PLS

(.)

26 2562

.

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 $\sum_i^n e_i^2$ $\qquad e_i^2 = (Y_i - \hat{Y}_i)^2$

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

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

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

$\sum_i^n e_i^2$ 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 Analysis Composite 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) Kurtosis-Skewness, Shapiro-Wilk

3) (no serial correlation) 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

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

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

(standardize)

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

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

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

Y

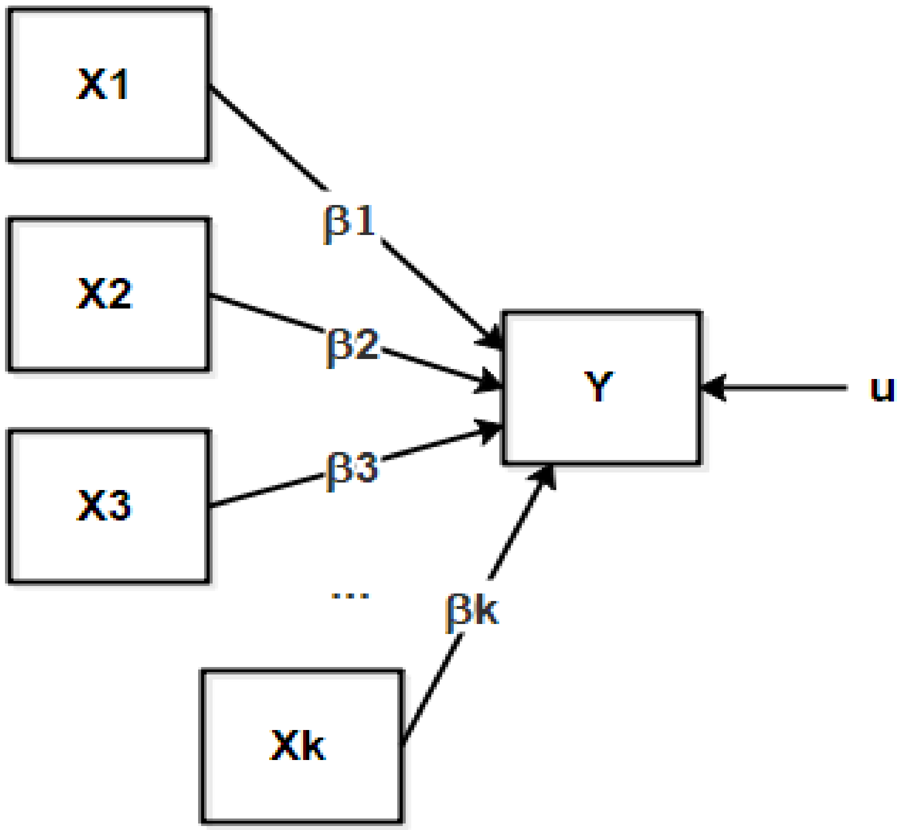
3) sign, size, significant

t-test

4)

MRA, Path analysis, SEM factor analysis

MRA



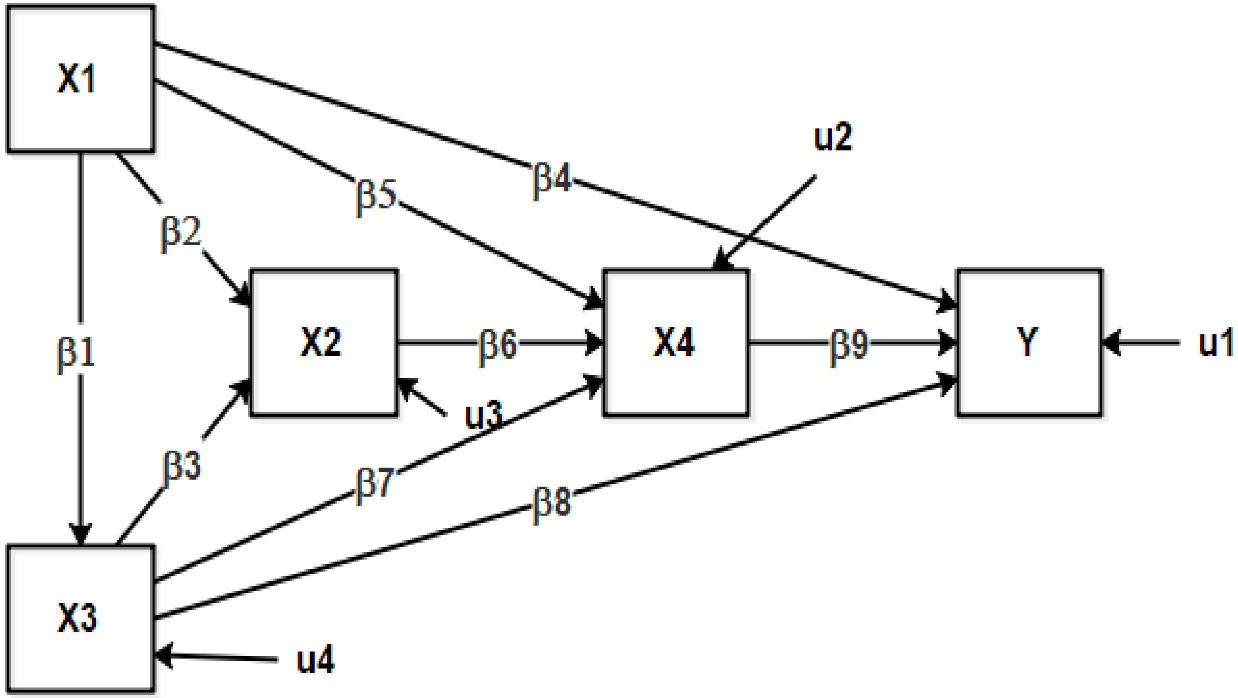
MRA, Path analysis, SEM factor analysis

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

MRA

MRA, Path analysis, SEM factor analysis

4



$$Y = \beta_0 + \beta_4 X_1 + \beta_8 X_3 + \beta_9 X_4 + u_1$$
$$X_4 = \beta_0 + \beta_5 X_1 + \beta_6 X_2 + \beta_7 X_3 + u_2$$
$$X_2 = \beta_o + \beta_2 X_1 + \beta_3 X_3 + u_3$$
$$X_3 = \beta_o + \beta_1 X_1 + u_4$$

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

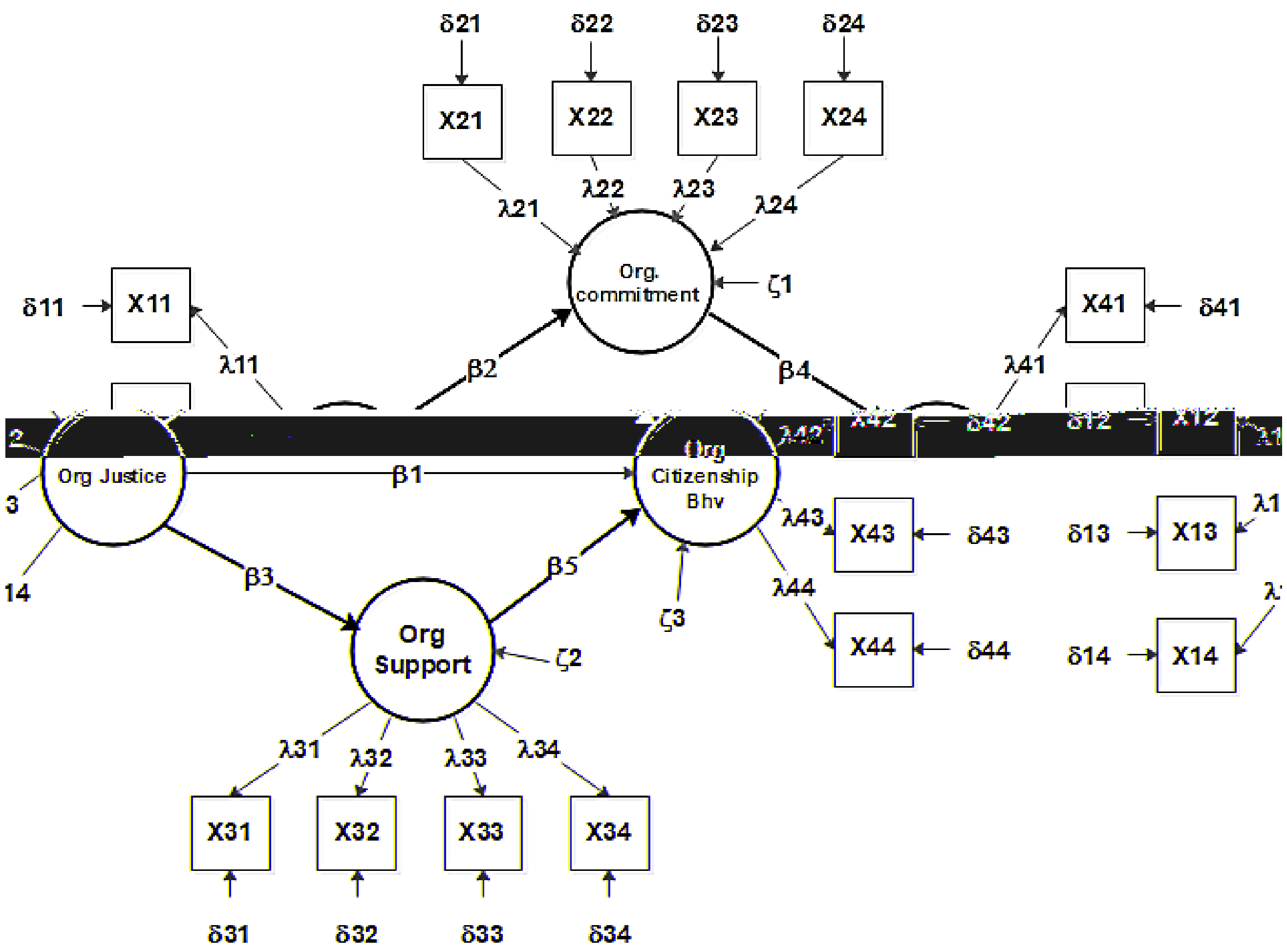
MRA, Path analysis, SEM factor analysis

American Customer Satisfaction Index (ACSI)

MRA, Path analysis, SEM factor analysis

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

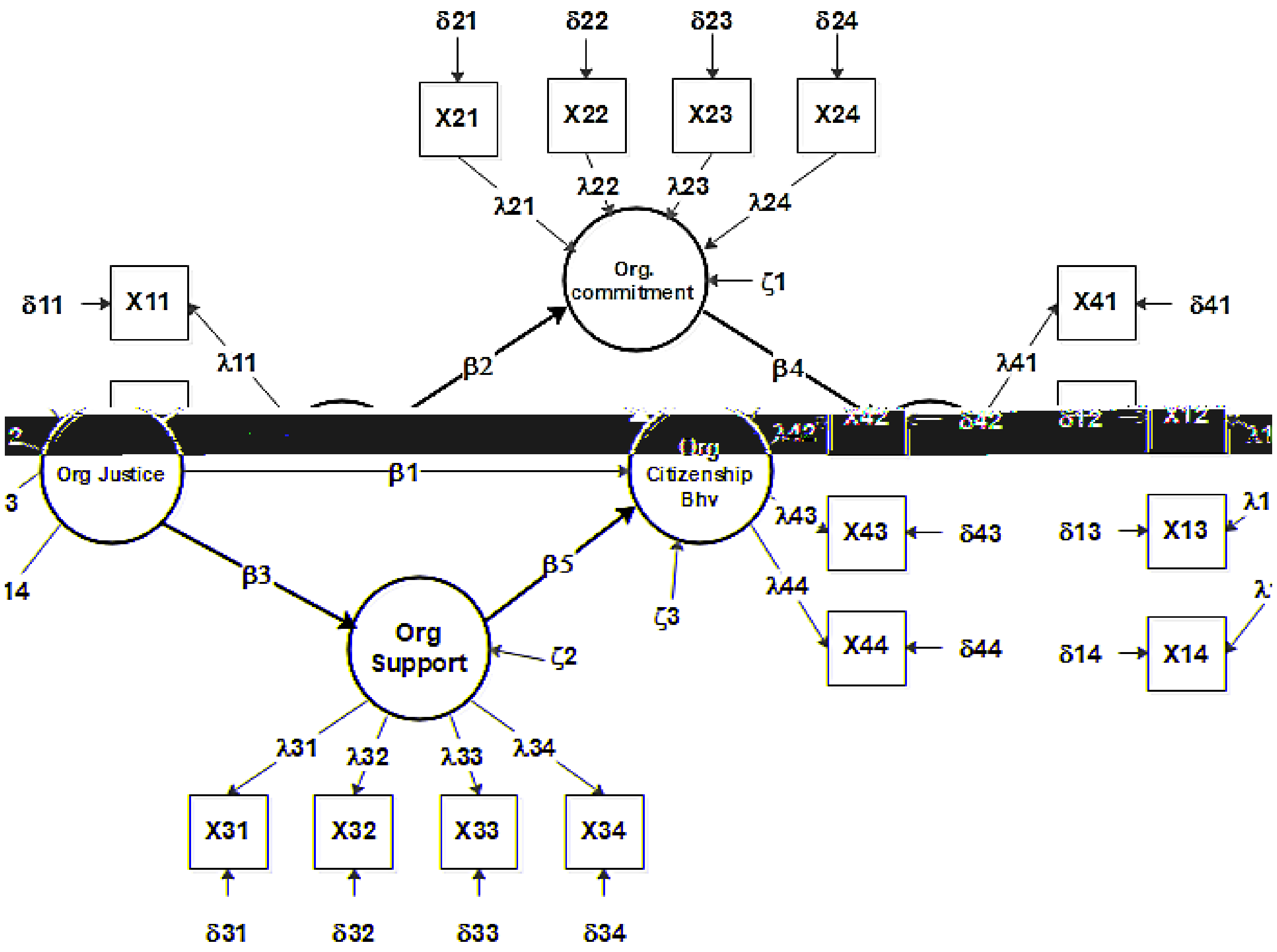
MRA, Path analysis, SEM factor analysis



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

$$X_{41} = \lambda_o + \lambda_{41} OCB + \delta_{41}$$
$$X_{42} = \lambda_o + \lambda_{42} OCB + \delta_{42}$$
$$X_{43} = \lambda_o + \lambda_{43} OCB + \delta_{43}$$
$$X_{44} = \lambda_o + \lambda_{44} OCB + \delta_{44}$$

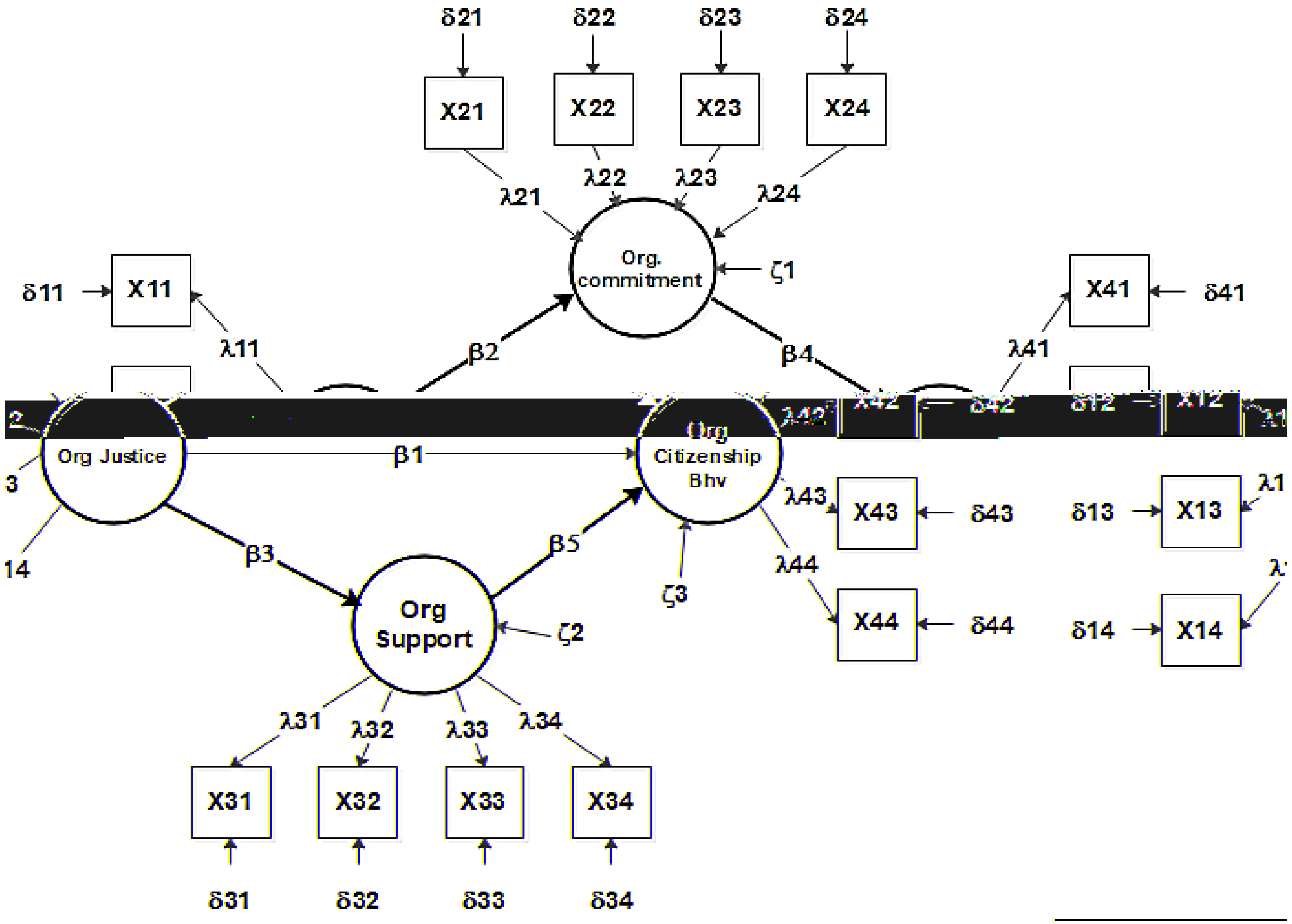
MRA, Path analysis, SEM factor analysis



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

$$X_{21} = \lambda_o + \lambda_{21} OC + \delta_{21}$$
$$X_{22} = \lambda_o + \lambda_{22} OC + \delta_{22}$$
$$X_{23} = \lambda_o + \lambda_{23} OC + \delta_{23}$$
$$X_{24} = \lambda_o + \lambda_{24} OC + \delta_{24}$$

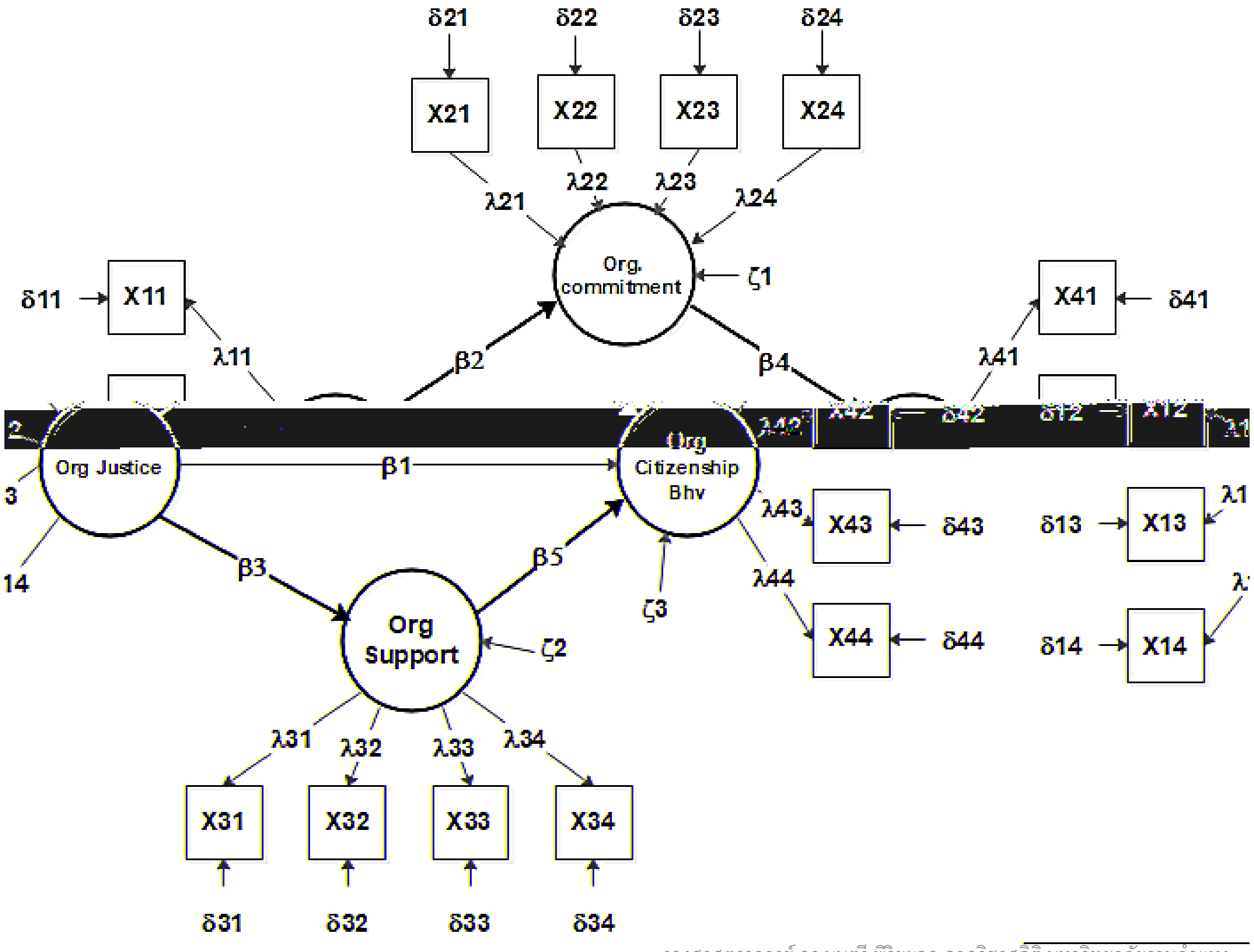
MRA, Path analysis, SEM factor analysis



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

$$X_{31} = \lambda_o + \lambda_{31} POS + \delta_{31}$$
$$X_{32} = \lambda_o + \lambda_{32} POS + \delta_{32}$$
$$X_{33} = \lambda_o + \lambda_{33} POS + \delta_{33}$$
$$X_{34} = \lambda_o + \lambda_{34} POS + \delta_{34}$$

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)

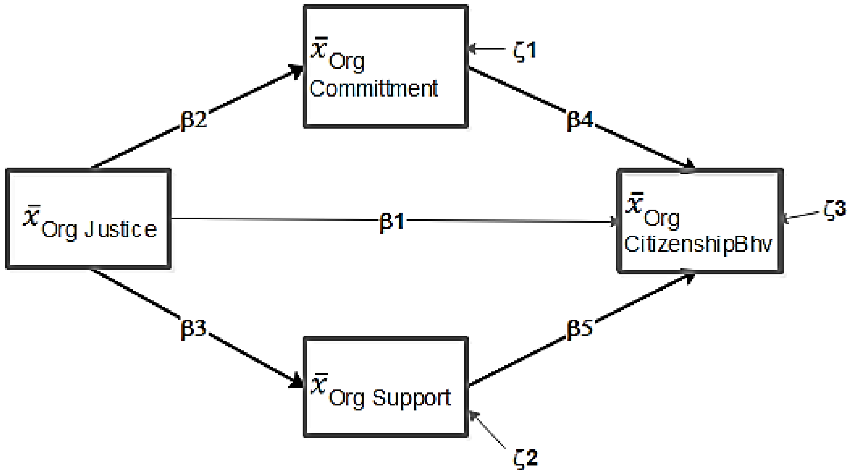
MRA, Path analysis, SEM factor analysis

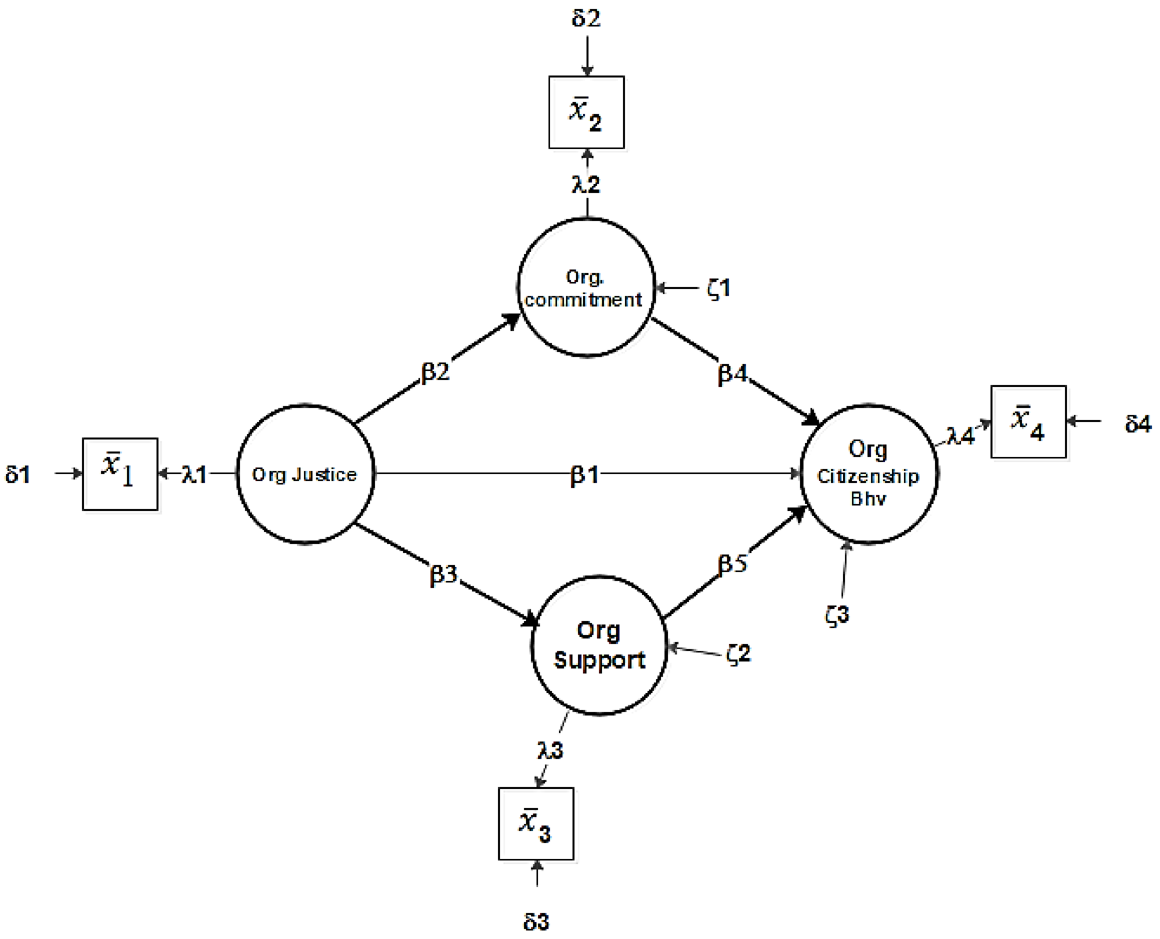
(aggregation) (sum) (mean)

(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 2 formative indicator reflective indicator

1. formative indicator (domain/dimension/ reality/parcel)

Formative-Reflective indicator

2. reflective indicator

(co-vary)

(interchangeability)

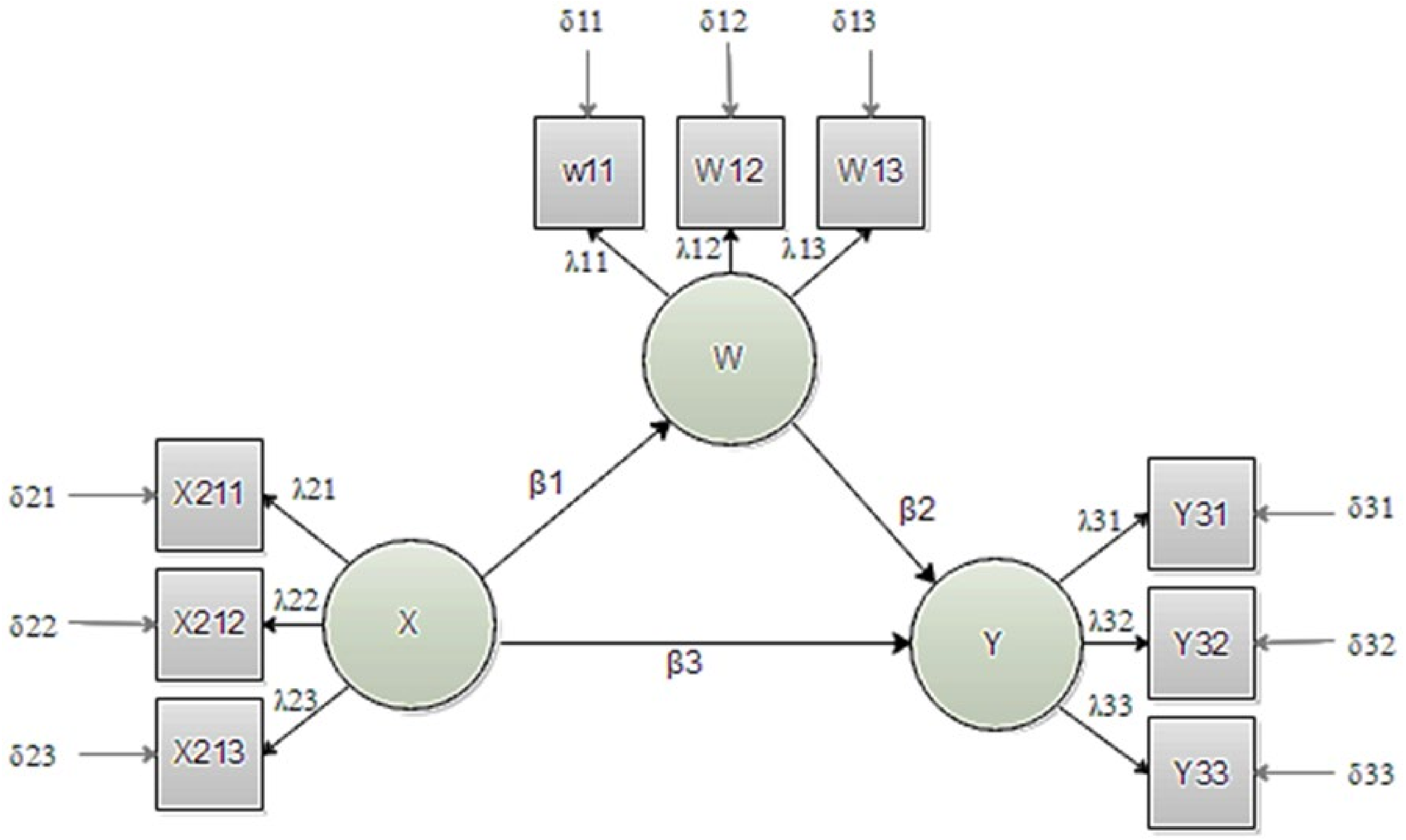
( )

loading

Formative-Reflective indicator

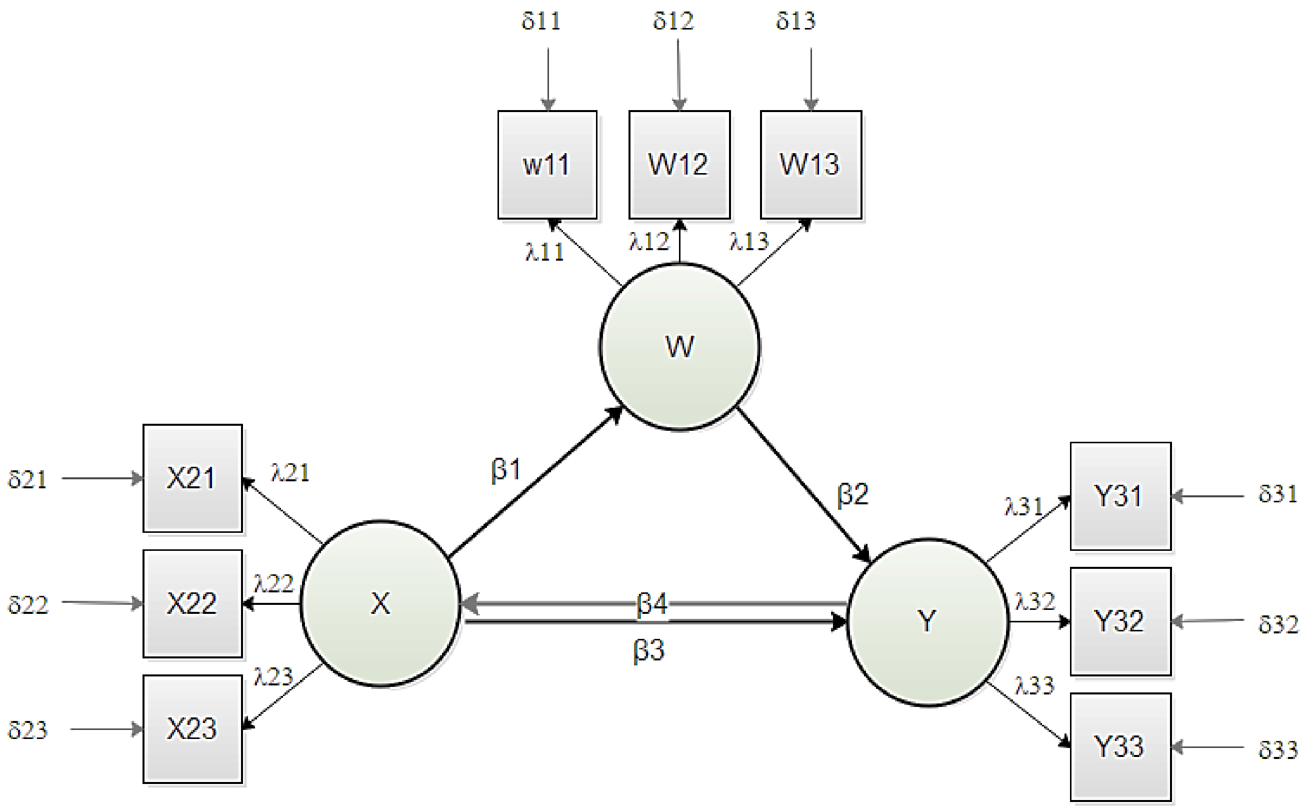
SEM Research Design

1. Causality



SEM Research Design

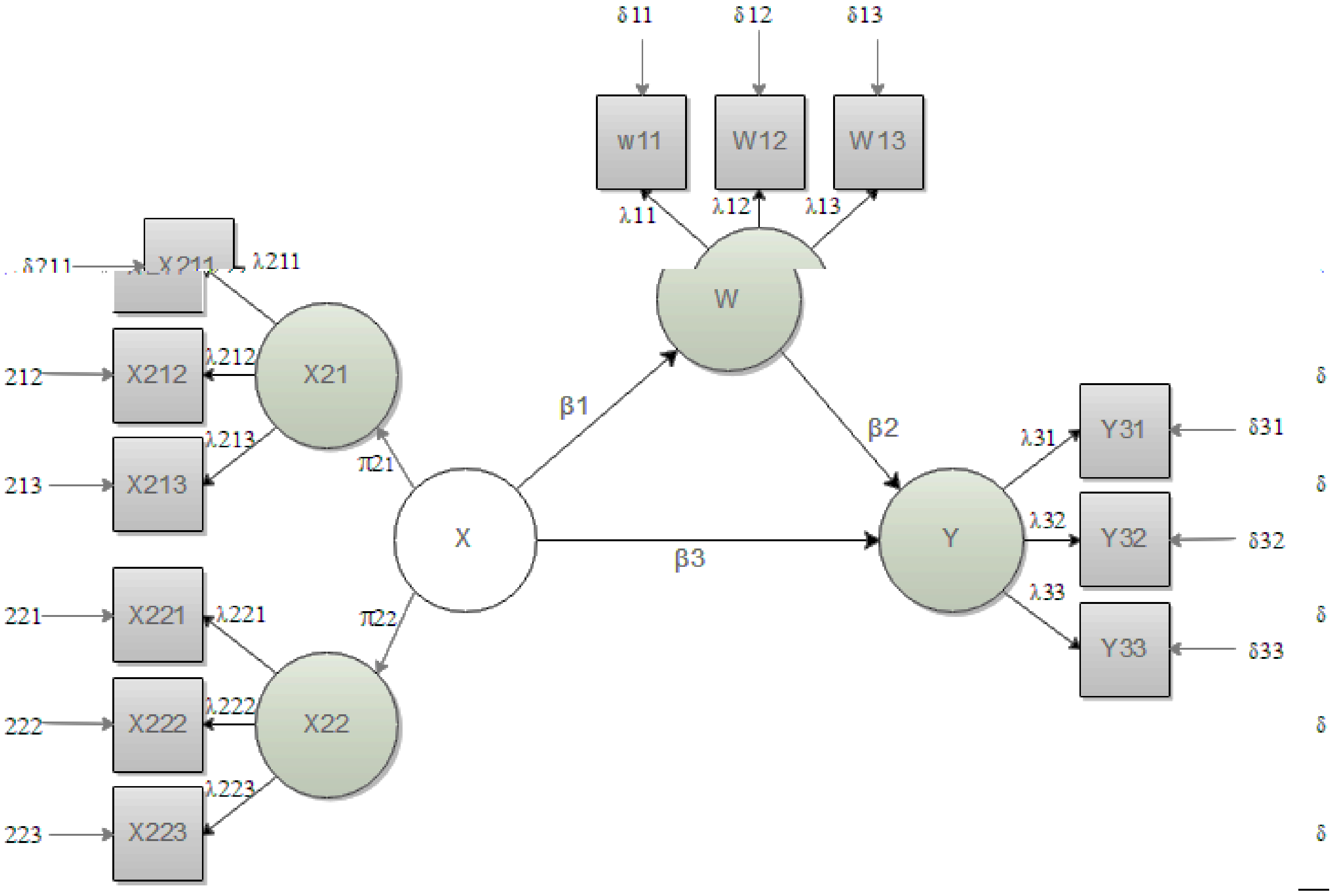
2. non-recursive model/reciprocal model



SEM Research Design

3. Second order model

sub-construct sub-domain



SEM Research Design

5. Moderation model

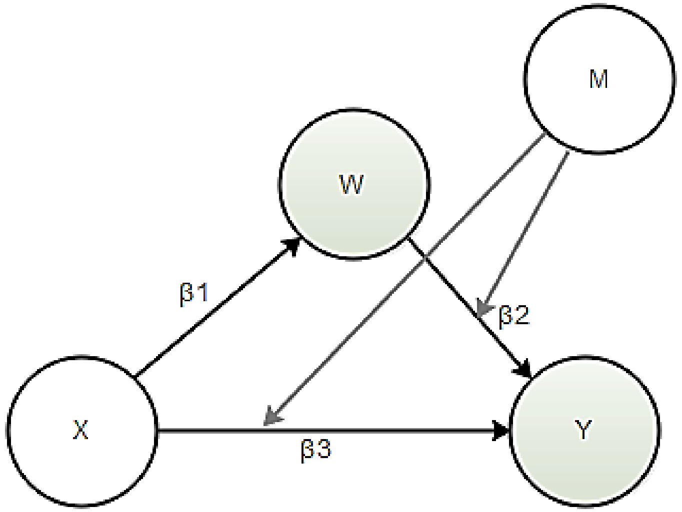
sequential exploratory

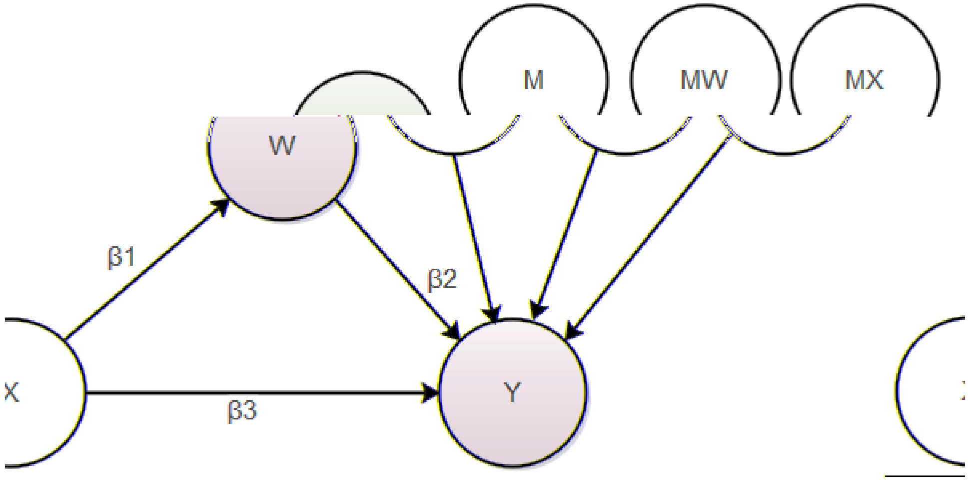
analysis (template)

(multigroup)

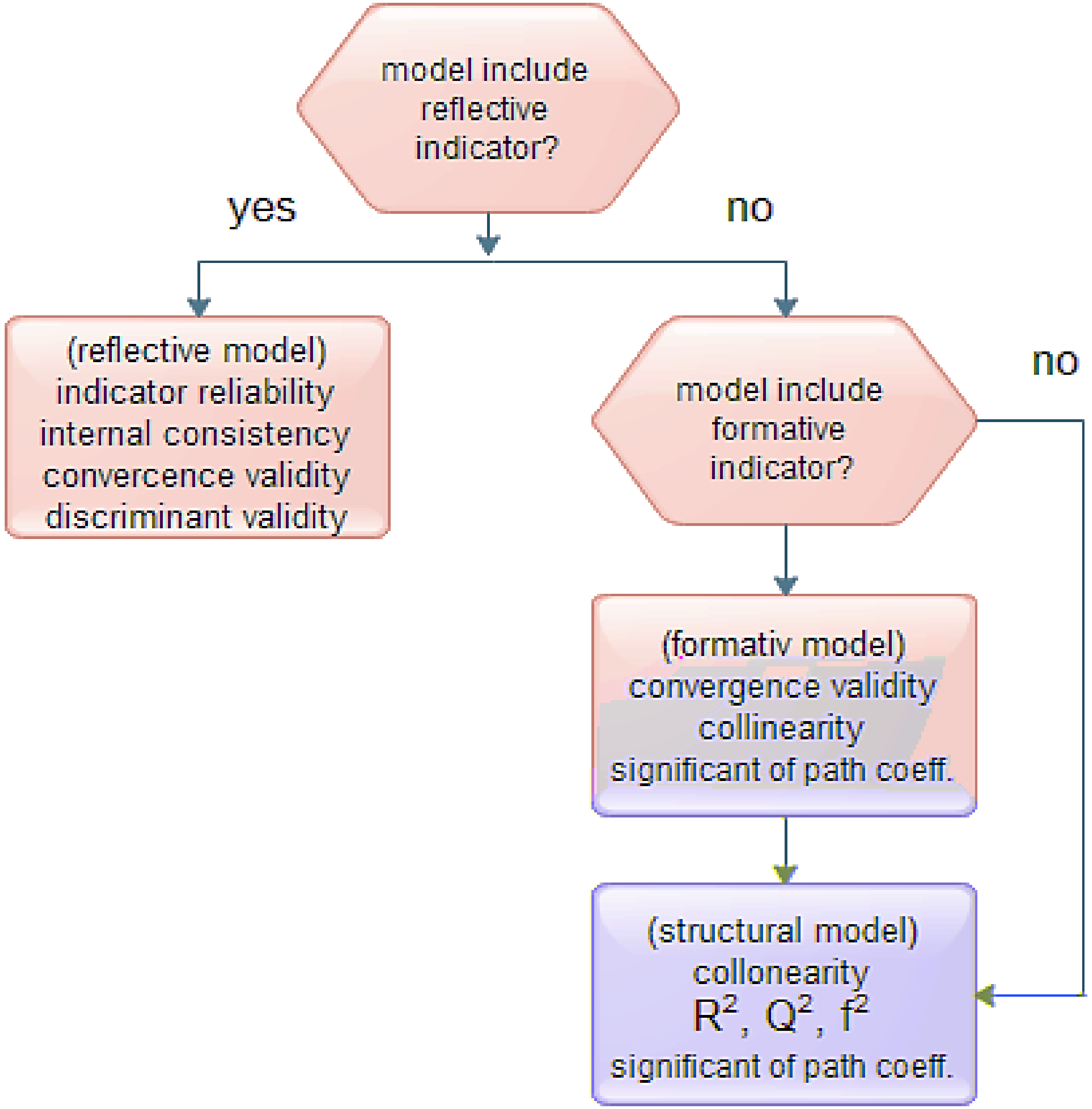
statistical model

conditional effect



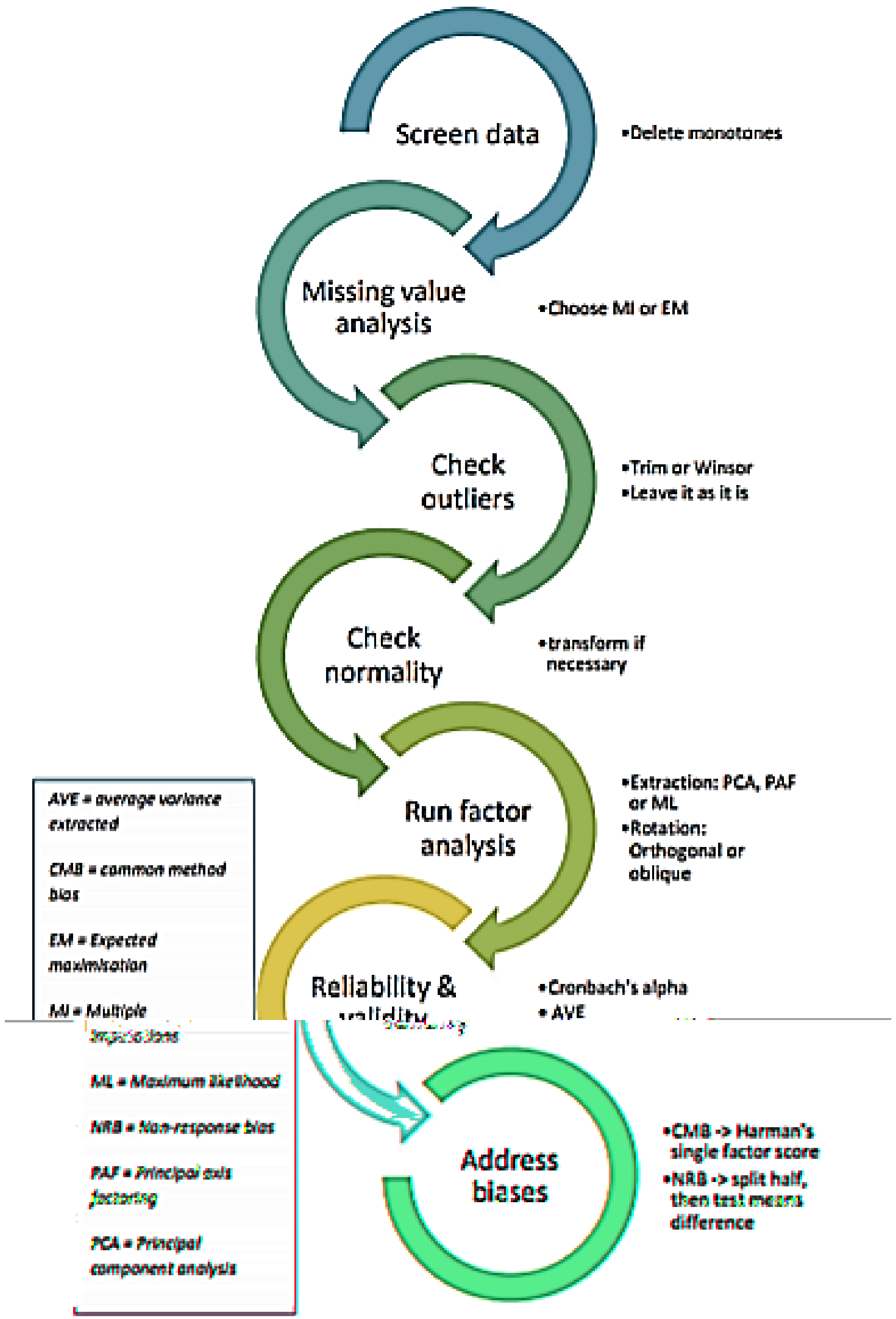


PLS running process

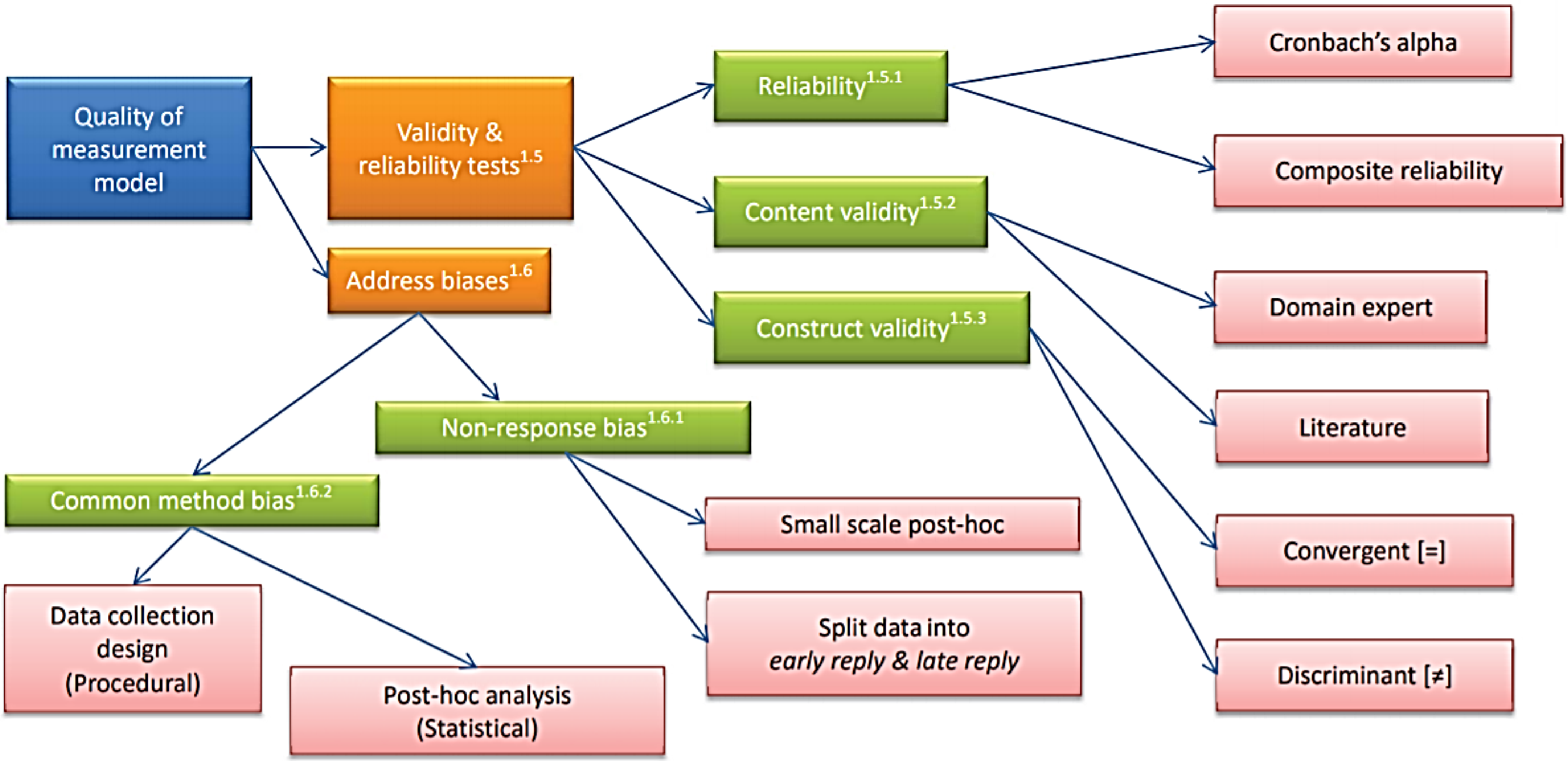


Preliminary data analysis checklist

Saiyidi Mat Roni (2014),Introduction to SPSS , https://www.researchgate.net/publication/262151892_Introduction_to_SPSS

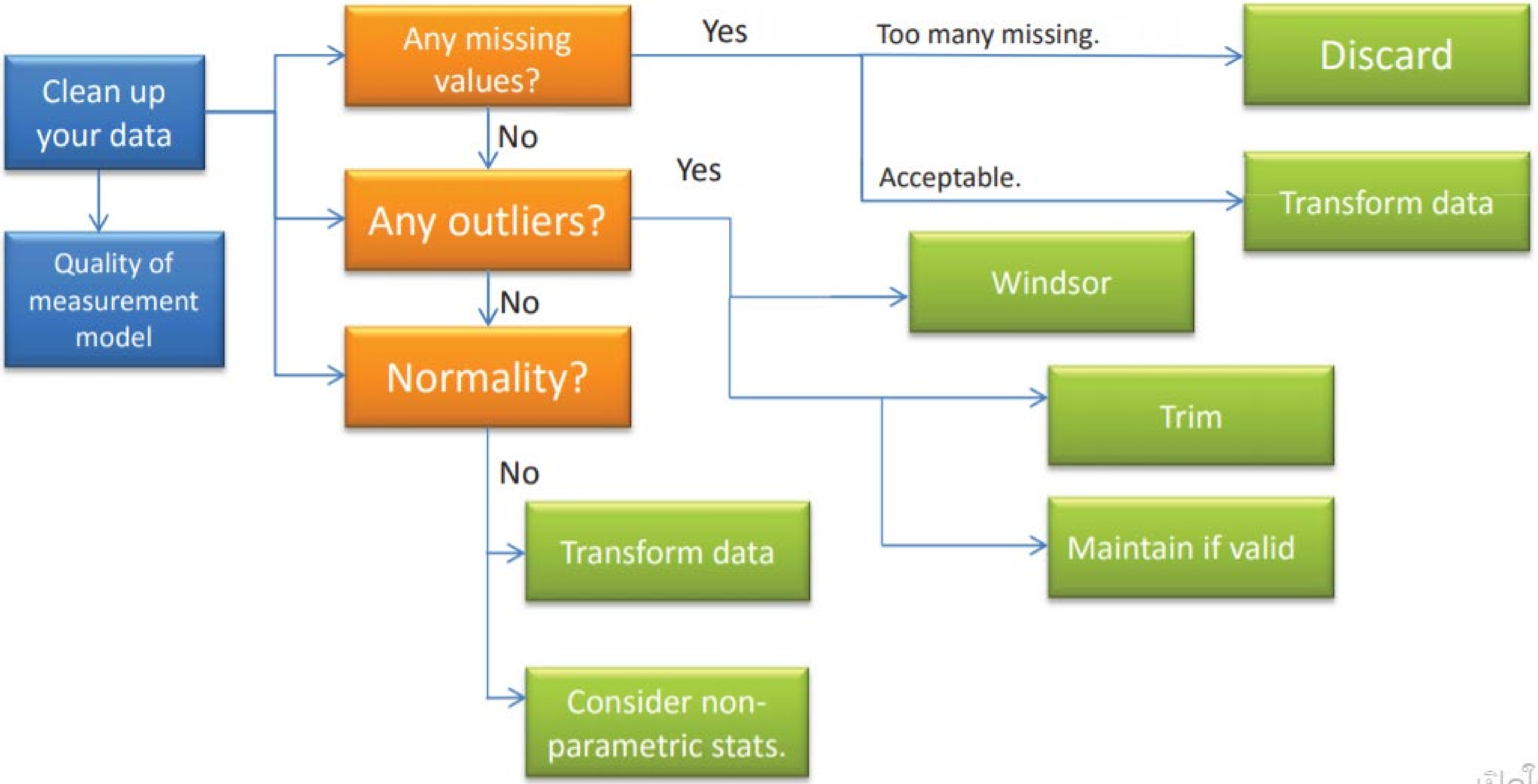


Quality of measurement model



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

Cleaning your data



(

$(CV = \frac{SD}{\bar{x}}$ (3 (

smart PLS 3 ADANCO

1. SPSS Excel

1) Smart PLS text file filename.csv filename.raw

2) ADANCO excel

2. missing data

reflective measurement model

; Convergence validity

1. Cronbach's alpha ≥ 0.70

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

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 $\mathrm{AVE} = \dfrac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \mathrm{Var}(\varepsilon_i)}$

$\mathrm{Var}(\varepsilon_i) = 1 - \lambda_i^2$

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

AVE indicator reliability construct reliability

$\mathrm{AVE_i} \geq 0.50$ cross loading

$\mathrm{AVE_i} = 0.50$ 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 construct5 score

$\rho_A \geq 0.60$ (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 $(Ho: \sigma_e^2 = 0 \text{ vs } H1: \sigma_e^2 \neq 0$

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

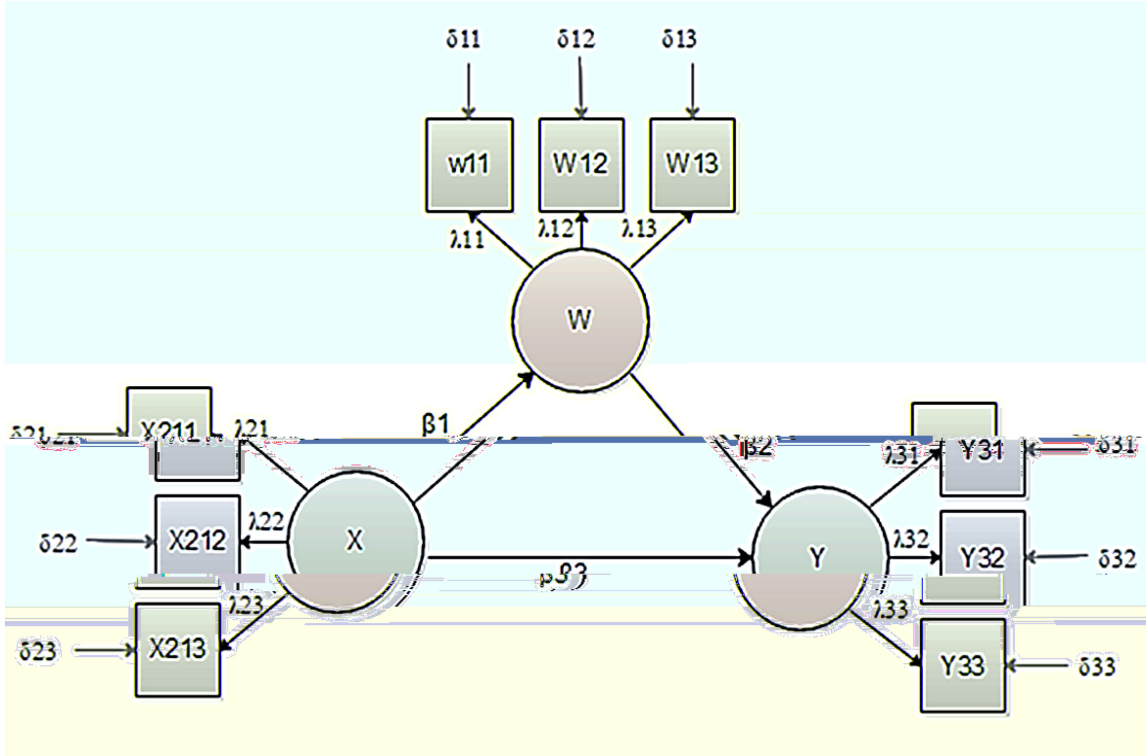
0.5

4) Loading < 0.707

(theoretical

importance)

4. alpha, ρ_A, ρ_c, AVE



discriminant validity

1. Cross loading item score construct score

item score construct score

construct score ( )

cross-loading 0.30, 0.40

(load) LV LV cross-loading

discriminant validity

2. Fornell-Larcker Criteria discriminant validity construct ($\sqrt{AVE_i}$) construct score i construct score

discriminant validity

Fornell-Larcker Criterion

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

2) $AVE_i > r_{ij}^2$ indicator reliability ($loading_j^2$

i AVE_i) i j

discriminant validity

3. HTMT (Heterotrait Monotrait ratio)

2

2 (Jörg Henseler & Christian M. Ringle & Marko Sarstedt, 2015)

HTMT < 1.00

หมายเหตุ trait construct

discriminant validity

Heterotrait-Monotrait Correlation Ratio (HTMT)

1 1

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

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

multicollinearity

multicollinearity

(multicollinearity)

1)

2) (formative measurement model)

1) t-statistics (SE $t_j = \frac{\hat{\beta}_j}{se_{\hat{\beta}_j}}$)

2)

multicollinearity

(multicollinearity) (antecedent)

well-fitting model

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

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

formative indicator

R_j^2

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

multicollinearity

multicollinearity

1)

parcel/sub-construct/sub-domain

second order model

2)

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 (Cohen, 1988)
Cohen R^2

Goodness of fit PLS-PM

2. Effect size (f^2)

(

)

Goodness of fit PLS-PM

effect size

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

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 $f_i^2 = \frac{R^2_{original} - R^2_{omitted}}{1 - R^2_{original}}$

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

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

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

Q^2 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. (sign) (size)

(significant) 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. $d_{ULS} = \frac{1}{2}\,trace(S - \hat{\Sigma})^2$ unweighted least square discrepancy square Euclidian distance indicator empirical correlation array indicator model implied correlation array P95 P99

Fit index

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

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

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

perfect fit

Fit index

PLS SRMR 0.12 d_{ULS} / d_G
(0)
CB-SEM (Smart PLS)

Vanishing tetrad

Vanishing tetrad

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

Ho: reflective indicator vs H_1: formative indicator

Importance-Performance Map Analysis (IPMA)

Importance-Performance Map Analysis (IPMA)

large Importance low performance

Importance-Performance Map Analysis (IPMA)

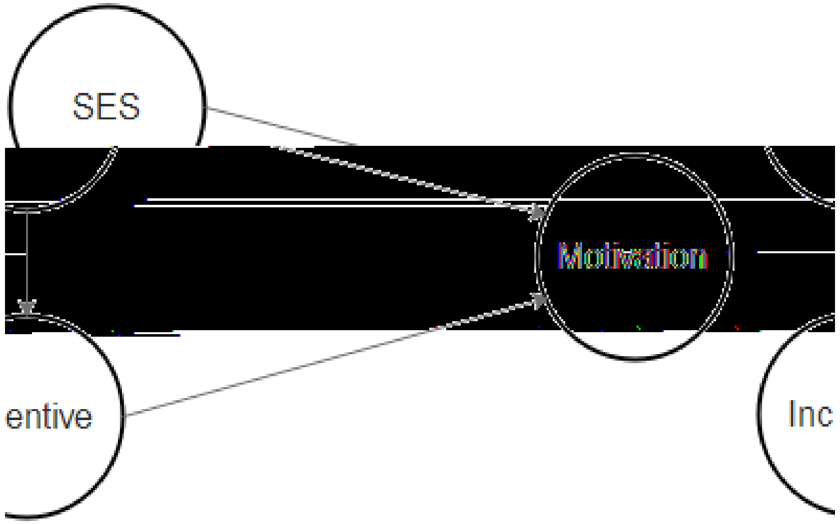
Importance = absolute total effect (

)

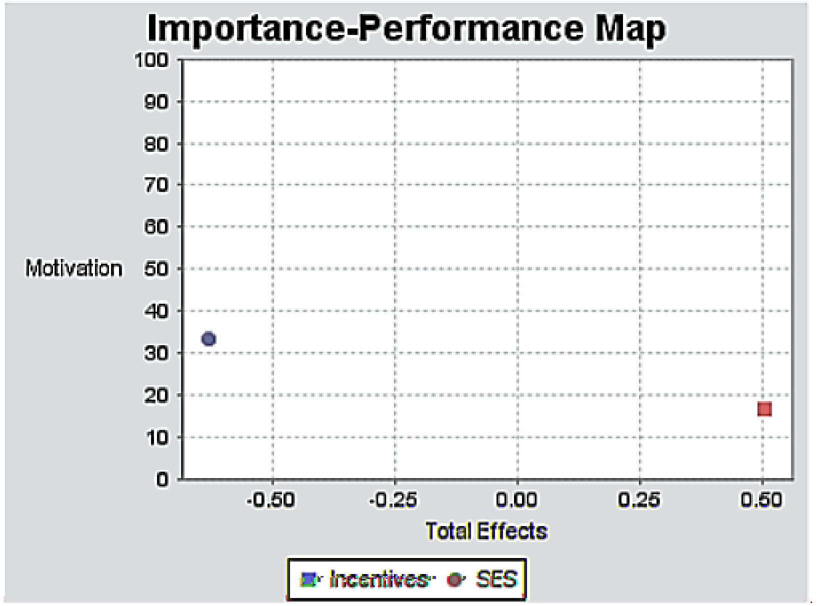
Performance = unstandardized latent variable score normalize

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

Importance-Performance Map Analysis (IPMA)



	16.558
SES	33.030
SES	-



Goodness of Fit (GoF)

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

R^2 global effect size

(หมายเหตุ $\sqrt{\overline{R^2}\ \overline{com}}$

)

(Henseler & Sarstedt, 2013)

(mispecified model) (Hair et al., 2014)

Goodness of Fit (GoF)

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

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

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

Redundancy

9

$_{i}{*}R_i^2$

Redundancy criterion

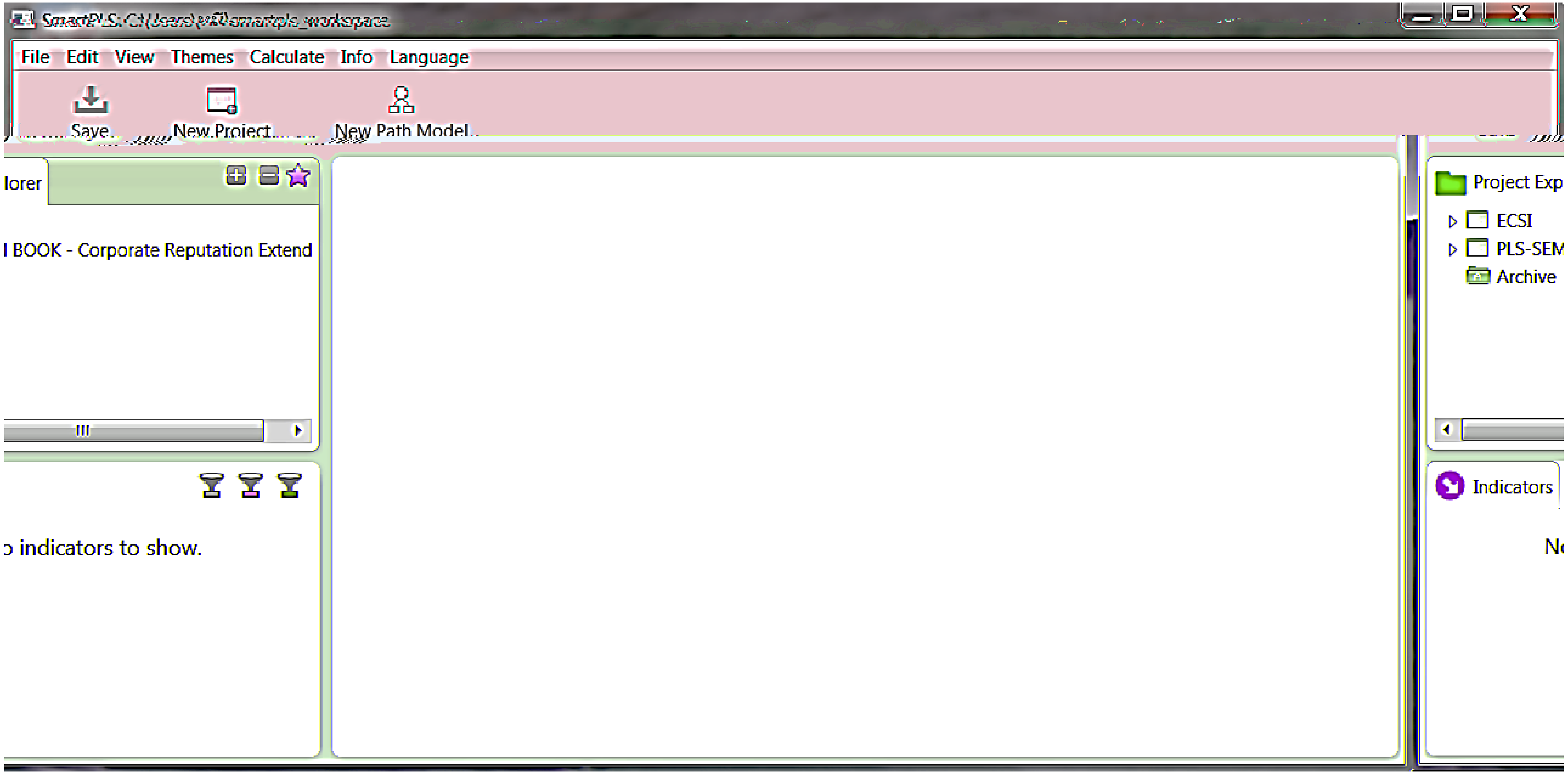
${}_{i}{}^{*}R_i^2$	
${}_{i}{}^{*}R_i^2$	
${}_{i}{}^{*}R_i^2$ 0.50	

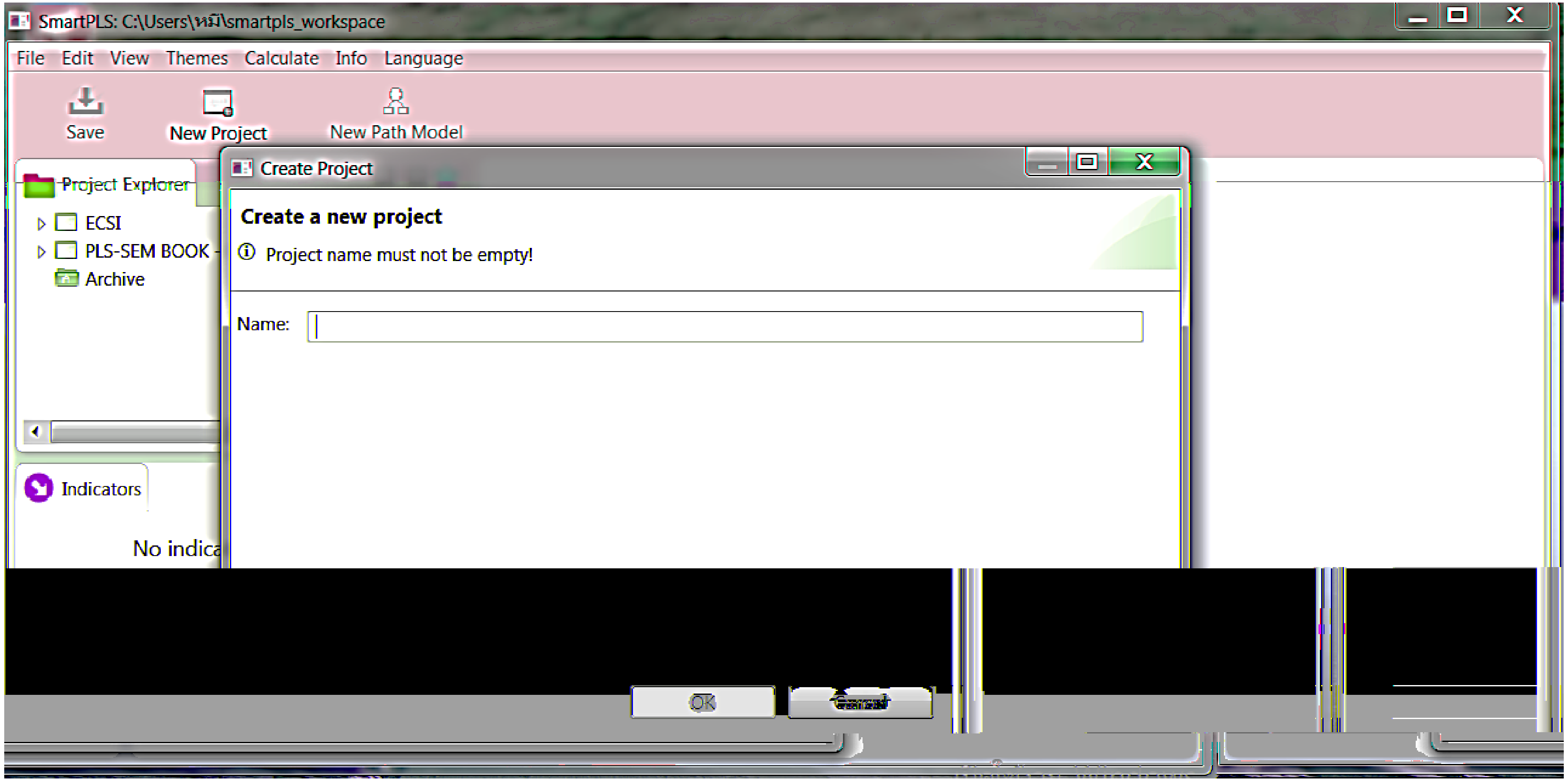
หมายเหตุ 3

โปรแกรม Smart PLS


PLS
SmartPLS 3

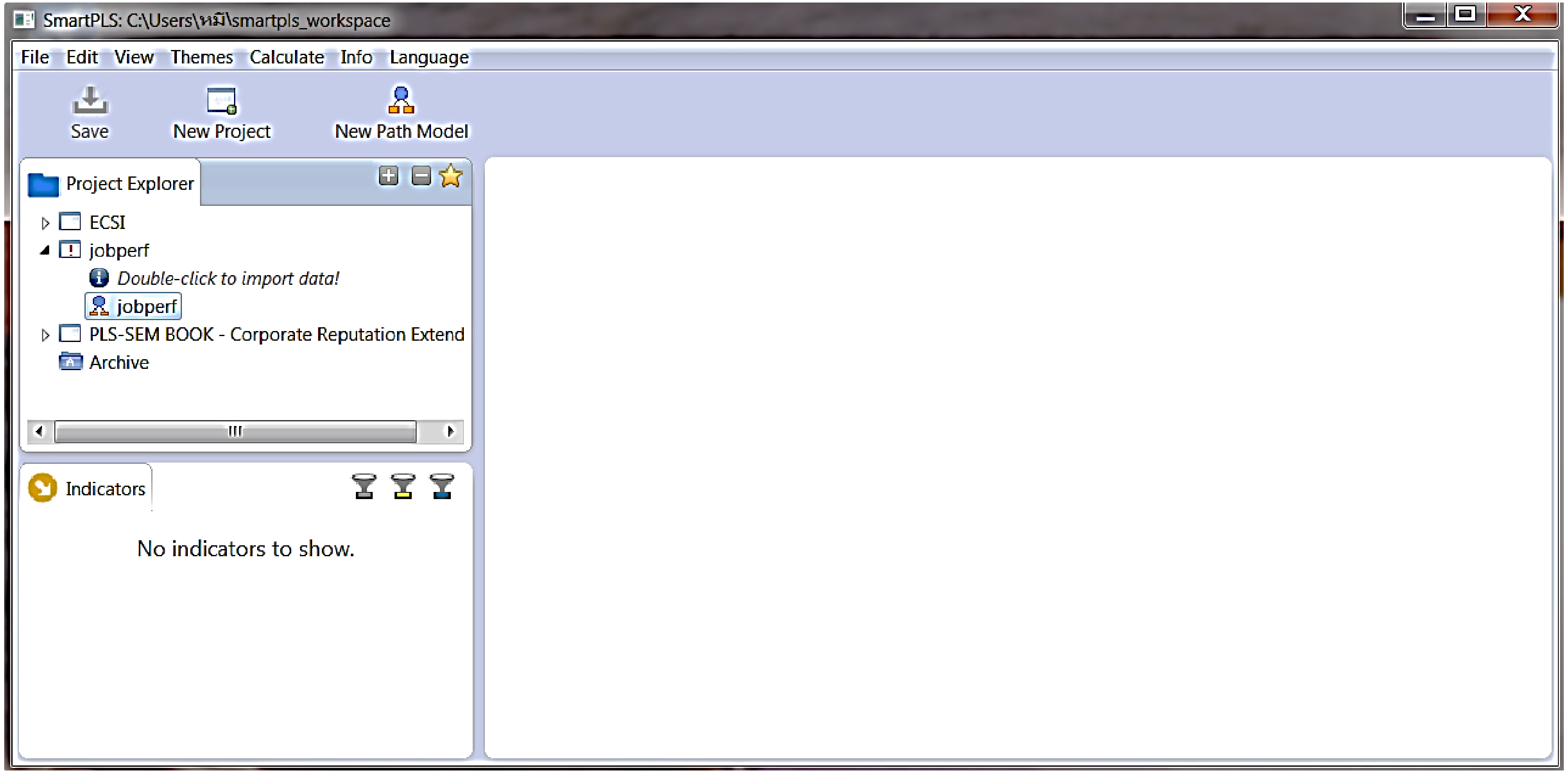
3


File
Edit
View
Themes
Calculate
Info
Language
Save
New Project
New Path Model
lorer
l BOOK - Corporate Reputation Extend
o indicators to show.
Project Exp
ECSI
PLS-SEM
Archive
Indicators

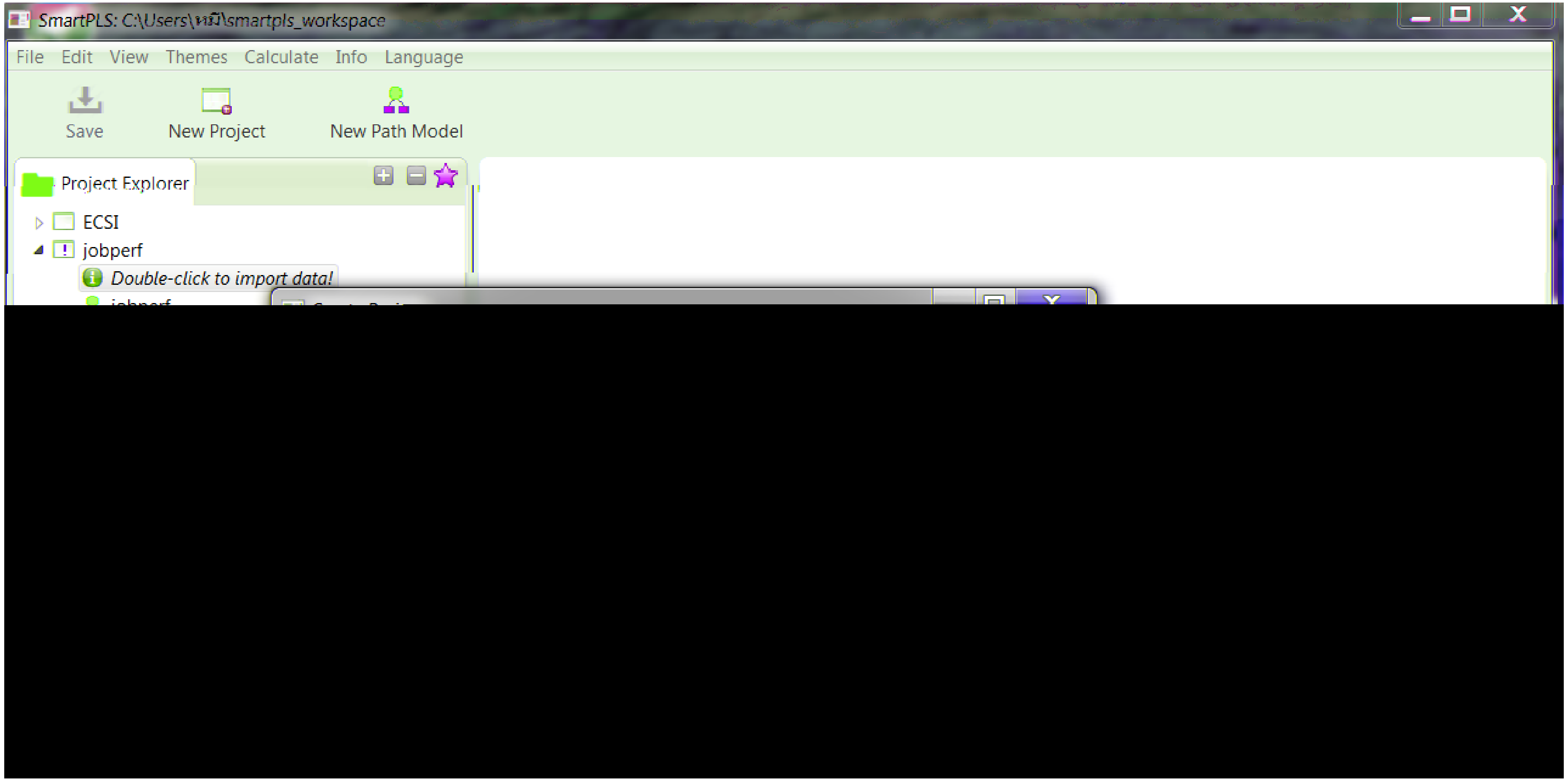

SmartPLS: C:\Users\หมี\smartpls_workspace
File Edit View Themes Calculate Info Language
Save
New Project
New Path Model
Project Explorer
ECSI
PLS-SEM BOOK
Archive
Indicators
No indica
Create Project
Create a new project
Project name must not be empty!
Name:
OK

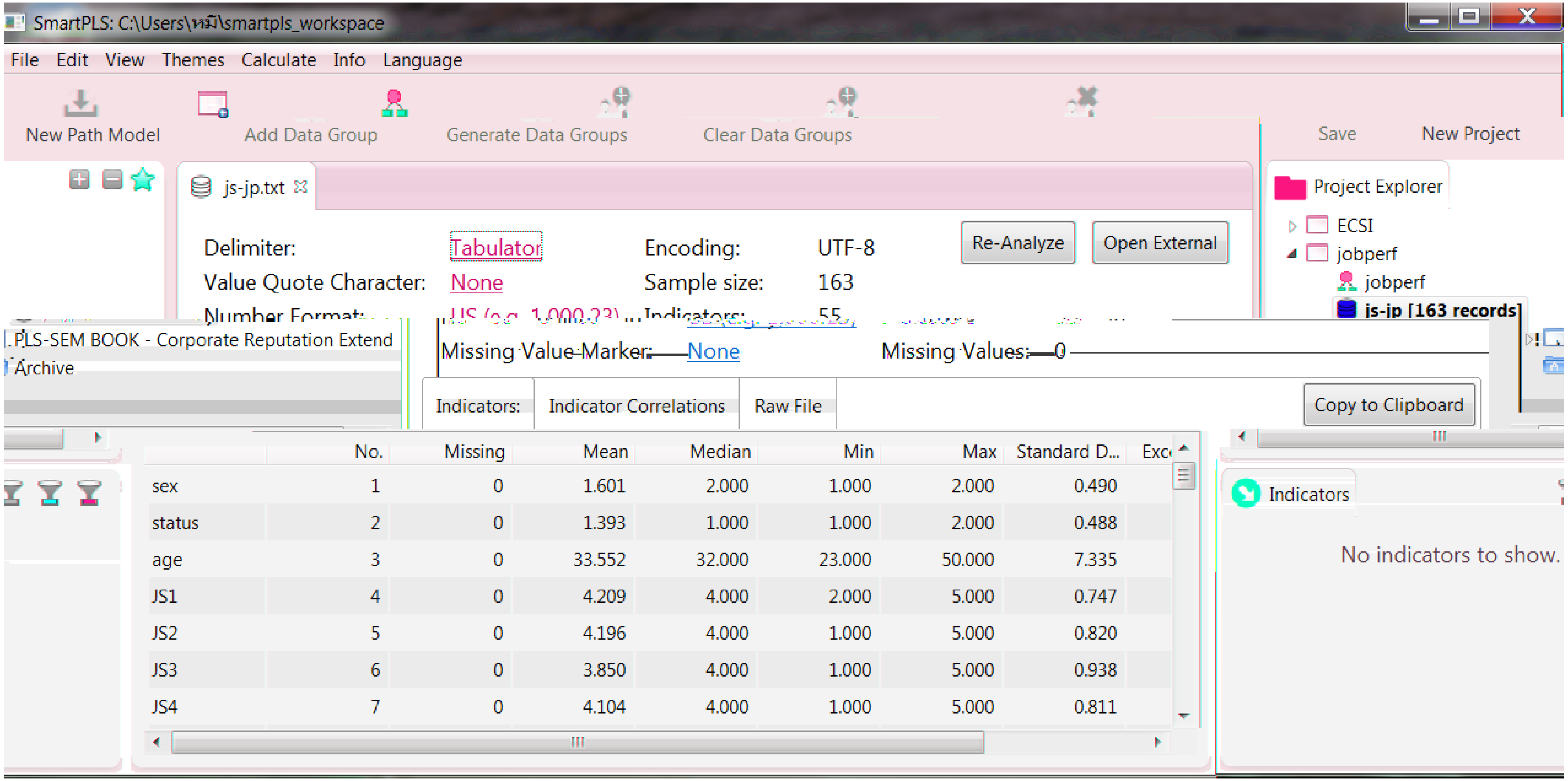
2

Double click to import data



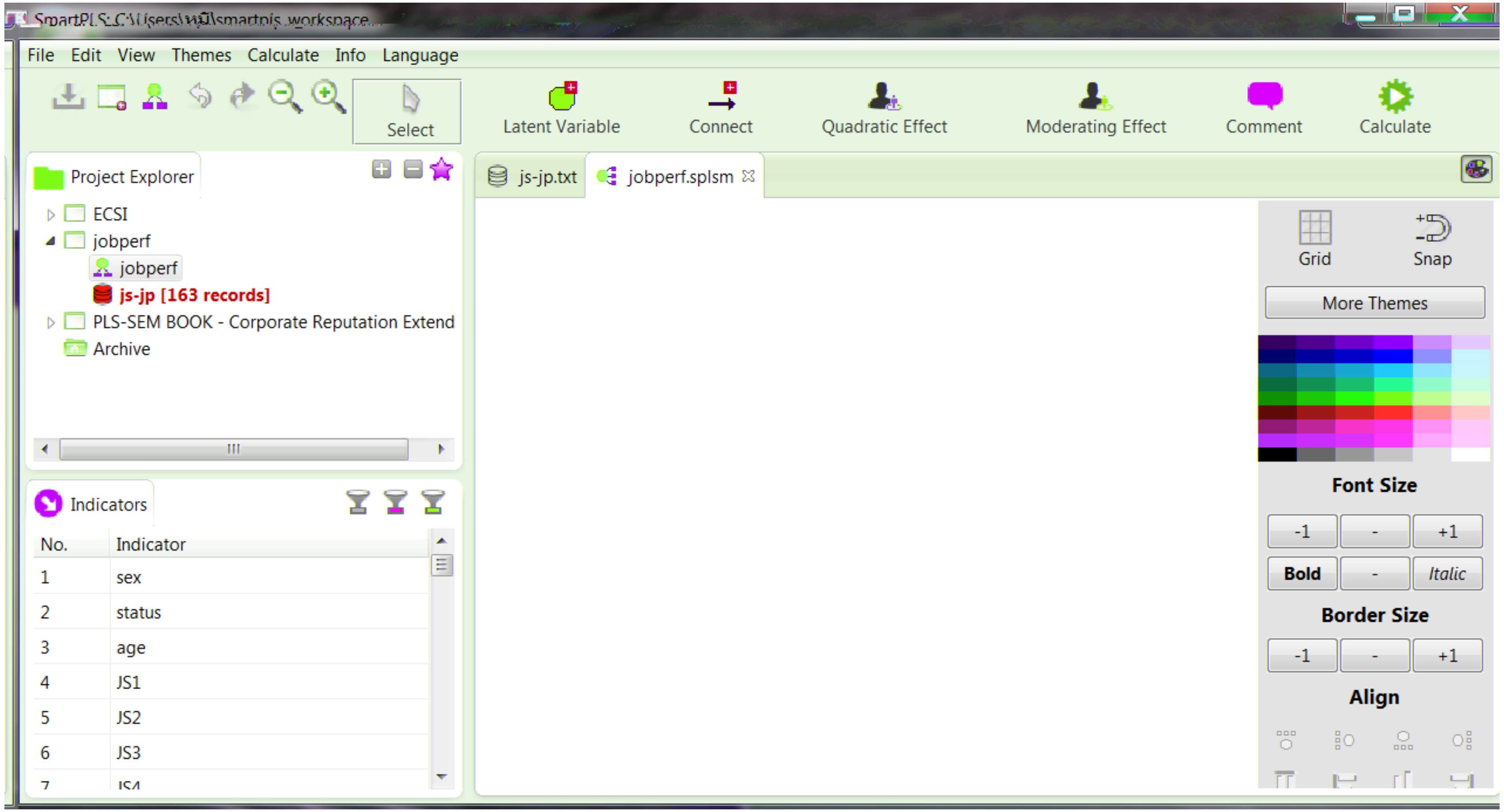
Dbl click *double click to import data* >



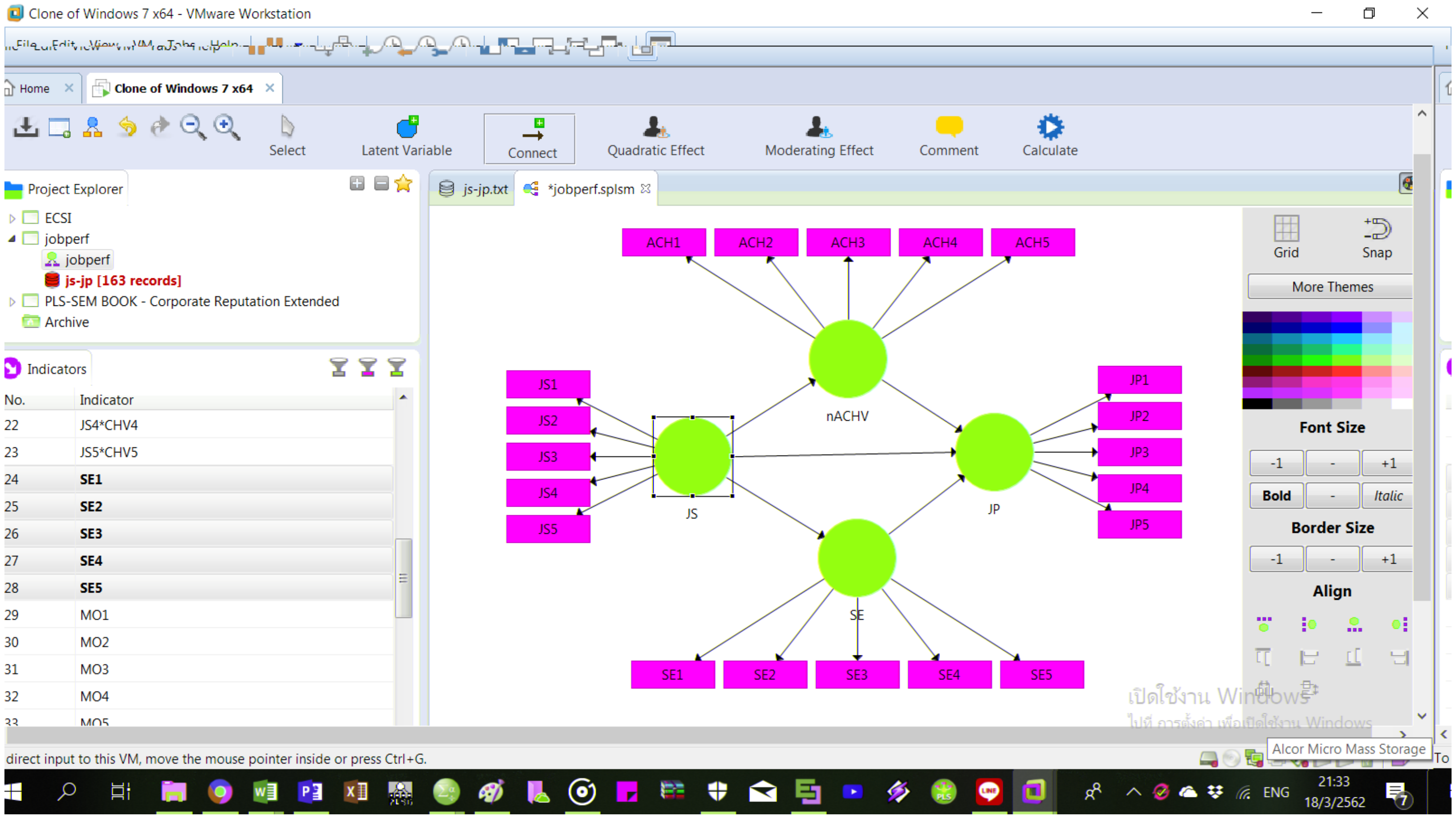

SmartPLS: C:\Users\หมี\smartpls_workspace
File Edit View Themes Calculate Info Language
New Path Model
Add Data Group
Generate Data Groups
Clear Data Groups
Save
New Project
js-jp.txt
Delimiter:
Tabulator
Encoding:
UTF-8
Re-Analyze
Open External
Value Quote Character:
None
Sample size:
163
Project Explorer
ECSI
jobperf
jobperf
js-jp [163 records]
PLS-SEM BOOK - Corporate Reputation Extend
Archive
Missing Value Marker:
None
Missing Values:
0
Indicators:
Indicator Correlations
Raw File
Copy to Clipboard
No.
Missing
Mean
Median
Min
Max
Standard D...
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 3

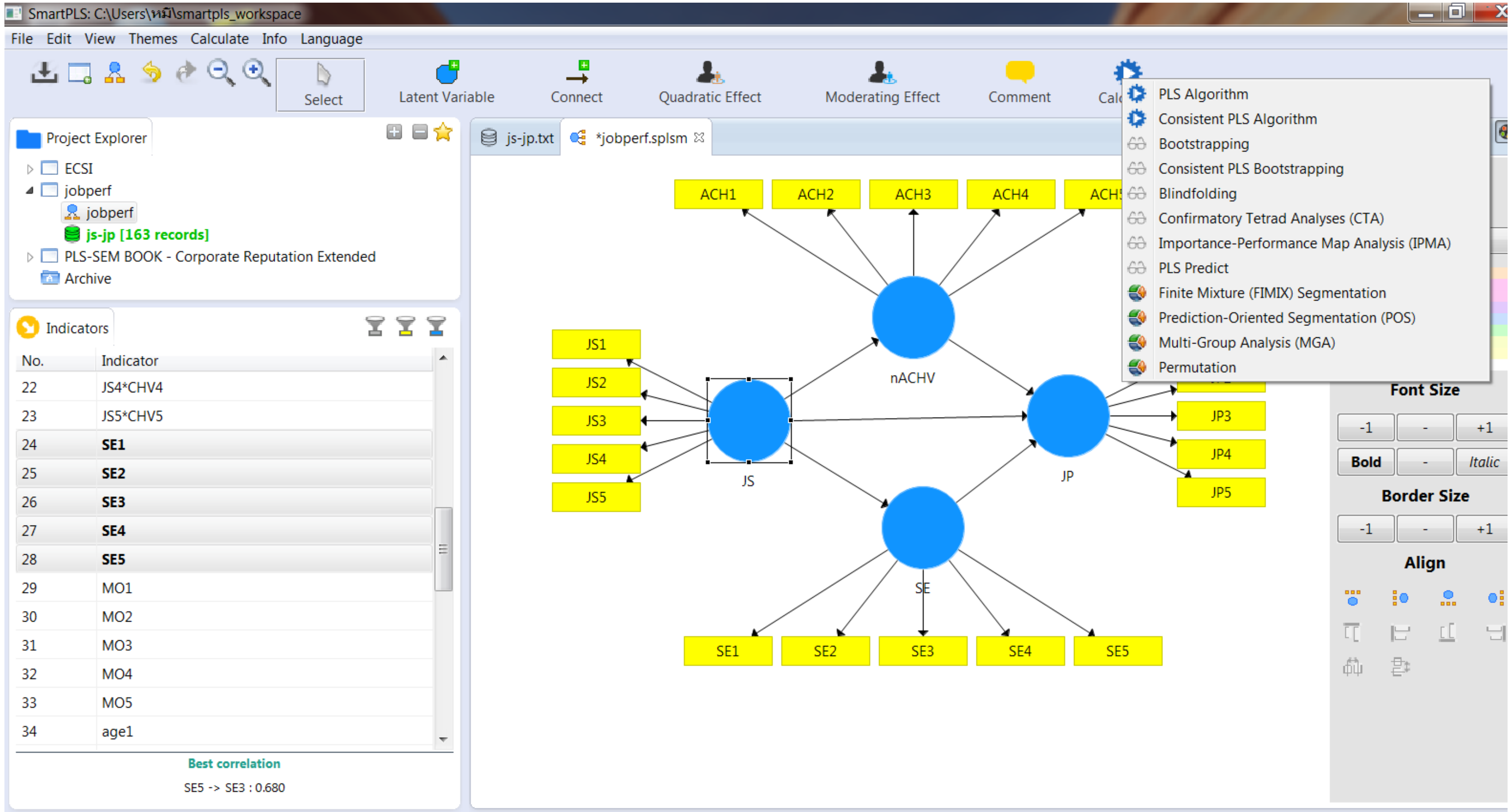
2


SmartPLS: C:\Users\หมี\smartpls_workspace
File Edit View Themes Calculate Info Language
Select
Latent Variable
Connect
Quadratic Effect
Moderating Effect
Comment
Calculate
Project Explorer
ECSI
jobperf
jobperf
js-jp [163 records]
PLS-SEM BOOK - Corporate Reputation Extend
Archive
js-jp.txt
jobperf.splsm
Grid
Snap
More Themes
Font Size
-1
-
+1
Bold
-
Italic
Border Size
-1
-
+1
Align
Indicators
No.
Indicator
1
sex
2
status
3
age
4
JS1
5
JS2
6
JS3

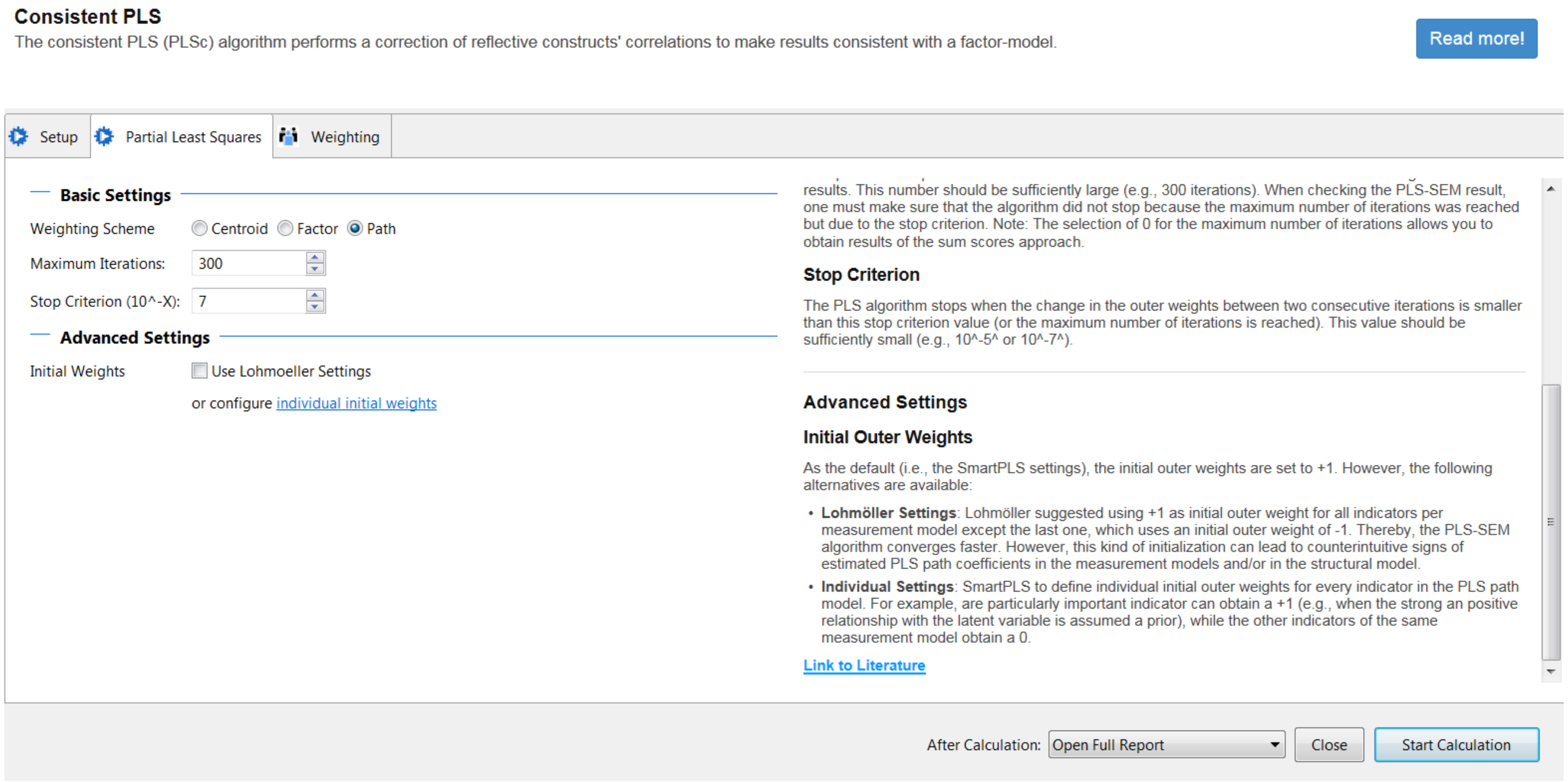
Shift click 2 3



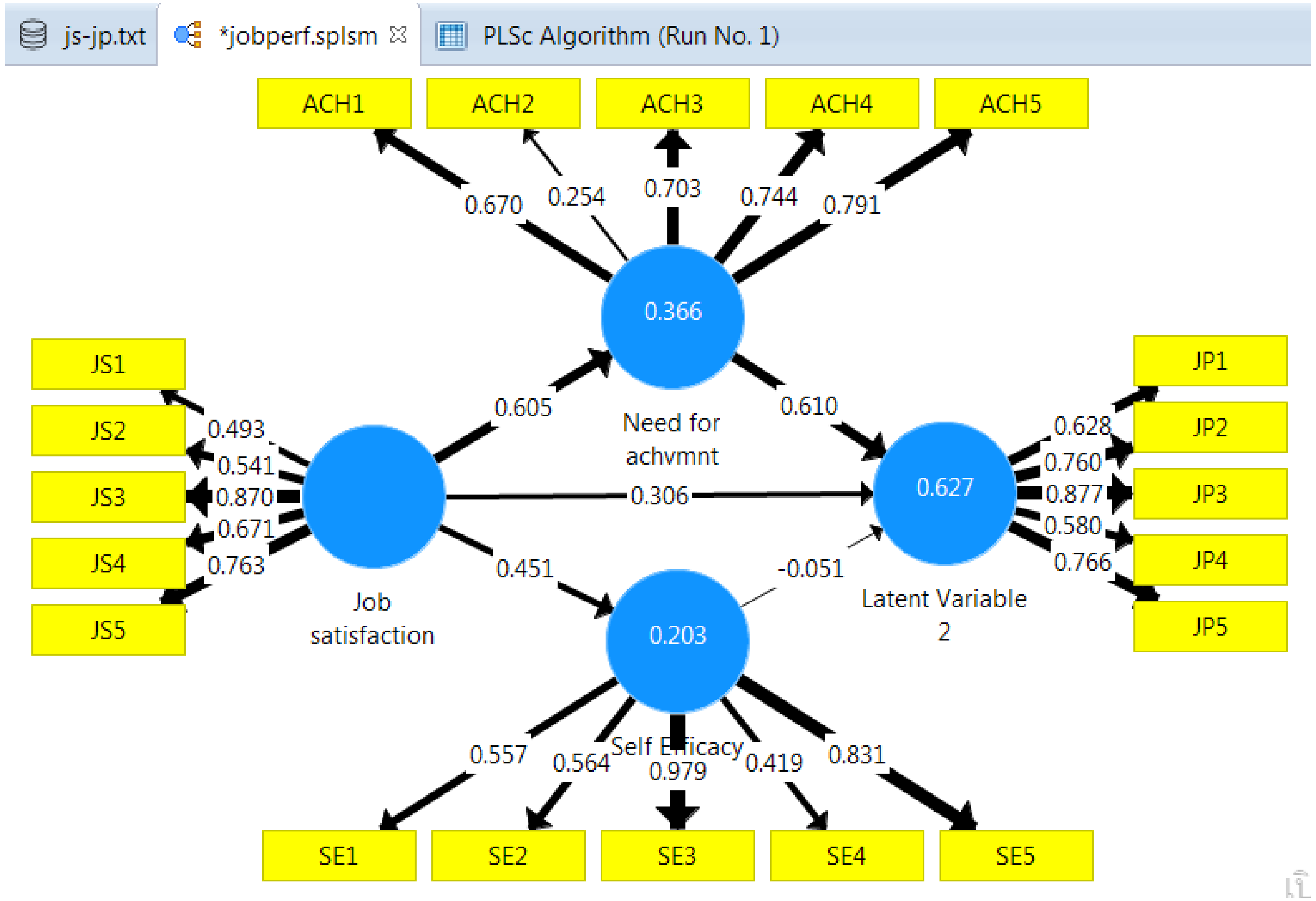
calculation Consistent PLS Algorithm



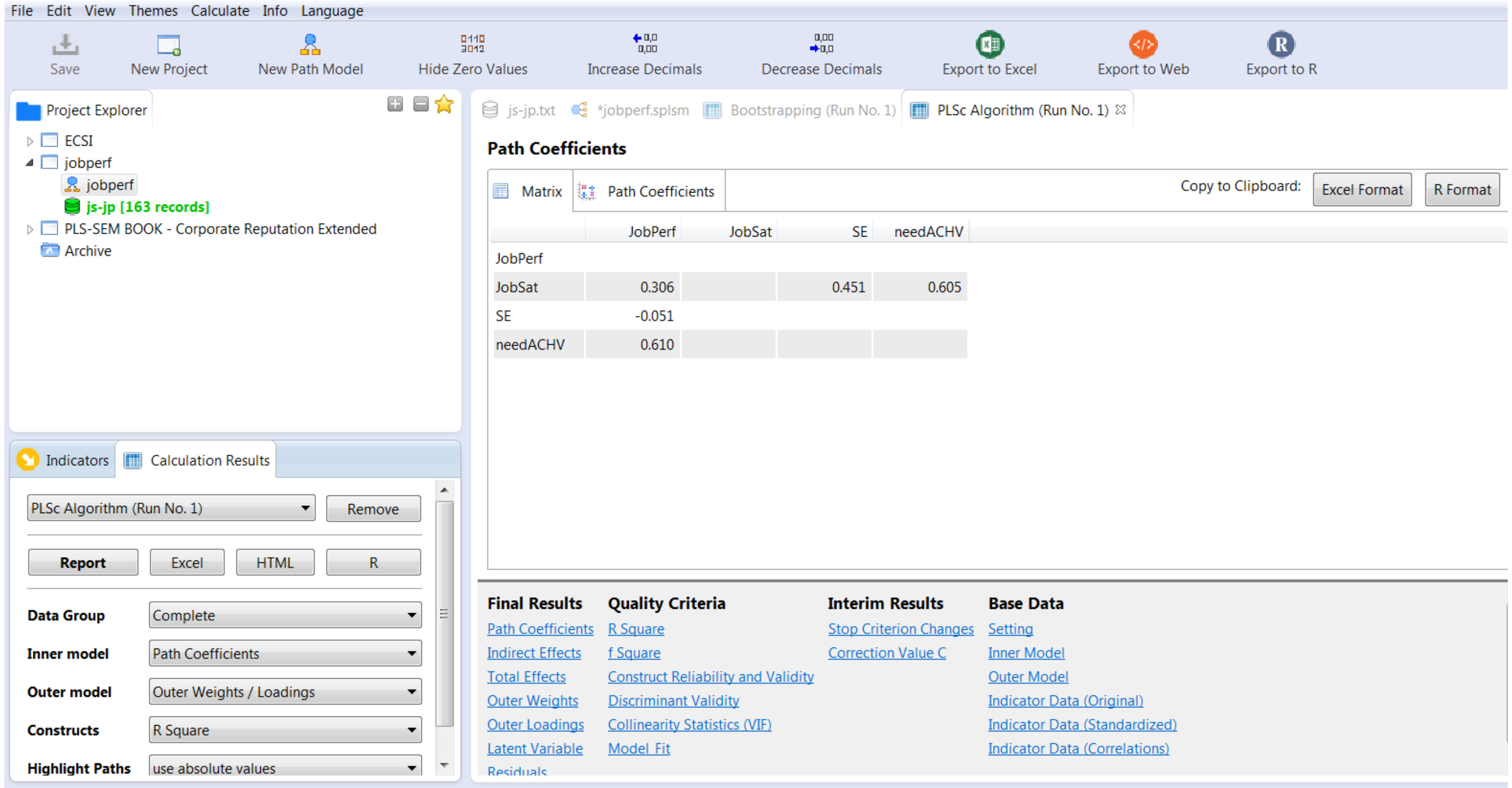
5 000-10


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:
300
Stop Criterion (10^-X):
7
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

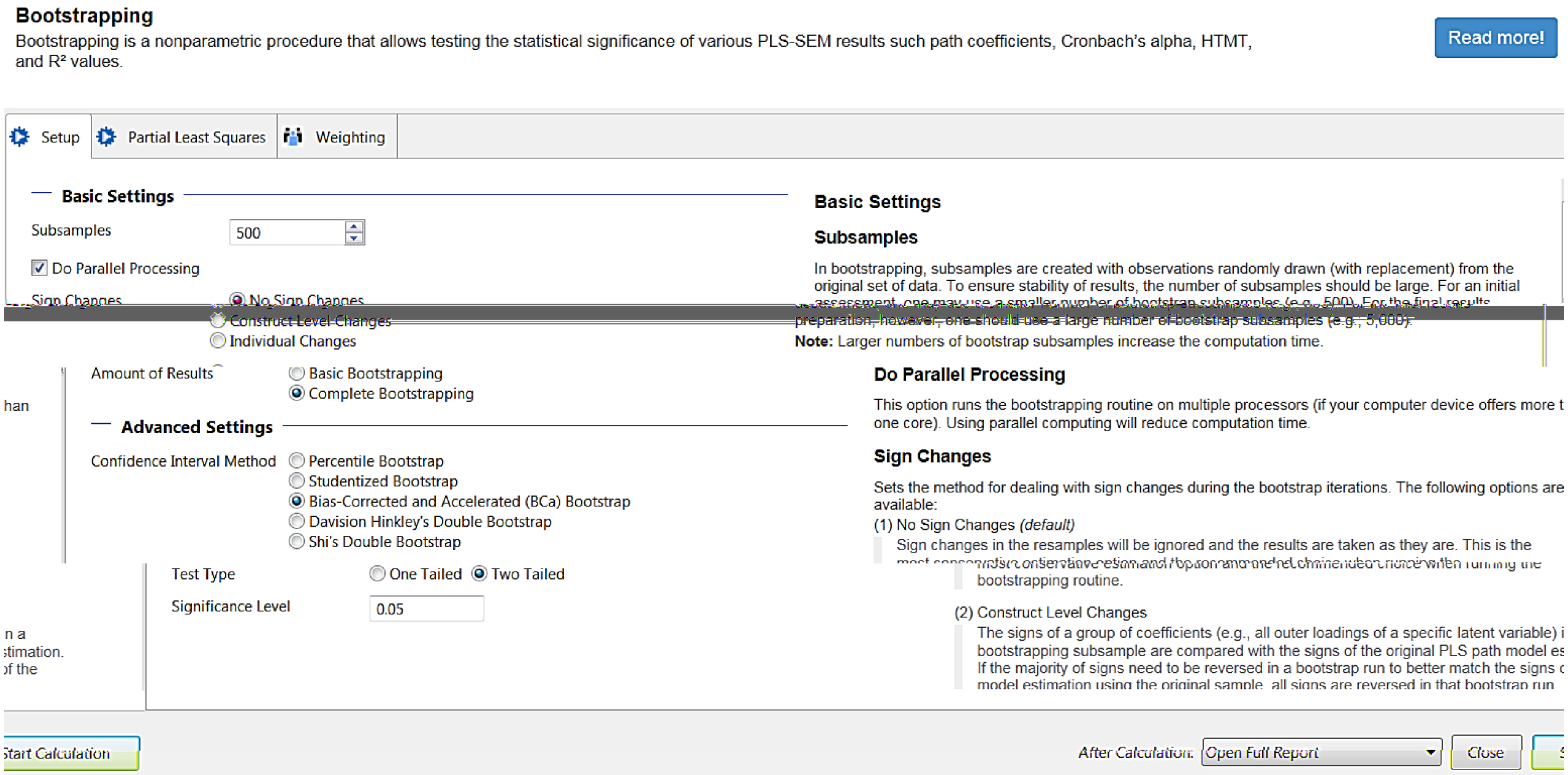
consistent PLS Algorithm



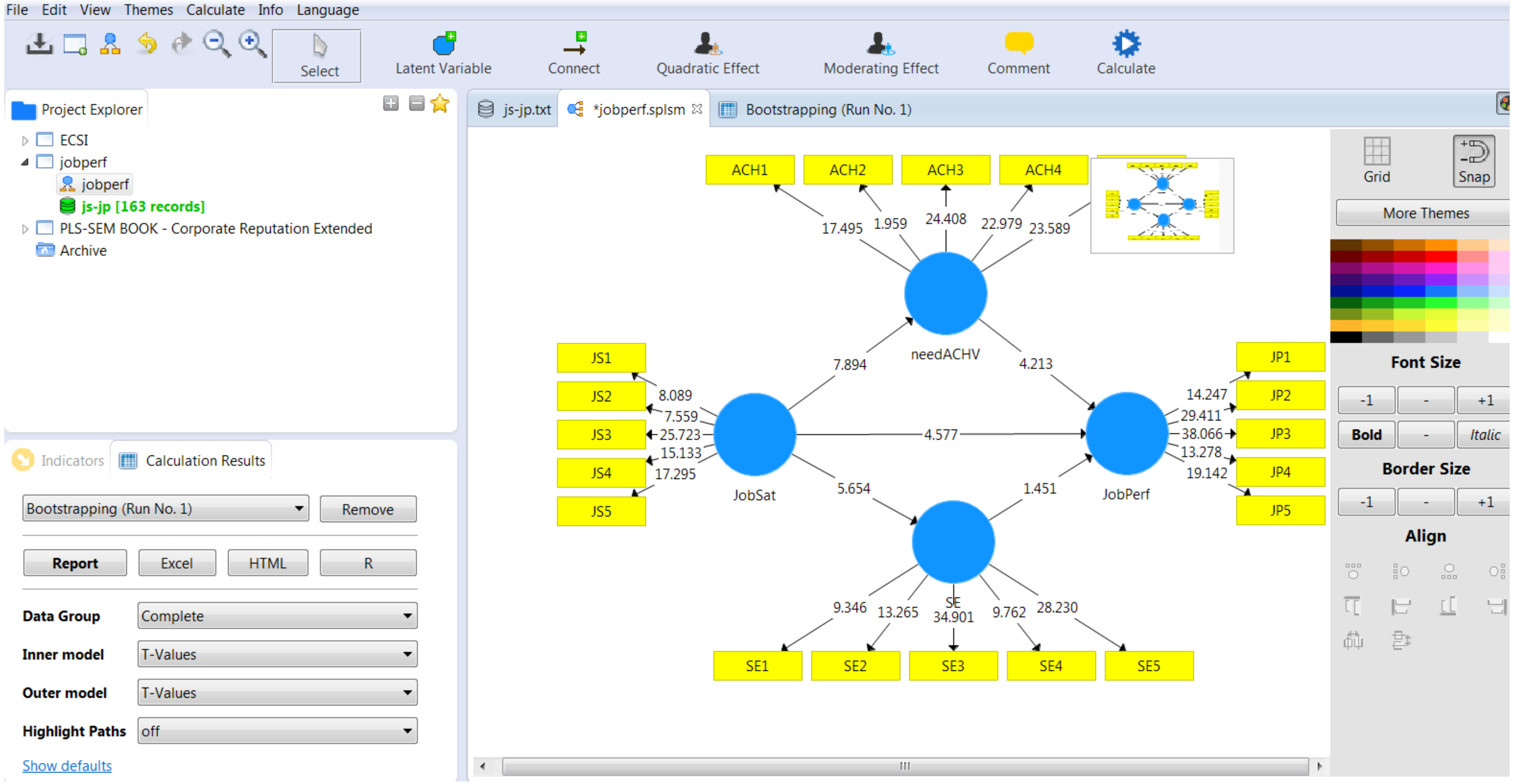
consistent PLS Algorithm



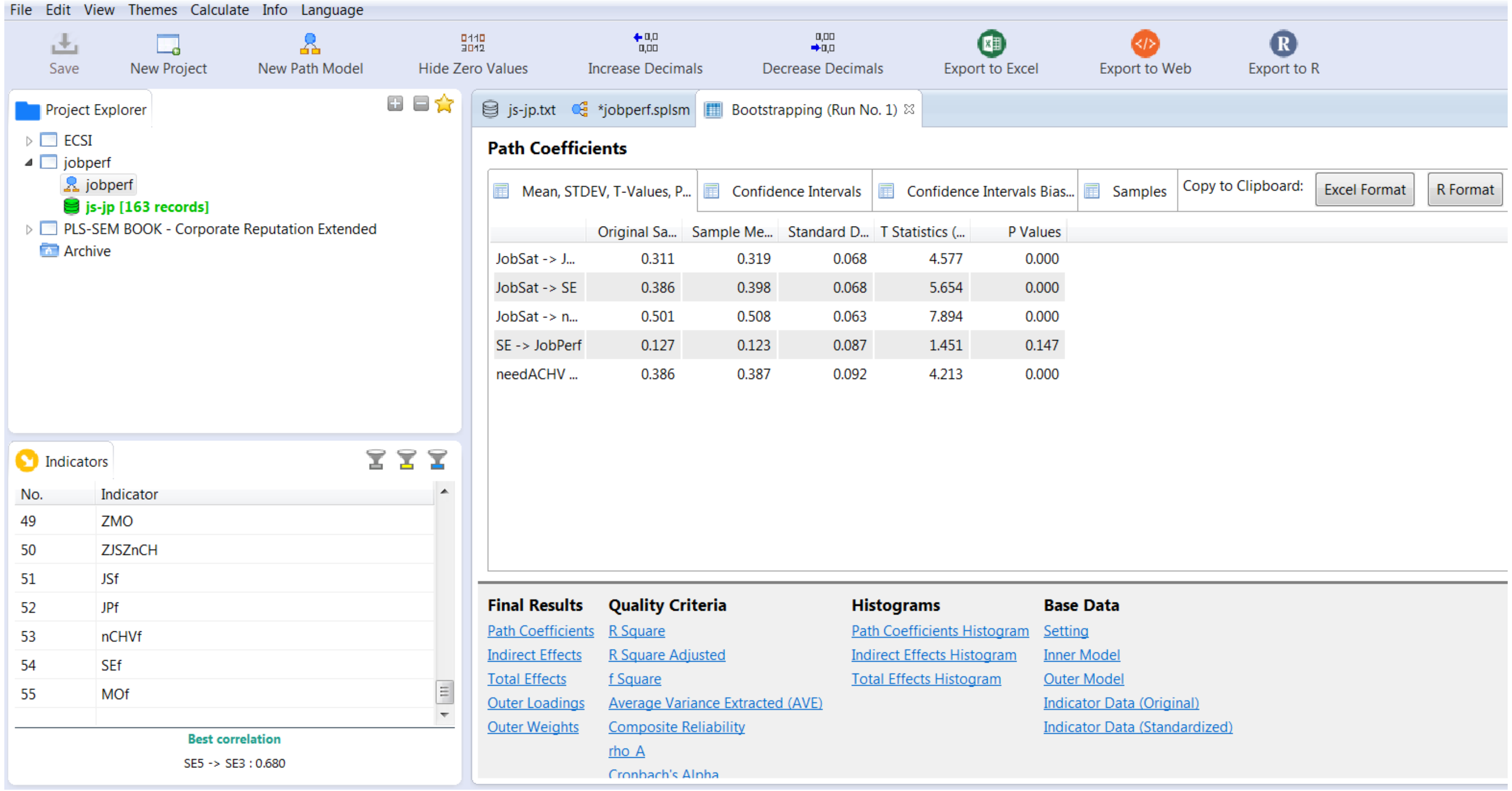
calculation Bootstrapping



Bootstrapping

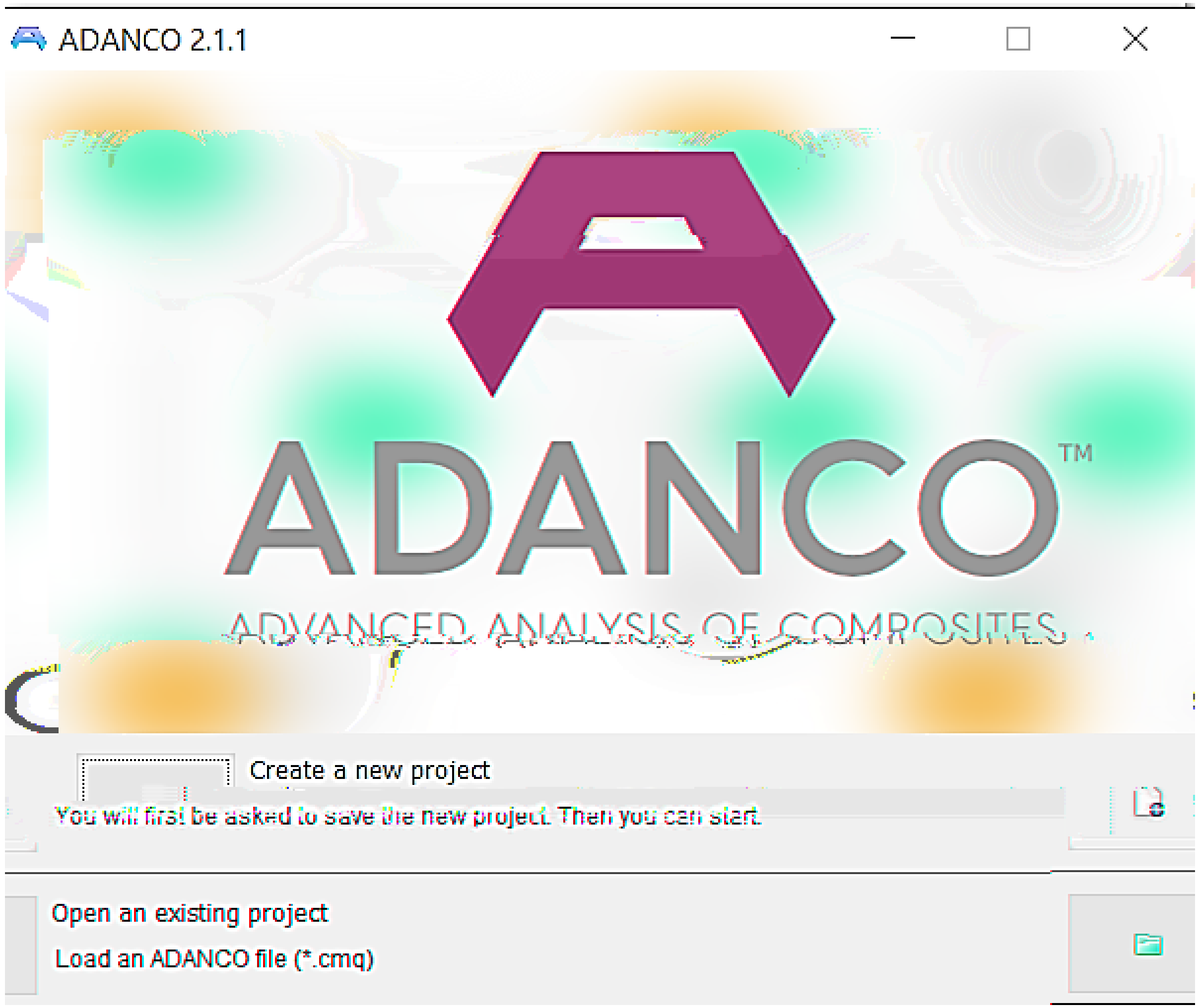


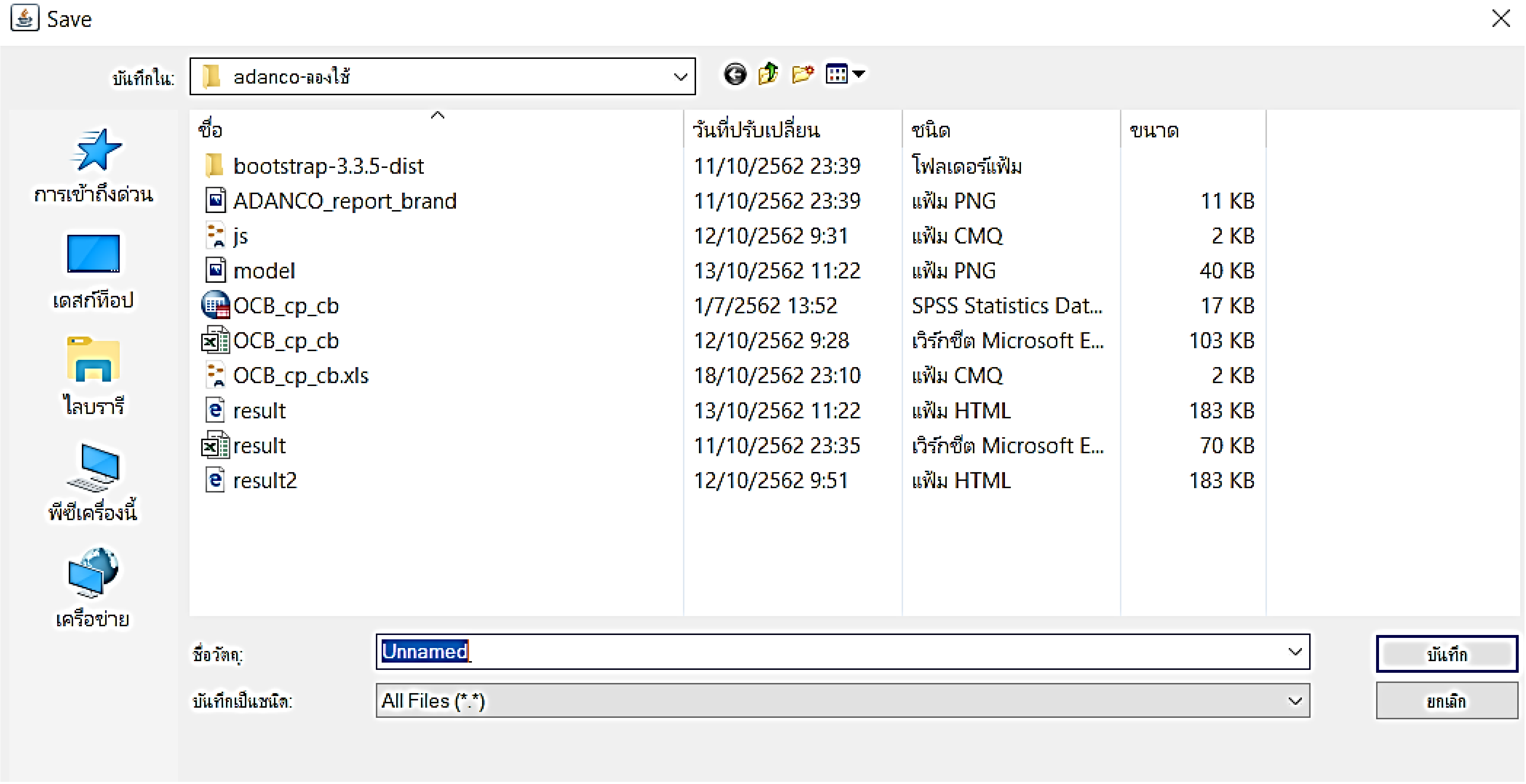
Bootstrapping



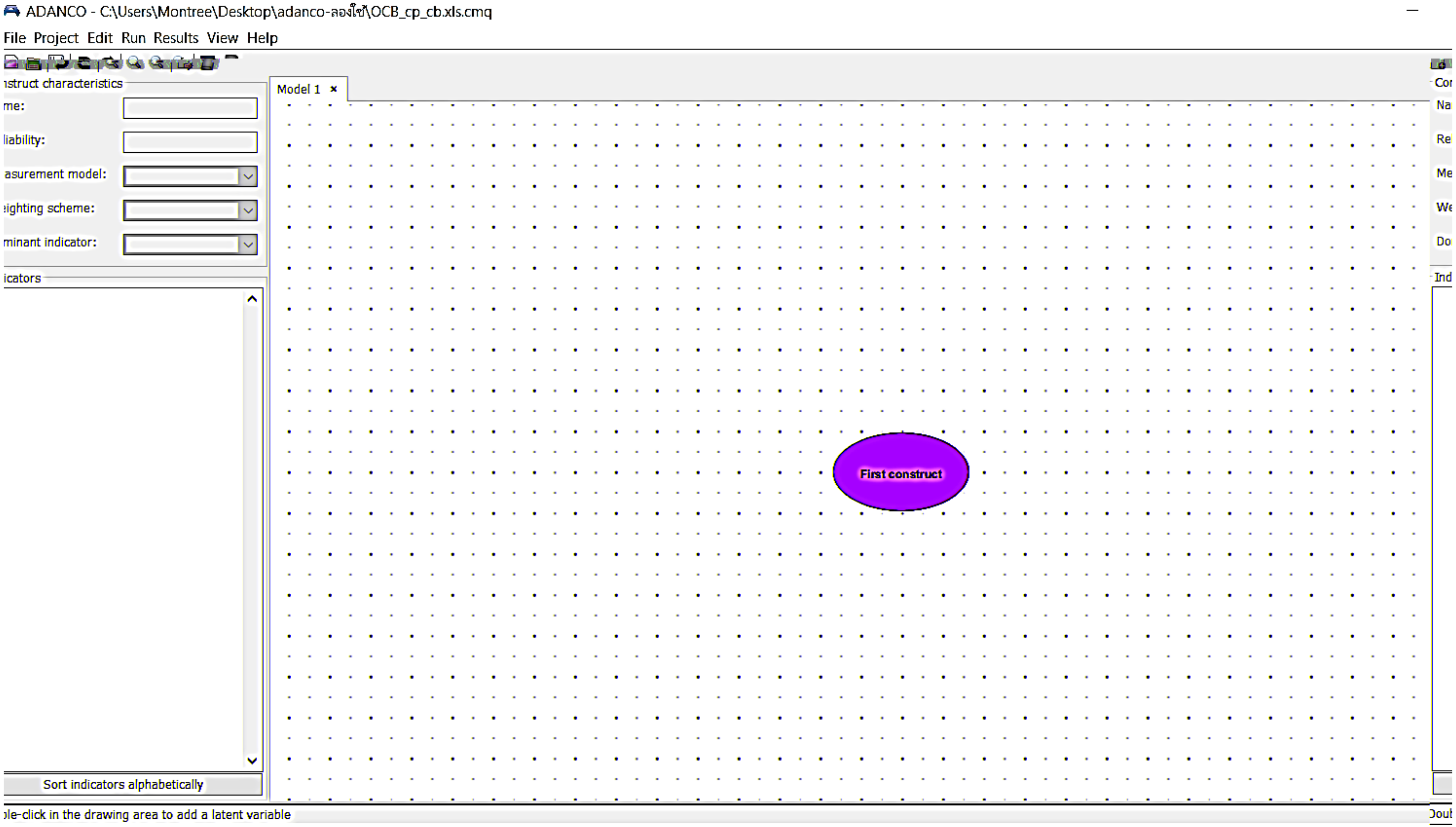
โปรแกรม ADANCO

Double click ADANCO.exe



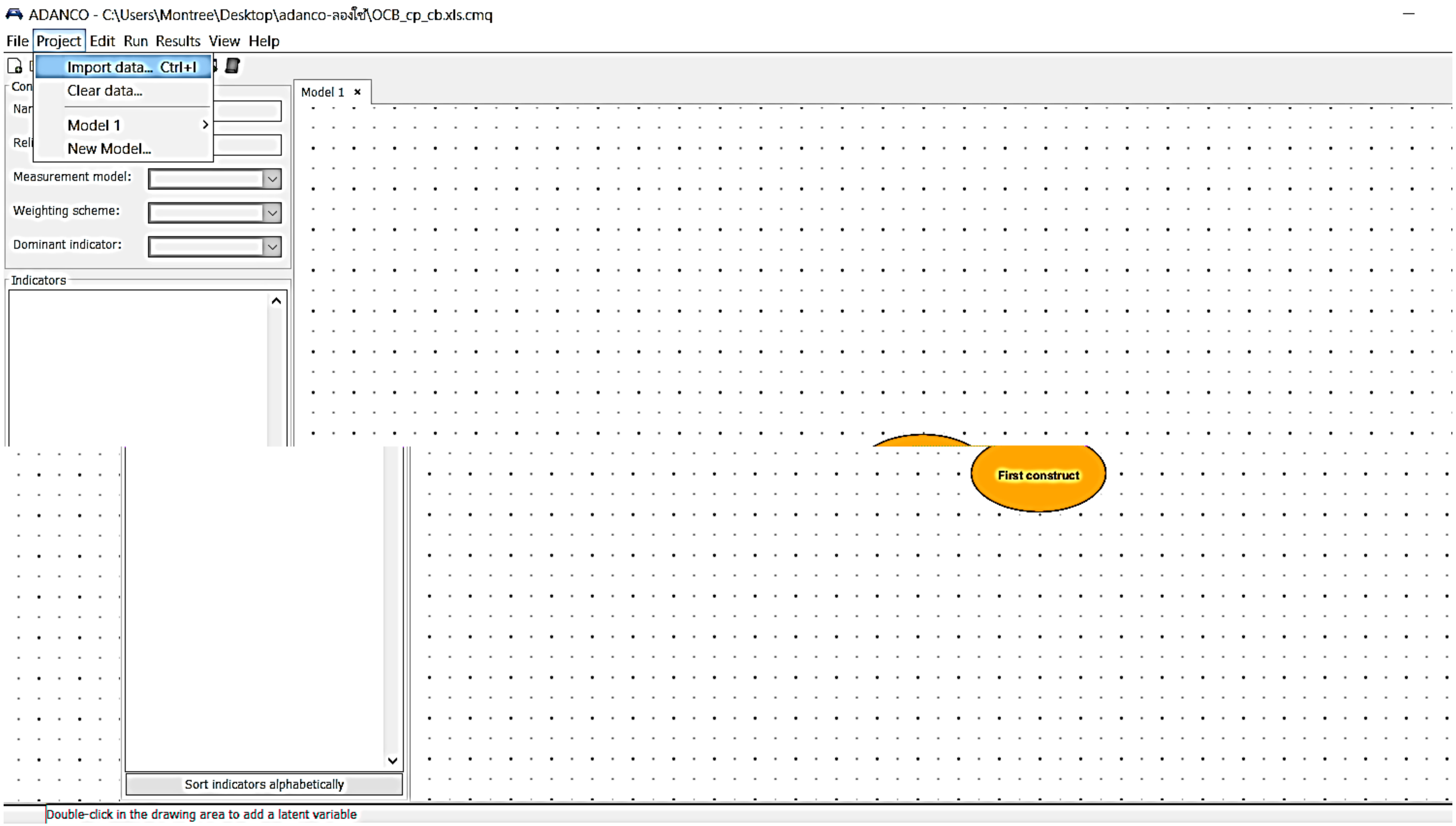

Save
บันทึกใน:
adanco-ลองใช้
ชื่อ
วันที่ปรับเปลี่ยน
ชนิด
ขนาด
bootstrap-3.3.5-dist
11/10/2562 23:39
โฟลเดอร์แฟ้ม
ADANCO_report_brand
11/10/2562 23:39
แฟ้ม PNG
11 KB
js
12/10/2562 9:31
แฟ้ม CMQ
2 KB
model
13/10/2562 11:22
แฟ้ม PNG
40 KB
OCB_cp_cb
1/7/2562 13:52
SPSS Statistics Dat...
17 KB
OCB_cp_cb
12/10/2562 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
การเข้าถึงด่วน
เดสก์ท็อป
ไลบรารี
พีซีเครื่องนี้
เครือข่าย
ชื่อวัตถุ:
Unnamed
บันทึกเป็นชนิด:
All Files (*.*)
บันทึก
ยกเลิก

OCB_cp_cb.xls



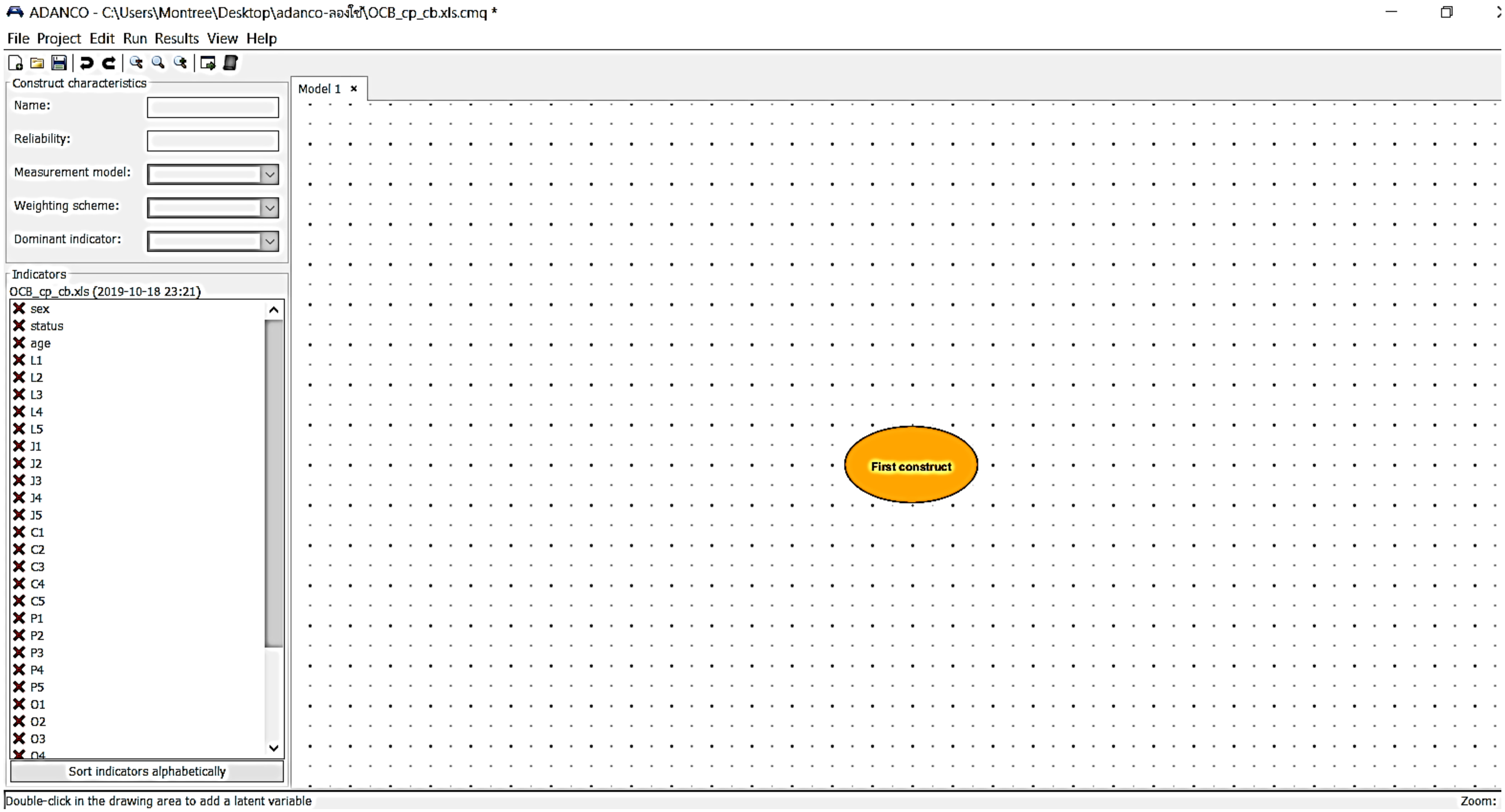
ADANCO - C:\Users\Montree\Desktop\adanco-ลองใช้\OCB_cp_cb.xls.cmq
File Project Edit Run Results View Help
ıstruct characteristics
me:
liability:
asurement model:
ighting scheme:
minant indicator:
icators
Sort indicators alphabetically
Model 1
First construct
ole-click in the drawing area to add a latent variable

Project Import Data

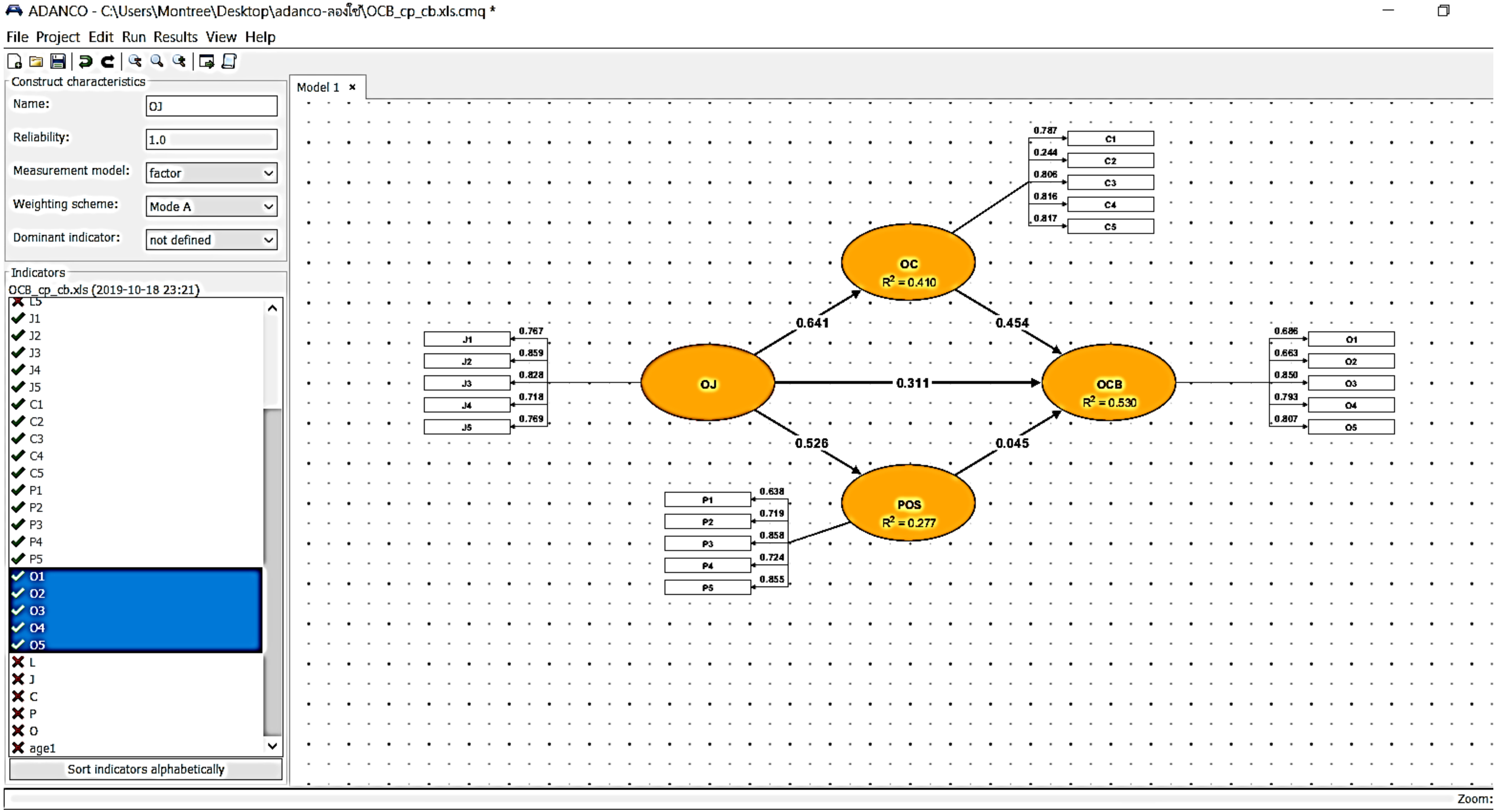


choose next next finish

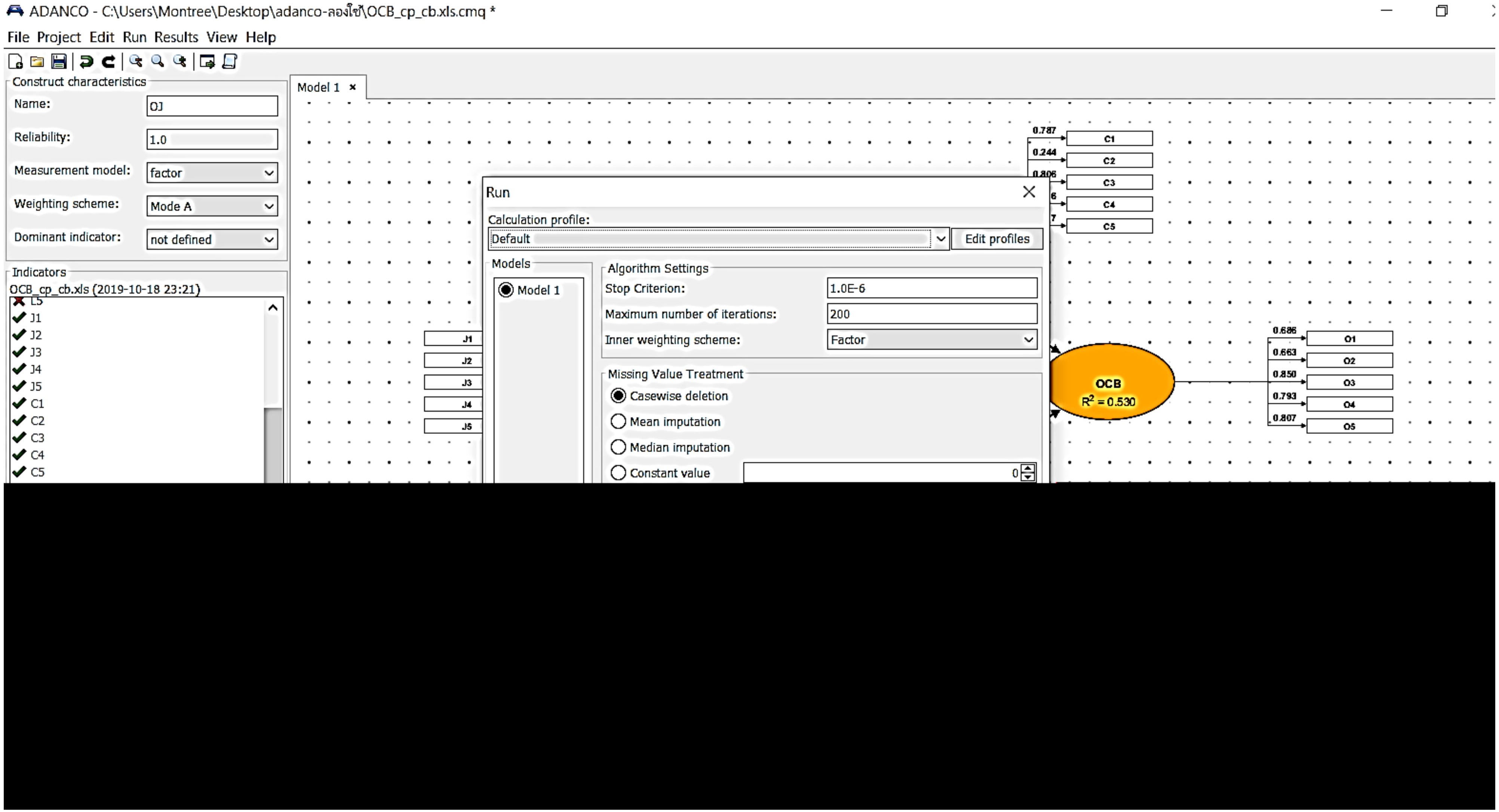
1 first construct



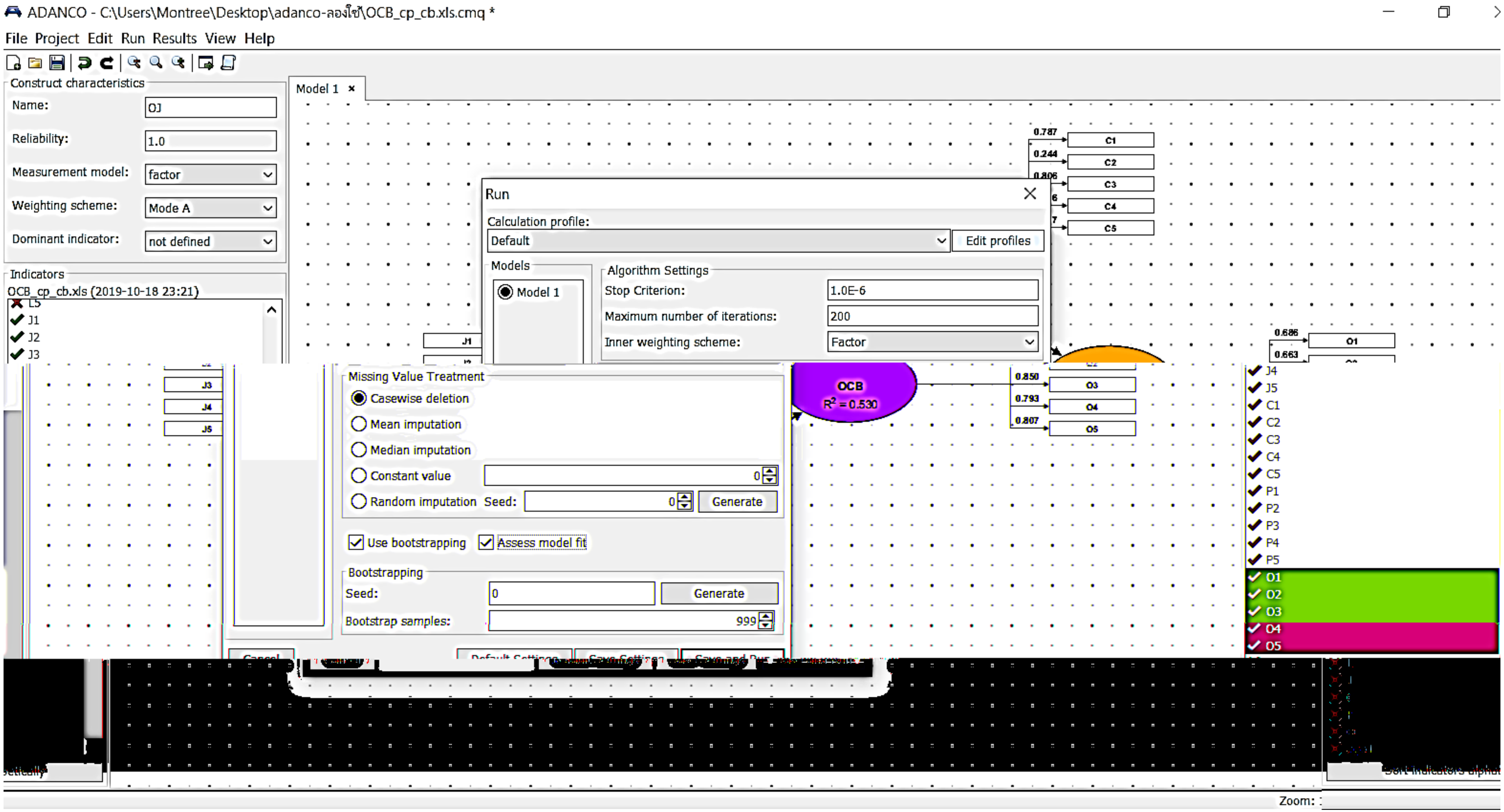
loading
bootstrapping



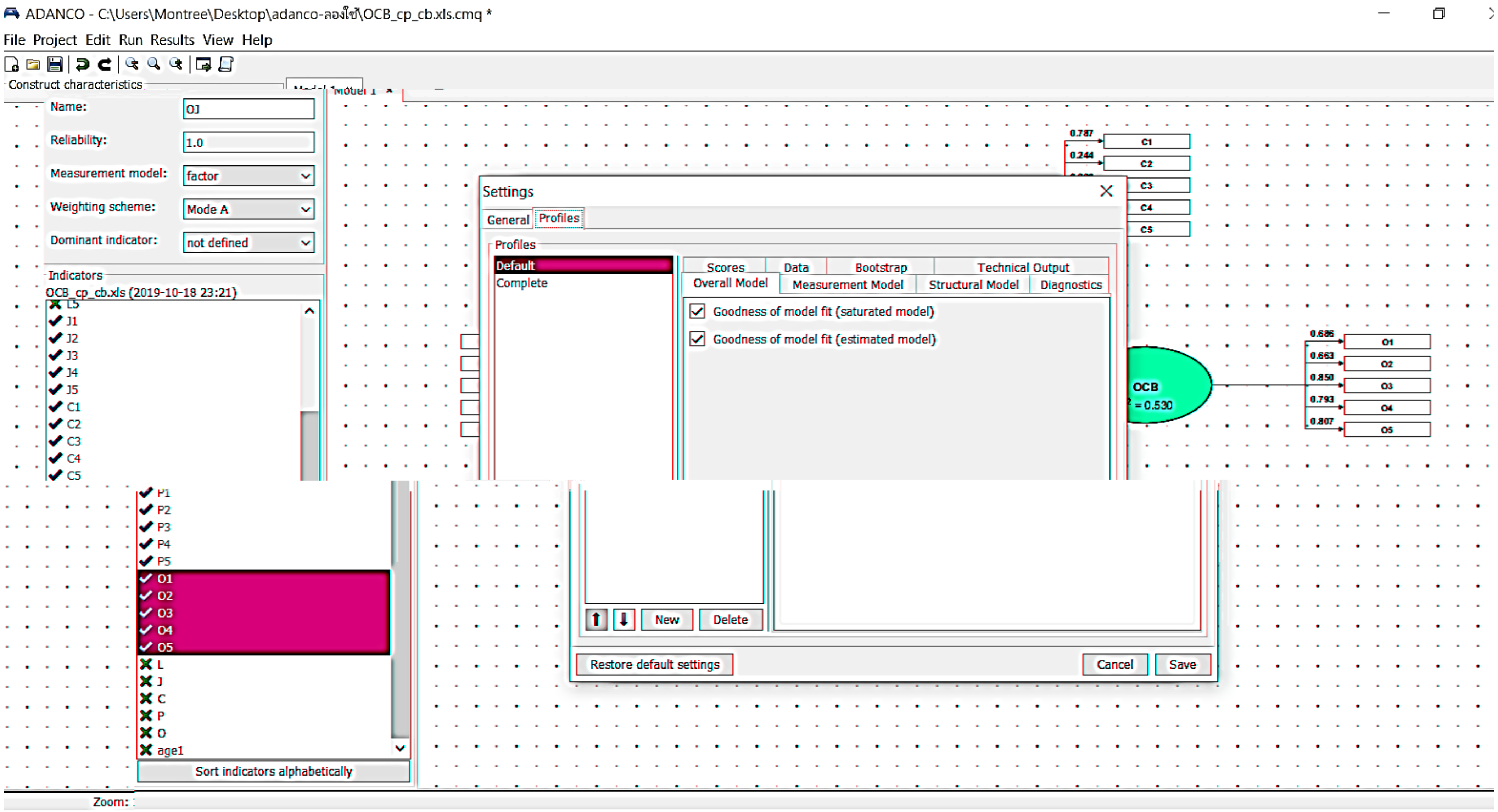
run> run ctrl+R run



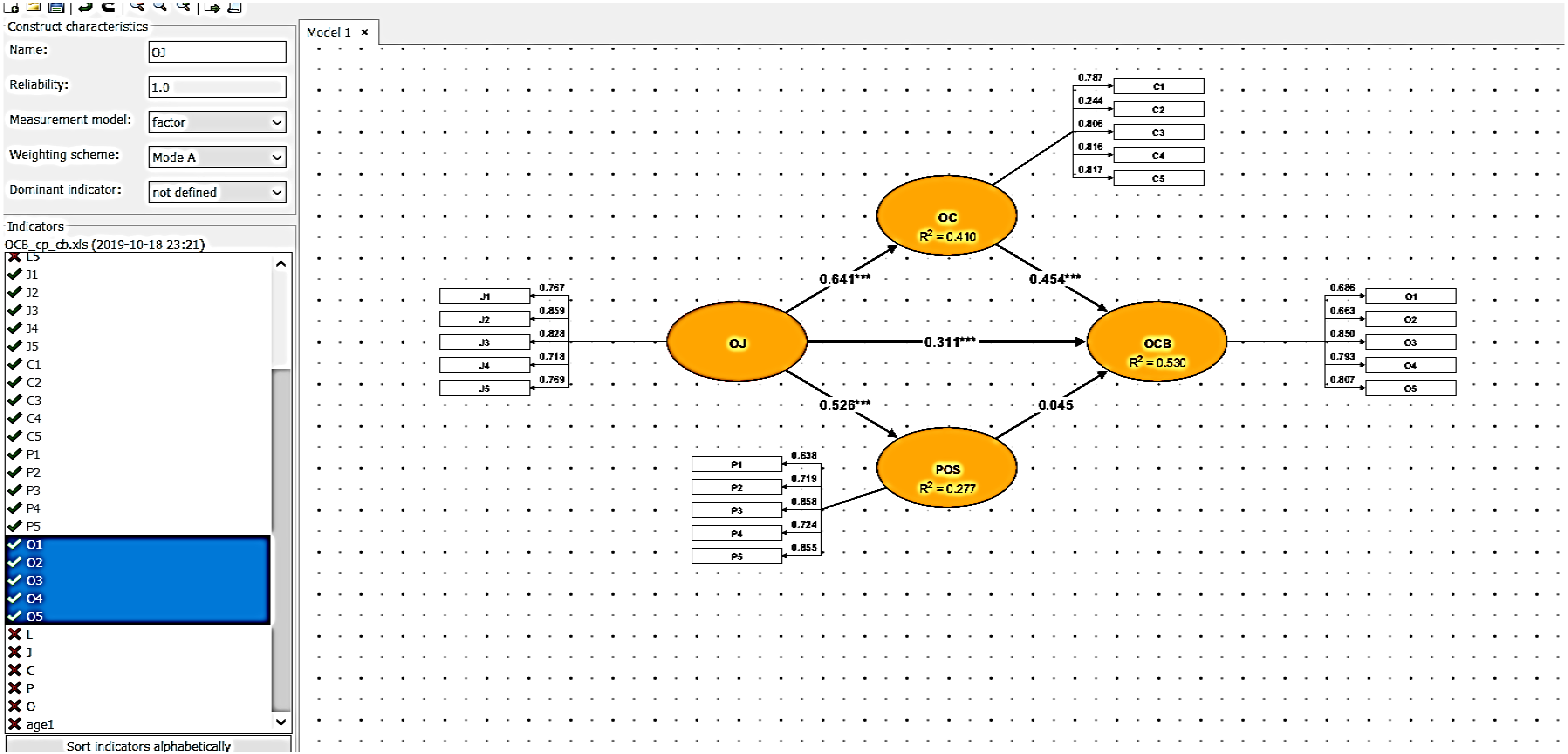
use boostrapping Asset model fit edit profile



save > save and run



result


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
Model 1
OC
$R^2 = 0.410$
OJ
OCB
$R^2 = 0.530$
POS
$R^2 = 0.277$
0.641***
0.454***
0.311***
0.526***
0.045
0.787
0.244
0.806
0.816
0.817
0.767
0.859
0.828
0.718
0.769
0.686
0.663
0.850
0.793
0.807
0.638
0.719
0.858
0.724
0.855

ADANCO - Results for C

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

Composite Modeling

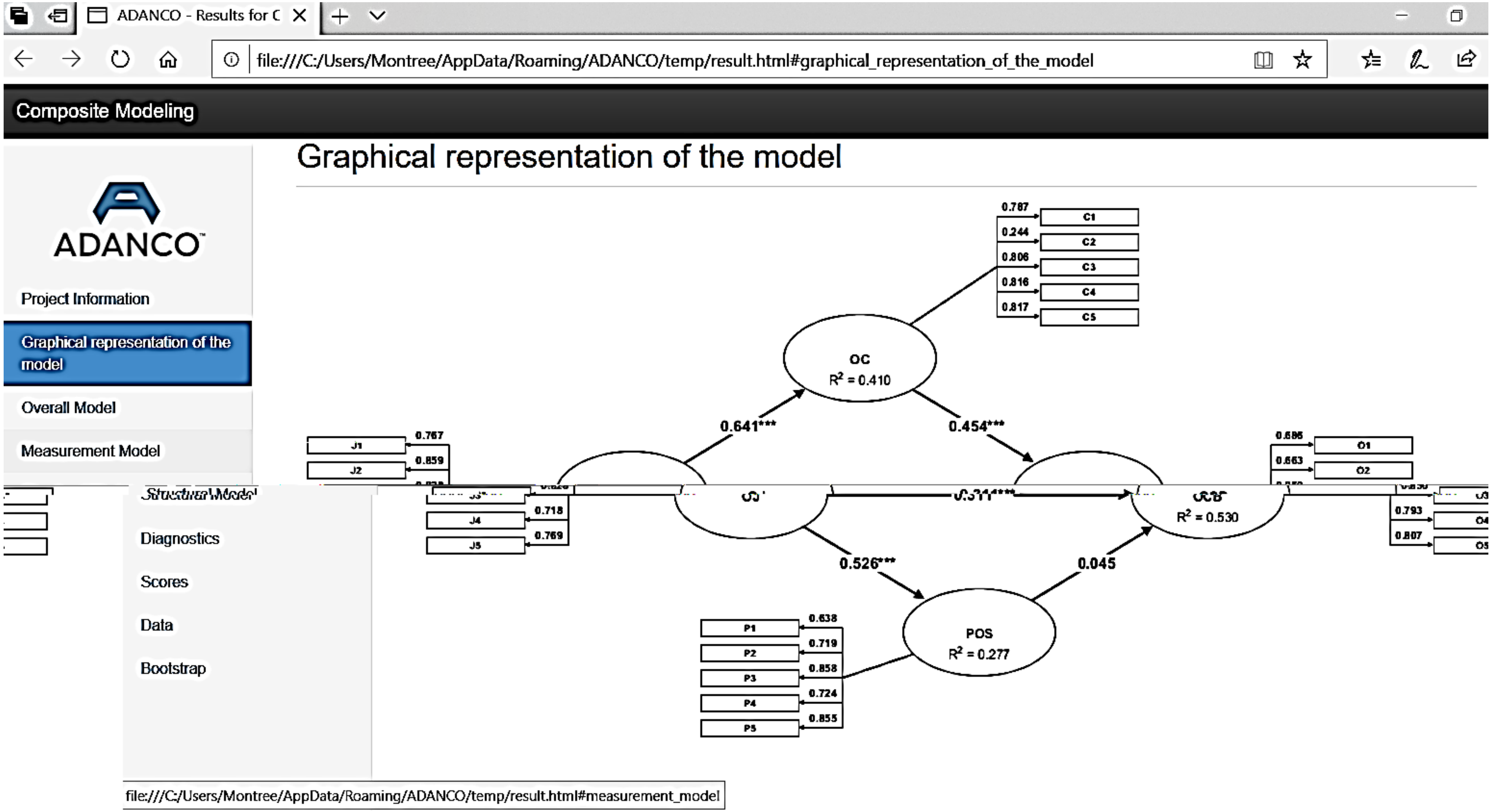
ADANCO

- 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).


ADANCO - Results for C
file:///C:/Users/Montree/AppData/Roaming/ADANCO/temp/result.html#graphical_representation_of_the_model
Composite Modeling
Graphical representation of the model
ADANCO
Project Information
Graphical representation of the model
Overall Model
Measurement Model
Diagnostics
Scores
Data
Bootstrap
OC
R^2 = 0.410
0.641***
0.454***
0.526***
0.045
POS
R^2 = 0.277
R^2 = 0.530
C1
C2
C3
C4
C5
0.787
0.244
0.806
0.816
0.817
J1
J2
J4
J5
0.767
0.859
0.718
0.769
O1
O2
0.686
0.663
0.793
0.807
P1
P2
P3
P4
P5
0.638
0.719
0.858
0.724
0.855
file:///C:/Users/Montree/AppData/Roaming/ADANCO/temp/result.html#measurement_model

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