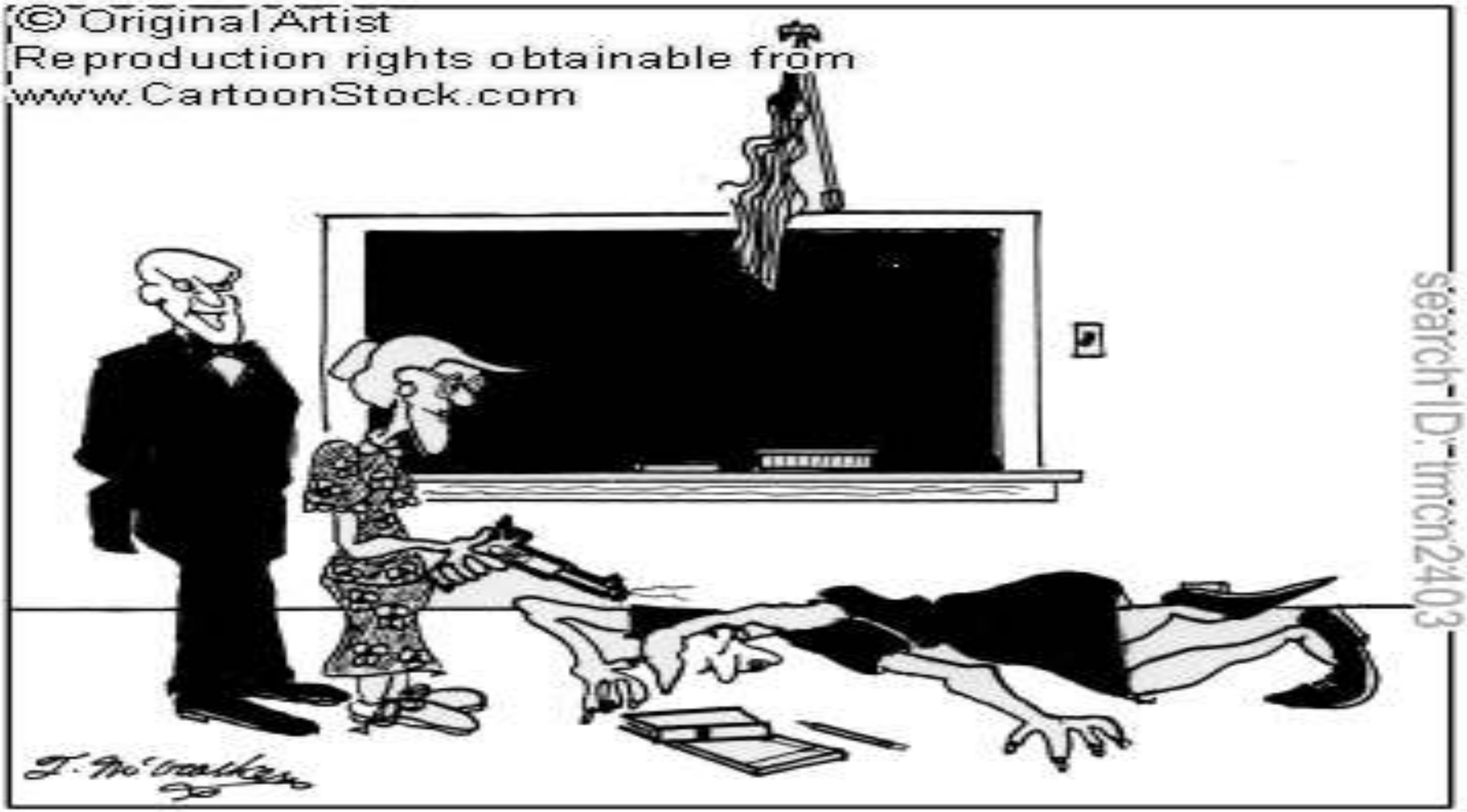

"Don't ever let someone tell you
that you can't do something.
Not even me. You got a dream,
you gotta protect it.
When people can't do
something themselves,
they're gonna tell you
that you can't do it.
You want something,
go get it. Period."
~ Will Smith
(The Pursuit of Happiness, film)


BELIEVING
In
Yourself is
The first
Secret to
SUCCESS..

Introduction to SEM – Using the Partial Least Squares (PLS)

Professor T. Ramayah
Room 118, Level 1,
School of Management,
Universiti Sains Malaysia,
11800 Minden,
Penang, Malaysia.
Tel: 604-653 3888 ext 3889
Fax: 604-657 7448
Email: ramayah@usm.my
ramayah@gmail.com

Publish or Perish



"Enforcing the publish or perish rule, Dean McWit?"

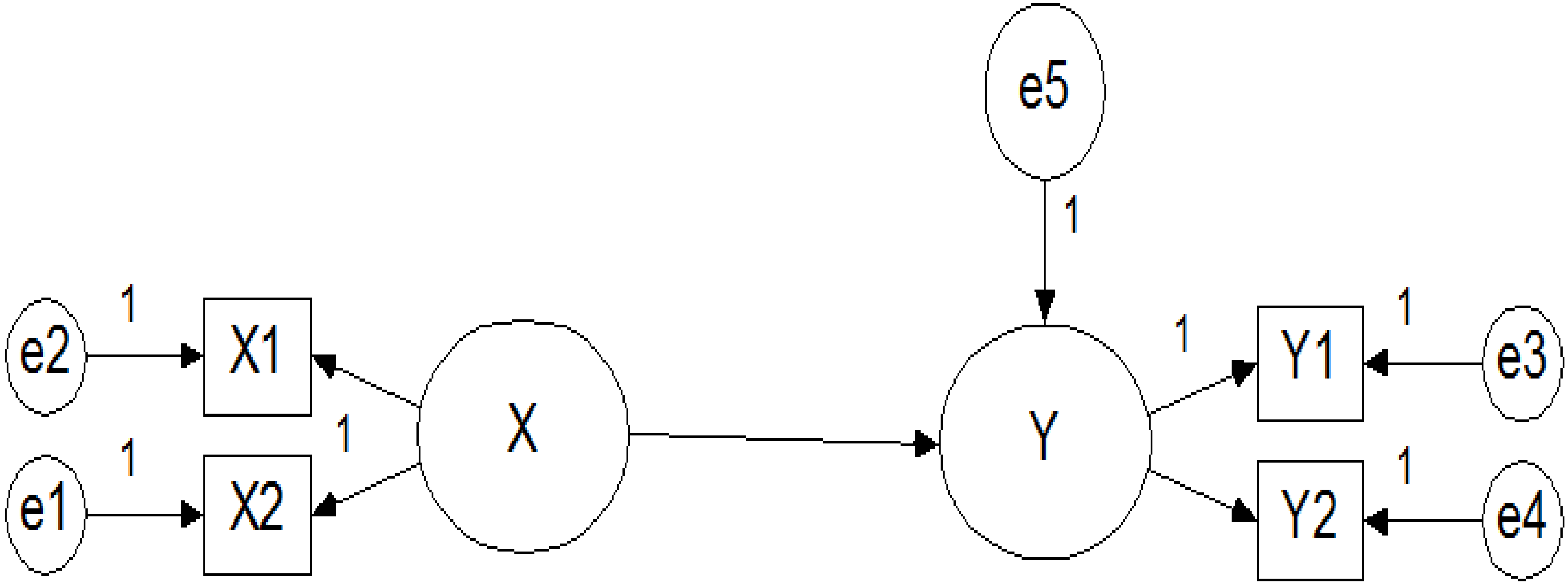
Structural Equations Modeling

- Structural Equations Modeling . . . is a family of statistical models that seek to explain the relationships among multiple variables.
- It examines the "structure" of interrelationships expressed in a series of equations, similar to a series of multiple regression equations.
- These equations depict all of the relationships among constructs (the dependent and independent variables) involved in the analysis.
- Constructs are unobservable or latent factors that are represented by multiple variables.
- Called 2nd Generation Techniques

1st vs 2nd Generation Technique

	Primarily exploratory	Primarily confirmatory
1st Generation Techniques	• multiple regression • logistic regression • analysis of variance • cluster analysis • exploratory factor analysis	• correspondence analysis
2nd Generation Techniques	PLS-SEM	CB-SEM, including CFA

Structural Equations Modeling



Distinguishing Features of SEM

- Compared to 1st Generation Techniques
  - It takes a confirmatory rather than exploratory
  - Traditional methods incapable of either assessing or correcting for measurement errors
  - Traditional methods use **observed** variables, SEM can use both unobserved (latent) and observed variables
  - Testing in one complete model

Components of Error

- Observed score comprises of 3 components (**Churchill, 1979**)
  - True score
  - Random error (ex; caused by the order of items in the questionnaire or respondent fatigue) (**Heeler & Ray, 1972**)
  - Systematic error such as method variance (ex; variance attributable to the measurement method rather than the construct of interest) (**Bagozzi et al., 1991**)

SEM

- SEM, as a second-generation technique, allows the simultaneous modeling of relationships among multiple independent and dependent constructs (**Gefen, Straub, & Boudreau, 2000**). Therefore, one no longer differentiates between dependent and independent variables but

  distinguishes between the exogenous and endogenous latent variables, the former being variables which are not explained by the postulated model (i.e. act always as independent variables) and the latter being variables that are explained by the relationships contained in the model. (Diamantopoulos, 1994, pp. 108)

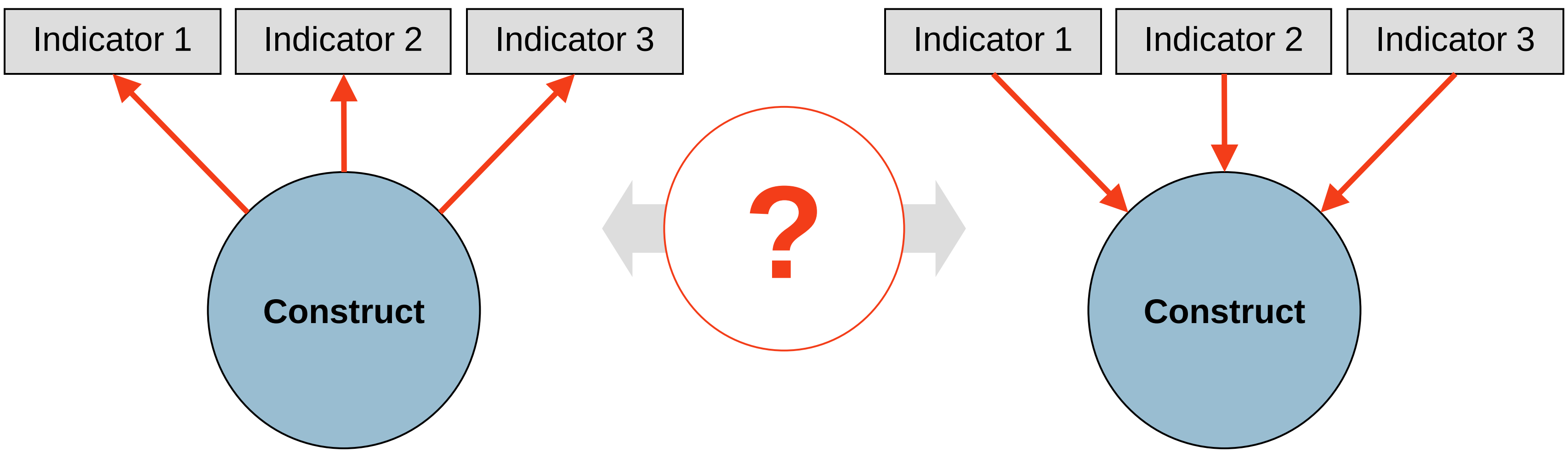
Terms

- Exogenous constructs are the latent, multi-item equivalent of independent variables. They use a variate (linear combination) of measures to represent the construct, which acts as an independent variable in the model.
  - Multiple measured variables (x) represent the exogenous constructs.
- Endogenous constructs are the latent, multi-item equivalent to dependent variables. These constructs are theoretically determined by factors within the model.
  - Multiple measured variables (y) represent the endogenous constructs.

Reflective (Scale) Versus Formative (Index) Operationalization of Constructs

A central research question in social science research, particularly marketing and MIS, focuses on the operationalization of complex constructs:

Are indicators causing or being caused by the latent variable/construct measured by them?

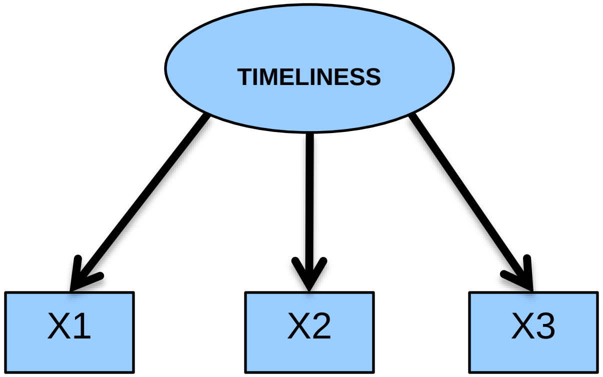


Changes in the latent variable directly cause changes in the assigned indicators

Changes in one or more of the indicators causes changes in the latent variable

Indicators

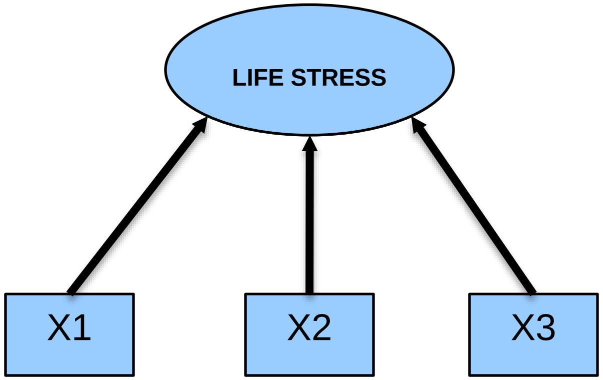
- Reflective



X1 = Accommodate last minute request
X2 = Punctuality in meeting deadlines
X3 = Speed of returning phone calls

- Indicators must be highly correlated (**Hulland, 1999**)

- Formative



X1 = Job loss
X2 = Divorce
X3 = Recent accident

- Indicators can have +, - or 0 correlation (**Hulland, 1999**)

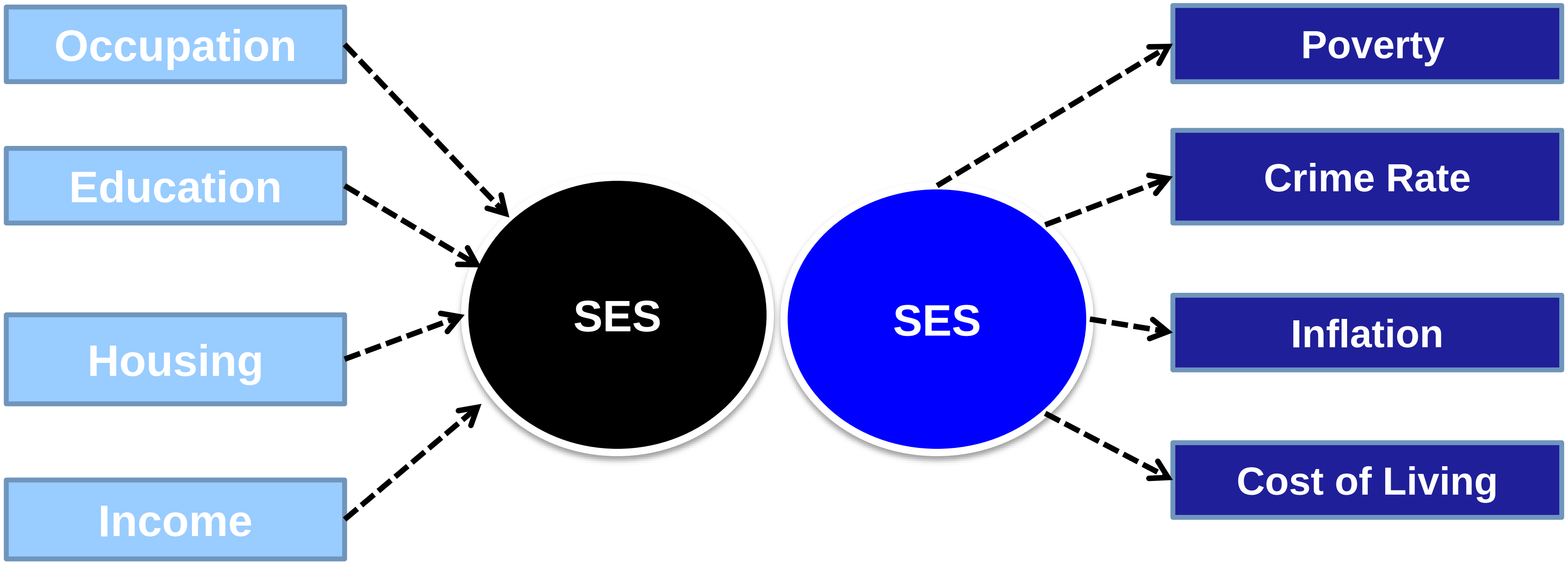
View of Formative Measures

1. **Composite (formative) constructs** – indicators completely determine the “latent” construct. They share similarities because they define a composite variable but may or may not have conceptual unity. In assessing validity, indicators are not interchangeable and should not be eliminated, because removing an indicator will likely change the nature of the latent construct.

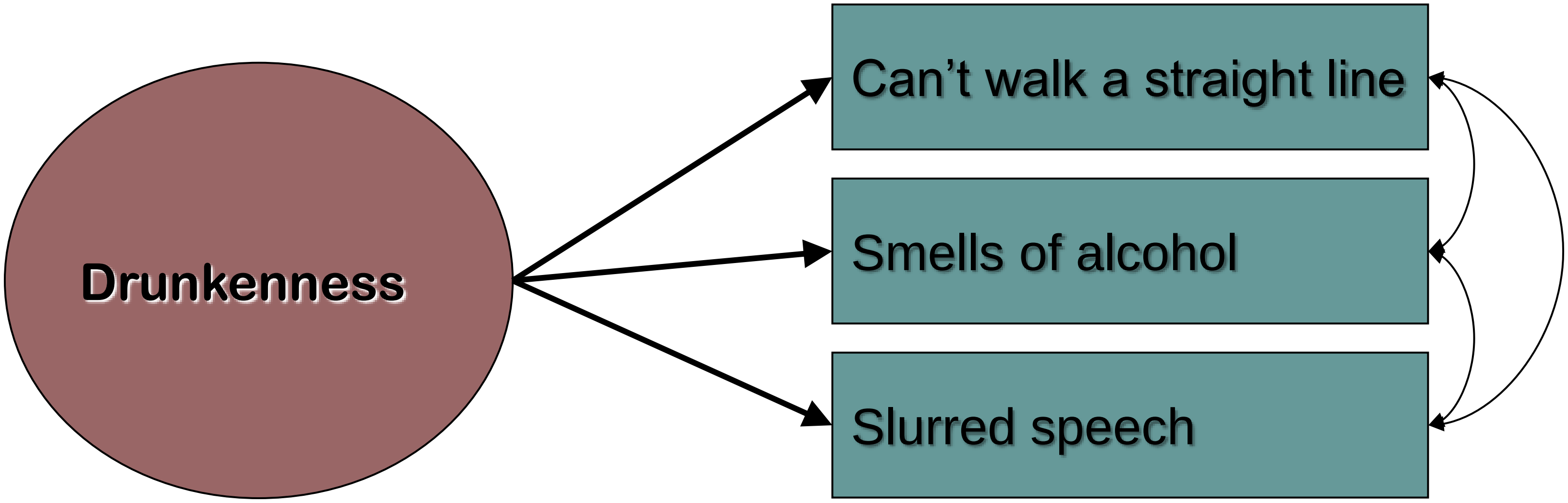
2. **Causal constructs** – indicators have conceptual unity in that all variables should correspond to the definition of the concept. In assessing validity some of the indicators may be interchangeable, and also can be eliminated.

Bollen, K.A. (2011), Evaluating Effect, Composite, and Causal Indicators in Structural Equations Models, *MIS Quarterly*, 35(2), 359-372.

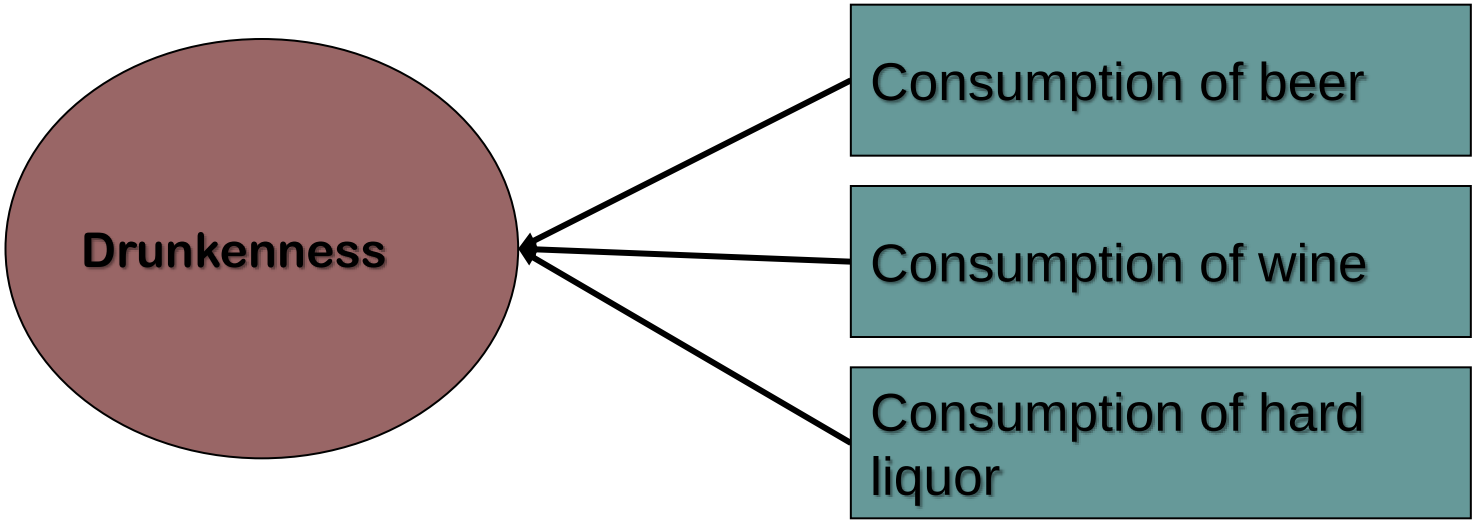
Example – Measuring SES



Example: Reflective vs. Formative World View



Example: Reflective vs. Formative World View



How to Decide

DECISION RULES FOR DETERMINING WHETHER A CONSTRUCT IS FORMATIVE OR REFLECTIVE

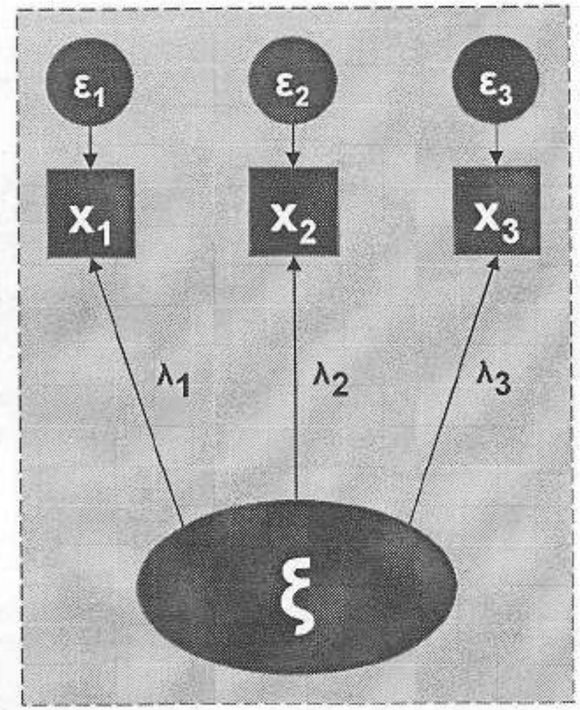
	Formative model	Reflective model
1. Direction of causality from construct to measure implied by the conceptual definition	Direction of causality is from items to construct	Direction of causality is from construct to items
Are the indicators (items) (*a*) defining characteristics or (*b*) manifestations of the construct?	Indicators are defining characteristics of the construct	Indicators are manifestations of the construct
Would changes in the indicators/items cause changes in the construct or not?	Changes in the indicators should cause changes in the construct	Changes in the indicator should not cause changes in the construct
Would changes in the construct cause changes in the indicators?	Changes in the construct do not cause changes in the indicators	Changes in the construct do cause changes in the indicators
2. Interchangeability of the indicators/items	Indicators need not be interchangeable	Indicators should be interchangeable
Should the indicators have the same or similar content? Do the indicators share a common theme?	Indicators need not have the same or similar content/indicators need not share a common theme	Indicators should have the same or similar content/indicators should share a common theme
Would dropping one of the indicators alter the conceptual domain of the construct?	Dropping an indicator may alter the conceptual domain of the construct	Dropping an indicator should not alter the conceptual domain of the construct
3. Covariation among the indicators	Not necessary for indicators to covary with each other	Indicators are expected to covary with each other
Should a change in one of the indicators be associated with changes in the other indicators?	Not necessarily	Yes
4. Nomological net of the construct indicators	Nomological net for the indicators may differ	Nomological net for the indicators should not differ
Are the indicators/items expected to have the same antecedents and consequences?	Indicators are not required to have the same antecedents and consequences	Indicators are required to have the same antecedents and consequences

How to Decide? Formative

- the indicators are viewed as defining characteristics of the construct,
- changes in the indicators are expected to cause changes in the construct,
- changes in the construct are not expected to cause changes in the indicators,
- the indicators do not necessarily share a common theme,
- eliminating an indicator may alter the conceptual domain of the construct,
- a change in the value of one of the indicators is not necessarily expected to be associated with a change in all of the other indicators,
- the indicators are not expected to have the same antecedents and consequences.

Reflective Measurement Models

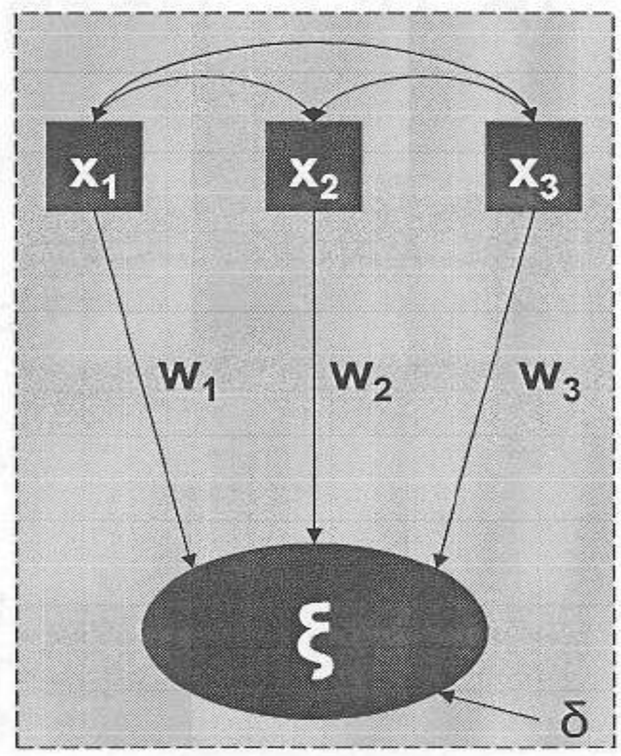
- Direction of causality is from construct to measure
- Indicators expected to be correlated
- Dropping an indicator from the measurement model does not alter the meaning of the construct
- Takes measurement error into account at the item level
- Similar to factor analysis
- Typical for management and social science researches



$$x_1 = \lambda_1 \cdot \xi + \varepsilon_1$$
$$x_2 = \lambda_2 \cdot \xi + \varepsilon_2$$
$$x_3 = \lambda_3 \cdot \xi + \varepsilon_3$$

Formative Measurement Models

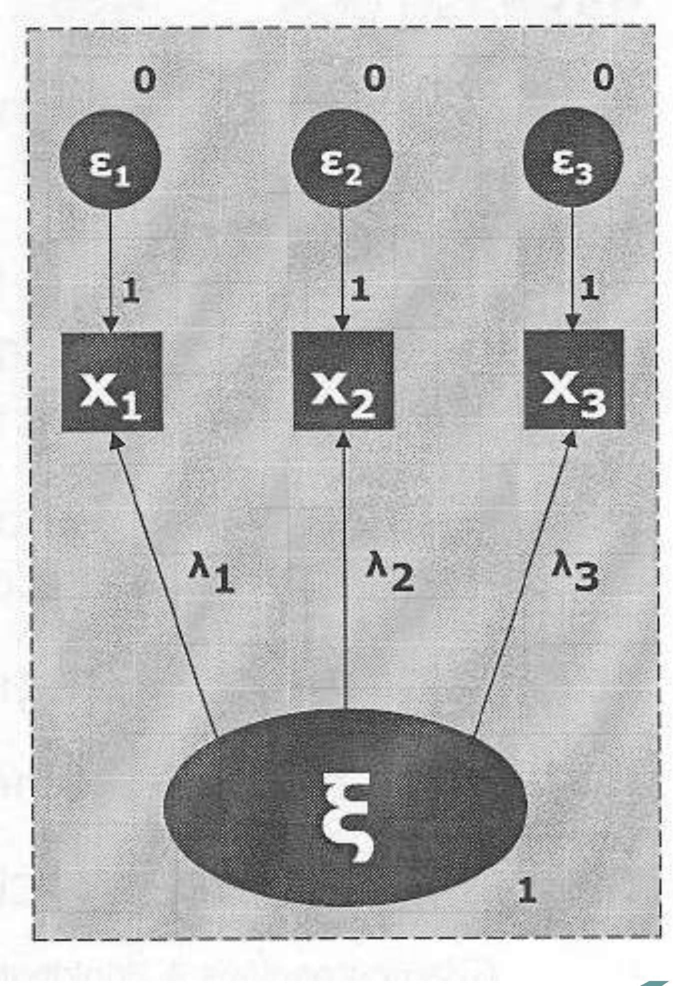
- Direction of causality is from measure to construct
- Indicators are not expected to be correlated
- Dropping an indicator from the measurement model may alter alter the meaning of the construct
  - No such thing as internal consistency reliability
- Based on multiple regression
  - Need to take care of multicollinearity
- Typical for success factor research (Diamantopolous & Winklhofer, 2001)



$$\xi = w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3 + \delta$$

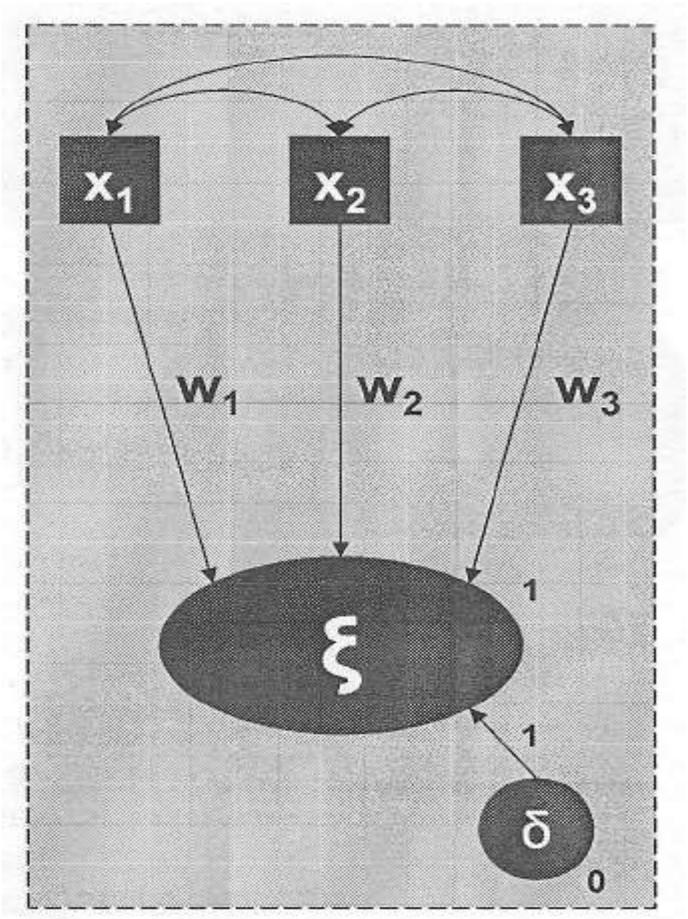
Reflective Measurement Models

- Similar to Principal Component Analysis (PCA)
- Measurement errors are expected to be zero
- The latent variable has a variance of 1.
- Usually the latent variable is centered. For some applications such as customer satisfaction indices, the latent mean is calculated.
- The weights are calculated too.



Formative Measurement Models

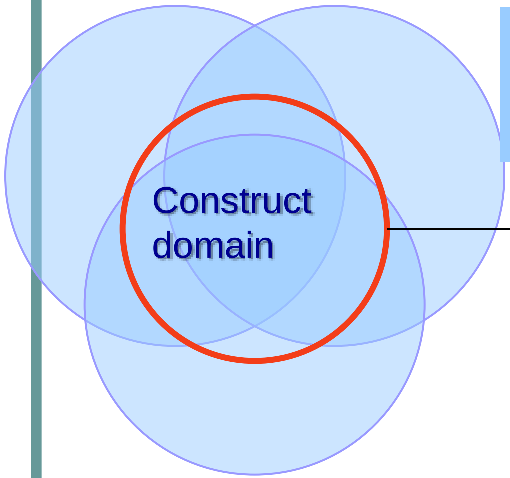
- Multiple regression analysis is performed
- Measurement error at the construct level is expected to be zero
- The latent variable has a variance of 1.
- Usually the latent variable is centered. For some applications such as success factor studies, the latent mean is calculated.
- The correlation between the latent variable and its indicators (loadings) are calculated too.



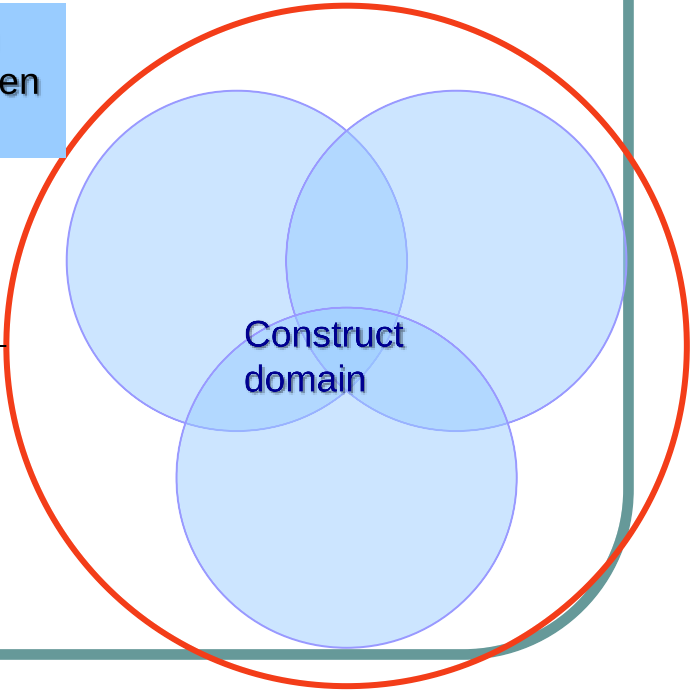
Comparison between Reflective and Formative

"Whereas reflective indicators are essentially interchangeable (and therefore the removal of an item does not change the essential nature of the underlying construct), with formative indicators 'omitting an indicator is omitting a part of the construct'."

(Diamantopoulos/Winklhofer, 2001, p. 271)



The formative measurement approach generally minimizes the overlap between complementary indicators



The reflective measurement approach focuses on maximizing the overlap between interchangeable indicators

Problems in Specification

Reflective measurement is most commonly used but in many cases a formative measurement would be appropriate

	Should be reflective	Should be formative	Total
Modelled as reflective	947 (65%)	**456 (31%)** (Type I error)	1403 (96%)
Modelled as formative	**17 (1%)** (Type II error)	41 (3%)	58 (4%)
Total	964 (66%)	497 (34%)	1461 (100%)

32% of constructs have been measured incorrectly

Data bases are the Top 3 German- and Top 4 English-language journals:

- JARVIS/BURKE/PODSAKOFF (2003): Journal of Consumer Research, Journal of Marketing, Journal of Marketing Research, Marketing Science (1977 – 2000): N = 1,192
- FASSOTT (2006): Zeitschrift für betriebswirtschaftliche Forschung, Zeitschrift für Betriebswirtschaft, Die Betriebswirtschaft (X - 2003): N = 269

SEM - Variations

- **CB-SEM (Covariance-based SEM)** – objective is to reproduce the theoretical covariance matrix, without focusing on explained variance.
- **PLS-SEM (Partial Least Squares SEM)** – objective is to maximize the explained variance of the endogenous latent constructs (dependent variables).

Two approaches to SEM

- **Covariance based**
  - **EQS, http://www.mvsoft.com/**
  - **AMOS, http://www-01.ibm.com/**
  - **SEPATH, http://www.statsoft.com/**
  - **LISREL, http://www.ssicentral.com/**
  - **MPLUS, http://www.statmodel.com/**
  - **lavaan, http://lavaan.ugent.be/**
  - **Ωnyx, http://onyx.brandmaier.de/**

Two approaches to SEM

- **Variance Based SEM**
  - **Smart PLS, http://www.smartpls.de/forum/**
  - **PLS-GUI, https://sem-n-r.wistia.com/projects/plgxttovlw**
  - **PLS Graph, http://www.plsgraph.com/**
  - **WarpPLS, http://www.scriptwarp.com/warppls/**
  - **Visual PLS, http://fs.mis.kuas.edu.tw/~fred/vpls/start.htm**
  - **PLS-GUI, http://www.rotman-baycrest.on.ca/index.php?section=84**
  - **SPAD-PLS, http://spadsoft.com/content/blogcategory/15/34/**
  - **GeSCA, http://www.sem-gesca.org/**

Why PLS?

- Like covariance based structural equation modeling (CBSEM), PLS is a latent variable modeling technique that incorporates multiple dependent constructs and explicitly recognizes measurement error (Karim, 2009)

- In general, two applications of PLS are possible (Chin, 1998a): It can either be used for theory confirmation or theory development. In the latter case, PLS is used to develop propositions by exploring the relationships between variables.

Reasons for using PLS

- Researchers' arguments for choosing PLS as the statistical means for testing structural equation models (Urbach & Ahleman, 2010) are as follows:
  - 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 better suited for theory development than for theory testing.
  - PLS is especially useful for prediction

Sample Size – Rule of 10

- With respect to PLS, the literature frequently uses the “10 times” rule of thumb as the guide for estimating the minimum sample size requirement.
- This rule of thumb suggests that PLS only requires a sample size of 10 times the most complex relationship within the research model.
- The most complex relationship is the larger value between (1) the construct with the largest number of formative indicators if there are formative constructs in the research model (i.e., largest measurement equation (LME)) and (2) the dependent latent variable (LV) with the largest number of independent LVs influencing it (i.e., the largest structural equation (LSE)).

Condition

- Researchers have suggested that the **“10 times” rule of thumb** for determining sample size adequacy in PLS analyses only applies when certain conditions, such as strong effect sizes and high reliability of measurement items, are met.
- PLS is used to test the research model, assuming certain conditions are met (e.g., adequate effect sizes, a sufficiently large number of items per construct, and highly reliable constructs).

Questionnaire Design

- The construct scores of the latent variables in PLS are created by aggregating indicator items that involve measurement errors, PLS estimates of construct scores are biased and are only consistent under the conditions of **"consistency at large",** which refer to a **large number of items per construct, high communality, and large sample sizes** (Wold, 1982, p. 25).
- Increasing the number of indicators per construct is one way to reduce the bias in the parameter estimate for reflective constructs in PLS, researchers can consider including a large number of items for reflective constructs in the survey questionnaire if they anticipate that PLS may be used in the analysis stage.
- It should be noted that researchers often face a tradeoff between response rate and questionnaire length, and that increasing the number of items per construct can adversely affect a survey's response rate.

Hair et al. (2013)

- PLS-SEM is advantageous when used with small sample sizes (**e.g., in terms of the robustness of estimations and statistical power; Reinartz et al., 2009**).
- However, some researchers abuse this advantage by relying on extremely small samples relative to the underlying population.
- All else being equal, the more heterogeneous the population in a structure is the more observations are needed to reach an acceptable sampling error level.

Sample Size (Green, 1991)

	Sample sizes based on power analysis		
Number of predictors		Effect size	
	Small	Medium	Large
1	390	53	24
2	481	66	30
3	547	76	35
4	599	84	39
5	645	91	42
6	686	97	46
7	726	102	48
8	757	108	51
9	788	113	54
10	844	117	56
15	952	138	67
20	1066	156	77
30	1247	187	94
40	1407	213	110

Choice

- Overall, PLS can be an adequate alternative to CBSEM if the problem has the following characteristics (Chin 1998b; Chin & Newsted 1999):
  - The phenomenon to be investigated is relatively new and measurement models need to be newly developed,
  - The structural equation model is complex with a large number of LVs and indicator variables,
  - Relationships between the indicators and LVs have to be modeled in different modes (i.e., formative and reflective measurement models),3
  - The conditions relating to sample size, independence, or normal distribution are not met, and/or
  - Prediction is more important than parameter estimation.

Selection

- The decision between these approaches is whether to use SEM for theory testing and development or for predictive applications (Anderson & Gerbing, 1988)
- In situations where prior theory is strong and further testing and development are the goal, covariance-based full-information estimation methods are more appropriate.

Justification

- However, for application and prediction, when the phenomenon under research is relatively new or changing, or when the theoretical model or measures are not well formed, a PLS approach is often more suitable (Chin& Newsted,1999)

- In addition, Chin (2010) states "**there are other instances beyond initial exploratory stages that PLS is well suited**“ (p. 660)

Incremental Study

- For example, when the research has an interactive character. This is the case of an incremental study, which is initially based on a prior model but **new measures** and **structural paths** are then introduced into it.
- In this respect these statements are confirmed by the study of Reinartz et al. (2009): **"PLS is the preferable approach when researchers focus on prediction and theory development, our simulations show that PLS requires only about half as many observations to reach a given level of statistical power as does ML-based CBSEM"** (p. 334).

Choice

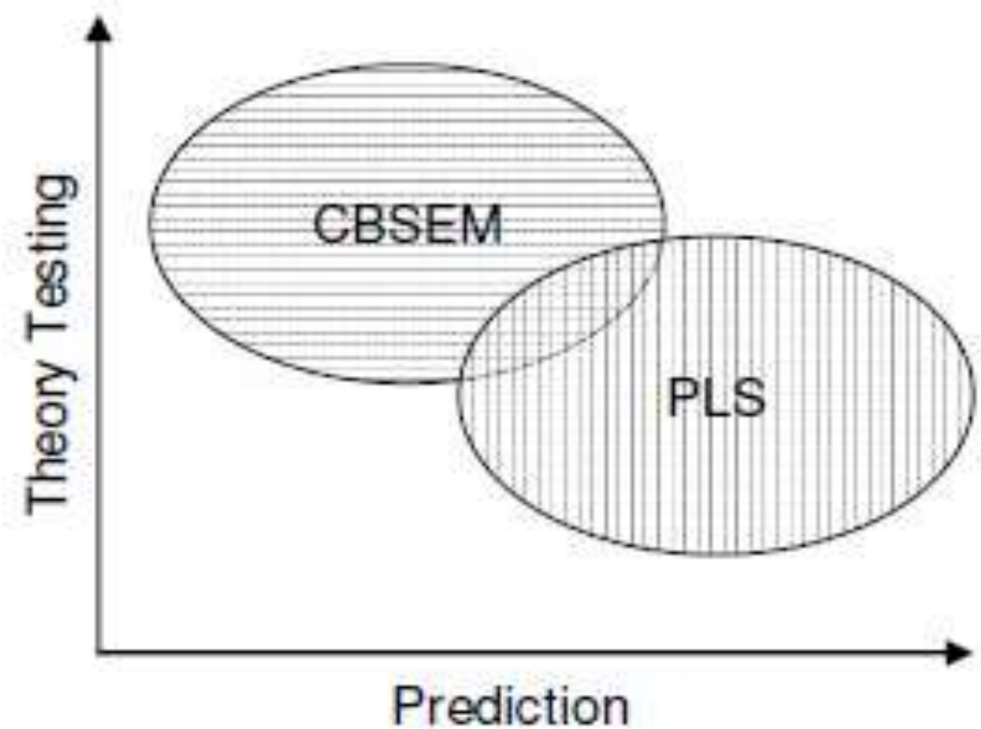
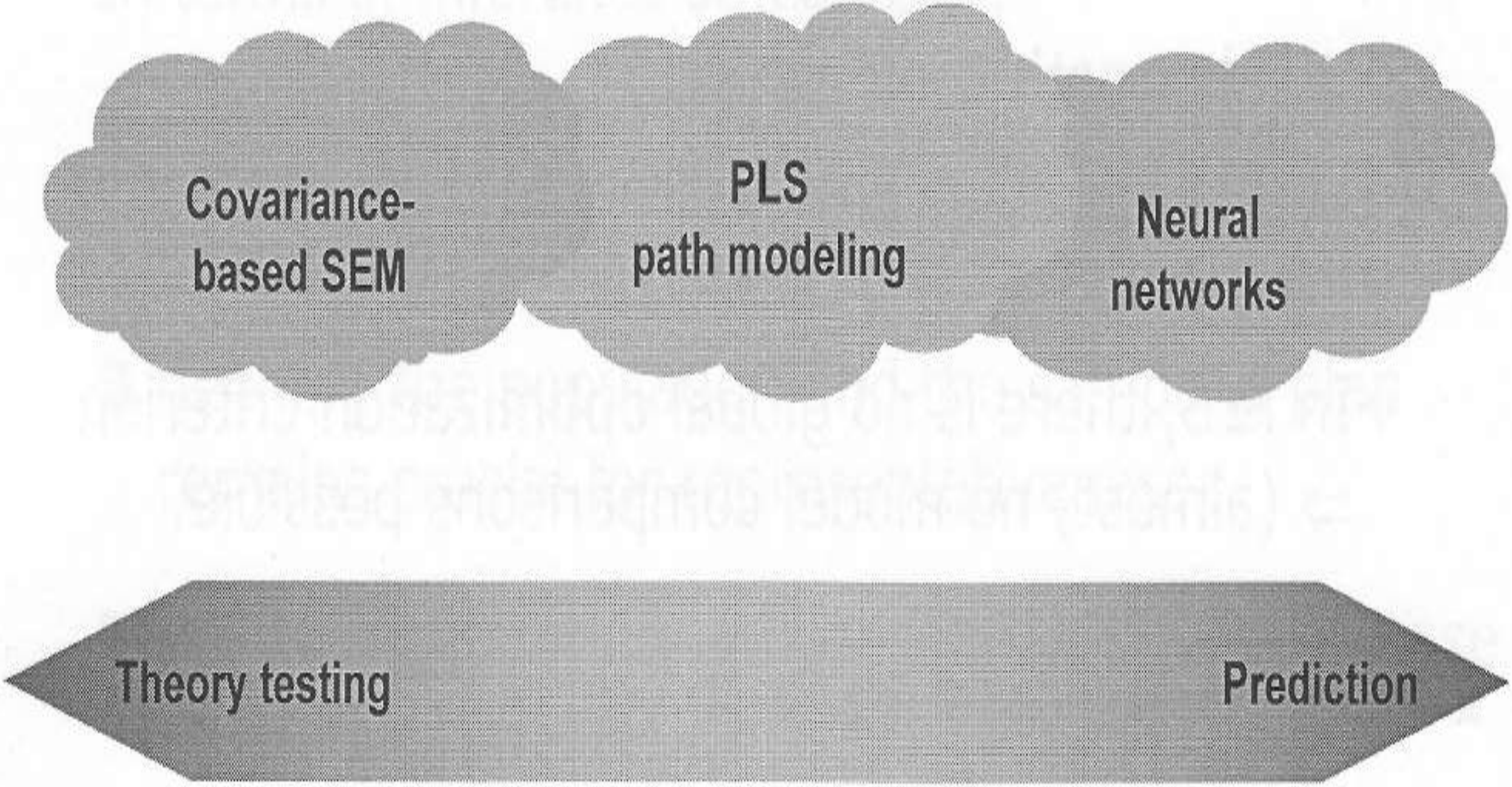


Figure 4: CBSEM vs. PLS (according to Henseler et al. 2009).

Choice



Covariance-based SEM
PLS path modeling
Neural networks
Theory testing
Prediction

Process

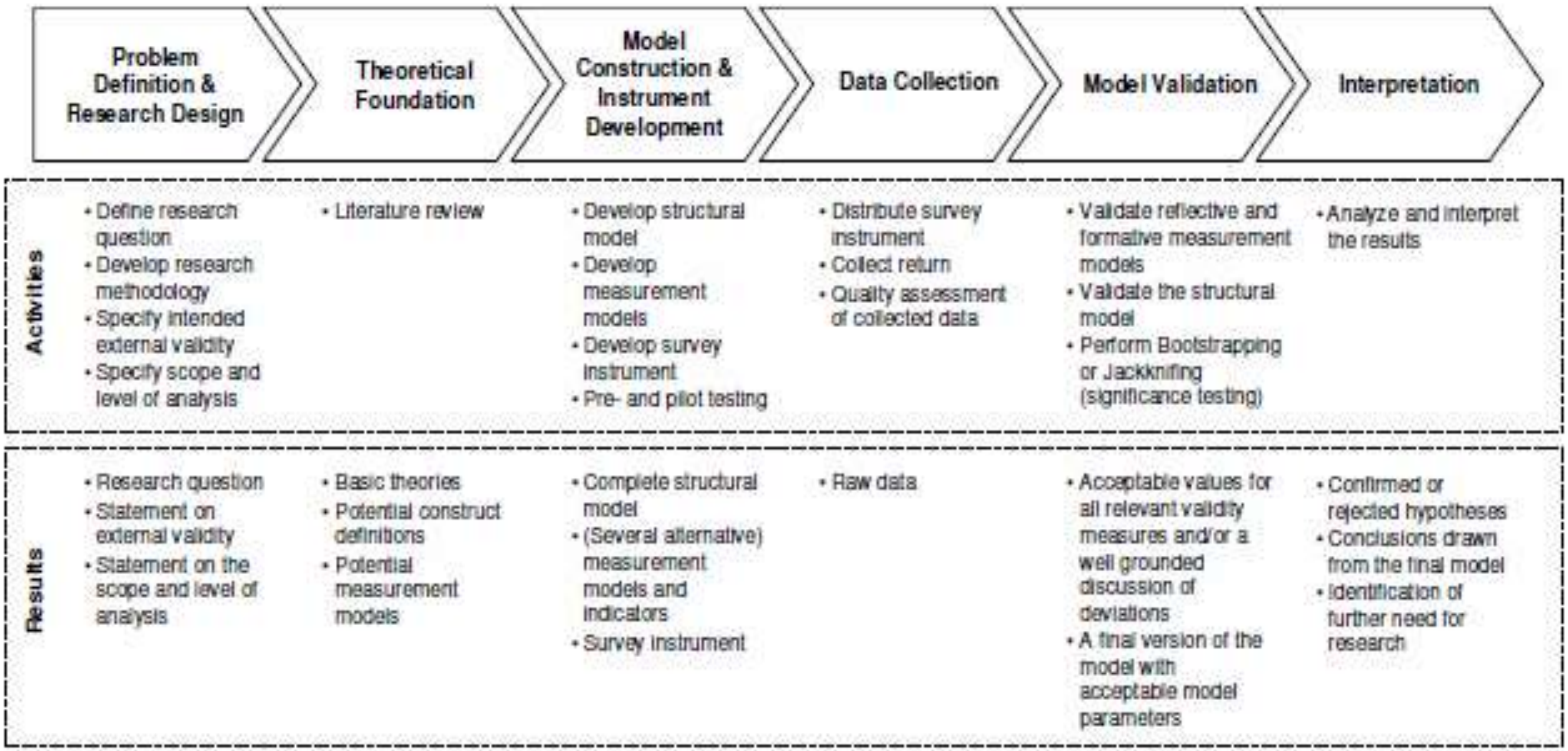


Figure 5: Framework for applying PLS in structural equation modeling.

Comparison

Table 3: Comparison of PLS and CBSEM (adapted from Chin and Newsted 1999)		
Criteria	**PLS**	**CBSEM**
Objective	Prediction-oriented	Parameter-oriented
Approach	Variance-based	Covariance-based
Assumption	Predictor specification (nonparametric)	Typically multivariate normal distribution and independent observations (parametric)
Parameter estimates	Consistent as indicators and sample size increase (i.e., consistency at large)	Consistent
Latent variable scores	Explicitly estimated	Indeterminate
Epistemic relationship between an LV and its measures	Can be modeled in either formative or reflective mode	Typically only with reflective indicators. However, the formative mode is also supported.
Implications	Optimal for prediction accuracy	Optimal for parameter accuracy
Model complexity	Large complexity (e.g., 100 constructs and 1,000 indicators)	Small to moderate complexity (e.g., less than 100 indicators)
Sample size	Power analysis based on the portion of the model with the largest number of predictors. Minimal recommendations range from 30 to 100 cases.	Ideally based on power analysis of specific model—minimal recommendations range from 200 to 800.
Type of optimization	Locally iterative	Globally iterative
Significance tests	Only by means of simulations; restricted validity	Available
Availability of global Goodness of Fit (GoF) metrics	Are currently being developed and discussed	Established GoF metrics available

Pre-testing

- Pretesting (See Hunt et al. 1982)
  - What items?
    - Length, layout, format, number of lines for replies, sequencing
    - Individual questions, respondents hesitate
    - Dummy tables and analysis (dry run)
  - What method?
    - Personal interviews, phone, and mail
    - Debriefing (after) or protocol (during)?

Pre-testing

- Who should do?
  - Best interviewers
- Who are the subjects?
  - Respondents who are as similar as possible
  - Representative vs convenience
- How large a sample?
  - Vary from 12, 20, 30 to 100

Pilot Test - Results

Table 3.2. Cronbach's Alpha for the measures

Scale	Number of items	Cronbach's Alpha
MLQ	28	.85
Consistency – OC	15	.79
Adaptability – OC	15	.61
Mission – OC	15	.82
Organizational Trust	9	.83
Psychological Empowerment	8	.10
OCB	15	.81
Organizational Effectiveness	9	.69

Justification

3.5.4 Psychological Empowerment

PE was measured using the modified version of psychological empowerment of Spreitzer (1992, 1995b). This scale showed to have high Cronbach's alpha of .84 and .90 previously in Malaysian organization (Nik Azida Abd. Ghani, Tengku Ahmad Badrul Shah bin Raja Hussin and Kamaruzaman Jusoff, 2009). However, in the present plot study this scale showed extremely low validity and reliability. The validity values ranged from .06 to .44 as shown in Table A6 (Appendix A) with Cronbach's alpha of .10 which indicates low internal consistency between items. The researcher decided not to omit any item because psychological empowerment is an important mediating variable between leadership styles and OCB. Also in the main study, ~~it was thought~~ that with a bigger sample size, the reliability and validity of the scale would improve. All eight ~~items were~~ utilized for the main study to measure the level of empowerment employees reported in the final data collection (Table B4 Appendix B).

Is this correct

Other Issues

- Non-Response
- Common Method Variance (CMV)
- Social Desirability
- Missing Value Imputation

Non-Response Bias

- The mail survey has been criticized for non-response bias. If persons who respond differ substantially from those who do not, the results do not directly allow one to say how the entire sample would have responded – certainly an important step before the sample is generalized to the population **(Armstrong & Overton, 1977)**
- Extrapolation methods are based on the assumption that subjects who respond less readily are more like non-respondents (Pace, 1939). **“Less readily” has been defined as answering later, or as requiring more prodding to answer**.

Non-Response Bias

- The most commonly recommended protection against non-response bias has been the reduction of non-response itself.
- Non-response can be kept under 30% in most situations if appropriate procedures are followed (Linsky, 1975).
- Another approach to the non-response problem is to sample non-respondents (Hansen & Hurwitz, 1946). For example, Reid (1942) chose a 9% subsample from his non-respondents and obtained responses from 95% of them.

Effect Size

- An effect size test as represented by the eta squared is necessary to determine whether statistical mean difference is truly adequate or is occurred by chance since large sample could enable very small differences to become statistically significant (**Cohen, 1988; Samat, Ramayah, & Yusoff, 2008**).

- The formula for calculating **eta squared** for *t-test* is as follows:

$$\text{Eta}^2 = \frac{t^2}{t^2 + (N1 + N2 - 2)}$$

Effect Size

- The formula for calculating **eta squared** for *One way ANOVA test* is as follows:

$$\text{Eta}^2 = \frac{\text{Sum of squares between-groups}}{\text{Total sum of squares}}$$

- Using the guideline proposed by **Cohen (1988),** the value of **eta squared** is interpreted as follows:
  - **0.01** = small effect
  - **0.06** = moderate effect; and
  - **0.14** = large effect size

What is Common Method Variance?

- Common method variance needs to be examined when data are collected **via self-reported questionnaires** and, in particular, **both the predictor and criterion variables are obtained from the same person** (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

- Podsakoff and Todor (1985) also noted that: "**Invariably, when self-reported measures obtained from the same sample are utilized in research, concern over same-source bias or general method variance arise**" (p. 65).

Testing Common Method Variance

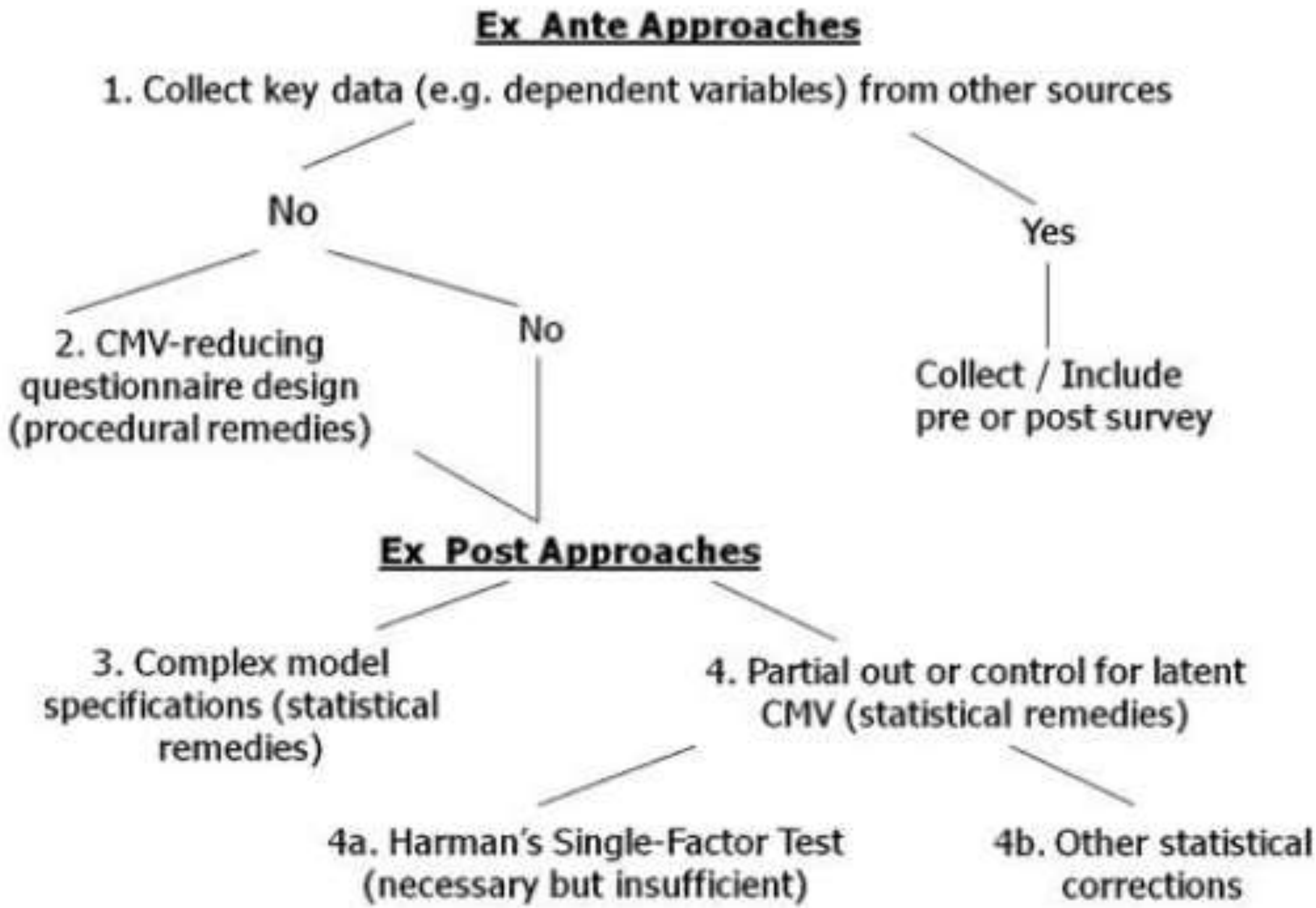
- According to **Podsakoff and Organ (1986),** common method bias is a serious threat if a single latent factor accounts for the majority of the explained variance. The presence of common method bias can be detected if

i. a single factor emerges from the factor analysis, or
ii. one general factor accounts for the majority of the covariance among the measures (Podsakoff et al., 2003).

Common Method Variance

- *Second,* we can also assess CMV by looking at the correlation matrix, common method bias is usually evidenced by extremely high correlations ($r > 0.90$) **(Bagozzi et al., 1991).**

Common Method Variance

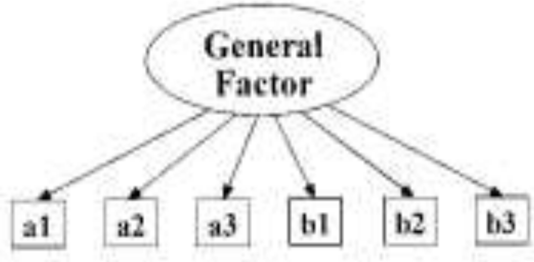


Social Desirability Measure

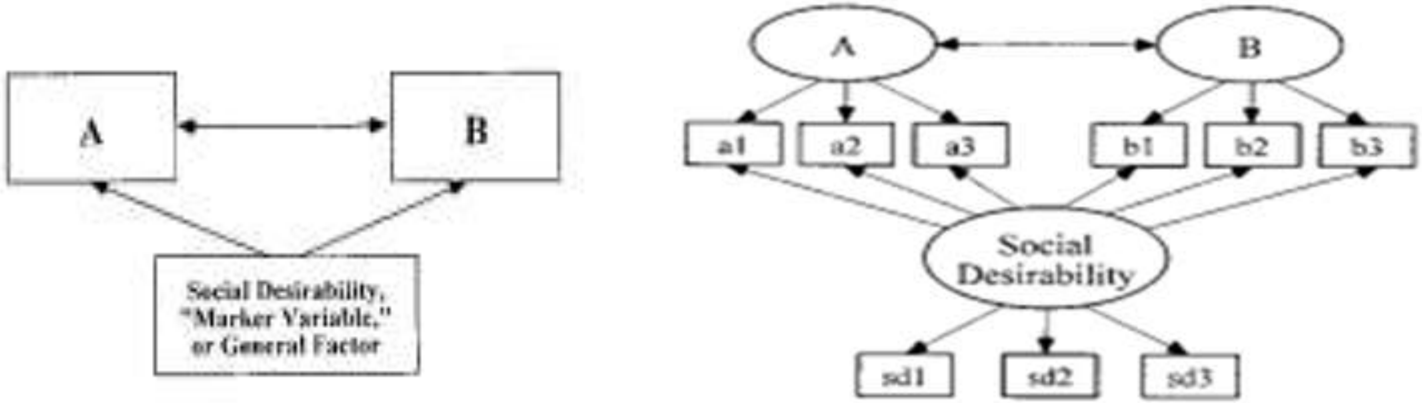
- Fischer and Fick (1993) shortened version (X1) of Crowne and Marlowe (1960) Social Desirability Scale
- I like to gossip at times
- There have been occasions where I took advantage of someone
- I'm always willing to admit it when I made a mistake
- I sometimes try to get even rather than forgive and forget
- At times I have really insisted on having things my own way
- I have never been irked when people expressed ideas very different from my own
- I have never deliberately said something that hurt someone's feeling

Testing Common Method Variance

- Harman's Single factor test



- Using Social Desirability



Explanation CMV Example

- We performed two tests to examine the common method bias. **First**, we performed an exploratory factor analysis by entered all measurement items, the results showed that the largest variance explained by an individual factor was 36.14%.

- Podsakoff and Organ (1986) claimed that if the variables all load on one factor or one factor explains the majority of the variance, common method variance may be a problem. The results show that neither a single factor nor a general factor accounts for the majority of the covariance in the measures.

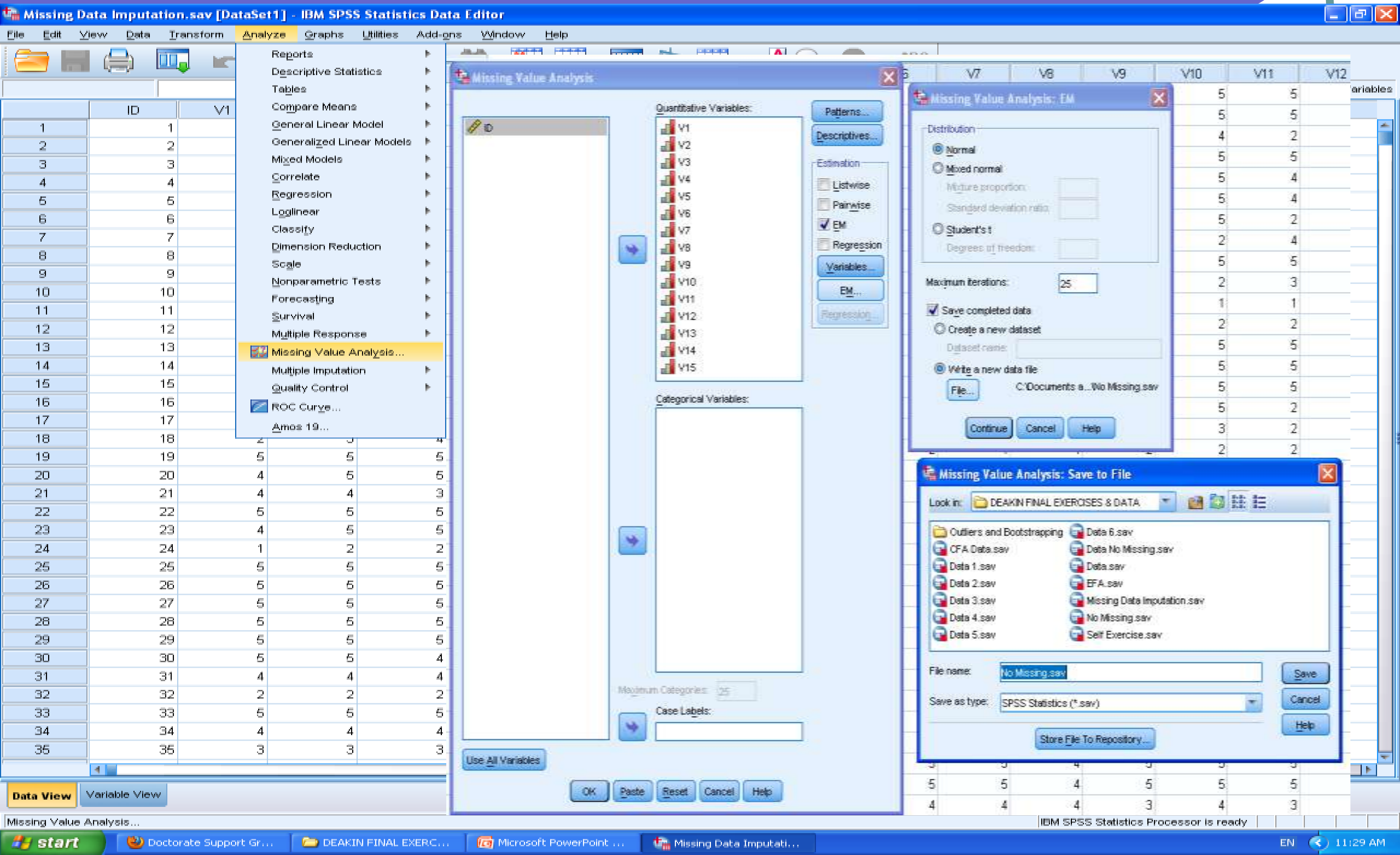
Explanation

- **Second**, we performed a confirmatory factor analysis by modelling all items as the indicators of a single factor, and the results show a poor fitness. Method biases are assumed to be substantial if the hypothesized model fits the data (Malhotra, Kim, & Patil, 2006). Thus, the results of both tests indicate that common method bias is not a significant problem for the current study.

Missing Value Imputation

- Traditional
  - No replacement
  - Mid point of the scale
  - Random number
  - Mean value of the other respondents
  - Mean value of the other responses
- Current
  - FIML
  - EM
  - MI

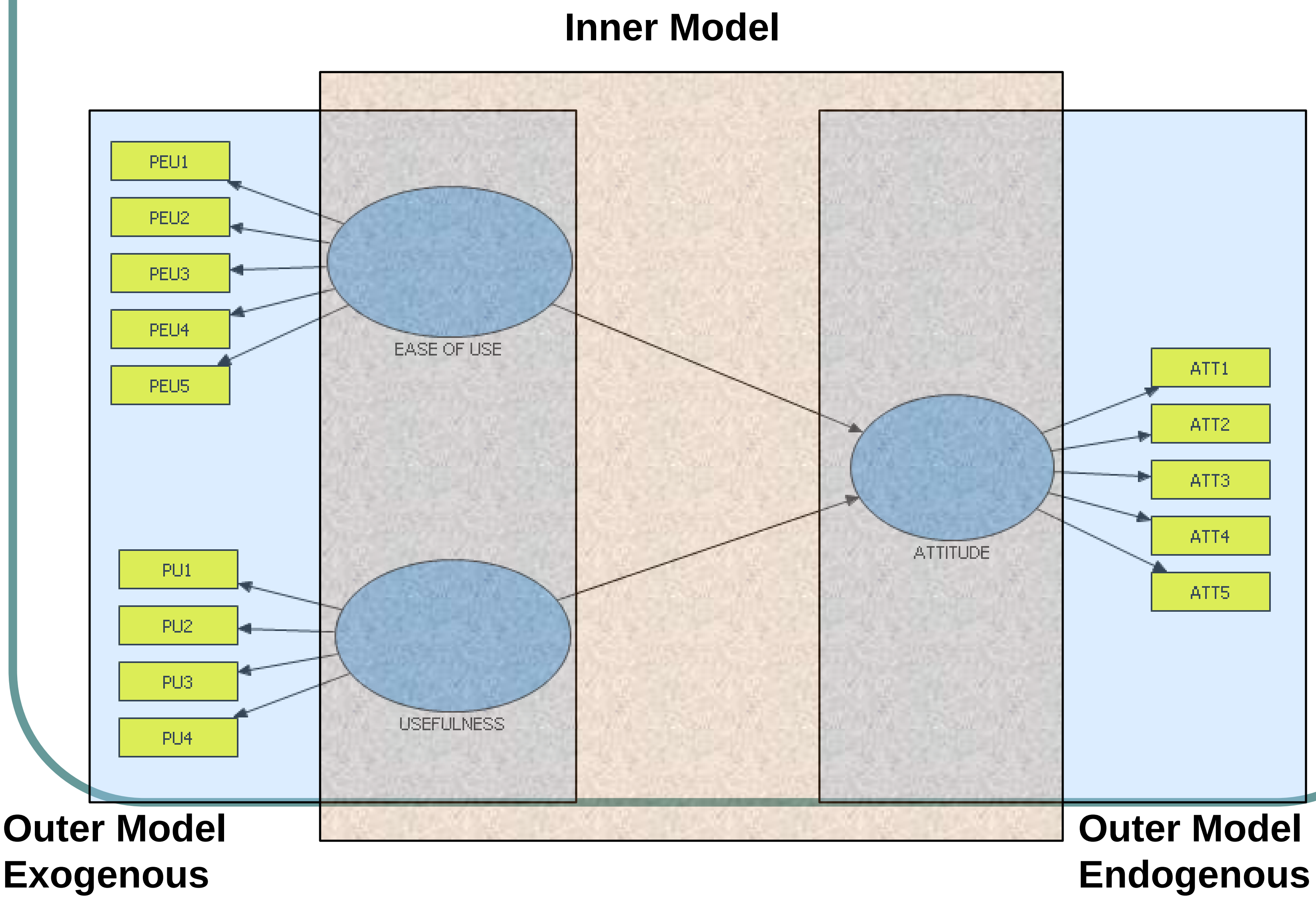
Missing Value Imputation



The 2 Step Approach

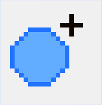
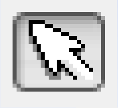
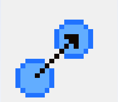
- A structural equation modeling process requires two steps:
  1. building and testing a measurement model, and
  2. building and testing a structural model.
- The measurement model serves to create a structural model including paths representing the hypothesized associations among the research constructs.

Modeling in PLS



Brief Instructions: Using SmartPLS

1. Load SmartPLS software – click on 

2. Create your new project – assign name and data.
3. Double-click to get Menu Bar.
4. Draw model – see options below:
   - Insertion mode = 
   - Selection mode = 
   - Connection mode = 
5. Save model.
6. Click on calculate icon  and select PLS algorithm on the Pull-Down menu. Now accept the default options by clicking Finish.

Confirmatory Factor Analysis (CFA)

- Confirmatory Factor Analysis (CFA) . . . is similar to EFA in some respects, but **philosophically it is quite different.**

- With CFA, the researcher must specify both the number of factors that exist within a set of variables and which factor each variable will load highly on **before** results can be computed.

- **So the technique does not assign variables to factors.** Instead the researcher must be able to make this assignment before any results can be obtained.

- SEM is then applied to test the extent to which a researcher's a-priori pattern of factor loadings represents the actual data.

Review of and Contrast with Exploratory Factor Analysis

- EFA (exploratory factor analysis) explores the data and provides the researcher with information about how many factors are needed to best represent the data. With **<u>EFA</u>**, all measured variables are related to **<u>every factor</u>** by a factor loading estimate.
- Simple structure results when each measured variable loads <u>highly</u> on only one factor and has smaller loadings on other factors (i.e., loadings < .40).

- The distinctive feature of EFA is that the factors are derived from **statistical results**, **not from theory**, and so **they can only be named after the factor analysis is performed**.
- EFA can be conducted without knowing how many factors really exist or which variables belong with which constructs. **In this respect, CFA and EFA are not the same.**

Measurement Model and Construct Validity

- One of the biggest advantages of CFA/SEM is its ability to assess the **construct validity** of a proposed measurement theory. **Construct validity** . . . is the extent to which a set of measured items actually reflect the theoretical latent construct they are designed to measure.

- Construct validity is made up of <u>two important components</u>:
  1. Convergent validity – three approaches:
     - Factor loadings.
     - Variance extracted.
     - Reliability.
  2. Discriminant validity

Assessing Measurement Model

- Elements of the model are separately evaluated based on certain quality criteria's:
  - Reflective measurement models
  - Formative measurement models
  - Structural model

Measurement Model
- Reliability
- Validity

Structural Model
- Assessment of effects
- Assessment of prediction quality

Validation of the measurement models is a requirement for assessing the structural model

Effect of Errors

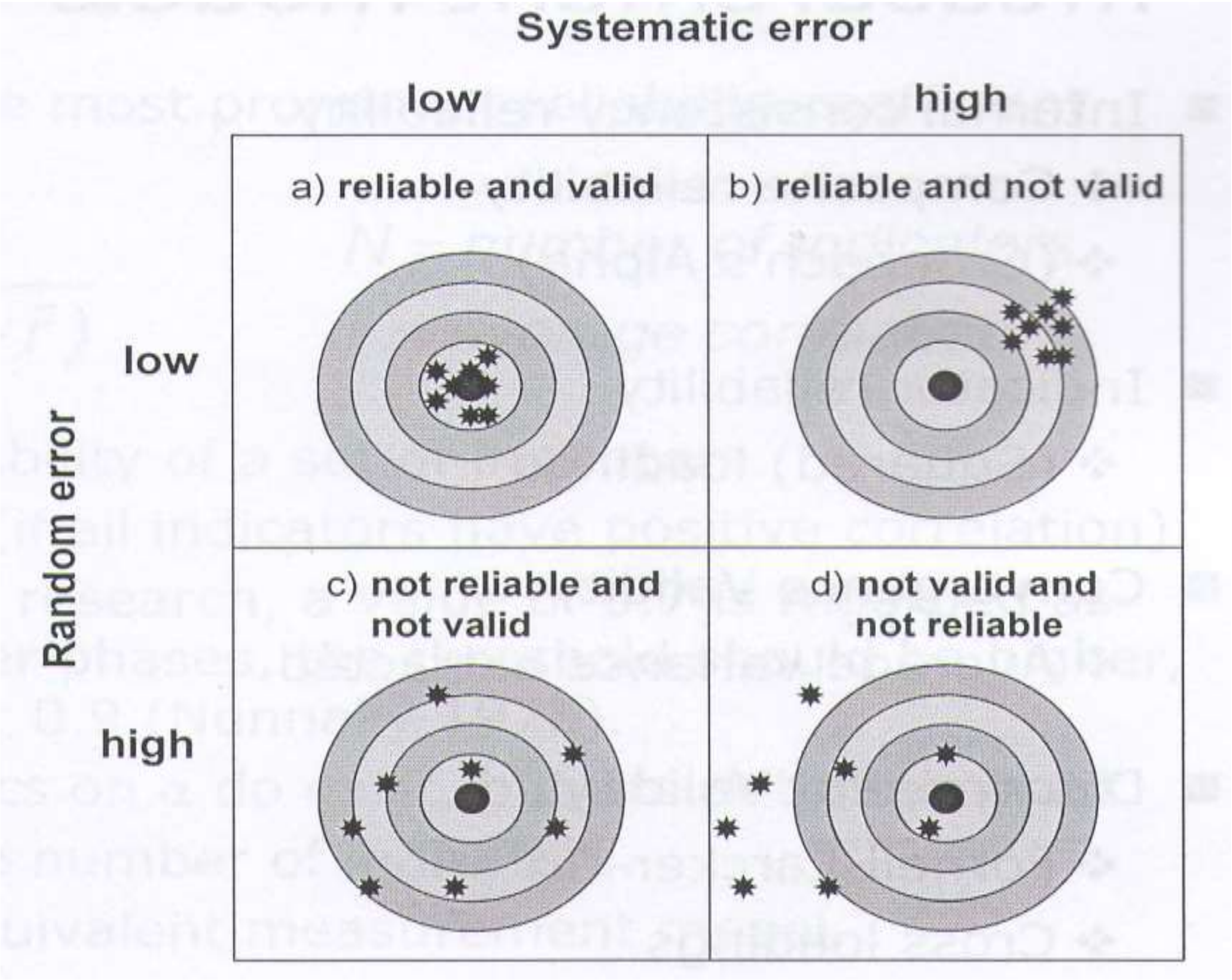
- What is the effect of error terms on measurement:

$$X_m = X_t + \varepsilon$$

$$X_m = X_t + \varepsilon_r + \varepsilon_s$$

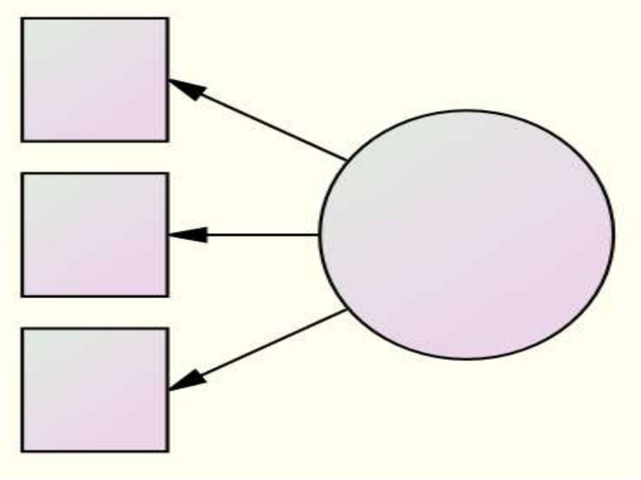
- X_m value as measured
- X_t true value
- ε error term
- ε_r random term
- ε_s systematic term

Consequences



Assessment of Reflective Models

- **Internal Consistency reliability**
  - Composite reliability
  - Cronbach's alpha
- **Indicator reliability**
  - Squared loadings
- **Convergence validity**
  - Average Variance Extracted (AVE)
- **Discriminant Validity**
  - Fornell-Larcker Criterion
  - Cross loadings



Internal Consistency (Cronbach α)

$$\text{Cronbach's alpha}: \alpha = \left(\frac{N}{N-1}\right) * \left(1 - \frac{\sum_{i=1}^{N} \sigma_i^2}{\sigma_t^2}\right)$$

N = number of indicators assigned to the factor
σ^2_i = variance of indicator ***i***
σ^2_t = variance of the sum of all assigned indicators' scores
j = flow index across all reflective measurement model

- Measures the reliability of indicators
- The value is between 0 and 1
- In early phase 0.7 acceptable, but in later phases values of 0.8 or 0.9 is more desirable (Nunnally, 1978)

Internal Consistency (Dhillon-Goldstein Rho)

$$\textit{Composite reliability}(\rho) = \frac{(\sum_i \lambda_{ij})^2}{(\sum_i \lambda_{ij})^2 + \sum_i \operatorname{var}(\varepsilon_{ij})}$$

λ_i = loadings of indicator ***i*** of a latent variable
ε_i = measurement error of indicator ***i***
j = flow index across all reflective measurement model

- Measures the reliability of indicators
- The value is between 0 and 1
- Composite reliability should be 0.7 or higher to indicate adequate convergence or internal consistency (Gefen et al., 2000).

Indicator Reliability

- The indicator reliability denotes the proportion of indicator variance that is explained by the latent variable
- The value is between 0 and 1.
- When indicator and latent variables are standardized, the indicator reliability equals the squared indicator loading
- Normally should be at least 0.25 to 0.5
- However, reflective indicators should be eliminated from measurement models if their loadings within the PLS model are smaller than 0.4 (Hulland 1999, p. 198).

Average Variance Extracted (AVE)

$$AVE = \frac{\sum_i \lambda_i^2}{\sum_i \lambda_i^2 + \sum_i \mathrm{var}(\varepsilon_i)}$$

λ^2_i = squared loadings of indicator ***i*** of a latent variable
$\mathrm{var}(\varepsilon_i)$ = squared measurement error of indicator ***i***

- Comparable to the proportion of variance explained in factor analysis
- Value ranges from 0 and 1.
- AVE should exceed 0.5 to suggest adequate convergent validity (Bagozzi & Yi, 1988; Fornell & Larcker, 1981).

Discriminant Validity

- Fornell & Larcker (1981) criterion
  - A latent variable should explain better the variance of its own indicators than the variance of other latent variables
  - The AVE of a latent variable should be higher than the squared correlations between the latent variable and all other variables. (Chin, 2010; Chin 1998b; Fornell & Larcker, 1981).
- Cross loadings
  - The loadings of an indicator on its assigned latent variable should be higher than its loadings on all other latent variables.

Discriminant Validity

Table 4 Discriminant validity of constructs

Constructs	1	2	3	4	5
1. Collaboration	**0.703**				
2. Commitment	0.051	**0.720**			
3. Communication	0.184	0.014	**0.695**		
4. Performance	0.146	0.078	0.226	**0.742**	
5. Trust	0.022	0.197	0.017	0.008	**0.543**

Diagonals (in bold) represent the average variance extracted while the other entries represent the squared correlations

Discriminant Validity

Table 1 Loadings and cross loadings

	Collaboration	Commitment	Communication	Performance	Trust
Collext1	**0.889**	0.063	0.375	0.343	0.101
Collext2	**0.689**	0.234	0.304	0.227	0.030
Collext3	**0.919**	0.267	0.393	0.375	0.212
Commit1	0.111	**0.734**	0.138	0.264	0.350
Commit4	0.239	**0.949**	0.089	0.239	0.411
Commun1	0.263	0.201	**0.758**	0.467	0.210
Commun2	0.380	0.130	**0.865**	0.380	0.082
Commun3	0.407	0.006	**0.874**	0.376	0.073
Perform1	0.219	0.243	0.371	**0.805**	0.099
Perform2	0.393	0.228	0.480	**0.917**	0.100
Perform3	0.337	0.263	0.366	**0.860**	0.042
Trust2	0.112	0.296	0.053	0.040	**0.696**
Trust3	0.057	0.326	0.169	0.222	**0.707**
Trust4	0.131	0.363	0.105	0.024	**0.804**

Bold values are loadings for items which are above the recommended value of 0.5

Multicollinearity

Table 4.2 Means, standard deviations and inter-correlations

Variables	M	SD	Transform	Transact	Consistency	Adapt	Mission	Trust	Empower	OCB	Effective
Transformational	81.96	14.17									
Transactional	35.93	6.63	92**								
Consistency	49.94	9.11	.72**	69**							
Adaptability	50.60	8.46	.71**	.68**	.81**						
Mission	51.80	9.05	.72**	.67**	.80**	.83**					
Trust	47.65	7.86	56**	49**	.54**	.55**	.58**				
Empowerment	40.30	6.02	.51**	.49**	.48**	.59**	.53**	.42**			
OCB	79.61	11.35	.62**	.60**	.61**	.60**	.64**	.58**	.57**		
Effectiveness	43.58	8.26	.50**	.48**	.61**	.63**	.60**	.48**	.54**	.48**	

Correlations are significant at the .001 level ** and the .05 level *

Results

Table 4.3 Summary table of R Square for organizational effectiveness

Models		R Square	F	Beta	T	Sig.
Model 1		.01	1.60			.202
	Education Level			-.07	-1.5	.146
	Job Position			-.04	-.83	.406
Model 2		.26	39.55			.000
	Education Level			-.10	-2.5	.013
	Job Position			.02	.58	.563
	Transformational			.40	3.9	.000
	Transactional			.12	1.1	.251
Model 3		.44	49.65			.000

see page 91

Justification

In this study MLQ was used to measure the two leadership styles namely transformational leadership and transactional leadership. Transformational leadership consisted of four dimensions namely idealized influence, inspirational motivation, intellectual stimulation and individual consideration. Transactional leadership on the other hand consisted of contingent reward, management by exception (active) and management by exception (passive). However, based on the present results from factor analysis, items of both transformational and transactional leadership styles loaded on the ~~same~~ construct indicating that respondents did ~~not clearly differentiate between~~ the transformational and transactional ~~leadership~~ styles. Therefore, this issue of the MLQ scale could be a limitation of this study and hence, it needs to be modified and clearer variations of the transformational and transactional scales developed. These recommendations are supported by Tejada, Scandura & Pillai (2001), who reported that a dimension of transactional leadership namely contingent ~~reward is related~~ to transformational leadership as much as it relates to transactional leadership. These

Reporting Measurement Model

Model Construct	**Measurement Item**	**Loading**	**CR**[a]	**AVE**[b]
Commitment	COMMIT1	0.686	0.856	0.601
	COMMIT2	0.767		
	COMMIT3	0.885		
	COMMIT4	0.751		
Communication	COMMUN1	0.842	0.873	0.696
	COMMUN2	0.831		
	COMMUN3	0.829		
Trust	TRUST1	0.580	0.759	0.527
	TRUST2	0.587		
	TRUST3	0.948		
Performance	PERFORM1	0.837	0.898	0.747
	PERFORM2	0.900		
	PERFORM2	0.853		

Presenting Measurement Items (Table)

Model Construct	Measurement Item	Standardized estimate	t-value
Commitment	COMMIT1	0.686	5.230**
	COMMIT2	0.767	6.850**
	COMMIT3	0.885	22.860**
	COMMIT4	0.751	6.480**
Communication	COMMUN1	0.842	20.628**
	COMMUN2	0.831	16.354**
	COMMUN3	0.829	15.011**
Trust	TRUST1	0.580	1.960*
	TRUST2	0.587	2.284**
	TRUST3	0.948	2.640**
Performance	PERFORM1	0.837	16.081**
	PERFORM2	0.900	33.456**
	PERFORM2	0.853	13.924**

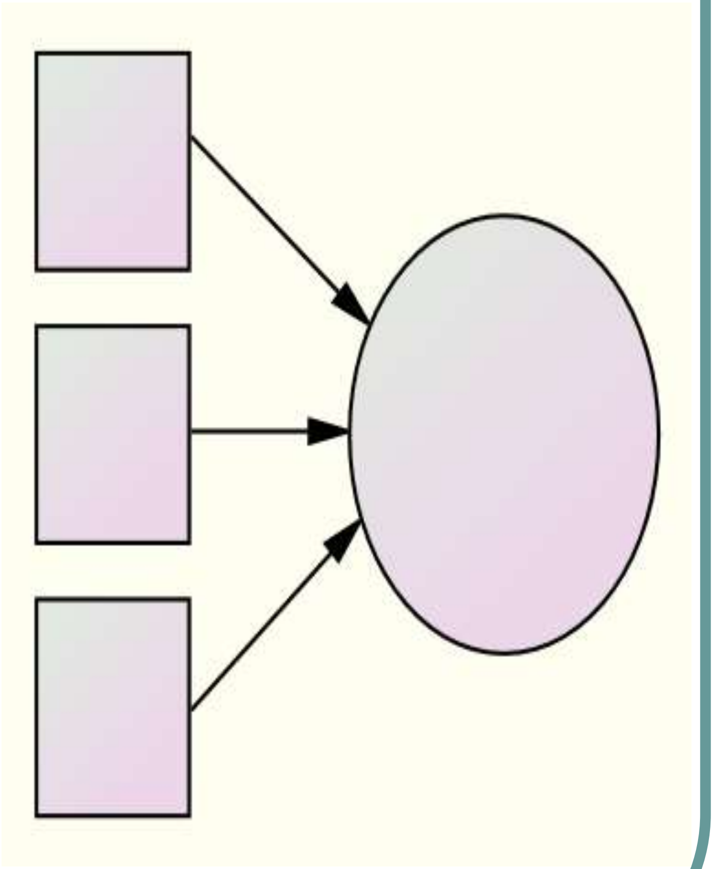
t-values > 1.96* (p< 0.05); t-values > 2.58** (p< 0.01)

Assessment of Formative Measurement Models

- Expert validity (Anderson & Gerbing, 1991)

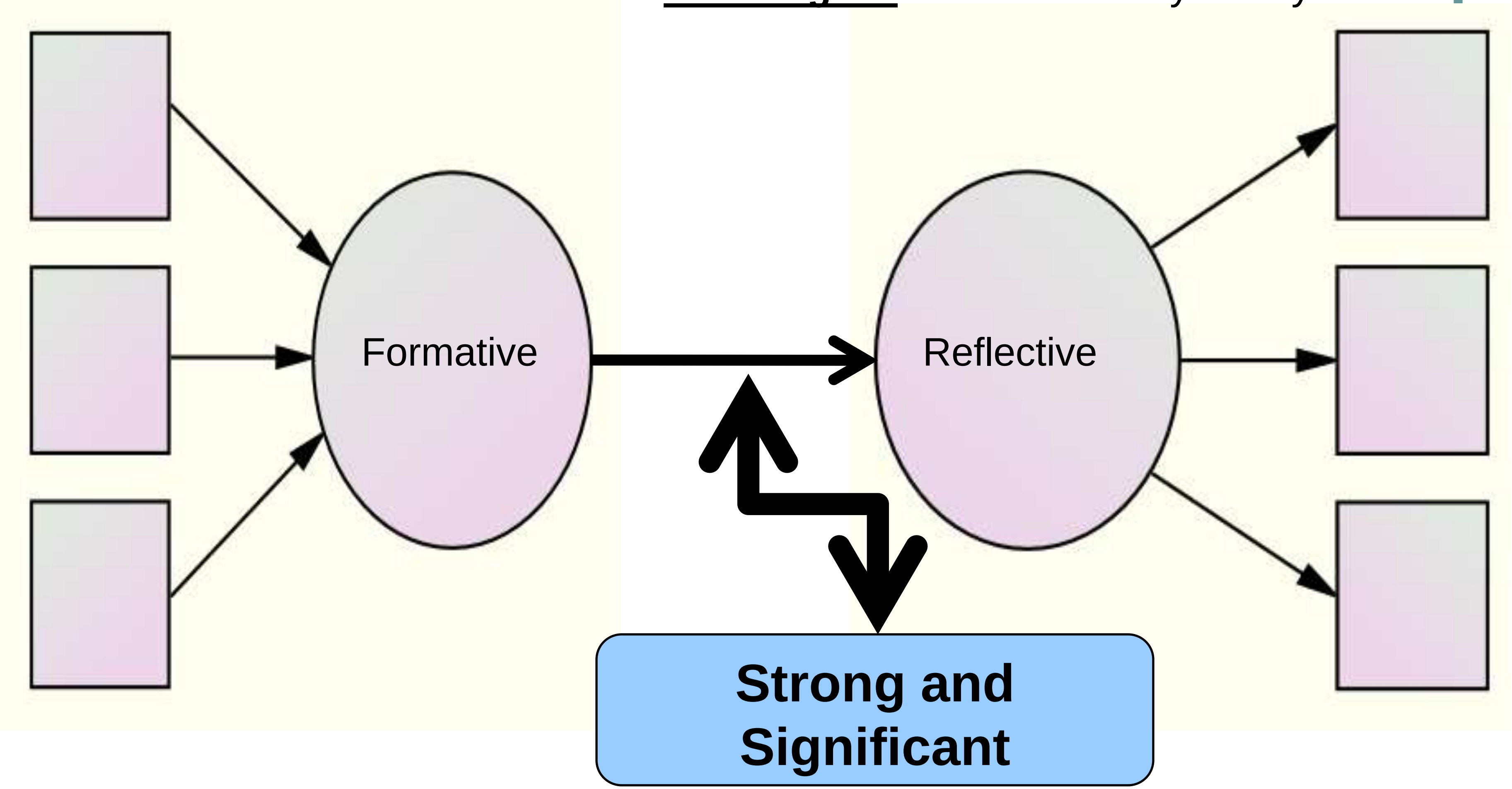
$$p_{sa} = \frac{n_c}{N} \qquad c_{sv} = \frac{n_c - n_0}{N}$$

  - Sa = substantive agreement
  - Sv = substantive validity
- Indicator relevance
- Indicator significance
- Multicollinearity



External Validity

- Does the measure of a construct correlate highly with a **second, different measure** of the construct
- Does a construct behave within a **nomological** net as stated by theory?



Bootstrapping

Example: Bootstrapping

- Is there a correlation between IQ and a methodology re-examination result?

ID	IQ	MR
1	105	5.6
2	106	5
3	114	7.1
4	123	7.4
5	134	6.1
6	141	8.6

- Corr (IQ,MR) = 0.733 Is this significant?

Building the Bootstrap Samples

Sample 1

ID	IQ	MR
6	141	8.6
4	123	7.4
3	114	7.1
5	134	6.1
2	106	5.0
5	134	6.1

corr = 0.546

Sample 2

ID	IQ	MR
3	114	7.1
3	114	7.1
1	105	5.6
3	114	7.1
3	114	7.1
5	134	6.1

corr = -0.060

Sample 3

ID	IQ	MR
2	106	5.0
2	106	5.0
2	106	5.0
2	106	5.0
4	123	7.4
4	123	7.4

corr = 1.000

...

Sample 500

ID	IQ	MR
6	141	8.6
4	123	7.4
3	114	7.1
5	134	6.1
2	106	5.0
5	134	6.1

corr = 0.546

- Standard deviation of corr = 0.277
  - $t = \frac{0.733}{0.277} = 2.646$
- Comparison
  - $t_{0.05,\ 499} = 1.965$
  - $t_{0.01,\ 499} = 2.586$

Bootstrapping

- Use matrix *X (n x m)* of manifest variables
- Create bootstrap sub-samples
  - Need to set a minimum number (eg; 500 or more)
  - The dimension of bootstrapping subsample should be identical to the original data matrix *(n x m)*
  - Randomly select (with replacement) cases from the original matrix
  - Cases are drawn with a probability of 1/n from the original matrix (a certain case can be selected 0 to n times when creating a bootstrap subsample)

Bootstrapping

- The routine estimates the PLS path model for each subsample (depending on the n suggested)
- The bootstrapping procedures provides mean values for
  - weights in the inner model (structural)
  - weights in the outer model (measurement), and
  - outer (measurement) models factor loadings

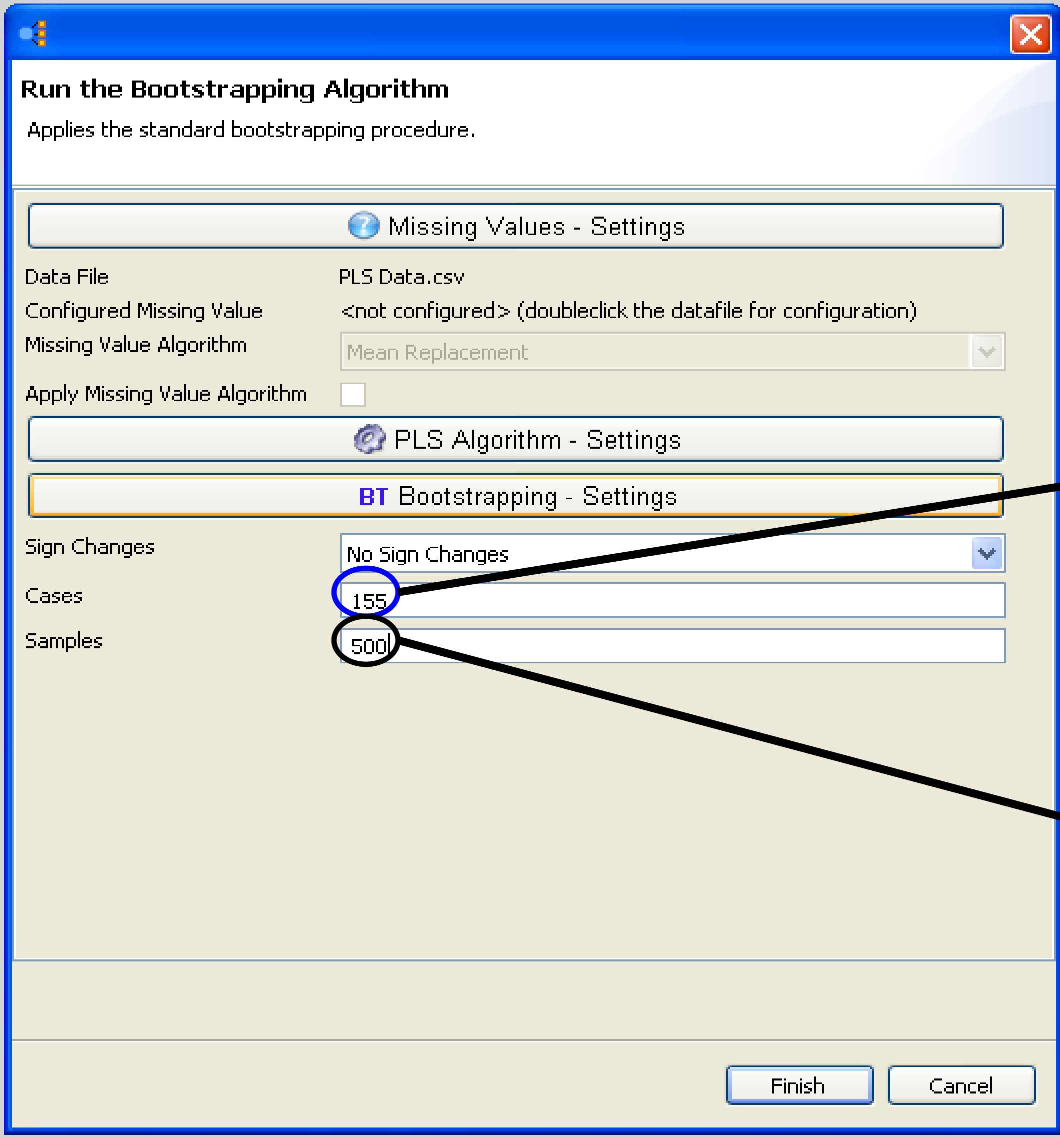
Testing for Significance

$$H_0: \beta = 0$$
$$H_1: \beta \neq 0$$

$$t = \frac{b - B_{H_0}}{se_b}$$

- The test will give indication whether the relationship is significant ie; statistically different from zero
- This result is used in research reports
- In practice it does not matter if an insignificant relationship remains in the PLS path model or is eliminated.

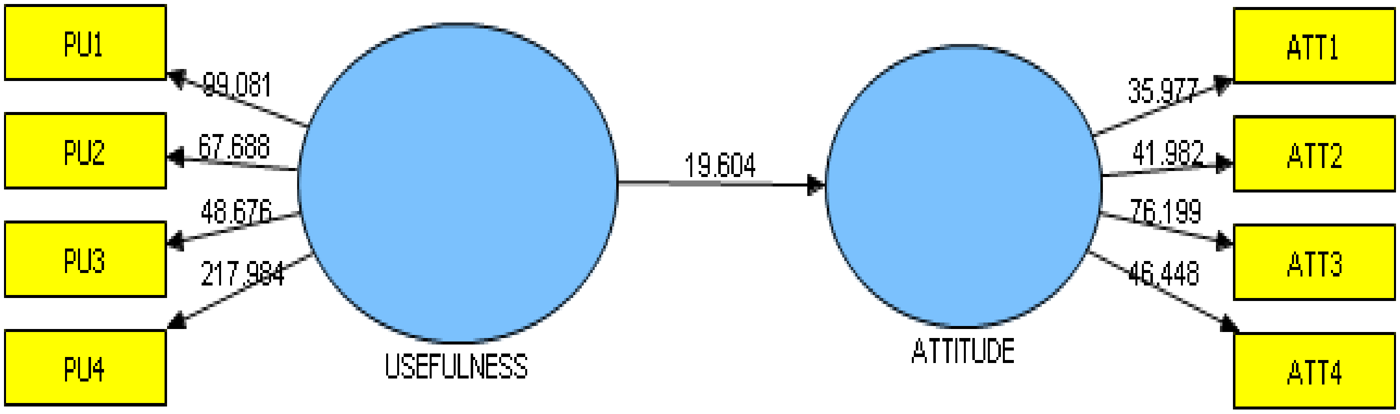
Bootstrapping in SmartPLS



- Number of observations in the original sample (~*n*)

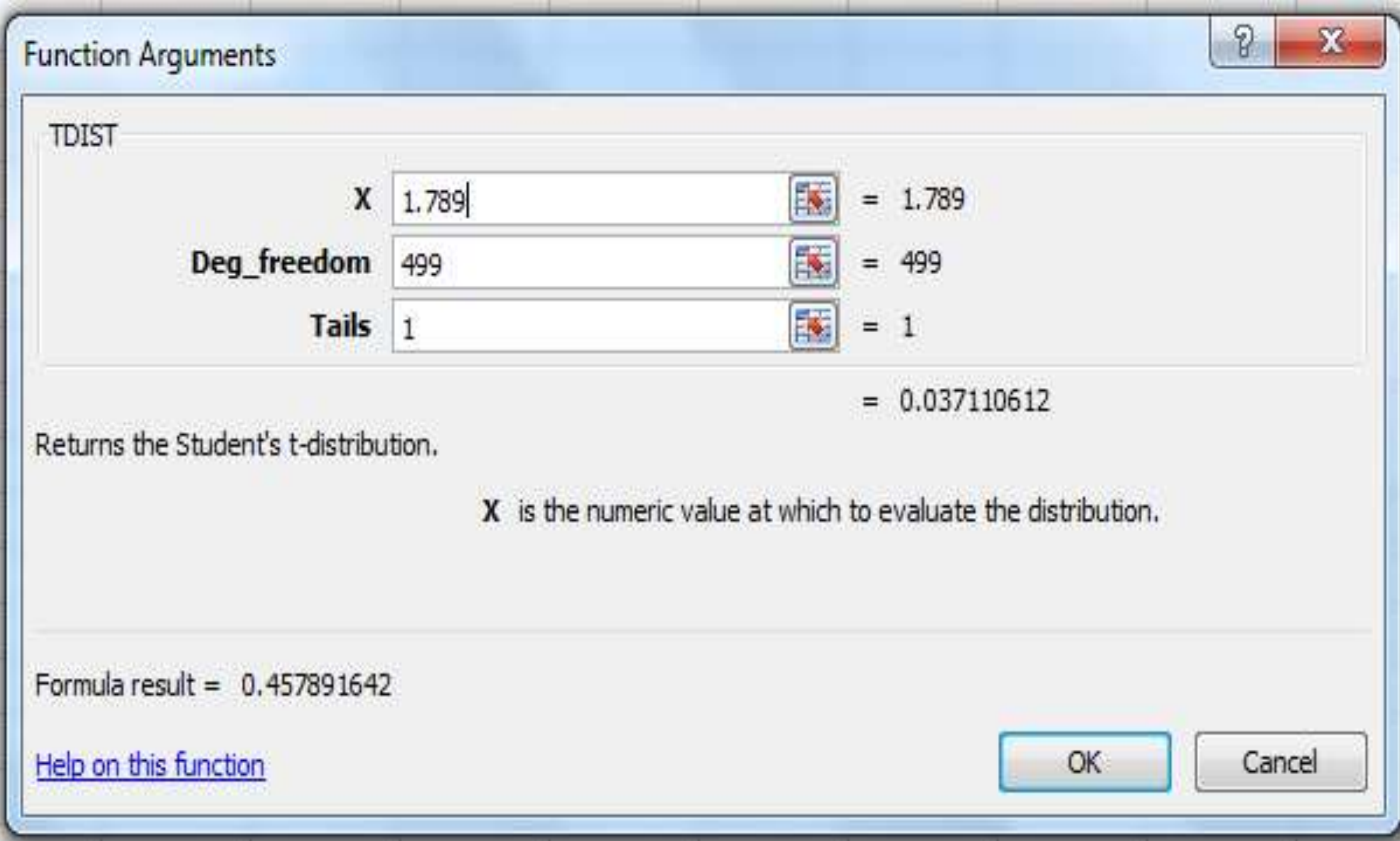
- Number of samples drawn (*m*)

Example



- Path **USEFULNESS → ATTITUDE**
  - t-value 19.604 > $t_{m-1,\, 1-\alpha/2} = t_{499,\, 0.975} = 1.972$
  - H0: β = 0 can be rejected
  - Conclusion path differs from 0 in population.

How to get p-values?



Assessment of the Structural Model

- Path Coefficients
- Explained Variances
- Effect Sizes

Goodness of Fit (GOF)

- What is Goodness of Fit (GOF)?

- Goodness-of-fit (GoF) (**Tenanhaus et al., 2005**) is used to judge the overall fit of the model.
- GoF, which is the geometric mean of the **average communality** (outer measurement model) and the **average R^2** of endogenous latent variables, represents an index for validating the PLS model globally, as looking for a compromise between the performance of the measurement and the structural model, respectively.
- GoF is normed between 0 and 1, where a higher value represents better path model estimations.

Assessing Goodness of Fit (GOF)?

- Assessing Goodness of Fit (GOF)

$$GOF = \sqrt{\overline{\mathrm{R}}^2 \ \mathrm{x} \ \ \mathrm{Average\,Communality}}$$

- Global validation of PLS models use these cut-off values (**Wetzels et al. 2009**):
  - $GoF_{small} = 0.10$
  - $GoF_{medium} = 0.25$
  - $GoF_{large} = 0.36$

$$GoF = \sqrt{\overline{AVE} \times \overline{R}^2}$$

- Allows to conclude that the model used has better explaining power in comparison with the baseline model

Assessing R^2

- According to **Chin (1998b),** *R^2 values for endogenous latent* variables *are assessed as follows:*
  - **0.67 substantial**
  - **0.33 moderate**
  - **0.19 weak**
- Also path coefficients range between 0.20 – 0.30 along with measures that explain 50% or more variance is acceptable (**Chin, 1998b**)

Assessing R^2

- According to **Cohen (1988),** *R^2 values for endogenous latent* variables *are assessed as follows:*
  - **0.26 substantial**
  - **0.13 moderate**
  - **0.02 weak**
- Also path coefficients range greater than 0.1 is acceptable (**Lohmoller, 1989**)

Evaluating R^2 values

- The R^2 values should be high enough for the model to **achieve a minimum level of explanatory power** (Urbach & Ahlemann, 2010).

- Falk and Miller (1992) recommended that **R^2 values should be equal to or greater than 0.10** in order for the variance explained of a particular endogenous construct to be deemed adequate.

Recommendations

- Hair et al. (2013) addressed the difficulty of providing rules of thumb for acceptable R^2 as it is reliant upon on the model complexity and the research discipline.

- While R^2 values of 0.20 are deemed as high in disciplines such as consumer behavior, R^2 values of 0.75 would be perceived as high in success driver studies (e.g., in studies that aim at explaining customer satisfaction or loyalty).

- Specifically, in scholarly research that focuses on marketing issues, R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can, as a rough rule of thumb, be respectively described as substantial, moderate, or weak. (Hair et al., 2011; Hair et al., 2013).

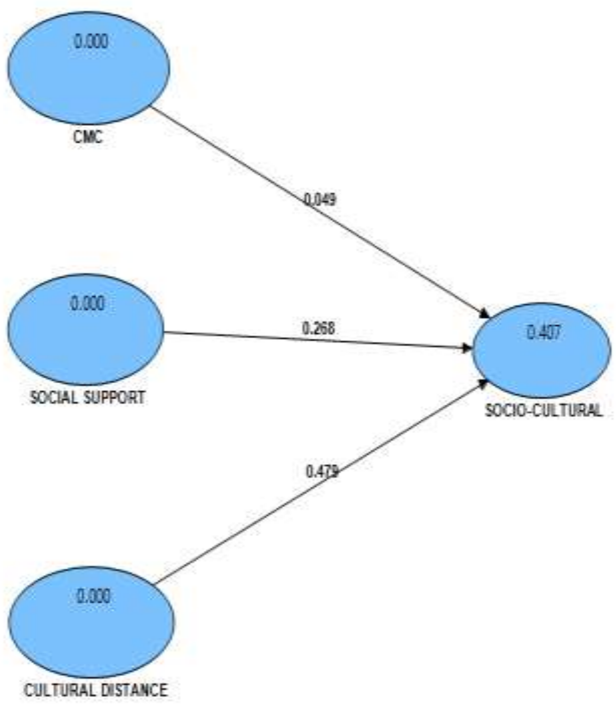
Calculating Effect Size (f^2)

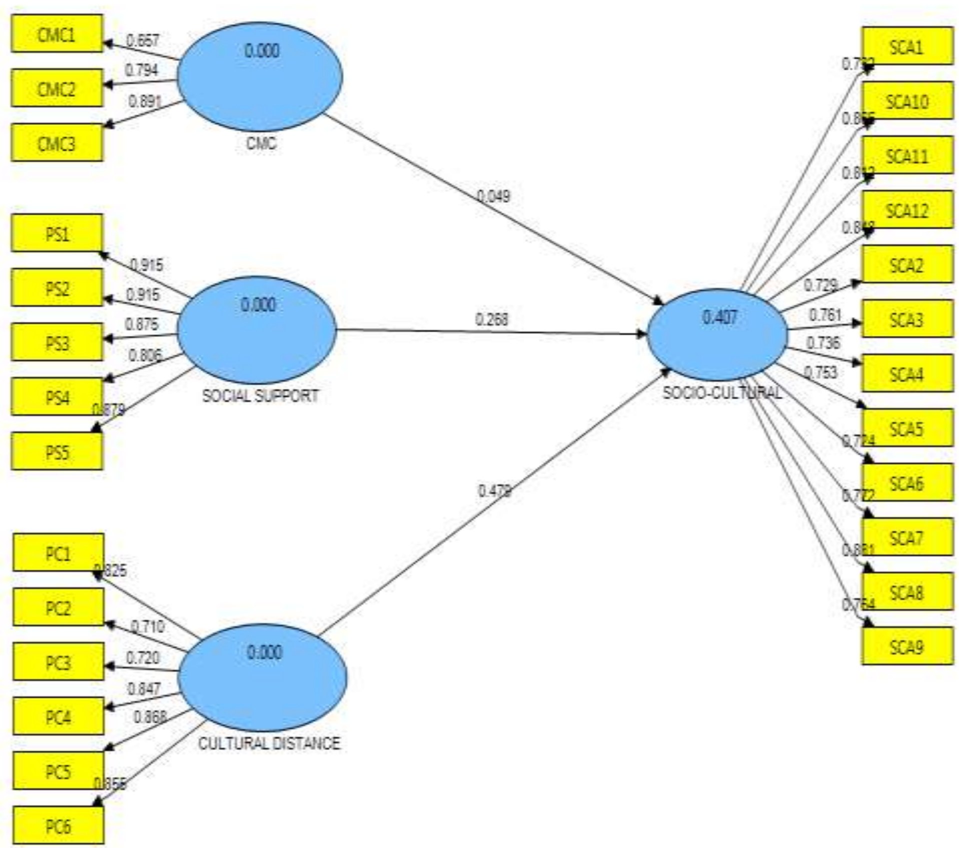
- Effect size f^2 is not automatically given in PLS, we have to do manual calculation using the formula:

$$\text{Effect size}: f^2 = \frac{R^2_{incl} - R^2_{excl}}{1 - R^2_{incl}}$$

- According to **Cohen (1988),** f^2 is assessed as:
  - **0.02** **small**
  - **0.15** **medium**
  - **0.35** **large**

Presenting the results (Figure)





Presenting the results (Table)

- The t-values are generated using the bootstrapping with re-samples of 200 (Chin, 1998b)

	Relationship	Coefficient	t-value	Supported
H1	SYS $\rightarrow$ SAT	0.23	2.588**	YES
H2	IQ $\rightarrow$ SAT	0.17	1.725*	YES
H3	SQ $\rightarrow$ SAT	0.24	2.645**	YES
H4	SAT $\rightarrow$ INT	0.38	3.895**	YES

t-values > 1.645* ($p < 0.05$); t-values > 2.33** ($p < 0.01$)

Blindfolding

- Using PLS for prediction purposes requires a measure of predictive capability
- Suggested approach – Blindfolding
- Wold (1982, p. 30), **“The cross-validation test of Stone (1974) and Geisser (1975) fits soft modeling like hand in glove”**

Blindfolding

- Set omission Distance *D*, eg: *D* = 3.
- Build D groups of data points that are successively deleted.

Standardized data:

MV 1	MV 2	MV 3
a	b	c
b	c	a
c	a	b
a	b	c
b	c	a
c	a	b
a	b	c

1. Round, omission of group **a**:

MV 1	MV 2	MV 3
	b	c
b	c	
c		b
	b	c
b	c	
c		b
	b	c

2. Round, omission of group **b**:

MV 1	MV 2	MV 3
a		c
	c	a
c	a	
a		c
	c	a
c	a	
a		c

3. Round, omission of group **c**:

MV 1	MV 2	MV 3
a	b	
b		a
	a	b
a	b	
b		a
	a	b
a	b	

Blindfolding

- PLS model estimation for every block of estimated data
- Calculate block wise the sum of squared of prediction errors (*e*) and the sum of squares of original (omitted) values (*O*)
- Calculation of predictive relevance: $Q^2 = 1 - \frac{\sum_D E_D}{\sum_D O_D}$
  - If $Q^2 > 0$ the model has predictive relevance
  - If $Q^2 < 0$ the model has lack of predictive relevance

Predictive Relevance Q^2

- Q^2 is a criterion to evaluate how ell the omitted data are estimated by the model
- The omitted data can be estimated in 2 modes: Cross validated communality (H^2) or Cross validated redundancy (F^2)
- H^2 is where the missing values of the manifest data are estimated using the latent variables scores and factor loadings.

$$\mathrm{Pred}(x_{jhi}) = \hat{\pi}_{jh} Y_{ji}$$

- F^2 is where the scores of the latent endogenous variables are estimated by the scores of latent exogenous variables and the weights in the measurement model. Then these newly estimated scores of latent exogenous variables are used to estimate the missing manifest variables scores

$$\mathrm{Pred}(Y_{ji}) = \sum_{j':\xi_{j'} \text{ explaining } \xi_j} \beta_{j'} Y_{j'i} \qquad \mathrm{Pred}(x_{jhi}) = \hat{\pi}_{jh} \mathrm{Pred}(Y_{ji})$$

Q-squares Statistics

- A The Q-squares statistics measure the predictive relevance of the model by reproducing the observed values by the model itself and its parameter estimates. A **Q-square greater than 0 means that the model has predictive relevance**; whereas **Q-square less than 0 mean that the model lacks predictive relevance** (Fornell & Cha, 1994).
- In PLS, **two kinds of Q-squares** statistics are estimated, that is, *cross-validated (c-v) communality* (H^2_j) *and cross-validated redundancy* (F^2_j).
- *Both statistics are obtained through* blindfolding procedure in PLS. Blindfolding procedure (while estimating Q-squares) ignores a part of the data for a particular block during parameter estimation (a block of indicators is the set of measures for a construct). The ignored data part is than estimated using the estimated parameters, and the procedure is repeated until every data point has been ignored and estimated. Omission and estimation of data point for the blindfolded construct depend on the chosen omission distance **G** (Chin, 1998a).

$$\text{Stone-Geisser test criterion}: Q_j^2 = 1 - \frac{\sum_k E_{jk}}{\sum_k O_{jk}}$$

Communality and Redundancy

Note: [a] Communality $_j$ = $1/p \, \Sigma \, cor^2 (X_{jh}, Y_j)$, where p = is the total number of MVs in the block; X_{jh} = h^{th} MV in j^{th} block; Y_j = latent variable. The communality index measures the quality of the measurement model for each block (Tenanhaus et al., 2005).

[b] H^2 = CV-communality index

[c] Redundancy $_j$ = communality $_j$ X R^2. The redundancy index measures the quality of the structural model for each endogenous block, taking into account the measurement model (Tenanhaus et al., 2005).

[d] CV-redundancy (F^2_j) = $1 - \Sigma_D = (\Sigma_D \, SSE_D) / (\Sigma_D \, SSO_D)$, where D is the omission distance, SSE is the sum of squares of prediction errors, and SSO is the sum of squares of observations (Henseler et al., 2009). It measures the capacity of the path model to predict the endogenous MVs indirectly from a prediction of their own LV using the related structural relation, by cross-validation (Tenanhaus et al., 2005).

[e] GoF = $\sqrt{\textit{average R square} \times \textit{average communality}}$ (Tenanhaus et al., 2005).

- H^2 and F^2 the values should be greater than the threshold of 0 (Fornell & Cha, 1994)

Predictive Relevance Q^2

- Sum of squares of manifest variables: $SSO_{jh} = \sum_i (x_{jhi})^2$

- Sum of squares of prediction errors: $SSE_{jh} = \sum_i (x_{jhi} - \hat{\pi}_{jh} Y_{ji})^2$

$$SSE'_{jh} = \sum_i \left(x_{jhi} - \hat{\pi}_{jh} \, \mathrm{Pred}(Y_{ji})\right)^2$$

- Sum of squares model of manifest variables (in the same measurement model j): $SSO_j = \sum_h SSO_{jh}$

- Sum of squares of prediction errors in measurement model j:

$$SSE_j = \sum_h SSE_{jh} \qquad SSE'_j = \sum_h SSE'_{jh}$$

Cv communality for measurement model j:

$$\boxed{H_j^2 = 1 - \frac{\sum_D SSEj}{\sum_D SSOj}}$$

Cv redundancy for measurement model j:

$$\boxed{F_j^2 = 1 - \frac{\sum_D SSE'j}{\sum_D SSOj}}$$

Q-squares Statistics

- A cross-validated communality H^2_j is obtained if prediction of the omitted data points in the manifest variables block is made by underlying latent variable (Chin, 1998). In other words, the cv-communality H^2_j measures the capacity of the path model to predict the manifest variables (MVs) directly from their own latent variable (LV) by cross-validation. It uses only the measurement model.
- The prediction of a MV of an endogenous block is carried out using only the MVs of this block (Tenanhaus et al., 2005). On the other hand, a cross-validated redundancy predicts the omitted data points by constructs that are predictors of the blindfolded construct in the PLS model (Chin, 1998a).
- In other words, the cv-redundancy F^2_j measures the capacity of the path model to predict the endogenous MVs indirectly from a prediction of their own LV using the related structural relation, by crossvalidation.
- The prediction of an MV of an endogenous block j is carried out using all the MVs of the blocks j* related with the explanatory LVs of the dependent LV_j (Tenanhaus et al., 2005). This index is used for measuring the quality of the path model. In accordance to effect size (f^2*), the relative impact of the structural model on the observed measures for* latent dependent variable is evaluated by means of q^2 (Henseler et al., 2009).
- The q^2 values of 0.02, 0.15, and 0.35 signify small, medium, and large predictive relevance of certain latent variable, thus explaining the endogenous latent variable under evaluation

Q-squares Statistics

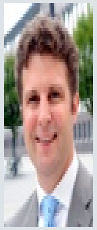
- **The cv-communality H^2_j** measures the capacity of the path model to predict the manifest variables (MVs) directly from their own latent variable (LV) by cross-validation. **<u>It uses only the measurement model.</u>**
- **The cv-redundancy F^2_j** measures the capacity of the path model to predict the endogenous MVs indirectly from a prediction of their own LV **<u>using the related structural relation</u>**, by cross validation.
- In accordance to effect size (f^2)*, the relative impact of the structural model on the observed measures for* latent dependent variable is evaluated by means of q^2 (Henseler et al., 2009).
- The q^2 values of 0.02, 0.15, and 0.35 signify small, medium, and large predictive relevance of certain latent variable, thus explaining the endogenous latent variable under evaluation.

Bug in Blindfolding

Back to top | profile | pm

Posted: Sun Jan 25, 2009 10:25 pm   Post subject: quote

Prof. Dr. Christian M. Ringle
TUHH - Hamburg University of Technology



SmartPLS Developer

Posts: 337

Hi,

the redundancy and communality computations run fine in SmartPLS.

However, cv-redundancy and cv-communality outcomes are different things. You use the blindfolding procedure to obtain these values and use them to compute Q^2 and q^2 (predictive relevance, Stone-Geisser-Test).

However, as reported elsewhere in this forum, the blindfolding procedure has a bug. It does correctly compute the cv-redundancy and cv-communality outcomes but you must follow specific rules:

cv-redundancy: check only a single latent variable in the blindfolding routine - you are then correctly analyzing the checked one.

cv-communality: check all latent variables exept a single one in the blindfolding procedure - you are then correctly analyzing the unchecked one.

Cheers
Christian

Reporting Q^2

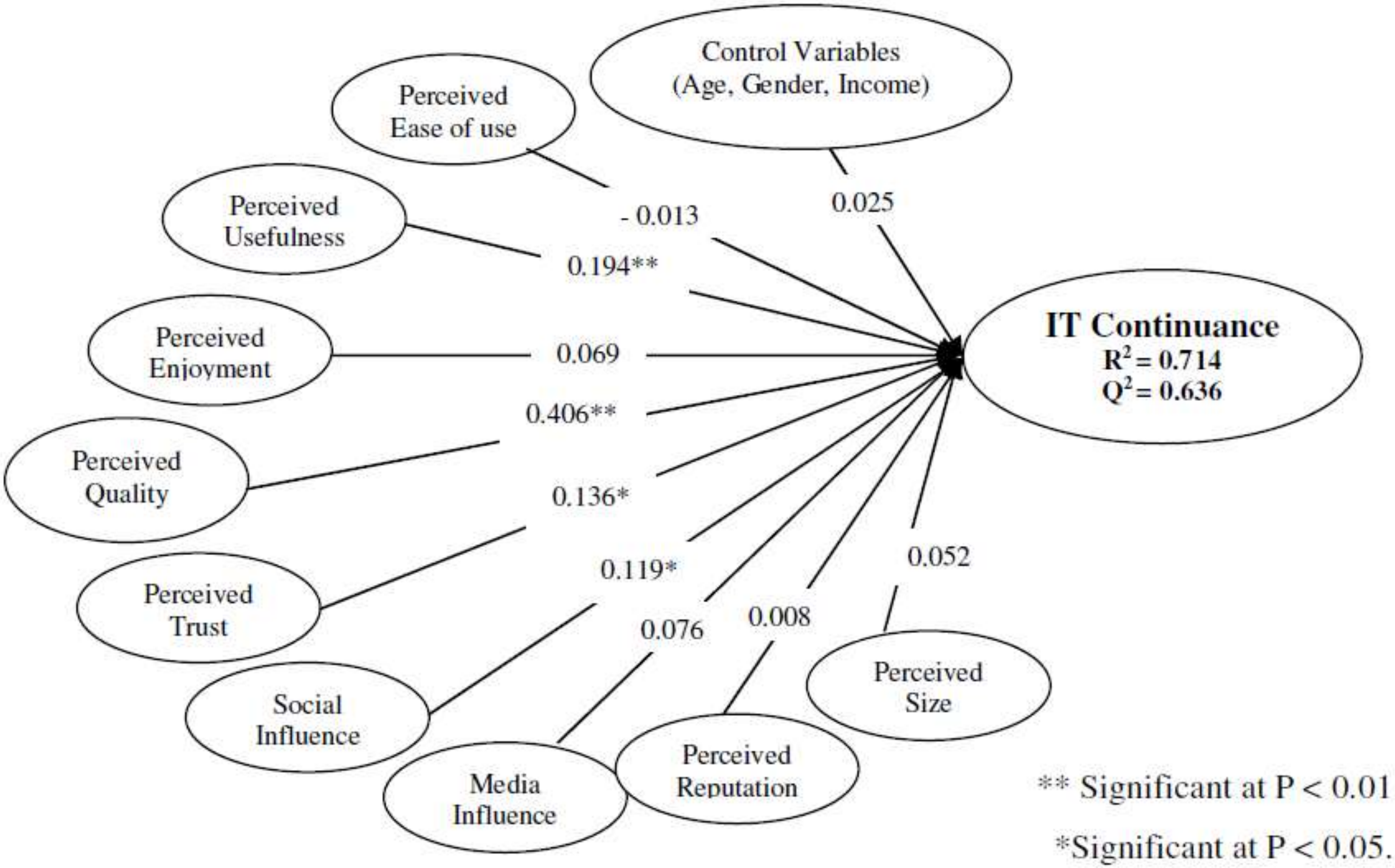
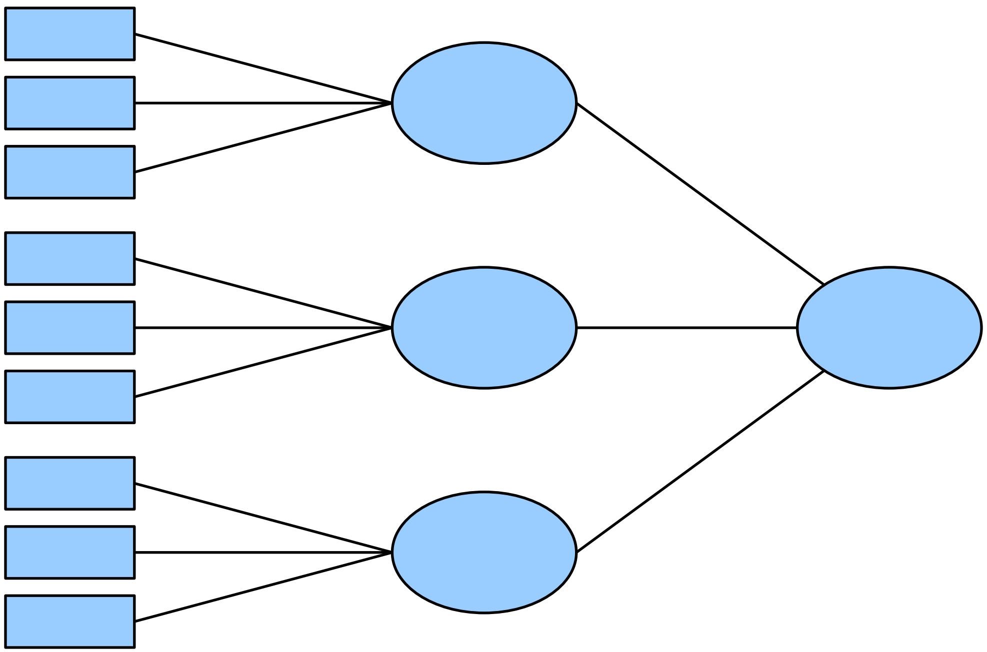


Figure 2: Q^2 in a complex model

Higher order constructs

- A number of recent papers have presented second order construct models.



- Higher level of abstraction?

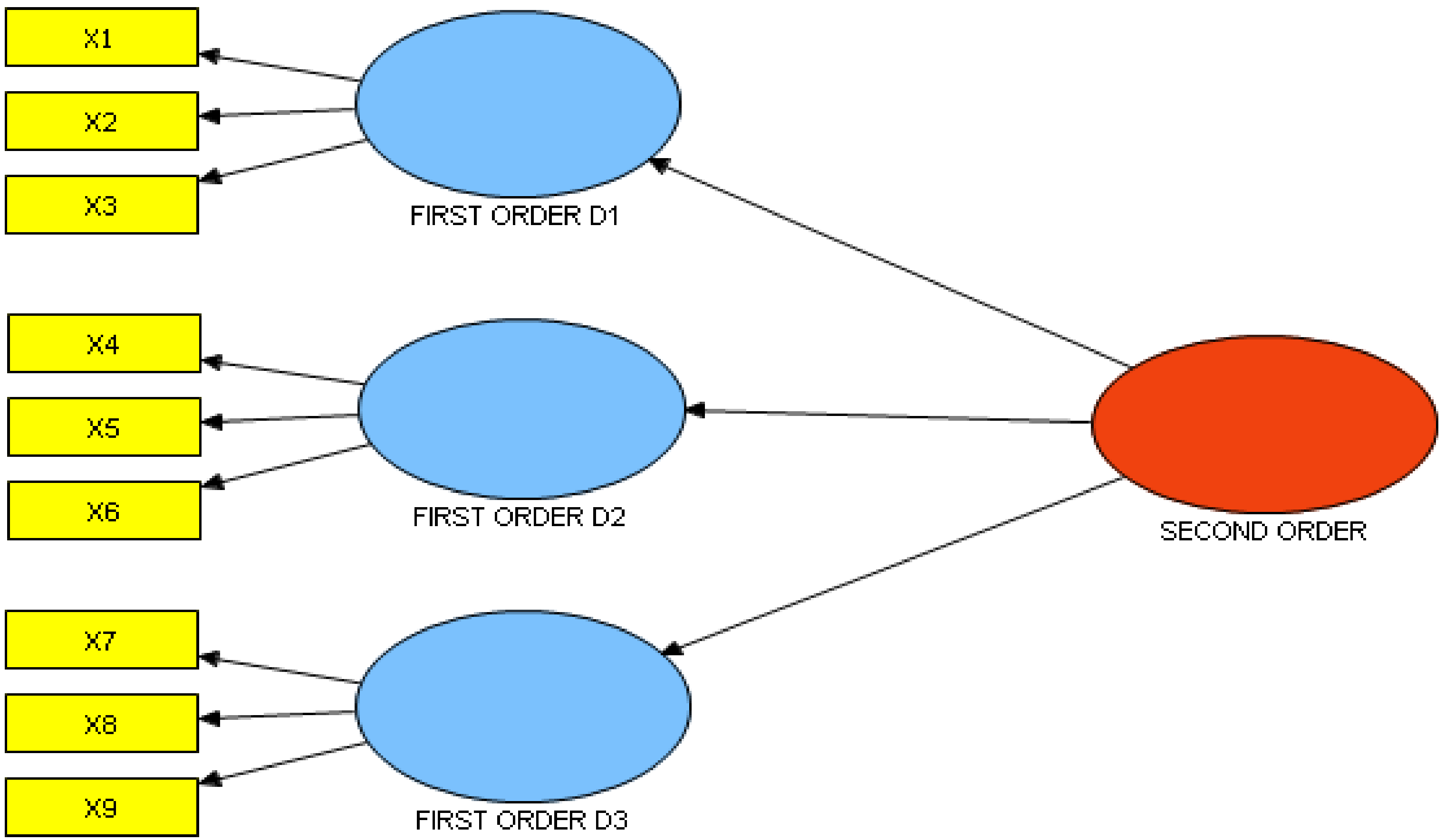
Reason for 2nd order factor

- As suggested by Hair et al. (2013) one of the main reasons to include second order construct in research is to reduce the number of relationships in the structural model, making the PLS path model more **parsimonious and easier to grasp**.

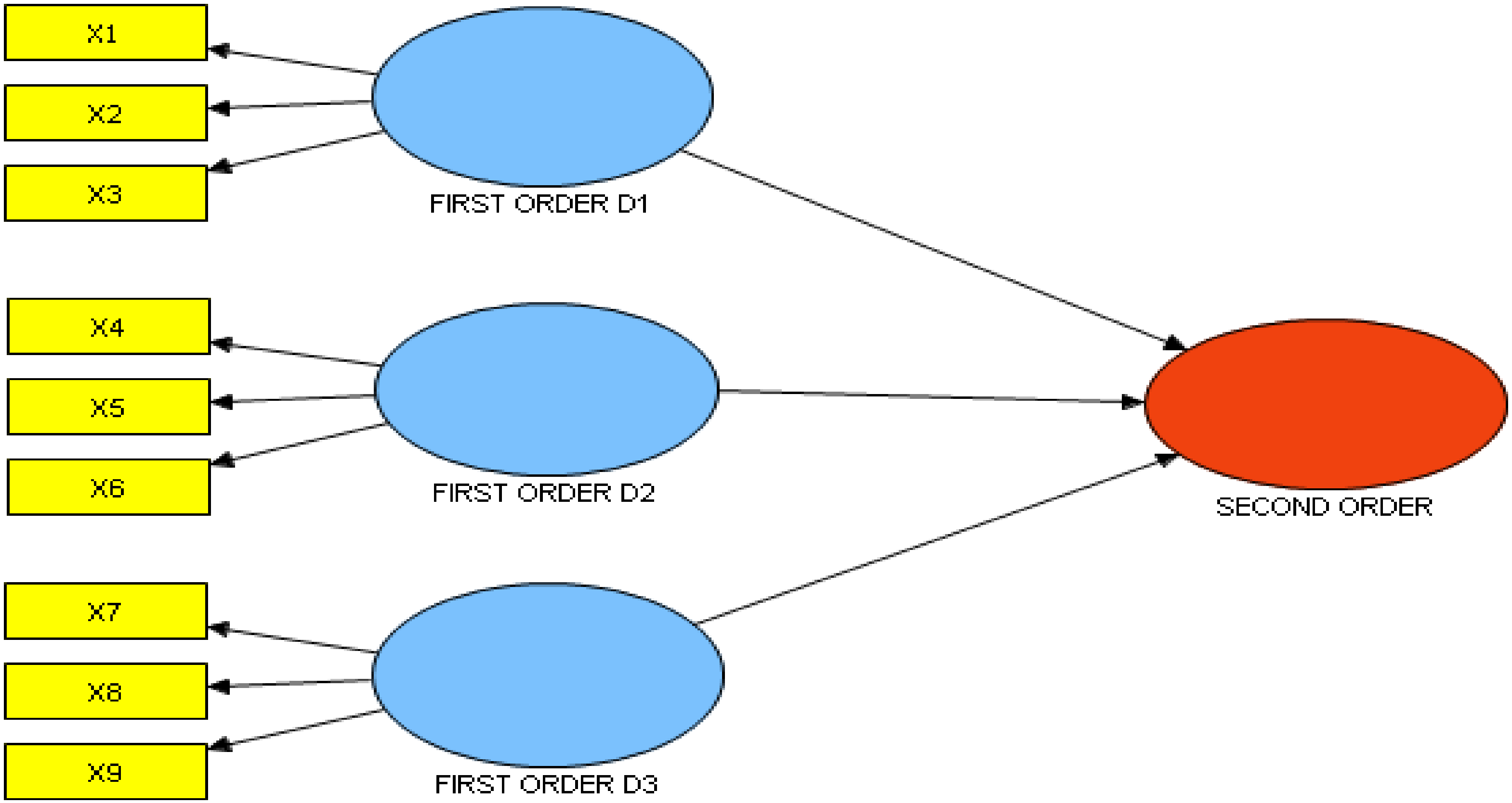
Higher Order Constructs

- When using higher order constructs, several issues need to be considered.
- The most important is the purpose of the model:
  - Often the initial answer is that a good model demonstrates that a general, more global factor exists that explains the first order factors.
- Is this second order factor expected to mediate fully the relationship of the first order factors when applied in a theoretical model?
- There are 4 possible types of second-order constructs.

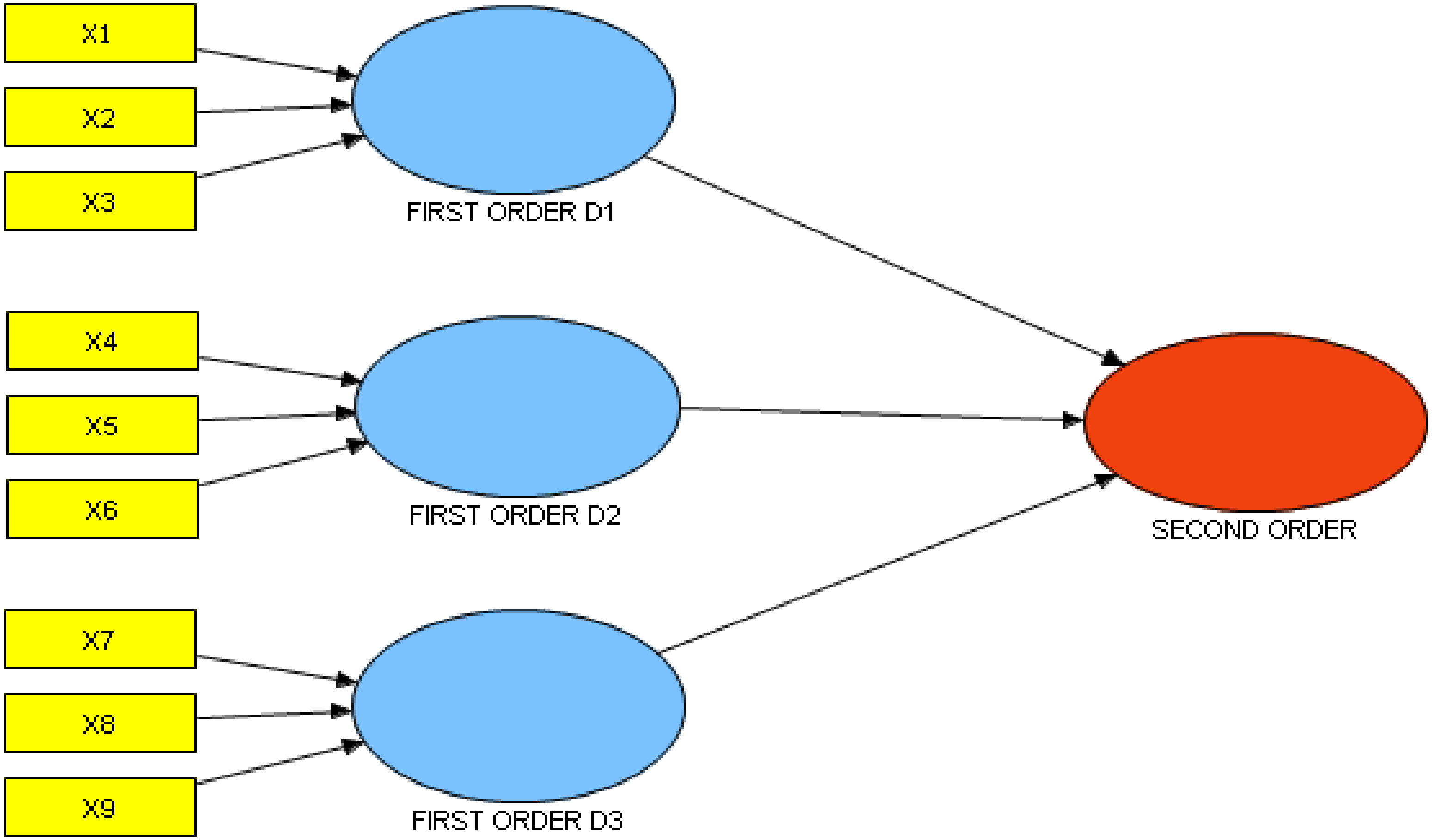
Type I: Reflective-reflective



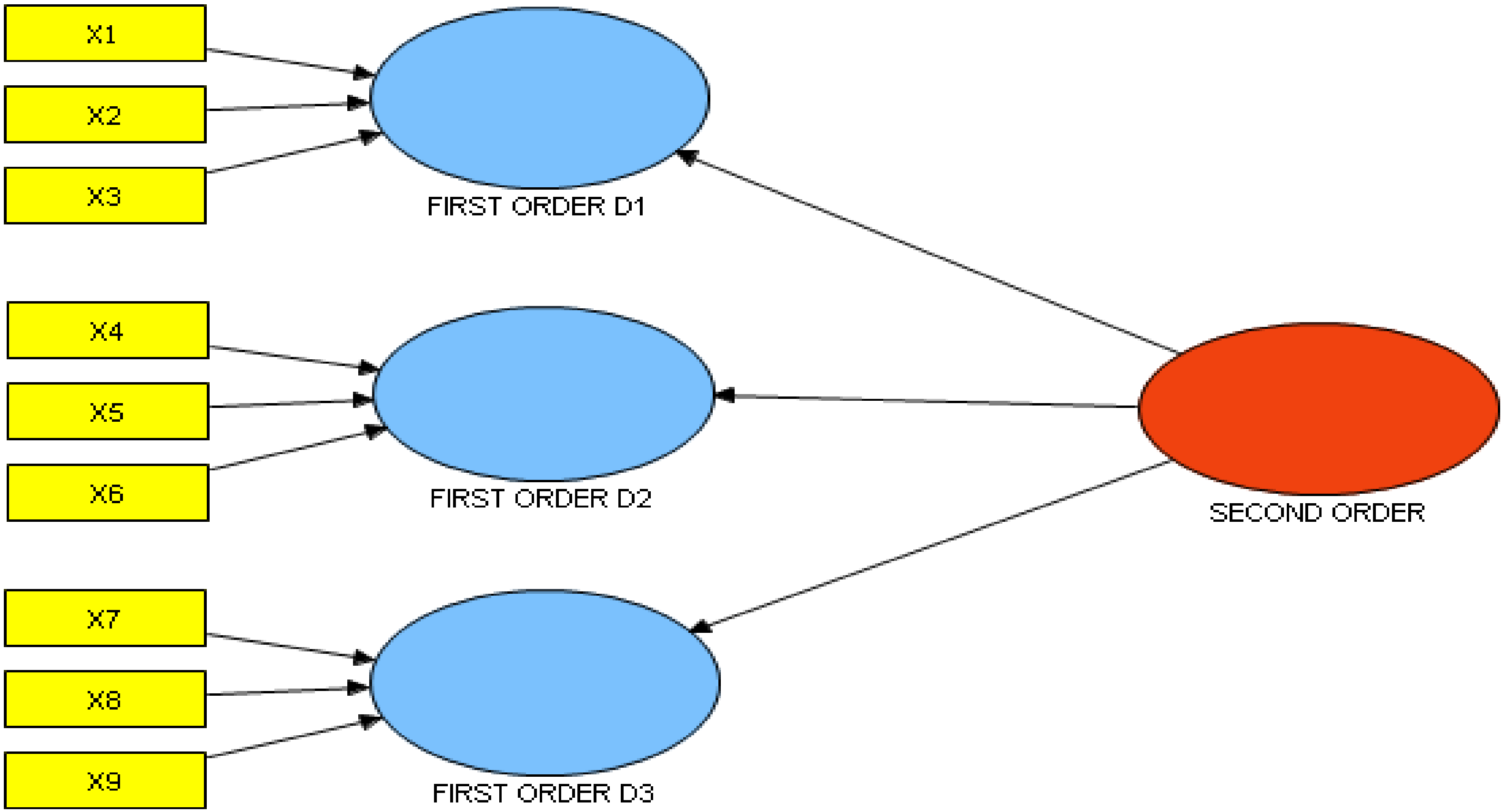
Type II: Reflective-formative



Type III: Formative-formative



Type IV: Formative-reflective

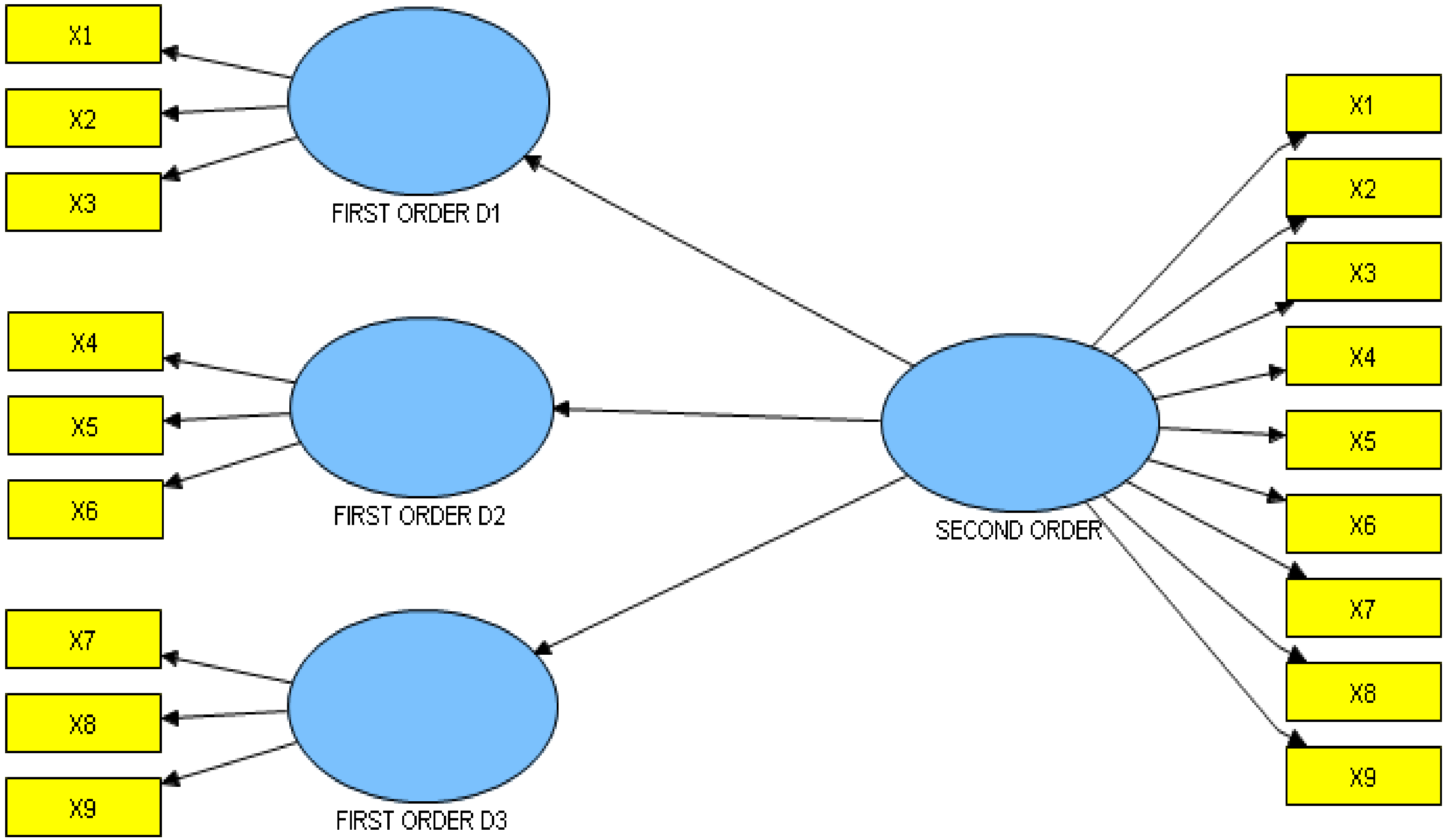


Technical Consideration

- The PLS path modeling algorithm requires that every latent variable has at least one manifest indicator
  - Phantom variables are not possible

- Solution
  - Repeated-indicator approach, (Wold, 1982; Lohmoller, 1989)

Type I



X1
X2
X3
FIRST ORDER D1
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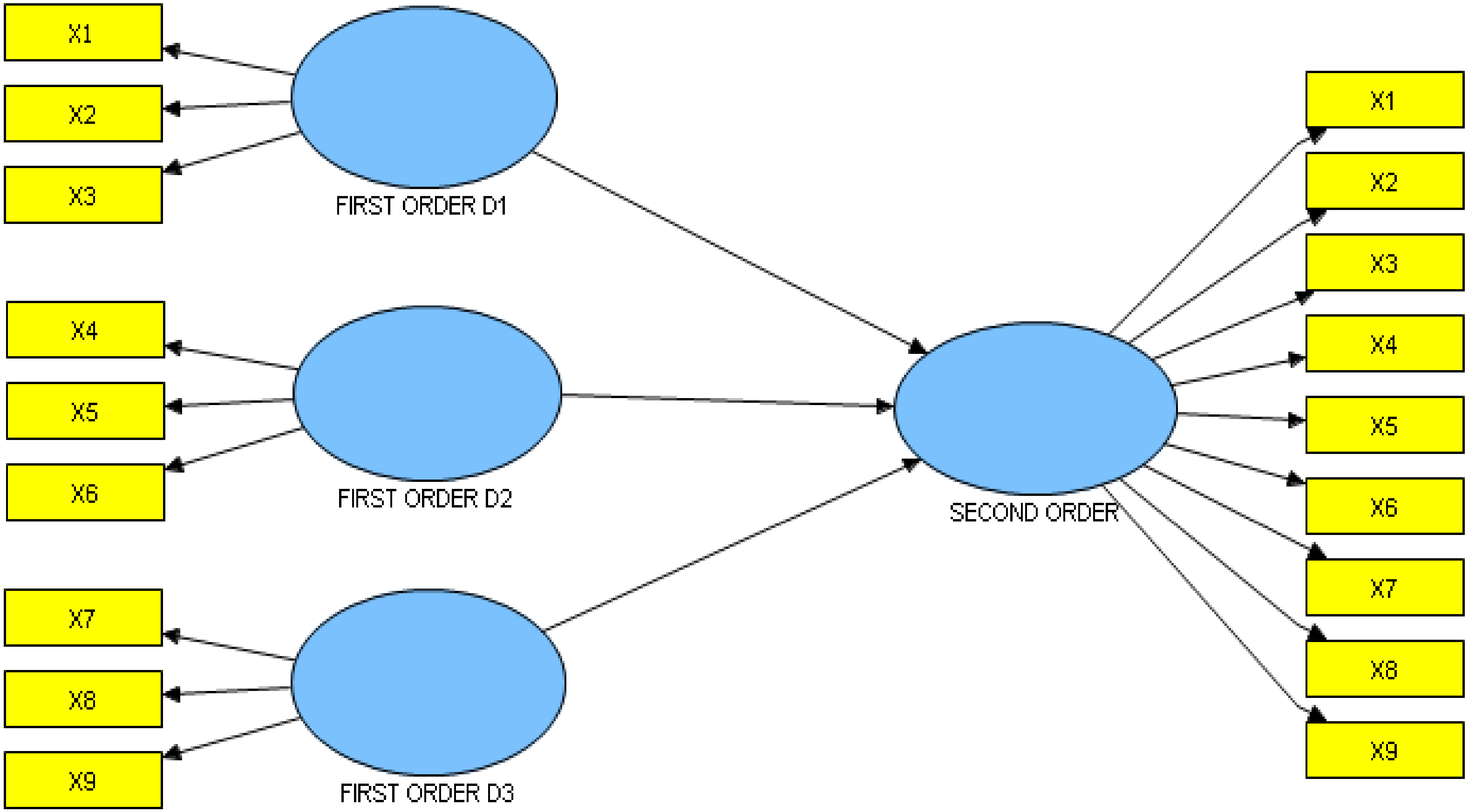
Type II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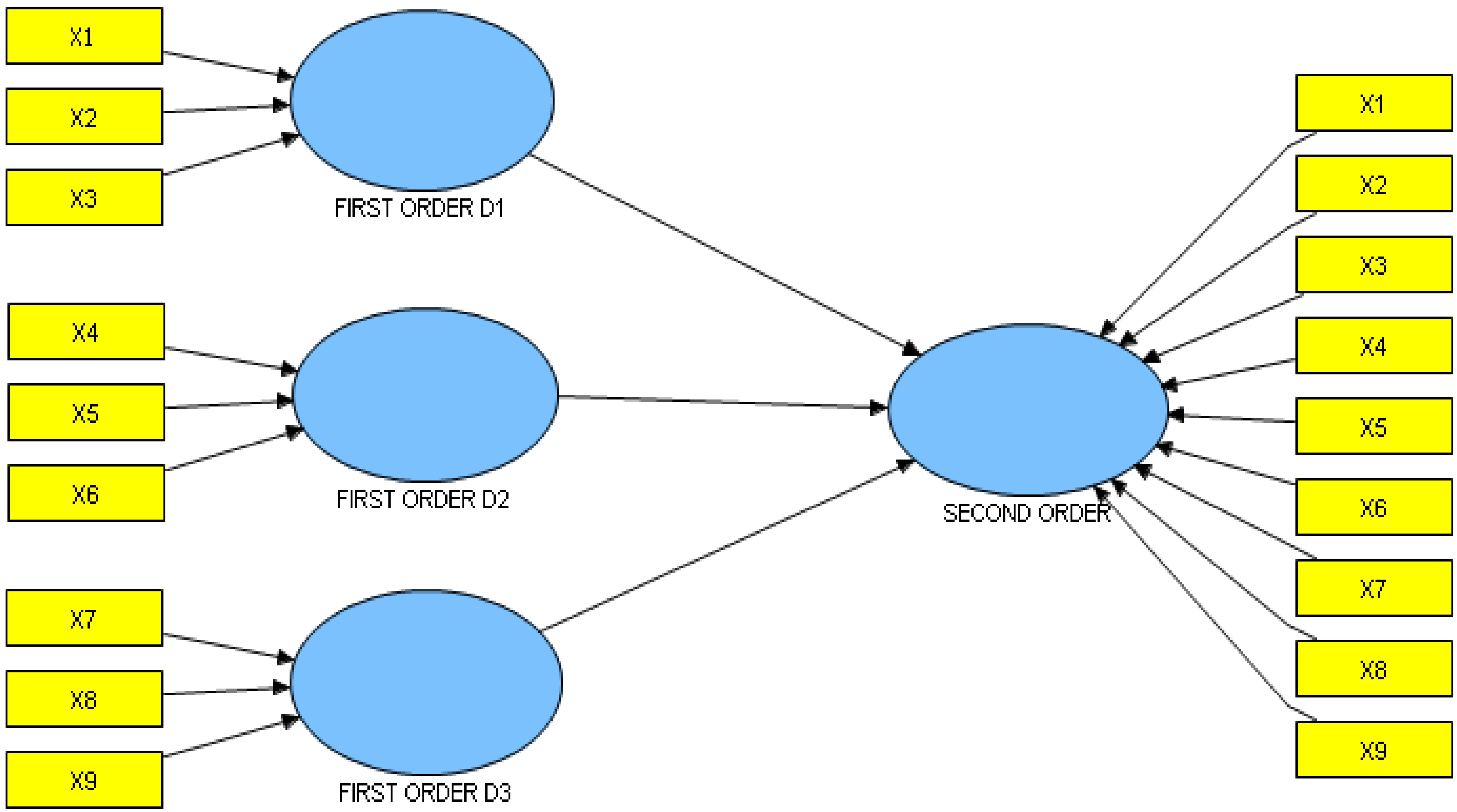
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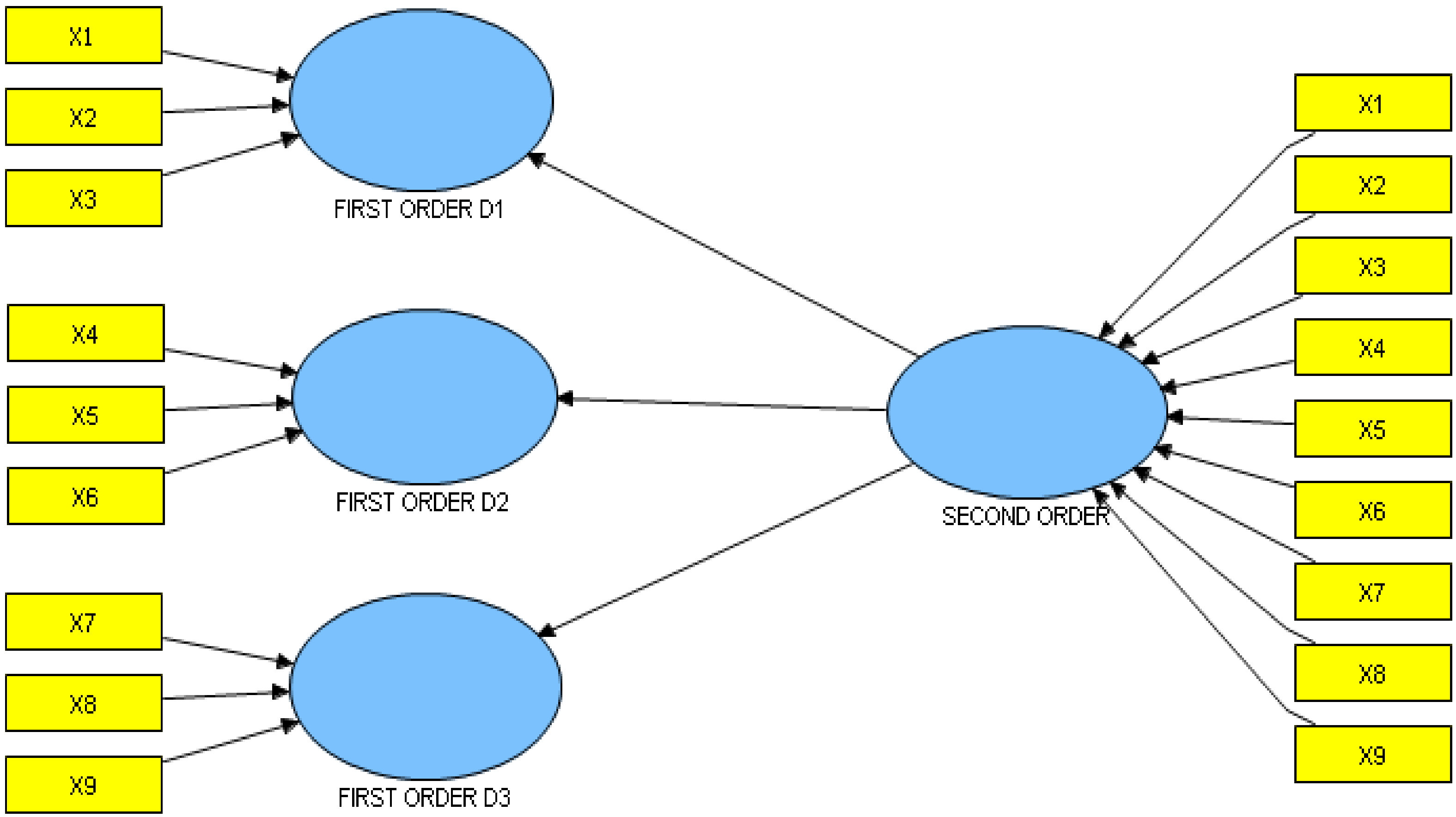
Type IV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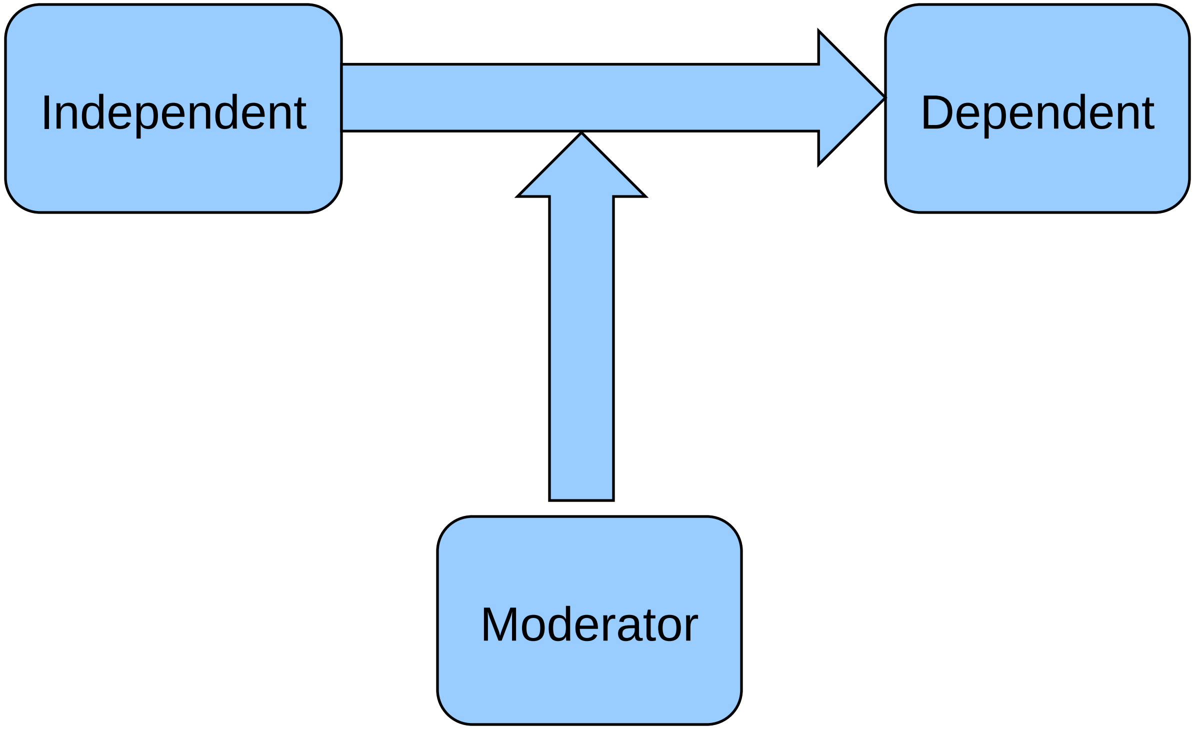
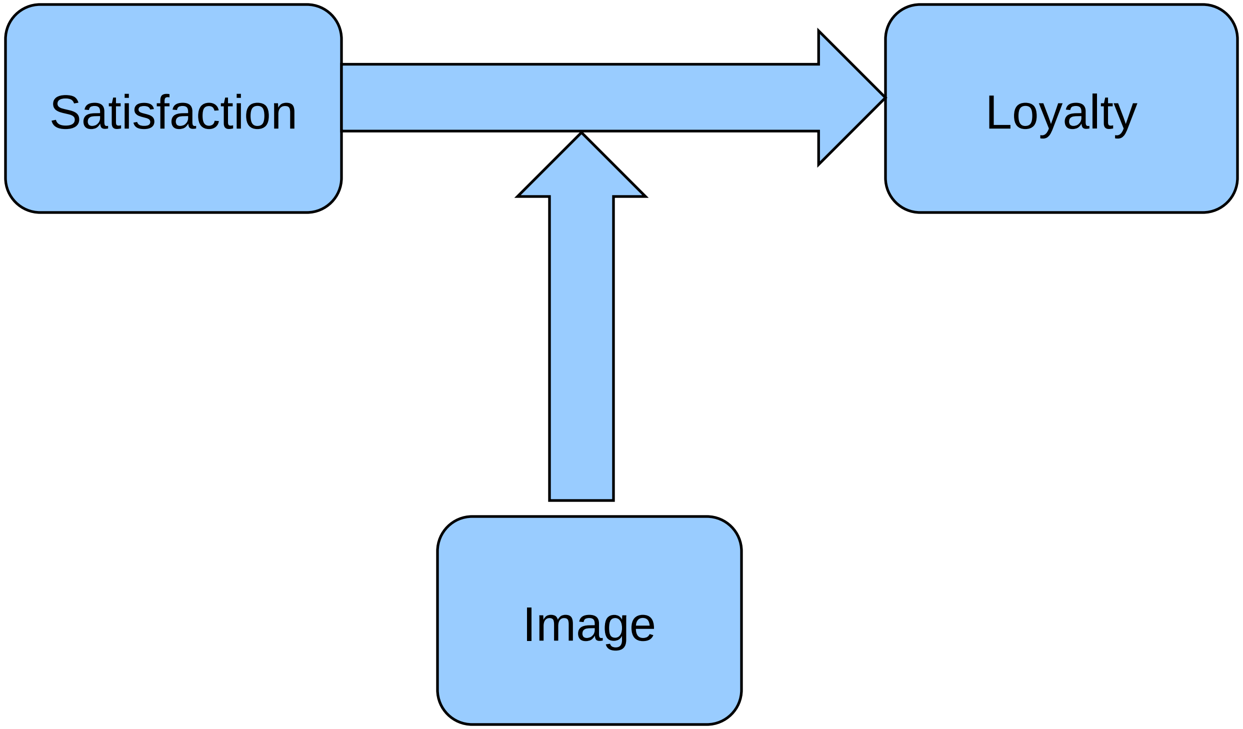
Model of a Moderator (Condition)



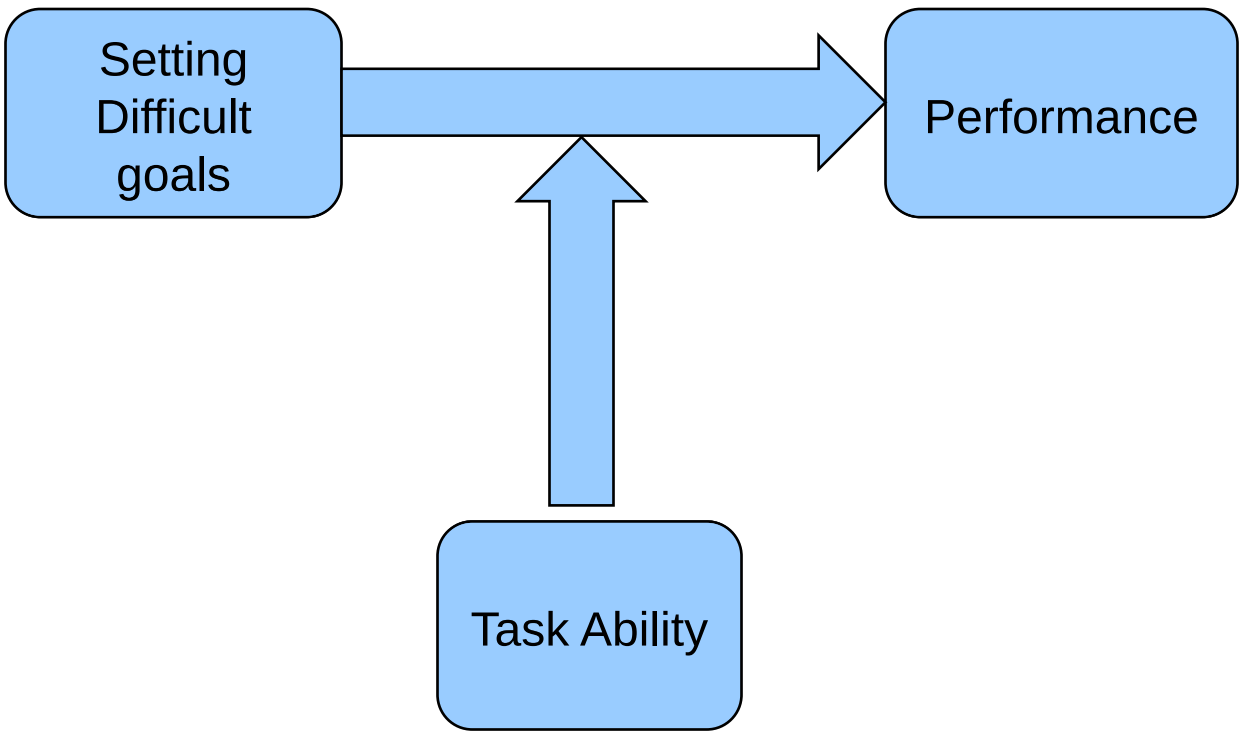
Who it did it work for?

Model of a Moderator (Condition)



Who it did it work for?

Goal Setting Theory (Locke et al., 1981)



Who it did it work for?

Moderator Variable

- A moderator specifies the conditions under which a given effect occurs, as well as the conditions under which the **direction (nature)** or **strength** of an effect vary. Baron and Kenny (1986, pp. 1174, 1178) describe a moderator variable as the following:

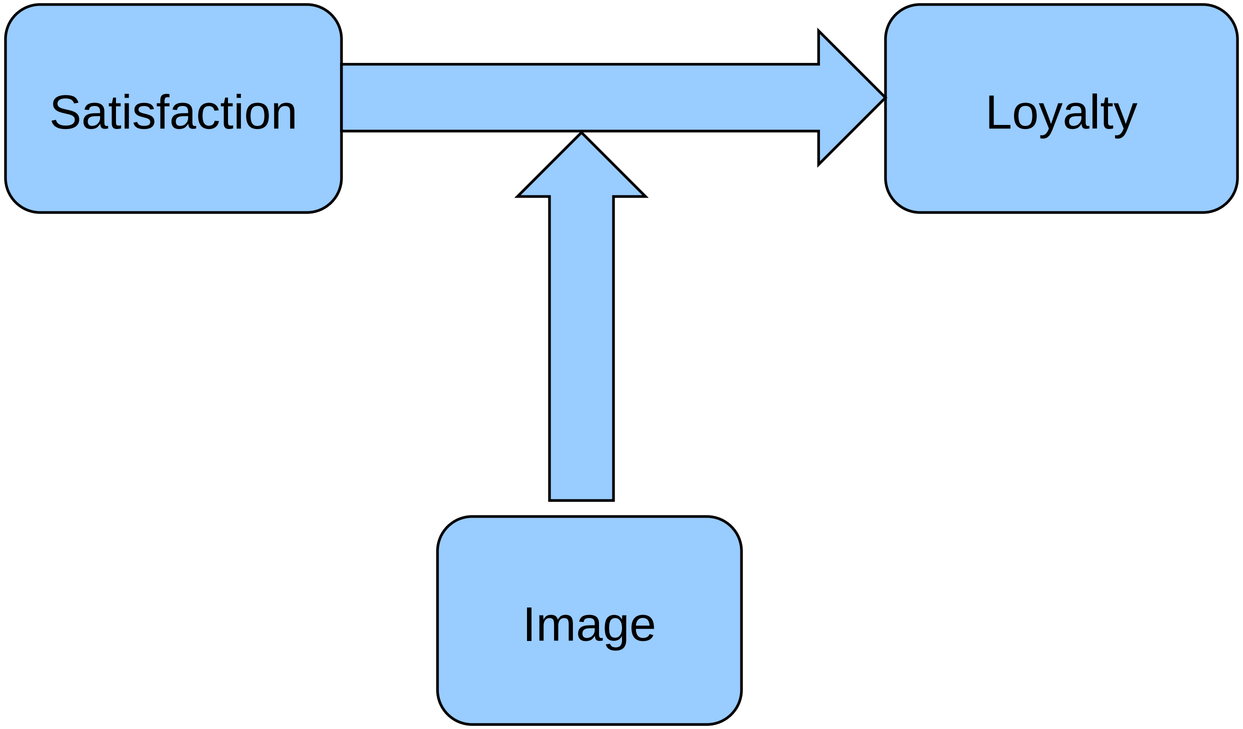
Moderator Variable

- *A **qualitative** (e.g., sex, race, class) or **quantitative** variable . . . that affects the direction and/or strength of a relation between an independent or predictor variable and a dependent or criterion variable . . . a basic moderator effect can be presented as an interaction between a focal independent variable and a factor (the moderator) that specifies the appropriate conditions for its operation . . .Moderator variables are typically introduced when there is an **unexpectedly weak or inconsistent relation between a predictor and a criterion variable**.*

Moderator Variable

- A moderator variable is one that affects the relationship between two variables, so that the nature of the impact of the predictor on the criterion varies according to the level or value of the moderator (Holmbeck, 1997).
- A moderator interacts with the predictor variable in such a way as to have an impact on the level of the dependent variable.

Model of a Moderator (Condition)



Hypothesis

- Should I Hypothesize the form of **My Interactions** in Advance?
  - **YES**, not only should the existence of an interaction effect be predicted, but also its form. In particular, whether a moderator increases or decreases the association between two other variables should be specified as part of the a priori hypothesis (Dawson, 2013).

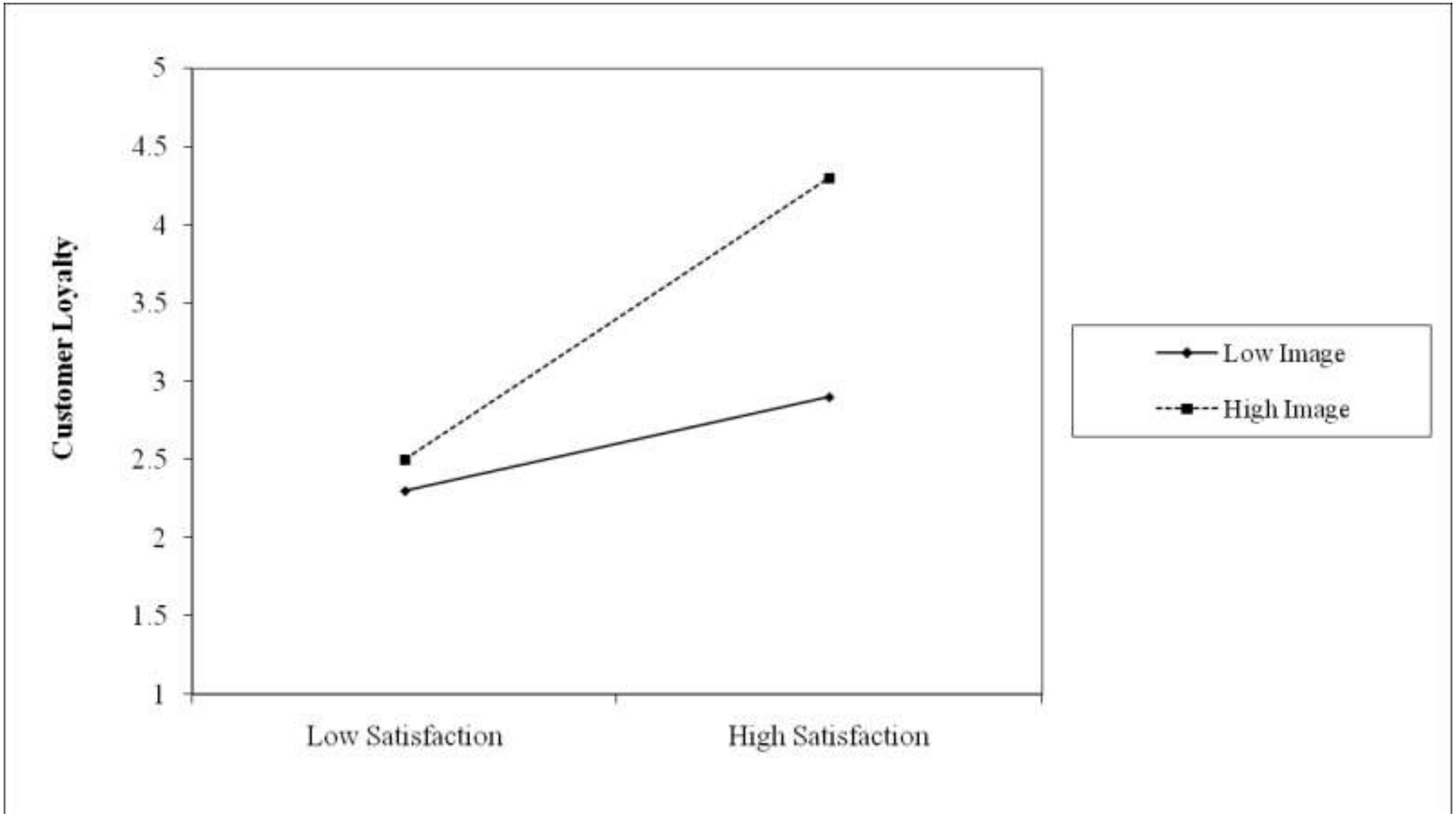
Hypothesis

H1: The positive relationship between satisfaction and loyalty will be **stronger** for those with **high perceived image**.

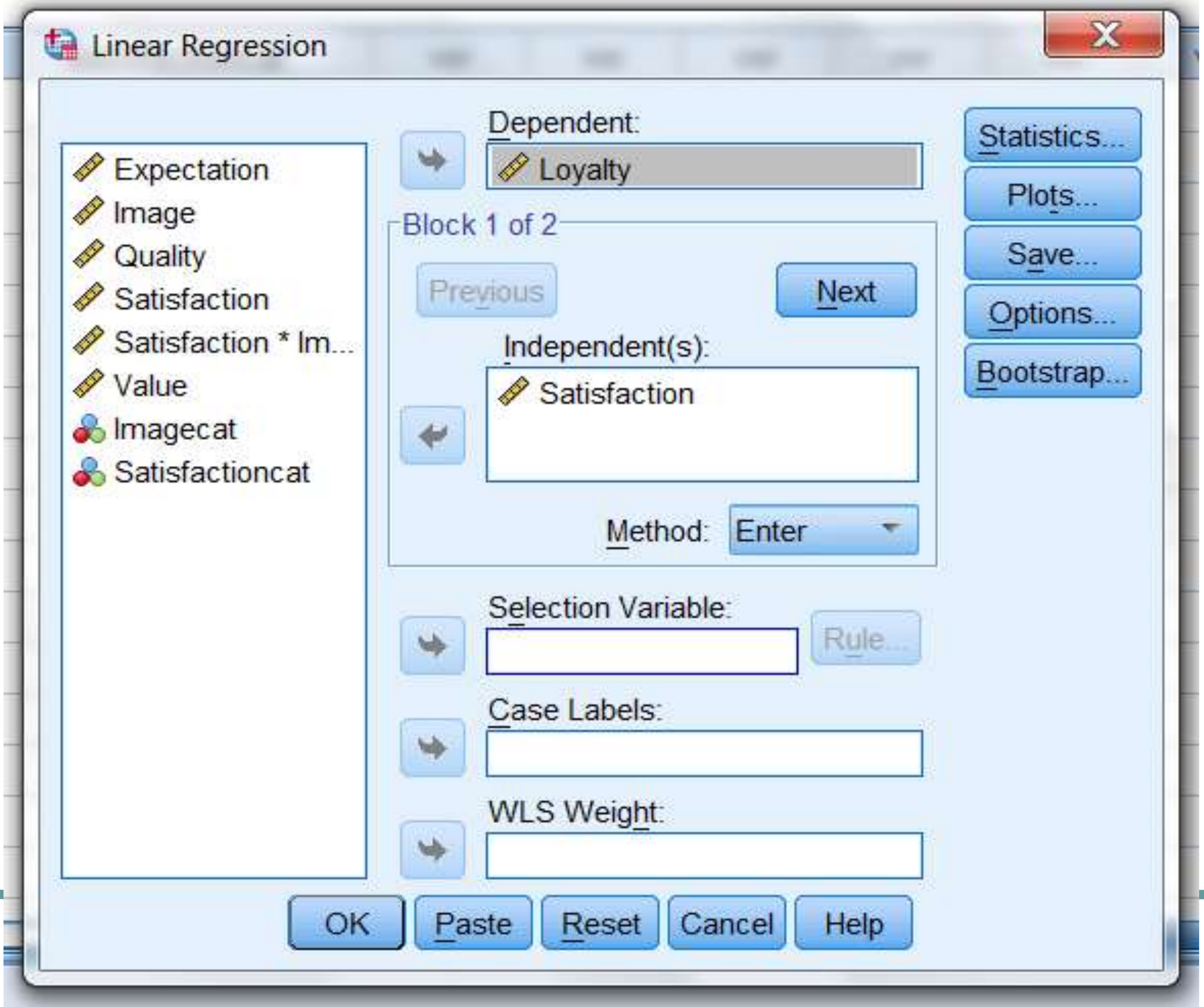
Why Plot?

- However, it is not entirely clear how it differs. If the you get a positive coefficient, the positive coefficient of the interaction term suggests that it becomes more positive as **Image** increases; however, the **size and precise nature** of this effect is not easy to divine from examination of the coefficients alone, and becomes even more so when one or more of the coefficients are negative, or the standard deviations of X and Z are very different (Dawson, 2013).

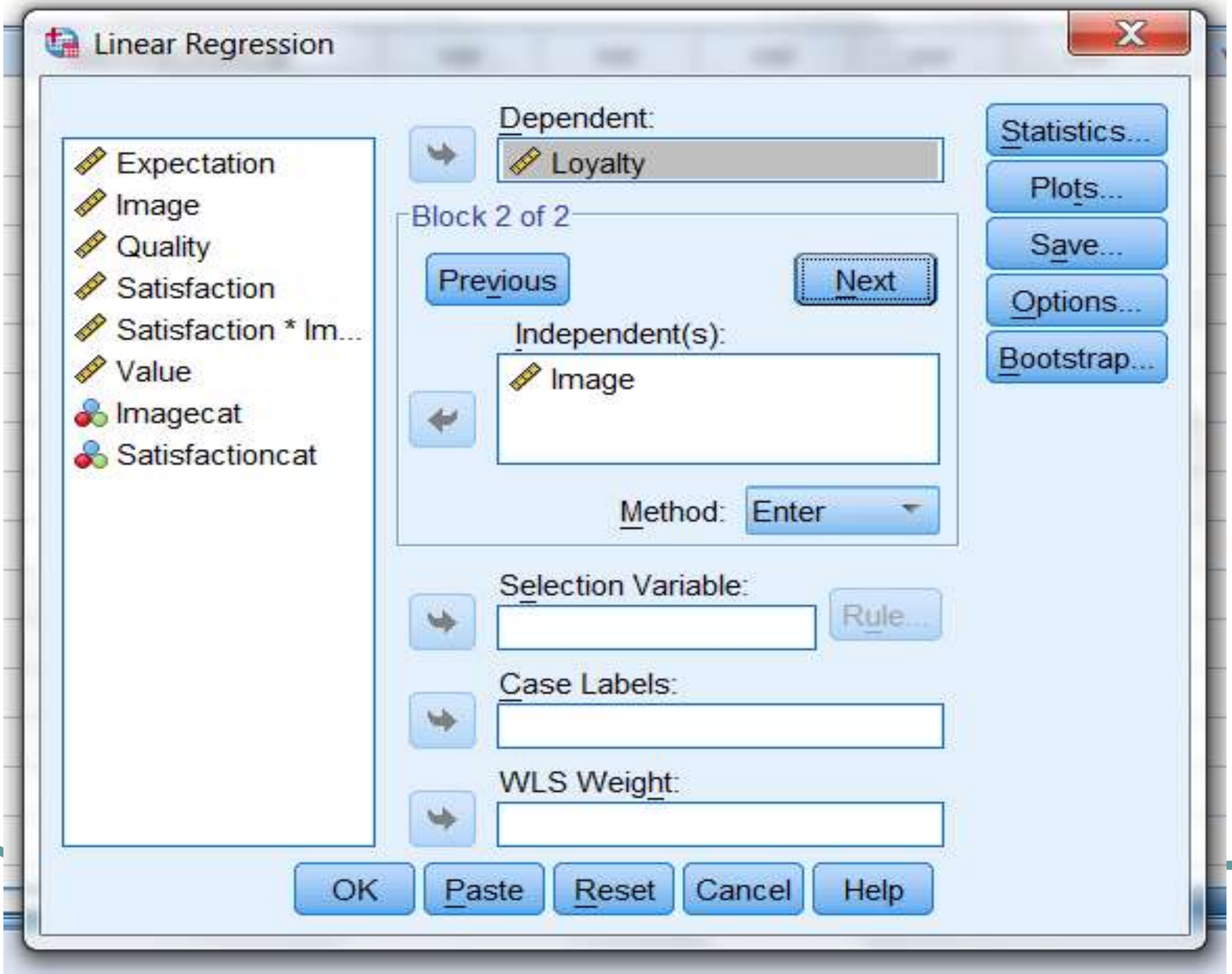
Interaction Plot



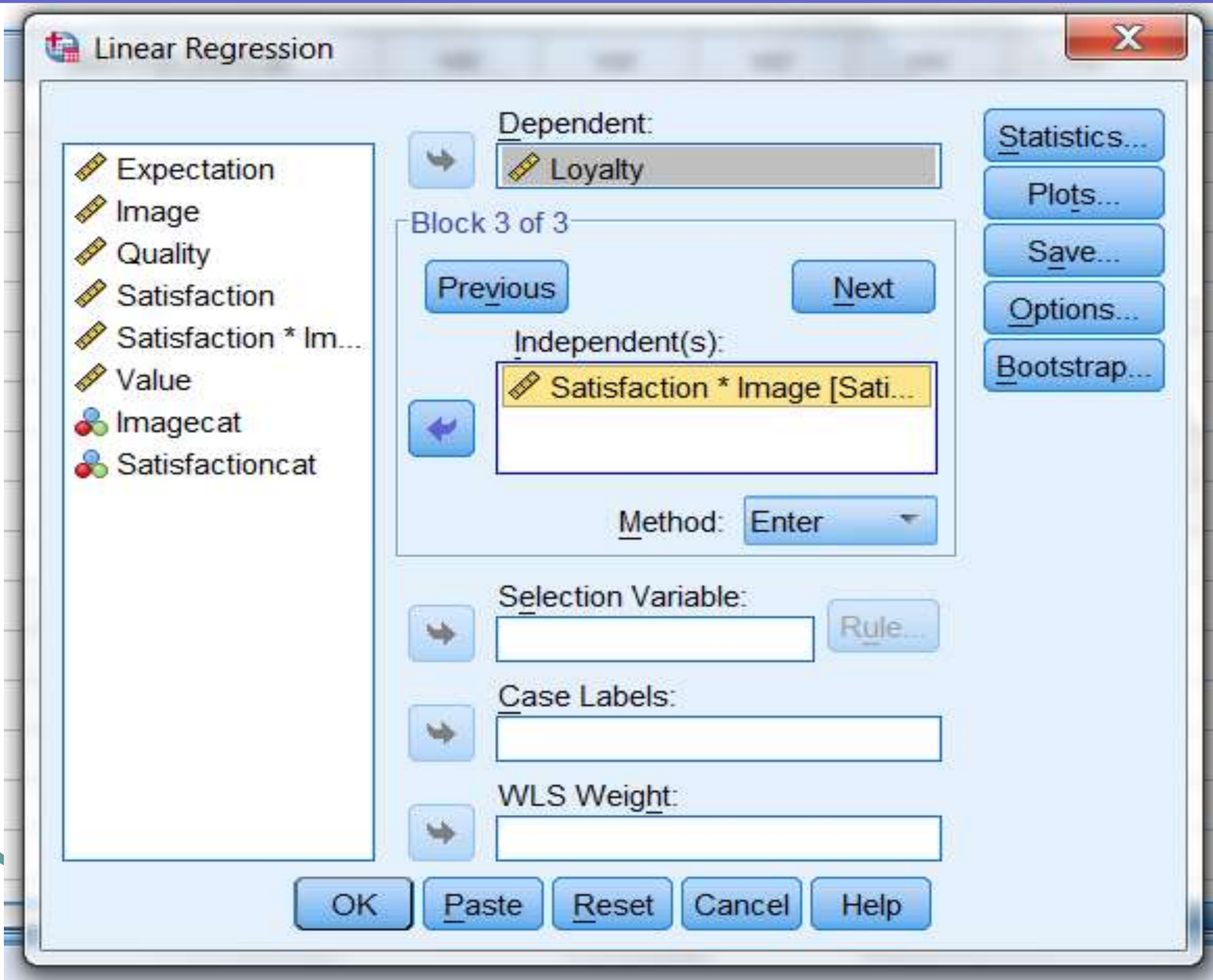
Testing in SPSS (Block 1)



Testing in SPSS (Block 2)

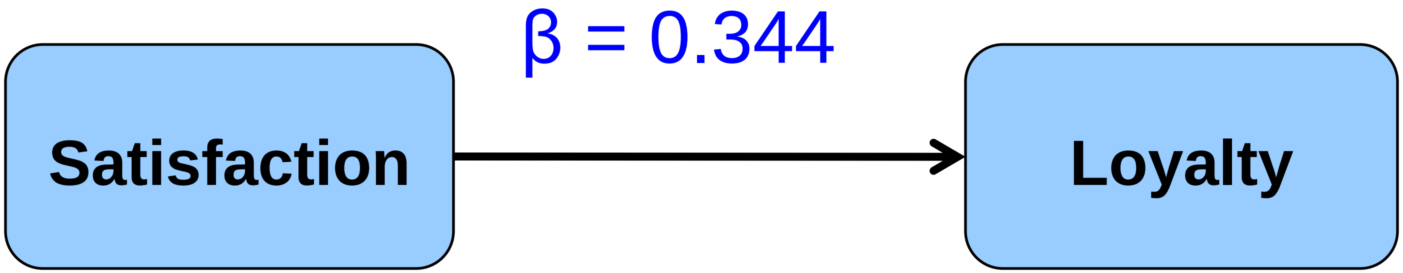


Testing in SPSS (Block 3)

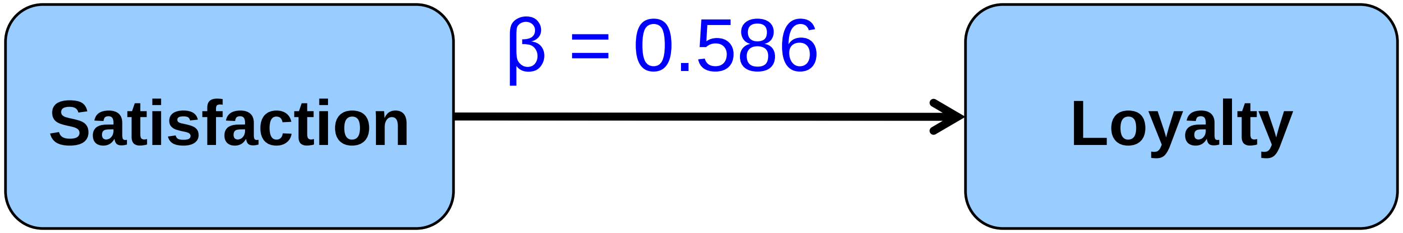


Testing in AMOS (Unconstrained)

- Low Image

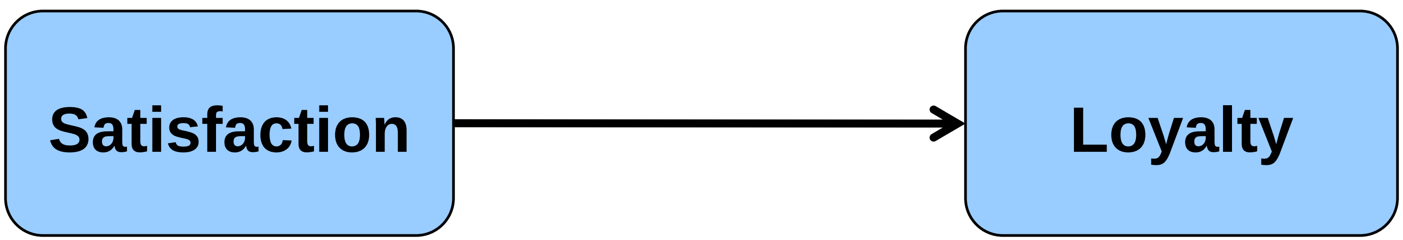


- High Image



Testing in AMOS (Constrained)

- Beta (Low Image = High Image)
- Look at the Chi Squared difference Test



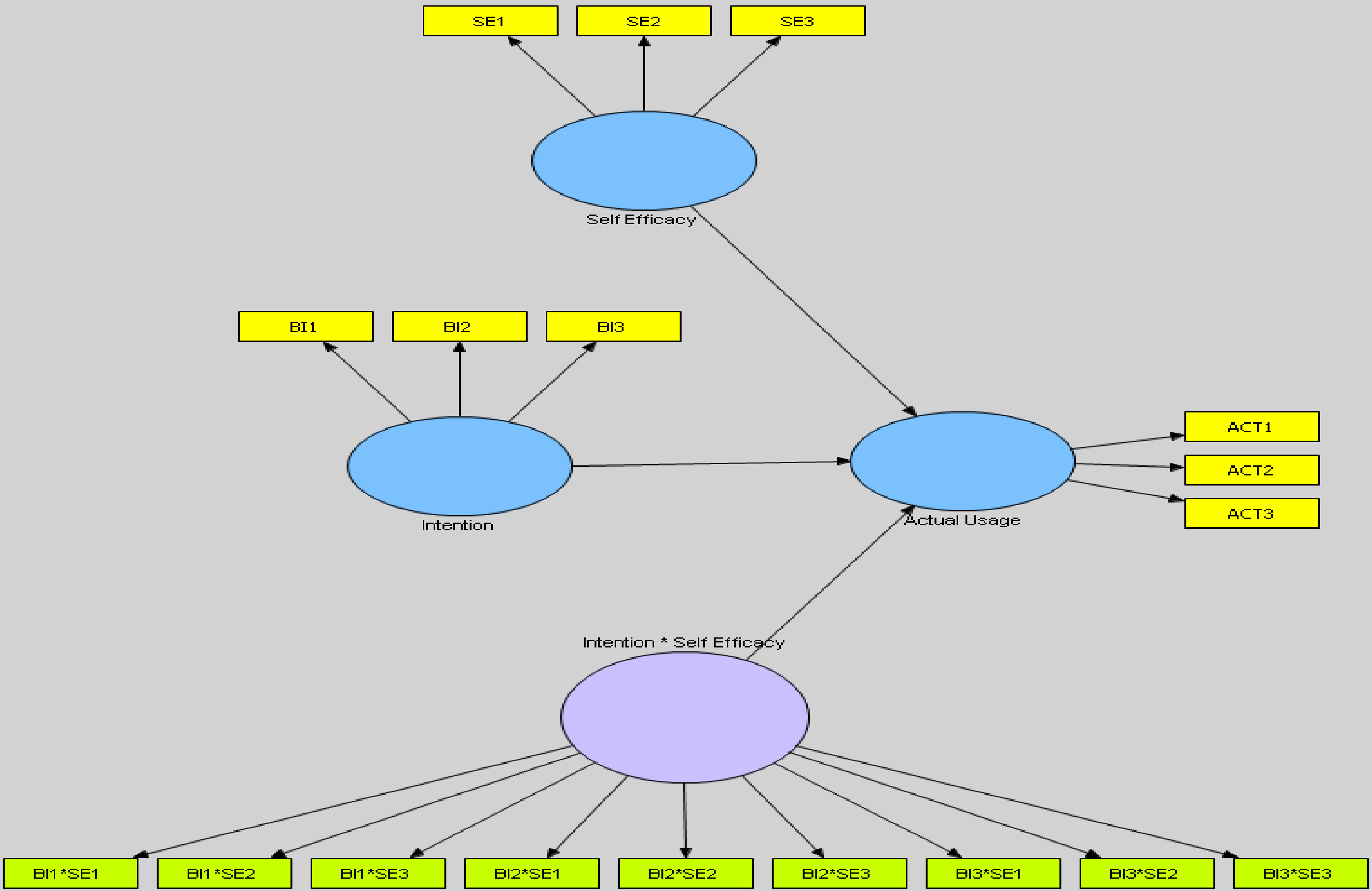
Caveat

- An important consideration about categorical moderators is that they should only be used when the variable was originally measured as categories. **Continuous variables should never be converted to categorical variables for the purpose of testing interactions.** Doing so **reduces the statistical power** of the test, making it more difficult to detect significant effects (Stone-Romero and Anderson 1994; Cohen et al. 2003), as well as **throwing up theoretical questions about why particular dividing points should be used** (Dawson, 2013).

Procedure

- Ideally, the regression should include all independent variables, the moderator, and interactions between the moderator and each independent variable.
- It is important in this situation that all predictors are mean-centered or z-standardized before the calculation of interaction terms and the regression analysis.

Testing in PLS



Moderator Effect Assessment

$$f^2 = \frac{R_i^2 - R_m^2}{1 - R_i^2} = \frac{0.664 - 0.659}{1 - 0.664} = 0.015$$

(Here, $i = \textit{interaction model}$, $m = \textit{main effect model}$)

- According to **Cohen (1988),** f^2 is assessed as:
  - **0.02 small**
  - **0.15 medium**
  - **0.35 large**

Suggested Reading

- Sharma, S., Durand, R. M., & Gur-Arie, O. (1981). ‘‘Identification and analysis of moderator variables’’. *Journal of Marketing Research*, 18(3), 291-300.

- Dawson, J. F. (2013). Moderation in Management Research: What, Why, When, and How. *Journal of Business and Psychology*, DOI 10.1007/s10869-013-9308-7

Mediation

Research Model

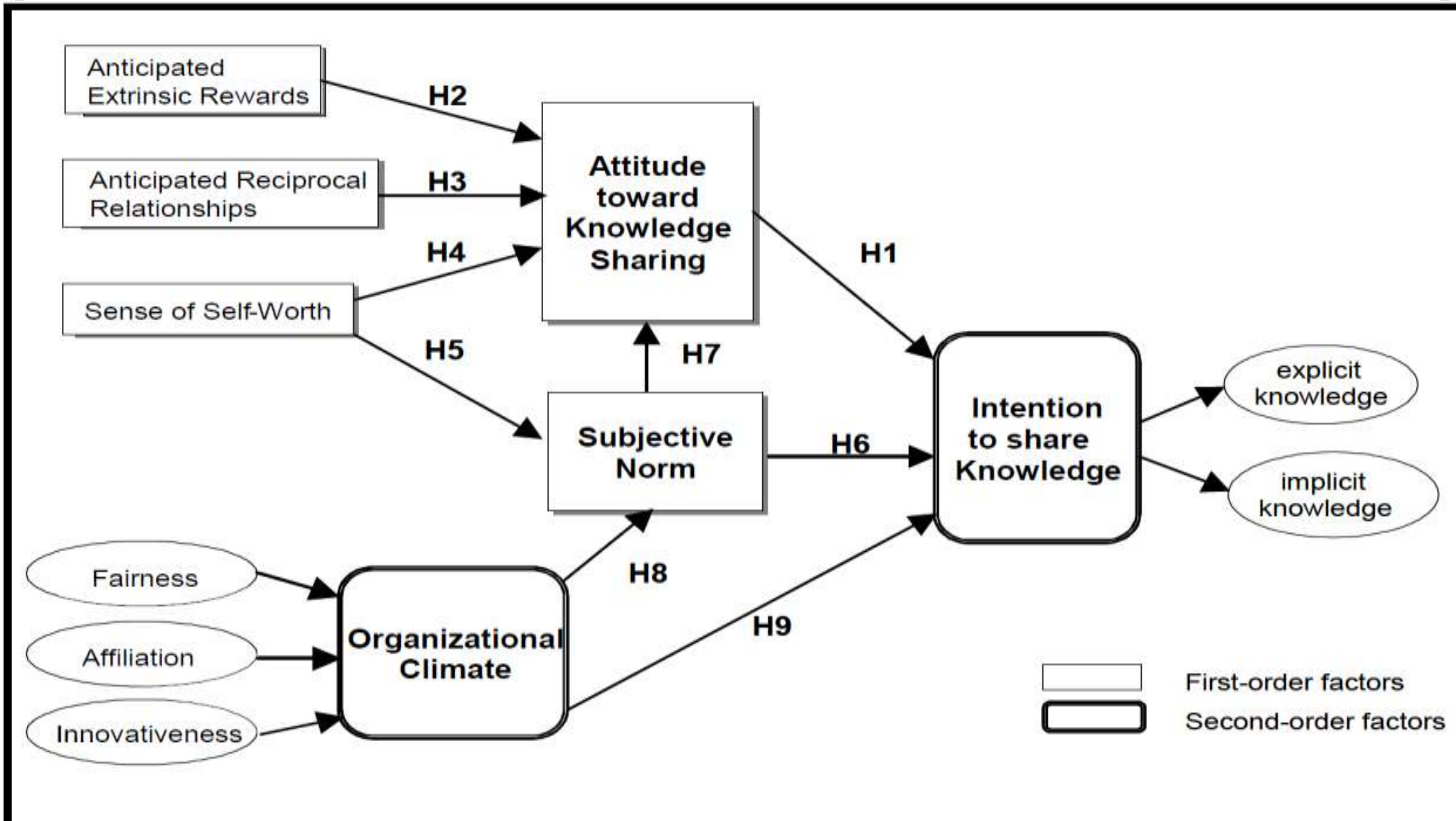


Figure 1. Research Model

Basic Requirement

- Despite the extensive use of complex statistical modeling in the behavioral sciences, the quality of a research project is largely determined by the design decisions that are made before any analysis is done and even before the study is conducted.

- The conceptualization of a mediation analysis requires forethought about the relationships between the variables of interest and the theoretical meaning behind those relationships. (McKinnon et al., 2012)

Mediator Variable (Mechanism)

- A mediator specifies how (or the mechanism by which) a given effect occurs (Baron & Kenny, 1986; James & Brett, 1984). Baron and Kenny (1986, pp. 1173, 1178) describe a mediator variable as the following:
- **How did it work?**

Mediator Variable

- *The generative mechanism through which the focal independent variable is able to influence the dependent variable of interest . . . (and) Mediation . . . is best done in the case of a strong relation between the predictor and criterion variable.*

Mediator Variable

- Shadish and Sweeney (1991) stated that "the independent variable causes the mediator which then causes the outcome". Also critical is the prerequisite that there be a significant association between the independent variable and the dependent variable before testing for a mediated effect.

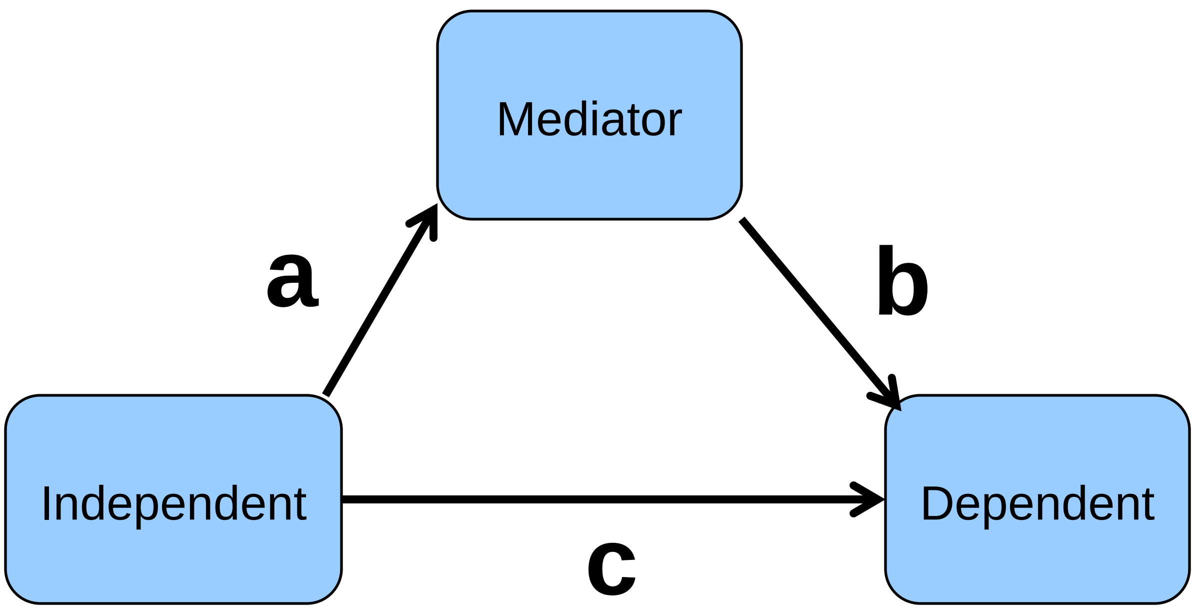
Mediator Effect

- According to McKinnon et al, (1995), mediation is generally present when:

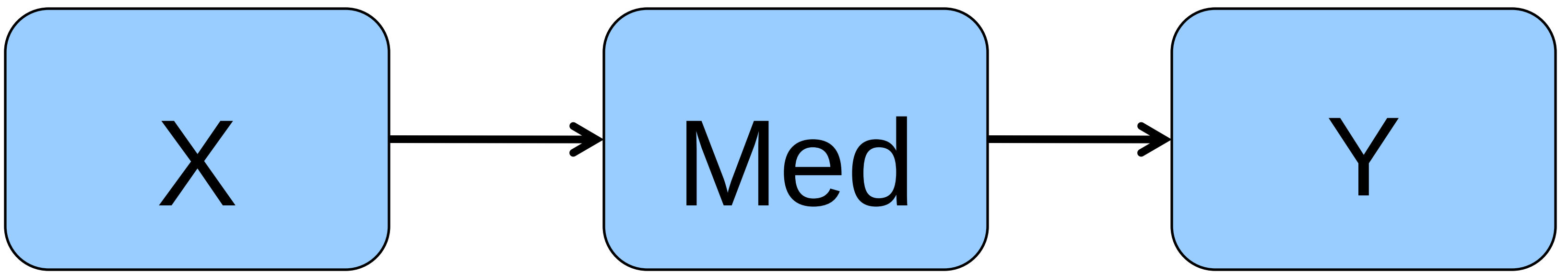
1. the IV significantly affects the mediator,
2. the IV significantly affects the DV in the absence of the mediator,
3. the mediator has a significant unique effect on the DV, and
4. the effect of the IV on the DV shrinks upon the addition of the mediator to the model.

Mediator Variable

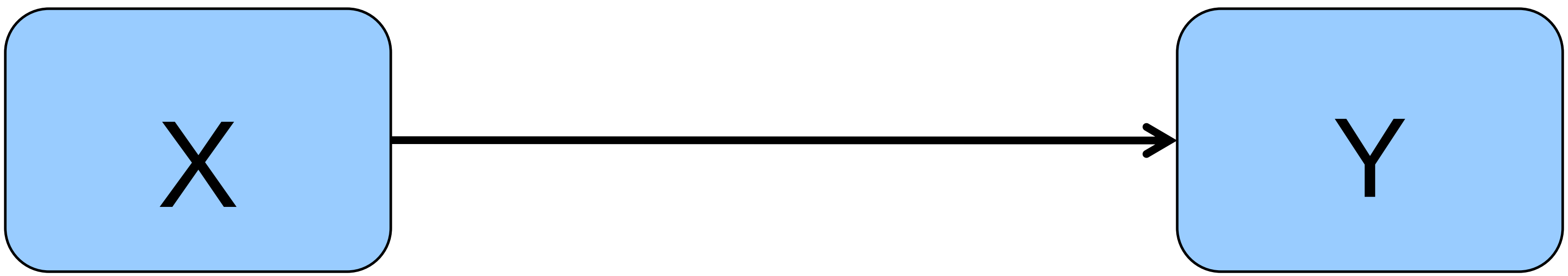
- Baron & Kenny (1986) has formulated the steps and conditions to ascertain whether full or partial mediating effects are present in a model.



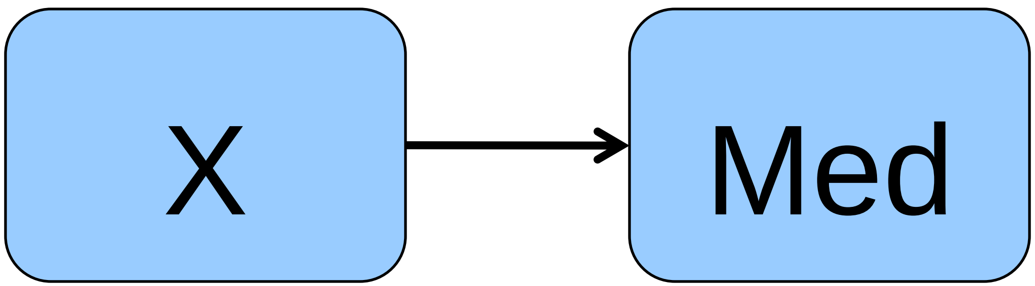
Mediation



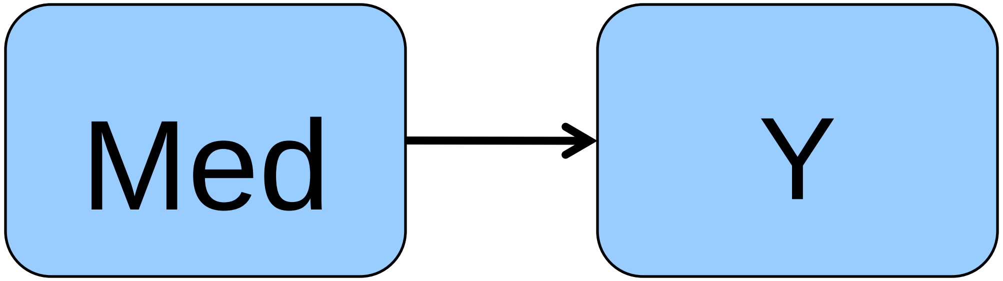
Mediation – Step 1



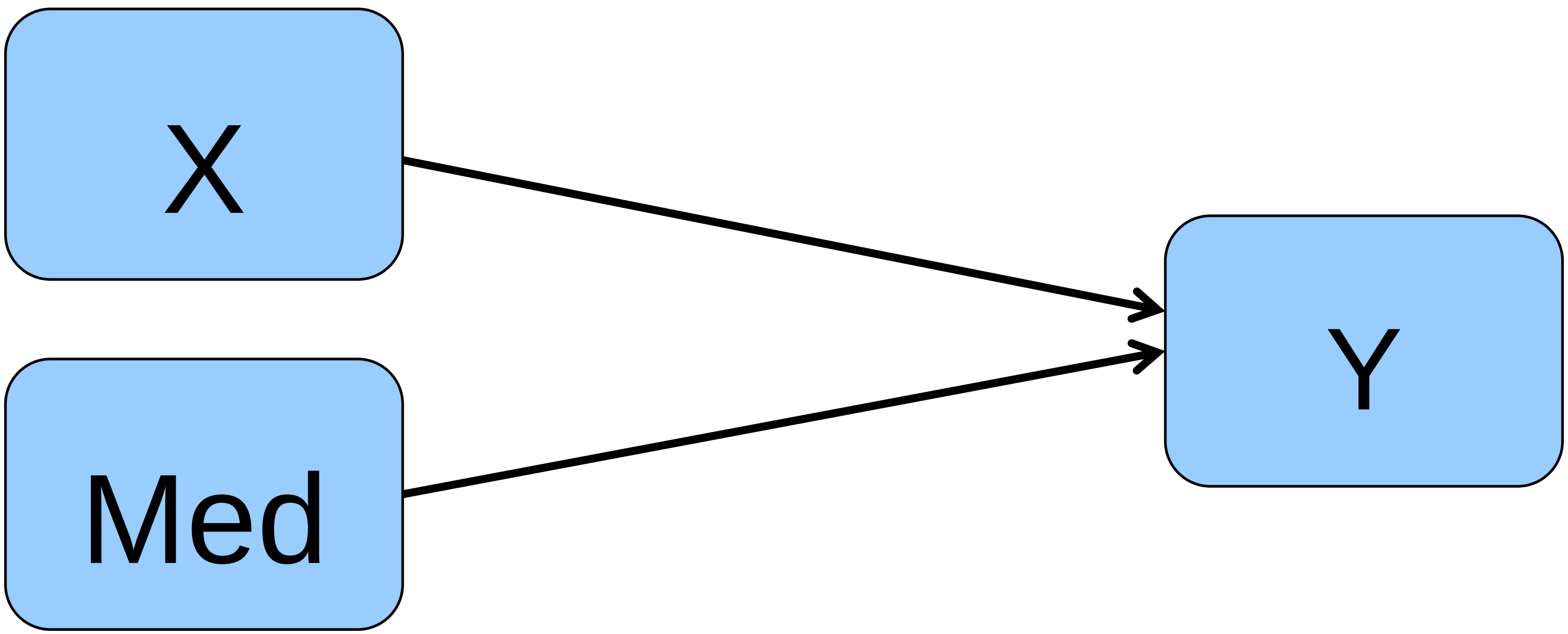
Mediation – Step 2



Mediation – Step 3



Mediation – Step 4



Mediator Analysis

- Judd and Kenny (1981), a series of regression models should be estimated. To test for mediation, one should estimate the three following regression equations:
  1. regressing the mediator on the independent variable;
  2. regressing the dependent variable on the independent variable;
  3. regressing the dependent variable on both the independent variable and on the mediator.

Mediator Analysis

1) variations in levels of the independent variable significantly account for variations in the presumed mediator (i.e., Path c),

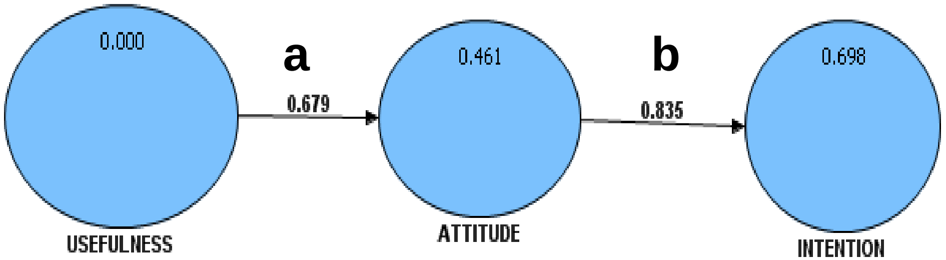
2) variations in the mediator significantly account for variations in the dependent variable (i.e., Path *b), and*

3) when Paths *a and b are controlled, a previously significant* relation between the independent and dependent variables is no longer significant, with the strongest demonstration of mediation occurring when Path *c is zero.*

Mediator Analysis

- Separate coefficients for each equation should be estimated and tested.
- There is no need for hierarchical or stepwise regression or the computation of any partial or semipartial correlations.

Mediator Effect Assessment – Testing Significance

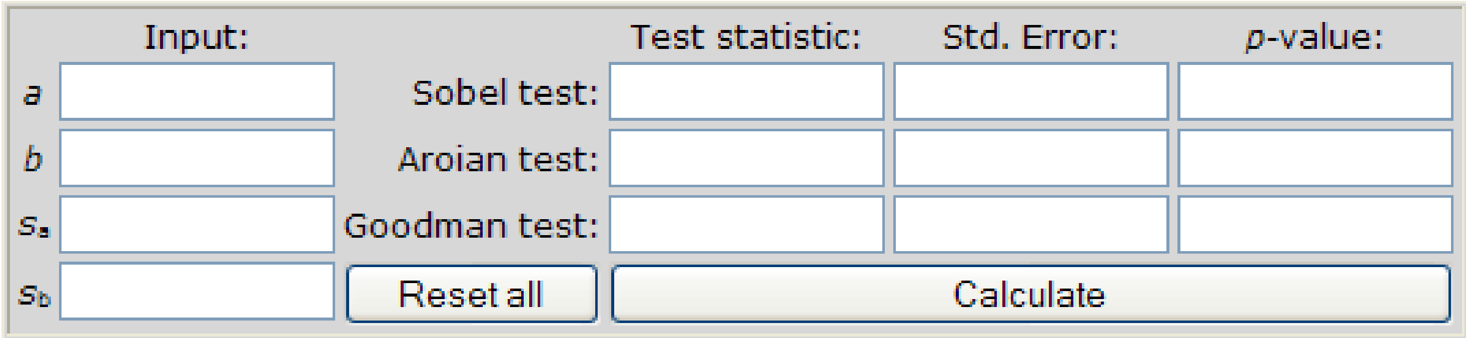


$$z = \frac{a \times b}{\sqrt{b^2 \times s_a^2 + a^2 \times s_b^2 + s_a^2 \times s_b^2}}$$

- Can Use the Sobel (1982) test
- Online: http://www.quantpsy.org/sobel/sobel.htm

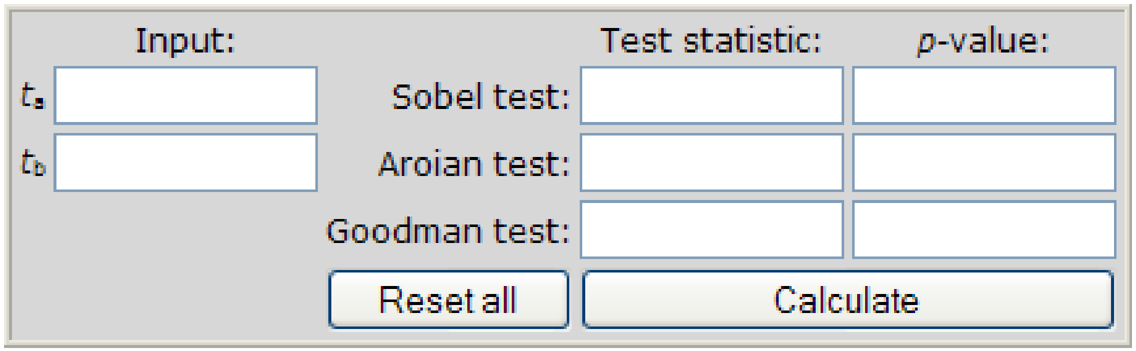
- The indirect effect is significant at:
  - **0.05 if z > 1.96**
  - **0.01 f z > 2.58**

http://quantpsy.org/sobel/sobel.htm



Input:			Test statistic:	Std. Error:	*p*-value:
a		Sobel test:			
b		Aroian test:			
s_a		Goodman test:			
s_b		Reset all	Calculate		

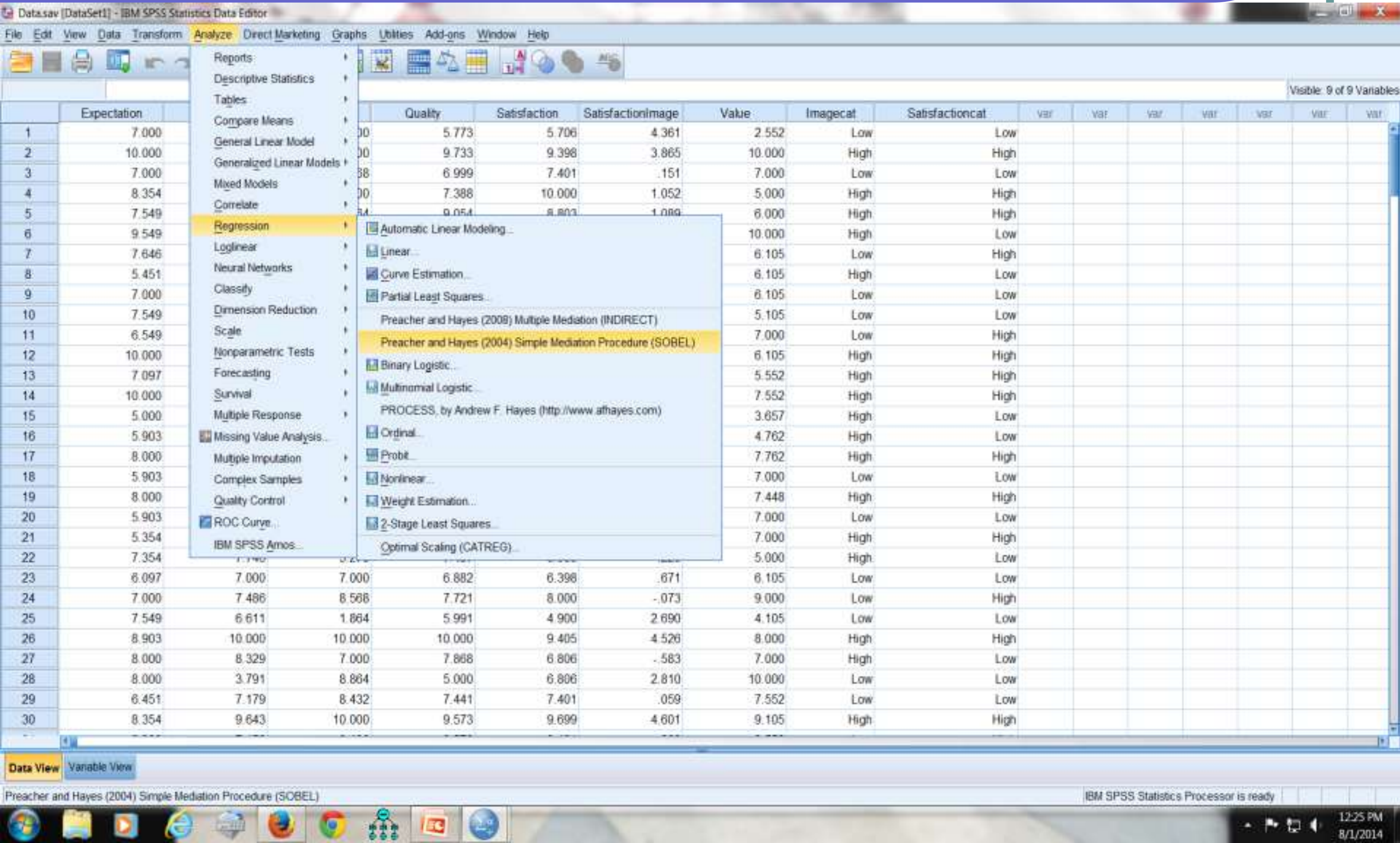
a and *b* = **path coefficient** s_a and s_b = **standard errors**



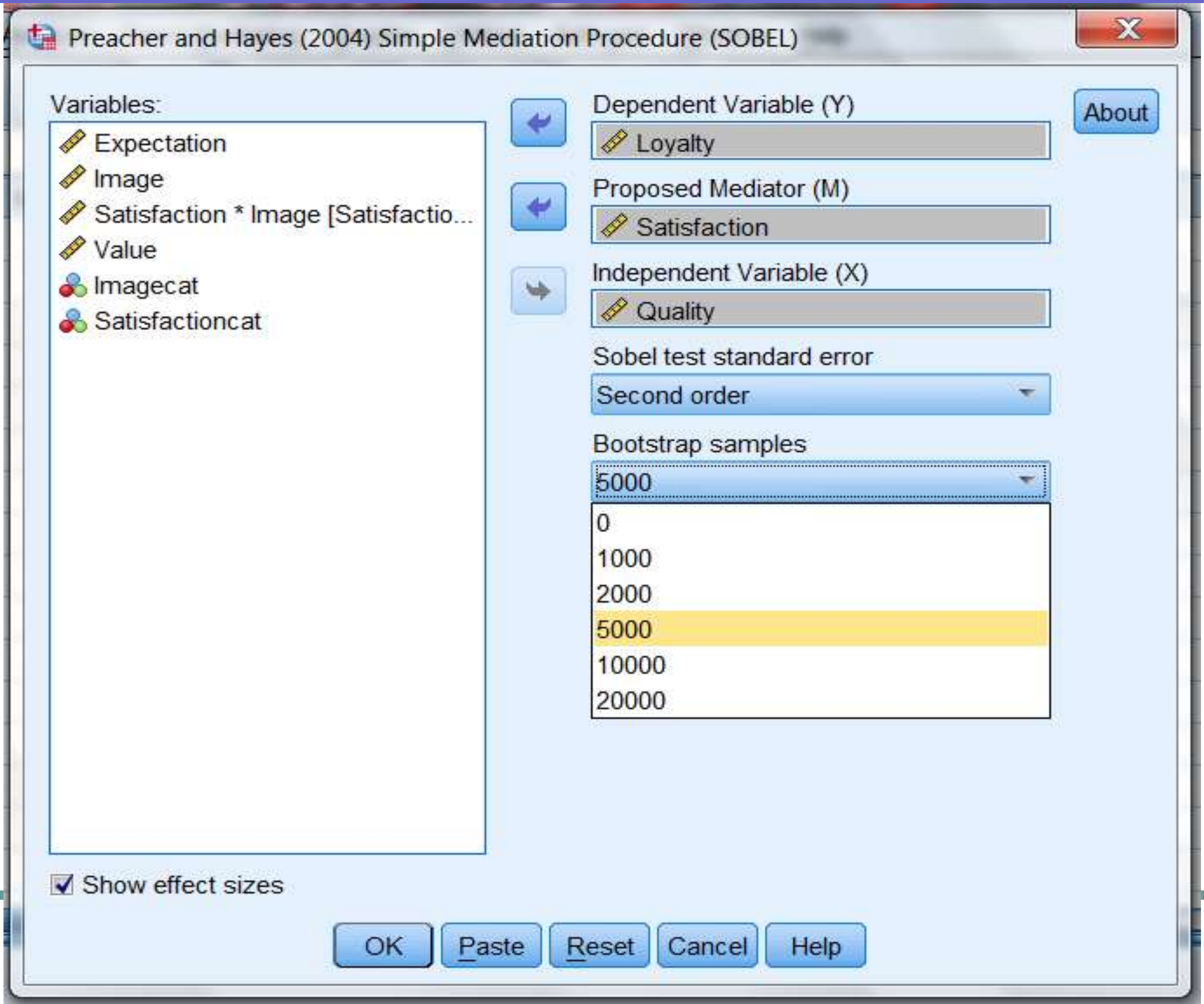
Input:			Test statistic:	*p*-value:
t_a		Sobel test:		
t_b		Aroian test:		
		Goodman test:		
		Reset all	Calculate	

t_a and t_b = **t-values for *a* and *b* path coefficients generated from bootstrapping**

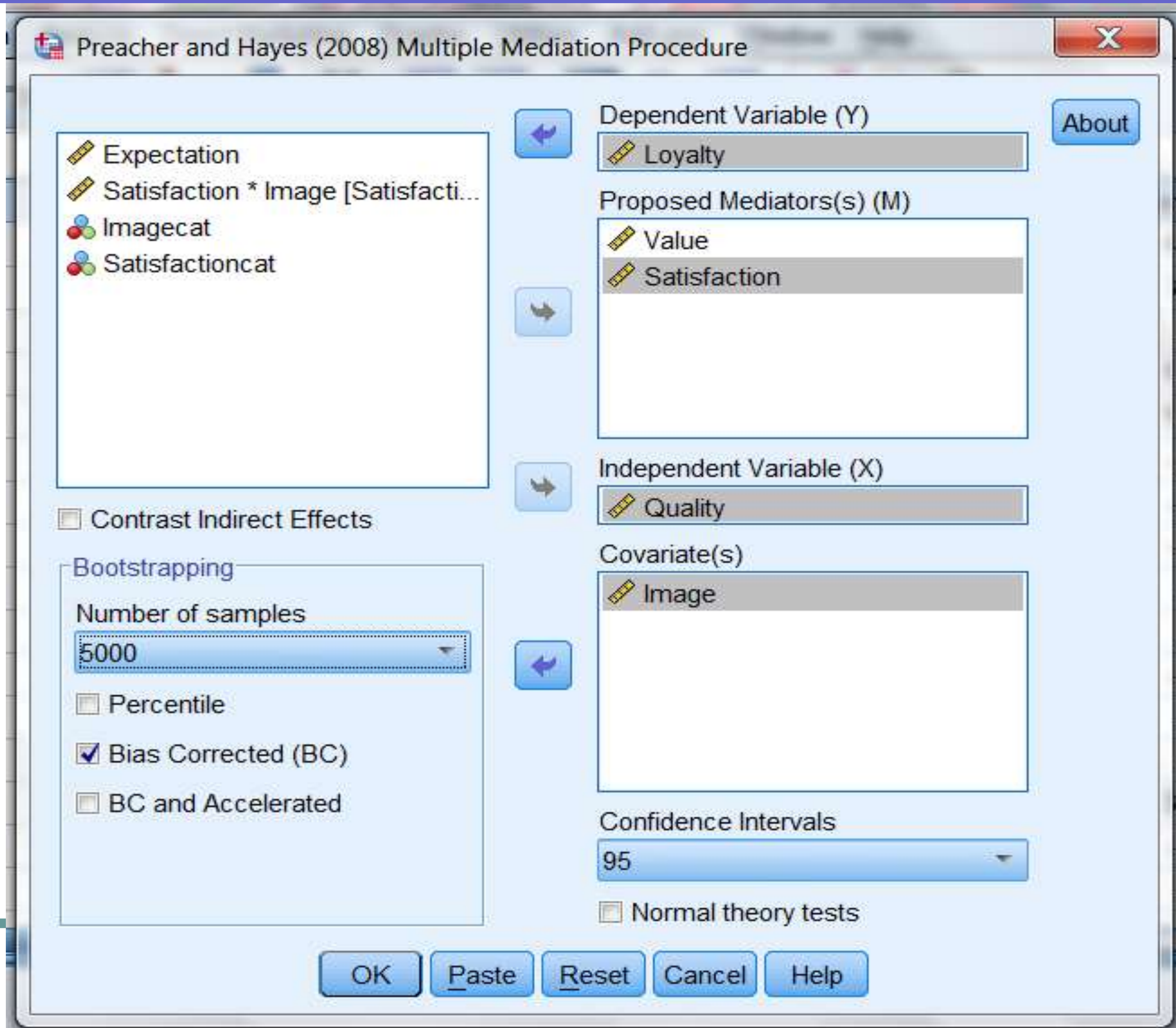
Testing in SPSS



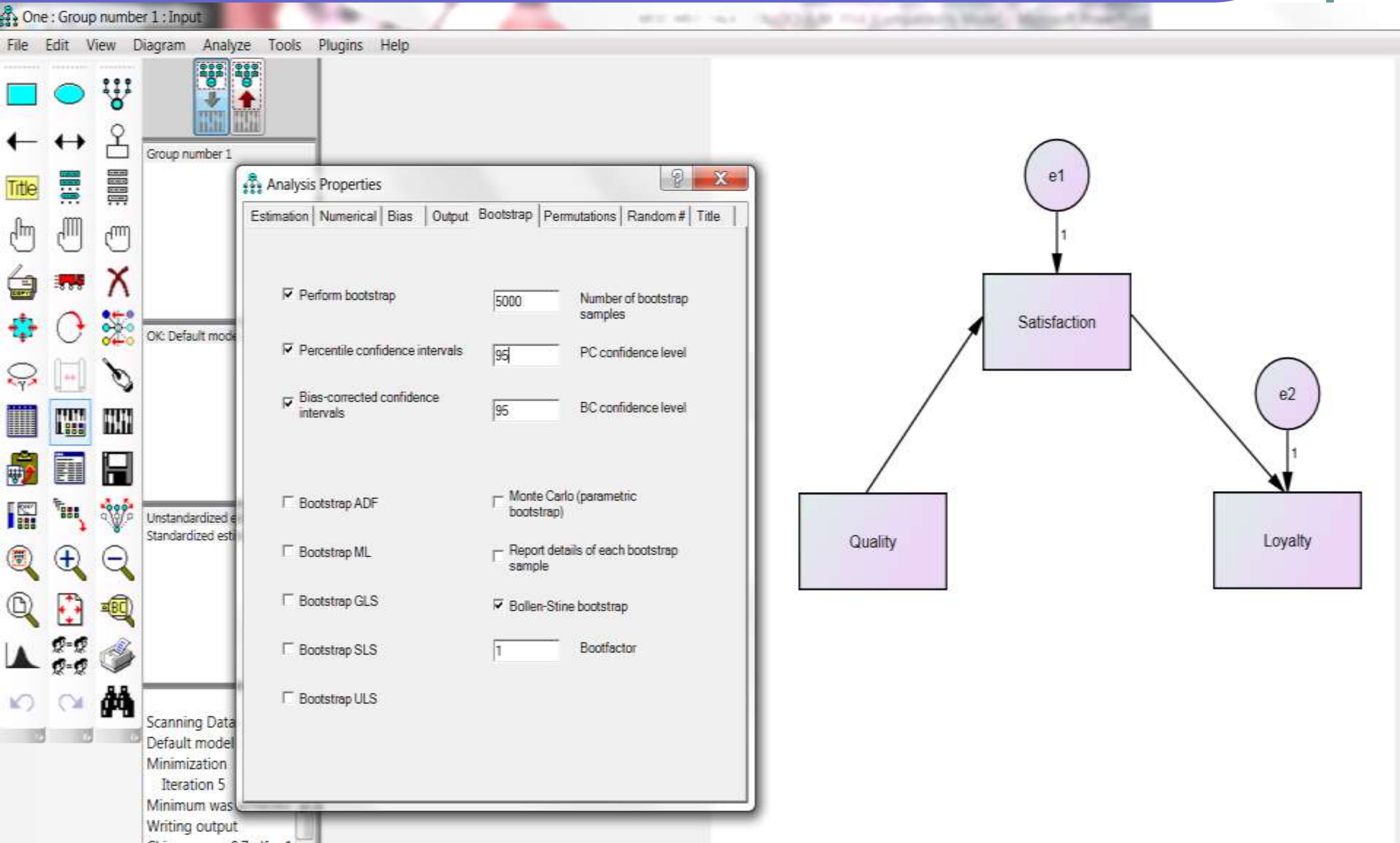
Testing in SPSS



Testing in SPSS



Testing in AMOS



Suggested Test for Mediator

- Based on Preacher and Hayes (2008)
- Bootstrap the indirect effect

Bootstrapping

- Bootstrapping, a nonparametric resampling procedure, has been recognized as one of the **more rigorous and powerful methods for testing the mediating effect** (Hayes, 2009; Shroud & Bolger, 2002; Zhao et al., 2010).
- The application of bootstrapping for mediation analysis has recently been advocated by Hair et al. (2013) whom noted that "**when testing mediating effects, researchers should rather follow Preacher and Hayes (2004, 2008) and bootstrap the sampling distribution of the indirect effect, which works for simple and multiple mediator models**" (p. 223).
- Furthermore, this method is said to be perfectly suited for PLS-SEM because it makes no assumption about the shape of the variables' distribution or the sampling distribution of the statistic and therefore can be applied to small sample sizes (Hair et al., 2013; Preacher & Hayes, 2008).

Bootstrapping Indirect Effect

- Hypothesis

$$H_0: a*b = 0$$
$$H_1: a*b \neq 0$$

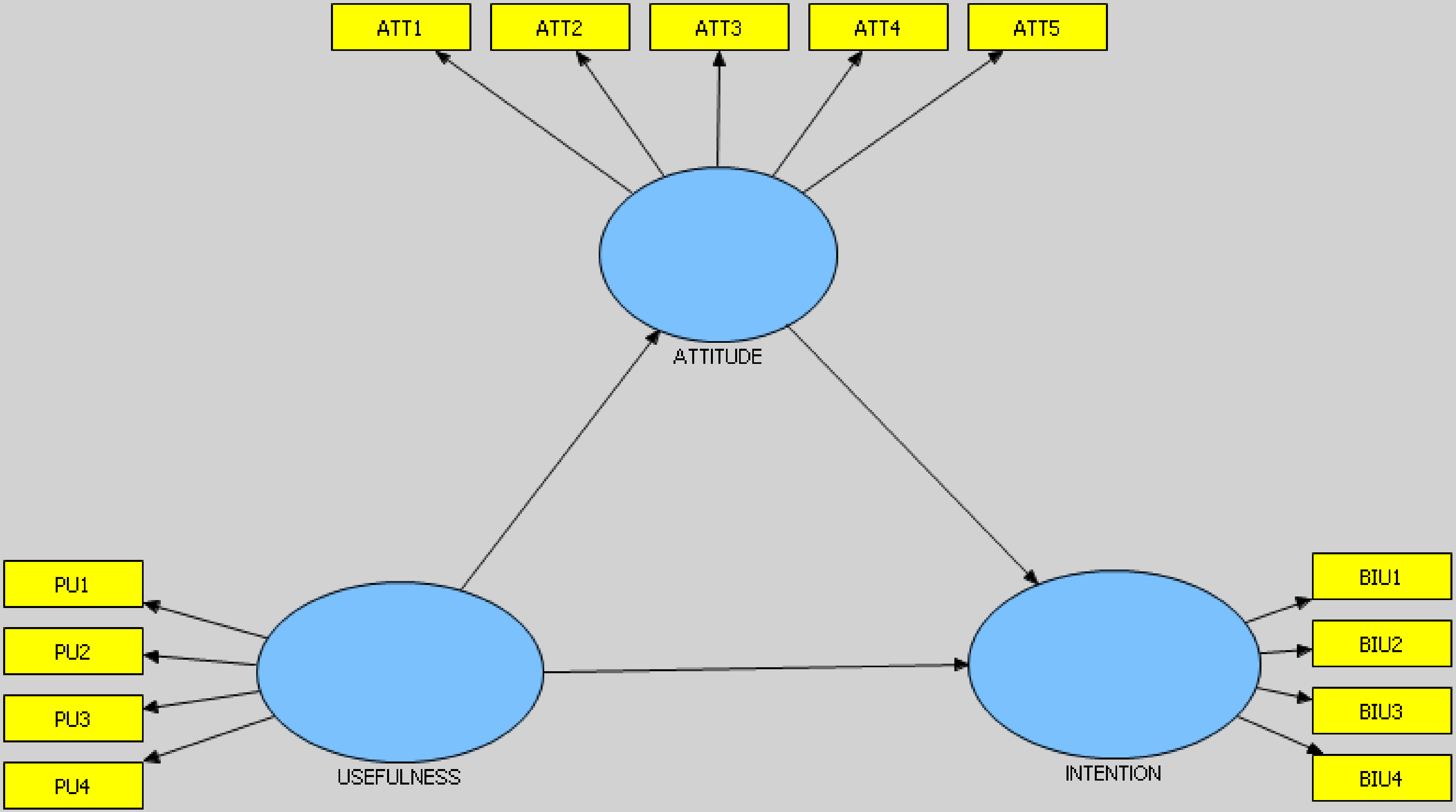
- For each bootstrap sample, calculate

$$a_i * b_i$$

- Create the bootstrap *t*-statistic

$$t = \frac{a*b}{sd\ (a_i*b_i)}$$

Testing Mediation in PLS



Testing Mediation in PLS

E2 =STDEV(D2:D192)

	ATTITUDE -> INTENTION	SN -> ATTITUDE	a*b	Std Error
Sample 0	0.837223	0.721428	0.603996114	0.040246283
Sample 1	0.822793	0.682056	0.561190902	
Sample 2	0.793366	0.660204	0.523783407	
Sample 3	0.793476	0.698009	0.553853389	
Sample 4	0.822039	0.688098	0.565643392	
Sample 5	0.796256	0.669747	0.533290067	
Sample 6	0.839571	0.70682	0.593425574	
Sample 7	0.83994	0.747936	0.628221364	
Sample 8	0.822785	0.67188	0.552812786	

$$t = \frac{a^*b}{sd\,(a_i^*b_i)}$$

Reporting

- The bootstrapping analysis showed that the indirect effect β = 0.159 (0.546*0.291) was significant with a t-value of 3.682. Also as indicated by Preacher and Hayes (2008) the indirect effect 0.159, 95% Boot CI: [LL = 0.074, UL = 0.243] does not straddle a 0 in between indicating there is mediation. Thus we can conclude that the mediation effect is statistically significant.

Suggested Reading

- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic and statistical considerations. *Journal of Personality and Social Psychology, 51*, 1173-1182.

- Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium. *Communication Monographs*, 76(4), 408-420.

Suggested Readings

- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879-891.

- Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, 36(4), 717-731.

Suggested Readings

- Hayes, A. F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York: Guilford Press.

- MacKinnon, D. P., Coxe, S., & Baraldi, A. N. (2012). Guidelines for the Investigation of Mediating Variables in Business Research. *Journal of Business and Psychology*, 27(1), 1-14.

Mediator Analysis

Assess significance of the direct effect without including the mediator variable in the PLS path model

The direct effect is <u>NOT</u> significant

No Mediating Effect

The direct effect is significant

See next slide

Mediator Analysis

Include the mediator variable in the PLS path model and assess significance of the indirect effect

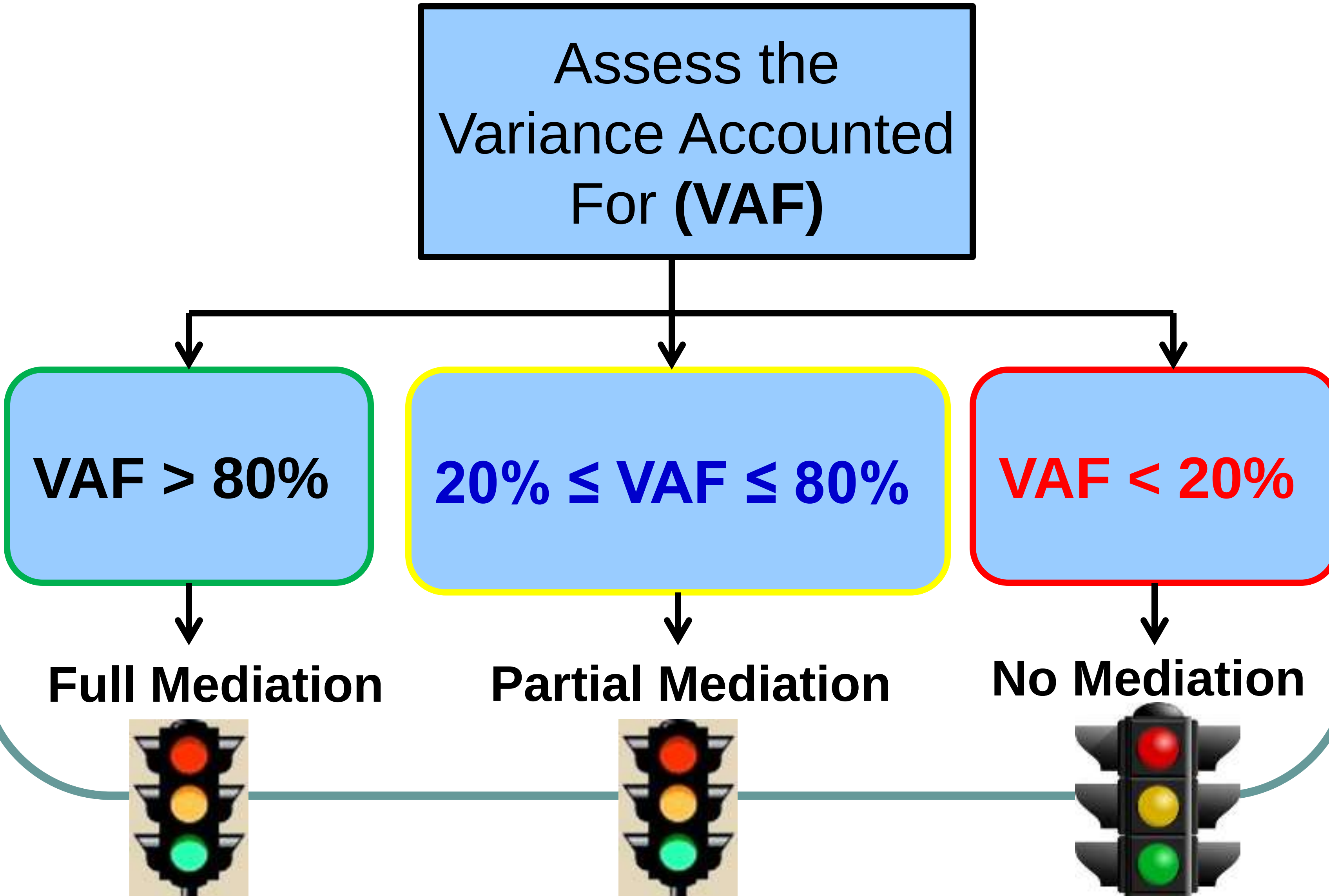
The Indirect effect is <u>NOT</u> significant

No Mediation

The indirect effect is significant

See next slide

Mediator Effect Assessment – Variance Accounted For (VAF)



Mediator Effect Assessment – Variance Accounted For (VAF)

$$VAF = \frac{a \times b}{a \times b + c} = \frac{0.840 \times 0.328}{0.840 \times 0.328 + 0.517} = 0.348$$

- VAF = Variance accounted for
- **Indirect effect / Total Effect**
- Shrout & Bolger (2002)
- VAF is converted into %

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Thank you for listening