UPM UNIVERSITI PUTRA MALAYSIA BERILMU BERBAKTI

SEKOLAH PERNIAGAAN DAN EKONOMI

School of Business and Economics

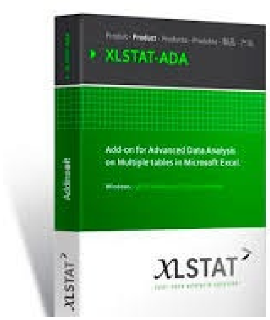
Research Methodology
Data Management and Analysis

IBM SPSS AMOS

Smart™ Next Generation Path Modeling PLS

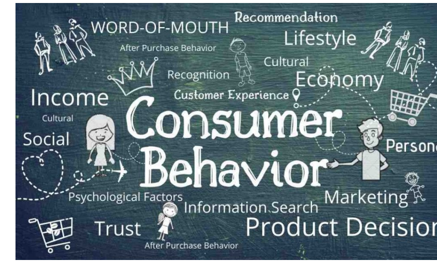
Mplus

stata



R Studio

Dr Jacky Cheah Jun-Hwa



International Attachment:

i. Visiting Scholar of OVGU, University Magdeburg (Germany)

ii. Marketing Cluster Member of Griffith University (AUS)

iii. Visiting Scholar of National Kaohsiung University of Hospitality and Tourism (Taiwan)

iv. Visiting Scholar of Ming Chuan University (Taiwan)

v. Visting Scholar of National Tsing Hua University (Taiwan)

vi. Visiting Scholar Padjadjaran University, Bandung (Indonesia)

vii. Visiting Scholar Atma Jaya Catholic University, Jakarta, (Indonesia)

Google Scholar: https://scholar.google.com/citations?user=gnJjp3AAAAAJ&hl=en&oi=ao

Cheah Jun-Hwa (Jacky)

FOLLOW

School of Business and Economics, Universiti Putra Malaysia
Verified email at upm.edu.my

Marketing Consumer Behaviour Structural Equation Modeling PLS Research Methods

Cited by

	All	Since 2016
Citations	3964	3950
h-index	27	27
i10-index	42	41

Research Gate: https://www.researchgate.net/profile/Cheah_Hwa

R^G Home Questions Jobs Search for researchers, publications, and more 1 Add new

Cheah Jun Hwa

26.45 · Doctor of Philosophy · Edit your information

Add your current activity

Add new research

SCOPUS ID: 57191585883

ORCID ID: 0000-0001-8440-9564

Editors and Reviewer Board

Co-Managing Editors:

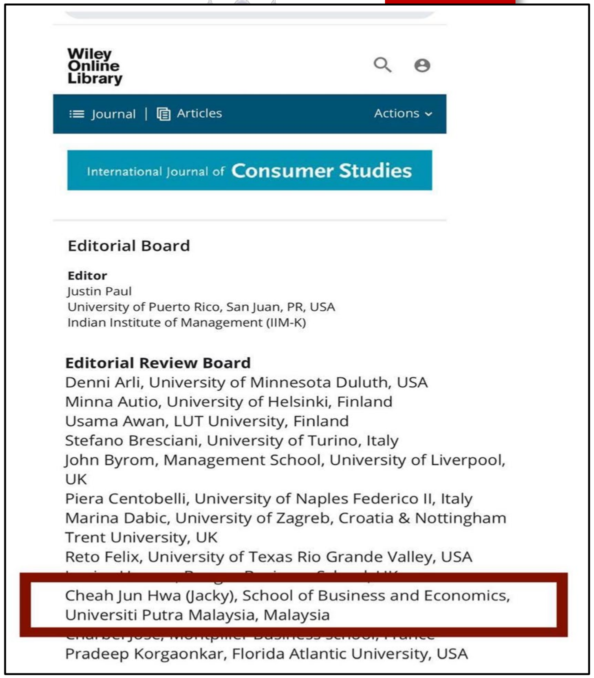
1. Journal of Applied Structural Equation Modeling (SCOPUS & ESCI Evaluation)
2. Journal of Marketing Advanced and Practices (myCite)

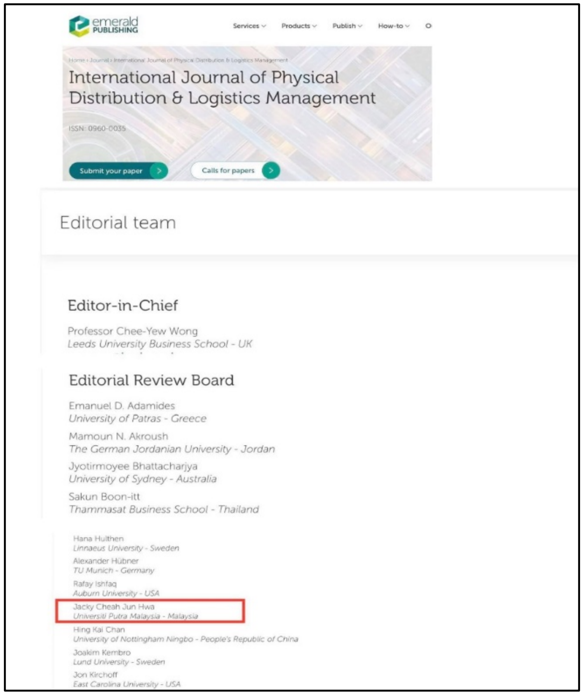
Guest Editor - ABS, ABDC, SSCI, & SCOPUS:

1. British Food Journal
2. Young Consumers
3. Journal of Marketing Analytics
4. European Business Reviews
5. Electronic Journal of Applied Statistical Analysis
6. Quality & Quantity
7. Journal of Consumer Behaviours
8. Journal of Hospitality and Tourism Technology
9. International Journal of Manpower
10. International Journal Physical Distribution & Logistics Management
11. Journal of Strategic Marketing

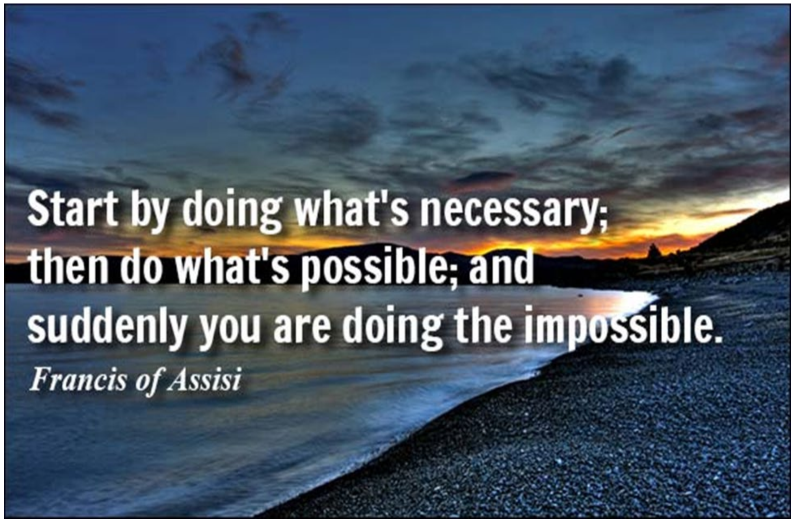
Associate Editor and Editorial Review Board:

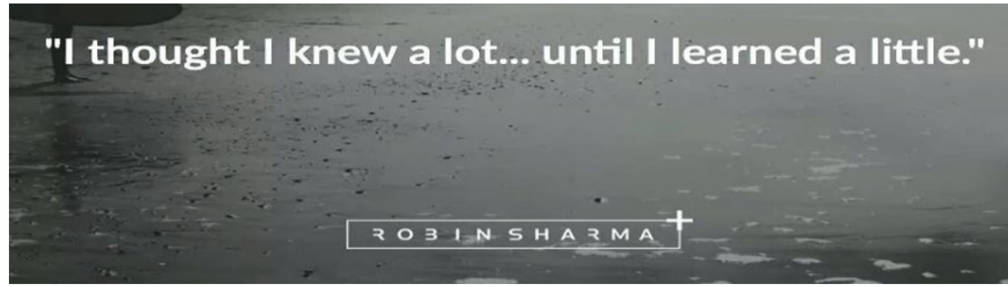
1. International Journal of Consumer Studies
2. Journal of Consumer Behaviour
3. International Journal Physical Distribution & Logistics Management
4. Asian Journal of Business Research
5. Asian Academy of Management Journal
6. International Journal of Economics and Management

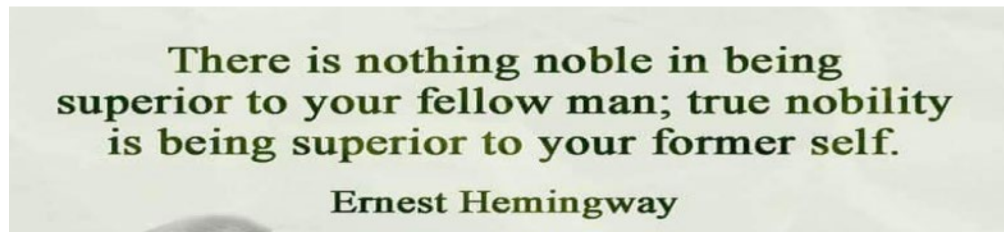


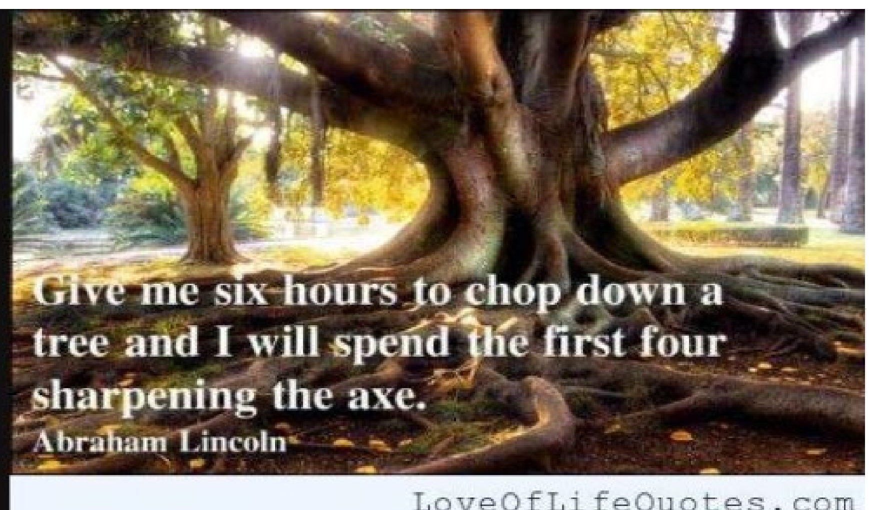


What I Personally Believe In









Statements about the Workshop

- This workshop only covers basic to intermediate content. I define ‘basic’ as ‘fundamental’ and you will see why.
- Feel free to ask questions at any point of time. If it is beyond the scope, we will respond if it benefits others.
- Understanding the reasons behind the clicking is more important than the clicking itself where you can learn by watching YouTube or reading our book.
- Whatever we say in the workshop, please keep it as a scholarly sharing and an attempt to make it interesting. Don’t take it personally.
- If you join certain sessions of the workshop, it is your duty to catch up. I can repeat but can’t do it all the time.
- I do not teach short-cuts at the expense of rigorous analysis.
- Good analysis does not mean you have a good research design and your framework, RQs, theory application and etc are correct.
- Learning to use quantitative softwares/tools must be accompanied with practice. Reading good and current papers as well as writing are important.
- We would appreciate notification and acknowledgement when our slides are used in other occasions.

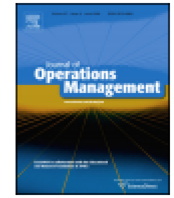
Statements about Methodology

Journal of Operations Management 37 (2015) v–viii

Contents lists available at ScienceDirect

Journal of Operations Management

journal homepage: www.elsevier.com/locate/jom



SSCI 4.899
SCOPUS Q1

Editorial

Notes from the Editors: Redefining some methodological criteria for the journal☆

If you cited Baron and Kenny (1986), Podsakoff and Organ (1986), Harman (1967), and Fornell and Larcker (1981) in your work back in the 1980s, you were probably fine. In 2015, you need to be careful. While statistical theory itself has not progressed all that much, the software applications that we all have on our desktops have massively improved. We have many solutions available to us now that we did not have in the 1980s; many of the shortcuts we took back in the day no longer need to be taken; many of the assumptions we were forced to make can now be relaxed. It behooves us to stay on top of current methodological developments, and accordingly, what was accepted in the journal ten, twenty years ago, is not necessarily acceptable anymore … It is no exaggeration to say that new methodological developments come out every month. Most of these developments are minor, but many of them are noteworthy … There is just no excuse for not using up-to-date tools. How about a check on Google Scholar to find out whether there have been any new developments in methodology relevant to your work before you submit your manuscript?

Content Outline

1. Recap on Quantitative and Qualitative Research
2. Basic Modeling in Quantitative Research
3. Types of Analysis
4. Levels of Measurement
5. Samples Size Consideration
6. Data Preparation & Data Analysis
7. 1st and 2nd Generation Software Available and Technique
8. More software and tools for analysis - Demonstration

Basic differences between quantitative and qualitative

- Quantitative Research
  - Making Observation
  - Test Theory
- Qualitative Research
  - Making Observations
  - Develop Theory

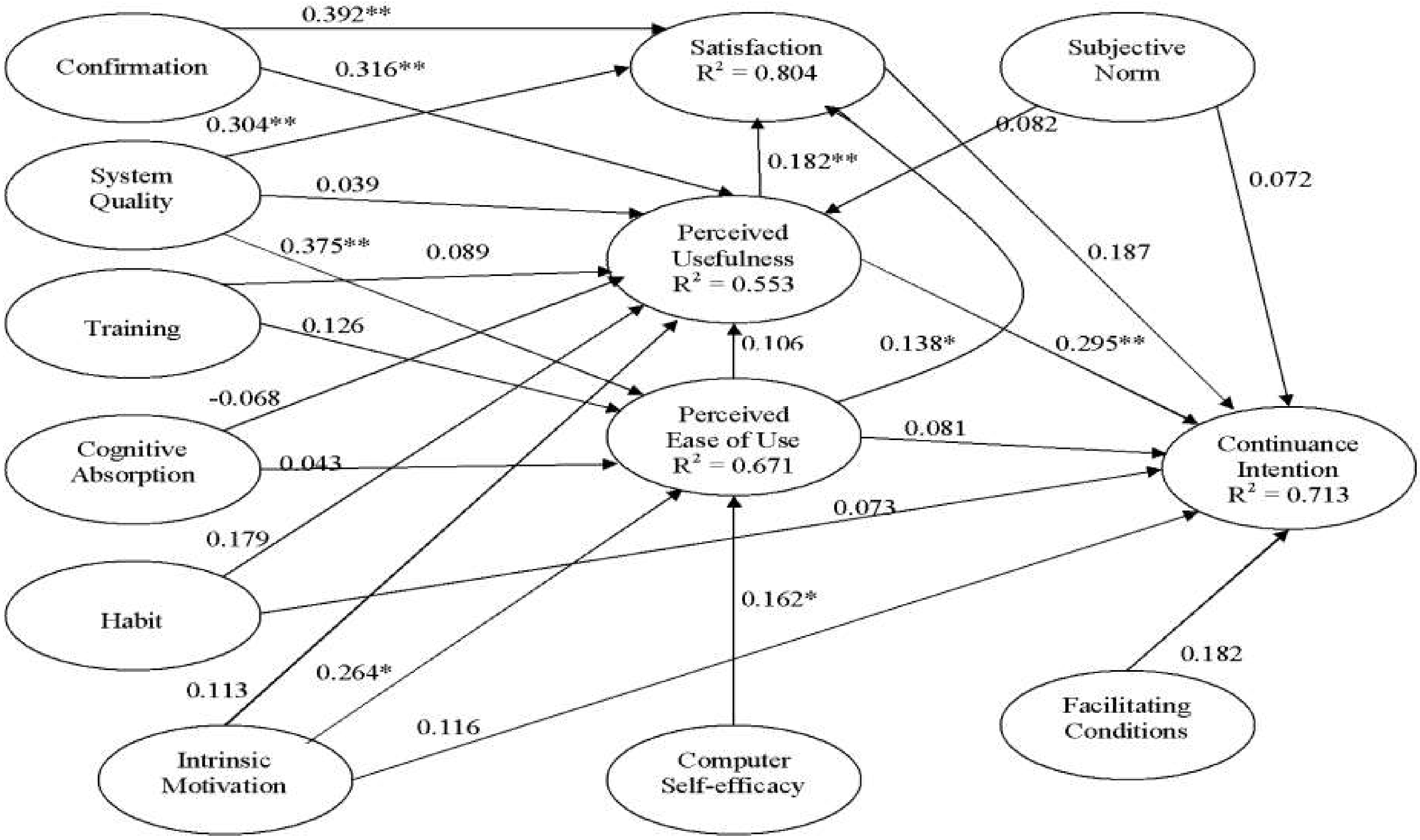
Types of Data in Quantitative Research

Types of Data	Secondary Data	Primary Data
Advantages	• Tends to be cheaper • Sample sizes tend to be greater • Tend to have more authority • Are usually quick to access • Are easier to compare to other research that uses the same data • Are sometimes more accurate (e.g. data on competitors	• Are recent • Are specific for the purpose • Are proprietary
Disadvantages	• May be outdated • May not completely fit the problem • There may be errors hidden in the data-difficult to assess data quality • Usually contains only factual data • No control over data collection • May not be reported in the required form (e.g., different units of measurement, definitions, aggregation levels of data)	• Are usually more expensive • Take longer to collect

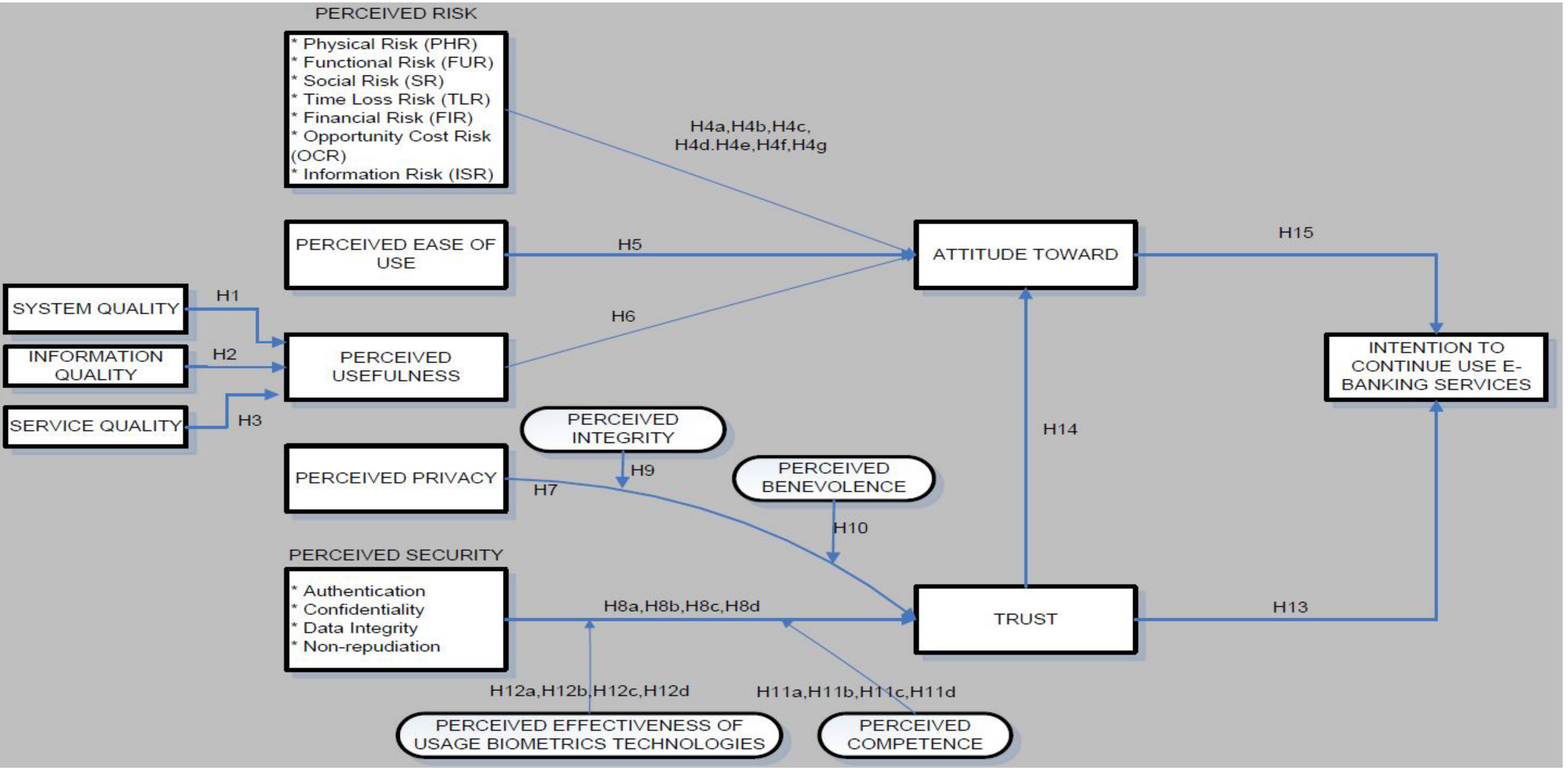
Research Plan and Design

Overview	Uses	Types
Exploratory Research	•Formulate problems more precisely •Develop Hypotheses •Establish priorities for research •Eliminate impractical ideas •Clarify concepts	•Literature search •Experience survey •Analysis of select cases •Interviews •Ethnographies •Focus groups
Descriptive Research	•Describe segment characteristics •Estimate proportion of people who behave in a certain way •Make specific predictions	•Longitudinal study •Panels •Sample Survey
Causal Research	•Provide evidence regarding causal relationships •Rule out all other explanations	•Laboratory experiment •Field experiment

What to expect for MBA research modeling?



What to expect for PhD research modeling?

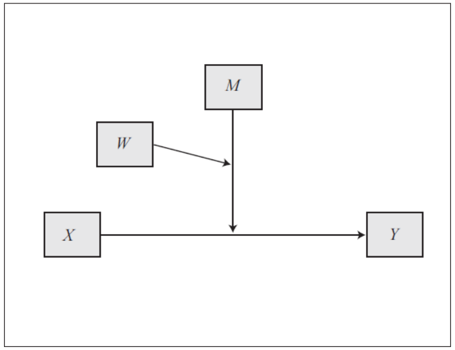


Basic Modeling in Quantitative Research

i. Independent
ii. Dependent
iii. Moderating
iv. Mediating
v. Control
vi. Moderated Mediated/ Mediated Moderator
vii. Moderated Moderator

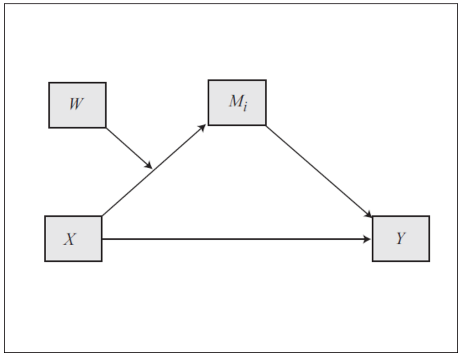
Model 3

Conceptual Diagram



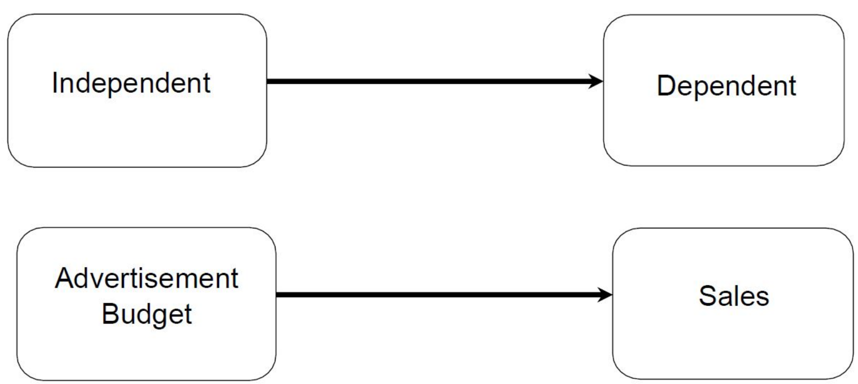
Model 7

Conceptual Diagram



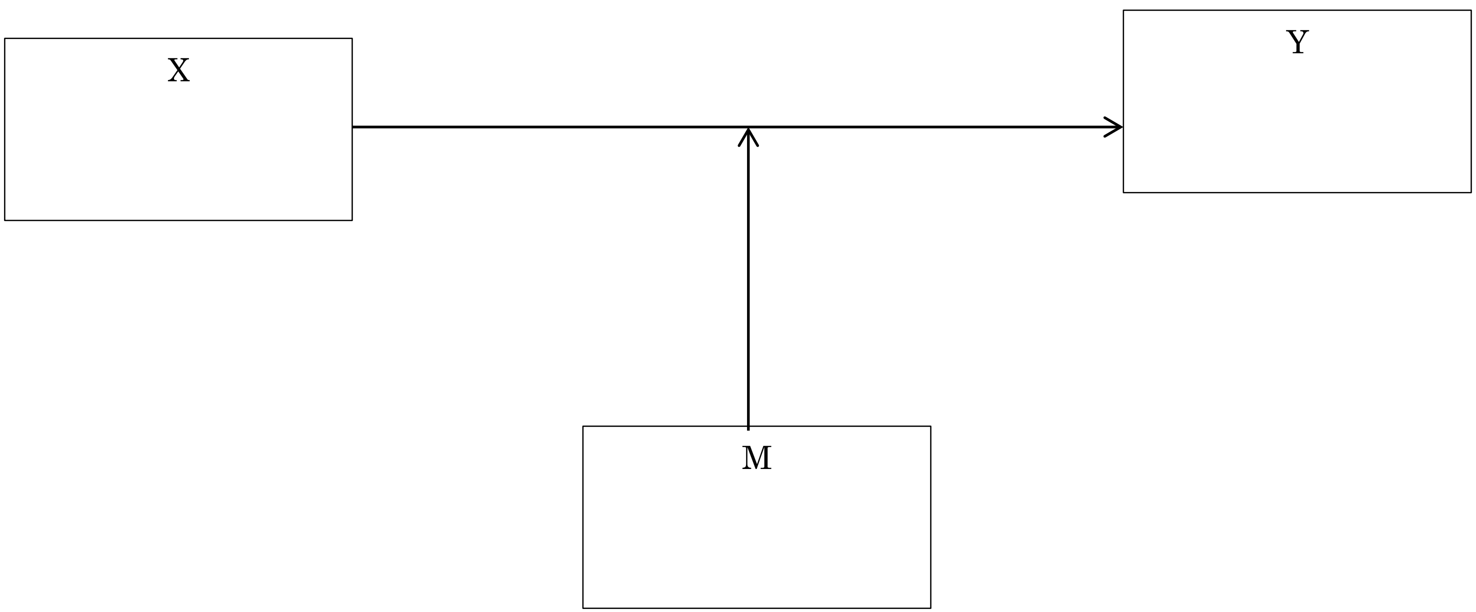
Basic Modeling in Quantitative Research

Independent Variable (IV)	Dependent Variable (DV)
• Predictor	• Criterion
• Presumed cause	• Presumed effect
• Stimulus	• Response
• Predicted from…	• Predicted to….
• Antecedent	• Consequence
• Manipulated	• Measured outcome



Model of a Moderator (Condition)

- A moderator is a variable that alters the relationship between an independent variable and a dependent variable.
- Who do it work for? & When does it work?

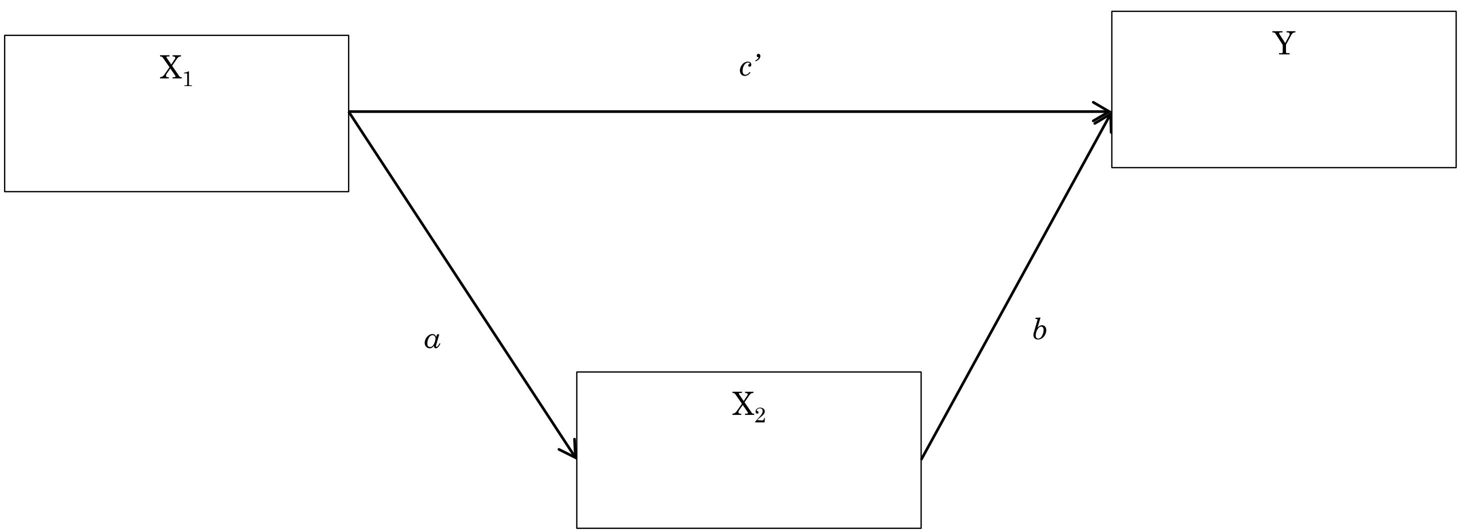


Model of a Moderator (Condition)

- Examples of “who do it work for?” & “when does it work?”

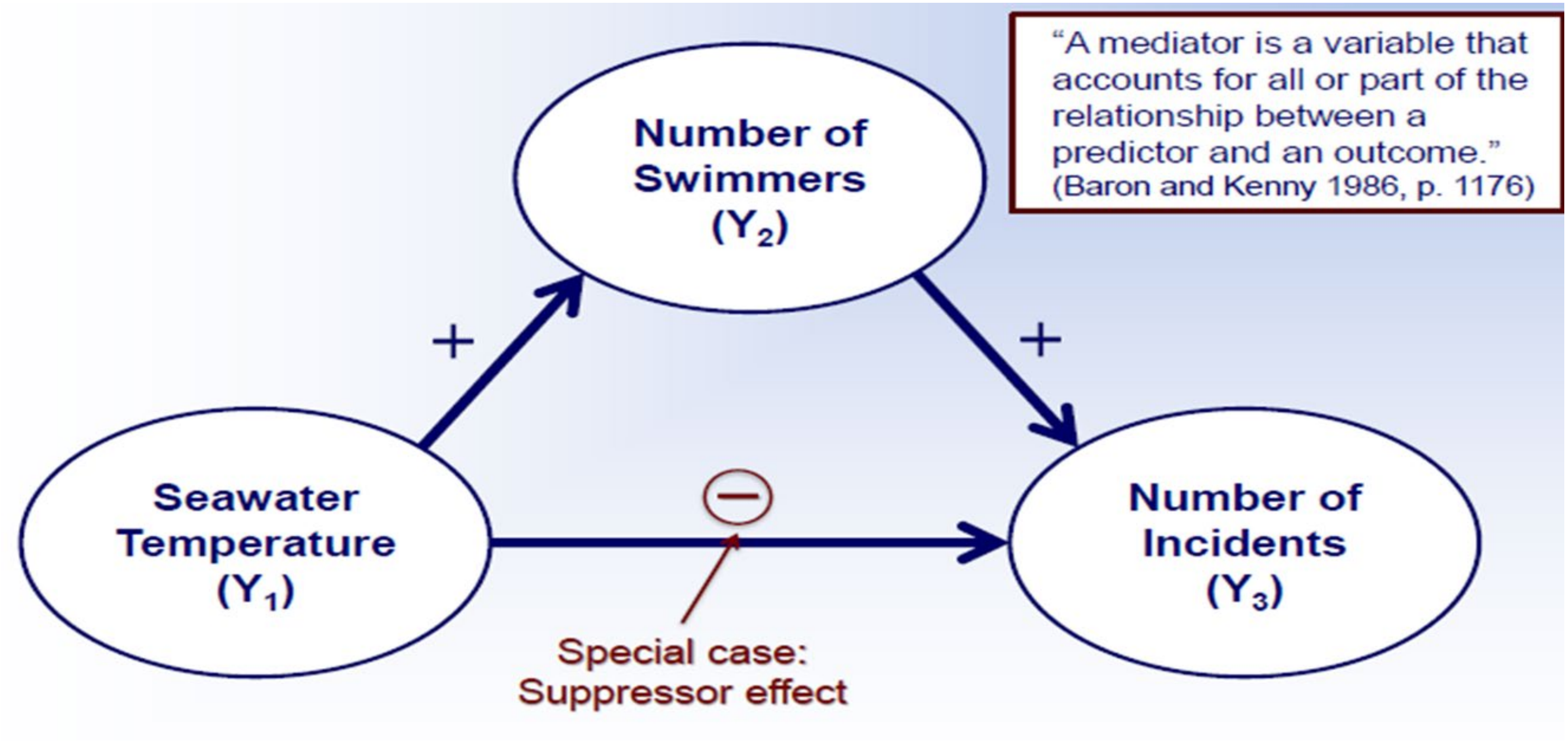
Model of a Mediator (Mechanism)

- An initial independent variable X_1 may influence the dependent variable Y through a mediator $X_{2.}$



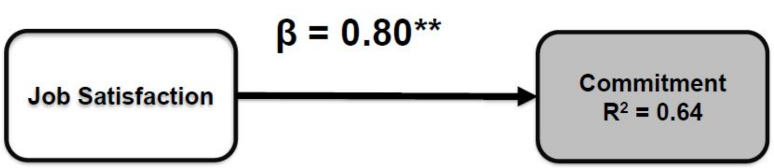
Model of a Moderator (Mechanism)

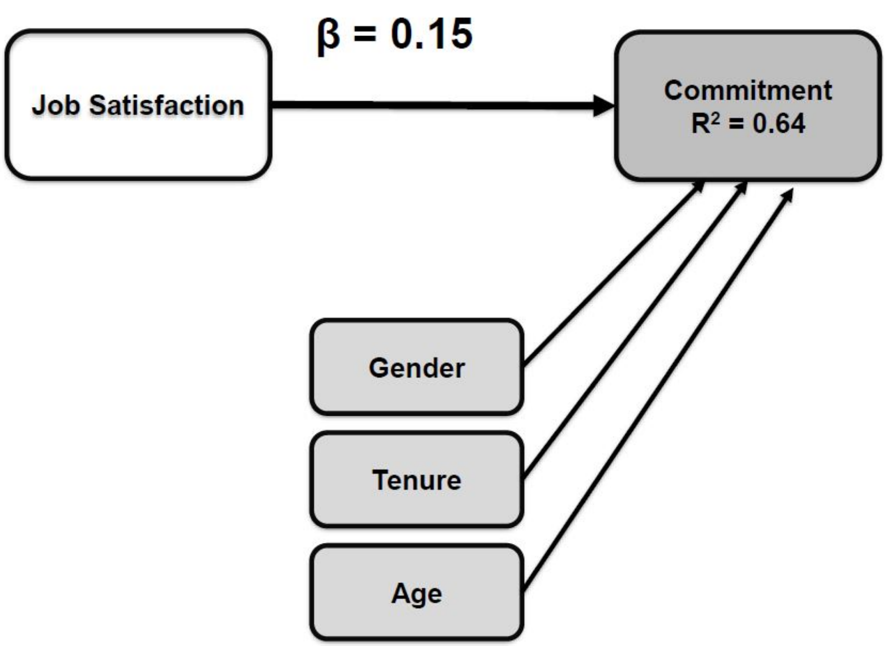
- Examples of “how do it work?” & “why did it work?”



Model of a Control Variable

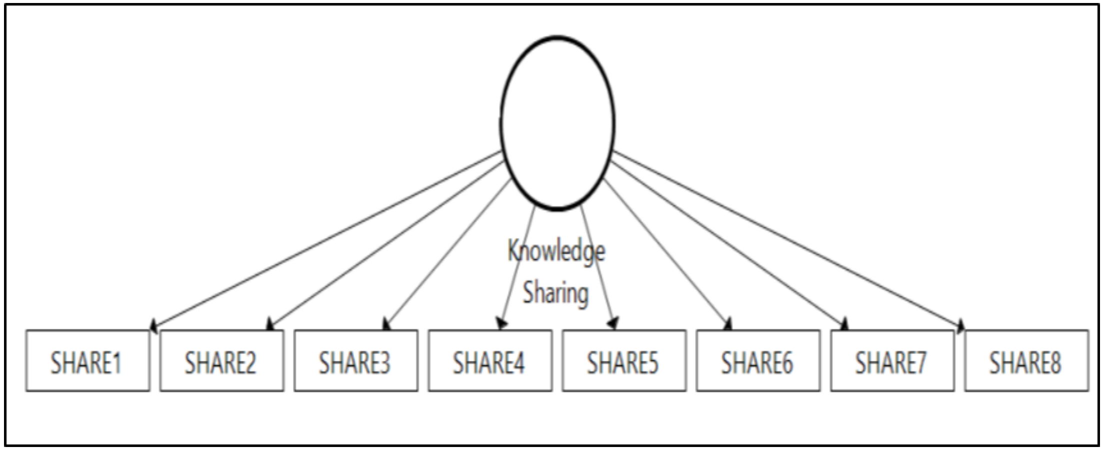
- One important characteristic of a good research design is to minimize the influence or effect of extraneous variable(s).



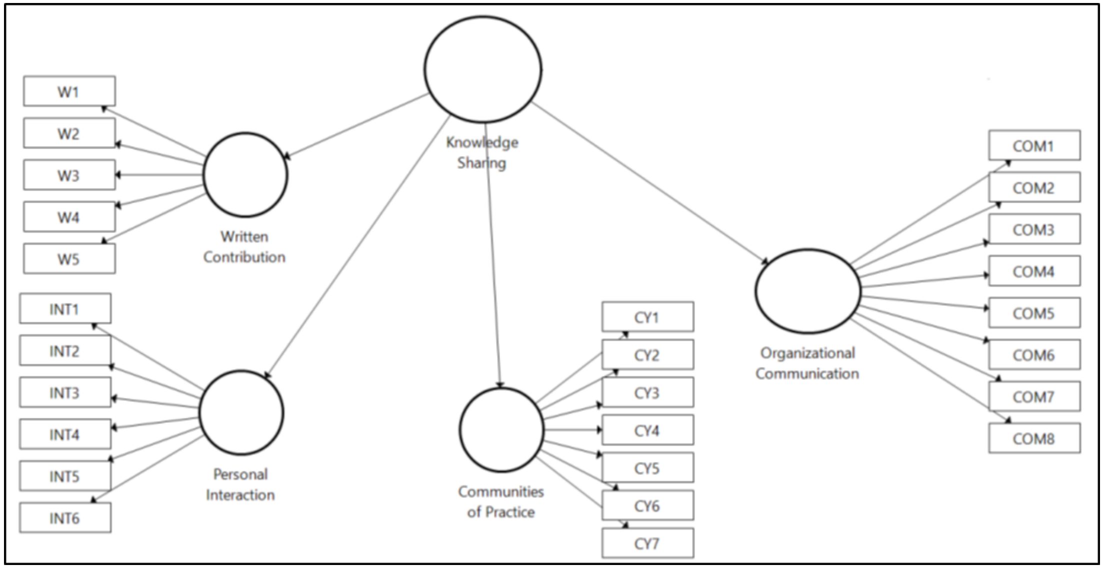


Characteristic of a Construct

i. Unidimensional



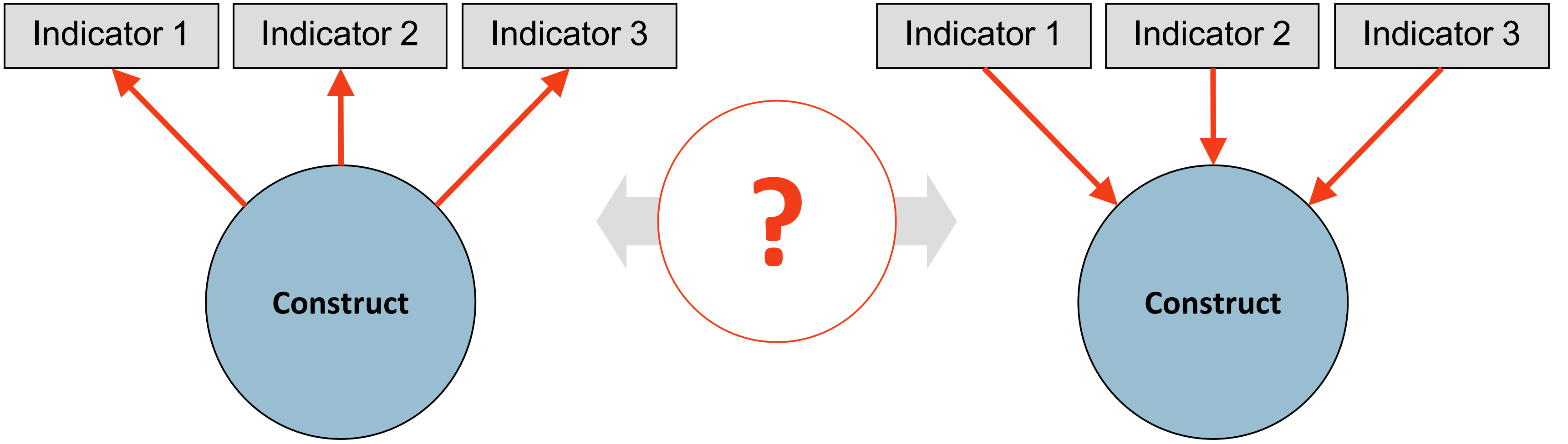
ii. Multi-dimensional



Characteristic of a Construct

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?

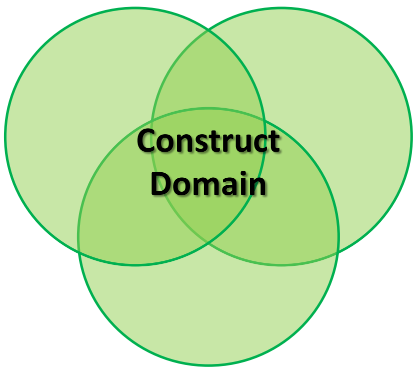


Changes in the latent variable directly cause changes in the assigned indicators

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

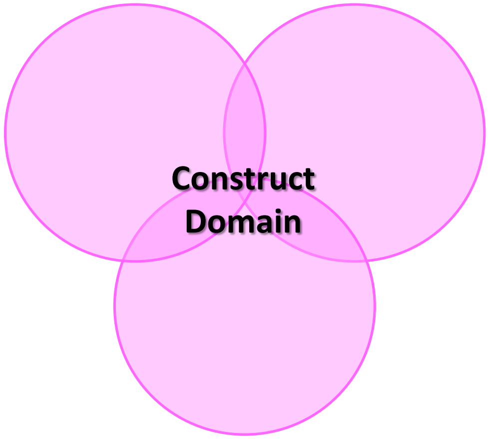
Characteristics of a Construct

Reflective indicators



Focuses on **maximizing** the **overlap** between interchangeable indicators

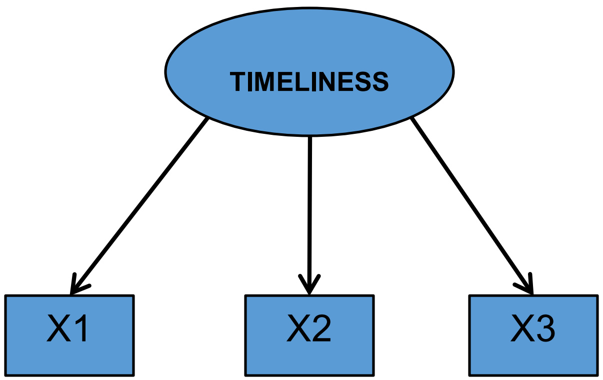
Formative indicators



Focuses on **minimizing** the **overlap** between complementary indicators

Characteristic of a Construct

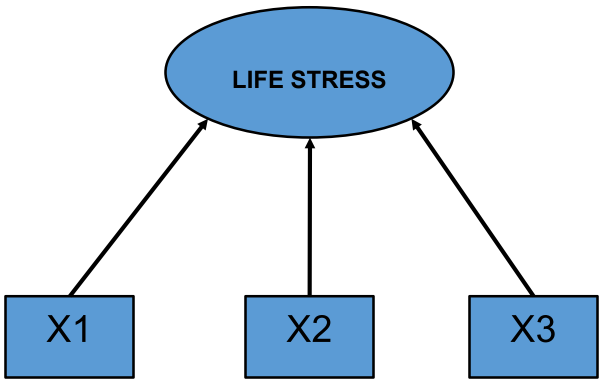
- Reflective



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

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

- Formative

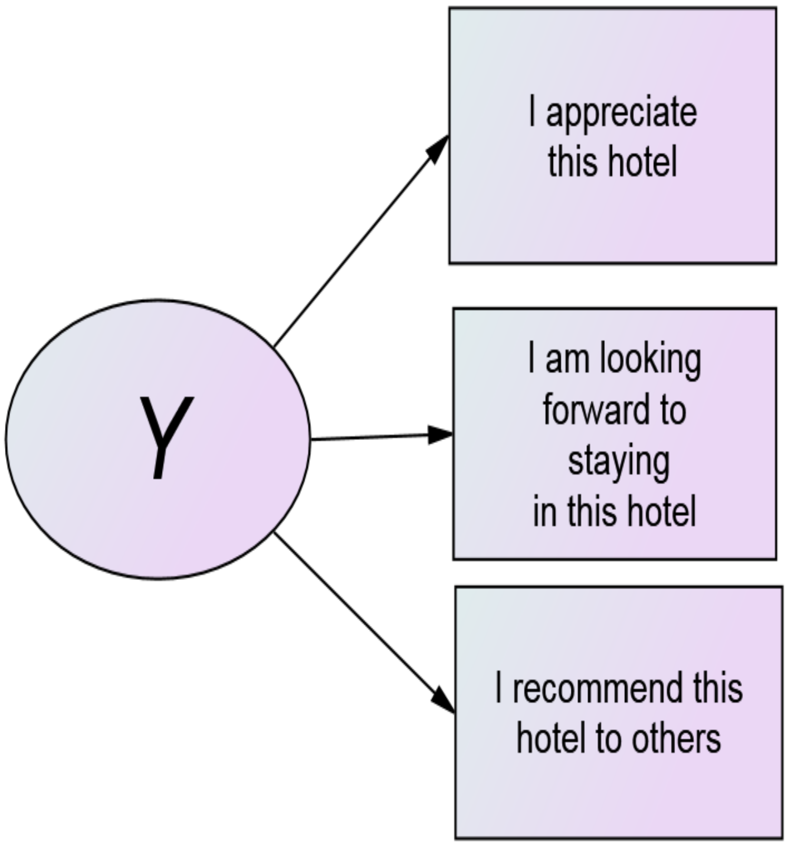


X1 = Job loss
X2 = Divorce
X3 = Recent accident

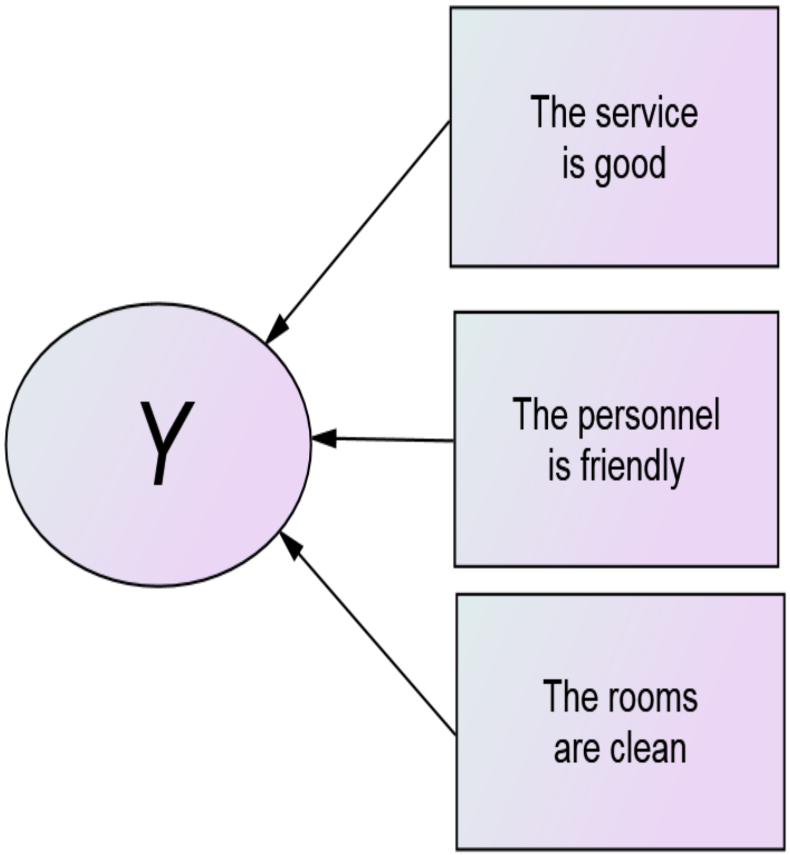
- Indicators can have +, - or 0 correlation (**Hulland, 1999**)

Characteristic of a Construct

Reflective Measurement Model



Formative Measurement Model



Key Considerations Prior to Data Analysis

A cautionary notes

Key Consideration Prior to Data Analysis

1. Sampling Technique
2. Sample Size
3. Pre-test & Pilot test
4. Common method variance
5. Reverse coded items
6. Exploratory Factor Analysis vs Confirmatory Factor Analysis vs Confirmatory Composite Analysis
7. Missing Value Imputation
9. Other Issues

Journal of Applied Structural Equation Modeling

Journal of Applied Structural Equation Modeling: 1(1), i-xiii, June 2017

EDITORIAL

A REVIEW OF THE METHODOLOGICAL MISCONCEPTIONS AND GUIDELINES RELATED TO THE APPLICATION OF STRUCTURAL EQUATION MODELING: A MALAYSIAN SCENARIO

Mumtaz Ali Memon[a*], Hiram Ting[b], T. Ramayah[c], Francis Chuah[d] and Jun-Hwa Cheah[e]

[a]*Centre of Social Innovation, Universiti Teknologi PETRONAS, Perak, Malaysia*
[b]*Sarawak Research Society, Sarawak, Malaysia*
[c]*School of Management, Universiti Sains Malaysia, Penang, Malaysia*
[d]*School of Business & Management, Universiti Utara Malaysia, Kedah, Malaysia*
[e]*International Business School, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia*

[*a]*mumtazutp@gmail.com*, [b]*hiramparousia@gmail.com*, [c]*ramayah@usm.my*,
[d]*francischuah@uum.edu.my*, [e]*junhwa@ibs.utm.my*

Sampling Techniques

Probability Sampling

- Simple random
- Systematic
- Stratified
- Cluster

Non-probability Sampling

- Convenience
- Snowball
- Quota
- Self-selection
- Purposive

Sampling Techniques

Probability Sampling

Pros:

- Generalizability is convincing
- Easy to select sample
- Comply assumption of many statistical techniques

Cons:

- Difficult to obtain a sampling frame

Non-probability Sampling

Pros:

- Generalizability is questionable
- Easy to reach sample

Cons:

- Difficult to select sample
- Potential coverage error
- Violate assumption of many statistical techniques

Sampling Techniques

The current issue and full text archive of this journal is available at
www.emeraldinsight.com/2040-8269.htm

MRR
37,3

308

Designing and using research questionnaires

Jenny Rowley
Languages, Information and Communications, Manchester Metropolitan University, Manchester, UK

Abstract

Purpose – This article aims to draw on experience in supervising new researchers, and the advice of other writers to offer novice researchers such as those engaged in study for a thesis, or in another small-scale research project, a pragmatic introduction to designing and using research questionnaires.

Design/methodology/approach – After a brief introduction, this article is organized into three main sections: designing questionnaires, distributing questionnaires, and analysing and presenting questionnaire data. Within these sections, ten questions often asked by novice researchers are posed and answered.

Findings – This article is designed to give novice researchers advice and support to help them to design good questionnaires, to maximise their response rate, and to undertake appropriate data analysis.

Originality/value – Other research methods texts offer advice on questionnaire design and use, but their advice is not specifically tailored to new researchers. They tend to offer options, but provide limited guidance on making crucial decisions in questionnaire design, distribution and data analysis and presentation.

Keywords Quantitative research, Quantitative data analysis, Research questionnaires

Paper type Conceptual paper

Rowley, J. (2014). Designing and using research questionnaires. *Management Research Review*, *37*(3), 308-330.

Sampling Techniques

There are a number of different approaches to selecting such a sample including probability and non-probability sampling, as summarized in Table I. Probability sampling is viewed as ideal, because a probabilistic sample is one that is representative of the population from which it is drawn, and therefore statistical generalizations about the population can be made on the basis of the analysis of the sample data. In probability sampling, based on a sampling frame or list of the members in the population, every case in the population has a known probability of being included in the sample, thus enhancing the likelihood of selecting cases that represent the total population. In contrast, in non-probability sampling, since every case in the population does not have a known probability of being included in the sample, the representativeness of the sample may be compromised. However, in reality most social science research relies heavily upon non-probability samples. First, researchers often do not have a clear view of the population to which they are seeking to generalize, and boundaries regarding who might or might not be included in the population are vague. Second, it is often very difficult to compile a complete sampling frame, although there may be a variety of partial lists of members of the population held by various organizations or government agencies. Finally, even in the unlikely instance that a researcher does manage to gather a good sampling frame, and apply probabilistic sampling, they are unlikely to achieve 100 percent response rate; non-response is another source of potential bias. For example, although the sample that you draw might have equal numbers of men and women, the response set may not; the same could be the case for any other important variable in your study.

Sampling Techniques

INTERNATIONAL JOURNAL OF ADVERTISING, 2017
https://doi.org/10.1080/02650487.2017.1348329

Routledge
Taylor & Francis Group

Check for updates

The use of sampling methods in advertising research: a gap between theory and practice

Marko Sarstedt[a,b], Paul Bengart[c], Abdel Monim Shaltoni[d] and Sebastian Lehmann[a]

[a]Department of Marketing, Otto-von-Guericke-University Magdeburg, Magdeburg, Germany; [b]Faculty of Business and Law, University of Newcastle, Callaghan, Australia; [c]Department of Empirical Economics, Otto-von-Guericke-University Magdeburg, Magdeburg, Germany; [d]College of Business, Alfaisal University, Riyadh, Saudi Arabia

ABSTRACT

In this research note, we reflect critically on the use of sampling techniques in advertising research. Our review of 1028 studies published between 2008 and 2016 in the four leading advertising journals shows that while current academic literature advocates probability sampling procedures, their actual usage is quite scarce. Most studies either lack information on the sampling method used, or engage in non-probability sampling without making adjustments to compensate for unequal selection probabilities, non-coverage, and sampling fluctuations. Based on our results, we call on researchers to revisit the fundamental aspects of sampling to increase their research results' rigour and relevance.

ARTICLE HISTORY
Received 20 April 2015
Accepted 21 June 2017

KEYWORDS
Sampling methods; data quality; representativeness; generalizability

Generalization

- Theory Generalization
- Sampling Generalization

Designing Research for Application

BOBBY J. CALDER
LYNN W. PHILLIPS
ALICE M. TYBOUT*

Two distinct types of generalizability are identified in consumer research. One entails the application of specific effects, whereas the other entails the application of general scientific theory. Effects application and theory application rest on different philosophical assumptions, and have different methodological implications. A failure to respect these differences has led to much confusion, regarding issues such as the appropriateness of student subjects and laboratory settings.

Calder, B. J., Phillips, L. W., & Tybout, A. M. (1981). Designing research for application. *Journal of consumer research*, *8*(2), 197-207.

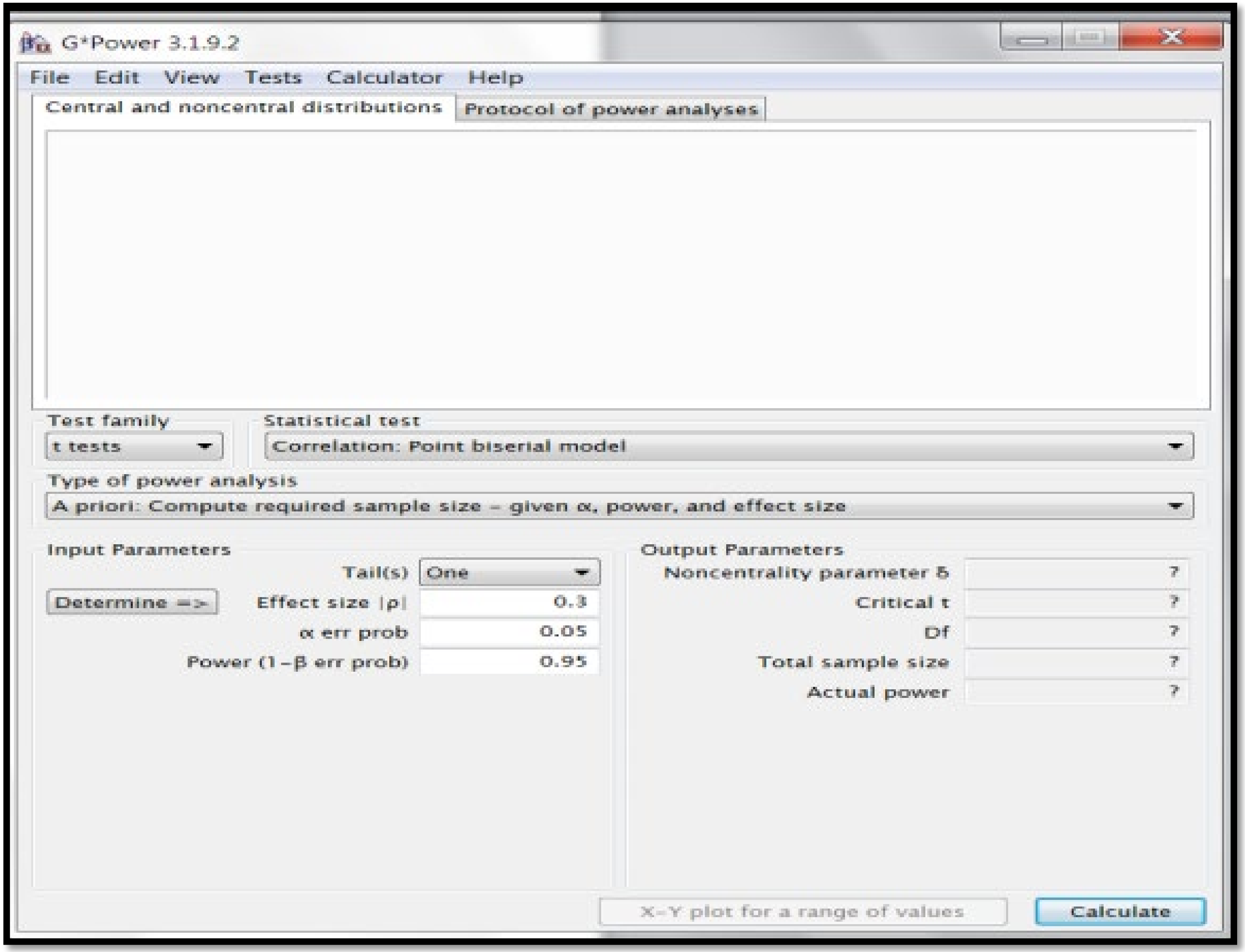
Sampling Size Considerations

- Sample size has been a major issue in quantitative research.
- The question : “How much is enough”
- Answers to the question will resort to the following aspect:
    - Sampling technique: Probability & Non probability
        - Krecjie & Morgan – Probability sampling
        - 10 times rules of thumb – per construct
        - Rules of Thumb for SEM (Hair et al. 2018; n > 200)
        - G*Power – Based on the complexity of model/framework
        - Gamma Exponential Method (n >146) and Inverse Square Root Method (n >160) (Kock and Hadaya, 2016)

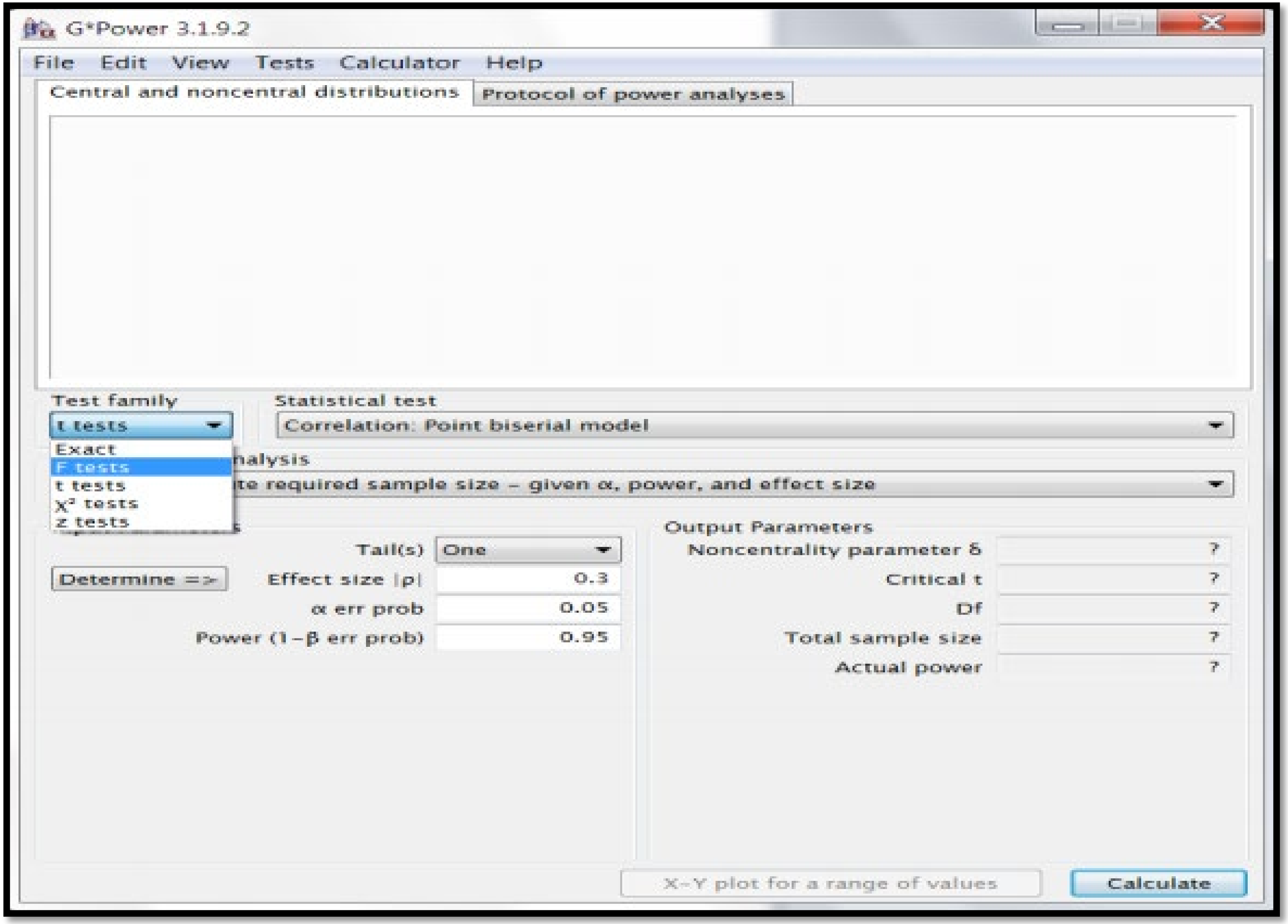
Sample size calculator

- www.raosoft.com
- www.danielsoper.com

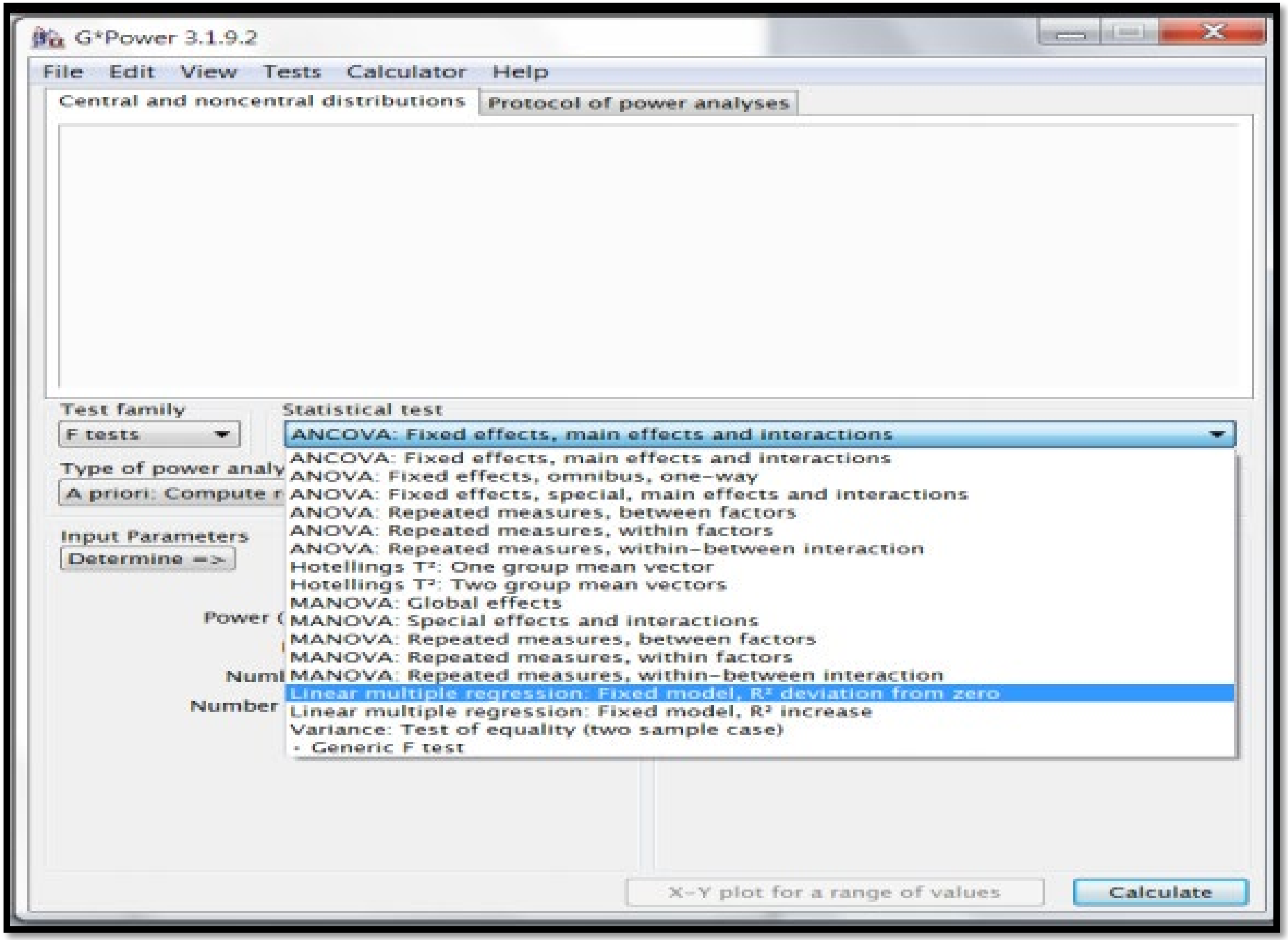
Sampling Size Estimation Using G*Power



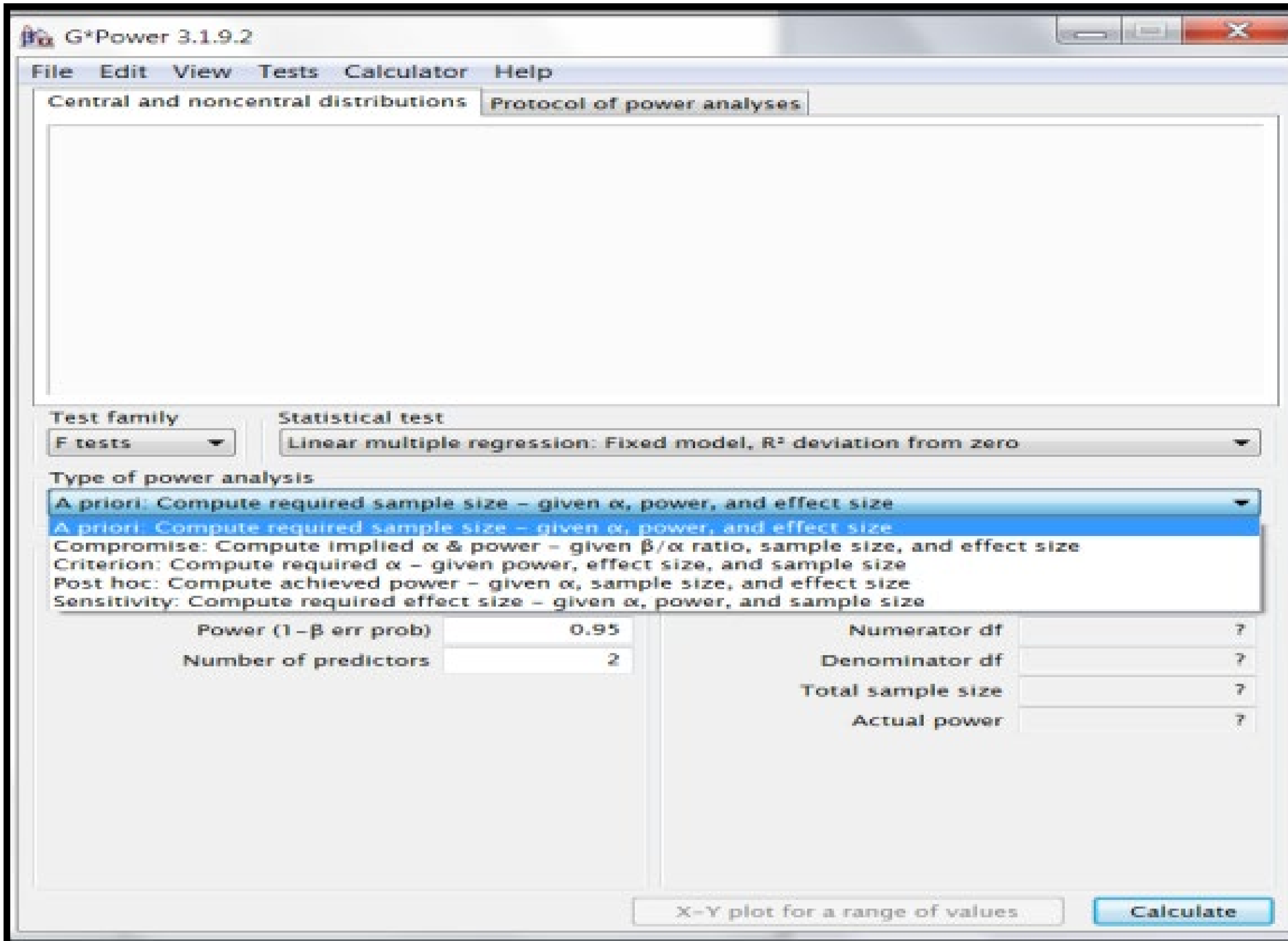
Sampling Size Estimation Using G*Power



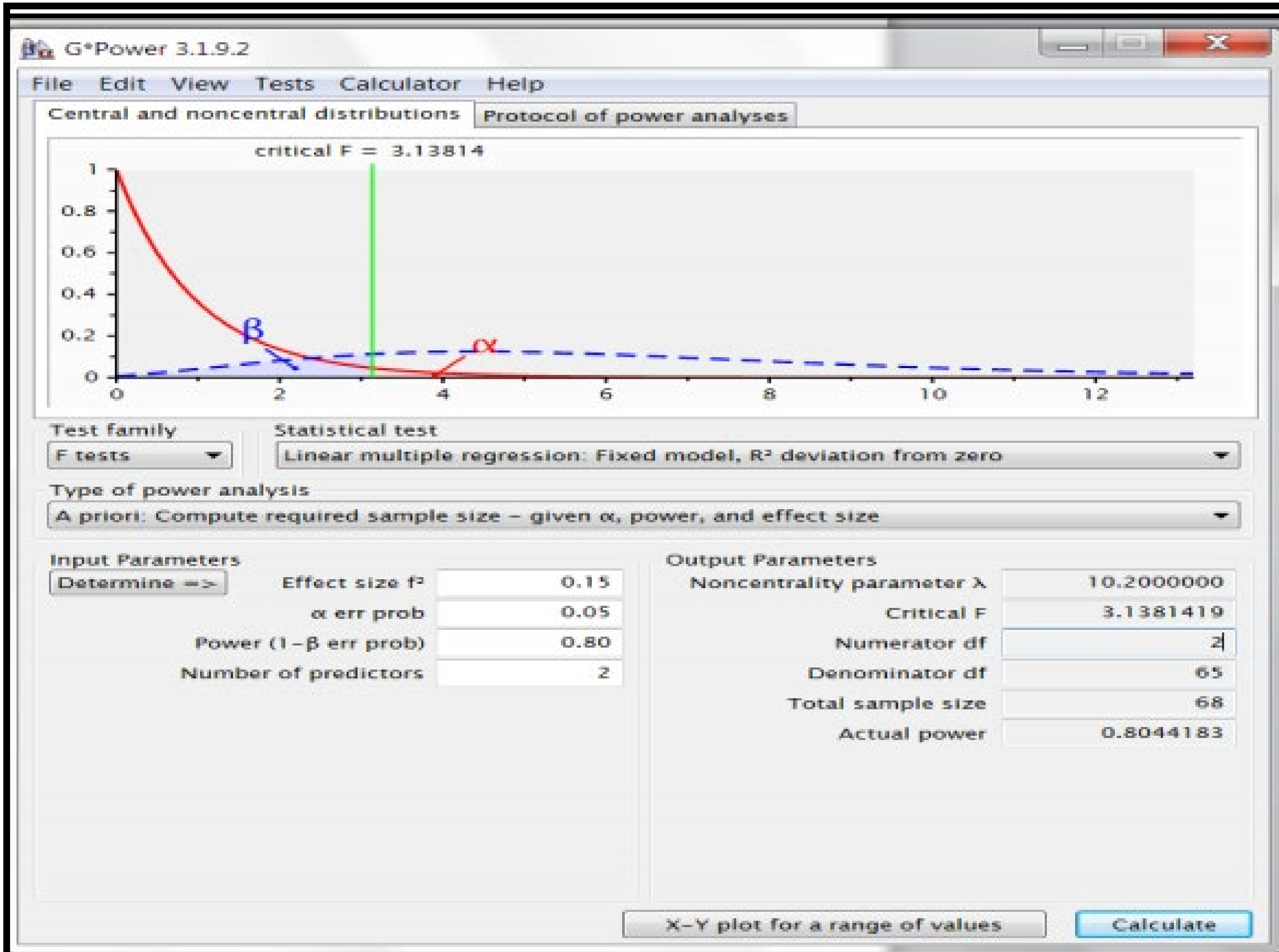
Sampling Size Estimation Using G*Power



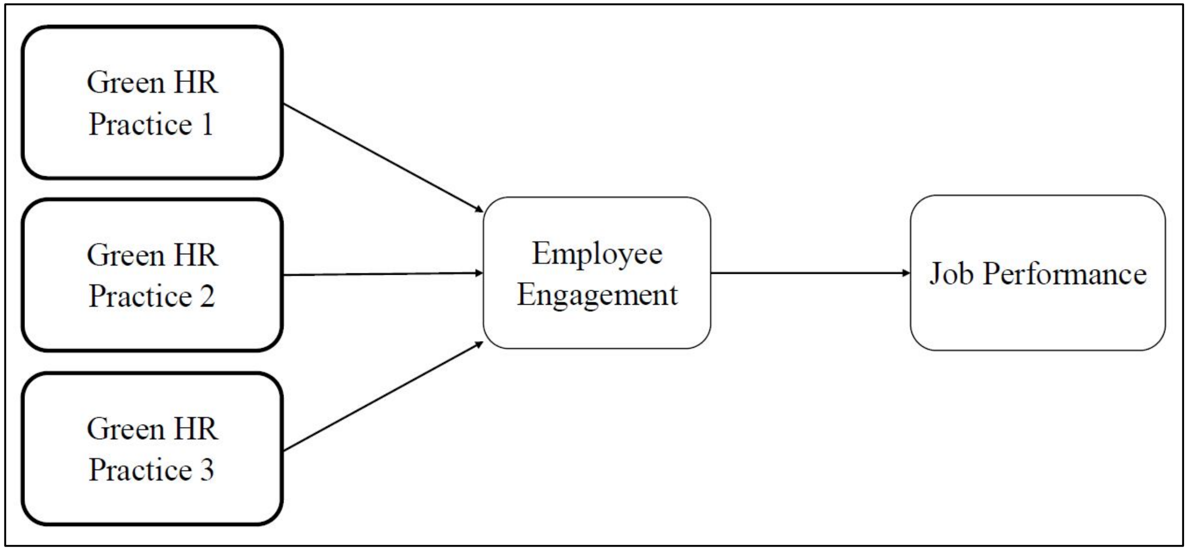
Sampling Size Estimation Using G*Power

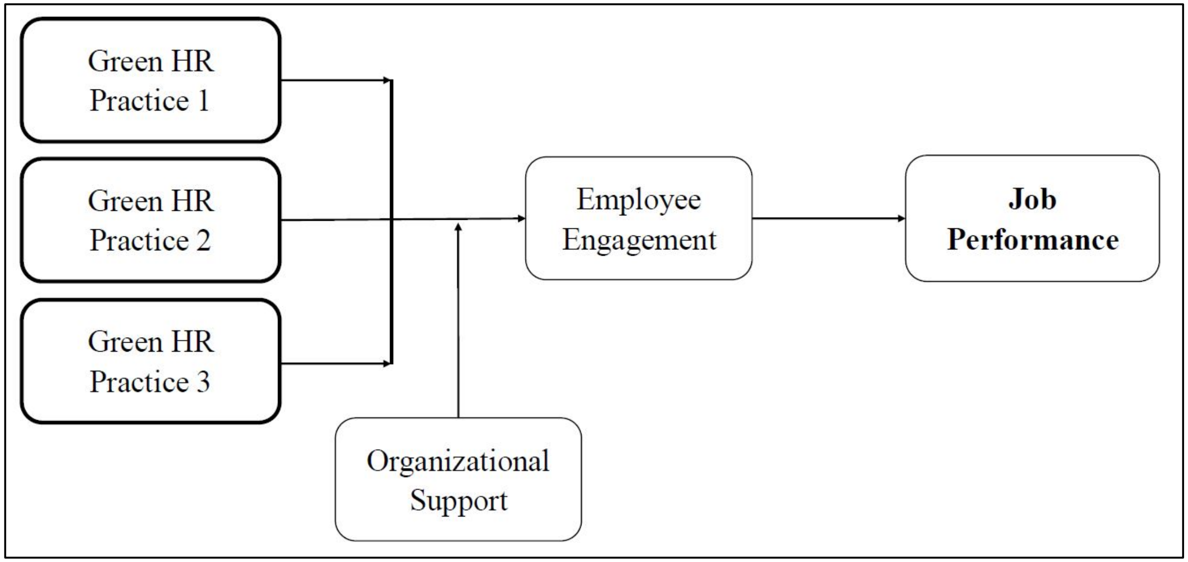


Sampling Size Estimation Using G*Power



How many predictors





Another Sample Size Criteria

Sample Size (Green, 1991)

	Sample sizes based on power analysis		
	Effect Size		
Number of predictors	**Small (0.02)**	**Medium (0.15)**	**Large (0.35)**
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	982	138	67
20	1060	156	77
30	1247	187	94
40	1407	213	110

Reading Material on Sample Size

Journal of Applied Structural Equation Modeling

eISSN: 2590-4221 *Journal of Applied Structural Equation Modeling: 4(2), i-xx, June 2020*

SAMPLE SIZE FOR SURVEY RESEARCH: REVIEW AND RECOMMENDATIONS

Mumtaz Ali Memon*[1], Hiram Ting[2], Jun-Hwa Cheah[3], Ramayah Thurasamy[4]
Francis Chuah[5] and Tat Huei Cham[6]

[1]*NUST Business School, National University of Sciences and Technology, Islamabad, Pakistan*
[2]*Faculty of Hospitality and Tourism Management, UCSI University, Sarawak, Malaysia*
[3]*School of Business and Economics, Universiti Putra Malaysia, Selangor, Malaysia*
[4]*School of Management, Universiti Sains Malaysia, Penang, Malaysia*
[5]*Othman Yeop Abdullah Graduate School of Business, Universiti Utara Malaysia, Kedah, Malaysia*
[6]*Faculty of Accountancy and Management, Universiti Tunku Abdul Rahman, Kajang, Malaysia*

**mumtazutp@gmail.com*

ABSTRACT

Determining an appropriate sample size is vital in drawing realistic conclusions from research findings. Although there are several widely adopted rules of thumb to calculate sample size, researchers remain unclear about which one to consider when determining sample size in their respective studies. 'How large should the sample be?' is one the most frequently asked questions in survey research. The objective of this editorial is three-fold. First, we discuss the factors that influence sample size decisions. Second, we review existing rules of thumb related to the calculation of sample size. Third, we present the guidelines to perform power analysis using the G*Power programme. There is, however, a caveat: we urge researchers not to blindly follow these rules. Such rules or guidelines should be understood in their specific contexts and under the conditions in which they were prescribed. We hope that this editorial does not only provide researchers a fundamental understanding of sample size and its associated issues, but also facilitates their consideration of sample size determination in their own studies.

Keywords: *Sample Size, Power Analysis, Survey Research, G*Power.*

Pre-test / Pilot Test

Pre-test

- Pre-testing is conducted mainly to address the following issues:
  - Length, layout, format, number of lines for replies, sequencing
  - Quality of questions, respondent's confusion and hesitation
- Pre-testing can be conducted through the following
  - Personal interviews, phone or mail
  - Debriefing (after) or protocol (during)
- Current trend of pre-testing – Card Sorting technique

Pilot test

- Is a small scale preliminary study conducted in order to evaluate **feasibility, time, cost, adverse events, and effect size** in an attempt to predict the appropriate sample size and **improve the study design** before the full scale survey is conducted.
- Benefits:
  - Appropriateness of questions
  - Correctness of instructions
  - Information on the whether the type of survey is effective
  - Save financial resource
  - To assess if large scale survey worth the effort
- Central Limit Theorem for pilot test sample size

Pre-test / Pilot Test

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)?

SHELBY D. HUNT, RICHARD D. SPARKMAN, JR., and JAMES B. WILCOX*

Despite their widely recognized importance in survey research, pretests have received little methodological attention. The authors summarize the current state of the art and report results from an empirical investigation of the effectiveness of respondent verbalizations in pretesting. The results suggest that pretesting is effective in identifying some types of problem questions but not others.

The Pretest in Survey Research: Issues and Preliminary Findings

The questionnaire-development process is normally considered to include seven steps: (1) specify what information will be sought, (2) select the type of questionnaire and method of administration, (3) determine the content of individual questions, (4) choose the form of response to each question, (5) determine the number of questions and sequence of each question, (6) re-examine steps 1–5 and revise if necessary, and (7) pretest the questionnaire and revise if necessary (Churchill 1979). Pretesting, the final stage, is the use of a questionnaire in a small pilot study to ascertain how well the questionnaire works. Pretesting an instrument is necessary because, as Backstrom and Hursch (1963) have pointed out, "No amount of intellectual exercise can substitute for testing an instrument designed to communicate with ordinary people."

Despite the generally accepted importance of pretesting, the pretesting process is given short shrift in both the marketing research literature and marketing research practice. In practice, the pretesting of questionnaires is often done in a hurried, nonsystematic fashion. As Lehmann (1979) has lamented, the pretesting stage in the research process is one "most likely to be squeezed out due to cost/time pressures." Similarly, reports of research on pretesting are almost nonexistent in the literature of marketing and other social sciences. The purpose of our research is to isolate several fundamental issues in the pretesting process, evaluate those issues, point out areas where empirical research is needed, and empirically examine four questions about the effectiveness of pretesting using respondent verbalizations.

*Shelby D. Hunt is Professor of Marketing and James B. Wilcox is Associate Professor of Marketing, College of Business Administration, Texas Tech University. Richard D. Sparkman, Jr., is Assistant Professor of Marketing, St. Mary's University, Halifax, Nova Scotia.

FUNDAMENTAL ISSUES IN PRETESTING

A review of the available literature on pretesting (which, unfortunately, is almost all of the "textbook" variety) and the authors' own experience in pretesting questionnaires suggest five fundamental issues in pretesting:

1. What specific items should be pretested?
2. What method should be used to conduct the pretest?
3. Who should do the pretesting?
4. Who should be the subjects in the pretest?
5. How large a sample is needed for the pretest?

Items that should be pretested can be separated into three categories: (1) items about the questionnaire itself, (2) items about specific questions, and (3) items about data analysis. First, items pertaining to the questionnaire itself that can and should be pretested include length, layout, the format for the questions used, the number of lines to leave for replies, and the sequencing of questions. The pretest can also be used as a device to estimate response rate for the questionnaire.

Second, individual questions should be pretested. The pretesting interviewer should carefully observe the respondent as he/she is filling out the questionnaire. If a respondent hesitates at a particular question, the question may be ambiguous or confusing, or may contain terminology unfamiliar to the respondent. The interviewer should probe the respondent after each question and/or at the end of the questionnaire to ascertain exactly

Journal of Marketing Research
Vol. XIX (May 1982), 269–73

Pre-test / Pilot Test

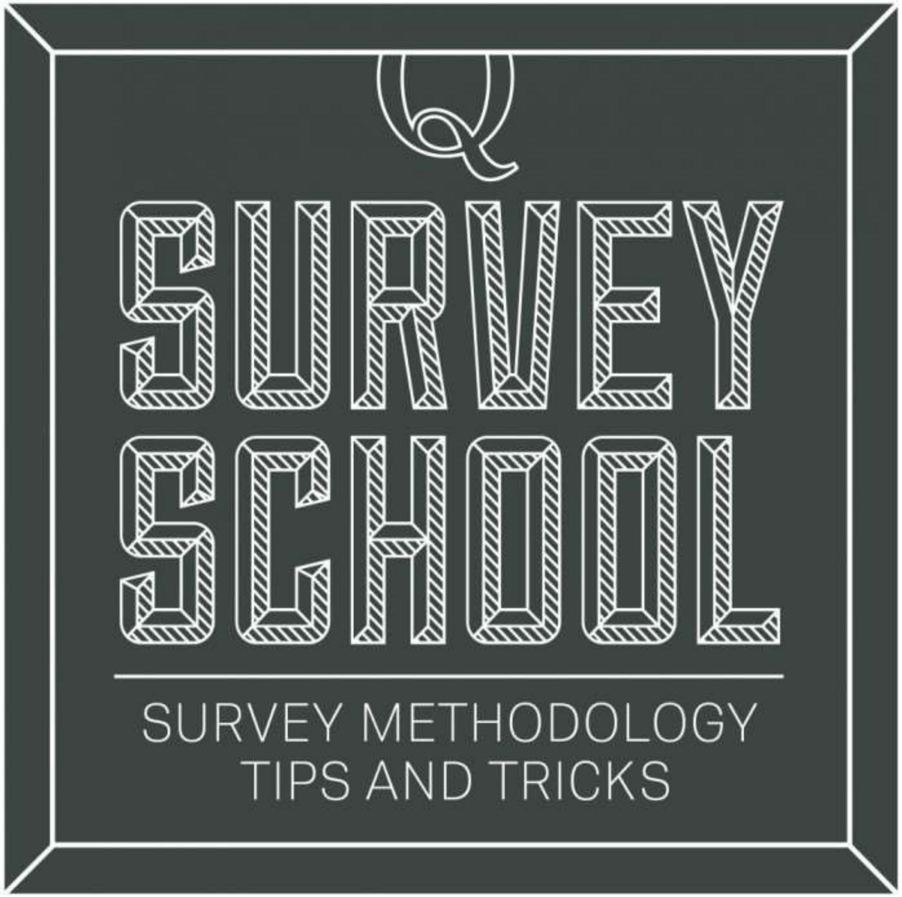
Pre-testing

- 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

Pre-test / Pilot Test

https://www.qualtrics.com/blog/6-ways-to-pretest-your-survey-before-you-send-it/

6 Ways to Pre-test Your Survey Before You Send It



Pre-test / Pilot Test

1. Respondent Debriefing

- For this approach, you will need to add several **evaluation questions to the end of your survey** for the respondents to answer.
- These **can be open-ended or closed-ended questions** and usually focus on **assessing respondent comprehension** and interpretation of survey questions.
- It should **also include overall evaluations of the survey content, time, satisfaction and difficulty**.

Pre-test / Pilot Test

2. Cognitive Interviewing

- "**Cognitive interviews**" are a good way to really understand what is going on the minds of your respondents when they are answering your questions.
- These are typically performed **face-to-face with a small sample of 5–15 respondents**.
- As the respondents answer each survey question, they are asked to "**think aloud**," which can include **paraphrasing, providing retrospective thinking or providing judgments of their confidence in what each question means**.

3. Expert Evaluation

- Your survey can be dramatically improved by feedback from two types of experts:

  1. **topic experts** that have deep knowledge and expertise about the subject matter of your survey, and
  2. **survey methodologists** that have expertise in how to collect the most accurate data for your research question.

- These expert evaluations can help shape the content and form of your survey and result in better data quality and more valuable insights.

Pre-test / Pilot Test

4. Focus Groups

- In the preliminary phases of questionnaire development, it can be **very helpful to ask a focus group discuss your survey**.
- These discussions, which are usually semi-structured discussions between 7–15 people led by a moderator, **are particularly helpful for clarifying basic concepts in the survey and evaluating perceptions of respondent burden or topic sensitivity**.

Pre-test / Pilot Test

5. Experiments

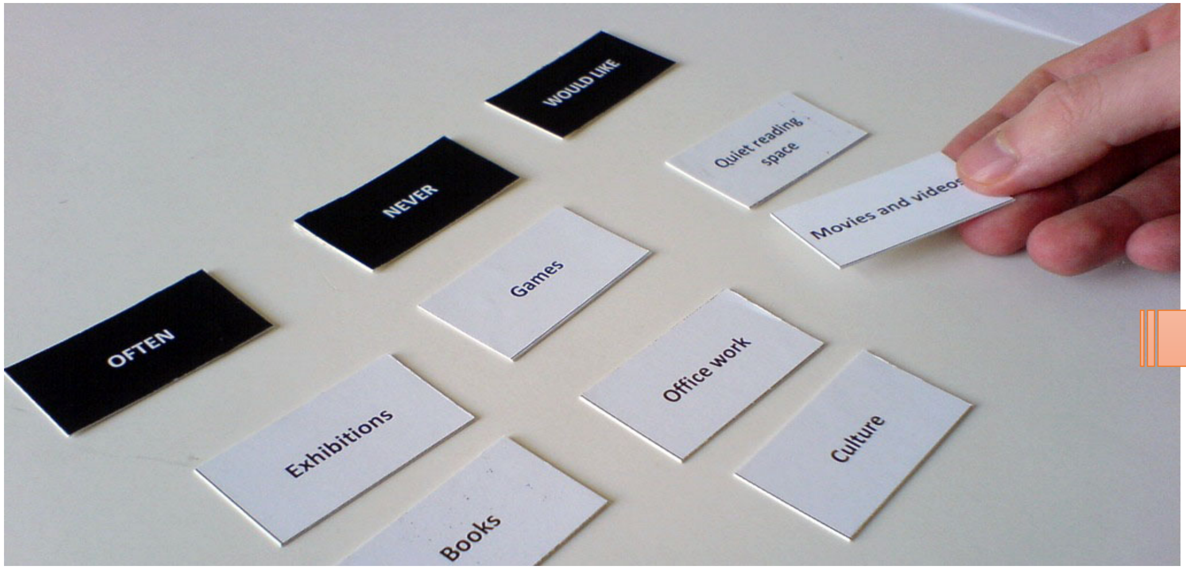
- Splitting a pre-test sample of respondents into groups and **testing different variations of your survey design and content** can be very powerful for understanding the results you will get when you field your main survey.

- These experiments are particularly useful for understanding **how changes in question wording, questionnaire design, visual layout, question order, and many other methodological factors may influence the data you collect**.

6. Pilot Test

- **Testing the final version of your survey on a small sample of your target population is critical** - it can give you a sense of the kind of responses you will receive and any issues that may arise during the real survey period.
- **Pilot studies often serve as a 'dry run'** and are typically done just before fielding the survey to the entire sample.
- It is usually a good idea to include some evaluative questions, such as respondent perceptions of the length or difficulty of the questionnaire, satisfaction with taking the survey, etc.
- At Qualtrics we typically recommend that our customers use a sample of about 50 respondents for these pilot studies, or **'soft launches,'** unless you need to do additional testing across different demographics.

Pre-test / Pilot Test



The Current Trend of Pre-Test to check on Content-Validity

Considering that the measures came from different sources, we conducted card sorting exercises to test the reliability and validity of the study's measurement items, following the method suggested by Moore and Benbasat (1991). The card-sorting judges were formed by one work professional, an academic scholar, and a research student. In the first round of the exercise, the judges were not provided with the construct names but were asked to label each item. In this round, the correct hit ratio was 85 percent. Based on the feedback provided by the judges, we revised some ambiguous wordings and the revised measures went to the second round of card sorting exercise conducted by a second group of judges with the same characteristics as the first group. In this round, the names of constructs were provided. A 97 percent correct hit ratio was achieved in this round, which indicates sufficient item-construct reliability (Moore and Benbasat, 1991) and so we did not proceed with a third-round of card sorting.

Further Reading:

The current issue and full text archive of this journal is available at
www.emeraldinsight.com/0959-3845.htm

Empowering employees through instant messaging

Carol X.J. Ou
The Hong Kong Polytechnic University, Hong Kong, People's Republic of China
Robert M. Davison
City University of Hong Kong, Hong Kong, People's Republic of China
Xuepan Zhong
University of Science and Technology of China, Hefei, People's Republic of China, and
Yi Liang
Tsinghua University, Beijing, People's Republic of China

Abstract

Purpose – This paper aims to develop a research model that explains how instant messaging (IM) technologies enable employees to be empowered.

Design/methodology/approach – The paper uses survey of 253 Chinese work professionals with respect to their use of IM tools at work.

Findings – IM does empower work teams via shaping the social networks and facilitating knowledge sharing in the workplace, resulting in heightened team performance.

Research limitations/implications – The survey was conducted in China so generalization to other national contexts is tentative. It focuses on the bright side of IM, but neglects the dark side, e.g. security concerns and work interruptions.

Practical implications – IM is not only a social tool, it also has the potential to contribute to work teams. However, IM cannot achieve better work performance alone. Its contribution to strengthen the social networks at work is also critical. These social networks at work can enable employees to overcome psychological barriers to knowledge sharing.

Originality/value – Studies of IM in the workplace have not previously considered social network perspectives, nor the value of such IM-facilitated social networks for work performance. This large scale survey of work professionals across four locations in China provides evidence for the considerable positive impacts of IM on work.

Keywords Social networks, Knowledge sharing, Team working, China, Communication technologies

Paper type Research paper

1. Introduction

Instant messaging (IM) technology is currently growing rapidly in a variety of contexts. An IM has the capability to connect individuals instantly, thus enabling almost real time interaction in a cost-effective manner, unlike other CMC tools such as e-mail, video conferencing and online communities. Although IM is widely used in social contexts, its adoption in the work place remains controversial. The controversy is associated with the difficulties involved in specifying organizational benefits,

An earlier version of this paper was presented at the IEEE Sponsored RCIS (Research Challenges in Information Science) conference in Nice, France, May 19-21, 2010.

Information Technology & People
Vol. 23 No. 2, 2010
pp. 193-211

0959-3845
DOI 10.1108/09593841011052165

Pre-test / Pilot Test

J. of the Acad. Mark. Sci.
DOI 10.1007/s11747-017-0532-y

CrossMark

METHODOLOGICAL PAPER

Marketing survey research best practices: evidence and recommendations from a review of *JAMS* articles

John Hulland[1] · Hans Baumgartner[2] · Keith Marion Smith[3]

Received: 19 August 2016 / Accepted: 29 March 2017

Abstract Survey research methodology is widely used in marketing, and it is important for both the field and individual researchers to follow stringent guidelines to ensure that meaningful insights are attained. To assess the extent to which marketing researchers are utilizing best practices in designing, administering, and analyzing surveys, we review the prevalence of published empirical survey work during the 2006–2015 period in three top marketing journals—*Journal of the Academy of Marketing Science* (*JAMS*), *Journal of Marketing* (*JM*), and *Journal of Marketing Research* (*JMR*)—and then conduct an in-depth analysis of 202 survey-based studies published in *JAMS*. We focus on key issues in two broad areas of survey research (issues related to the choice of the object of measurement and selection of raters, and issues related to the measurement of the constructs of interest), and we describe conceptual considerations related to each specific issue, review how marketing researchers have attended to these issues in their published work, and identify appropriate best practices.

Surveys are ubiquitous, used to inform decision making in every walk of life. Surveys are also popular in academic marketing research, in part because it is difficult to imagine how certain topics could be studied without directly asking people questions, rather than, say, observing their behaviors, possibly in response to different experimental conditions manipulated by the researcher. In their review of academic marketing research published in the *Journal of Marketing* (*JM*) and the *Journal of Marketing Research* (*JMR*) between 1996 and 2005, Rindfleisch et al. (2008) found that roughly 30% of the articles—representing 178 published papers—used survey methods. In this research, we conduct a follow-up investigation of the use of surveys during the decade since their review (i.e., 2006 to 2015), adding the *Journal of the Academy of Marketing Science* (*JAMS*) to the set of journals studied since (1) many articles published in *JAMS* rely on surveys and (2) *JAMS* has an impact factor comparable to *JM* and *JMR*. We classify each article as either survey-based or non-survey-based empirical work, as a conceptual paper, or as something

Common Method Variance

Methods variance and its effects are at the center of a debate in organizational science. Most of the debate, however, is focused on the prevalence of common methods variance and ignores common methods bias, or the divergence between observed and true relationships among constructs. This article assesses the level of common methods bias in all multitrait- multimethod correlation matrices published over a 12-year period in a set of six social science journals using a combination of structural equation modeling and meta-analysis.

The results indicate that only **46% of the variation in measures is attributable to the constructs**, that ***32% of the observed variation in measures is attributable to common methods variance***, and that **common methods variance results in a 26% bias in the observed relationships among constructs**. This level of bias is cause for concern but does not invalidate many research findings.


Common Methods Bias: Does Common Methods Variance Really Bias Results?

D. HAROLD DOTY
Syracuse University
WILLIAM H. GLICK
Arizona State University

Methods variance and its effects are at the center of a debate in organizational science. Most of the debate, however, is focused on the prevalence of common methods variance and ignores common methods bias, or the divergence between observed and true relationships among constructs. This article assesses the level of common methods bias in all multitrait-multimethod correlation matrices published over a 12-year period in a set of six social science journals using a combination of structural equation modeling and meta-analysis. The results indicate that only 46% of the variation in measures is attributable to the constructs, that 32% of the observed variation in measures is attributable to common methods variance, and that common methods variance results in a 26% bias in the observed relationships among constructs. This level of bias is cause for concern but does not invalidate many research findings.

Construct validity is a prerequisite to developing and meaningfully testing organizational theories. Conclusions from organizational research that lacks sufficient construct validity may be based on artifacts or inadequacies in the research rather than on the theoretically specified relationships among constructs. Simply stated, if researchers fail to measure what they purport to measure, they are likely to draw the wrong conclusions from their data.

One of the primary threats to construct validity in the organizational sciences is common methods variance, which occurs when the measurement technique introduces systematic variance into the measure. This systematic error variance can cause observed relationships to differ from the true relationships among constructs. If

Authors' Note: The authors would like to thank Daniel C. Ganster, Nina Gupta, Jerry G. Hunt, G. Douglas Jenkins, Jr. (posthumously), Mark Peterson, Larry J. Williams, and three anonymous reviewers for helpful comments on previous versions of this article, and Rick Bagozzi, John C. Loehlin, Ingram Olkin, and Thomas W. Sager for advice on the data analysis. A previous version of this article was presented at the Research Methods Division of the Academy of Management for the 1989 Annual Meetings, Washington, DC.

Organizational Research Methods, Vol. 1 No. 4, October 1998 374-406

Doty & Glick (1988)

Common Method Variance

- ❑ CMV is the amount of spurious correlation between variables that is the result of using the same measurement method to measure each variables
- ❑ CMV may lead to erroneous conclusion about relationships between variables by inflating/deflating findings
- ❑ CMV needs to be examine when data are collected via self-reported questionnaires and, in particular, when the same person is answering on both predictor and criterion variables
- ❑ Two ways to control for CMV
  - ❑ Procedural control
  - ❑ Statistical control

ANNUAL REVIEWS Further
Click here for quick links to Annual Reviews content online, including:
- Other articles in this volume
- Top cited articles
- Top downloaded articles
- Our comprehensive search

Sources of Method Bias in Social Science Research and Recommendations on How to Control It

Philip M. Podsakoff,[1] Scott B. MacKenzie,[2] and Nathan P. Podsakoff[3]

[1]Department of Management, Kelley School of Business, Indiana University, Bloomington, Indiana 47405; email: podsakof@indiana.edu
[2]Department of Marketing, Kelley School of Business, Indiana University, Bloomington, Indiana 47405; email: mackenz@indiana.edu
[3]Department of Management and Organizations, Eller College of Management, University of Arizona, Tucson, Arizona 85721; email: podsakof@email.arizona.edu

Annu. Rev. Psychol. 2012. 63:539–69

First published online as a Review in Advance on August 11, 2011

The *Annual Review of Psychology* is online at psych.annualreviews.org

This article's doi: 10.1146/annurev-psych-120710-100452

0066-4308/12/0110-0539$20.00

Keywords

common method variance, response style biases, marker variable technique, instrumental variable technique, unmeasured latent variable technique

Abstract

Despite the concern that has been expressed about potential method biases, and the pervasiveness of research settings with the potential to produce them, there is disagreement about whether they really are a problem for researchers in the behavioral sciences. Therefore, the purpose of this review is to explore the current state of knowledge about method biases. First, we explore the meaning of the terms "method" and "method bias" and then we examine whether method biases influence all measures equally. Next, we review the evidence of the effects that method biases have on individual measures and on the covariation between different constructs. Following this, we evaluate the procedural and statistical remedies that have been used to control method biases and provide recommendations for minimizing method bias.

539

Ex Ante Approaches (Procedure)

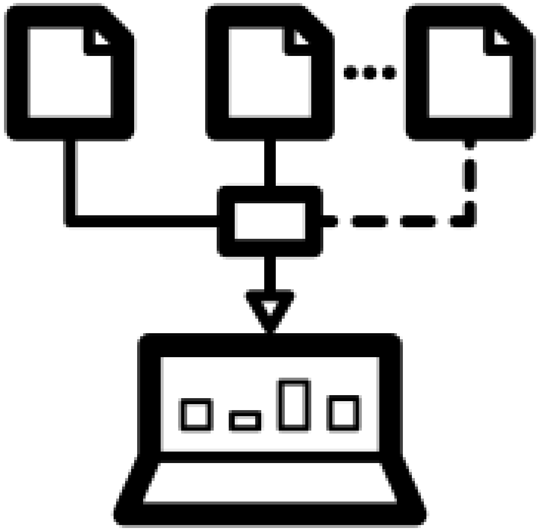
- ➢ Collect data from different source
  - ➢ NO – Reduce CMV through questionnaire design
  - ➢ YES – Collect Pre / Post Survey

Post Ante Approaches (Statistical)

- ➢ Complex model specification
- ➢ Partial out / control for latent
  - ➢ Harman Single Factor test
  - ➢ Partial correlation method
  - ➢ Social desirability construct
  - ➢ Correlation matrix
  - ➢ Measured Latent Marker Variable
  - ➢ Full Collinearity
  - ➢ Unmeasured Latent Method Construct

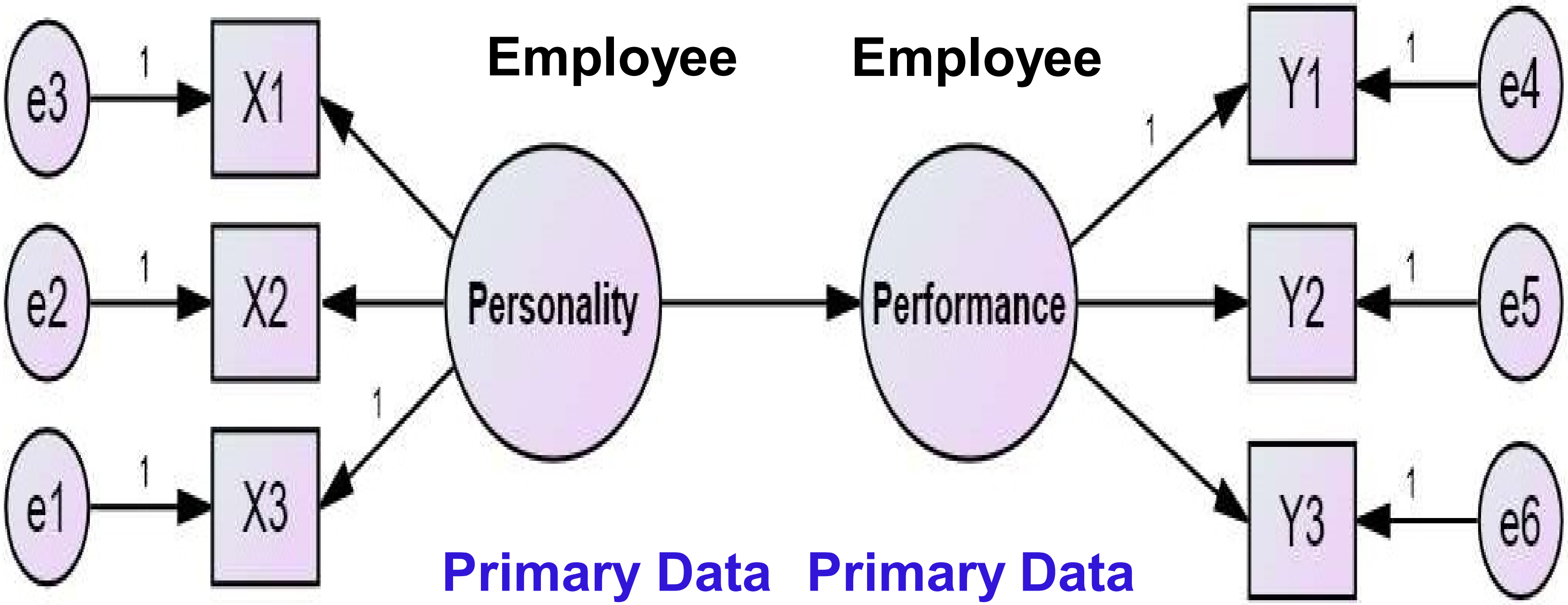
Understanding Data Source

- Single Source
- Multiple Source
- Multilevel



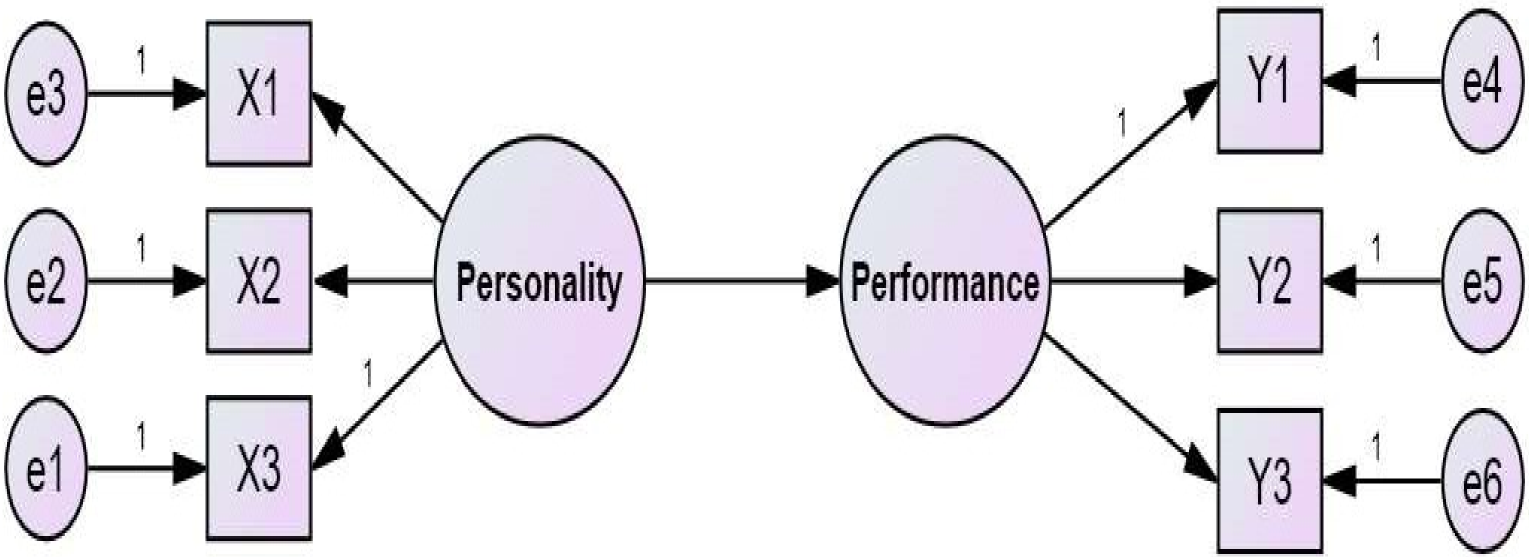
Single Source Data

Same Source – Same Method



Multiple Source Data

Multiple Source – Same Method

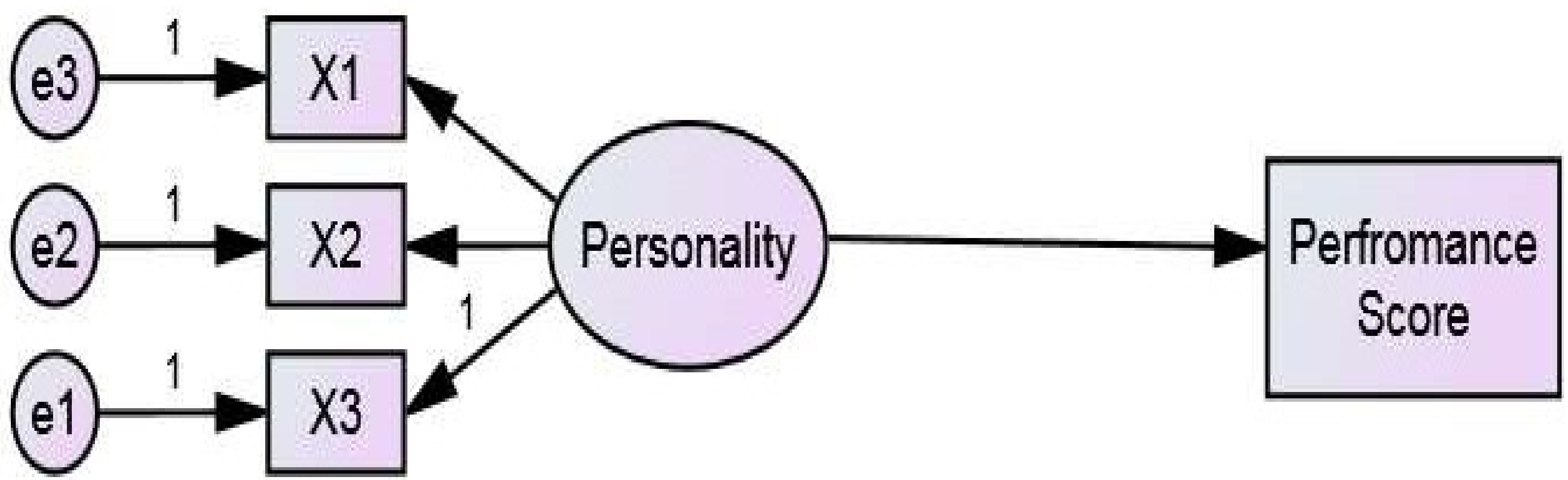


Employee **Supervisor**

Primary Data **Primary Data**

Multiple Source Data

Multiple Source – Different Method



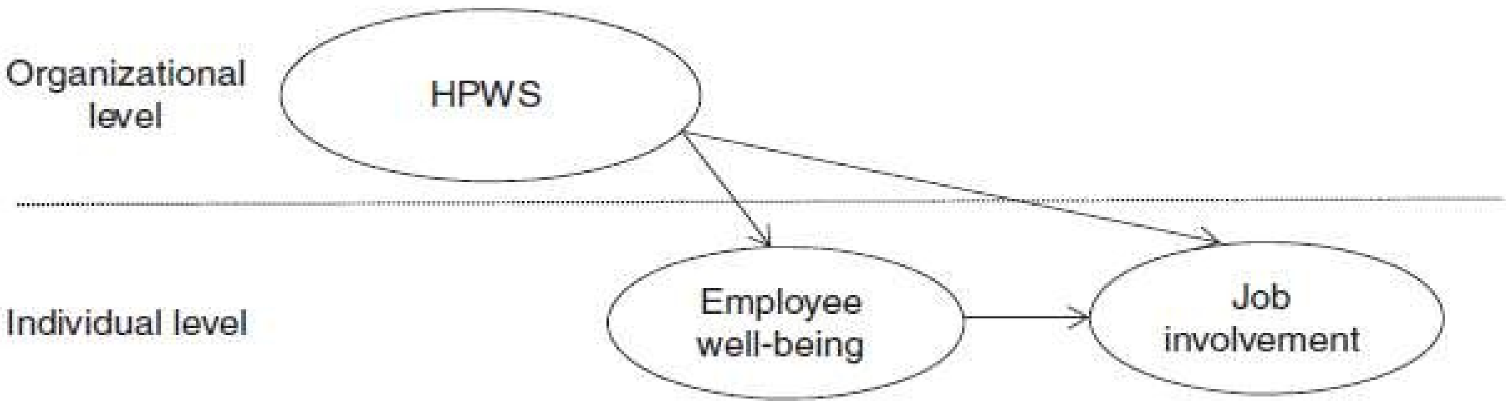
Employee

Annual Evaluation

Primary Data

Secondary Data

Multilevel Modeling

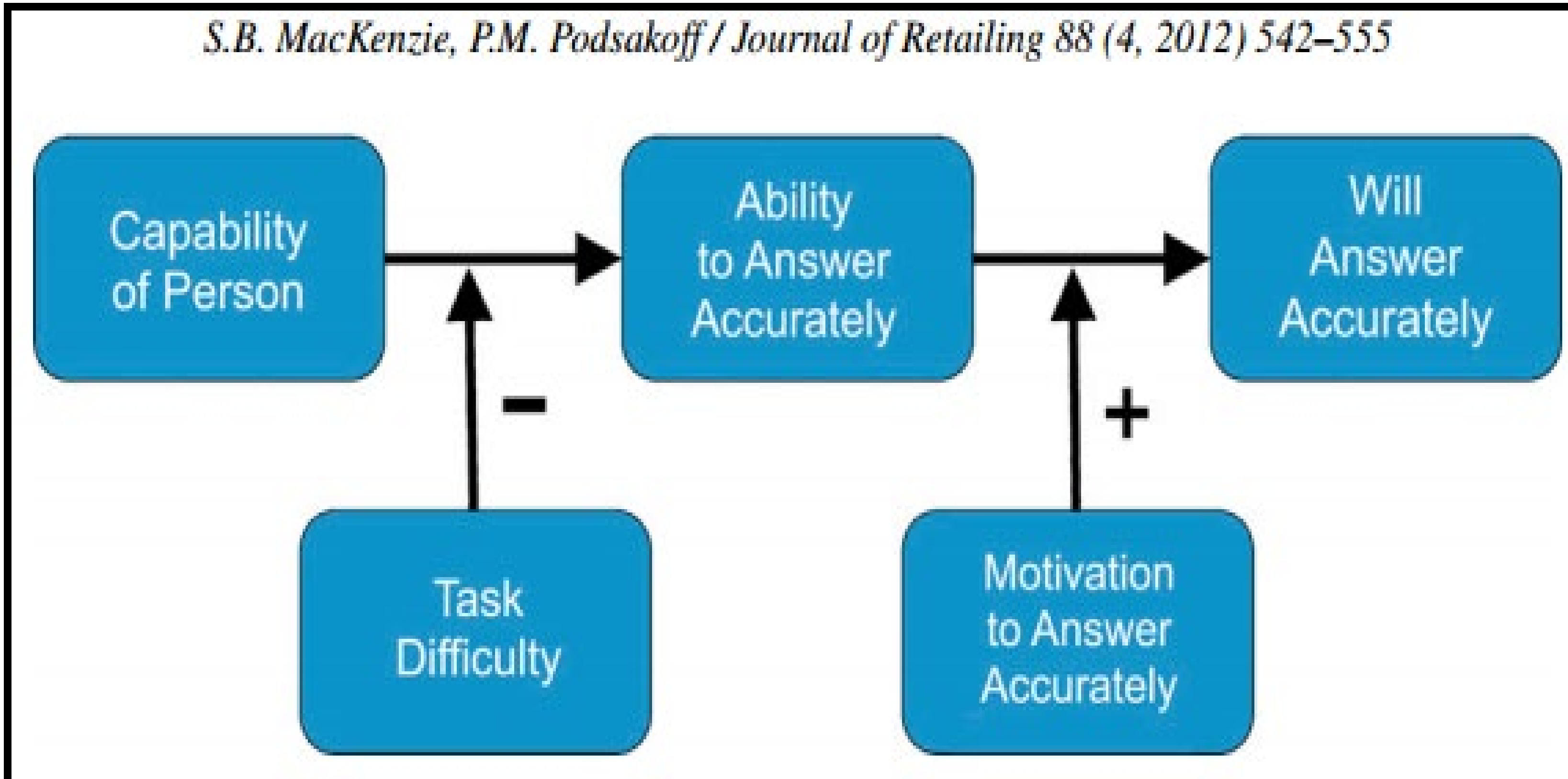


	Mean	SD	1	2	3	4	5
Organization level ($n = 50$)							
1. Company size	6.88	1.60	0.06				
2. HPWS	4.42	0.58	(0.76)				
Individual level ($n = 451$)							
3. Year of service	7.65	6.76					
4. Employee well-being	4.06	0.57			0.07	(0.91)	
5. Job involvement	3.89	0.73			0.17**	0.19**	(0.81)

Notes: Coefficient αs are on diagonal. $^{**}p < 0.01$

Common Method Variance

Steps to reduce CMV



Common Method Variance

ARTICLE IN PRESS

JBR-08737; No of Pages 6

Journal of Business Research xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Research

ELSEVIER

Heresies and sacred cows in scholarly marketing publications☆

Barry J. Babin [a,*], Mitch Griffin [b,1], Joseph F. Hair Jr. [c]

[a] Max P. Watson Jr., College of Business Research, Louisiana Tech University, Ruston, LA 71227, USA
[b] Department of Marketing, Bradley University, Peoria, IL 61625, USA
[c] Department of Marketing, Kennesaw State University, Kennesaw, GA 30144, USA

ARTICLE INFO

Article history:
Received 1 April 2015
Received in revised form 1 September 2015
Accepted 1 September 2015
Available online xxxx

Keywords:
Heresy
Knowledge
Journals
Method
Marketing Research

ABSTRACT

Merriam-Webster defines *heresies* as "dissent or deviation from a dominant theory, opinion, or practice." This *Journal of Business Research* special issue and the editorial examine heresies and sacred cows in marketing research. Seven papers investigate different aspects of typical academic business journal presentations. Each manuscript critically analyzes generally accepted practices for the pursuit of publication in academic journals and reveals ways these practices may do more harm than good, hindering the goal of presenting true growth of knowledge through publication. The editorial provides an integrative schema for the manuscripts in the special issue. Providing a series of broader topics to tie the papers together, this special issue illustrates how the findings of each study can help improve our pursuit of knowledge. In addition, the editorial discusses heresies and sacred cows not covered by manuscripts in the current issue. The editorial concludes with recommendations for both authors and reviewers that may enhance the approach to research, methodologies employed, and reporting of scholarly research.

Remedy to CMV

- If we find evidence of common method bias, **is there anything we can do to eliminate or at least reduce it?**
- The answer is arguably **“yes”,** and, given the focus of our discussion, the steps discussed by **Kock & Lynn (2012)** for dealing with collinearity are an obvious choice:
    1. indicator removal,
    2. indicator re-assignment,
    3. latent variable removal,
    4. latent variable aggregation, and
    5. hierarchical analysis.

Reverse Coding Issue

ATTITUDE					
My information sharing with other organizational members is good	1	2	3	4	5
My information sharing with other organizational members is harmful	1	2	3	4	5
My information sharing with other organizational members is an enjoyable experience	1	2	3	4	5
My information sharing with other organizational members is valuable to me	1	2	3	4	5
My information sharing with other organizational members is a wise move	1	2	3	4	5

Reverse Coding Issue

Journal of Cross-Cultural Psychology
http://jcc.sagepub.com/

The Relation Between Culture and Response Styles : Evidence From 19 Countries
Timothy Johnson, Patrick Kulesa, Isr Llc, Young Ik Cho and Sharon Shavitt
Journal of Cross-Cultural Psychology 2005 36: 264
DOI: 10.1177/0022022104272905

Do Reverse-Worded Items Confound Measures in Cross-Cultural Consumer Research? The Case of the Material Values Scale

NANCY WONG
ARIC RINDFLEISCH
JAMES E. BURROUGHS*

EFA vs CFA

Exploratory Factor Analysis

- Explore data and provide the researcher with information about how many factors are needed to best represent the data. All indicators are related to every factor by a factor loading estimate
- Is based on software decision in which the result are produced from correlation statistic result but not from theory.
- Can be performed when little is known about factor structure

Confirmatory Factor Analysis

- Is based on well-developed measurement theory to confirm that the indicator is measuring the construct.
- Is used when a priori factor structure exists.
- When conducting CFA, one cannot drop more than 20% of the items in the model. Doing so one has to resort to EFA.
- It is not entirely appropriate to conduct CFA based on EFA results and that CFA and EFA cannot be conducted using the same set of data (Kline, 2015; Green et al., 2016)

EFA vs CFA

Article

Organizational Research Methods
1-32

DOI: 10.1177/1094428116631417
orm.sagepub.com
SAGE

Getting Through the Gate: Statistical and Methodological Issues Raised in the Reviewing Process

Jennifer P. Green[1], Scott Tonidandel[2] and Jose M. Cortina[1]

Issue	Recommendation	References
There are issues with choice of EFA or CFA (e.g., why EFA instead of CFA, or vice-versa).	EFA is more appropriate when little is known about factor structure. If an a priori factor structure exists, then CFA is more appropriate.	Bandalos and Boehm-Kaufman (2009); Floyd and Widaman (1995); Henson and Roberts (2006)
Authors conducted EFA and CFA on same data set.	Factor structure from an EFA should be confirmed with CFA on a different data set.	Henson and Roberts (2006)
Authors used questionable factor analytic methods (e.g., improperly eliminated items in CFA/ SEM).	Be aware of best practices for factor analyses, such as EFA methods to determine the number of factors to retain (e.g., parallel analysis).	O'Connor (2000); Zwick and Velicer (1986)

CFA vs CCA

CCA Confirmatory Composite Analysis	CFA Confirmatory Factor Analysis
Total Variance	Common Variance Only
Both Exploratory and Confirmatory Analyzes Independent and Dependent Variables Together, but Focuses on Measurement Confirmation Objective is Confirming Measurement Models and also Prediction of Dependent Variables Composites (constructs) are Correlated	Confirmatory Only Analyzes All Variables Together as Measurement Models Objective is Confirming Measurement Models Composites (constructs) are Correlated
Reliability Examined Typically Composite Reliability Reflective Measurement Models Convergent Validity Reflective Measurement Models Discriminant Validity Construct Composite Scores applied in Structural Modeling	Reliability Examined Typically Composite Reliability Reflective Measurement Models Convergent Validity Reflective Measurement Models Discriminant Validity Construct Latent Factors applied in Structural Modeling
Construct Composite Scores are Determinant	Construct Factor Scores are Indeterminant

CCA by Hair et al. (2020)

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Assessing measurement model quality in PLS-SEM using confirmatory composite analysis

Joe F. Hair Jr.[a,*], Matthew C. Howard[a], Christian Nitzl[b]

[a] *Department of Marketing & Quantitative Methods, Mitchell College of Business, University of South Alabama, Mobile, AL, USA*
[b] *Center for Intelligence and Security Studies, University of the German Armed Forces, Munich, Germany*

A R T I C L E I N F O

Keywords:
Confirmatory composite analysis
CCA
PLS-SEM
Confirmatory factor analysis
CFA
Measurement model confirmation

A B S T R A C T

Confirmatory factor analysis (CFA) has historically been used to develop and improve reflectively measured constructs based on the domain sampling model. Compared to CFA, confirmatory composite analysis (CCA) is a recently proposed alternative approach applied to confirm measurement models when using partial least squares structural equation modeling (PLS-SEM). CCA is a series of steps executed with PLS-SEM to confirm both reflective and formative measurement models of established measures that are being updated or adapted to a different context. CCA is also useful for developing new measures. Finally, CCA offers several advantages over other approaches for confirming measurement models consisting of linear composites.

CCA by Schuberth et al. (2020) & Henseler (2020)

Table 1 Main differences between confirmatory composite analysis and the method of confirming measurement quality

	Confirmatory composite analysis (CCA, Schuberth et al. 2018)	Method of confirming measurement quality (MCMQ, Hair et al. 2020)
Purpose:	Assessing composite models	Confirming the quality of reflective and formative measurement models
Steps:	Model specification, model identification, model estimation, model assessment	Seven steps to assess reflective measurement models and five steps to assess formative measurement models
Relation to PLS:	Not tied to PLS, but it can serve as an estimator	MCMQ is the evaluation step of PLS-SEM
Role of Fit:	Assessment of model fit is an essential step of CCA	MCMQ does not require the assessment of model fit
Efficacy:	Evidence of its efficacy (mathematical and empirical)	Counterevidence of its efficacy

Review of Managerial Science
https://doi.org/10.1007/s11846-020-00405-0

ORIGINAL PAPER

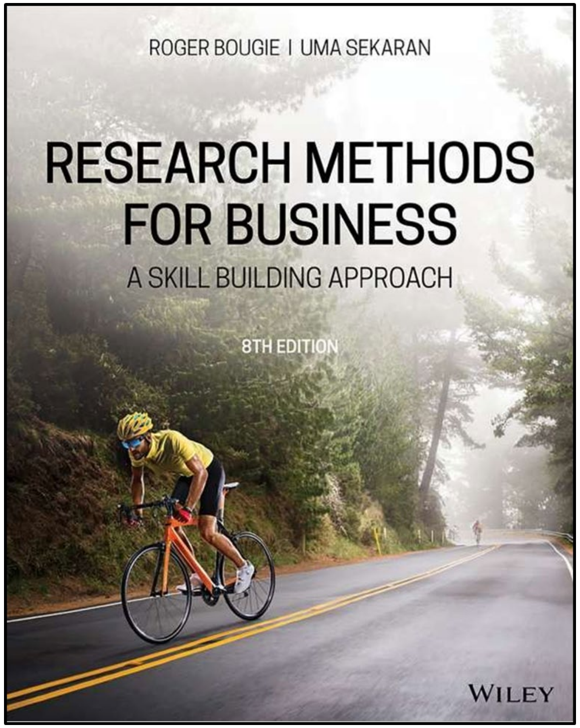
Check for updates

Confirmatory composite analysis using partial least squares: setting the record straight

Florian Schuberth[1]

Missing Value Imputation

Traditional Trend of MV Imputation
- No replacement
- Mid point of the scale
- Random number
- Mean value of other respondents
- Mean value of other responses



Current Trend of MV Imputation
- Full Information Maximum Likelihood (FIML)
- **Expectation Maximization (EM)**
- **Multiple Imputation (MI)**

https://www.youtube.com/watch?v=P57sC7sGVm8

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.

Social Desirability Measure

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

EDUCATIONAL AND PSYCHOLOGICAL MEASUREMENT
1993, 53

MEASURING SOCIAL DESIRABILITY: SHORT FORMS OF THE MARLOWE-CROWNE SOCIAL DESIRABILITY SCALE

DONALD G. FISCHER[1] AND CAROL FICK
University of Saskatchewan, Saskatoon, Canada

A practical difficulty with the Marlowe-Crowne Social Desirability Scale (SDS) is its length. Preferring a shorter measure of social desirability, researchers have devised a number of short forms of the SDS. The present study used confirmatory factor analysis to establish the adequacy of these subscales in measuring social desirability. Results showed that (a) of the six short forms of SDS considered two models (X1 and X2) provide the best measures of social desirability, (b) improved measures of all of the models can be constructed, and (c) improved measures of the dimensions, denial and attribution, thought to measure the latent construct of social approval can also be constructed.

THE Marlowe-Crowne Social Desirability Scale (SDS) was developed as a means of measuring socially desirable responding (Crowne and Marlowe, 1960). The SDS contains 33 true-false items describing culturally approved behaviors with a low probability of occurrence and is generally used in conjunction with other self-report measures to control for socially desirable response tendencies in personality research. A practical difficulty with the SDS for many users is its length. Not surprisingly, a number of short forms of the SDS have emerged, devised with the aid of factor analysis on the original scale (Reynolds, 1982; Strahan and Gerbasi, 1972). Strahan and Gerbasi (1972) produced two 10-item short forms and one 20-item short form (the 10-item scales combined), while Reynolds (1982) developed three scales, each with 11, 12 and 13 items,

Requests for reprints should be sent to Donald G. Fischer, Department of Psychology, University of Saskatchewan, Saskatoon, SASK., Canada S7H 0W0.

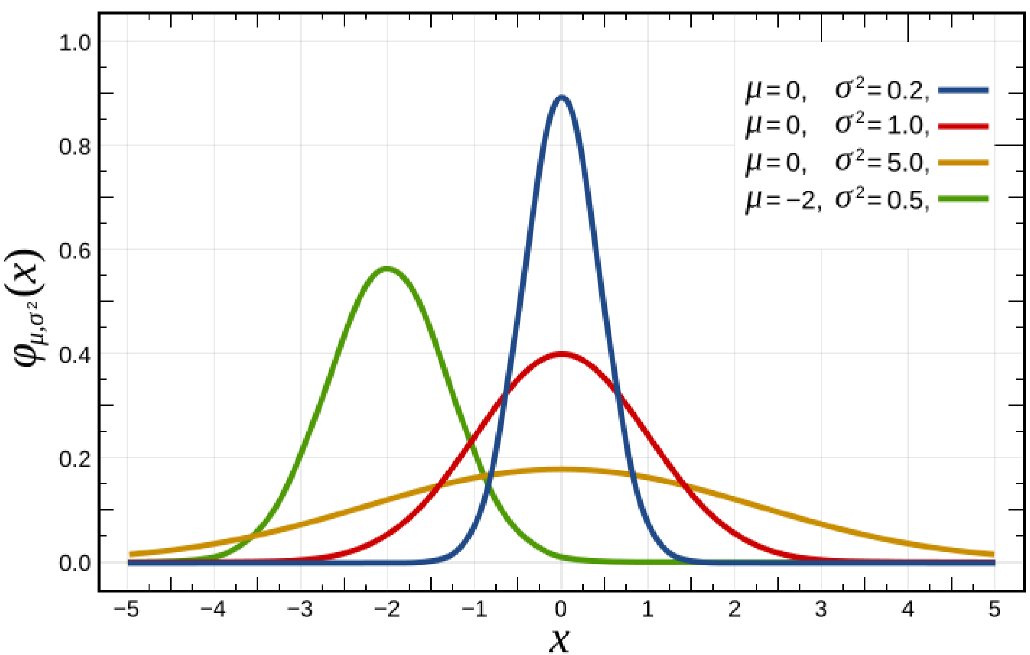
Type of Analysis

i. Parametric

- Assumption-Normal Distribution

ii. Non-Parametric

- Assumption- Distribution Free



Details difference of type of analysis

BASIS FOR COMPARISON	PARAMETRIC TEST	NONPARAMETRIC TEST
Meaning	A statistical test, in which specific assumptions are made about the population parameter is known as parametric test.	A statistical test used in the case of non-metric independent variables, is called non-parametric test.
Basis of test statistic	Distribution	Arbitrary
Measurement level	Interval or ratio	Nominal or ordinal
Measure of central tendency	Mean	Median
Information about population	Completely known	Unavailable
Applicability	Variables	Variables and Attributes
Correlation test	Pearson	Spearman

Details difference of type of analysis

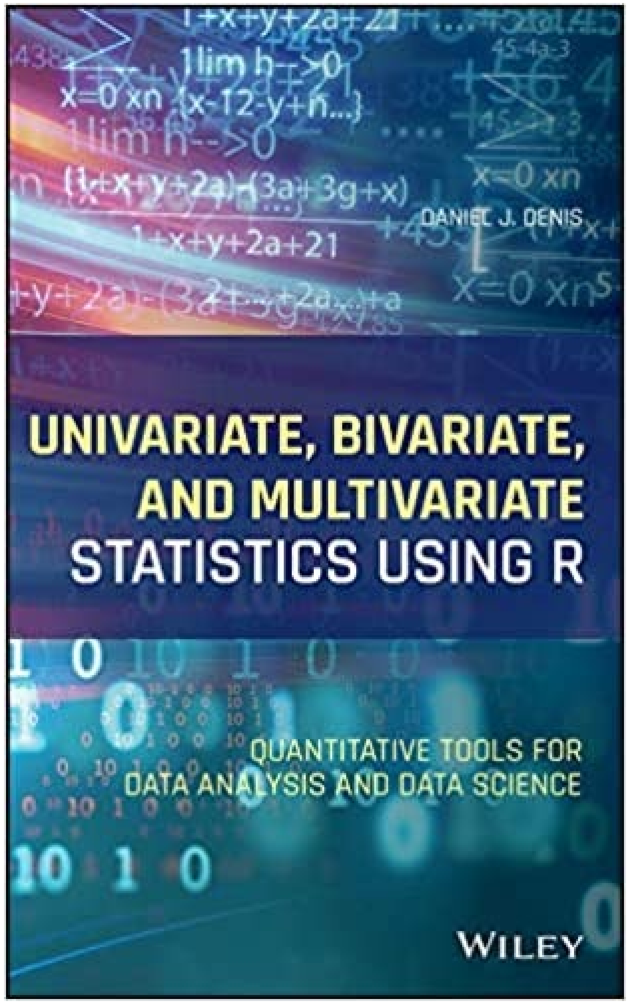
			Criterion / Measure / Dependent Variable (Continuous)	
			Non-Parametric Test	Parametric Equivalent
Predictor / Covariate / Independent Variable	Categorical	1 Variable 2 Categories Between-subjects	**Mann-Whitney U Test** (Nonparametric Tests → Legacy Dialogs → 2 Independent Samples)	**Independent *t* Test**
		1 Variable 2 Categories Within-subjects	**Wilcoxon Signed Rank Test** (Nonparametric Tests → Legacy Dialogs → 2 Related Samples)	**Paired *t* Test**
		1 Variable >2 Categories Between-subjects	**Kruskal-Wallis H Test** (Nonparametric Tests → Legacy Dialogs → K Independent Samples)	**One-Way ANOVA**
		1 Variable >2 Categories Within-subjects	**Friedman Test** (Nonparametric Tests → Legacy Dialogs → K Related Samples)	**Repeated Measures ANOVA**
	Correl	1 Variable	**Spearman's ρ (rho)** (Correlate → Bivariate → ☑ Spearman)	**Pearson's *r***

Number of Variables Involved

i. Univariate

ii. Bivariate

iii. Multivariate



Levels of Measurement

(1) Nominal

- Assigns a value to an object for identification or classification purposes.
- Most elementary level of measurement.

(2) Ordinal

- Ranking scales allowing things to be arranged based on how much of some concept they possess.

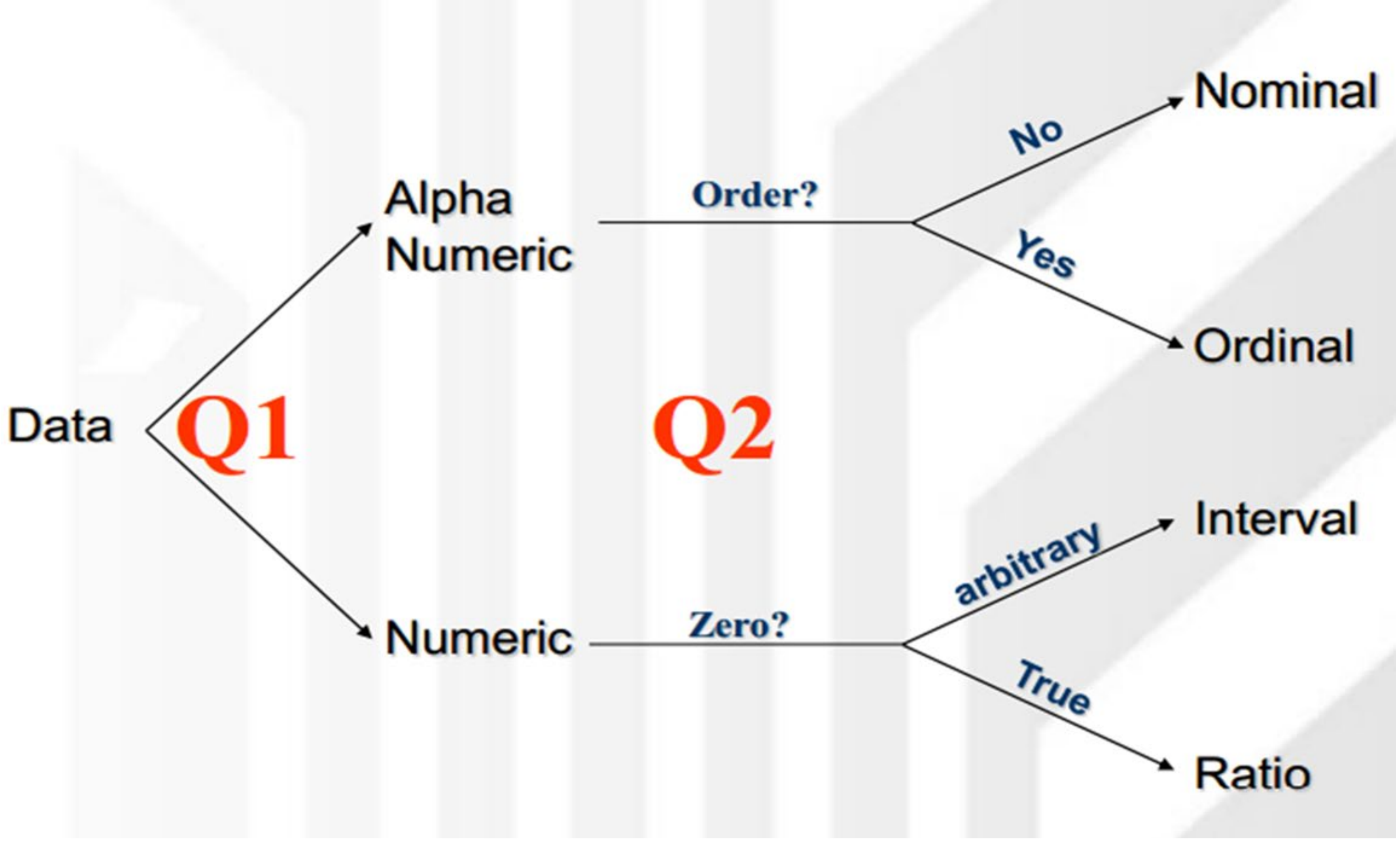
(3) Interval

- Interval scales have both nominal and ordinal properties.
- But they also capture information about differences in quantities of a concept.

(4) Ratio

- Highest form of measurement.
- Have all the properties of interval scales with the additional attribute of representing absolute quantities.
- Absolute zero.

Steps to Determine Scales of Measurement



Summary of Scales by Data Levels

Scale Type	Characteristics	Empirical Operations
Nominal	Classification (mutually exclusive and collectively exhaustive categories), but no order, distance, or natural origin	• Count (frequency distribution); *mode* as central tendency; No measure of dispersion • Used with other variables to discern patterns, reveal relationships
Ordinal	Classification and order, but no distance or natural origin	• Determination of greater or lesser value • Count (frequency distribution); median as central tendency; nonparametric statistics
Interval	Classification, order, and distance (equal intervals), but no natural origin	• Determination of equality of intervals or differences • Count (frequency distribution); mean or median as measure of central tendency; measure of dispersion is standard deviation or interquartile range; parametric tests
Ratio	Classification, order, distance, and natural origin	• Determination of equality of ratios • Any of the above statistical operations, plus multiplication and division; mean as central tendency; coefficients of variation as measure of dispersion

Mathematical and Statistical Analysis of Scales

- **Discrete Measures**
  - Measures that can take on only one of a finite number of values.

- **Continuous Measures**
  - Measures that reflect the intensity of a concept by assigning values that can take on any value along some scale range.

Data Preparation

i. Data entry (*Will show manually*)
ii. Data Screening (Will show manually using excel)
iii. Missing Values
iv. Data Cleaning
v. Compute & Recode
vi. Assumptions (i.e., Common Method Bias, Reliability, and Validity using EFA)

Note: All these can be done via Excel, SPSS, and some web software tools.

Handling Blank Response

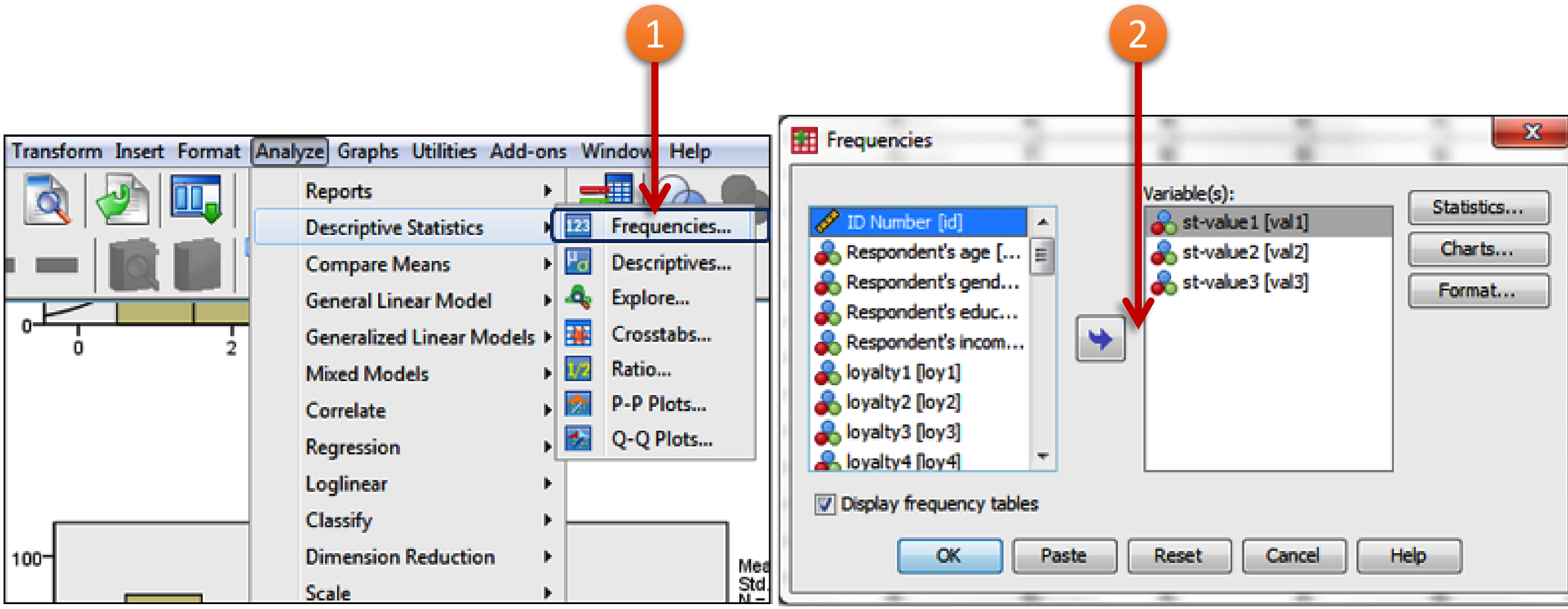
- **How do we take care of missing response?**
  - If > 25% missing, throw out the questionnaire
  - If majority data point missing for dependent variable, throw out the particular questionnaire

- **Other ways of handling**
  - Use the midpoint of the scale
  - Ignore (system missing)
  - Mean of those responding
  - Mean of the respondent
  - Random number

- **Advanced ways of handling**
  - Full Information Maximum Likelihood (FIML)
  - Expectation Maximization (EM)
  - Multiple Imputation (MI)

https://www.youtube.com/watch?v=P57sC7sGVm8

Detecting Missing Data



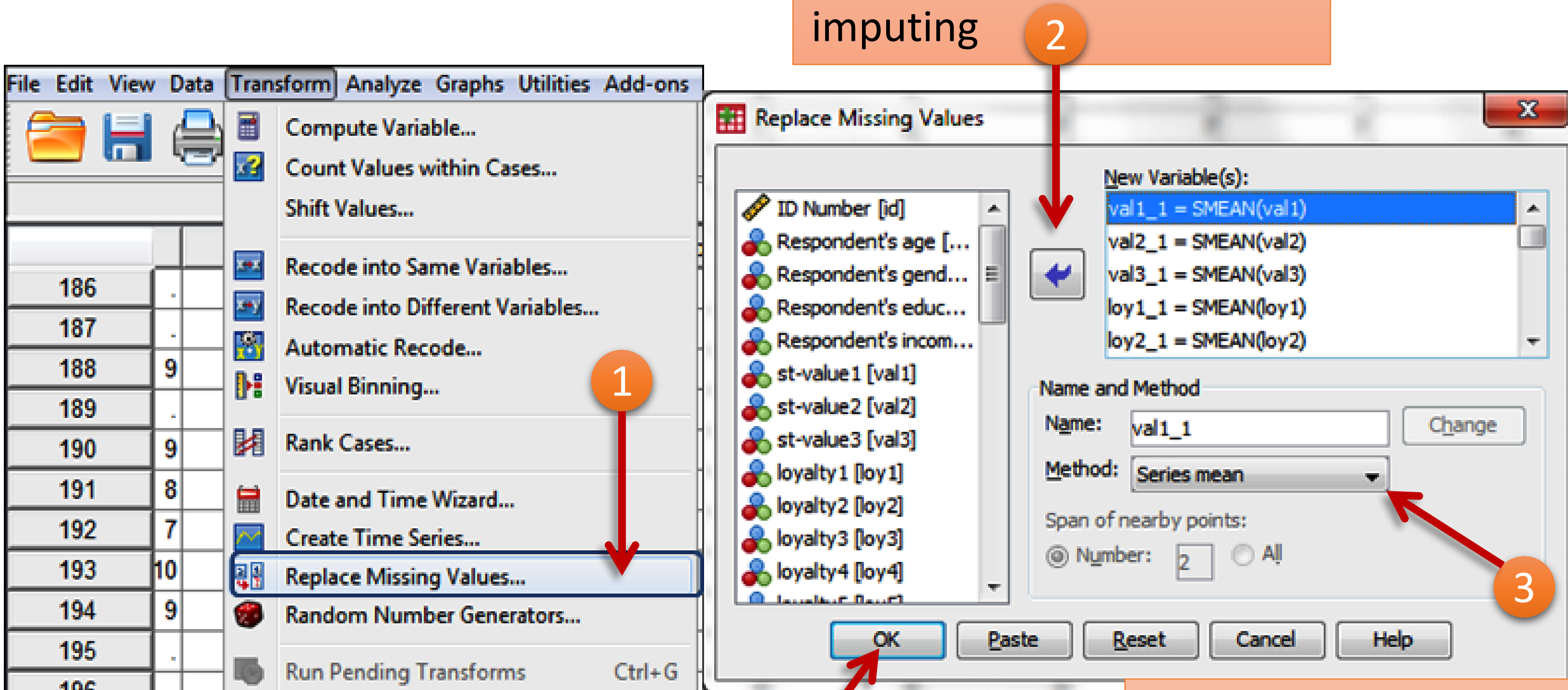
Statistics

		st-value1	st-value2	st-value3
N	Valid	317	297	299
	Missing	23	43	41

3

Handling Missing Data

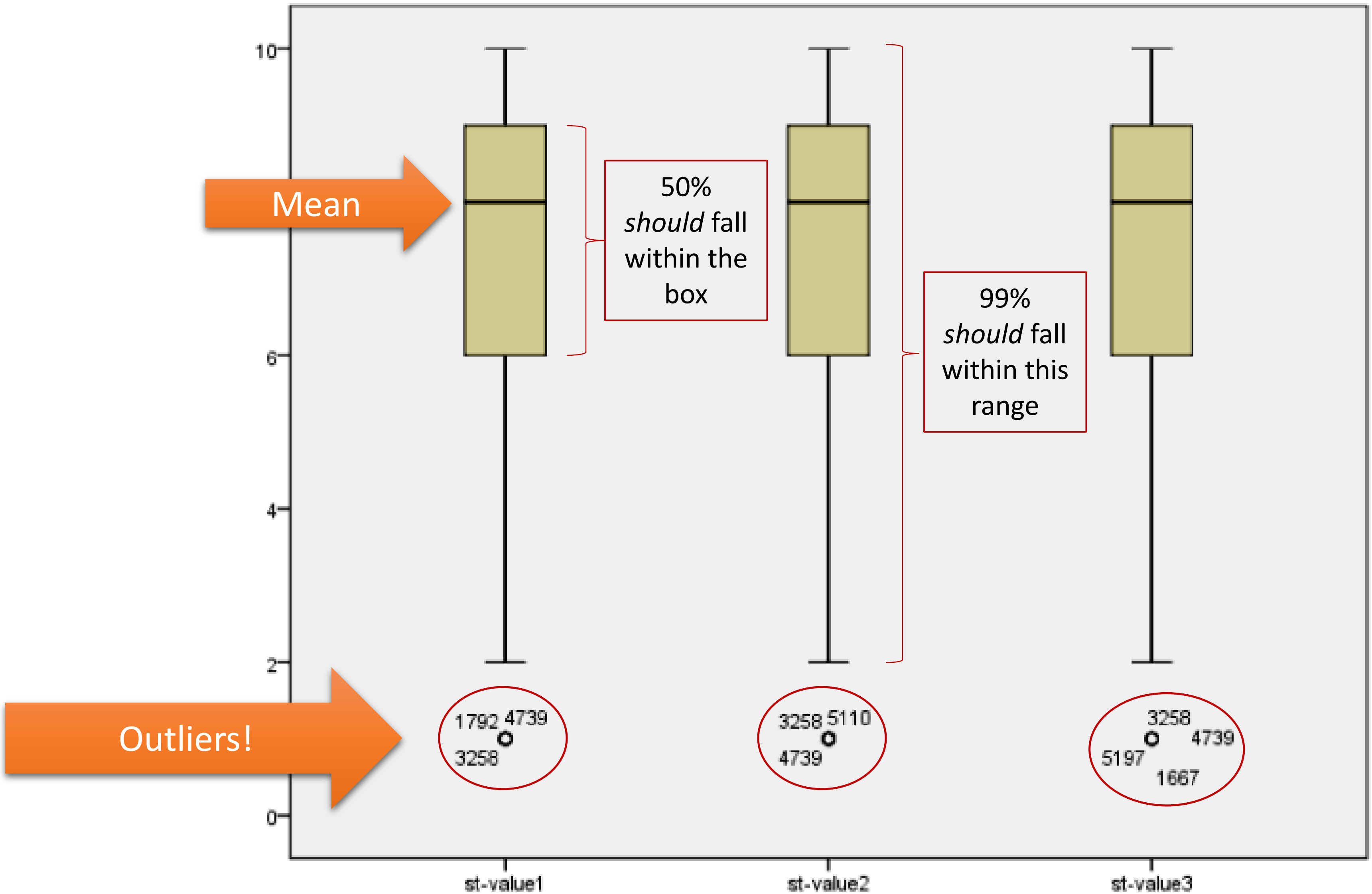
2. Include each variable that has values that need imputing



4

3. For each variable you can choose the new name (for the imputed column) and the type of imputation

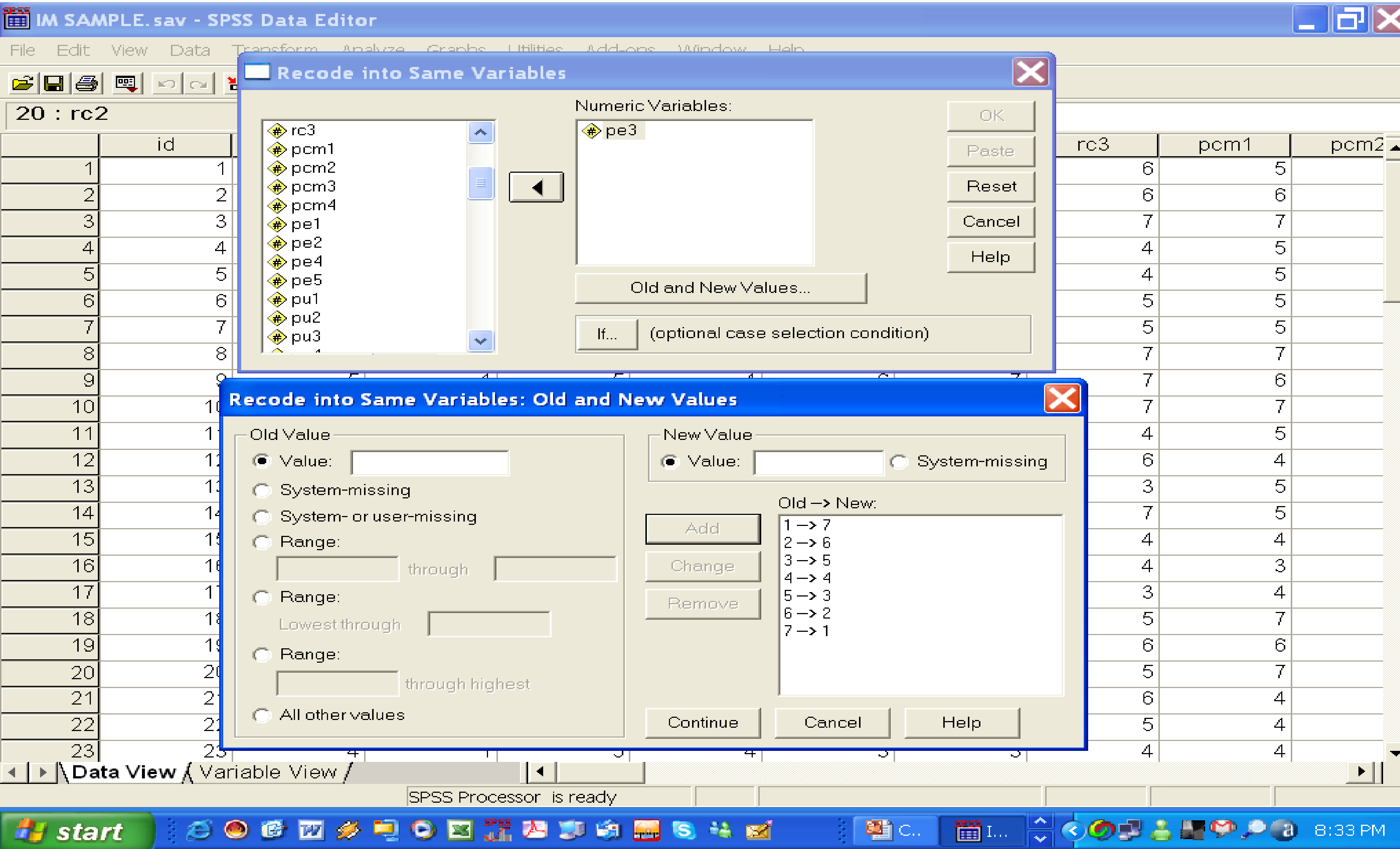
Detecting Univariate Outliers



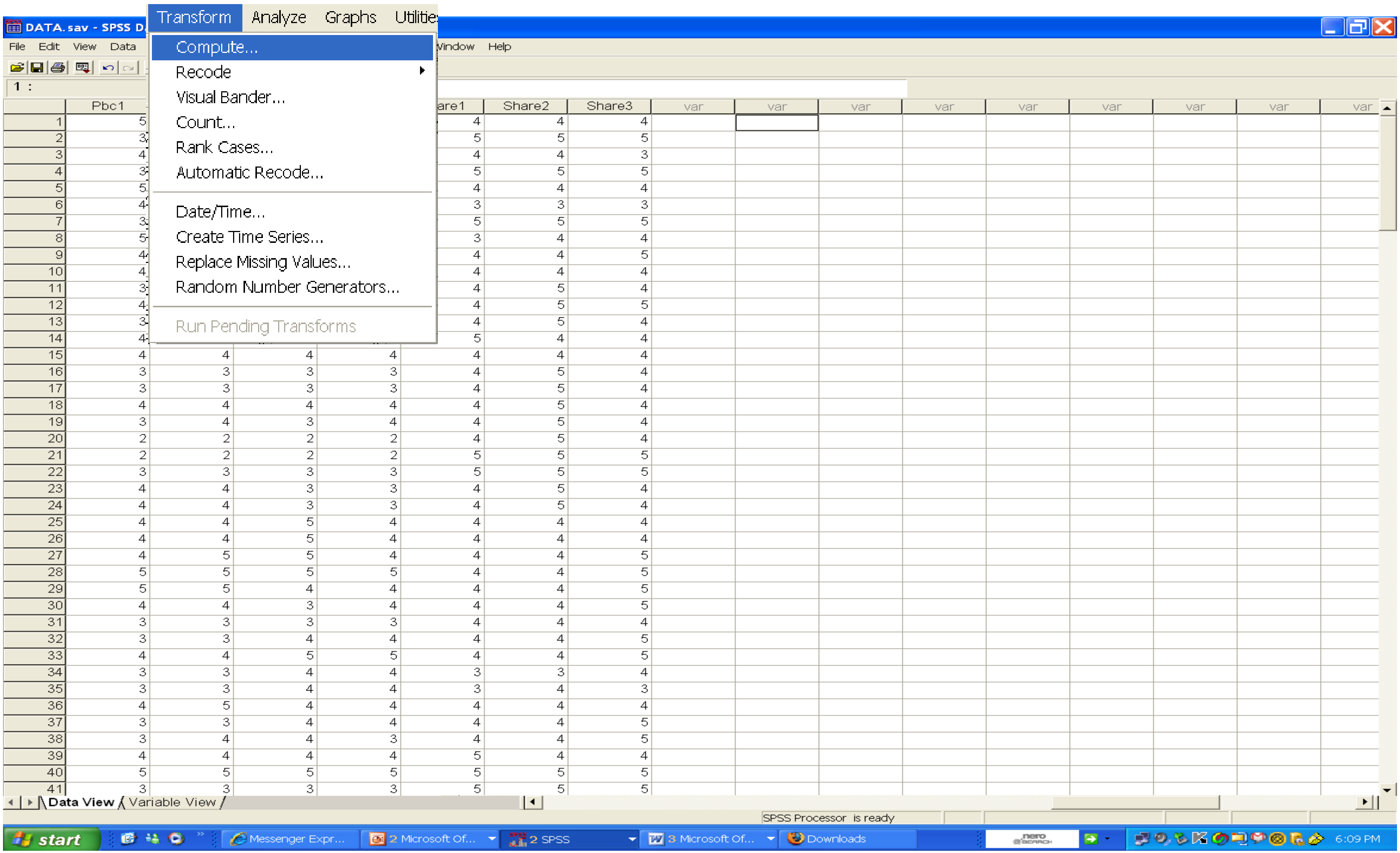
Example - Recoding

	Perceived Enjoyment							
PE1	The actual process of using Instant Messenger is pleasant	1	2	3	4	5	6	7
PE2	I have fun using Instant Messenger	1	2	3	4	5	6	7
PE3	Using Instant Messenger bores me	1	2	3	4	5	6	7
PE4	Using Instant Messenger provides me with a lot of enjoyment	1	2	3	4	5	6	7
PE5	I enjoy using Instant Messenger	1	2	3	4	5	6	7

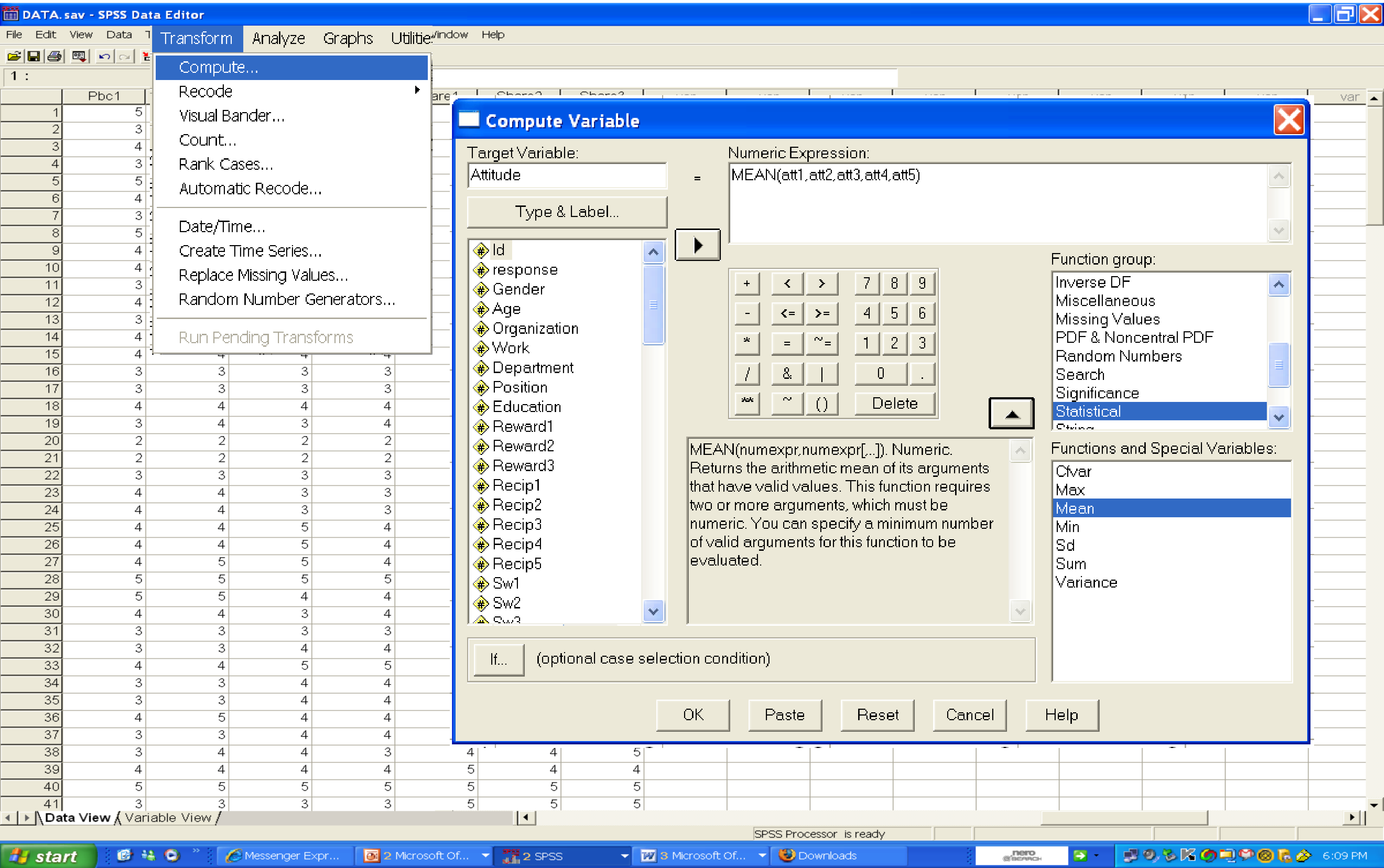
Recoding - Command



Computation



Computing New Variable - Command



Data after Transformation

DATA.sav - SPSS Data Editor

1 : filter_$ 1

	Share1	Share2	Share3	Attitude	subjective	Pbcontrol	Intention	Actual
1	4	4	4	4.40	3.75	4.75	4.20	4.00
2	5	5	5	4.00	4.25	3.50	4.40	5.00
3	4	4	3	4.00	3.75	3.50	4.00	3.67
4	5	5	5	4.60	3.75	3.00	5.00	5.00
5	4	4	4	4.80	3.75	5.00	4.60	4.00
6	3	3	3	4.20	3.75	4.50	4.00	3.00
7	5	5	5	4.80	5.00	3.00	5.00	5.00
8	3	4	4	2.80	3.50	4.50	3.20	3.67
9	4	4	5	4.00	3.75	3.50	4.00	4.33
10	4	4	4	4.20	3.75	3.50	4.00	4.00
11	4	5	4	4.80	3.75	3.00	5.00	4.33
12	4	5	5	4.00	4.25	4.75	4.40	4.67
13	4	5	4	4.00	3.75	3.50	4.00	4.33
14	5	4	4	4.00	4.00	3.50	4.00	4.33
15	4	4	4	4.00	3.75	4.00	3.80	4.00
16	4	5	4	4.00	3.75	3.00	4.00	4.33
17	4	5	4	4.00	3.75	3.00	4.00	4.33
18	4	5	4	4.00	4.00	4.00	4.00	4.33
19	4	5	4	4.00	3.75	3.50	3.60	4.33
20	4	5	4	3.80	3.75	2.00	3.20	4.33
21	5	5	5	5.00	4.00	2.00	4.00	5.00
22	5	5	5	4.80	5.00	3.00	5.00	5.00
23	4	5	4	4.00	3.75	3.50	4.00	4.33
24	4	5	4	4.00	4.00	3.50	4.00	4.33
25	4	4	4	4.00	3.75	4.25	3.80	4.00
26	4	4	4	4.20	3.75	4.25	4.00	4.00
27	4	4	5	4.00	3.75	4.50	4.00	4.33
28	4	4	5	3.80	3.00	5.00	4.00	4.33
29	4	4	5	4.00	3.75	4.50	4.00	4.33
30	4	4	5	3.80	4.25	3.75	4.00	4.33
31	4	4	4	4.00	3.75	3.00	4.00	4.00
32	4	4	5	4.00	3.75	3.50	4.00	4.33
33	4	4	5	2.80	3.25	4.50	3.80	4.33
34	3	3	4	3.00	3.00	3.50	3.20	3.33
35	3	4	3	3.00	3.00	3.50	3.20	3.33
36	4	4	4	4.20	3.75	4.25	4.00	4.00
37	4	4	5	4.00	4.00	3.50	4.00	4.33
38	4	4	5	4.00	3.75	3.50	4.00	4.33
39	5	4	4	4.00	4.00	4.00	4.20	4.33
40	5	5	5	4.00	3.00	5.00	4.80	5.00
41	5	5	5	5.00	5.00	3.00	5.00	5.00

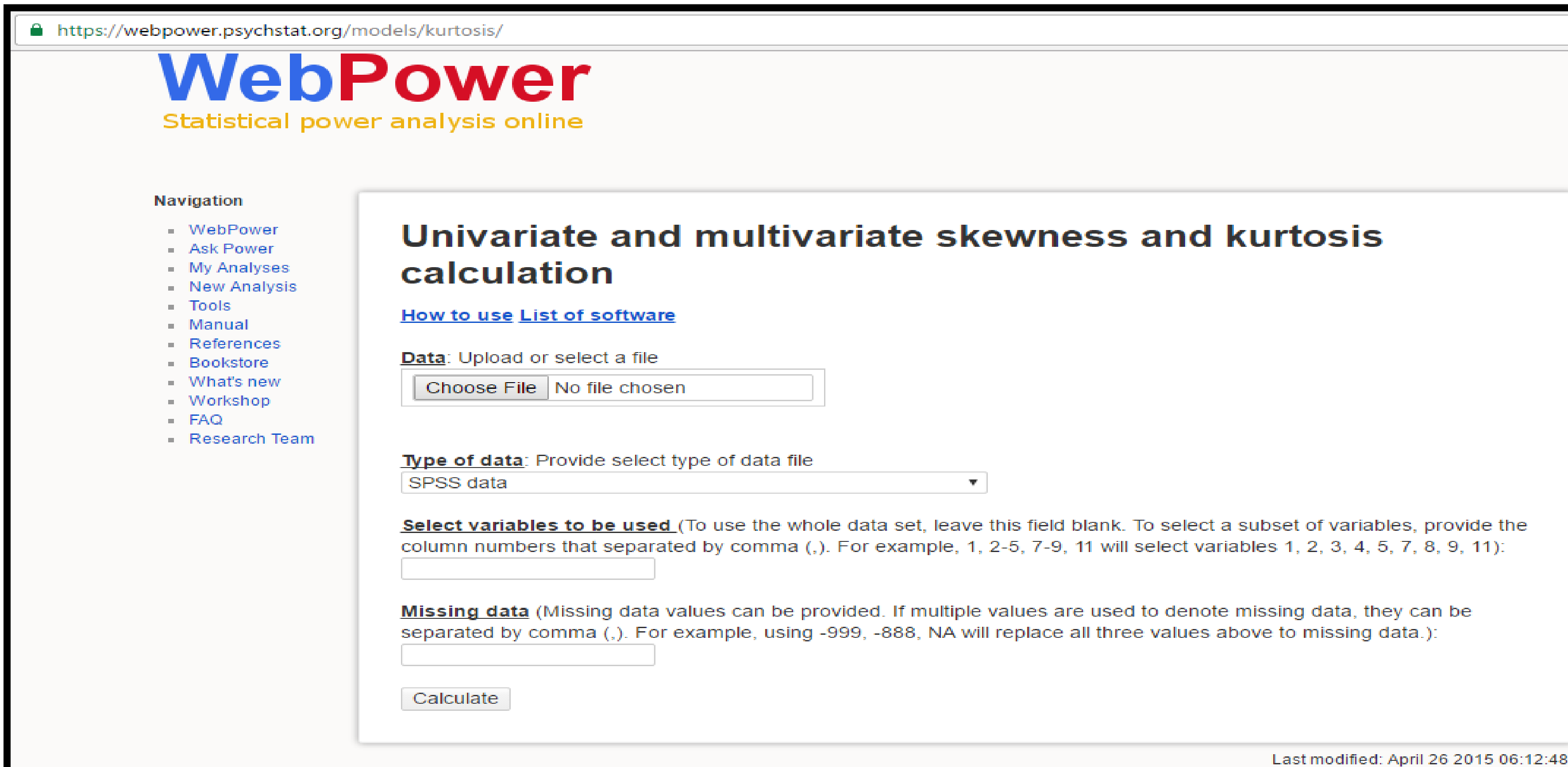
Data View / Variable View

SPSS Processor is ready

Assessment of Normality

i. Univariate Normality

ii. Multivariate Normality



https://webpower.psychstat.org/models/kurtosis/

Assessment of Normality

Data file

The data file can be chosen by clicking the Choose File button (it might appear differently for different browsers). We DO NOT save your data file and it is deleted immediately after calculation.

Type of data

The following types of data are allowed:

- SPSS data file with the extension name .sav
- SAS data file with the extension name .sas7bdat
- Excel data file with the extension name .xls or .xlsx
- CSV file (comma separated value data file) with extension name .csv
- TXT file (text file) with extension name .txt

Select variables

A subset of variables can be used. To use the whole data set, leave this field blank. To select a subset of variables, provide the column numbers that separated by comma (,). For example

```
1, 2-5, 7-9, 11
```

will select variables 1, 2, 3, 4, 5, 7, 8, 9, 11

Assessment of Normality

Missing data

Missing data values can be provided. If multiple values are used to denote missing data, they can be separated by comma (,). For example,

```
-999, -888, NA
```

will replace all three values above to missing data.

The output of the Web application looks like

```
Sample size:  563
Number of variables:  4

Univariate skewness and kurtosis
      Skewness   SE_skew   Kurtosis   SE_kurt
V1  0.69321372 0.1029601  0.2295460 0.2055599
V2  0.03685117 0.1029601 -0.4178298 0.2055599
V3 -0.22527112 0.1029601 -0.2521029 0.2055599
V4 -1.00006618 0.1029601  1.2898344 0.2055599

Mardia's multivariate skewness and kurtosis
                 b          z    p-value
Skewness  2.261878 212.239506 0.00000000
Kurtosis 25.468192   2.514123 0.01193288
```

Mardia's multivariate skewness and kurtosis *p-value < 0.05* indicates that the multivariate data is **not normal**

Assessment of Normality

Statistical power analysis online

Navigation

- WebPower
- Ask Power
- My Analyses
- New Analysis
- Tools
- Manual
- References
- Bookstore
- What's new
- Workshop
- FAQ
- Research Team

Univariate and multivariate skewness and kurtosis calculation

How to use List of software

Data: Upload or select a file

Choose File HairHBAT.csv

Type of data: Provide select type of data file

CSV (comma seperated value) data with variable names

Select variables to be used (To use the whole data set, leave this field blank. To select a subset of variables, provide the column numbers that separated by comma (,). For example, 1, 2-5, 7-9, 11 will select variables 1, 2, 3, 4, 5, 7, 8, 9, 11):

29-33

Missing data (Missing data values can be provided. If multiple values are used to denote missing data, they can be separated by comma (,). For example, using -999, -888, NA will replace all three values above to missing data.):

Calculate

Last modified: April 26 2015 06:12:48.

Common Method Variance

- CMV is the amount of spurious correlation between variables that is the result of using the same measurement method to measure each variables
- CMV may lead to erroneous conclusion about relationships between variables by inflating/deflating findings
- CMV needs to be examine when data are collected via self-reported questionnaires and, in particular, when the same person is answering on both predictor and criterion variables
- Two ways to control for CMV
  - Procedural control
  - Statistical control

Ex Ante Approaches (Procedure)

- Collect data from different source
  - NO – Reduce CMV through questionnaire design
  - YES – Collect Pre / Post Survey

Post Ante Approaches (Statistical)

- Complex model specification
- Partial out / control for latent
  - ***Harman Single Factor test***
  - Partial correlation method
  - Social desirability construct
  - Correlation matrix
  - Measured Latent Marker Variable
  - Full Collinearity
  - Unmeasured Latent Method Construct

Common Method Variance

ARTICLE IN PRESS

JBR-08737; No of Pages 6

Journal of Business Research xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Research

ELSEVIER

Heresies and sacred cows in scholarly marketing publications☆

Barry J. Babin [a,*], Mitch Griffin [b,1], Joseph F. Hair Jr. [c]

[a] *Max P. Watson Jr., College of Business Research, Louisiana Tech University, Ruston, LA 71227, USA*
[b] *Department of Marketing, Bradley University, Peoria, IL 61625, USA*
[c] *Department of Marketing, Kennesaw State University, Kennesaw, GA 30144, USA*

ARTICLE INFO

Article history:
Received 1 April 2015
Received in revised form 1 September 2015
Accepted 1 September 2015
Available online xxxx

Keywords:
Heresy
Knowledge
Journals
Method
Marketing Research

ABSTRACT

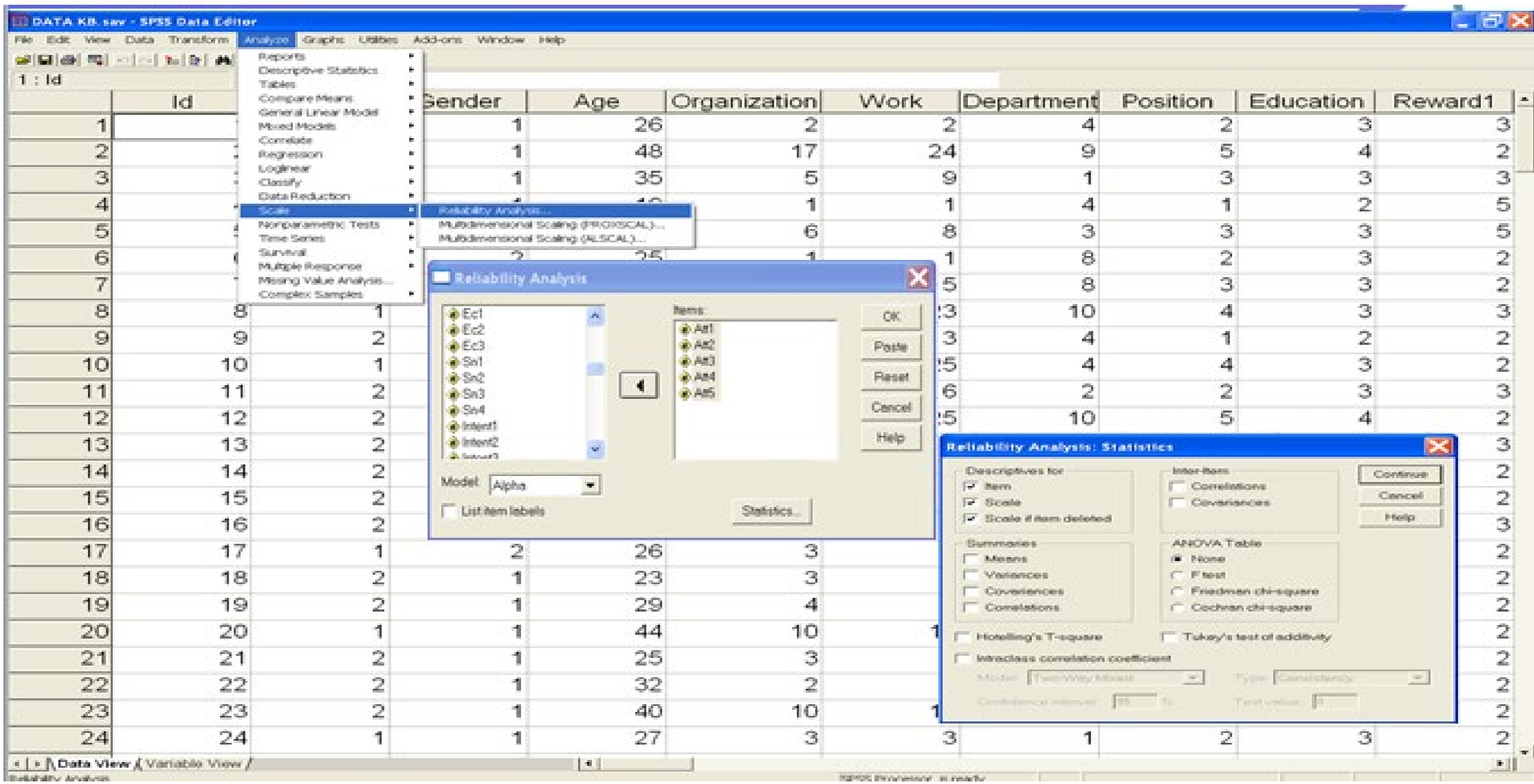
Merriam-Webster defines *heresies* as “dissent or deviation from a dominant theory, opinion, or practice.” This *Journal of Business Research* special issue and the editorial examine heresies and sacred cows in marketing research. Seven papers investigate different aspects of typical academic business journal presentations. Each manuscript critically analyzes generally accepted practices for the pursuit of publication in academic journals and reveals ways these practices may do more harm than good, hindering the goal of presenting true growth of knowledge through publication. The editorial provides an integrative schema for the manuscripts in the special issue. Providing a series of broader topics to tie the papers together, this special issue illustrates how the findings of each study can help improve our pursuit of knowledge. In addition, the editorial discusses heresies and sacred cows not covered by manuscripts in the current issue. The editorial concludes with recommendations for both authors and reviewers that may enhance the approach to research, methodologies employed, and reporting of scholarly research.

Reliability Test

- Reliability relates to the study instrument. Specifically, reliability is a measure of internal consistency of the study instrument.

- The most commonly use measure of internal consistency is Cronbach alpha*. Cronbach alpha coefficient ranges between 0 to 1. An instrument is considered to be reliable if Cronbach Alpha is at least 0.7

Command for Reliability Test



How reliable our instrument?

Reliability Statistics

Cronbach's Alpha	N of Items
.977	5

Should be preferably > 0.3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Att1	15.25	6.681	.973	.965
Att2	15.26	6.560	.925	.972
Att3	15.24	6.906	.929	.972
Att4	15.21	6.825	.900	.975
Att5	15.25	6.555	.935	.970

Table in Report

Variable	N of Item	Item Deleted	Alpha
Attitude	5	-	0.977
SN	4	-	0.912
Pbcontrol	4	-	0.919
Intention	5	-	0.966
Actual	3	-	0.933

EFA vs CFA

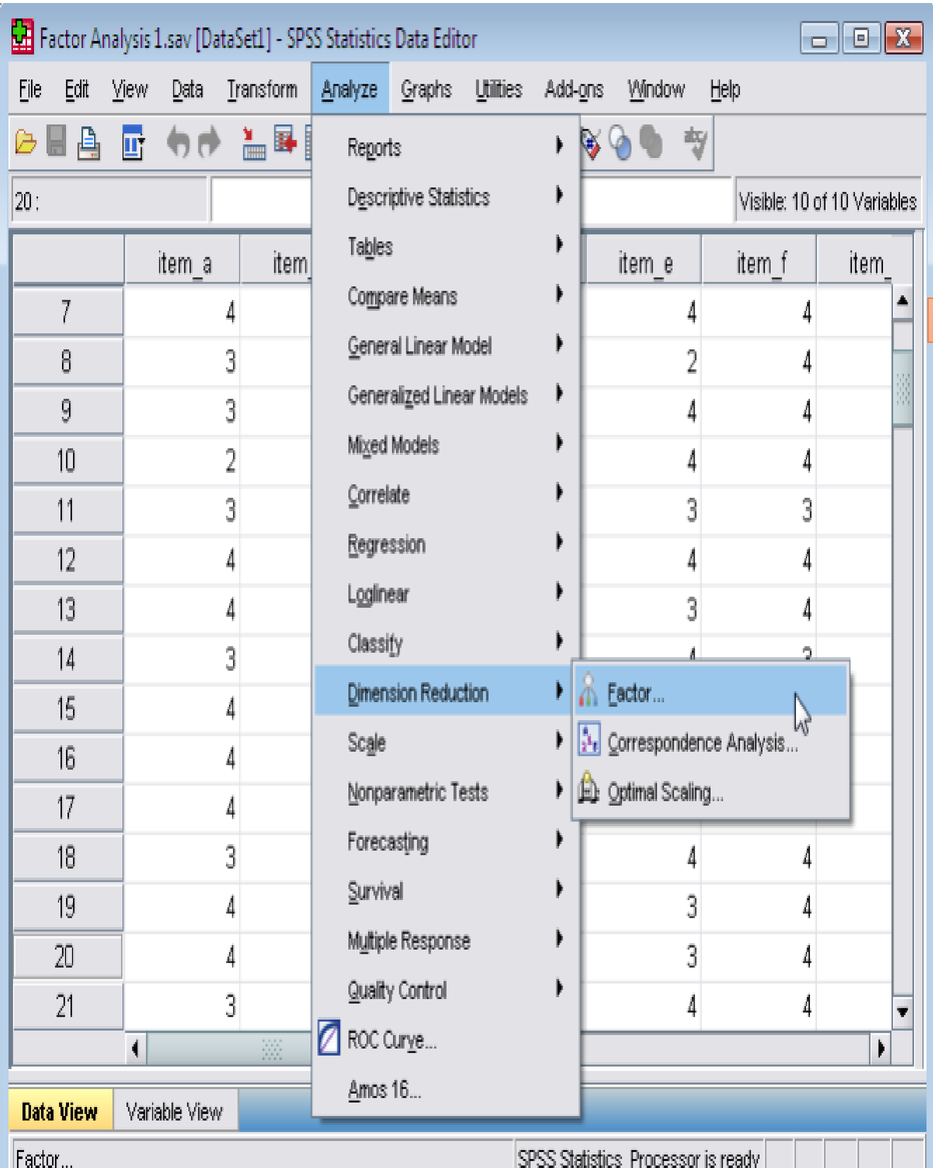
Exploratory Factor Analysis

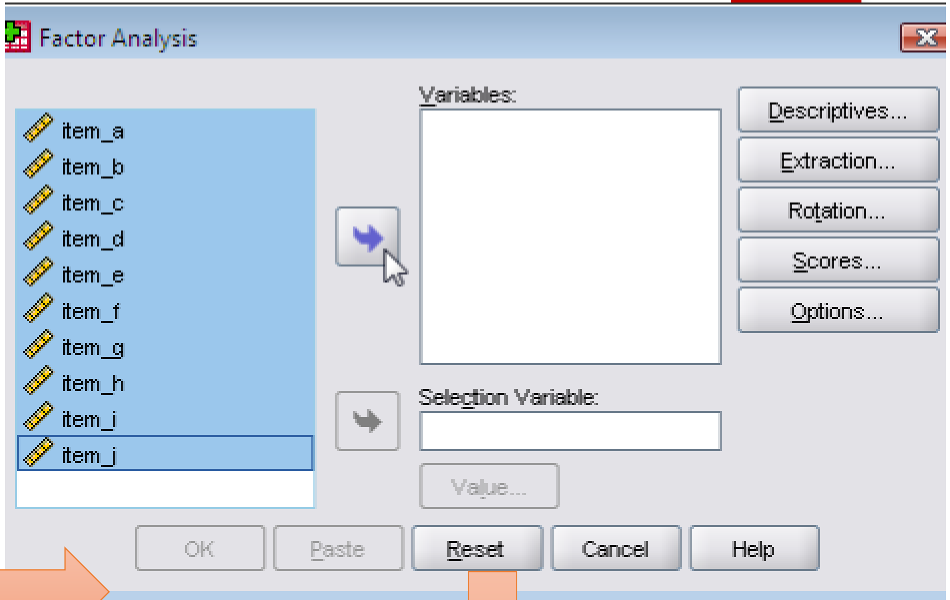
- Explore data and provide the researcher with information about how many factors are needed to best represent the data. All indicators are related to every factor by a factor loading estimate
- Is based on software decision in which the result are produced from correlation statistic result but not from theory.
- Can be performed when little is known about factor structure

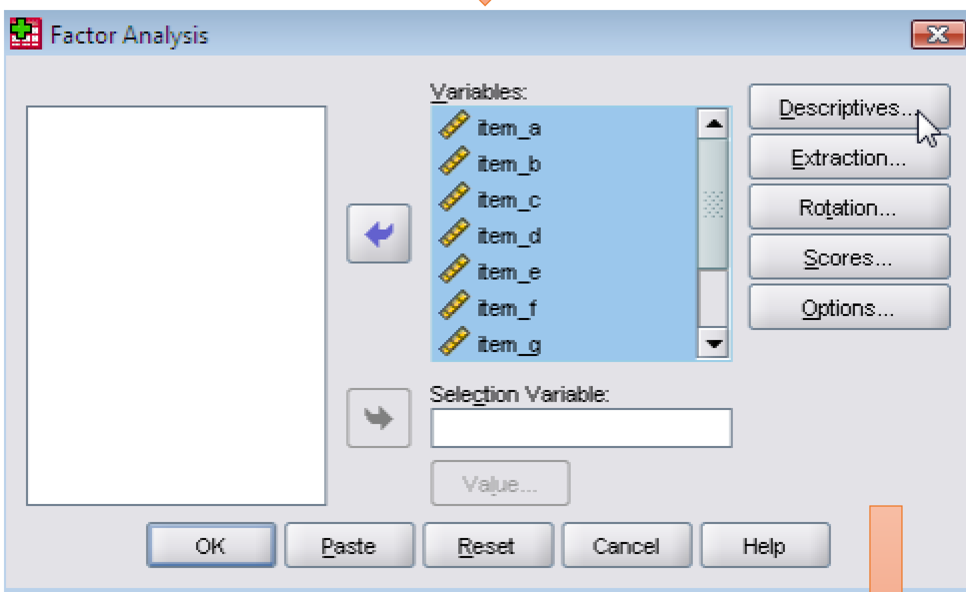
Confirmatory Factor Analysis

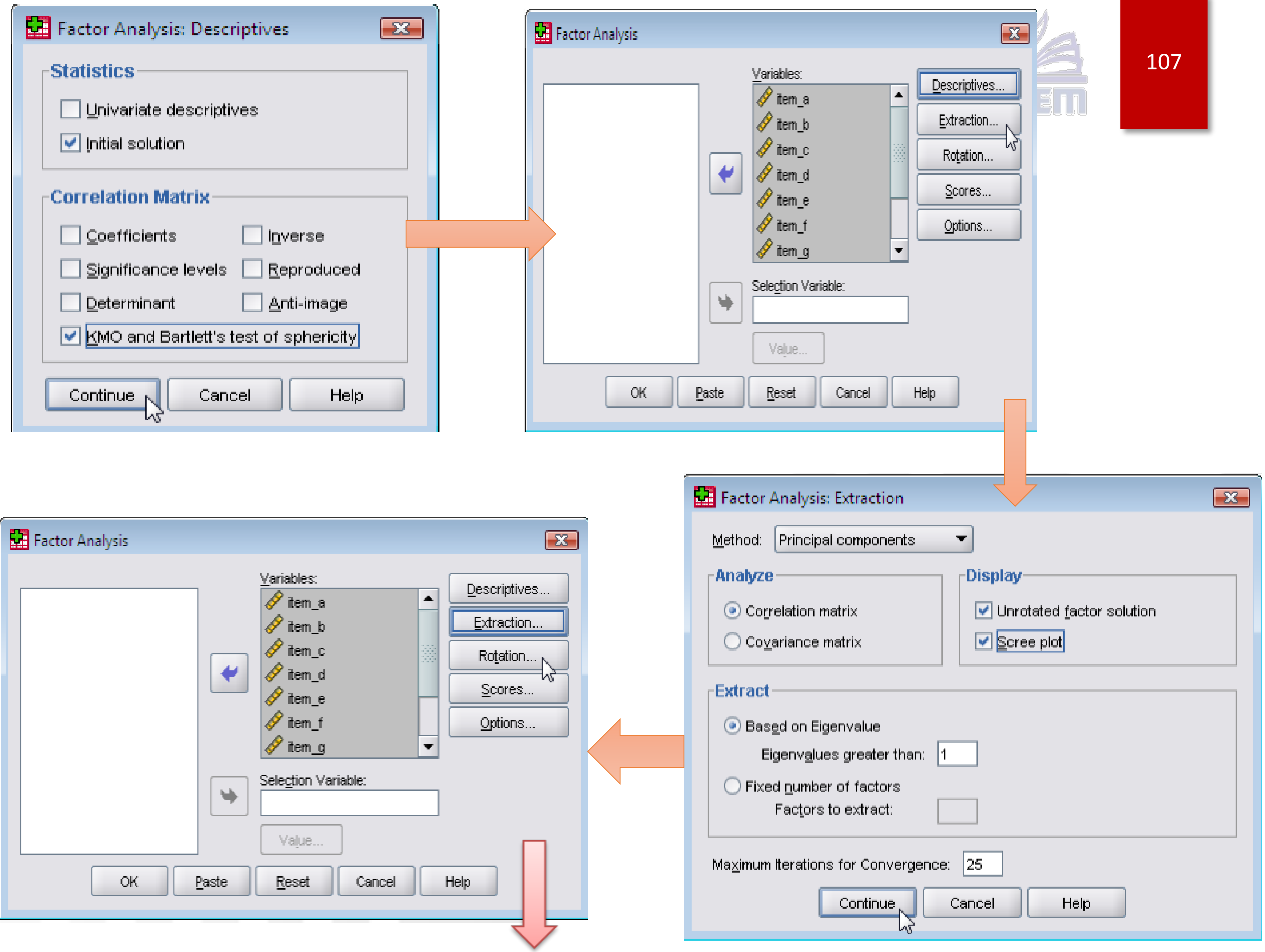
- Is based on well-developed measurement theory to confirm that the indicator is measuring the construct.
- Is used when a priori factor structure exists.
- When conducting CFA, one cannot drop more than 20% of the items in the model. Doing so one has to resort to EFA.
- It is not entirely appropriate to conduct CFA based on EFA results and that CFA and EFA cannot be conducted using the same set of data (Kline, 2015; Green et al., 2016)

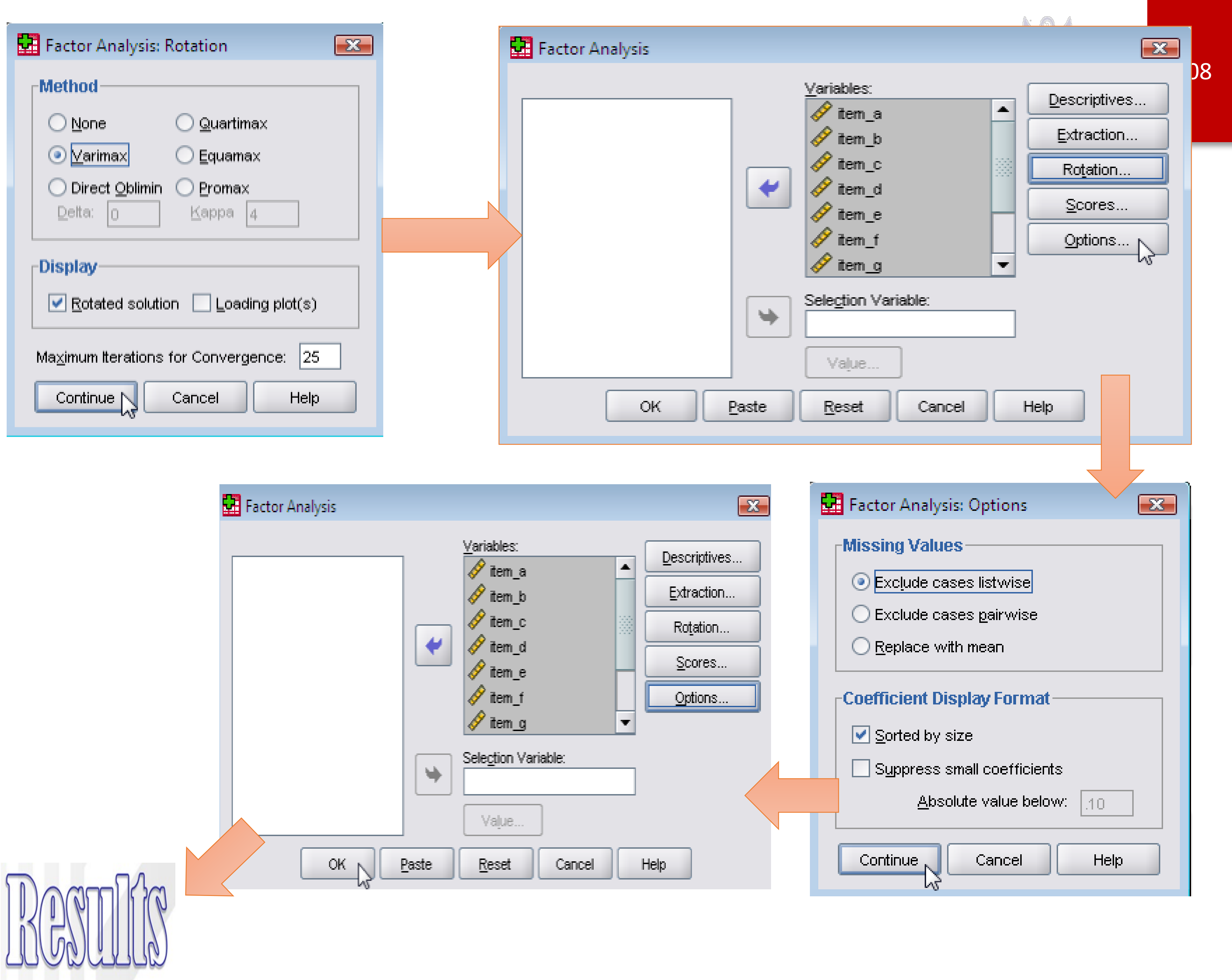
Basic EFA to check on validity








Factor Analysis: Descriptives
Statistics
Univariate descriptives
Initial solution
Correlation Matrix
Coefficients
Inverse
Significance levels
Reproduced
Determinant
Anti-image
KMO and Bartlett's test of sphericity
Continue
Cancel
Help
Factor Analysis
Variables:
item_a
item_b
item_c
item_d
item_e
item_f
item_g
Descriptives...
Extraction...
Rotation...
Scores...
Options...
Selection Variable:
Value...
OK
Paste
Reset
Cancel
Help
Factor Analysis: Extraction
Method:
Principal components
Analyze
Correlation matrix
Covariance matrix
Display
Unrotated factor solution
Scree plot
Extract
Based on Eigenvalue
Eigenvalues greater than:
1
Fixed number of factors
Factors to extract:
Maximum Iterations for Convergence:
25
Continue
Cancel
Help


Factor Analysis: Rotation
Method
None
Quartimax
Varimax
Equamax
Direct Oblimin
Promax
Delta: 0
Kappa 4
Display
Rotated solution
Loading plot(s)
Maximum Iterations for Convergence: 25
Continue
Cancel
Help
Factor Analysis
Variables:
item_a
item_b
item_c
item_d
item_e
item_f
item_g
Descriptives...
Extraction...
Rotation...
Scores...
Options...
Selection Variable:
Value...
OK
Paste
Reset
Cancel
Help
Factor Analysis: Options
Missing Values
Exclude cases listwise
Exclude cases pairwise
Replace with mean
Coefficient Display Format
Sorted by size
Suppress small coefficients
Absolute value below: .10
Continue
Cancel
Help
Factor Analysis
Variables:
item_a
item_b
item_c
item_d
item_e
item_f
item_g
Descriptives...
Extraction...
Rotation...
Scores...
Options...
Selection Variable:
Value...
OK
Paste
Reset
Cancel
Help
Results

EFA vs CFA

Article

Organizational Research Methods
1-32

DOI: 10.1177/1094428116631417
orm.sagepub.com
SAGE

Getting Through the Gate: Statistical and Methodological Issues Raised in the Reviewing Process

Jennifer P. Green[1], Scott Tonidandel[2] and Jose M. Cortina[1]

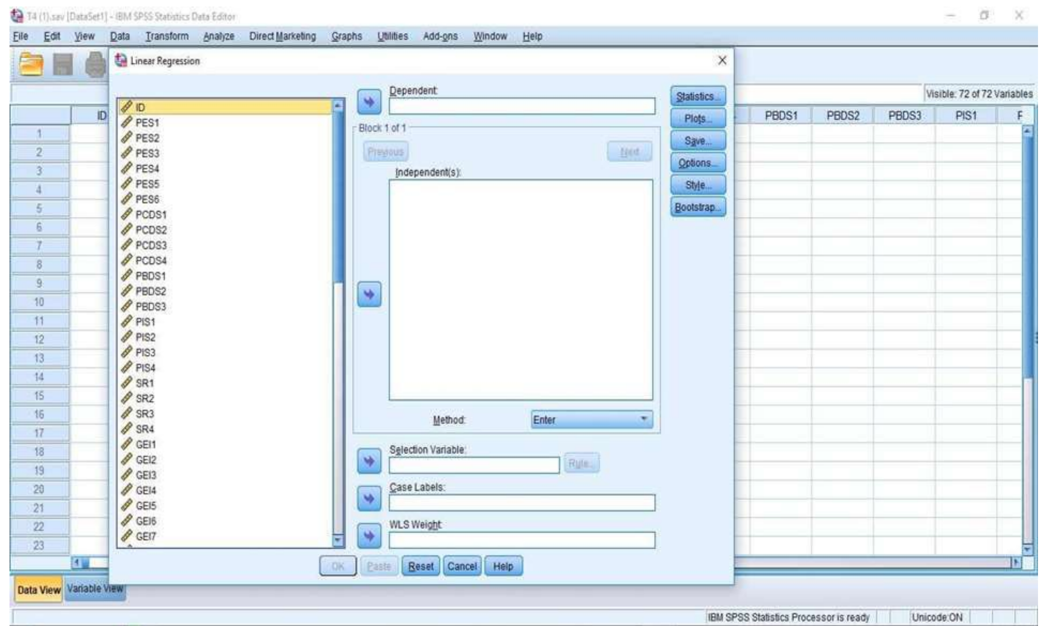
Issue	Recommendation	References
There are issues with choice of EFA or CFA (e.g., why EFA instead of CFA, or vice-versa).	EFA is more appropriate when little is known about factor structure. If an a priori factor structure exists, then CFA is more appropriate.	Bandalos and Boehm-Kaufman (2009); Floyd and Widaman (1995); Henson and Roberts (2006)
Authors conducted EFA and CFA on same data set.	Factor structure from an EFA should be confirmed with CFA on a different data set.	Henson and Roberts (2006)
Authors used questionable factor analytic methods (e.g., improperly eliminated items in CFA/ SEM).	Be aware of best practices for factor analyses, such as EFA methods to determine the number of factors to retain (e.g., parallel analysis).	O'Connor (2000); Zwick and Velicer (1986)

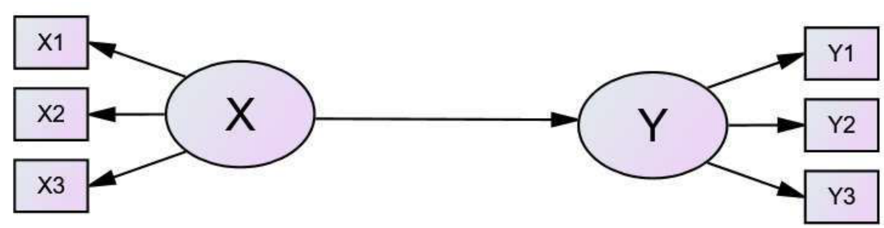
1st and 2nd Generation Technique

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

1st Generation Software Available for Selection

i. SPSS
ii. SYSTAT
iii. MINITAB
iv. STATA
v. STATISTICA
vi. SAS
vii. JASP
viii. JAMOVI
ix. XLSTAT





Data Analysis

i. **Frequency Test (Demographic Profiling)**
ii. Descriptive Statistics (Mean, Standard Deviation, Skewness and Kurtosis)
iii. Independent Sample T-Test
iv. ANOVA
v. Pearson Correlation
vi. Multiple Regression

Frequency Test: What are our respondents?

In any report typically there will be a description of the profile of respondents. This is done to highlight that the profile suits the purpose of the study and also if it does not it can be used later to justify the non significance of some research hypotheses.

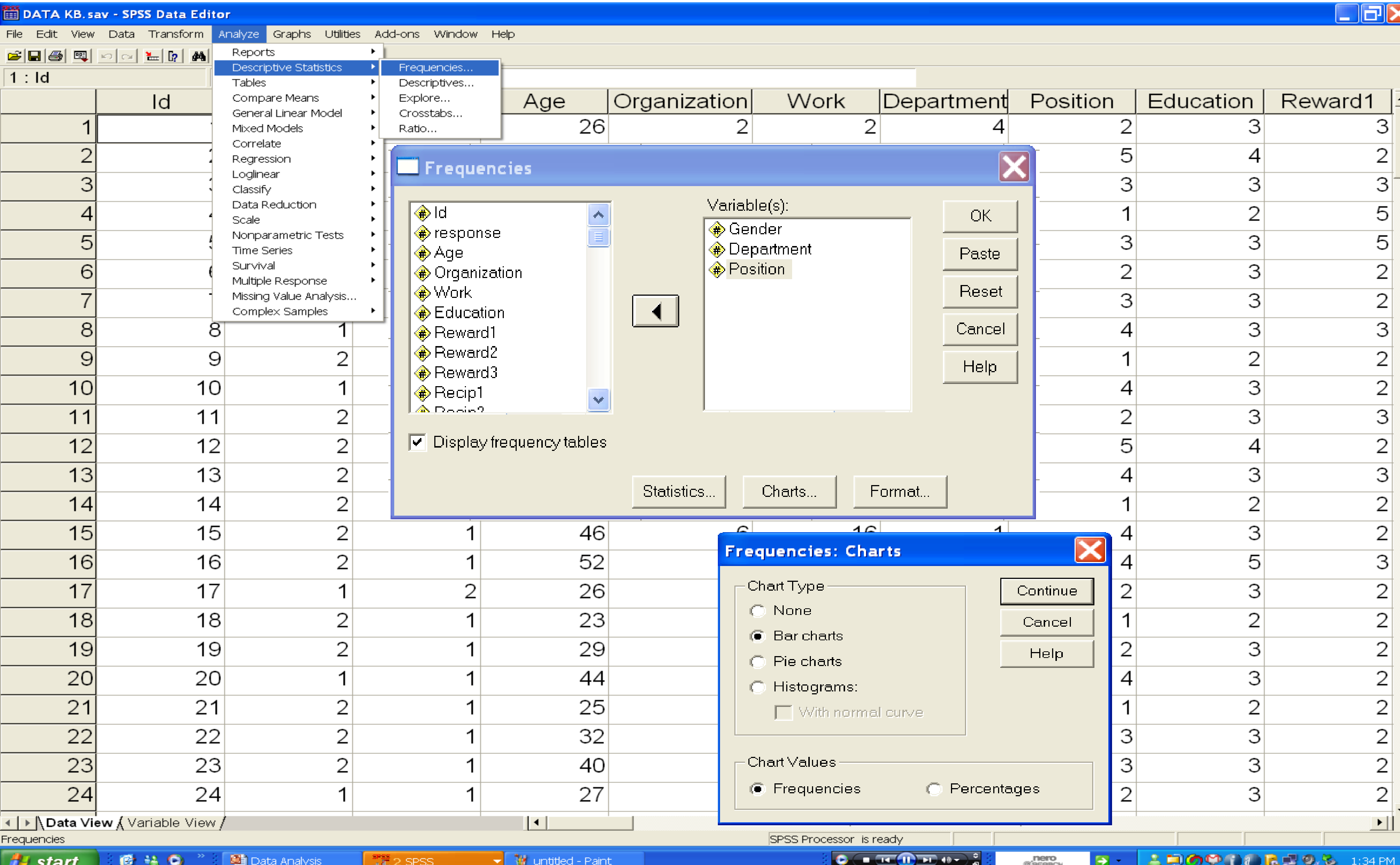
To do this we will ask for the frequency distribution of the nominal variables that we included in the profile section of our questionnaire.

Analyze → Descriptive Statistics → Frequencies

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	144	75.0	75.0	75.0
	Female	48	25.0	25.0	100.0
	Total	192	100.0	100.0	

Frequencies - Command



Question:

1. **Is our sample representative?**
2. **Data entry error**

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	144	75.0	75.0	75.0
	Female	48	25.0	25.0	100.0
	Total	192	100.0	100.0	

Current Position

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Technician	34	17.7	17.7	17.7
	Engineer	66	34.4	34.4	52.1
	Sr Engineer	54	28.1	28.1	80.2
	Manager	32	16.7	16.7	96.9
	Above manager	6	3.1	3.1	100.0
	Total	192	100.0	100.0	

Data Analysis

i. Frequency Test (Demographic Profiling)
ii. **Descriptive Statistics (Mean, Standard Deviation, Skewness and Kurtosis)**
iii. Independent Sample T-Test
iv. ANOVA
v. Pearson Correlation
vi. Multiple Regression

Descriptive – Mean, Standard Deviation, Skewness & Kurtosis

What is the Current State of Affair for the Variables of Interest?

- What is the current level of the variables of interest?

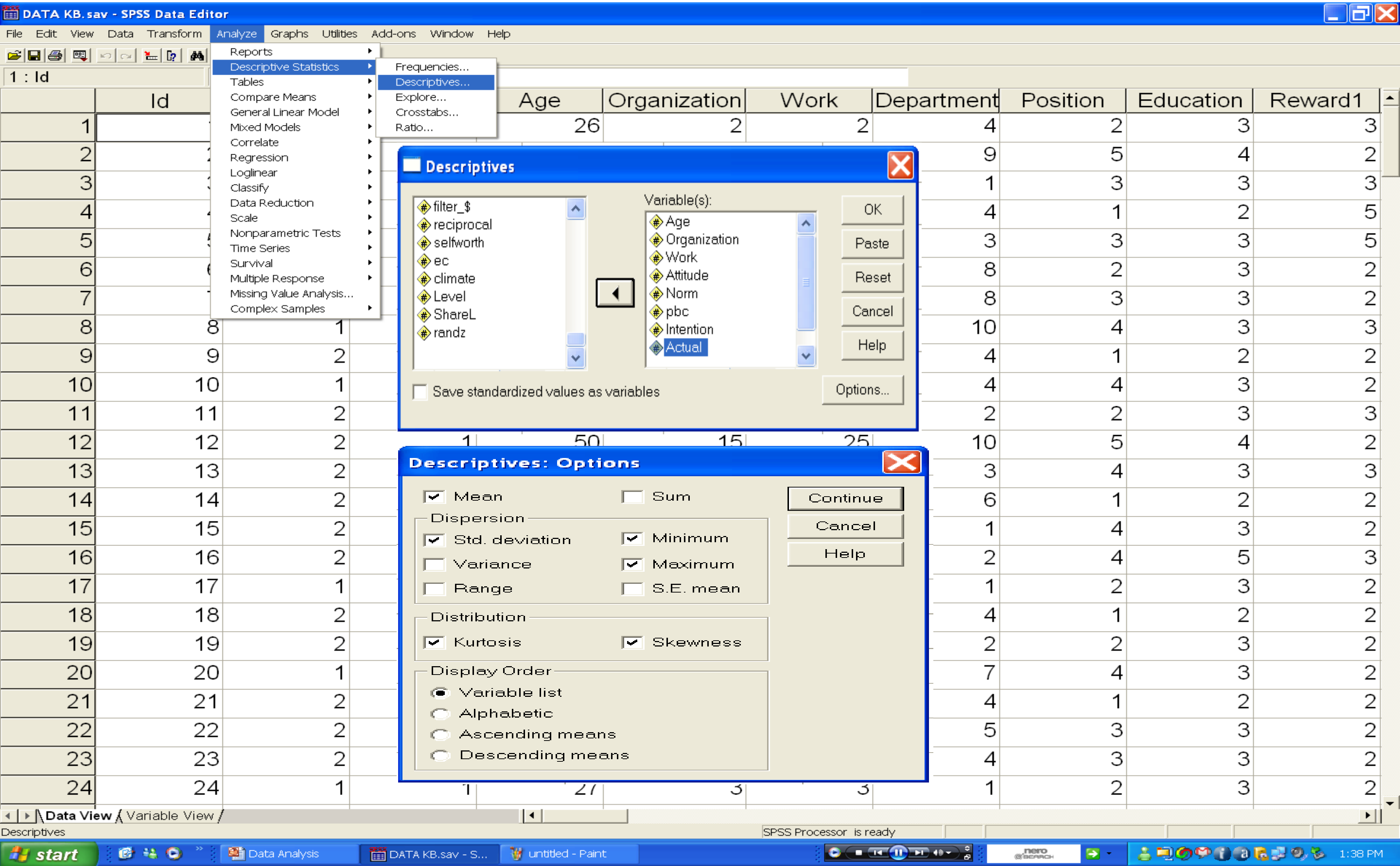
TYPICAL QUESTIONS

- What is the level of intention to share information in the organization?
- What is the level of actual sharing in the organization?

To do this we will ask for the descriptive analysis of the continuous variables that we computed from our questionnaire.

Analyze → Descriptive Statistics → Descriptives

Descriptive - Command



Descriptive Result

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Age	192	19	53	33.39	8.823	.667	.175	-.557	.349
Years working in the organization	192	1	18	5.36	4.435	1.448	.175	1.333	.349
Total years of working experience	192	1	28	9.04	7.276	1.051	.175	-.025	.349
Attitude	192	2.00	5.00	3.8104	.64548	-.480	.175	.242	.349
subjective	192	2.00	5.00	3.7031	.67034	-.101	.175	.755	.349
Pbcontrol	192	2.00	5.00	3.4792	.73672	.015	.175	-.028	.349
Intention	192	2.00	5.00	3.8188	.63877	-.528	.175	.687	.349
Actual	192	2.33	5.00	4.0625	.58349	-.361	.175	-.328	.349
Valid N (listwise)	192								

Question:

1. **Is there variation in our data?**
2. **What is the level of the phenomenon we are measuring?**

Data Analysis

i. Frequency Test (Demographic Profiling)
ii. Descriptive Statistics (Mean, Standard Deviation, Skewness and Kurtosis)
iii. Independent Sample T-Test
iv. ANOVA
v. Pearson Correlation
vi. Multiple Regression

Independent-sample t-test

- Used to compare the mean of a variable between two unrelated groups.
- H3: The mean score of customer satisfaction between males and females is not equal.
- Bivariate analysis.
- Gender = Nominal
- CS = Interval
- **SPSS Steps**: Click ***Analyze/Compare means/Independent-sample t-test***/bring CS to test variable box/bring gender to grouping variable box/define groups: 1 into group 1 box, 2 into group 2 box/continue/OK

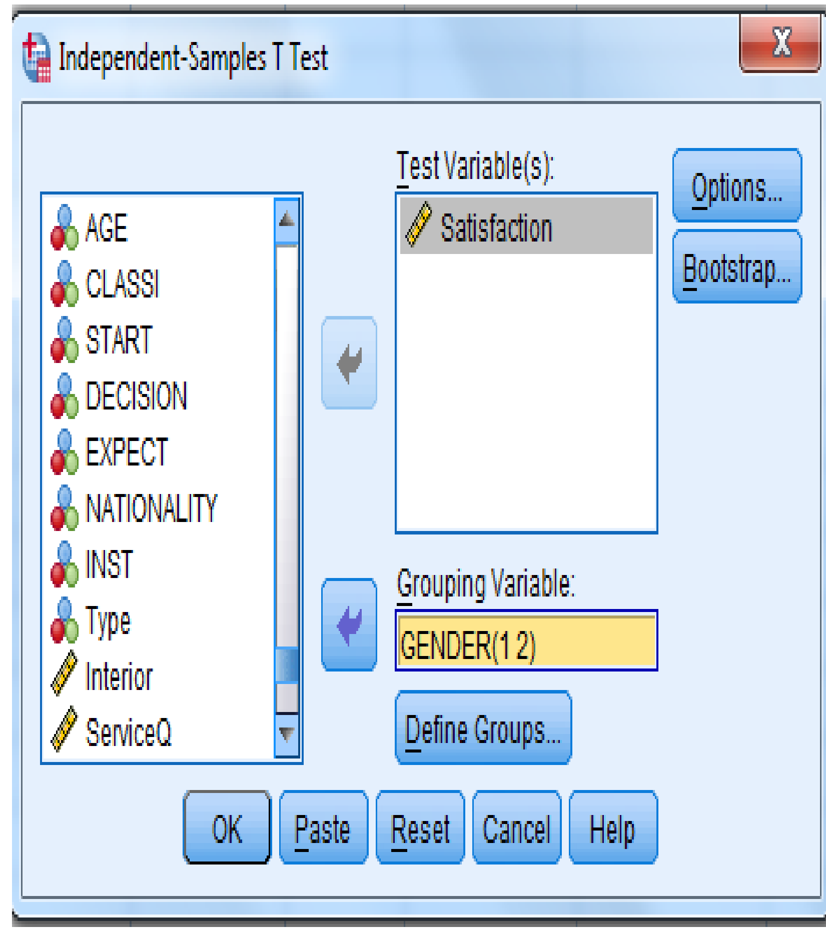


Exhibit 11.15: Group Statistics

	Gender	N	Mean	Standard Deviation	Standard Error Mean
Satisfaction	1	191	3.3426	0.72001	0.05210
	2	245	3.3845	0.75694	0.04836

Exhibit 11.16: Independent Samples Test

		Levene's Test for Equality of Variances		T-Test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Standard Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Satisfaction	Equal variances assumed	0.001	0.980	-0.586	434	0.558	-0.04190	0.07153	-0.18248	0.09868
	Equal variances not assumed			-0.590	417.257	0.556	-0.04190	0.07108	-0.18163	0.09782

To evaluate the assumption of homogeneity of variance, p should be larger than 0.05.

To determine whether the test was significant, p-value should be smaller than 0.05.

SPSS output:

a) Examine group statistics; mean male is 3.34, mean female is 3.38, not significantly difference, concluded means for male and female are the same.

Thus, H3 is not supported.

Data Analysis

i. Frequency Test (Demographic Profiling)
ii. Descriptive Statistics (Mean, Standard Deviation, Skewness and Kurtosis)
iii. Independent Sample T-Test
iv. **ANOVA**
v. Pearson Correlation
vi. Multiple Regression

One-way Analysis of Variance (ANOVA)

- Used to compare the mean of a variable between two or more independent groups.
- H4: The mean score of the employees' job performance after the training programmes A, B and C is not equal.
- Bivariate analysis.
- Performance: Interval
- Training: Nominal
- SPSS steps: Click ***Analyze/compare means/one way ANOVA***/move performance to dependent list box/move training to factor box/options/tick descriptive/tick homogeneity of variance test/continue/OK

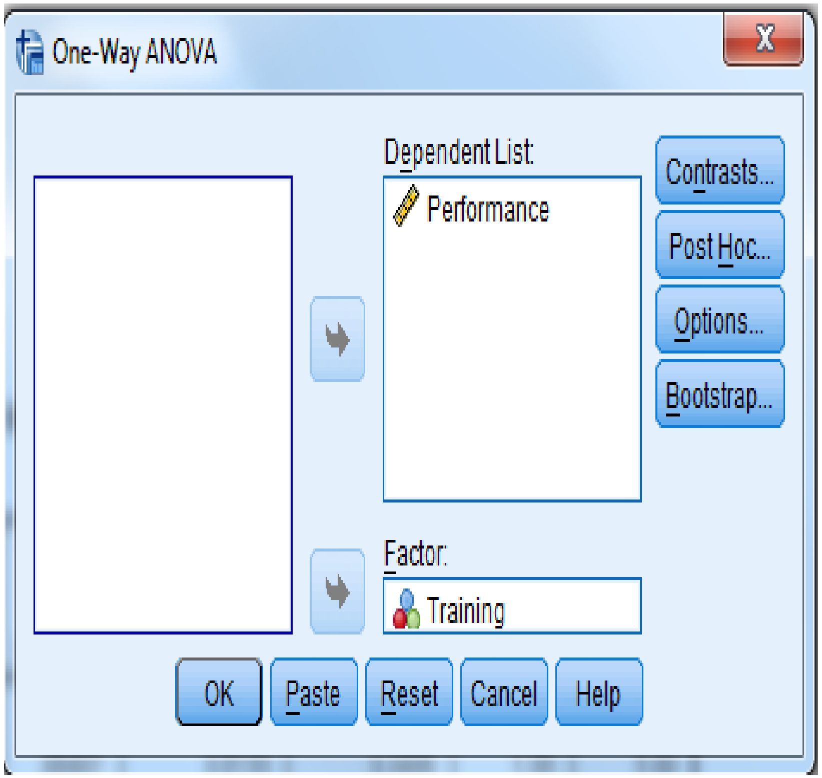


Exhibit 11.18: Descriptives

Performance								
	N	Mean	Standard Deviation	Standard Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Programme A	74	3.6453	0.63839	0.07421	3.4974	3.7932	2.50	5.00
Programme B	72	3.1810	0.71333	0.08407	3.0133	3.3486	1.00	5.00
Programme C	80	3.2063	0.70011	0.07827	3.0504	3.3621	1.00	5.00
Total	226	3.3419	0.71414	0.04750	3.2483	3.4356	1.00	5.00

Exhibit 11.19: Test of Homogeneity of Variances

Performance			
Levene Statistic	df1	df2	Sig.
0.014	2	223	0.986

To determine if the data have met or violated assumptions of homogeneity of variances. P-value should larger than 0.05.

Exhibit 11.20: ANOVA

Performance					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10.147	2	5.074	10.817	0.000
Within Groups	104.601	223	0.469		
Total	114.748	225			

F(2,223) = 10.82. To determine whether the test was significant, p-value should be smaller than 0.05.

SPSS output:

a) Examine homogeneity of variances table, P-value is 0.986, met assumptions of homogeneity variance.

b) Examine ANOVA table, P-value is 0.00 (<0.05). There is a significant difference.

Thus, H4 is supported.

Data Analysis

i. Frequency Test (Demographic Profiling)
ii. Descriptive Statistics (Mean, Standard Deviation, Skewness and Kurtosis)
iii. Independent Sample T-Test
iv. ANOVA
v. Pearson Correlation
vi. Multiple Regression

Pearson Correlation Coefficient

- Used to measure the strength of a linear association between two variables.
- H5: There is a relationship between employee motivation and performance.
- Bivariate analysis.
- Employee motivation & performance = interval
- SPSS steps: Click ***analyze/correlate/bivariate***/move motivation & performance to variable box/tick pearson/OK

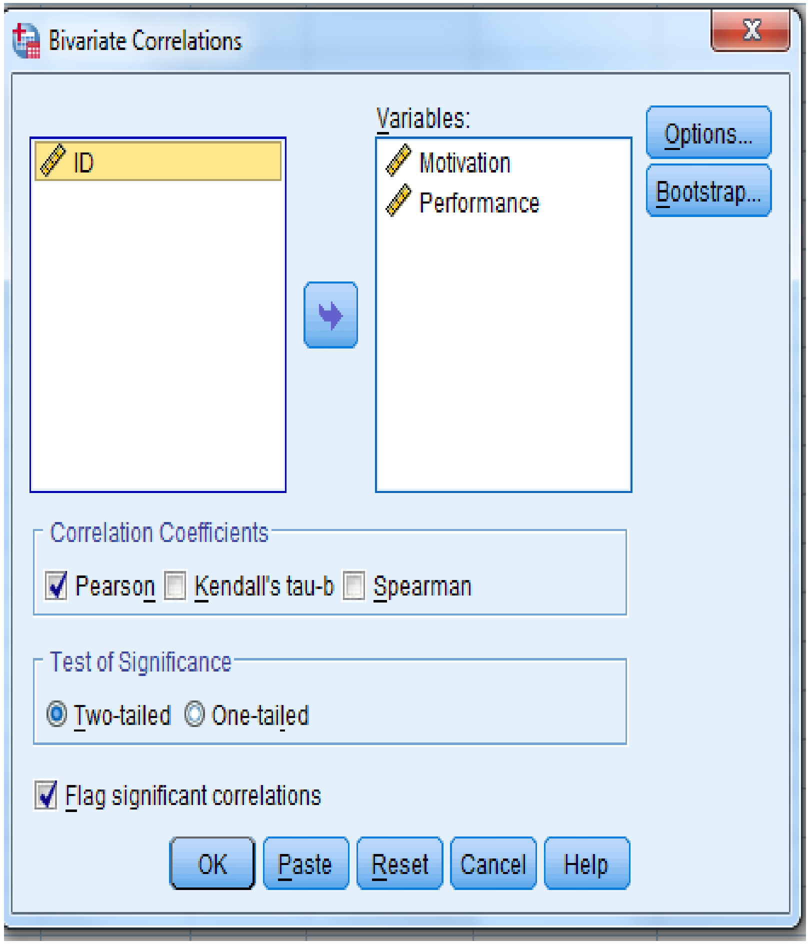


Exhibit 11.22: Correlations

		Motivation	Performance
Motivation	Pearson Correlation	1	0.588**
	Sig. (2-tailed)		0.000
	N	226	226
Performance	Pearson Correlation	0.588**	1
	Sig. (2-tailed)	0.000	
	N	226	226

**. Correlation is significant at the 0.01 level (2-tailed).

The r = 0.59. To determine whether the test was significant, p-value should be smaller than 0.05, p = 0.0001.

The degrees of freedom (df), N - 2 = 224.

SPSS output:

a) Refer correlations table: r=0.59, p-value = 0.00 (<0.05) indicate significant results.

H5 is supported.

b) Since r is positive, there is a positive and significant relationship between employee motivation and performance.

Data Analysis

i. Frequency Test (Demographic Profiling)
ii. Descriptive Statistics (Mean, Standard Deviation, Skewness and Kurtosis)
iii. Independent Sample T-Test
iv. ANOVA
v. Pearson Correlation
vi. **Multiple Regression**

Linear Regression

- Used to predict changes in the dependent variable based on the value of independent variable(s) or predictor(s).
- H6: There is a relationship between performance and involvement.
- H7: There is a relationship between performance and welfare.
- Multivariate analysis.
- Dependent variable: performance = interval
- Independent variable: Involvement & welfare = interval.
- SPSS steps: Click ***Analyze/regression/linear***/move performance to dependent box/move involvement & welfare to independent box/statistics/tick estimates, model fit, descriptives & collinearity diagnostics/continue/OK

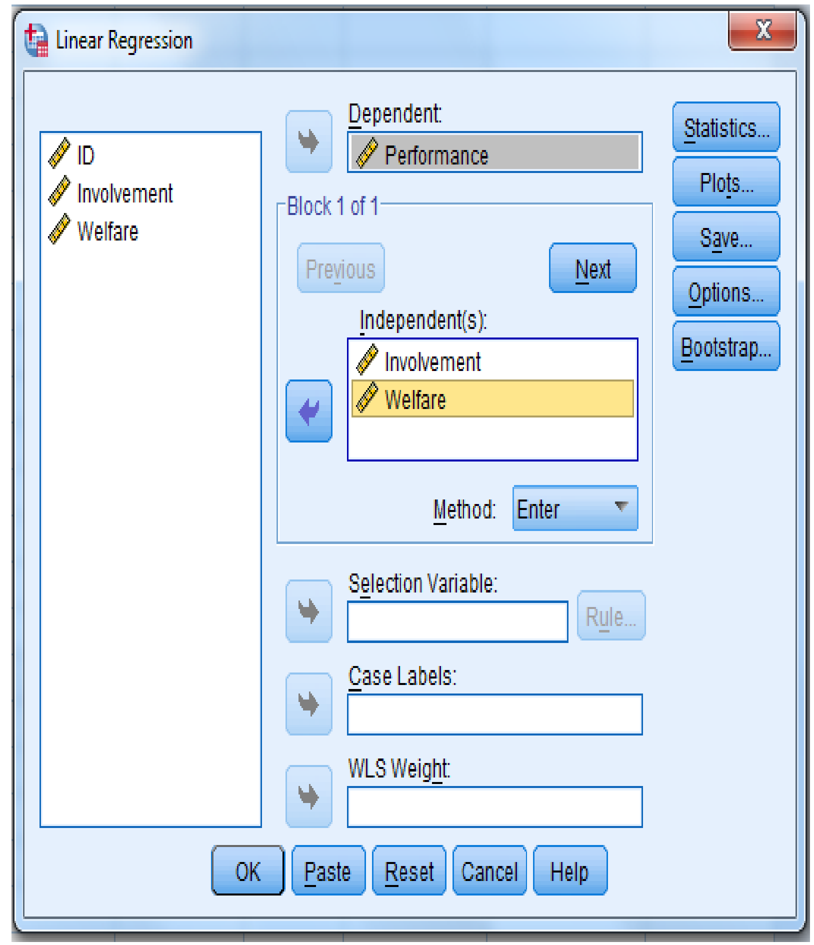


Exhibit 11.27: Model Summary

Model	R	R Square	Adjusted R Square	Standard Error of the Estimate
1	0.677[a]	0.458	0.453	0.52967

a. Predictors: (Constant), Welfare, Involvement

Multiple correlation coefficient, R = 0.68 indicates a high degree of correlation.

Adjusted R Square (R2) indicates that 45% of the variance in the dependent variable can be predicted from the independent variable.

Exhibit 11.28: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	52.420	2	26.210	93.424	0.000[b]
	Residual	62.002	221	0.281	.	
	Total	114.422	223		.	

a. Dependent Variable: Performance
b. Predictors: (Constant), Welfare, Involvement

The p-value < 0.05, indicates the equation is a good fit, F(2,221) = 93.42, p = 0.001.

Exhibit 11.29: Coefficients[a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Standard Error	Beta			Tolerance	VIF
1	(Constant)	0.946	0.198		4.772	0.000		
	Involvement	0.414	0.060	0.435	6.870	0.000	0.612	1.635
	Welfare	0.407	0.082	0.314	4.959	0.000	0.612	1.635

a. Dependent Variable: Performance

β_1 = 0.41 and β_2 = 0.41, indicate the effect of the independent variables on the dependent variable.

To determine the multicollinearity problem. Tolerance value should be larger than $1 - R^2$ $(1 - 0.45 = 0.55)$.

Both independent variables are significantly contributing to the equation.

SPSS output:

- Refer model summary: Adjusted R square = 0.45, indicates that 5% of the variance in the dependent variable can be predicted from independent variables.
- Refer ANOVA table: P-value=0.00 (<0.05) indicates the equation is a good fit.
- Refer coefficient table: standard coefficient of involvement is 0.435 (p=0.00) and welfare is 0.314 (p=0.00) indicates both significantly related to performance.
- Thus H6 & H7 is supported.

Extension of SPSS using PROCESS

Not secure | processmacro.org/download.html

Apps | Altmetric it! | International Entrepren... | Khu Li FangNov 14Than... | New Tab | Sign out | Predicting who will publ... | Ramayah | Home

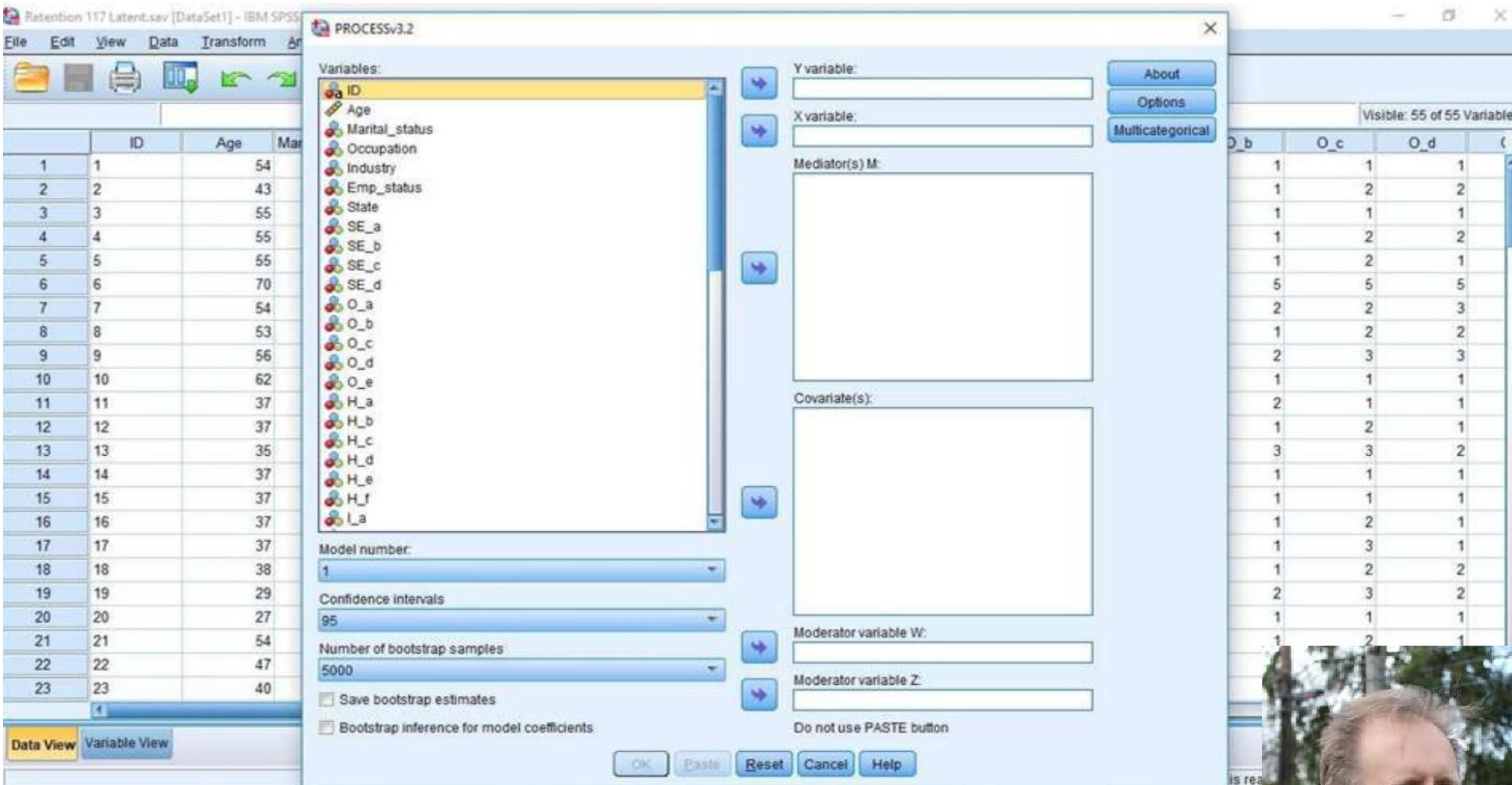
Version 3 of PROCESS is described and documented in the **2nd edition** of *Introduction to Mediation, Moderation, and Conditional Process Analysis*. Click the button below to download version 3.5 (released 1 May 2020). When you do so, a .zip archive will download in accordance with your browser settings. The installation and use of PROCESS is documented in Appendix A as well as throughout the book. Appendix A also contains the model number templates for preprogrammed models. Instructions for creating your own models or modifying numbered models can be found in Appendix B. The appendices are not electronically available except in the e-book edition. However, an addendum to the documentation that describes features added since the publication of the book is available as a PDF here.

ATTENTION: MacOS "Catalina" users: There is a bug in the latest release of MacOS related to file access permissions that also affects SPSS. It has nothing to do with PROCESS or its operation on the Mac or SPSS. Consult your local tech support person for advice. Here is a video that might be helpful in solving your problem.

Download PROCESS v3.5

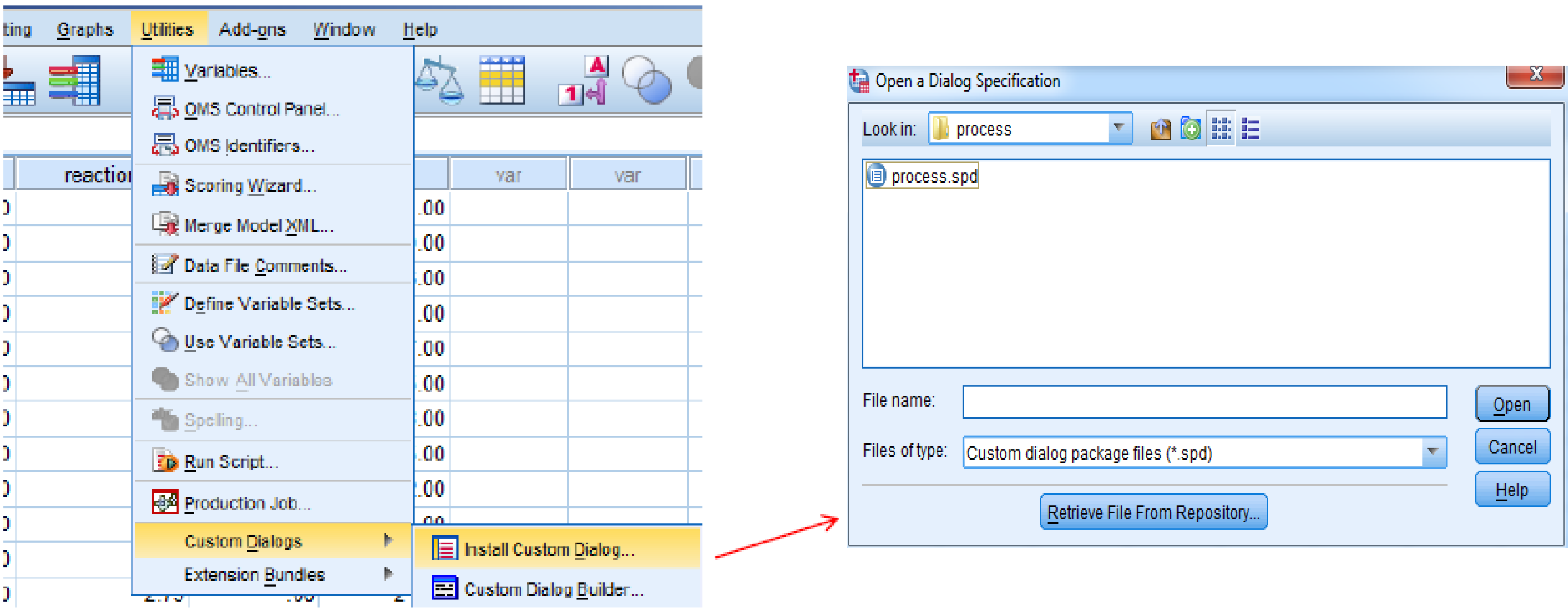
PROCESS version 2, introduced in 2013 in the first edition of *Introduction to Mediation, Moderation, and Conditional Process Analysis* (the cover of the first edition is blue; the second edition is white) is no longer available or supported. If you have used PROCESS

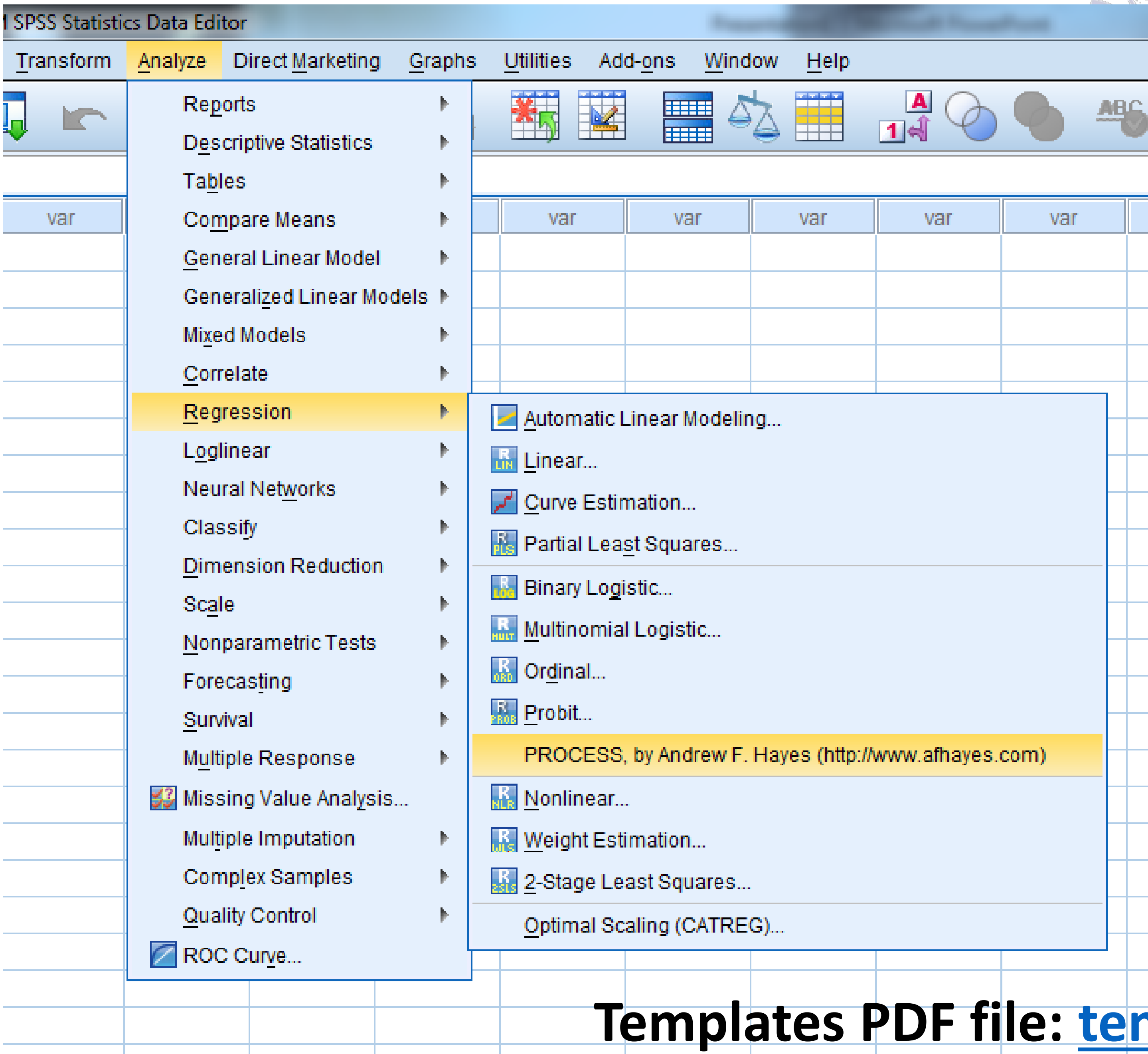
Extension of SPSS using PROCESS



Developed by Andrew Hayes

Installing PROCESS





Templates PDF file: templates.pdf

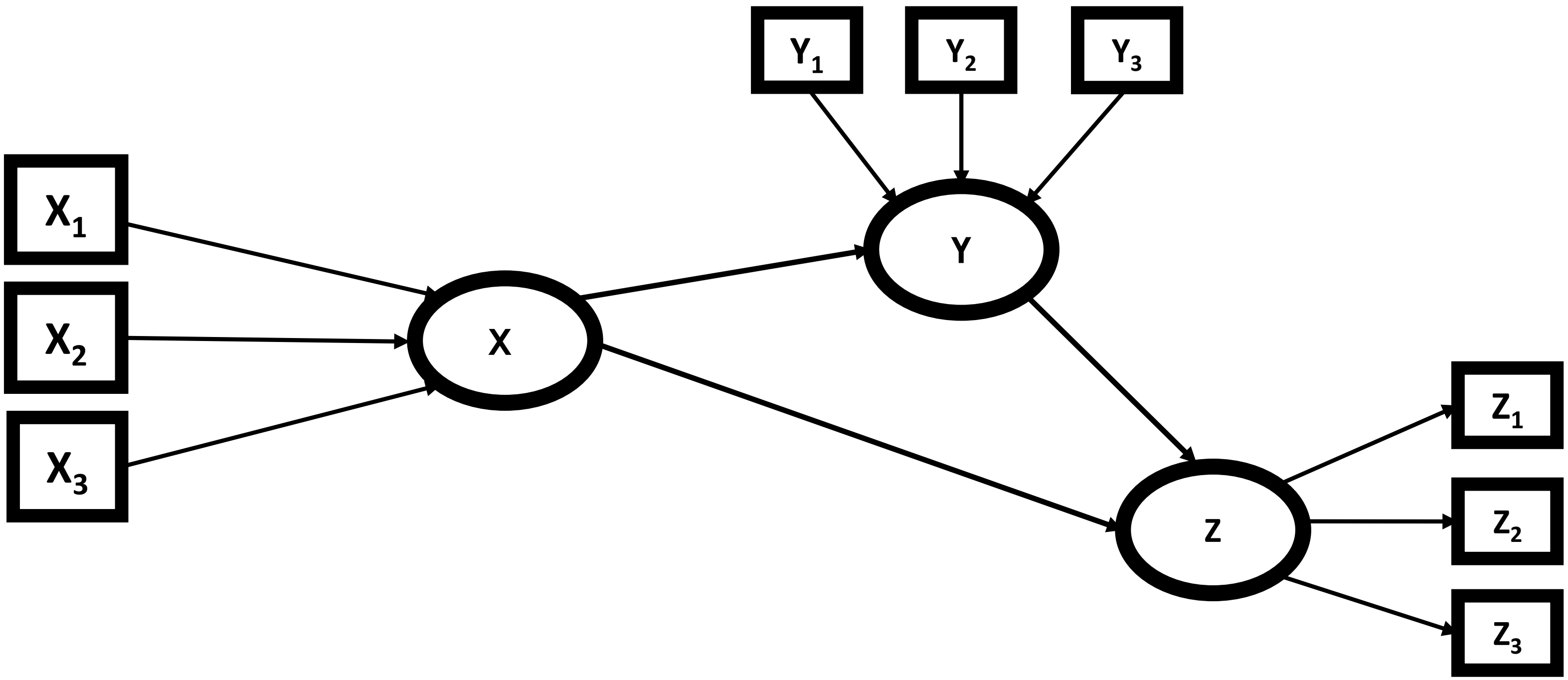
What is Structural Equation Modeling (SEM)?

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

1st Generation vs 2nd Generation

SEM Techniques	Primarily Exploratory	Primarily Confirmatory
First-generation	• Cluster analysis • Exploratory factor analysis • Multidimensional scaling	• Analysis of variance • Logistic regression • Multiple regression • Confirmatory factor analysis
Second-generation	• Partial least squares structural equation modeling **(PLS-SEM)**	• Covariance-based structural equation modeling **(CB-SEM)**

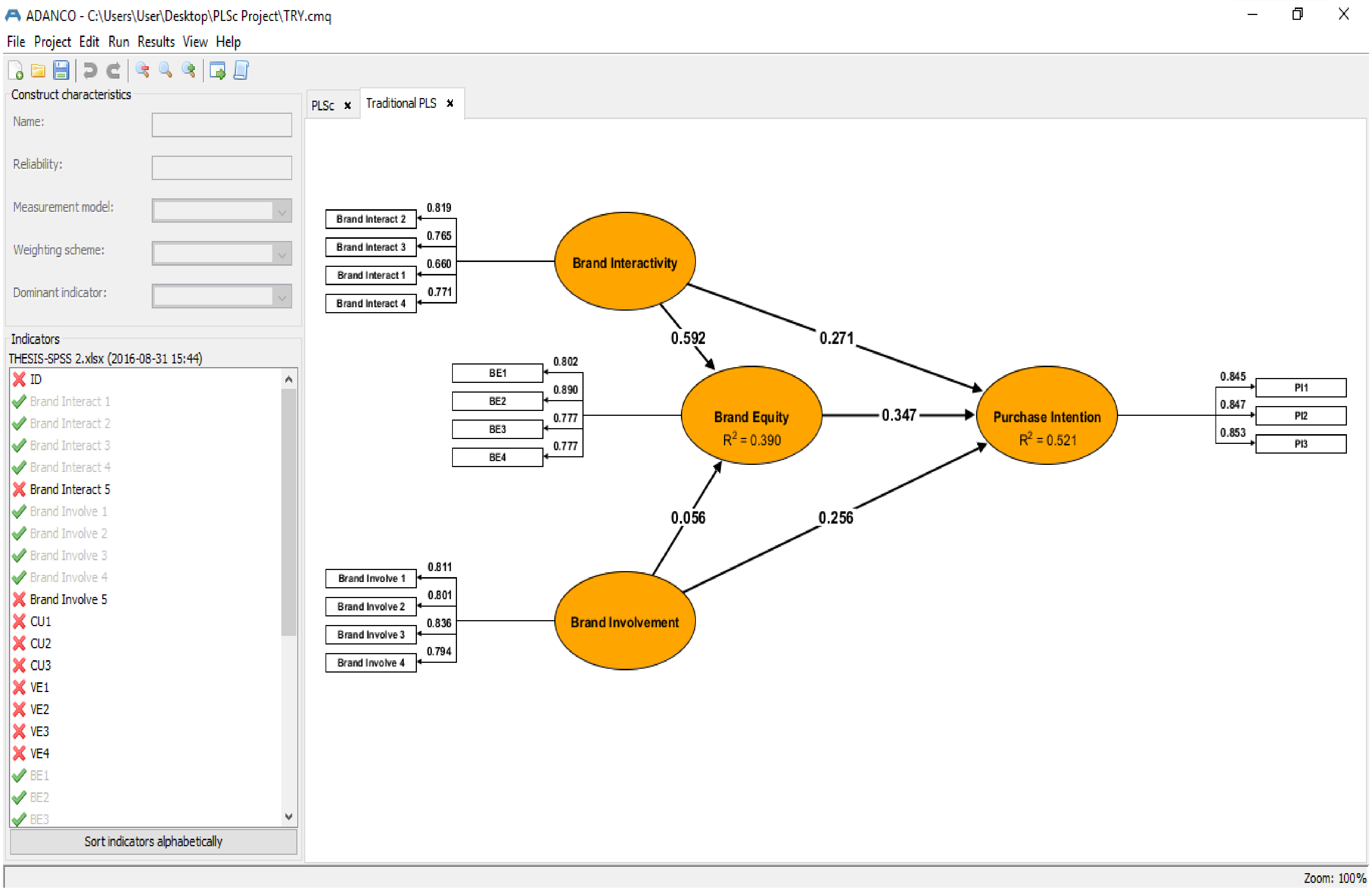
How SEM look like?



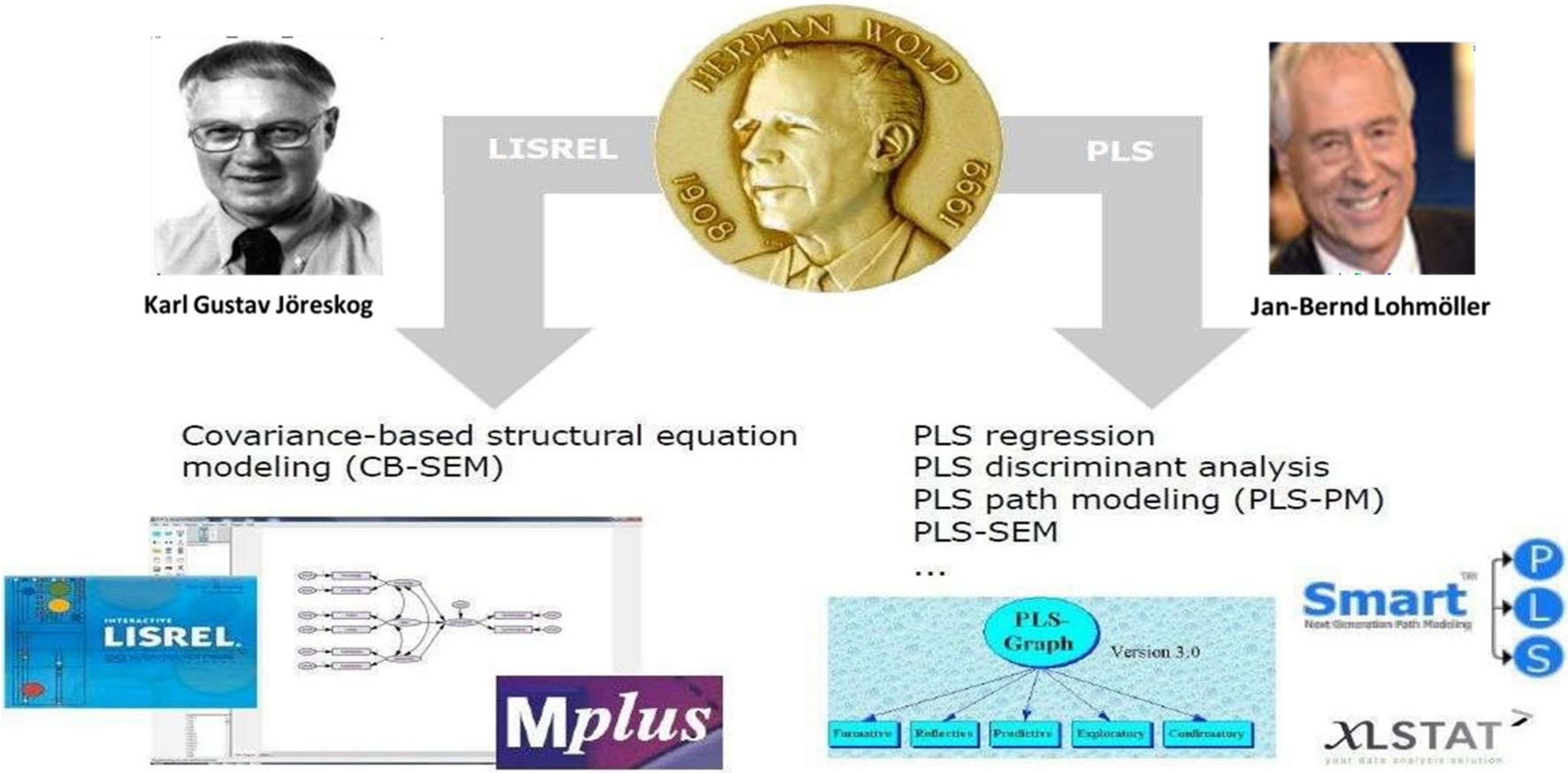
Why Structural Equation Modeling (SEM)

- Modeling causal relationship within their **nomological net**
  - Representation and testing of entire theories
    - Measurement Theory (auxiliary theory)
    - Substantive Theory
  - Inclusion of direct, indirect and total effects of factors
- Taking **measurement error** into account
  - Assessing measurement reliability/ validity
  - Correcting for measurement error
- Intuitive **graphical representation** of theory

Example for Graphical Visualization



Types of SEM techniques



Why Structural Equation Modeling (SEM)

- **CB-SEM (Covariance-based SEM)**
  - objective is to reproduce the theoretical covariance matrix, without focusing on explained variance.
  - confirmatory purpose

- **PLS-SEM (Partial Least Squares SEM)**
  - objective is to maximize the explained variance of the endogenous latent constructs (dependent variables).
  - prediction-oriented purpose in modeling.

Softwares

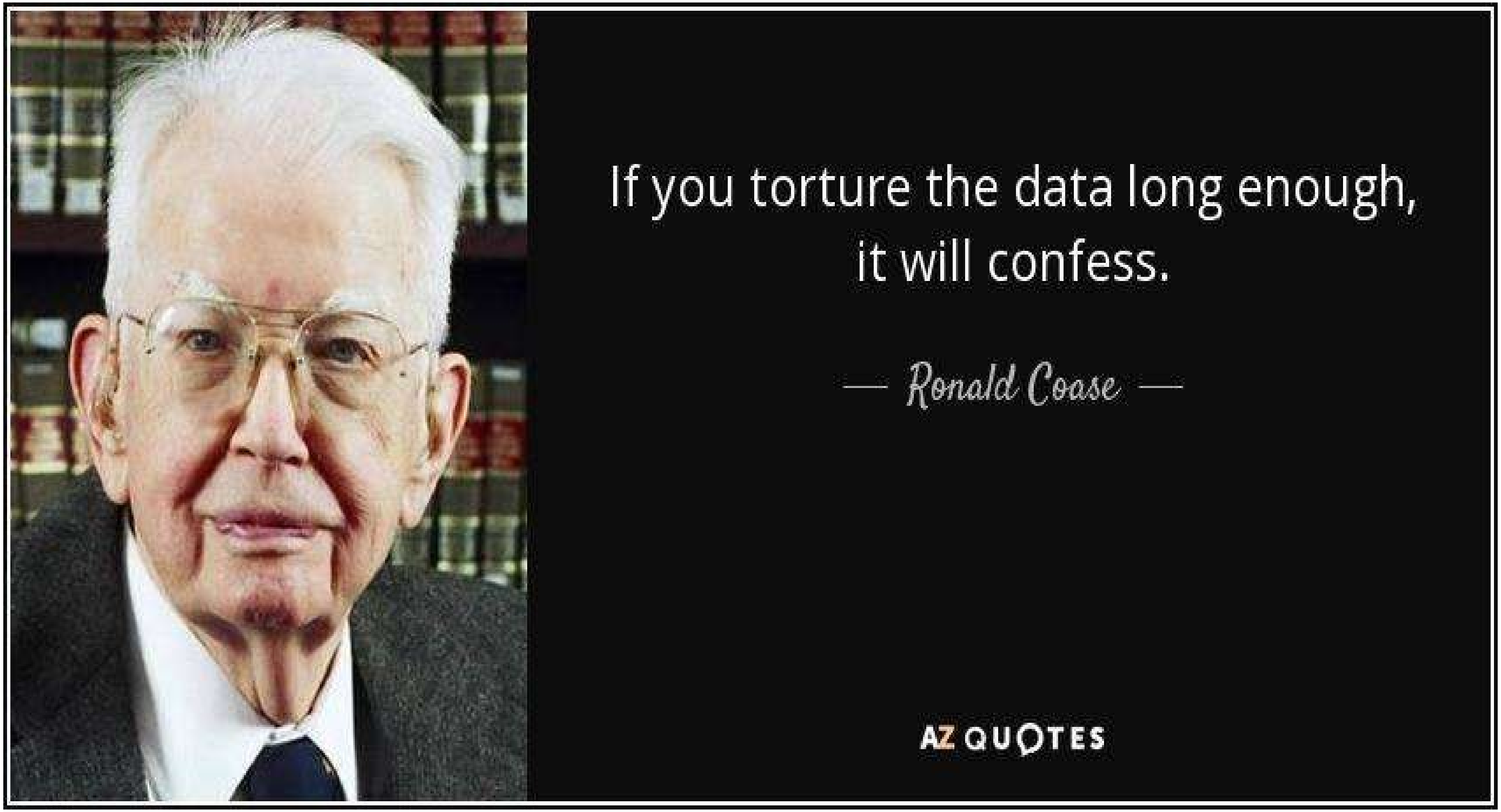
Covariance-based SEM (CB-SEM)

- EQS: http://www.mvsoft.com
- **AMOS**: http://www.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

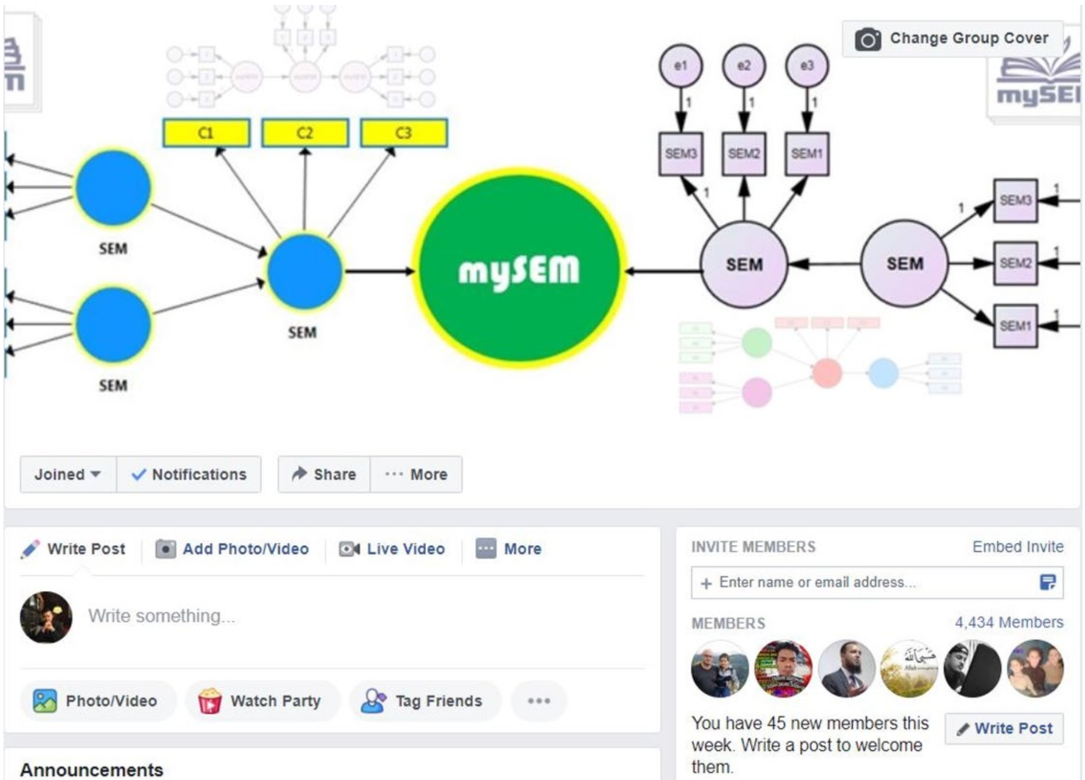
Variance-based SEM

- **SmartPLS**: http://www.smartpls.de
- WarpPLS: http://www.scriptwarp.com
- PLS-GUI: https://pls-gui.com
- ADANCO: http://www.composite-modeling.com
- XLSTAT: https://www.xlstat.com/en/
- GeSCA: http://www.sem-gesca.org

Hacking and Harking



The Network from mySEM



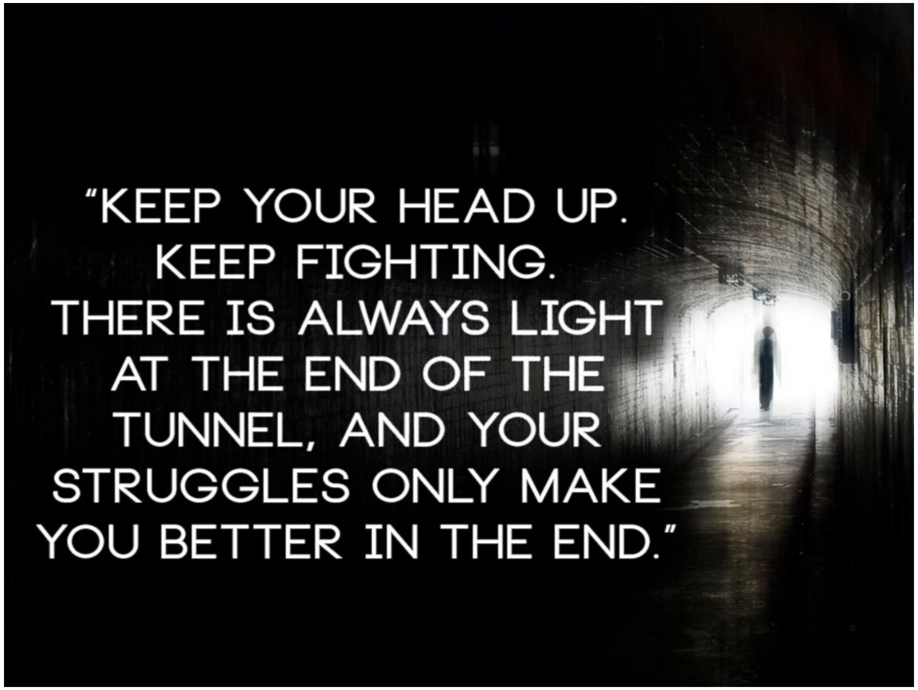
Gabi Cepeda Carrión
Associate professor at University of Seville
Joined
Added by Mostafa Rasoolimanesh about 5 months ago

JoséLuis Roldán
Profesor Titular de Universidad at Universidad de Sevilla
Joined
Added by Francis Chuah about 4 months ago

Marko Sarstedt
Chief Marketing Officer at Zorin Industries
Joined
Added by Gabi Cepeda Carrión about 3 months ago

Edward Rigdon
Professor at Georgia State University
Joined
Added by Jacky Cheah about 6 months ago

Ned Kock
Works at Texas A&M International University
Joined
Added by Mumtaz Ali Memon about 9 months ago


"KEEP YOUR HEAD UP.
KEEP FIGHTING.
THERE IS ALWAYS LIGHT
AT THE END OF THE
TUNNEL, AND YOUR
STRUGGLES ONLY MAKE
YOU BETTER IN THE END."


No matter how many mistakes
you make or how slow you
progress, you are still way ahead
of everyone who isn't trying.
Tony Robbins
quotefancy

Contact:

Jacky Cheah Jun Hwa, PhD

Senior Lecturer

Faculty of Economics and Management,

Universiti Putra Malaysia

External member of Relationship Marketing for Impact cluster at Griffith University in Australia

Visiting Virtual Professor at Prince of Songkla University

Adjunct Lecturer of Faculty of Hospitality and Tourism Management at UCSI in KL & Sarawak Campus

jackycheahjh@gmail.com/ junhwa@upm.edu.my