POLITECNICO MILANO 1863

# Structural Equation Modeling

AY 2024/2025 - Gloria Peggiani

# Agenda

- Exploratory and Confirmatory Factor Analysis
- PLS-SEM

specific

Candiani_B6_B6....: Can you hear me well? I ask to the people from home mainly.
Candiani_B6_B6....: A tradical point of view and we will see also how we typically assess these models. At the previous time this lecture is theoretical, so we will not see together yet the exercises

# Multivariate Statistics

**Multivariate statistics** refers to a branch of statistics that involves the application of statistical methods that **simultaneously analyze multiple variables**. This is in contrast to univariate statistics, which involves the analysis of a single variable. In multivariate statistics, the goal is often to understand the relationships among variables, identify patterns, and make predictions.

Traditional classification of multivariate statistical methods revolves around the idea of **dependency between variables** (Kendall 1957):

**Dependence multivariate methods**

analyze the associations between **two sets of variables**, where one set represents the dependent variable (or variables) and the other set several independent variables.

**Interdependence multivariate methods**

explore the mutual association across all variables **without distinguishing** between variable types.

# Multivariate Statistics

These methods can be used to either confirm a priori established theories or identify data patterns and relationships. Specifically, they are **confirmatory** when testing the hypotheses of existing theories and concepts, and **exploratory** when they search for patterns in the data in case there is no or only little prior knowledge on how the variables are related.

Common techniques used in multivariate statistics include:

| | Primarily Exploratory | Primarily Confirmatory Techniques |
|---|---|---|
| **Dependence Multivariate Methods** | e.g., **Partial Least Square Structural Equation Modeling** … online surveys | e.g., MANOVA, Multiple Regressions, Covariance-based Structural Equation Modeling … |
| **Interdependence Multivariate Methods** | e.g., Cluster Analysis, RFM Analysis, **Exploratory Factor Analysis**, Principal Component Analysis … | e.g., **Confirmatory Factor Analysis** … |

# Exploratory and Confirmatory Factor Analysis

01

another classification:

# First-generation multivariate data analysis techniques

usuall regression and all the basic methods
multivariate regression, anova, manova,

seconds are developed later => solved issues of first gen

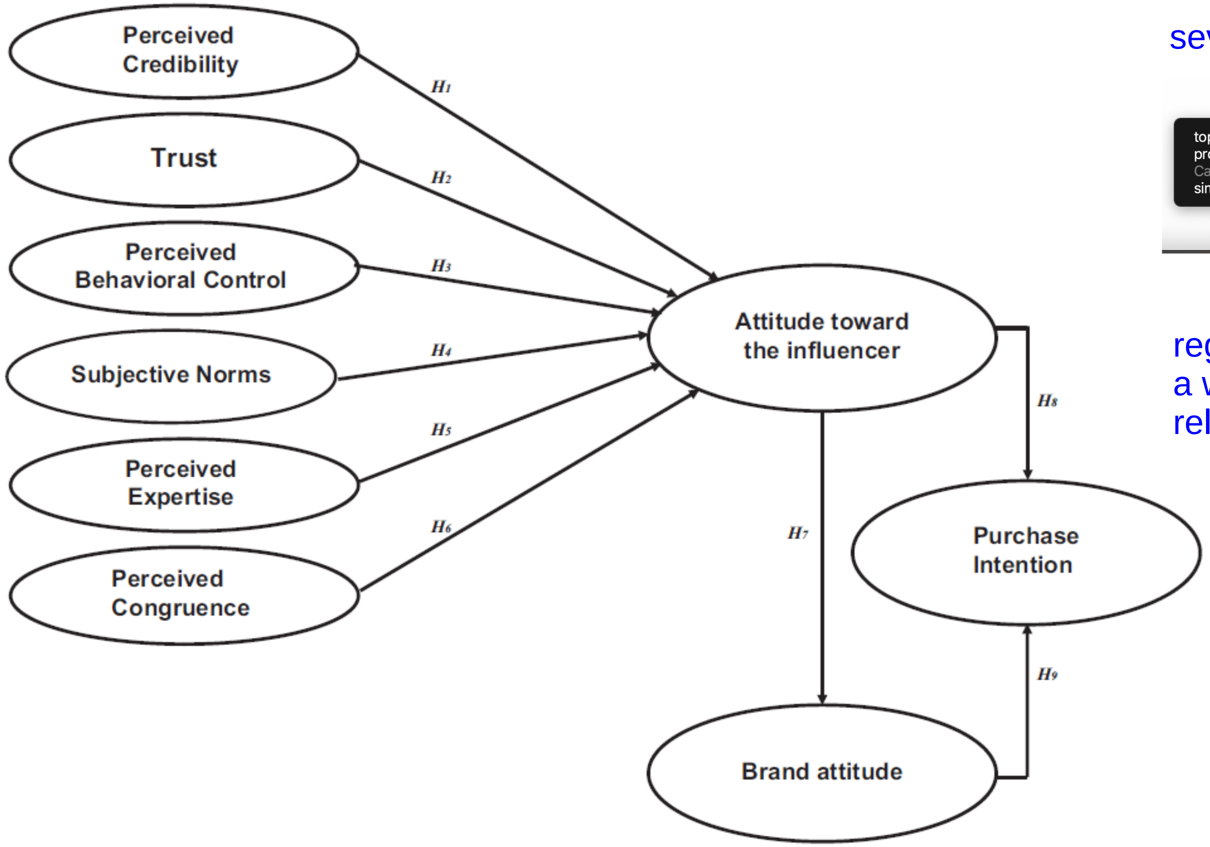
Multivariate multiple regression, multivariate logistic regression, analysis of variance, etc. belong to a core set of statistical methods employed by researchers to empirically test hypothesized relationships between variables of interest called **first-generation multivariate data analysis techniques.**

However, these techniques have three important limitations (Haenlein & Kaplan, 2004):

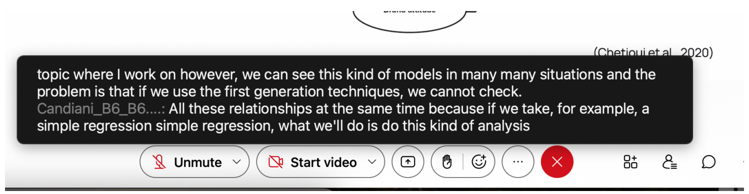
1. **The postulation of a simple model structure**
2. **Requiring that all variables can be considered observable**
3. **The assumption that all variables are measured without error**

assumed only simple situation, next page:

# Limitation of first-generation multivariate data analysis techniques: The postulation of a simple model structure




several variables are related to each other

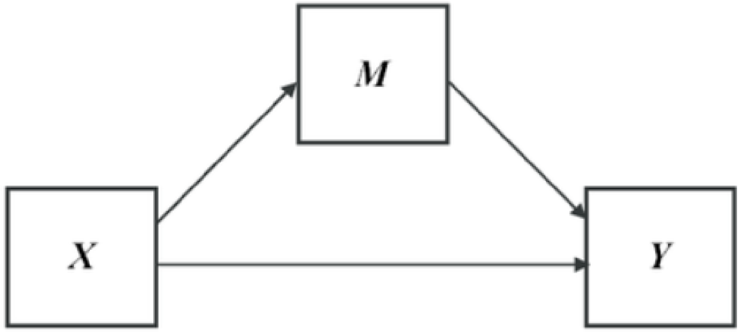



regression limit:
a with b and b with c is not possible all of the relation at the same time

(Chetioui et al., 2020)

# Limitation of first-generation multivariate data analysis techniques: The postulation of a simple model structure

A **mediation** effect occurs when the relationship between two variables can be explained via the inclusion of a third variable.




Full and Partial mediation

A **direct effect** describes the relationships linking two constructs with a single arrow.

**Indirect effects** are paths that involve a sequence of relationships with at least one mediator involved.

# Limitation of first-generation multivariate data analysis techniques: requiring that all variables can be considered observable

- Regression-type methods are restricted to processing **observable variables** (e.g., age or sales in units or dollars).

the problem is when we want to take the attitude and thoughts.

- Some information could not be measured by a single variable! Often variables are difficult to measure such as IQ, depression or extraversion. For measuring these, we often try to write multiple questions that - at least partially - reflect such factors

- Theoretical concepts, which are "abstract, unobservable properties or attributes of a social unit of entity" (Bagozzi & Philipps, 1982, p. 465).

# Psychometric Scales

use in factor analysis

Candiani_B6_B6....: So when we want to measure something like attitudes.
Candiani_B6_B6....: Believings so something that you think can be feel towards the brand or towards the product. What we typically use are these psychometric scales.
Candiani_B6_B6....: Probably you have talked a bit about this

"A psychometric scale comprises multiple items measuring the same focal variable in a **reliable** and **valid** manner and yielding **parametric data**."

(Robinson, 2017)

The items should have 3 characteristics: Questions must be:

- they are substantively different.
- the items cover a broad range of possible items (i.e., they are not selected so that they inadvertently only relate to a specific aspect of the concept being measured).
- the variance of each item is approximately equal.

cannot ask questions that are too similar between each other, otherwise it's useless. The second characteristic is that they should cover a range of a broad range of possible.

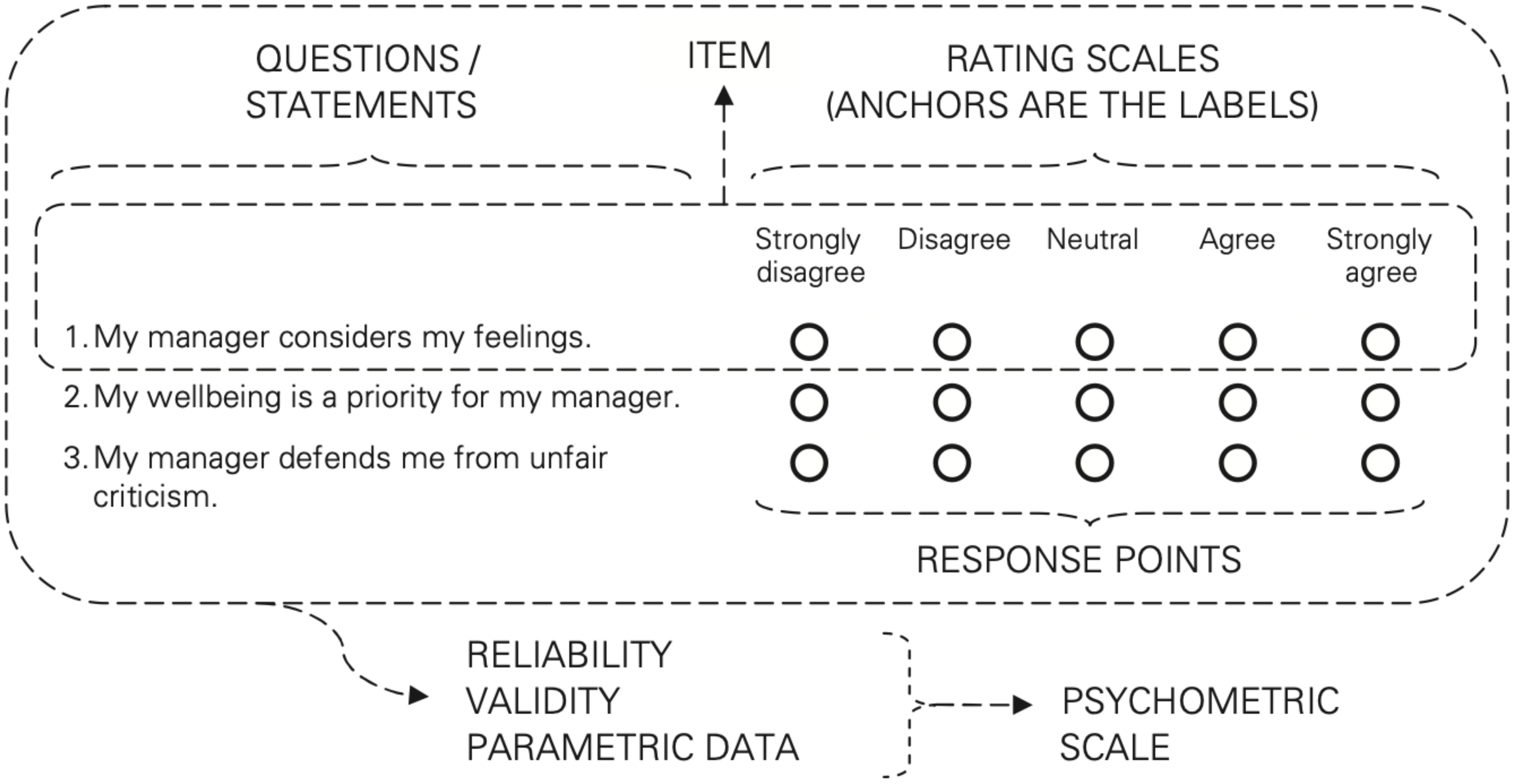
Candiani_B6_B6.3.2 19:16
Items. It means that I should be able to cover multiple aspects of the concept. For example, if I want to understand the concept of intelligence to a questionnaire, I cannot simply ask how much do you think.

Candiani_B6_B6.3.2 19:37
That you are intelligent from one to seven, of course, because also it doesn't make a lot of sense, but what I should do is asking acceptor of questions so preparing a set of items. Each focusing on a different aspect of intelligence. So there will be some items focused on spe.

Candiani_B6_B6.3.2 19:57
Intelligence, so the ability also to understand the distances and so on. There will be some questions about more logical intelligence so how we actually.

Candiani_B6_B6.3.2 20:11
Deduct things. So we always need the two other items that cover different aspects of the concept. And, the variance weight should be more or less so the same.

# Psychometric Scales




(Robinson, 2017)

# The process of scale development

1

**Conceptual Development**
The essential first step is to develop a theory to define the concepts for which one is seeking to develop a measure. If a construct is multidimensional, then the dimensions will also have to be defined.

**Example:**

*"Intelligence can be defined as a multifaceted cognitive capacity encompassing the ability to effectively acquire, process, and apply information in various domains"*

# The process of scale development

2

**Initial item pool definition**
A set of experts define a wide pool of items (questions) associated to each of the constructs (factors). This is usually informed by prior research.

**Example:**

*Please select your degree of agreement with the following sentences:*

- *"I can quickly analyze numerical data and draw meaningful conclusions from it."*
- *"I can mentally rotate objects and visualize them from different perspectives."*
- *"I feel confident in my ability to solve mathematical problems across various domains."*
- *"I can easily recognize and apply analogies in verbal contexts."*
- *"I can mentally visualize and manipulate spatial arrangements easily."*
- *"I have a strong sense of direction and can navigate through unfamiliar spaces confidently."*

# The process of scale development

توضیحات درباره واریانس و این اسلاید رو ببین دوباره اگر
نفهمیدی...

have twenty items and we find.

Candiani_B6_B6.3.2 24:52
Three variables. However, it's a bit different because there is a different mechanism underlying this procedure.

Candiani_B6_B6.3.2 25:03
The main difference is this one last time when we were talking about PCAE, we said that we want to find the new variables that can explain the the biggest amount of variance of the original data set with with fewer variables. So instead of using a twenty.

Candiani_B6_B6.3.2 25:22
Variables, I might use four variables to explain the ninety percent of the variance of the original data set.

Candiani_B6_B6.3.2 25:32
In this case instead, the objective is different. We don't want to find the variables that can explain the maximum level of total variance, but we want to find that the latent variables that are the variables where we have the maximum level of common vari.

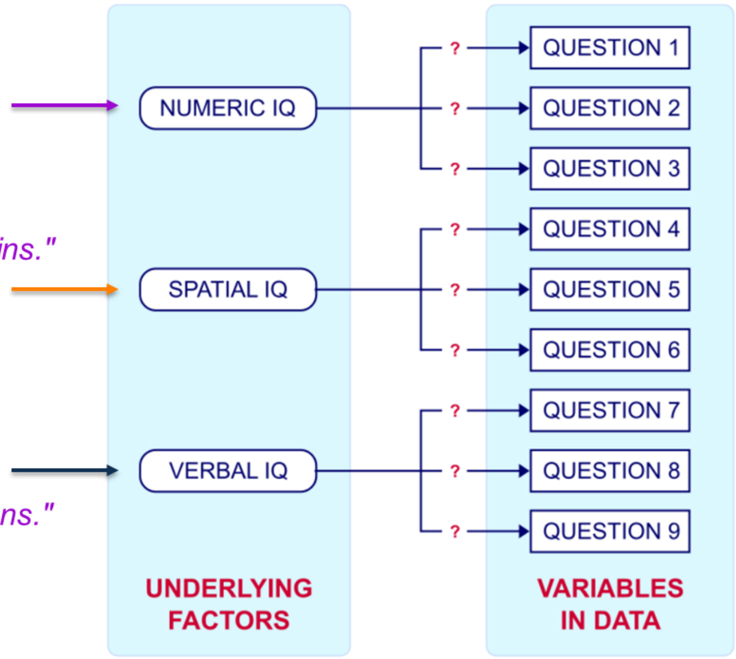
3

## Empirical development of scale

The general process is to follow an iterative process of performing EFA analyses on an item pool, refining the item pool, and then repeating the process. Once the item pool is refined, then a CFA analysis is needed to support the measurement model and to provide evidence of convergent and discriminant validity.

**Example:**

*"I can quickly analyze numerical data and draw meaningful conclusions from it."*
*"I can mentally rotate objects and visualize them from different perspectives."*
*"I am comfortable using a wide range of words in my spoken and written communication."*
*"I feel confident in my ability to understand and interpret written passages across various topics and genres."*
*"I feel confident in my ability to solve mathematical problems across various domains."*
*"I can easily recognize and apply analogies in verbal contexts."*
*"I can mentally visualize and manipulate spatial arrangements easily."*
*"I have a strong sense of direction and can navigate through unfamiliar spaces confidently."*
*"I feel confident in my capacity to think critically and draw logical conclusions from verbal information."*
*"I find it easy to understand and apply mathematical concepts in real-world situations."*
*g and*




it's like pca, we reduced the dimentionality

Candiani_B6_B6....: The main difference is this one last time when we were talking about PCAE, we said that we want to find the new variables that can explain the the biggest amount of variance of the original data set with with fewer variables. So instead of using a twenty.
Candiani_B6_B6....: Variables

# EFA: Exploratory Factor Analysis

نقهميدم

- EFA assumes that some **latent factors** exert influence on some observed variables. **EFA is used when it is not possible to know which factors in advance**, therefore it is adopted to identify these underlying factors.

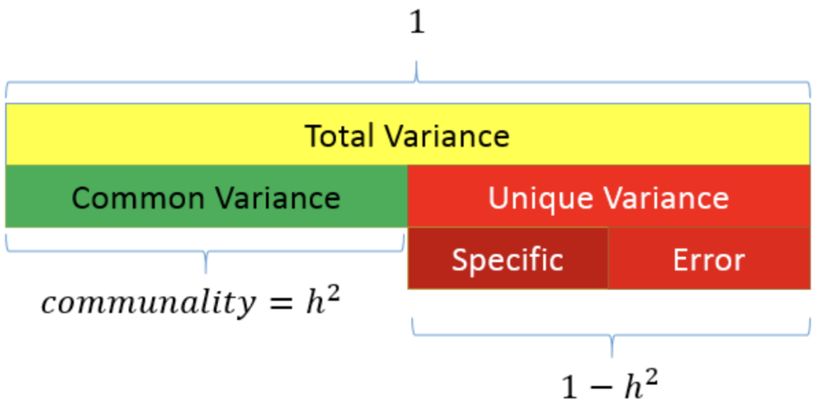
- The key objective is to **extract the maximum common variance** from the variables to arrange them under common factors to understand how much each variable contributes to each factor.

- The proportion of variance which can be explained by a set of factors which are common to the other observed variables is called **communality**. The degree of communality provides information to decide whether a particular factor should be retained. There is also a unique variance to that variable not explained by the factors, known as **uniqueness**.

# EFA: Exploratory Factor Analysis

نفهمیدم

- **Common variance** is the variance that is shared among a certain set of items. Highly correlated items share a lot of variance. Communality is an index of common variance that ranges between 0 and 1. **Unique variance** is any portion of variance that's not common.
- **Specific variance** is the variance that is specific to a particular item.
- **Error variance** comes from errors of measurement and basically anything unexplained by common or specific variance (e.g., one respondent did not understand the question).



# Previous lecture: PCA

- Principal Component Analysis, commonly known as PCA, is a technique for **reducing the dimensionality of large datasets**. It accomplishes this by converting a substantial set of variables into a more compact one while **retaining the majority of information** from the original dataset.

- **Important note:** principal components analysis **is conceptually different from factor analysis.** However, the two terms are often used interchangeably in several disciplines.

# PCA vs EFA

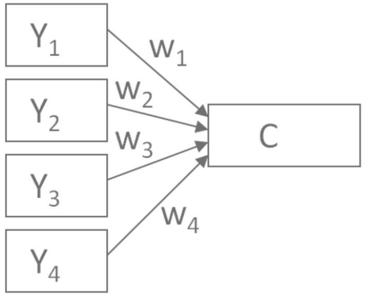
## PCA

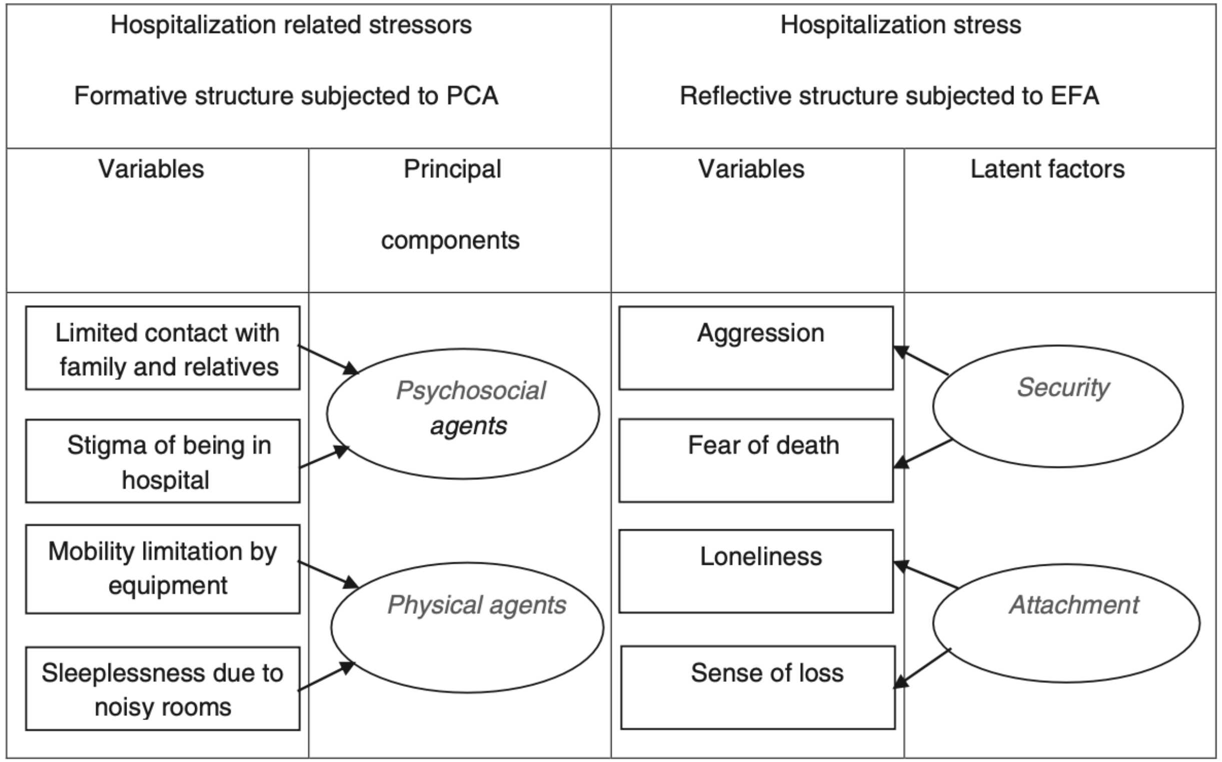
- It tries to reduce the dimensionality of the dataset down to fewer unobserved variables.
- It aims to explain the maximum amount of the **total variance** in the variables by analyzing all of the observed variance
- **Each component is a linear combination** of starting variables, thus it implies a **formative measurement model**, assuming item scores to be the causes of a construct.

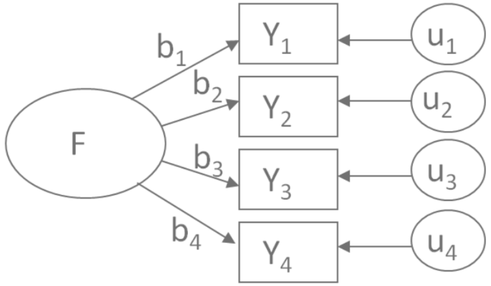
## EFA

- It tries to reduce the dimensionality of the dataset down to fewer unobserved variables.
- It aims to explain the maximum amount of **common variance among the variables.**
- FA assumes that a **latent factor exerts influence on some observed variables**. EFA is used to identify these underlying factors, thus it implies a **reflective** measurement model, assuming a direct effect from the construct on the item scores.

# PCA vs EFA: a different meaning




$C = w_1(Y_1) + w_2(Y_2) + w_3(Y_3) + w_4(Y_4)$

$Y_1 = b_1 * F + u_1;\ Y_2 = b_2 * F + u_2;\ \ldots$

**Weights**

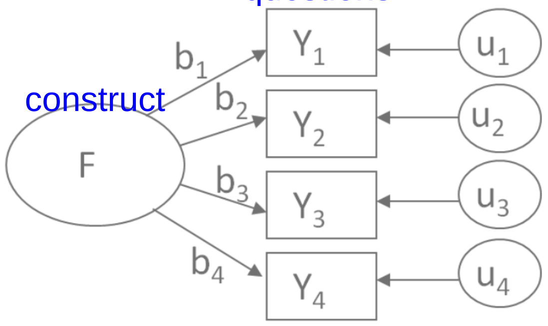
**Loadings**

# Reflective constructs

items are effect of consturcts

indicators are corrolated

questions




**Reflective indicators are considered "effects" of the Latent Variables**
→ the Latent Variables cause or form the indicators (Chin, 1998).

All reflective indicators measure the same underlying phenomenon, namely the latent variables. **Whenever the latent variable changes, all reflective indicators should change accordingly**, which refers to internal consistency (Bollen, 1984). Consequently, all reflective indicator should correlate positively. (Urbach & Ahlemann, 2010)

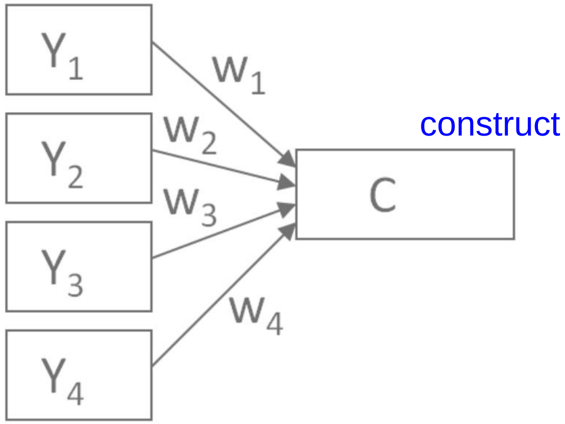
- Direction of causality is from construct to measure
- Indicators expected to be correlated
- Dropping an indicator from the measurement model does not alter the meaning of the construct
- Takes measurement error into account at the item level

# Formative constructs

what we get after PCA

**Formative indicators cause or form the Latent Variable by definition** (Chin, 1998).

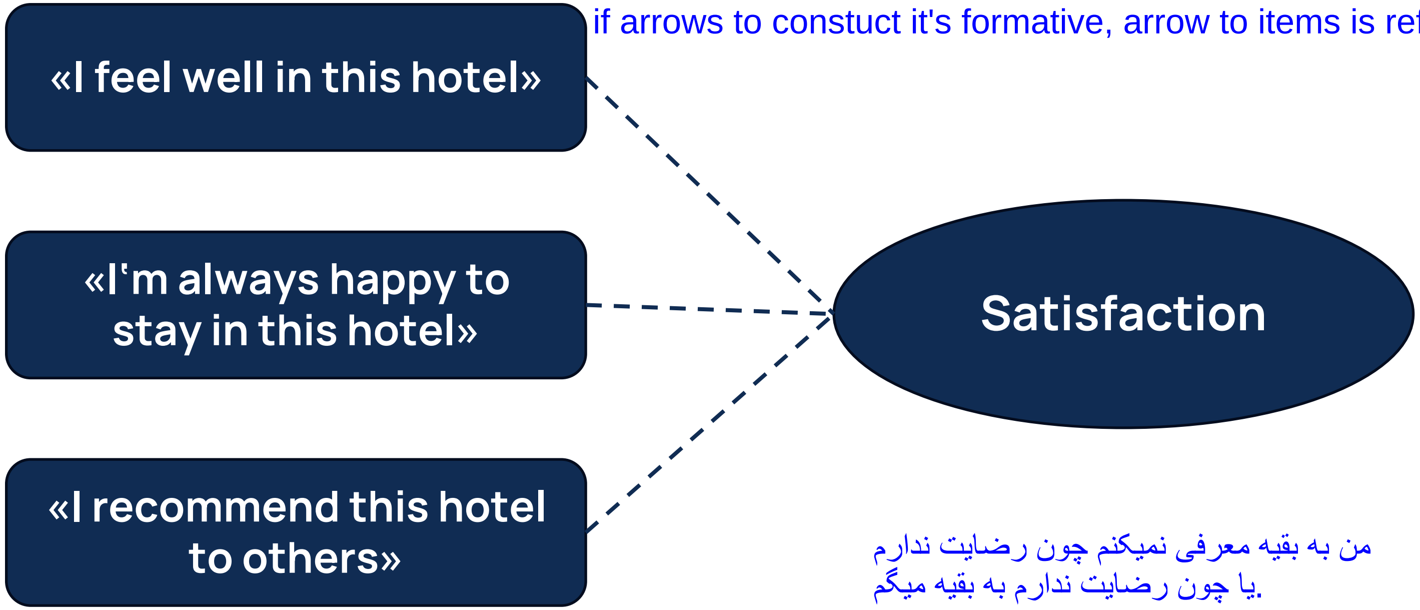
- Direction of causality is from measure to construct
- Indicators are not expected to be correlated
- Dropping an indicator from the measurement model may alter the meaning of the construct
- No such thing as internal consistency reliability



# Reflective vs. Formative Constructs

## Reflective or formative?

three rates and one construct. which is cause and which is effects.
if arrows to constuct it's formative, arrow to items is reflective (factor analysis?)



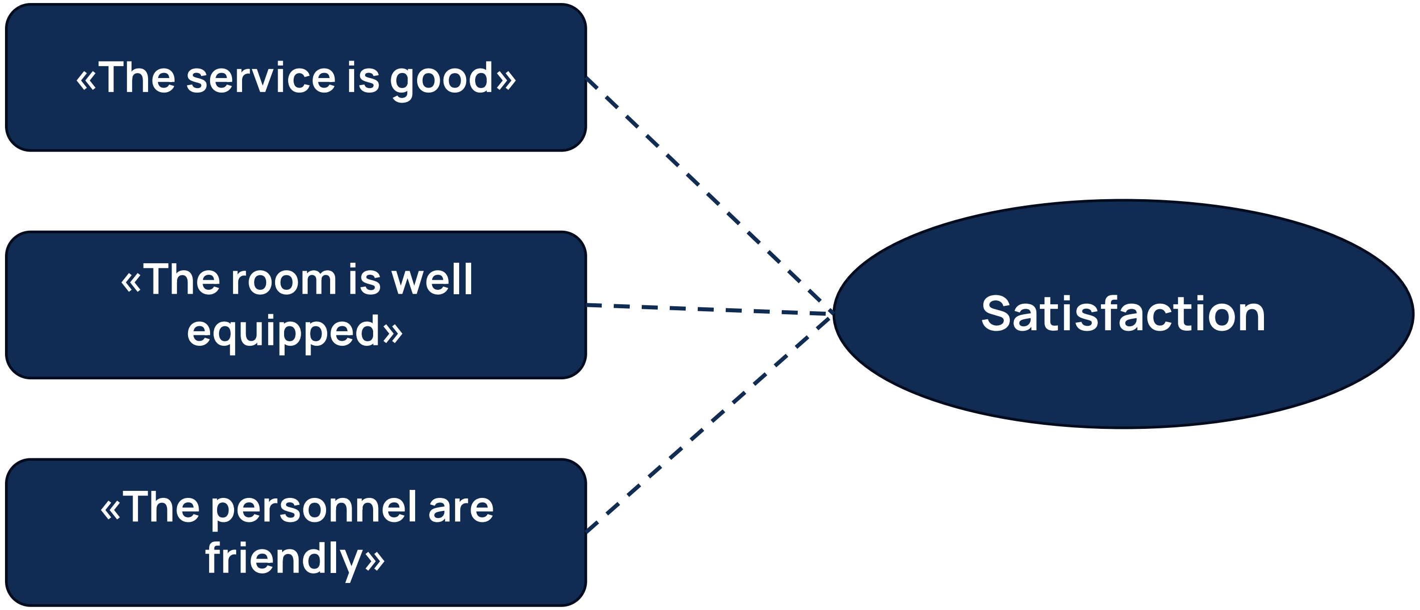

من به بقیه معرفی نمیکنم چون رضایت ندارم
یا چون رضایت ندارم به بقیه میگم.

افکت های ستیفکشن میشه ریفلکتیو
برعکس میشه

# Reflective vs. Formative Constructs

## Reflective or formative?

these are the reasons why I am satistied or vice versa



# PCA vs EFA

## PCA

- It tries to reduce the dimensionality of the dataset down to fewer unobserved variables.
- It aims to explain the maximum amount of the **total variance** in the variables by analyzing all of the observed variance
- **Each component is a linear combination** of starting variables, thus it implies a **formative measurement model**, assuming item scores to be the causes of a construct.
- **PCA does not include any measurement errors.**

## EFA

- It tries to reduce the dimensionality of the dataset down to fewer unobserved variables.
- It aims to explain the maximum amount of **common variance among the variables.**
- FA assumes that a **latent factor exerts influence on some observed variables**. EFA is used to identify these underlying factors, thus it implies a **reflective** measurement model, assuming a direct effect from the construct on the item scores.
- **EFA includes measurement errors.**

3rd

# Limitation of first-generation multivariate data analysis techniques: Assuming that all variables are measured without error

First-generation techniques are only applicable when measured variables contain neither systematic nor random error.

Social sciences (including marketing) usually deal with **theoretical concepts** (e.g., perceptions, attitudes, and intentions), and **each observation of the real world is always accompanied by a certain degree of measurement error**, which can be systematic or random.

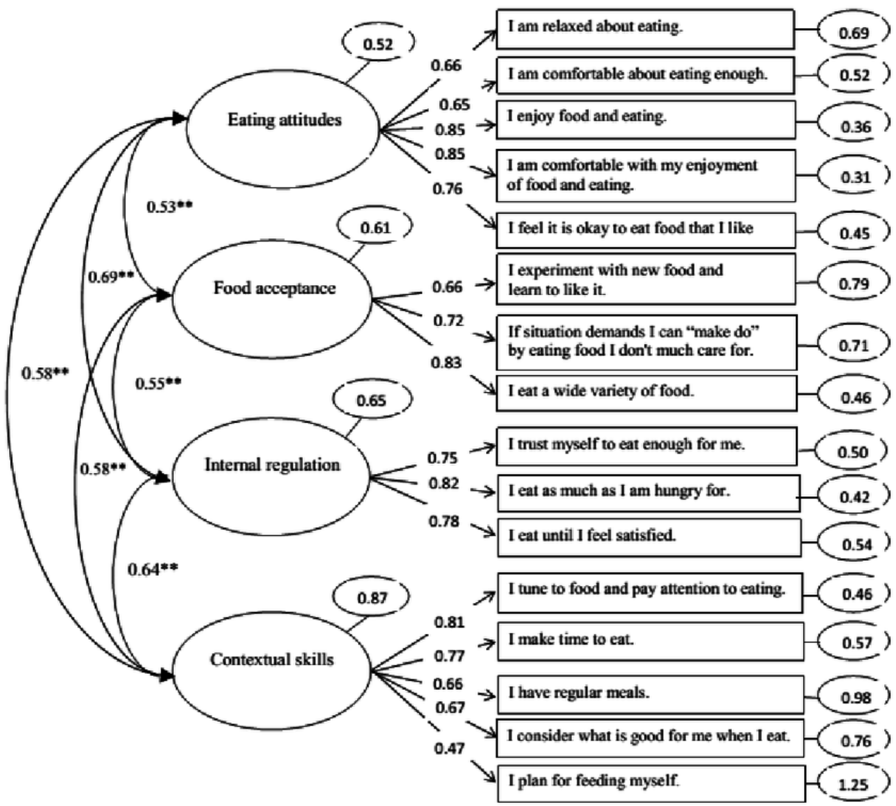
we do efa when we don't

# Using Psychometric Scales

4

## Measurement Quality Assessment

When prior studies have validated the construct of a certain scale through EFA, **Confirmatory Factor Analysis confirms or disconfirms the underlying factor structures**, or dimensions, with <u>a different set of data</u>. CFA tests how well the new data “fit” to the proposed model or theory.




common variance and find.

Candiani_B6_B6.3.2 44:34
The latent variables. All the latent variables are reflected constructor, it means that all the items that I have prepared are the effects the consequences of the latent variables. And after that we typically run the subfolder confirmatory factor analysis. This is the.

Candiani_B6_B6.3.2 44:54
Second type of factor analysis and as the name suggests it is used to confirm what we have already found. So we do the exploratory factor analysis when we don't know which are the underlying factors the latent variables and we want to find them. So before I ran the exploratory factor analysis and they found.

Candiani_B6_B6.3.2 45:15
The three types of IQ, but they didn't know them in advance.

Candiani_B6_B6.3.2 45:20
Instead, when we do confirmatory factor analysis I know in advance which are the constructs and I test if they are actually explained through this kind of items. So I actually checked that this contracts have these items as a defect.

actually checked that this contracts have these items as a defect.
Candiani_B6_B6....: Of the latent variable. So typically after I did an exploratory factor analysis I also do a confirmatory factor analysis to test the result.

This is the.

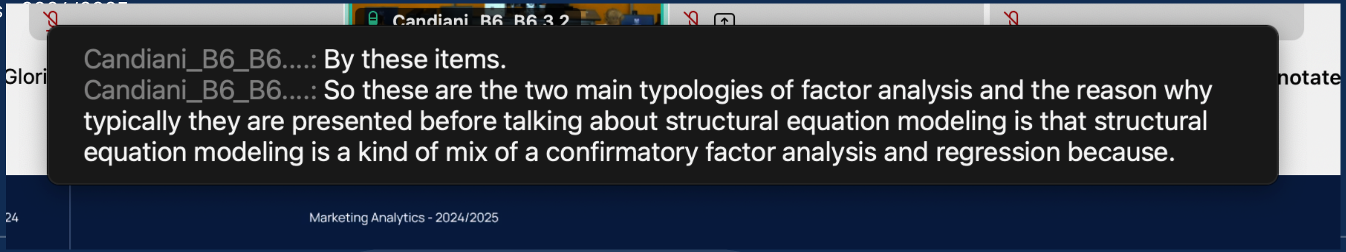
# CFA vs EFA vs PCA: different objectives

- CFA is distinct from PCA and EFA in that it constitutes a method of **hypothesis testing** applicable when the focus of the hypothesis is the structural relationship among variables. Indeed, CFA allows the researcher to specify how items relate to factors and how factors relate to each other.

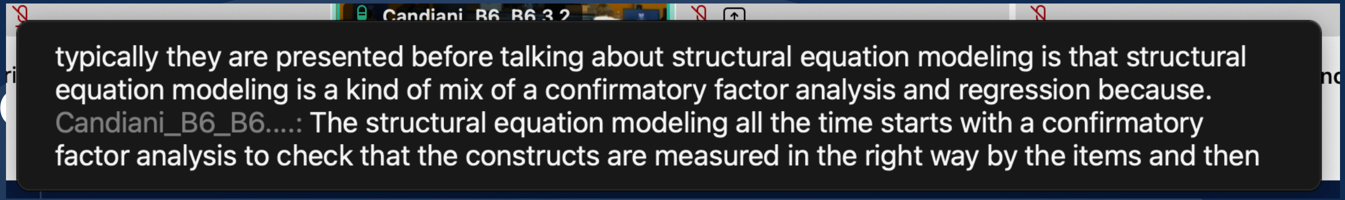
- This is very different from exploratory methods like PCA and EFA, with which a priori hypotheses cannot be tested. Thus, PCA and EFA are methods for **theory development** and CFA is better suited to **theory testing**.

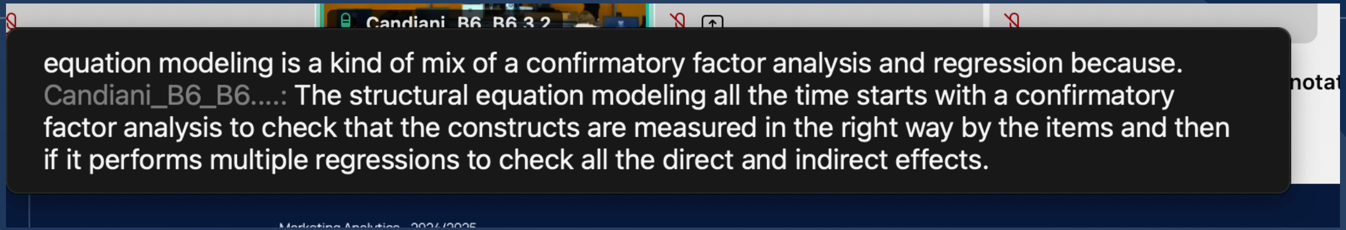
- CFA assumes latent variable causes the indicators, and it is based on a **reflective measurement model**.

توضیحات حدود ساعت ۱۵:۲۵ تا ۱۰ مین رو ببین. میاد روی اسلاید بعد و تازه توضیح میدهj


Candiani_B6_B6....: By these items.
Candiani_B6_B6....: So these are the two main typologies of factor analysis and the reason why typically they are presented before talking about structural equation modeling is that structural equation modeling is a kind of mix of a confirmatory factor analysis and regression because.
Marketing Analytics - 2024/2025

# Introdu


typically they are presented before talking about structural equation modeling is that structural equation modeling is a kind of mix of a confirmatory factor analysis and regression because.
Candiani_B6_B6....: The structural equation modeling all the time starts with a confirmatory factor analysis to check that the constructs are measured in the right way by the items and then


equation modeling is a kind of mix of a confirmatory factor analysis and regression because.
Candiani_B6_B6....: The structural equation modeling all the time starts with a confirmatory factor analysis to check that the constructs are measured in the right way by the items and then if it performs multiple regressions to check all the direct and indirect effects.

02

# Second-generation multivariate data analysis techniques

Structural equation modeling (SEM) is an umbrella term including a series of **second-generation data analysis techniques** that overcomes the limitations of first-generation techniques. These methods:

1. enable to simultaneously model and estimate **complex relationships** among multiple dependent and independent variables
2. Include concepts that are typically **unobservable** and measured indirectly by multiple indicators.
3. In estimating the relationships, SEM accounts for **measurement error** in observed variables.

As a result, the method obtains a more precise measurement of the theoretical concepts of interest (Cole & Preacher, 2014).

# Second-generation multivariate data analysis techniques

!

Even when the constructs of interest can be measured with limited ambiguity (e.g., price, weight,…), there are advantages to SEM over linear regression in that SEM allows the **creation and estimation of models with multiple dependent variables and their interconnections at the same time**(Gefen et al., 2011).

# Exogenous vs. Endogenous constructs

## Exogenous Constructs

independent variables

- Exogenous constructs are the latent, multi-item **equivalent of independent variables**. They use a linear combination of measures to represent the construct, which acts as an independent variable in the model.
- The term exogenous is used to describe latent constructs that **do not have any structural path relationships pointing at them**.

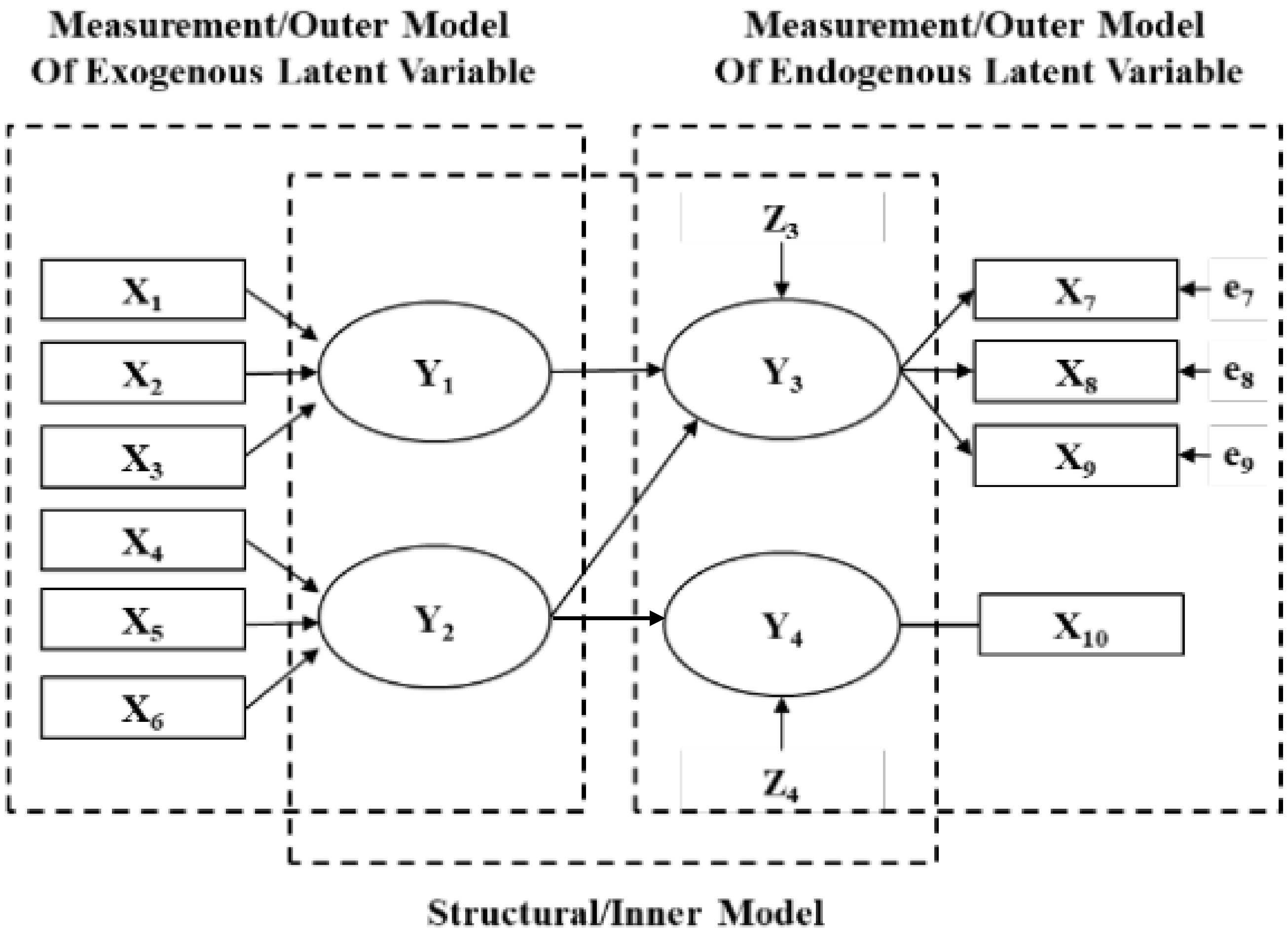
## Endogenous constructs

dependents

- Endogenous constructs are the latent, multi-item **equivalent to dependent variables.** These constructs are theoretically determined by factors within the model.
- The term endogenous describes latent target constructs in the structural model **that are explained by other constructs** via structural model relationships.

# Exogenous vs. Endogenous constructs

kodom indep and kodom dep?



# Inner model vs. Outer model

A structural equation model consists of different sub-models.

## Structural Model or Inner Model

- The structural model (or inner model) comprises the **relationships between the latent variables**, which has to be derived from theoretical considerations.

## Measurement Model/Outer Model

- For **each** of the **latent variable** within the structural equation model, a **measurement model** has to be defined.
- These models embody the relationship between the empirically observable **indicator variables and the latent variables**.

**→ The combination of structural model and measurement models leads to a complete structural equation model.**

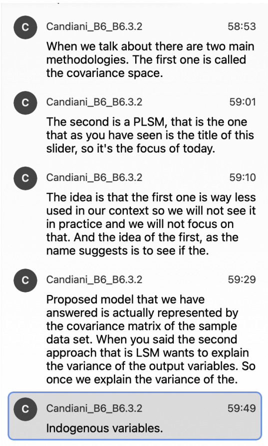
# Second-generation multivariate data analysis techniques

Two popular methods dominate SEM in practice:

- Covariance-Based SEM (CB-SEM)
- Partial Least Squares SEM (PLS-SEM, also called PLS path modeling).

PLS-SEM techniques combine **factorial analysis** with **multiple regression analyses** simultaneously. Testing theory using PLS-SEM follows a two-step process:

- Measurement theory testing: to confirm the **reliability** and **validity** of the measurement models.
- Structural theory testing: to confirm the **structural relationships** between the constructs in the model.


Candiani_B6_B6.3.2 58:53
When we talk about there are two main methodologies. The first one is called the covariance space.

Candiani_B6_B6.3.2 59:01
The second is a PLSM, that is the one that as you have seen is the title of this slider, so it's the focus of today.

Candiani_B6_B6.3.2 59:10
The idea is that the first one is way less used in our context so we will not see it in practice and we will not focus on that. And the idea of the first, as the name suggests is to see if the.

Candiani_B6_B6.3.2 59:29
Proposed model that we have answered is actually represented by the covariance matrix of the sample data set. When you said the second approach that is LSM wants to explain the variance of the output variables. So once we explain the variance of the.

Candiani_B6_B6.3.2 59:49
Indogenous variables.

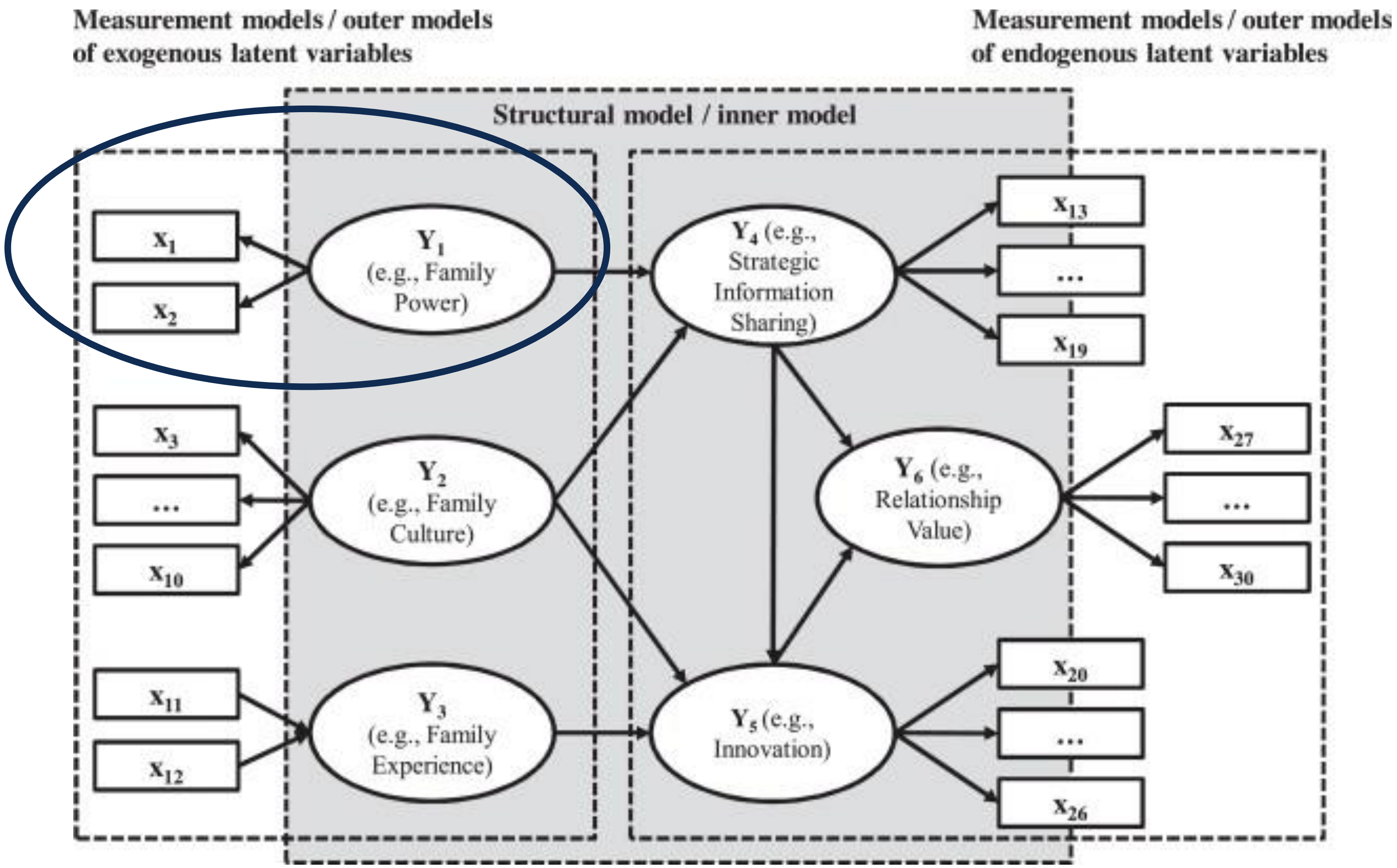
# Advantages of PLS-SEM

Researchers' arguments for choosing PLS as the statistical means for testing structural equation models (Urbach & Ahlemann, 2010) are:

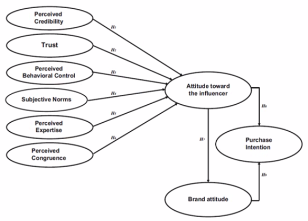
- PLS makes **fewer demands regarding sample size** than other methods
- PLS does **not require normal-distributed input data**.
- PLS can be applied to complex structural equation models with a **large number of constructs.**
- PLS is able to **handle both reflective and formative** constructs.
- PLS is especially useful for **prediction**

we focus on reflective

# Second-generation multivariate data analysis techniques



# Measurement Model Assessment




we collected the answer for this constructs

1. Assess the **indicator reliability**
2. Assess the **internal consistency reliability**
3. Assess the **convergent validity**
4. Assess the **discriminant validity**

Candiani_B6_B6.3.2 01:02:51
I have something like this when I start.

Candiani_B6_B6.3.2 01:02:59
Okay, so at the beginning of the I have collected for example on a survey all the answers for all these contract and I have the idea that maybe these are the relationship, but.

Candiani_B6_B6.3.2 01:03:15
I have got all the answers, all the data about this.

Candiani_B6_B6.3.2 01:03:19
What I do then is that I run the algorithm and I will obtain, first of all the measurement model that is.

Candiani_B6_B6.3.2 01:03:29
How the items of each contractor related to the constructor and then I will obtain a structural model that is the one that you can see here. So there are rowsers that connect between each other, all the constructs. So after I run the algorithm, the first thing that I should do is.

Candiani_B6_B6.3.2 01:03:49
Checking the measurement model.

Candiani_B6_B6.3.2 01:03:53
So I go back.

Candiani_B6_B6 01:03:56

Candiani_B6_B6.3.2 01:04:01
I always expect to check the score criteria. The very first one is the indicator of reliability. So the first thing is that I need to assess how much each indicator is explained by the construct. So I need to find the famous loading.

Candiani_B6_B6.3.2 01:04:21
To see how much the construct is able to explain the indicator. So they said before, I will never have the four hundred percent, but I need to find what is this kind of loading. So, this.

Candiani_B6_B6.3.2 01:04:36
Factor loading is basically like the correlation coefficient between the variable and the factor, and I obtain numbers that range between zero and one. The idea is that if I have a value that is higher than zero point seven, it's very good because it means that I can explain more than the seven.

# Measurement model assessment: Indicator Reliability

- Indicator reliability is assessed by examining **how much of each indicator's variance is explained by its construct**, which is indicative of indicator reliability.

- **Factor loading** is the **correlation coefficient for the variable and factor**, then shows the variance explained by the variable on that particular factor.

- As such, the indicator reliability indicates the **communality of an indicator**. Indicator loadings **above 0.7** are recommended, since they indicate that the construct explains more than 50 percent of the indicator's variance, thus providing acceptable indicator reliability (Hair et al., 2020).

- Reflective indicators should be eliminated from measurement models if their loadings within the PLS model are **< 0.4** (Hulland, 1999).

# Measurement model assessment: Internal Consistency Reliability

- Internal consistency reliability (also called *construct reliability*) is the extent to which **indicators measuring the same construct are associated with each other.**

- The main measures used in PLS-SEM are Jöreskog's (1971) **composite reliability rho$_c$** and **Cronbach's alpha.**

- Higher values indicate higher levels of reliability. Values **between 0.70 and 0.90** range from "satisfactory to good" (Hair et al., 2022). However**, values above 0.95 are problematic**, since they indicate that the **indicators are redundant**, thereby reducing construct validity. Possible motivations can be undesirable response patterns (e.g., straight-lining), thereby triggering inflated correlations among the error terms of the indicators.

# Measurement model assessment: Convergent Validity

how much varicance

Candiani_B6_B6....: So I always need to check also these two values. First point is still for the measurement measurement model is a conversion, so I want to understand in general.
Candiani_B6_B6....: How much variance is related to the constructor. So what they typically do is measuring this average variance extracted ABE, that is measured in this way

- Convergent validity (of a construct) is the extent to which **the construct converges in order to explain the variance of its indicators**.

- The metric used for evaluating a construct's convergent validity is the **average variance extracted (AVE)** <u>for all indicators on each construct.</u>

| Factor | Indicator | Loading (*t*-value Bootstrap) |
|---|---|---|
| Media richness | MR1 | 0.896 (48.290) |
| | MR2 | 0.918 (55.714) |
| | MR3 | 0.834 (23.659) |
| | MR4 | 0.881 (35.497) |

$$AVE = \frac{\left(0.896^2+0.918^2+0.834^2+0.881^2\right)}{4} = 0.779$$

- AVE is equivalent to the **communality of a construct**. Higher values indicate higher levels of convergent validity. The **minimum acceptable AVE is 0.50** (Hair et al., 2022).

# Measurement model assessment: Discriminant Validity

- Discriminant validity measures the extent to which **a construct** is empirically **distinct from other constructs** in the structural model.

- Heterotrait-monotrait ratio (HTMT) of correlations (Henseler et al., 2015) is a metric to assess discriminant validity. The HTMT is defined as the **mean value of the indicator correlations across constructs** (i.e., the heterotrait-heteromethod correlations) **relative to** the **mean of the average correlations for the indicators measuring the same construct** (i.e., the monotrait-heteromethod correlations).

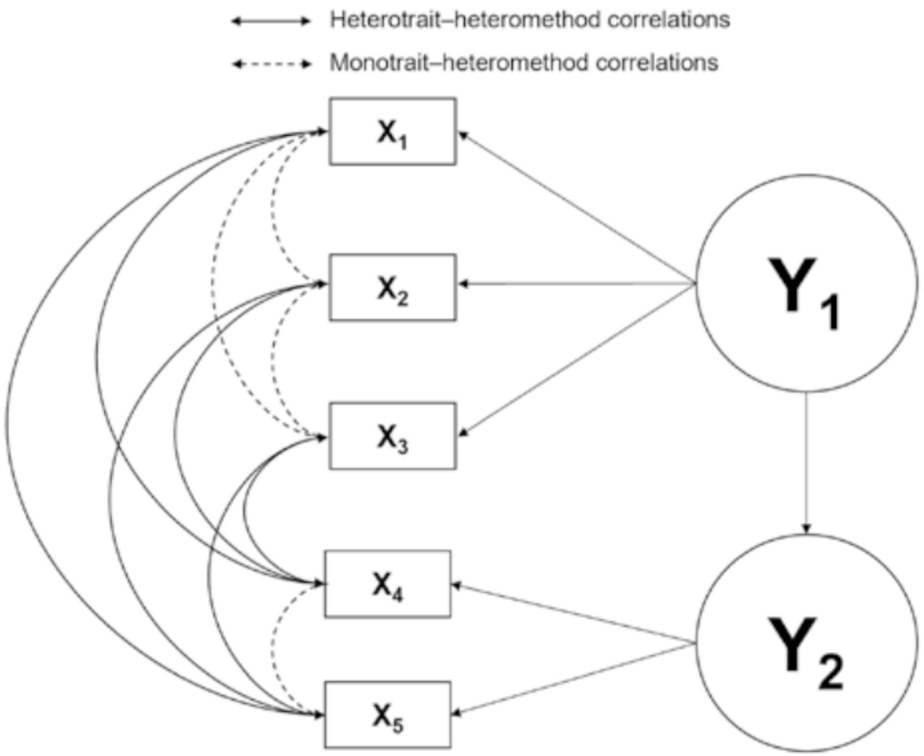
**Heterotrait →** Relationships between different constructs (traits) in the model (e.g., “information quality” with “purchase intentions”).

**Monotrait →** Relationships between items measuring the same construct (e.g., different items all measuring “purchase intentions").

# Measurement model assessment: Discriminant Validity

- For conceptually similar constructs, **HTMT < 0.90**
- For conceptually different constructs, **HTMT < 0.85**

- Bootstrap confidence intervals can be used to test if the HTMT is significantly different from 1.0 (or other lower thresholds)



# Measurement model assessment: Example

| Factor | Indicator | Loading (*t*-value Bootstrap) | Cronbach's $\alpha$ | CR | AVE |
|---|---|---|---|---|---|
| Media richness | MR1 | 0.896 (48.290) | 0.905 | 0.934 | 0.779 |
| | MR2 | 0.918 (55.714) | | | |
| | MR3 | 0.834 (23.659) | | | |
| | MR4 | 0.881 (35.497) | | | |
| Interactivity | IN1 | 0.857 (40.177) | 0.738 | 0.884 | 0.792 |
| | IN2 | 0.883 (24.057) | | | |
| | IN3 | 0.794 (16.939) | | | |
| Presence: self-location | SL1 | 0.950 (103.953) | 0.967 | 0.976 | 0.910 |
| | SL2 | 0.955 (106.733) | | | |
| | SL3 | 0.953 (100.902) | | | |
| | SL4 | 0.958 (102.857) | | | |
| Presence: possible actions | PA1 | 0.911 (57.360) | 0.924 | 0.946 | 0.815 |
| | PA2 | 0.917 (49.447) | | | |
| | PA3 | 0.909 (59.726) | | | |
| | PA4 | 0.874 (38.421) | | | |
| Enjoyment | ENJO1 | 0.908 (37.924) | 0.955 | 0.965 | 0.848 |
| | ENJO2 | 0.902 (28.420) | | | |
| | ENJO3 | 0.961 (116.507) | | | |
| | ENJO4 | 0.912 (72.743) | | | |
| | ENJO5 | 0.921 (60.125) | | | |
| Product knowledge | PN1 | 0.902 (44.519) | 0.882 | 0.927 | 0.809 |
| | PN2 | 0.912 (57.342) | | | |
| | PN3 | 0.883 (33.021) | | | |
| Brand attitude | ACT1 | 0.802 (17.561) | 0.874 | 0.906 | 0.661 |
| | ACT2 | 0.654 (8.222) | | | |
| | ACT3 | 0.898 (45.593) | | | |
| | ACT4 | 0.839 (17.779) | | | |
| | ACT5 | 0.849 (12.030) | | | |
| Purchase intent | PURIN1 | 0.884 (20.360) | 0.944 | 0.960 | 0.856 |
| | PURIN2 | 0.942 (86.002) | | | |
| | PURIN3 | 0.952 (117.56) | | | |
| | PURIN4 | 0.921 (52.475) | | | |

**Loadings > 0.707 indicate good indicators reliability.**

**Chronbach's Alpha and Composite reliability > 0.7 indicate good internal consistency reliability.**

**AVE > 0.5 indicate good convergent validity.**

(Martinez-Moles et al., 2021)

# Structural Model Assessment

1. Assess **collinearity issues** the structural model

2. Assess the **significance and relevance** of the structural model relationships

3. Assess the model's **explanatory power**

# Structural Model: Collinearity Issues

- **Structural model coefficients** for the relationships between constructs are **derived from estimating** a series of **regression equations**. Therefore, the structural model regressions must be examined for potential collinearity issues.

- The construct scores of the predictor constructs in each regression in the structural model are used to calculate the **variance inflation factor (VIF)** values. **VIF values above 5 are indicative of probable collinearity issues** among predictor constructs.

$$\mathrm{VIF}_i = \frac{1}{1 - R_i^2}$$

where $R^2_i$ is the **coefficient of determination** of the regression equation having the predictor i on the left-hand side, and all other predictor variables on the right-hand side.

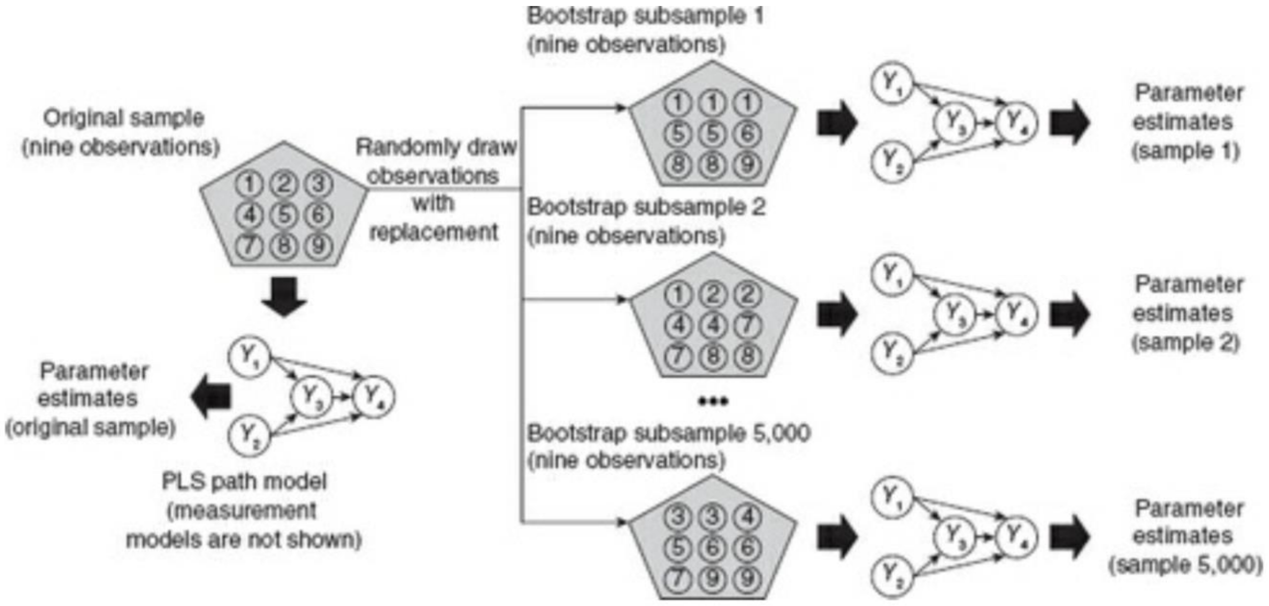
# Structural Model: Significance and Relevance of Path Coefficients

- **The path coefficients are standardized regression coefficients.** They indicate the direct *effect of a variable assumed to be a cause on another variable assumed to be an effect.* Interpretation: if $X_i$ changes by one standard deviation Y changes by $b_i$ standard deviations.

- In terms of **relevance**, path coefficients are usually ***between −1 and +1***, with coefficients closer to **−1** representing **strong negative relationships** and those closer to **+1** indicating **strong positive relationships.**

- The **bootstrap standard error** enables computing the empirical *t values* and *p values* for all structural path coefficients. ***p-values*** **below 0.05** **indicate a significant relationship.** In PLS-SEM applications **at least 10,000 bootstrap samples** are recommended.

# Structural Model: Significance and Relevance of Path Coefficients




The bootstrap samples are used to estimate the PLS path model. That is, when using 5,000 bootstrap samples, 5,000 PLS path models are estimated.

The estimates of the coefficients form a **bootstrap distribution**, which can be viewed as an approximation of the sampling distribution. It is now possible to determine the **standard error** of the estimated coefficients.

(Hair et al., 2017)

# Structural Model: Explanatory Power

- **Coefficient of determination ($R^2$)** represents the **variance explained in each of the endogenous constructs** and is a measure of the model's explanatory power, also referred to as in-sample predictive power.

- $R^2$ tends to increase as more explanatory variables are introduced to a model. The **adjusted $R^2$ metric** accounts for this by adjusting the $R^2$ value based upon the number of explanatory variables in relation to the data size and is seen as a more conservative estimate of $R^2$.

- An **R-squared** **below 0.09** is usually too low for an empirical model in consumer marketing research. This range of R-squared is **not acceptable**. An **R-squared between 0.10 and 0.50 is acceptable** in consumer marketing research when some or most of the explanatory variables are statistically significant. An R-squared **higher than 0.50** ranges **from satisfactory to good.**

# Structural Model Assessment - example

| Hypothesis | Hypothesis result | $\beta$ | $t$-value (bootstrap) |
|---|---|---|---|
| *H1*: Media richness → Presence | Accepted | 0.52 | 6.91*** |
| *H2*: Interactivity → Presence | Accepted | 0.34 | 4.33*** |
| *H3*: Presence → Enjoyment | Accepted | 0.82 | 29.64*** |
| *H4a*: Presence → Product knowledge | Accepted | 0.57 | 4.76*** |
| *H4b*: Presence → Brand attitude | Accepted | 0.34 | 2.83*** |
| *H4c*: Presence → Purchase intent | Accepted | 0.39 | 2.53** |
| *H5a*: Enjoyment → Product knowledge | Rejected | 0.09 | 0.72 |
| *H5b*: Enjoyment → Brand attitude | Accepted | 0.30 | 2.47** |
| *H5c*: Enjoyment → Purchase intent | Rejected | 0.15 | 1.19 |

**Notes:** N = 128; ***$p$ < 0.01; **$p$ < 0.05. $R^2$(Presence) = 0.65; $R^2$(Enjoyment) = 0.68; $R^2$(Product Knowledge) = 0.43; $R^2$(Brand attitude) = 0.37; $R^2$(Purchase intention) = 0.28

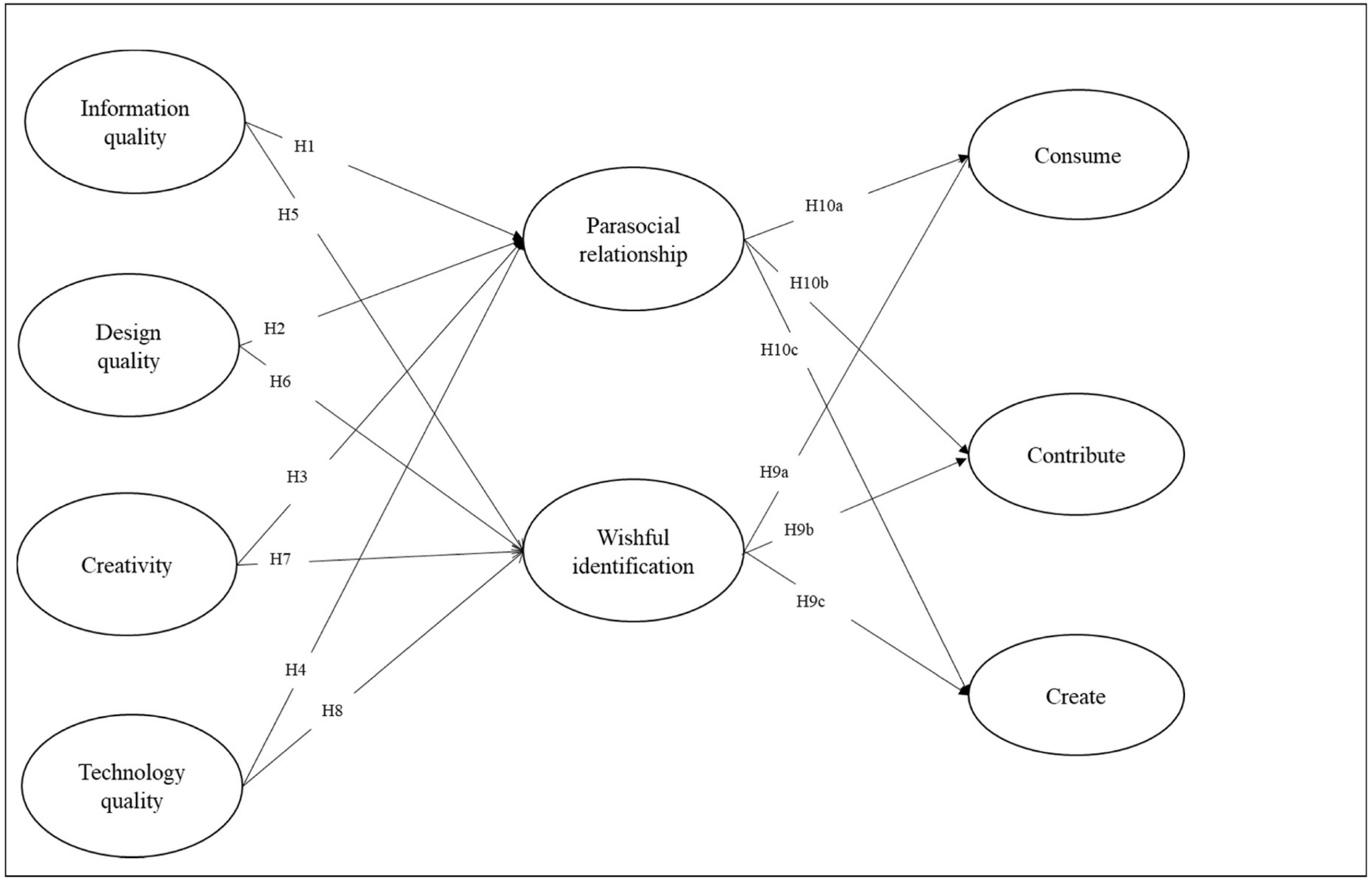
**R squared > 0.2 indicates acceptable explanatory power.**

**Path coefficients indicate the relevance of the relationship between the constructs.**

**to assess the significance of the relationships.**

(Martinez-Moles et al., 2021)

# Example




**Information quality**

The content in the posts of [SMI] is easy to understand.

The content in the posts of [SMI] is new

The content in the posts of [SMI] is relevant for users

**Design quality**

The design of the posts shared by [SMI] is well organized.

The content of the posts, such as texts, graphics and sounds, are well unified in the structure.

The content of videos, graphics and audios is appropriately assembled in the structure of the posts shared by [SMI].

Components of the posts shared by [SMI] are well harmonized.

**Wishful identifications**

[SMI] is the sort of person I want to be like myself.

[SMI] is someone I would like to emulate

I'd like to do the kinds of things [SMI] does

...

(Cheung et al., 2022)

# Example

Outer model results.

| Construct | Loading | *Alpha* | Composite reliability | AVE |
|---|---|---|---|---|
| **Information quality** | | .813 | .889 | .728 |
| The content in the posts of [SMI] is easy to understand. | .868 | | | |
| The content in the posts of [SMI] is new | .874 | | | |
| The content in the posts of [SMI] is relevant for users | .816 | | | |
| **Design quality** | | .927 | .948 | .820 |
| The design of the posts shared by [SMI] is well organized. | .899 | | | |
| The content of the posts, such as texts, graphics and sounds, are well unified in the structure. | .927 | | | |
| The content of videos, graphics and audios is appropriately assembled in the structure of the posts shared by [SMI]. | .914 | | | |
| Components of the posts shared by [SMI] are well harmonized. | .881 | | | |

1. **Assess the indicator reliability**
2. **Assess the internal consistency reliability**
3. **Assess the convergent validity**
4. **Assess the discriminant validity**

(Cheung et al., 2022)

# Example

1. **Assess the indicator reliability**
2. **Assess the internal consistency reliability**
3. **Assess the convergent validity**
4. **Assess the discriminant validity**

Discriminant validity of measurement model: HTMT ratio.

| | Consumption | IQ | Contribution | Creation | Creativity | DQ | PSR | TQ |
|---|---|---|---|---|---|---|---|---|
| Consumption | | | | | | | | |
| IQ | .428 | | | | | | | |
| Contribution | .804 | .263 | | | | | | |
| Creation | .577 | .146 | .873 | | | | | |
| Creativity | .426 | .754 | .395 | .323 | | | | |
| DQ | .408 | .696 | .279 | .201 | .548 | | | |
| PSR | .480 | .501 | .568 | .416 | .561 | .542 | | |
| TQ | .541 | .884 | .392 | .298 | .611 | .809 | .590 | |
| WI | .531 | .399 | .504 | .395 | .477 | .497 | .754 | .474 |

Note(s): IQ = Information quality, DQ = Design quality, PSR = Parasocial relationship, TQ = Technology quality, WI = Wishful identification.

(Cheung et al., 2022)

# Example

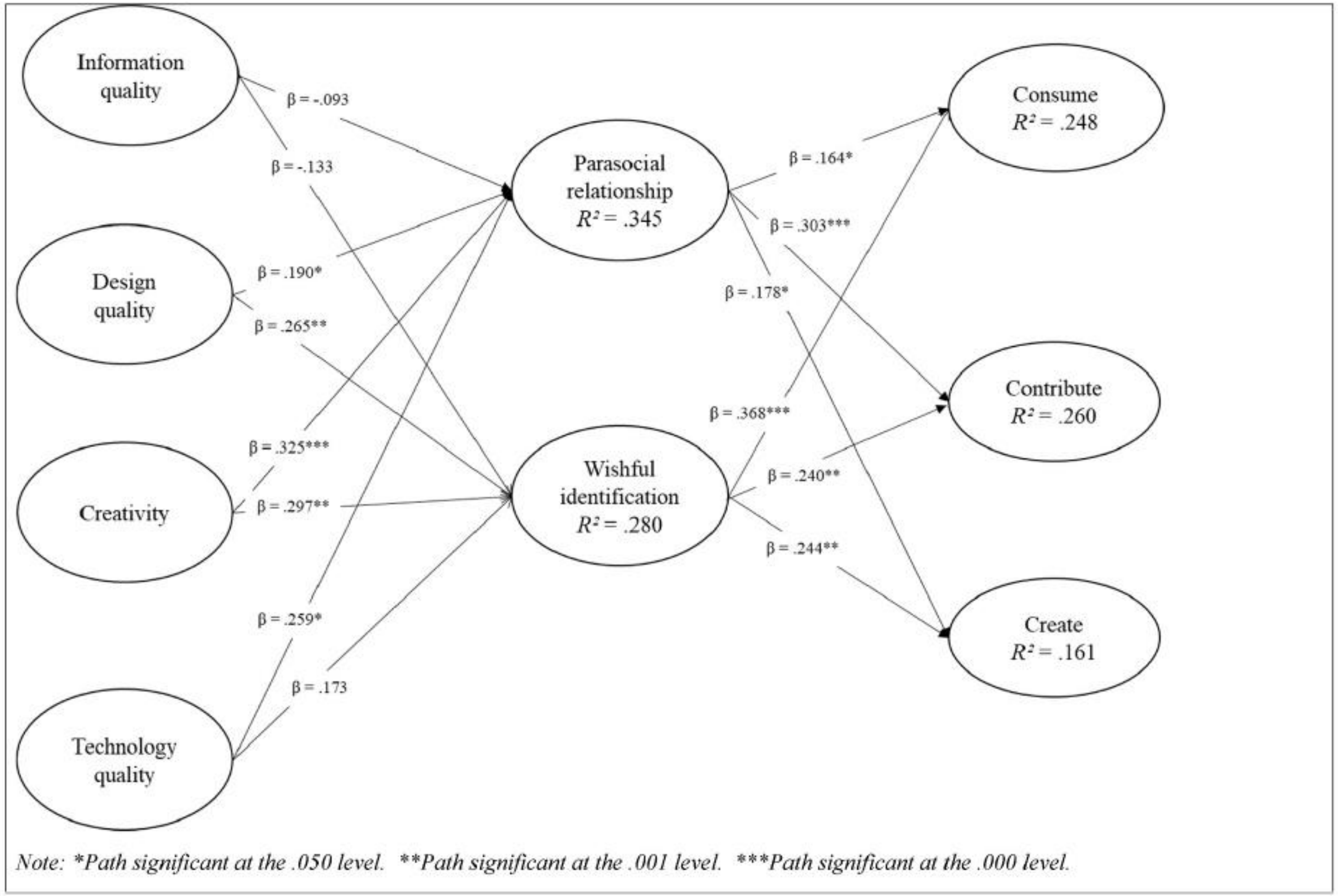



**Fig. 2.** Results of the structural model.
Note: *Path significant at the 0.050 level. **Path significant at the 0.001 level. ***Path significant at the 0.000 level.

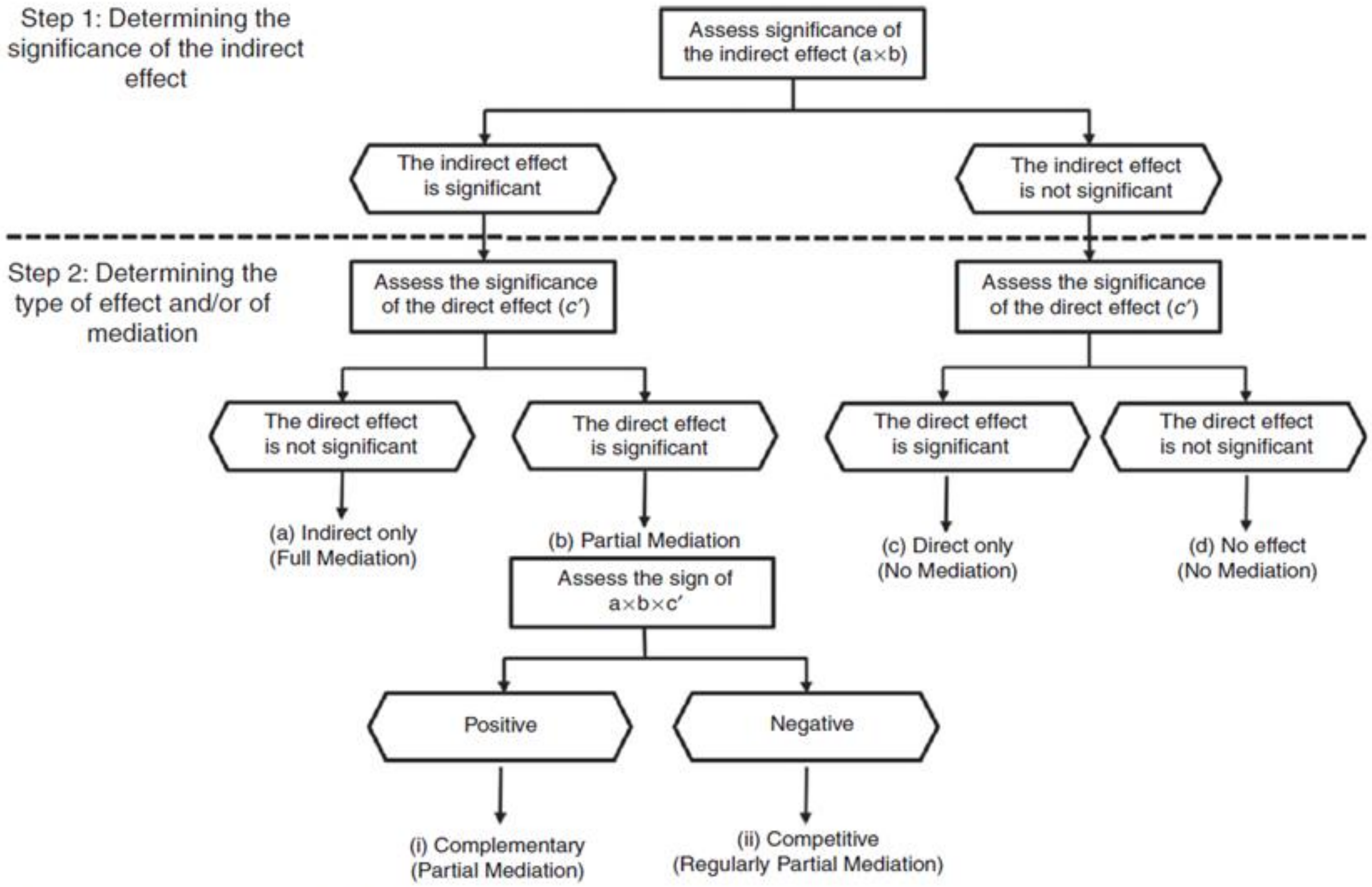
1. **Assess collinearity issues the structural model**
2. **Assess the significance and relevance of the structural model relationships**
3. **Assess the model's explanatory power**

**CMB: Full collinearity assessment.**

| Variable | VIF values |
|---|---|
| Consumption | 2.164 |
| IQ | 2.044 |
| Contribution | 3.700 |
| Creation | 2.530 |
| Creativity | 1.299 |
| DQ | 2.080 |
| PSR | 2.175 |
| TQ | 2.553 |
| WI | 1.561 |

(Cheung et al., 2022)

# Mediation Effects




**Source:** cf. Zhao *et al*. (2010)

# Mediation Effects

- **Complementary mediation**: the *indirect effect and the direct effect* are significant and point in the same direction.
- **Competitive mediation**: the *indirect effect and the direct effect* are significant but point in opposite directions.
- **Indirect-only mediation**: the *indirect effect* is significant, but not the direct effect (also called full-mediation).
- **Direct-only non-mediation**: the *direct effect* is significant, but not the indirect effect.
- **No-effect non-mediation**: neither the direct nor the indirect effect is significant.

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