

PLS

(.)

26

2562

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Email: mpiriyakul@yahoo.com line ID: mpiriyakul

PLS

PLS (partial least square)

(convergence)

least square

Herman Wold (1982)

Least square

minimize square

Euclidian distance

(Y)

Y $\hat{Y}$

partial

PLS

minimize square Euclidian distance $\sum_i^n e_i^2$ $e_i^2 = (Y_i - \hat{Y}_i)^2$

$$\frac{\partial}{\partial \hat{\beta}_j} \sum_{i=1}^n e_i^2 = 0; j = 1, 2, \dots, k$$

$$\hat{\beta} = (X'X)^{-1}X'Y \quad \text{OLS estimator}$$

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_3 + \dots + \hat{\beta}_k X_k + u_i$$

$\sum_i^n e_i^2$ sum square error degree of freedom $n-(k+1)$

mean square error error variance

Smart PLS

smart PLS 3

variance-based SEM

1

<https://www.smartpls.com/downloads>

smart PLS 2

3

Smart PLS

Christian M. Ringle, Sven Wende, and Will

2.0

2005

3

2014-

2018

Variance-based

minimize $\sum_i^n e_i^2$

ADANCO

ADANCO

variance-based SEM

1 <https://adanco.software.informer.com/>

ADANCO

Advanced **A**nalysis **C**omposite

ADANCO

Jörg

Henseler

Theo K. Dijkstra

2014, 2015, 2016, 2017

2.1

Smart PLS

Q-square

moderation

MRA, Path analysis, SEM factor analysis

MRA (multiple regression analysis)

(independent variable, predictor)

(dependent variable, criterion)

MRA, Path analysis, SEM factor analysis

1)

(no multicollinearity)

VIF, Tolerance

mean centered

differencing

MRA, Path analysis, SEM

factor analysis

2) (residual, u)
Skewness, Shapiro-Wilk

Kurtosis-

3)
correlation)

(no serial

Durbin, Durbin-Watson

(residual)

u

MRA, Path analysis, SEM factor analysis

4) (stability of variance)

White test, Goldfeld-Quandt test

5) (no error in variable)

MRA, Path analysis, SEM factor analysis

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i; i = 1, 2, \dots, n$$

$$Y_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \cdots + \hat{\beta}_k X_{ki}$$

(standardize)

$$z_{yi} = \rho_1 z_{x1i} + \rho_2 z_{x2i} + \cdots + \rho_k z_{ki} + u_i; i = 1, 2, \dots, n$$

$$z_{yi} = \hat{\rho}_1 z_{x1i} + \hat{\rho}_2 z_{x2i} + \cdots + \hat{\rho}_k z_{ki}$$

MRA, Path analysis, SEM factor analysis

$$z_{yi} = \hat{\rho}_1 z_{x1i} + \hat{\rho}_2 z_{x2i} + \cdots + \hat{\rho}_k z_{ki}$$

1)

$$2) R^2_Y = \frac{\sum_{i=1}^n \hat{y}_i^2}{\sum_{i=1}^n y_i^2}$$

3)

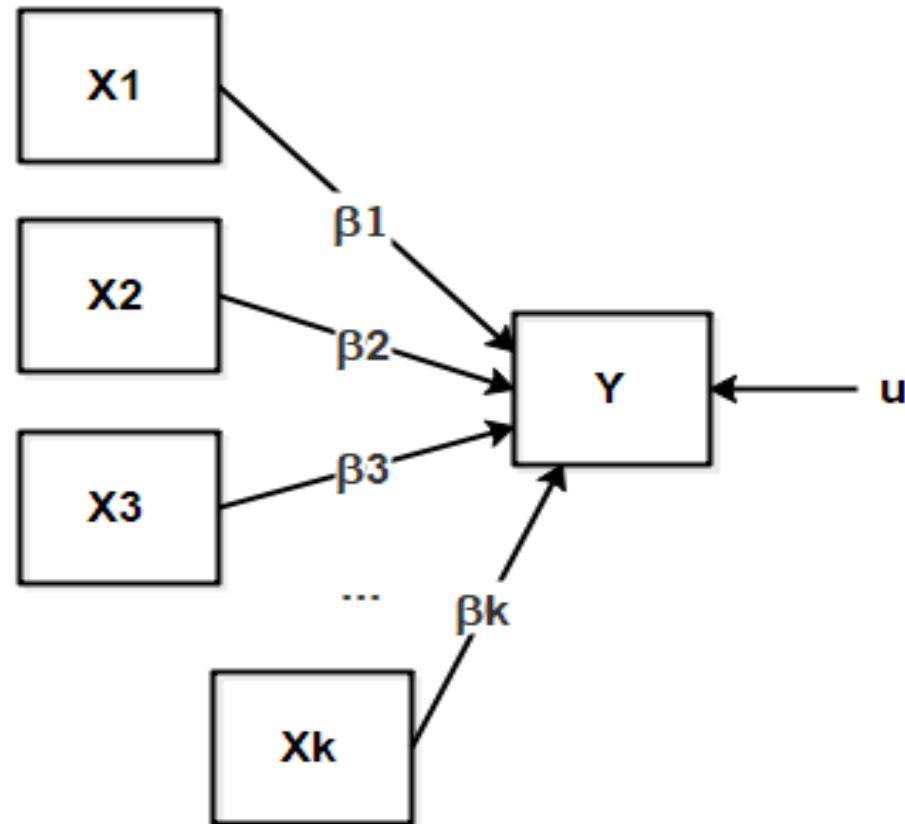
sign, size, significant

t-test

4)

MRA, Path analysis, SEM factor analysis

MRA



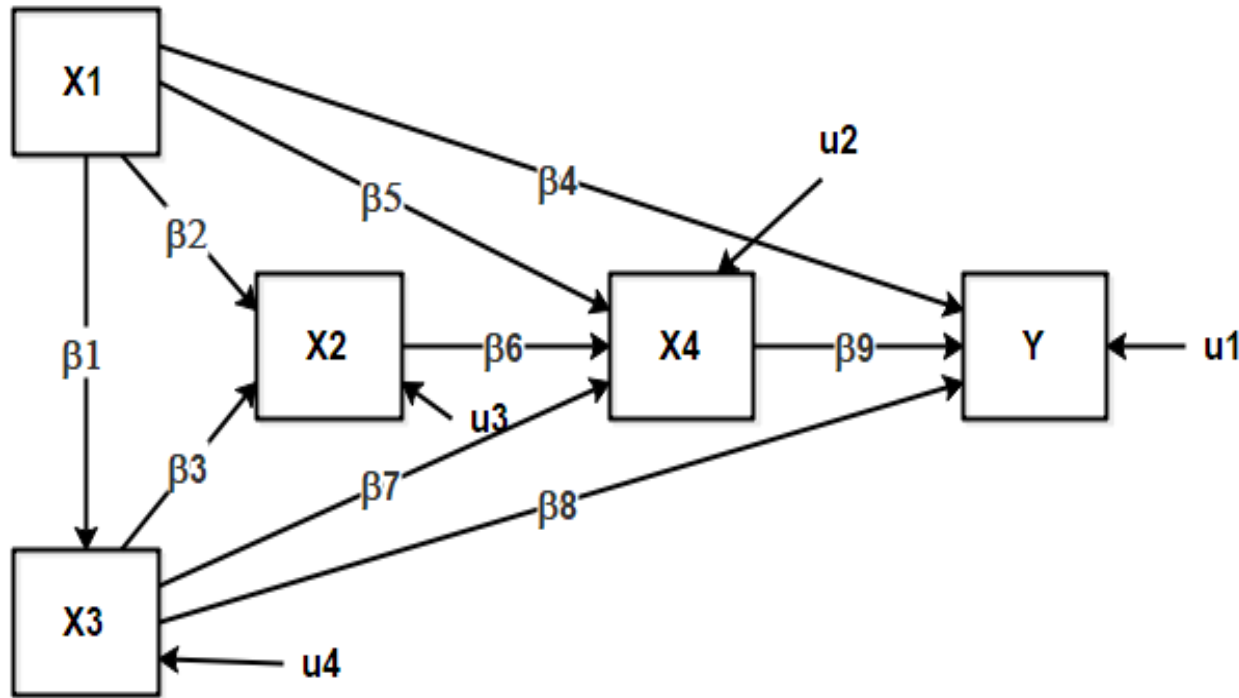
MRA, Path analysis, SEM factor analysis

Path Analysis (Path Analysis--PA, Path Model--PM)

MRA

MRA, Path analysis, SEM factor analysis

4



$$\begin{aligned} Y &= \beta_0 + \beta_4 X_1 + \beta_8 X_3 + \beta_9 X_4 + u_1 \\ X_4 &= \beta_0 + \beta_5 X_1 + \beta_6 X_2 + \beta_7 X_3 + u_2 \\ X_2 &= \beta_0 + \beta_2 X_1 + \beta_3 X_3 + u_3 \\ X_3 &= \beta_0 + \beta_1 X_1 + u_4 \end{aligned}$$

MRA, Path analysis, SEM factor analysis

SEM PM

(concept, construct, trait, Latent)

MRA, Path analysis, SEM factor analysis

test inventory
(adapt)

(adopt)

MRA, Path analysis, SEM factor analysis

MRA PM

MRA, Path analysis, SEM factor analysis

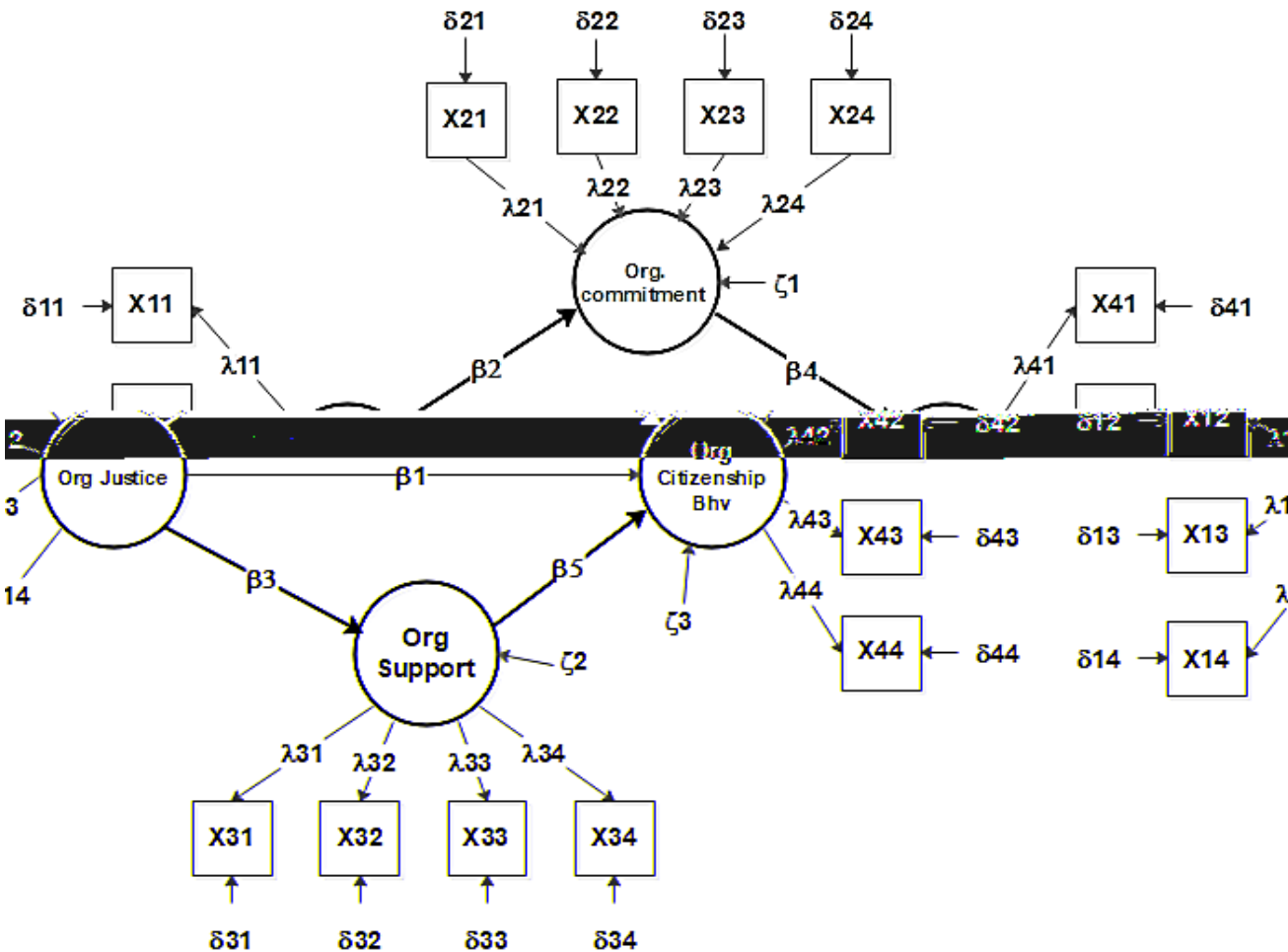
American Customer Satisfaction Index (ACSI)

MRA, Path analysis, SEM factor analysis

SEM Organization Justice (OJ)
OCB Organization Commitment (OC) Perceived
Organization Support (POS) mediator

MRA, Path analysis, SEM

factor analysis



$$1. OCB = \beta_o + \beta_4 OC + \beta_1 OJ + \beta_5 POS + \zeta_3$$

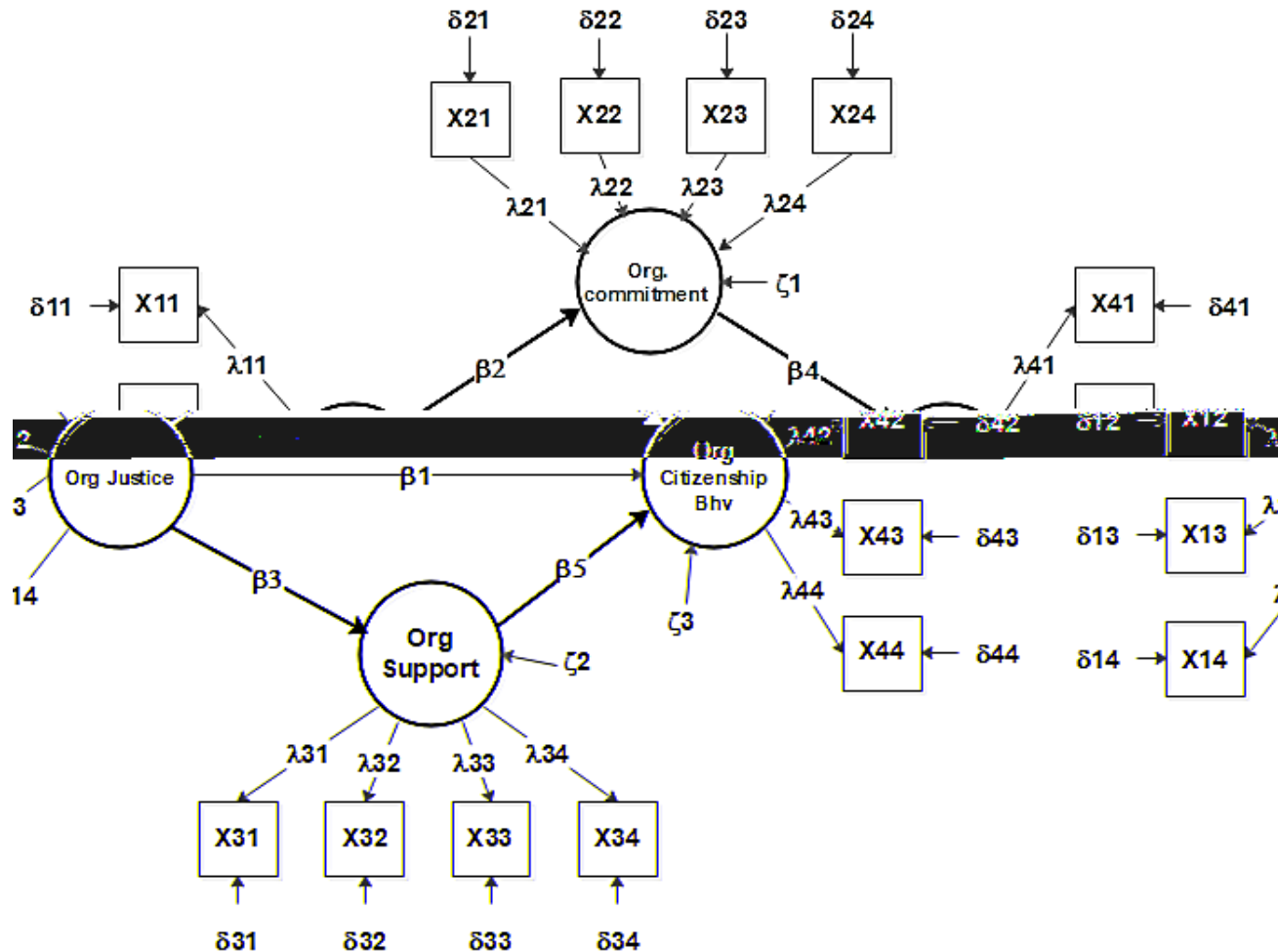
$$X_{41} = \lambda_o + \lambda_{41} OCB + \delta_{41}$$

$$X_{42} = \lambda_o + \lambda_{42} OCB + \delta_{42}$$

$$X_{43} = \lambda_o + \lambda_{43} OCB + \delta_{43}$$

$$X_{44} = \lambda_o + \lambda_{44} OCB + \delta_{44}$$

MRA, Path analysis, SEM factor analysis



$$2. OC = \beta_0 + \beta_2 OJ + \zeta_1$$

$$X_{21} = \lambda_0 + \lambda_{21} OC + \delta_{21}$$

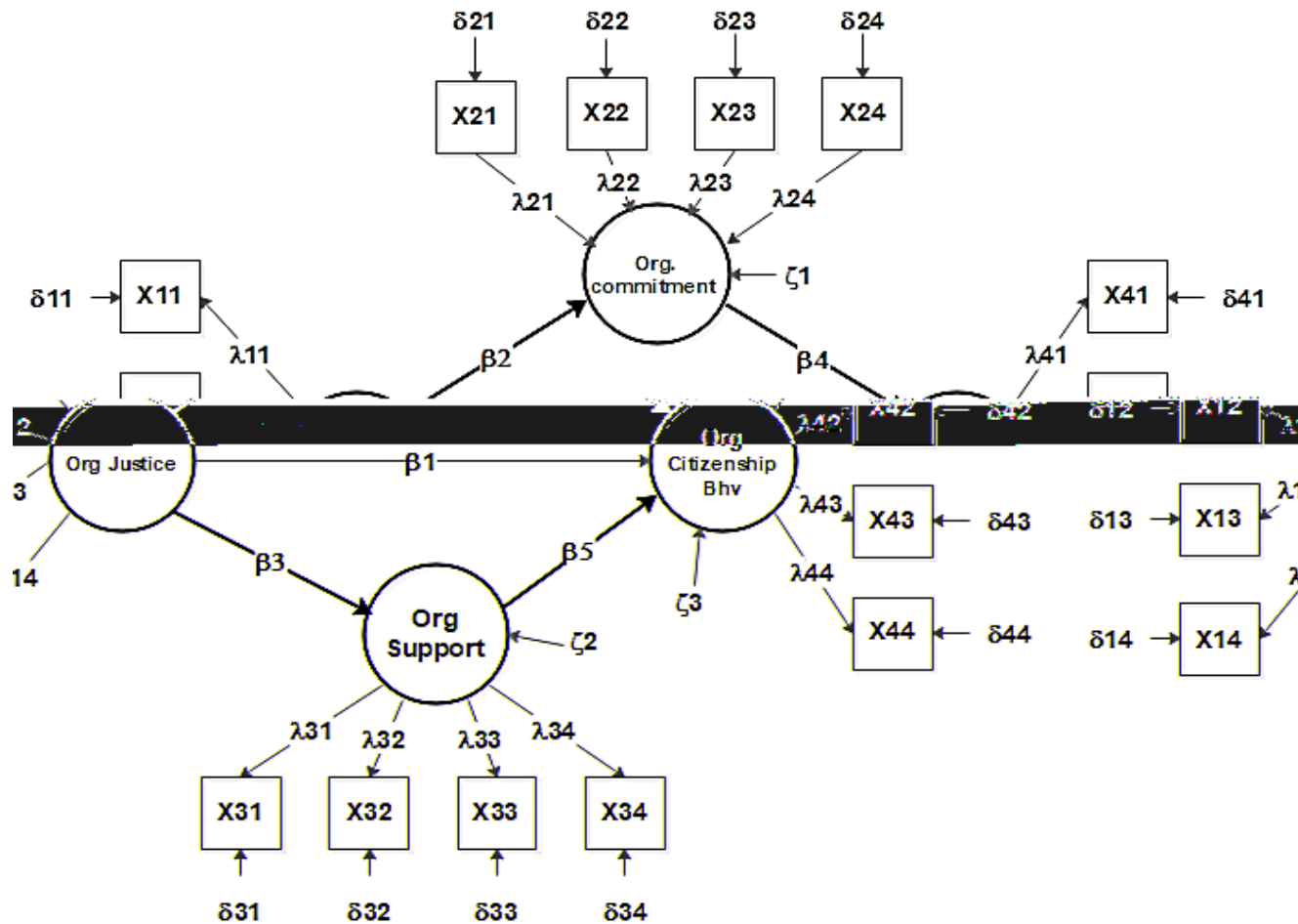
$$X_{22} = \lambda_0 + \lambda_{22} OC + \delta_{22}$$

$$X_{23} = \lambda_0 + \lambda_{23} OC + \delta_{23}$$

$$X_{24} = \lambda_0 + \lambda_{24} OC + \delta_{24}$$

MRA, Path analysis, SEM

factor analysis



$$3. POS = \beta_0 + \beta_3 OJ + \zeta_2$$

$$X_{31} = \lambda_0 + \lambda_{31} POS + \delta_{31}$$

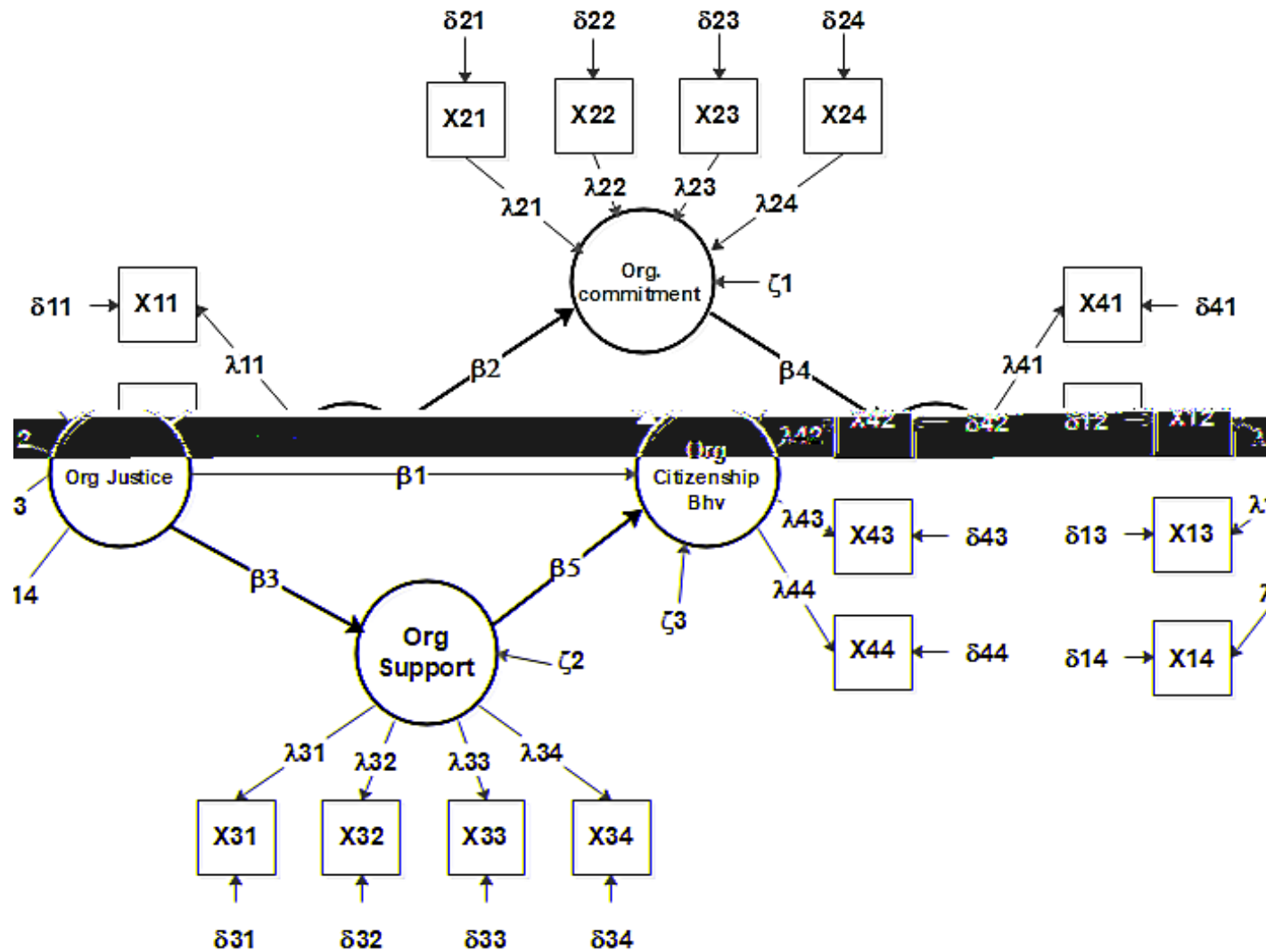
$$X_{32} = \lambda_0 + \lambda_{32} POS + \delta_{32}$$

$$X_{33} = \lambda_0 + \lambda_{33} POS + \delta_{33}$$

$$X_{34} = \lambda_0 + \lambda_{34} POS + \delta_{34}$$

MRA, Path analysis, SEM

factor analysis



OJ

$$X_{11} = \lambda_o + \lambda_{11} OJ + \delta_{11}$$

$$X_{12} = \lambda_o + \lambda_{12} OJ + \delta_{12}$$

$$X_{13} = \lambda_o + \lambda_{13} OJ + \delta_{13}$$

$$X_{14} = \lambda_o + \lambda_{14} OJ + \delta_{14}$$

MRA, Path analysis, SEM

factor analysis

Factor analysis

factor loading

factor loading
principal component analysis

2

MRA, Path analysis, SEM

factor analysis

1.

latent variable

2.

weighted sum

regression

factor score

MRA, Path analysis, SEM

factor analysis

Factor score factor loading PLS
indicator reliability, cross loading, AVE, CR,
Fornell-Larcker criterion,

MRA, Path analysis, SEM

factor analysis

1. SEM FA exploratory factor analysis (EFA)

2. ()

EFA

MRA, Path analysis, SEM

factor analysis

SEM

(iteration)

λ

(inner model)

(outer model)

MRA, Path analysis, SEM

factor analysis

(aggregation)

(sum)

(mean)

(factor score)

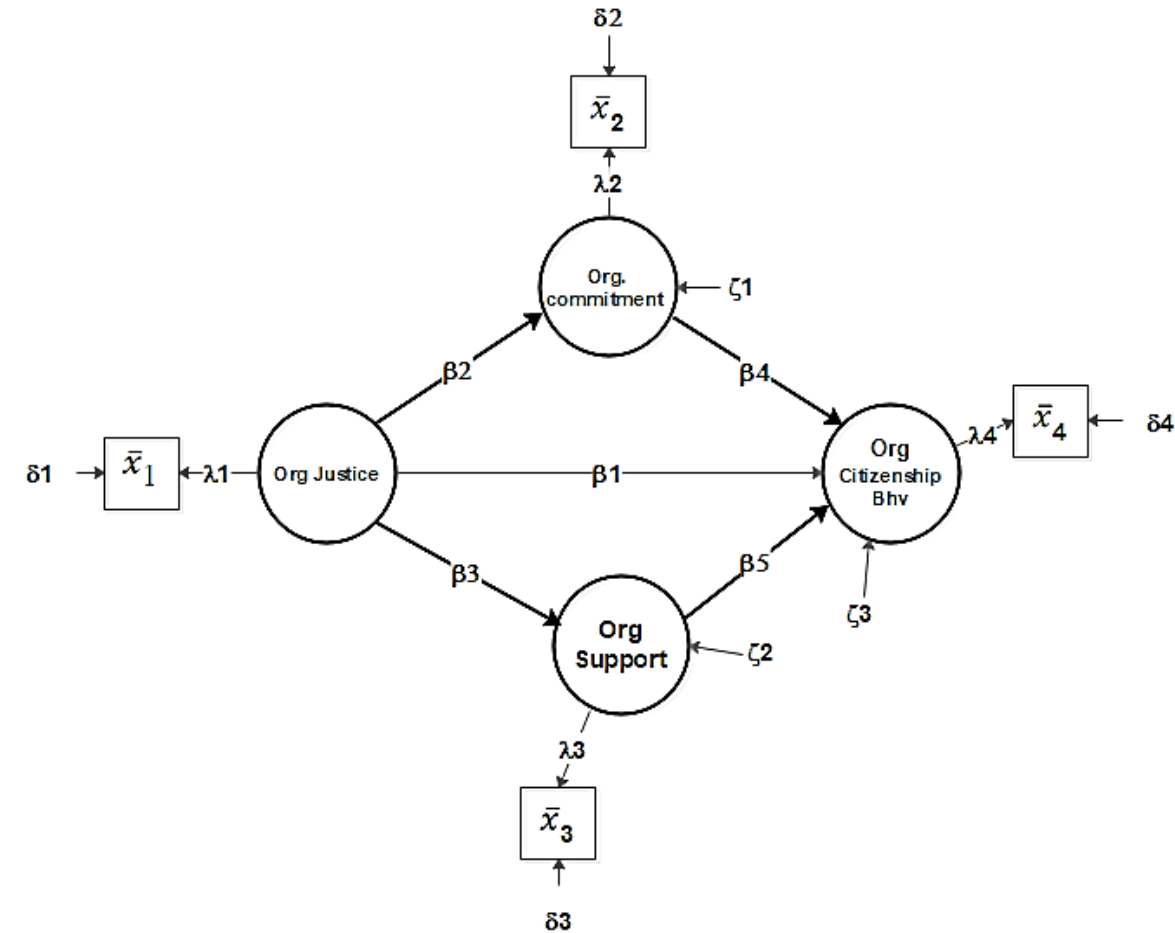
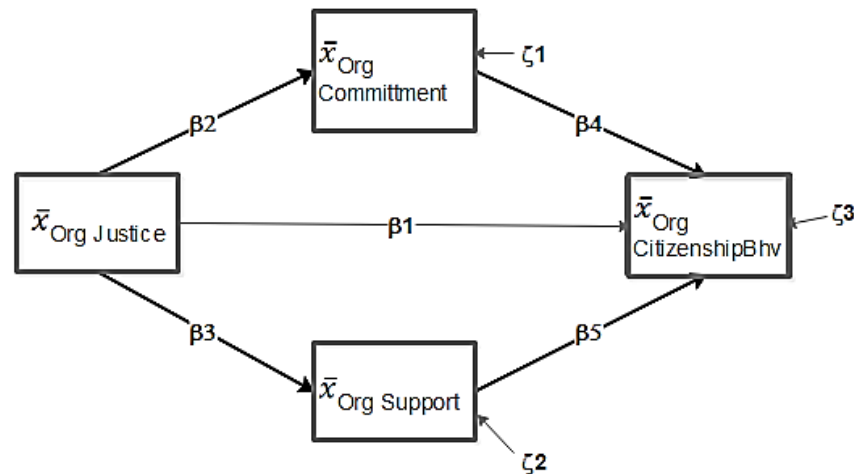
SEM

PM (

SPSS, excel,

PROCESS

SEM software)



MRA, Path analysis, SEM

factor analysis

PM

SEM

MRA

PLS algorithm

PLS

least square estimation

(structural model, inner model)

(measurement model, outer model)

1)

2)

LV

normalized MV

LV

SD =1

3)

4)

5)

LV

MV

6)

2)

5)

Formative-Reflective indicator

MV (manifest variable) indicator	indicator	2	formative indicator	reflective
1. formative indicator reality/parcel)			(domain/dimension/	

Formative-Reflective indicator

2. reflective indicator

(co-vary)

(interchangeability)

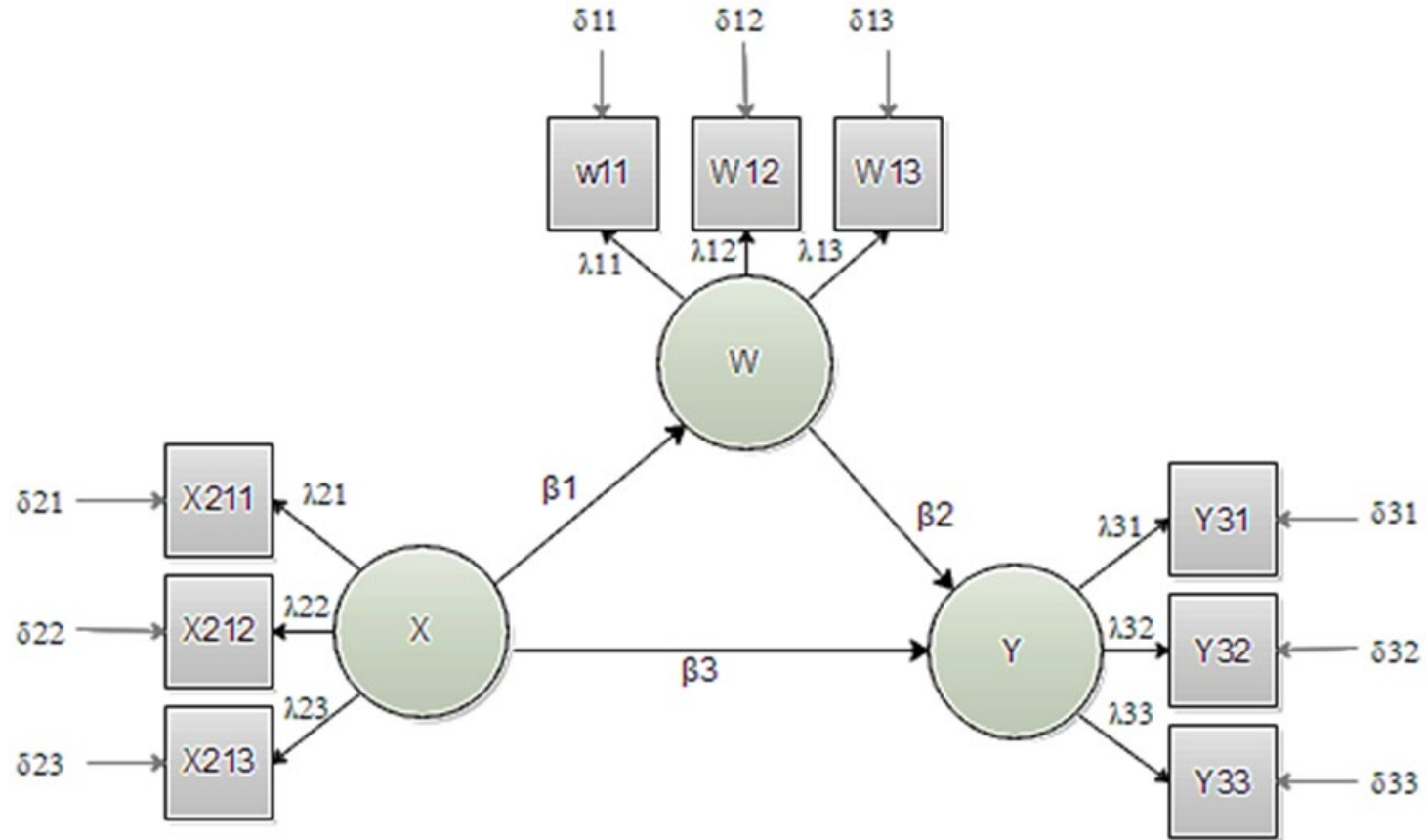
()

loading

Formative-Reflective indicator

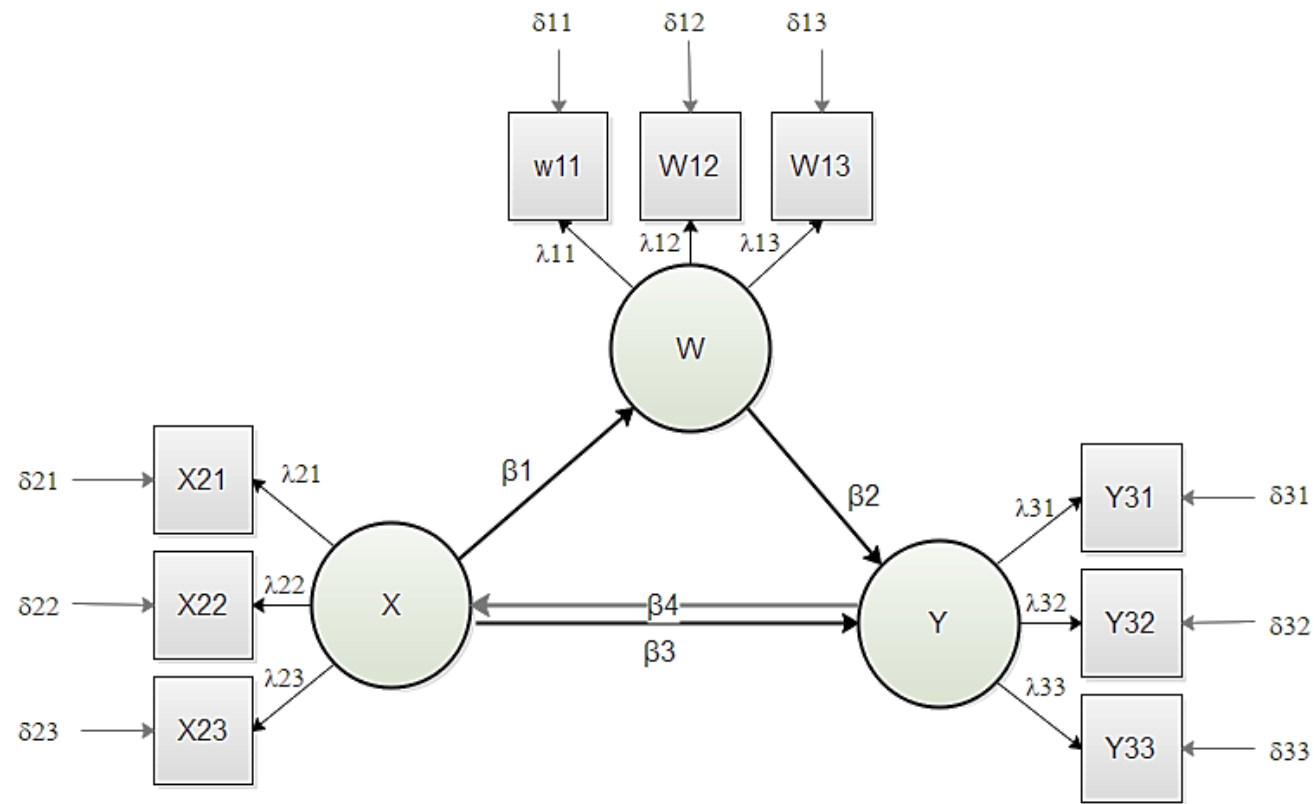
SEM Research Design

1. Causality



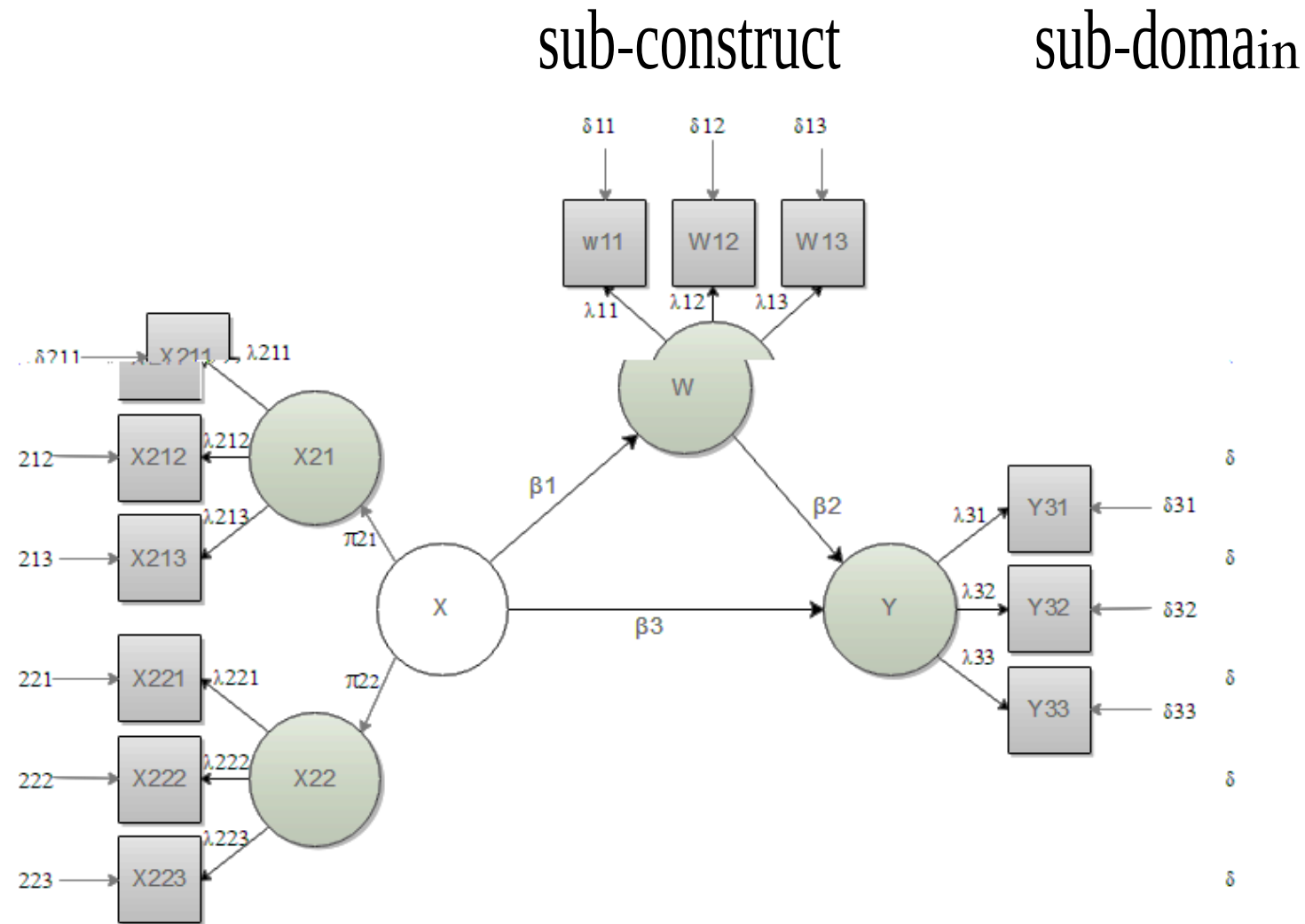
SEM Research Design

2. non-recursive model/reciprocal model



SEM Research Design

3. Second order model



SEM Research Design

5. Moderation model

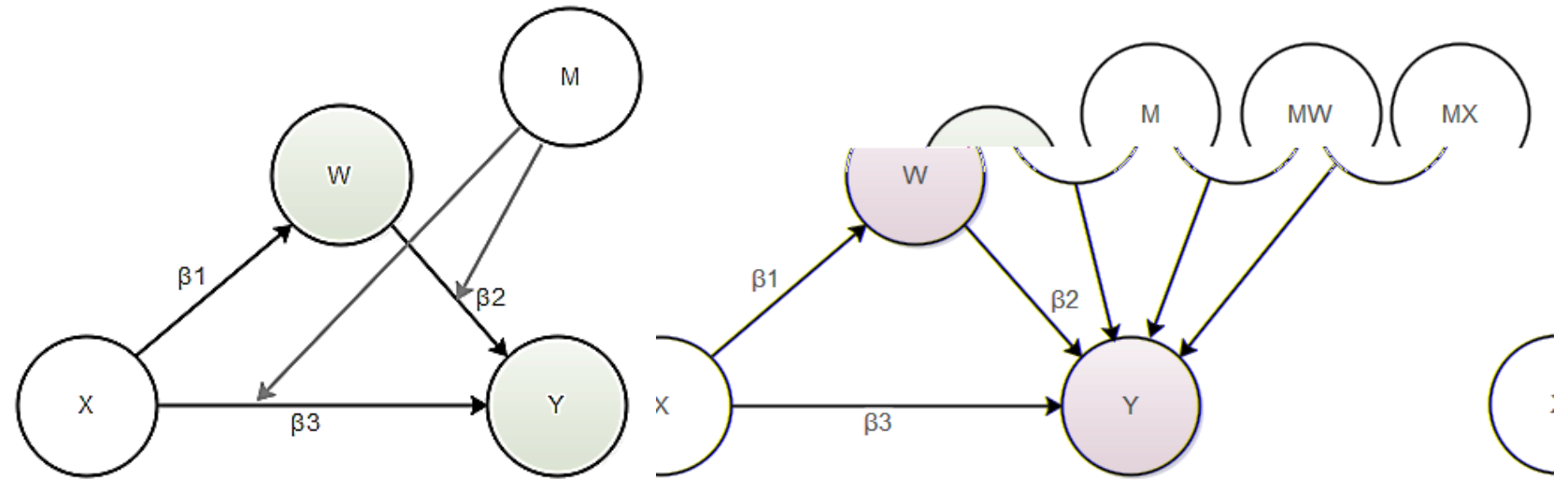
analysis

(template)

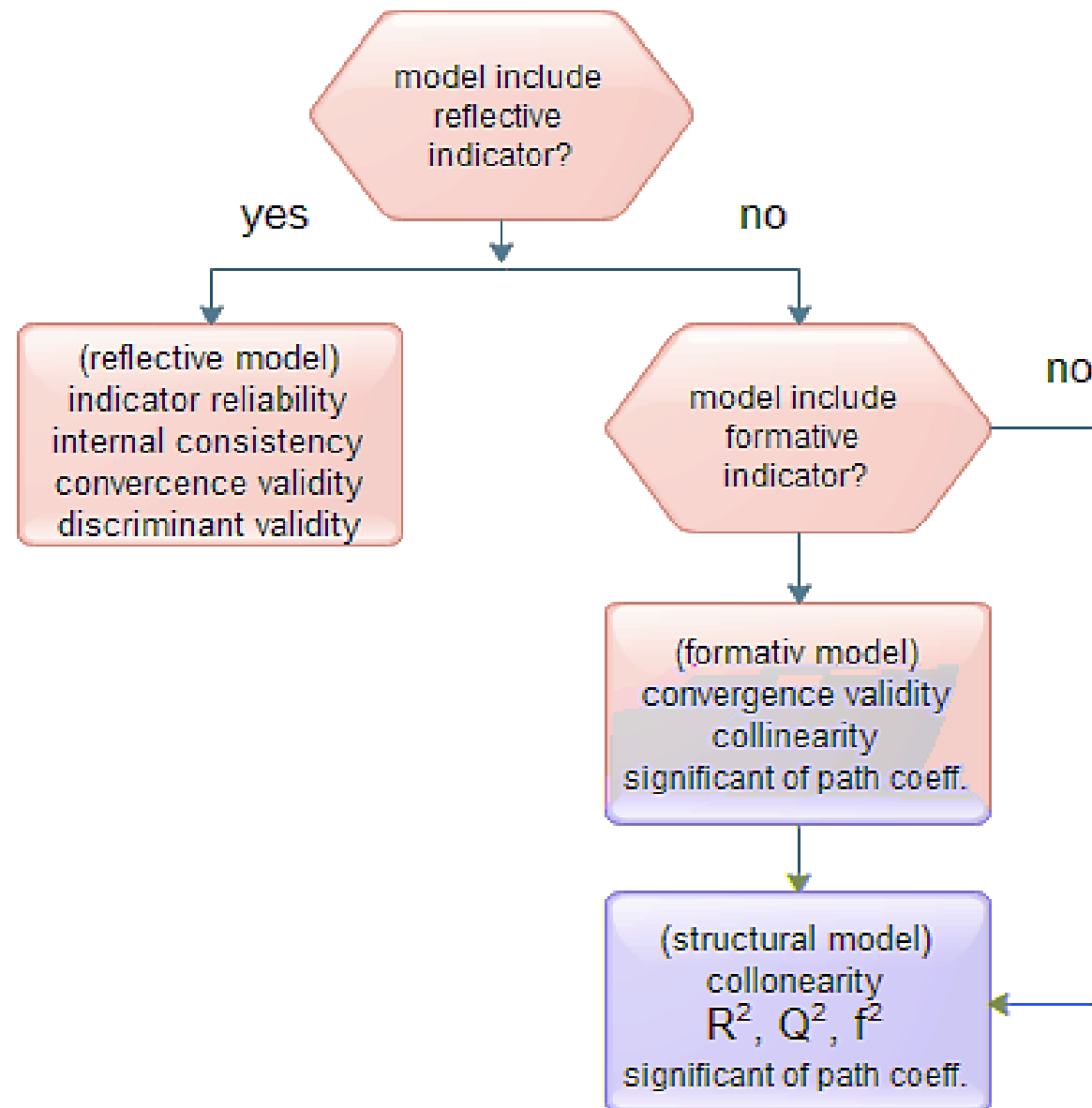
conditional effect

sequential exploratory

(multigroup)
statistical model



PLS running process

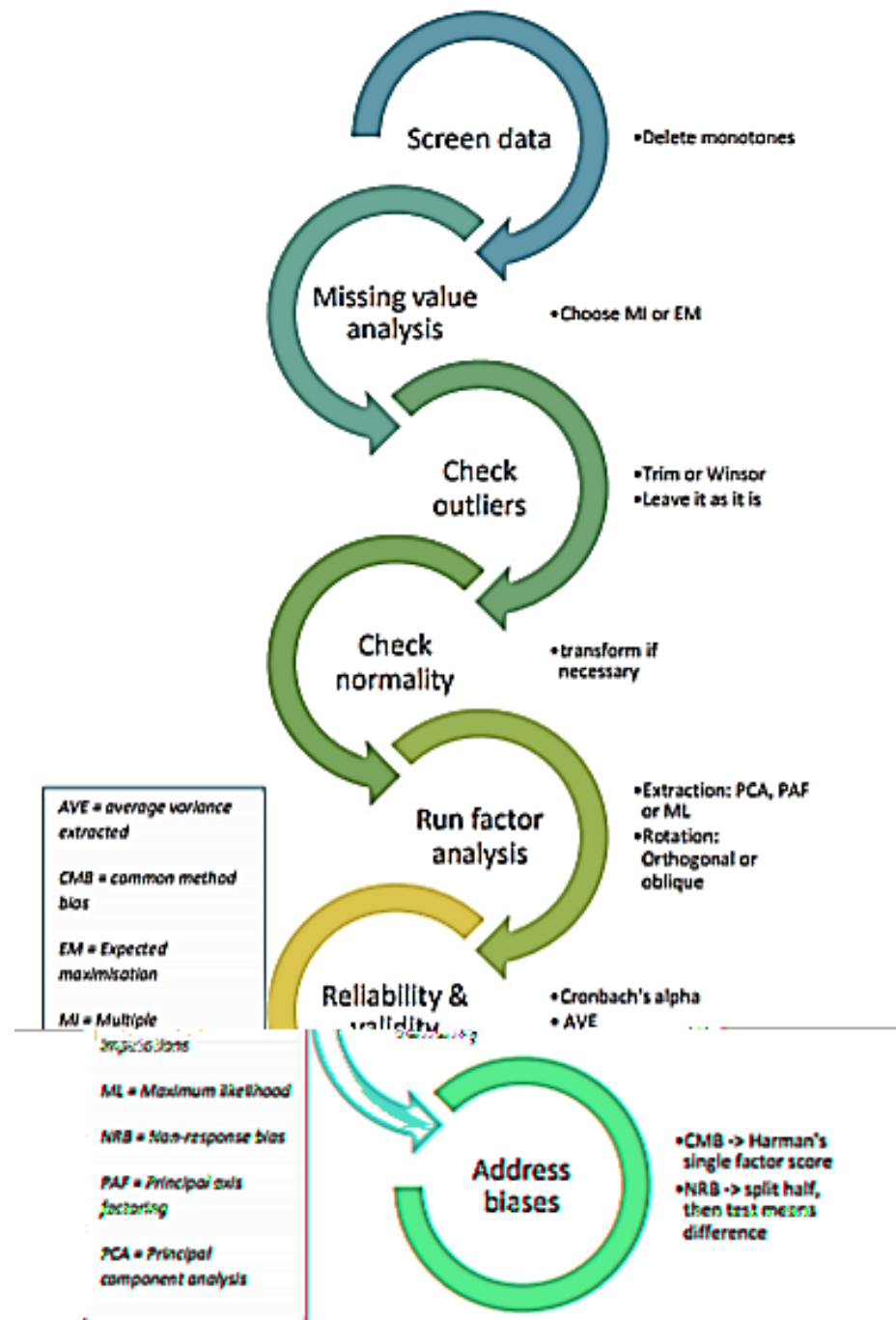


Preliminary data analysis checklist

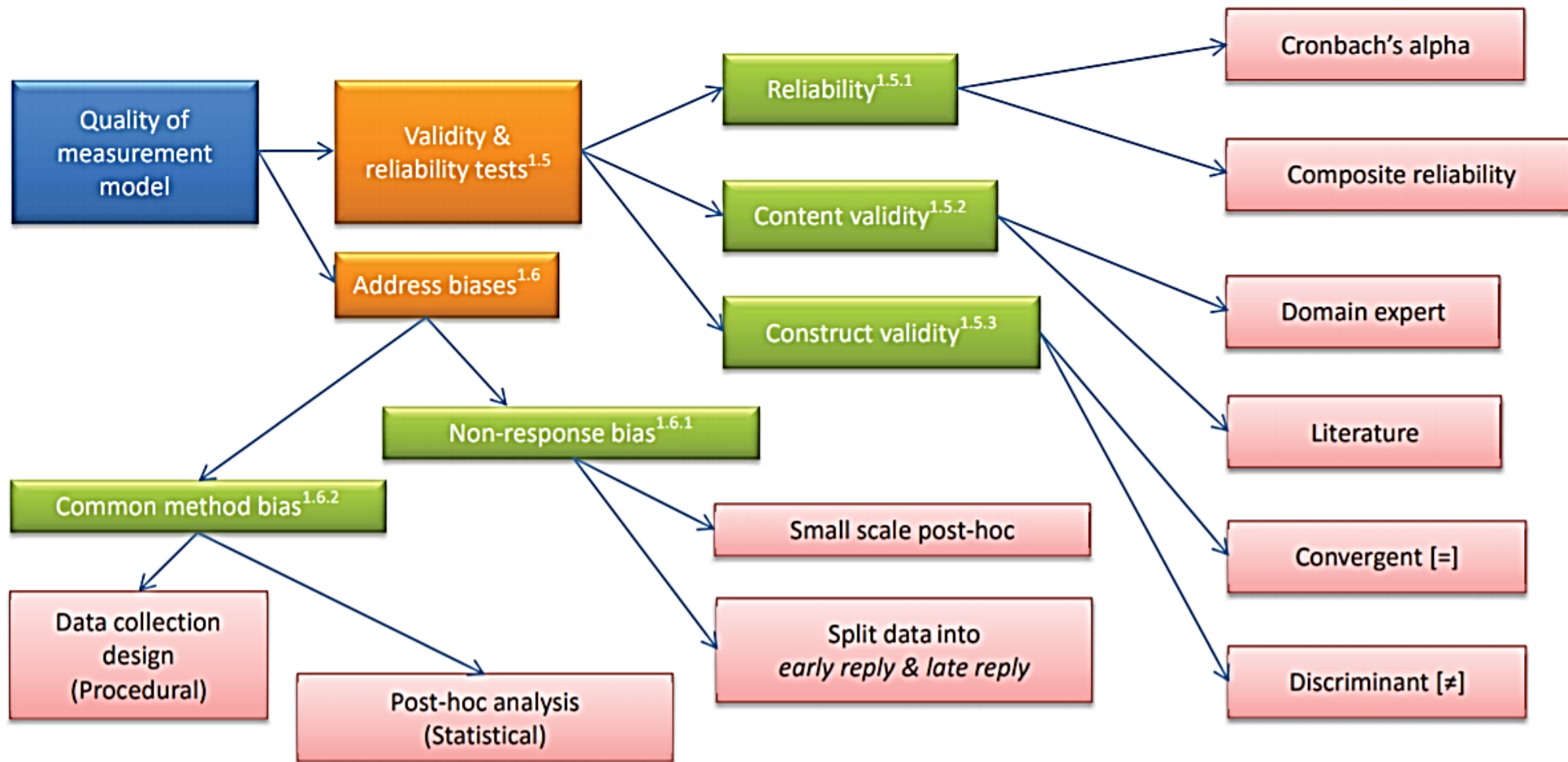
Saiyidi Mat Roni

(2014), Introduction to SPSS ,

https://www.researchgate.net/publication/262151892_Introduction_to_SPSS



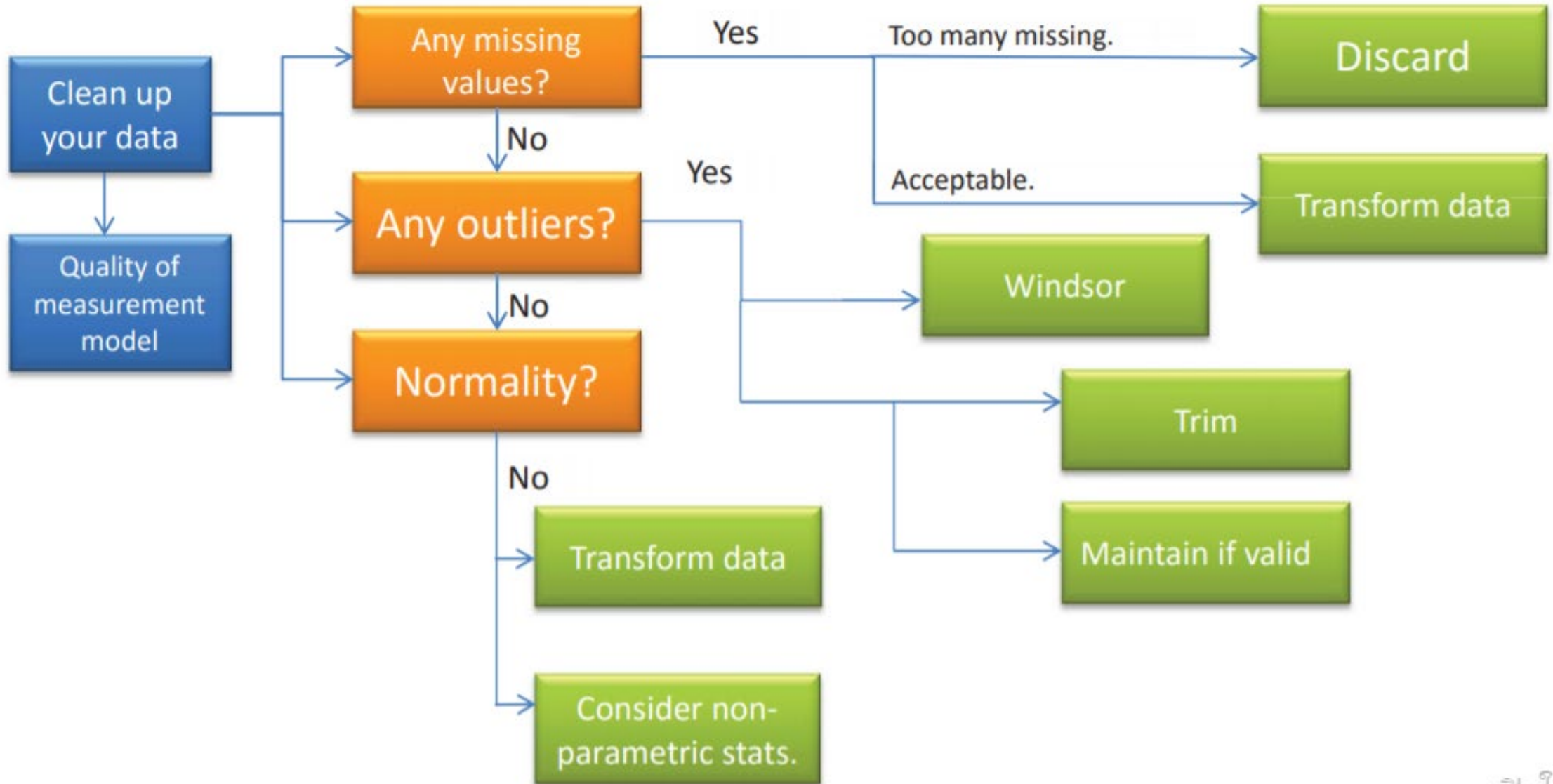
Quality of measurement model



common method bias

Podsakoff, P.M., MacKenzie, S.B., & Podsakoff, N.P. (2012)

Cleaning your data



$$(CV = \frac{SD}{\bar{x}} \quad (\quad \quad \quad \frac{(\quad \quad \quad ($$

smart PLS 3 ADANCO

1.
 - 1) Smart PLS SPSS Excel
filename.raw text file filename.csv
 - 2) ADANCO excel
2. missing data

reflective measurement model ; Convergence validity

1. Cronbach's alpha ≥ 0.70

$$2. \rho_c = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \text{Var}(\varepsilon_i)} = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + m - \sum \lambda_i^2} \geq 0.60$$

composite reliability

Dillon-Goldstein's rho

Joreskog's rho

Macdonald's omega

factor reliability (Henseler, Hubona, and Ray, 2015)

reflective measurement model

; Convergence validity

3. Average variance extracted $AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \text{Var}(\epsilon_i)}$

$$\text{Var}(\epsilon_i) = 1 - \lambda_i^2$$

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum (1 - \lambda_i^2)} = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + m - \sum \lambda_i^2} = \frac{\sum \lambda_i^2}{m}$$

AVE

indicator reliability

construct reliability

$$AVE_i \geq 0.50$$

cross loading

$$AVE_i = 0.50$$

LV

50

(Note: Reliability is a capability to measure the right concept. Reliability is the accuracy in measurements when the measurements are repeated)

reflective measurement model ; Convergence validity

4. Dijkstra-Henseler's rho reliability construct score

$$\rho_A \geq 0.60 \text{ (Theo K. Dijkstra Jörg Henseler, 2015)}$$

reflective measurement model ; Convergence validity

5. Loading

	LV			LV
1)		SEM	MV	LV
2)	0.707		(Henseler, Ringle and Sarstedt, 2012)	
0.707		0.50	AVE _i	0.50 (Hair et al., 2014)
loading _j ²	λ _i ²	indicator reliability		i (Hair et al., 2014)

reflective measurement model

; Convergence validity

6. Indicator reliability

- | | loading | weight |
|------------|---------|------------------------------------|
| 1) Loading | 0.707 (| $\lambda_i^2 \geq 0.50$) |
| 2) loading | 0.50 | weight
(theoretical importance) |
| 3) loading | | weight
(theoretical importance) |

หมายเหตุ theoretical importance

reflective measurement model ; Convergence validity

7

$\pm 1.$

8

($H_0: \sigma_e^2 = 0$ vs $H_1: \sigma_e^2 \neq 0$)

formative measurement model

1. / (Theoristic
reasonale and expert opinion)
- 2.
3. multicollinearity

construct

1) Loading

2) Loading ≥ 0.707

3) 0.707

AVE 0.50 AVE

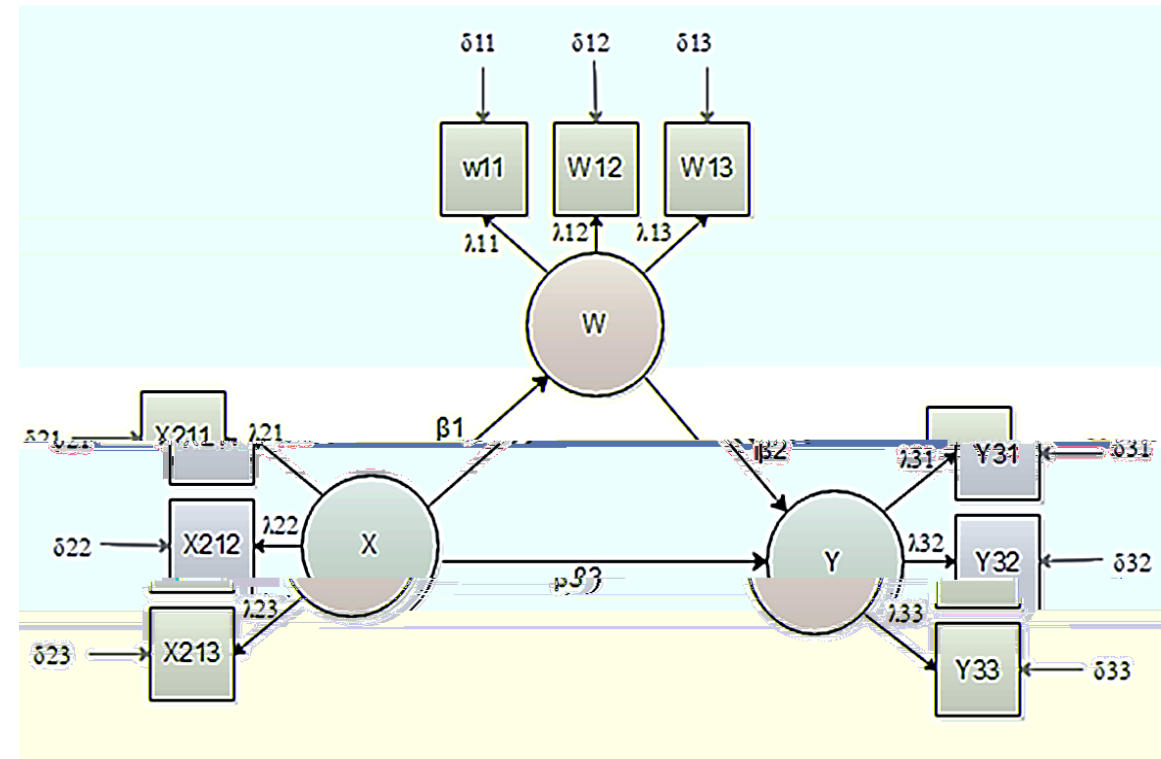
0.5

4) Loading < 0.707

(theoretical

importance)

4. α , ρ_A , ρ_C , AVE



discriminant validity

1. Cross loading

	item score	construct score
item score		
construct score	()	
	cross-loading	0.30, 0.40
(load)	LV	LV cross-loading

discriminant validity

2. Fornell-Larcker Criteria

$$\frac{\text{construct score}}{\text{score}} > \sqrt{\text{discriminant validity construct } i \text{ construct}}$$

discriminant validity

Fornell-Larcker Criterion

$$1) \sqrt{AVE_i} > r_{ij} ; \text{all } i \neq j$$

$$2) AVE_i > r_{ij}^2$$

indicator reliability (loading_j²)

i AVE_i i j

discriminant validity

3. HTMT (Heterotrait Monotrait ratio)

$$\frac{2}{2} \quad (\text{Jörg Henseler \& Christian M. Ringle \& Marko$$

Sarstedt, 2015)

$$\text{HTMT} < 1.00$$

หมายเหตุ trait construct

discriminant validity

Heterotrait-Monotrait Correlation Ratio (HTMT)

1

1

$$\text{HTMT}(ij) \leq 1.00, 0.90, 0.85; i \neq j$$

$$\underbrace{\text{HTMT}_{ij} = \frac{1}{K_i K_j} \sum_{g=1}^{K_i} \sum_{h=1}^{K_j} r_{ig,jh}}_{\text{average heterotrait-heteromethod}} \div \underbrace{\left(\frac{2}{K_i(K_i-1)} \cdot \sum_{g=1}^{K_i-1} \sum_{h=g+1}^{K_i} r_{ig,ih} \cdot \frac{2}{K_j(K_j-1)} \cdot \sum_{g=1}^{K_j-1} \sum_{h=g+1}^{K_j} r_{jg,jh} \right)^{\frac{1}{2}}}_{\text{geometric mean of the average monotrait-heteromethod correlation of construct } \xi_i \text{ and the average monotrait-heteromethod correlation of construct } \xi_j}$$

multicollinearity

multicollinearity

(multicollinearity)

1)

2)
model)

(formative measurement

1) t-statistics (SE

2)

$$t_j = \frac{\hat{\beta}_j}{se_{\hat{\beta}_j}} \quad)$$

multicollinearity

(multicollinearity)

(antecedent)

well-fitting model

$$VIF_j = \frac{1}{1-R_j^2} < 4 \quad 5$$

$$R_j^2 = 0.75, 0.80 \quad (0.90)$$

formative indicator

$$R_j^2$$

$$X_j = f(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{j-1} X_{j-1} + \beta_{j+1} X_{j+1} + \cdots + \beta_k X_k + u; j = 1, 2, \dots, k)$$

multicollinearity

- 1) multicollinearity
parcel/sub-construct/sub-domain
- 2) second order model
- 3) multicollinearity
(item/indicator/MV)
- 4) (case/record)
- 5) path model mean-centered
multicollinearity f_i^2

Goodness of fit

PLS-PM

Goodness of fit PLS-PM

1. R^2 , overall effect size

$$R^2 = 0.19, 0.33, 0.67$$

(Chin, 1998; Hock and Ringle, 2006)

$$R^2 = 0.02, 0.13, 0.26 \text{ (Cohen, 1988)}$$

Cohen

R^2

Goodness of fit

PLS-PM

2. Effect size (f^2)

(

)

Goodness of fit PLS-PM

effect size

$$f_i^2 = \frac{R_{\text{included}}^2 - R_{\text{excluded}}^2}{1 - R_{\text{included}}^2} ; \text{all } i$$

effect size

()

effect size

Goodness of fit PLS-PM

(Cohen, 1988; Henseler et al. 2009; Hair, Hult, Ringle, Sarstedt, 2014)

$$f^2 < 0.02$$

$$0.02 \leq f^2 < 0.15$$

$$0.15 \leq f^2 < 0.35$$

$$0.35 \leq f^2$$

effect size

http://www.psychometrica.de/effect_size.html

effect size

R^2_{changed}

Goodness of fit PLS-PM

$$Y = f(X_1, X_2) + u$$

$$f_i^2$$

$$f_i^2 \frac{R_{\text{original}}^2 - R_{\text{omitted}}^2}{1 - R_{\text{original}}^2}$$

	R^2	ΔR_i^2	f_i^2
	0.4308	-	-
		-	$\frac{0.0480}{0.5692} = 0.0843$
		-	$\frac{0.2122}{0.5692} =$
$1 - R_{\text{original}}^2$ -			

Goodness of fit PLS-PM

3. Q^2

q^2

prediction relevance

(restructure)

Q^2

q^2

f^2

Goodness of fit

PLS-PM

- Q

$$Q^2 = 1 - \frac{SSE}{SSO}$$

Q² 0.15 0.35

(

(

-

-

$$Q^2 \leq$$

Goodness of fit PLS-PM

Q^2

(

$$Q^2 = 1 - \frac{SSE}{SSO}$$

Goodness of fit

PLS-PM

4.
(significant)

(sign)

(size)

data cleaning

Fit index

PLS

2017

SRMR

discrepancy $s - \hat{\Sigma}$ s
(empirical indicator data array) $\hat{\Sigma}$

(model-implied indicator data array)

Fit index

1. SRMR (standardized root mean square residual) ≤ 0.08 0.12 (PLS
0.12 CB-SEM

Fit index

2. $d_{ULS} = \frac{1}{2} \text{trace}(S - \hat{\Sigma})^2$ unweighted least square discrepancy square
Euclidian distance indicator empirical correlation array
indicator model implied correlation array

P95

P99

Fit index

$$3. d_G = \frac{1}{2} \sum_k^m (\log \varphi_k)^2 \quad \text{geodesic distance} \quad \varphi_k \quad \text{Eigen value} \quad k$$

$$S^{-1} \hat{\Sigma} \quad \text{P95} \quad \text{P99}$$

$$d_{\text{ULS}}, d_G \quad S - \hat{\Sigma} = 0$$

perfect fit

Fit index

PLS SRMR 0.12 d_{ULS} / d_G
(o)
CB-SEM (Smart PLS)

Vanishing tetrad

Vanishing tetrad

- | | | |
|----|------------------|----------------------|
| 1) | Vanishing tetrad | reflective indicator |
| 2) | Vanishing tetrad | formative indicator |

Ho: reflective indicator vs H1: formative indicator

Importance-Performance Map Analysis (IPMA)

Importance-Performance Map Analysis (IPMA)

large Importance low performance

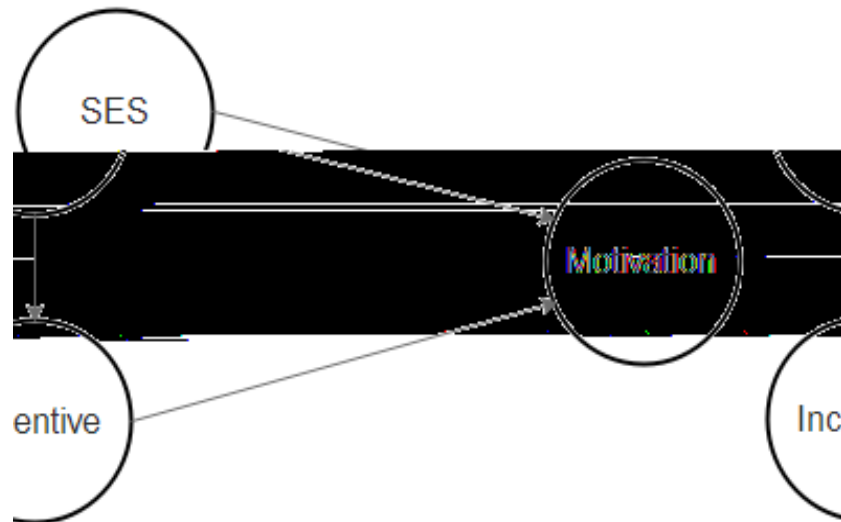
Importance-Performance Map Analysis (IPMA)

Importance = absolute total effect ()

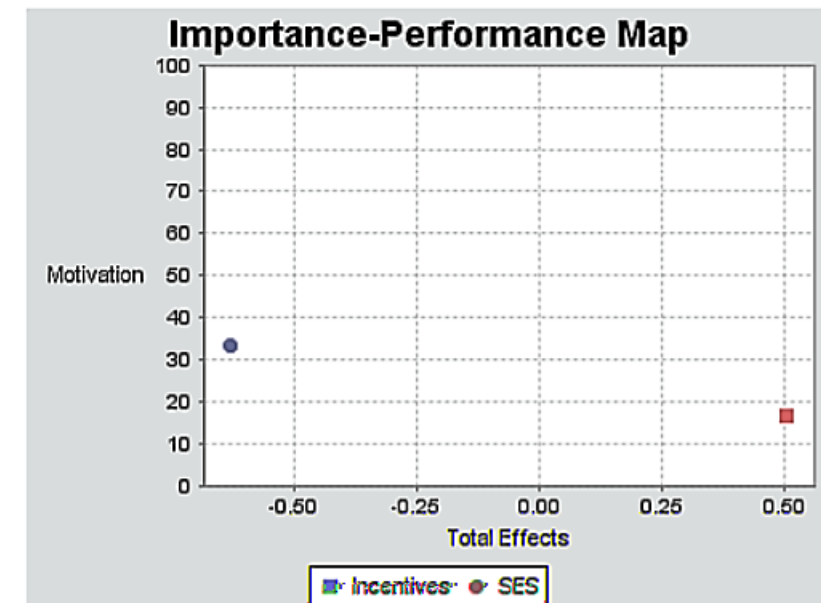
Performance = unstandardized latent variable score normalize

$$\text{Normalized latent score variable} = \frac{x - \min}{\max - \min} * 100$$

Importance-Performance Map Analysis (IPMA)



	16.558
SES	33.030
SES	-



Goodness of Fit (GoF)

$$\text{GoF} = \sqrt{R^2_{\text{com}}} \quad (\text{Tenenhaus et al., 2005}) \quad \text{com (= AVE)} \quad \text{global criteria}$$

R^2 global effect size

$$(\text{หมายเหตุ} \quad \sqrt{R^2_{\text{com}}})$$

(Henseler & Sarstedt, 2013)
(mispecified model) (Hair et al., 2014)

Goodness of Fit (GoF)

$$\sqrt{R^2_{\text{com}}} \quad \sqrt{0.50 * 0.19}$$

$$\sqrt{R^2_{\text{com}}} \quad \sqrt{0.50 * 0.35} \quad 0.406$$

$$\sqrt{R^2_{\text{com}}} \quad \sqrt{0.50 * 0.67}$$

Redundancy

9

$$_i * R_i^2$$

Redundancy criterion

$\sum_i R_i^2$	
$\sum_i R_i^2$	
$\sum_i R_i^2$ 0.50	

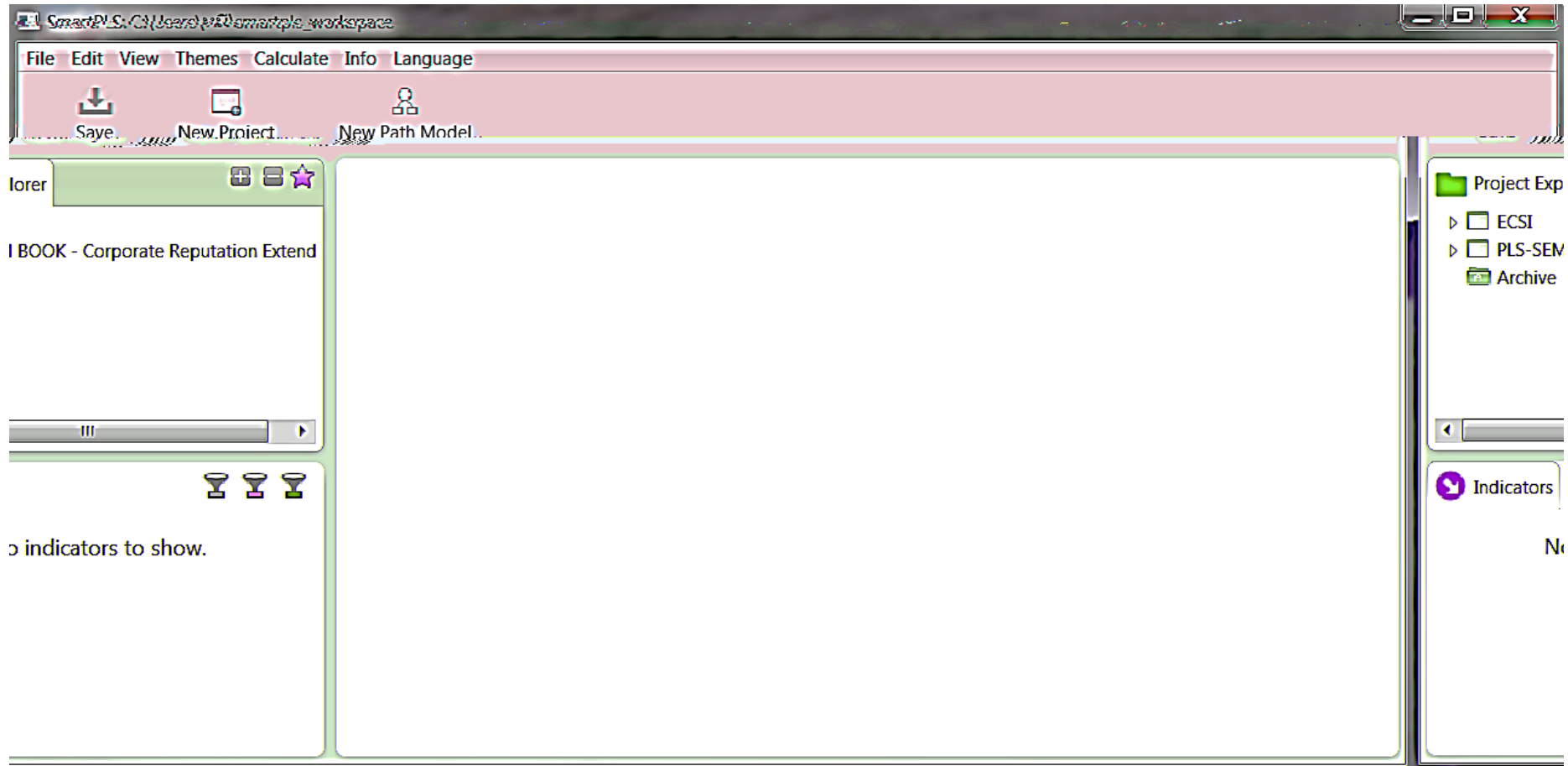
หมายเหตุ

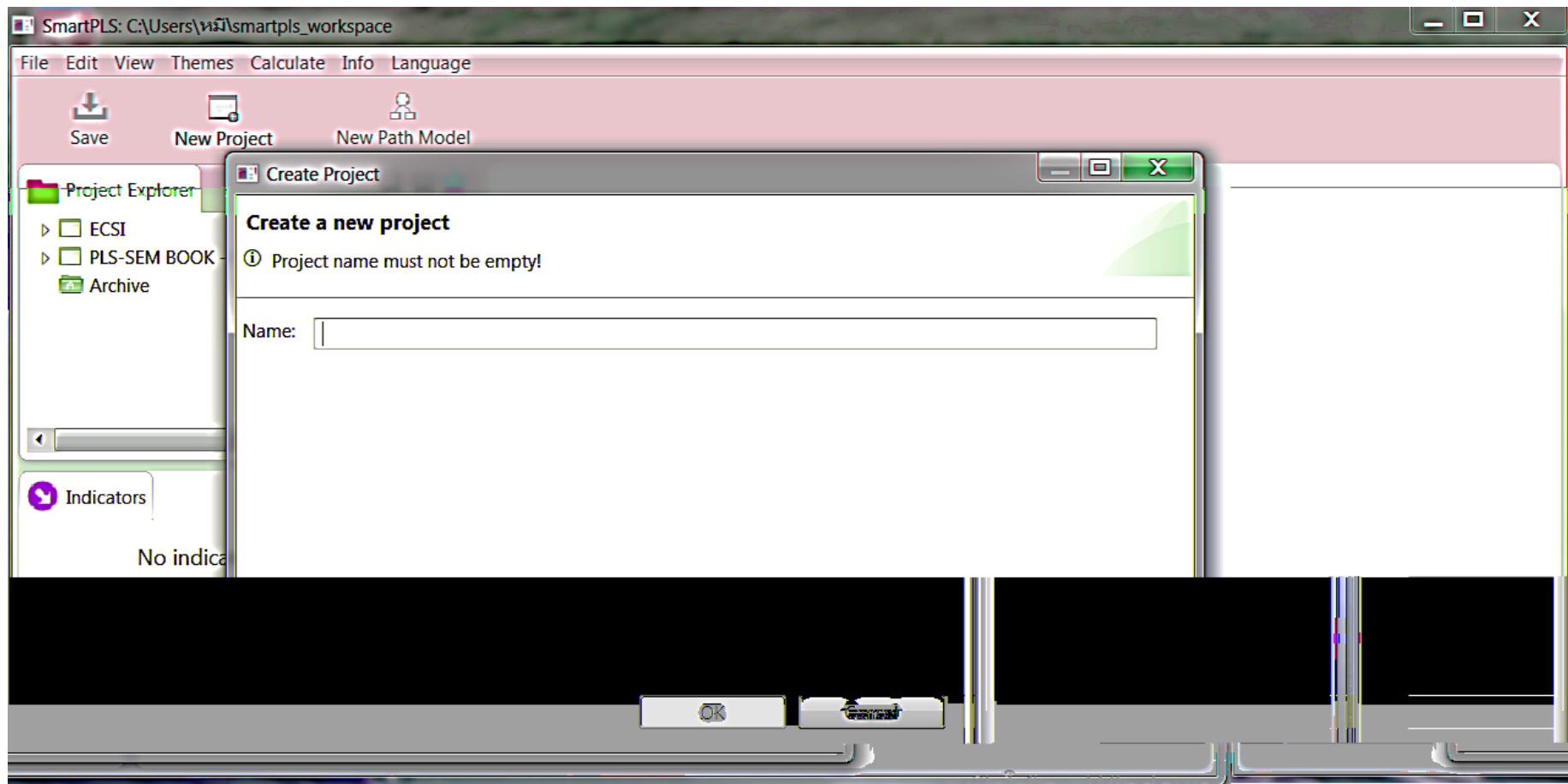
3

โปรแกรม Smart PLS



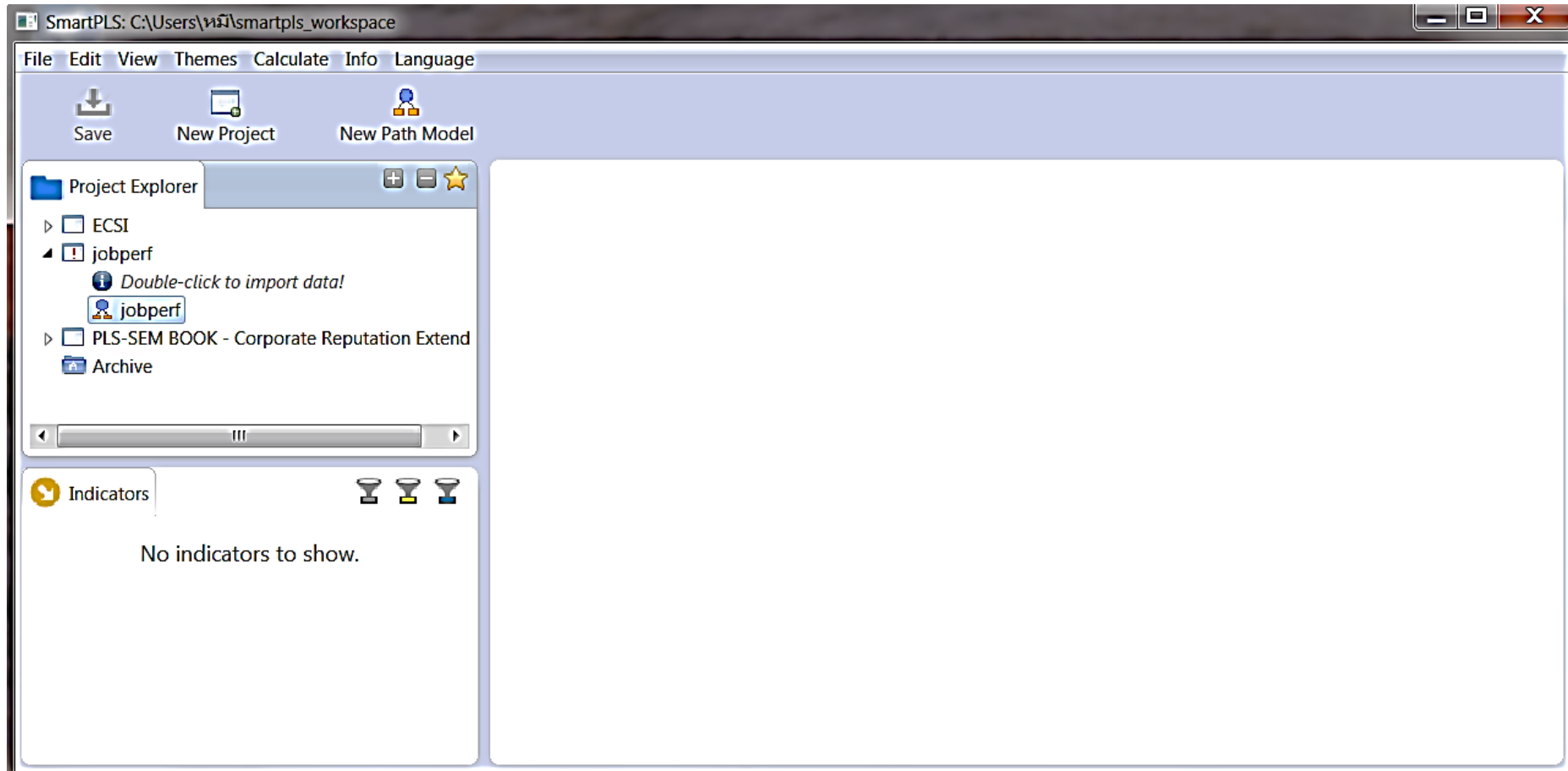
3





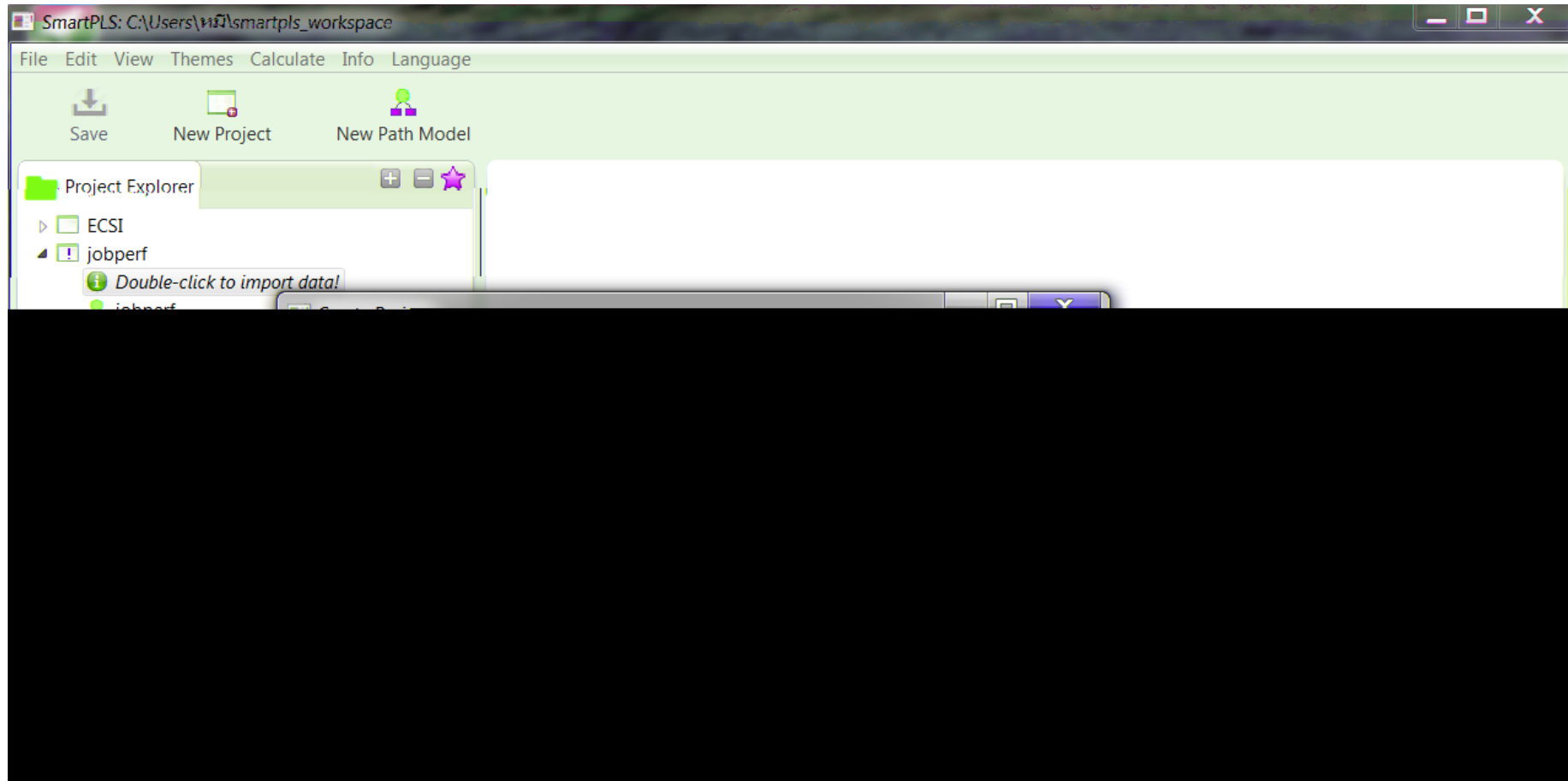
2

Double click to import data



Dbl click

double click to import data >



SmartPLS: C:\Users\หรรษา\smartpls_workspace

File Edit View Themes Calculate Info Language

New Path Model Add Data Group Generate Data Groups Clear Data Groups Save New Project

js-jp.txt

Delimiter: **Tabulator** Encoding: UTF-8 Re-Analyze Open External

Value Quote Character: **None** Sample size: 163

Number Format: **JS (e.g. 1,000.22)** Indicators: **55**

Missing Value-Marker: **None** Missing Values: **0**

Copy to Clipboard

Project Explorer

- ECSI
- jobperf
- jobperf
- is-ip [163 records]

PLS-SEM BOOK - Corporate Reputation Extend Archive

	No.	Missing	Mean	Median	Min	Max	Standard D...	Exc...
sex	1	0	1.601	2.000	1.000	2.000	0.490	
status	2	0	1.393	1.000	1.000	2.000	0.488	
age	3	0	33.552	32.000	23.000	50.000	7.335	
JS1	4	0	4.209	4.000	2.000	5.000	0.747	
JS2	5	0	4.196	4.000	1.000	5.000	0.820	
JS3	6	0	3.850	4.000	1.000	5.000	0.938	
JS4	7	0	4.104	4.000	1.000	5.000	0.811	

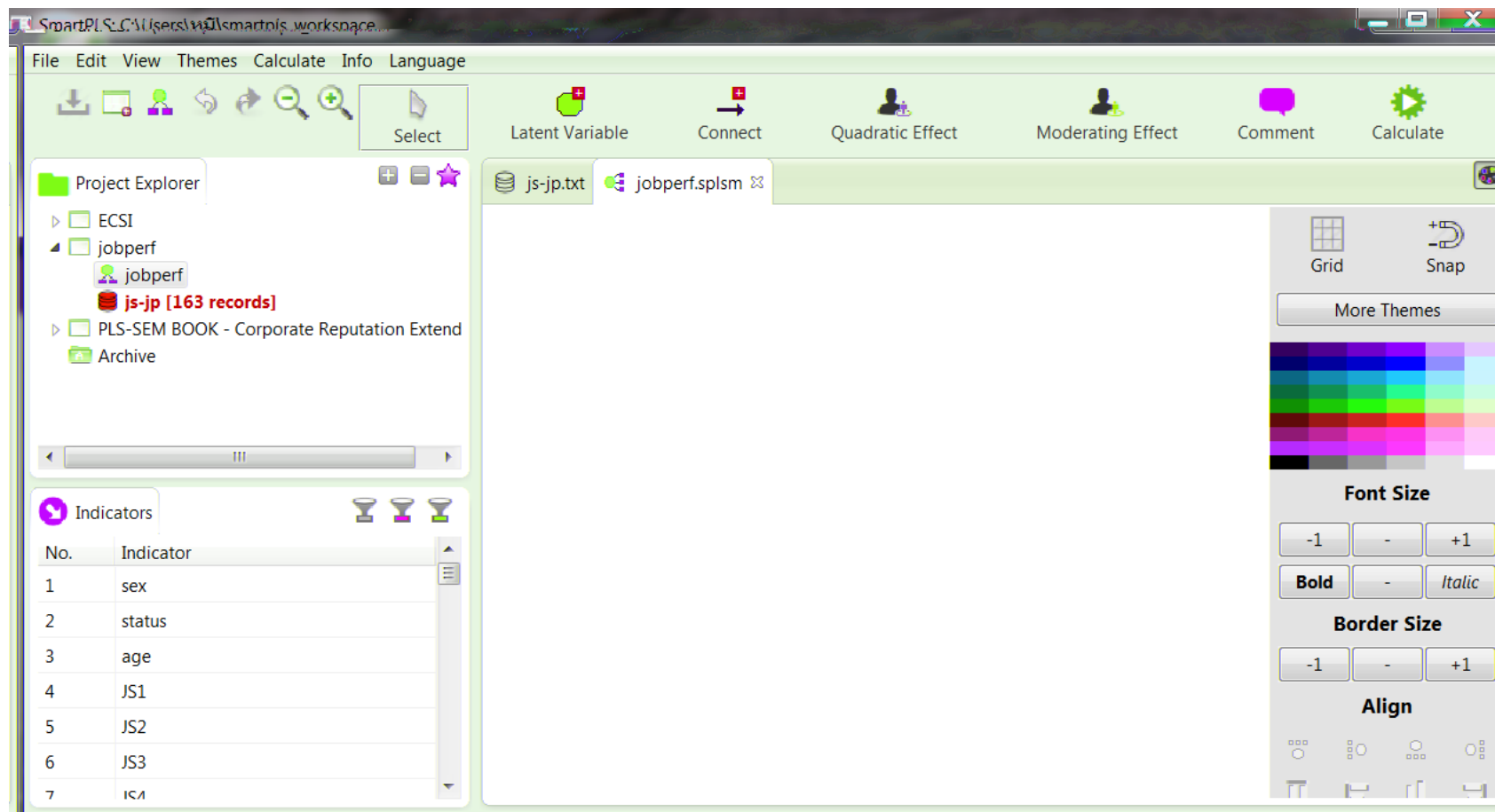
Indicators

No indicators to show.

2

2

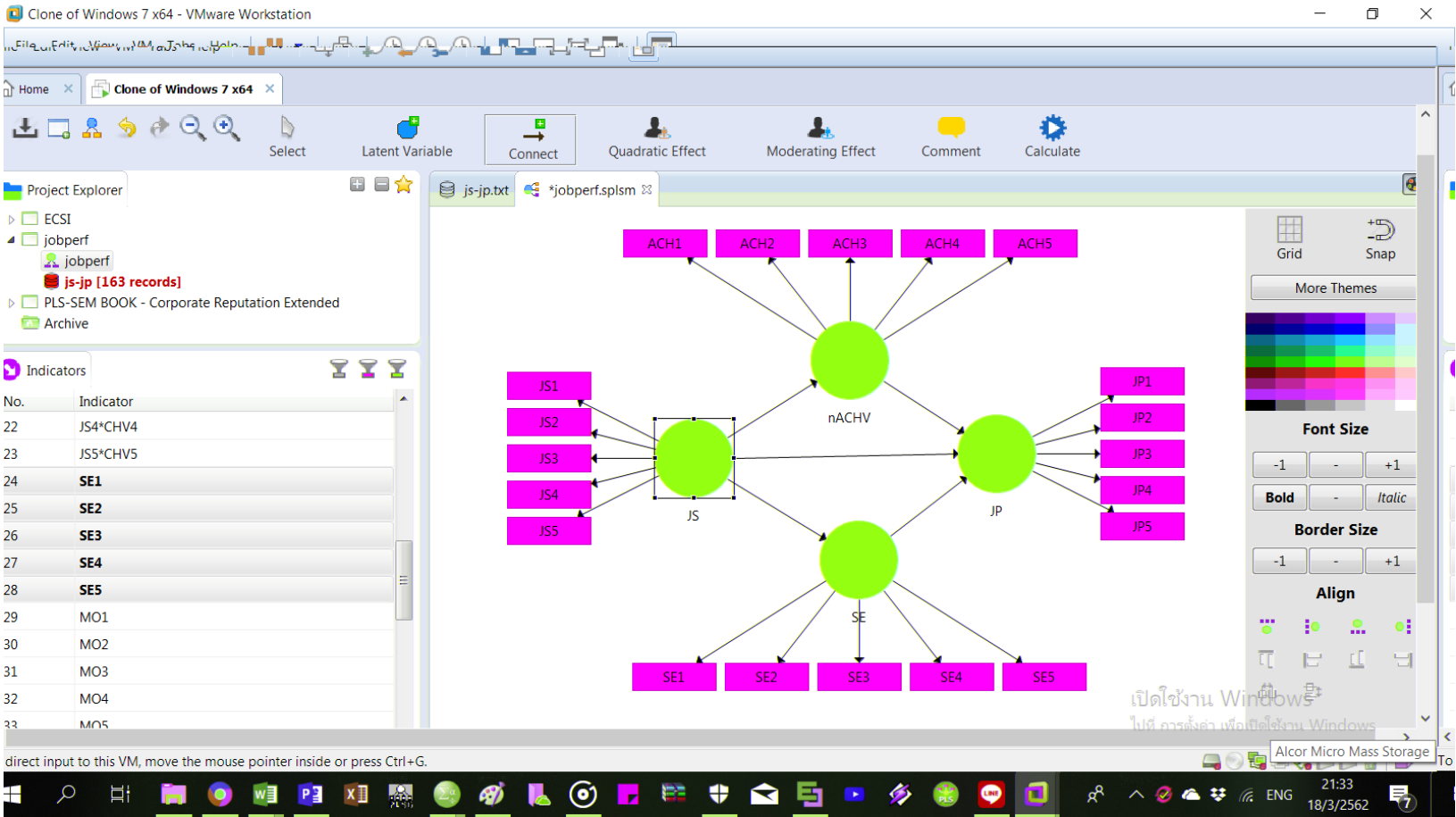
3



Shift click

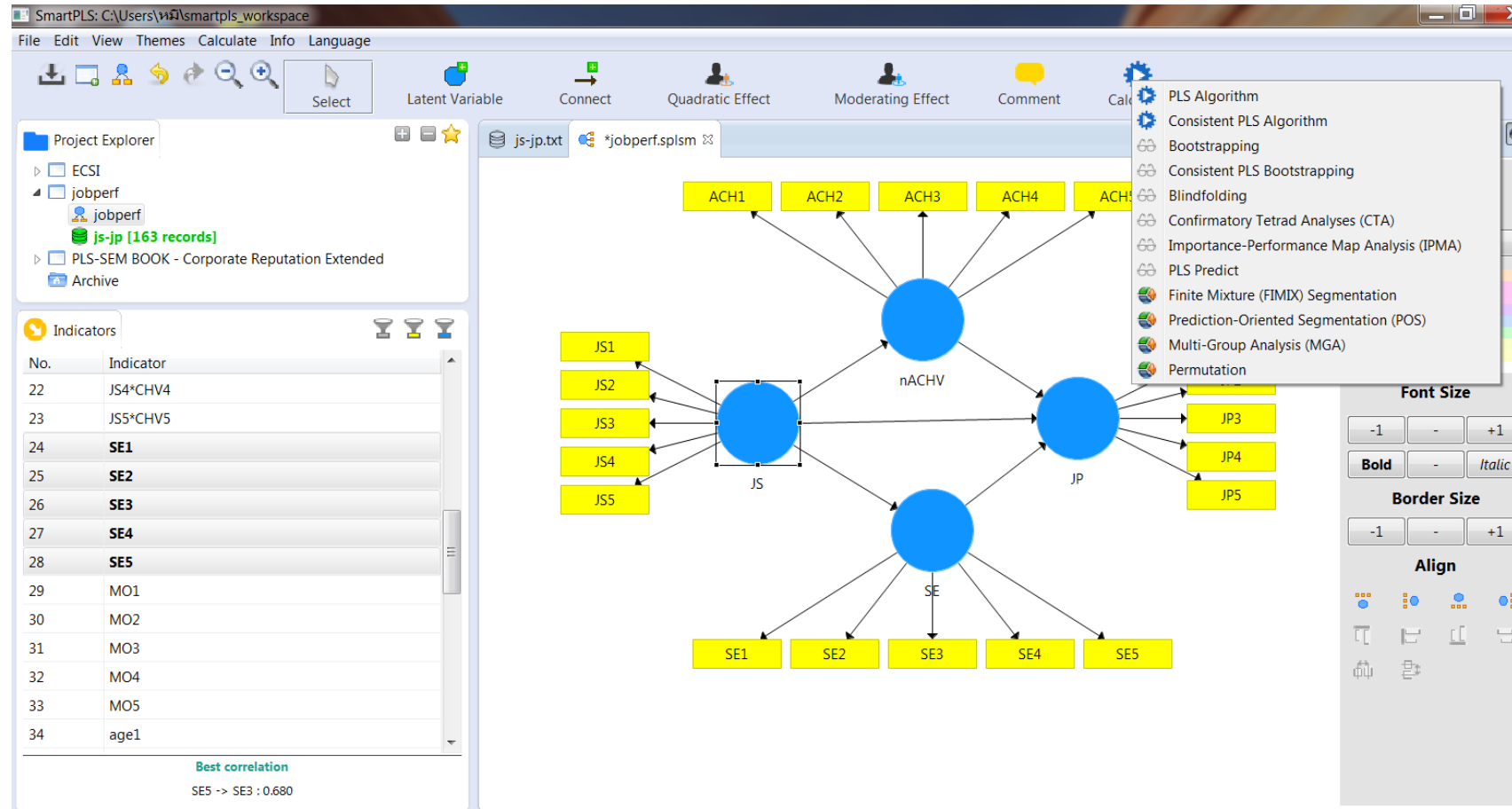
2

3



calculation

Consistent PLS Algorithm



5 000-10

Consistent PLS

The consistent PLS (PLSc) algorithm performs a correction of reflective constructs' correlations to make results consistent with a factor-model.

[Read more!](#)

Setup

Partial Least Squares

Weighting

Basic Settings

Weighting Scheme

☐ Centroid ☐ Factor ☒ Path

Maximum Iterations:

Stop Criterion (10^{-X}):

Advanced Settings

Initial Weights

☐ Use Lohmoeller Settings

or configure [individual initial weights](#)

results. This number should be sufficiently large (e.g., 300 iterations). When checking the PLS-SEM result, one must make sure that the algorithm did not stop because the maximum number of iterations was reached but due to the stop criterion. Note: The selection of 0 for the maximum number of iterations allows you to obtain results of the sum scores approach.

Stop Criterion

The PLS algorithm stops when the change in the outer weights between two consecutive iterations is smaller than this stop criterion value (or the maximum number of iterations is reached). This value should be sufficiently small (e.g., 10⁻⁵ or 10⁻⁷).

Advanced Settings

Initial Outer Weights

As the default (i.e., the SmartPLS settings), the initial outer weights are set to +1. However, the following alternatives are available:

- **Lohmöller Settings:** Lohmöller suggested using +1 as initial outer weight for all indicators per measurement model except the last one, which uses an initial outer weight of -1. Thereby, the PLS-SEM algorithm converges faster. However, this kind of initialization can lead to counterintuitive signs of estimated PLS path coefficients in the measurement models and/or in the structural model.
- **Individual Settings:** SmartPLS to define individual initial outer weights for every indicator in the PLS path model. For example, are particularly important indicator can obtain a +1 (e.g., when the strong an positive relationship with the latent variable is assumed a prior), while the other indicators of the same measurement model obtain a 0.

[Link to Literature](#)

After Calculation:

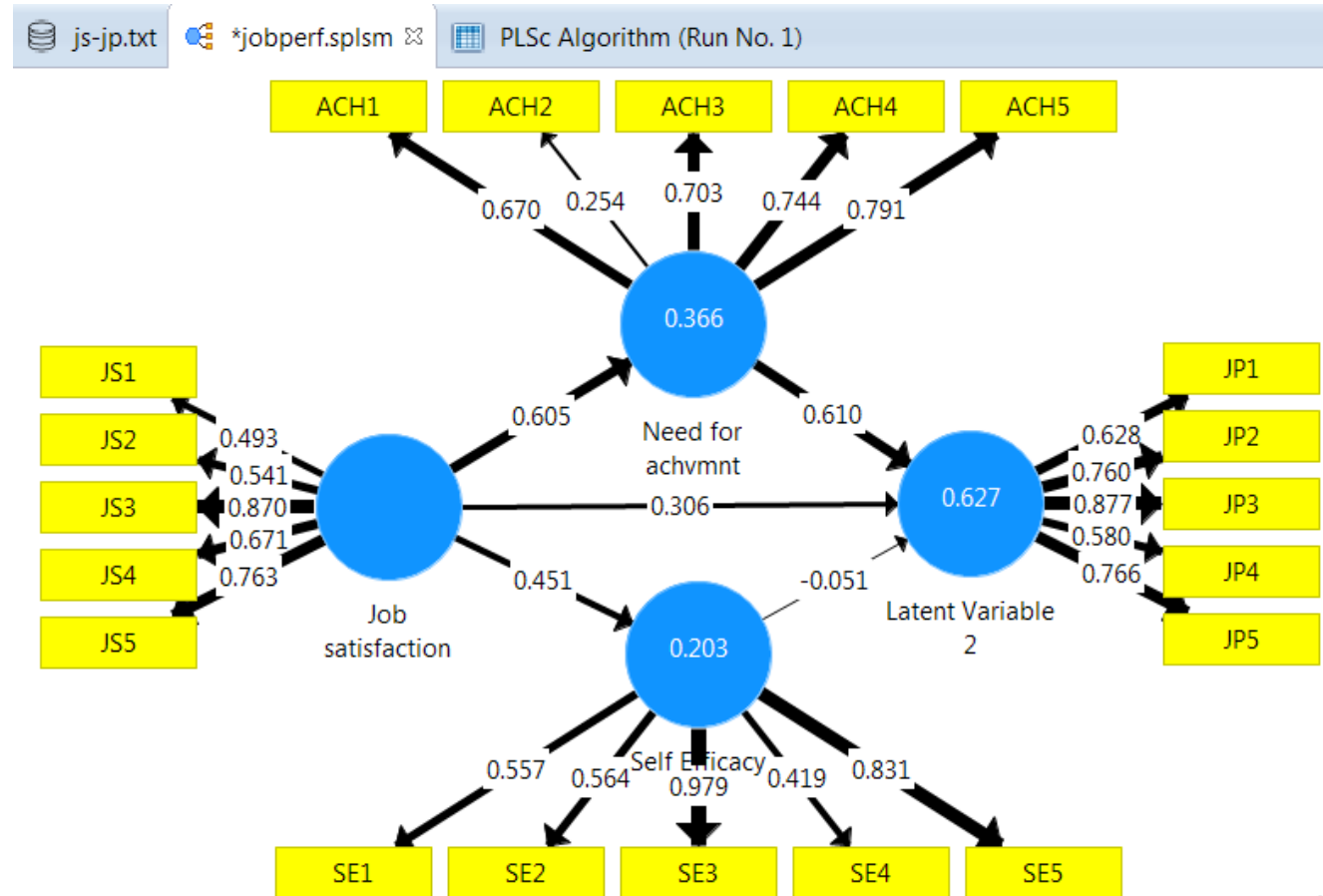
Open Full Report

Close

Start Calculation

รองศาสตราจารย์ ดร.มนตรี พิริยะกุล ภาควิชาสถิติ มหาวิทยาลัยรามคำแหง

consistent PLS Algorithm



เจ

consistent PLS Algorithm

File Edit View Themes Calculate Info Language

Save New Project New Path Model Hide Zero Values Increase Decimals Decrease Decimals Export to Excel Export to Web Export to R

Project Explorer

- ▷ ECSI
- ▷ jobperf
 - ▷ jobperf
 - ▷ js-jp [163 records]
- ▷ PLS-SEM BOOK - Corporate Reputation Extended
 - ▷ Archive

js-jp.txt *jobperf.splsm Bootstrapping (Run No. 1) PLS Algorithm (Run No. 1)

Path Coefficients

Matrix Path Coefficients Copy to Clipboard: Excel Format R Format

	JobPerf	JobSat	SE	needACHV
JobPerf				
JobSat	0.306		0.451	0.605
SE	-0.051			
needACHV	0.610			

Indicators Calculation Results

PLSc Algorithm (Run No. 1) Remove

Report Excel HTML R

Data Group Complete

Inner model Path Coefficients

Outer model Outer Weights / Loadings

Constructs R Square

Highlight Paths use absolute values

Final Results

- [Path Coefficients](#)
- [Indirect Effects](#)
- [Total Effects](#)
- [Outer Weights](#)
- [Outer Loadings](#)
- [Latent Variable](#)
- [Residuals](#)

Quality Criteria

- [R Square](#)
- [f Square](#)
- [Construct Reliability and Validity](#)
- [Discriminant Validity](#)
- [Collinearity Statistics \(VIP\)](#)
- [Model Fit](#)

Interim Results

- [Stop Criterion Changes](#)
- [Correction Value C](#)

Base Data

- [Setting](#)
- [Inner Model](#)
- [Outer Model](#)
- [Indicator Data \(Original\)](#)
- [Indicator Data \(Standardized\)](#)
- [Indicator Data \(Correlations\)](#)

calculation

Bootstrapping

Bootstrapping

Bootstrapping is a nonparametric procedure that allows testing the statistical significance of various PLS-SEM results such path coefficients, Cronbach's alpha, HTMT, and R² values.

[Read more!](#)

Setup

Partial Least Squares

Weighting

Basic Settings

Subsamples500

☒ Do Parallel Processing

Sign Changes

☒ No Sign Changes

☐ Construct Level Changes

☐ Individual Changes

Amount of Results

☐ Basic Bootstrapping

☒ Complete Bootstrapping

Advanced Settings

Confidence Interval Method

☐ Percentile Bootstrap

☐ Studentized Bootstrap

☒ Bias-Corrected and Accelerated (BCa) Bootstrap

☐ Davison Hinkley's Double Bootstrap

☐ Shi's Double Bootstrap

Test Type

☐ One Tailed

☒ Two Tailed

Significance Level

0.05

Basic Settings

Subsamples

In bootstrapping, subsamples are created with observations randomly drawn (with replacement) from the original set of data. To ensure stability of results, the number of subsamples should be large. For an initial assessment, one may use a smaller number of bootstrap subsamples (e.g., 500). For the final results preparation, however, one should use a large number of bootstrap subsamples (e.g., 5,000).

Note: Larger numbers of bootstrap subsamples increase the computation time.

Do Parallel Processing

This option runs the bootstrapping routine on multiple processors (if your computer device offers more than one core). Using parallel computing will reduce computation time.

Sign Changes

Sets the method for dealing with sign changes during the bootstrap iterations. The following options are available:

(1) No Sign Changes (default)

Sign changes in the resamples will be ignored and the results are taken as they are. This is the most conservative approach and is recommended for the initial assessment of the model.

(2) Construct Level Changes

The signs of a group of coefficients (e.g., all outer loadings of a specific latent variable) in the bootstrapping subsample are compared with the signs of the original PLS path model estimates. If the majority of signs need to be reversed in a bootstrap run to better match the signs of the original model estimation using the original sample, all signs are reversed in that bootstrap run.

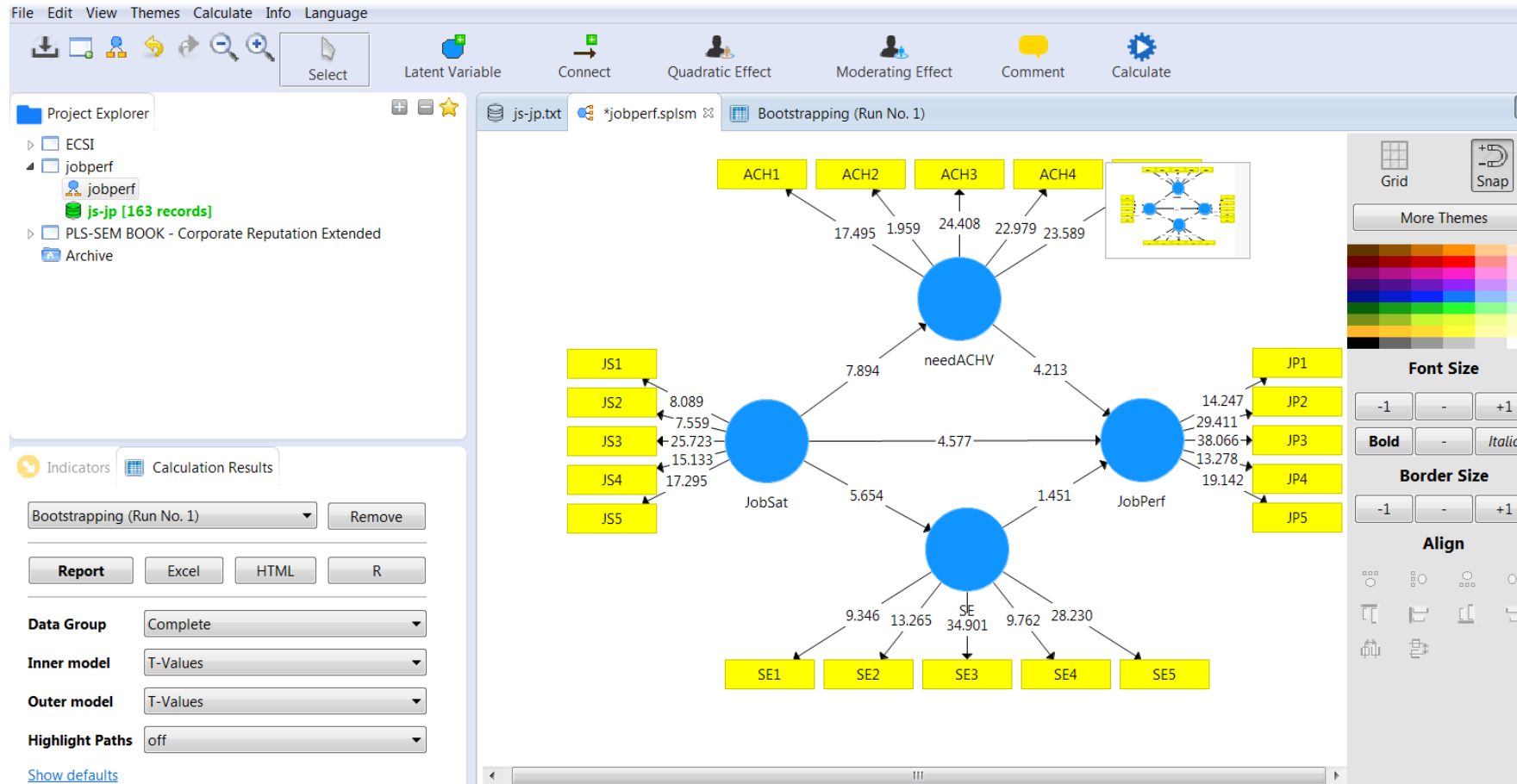
Start Calculation

After Calculation:

Open Full Report

Close

Bootstrapping



Bootstrapping

File Edit View Themes Calculate Info Language

Save New Project New Path Model Hide Zero Values Increase Decimals Decrease Decimals Export to Excel Export to Web Export to R

Project Explorer

- ECSI
- jobperf
 - js-jp [163 records]
- PLS-SEM BOOK - Corporate Reputation Extended
 - Archive

Indicators

No.	Indicator
49	ZMO
50	ZJSZnCH
51	JSf
52	JPf
53	nCHVf
54	SEf
55	MOF

Best correlation
SE5 -> SE3 : 0.680

js-jp.txt *jobperf.splsm Bootstrapping (Run No. 1)

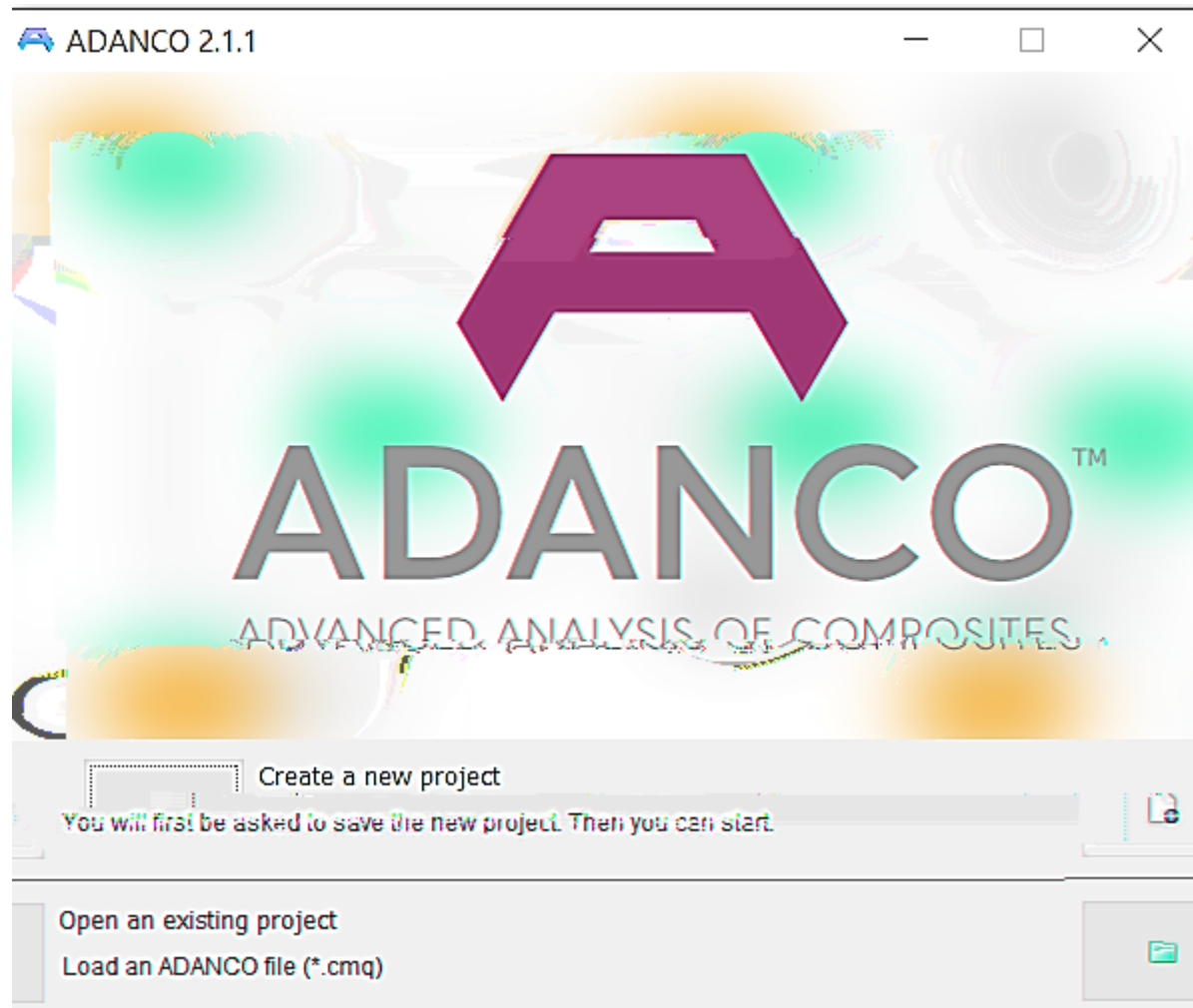
Path Coefficients

	Mean, STDEV, T-Values, P...	Confidence Intervals	Confidence Intervals Bias...	Samples	Copy to Clipboard:	Excel Format	R Format
	Original Sa...	Sample Me...	Standard D...	T Statistics (...)	P Values		
JobSat -> J...	0.311	0.319	0.068	4.577	0.000		
JobSat -> SE	0.386	0.398	0.068	5.654	0.000		
JobSat -> n...	0.501	0.508	0.063	7.894	0.000		
SE -> JobPerf	0.127	0.123	0.087	1.451	0.147		
needACHV ...	0.386	0.387	0.092	4.213	0.000		

Final Results	Quality Criteria	Histograms	Base Data
Path Coefficients	R Square	Path Coefficients Histogram	Setting
Indirect Effects	R Square Adjusted	Indirect Effects Histogram	Inner Model
Total Effects	f Square	Total Effects Histogram	Outer Model
Outer Loadings	Average Variance Extracted (AVE)		Indicator Data (Original)
Outer Weights	Composite Reliability		Indicator Data (Standardized)
	rho A		
	Cronbach's Alpha		

โปรแกรม ADANCO

Double click ADANCO.exe



Save



บันทึกใน:

adanco-ลองใช้



การเข้าถึงด่วน



เดสก์ท็อป



ไลบรารี



พีซีเครื่องนี้



เครือข่าย

ชื่อ	วันที่ปรับเปลี่ยน	ชนิด	ขนาด
bootstrap-3.3.5-dist	11/10/2562 23:39	โฟลเดอร์แฟ้ม	
ADANCO_report_brand	11/10/2562 23:39	แฟ้ม PNG	11 KB
js	12/10/2562 9:31	แฟ้ม CMQ	2 KB
model	13/10/2562 11:22	แฟ้ม PNG	40 KB
OCB_cp_cb	1/7/2562 13:52	SPSS Statistics Dat...	17 KB
OCB_cp_cb	12/10/2562 9:28	เวิร์กชีต Microsoft E...	103 KB
OCB_cp_cb.xls	18/10/2562 23:10	แฟ้ม CMQ	2 KB
result	13/10/2562 11:22	แฟ้ม HTML	183 KB
result	11/10/2562 23:35	เวิร์กชีต Microsoft E...	70 KB
result2	12/10/2562 9:51	แฟ้ม HTML	183 KB

ชื่อวัตถุ:

Unnamed

บันทึกเป็นชนิด:

All Files (*.*)

บันทึก

ยกเลิก

OCB_cp_cb.xls

ADANCO - C:\Users\Montree\Desktop\adanco-ลองใช้\OCB_cp_cb.xls.cmq

File Project Edit Run Results View Help

Construct characteristics

name:

liability:

Measurement model:

Lighting scheme:

Latent indicator:

Indicators

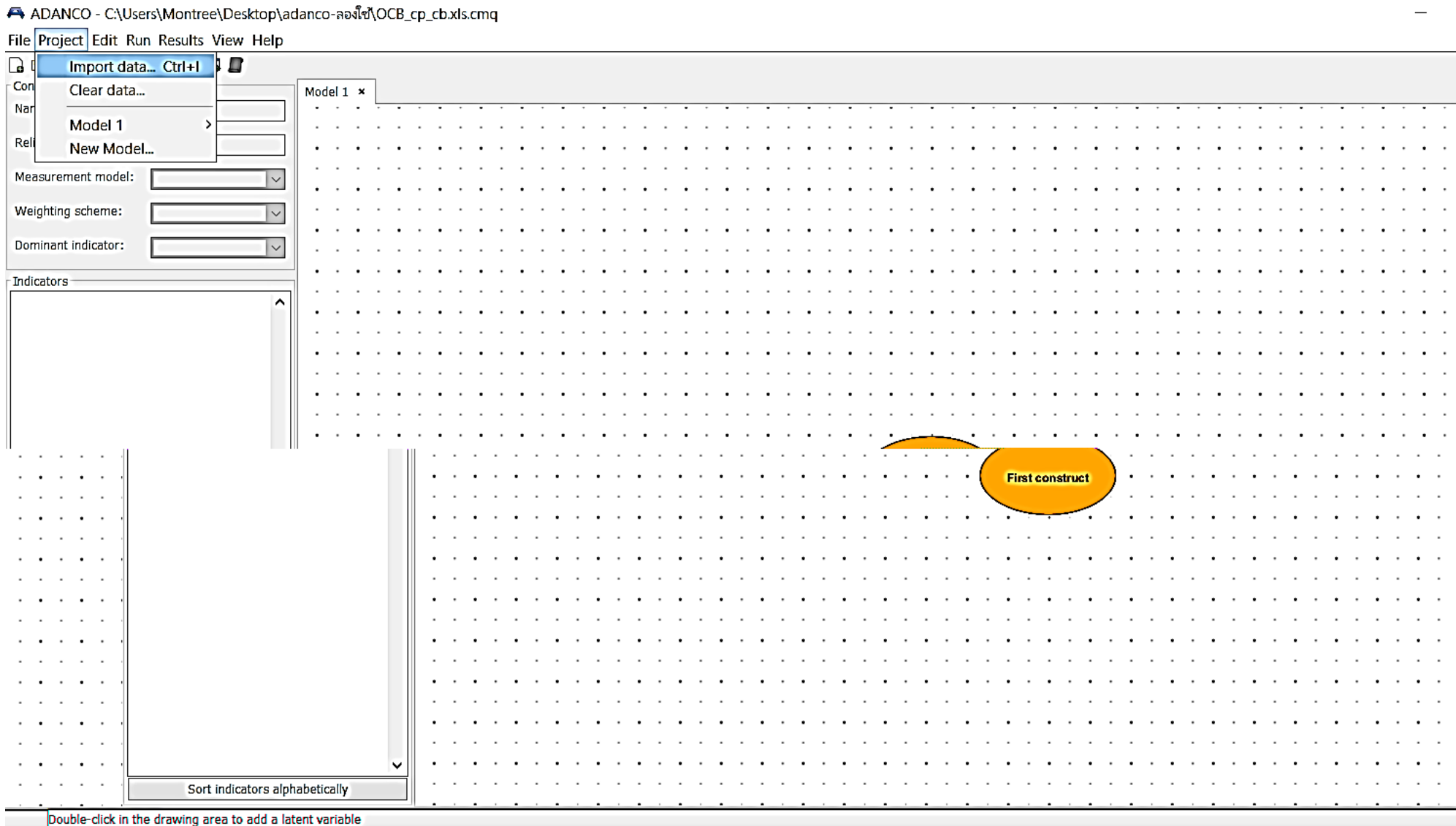
Sort indicators alphabetically

Model 1

First construct

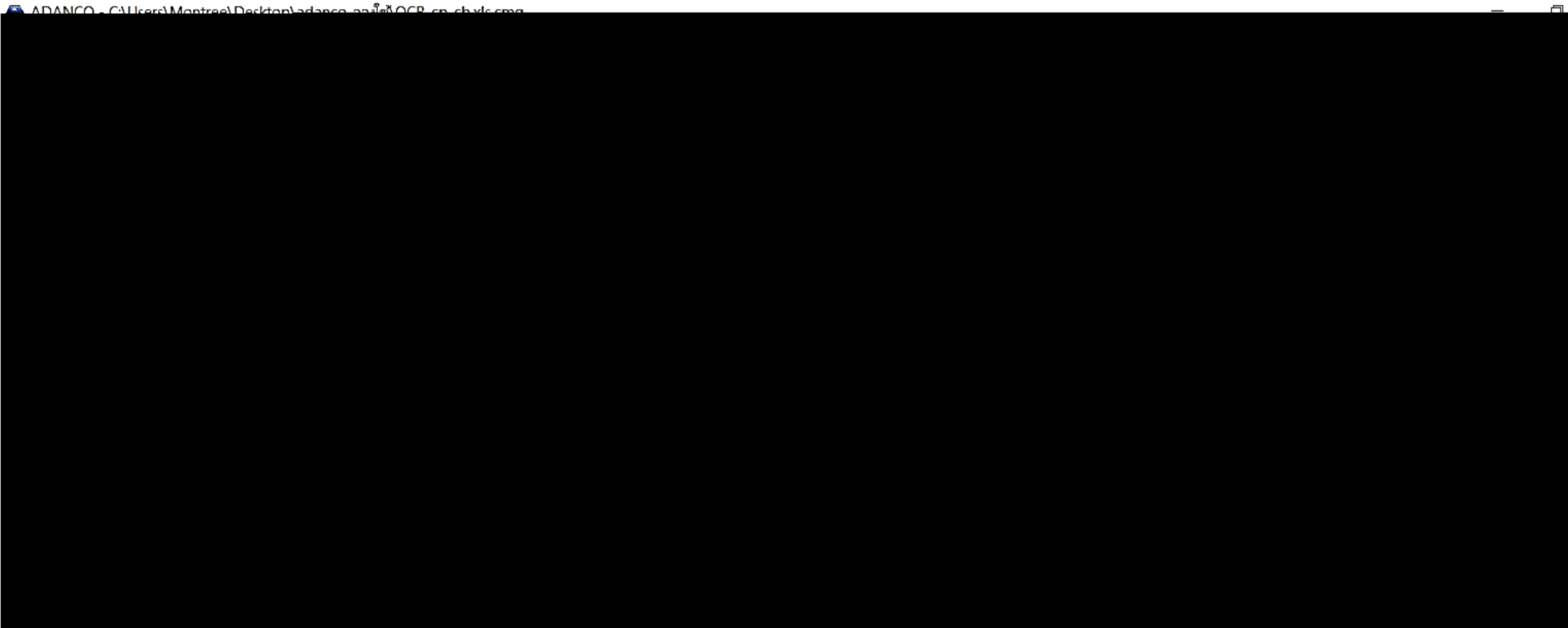
Double-click in the drawing area to add a latent variable

Project Import Data



choose

next next finish



1 first construct

ADANCO - C:\Users\Montree\Desktop\adanco-ลองใช้\OCB_cp_cb.xls.cmq *

File Project Edit Run Results View Help

Construct characteristics

Name:

Reliability:

Measurement model:

Weighting scheme:

Dominant indicator:

Indicators

OCB_cp_cb.xls (2019-10-18 23:21)

- ✗ sex
- ✗ status
- ✗ age
- ✗ L1
- ✗ L2
- ✗ L3
- ✗ L4
- ✗ L5
- ✗ J1
- ✗ J2
- ✗ J3
- ✗ J4
- ✗ J5
- ✗ C1
- ✗ C2
- ✗ C3
- ✗ C4
- ✗ C5
- ✗ P1
- ✗ P2
- ✗ P3
- ✗ P4
- ✗ P5
- ✗ O1
- ✗ O2
- ✗ O3
- ✗ O4

Sort indicators alphabetically

Model 1 x

First construct

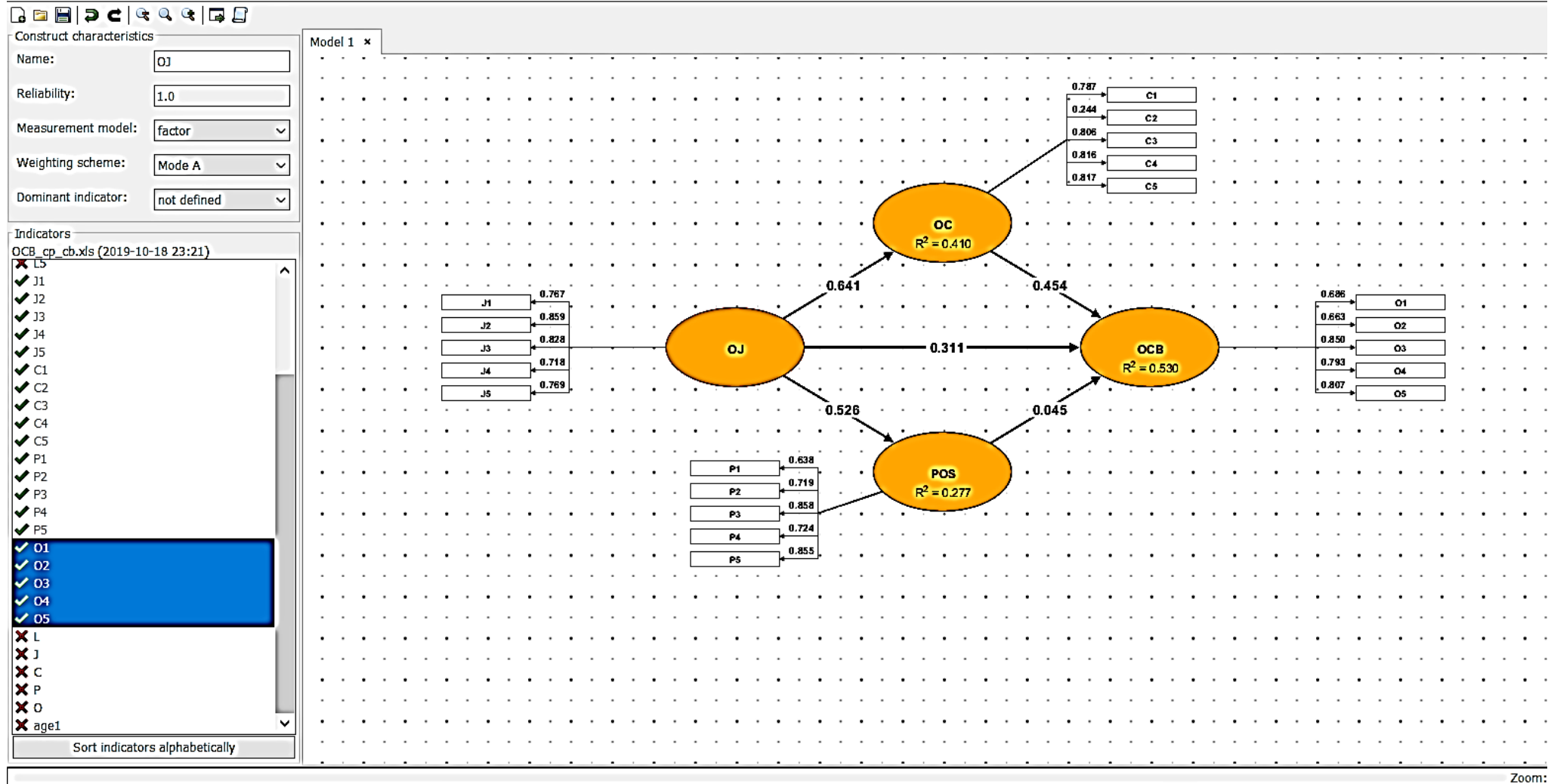
Double-click in the drawing area to add a latent variable

Zoom:

loading bootstrapping

ADANCO - C:\Users\Montree\Desktop\adanco-ลองใช้\OCB_cp_cb.xls.cmq *

File Project Edit Run Results View Help



run> run ctrl+R

run

ADANCO - C:\Users\Montree\Desktop\adanco-ลองใช้\OCB_cp_cb.xls.cmq *

File Project Edit Run Results View Help

Construct characteristics

Name: OJ

Reliability: 1.0

Measurement model: factor

Weighting scheme: Mode A

Dominant indicator: not defined

Indicators

OCB_cp_cb.xls (2019-10-18 23:21)

- ✓ J1
- ✓ J2
- ✓ J3
- ✓ J4
- ✓ J5
- ✓ C1
- ✓ C2
- ✓ C3
- ✓ C4
- ✓ C5

Model 1 x

Run

Calculation profile: Default

Models

- Model 1

Algorithm Settings

Stop Criterion: 1.0E-6

Maximum number of iterations: 200

Inner weighting scheme: Factor

Missing Value Treatment

- ☒ Casewise deletion
- ☐ Mean imputation
- ☐ Median imputation
- ☐ Constant value

0.787 → C1

0.244 → C2

0.806 → C3

6 → C4

7 → C5

0.686 → O1

0.663 → O2

0.850 → O3

0.793 → O4

0.807 → O5

OCB

$R^2 = 0.530$

use bootstrapping

Asset model fit

edit profile

ADANCO - C:\Users\Montree\Desktop\adanco-ลงใช้\OCB_cp_cb.xls.cmq *

File Project Edit Run Results View Help

Construct characteristics

Name: OJ

Reliability: 1.0

Measurement model: factor

Weighting scheme: Mode A

Dominant indicator: not defined

Indicators

OCB_cp_cb.xls (2019-10-18 23:21)

✓ J1
✓ J2
✓ J3

Model 1 x

Run

Calculation profile: Default

Models

Model 1

Algorithm Settings

Stop Criterion: 1.0E-6

Maximum number of iterations: 200

Inner weighting scheme: Factor

Missing Value Treatment

☒ Casewise deletion

☐ Mean imputation

☐ Median imputation

☐ Constant value 0

☐ Random imputation Seed: 0 Generate

☒ Use bootstrapping ☒ Assess model fit

Bootstrapping

Seed: 0 Generate

Bootstrap samples: 999

OCB $R^2 = 0.530$

0.787 C1
0.244 C2
0.806 C3
6 C4
7 C5

0.850 O3
0.793 O4
0.807 O5

0.686 O1
0.663 O2

✓ J4
✓ J5
✓ C1
✓ C2
✓ C3
✓ C4
✓ C5
✓ P1
✓ P2
✓ P3
✓ P4
✓ P5
✓ O1
✓ O2
✓ O3
✓ O4
✓ O5

Zoom: 100%

save > save and run

ADANCO - C:\Users\Montree\Desktop\adanco-ลองใช้\OCB_cp_cb.xls.cmq *

File Project Edit Run Results View Help



Construct characteristics

Name: OJ
Reliability: 1.0
Measurement model: factor
Weighting scheme: Mode A
Dominant indicator: not defined

- Indicators
OCB_cp_cb.xls (2019-10-18 23:21)
- ✓ J1
 - ✓ J2
 - ✓ J3
 - ✓ J4
 - ✓ J5
 - ✓ C1
 - ✓ C2
 - ✓ C3
 - ✓ C4
 - ✓ C5

- ✓ P1
- ✓ P2
- ✓ P3
- ✓ P4
- ✓ P5
- ✓ O1
- ✓ O2
- ✓ O3
- ✓ O4
- ✓ O5
- ✗ L
- ✗ J
- ✗ C
- ✗ P
- ✗ O
- ✗ age1

Sort indicators alphabetically

Settings

General Profiles

Profiles
Default
Complete

Scores Data Bootstrap Technical Output
Overall Model Measurement Model Structural Model Diagnostics

- ✓ Goodness of model fit (saturated model)
- ✓ Goodness of model fit (estimated model)

↑ ↓ New Delete

Restore default settings

Cancel Save

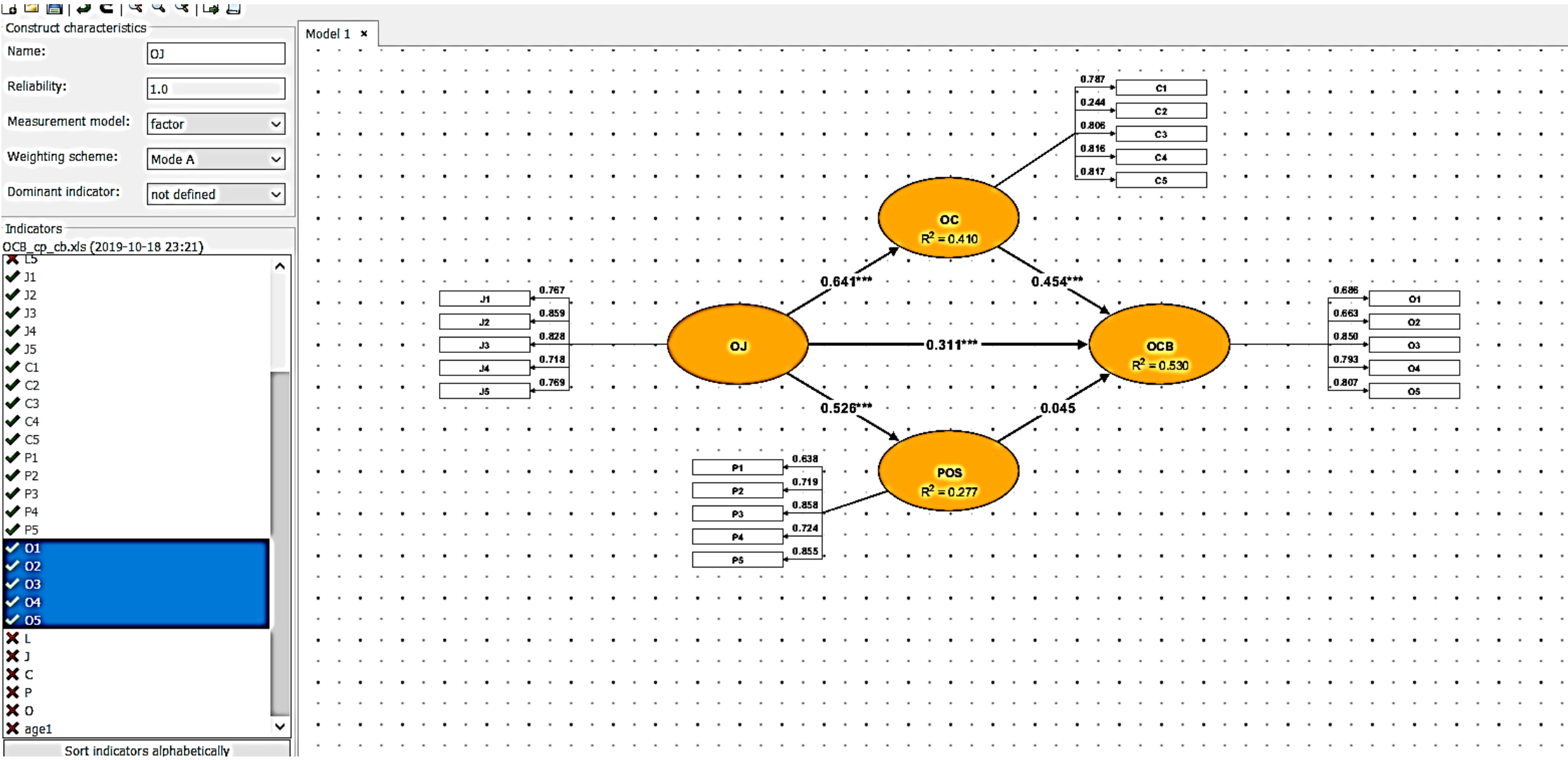
0.787
0.244
C1
C2
C3
C4
C5

0.686
0.663
0.850
0.793
0.807
O1
O2
O3
O4
O5

OCB
= 0.530

Zoom: :

result



ADANCO - Results for C

file:///C:/Users/Montree/AppData/Roaming/ADANCO/temp/result.html

Composite Modeling



ADANCO™

Project Information

Graphical representation of the model

Overall Model

Measurement Model

Structural Model

Diagnostics

Scores

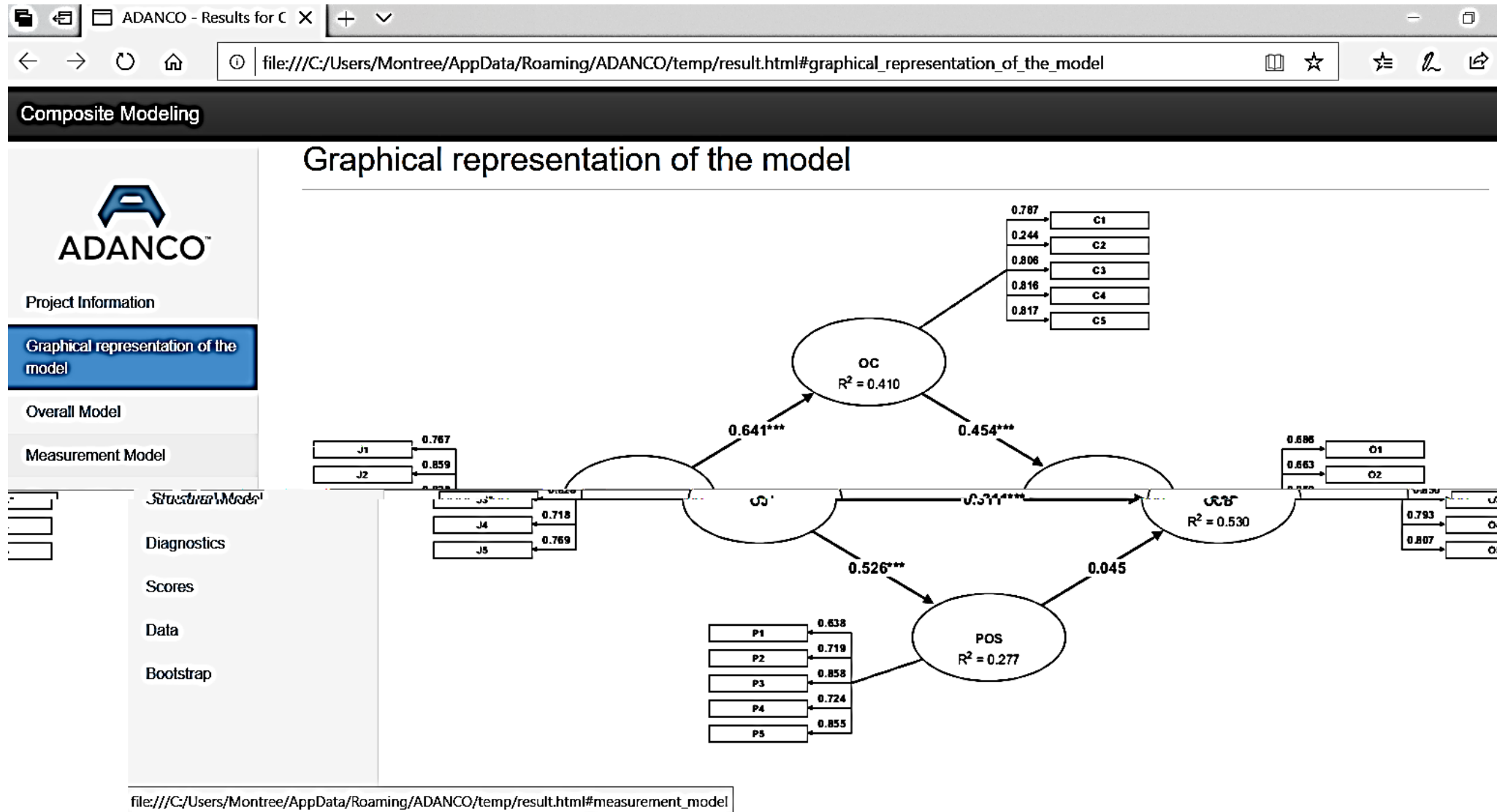
Data

Bootstrap

Report

Project Information

ADANCO version	This report was created with ADANCO 2.1.1
Date/Time	2019/10/18 23:43
Project Name	OCB_cp_cb.xls
Project file name	C:\Users\Montree\Desktop\adanco-ลองใช้
Data file name	OCB_cp_cb.xls
Number of observations	163
Algorithm status	The iterative algorithm converged after 7 iteration(s).
Bootstrap status	999 bootstrap samples have been evaluated (999 attempts).



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