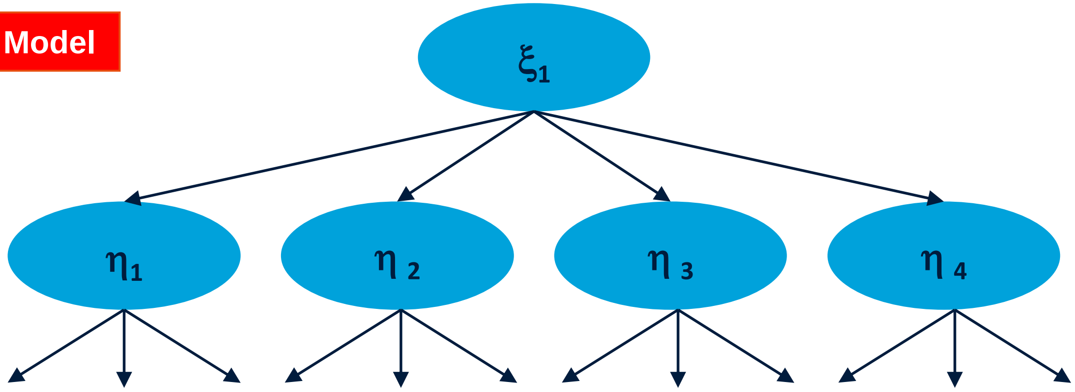
```
Variances:
                   Estimate  Std.Err  Z-value  P(>|z|)   Std.lv  Std.all
    q1                0.170    0.017    9.741    0.000    0.170    0.191
    q2                0.174    0.018    9.709    0.000    0.174    0.190
    q3                0.181    0.020    9.266    0.000    0.181    0.178
    q4                0.198    0.020   10.082    0.000    0.198    0.212
    q5                0.188    0.021    9.169    0.000    0.188    0.185
    q6                0.192    0.020    9.482    0.000    0.192    0.194
    q7                0.158    0.019    8.175    0.000    0.158    0.166
    q8                0.210    0.020   10.463    0.000    0.210    0.234
    q9                0.204    0.020    9.949    0.000    0.204    0.216
    q10               0.645    0.052   12.469    0.000    0.645    0.420
    q11               0.179    0.023    7.694    0.000    0.179    0.206
    q12               0.201    0.025    8.085    0.000    0.201    0.218
    A                 0.720    0.061   11.900    0.000    1.000    1.000
    B                 0.735    0.063   11.622    0.000    1.000    1.000
    C                 0.792    0.065   12.124    0.000    1.000    1.000
    D                 0.889    0.098    9.067    0.000    1.000    1.000
```

Nested Model Approach - Extended

Group-Factor Model

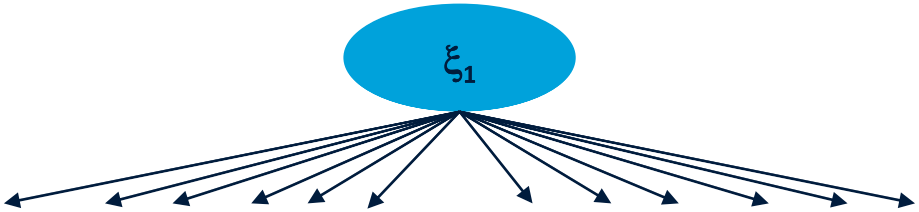


Second-Order Factor Model



Nested Model Approach - Extended

One-Factor Model



Nested Model Approach – Extended

(Rindskopf and Rose, 1988)

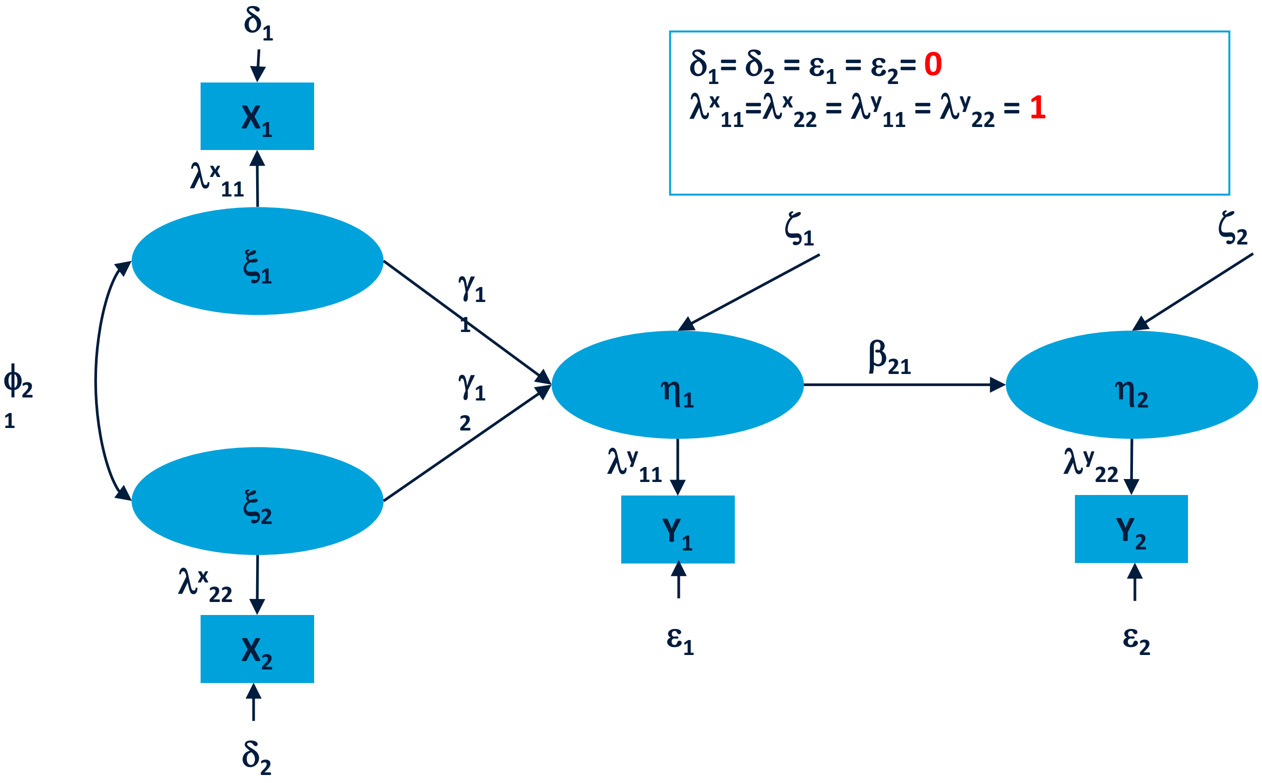
- Restrictions
  - One-Factor Model (Df=54)
  - Second-Order Factor Model (Df=50)
    - *The one-factor model is a special case of the second-order factor model where the (unique) variances of the first-order factors are set equal to zero*
    - *The second-order factor restricts the correlations among the first-order factors to a "structural model"*
  - Group-(Four-)Factor Model (Df=48)
    - *The one-factor model is a special case of the group-factor model where all correlations among the group factors are set equal to one*

Restrictions↑

Nested Model Approach – Extended χ^2 Difference Test

Model	$\chi 2$	df	$\Delta\chi 2$	Δdf	*p*
Group-Factor	47.33	48	NA	NA	NA
Second-Order Factor	57.35	50	10.02	2	0.007
One-Factor	2323.52	54	2276.19	6	<0.001

Structural Model with Manifest Variables



R LAVAAN

Editor

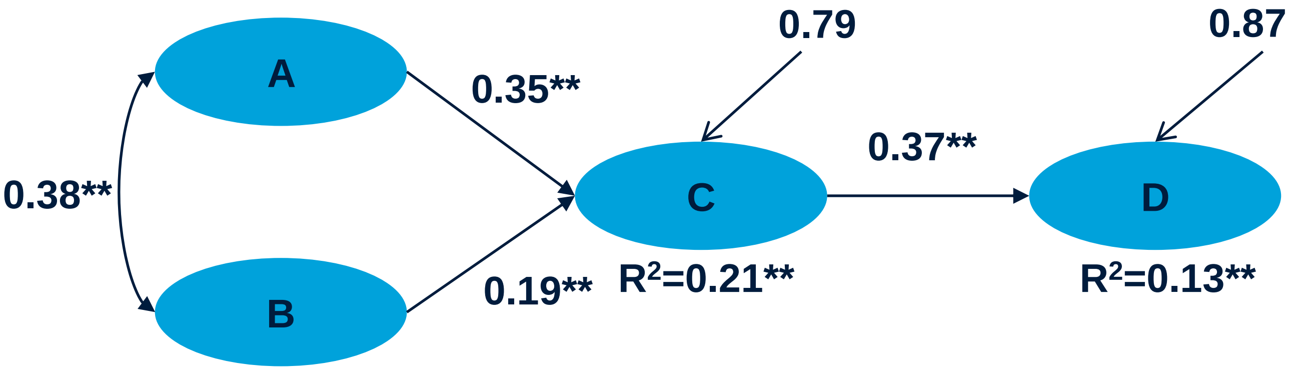
```
# SEM Observed Variables

PATH.Model.OBS<-'
ATT ~ PEU + PU
INT ~ ATT
'

FITPATHOBS<-sem(PATH.Model.OBS, data=Data.01.PPT, mimic="eqs")

summary(FITPATHOBS, fit.measures=TRUE)

modificationIndices(FITPATHOBS)

standardizedSolution(FITPATHOBS)


semPaths(FITPATHOBS,"std", curveAdjacent = FALSE, layout="tree", style = "lisrel")
```

R LAVAAN

Console

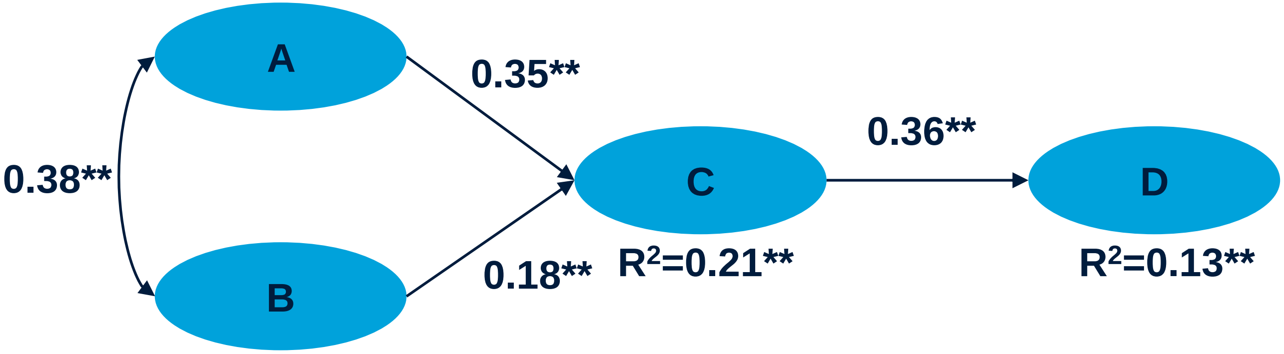
```
                Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Regressions:
  ATT ~
    PEU            0.347    0.045    7.648    0.000    0.347    0.352
    PU             0.179    0.045    4.010    0.000    0.179    0.185
  INT ~
    ATT            0.382    0.047    8.203    0.000    0.382    0.365

Covariances:
  PEU ~~
    PU             0.319    0.043    7.447    0.000    0.319    0.381

Variances:
    ATT            0.635    0.043   14.799    0.000    0.635    0.793
    INT            0.761    0.051   14.799    0.000    0.761    0.867
    PEU            0.823    0.056   14.799    0.000    0.823    1.000
    PU             0.853    0.058   14.799    0.000    0.853    1.000
```

OLS Regression Analysis
Results



** p<0.01

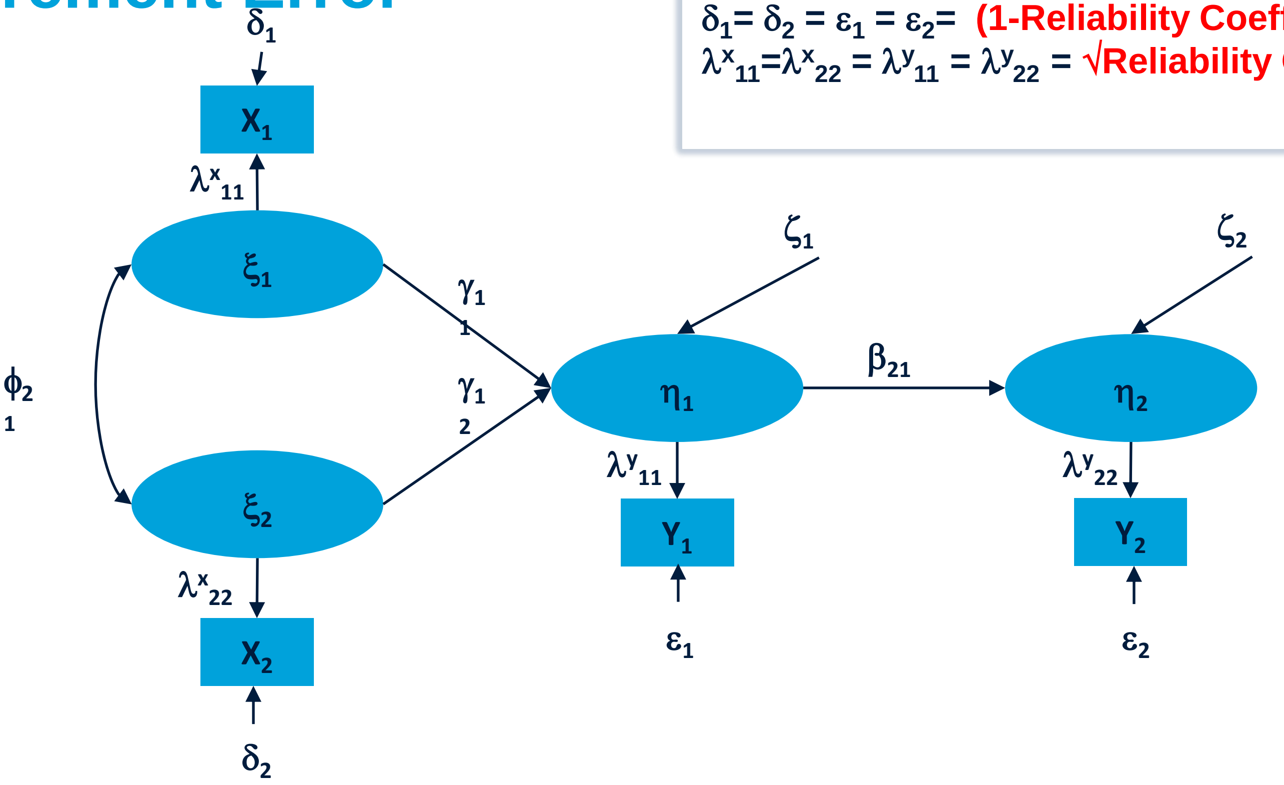
Structural Model with Manifest Variables Results



** p<0.01

Structural Model with Manifest Variables Corrected for Measurement Error

$\delta_1 = \delta_2 = \varepsilon_1 = \varepsilon_2 =$ **(1-Reliability Coefficient)*VAR**
$\lambda^x_{11} = \lambda^x_{22} = \lambda^y_{11} = \lambda^y_{22} =$ **√Reliability Coefficient**



R LAVAAN

Editor

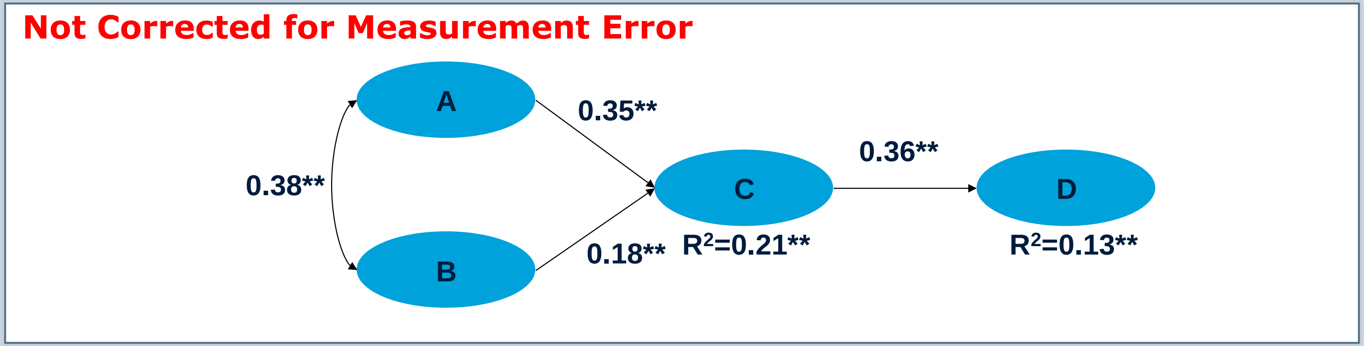
```
# SEM Observed Variables Corrected

PATH.Model.OBS.COR<-'
LPEU =~ 0.96*PEU
LPU =~ 0.96*PU
LATT =~ 0.96*ATT
LINT =~ 0.93*INT
PEU ~~ 0.06*PEU
PU ~~ 0.06*PU
ATT ~~ 0.06*ATT
INT ~~ 0.11*INT
LATT ~ LPEU + LPU
LINT ~ LATT
'

FITPATHOBS.COR<-sem(PATH.Model.OBS.COR, data=Data.01.PPT, mimic="eqs")

summary(FITPATHOBS.COR, standardized=TRUE, fit.measures=TRUE)

modificationIndices(FITPATHOBS.COR)

standardizedSolution(FITPATHOBS.COR)


semPaths(FITPATHOBS.COR,"std", curveAdjacent = FALSE, layout="tree", style = "lisrel")
```

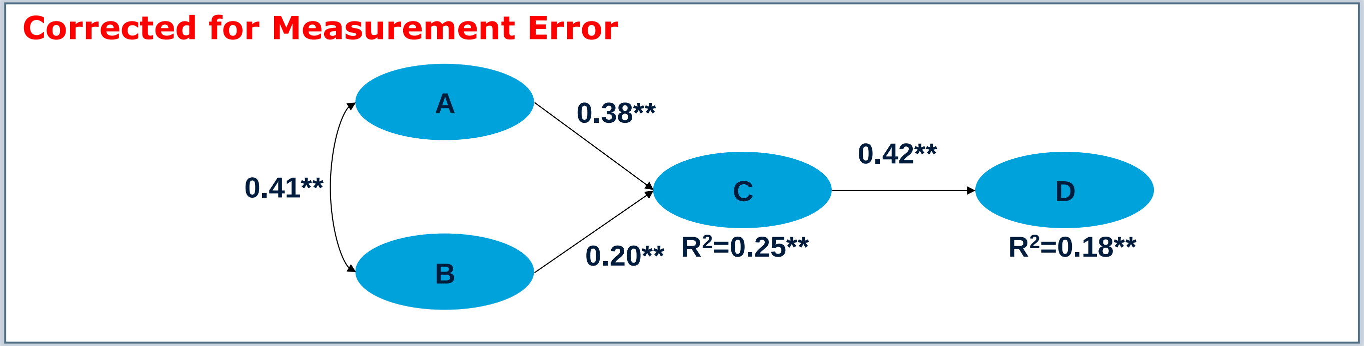
R LAVAAN

Console

```
Regressions:
  LATT ~
    LPEU              0.376    0.050    7.506    0.000    0.381    0.381
    LPU               0.192    0.049    3.919    0.000    0.199    0.199
  LINT ~
    LATT              0.441    0.052    8.541    0.000    0.420    0.420

Covariances:
  LPEU ~~
    LPU               0.346    0.046    7.447    0.000    0.410    0.410

Variances:
    PEU               0.060                               0.060    0.073
    PU                0.060                               0.060    0.070
    ATT               0.060                               0.060    0.075
    INT               0.110                               0.110    0.125
    LPEU              0.828    0.060   13.720    0.000    1.000    1.000
    LPU               0.860    0.063   13.757    0.000    1.000    1.000
    LATT              0.605    0.046   13.138    0.000    0.753    0.753
    LINT              0.731    0.059   12.426    0.000    0.824    0.824

>
```

Structural Model with Manifest Variables Corrected for Measurement Error



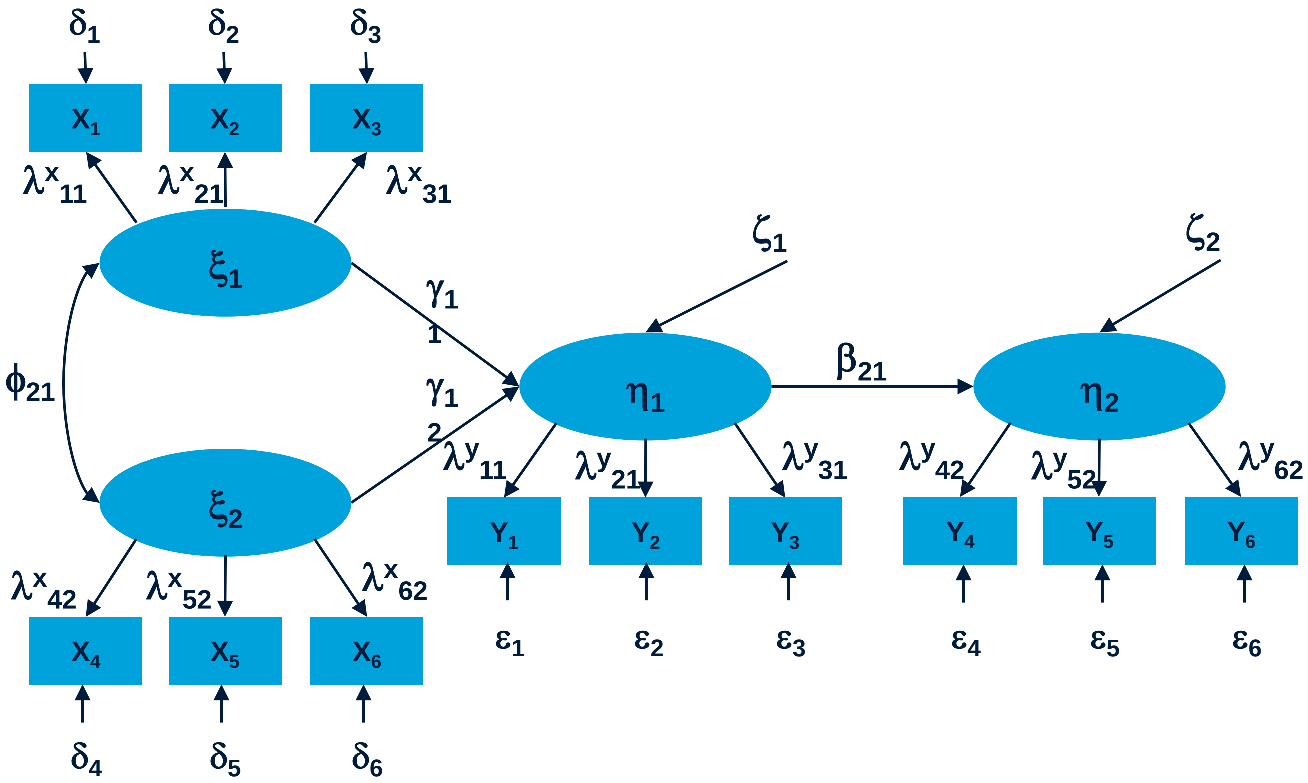


Path Models with Manifest Variables
Literature Suggestions

Bollen, K.A. (1989). *Structural Equations with Latent Variables.* New York: John Wiley & Sons.

Williams, L.J. & Hazer, J.T. (1986). Antecedents and Consequences of Satisfaction and Commitment in Turnover Models: A Reanalysis Using Latent Variable Structural Equation Methods*. Journal of Applied Psychology, 71* (2), 219-231.

Introducing the “LISREL” Model



LISREL EXAMPLE
SIMPLIS LANGUAGE

```
Path Analysis with Latent
Variables

SPSS-Data from File: Data-01.sav

LATENT VARIABLES:
A B C D

EQUATIONS:

!Measurement Model

Q1 = 1*A
Q2 = A
Q3 = A

Q4 = 1*B
Q5 = B
Q6 = B

Q7 = 1*C
Q8 = C
Q9 = C
```

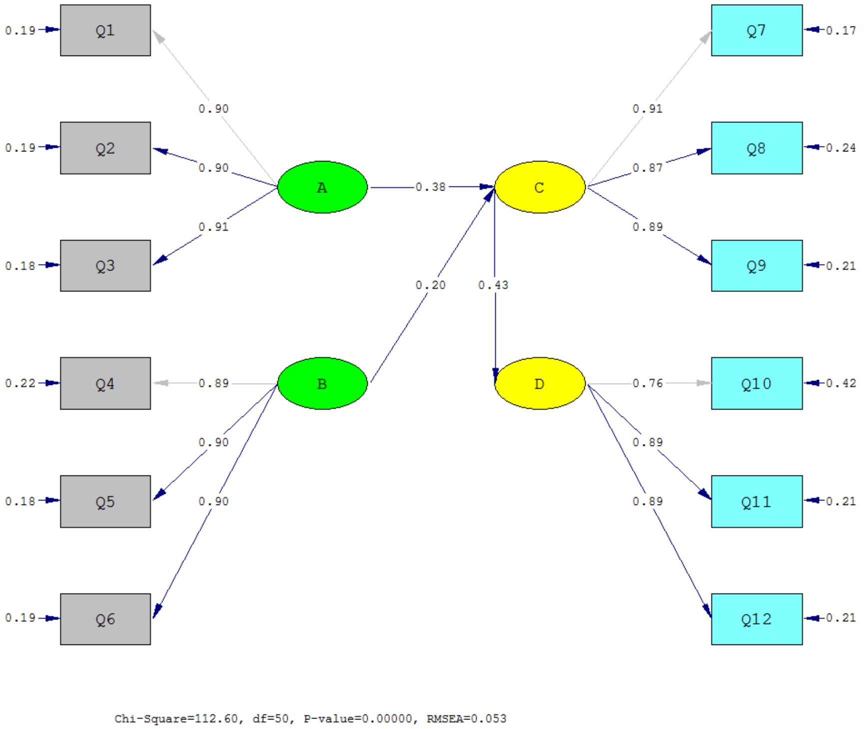
```
Q10 = 1*D
Q11 = D
Q12 = D

! Structural Model
C = A + B
D = C

OPTIONS:
Number of decimals = 2

LISREL OUTPUT: SS SC MI RS

PATH DIAGRAM

END OF PROBLEM
```

LISREL EXAMPLE
SIMPLIS LANGUAGE

```
Path Analysis with Latent Variables

SPSS-Data from File: Data-01.sav

LATENT VARIABLES:
A B C D

EQUATIONS:

Q1 = A
Q2 = A
Q3 = A

Q4 = B
Q5 = B
Q6 = B

Q7 = C
Q8 = C
Q9 = C
```

```
Q10 = D
Q11 = D
Q12 = D

C = A + B
D = C

Set Variance of A to 1
Set Variance of B to 1
Set Variance of C to 1
Set Variance of D to 1

OPTIONS:
Number of decimals = 3

LISREL OUTPUT: SS SC MI RS

PATH DIAGRAM

END OF PROBLEM
```

Path Analysis with Latent Variables Results



R LAVAAN

Editor

```
# SEM Path Model


PATH.Model<-'
A =~ q1 + q2 + q3
B =~ q4 + q5 + q6
C =~ q7 + q8 + q9
D =~ q10 + q11 + q12
C ~ A + B
D ~ C
'




FITPATH<-sem(PATH.Model, data=Data.01.PPT, mimic="eqs")
#se="bootstrap"

```

R LAVAAN

Console

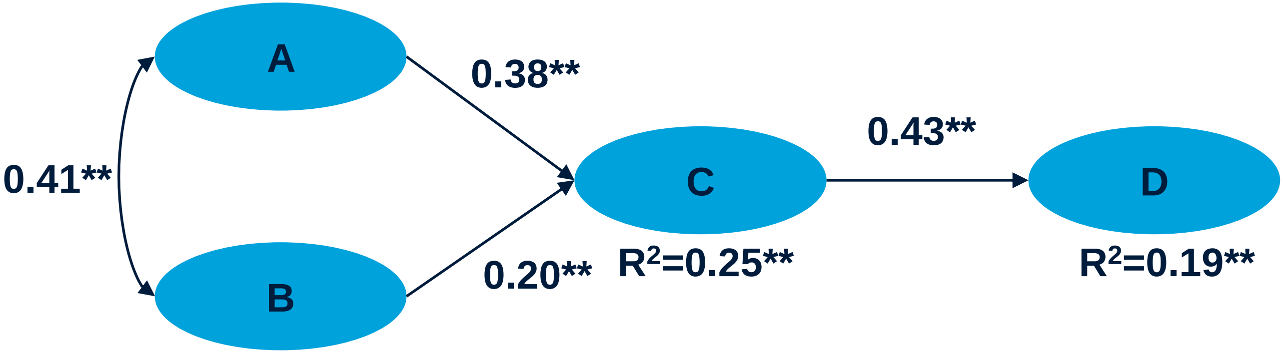
```
                   Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Latent variables:
  A =~
    q1                1.000                               0.849    0.900
    q2                1.013    0.036   27.819    0.000    0.860    0.900
    q3                1.077    0.038   28.191    0.000    0.914    0.906
  B =~
    q4                1.000                               0.855    0.886
    q5                1.068    0.040   26.817    0.000    0.913    0.905
    q6                1.047    0.039   26.521    0.000    0.896    0.898
  C =~
    q7                1.000                               0.888    0.911
    q8                0.931    0.036   26.175    0.000    0.827    0.873
    q9                0.969    0.036   26.917    0.000    0.860    0.887
  D =~
    q10               1.000                               0.943    0.762
    q11               0.876    0.047   18.777    0.000    0.826    0.887
    q12               0.902    0.048   18.779    0.000    0.851    0.888

Regressions:
  C ~
    A                 0.399    0.054    7.347    0.000    0.382    0.382
    B                 0.210    0.053    3.934    0.000    0.202    0.202
  D ~
    C                 0.460    0.055    8.298    0.000    0.433    0.433

Covariances:
  A ~~
    B                 0.299    0.041    7.268    0.000    0.412    0.412
```

R LAVAAN

Console

```
Variances:
    q1          0.170   0.018    9.711   0.000   0.170   0.191
    q2          0.174   0.018    9.698   0.000   0.174   0.190
    q3          0.181   0.020    9.263   0.000   0.181   0.178
    q4          0.201   0.020   10.125   0.000   0.201   0.216
    q5          0.185   0.021    8.956   0.000   0.185   0.181
    q6          0.192   0.020    9.382   0.000   0.192   0.193
    q7          0.162   0.019    8.406   0.000   0.162   0.171
    q8          0.213   0.020   10.577   0.000   0.213   0.237
    q9          0.201   0.020    9.887   0.000   0.201   0.213
    q10         0.644   0.052   12.392   0.000   0.644   0.420
    q11         0.184   0.024    7.575   0.000   0.184   0.213
    q12         0.195   0.026    7.563   0.000   0.195   0.212
    A           0.721   0.061   11.904   0.000   1.000   1.000
    B           0.731   0.063   11.570   0.000   1.000   1.000
    C           0.591   0.051   11.657   0.000   0.750   0.750
    D           0.723   0.081    8.889   0.000   0.813   0.813
```

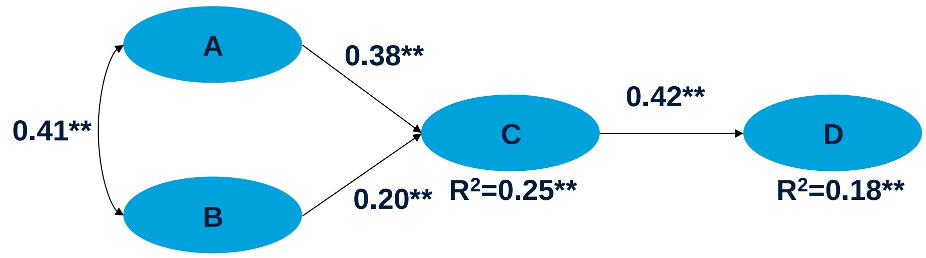
Path Analysis with Latent Variables
Results



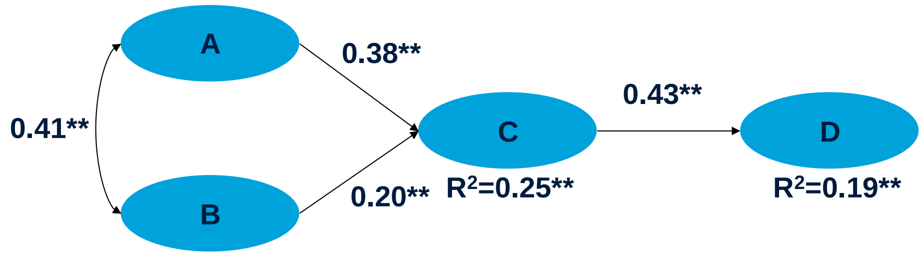
** p<0.01

Path Analysis with Latent Variables Results

Corrected for Measurement Error



Latent Variables



Path Models with Latent Variables
Literature Suggestions

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, *103*(3), 411.

Bentler, P.M. & Chou, C. (1987). Practical Issues in Structural Modeling. *Sociological Methods & Research, 16(1)*, 78-117.

Bollen, K.A. (1989). *Structural Equations with Latent Variables.* New York: John Wiley & Sons.

Brown, T. A. (2015). *Confirmatory Factor Analysis for Applied Research*. New York, NY: Guilford Press.

Byrne, B. (1998). *Structural Equation Modeling with LISREL, PRELIS, and SIMPLIS.* Mahwah, NJ: Lawrence Erlbaum.

Diamantopoulos, A. & Siguaw, J.A. (2005). *Introducing LISREL.* London: Sage Publications.

Hair, J.F., Jr., Black, W.C., Babin, B.J, and Anderson, R.E. (2018). *Multivariate Data Analysis.* Cengage.

Path Models with Latent Variables
Literature Suggestions

Hu, L., & Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. *Structural Equation Modeling*, *6*, 1-55.

Kline, R.B. (2015). *Principles and Practice of Structural Equation Modeling.* New York: The Guilford Press.

Rindskopf, D., & Rose, T. (1988). Some theory and applications of confirmatory second-order factor analysis. *Multivariate Behavioral Research*, *23*(1), 51-67.

Tabachnick, B.G. & Fidell, L.S. (2007). *Using Multivariate Statistics.* Boston: Allyn and Bacon.

Path Models with Latent Variables
Literature Suggestions

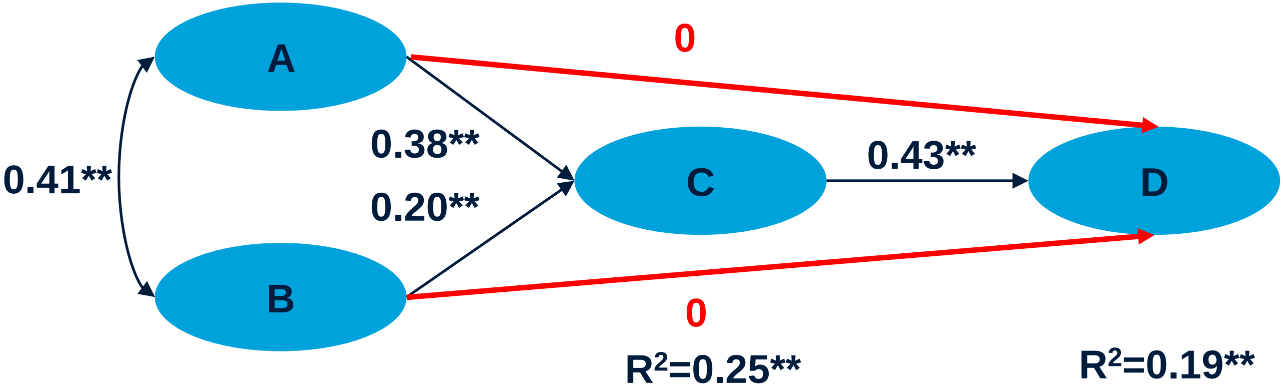
Beaujean, A. A. (2014). *Latent Variable Modeling Using R: A Step-by-Step Guide*. Routledge.

Finch, W. H., & French, B. F. (2015). *Latent Variable Modeling with R*. Routledge.

Rosseel, Y. (2012). Lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software, 48*(2), 1-36. (URL http://www.jstatsoft.org/v48/i02/).

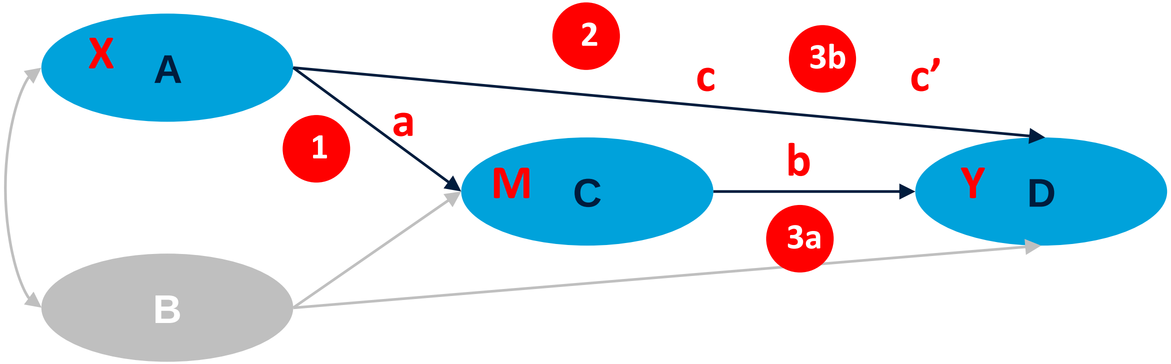
Mediation Analysis Using SEM

M0: excluding “direct” effects of A and B on D
M1: including “direct” effects of A and B on D



** p<0.01

Mediation Analysis Using SEM Regression Approach (Baron and Kenny, 1986)



Sobel (1982) test: c’<c, or a*b ≠ 0

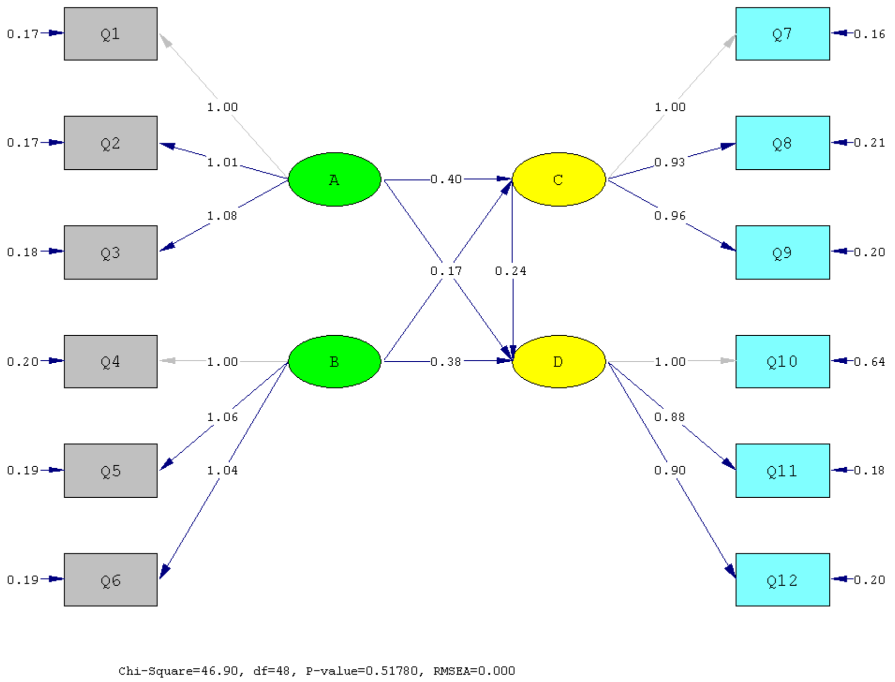
LISREL EXAMPLE
SIMPLIS LANGUAGE

```
Path Analysis with Latent
Variables

SPSS-Data from File: Data-01.sav

LATENT VARIABLES:
A B C D

EQUATIONS:

Q1 = 1*A
Q2 = A
Q3 = A

Q4 = 1*B
Q5 = B
Q6 = B

Q7 = 1*C
Q8 = C
Q9 = C
```

```
Q10 = 1*D
Q11 = D
Q12 = D

C = A + B
D = C + A + B

OPTIONS:
Number of decimals = 2

LISREL OUTPUT: SS SC MI RS EF

PATH DIAGRAM

END OF PROBLEM
```

Mediation Analysis Using SEM

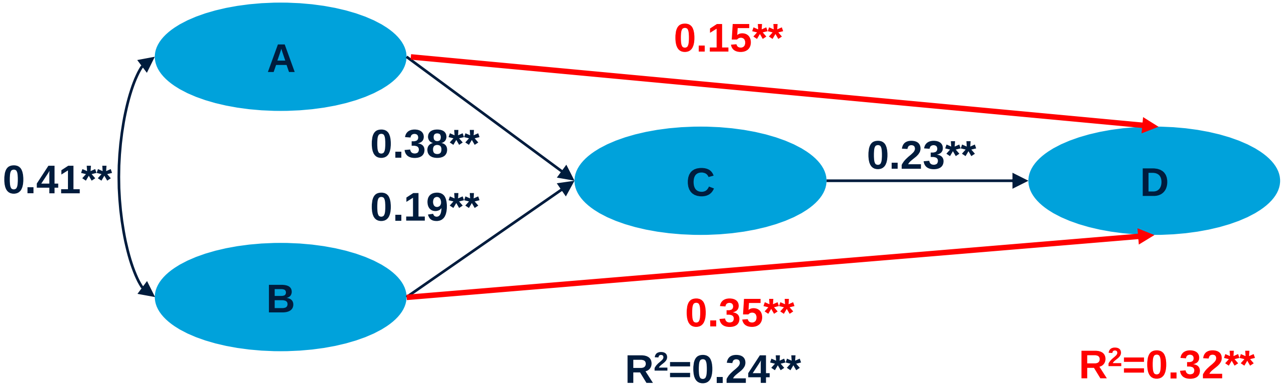
Iacobucci et al. (2007)



Mediation Analysis Using SEM

Iacobucci et al. (2007)

M0: $\chi^2(50)=115.397$
M1: $\chi^2(48)= 47.328$ ($\Delta \chi^2(2)=68.07$, $p<0.001$)



Follow-up by Sobel (1982) test: c'<c, or a*b ≠ 0

** $p<0.01$

R LAVAAN

Editor

```r
# Mediation

PATH.Model.MED<-'
A =~ q1 + q2 + q3
B =~ q4 + q5 + q6
C =~ q7 + q8 + q9
D =~ q10 + q11 + q12
C ~ a1*A + a2*B
D ~ b*C + A + B
a1b := a1*b
a2b := a2*b
'

FITPATH<-sem(PATH.Model.MED, data=Data.01.PPT, mimic="eqs")
#se="bootstrap"

summary(FITPATH, standardized=TRUE, fit.measures=TRUE)
```

Mediation Analysis Using SEM

Iacobucci et al. (2007)

```
Indirect Effects of KSI on ETA

                 A          B
          --------   --------
 C             - -        - -
 D            0.10       0.05
            (0.03)     (0.02)
              3.71       2.83
```

```
Defined parameters:
    a1b              0.096    0.026    3.707    0.000    0.087    0.087
    a2b              0.048    0.017    2.832    0.005    0.043    0.043

>
```

Mediation Analysis Using SEM
Literature Suggestion

Iacobucci, D., Saldanha, N. and Deng, X. (2007). A Meditation on Mediation: Evidence that Structural Equation Models Perform Better than Regressions. *Journal of Consumer Psychology, 17* (2), 139-153.

Partial Least Squares Path Modeling

- *"…second generation of multivariate analysis"*

  Fornell (1987)

- Partial Least Squares Path Modeling
  - Latent Variables (Measurement Error)
  - Assumes minimally ordinally-scaled variables
  - Non-Normal Distributions
  - Assess Reliability and Construct Validity of Measures
  - Large number of indicators
  - Formative and Reflective Measures

Partial Least Squares Path Modeling

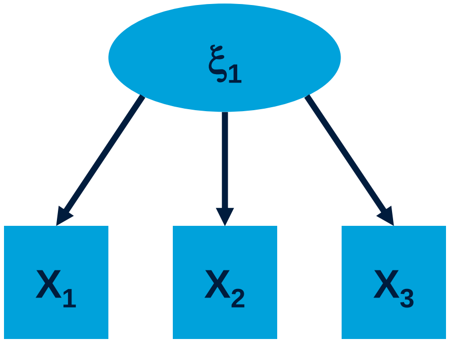
(Chin, 1998; Hair et al. 2018; Tenenhaus et al., 2005)

PLS (Variance-Based SEM)	Covariance-Based SEM ("*LISREL*")
Prediction Oriented	Parameter Oriented
Maximalization of VAR	"Reproduction" of VAR-COV Matrix
"Nonparametric" ▸ At least ordinally scaled ▸ No Multivariate Normality	Parametric ▸ At least intervally scaled (ordinal requires large sample size) ▸ Multivariate Normality
Latent Variables Are Explicitely Estimated	Indeterminate
Reflective and Formative Indicators	Typically Reflective Indicators
Large Model Complexity (Constructs and/or Indicators)	Moderate Model Complexity (constructs and/or indicators)
Small Sample Sizes (n > 30)	Large Sample Size (n > 200 [400])

Partial Least Squares Path Modeling

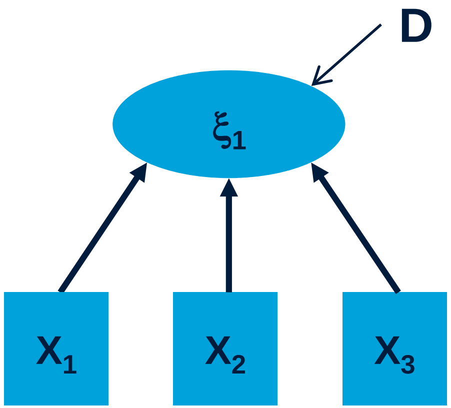
(Chin, 1998; Hair et al. 2018; Tenenhaus et al., 2005)

Reflective Indicators



- Measures should covary (internal consistency)

Formative Indicators



- Measures need not covary
- Measures of internal consistency do not apply

Partial Least Squares Path Modeling
Assessing Validity (Chin, 1998; Hair et al. 2018; Tenenhaus et al., 2005)

- **PLS (Variance-Based SEM)**
  - **Measurement Model** ***("Outer Model")***
    - Reliability
    - Construct Validity
  - **Structural Model** ***("Inner Model")***
    - Hypothesis Testing
    - Bootstrapping to obtain SE of estimate
    - Model Fit (R^2 for Endogeneous Constructs)
    - GOF (Tenenhaus et al., 2005)

$$GOF = \sqrt{MEAN(Communality) * Mean(R^2)}$$

Partial Least Squares Path Modeling

- Sample Size
  - Heuristic
    - Ten times the greater of
      1. Construct with largest number of formative indicators
      2. Constructs with the largest number of structural paths going to it
  - Power Analysis (cf. Green, 1991)

Partial Least Squares Path Modeling
Psychometric Properties

- **Reliability**
  - Composite Reliability (CR) > 0.7 (Nunally and Bernstein, 1994)
  - Average Variance Extracted (AVE) > 0.5 (Fornell and Larcker, 1981)

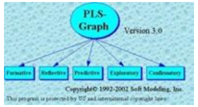
- **Convergent Validity**
  - Standarized Loadings (SL) > 0.5 (Hulland, 1999)

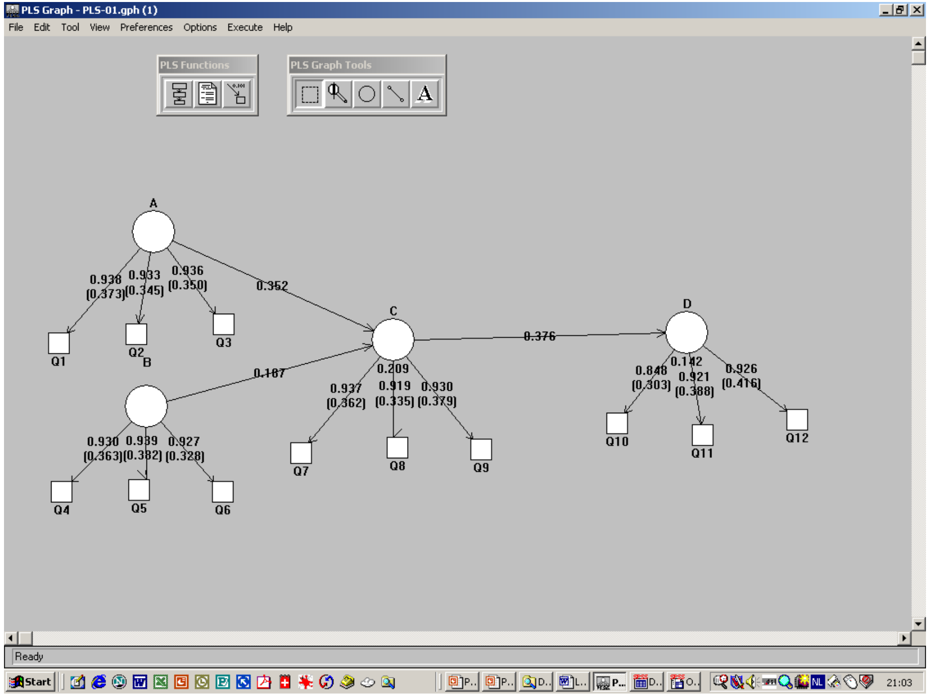
- **Discriminant Validity**
  - $\sqrt{AVE\ LV_i} > CORR(LV_i, LV_j)$ (Fornell and Larcker, 1981)
  - Cross Loadings are not substantial in magnitude (Hulland, 1999)

Partial Least Squares Path Modeling
PLS Graph

- PLS Graph is developed by
  - Dr. Wynne W. Chin, University of Houston
  - More info at: http://disc-nt.cba.uh.edu/chin/indx.html
  - The program can be obtained for academic purposes by sending an email to Dr. Wynne W. Chin (wchin@uh.edu)

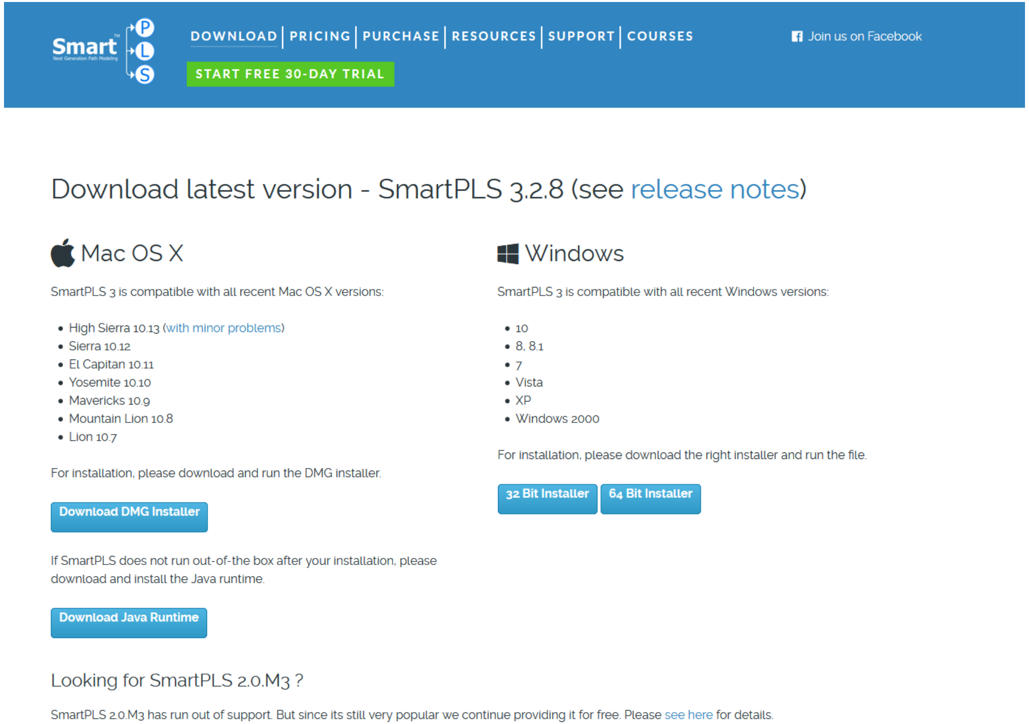
Partial Least Squares Path Modeling
PLS-Graph





SmartPLS 3

www.smartpls.com


Smart PLS

DOWNLOAD | PRICING | PURCHASE | RESOURCES | SUPPORT | COURSES

Join us on Facebook

START FREE 30-DAY TRIAL

Download latest version - SmartPLS 3.2.8 (see release notes)

Mac OS X

SmartPLS 3 is compatible with all recent Mac OS X versions:

- High Sierra 10.13 (with minor problems)
- Sierra 10.12
- El Capitan 10.11
- Yosemite 10.10
- Mavericks 10.9
- Mountain Lion 10.8
- Lion 10.7

For installation, please download and run the DMG installer.

Download DMG Installer

If SmartPLS does not run out-of-the box after your installation, please download and install the Java runtime.

Download Java Runtime

Windows

SmartPLS 3 is compatible with all recent Windows versions:

- 10
- 8, 8.1
- 7
- Vista
- XP
- Windows 2000

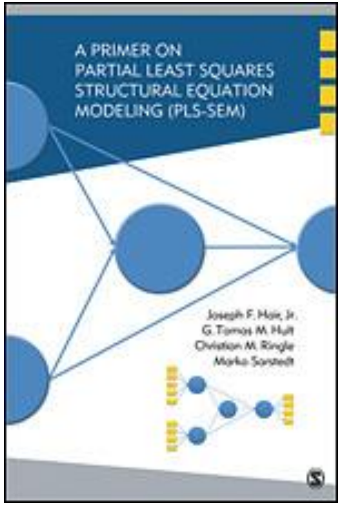
For installation, please download the right installer and run the file.

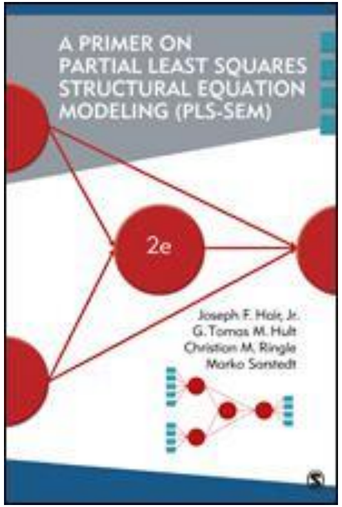
32 Bit Installer | 64 Bit Installer

Looking for SmartPLS 2.0.M3 ?

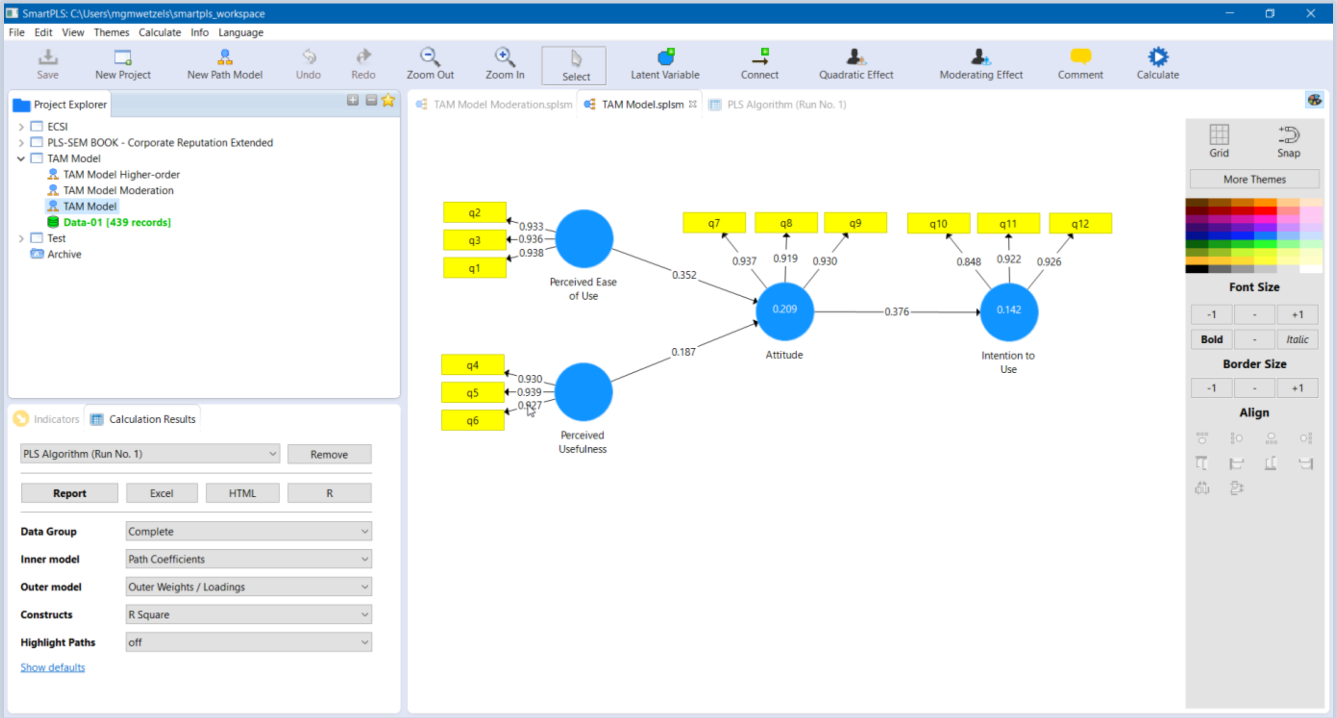
SmartPLS 2.0.M3 has run out of support. But since its still very popular we continue providing it for free. Please see here for details.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2014). *A Primer on Partial Least Squares Equation Modeling (PLS-SEM)*. Los Angeles, CA: Sage Publications.



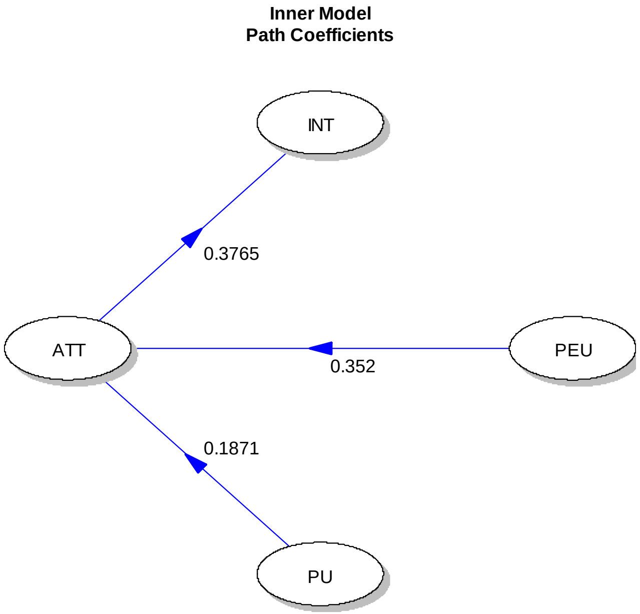


Partial Least Squares Path Modeling SmartPLS

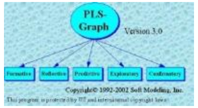


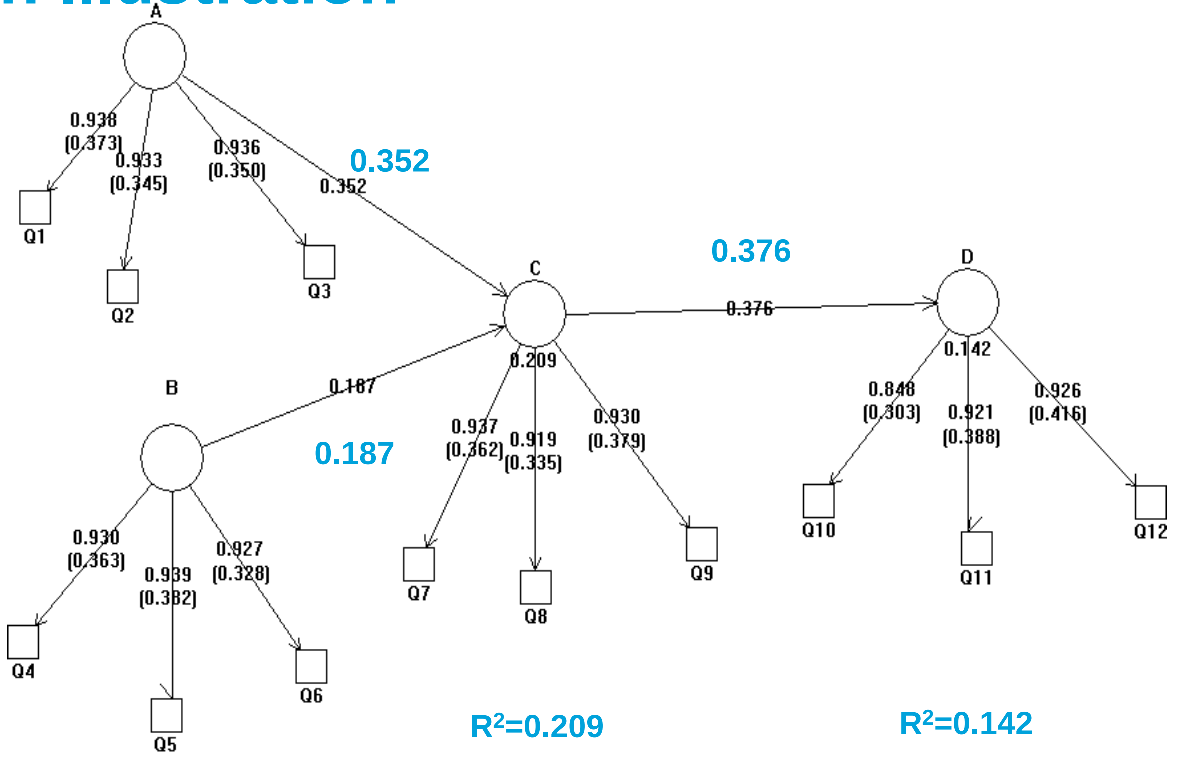
Partial Least Squares Path Modeling

R PLSPM (www.plsmodeling.com)

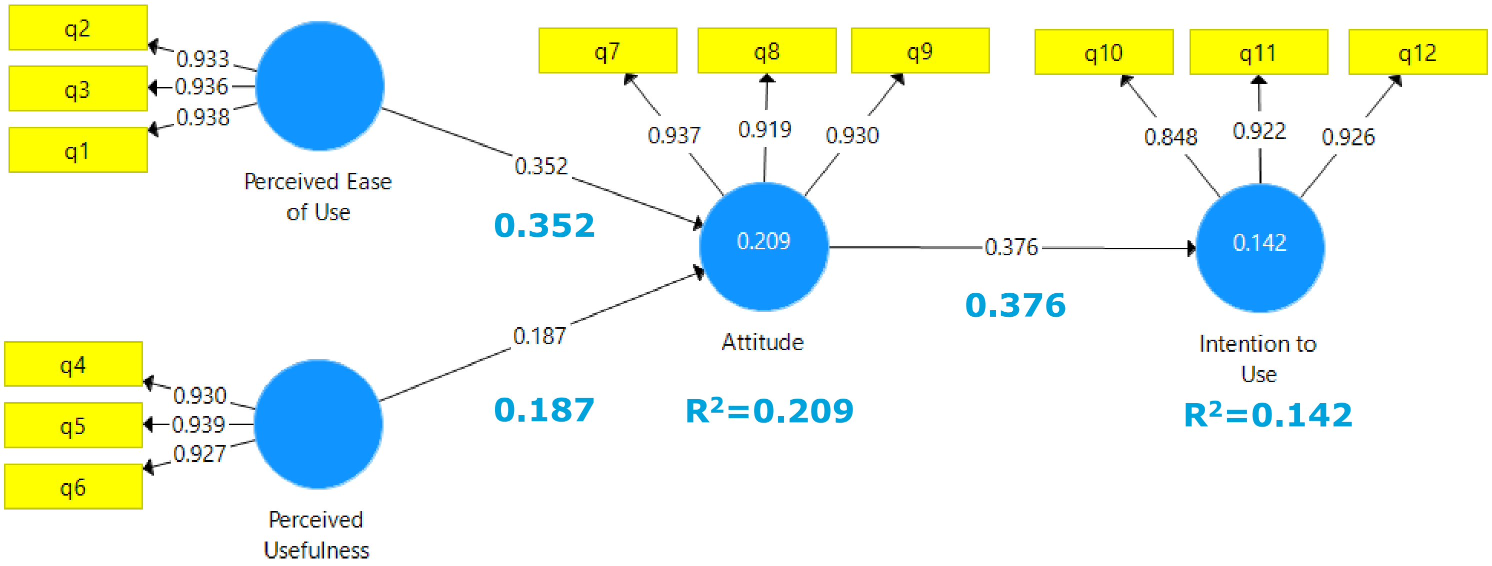


Partial Least Squares Path Modeling
PLS-Graph Illustration





Partial Least Squares Path Modeling SmartPLS Illustration



Partial Least Squares Path Modeling
SmartPLS Illustration

TAM Model Moderation.splsm | TAM Model.splsm | PLS Algorithm (Run No. 1)

Outer Loadings

Matrix — Copy to Clipboard: Excel Format | R Format

	Attitude	Intention to...	Perceived E...	Perceived U...
q10		0.848		
q11		0.922		
q12		0.926		
q2			0.933	
q3			0.936	
q4				0.930
q5				0.939
q6				0.927
q7	0.937			
q8	0.919			
q9	0.930			
q1			0.938	

Partial Least Squares Path Modeling
SmartPLS Illustration

TAM Model Moderation.splsm | TAM Model.splsm | PLS Algorithm (Run No. 1)

Construct Reliability and Validity

Matrix | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE)

Copy to Clipboard: Excel Format | R Format

	Cronbach's ...	rho_A	Composite ...	Average Va...
Attitude	0.920	0.924	0.950	0.862
Intention to ...	0.882	0.904	0.927	0.809
Perceived E...	0.929	0.931	0.955	0.876
Perceived U...	0.924	0.929	0.952	0.869

Partial Least Squares Path Modeling
SmartPLS Illustration

TAM Model Moderation.splsm | TAM Model.splsm | PLS Algorithm (Run No. 1)

Discriminant Validity

Fornell-Larcker Criterion | Cross Loadings | Heterotrait-Monotrait Ratio (HTMT) | Heterotrait-Monotrait Ratio (HTMT) | Copy to Clipboard: Excel Format | R Format

	Attitude	Intention to...	Perceived E...	Perceived U...
Attitude	0.929			
Intention to ...	0.376	0.899		
Perceived E...	0.423	0.359	0.936	
Perceived U...	0.321	0.441	0.379	0.932

Partial Least Squares Path Modeling
SmartPLS Illustration

TAM Model Moderation.splsm | TAM Model.splsm | PLS Algorithm (Run No. 1)

Discriminant Validity

Fornell-Larcker Criterion | Cross Loadings | Heterotrait-Monotrait Ratio (HTMT) | Heterotrait-Monotrait Ratio (HTMT) | Copy to Clipboard: Excel Format | R Format

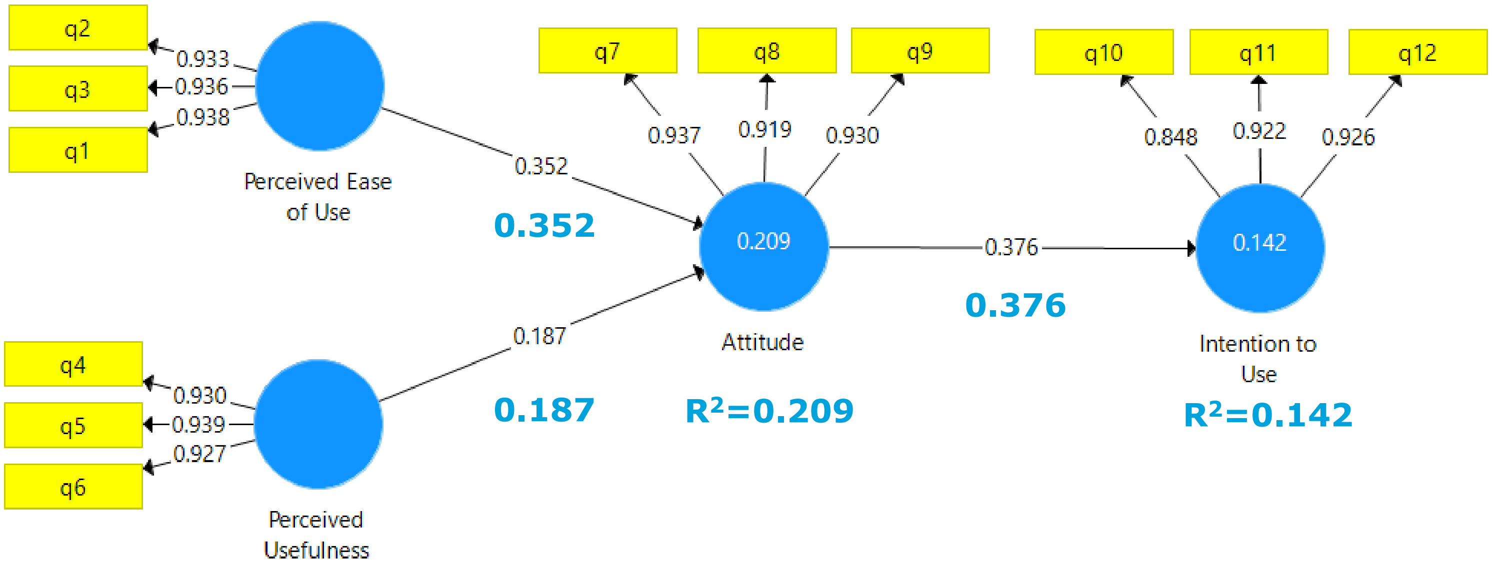
	Attitude	Intention to...	Perceived E...	Perceived U...
q10	0.275	0.848	0.280	0.346
q11	0.351	0.922	0.344	0.425
q12	0.377	0.926	0.338	0.411
q2	0.383	0.332	0.933	0.349
q3	0.389	0.344	0.936	0.373
q4	0.302	0.425	0.328	0.930
q5	0.318	0.404	0.364	0.939
q6	0.273	0.405	0.370	0.927
q7	0.937	0.341	0.406	0.301
q8	0.919	0.315	0.382	0.268
q9	0.930	0.388	0.390	0.321
q1	0.414	0.331	0.938	0.344

Empirical Findings
Model Validation

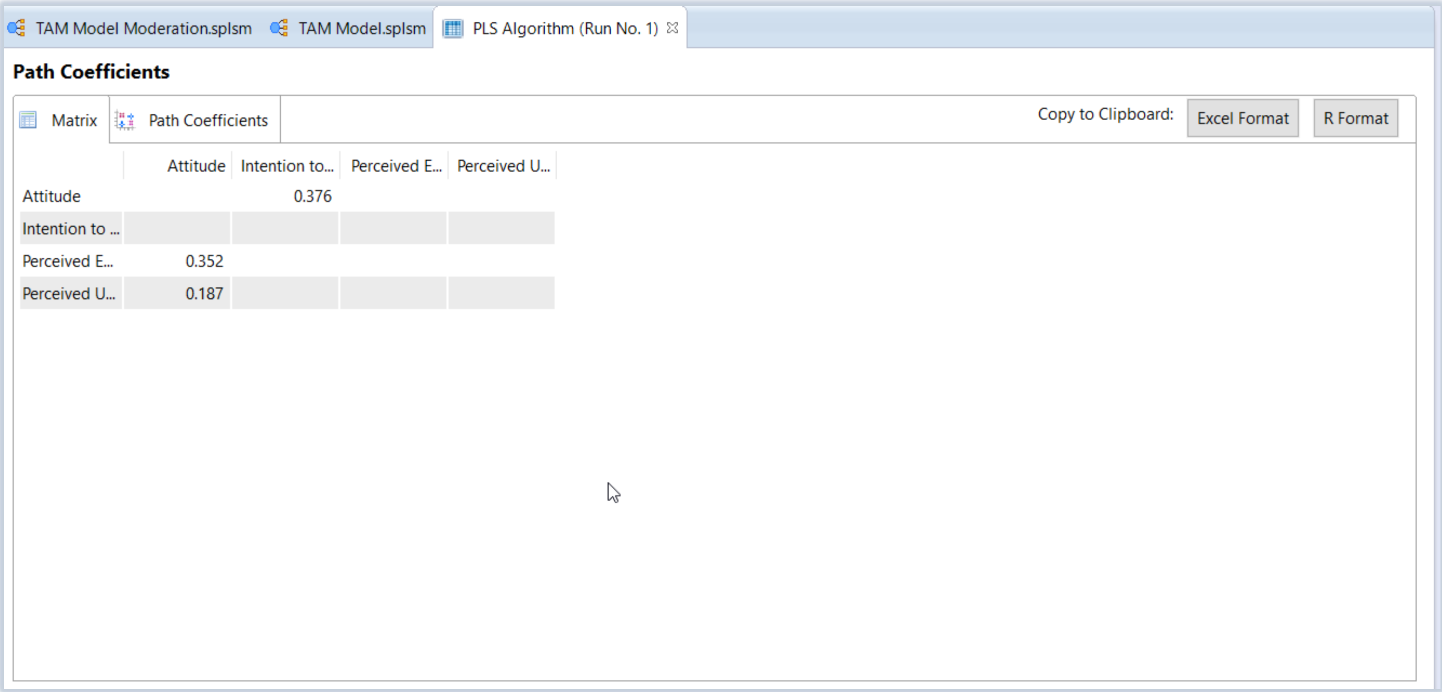
- **Model Validation**

  - **Measurement Model (Psychometric Properties)**
    - **Convergent Validity**
      - All SL > 0.5 ✓
    - **Reliability**
      - CR > 0.7 ✓
      - AVE > 0.5 ✓
    - **Discriminant Validity**
      - $\sqrt{}$ AVE LV_i > CORR(LV_i, LV_j) ✓
      - Cross Loadings not substantial in magnitude ✓

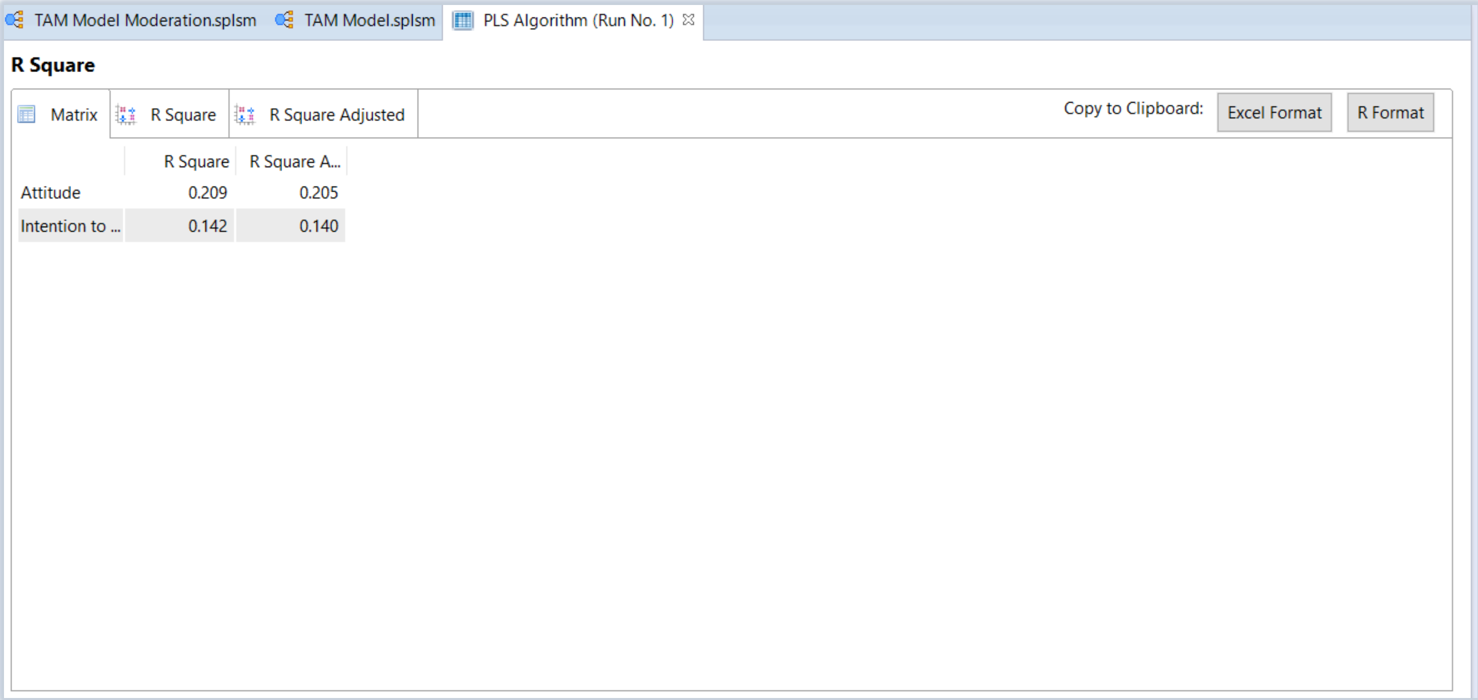
Partial Least Squares Path Modeling SmartPLS Illustration



Partial Least Squares Path Modeling
SmartPLS Illustration



Partial Least Squares Path Modeling
SmartPLS Illustration



	R Square	R Square A...
Attitude	0.209	0.205
Intention to ...	0.142	0.140

Partial Least Squares Path Modeling
SmartPLS Illustration

TAM Model Moderation.splsm | TAM Model.splsm | PLS Algorithm (Run No. 1) | TAM Model Higher-order.splsm | Bootstrapping (Run No. 1)

Path Coefficients

Mean, STDEV, T-Values, P-Values | Confidence Intervals | Confidence Intervals Bias Corrected | Samples

Copy to Clipboard: Excel Format | R Format

	Original Sa...	Sample Me...	Standard D...	T Statistics (...	P Values
Attitude -> ...	0.376	0.377	0.041	9.077	0.000
Perceived E...	0.352	0.351	0.046	7.575	0.000
Perceived U...	0.187	0.187	0.042	4.482	0.000

Partial Least Squares Path Modeling
SmartPLS Illustration

TAM Model Moderation.splsm | TAM Model.splsm | PLS Algorithm (Run No. 1)

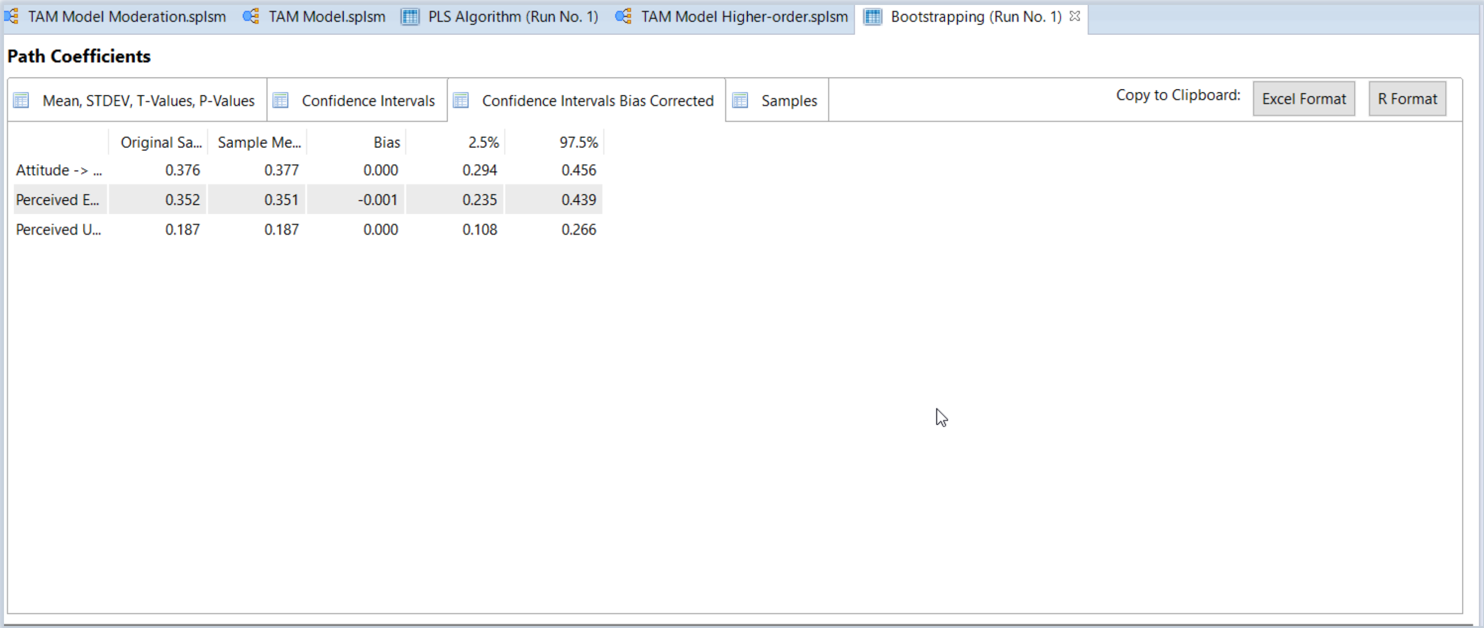
Indirect Effects

Total Indirect Effects | Specific Indirect Effects

Copy to Clipboard: Excel Format | R Format

	Attitude	Intention to...	Perceived E...	Perceived U...
Attitude				
Intention to ...				
Perceived E...		0.133		
Perceived U...		0.070		

Partial Least Squares Path Modeling
SmartPLS Illustration



	Original Sa...	Sample Me...	Bias	2.5%	97.5%
Attitude -> ...	0.376	0.377	0.000	0.294	0.456
Perceived E...	0.352	0.351	-0.001	0.235	0.439
Perceived U...	0.187	0.187	0.000	0.108	0.266

Partial Least Squares Path Modeling
SmartPLS Illustration

TAM Model Moderation.s... | TAM Model.splsm | PLS Algorithm (Run No. 1) | TAM Model Higher-order... | Bootstrapping (Run No. 1) | PLSc Algorithm (Run No. 1) | PLS Algorithm (Run No. 1)

Total Indirect Effects

Mean, STDEV, T-Values, P-Values | Confidence Intervals | Confidence Intervals Bias Corrected | Samples

Copy to Clipboard: Excel Format | R Format

	Original Sa...	Sample Me...	Standard D...	T Statistics (...	P Values
Attitude -> ...					
Perceived E...					
Perceived E...	0.1325173	0.1324954	0.0247589	5.3523036	0.0000001
Perceived U...					
Perceived U...	0.0704009	0.0712795	0.0201282	3.4976182	0.0005113

Empirical Findings
Structural Model

- **Structural Model**
  - R^2 > 0.09 (Effect Size Medium)
    - C *[R^2=0.2088]* ✓
    - D *[R^2=0.1417]* ✓

- **Global Goodness of Fit (GOF; Tenenhaus et al., 2005)**

$$GOF = \sqrt{MEAN(Communality) * Mean(R^2)}$$

- Criteria
  - AVE (Minimum 0.50; Fornell & Larcker, 1981)
  - R^2 (s 0.01, m 0.09, l 0.25; Cohen, 1988)
  - GOF (0.07, 0.21, 0.35)

- Model GOF = 0.3869 (exceeds baseline value of 0.35) ✓

R PLSPM

Editor

```
library(plspm)


# Inner Model
PEU = c(0,0,0,0)
PU =  c(0,0,0,0)
ATT = c(1,1,0,0)
INT = c(0,0,1,0)

inner = rbind(PEU, PU, ATT, INT)

# Plot Inner Model
innerplot(inner)

# Blocks Outer Model
outer = list(1:3, 4:6, 7:9, 10:12)

# Modes (reflective indicators)
mode = rep("A", 4)

PLS.1 = plspm(Data.01.PPT, inner, outer, modes = mode, scaled = TRUE, boot.val=TRUE, br=1000)
summary(PLS.1)


# Plot Inner Model
innerplot(PLS.1)

# Plot Outer Loadings
outerplot(PLS.1, what = "loadings")

# Plot Outer Weights
outerplot(PLS.1, what = "weights")
```

R PLSPM

Console

```
-----------------------------------------------------------
OUTER MODEL
          weight  loading  communality  redundancy
PEU
  1 q1     0.373    0.938        0.880       0.000
  1 q2     0.345    0.933        0.871       0.000
  1 q3     0.350    0.936        0.876       0.000
PU
  2 q4     0.363    0.930        0.865       0.000
  2 q5     0.382    0.939        0.881       0.000
  2 q6     0.328    0.927        0.860       0.000
ATT
  3 q7     0.363    0.937        0.878       0.183
  3 q8     0.334    0.919        0.844       0.176
  3 q9     0.380    0.930        0.866       0.181
INT
  4 q10    0.303    0.848        0.719       0.102
  4 q11    0.388    0.922        0.849       0.120
  4 q12    0.416    0.926        0.857       0.121

-----------------------------------------------------------
CROSSLOADINGS
```

R PLSPM

Console

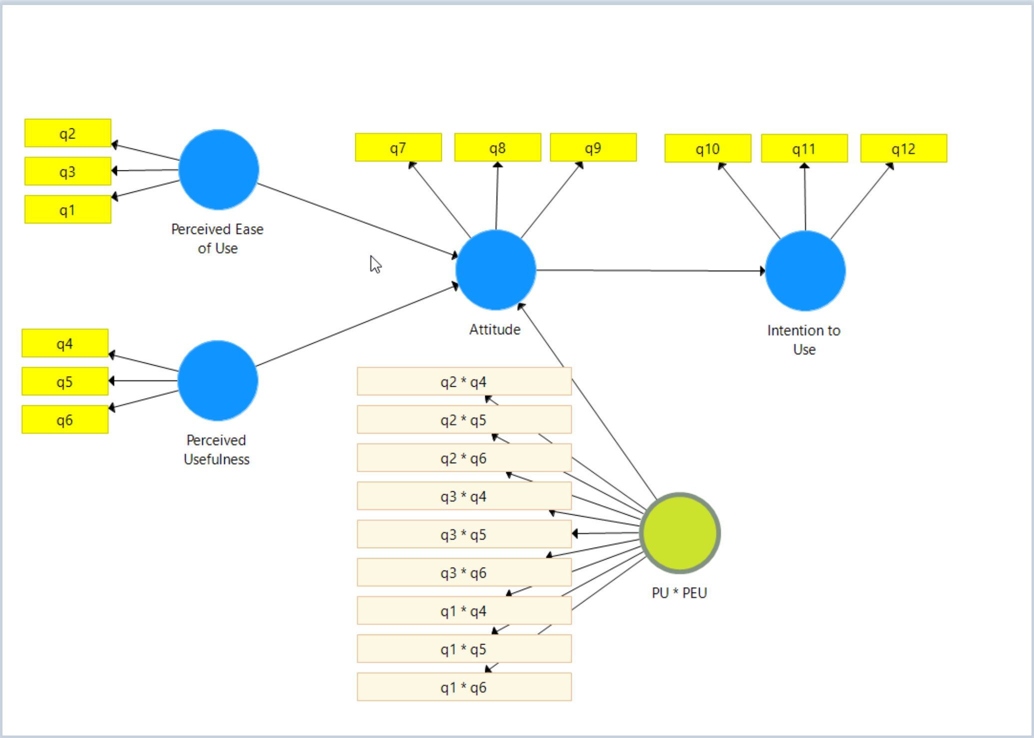
```
------------------------------------------------------------
INNER MODEL
$ATT
                    Estimate   Std. Error              t value            Pr(>|t|)
Intercept   -0.000000000000000252       0.0426  -0.00000000000000592   0.999999999999995
PEU          0.351986623044817593       0.0460   7.64537268803520220   0.000000000000134
PU           0.187050393612872207       0.0460   4.06285317959939274   0.000057493829380

$INT
                    Estimate   Std. Error             t value             Pr(>|t|)
Intercept   0.0000000000000000745       0.0443  0.00000000000000168  0.99999999999999867
ATT         0.3765317740007353420       0.0443  8.49653921164481574  0.00000000000000031

------------------------------------------------------------
CORRELATIONS BETWEEN LVs
       PEU     PU    ATT    INT
PEU  1.000  0.379  0.423  0.359
PU   0.379  1.000  0.321  0.441
ATT  0.423  0.321  1.000  0.376
INT  0.359  0.441  0.376  1.000

------------------------------------------------------------
SUMMARY INNER MODEL
           Type     R2  Block_Communality  Mean_Redundancy    AVE
PEU   Exogenous  0.000              0.876            0.000  0.876
PU    Exogenous  0.000              0.869            0.000  0.869
ATT  Endogenous  0.209              0.862            0.180  0.862
INT  Endogenous  0.142              0.809            0.115  0.809

------------------------------------------------------------
GOODNESS-OF-FIT
[1]  0.3869

------------------------------------------------------------
```

R PLSPM

Console

```
paths
             Original  Mean.Boot  Std.Error  perc.025  perc.975
PEU -> ATT      0.352      0.351     0.0456    0.2640     0.439
PU -> ATT       0.187      0.188     0.0434    0.0999     0.274
ATT -> INT      0.377      0.377     0.0442    0.2892     0.462

rsq
     Original  Mean.Boot  Std.Error  perc.025  perc.975
ATT     0.209      0.211     0.0356    0.1421     0.282
INT     0.142      0.144     0.0334    0.0836     0.214

total.efs
             Original  Mean.Boot  Std.Error  perc.025  perc.975
PEU -> PU      0.0000     0.0000     0.0000    0.0000     0.000
PEU -> ATT     0.3520     0.3506     0.0456    0.2640     0.439
PEU -> INT     0.1325     0.1326     0.0253    0.0867     0.187
PU -> ATT      0.1871     0.1877     0.0434    0.0999     0.274
PU -> INT      0.0704     0.0714     0.0204    0.0339     0.114
ATT -> INT     0.3765     0.3773     0.0442    0.2892     0.462
```

Partial Least Squares Path Modeling
Advanced Models: Moderation

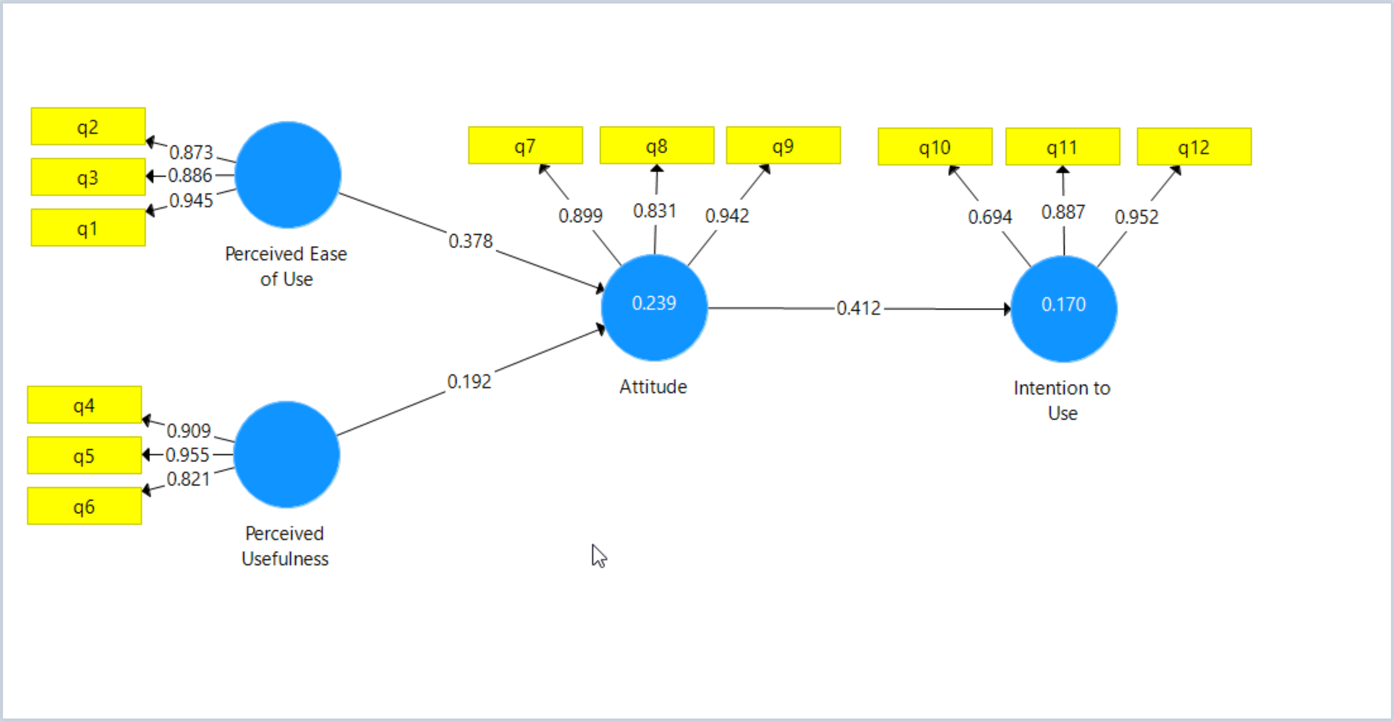


Chin et al. (2003)

A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and an Electronic-Mail Emotion/Adoption Study

Wynne W. Chin • Barbara L. Marcolin • Peter R. Newsted
C. T. Bauer College of Business, University of Houston, Houston, Texas 77204
Haskayne School of Business, University of Calgary, 2500 University Drive NW, Calgary, Alberta, Canada, T2N 1N4
Centre for Innovative Management, Athabasca University, 22 Sir Winston Churchill Avenue, St. Alberta, Alberta, Canada, T8N 1B4
wchin@uh.edu • marcolin@ucalgary.ca • pnewsted@mba.athabascau.ca

Partial Least Squares Path Modeling
Advanced Models: Consistent PLS (PLSc)



Dijkstra and Henseler (2015)

MIS Quarterly

RESEARCH ESSAY

CONSISTENT PARTIAL LEAST SQUARES PATH MODELING[1]

Theo K. Dijkstra

Faculty of Economics and Business, University of Groningen, Nettelbosje 2,
9747 AE Groningen THE NETHERLANDS {t.k.dijkstra@rug.nl}

Jörg Henseler

Faculty of Engineering Technology, University of Twente, Drienerlolaan 5,
7522 NB Enschede THE NETHERLANDS {j.henseler@utwente.nl}
NOVA IMS, Universidade Nova de Lisboa, 1070-312 Lisbon PORTUGAL {jhenseler@isegi.unl.pt}

R matrixpls

Introduction to matrixpls

Mikko Rönkkö
Aalto University

Abstract

matrixpls calculates composite variable models using partial least squares (PLS) algorithm and related methods. In contrast to most other PLS software which implement the raw data version of the algorithm, **matrixpls** works with data covariance matrices. The algorithms are designed to be computationally efficient, modular in programming, and well documented. **matrixpls** integrates with **simsem** to enable Monte Carlo simulations with as little custom programming as possible.

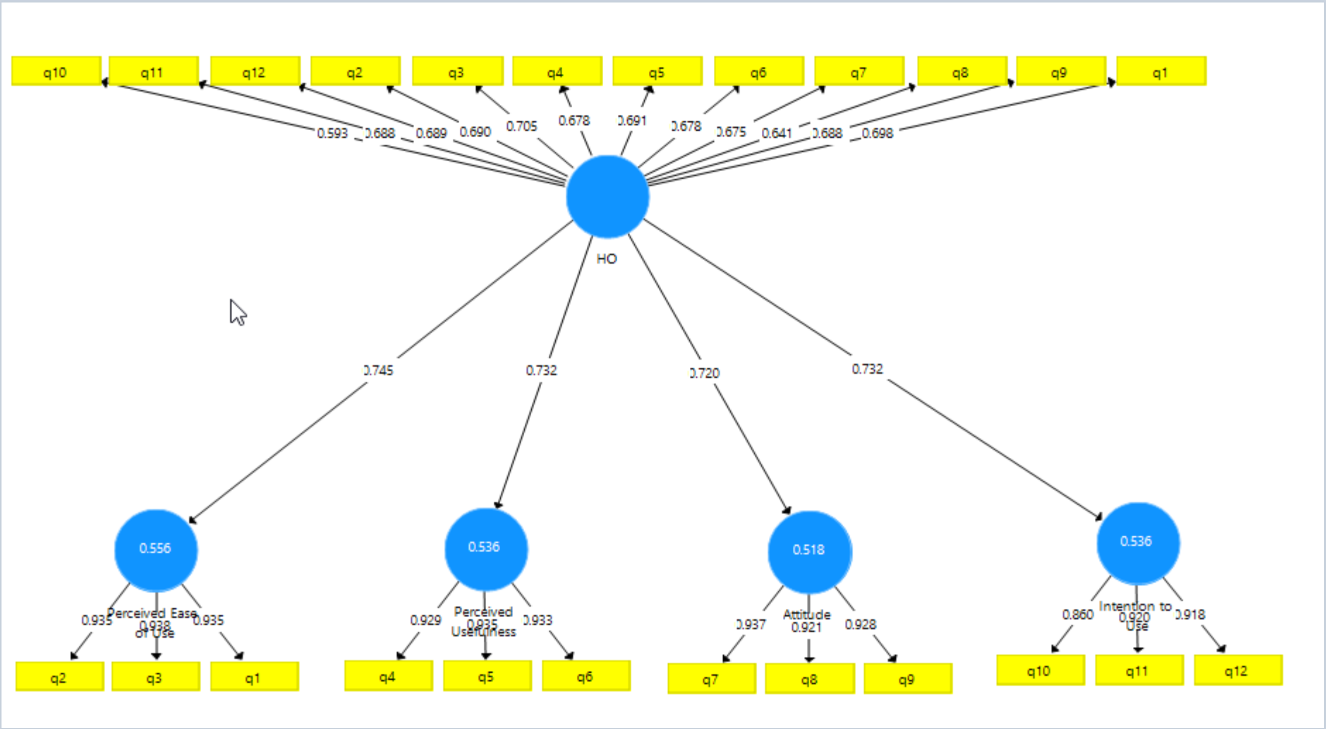
Keywords: partial least squares, generalized structured component analysis, composite-based modeling, R.

R matrixpls

Console

```
> cbind(TAM.output.01, TAM.output.02)
          TAM.output.01 TAM.output.02
ATT~PEU       0.3779332     0.3519938
ATT~PU        0.1917560     0.1869996
BI~ATT        0.4119563     0.3764761
PEU=~q1       0.9451009     0.9378307
PEU=~q2       0.8733766     0.9334087
PEU=~q3       0.8863560     0.9358589
PU=~q4        0.9093418     0.9301724
PU=~q5        0.9554940     0.9386165
PU=~q6        0.8209743     0.9271021
ATT=~q7       0.8986349     0.9367512
ATT=~q8       0.8312829     0.9189897
ATT=~q9       0.9416552     0.9302690
BI=~q10       0.6937215     0.8481800
BI=~q11       0.8869143     0.9215449
BI=~q12       0.9523309     0.9256767
PEU=+q1       0.3734003     0.3734003
PEU=+q2       0.3450627     0.3450627
PEU=+q3       0.3501908     0.3501908
PU=+q4        0.3631826     0.3631826
PU=+q5        0.3816154     0.3816154
PU=+q6        0.3278895     0.3278895
ATT=+q7       0.3621001     0.3621001
ATT=+q8       0.3349610     0.3349610
ATT=+q9       0.3794349     0.3794349
BI=+q10       0.3032951     0.3032951
BI=+q11       0.3877590     0.3877590
BI=+q12       0.4163591     0.4163591
```

Partial Least Squares Path Modeling
Advanced Models: Higher-Order Model



Wetzels et al. (2009)

MIS Quarterly

SPECIAL ISSUE

USING PLS PATH MODELING FOR ASSESSING HIERARCHICAL CONSTRUCT MODELS: GUIDELINES AND EMPIRICAL ILLUSTRATION[1]

By: **Martin Wetzels**
Department of Marketing
Maastricht University
Tongersestraat 53
6211 LM Maastricht
THE NETHERLANDS
m.wetzels@mw.unimaas.nl

archical construct model using PLS path modeling. This approach is illustrated empirically using a reflective, fourth-order latent variable model of online experiential value in the context of online book and CD retailing. Moreover, the guidelines for the use of PLS path modeling to estimate parameters in a hierarchical construct model are extended beyond the scope of the empirical illustration. The findings of the empirical illustration are used to discuss the use of

R PLSPM

Console

```
# Hierarchical Model

# Inner Model
G =    c(0,0,0,0,0)
PEU = c(1,0,0,0,0)
PU =  c(1,0,0,0,0)
ATT = c(1,0,0,0,0)
INT = c(1,0,0,0,0)

inner.HM<-rbind(G,PEU,PU,ATT,INT)


# Plot Inner Model
innerplot(inner.HM)

# Blocks Outer Model
outer.HM = list(1:12, 1:3, 4:6, 7:9, 10:12)

# Modes (reflective indicators)
mode.HM = rep("A", 5)

PLS.2 = plspm(Data.01.PPT, inner.HM, outer.HM, modes = mode.HM, scheme="path", scaled = TRUE)
summary(PLS.2)

# Plots

innerplot(PLS.2)
outerplot(PLS.2, what="loadings")
```

References

Chin, W. (2001). *PLS-Graph User's Guide Version 3.0.* Houston, TX: C.T. Bauer College of Business, University of Houston.

Chin, W. W., Marcolin, B. L., & Newsted, P. N. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: results from a monte carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14*(2), 189–217.

Dijkstra, T. K., and Henseler, J. (2015). Consistent Partial Least Squares Path Modeling, *MIS Quarterly*, 39(2): 297-316.

Fornell, C. and Larcker, D.F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39-50.

Green, S.B. (1991). How Many Subjects Does It Take To Do A Regression Analysis? *Multivariate Behavioral Research, 26* (3), 499-510.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2014). *A Primer on Partial Least Squares Equation Modeling (PLS-SEM)*. Los Angeles, CA: Sage Publications.

References

Hulland, J. (1999). Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies. *Strategic Management Journal, 20*(2), 195-204.

Nunnally, J.C. and Bernstein, I.H. (1994). *Psychometric Theory*. New York: McGraw-Hill.

Tenenhaus, M, Vinzi, V.E.,Chatelin, Y.-M. and Lauro, C. (2005). *PLS Path Modeling*. *Computational Statistics & Data Analysis, 48*(1), 159-205.

Wetzels, M., Odekerken-Schröder, G. and Oppen, C. van (2009). Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration, *MIS Quarterly, 33*(1), 177-196.

References

Rönkkö, M. *Introduction to matrixpls* (https://cran.r-project.org/web/packages/matrixpls/vignettes/matrixpls-intro.pdf)

Sanchez, G. (2013). *PLS Path Modeling with R. Trowchez Editions*. Berkeley, 2013. (http://www.gastonsanchez.com/PLS Path Modeling with R.pdf)

Thank you for Your Attention!