Técnicas Quantitativas de Investigação em Gestão

PART B

4 & 5 • DECEMBER • 2023

Nuno Fernandes Crespo

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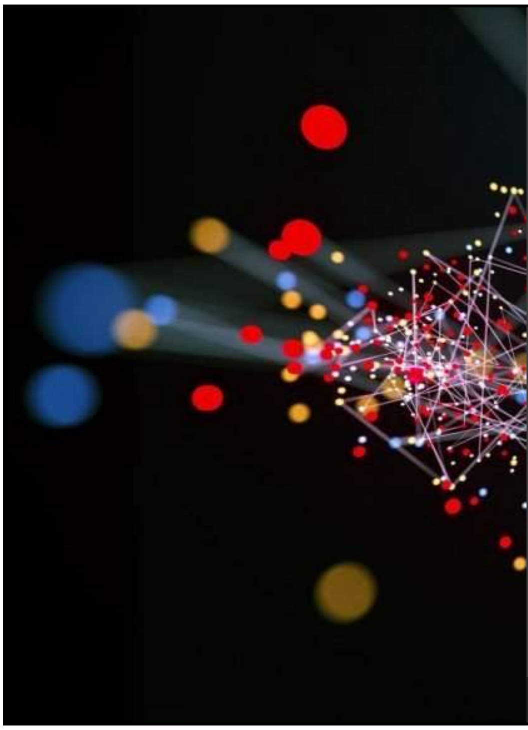

AGENDA

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CONTACT INFORMATION

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  - Research Interests:
    - Entrepreneurship, SMEs, family firms;
    - International business, international marketing;
    - International entrepreneurship, INVs, BG, international entrepreneurs.

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Introduction to structural equation modeling

CHAPTER B.1

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B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
→ *INITIAL DEFINITIONS*

- SEM is an extension of **Generalized Linear Models**;
- It is a technique of generalized modeling (theoretical models on how different latent variables or constructs are operationalized and how they are related to each other);
- Allow measurement errors to be explicitly considered.

- In simplistic terms:

SEM = **Factorial Analysis (measurement model)** + **Linear Regression (structural model)**

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B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
→ *INITIAL DEFINITIONS*

- SEM Definition:
  - “Structural equation modeling (SEM) does not designate a single statistical technique but instead refers to a **family of related procedures**. Other terms such as covariance structure analysis, covariance structural modeling, or analysis of covariance structures are essentially interchangeable. Another term (…) **is causal modeling**, which is used mainly in association with the technique of path analysis.” (Kline, 2005, p. 9)

- SEM techniques are known as the **second generation of data analysis techniques** (Bagozzi & Fornell, 1982).

	Primarily exploratory	Primarily Confirmatory
First-generation techniques	▪ Cluster analysis ▪ Exploratory factor analysis ▪ Multidimensional scalling	▪ Analysis of variance ▪ Logistic regression ▪ Multiple regression ▪ Confirmatory factor analysis
Second-generation techniques	▪ Partial least squares structural equation modeling (PLS-SEM)	▪ Covariance-based structural equation modeling (CB-SEM)

Source: Hair et al., 2017, p. 2.

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B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *INITIAL DEFINITIONS*

- It differs from most of first-generation regression models such as linear regression, Logit, ANOVA or MANOVA, because these techniques are only able to analyze **one set of relationships between independent and dependent variables at a time** (Gefen et al., 2000).
- Compared to linear regression, SEM has the advantage to analyze path diagrams with latent variables with **multiple indicators** (Gefen et al., 2000).
- Even when the constructs included in a model are observable variables (e.g. number of patents, international experience in years, price variation, growth of sales, ROS, ROE, etc), compared to linear regression SEM has advantages related with the **creation and estimation of models that simultaneously include several dependent and independent variables**.
- So in a glance, why is SEM so popular today?
  - **Not all variables involved in a particular "phenomenon" are manifest**, that is, observable or directly manipulable;
  - **Increased complexity of theoretical models** capable of explaining a given event;
  - SEM allows for the **modeling and testing of relationships among multiple independent and dependent constructs, all at once**.
  - Software for SEM are **easy to use**.

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B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *PLS-SEM vs CB-SEM*

- Some authors argue that SEM techniques can be:
  - Covariance-based (CB-SEM) – **LISREL**, **AMOS**, EQS, Mplus; SePath;
  - Variance-based or partial least squares (PLS-SEM): **SmartPLS**, WarpPLS, PLS Graph, ...
- The most important reason to select CB-SEM or PLS-SEM is the research goal (Hair et al., 2011):
  - If the goal is theory testing, theory confirmation, or comparison of alternative theories, select **CB-SEM**.
  - If the research is exploratory or an extension of an existing structural theory, select **PLS-SEM**.

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B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *PLS-SEM vs CB-SEM*

- It all starts with Swedish econometrician Herman Wold (1908-1992):
  - He was PhD supervisor of Karl Jöreskog – one of the LISREL CB-SEM software developers;
  - He was also PhD supervisor of Jan-Bernd Lohmöller – one of the first authors to write about PLS.
- Wold called CB-SEM as **hard modeling** and PLS-SEM as **soft modeling**.
- Wold developed the variance-based SEM or PLS-SEM in the 1970s (Wold, 1973; 1975), but the software packages that explore PLS-SEM only appear much years later:
  - PLSGraph – Chin, 1990s;
  - SmartPLS – Ringle, Wende and Will, 2005;
  - WarpPLS – Kock, 2009.
- The first commercial version (version 3) of LISREL software (CB-SEM) was released in 1975.
- Jöreskog & Wold (1982) classified CB-SEM and PLS-SEM as **complementary approaches**, instead of competitive.
- Wold recognized CB-SEM potential for social sciences but (Hair et al., 2011; Dijkstra, 2010):
  - He was concerned with the **distributional requirements** that he classified as **unrealistic** for empirical research;
  - He believed that it emphasized estimation and description too much and prediction too little.

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B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *PLS-SEM vs CB-SEM*

- **PLS-SEM** and **CB-SEM** are applied when unobserved variables are included in the model, but they employ different algorithms and have different objectives (Richter et al., 216).
- **CB-SEM** is a factor-based approach of SEM while **PLS-SEM** is a composite-based form of SEM (Rigdon et al., 2017).
- **CB-SEM** considers a construct as a common factor and focuses on **minimizing the difference between the model-implied and empirical covariance matrices** (Rigdon et al., 2017);
- **PLS-SEM** focuses on the **maximization of explained variance of endogenous constructs** and is a more prediction-oriented approach (Rigdon et al., 2017; Cepeda-Carrión et al., 2016; Shmueli et al., 2016).

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B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *CB-SEM vs PLS-SEM*

- Some differences between the two SEM methods:

CB - SEM	PLS-SEM
The model parameters are estimated in order to **minimize the difference between the estimated and sample covariance matrices.**	The model parameters are estimated in order to **maximize the explained variance** of the endogenous latent variables.
Parameter oriented, and thus optimal for **parameter accuracy**.	**Prediction oriented**, and thus optimal for **prediction accuracy**.
Considers multivariate **normal distribution**.	Makes **no distributional assumptions**.
Requires high sample sizes. Recommendations for the minimum number of observation: **200 – 800**.	Works with small sample sizes. Recommendations for the minimum number of observation: **30 - 100**.
Defines convergence as the increase/decrease in the function value beyond a certain threshold.	Defines convergence as the point at which no substantial difference occurs from one iteration to the next.
Included **goodness-of-fit statistics**.	**No** (established) **goodness-of-fit statistics**.
Typically, only supports **reflective indicators**.	Supports **reflective** and **formative indicators**.
Calculates constructs as common **factors**: common variance is used to estimate model parameters.	Calculates constructs as **composites** of indicators: the total variance is used to estimate model parameters.

Source: Adapted from Hair et al., 2017; Sarstedt, Ringle & Hair, 2014.

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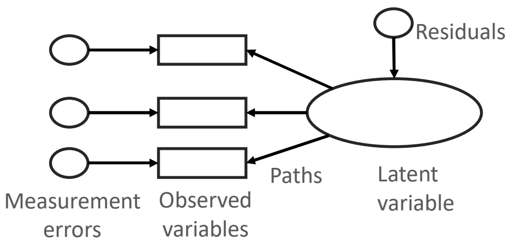
B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *VARIABLES*

- Both SEM start in the same point:
  - **Manifest or observed variables (or indicator or item)**
    These variables are measured or observed directly;
  - **Latent variables, factors or constructs**
    These variables are not directly observable or measured;
    Some examples are related with beliefs, intentions and feelings;
    Their 'existence' is indicated by their manifestation in indicator or manifest variables.



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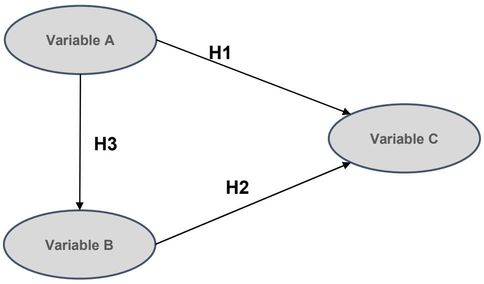
B.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *VARIABLES*

- Both types of variables (latent or manifest) can be independent or dependent:
  - **Independent variables (or exogenous variables)**
  The causes of these variables reside outside the model, thus they are not influenced by any other variable in the model.
  - **Dependent variables (or endogenous variables)**
  The causes of the variation of these variables reside in the model, thus the variation of these variables is explained by variables in the model.



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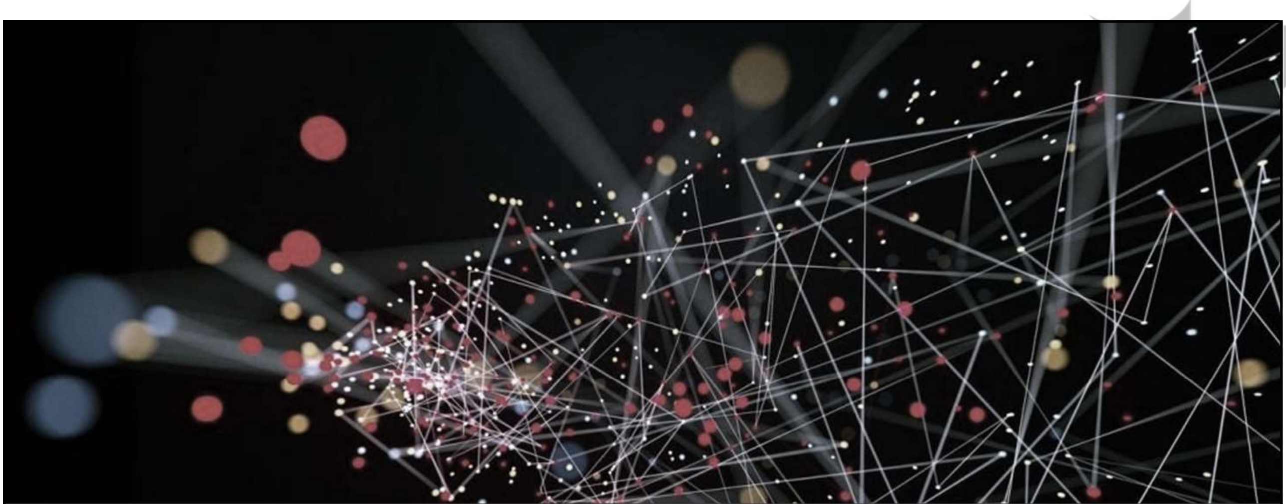

CB-SEM

CHAPTER B.2

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Introduction to CB-SEM & AMOS

B.2.1

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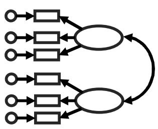
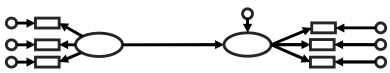
B.2.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔MEASUREMENT AND STRUCTURAL MODEL

- **The SEM presents usually two different components:**
  - **Measurement Model:** Defines the way the latent variables are operationalized/ measured by observed variables.



  - **Structural Model:** Defines the causal or association relations between latent variables.



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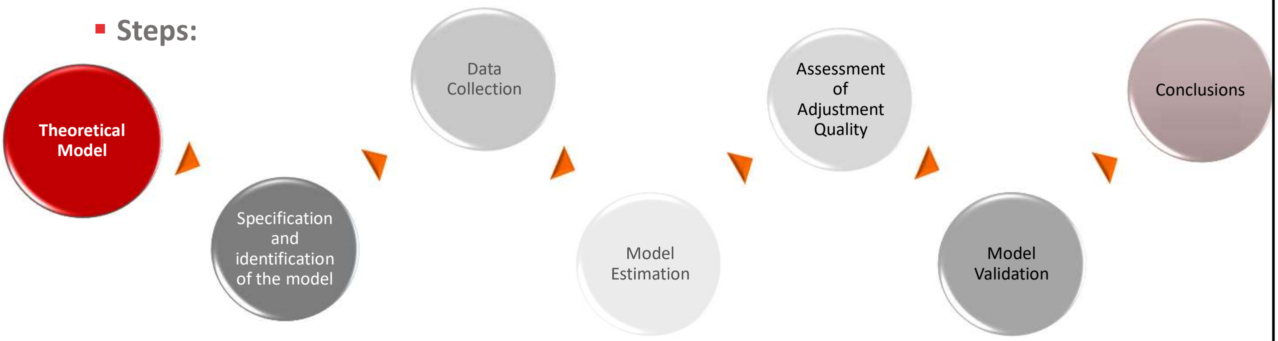
B.2.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔STEPS

- **Steps:**



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B.2. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ SAMPLE

- Sample dimension:
  - Minimum of 200 cases (Boomsma, 1985);
  - 10 cases per variable (Nunnally, 1967);
  - Rule of thumb 10:1 or 5:1, comparing the number of observations and the number of estimated parameters (Bentler & Chou, 1987; Bollen, 1989);

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Creating Projects with AMOS

B.2.2

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B.2.2. CREATING PROJECTS WITH AMOS

→EXISTING SOFTWARES

- Examples of CB-SEM softwares:
  - **AMOS;**
  - LISREL;
  - EQS;
  - Mplus;
  - SePath;
  - …

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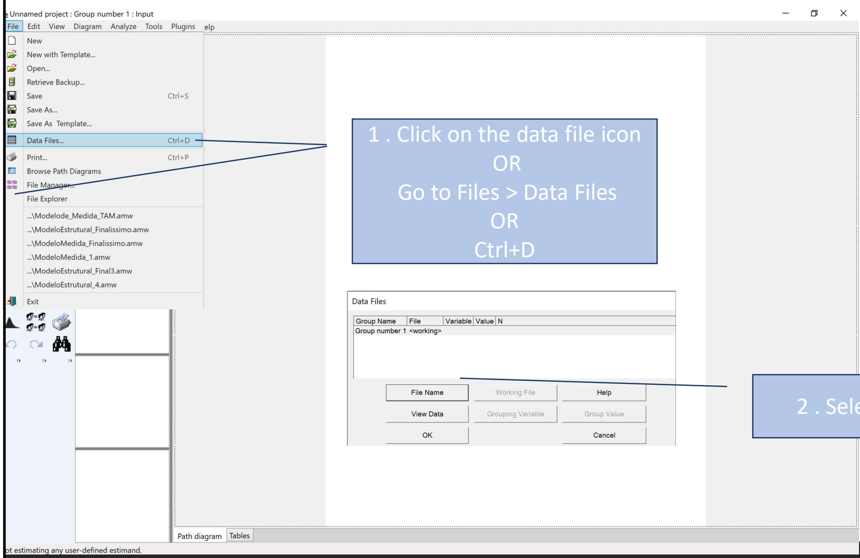
B.2.2. CREATING PROJECTS WITH AMOS
➔FIRST STEPS



1 . Click on the data file icon
OR
Go to Files > Data Files
OR
Ctrl+D

2 . Select the data file.

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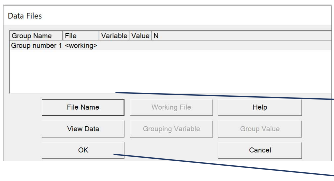
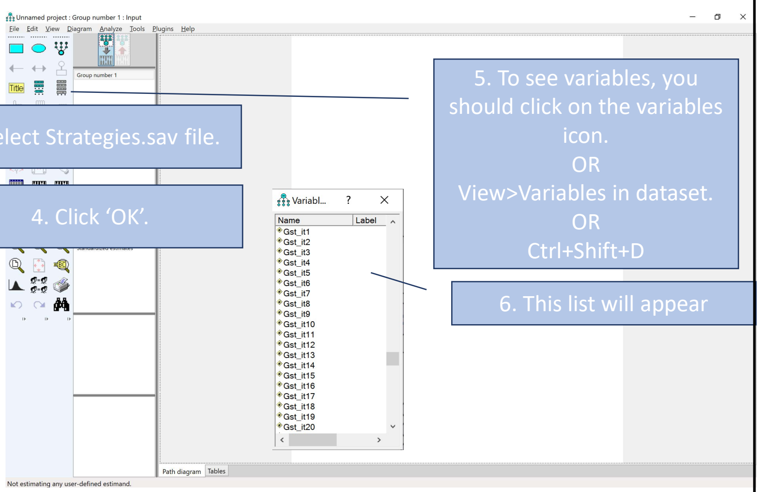
B.2.2. CREATING PROJECTS WITH AMOS
➔FIRST STEPS



3. Select Strategies.sav file.

4. Click 'OK'.

AMOS accepts several types of data files, such as *.dbf; *.csv; *.txt; *.xls; *.xlsx and *.sav files.



5. To see variables, you should click on the variables icon.
OR
View>Variables in dataset.
OR
Ctrl+Shift+D

6. This list will appear

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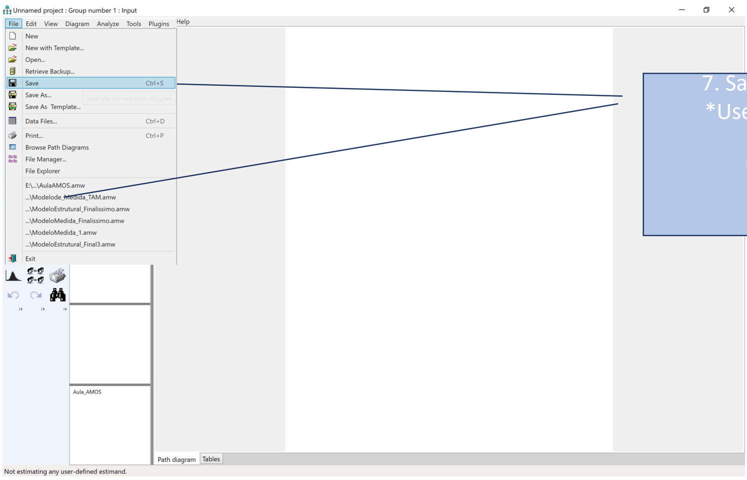
B.2.2. CREATING PROJECTS WITH AMOS
→ FIRST STEPS



7. Save the project:
*Use the save icon
OR
*File>Save
OR
Ctrl+S

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B.2.2. CREATING PROJECTS WITH AMOS
→ INITIAL SCREENING

- But before we advance, we need to do the initial screening of data:
  - Missing data in rows (analysis by case) → Use Excel or SPSS;
  - Missing data in columns (analysis by variable) → Use Excel or SPSS;
  - Unengaged responses → Use Excel or SPSS;
  - Outliers (relevant for continuous variables) → Use SPSS;
  - Normality (Kline, 2015) → Use SPSS:
    - Skewness: needs to be less than |10|;
    - Kurtosis: needs to be less than |3|.
- Other issues:
  - **Nonresponse bias** (comparison between first 75% responses with last 25% responses);
  - **Common-method bias** (Harman's one factor).

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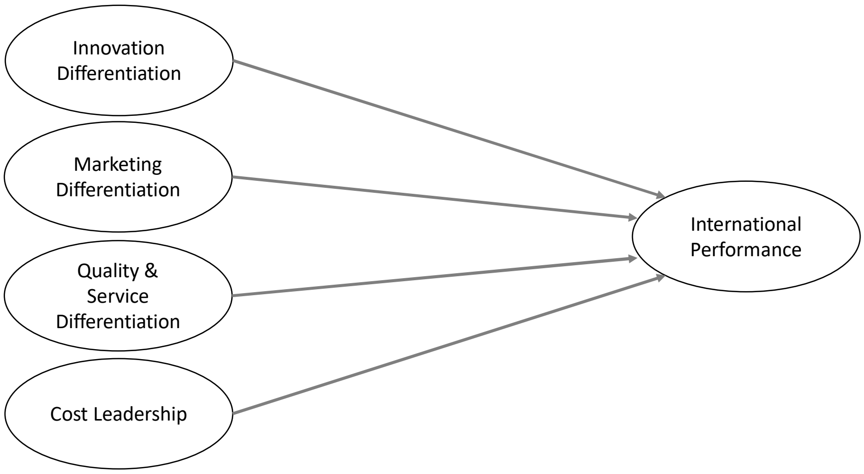
B.2.2. CREATING PROJECTS WITH AMOS
➔FIRST STEPS (example)

- But first, we need to know more about the conceptual model.



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B.2.2. CREATING PROJECTS WITH AMOS
➔FIRST STEPS (example)

- Measures:

	INNOVATION DIFFERENTIATION (Beal., 2000) *(seven-point Likert scale anchored with 1='Much worse than main competitors' to 7='Much better than main competitors')*
Gst_it1	R&D of new products
Gst_it2	Marketing of new products
Gst_it3	Selling high-priced products
	MARKETING DIFERENTIATION (Beal., 2000) *(seven-point Likert scale anchored with 1='Much worse than main competitors' to 7='Much better than main competitors')*
Gst_it4	Obtaining patents or copyrights
Gst_it5	Innovative marketing techniques
Gst_it6	Building brand/company identification
Gst_it7	Advertising/promotional programs
Gst_it8	Securing reliable distribution channels
	QUALITY & SERVICE DIFERENTIATION (Beal., 2000) *(seven-point Likert scale anchored with 1='Much worse than main competitors' to 7='Much better than main competitors')*
Gst_it9	Improving existing products
Gst_it16	Strict product quality control
Gst_it19	Immediate resolution of customer problems
Gst_it20	Product improvements based on gaps in meeting customer expectations
Gst_it21	New customer services
Gst_it22	Improvement of existing customer services

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B.2.2. CREATING PROJECTS WITH AMOS
➔FIRST STEPS (example)

- Measures:

	COST LEADERSHIP (Beal., 2000) *(seven-point Likert scale anchored with 1='Much worse than main competitors' to 7='Much better than main competitors')*
Gst_it11	Improving efficiency and productivity
Gst_it12	Developing new manufacturing processes
Gst_it13	Improving existing manufacturing processes
Gst_it14	Reducing overall costs
Gst_it15	Reducing manufacturing costs

	INTERNATIONAL PERFORMANCE (Jantunen et al., 2008) *(seven-point Likert scale anchored with (1 = Very unsatisfied; 7 = Very satisfied))*
IPerf_it1	Sales volume
IPerf_it2	Market share
IPerf_it3	Profitability
IPerf_it4	Market entry
IPerf_it5	Image development
IPerf_it6	Knowledge development

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B.2.2. CREATING PROJECTS WITH AMOS
➔FIRST STEPS (example)

- Our database:
  - Empirical data used to test the hypotheses was drawn from a online structured questionnaire conducted in 2011;
  - Population:
    - Multi-industry Portuguese new ventures (1.993 eligible firms);
    - Weight of foreign sales was defined as 25% of total sales.
    - Firms took 6 or less years to achieve that weight in the total sales.
  - Initial pretest with a dozen firms;
  - Initial contact with firms by telephone;
  - Final sample: 319usable responses (response rate of 20.9%).
- Reference:
  - Crespo, N.F., Simões, V.C. & Fontes, M. (2020), Competitive strategies and international new ventures' performance: Exploring the moderating effects of internationalization duration and preparation, *Business Research Quarterly*, 23(2), p. 120-140.

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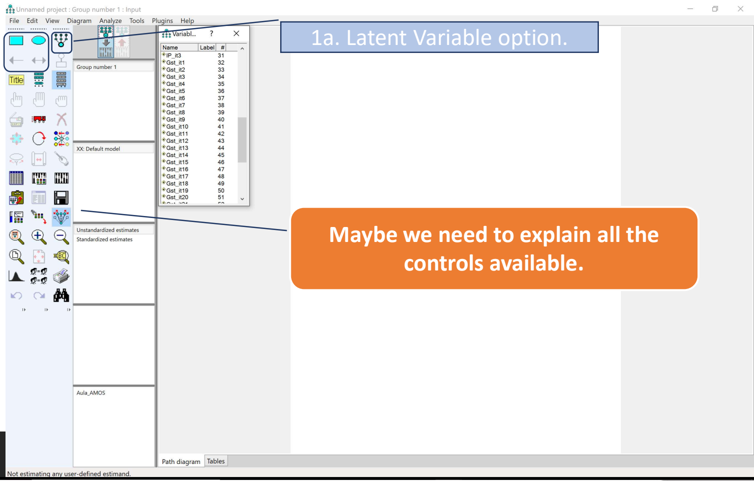
B.2.2. CREATING PROJECTS WITH AMOS
➔FIRST STEPS

- Let's setup our model. Two options:
  - Using the latent variable option (EASIER);
  - Design each latent variable by hand.

1a. Latent Variable option.

1b. Design by hand.



Maybe we need to explain all the controls available.

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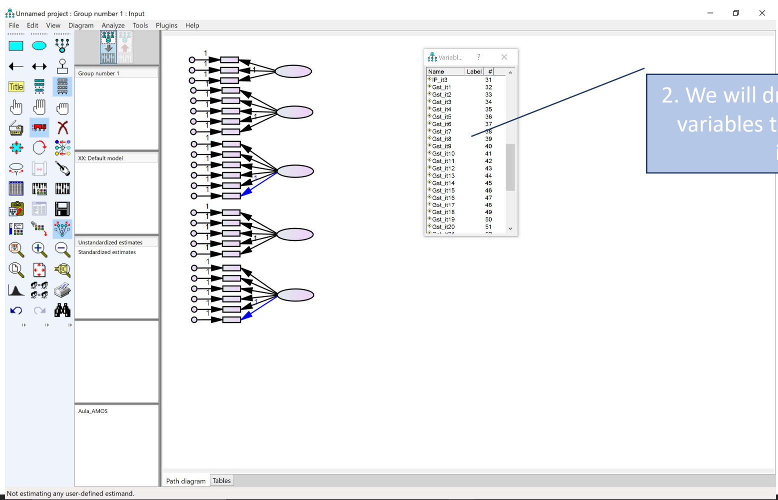
B.2.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS

- Now let's start to include the items:



2. We will drag the respective variables to the respective items.

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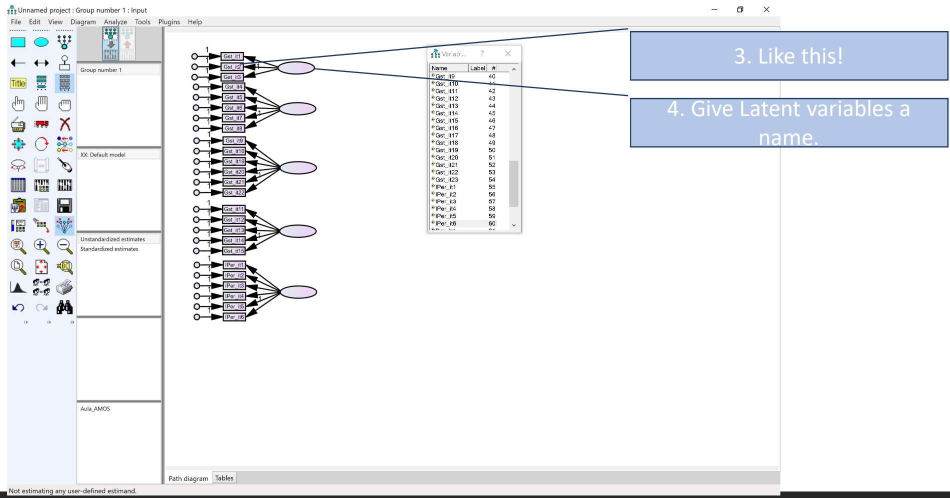
B.2.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS

- Latent variables names:



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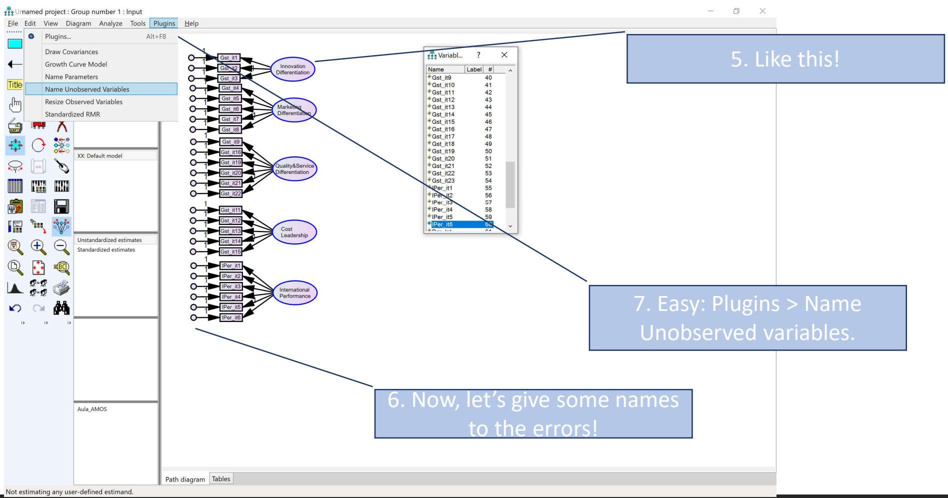
B.2.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS

- Errors names:



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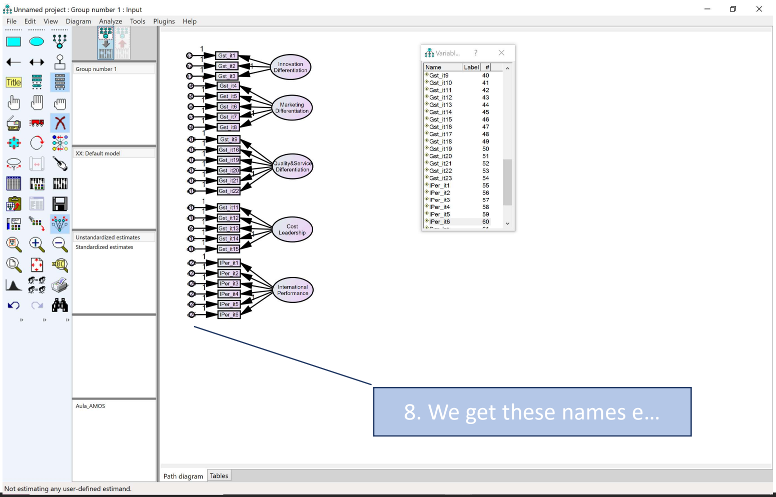
B.2.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS

- Errors names:



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Measurement Models | **B.2.3**

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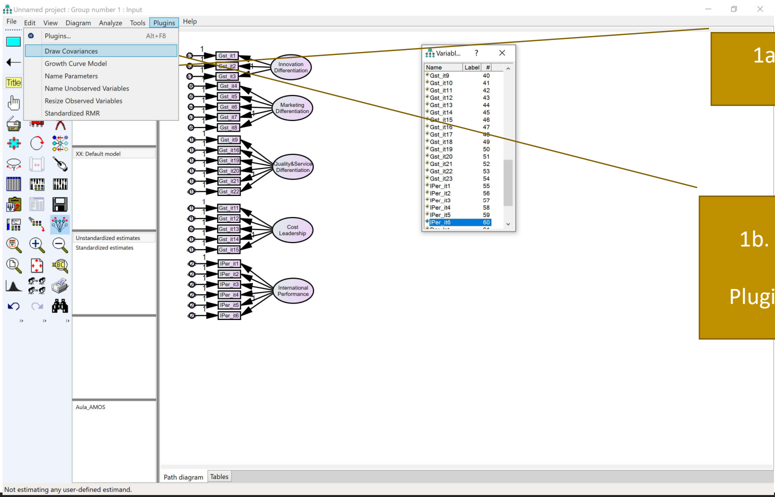
B.2.3. MEASUREMENT MODEL
➔INTRODUCTION

- Include covariances:



1a. Manually: Use 'draw covariances tool

1b. Easier way: Select all latent variables + Plugins>Draw covariances.

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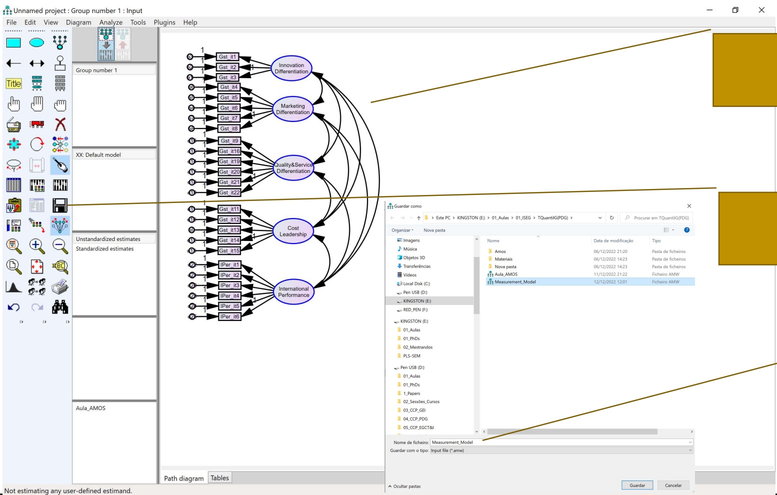
B.2.3. MEASUREMENT MODEL
➔INTRODUCTION

- Save the model:



2. Like this!

3. Save

4. Give name: Measurement Model

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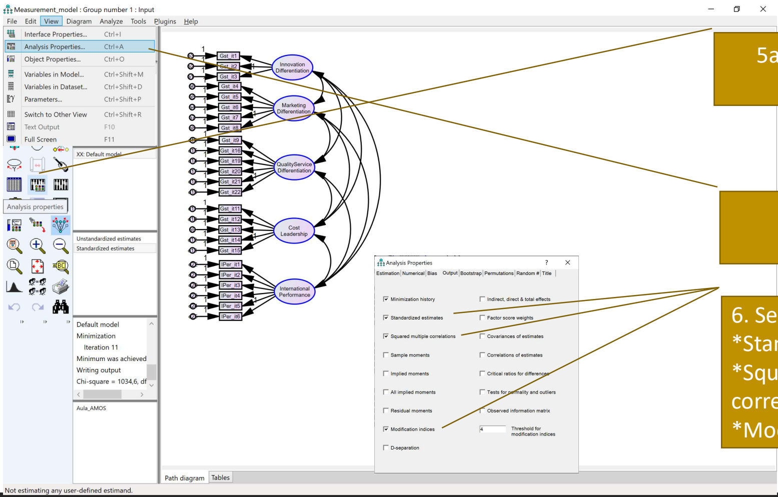
B.2.3. MEASUREMENT MODEL ➔INTRODUCTION

- Run de model:



5a. Click on the Analysis Properties icon!

5b. View> Analysis Propperties.

6. Select:
*Standardized estimates;
*Squared multiple correlations;
*Modification indices.

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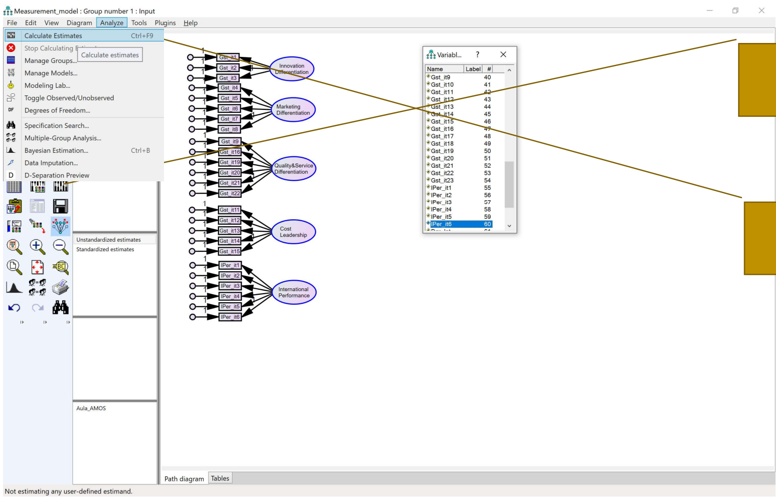
B.2.3. MEASUREMENT MODEL ➔INTRODUCTION

- Run the model:



7a. Click on the Abacus!

7b. Analyse> Calculate Estimates.

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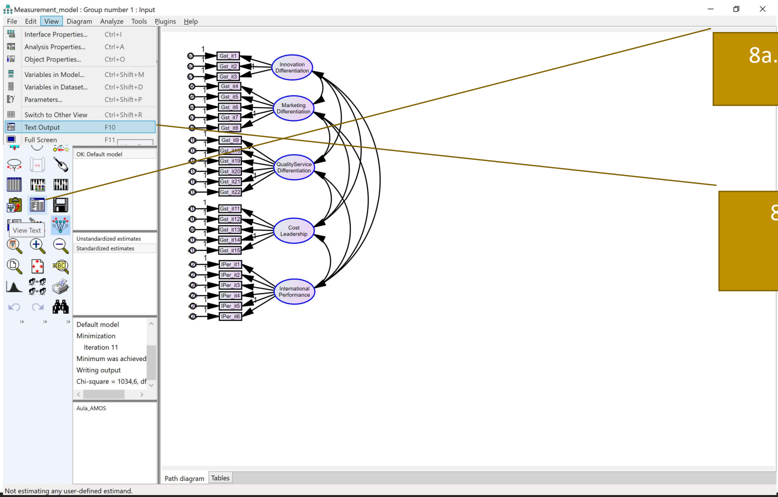
B.2.3. MEASUREMENT MODEL
➔INTRODUCTION

- See the results:



8a. Click on the View text icon.

8b. View> Text output
OR
F10

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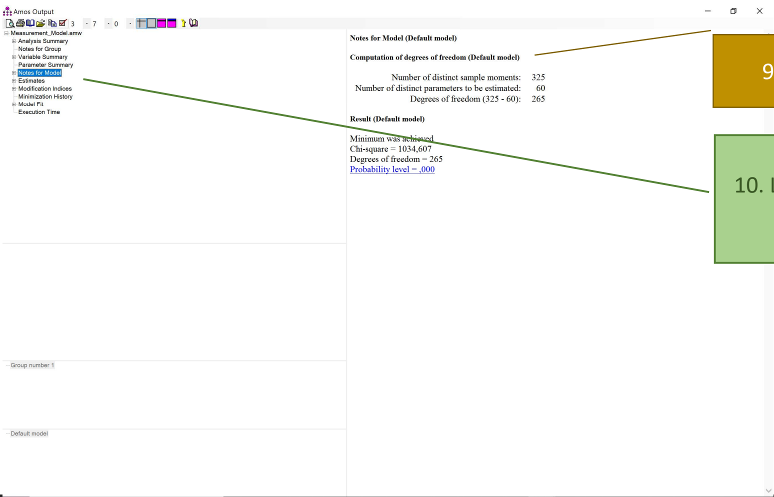
B.2.3. MEASUREMENT MODEL
➔INTRODUCTION

- See the results:



9. This report appears.

10. Let's do a jam session on the report.

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Evaluating CB-SEM Models

B.2.4

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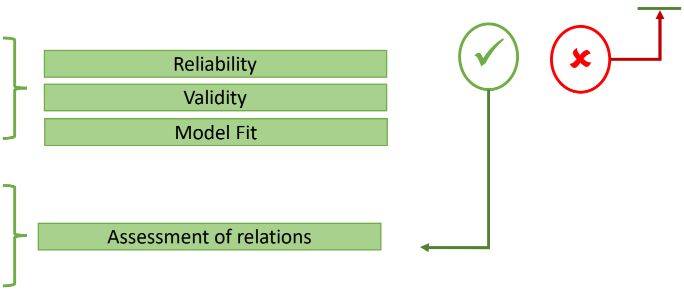
B.2.4. EVALUATING CB-MODELS

➔ *STEPS*

- The two-stages process is followed (Anderson and Gerbing, 1988; Hair et al., 2019):
  - **STAGE 1:** Measurement model
  - **STAGE 2:** Structural model.
- Measurement Models:
  - Reflective measurement models.
- Structural Models.



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B.2.4. EVALUATING CB-SEM MODELS
➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

Measurement Model		Cut-off
Unidimensionality & Reliability	Loadings of the items	≥0.60 or **≥0.70** (Bagozzi & Yi, 1988, 2012)
	Cronbach's Alpha	**α≥0.70** (Cronbach, 1951)
	Composite Reliability (CR)	CR≥0.60 or **CR≥0.70** (Hair et al., 2009; Bagozzi & Yi, 2012)
Convergent Validity	Loadings of the items	≥0.60 or **≥0.70** (Bagozzi & Yi, 1988, 2012)
	Average Variance Extracted (AVE)	CR≥0.50 (Hair et al., 2008)
Discriminant Validity	Average Variance Extracted (AVE)	CR≥0.50 (Hair et al., 2008)
	AVE vs r^2	AVE > r^2 or $\sqrt{AVE}$>r (Fornell & Larcker, 1981)

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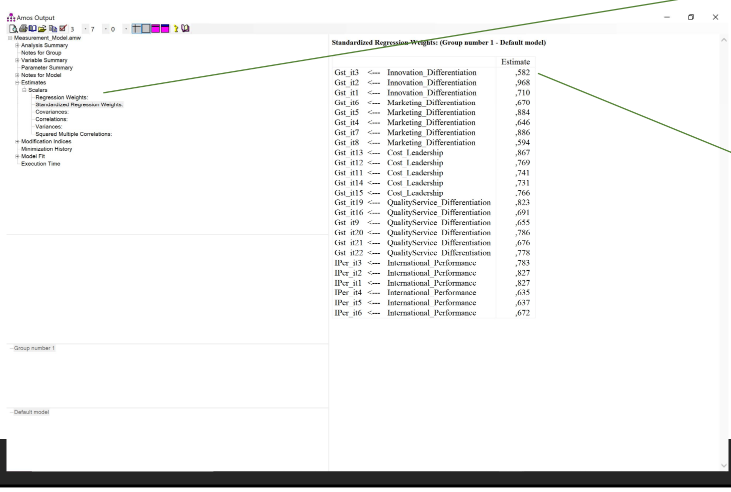
B.2.4. EVALUATING CB-SEM MODELS
➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Loadings of the items:**



Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
Gst_it3	<---	Innovation_Differentiation	,582
Gst_it2	<---	Innovation_Differentiation	,968
Gst_it1	<---	Innovation_Differentiation	,710
Gst_it6	<---	Marketing_Differentiation	,670
Gst_it5	<---	Marketing_Differentiation	,884
Gst_it4	<---	Marketing_Differentiation	,646
Gst_it7	<---	Marketing_Differentiation	,886
Gst_it8	<---	Marketing_Differentiation	,594
Gst_it13	<---	Cost_Leadership	,867
Gst_it12	<---	Cost_Leadership	,769
Gst_it11	<---	Cost_Leadership	,741
Gst_it14	<---	Cost_Leadership	,731
Gst_it15	<---	Cost_Leadership	,766
Gst_it19	<---	QualityService_Differentiation	,823
Gst_it16	<---	QualityService_Differentiation	,691
Gst_it9	<---	QualityService_Differentiation	,655
Gst_it20	<---	QualityService_Differentiation	,786
Gst_it21	<---	QualityService_Differentiation	,676
Gst_it22	<---	QualityService_Differentiation	,778
IPer_it3	<---	International_Performance	,783
IPer_it2	<---	International_Performance	,827
IPer_it1	<---	International_Performance	,827
IPer_it4	<---	International_Performance	,635
IPer_it5	<---	International_Performance	,637
IPer_it6	<---	International_Performance	,672

1. Look at the Standardized Regression Weights.

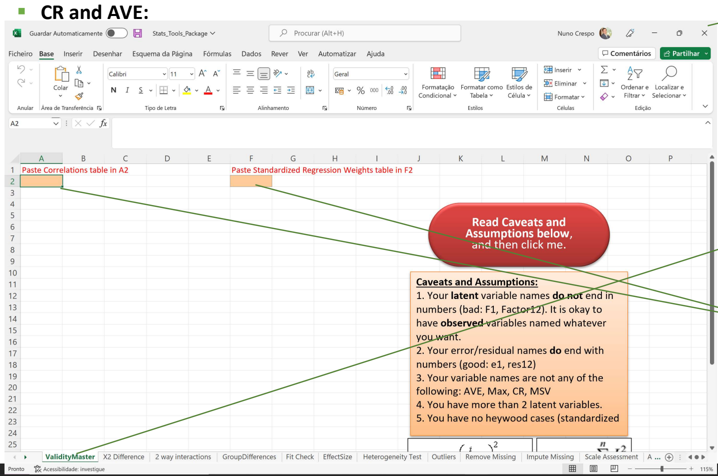
It seems that here we have a problem. Less than 0.60… But let's see if this is problematic…

44

B.2.4. EVALUATING CB-SEM MODELS

➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **CR and AVE:**



2. Open the Excel file ‘Stats_Tools_Package.xlsx’.

3. Go to the ValidityMaster sheet.

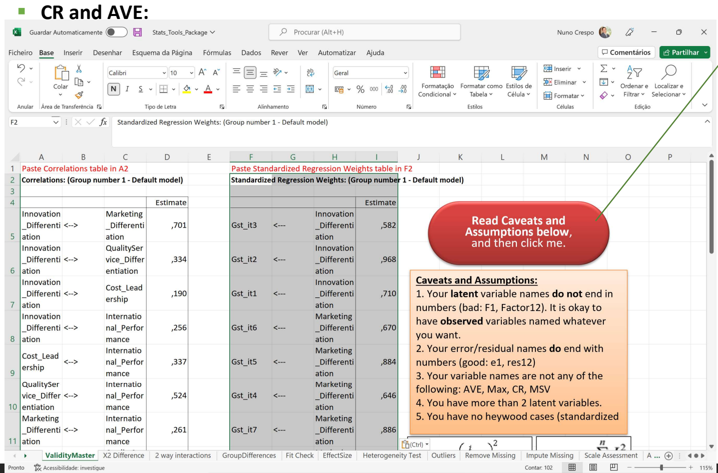
4. Copy & Paste both Correlations table and Standardized Regression Weights table.

45

B.2.4. EVALUATING CB-SEM MODELS

➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **CR and AVE:**



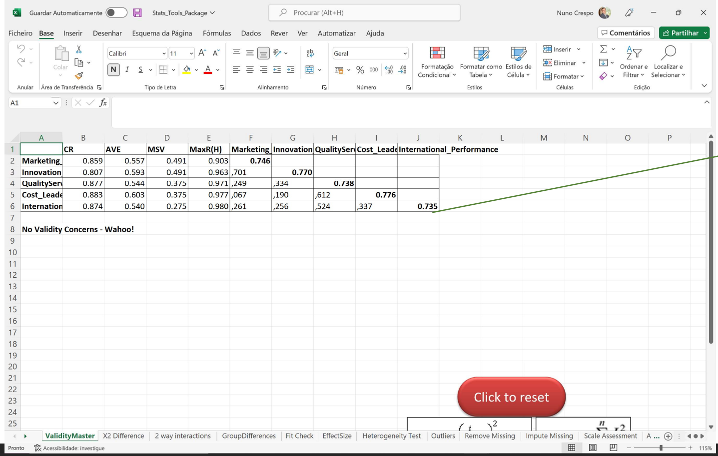
5. Press on this button to start a Macro

46

B.2.4. EVALUATING CB-SEM MODELS

➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **CR and AVE:**



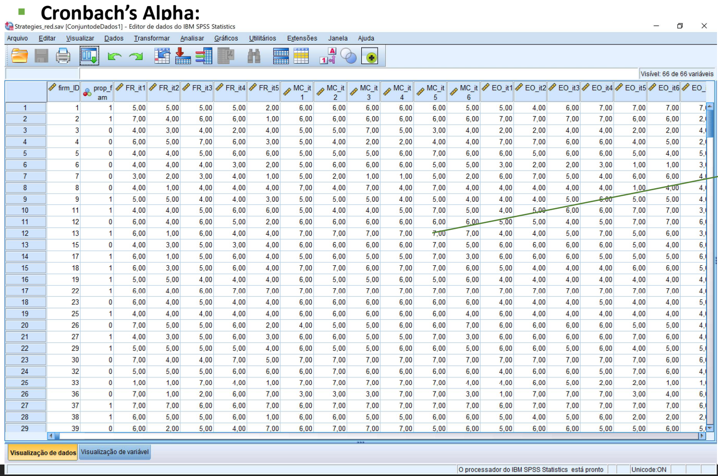
6. You will get this Table.
Here we can see:
- CR;
- AVE
  and
- Fornell & Larcker Criteria.

47

B.2.4. EVALUATING CB-SEM MODELS

➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Cronbach's Alpha:**



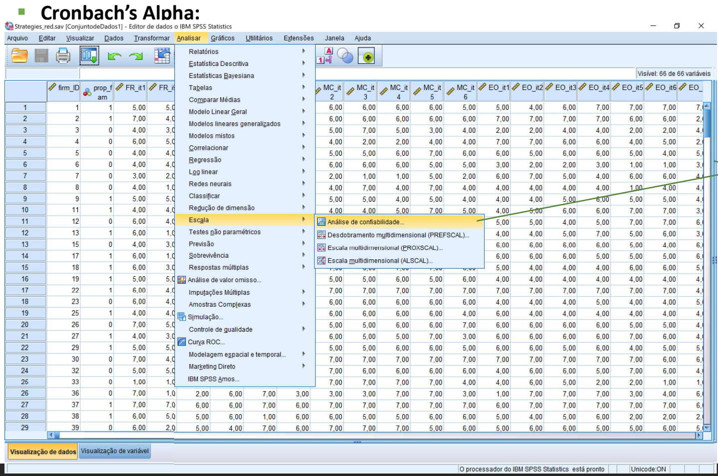
7. In the SPSS, open the File Strategies.sav

48

B.2.4. EVALUATING CB-SEM MODELS

➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Cronbach's Alpha:**



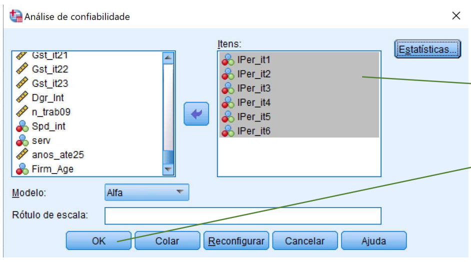
8. Analyse > Scale > Reliability Analysis
OR
Analisar > Escala > Análise de Confiabilidade

49

B.2.4. EVALUATING CB-SEM MODELS

➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Cronbach's Alpha:**



9. For each latent variable, include the items that measure the variable.
Then, press ok.

50

B.2.4. EVALUATING CB-SEM MODELS

➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Model Fit:**

Fit Index	Cut-off
χ^2/df (Normed Chi-square)	3.0 - 5.0: medíocre fit. 2.0 - 3.0: good fit.
RMSEA (Root Mean Square Error of Approximation)	≤0.06: good fit; 0.06-0.08: reasonable fit; 0.08-0.1: mediocre fit; >0.1: poor fit.
GFI (Goodness-of-Fit Index)	>0.90: good fit.
NFI (Normed Fit Index)	>0.90: good fit.
CFI (Comparative Fit Index)	>0.90: good fit.
IFI (Incremental Fit Index)	>0.90: good fit.

Source: Based on Diamantopoulos & Siguaw, 2008; Bagozzi & Yi, 2012; Vieira, 2010; Iacobucci, 2010, Hooper el al, 2008; Hair et al. 2019.

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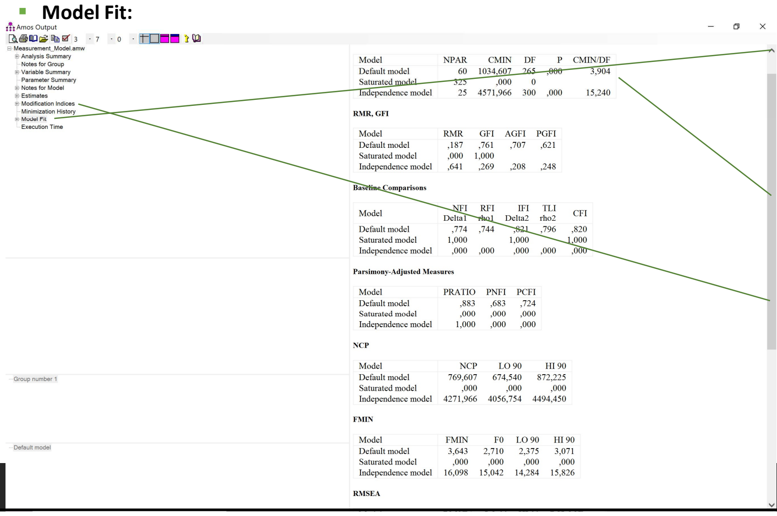
B.2.4. EVALUATING CB-SEM MODELS

➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Model Fit:**



Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	60	1034,607	265	,000	3,904
Saturated model	325	,000	0		
Independence model	25	4571,966	300	,000	15,240

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,187	,761	,707	,621
Saturated model	,000	1,000		
Independence model	,641	,269	,208	,248

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,774	,744	,821	,796	,820
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,883	,683	,724
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	769,607	674,540	872,225
Saturated model	,000	,000	,000
Independence model	4271,966	4056,754	4494,450

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	3,643	2,710	2,375	3,071
Saturated model	,000	,000	,000	,000
Independence model	16,098	15,042	14,284	15,826

RMSEA

11. In the Report section, go to Model Fit.

12. The indices are not Exceptional, but we can improve the fit.

13. Go to Modification Indices, and identify the highest values, suggesting the covariances between errors of variables.

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B.2.4. EVALUATING CB-SEM MODELS

➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Model Fit:**

Amos Output

Measurement_Model.amw
- Analysis Summary
- Notes for Group
- Variable Summary
- Parameter Summary
- Notes for Model
- Estimates
- Modification Indices
- Minimization History
- Model Fit
- Execution Time

Group number 1

Default model

Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

			M.I.	Par Change
e24	<-->	Marketing_Differentiation	21,796	,222
e24	<-->	e25	60,236	,344
e22	<-->	e24	25,219	-,201
e18	<-->	e19	34,845	,266
e16	<-->	Cost_Leadership	22,394	,222
e12	<-->	e13	118,313	,526
e11	<-->	e16	29,698	,236
e10	<-->	e12	21,593	-,256
e9	<-->	e12	24,618	-,197
e9	<-->	e10	45,245	,334
e3	<-->	Cost_Leadership	25,195	,341

Variances: (Group number 1 - Default model)

	M.I.	Par Change

Regression Weights: (Group number 1 - Default model)

			M.I.	Par Change
IPer_it6	<---	IPer_it5	33,493	,245
IPer_it5	<---	Marketing_Differentiation	31,357	,290
IPer_it5	<---	IPer_it6	30,379	,285
IPer_it5	<---	Gst_it7	34,264	,169
IPer_it5	<---	Gst_it5	21,290	,138
IPer_it5	<---	Gst_it6	29,128	,167
Gst_it9	<---	Gst_it11	34,021	,248
Gst_it15	<---	Gst_it14	49,644	,336
Gst_it14	<---	Gst_it15	42,727	,243
Gst_it11	<---	Gst_it9	36,814	,284
Gst_it12	<---	Gst_it1	23,074	,182
Gst_it6	<---	Gst_it9	21,792	,347
Gst_it6	<---	Gst_it11	21,097	,310
Gst_it1	<---	Cost_Leadership	30,877	,408
Gst_it1	<---	Gst_it12	44,092	,310
Gst_it1	<---	Gst_it13	32,693	,314

14. For instasse, include a covariance between e12 and e13, will improve the X2 in 118,31.

53

B.2.4. EVALUATING CB-SEM MODELS

➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Model Fit:**

Amos Output

Measurement_Model.amw
- Analysis Summary
- Notes for Group
- Variable Summary
- Parameter Summary
- Notes for Model
- Estimates
- Modification Indices
- Minimization History
- Model Fit
- Execution Time

Group number 1

Default model

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	60	1034,607	265	,000	3,904
Saturated model	325	,000	0		
Independence model	25	4571,966	300	,000	15,240

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,187	,761	,707	,621
Saturated model	,000	1,000		
Independence model	,641	,269	,208	,248

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,774	,744	,821	,796	,820
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,883	,683	,724
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	769,607	674,540	872,225
Saturated model	,000	,000	,000
Independence model	4271,966	4056,754	4494,450

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	3,643	2,710	2,375	3,071
Saturated model	,000	,000	,000	,000
Independence model	16,098	15,042	14,284	15,826

RMSEA

11. In the Report section, go to Model Fit.

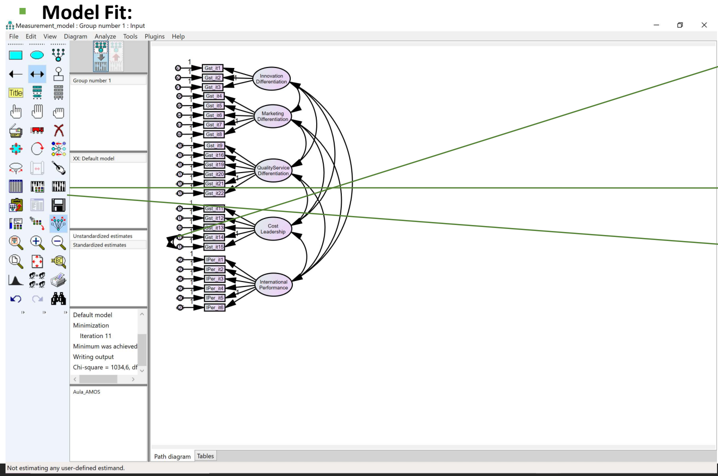
12. The indices are not Exceptional, but we can improve the fit.

13. Go to Modification Indices, and identify the highest values, suggesting the covariances between errors of variables.

54

B.2.4. EVALUATING CB-SEM MODELS
➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Model Fit:**



14. Include the variance between e12 and e13.

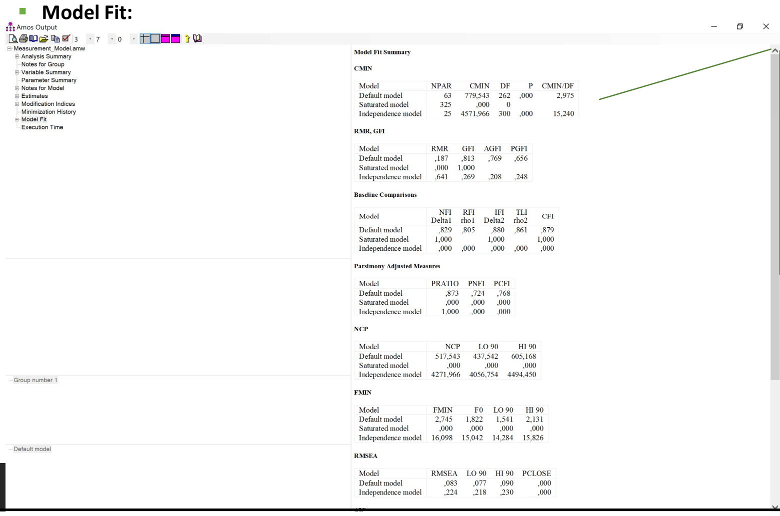
15. Run the model.

16. Repeat the process until no modification indices appear.

55

B.2.4. EVALUATING CB-SEM MODELS
➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**
  - **Model Fit:**



Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	63	779,543	262	,000	2,975
Saturated model	325	,000	0		
Independence model	25	4571,966	300	,000	15,240

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,187	,813	,769	,656
Saturated model	,000	1,000		
Independence model	,641	,269	,208	,248

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,829	,805	,880	,861	,879
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,873	,724	,768
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	517,543	437,542	605,168
Saturated model	,000	,000	,000
Independence model	4271,966	4056,754	4494,450

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	2,745	1,822	1,541	2,131
Saturated model	,000	,000	,000	,000
Independence model	16,098	15,042	14,284	15,826

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,083	,077	,090	,000
Independence model	,224	,218	,230	,000

17. The values improve:
- X2/df=2.975
- GFI=0.813
- CFI=0.879
- IFI=0.880
- NFI=0.829
- RMSEA=0.083

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Structural Model

B.2.5

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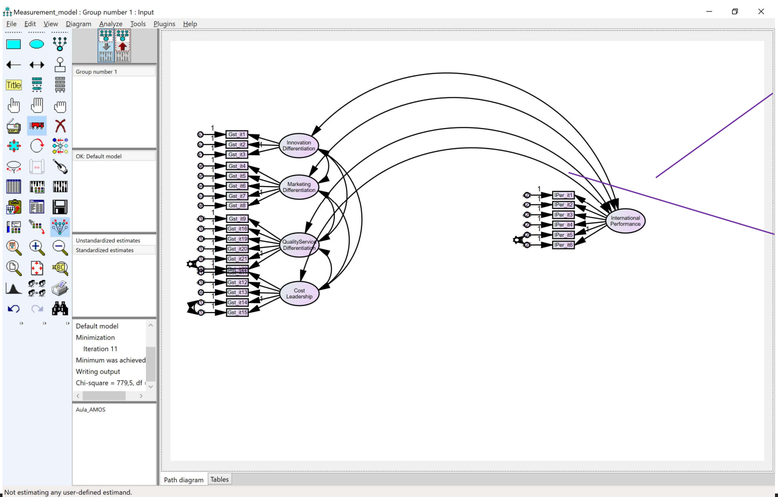
B.2.5. STRUCTURAL MODEL

- Let's organize the model:



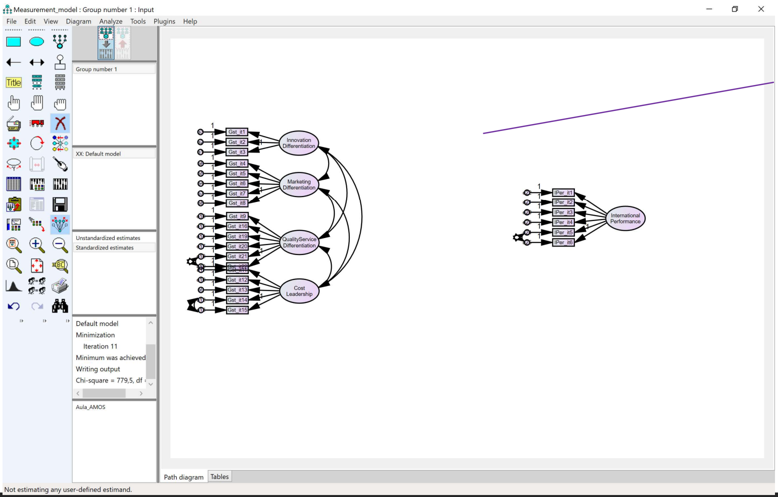
1 . Move the variables according to the alignment of the conceptual framework.

2 . Remove the covariances between independent and dependent variables.

58

B.2.5. STRUCTURAL MODEL

- Let's organize the model:

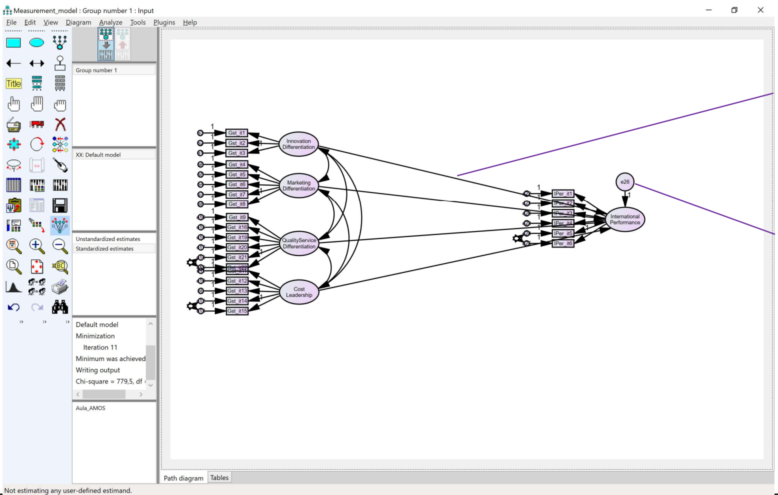


3 . Now we need to connect these variables.

59

B.2.5. STRUCTURAL MODEL

- Let's organize the model:



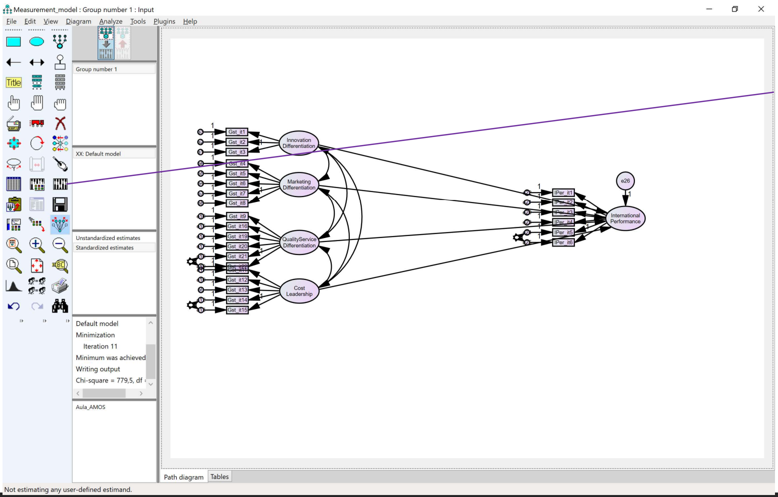
4 . We include these arrows, like presenting causality beween the strategies and the performance.

5 . We also include this for the residuals.

60

B.2.5. STRUCTURAL MODEL

- Let's organize the model:

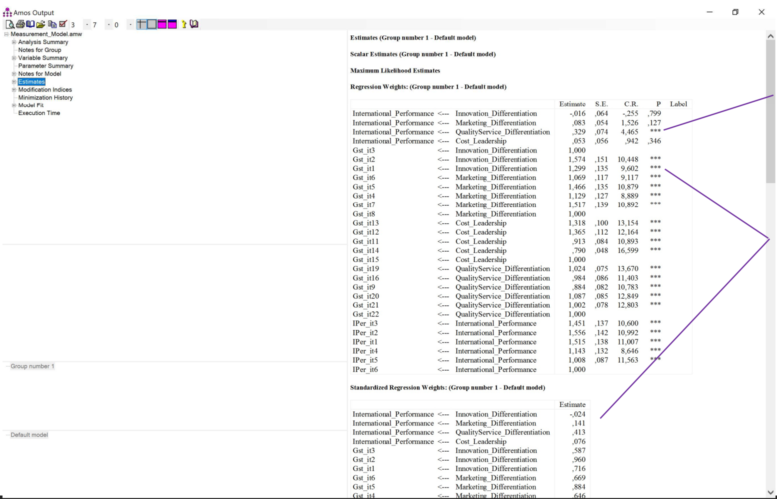


6 . Next step: Run the model!
(i.e. Calculate estimates)

61

B.2.5. STRUCTURAL MODEL

- Let's organize the model:



Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
International_Performance	<---	Innovation_Differentiation	-,016	,064	-,255	,799	
International_Performance	<---	Marketing_Differentiation	,083	,054	1,526	,127	
International_Performance	<---	QualityService_Differentiation	,329	,074	4,465	***	
International_Performance	<---	Cost_Leadership	,053	,056	,942	,346	
Gst_it3	<---	Innovation_Differentiation	1,000				
Gst_it2	<---	Innovation_Differentiation	1,574	,151	10,448	***	
Gst_it1	<---	Innovation_Differentiation	1,299	,135	9,602	***	
Gst_it6	<---	Marketing_Differentiation	1,069	,117	9,117	***	
Gst_it5	<---	Marketing_Differentiation	1,466	,135	10,879	***	
Gst_it4	<---	Marketing_Differentiation	1,129	,127	8,889	***	
Gst_it7	<---	Marketing_Differentiation	1,517	,139	10,892	***	
Gst_it8	<---	Marketing_Differentiation	1,000				
Gst_it13	<---	Cost_Leadership	1,318	,100	13,154	***	
Gst_it12	<---	Cost_Leadership	1,365	,112	12,164	***	
Gst_it11	<---	Cost_Leadership	,913	,084	10,893	***	
Gst_it14	<---	Cost_Leadership	,790	,048	16,599	***	
Gst_it15	<---	Cost_Leadership	1,000				
Gst_it19	<---	QualityService_Differentiation	1,024	,075	13,670	***	
Gst_it16	<---	QualityService_Differentiation	,984	,086	11,403	***	
Gst_it9	<---	QualityService_Differentiation	,884	,082	10,783	***	
Gst_it20	<---	QualityService_Differentiation	1,087	,085	12,849	***	
Gst_it21	<---	QualityService_Differentiation	1,002	,078	12,803	***	
Gst_it22	<---	QualityService_Differentiation	1,000				
IPer_it3	<---	International_Performance	1,451	,137	10,600	***	
IPer_it2	<---	International_Performance	1,556	,142	10,992	***	
IPer_it1	<---	International_Performance	1,515	,138	11,007	***	
IPer_it4	<---	International_Performance	1,143	,132	8,646	***	
IPer_it5	<---	International_Performance	1,008	,087	11,563	***	
IPer_it6	<---	International_Performance	1,000				

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
International_Performance	<---	Innovation_Differentiation	-,024
International_Performance	<---	Marketing_Differentiation	,141
International_Performance	<---	QualityService_Differentiation	,413
International_Performance	<---	Cost_Leadership	,076
Gst_it3	<---	Innovation_Differentiation	,587
Gst_it2	<---	Innovation_Differentiation	,960
Gst_it1	<---	Innovation_Differentiation	,716
Gst_it6	<---	Marketing_Differentiation	,669
Gst_it5	<---	Marketing_Differentiation	,884
Gst_it4	<---	Marketing_Differentiation	,646

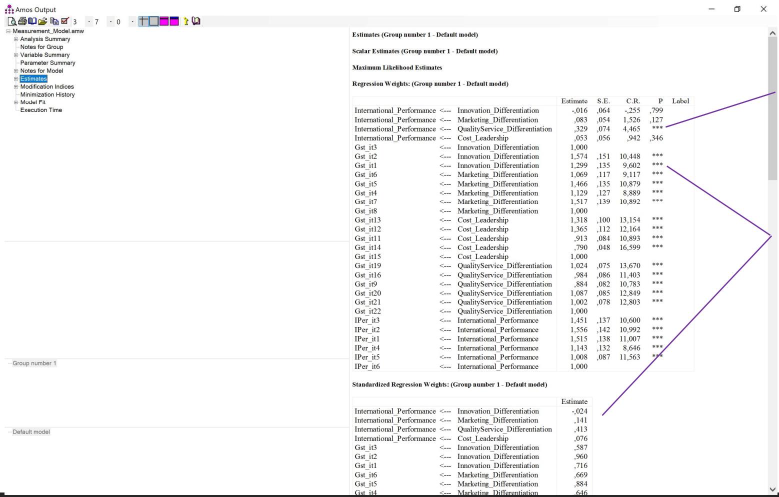
7 . The results shows that only Quality & Service Differentiation promote International Performance.

8 . You report the standardized estimates, with the p-values presented in the Regression weight table.

62

B.2.5. STRUCTURAL MODEL

- Let's organize the model:



Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
International_Performance	<---	Innovation_Differentiation	-,016	,064	-,255	,799	
International_Performance	<---	Marketing_Differentiation	,083	,054	1,526	,127	
International_Performance	<---	QualityService_Differentiation	,329	,074	4,465	***	
International_Performance	<---	Cost_Leadership	,053	,056	,942	,346	
Gst_it3	<---	Innovation_Differentiation	1,000				
Gst_it2	<---	Innovation_Differentiation	1,574	,151	10,448	***	
Gst_it1	<---	Innovation_Differentiation	1,299	,135	9,602	***	
Gst_it6	<---	Marketing_Differentiation	1,069	,117	9,117	***	
Gst_it5	<---	Marketing_Differentiation	1,466	,135	10,879	***	
Gst_it4	<---	Marketing_Differentiation	1,129	,127	8,889	***	
Gst_it7	<---	Marketing_Differentiation	1,517	,139	10,892	***	
Gst_it8	<---	Marketing_Differentiation	1,000				
Gst_it13	<---	Cost_Leadership	1,318	,100	13,154	***	
Gst_it12	<---	Cost_Leadership	1,365	,112	12,164	***	
Gst_it11	<---	Cost_Leadership	,913	,084	10,893	***	
Gst_it14	<---	Cost_Leadership	,790	,048	16,599	***	
Gst_it15	<---	Cost_Leadership	1,000				
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Gst_it16	<---	QualityService_Differentiation	,984	,086	11,403	***	
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IPer_it5	<---	International_Performance	1,008	,087	11,563	***	
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Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
International_Performance	<---	Innovation_Differentiation	-,024
International_Performance	<---	Marketing_Differentiation	,141
International_Performance	<---	QualityService_Differentiation	,413
International_Performance	<---	Cost_Leadership	,076
Gst_it3	<---	Innovation_Differentiation	,587
Gst_it2	<---	Innovation_Differentiation	,960
Gst_it1	<---	Innovation_Differentiation	,716
Gst_it6	<---	Marketing_Differentiation	,669
Gst_it5	<---	Marketing_Differentiation	,884
Gst_it4	<---	Marketing_Differentiation	,646

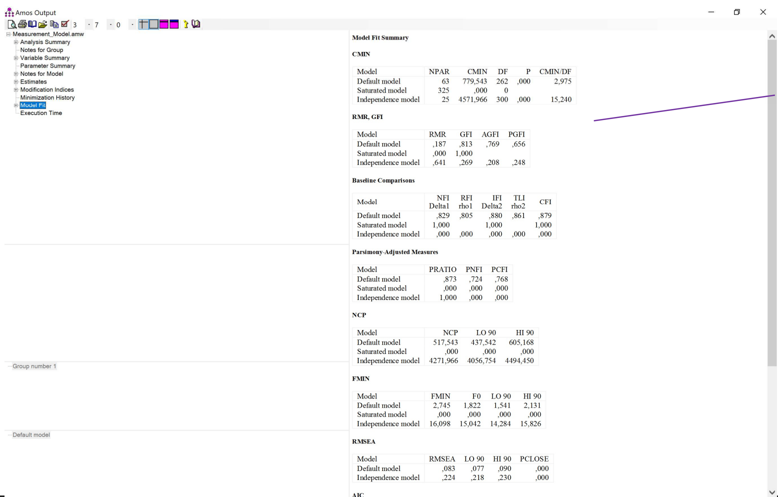
7 . The results shows that only Quality & Service Differentiation promote International Performance.

8 . You report the standardized estimates, with the p-values presented in the Regression weight table.

63

B.2.5. STRUCTURAL MODEL

- Let's organize the model:



Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	63	779,543	262	,000	2,975
Saturated model	325	,000	0		
Independence model	25	4571,966	300	,000	15,240

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,187	,813	,769	,656
Saturated model	,000	1,000		
Independence model	,641	,269	,208	,248

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,829	,805	,880	,861	,879
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,873	,724	,768
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	517,543	437,542	605,168
Saturated model	,000	,000	,000
Independence model	4271,966	4056,754	4494,450

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	2,745	1,822	1,541	2,131
Saturated model	,000	,000	,000	,000
Independence model	16,098	15,042	14,284	15,826

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,083	,077	,090	,000
Independence model	,224	,218	,230	,000

AIC

9 . You also show the Model fit for the structural model.

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Mediation

B.2.6

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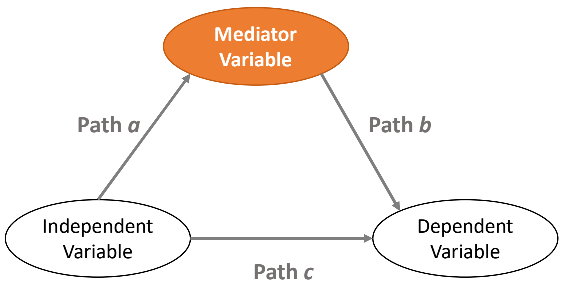
B.2.6. MEDIATION

→DEFINITION

- A variable functions as a mediator when it meets the following conditions (Baron & Kenny, 1986):
  - Variations in levels of the independent variable significantly account for variations in the presumed mediator (i.e. **Path *a***)
  - Variations in the mediator significantly account for variations in the dependent variable (i.e. **Path *b***), and
  - When paths **a** and **b** are controlled, a previously significant relation between the independent and dependent variables (i.e. **Path *c***) is no longer significant.



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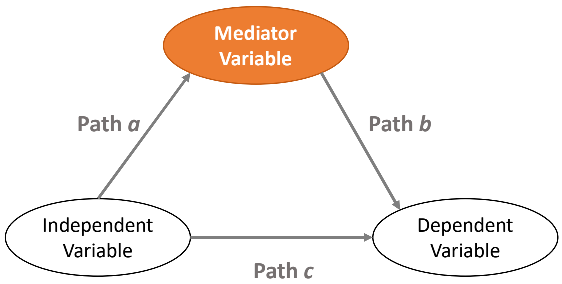
B.2.6. MEDIATION

➔*DEFINITION*

- **Partial Mediation:**
  - The ***independent variable*** still has a significant direct effect on the ***dependent variable***.
  - The magnitude of the influence of **Path *c*** is diminished (but still significant) upon introducing the mediator variable (and **Paths *a*** and ***b***).
- **Full Mediation:**
  - The **independent variable** does not have a significant effect on the **dependent variable** after inclusion of the **mediator variable**. That is, the effect of the **independent variable** on the **dependent variable** is not significantly different from zero.
  - The magnitude of the effect of **Path *c*** drops to zero.



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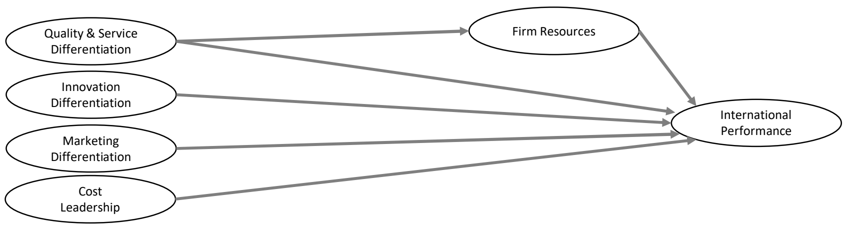
B.2.6. MEDIATION

➔Example

- The framework Strategy-Resources-Performance, may be explored here.



- Let's consider the Firm Resource variable:

	FIRM RESOURCES (Wu, Wang, Chen & Pan, 2008) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
FR_it1	The specialized expertise of the firm was above the industry average.
FR_it2	Firm capital was above the industry average.
FR_it3	The operational management capability of the companywas above the industry average.
FR_it4	The reputation of the company was above the industry average.
FR_it5	The cooperative aliance experience of the company was above the industry average.

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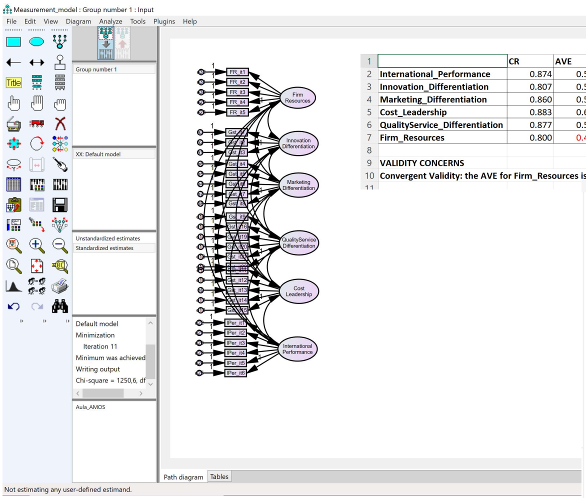
B.2.6. MEDIATION

➔Example

- We need to redo the measurement model, with this additional variable:



		CR	AVE	MSV	MaxR(H)	Internation	Innovation_	Marketing_	Cost_Leade	QualitySer	Firm_Resources
1											
2	International_Performance	0.874	0.540	0.274	0.890	**0.735**					
3	Innovation_Differentiation	0.807	0.593	0.496	0.956	,259	**0.770**				
4	Marketing_Differentiation	0.860	0.557	0.496	0.969	,260	,704	**0.747**			
5	Cost_Leadership	0.883	0.603	0.375	0.975	,337	,198	,068	**0.776**		
6	QualityService_Differentiation	0.877	0.544	0.375	0.979	,523	,340	,250	,612	**0.738**	
7	Firm_Resources	0.800	0.450	0.212	0.981	,460	,341	,362	,204	,337	**0.670**
8											
9	**VALIDITY CONCERNS**										
10	**Convergent Validity: the AVE for Firm_Resources is less than 0.50.**										

Standardized Regression Weights: (Group number 1 - Default mo

			Estimate
Gst_it3	<---	Innovation_Differentiation	,586
Gst_it2	<---	Innovation_Differentiation	,961
Gst_it1	<---	Innovation_Differentiation	,715
Gst_it6	<---	Marketing_Differentiation	,672
Gst_it5	<---	Marketing_Differentiation	,880
Gst_it4	<---	Marketing_Differentiation	,647
Gst_it7	<---	Marketing_Differentiation	,888
Gst_it8	<---	Marketing_Differentiation	,595
Gst_it13	<---	Cost_Leadership	,869
Gst_it12	<---	Cost_Leadership	,770
Gst_it11	<---	Cost_Leadership	,740
Gst_it14	<---	Cost_Leadership	,730
Gst_it15	<---	Cost_Leadership	,765
Gst_it19	<---	QualityService_Differentiation	,823
Gst_it16	<---	QualityService_Differentiation	,692
Gst_it9	<---	QualityService_Differentiation	,656
Gst_it20	<---	QualityService_Differentiation	,786
Gst_it21	<---	QualityService_Differentiation	,675
Gst_it22	<---	QualityService_Differentiation	,777
IPer_it3	<---	International_Performance	,787
IPer_it2	<---	International_Performance	,827
IPer_it1	<---	International_Performance	,827
IPer_it4	<---	International_Performance	,631
IPer_it5	<---	International_Performance	,635
IPer_it6	<---	International_Performance	,671
FR_it5	<---	Firm_Resources	,545
FR_it4	<---	Firm_Resources	,769
FR_it3	<---	Firm_Resources	,747
FR_it2	<---	Firm_Resources	,575

1. We got this problem with the AVE of Firm Resources.

2. Maybe we can solve that by excluding FR_it5 and FR_it2, with loading below 0.60.

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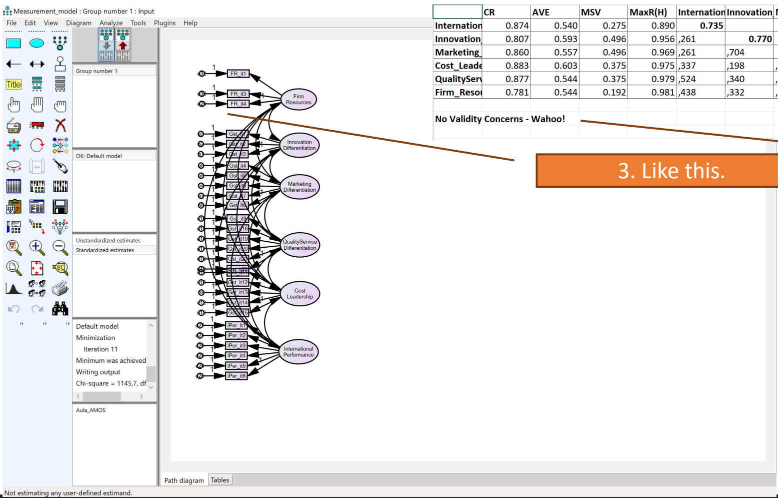
B.2.6. MEDIATION

➔Example

- We need to redo the measurement model, with this additional variable:



	CR	AVE	MSV	MaxR(H)	Internation	Innovation_	Marketing_	Cost_Leade	QualitySer	Firm_Resources
Internation	0.874	0.540	0.275	0.890	**0.735**					
Innovation_	0.807	0.593	0.496	0.956	,261	**0.770**				
Marketing_	0.860	0.557	0.496	0.969	,261	,704	**0.747**			
Cost_Leade	0.883	0.603	0.375	0.975	,337	,198	,068	**0.776**		
QualitySer	0.877	0.544	0.375	0.979	,524	,340	,250	,612	**0.738**	
Firm_Resou	0.781	0.544	0.192	0.981	,438	,332	,341	,220	,365	**0.738**

No Validity Concerns - Wahoo!

3. Like this.

4. Everything OK.

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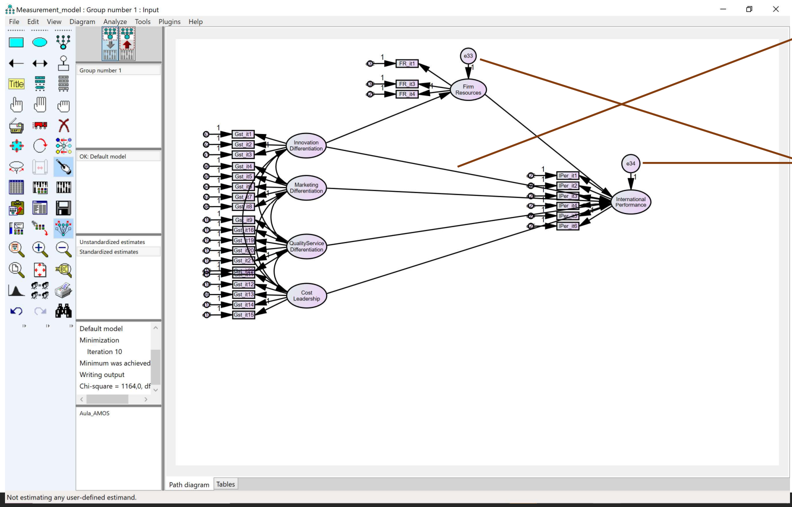
B.2.6. MEDIATION

➔Example

- Now the structural model:



5. Like this.

6. All dependent variables need to include the residuals.

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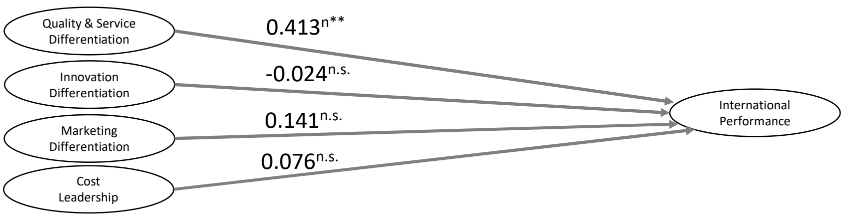
B.2.6. MEDIATION

➔Example

- Initially, we had:



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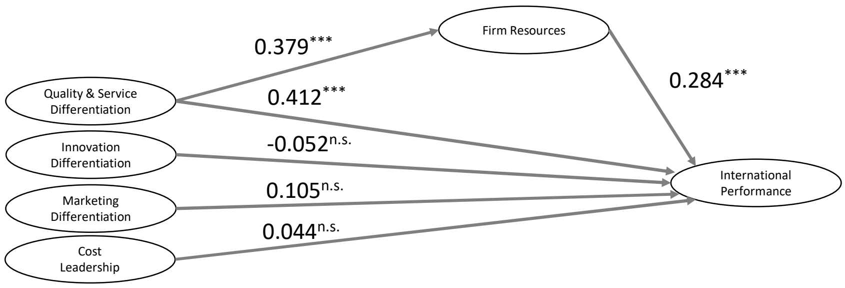
B.2.6. MEDIATION

→Example

- And now we have:



- Hence, it seems that:
  - The direct effect that **Quality & Service Differentiation** has on **International Performance,** is **partially mediated** by **Firm Resources**.

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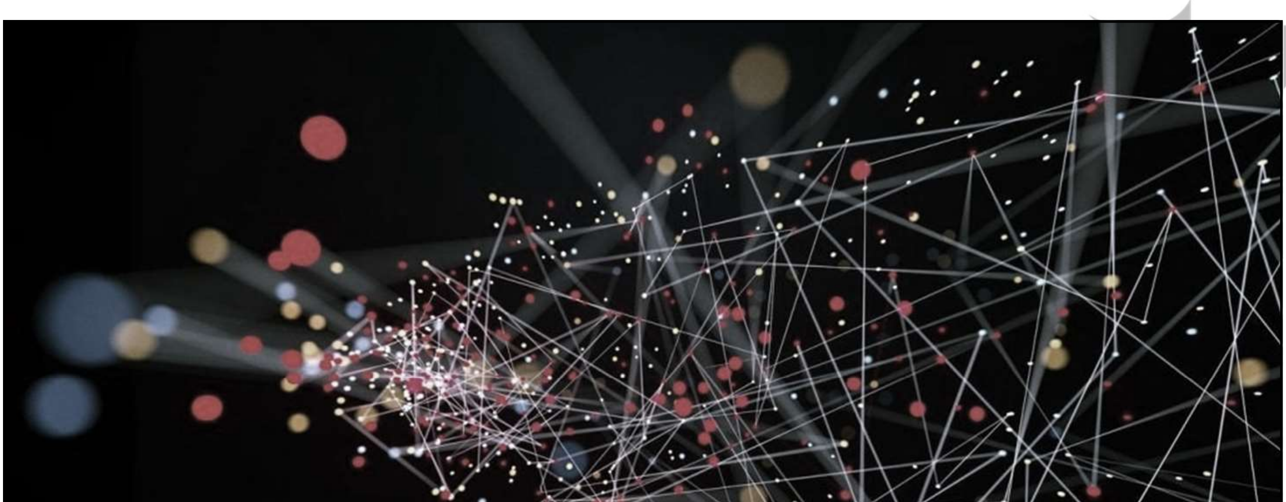

PLS-SEM

CHAPTER B.3

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Introduction to PLS-SEM & SmartPLS

B.3.1

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B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
→INNER MODEL AND OUTER MODEL

- **Measurement Model:**
  - In PLS-SEM the measurement model is called **outer model**.
  - Relationships between each latent variable and their observed indicators.
  - The same indicator can not be associated to different latent variables, that is multiple relations are not possible (Hair et al., 2011).
- **Structural Model:**
  - In PLS-SEM the structural model is called **inner model**.
  - The paths between the latent variables can only head in a single direction (Hair et al., 2011). In other words, causal loops are not possible.

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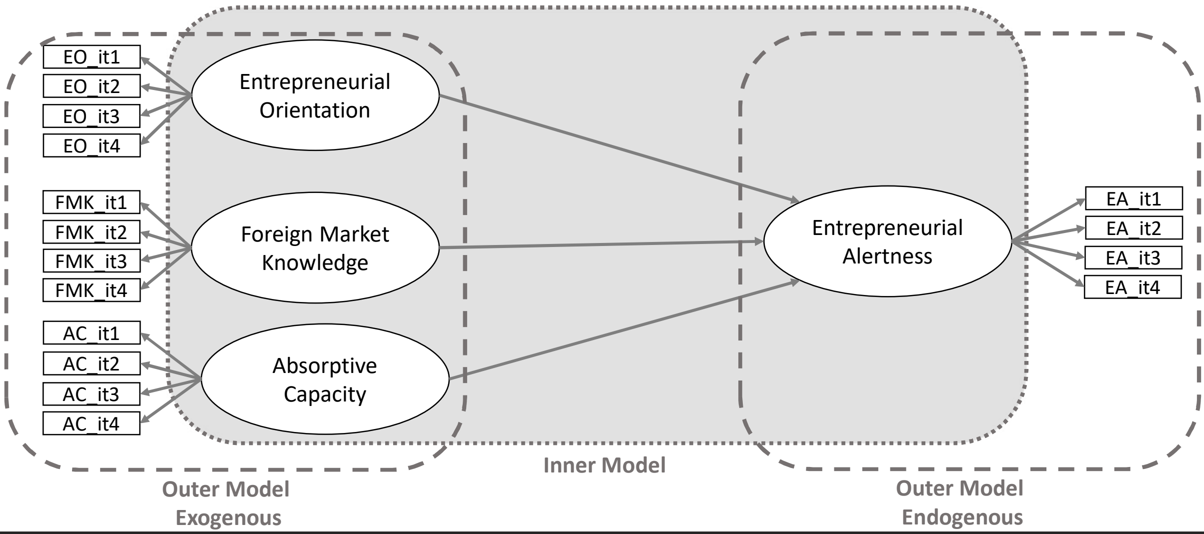
B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔*INNER MODEL AND OUTER MODEL*



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B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *WHY PLS-SEM? + SAMPLE*

- Reasons used by researchers to choose PLS-SEM as the statistical approach for assessing structural equation models (Urbach & Ahlemann, 2010):
  - It is **less demanding** than other methods about the sample size (10:1 rule; minimum of 100);
  - It is **not necessary** to have **normal-distributed data**;
  - Can handle with both **reflective** and **formative** latent **variables**;
  - Addresses better **theory development** than theory testing;
  - It is particularly valuable for **prediction**;
  - Can be used for complex structural equation models with a **large number of constructs**;
  - …

- Sample rule of thumb 10:1:
  - In **formative variables** identify the maximum number of indicators that is used to measure a latent variable (LV);
  - In the inner model (including formative and/or reflective variables), identify the LV with the maximum **number of exogeneous (independent) LV**;
  - The **maximum between those two** values is **multiplied by 10**, and we obtain the **minimum sample size**.

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B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *REFLECTIVE vs FORMATIVE*

- Each construct is associated with one or more indicators or items (observed variables).
- We can identify three different outer model "modes" (Hair et al., 2011; Rigdon et al., 2010):
  - Mode A – Reflective measurement model (scales);
  - Mode B – Formative measurement model (indices);
  - Mode C – "Mixed" measurement model:
    - **Different modes** for **different latent variables**.
    - Even so, is **not possible** to have **both reflective and formative indicators** for the **same latent variable**.

- PLS-SEM can handle with all these outer models.

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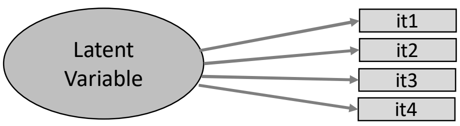
B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *REFLECTIVE vs FORMATIVE*

- REFLECTIVE INDICATORS
  - **These are seen as functions or "effects" of the latent variable;**
  - Changes in the latent variables can be reflected in the indicators (observable variables);
  - These can be represented in PLS-SEM by single headed arrows pointing away from the latent variable to the indicators;
  - The coefficients related to these relationships are called ***outer loadings****;*
  - Takes measurement error into account at the item level;
  - **Reducing an indicator or item does not alter the meaning of the construct**. So, it is possible to have substitution or omission of items in subsequent studies.



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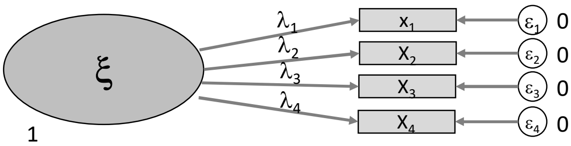
B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *REFLECTIVE vs FORMATIVE*

- **REFLECTIVE MEASUREMENT MODEL WITH SmartPLS**
  - Similar to **factor analysis** or **principal component analysis (PCA);**
  - Measurement errors are expected to be **zero**;
  - Indicators should be **positively correlated**;
  - The latent variables has a variance of **one**;
  - Usually, the latent variable is centered, and the **latent mean is calculated**;
  - The **weights are calculated**, also.



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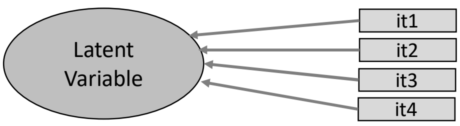
B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *REFLECTIVE vs FORMATIVE*

- **FORMATIVE INDICATORS**
  - **These cause** or **form the latent variable;**
  - Changes in the formative indicators "lead to changes" in latent variables;
  - These can be represent in PLS-SEM by single headed arrows pointing from the indicators to the latent variable;
  - Items are included to capture the latent variable in its globality. So, dropping an indicator or item may alter the conceptual meaning of the construct.



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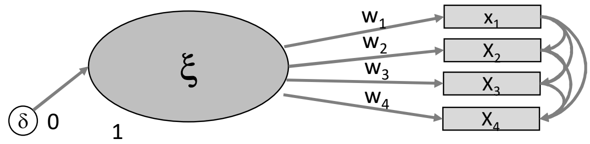
B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *REFLECTIVE vs FORMATIVE*

- **FORMATIVE MEASUREMENT MODEL WITH SmartPLS**
  - Based on **multiple regression**;
  - Measurement errors at construct level:
    - Represent the **missing indicators**;
    - Is expected to be **zero.**
  - Indicators are **not expected to be correlated**, can be mutually exclusive. But **multicollinearity can be a problem** in formative items;
  - The latent variable has a variance of **one**;
  - Usually, the latent variable is centered, and the **latent mean is calculated**;
  - Weights are estimated and rely on others variables, not the latent construct that they "form";
  - The correlations between the latent variable and its **indicators (loadings) are also calculated**.



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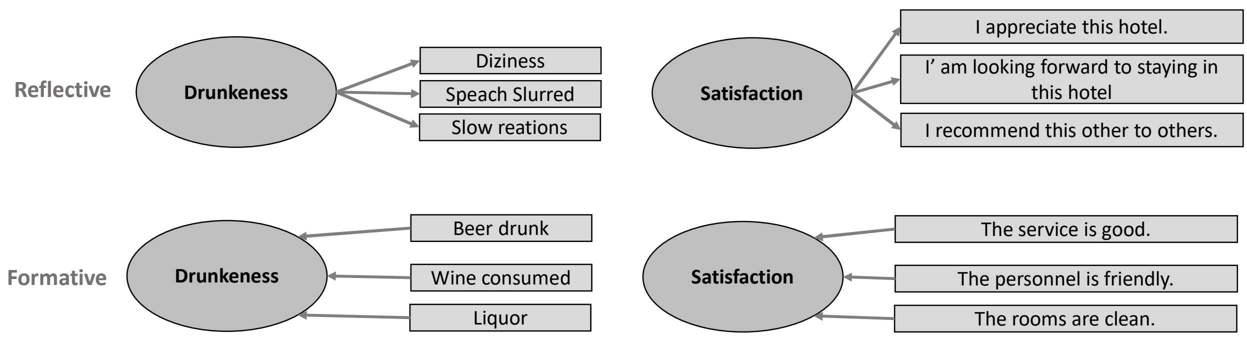
B.3.1. INTRODUCTION TO STRUCTURAL EQUATION MODELING
➔ *REFLECTIVE vs FORMATIVE*

- **Examples:**



Source: Adapted from Albers, 2010.

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Creating Projects with SmartPLS | B.3.2

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B.3.2. CREATING PROJECTS WITH SMARTPLS
→ EXISTING SOFTWARES

- Examples of PLS-SEM softwares:
  - ADANCO;
  - GeSCA;
  - LVPLS;
  - PLSPATH (R software);
  - PLS-Graph.
  - PLS-GUI (R software);
  - SPAD-PLS;
  - **SmartPLS – www.smartpls.com**
  - WarpPLS;
  - Visual PLS;
  - Some are paid and other are freeware.

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B.3.2. CREATING PROJECTS WITH SMARTPLS
➔INITIAL FEATURES

- Some information about the software (Temme, Kreis & Hildrebrandt, 2010):
  - It is **independent from the user's operating system**, because it is Java-based.
  - Uses **raw data** as input;
  - The specification of the model is done by drawing the structural model (with the latent variables) and allocating (**using drag & drop**) the items or indicators to the latent variables;
  - The **output reports**, besides exhibited within the software, **can be exported as Excel, HTML or R formats**.
  - Besides the **PLS Algorithm**, **bootstrapping** and **blindfolding** are the resampling methods available.
  - It includes the specification of **moderation effects** and **quadratic effects**.
  - Supports **multigroup analysis**;
  - Other features: finite mixture routine (FIMIX), importance-performance map analysis (IPMA), PLS Predict, Confirmatory Tetrad analyses (CTA).

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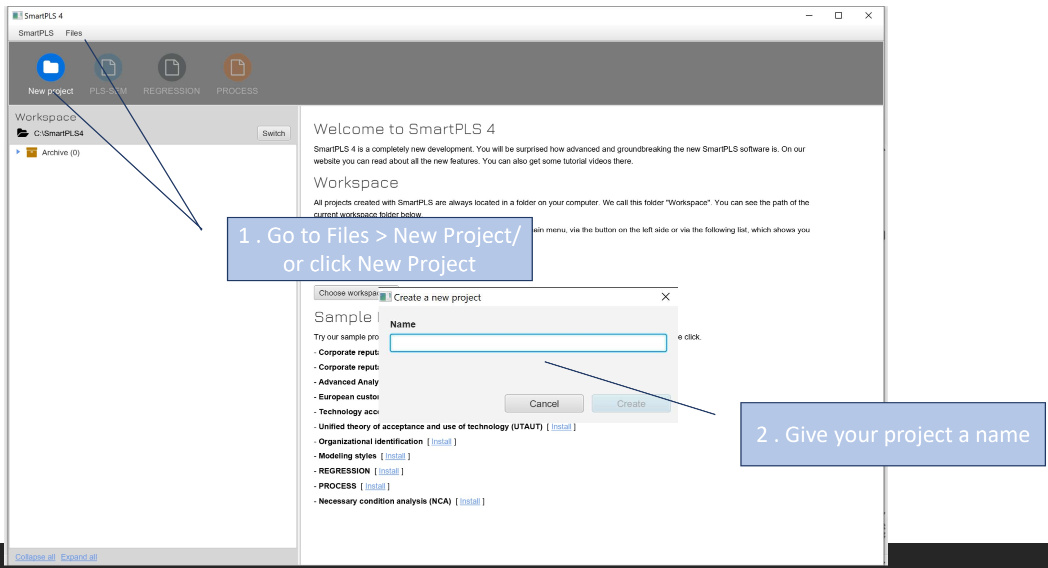
B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS



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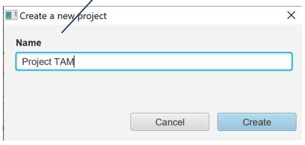
B.3.2. CREATING PROJECTS WITH SMARTPLS
→ FIRST STEPS

3. Give your project a name (I called it Project TAM)

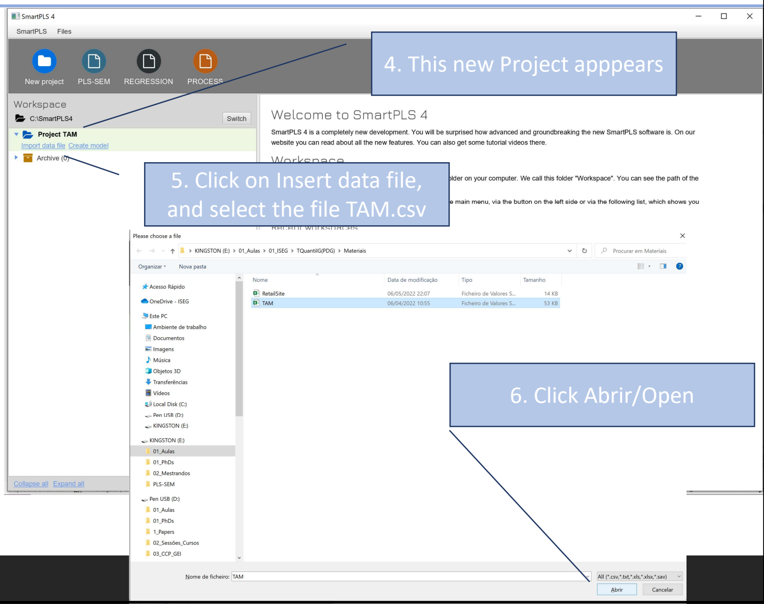


SmartPLS accepts *.csv; *.txt; *.xls; *.xlsx and *.sav files.

4. This new Project appears

5. Click on Insert data file, and select the file TAM.csv

6. Click Abrir/Open



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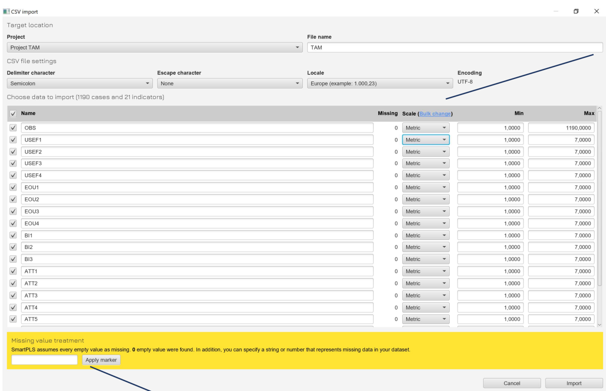
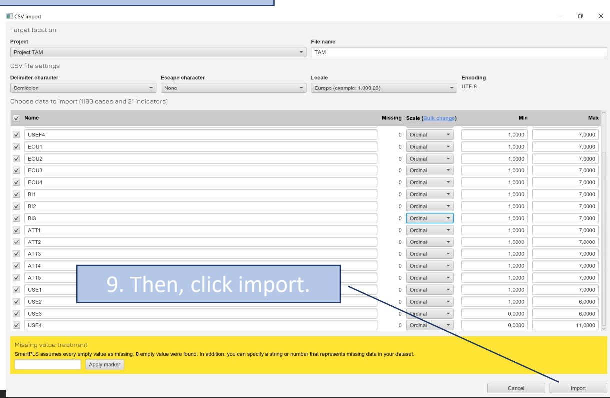
B.3.2. CREATING PROJECTS WITH SMARTPLS
→ FIRST STEPS



7. This new tab will appear. Since our variables are Likert type scales, classify them as 'Ordinal'.

8. In this case we have no missing values. If we did, they would be identified here. The existence of missing values will not affect the procedures.



9. Then, click import.

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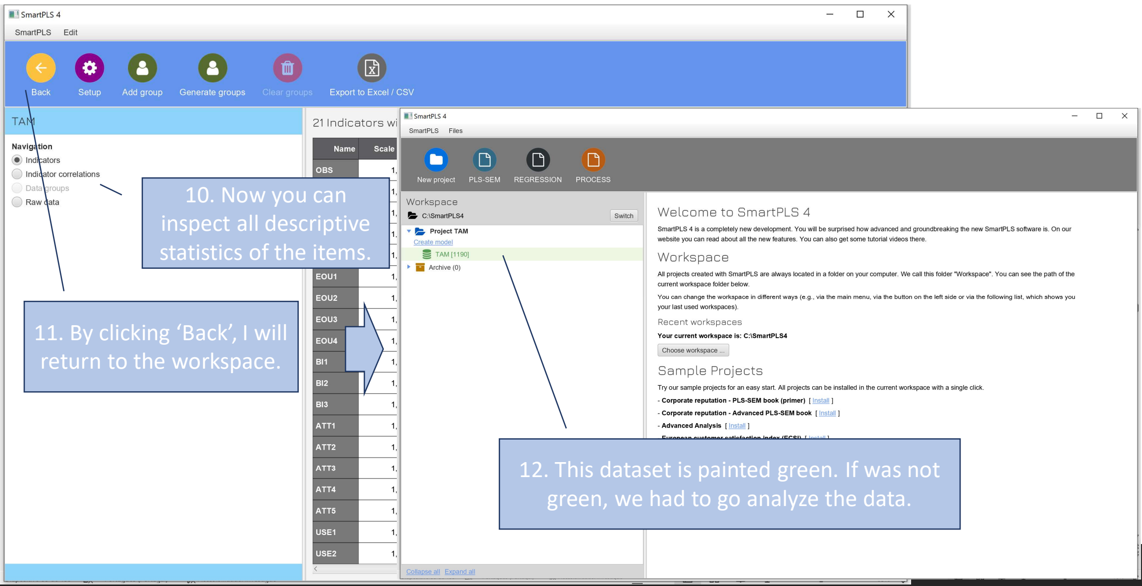
B.3.2. CREATING PROJECTS WITH SMARTPLS

➔FIRST STEPS



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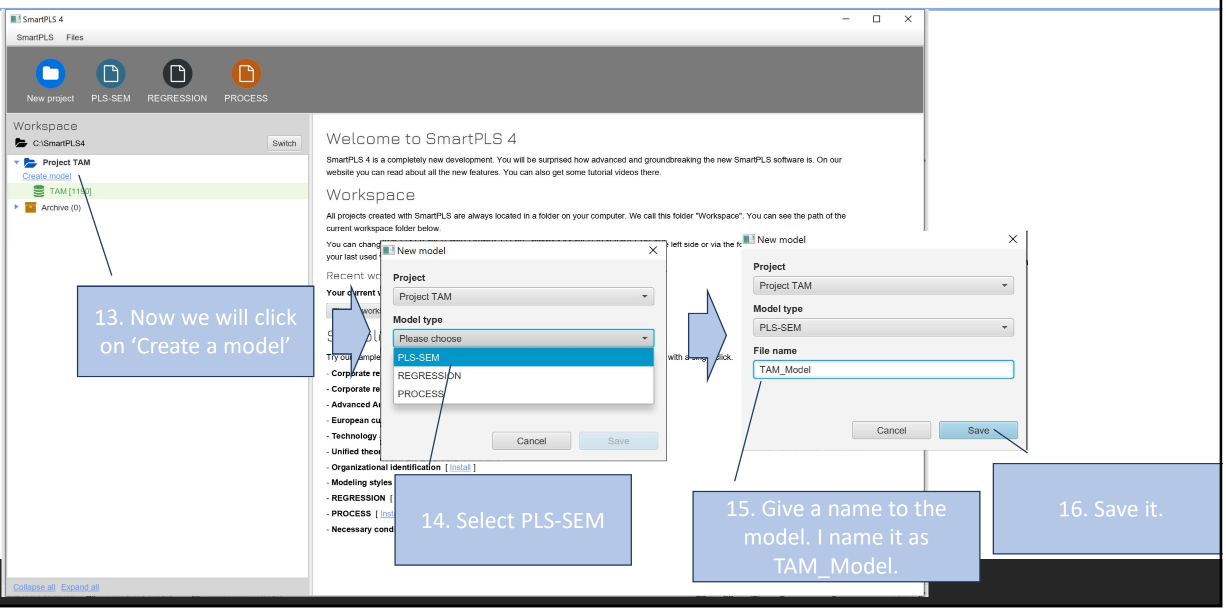
B.3.2. CREATING PROJECTS WITH SMARTPLS

➔FIRST STEPS



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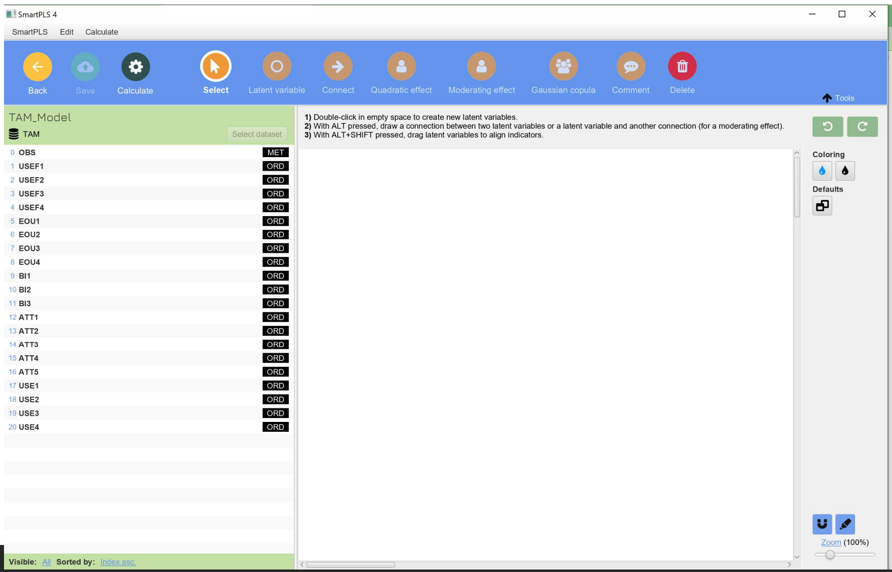
B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS

17. And we will get the new workspace view.



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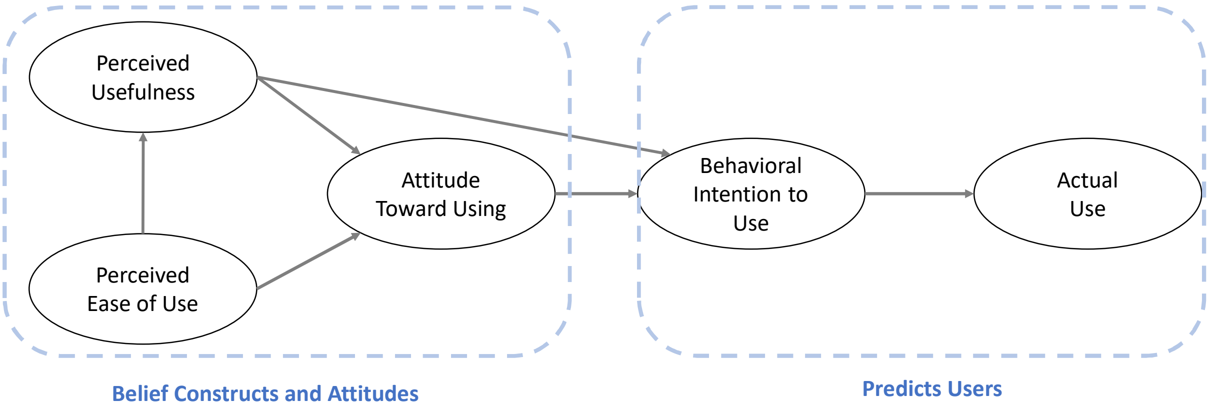
B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS (example)

- But first, we need to know more about the conceptual model.
- Consider this Technology Acceptance Model (TAM)



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B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS (example)

- Measures:

	PERCEIVED USEFULNES (Venkatesh *et al.*, 2000) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
USEF1	I find computers useful in my job.
USEF2	Using computers in my job enables me to accomplish tasks more quickly.
USEF3	Using computers in my job increases my productivity.
USEF4	Using computers enhances my effectiveness on the job.

	PERCEIVED EASE OF USE (Venkatesh *et al.*, 2000) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
EOU1	My interactions with computers are clear and understandable.
EOU2	It is easy for me to become skillful using computers.
EOU3	I find computers easy to use.
EOU4	Learning to use computers is easy for me.

	BEHAVIORAL INTENTION OF USE (Mathieson, 1991) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
BI1	I predict I will continue to use computers on a regular basis.
BI2	I predict I will use computers on a regular basis in the future.
BI3	To do my work, I would use computers rather than any other means available.

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B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS (example)

- Measures:

	ATTITUDE TOWARD USING (Mathieson, 1991) *(seven-point Likert scale with different anchors)*
ATT1	All things considered, my using computers is (extremely bad ~ extremely good).
ATT2	All things considered, my using computers is (extremely foolish ~ extremely wise).
ATT3	All things considered, my using computers is (extremely unfavorable ~ extremely favorable).
ATT4	All things considered, my using computers is (extremely harmful ~ extremely beneficial).
ATT5	All things considered, my using computers is (extremely negative ~ extremely positive).

	ACTUAL SYSTEM USE (Al-Gahtani *et al.*, 2007)
USE1	On an average working day, how much time do you spend using computers? (1) Almost never; (2) less than30 min; (3) from 30 min to 1 h; (4) from 1 to 2 h;(5) from 2 to 3 h; and (6) more than 3 h
USE2	On average, how frequently do you use computers?(1) Less than once a month; (2) once a month; (3) a few times a month; (4) a few times a week; (5) about once a day; and (6) several times a day
USE3	How many different computer applications have you worked with or used in your job? (1) None; (2) one;(3) two; (4) three to five applications; (5) six to ten applications; and (6) more than 10 applications
USE4	According to your job requirements, please indicate each task you use computers to perform (count of all that apply)? (1) Letters and memos; (2) producing reports;(3) data storage and retrieval; (4) making decisions;(5) analyzing trends; (6) planning and forecasting;(7) analyzing problems and alternatives; (8) budgeting;(9) controlling and guiding activities; (10) electronic communications with others; and (11) others (please indicate)

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B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS (example)

- Our database:
  - Study about the acceptance and use of a technology "desktop computers for any work-related purpose" in Saudi Arabia;
  - 1.190 responses from a survey;
  - Respondents: white collar workers;
  - Multiple industries and companies.
- Available in:
  - https://www.smartpls.com/documentation/sample-projects/tam
- Reference:
  - Anderson, C., Al-Gahtani, S. S., and Hubona, G. S. (2011). The Value of TAM Antecedents in Global IS Development and Research. *Journal of Organizational and End User Computing*, 23(1), 18-37.

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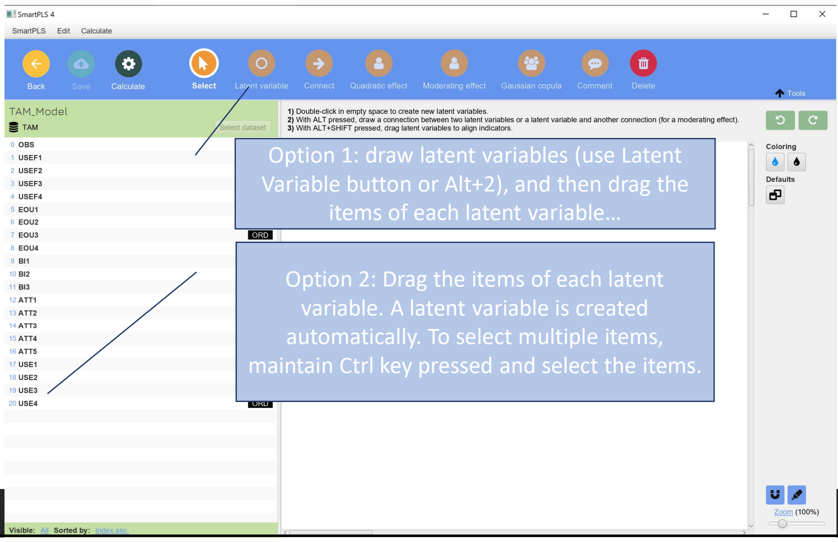
B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS

- Let's setup our model. Two options:



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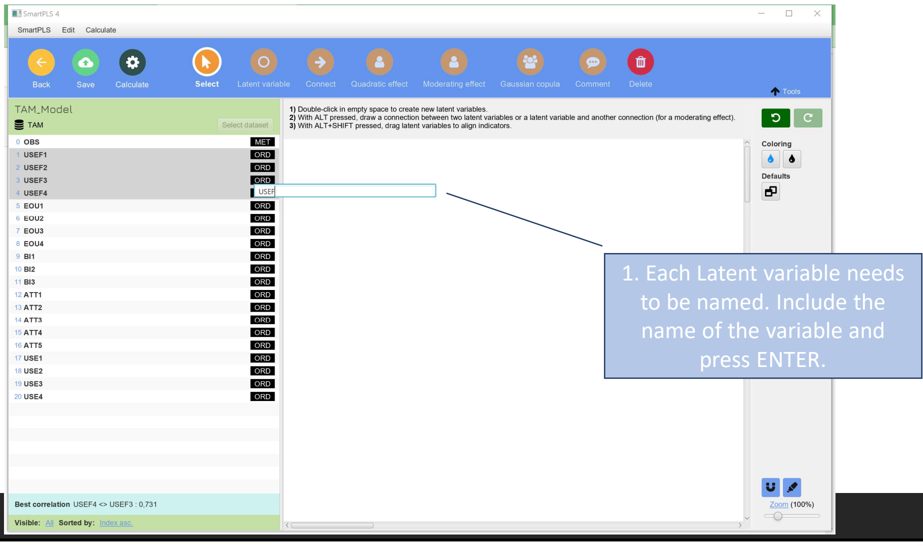
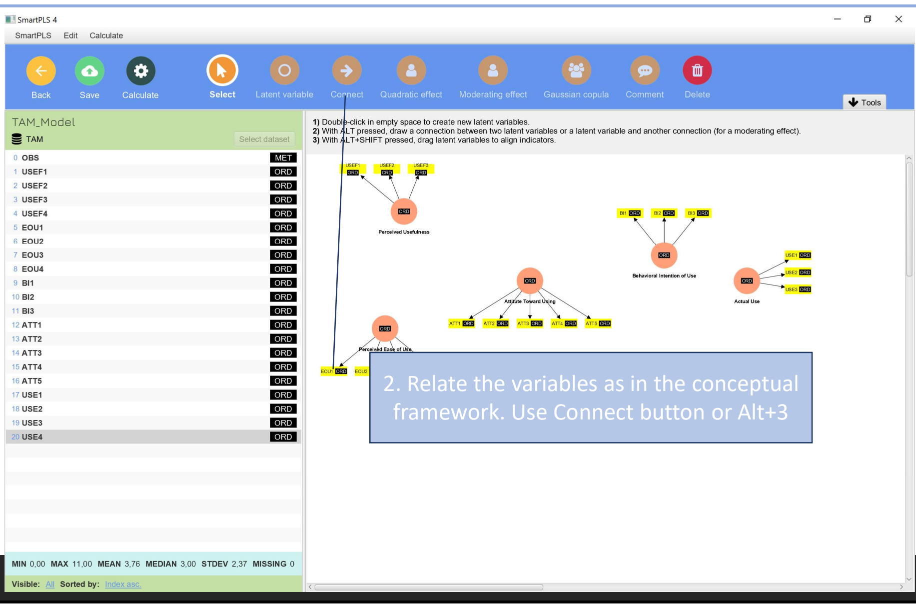
B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS

- Let's setup our model. Two options:



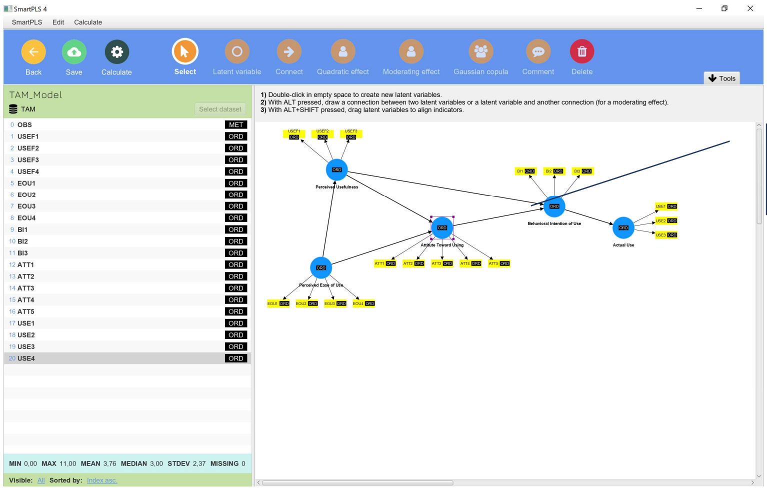
99

B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS



100

B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS



3. After doing the previous tasks, the latent variables turn blue.
Everything is ready to start the estimation.

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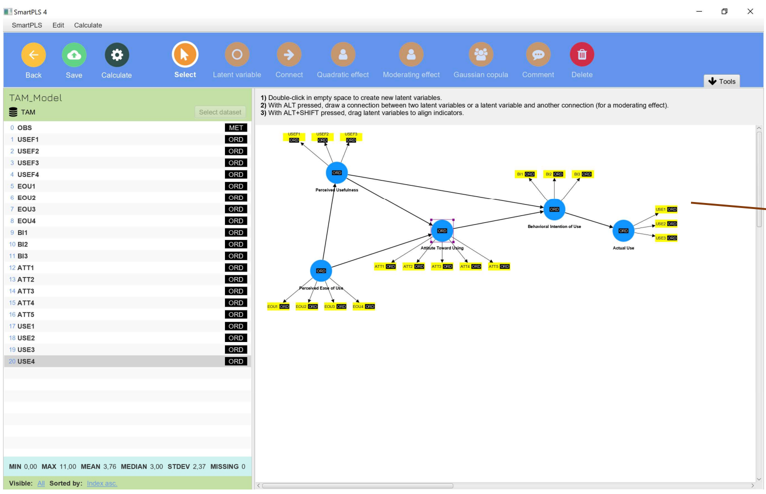
B.3.2. CREATING PROJECTS WITH SMARTPLS
➔FIRST STEPS



4. Let's do a "software jam session" on all buttons and sections.

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SmartPLS Procedures

B.3.3

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B.3.3. SMARTPLS PROCEDURES
➔INTRODUCTION

- Two main procedures:
  - PLS Algorithm;
  - Bootstrapping.

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B.3.3. SMARTPLS PROCEDURES
→ PLS ALGORITHM

- In PLS path modeling, parameter estimation is accomplished through a multi-stage algorithm.
- Stages involve a sequence of regressions in terms of weight vectors.
  - Iteration leads to convergence on a final set of weights.
- Weight vectors obtained at convergence satisfy fixed point equations.

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B.3.3. SMARTPLS PROCEDURES
→ PLS ALGORITM

- This calculation is important mainly for the measurement model:
  - Standardized loadings of the items;
  - Reliability and validity assessment;
  - Explained variance of the endogenous variables;
  - Multicollinearity assessment.
- It uses the CCA - Confirmatory Composite Analysis (and not the CFA - Confirmatory Factor Analysis, like in CB-SEM).

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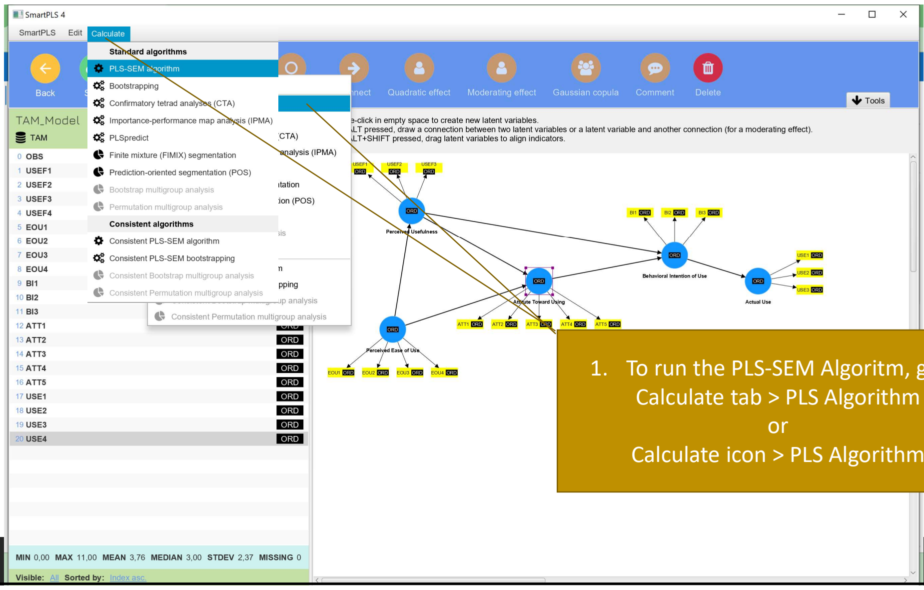
B.3.3. SMARTPLS PROCEDURES
➔PLS ALGORITM



1. To run the PLS-SEM Algoritm, go to Calculate tab > PLS Algorithm
or
Calculate icon > PLS Algorithm

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B.3.3. SMARTPLS PROCEDURES
➔PLS ALGORITM

2. Press Start Calculation

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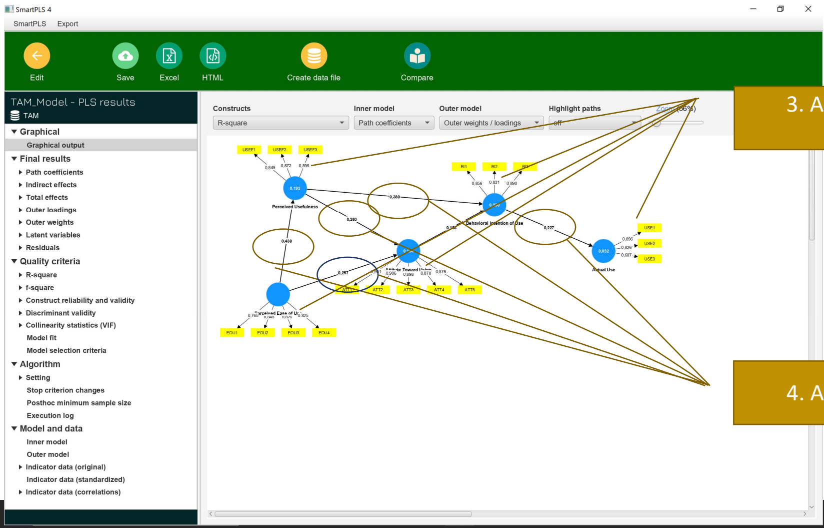
B.3.3. SMARTPLS PROCEDURES

→PLS ALGORITM



3. Analyse the values of the item loadings

4. Analyse the path coeffficients.

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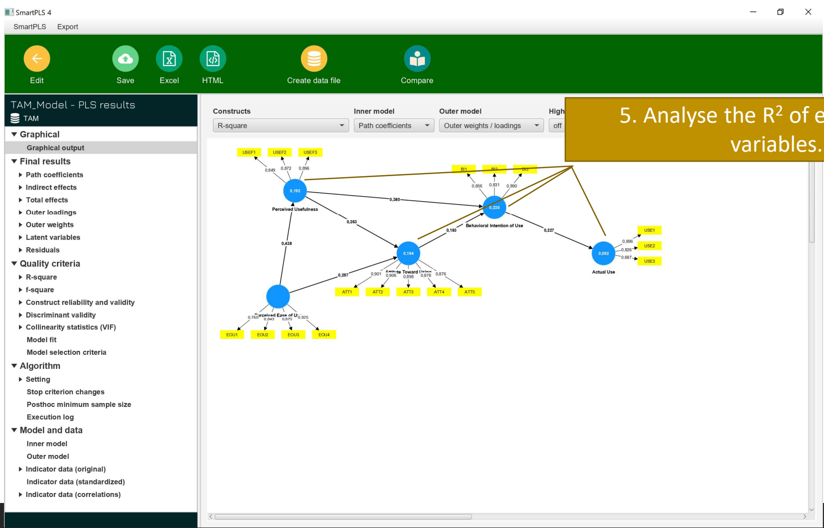
B.3.3. SMARTPLS PROCEDURES

→PLS ALGORITM



5. Analyse the R^2 of endogenous variables.

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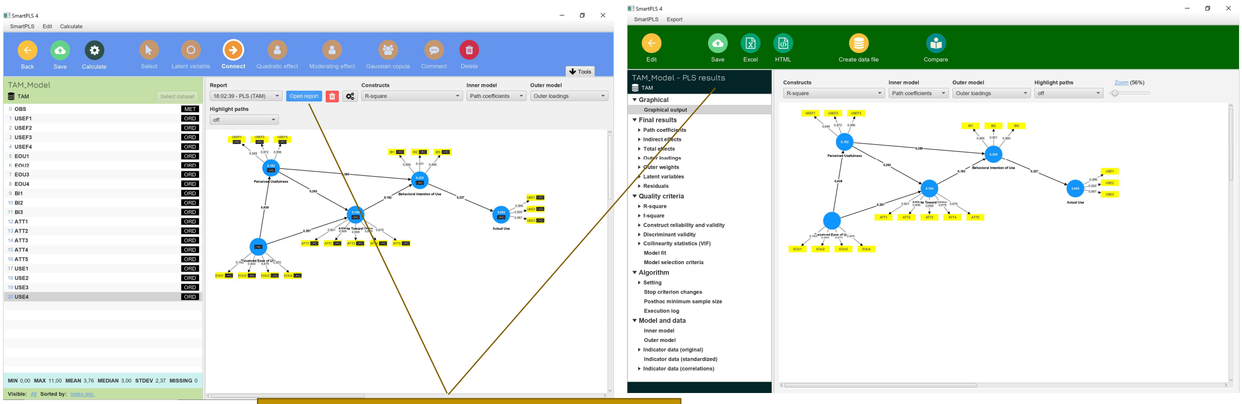
B.3.3. SMARTPLS PROCEDURES
➔PLS ALGORITM



6. Analyse Report.

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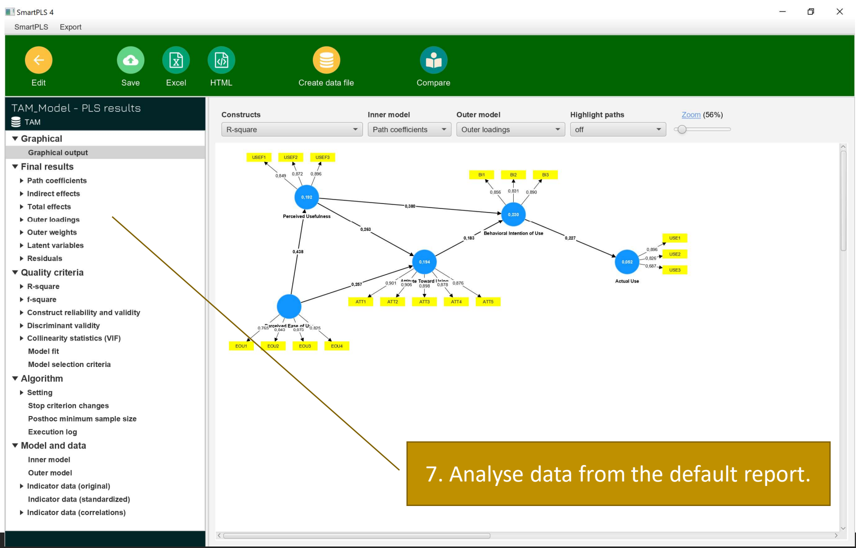
B.3.3. SMARTPLS PROCEDURES
➔PLS ALGORITM



7. Analyse data from the default report.

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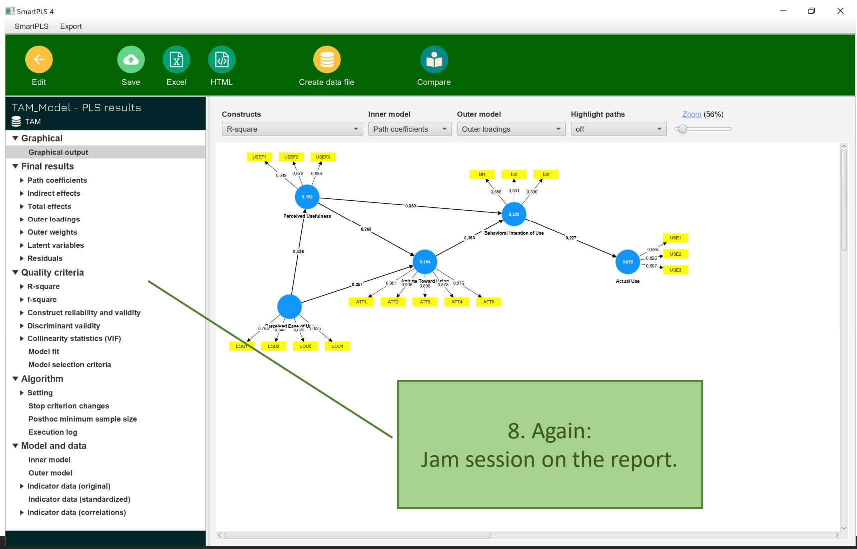
B.3.3. SMARTPLS PROCEDURES
➔PLS ALGORITM



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B.3.3. SMARTPLS PROCEDURES
➔ BOOTSTRAPPING

- Bootstrapping provides t-values for:
  - Inner (structural) model path coefficients;
  - Outer (measurement) model item loadings.

- Bootstrapping procedure provides mean values for:
  - Weights in the inner (structural) model;
  - Weights in the outer (measurement) model;
  - Outer (measurement) model item loadings.

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B.3.3. SMARTPLS PROCEDURES
➔BOOTSTRAPPING

- This calculation is important for both the measurement and structural models:
  - Estimates t-values of item (factor) loadings (outer model) and path coefficients (inner model);
  - Establish a number of subsamples to be created (e.g. 500, 1000, 5000);
  - Randomly selects the same number of cases of the original database (with replacement), and estimates the model 500 (or 1000, or 5000) times;
  - Cases are drawn with the probability of 1/(nb. of cases) from the data set (a specific case may be selected 0 to (nb. of cases) times when creating a bootstrap subsample).

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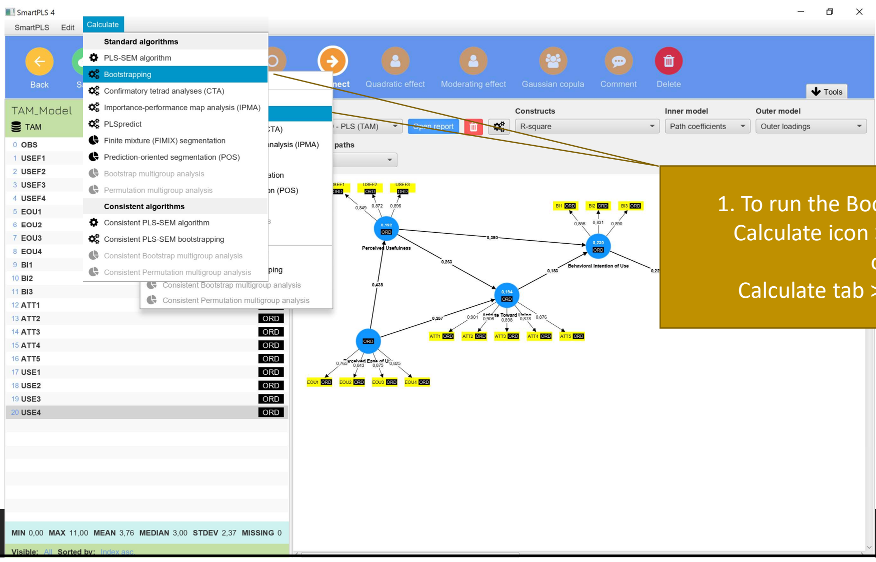
B.3.3. SMARTPLS PROCEDURES
➔BOOTSTRAPPING



1. To run the Bootstrapping, go to Calculate icon > Bootstrapping
or
Calculate tab > Bootstrapping

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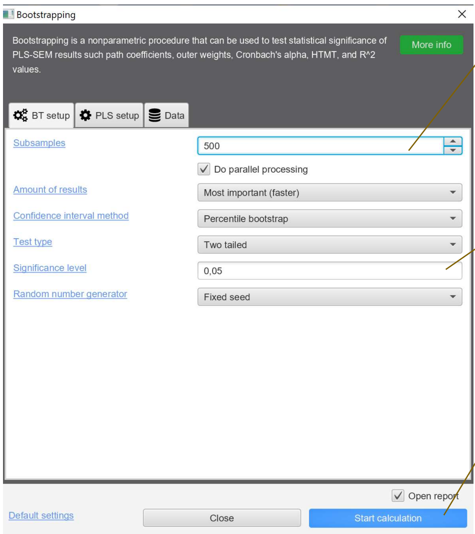
B.3.3. SMARTPLS PROCEDURES
➔BOOTSTRAPPING



2. Define the number of subsamples.
Initial assessment: 500 is enough.
Final results: 5000 is adequate.

3. Define test type and significance level.
By default two-tailed and significance level of 0.05.

4. Press 'Start calculation'

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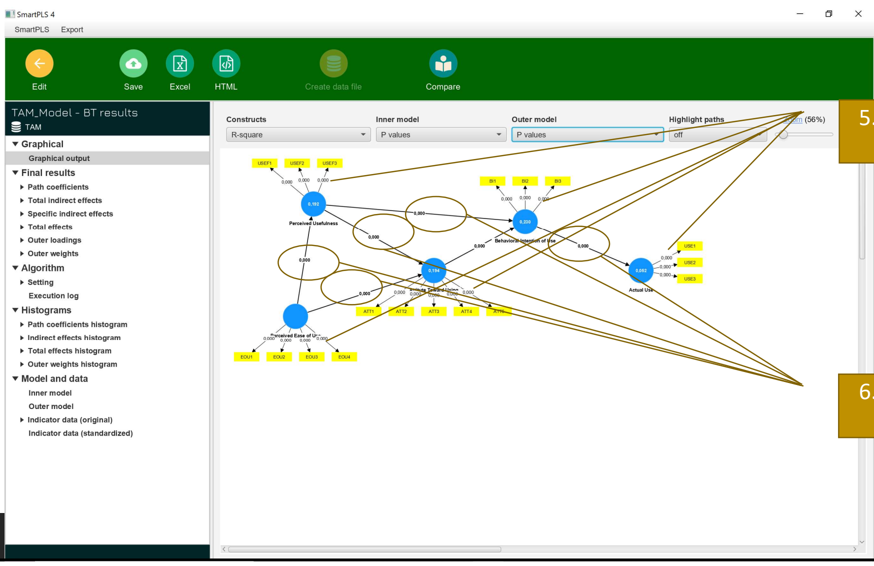
B.3.3. SMARTPLS PROCEDURES
➔ BOOTSTRAPPING



5. Analyse the P values or T-statistics of the outer loadings.

6. Analyse the P values or T-statistics of the path coefficients.

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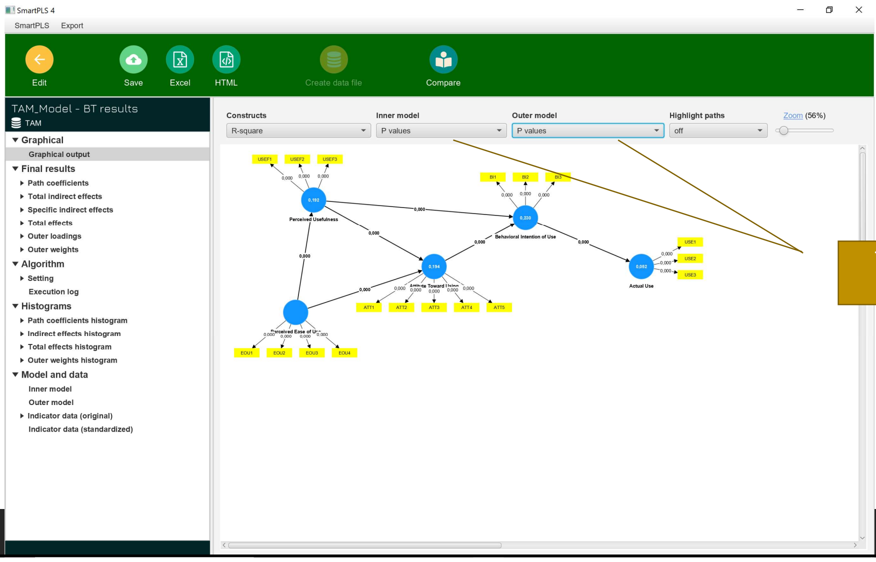
B.3.3. SMARTPLS PROCEDURES
➔ BOOTSTRAPPING



7. To change P values / T values, use these commands.

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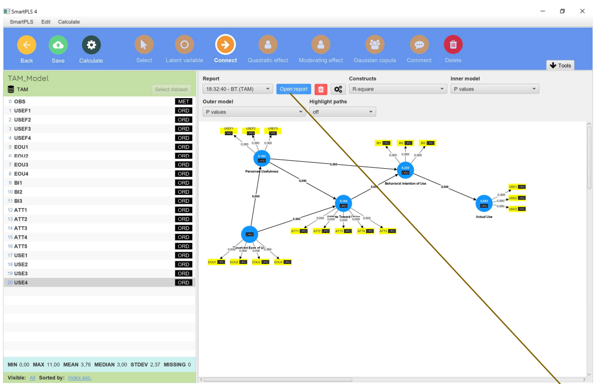
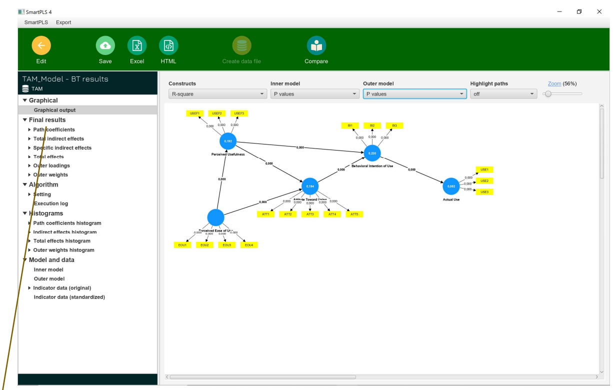
B.3.3. SMARTPLS PROCEDURES
➔ BOOTSTRAPPING





8. Analyse Report.

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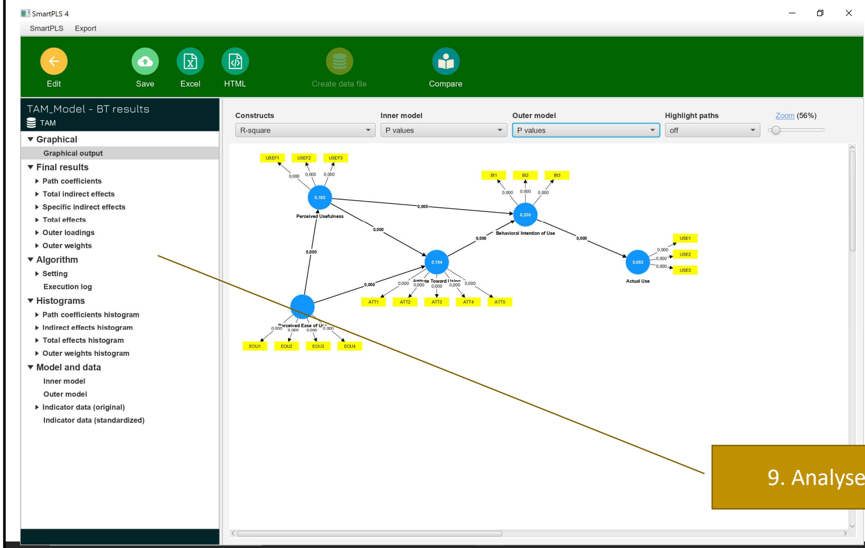
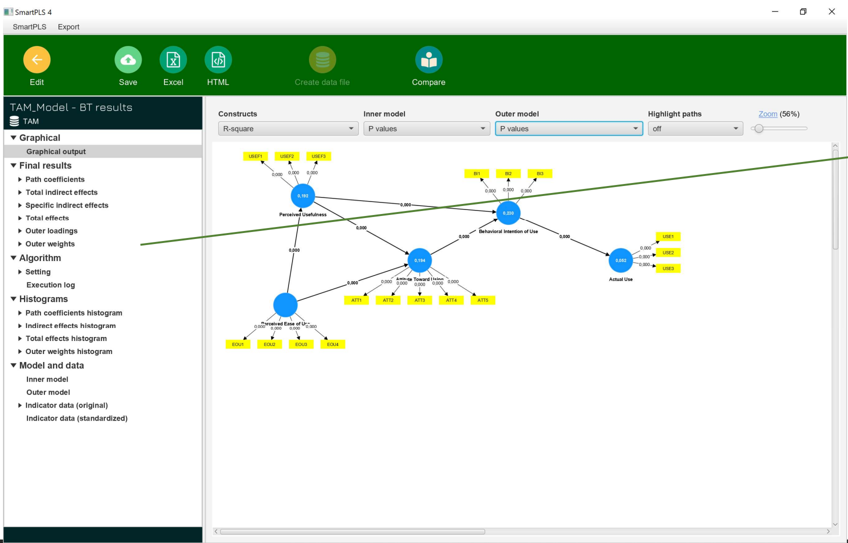
B.3.3. SMARTPLS PROCEDURES
➔ BOOTSTRAPPING



9. Analyse data from the report.

121

B.3.3. SMARTPLS PROCEDURES
➔ BOOTSTRAPPING



10. Again:
Jam session on the report.

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Evaluating PLS-SEM Models

B.3.4

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B.3.4. EVALUATING PLS-SEM MODELS

➔ *STEPS*

- The two-stages process is followed (Hair et al., 2021):
  - **STAGE 1:** Measurement model
  - **STAGE 2:** Structural model.
- Measurement Models:
  - Reflective measurement models;
  - Formative measurement models;

Reliability

Validity

- Structural Models.

Assessment of effects

Assessment of prediction quality

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B.3.4. EVALUATING PLS-SEM MODELS
→ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

A - Indicator Reliability

Outer loadings

B - Internal Consistency

Cronbach's alfa (α); Composite reliability (CR).

C - Convergent Validity

Average Variance Extracted (AVE).

D - Discriminant Validity

Fornell-Larcker criterion; HTMT; Cross loadings.

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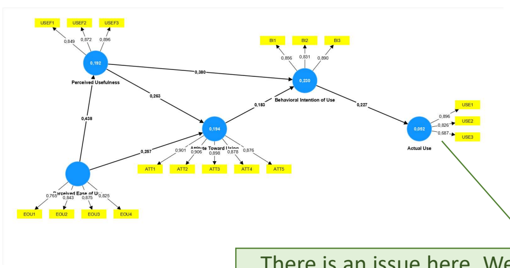
B.3.4. EVALUATING PLS-SEM MODELS
→ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

A - Indicator Reliability

- The item loadings should be higher than 0.70 (Hair et al., 2017; Hair et al., 2019).
- Hence, the squared loadings are approximately higher than 0.50.



	Actual Use	Attitute Toward Using	Behavioral Intention of Use	Perceived Ease of Use	Perceived Usefulness
ATT1		0,901			
ATT2		0,906			
ATT3		0,898			
ATT4		0,878			
ATT5		0,876			
BI1			0,856		
BI2			0,831		
BI3			0,890		
EOU1				0,765	
EOU2				0,843	
EOU3				0,875	
EOU4				0,825	
USE1	0,896				
USE2	0,826				
USE3	0,687				
USEF1					0,849
USEF2					0,872
USEF3					0,896

There is an issue here. We can drop this indicator if it is problematic.

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B.3.4. EVALUATING PLS-SEM MODELS

➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

B - Internal Consistency

- The Cronbach's alphas need to be higher than 0.70 (or 0.60) (Hair et al., 2019).
- The composite reliabilities need also to be higher than 0.70.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Actual Use	0,733	0,792	0,848	0,652
Attitute Toward Using	0,936	0,941	0,951	0,796
Behavioral Intention of Use	0,825	0,848	0,894	0,738
Perceived Ease of Use	0,846	0,851	0,897	0,685
Perceived Usefulness	0,843	0,843	0,905	0,761

All the constructs show α and CR above 0.70.

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B.3.4. EVALUATING PLS-SEM MODELS

➔ *STEPS*

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

C – Convergent Validity

- Average Variance Extracted (AVE) should be higher than 0.50 (Hair et al., 2019).

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Actual Use	0,733	0,792	0,848	0,652
Attitute Toward Using	0,936	0,941	0,951	0,796
Behavioral Intention of Use	0,825	0,848	0,894	0,738
Perceived Ease of Use	0,846	0,851	0,897	0,685
Perceived Usefulness	0,843	0,843	0,905	0,761

All the constructs show AVE above the threshold of 0.50.

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

D - Discriminant Validity

- Fornell & Larcker (1981): the AVE for each variable needs to be higher than the correlation between that variable and all the other variables.

	Actual Use	Attitute Toward Using	Behavioral Intention of Use	Perceived Ease of Use	Perceived Usefulness
Actual Use	0,808				
Attitute Toward Using	0,291	0,892			
Behavioral Intention of Use	0,227	0,325	0,859		
Perceived Ease of Use	0,309	0,372	0,544	0,828	
Perceived Usefulness	0,209	0,375	0,449	0,438	0,872

Fornell & Larcker rule is fulfilled.

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

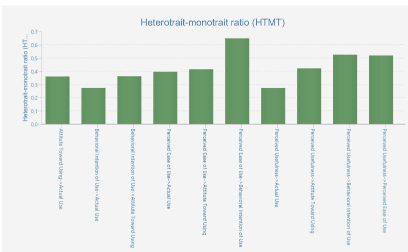
- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

D - Discriminant Validity

- Heterotrait-monotrait Ratio: needs to be below 0.90 for all the latent variables (Hair et al., 2019).

HTMT values are within the limits.

	Actual Use	Attitute Toward Using	Behavioral Intention of Use	Perceived Ease of Use	Perceived Usefulness
Actual Use					
Attitute Toward Using	0,360				
Behavioral Intention of Use	0,274	0,362			
Perceived Ease of Use	0,395	0,414	0,647		
Perceived Usefulness	0,273	0,421	0,524	0,518	



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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF REFLECTIVE MEASUREMENT MODELS:**

D - Discriminant Validity

- Cross-loading: the loadings with the related latent variables should be higher than the loadings with the other variables included in the model (Hair et al., 2017).

	Actual Use	Attitute Toward Using	Behavioral Intention of Use	Perceived Ease of Use	Perceived Usefulness
ATT1	0,270	0,901	0,316	0,350	0,349
ATT2	0,258	0,906	0,319	0,363	0,341
ATT3	0,261	0,898	0,315	0,345	0,330
ATT4	0,267	0,878	0,257	0,307	0,348
ATT5	0,242	0,876	0,231	0,280	0,300
BI1	0,198	0,326	0,856	0,493	0,431
BI2	0,120	0,245	0,831	0,438	0,287
BI3	0,246	0,258	0,890	0,465	0,411
EOU1	0,187	0,281	0,433	0,765	0,320
EOU2	0,238	0,321	0,425	0,843	0,361
EOU3	0,340	0,330	0,479	0,875	0,379
EOU4	0,247	0,296	0,464	0,825	0,387
USE1	0,896	0,232	0,228	0,263	0,167
USE2	0,826	0,231	0,169	0,220	0,161
USE3	0,687	0,259	0,139	0,277	0,191
USEF1	0,159	0,315	0,384	0,403	0,849
USEF2	0,208	0,341	0,377	0,371	0,872
USEF3	0,181	0,325	0,413	0,372	0,896

All the loadings are higher for the related latent variables than for the others.

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF FORMATIVE MEASUREMENT MODELS:**

Indicator relevance/ Content Validity

Do the indicators or items **"make sense"**? Do they **comprehensively capture** the essence of the latent factor?

Convergent Validity

Redundancy analysis; or Nomological Validity.
Or with other constructs indicated by the theory (nomological validity)?

Multicollinearity

Variance Inflaction Factor (VIF).

Indicator Significance

Outer Weights of formative indicators.

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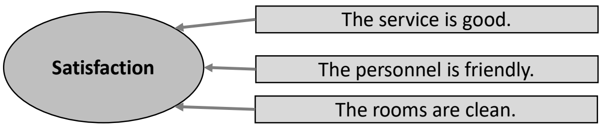
B.3.4. EVALUATING PLS-SEM MODELS
➔ *STEPS*

- **ASSESSMENT OF FORMATIVE MEASUREMENT MODELS:**

Indicator relevance/ Content Validity

- Include a comprehensive set of indicators that exhausts the formative LV.
- Should be identified by using a rigorous qualitative approach (e.g. experts assessment)
- Perform a literature review to guarantee a theoretical grounding during the process of construction of the measures (Hair et al., 2017).
- Example:



Source: Adapted from Albers, 2010.

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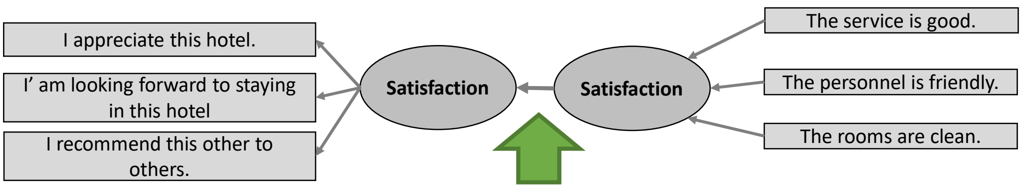
B.3.4. EVALUATING PLS-SEM MODELS
➔ *STEPS*

- **ASSESSMENT OF FORMATIVE MEASUREMENT MODELS:**

Convergent validity

- **Redundancy analysis**
- High correlation between the formative measure of LV and a different measure for the same LV (reflective). Should be higher than 0,7 or R^2 of endogenous LV above 0,50.(Hair et al., 2017).
- Example:



- Other possibility is to relate with a global item (single item LV).

Source: Adapted from Albers, 2010.

- Or with other LV indicated by the theory (nomological validity).

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF FORMATIVE MEASUREMENT MODELS:**

Multicollinearity

- **Look at VIF of the formative LV.**
- VIF needs to be below the value of 5,0 (Hair et al., 2011; Hair et al., 2017).
- If the level of collinearity is higher than 5,0 for a LV, some item needs to be removed. It is necessary to have VIF<5,0 to advance with the analysis.
- **What item?**
- One that exhibits bivariate correlations above 0,60.
- Still, the remaining indicators need to capture the construct's content from theoretical perspective.

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF FORMATIVE MEASUREMENT MODELS:**

Indicator Significance

- We need to analyses the **outer weights of the formative LV**.
- The outer weights in formative measurement are usually bellow than the outer loadings of reflective LV (Hair et al., 2017).
- **The outer weights of the indicators of formative LV, need to be significant** (Hair et al., 2017)**.**

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B.3.4. EVALUATING PLS-SEM MODELS

➔ STEPS

- **ASSESSMENT OF STRUCTURAL MODELS:**
  - If the existing goodness-of-fit measures were widely accepted, it would be helpful… (GoF, SEME, RMS_{theta}…)
  - So, usually the following results are presented:
    1. Analysis of collinearity (VIF);
    2. Coefficients of determination (R^2);
    3. Effect size (f^2);
    4. Predictive relevance (Q^2).
    5. Size and significance of path coefficients (hypotheses evaluation).

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B.3.4. EVALUATING PLS-SEM MODELS

➔ STEPS

- **ASSESSMENT OF STRUCTURAL MODELS:**
  1. **Analysis of collinearity (VIF)**
     - VIF values need to be below 5,0 (Hair et al., 2019).

- TAM example:

All the VIF values are below the cutoff 5,0.

	Actual Use	Attitute Toward Using	Behavioral Intention of Use	Perceived Ease of Use	Perceived Usefulness
Actual Use					
Attitute Toward Using			1,164		
Behavioral Intention of Use	1,000				
Perceived Ease of Use		1,238			1,000
Perceived Usefulness		1,238	1,164		

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF STRUCTURAL MODELS:**
  2. **Coefficients of determination (R^2)**
     - Examine the R^2 of the endogenous LVs. Evaluation (Hair et al., 2011):
       - R^2 >0,75 – Substantial;
       - 0,50>R^2 >0,75 – Moderate;
       - 0,25>R^2 >0, 50 – Weak.
     - Even so, sometimes to present values above 0,10 is considered satisfactory (Raithel et al., 2012; Falk & Miller, 1992).

- TAM example:

Three variables show R^2 above 0,10, but one of the variables show a very weak R^2 (R^2=0,052).

	R-square	R-square adjusted
Actual Use	0,052	0,051
Attitute Toward Using	0,194	0,192
Behavioral Intention of Use	0,230	0,229
Perceived Usefulness	0,192	0,191

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF STRUCTURAL MODELS:**
  3. **Effect size (f^2)**
     - Assesses the relevance of removing an exogenous LV as a specific predictor of an endogenous LV. Rules of thumb (Cohen, 1988; Hair et al., 2017):
       - f^2 >0,35 – large effect size;
       - 0,15>f^2 >0,35 – medium effect size;
       - 0,02>f^2 >0,15 – small effect size.

- TAM example:

Small Effect sizes

	Actual Use	Attitute Toward Using	Behavioral Intention of Use	Perceived Ease of Use	Perceived Usefulness
Actual Use					
Attitute Toward Using			0,037		
Behavioral Intention of Use	0,054				
Perceived Ease of Use		0,066			0,238
Perceived Usefulness		0,069	0,162		

Medium Effect sizes

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF STRUCTURAL MODELS:**
  4. **Predictive relevance (Q^2)**
     - Uses the blindfolding procedure. Removes specific values of the samples and replaces those values by the mean and estimates the model parameters (Rigdon, 2014).
     - Small differences between the predicted and the initial values lead to higher Q^2, so higher predictive relevance. Reference values (Hair et al., 2019):
       - Q^2>0,50 – large predictive relevance;
       - 0,25>Q^2>0,50 – medium predictive relevance;
       - 0,0>Q^2>0,25 – small predictive relevance.
     - How to obtain Q^2?
     - Follow the path:
       - **Calculate > PLSpredict > PLS setup > Start calculation**
     - Report:
       - LV prediction summary

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B.3.4. EVALUATING PLS-SEM MODELS
➔ STEPS

- **ASSESSMENT OF STRUCTURAL MODELS:**
  4. **Predictive relevance (Q^2)**
     - Uses the blindfolding procedure. Removes specific values of the samples and replaces those values by the mean and estimates the model parameters (Rigdon, 2014).
     - Small differences between the predicted and the initial values lead to higher Q^2, so higher predictive relevance. Reference values (Hair et al., 2019):
       - Q^2>0,50 – large predictive relevance;
       - 0,25>Q^2>0,50 – medium predictive relevance;
       - 0,0>Q^2>0,25 – small predictive relevance.

- TAM example:

	Q^2predict	RMSE	MAE
Actual Use	0,030	0,988	0,755
Attitute Toward Using	0,135	0,934	0,674
Behavioral Intention of Use	0,198	0,898	0,683
Perceived Usefulness	0,187	0,907	0,614

Small predictive relevance

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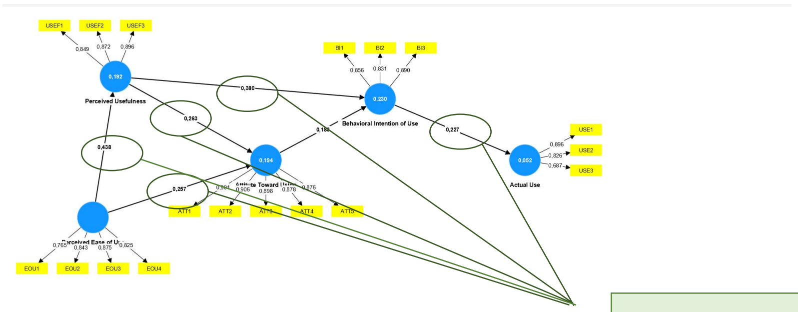
B.3.4. EVALUATING PLS-SEM MODELS
→ *STEPS*

- **ASSESSMENT OF STRUCTURAL MODELS:**
  5. **Size and significance of path coefficients (hypotheses evaluation).**

- TAM example:



Analysis of path coeffficients.

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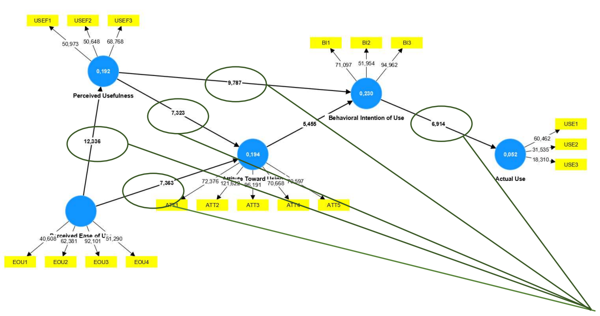
B.3.4. EVALUATING PLS-SEM MODELS
→ *STEPS*

- **ASSESSMENT OF STRUCTURAL MODELS:**
  5. **Size and significance of path coefficients (hypotheses evaluation).**

- TAM example:



Analysis of T-statistics of the path coefficients.

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Mediation

B.3.5

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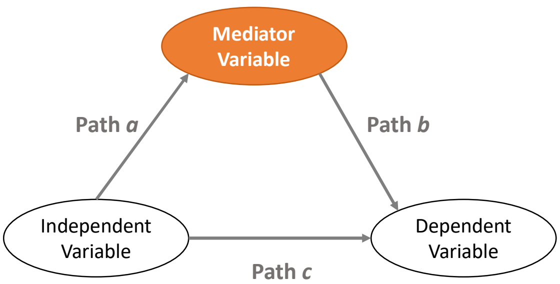
B.3.5. MEDIATION

➔DEFINITION

- A variable functions as a mediator when it meets the following conditions (Baron & Kenny, 1986):
  - Variations in levels of the independent variable significantly account for variations in the presumed mediator (i.e. **Path *a***)
  - Variations in the mediator significantly account for variations in the dependent variable (i.e. **Path *b***), and
  - When paths **a** and **b** are controlled, a previously significant relation between the independent and dependent variables (i.e. **Path *c***) is no longer significant.



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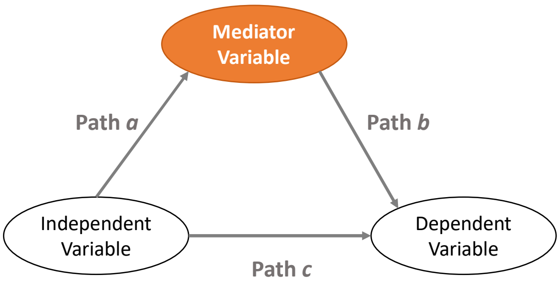
B.3.5. MEDIATION

→*DEFINITION*

- **Partial Mediation:**
  - The ***independent variable*** still has a significant direct effect on the ***dependent variable***.
  - The magnitude of the influence of **Path *c*** is diminished (but still significant) upon introducing the mediator variable (and **Paths *a*** and ***b***).
- **Full Mediation:**
  - The **independent variable** does not have a significant effect on the **dependent variable** after inclusion of the **mediator variable**. That is, the effect of the **independent variable** on the **dependent variable** is not significantly different from zero.
  - The magnitude of the effect of **Path *c*** drops to zero.



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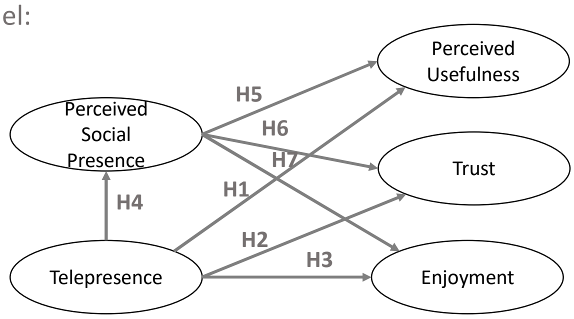
B.3.5. MEDIATION

→*Example*

- Sometimes in SEM, the mediating effects are suggested but often not explicitly tested.
  - For example, it is already known that **social presence** impact on **trust** and **enjoyment** in online environments, but few studies investigate whether this **social presence** mediates the influence of other variables on **trust** and **enjoyment.**
  - For example, consider this research model:
  - Our database:
    - Study about the online shopping experiences;
    - 216 responses from a survey;
    - Respondents: online shoppers;
    - They were identified as online shoppers in an online clothing store.



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B.3.5. MEDIATION

→ Example

- Measures:

	PERCEIVED SOCIAL PRESENCE (Gefen & Straub, 2003) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
PSP1	There was a sense of human contact on the [X vendor site/Internet e-commerce site].
PSP2	There was a sense of sociability on the [X vendor site/Internet e-commerce site].
PSP3	There was a sense of human warmth on the [X vendor site/Internet e-commerce site].

	TELEPRESENCE (Kim & Biocca, 1997) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
TL1	I forget about my immediate surroundings when I am on the [X vendor site/Internet e-commerce site].
TL2	Browsing the [X vendor site/Internet e-commerce site] often makes me forget where I am.
TL3	After browsing the [X vendor site/Internet e-commerce site], I feel like I come back to the “real world” after a journey.
TL4	Using a [virtual world/web site] creates a new world for me, and this world suddenly disappears when I stop using it.

	PERCEIVED USEFULNESS (Chen, Gillenson & Sherrell, 2002; Moon & Kim, 2001) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
PU1	The [X vendor site/Internet e-commerce site] provided good quality information.
PU2	The [X vendor site/Internet e-commerce site] improved my performance in assessing product features.
PU3	The [X vendor site/Internet e-commerce site] increased my effectiveness in assessing product features.
PU4	The [X vendor site/Internet e-commerce site] was useful for assessing product features.

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B.3.5. MEDIATION

→ Example

- Measures:

	TRUST (Gefen, Karahanna & Straub, 2003) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
TRS1	I felt that the [X vendor site/Internet e-commerce site] was honest.
TRS2	I felt that the [X vendor site/Internet e-commerce site] was trustworthy.
TRS3	I felt that the [X vendor site/Internet e-commerce site] cared for customers.
TRS4	I felt that the [X vendor site/Internet e-commerce site] provided me with good service.

	ENJOYMENT (Koufaris, 2002; Agarwal & Karahanna, 2000) *(seven-point Likert scale anchored with strongly disagree to strongly agree)*
ENJ1	I found my visit to the [X vendor site/Internet e-commerce site] to be interesting.
ENJ2	I found my visit to the [X vendor site/Internet e-commerce site] to be entertaining.
ENJ3	I found my visit to the [X vendor site/Internet e-commerce site] to be enjoyable.
ENJ4	I found my visit to the [X vendor site/Internet e-commerce site] to be pleasant.

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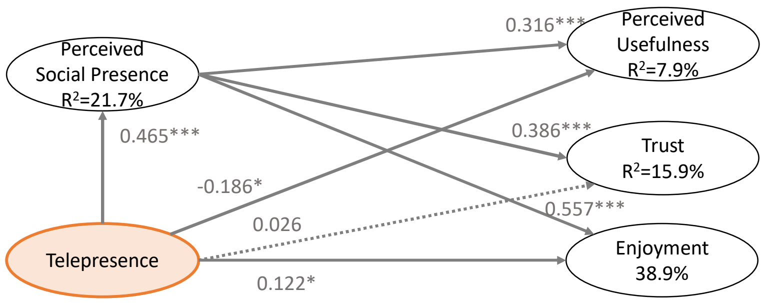
B.3.5. MEDIATION

➔Example

- The results of the structural (inner) model are:



- **Telepresence** seemingly has no impact on **trust**, has a positive impact on **enjoyment** and a negative on **perceived usefulness**.

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B.3.5. MEDIATION

➔Example

- Let's try to get there with the file: RetailSite.csv.
- Analyse the measurement model
  - Reliability;
  - Validity;
- Analyse the structural model.

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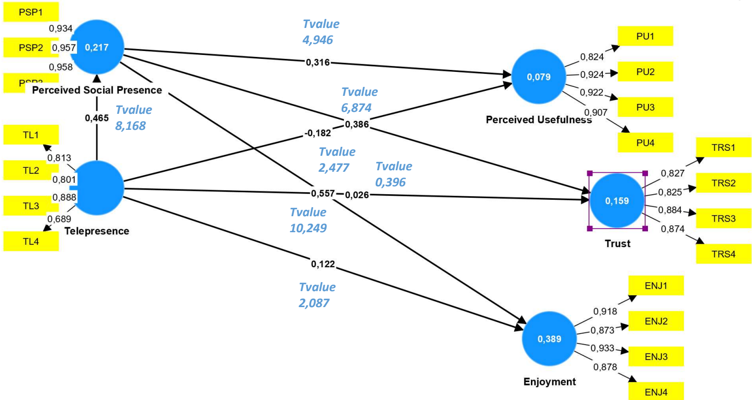
B.3.5. MEDIATION

➔Example

- Something like this?

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Enjoyment	0,922	0,925	0,945	0,811
Perceived Social Presence	0,946	0,953	0,965	0,902
Perceived Usefulness	0,917	0,919	0,942	0,802
Telepresence	0,814	0,882	0,877	0,641
Trust	0,888	1,004	0,914	0,727



	Enjoyment	Perceived Social Presence	Perceived Usefulness	Telepresence	Trust
Enjoyment	0,901				
Perceived Social Presence	0,614	0,950			
Perceived Usefulness	0,419	0,231	0,895		
Telepresence	0,381	0,465	-0,035	0,801	
Trust	0,642	0,398	0,480	0,205	0,853

	Enjoyment	Perceived Social Presence	Perceived Usefulness	Telepresence	Trust
Enjoyment					
Perceived Social Presence	0,652				
Perceived Usefulness	0,462	0,246			
Telepresence	0,414	0,503	0,063		
Trust	0,679	0,373	0,520	0,194	

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B.3.5. MEDIATION

➔Example

- Something like this?

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
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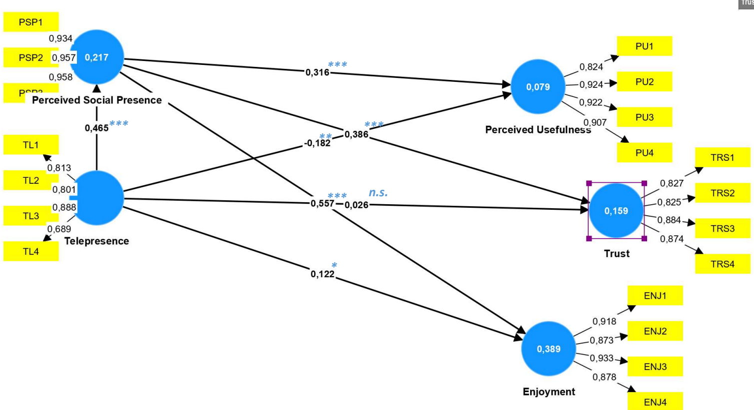

	Enjoyment	Perceived Social Presence	Perceived Usefulness	Telepresence	Trust
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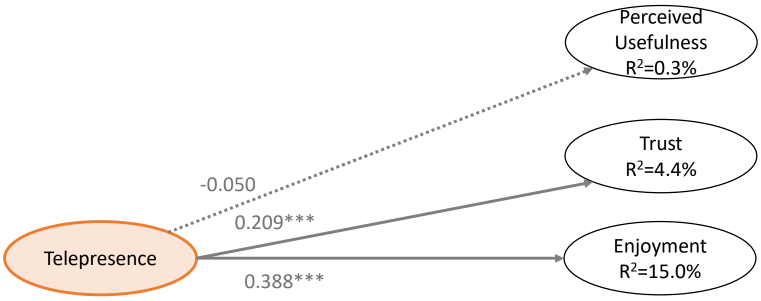
B.3.5. MEDIATION

➔Example

- What if we omit the **perceived social presence** (mediator)?



- Now, **telepresence** has a significant direct effect on both **trust** and **enjoyment** (but not on **perceived usefulness**).

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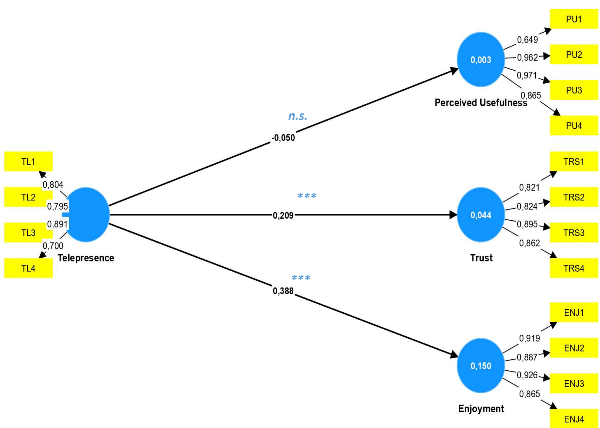
B.3.5. MEDIATION

➔Example

- Something like this?



	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Enjoyment	0,922	0,940	0,944	0,809
Perceived Usefulness	0,917	0,908	0,925	0,760
Telepresence	0,814	0,886	0,876	0,640
Trust	0,888	1,059	0,913	0,724

	Enjoyment	Perceived Usefulness	Telepresence	Trust
Enjoyment	0,900			
Perceived Usefulness	0,336	0,871		
Telepresence	0,388	-0,050	0,800	
Trust	0,635	0,413	0,209	0,851

	Enjoyment	Perceived Usefulness	Telepresence	Trust
Enjoyment				
Perceived Usefulness	0,462			
Telepresence	0,414	0,063		
Trust	0,679	0,520	0,194	

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B.3.5. MEDIATION

➔Example

- So, it seems that:
  - The direct effect that **telepresence** has on **trust,** is **fully mediated** by **perceived social presence**.
  - The direct effect that **telepresence** has on **enjoyment,** is **partially mediated** by **perceived social presence**.

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Moderation Effects

B.3.6

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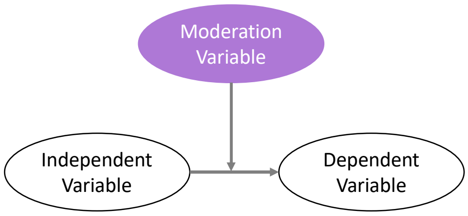
B.3.6. MODERATION EFFECTS

- How depict moderating effects in a PLS Path Model when the software only permits drawing direct effects?
- How estimate and interpret the coefficients of moderating effects?
- How determine the significance of moderating effects?
- How do formative versus reflective latent variables influence the detection, estimation and interpretation?
- Before model estimation, how prepare the data?
  - Should indicators be centered? (e.g. mean of zero);
  - Should indicators be standardized? (e.g. mean of zero and standard deviation of one)
  - Manipulated in some other way?



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B.3.6. MODERATION EFFECTS ➔WHAT'S THE RELEVANCE?

- Simply investigating the direct impact of one exogenous latent variable upon an endogenous variable belies the possibility of more complex, 'cascading' cause-and-effect relationships.
  - Especially with respect to human behavior.
  - For example, consider the factors that influence what clothes you might wear on any particular day:
    - Function you are attending
    - People you will be around
    - Weather (hot/cold; wet/dry; sunny/cloudy; seasonal influences; etc.)
- Moderating effects are not regarded, even if literature points out their relevance for explaining complex cause-effect relationships.
    - For example, levels of experience and age using computer technology is known to impact technology acceptance, but, usually, studies do not look for interactions of experience with other exogenous variables on technology acceptance.

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B.3.6. MODERATION EFFECTS
➔TWO APPROACHES

APPROACH 1

- Introduce and evaluate **interaction terms** in the structural model
  - Also called ***product indicator approach***
  - Best for ***continuous*** moderator variables
  - ***Independent*** and ***moderator*** variables are both ***reflective***.

APPROACH 2

- Determining moderating effects through ***group comparisons***
  - Best for ***categorical*** moderator variables, or otherwise non-continuous and discrete variables.
  - Or they can be made discrete (e.g. high value – low value groupings)
  - Also must be ***reflective*** indicators.

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B.3.6. MODERATION EFFECTS
➔*INTERACTION*

- Involves a moderator variable which may be:
  - Qualitative (e.g. gender, race, …)
  - Quantitative (e.g., age, income, firm size, …)
- The moderator, in turn, affects the direction and/or strength of the relation between the independent (or predictor) variable and a dependent (or criterion) variable.
- Thus, moderator variables provide information as to the conditions in which we would expect a relationship between two variables to exist.
- SmartPLS offers a latent variable modeling approach for better estimation and detection of the interaction effect between quantitative (i.e., continuous) predictor and moderator variables.
- Product Indicator approach:
  - Product term (x*z) used to examine the influence that a moderator z would have on the relationship between the predictor x and the dependent variable of interest y.

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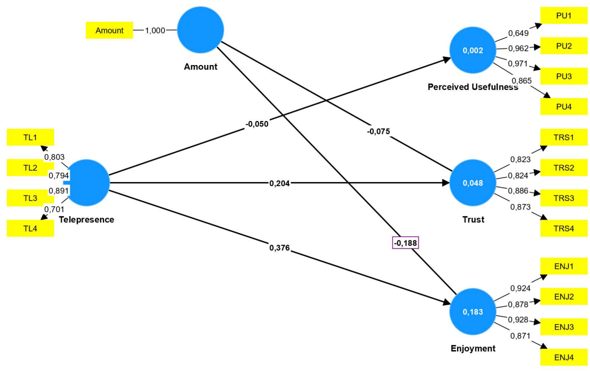
B.3.6. MODERATION EFFECTS
→INTERACTION

- Shall we start with this model?
- We will now include a variable related with the **total expense** of the items in the online store.



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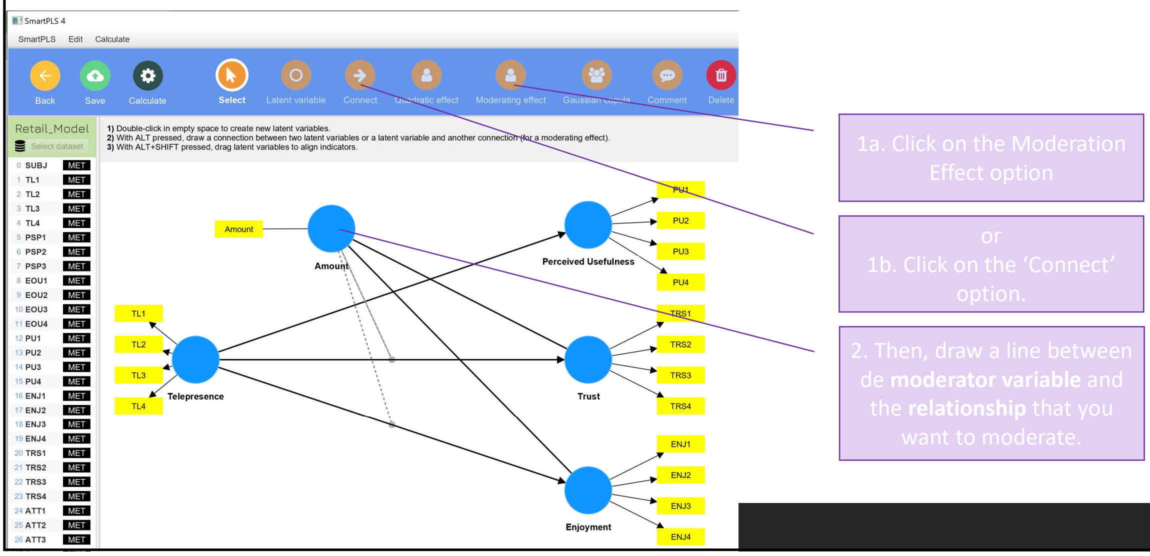
B.3.6. MODERATION EFFECTS
→INTERACTION

- Let's test if the **total expense** moderates the impact of telepresence in **trust** and **enjoyment**:



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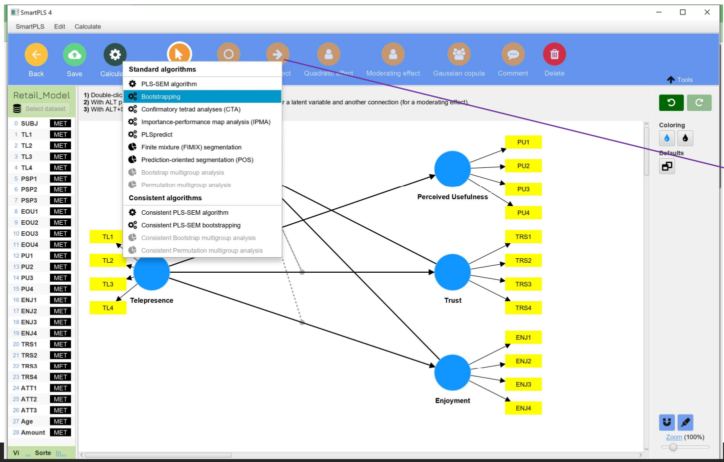
B.3.6. MODERATION EFFECTS
→ *INTERACTION*

- Let's test if the **total expense** moderates the impact of telepresence in **trust** and **enjoyment**:



3 . Then, you should simply run the Bootstrapping!

Note: our variable was only a single item variable. Otherwise, we need to run the PLS-SEM Algorithm and check for validity and reliability of the moderator variable.

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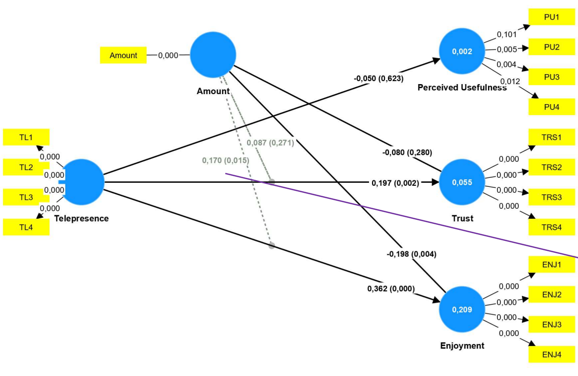
B.3.6. MODERATION EFFECTS
→ *INTERACTION*

- Now the results:



	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Amount -> Enjoyment	-0,198	-0,207	0,069	2,861	0,004
Amount -> Trust	-0,080	-0,091	0,074	1,081	0,280
Telepresence -> Enjoyment	0,362	0,366	0,052	6,970	0,000
Telepresence -> Perceived Usefulness	-0,050	-0,053	0,101	0,492	0,623
Telepresence -> Trust	0,197	0,206	0,063	3,145	0,002
Amount x Telepresence -> Enjoyment	0,170	0,171	0,070	2,426	0,015
Amount x Telepresence -> Trust	0,087	0,085	0,079	1,101	0,271

4. Looks like we have something...

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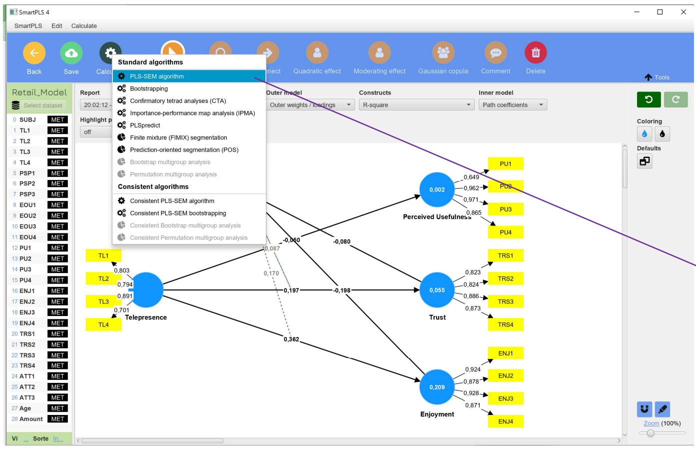
B.3.6. MODERATION EFFECTS
→ *INTERACTION*

- How about a graphical analysis of this moderation effect?



6. Calculate > PLS-SEM Algorithm > Start calculation

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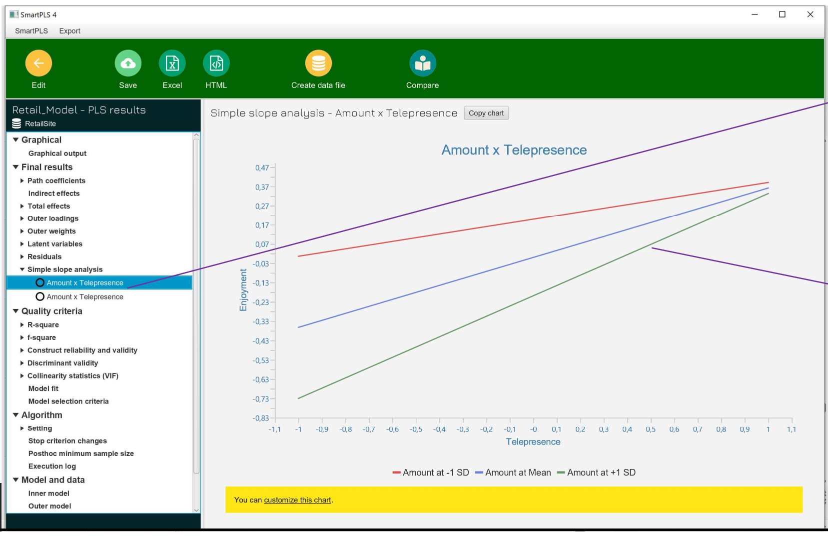
B.3.6. MODERATION EFFECTS
→ *INTERACTION*

- How about a graphical analysis of this moderation effect?



6. Report > Simple slope analysis

7. The slope here is more steeper, don't you think?

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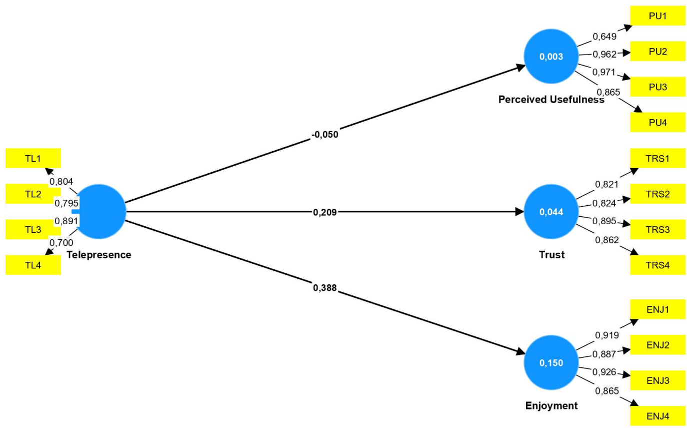
B.3.6. MODERATION EFFECTS
→ *MULTIGROUP ANALYSIS*

- The same model?



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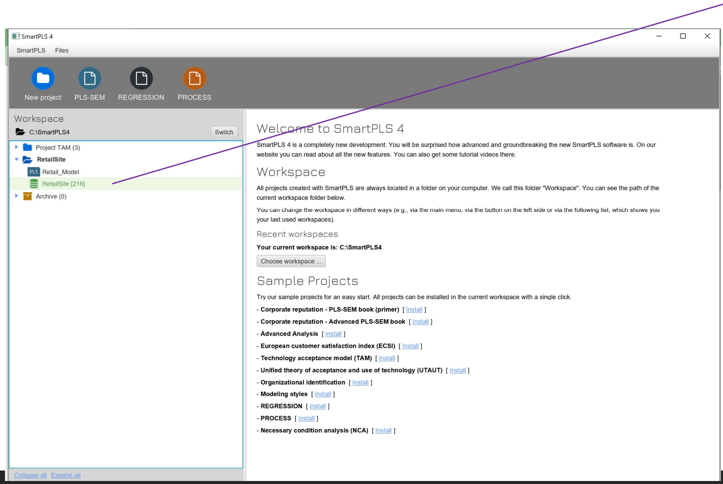
B.3.6. MODERATION EFFECTS
→ *MULTIGROUP ANALYSIS*

- We will now include a variable related with the **total expense** as the variable that enables the construction of groups.

1. Go to the data set.



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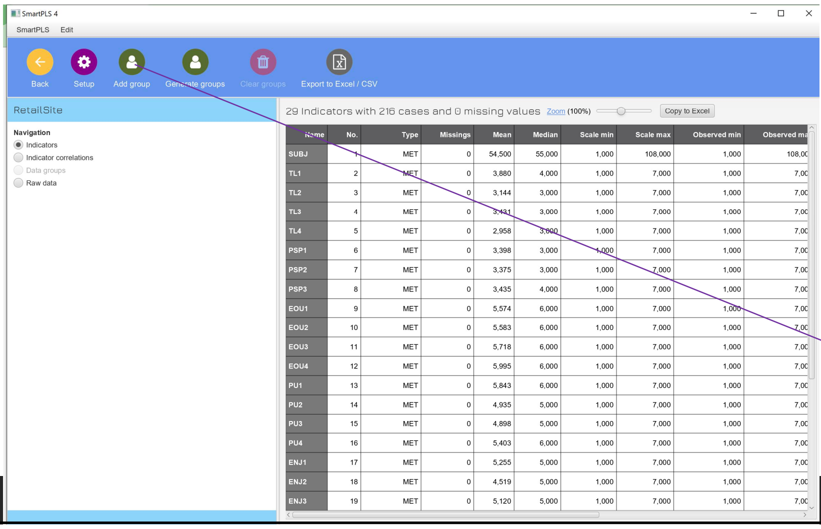
B.3.6. MODERATION EFFECTS
➔ *MULTIGROUP ANALYSIS*

- We will now include a variable related with the **total expense** as the variable that enables the construction of groups.



2. Click on 'Add Group'.

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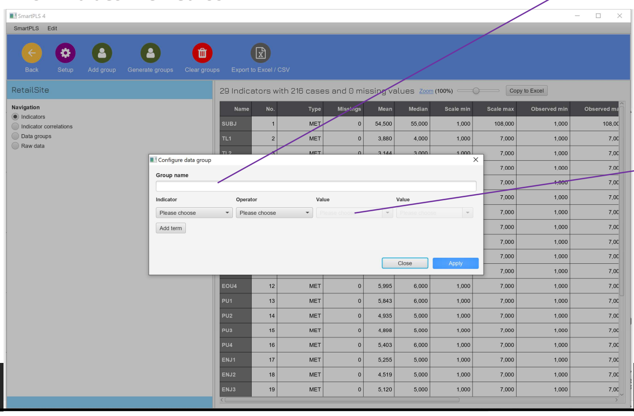
B.3.6. MODERATION EFFECTS
➔ *MULTIGROUP ANALYSIS*

- We saw that **amount** has a mean value of 191,5 euros.
- We will define 2 groups:
  - High: values ≥ 191 euros
  - Low: values <191 euros



3. Define group names.

4. Define the terms or each group.

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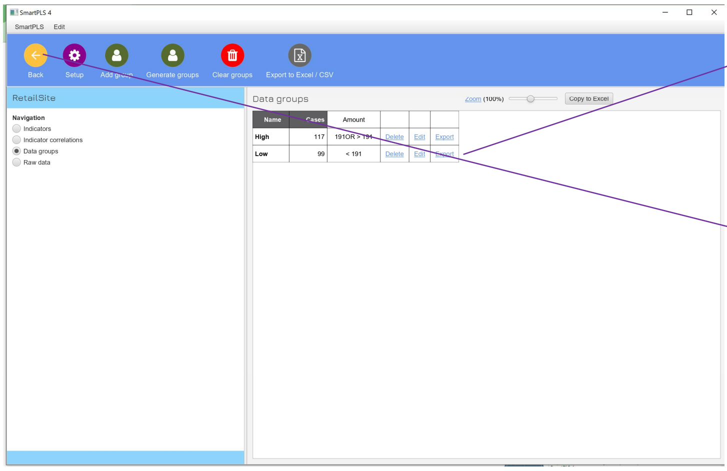
B.3.6. MODERATION EFFECTS
→ *MULTIGROUP ANALYSIS*

- We get these two groups:



5. Group high with 117 cases and group low with 99 cases.

6. Back to the project.

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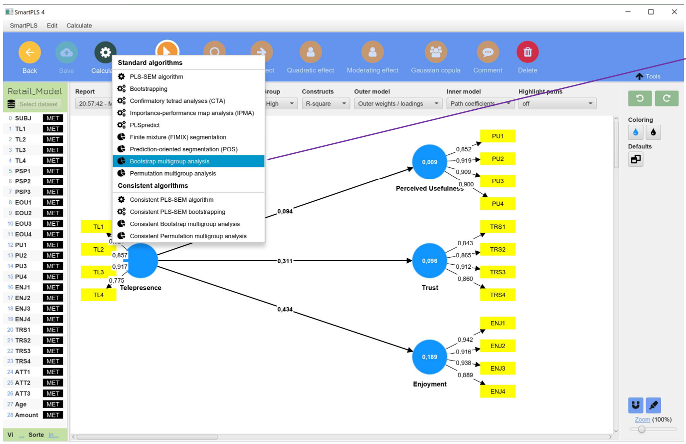
B.3.6. MODERATION EFFECTS
→ *MULTIGROUP ANALYSIS*

- Now the analysis:



7. Select 'Bootstrap multiple analysis'.

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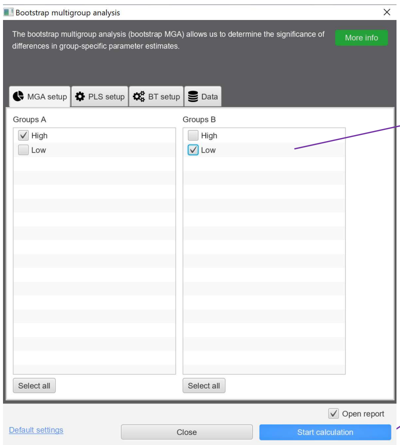
B.3.6. MODERATION EFFECTS
➔ *MULTIGROUP ANALYSIS*

- Now the analysis:



8. Allocate the goups.

9. Start Calculation.

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B.3.6. MODERATION EFFECTS
➔ *MULTIGROUP ANALYSIS*

- Results:

	Original (High)	Original (Low)	Mean (High)	Mean (Low)	STDEV (High)	STDEV (Low)	t value (High)	t value (Low)	p value (High)	p value (Low)
Telepresence -> Enjoyment	0,434	0,321	0,444	0,357	0,062	0,107	7,019	3,000	0,000	0,003
Telepresence -> Perceived Usefulness	0,094	-0,237	0,101	-0,254	0,127	0,094	0,736	2,520	0,462	0,012
Telepresence -> Trust	0,311	0,054	0,329	0,006	0,072	0,208	4,319	0,258	0,000	0,796

10. Some diferences of results between groups, and…

	Difference (High - Low)	t value (|High vs Low|)	p value (High vs Low)
Telepresence -> Enjoyment	0,113	0,952	0,342
Telepresence -> Perceived Usefulness	0,331	2,035	0,043
Telepresence -> Trust	0,257	1,249	0,213

11 … one diference is significant.

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Second-order variables

B.3.7

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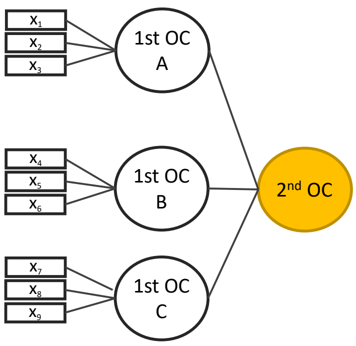
B.3.7. SECOND-ORDER LATENT VARIABLE

➔DEFINITION

- In the last years, the use of PLS-SEM methods moved from simple and small models to more advanced model designs, like higher-order constructs (Sarstedt *et al.*, 2019).
- Higher-order constructs, can also be called as hierarchical component models in the PLS-SEM.
- It refers to a specific framework where a latent variable (or construct) on a more abstract facet (like a second-order construct) combines different dimensions (like first-order constructs). Therefore, these latent variables have additional layers of abstraction, when compared to first order constructs.



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B.3.7. SECOND-ORDER LATENT VARIABLE
➔*DEFINITION*

- Some advantages of high-order constructs:
  - It helps to reduce the number of path model relationships within the frameworks – reduce complexity;
  - It helps to overcome the bandwidth-fidelity dilemma;
  - Higher-order constructs help to reduce collinearity between formative indicators (because they are rearranged in subdimensions).

- Main concerns related with the development of high-order constructs:
  - The conceptualization and specification of a high-order construct needs to be grounded in a well-supported measurement theory (reflective-R/formative-F) – there are four types of high-order constructs (RR, RF, FR, FF);
  - There are different approaches to specify high-order constructs (repeated indicator approach, two-stage approach and hybrid approach);
  - The evaluation of the measurement quality of high-order constructs needs to be assessed separately.

References: Hair *et al.*, 2018; Sarstedt *et al.*, 2019

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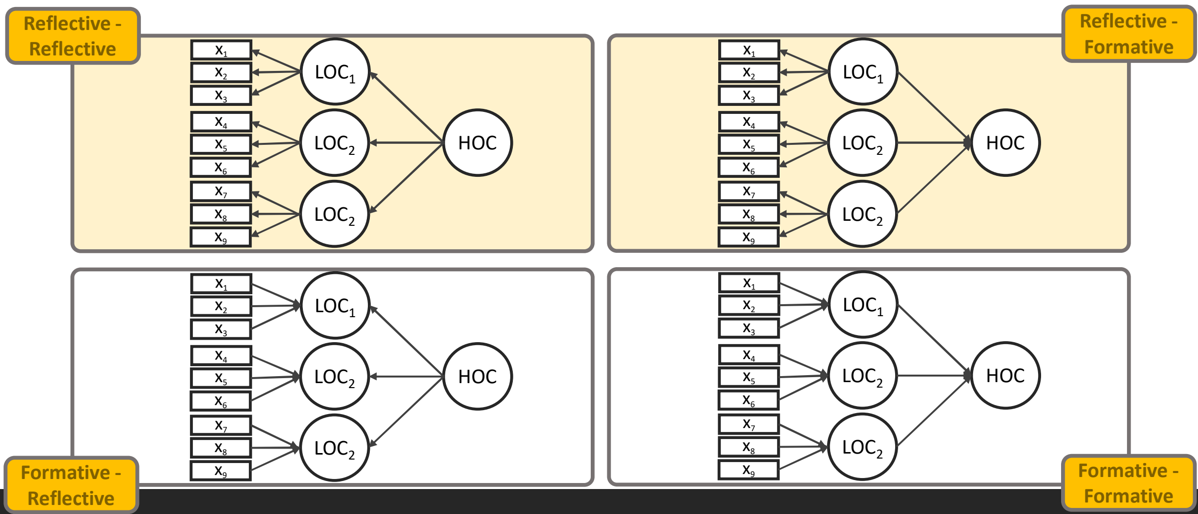
B.3.7. SECOND-ORDER CONSTRUCTS
➔*TYPES*

- There are four types of high-order constructs:



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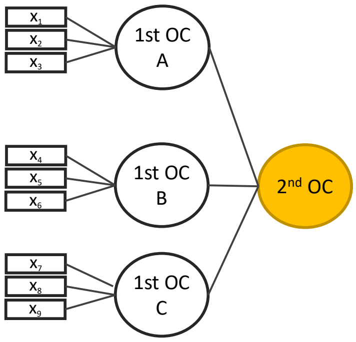
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ *DEFINITION*

- Some advantages of high-order constructs: In the last years, the use of PLS-SEM method moved from simple and small models to more advanced model designs, like higher-order constructs (Sarstedt *et al.*, 2019).
- Three different approaches to model hierarchical latent variables in PLS-SEM:
  - The **repeated indicator approach**;
  - The **two-stage approach** or sequential latent variable score method;
  - The **hybrid approach**.



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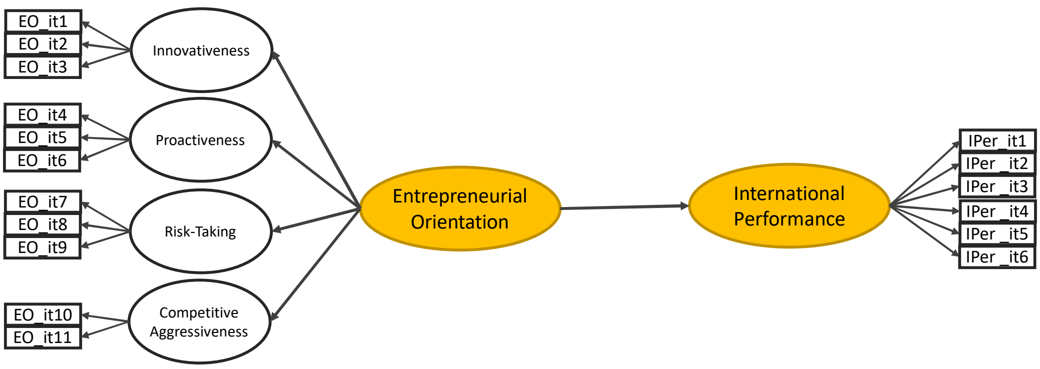
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ *EXAMPLE*

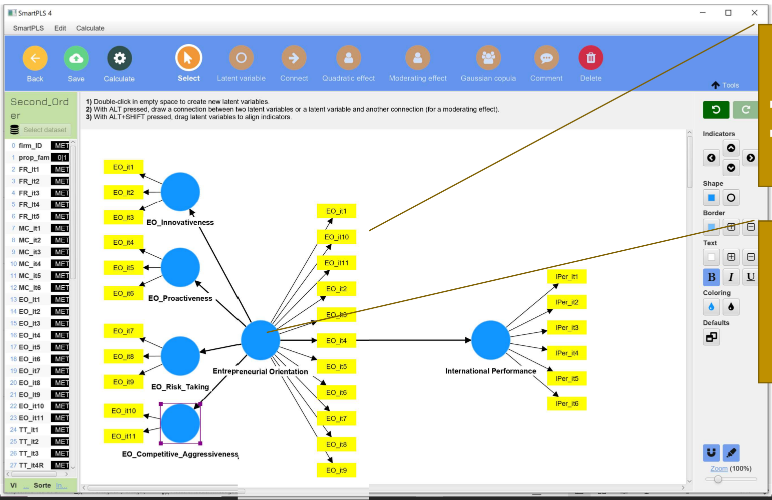
- REFLECTIVE-REFLECTIVE:
  - Open the file "Strategies_red.sav";
  - Replicate the model presented below:



182

B.3.7. SECOND-ORDER LATENT VARIABLE
➔ EXAMPLE

- REFLECTIVE-REFLECTIVE:



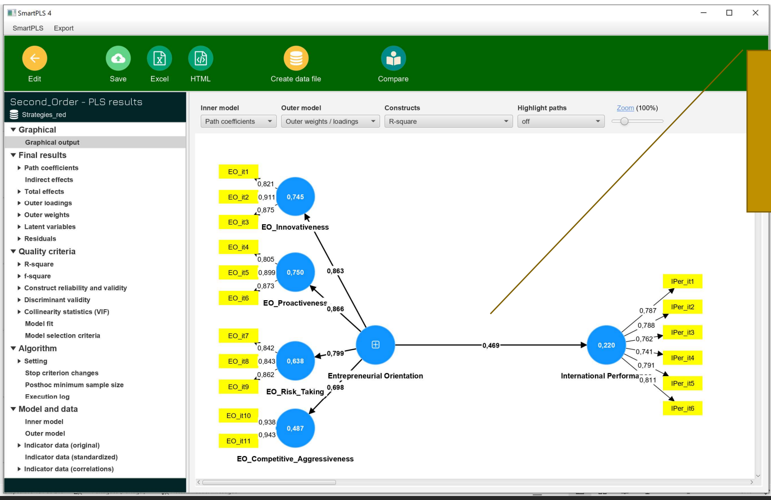
1. Like this. Now run the usual Processes:
   - PLS-SEM Algorithm
   - Bootstrapping

2. Attention: All EO items need also to be here.

183

B.3.7. SECOND-ORDER LATENT VARIABLE
➔ EXAMPLE

- REFLECTIVE-REFLECTIVE:



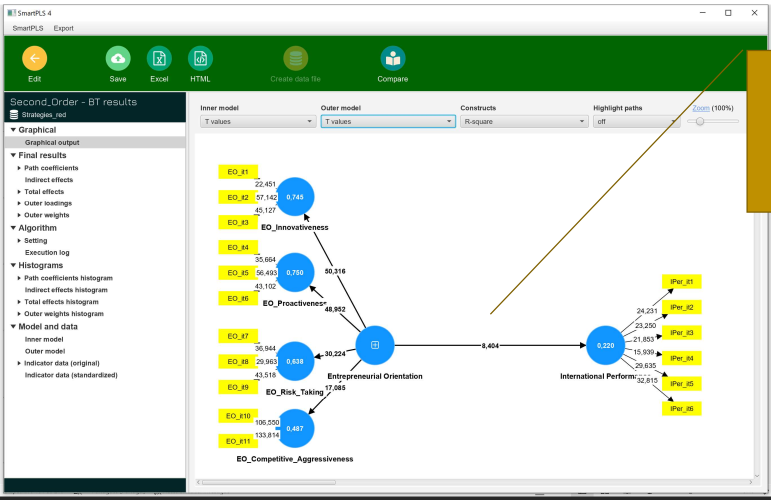
3. Results of PLS-SEM Algorithm.

184

B.3.7. SECOND-ORDER LATENT VARIABLE

➔ EXAMPLE

- REFLECTIVE-REFLECTIVE:



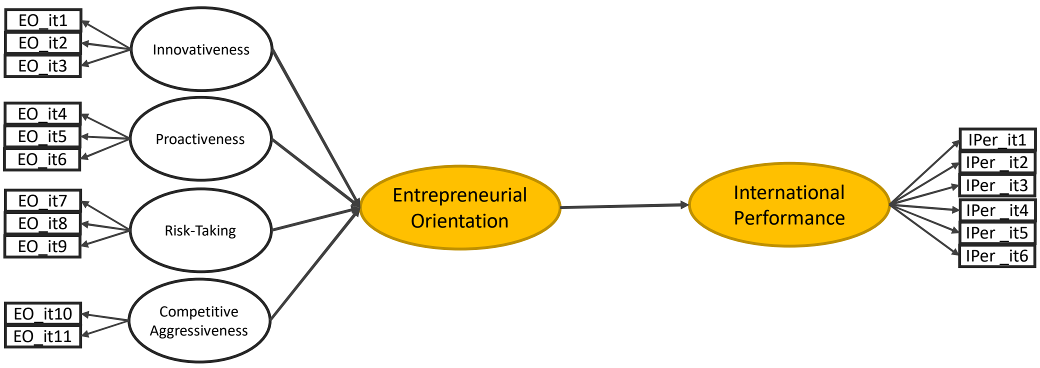
4. Results of Bootstrapping.

185

B.3.7. SECOND-ORDER LATENT VARIABLE

➔ EXAMPLE

- REFLECTIVE-FORMATIVE:
  - Consider that, based on theoretical support, Entrepreneurial Orientation had 4 formative dimensions:
  - Replicate the model presented below:



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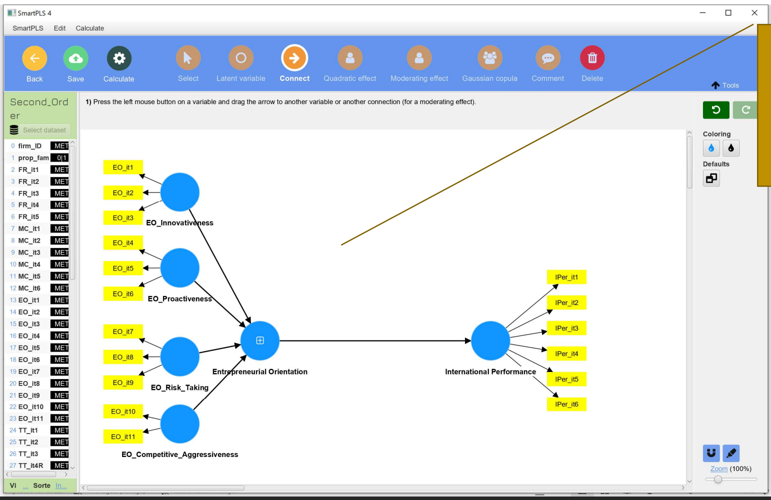
B.3.7. SECOND-ORDER LATENT VARIABLE

➔EXAMPLE

- REFLECTIVE-REFLECTIVE:



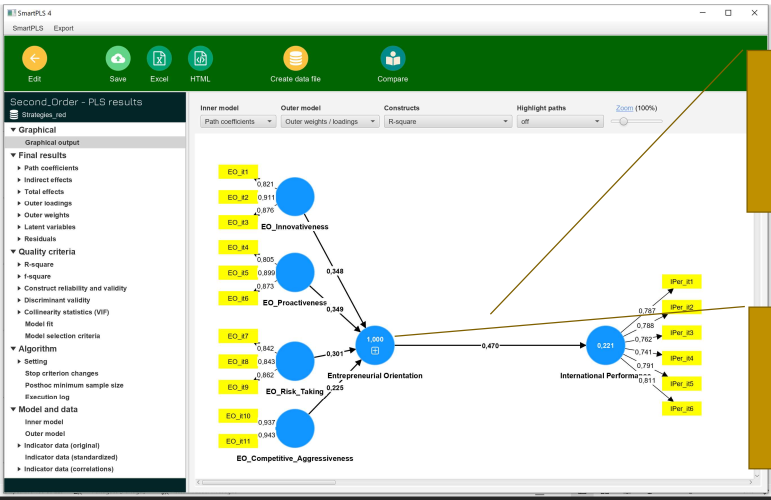
1. Like this. Now try to run PLS-SEM Algorithm.

187

B.3.7. SECOND-ORDER LATENT VARIABLE

➔ EXAMPLE

- REFLECTIVE-REFLECTIVE:



2. Results of PLS-SEM Algorithm. Everything seems ok…

3. But, we obtain this R^2=100%, or 1,000. This does not make sense.

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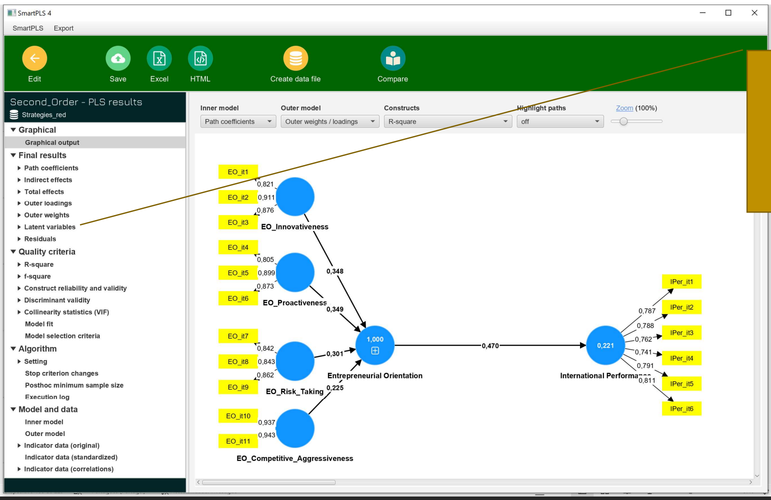
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ *EXAMPLE*

- REFLECTIVE-REFLECTIVE:



4. Go to the report > Latent Variables > Scores

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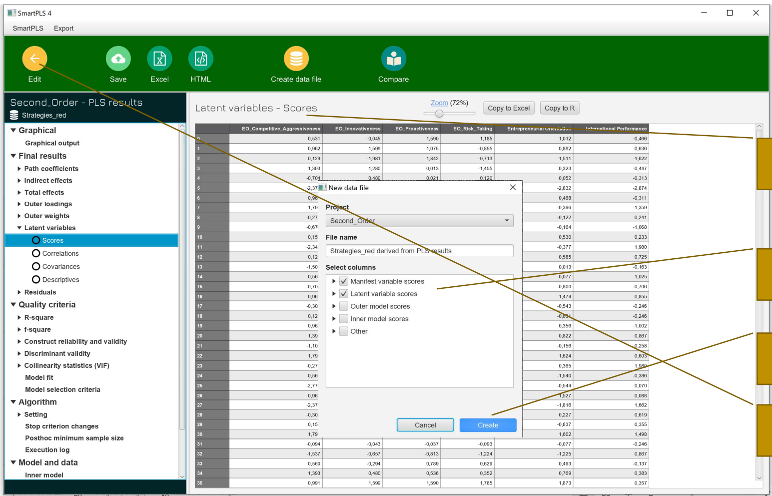
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ *EXAMPLE*

- REFLECTIVE-REFLECTIVE:



5. Click on 'Create data file'

6. Select Manifest variable scores + Latent variable scores

7. Click on create.

8. Press 'Back'.

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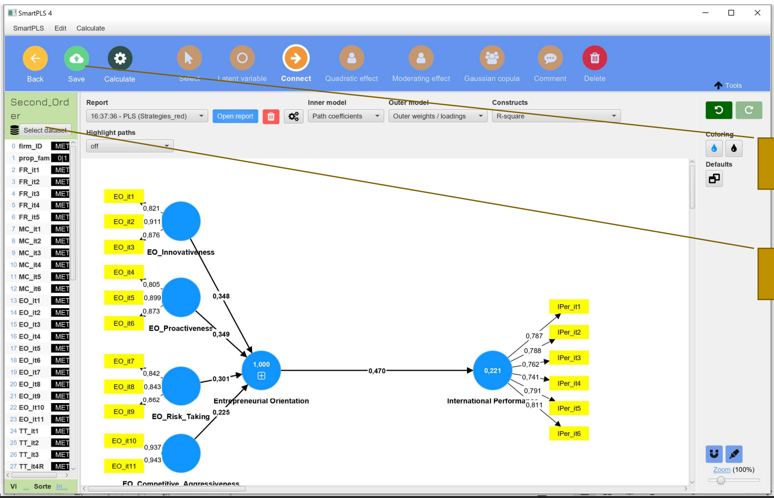
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ *EXAMPLE*

- REFLECTIVE-REFLECTIVE:



9. Press 'Save'.

10. Click on Select dataset.

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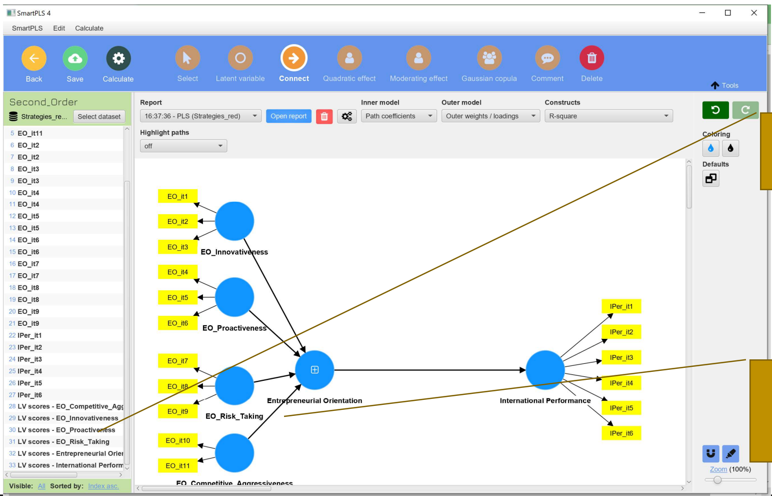
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ *EXAMPLE*

- REFLECTIVE-REFLECTIVE:



11. We now have these new observed variables, one for each dimension/LV.

12. So, we will delete the second-order variables, and replace them by the new observed dimensions.

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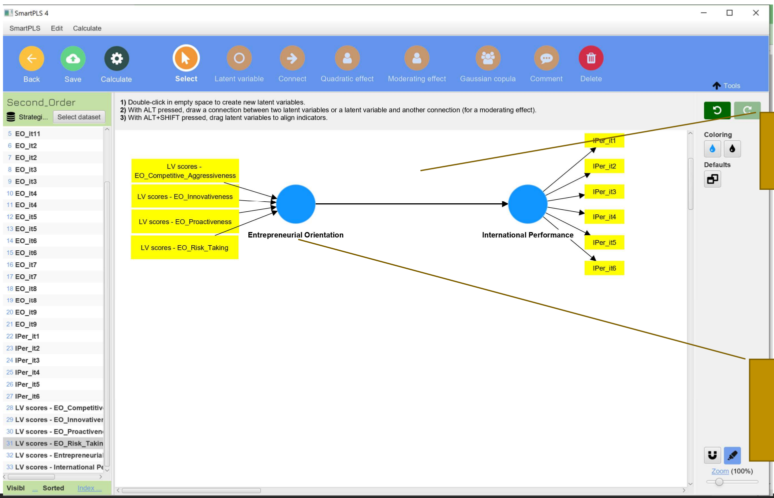
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ EXAMPLE

- REFLECTIVE-REFLECTIVE:



13. Like this!

14. Now we can run the PLS-SEM Algorithm, and analyse EO like a normal formative variable.

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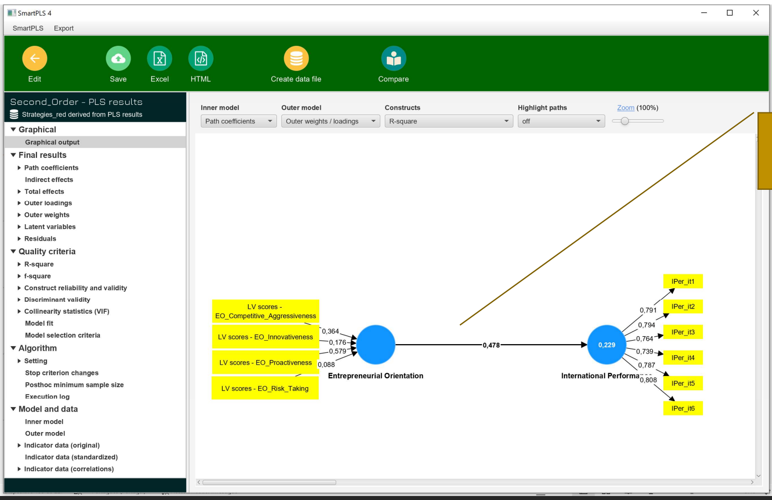
B.3.7. SECOND-ORDER LATENT VARIABLE

➔ EXAMPLE

- REFLECTIVE-REFLECTIVE:



15. Like this!

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Q&A

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