Quantitative Data Analysis: A Companion for Accounting and Information Systems Research

Teaching Materials

Created by Willem Mertens, Amedeo Pugliese & Jan Recker

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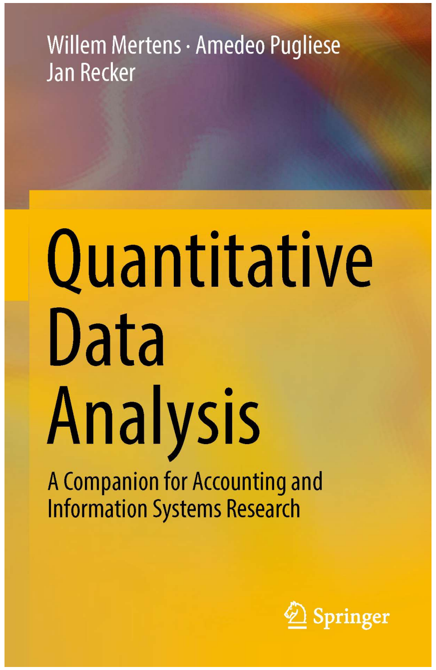
What these materials are about

Offering a guide through the essential steps required in quantitative data analysis

1. **Introduction**
2. Comparing Differences Across Groups
3. Assessing (Innocuous) Relationships
4. Models with Latent Concepts and Multiple Relationships: Structural Equation Modeling
5. Nested Data and Multilevel Models: Hierarchical Linear Modeling
6. Analyzing Longitudinal and Panel Data
7. Causality: Endogeneity Biases and Possible Remedies
8. How to Start Analyzing, Test Assumptions and Deal with that Pesky p-Value
9. Keeping Track and Staying Sane



Part 4:
Structural Equation Modeling

Recap: Which statistical approach for which question?

- When should you use…

1. Descriptive statistics
2. Regression models?
3. Analysis of variance models?
4. Time-series models?
5. Structural equation models?

Structural Equation Modelling

- A so-called *second generation data analysis method*
  - First generation data analysis methods include techniques such as **regression**, (multivariate) analysis of (co-)variance (ANOVA).
  - They are characterized by their shared limitation of being able to analyse only one layer of linkages between independent and dependent variables at a time.
  - 2nd generation methods allow for the simultaneous analysis of multiple independent and dependent variables

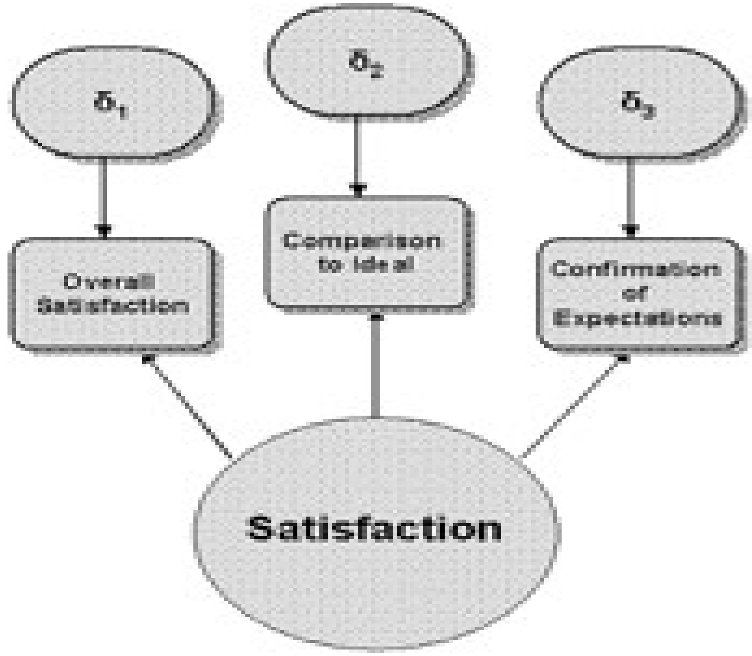
- encourages confirmatory rather than exploratory analysis.

When do we use SEM?

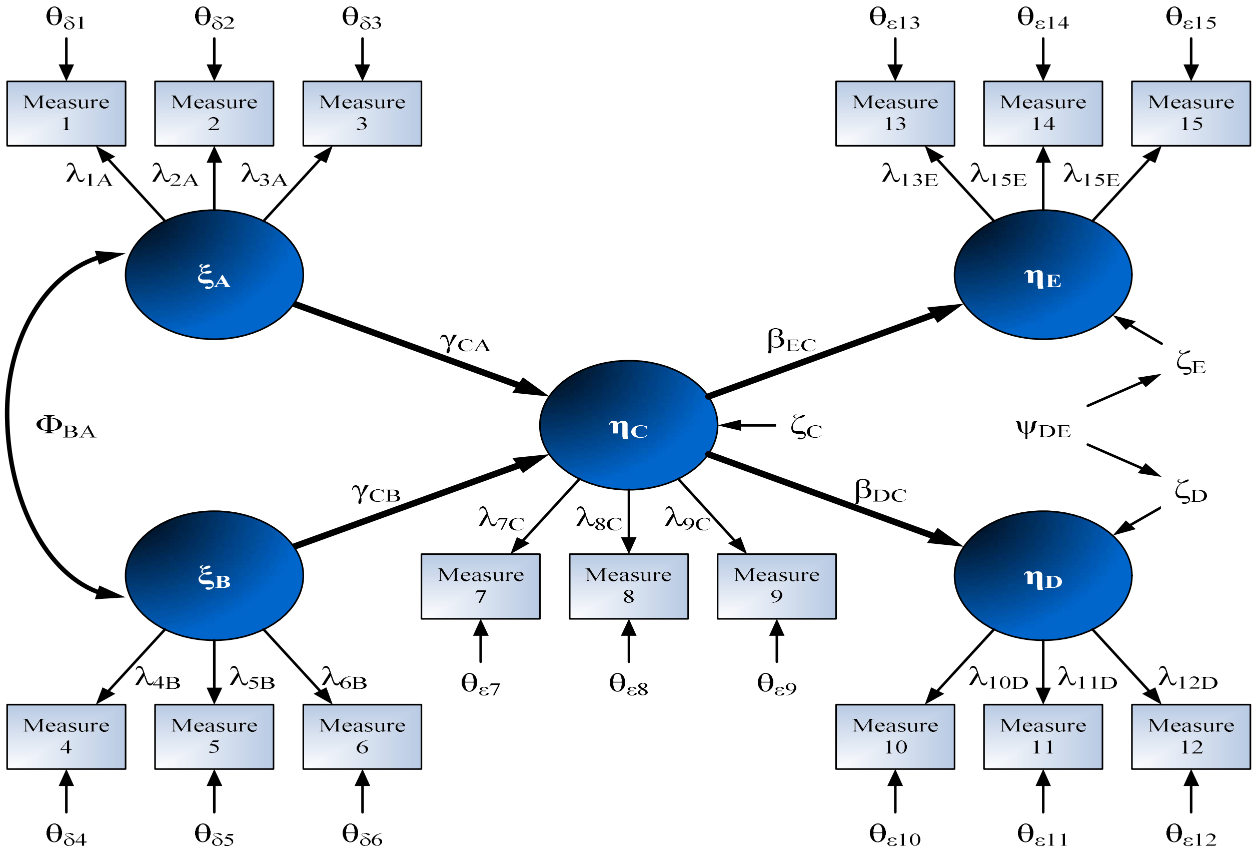
- Complex research models:
  - Multiple associations between multiple independent and multiple dependent variables
  - Usually also mediating and/or moderating variables present
- Latent concepts: Multi-dimensional constructs with several underlying dimensions
  - Satisfaction, usefulness, attitude etc.
  - Constructs that have multiple measures
  - Often measured with perceptual (self-report) data
- Often: survey research but also in experiments and others

Latent constructs

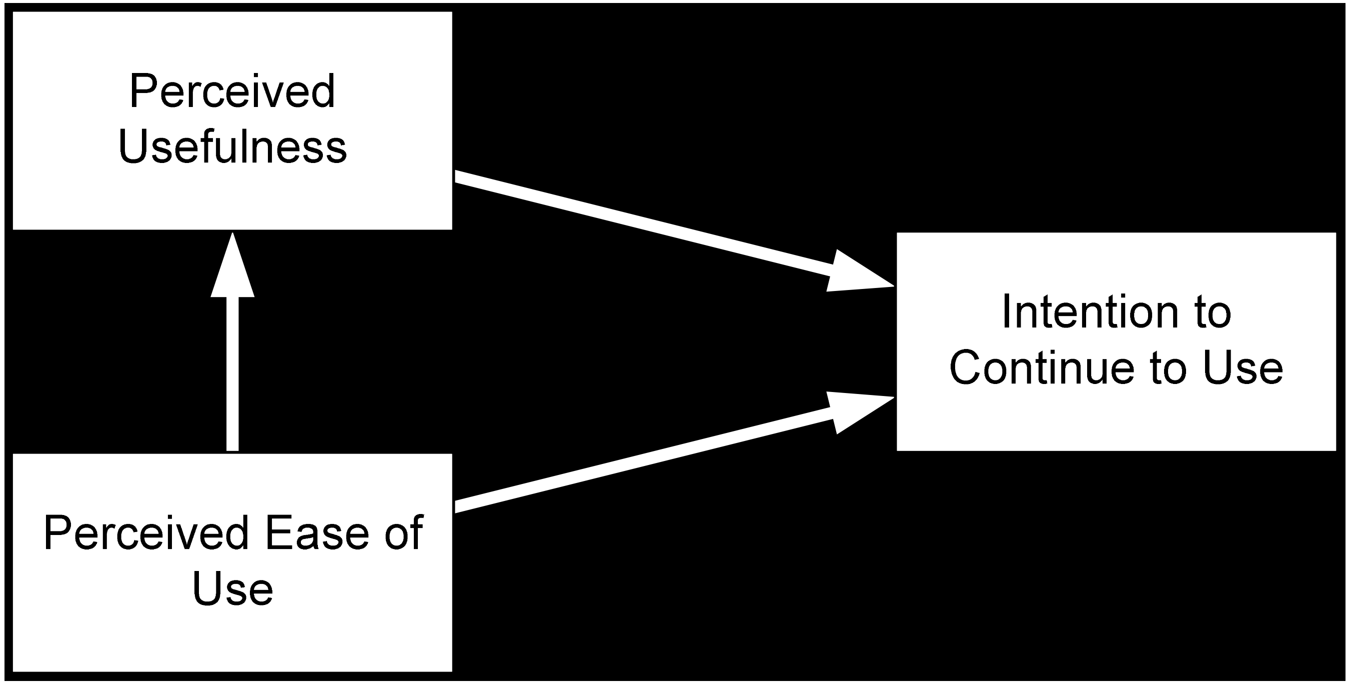
- abstractions about a phenomenon (e.g. usefulness, time, satisfaction, enjoyment) that are **latent** in that they relate to a real thing but do not have a tangible existence:
  - Thus they cannot be measured directly
- have indicators associated with them:
  - **Measures** are our approximations to latent constructs – our empirical indicators that allow us to 'grasp' the latent construct.
  - 1+ measure required per construct dimension (also called substratum)
  - Typically multiple items because most constructs are indeed complex concepts that have multiple domains of meaning.



Components of a Structural Equation Model



A Simple Example



The corresponding construct table

PU	PEOU	ITU
PU1	PEOU1	ITU1
PU2	PEOU2	ITU2
PU3	PEOU3	ITU3
…	…	…
…	…	…

A Simple Example: the corresponding data

grammarA.sav [DataSet1] - IBM SPSS Statistics Data Editor

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	VOL1	VOL2	VOL3	FAM1	FAM2	FAM3	REQ1	REQ2	REQ3	REQ4	PU1	PU2	PU3	SAT1
1	4.000	.000	12.000	1.000	30.000	1.000	5.000	.000	2.000	2.000	7.000	7.000	7.000	5.000
2	12.000	1.000	8.000	1.000	100.000	1.000	5.000	.000	5.000	6.000	2.000	3.000	1.000	2.000
3	20.000	1.000	3.000	.000	50.000	1.000	7.000	.000	1.000	1.000	7.000	7.000	7.000	7.000
4	3.000	.000	1.000	.000	10.000	.000	6.000	.000	7.000	7.000	7.000	7.000	7.000	6.000
5	1.000	.000	6.000	1.000	20.000	1.000	5.000	.000	5.000	7.000	5.000	6.000	6.000	5.000
6	20.000	1.000	36.000	1.000	30.000	1.000	4.000	.000	2.000	4.000	6.000	6.000	6.000	5.000
7	1.000	.000	6.000	1.000	3.000	.000	1.000	1.000	4.000	4.000	4.000	4.000	3.000	3.000
8	6.000	1.000	2.000	.000	10.000	.000	6.000	.000	6.000	6.000	6.000	5.000	6.000	6.000
9	7.000	1.000	8.000	1.000	10.000	.000	5.000	.000	5.000	4.000	6.000	6.000	6.000	6.000
10	10.000	1.000	36.000	1.000	1800.000	1.000	5.000	.000	.	.	2.000	3.000	6.000	4.000
11	8.000	1.000	6.000	1.000	50.000	1.000	5.000	.000	4.000	7.000	6.000	7.000	7.000	6.000
12	5.000	1.000	6.000	1.000	10.000	.000	5.000	.000	2.000	6.000	7.000	7.000	7.000	7.000
13	5.000	1.000	1.000	.000	10.000	.000	5.000	.000	.	.	2.000	2.000	1.000	1.000
14	7.000	1.000	2.000	.000	50.000	1.000	5.000	.000	.	.	7.000	7.000	7.000	6.000
15	1.000	.000	7.000	1.000	15.000	1.000	3.000	1.000	.	.	6.000	6.000	6.000	4.000
16	2.000	.000	3.000	.000	4.000	.000	5.000	.000	3.000	3.000	6.000	6.000	6.000	6.000
17	7.000	1.000	3.000	.000	60.000	1.000	5.000	.000	4.000	4.000	7.000	7.000	7.000	7.000
18	4.000	.000	2.000	.000	5.000	.000	5.000	.000	5.000	1.000	7.000	7.000	6.000	7.000
19	3.000	.000	28.000	1.000	60.000	1.000	2.000	1.000	2.000	5.000	6.000	6.000	6.000	5.000
20	3.000	.000	24.000	1.000	10.000	.000	1.000	1.000	.	.	7.000	7.000	7.000	6.000
21	10.000	1.000	12.000	1.000	5.000	.000	6.000	.000	3.000	5.000	6.000	6.000	6.000	5.000
22	8.000	1.000	12.000	1.000	20.000	1.000	5.000	.000	4.000	4.000	6.000	6.000	6.000	6.000
23	2.000	.000	24.000	1.000	50.000	1.000	4.000	.000	4.000	1.000	6.000	6.000	6.000	6.000
24	30.000	1.000	4.000	1.000	10.000	.000	7.000	.000	4.000	5.000	7.000	7.000	7.000	7.000
25	10.000	1.000	11.000	1.000	500.000	1.000	5.000	.000	4.000	4.000	6.000	6.000	6.000	6.000
26	15.000	1.000	10.000	1.000	230.000	1.000	5.000	.000	4.000	1.000	6.000	6.000	6.000	5.000
27	4.000	.000	12.000	1.000	75.000	1.000	2.000	1.000	1.000	1.000	3.000	4.000	3.000	4.000

SEM Overview

Four phases of analysis

1. (Descriptive statistics)
2. Measurement model estimation
3. Structural model estimation
4. Mediation/Moderation/supplementary analyses

Descriptive Statistics

e.g., assessment of non-response error

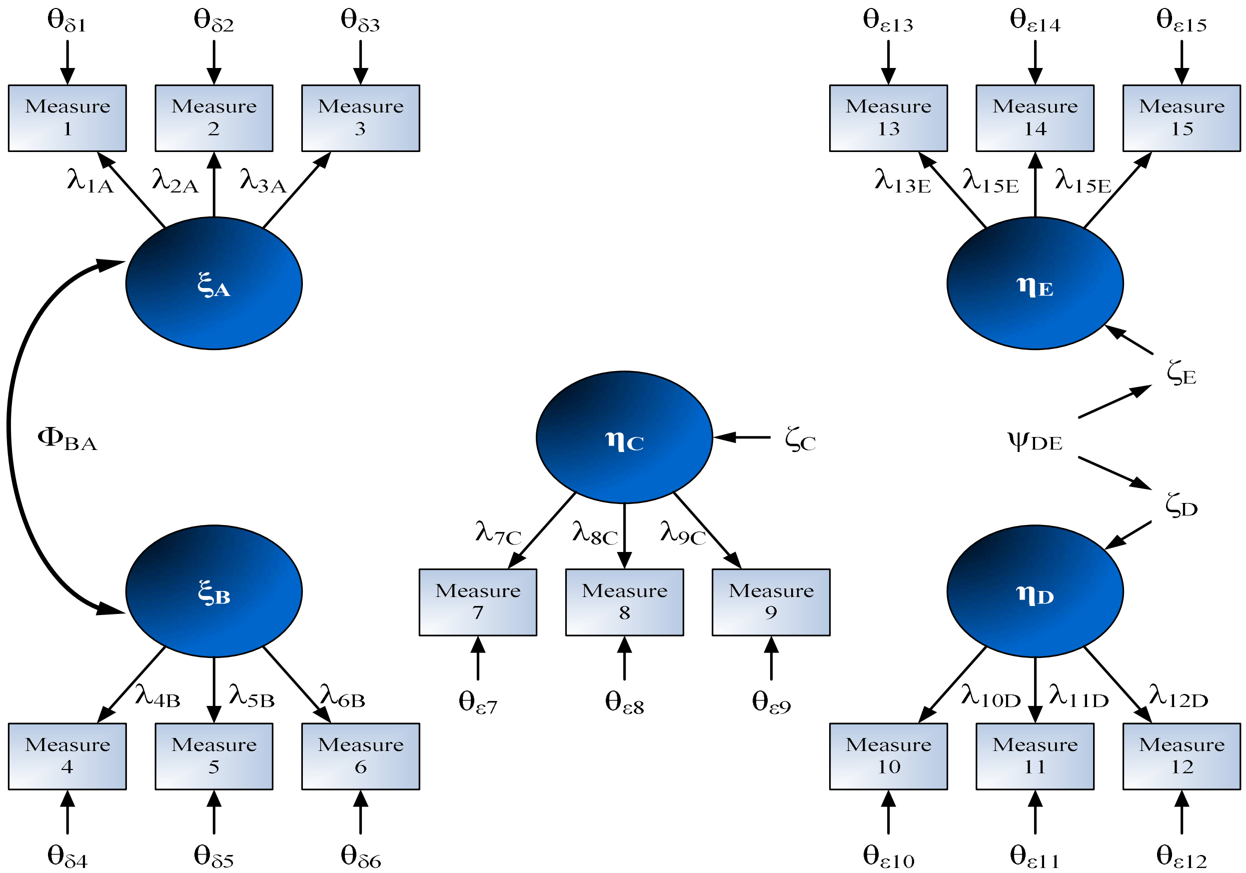
- Chi-square test of early versus late survey respondents

Demographic variable	p-value
Type of organisation	.206
Size of organisation	.436
Size of modelling team	.305
Country of origin	.100
Years of experience in process modelling overall	.346
Months of experience in process modelling with BPMN	.639
Number of BPMN models created	.345
Type of training	.784
Use of modelling tool	.060
Use of modelling guidelines	.311
Use of BPMN constructs	.542

Structural Model Estimation: 5-stage process

- **Model specification**
  - Specification of an a-priori research model with theoretical constructs and hypothesized relationships between them.
- **Model identification**
  - Estimation of unknown parameters (such as factor loadings, path coefficients or explained variance) based on observed correlations or covariances.
- **Model estimation**
  - Finding of one set of model parameters that best fits the data.
- **Model fit testing**
  - Assessment of how well a model fits the data.
- **Model re-specification**
  - Improvement of either model parsimony or fit.

Measurement Model Estimation



Measurement Model Estimation

- Examines whether the model of what we measure fits the properties of the data we collected
- Often confused with confirmatory factor analysis.
- The actual test criteria (for reflective models) is Goodness of Fit.

> Goodness of fit statistics for the measurement model (GFI = 0.91, NFI = 0.97, NNFI = 0.98, CFI = 0.98, SRMR = 0.05, RMSEA = 0.06, $\chi 2$ = 436.71, df = 155) suggest good fit of the measurement model to the data set, considering the approximate benchmarks suggested by Im and Grover (2004).

Measurement Model Estimation for Reflective Measures

- Assessment of the reliability and validity of the scales used.
- Tests
  - Uni-dimensionality
    - A construct is uni-dimensional if its constituent items represent one underlying trait
  - Reliability and composite reliability
    - Reliability is defined as the degree to which scale items are free from error and, therefore, yield consistent results.
  - Convergent validity
    - Convergent validity tests if measures that should be related are in fact related.
  - Discriminant validity
    - Discriminant validity refers to the degree to which items of different constructs are unique from each other.

Measurement Model Estimation

- Validation via standard set of indices (e.g., Fornell and Larcker, 1981)
  - Uni-dimensionality:
    - Cronbach's Alpha (α) > 0.7
  - Reliability:
    - Cronbach's Alpha (α) > 0.8
    - Composite reliability (p_c) > 0.5
  - Convergent validity:
    - Average variance extracted (AVE) > 0.5
    - Indicator factor loadings (λ) > 0.6
    - Indicator factor loadings significant at $p < 0.05$
    - Composite reliability (p_c) > 0.8
  - Discriminant validity:
    - AVE should exceed the squared correlations between each of the constructs

Reporting Measurement Model Results

Scale item	Item mean	Item S.D.	Item loading	Sig.
PU1	6.01	1.058	.798	.000
PU2	5.90	1.060	.803	.000
PU3	5.48	1.598	.774	.000
SAT1	5.19	1.273	.797	.000
SAT2	5.09	1.304	.806	.000
SAT3	4.78	1.458	.776	.000
CON1	4.94	1.226	.835	.000
CON2	4.95	1.299	.856	.000
CON3	4.90	1.293	.852	.000
PEOU1	5.14	1.315	.777	.000
PEOU2	5.05	1.353	.876	.000
PEOU3	5.05	1.339	.875	.000
ItU1	6.00	.977	.820	.000
ItU2	6.03	.926	.843	.000
ItU3	5.60	1.329	.712	.000

Reporting Measurement Model Results

Construct Correlations

	PU	SAT	CON	PEOU	ItU
PU	1.000				
SAT	.621	1.000			
CON	.535	.607	1.000		
PEOU	.464	.467	.604	1.000	
ItU	.577	.642	.652	.593	1.000

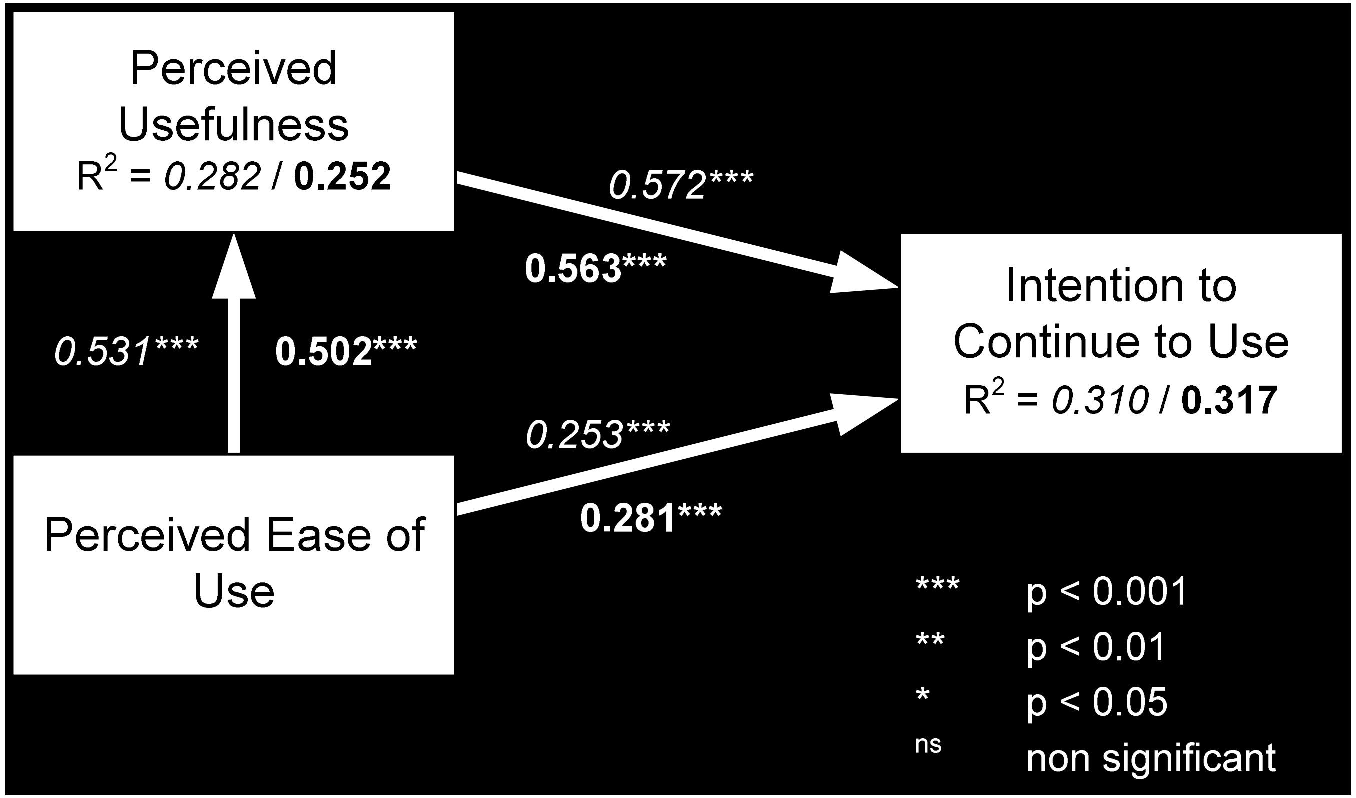
Scale Properties

Construct	Mean	S.D.	Cronbach's α	ρ_c	AVE
PU	17.39	3.366	.865	.820	.909
SAT	15.06	3.792	.932	.872	.940
CON	14.78	3.660	.956	.914	.959
PEOU	15.24	3.684	.908	.850	.922
ItU	17.63	2.960	.887	.842	.923

Model Fit

Fit index	Suggested value	TAM (EPC)	ECT (EPC)	Hybrid (EPC)		TAM (BPMN)	ECT (BPMN)	Hybrid (BPMN)
GFI	> 0.900	0.942	0.932	0.926		0.956	0.950	0.934
AGFI	> 0.900	0.933	0.913	0.901		0.918	0.920	0.902
NFI	> 0.900	0.956	0.932	0.915		0.982	0.986	0.982
NNFI	> 0.900	0.946	0.923	0.905		0.979	0.986	0.985
CFI	> 0.900	0.964	0.943	0.927		0.986	0.990	0.988
SRMR	< 0.050	0.0439	0.0489	0.0496		0.0466	0.0433	0.0471
RMSEA	< 0.080	0.0731	0.0742	0.0784		0.0831	0.0693	0.070
χ^2 (df, p)	-	119.383 (24, 0.000)	292.705 (*49, 0.000*)	537.519 (*81, 0.000*)		119.863 (*24, 0.000*)	190.000 (*49, 0.000*)	307.129 (*81, 0.000*)
R^2 for ItU	-	0.310	0.151	0.355		0.317	0.269	0.396

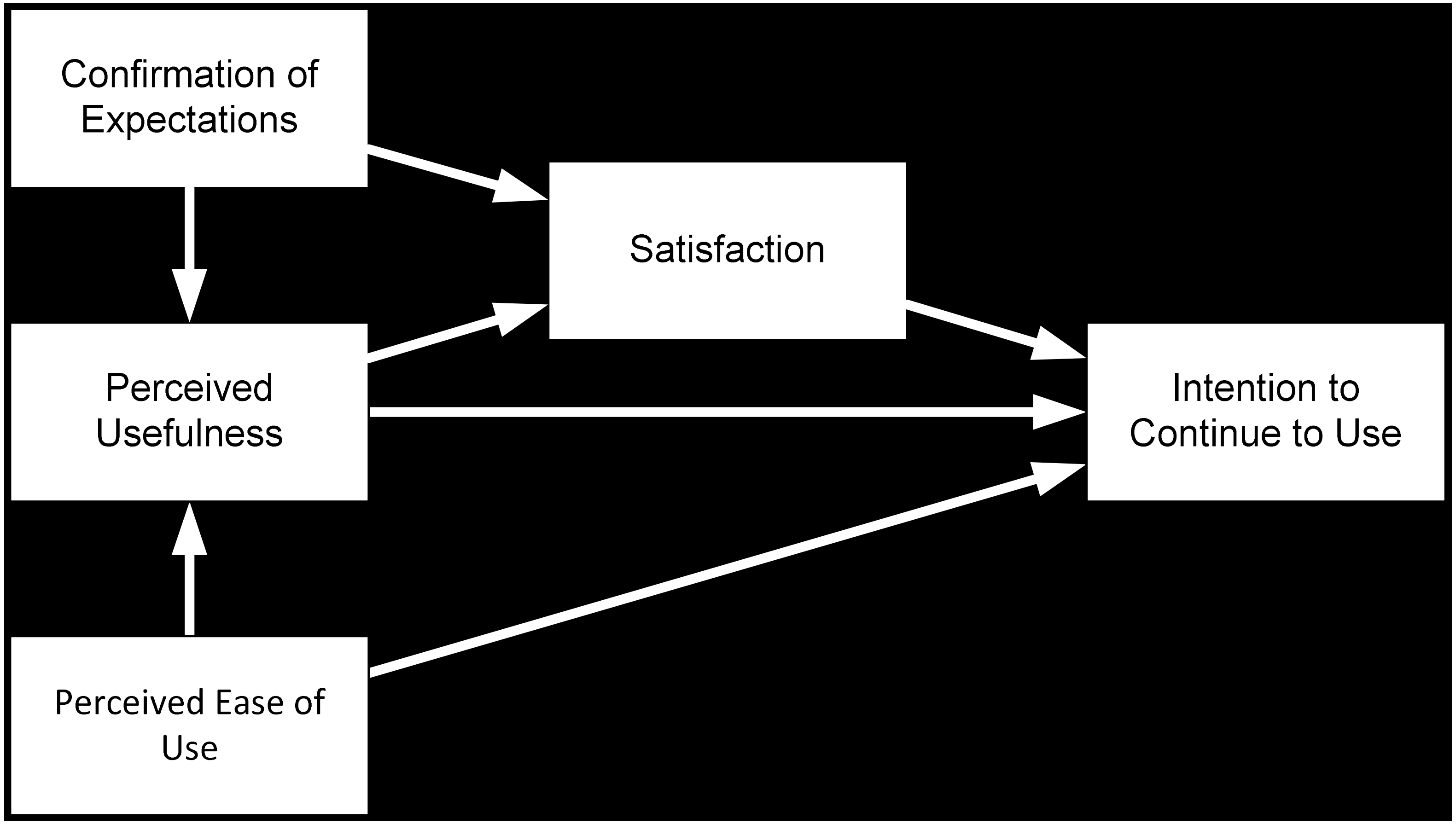
Structural Model Estimation: Results Reporting



Let’s do it.

- SEM Exercise based on
- *Recker, J. (2010): Explaining Usage of Process Modeling Grammars: Comparing Three Theoretical Models in the Study of Two Grammars. Information & Management, Vol. 47, No. 5-6, pp. 316-324*
- freely available from http://eprints.qut.edu.au/34162/

Our Research Model



SEM: Advanced matters: for Discussion

- PLS versus LISREL (or AMOS)
- Reflective vs formative models
- Moderator analysis & mediation analysis
- Missing data

1. PLS versus LISREL

- Or: correlation- versus covariance-based SEM
- What are current beliefs?
- What are strengths?
- What are weaknesses?

Reported Reasons for using PLS in Marketing:

- non-normal data (50%), small sample size (46%), formative measures (33%), prediction = research objective (28%), complex models (13%), categorical variables (13%).
- Average PLS sample size is 211 compared to 246 for CB-SEM. But 25% had less than 100 observations, and 9% did not meet recommended sample size criteria.
- No studies report skewness or kurtosis.
- 42% reflective only; 6% formative only; 40% mixed; 12% no indication.

Reported Reasons for using PLS in IS:

Table 1. Reasons for Using PLS-SEM

	Number of Studies in *MISQ* Reporting (N = 65)	Proportion Reporting (%)	Number of studies in *JM*, *JMR*, and *JAMS* Reporting (N = 60)	Proportion Reporting (%)
Total	46	70.77	20	33.33
Specific Reasons:				
Small Sample Size	24	36.92	15	25.00
Non-Normal Data	22	33.85	19	31.67
Formative Measures	20	30.77	19	31.67
Focus on Prediction	10	15.38	14	23.33
Model Complexity	9	13.85	6	10.00
Exploratory Research	7	10.77	1	1.67
Theory Development	6	9.23	0	0.00
Use of Categorical Variables	4	6.15	6	10.00
Convergence ensured	2	3.08	2	3.33
Theory Testing	1	1.54	5	8.33
Interaction Terms	1	1.54	5	8.33

Ringle, C.M., Sarstedt, M., and Straub, D.W. "Editor's Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly," *MIS Quarterly (36:1) 2012, pp iii-xiv.*

Reported PLS-SEM Model Types in IS:

Criterion	Number of Studies in *MISQ* Reporting (N = 65)	Proportion Reporting (%)	Number of Studies in *JM, JMR,* and *JAMS* Reporting (N = 41)	Proportion Reporting (%)
Mode of Measurement Models				
Only Reflective	46	42.20	18	30.00
Only Formative	2	1.83	1	1.67
Reflective and Formative	33	30.28	32	53.33
Not Specified	28	25.69	9	15.00
Number of Indicators per Reflective Construct [b]				
Mean[a]	3.58	–	3.57	–
Median	3.5		3	
Range	(1; 400)		(1; 46)	
Number of Indicators per Formative Construct [c]				
Mean[a]	3.03	–	4.12	–
Median	3		3.5	
Range	(1; 11)		(1; 25)	
Number of Models with Control Variables	29		28	
Number of Control Variables				
Mean	3.69	–	1.82	–
Median	4		0	
Range	(1; 6)		(0; 8)	
Number of Studies with				
Single-Item Constructs	31	47.69	21	51.22
Higher Order Constructs (i.e., Hierarchical Component Analysis)	15	23.08	15	36.59
Nonlinear Relationships	3	4.62	4	9.76
Model Modified in the Course of the Analysis	18	27.69	8	19.51
If yes, Comparison with Initial Model?	6	9.23	0	0.00
Item Wordings Reported	58	89.23	34	82.93
Scales Reported	55	84.62	34	82.93
Scale Means and Standard Deviations Reported	43	66.15	27	65.85
Correlation/Covariance Matrix	54	83.08	29	70,73

Ringle, C.M., Sarstedt, M., and Straub, D.W. "Editor's Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly," *MIS Quarterly (36:1) 2012, pp iii-xiv.*

Criteria	Variance-Based Modeling (e.g. SmartPLS, PLS Graph)	Covariance-Based Modeling (e.g. LISREL, AMOS, Mplus)
Objective	Prediction oriented	Parameter oriented
Distribution Assumptions	Non-parametric	Normal distribution (parametric)
Required sample size	Small (min. 30 – 100)	High (min. 100 – 800)
Model complexity	Large models OK	Large models problematic (50+ indicator variables)
Parameter Estimates	Potential Bias	Stable, if assumptions met
Indicators per construct	One – two OK Large number OK	Typically 3 – 4 minimum to meet identification requirements
Statistical tests for parameter estimates	Inference requires Jackknifing or Bootstrapping	Assumptions must be met
Measurement Model	Formative and Reflective indicators OK	Typically only Reflective indicators
Goodness-of-fit measures	None	Many

2. Formative vs reflective models

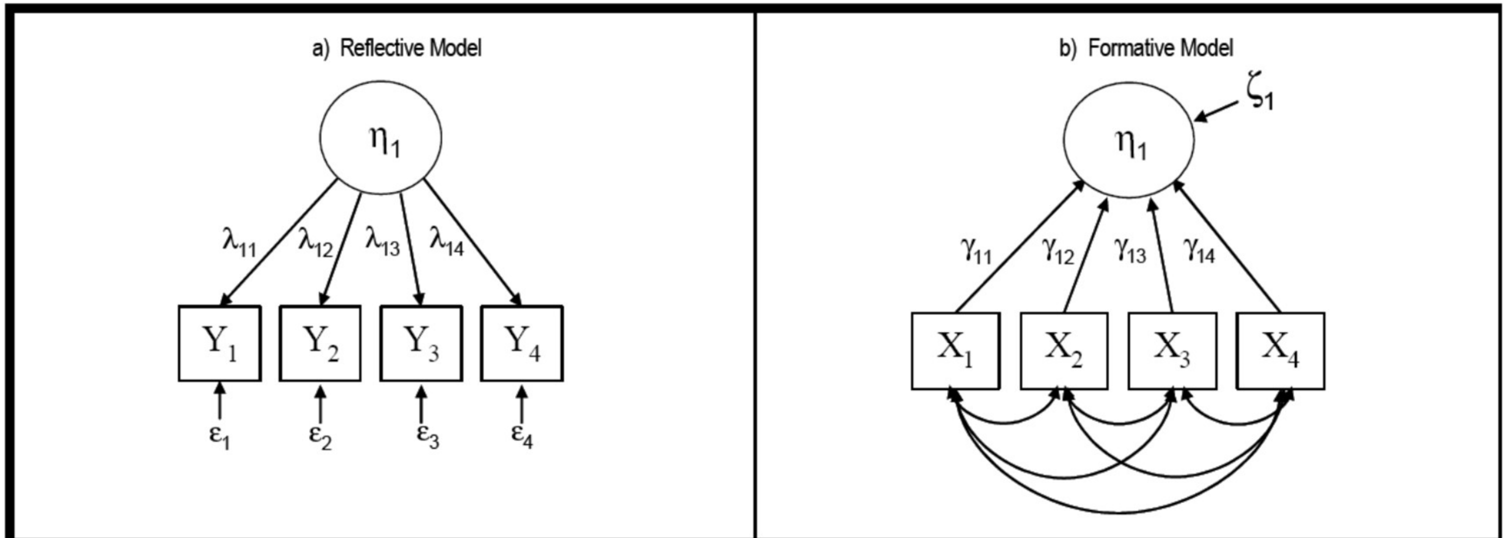
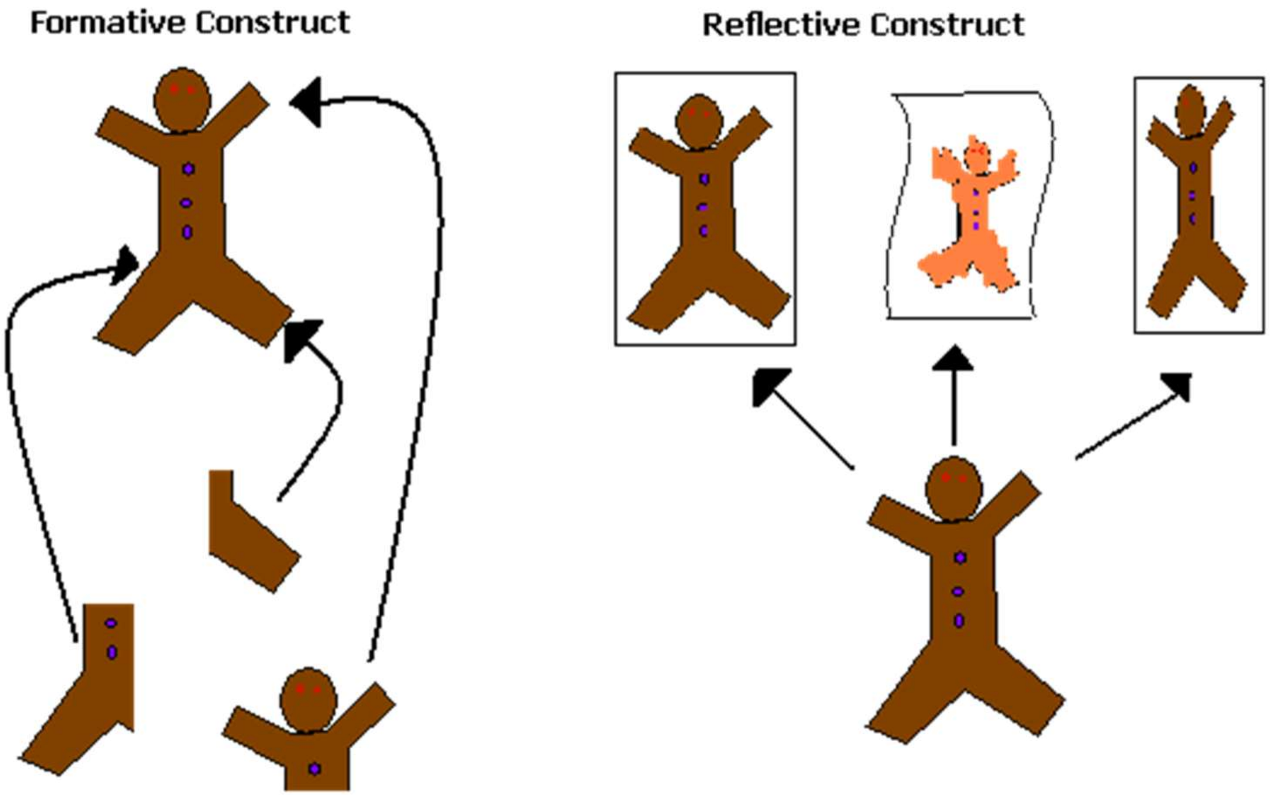


Figure 1. Diagram of Reflective and Formative Measurement Models (From K. Bollen and R. Lennox, "Conventional Wisdom on Measurement: A Structural Equation Perspective," *Psychological Bulletin* (110:2), 1991, pp. 305-314. Copyright © 1991 by the American Psychological Association. Reproduced with permission.)

A construct could be measured reflectively or formatively.
Constructs are not necessarily (inherently) reflective or formative.

Formative vs reflective: Illustration



[Graphic courtesy of Robert Sainsbury, Mississippi State University]

Formative vs reflective: Example

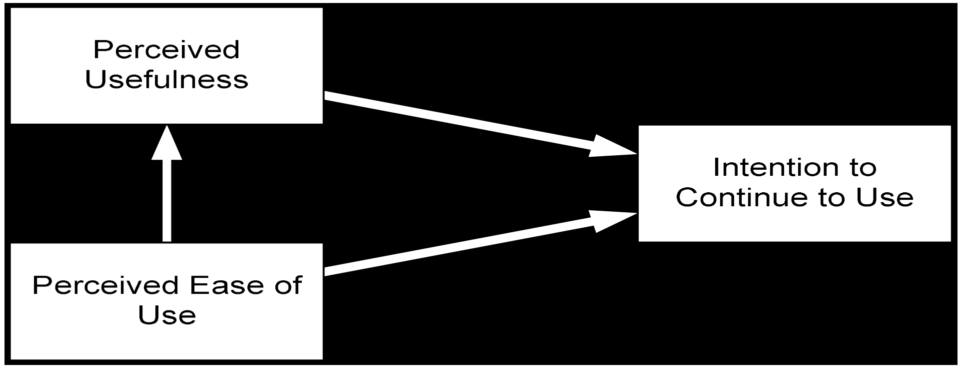
- Formative vs. Reflective
  - Let’s take **firm performance** as an example.

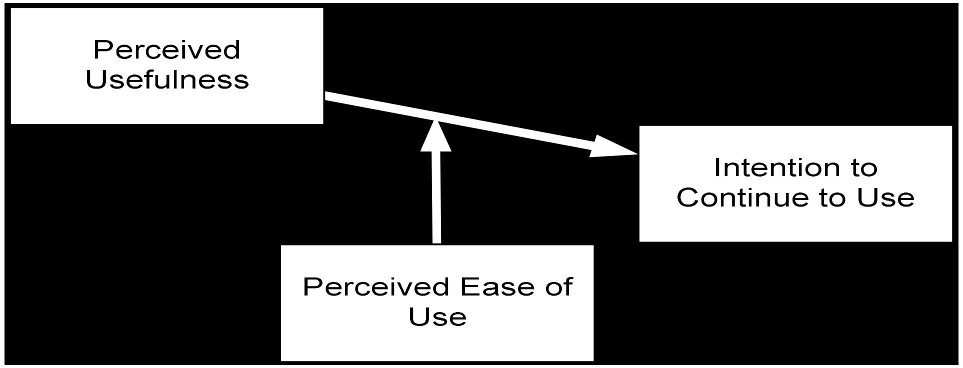
1. We can create a reflective scale that measures top managers’ views of how well the firm is performing.
   - These scale items can be interchangeable, and in this way let the researcher assess the reliability of the measures in reflecting the construct.
2. Or we can create a set of metrics for firm performance that measure disparate elements such as ROI, profitability, return on equity, market share, etc.
   - These items are not interchangeable and, thus, are formative.

Some issues with formative measures

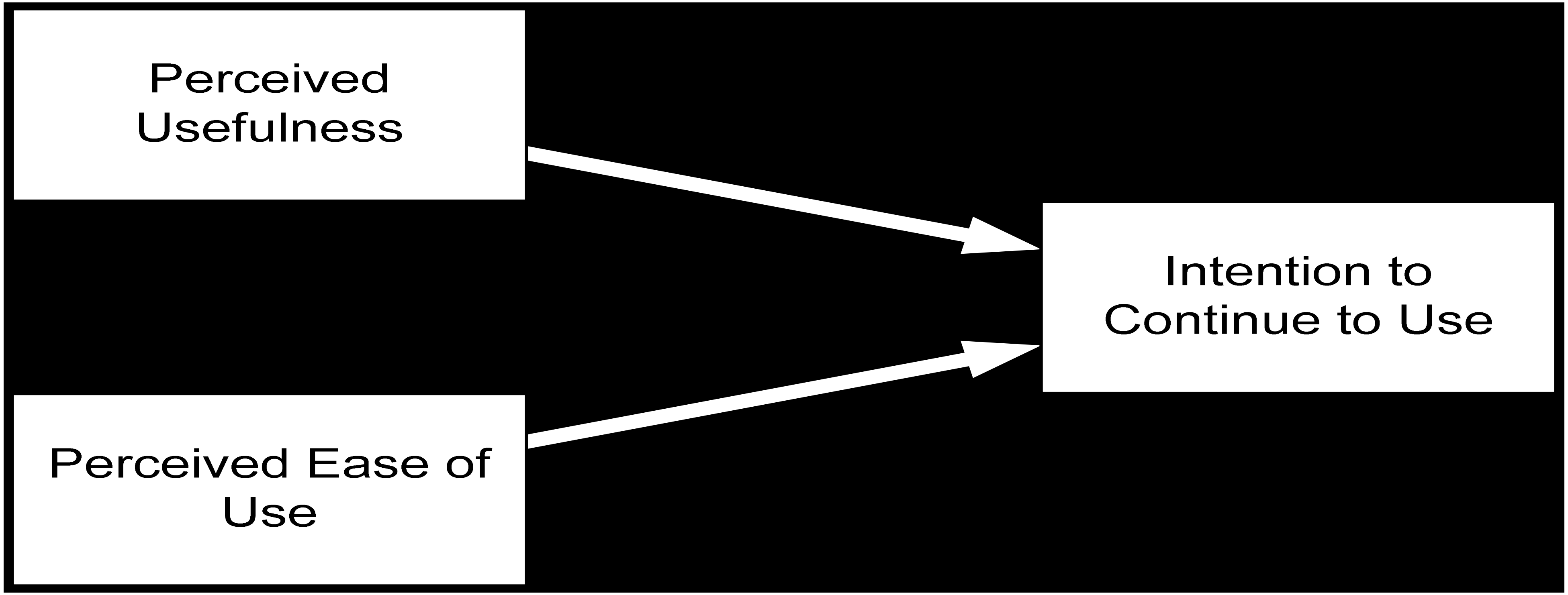
- Reliability or internal consistency, as is traditionally measured, is not a factor in formative constructs. We want multicollinearity and unidimensionality in reflective constructs. Formative constructs are destabilized when this occurs. May need to eliminate items if they are redundant.
- Decomposed models or indices can change the meaning of the theoretical relationship.
  - Consider the theoretical implications (not just empirical).
- Even if empirical results are weak, theoretically certain (formative) measures may be (very/not) important.
  - Unclear how to handle.
  - Debates for validation and measurement remain ongoing

3. Mediation vs Moderation

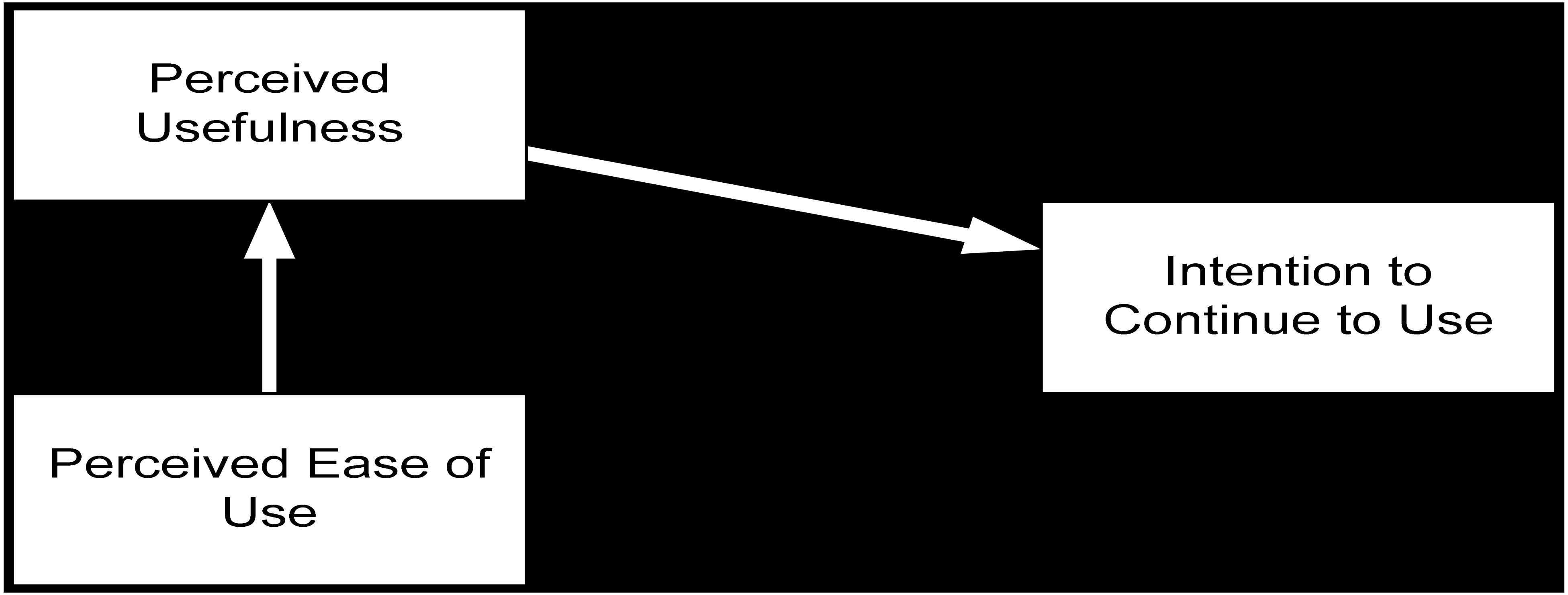




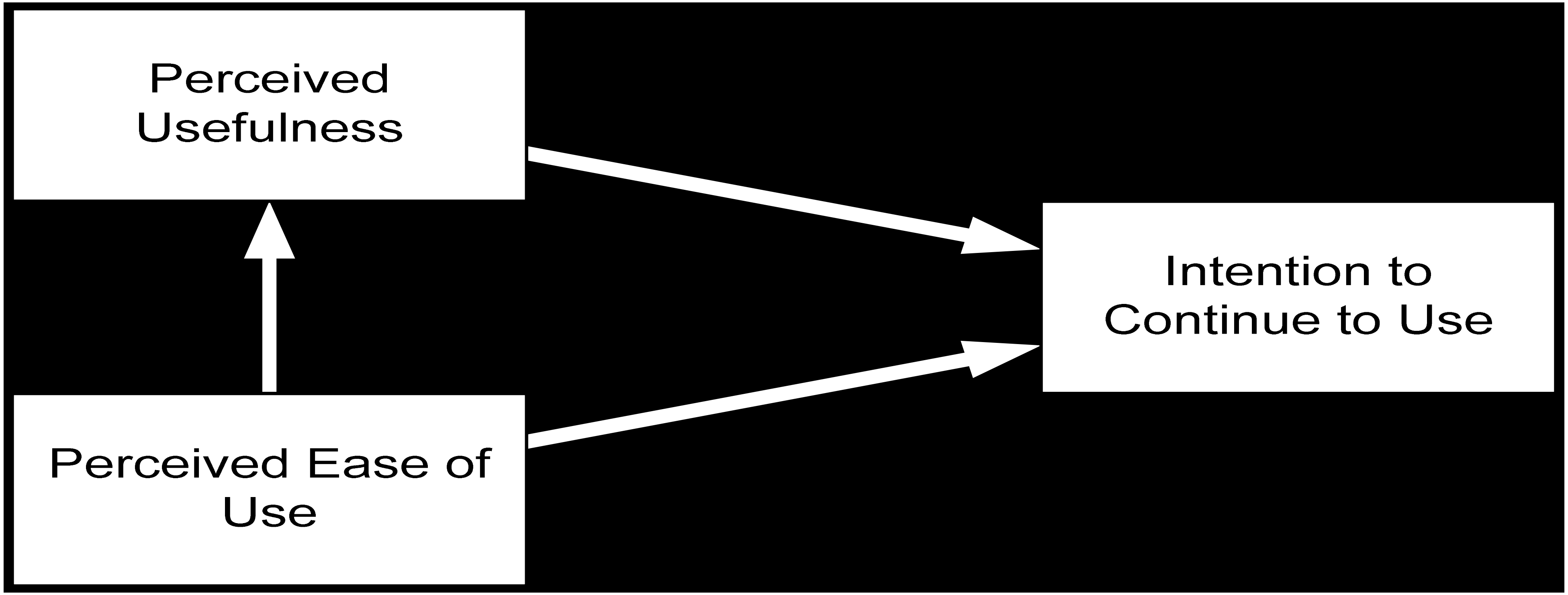
No Mediation



Full Mediation

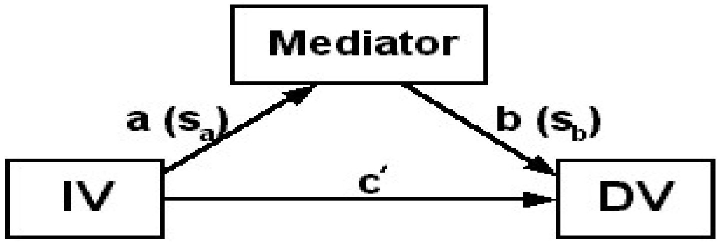


Partial Mediation



Sobel Mediation Test

- Numbers needed
  - a = raw (unstandardized) regression coefficient for the association between IV and mediator.
  - sa = standard error of a.
  - b = raw coefficient for the association between the mediator and the DV (when the IV is also a predictor of the DV).
  - sb = standard error of b.



- The Sobel test works well *only in large samples*. A better example includes bootstrapping of raw data: Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple Mediation models. Behavior Research Methods, Instruments, & Computers, 36, 717-731.

Sobel, M. E. (1982). Asymptotic intervals for indirect effects in structural equations models. In S. Leinhart (Ed.), *Sociological methodology 1982* (pp.290-312). San Francisco: Jossey-Bass.

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

Calculation for the Sobel Test

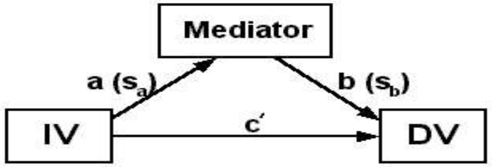
An interactive calculation tool for Mediation tests

- Curriculum vitae
- Selected publications
- Supplemental material for publications
- Online utilities
- Mediation & moderation material
- PSY-PC 2101: Intro. to Statistical Analysis
- PSY-GS 321: Multilevel Modeling
- Vanderbilt Psychological Sciences
- Vanderbilt Quantitative Methods
- Organizations
- Friends and colleagues
- Contact me

given independent variable (IV) to a given dependent variable (DV). Generally speaking, Mediation can be said to occur when (1) the IV significantly affects the mediator, (2) the IV significantly affects the DV in the absence of the mediator, (3) the mediator has a significant unique effect on the DV, and (4) the effect of the IV on the DV shrinks upon the addition of the mediator to the model. These criteria can be used to informally judge whether or not Mediation is occurring, but MacKinnon & Dwyer (1993) and MacKinnon, Warsi, & Dwyer (1995) have popularized statistically based methods by which Mediation may be formally assessed.

An illustration of Mediation

a, *b*, and *c'* are path coefficients. Values in parentheses are standard errors of those path coefficients.



Description of numbers needed

a = raw (unstandardized) regression coefficient for the association between IV and mediator.
s_a = standard error of *a*.
b = raw coefficient for the association between the mediator and the DV (when the IV is also a predictor of the DV).
s_b = standard error of *b*.

To get numbers

1. Run a regression analysis with the IV predicting the mediator. This will give *a* and s_a.
2. Run a regression analysis with the IV and mediator predicting the DV. This will give *b* and s_b. Note that s_a and s_b should never be negative.

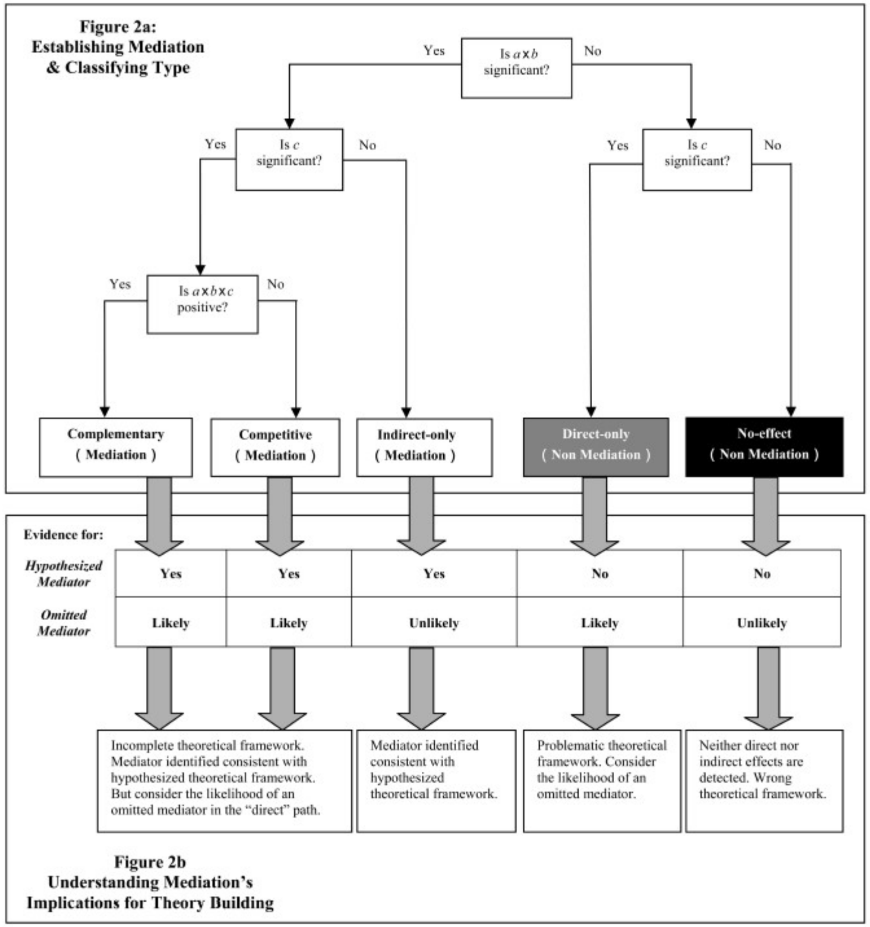
To conduct the Sobel test

Details can be found in Baron and Kenny (1986), Sobel (1982), Goodman (1960), and MacKinnon, Warsi, and Dwyer (1995). Insert the *a*, *b*, s_a, and s_b into the cells below and this program will calculate the critical ratio as a test of whether the indirect effect of the IV on the DV via the mediator is significantly different from zero.

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

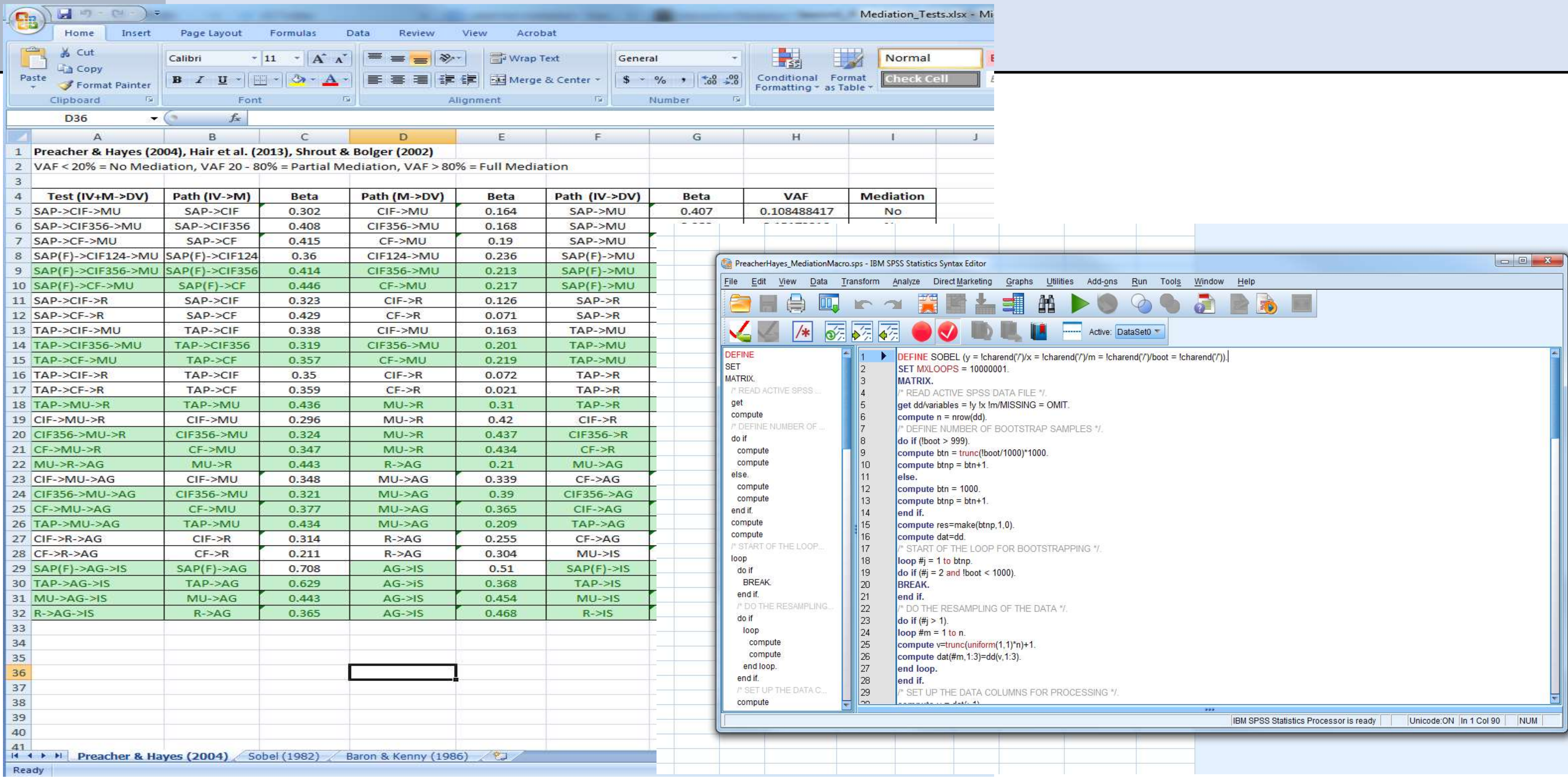
Alternatively, you can insert t_a and t_b into the cells below, where t_a and t_b are the *t*-test statistics for the difference between the *a* and *b* coefficients and zero. Results should be

Procedure: Zhao et al. (2010)

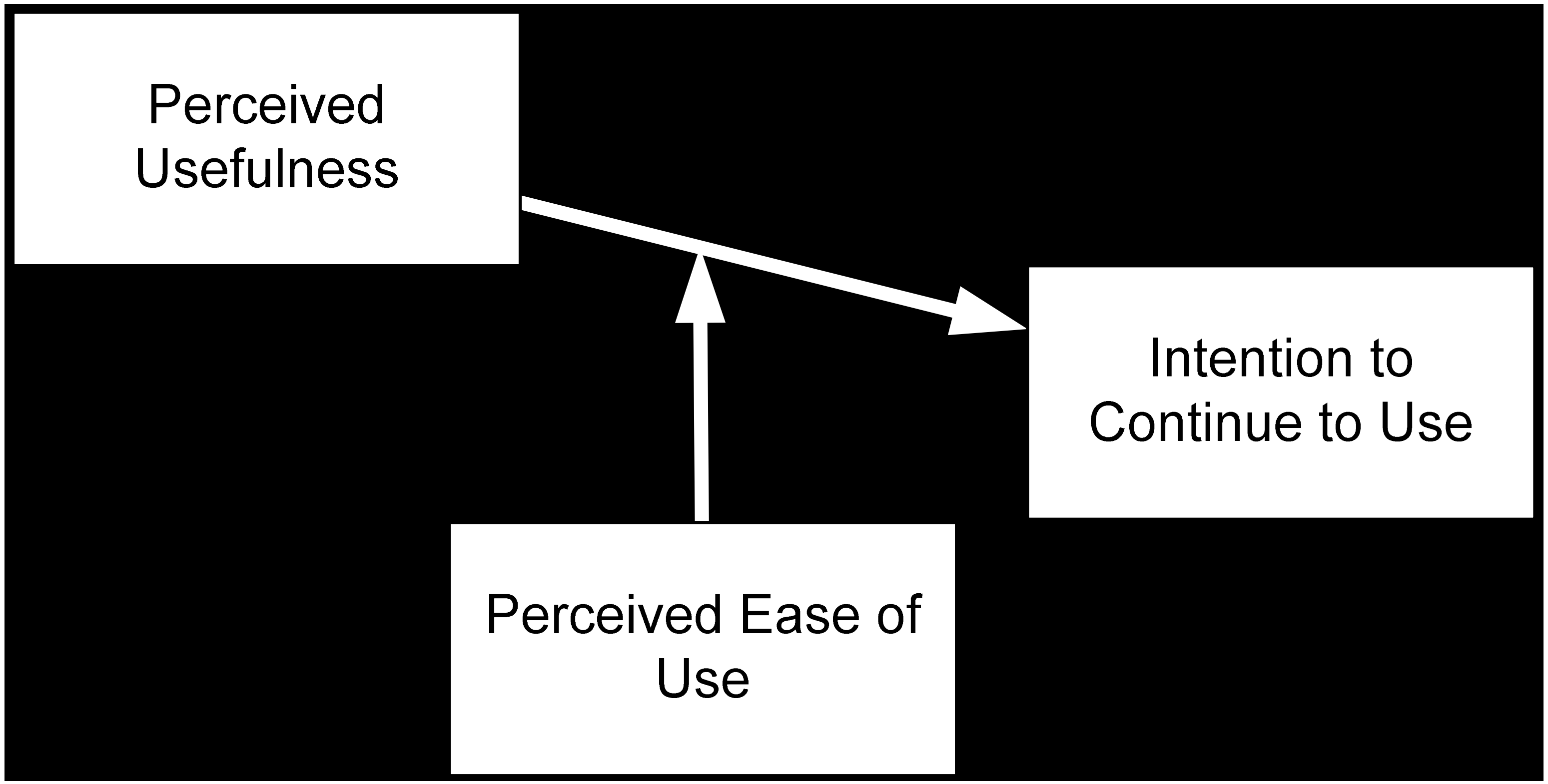


Zhao, X., Lynch Jr., J.G., and Chen, Q. "Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis," *The Journal of Consumer Research (37:2) 2010, pp 197-206.*

Example


Mediation_Tests.xlsx
Preacher & Hayes (2004), Hair et al. (2013), Shrout & Bolger (2002)
VAF < 20% = No Mediation, VAF 20 - 80% = Partial Mediation, VAF > 80% = Full Mediation
Test (IV+M->DV) | Path (IV->M) | Beta | Path (M->DV) | Beta | Path (IV->DV) | Beta | VAF | Mediation
SAP->CIF->MU | SAP->CIF | 0.302 | CIF->MU | 0.164 | SAP->MU | 0.407 | 0.108488417 | No
SAP->CIF356->MU | SAP->CIF356 | 0.408 | CIF356->MU | 0.168 | SAP->MU
SAP->CF->MU | SAP->CF | 0.415 | CF->MU | 0.19 | SAP->MU
SAP(F)->CIF124->MU | SAP(F)->CIF124 | 0.36 | CIF124->MU | 0.236 | SAP(F)->MU
SAP(F)->CIF356->MU | SAP(F)->CIF356 | 0.414 | CIF356->MU | 0.213 | SAP(F)->MU
SAP(F)->CF->MU | SAP(F)->CF | 0.446 | CF->MU | 0.217 | SAP(F)->MU
SAP->CIF->R | SAP->CIF | 0.323 | CIF->R | 0.126 | SAP->R
SAP->CF->R | SAP->CF | 0.429 | CF->R | 0.071 | SAP->R
TAP->CIF->MU | TAP->CIF | 0.338 | CIF->MU | 0.163 | TAP->MU
TAP->CIF356->MU | TAP->CIF356 | 0.319 | CIF356->MU | 0.201 | TAP->MU
TAP->CF->MU | TAP->CF | 0.357 | CF->MU | 0.219 | TAP->MU
TAP->CIF->R | TAP->CIF | 0.35 | CIF->R | 0.072 | TAP->R
TAP->CF->R | TAP->CF | 0.359 | CF->R | 0.021 | TAP->R
TAP->MU->R | TAP->MU | 0.436 | MU->R | 0.31 | TAP->R
CIF->MU->R | CIF->MU | 0.296 | MU->R | 0.42 | CIF->R
CIF356->MU->R | CIF356->MU | 0.324 | MU->R | 0.437 | CIF356->R
CF->MU->R | CF->MU | 0.347 | MU->R | 0.434 | CF->R
MU->R->AG | MU->R | 0.443 | R->AG | 0.21 | MU->AG
CIF->MU->AG | CIF->MU | 0.348 | MU->AG | 0.339 | CF->AG
CIF356->MU->AG | CIF356->MU | 0.321 | MU->AG | 0.39 | CIF356->AG
CF->MU->AG | CF->MU | 0.377 | MU->AG | 0.365 | CIF->AG
TAP->MU->AG | TAP->MU | 0.434 | MU->AG | 0.209 | TAP->AG
CIF->R->AG | CIF->R | 0.314 | R->AG | 0.255 | CF->AG
CF->R->AG | CF->R | 0.211 | R->AG | 0.304 | MU->IS
SAP(F)->AG->IS | SAP(F)->AG | 0.708 | AG->IS | 0.51 | SAP(F)->IS
TAP->AG->IS | TAP->AG | 0.629 | AG->IS | 0.368 | TAP->IS
MU->AG->IS | MU->AG | 0.443 | AG->IS | 0.454 | MU->IS
R->AG->IS | R->AG | 0.365 | AG->IS | 0.468 | R->IS
Preacher & Hayes (2004) | Sobel (1982) | Baron & Kenny (1986)
PreacherHayes_MediationMacro.sps - IBM SPSS Statistics Syntax Editor
DEFINE SOBEL (y = !charend('/')/x = !charend('/')/m = !charend('/')/boot = !charend('/')).
SET MXLOOPS = 10000001.
MATRIX.
/* READ ACTIVE SPSS DATA FILE */.
get dd/variables = !y !x !m/MISSING = OMIT.
compute n = nrow(dd).
/* DEFINE NUMBER OF BOOTSTRAP SAMPLES */.
do if (!boot > 999).
compute btn = trunc(!boot/1000)*1000.
compute btnp = btn+1.
else.
compute btn = 1000.
compute btnp = btn+1.
end if.
compute res=make(btnp,1,0).
compute dat=dd.
/* START OF THE LOOP FOR BOOTSTRAPPING */.
loop #j = 1 to btnp.
do if (#j = 2 and !boot < 1000).
BREAK.
end if.
/* DO THE RESAMPLING OF THE DATA */.
do if (#j > 1).
loop #m = 1 to n.
compute v=trunc(uniform(1,1)*n)+1.
compute dat(#m,1:3)=dd(v,1:3).
end loop.
end if.
/* SET UP THE DATA COLUMNS FOR PROCESSING */.

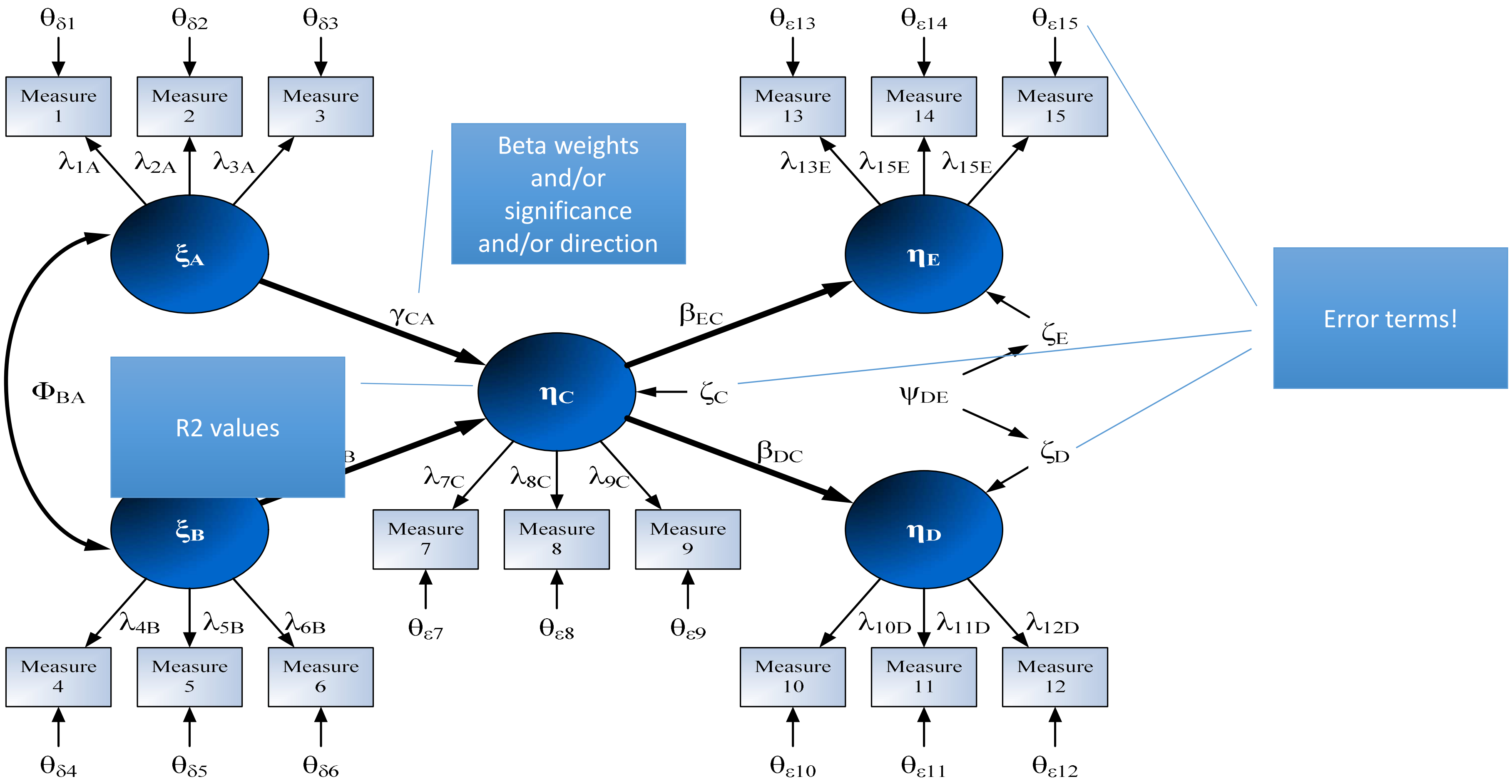
Moderation


Perceived Usefulness
Intention to Continue to Use
Perceived Ease of Use

The problem with moderation analysis

- Moderation usually involves testing two SEMs: one for the sub-sample where the values for the moderator are low; against the sub-sample where the values for the moderator are high.
  - Example: PU → ITU in the group where PEOU ratings are low/high.
- Problem:
  - SEM are more complex and involves more than 1 relationship between 2 variables (or constructs)
  - If not, we could run a (M)AN(C)OVA.
  - Conceptually, this is tricky theorizing: what should/would change exactly and why?

What could be different between two groups?



Multi-sample path analysis in LISREL

- For each moderator, split the data sample into two groups (high/low) and compare the SEMs across the two sub-samples
- Once model 1 is identified, the parameter from this model are used to constrain model 2:
  - Model2a has **factor loadings** and **error variances** *constrained* to the parameters of model 1.
  - Model2b has **factor loadings** *free* but **error variances** *constrained* to the parameters of model 1.
  - Model2c has **factor loadings** and **error variances** *free*.
  - Model2d has **factor loadings** *constrained* to the parameters of model 1 but **error variances** *free*.

Moderation Test

- Two tests of $\Delta\chi^2$ / Δdf:
  - Compare model 2b to 2c: if sig. different, this is caused by error variances: ie measurement error, not moderation effect.
  - Compare model 2a to 2b: : if sig. different, this is caused by different factor loadings and path coefficients: ie moderation effect.
  - If both tests are sig. different, there is moderation and error variance. In this case, shared error correlations (φ and ψ) must be set to invariant to extract ‘true’ moderation effects.

Example

App. D.9: SEM results for moderating effects[1338]

Tab. 7.13: Changes in standardised γ coefficients due to moderating effects[1269]

Moderating variable	Group	CD1 → PU	CD3 → PU	CR1 → PEOU	CR3 → PEOU	CO1 → PEOU	CO2 → PEOU	CE1 → PEOU	CE3 → PEOU
	Whole sample	*-0.19***	*-0.13**	*-0.17**	*-0.11**	*-0.14**	*-0.15**	*-0.13**	*-0.13**
Process modelling experience	Low	0.07^{ns}	-0.03^{ns}						
	High	-0.02^{ns}	-0.40***						
Process modeller role	Low	-0.20*	-0.31***						
	High	0.01^{ns}	-0.18*						
Familiarity with the BPMN grammar	Low	0.03^{ns}	-0.25**	-0.17*	-0.18*			-0.01^{ns}	-0.22**
	High	-0.11^{ns}	-0.15*	-0.07^{ns}	-0.11^{ns}			-0.29*	-0.15*
Type of training received	Low	-0.14*	-0.18**	-0.23^{ns}	-0.29***			-0.13*	-0.21***
	High	0.08^{ns}	-0.21^{ns}	-0.45***	0.15^{ns}			-0.17^{ns}	-0.00^{ns}
Use of access to other modelling grammars	Low	-0.09^{ns}	-0.12^{ns}						
	High	-0.01^{ns}	-0.36***						
Use of access or hyperlinks to other documentation from within the process models	Low	0.01^{ns}	-0.11^{ns}						
	High	-0.21*	-0.27**						
Use of a method filter for restricting and specifying the set of constructs to be used	Low	-0.00^{ns}	-0.19*			-0.09^{ns}	-0.21*	-0.17**	-0.19***
	High	-0.09^{ns}	-0.23^{ns}			-0.28^{ns}	-0.02^{ns}	-0.06^{ns}	-0.10^{ns}

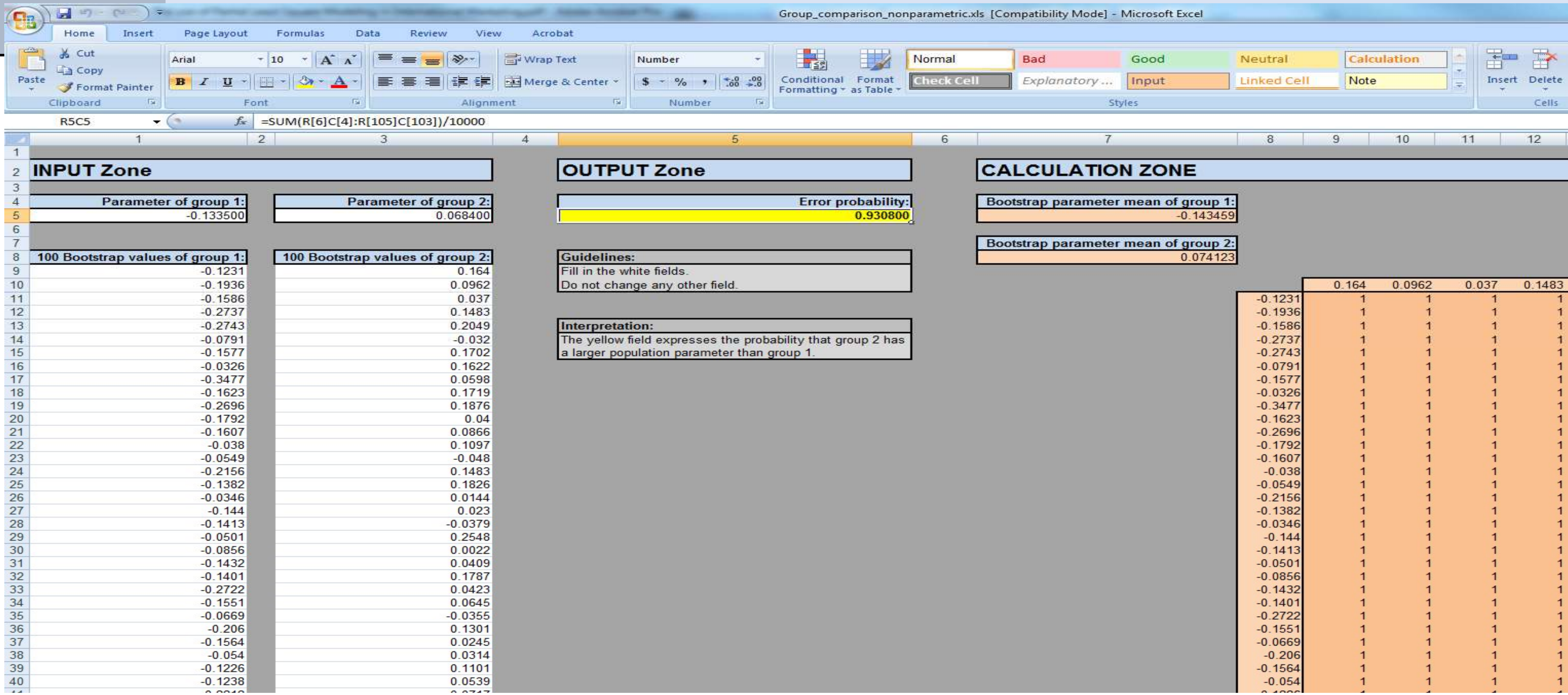
ns Insignificant at $p = 0.05$.
* Significant at $p < 0.05$.
** Significant at $p < 0.01$.
*** Significant at $p < 0.001$.

Multi-group analysis in PLS

- Multi-group analysis (MGA) in PLS is done by comparing bootstrap parameters across models estimated for two groups.

- Essentially tests whether $\beta(1) \neq \beta(2)$.

- Much simpler but less accurate than LISREL.



Group_comparison_nonparametric.xls [Compatibility Mode] - Microsoft Excel

R5C5 =SUM(R[6]C[4]:R[105]C[103])/10000

INPUT Zone

Parameter of group 1:	Parameter of group 2:
-0.133500	0.068400

OUTPUT Zone

Error probability:
0.930800

Guidelines:
Fill in the white fields.
Do not change any other field.

Interpretation:
The yellow field expresses the probability that group 2 has a larger population parameter than group 1.

CALCULATION ZONE

Bootstrap parameter mean of group 1:
-0.143459

Bootstrap parameter mean of group 2:
0.074123

Row	100 Bootstrap values of group 1:	100 Bootstrap values of group 2:
9	-0.1231	0.164
10	-0.1936	0.0962
11	-0.1586	0.037
12	-0.2737	0.1483
13	-0.2743	0.2049
14	-0.0791	-0.032
15	-0.1577	0.1702
16	-0.0326	0.1622
17	-0.3477	0.0598
18	-0.1623	0.1719
19	-0.2696	0.1876
20	-0.1792	0.04
21	-0.1607	0.0866
22	-0.038	0.1097
23	-0.0549	-0.048
24	-0.2156	0.1483
25	-0.1382	0.1826
26	-0.0346	0.0144
27	-0.144	0.023
28	-0.1413	-0.0379
29	-0.0501	0.2548
30	-0.0856	0.0022
31	-0.1432	0.0409
32	-0.1401	0.1787
33	-0.2722	0.0423
34	-0.1551	0.0645
35	-0.0669	-0.0355
36	-0.206	0.1301
37	-0.1564	0.0245
38	-0.054	0.0314
39	-0.1226	0.1101
40	-0.1238	0.0539

Row		0.164	0.0962	0.037	0.1483
11	-0.1231	1	1	1	1
12	-0.1936	1	1	1	1
13	-0.1586	1	1	1	1
14	-0.2737	1	1	1	1
15	-0.2743	1	1	1	1
16	-0.0791	1	1	1	1
17	-0.1577	1	1	1	1
18	-0.0326	1	1	1	1
19	-0.3477	1	1	1	1
20	-0.1623	1	1	1	1
21	-0.2696	1	1	1	1
22	-0.1792	1	1	1	1
23	-0.1607	1	1	1	1
24	-0.038	1	1	1	1
25	-0.0549	1	1	1	1
26	-0.2156	1	1	1	1
27	-0.1382	1	1	1	1
28	-0.0346	1	1	1	1
29	-0.144	1	1	1	1
30	-0.1413	1	1	1	1
31	-0.0501	1	1	1	1
32	-0.0856	1	1	1	1
33	-0.1432	1	1	1	1
34	-0.1401	1	1	1	1
35	-0.2722	1	1	1	1
36	-0.1551	1	1	1	1
37	-0.0669	1	1	1	1
38	-0.206	1	1	1	1
39	-0.1564	1	1	1	1
40	-0.054	1	1	1	1

Example

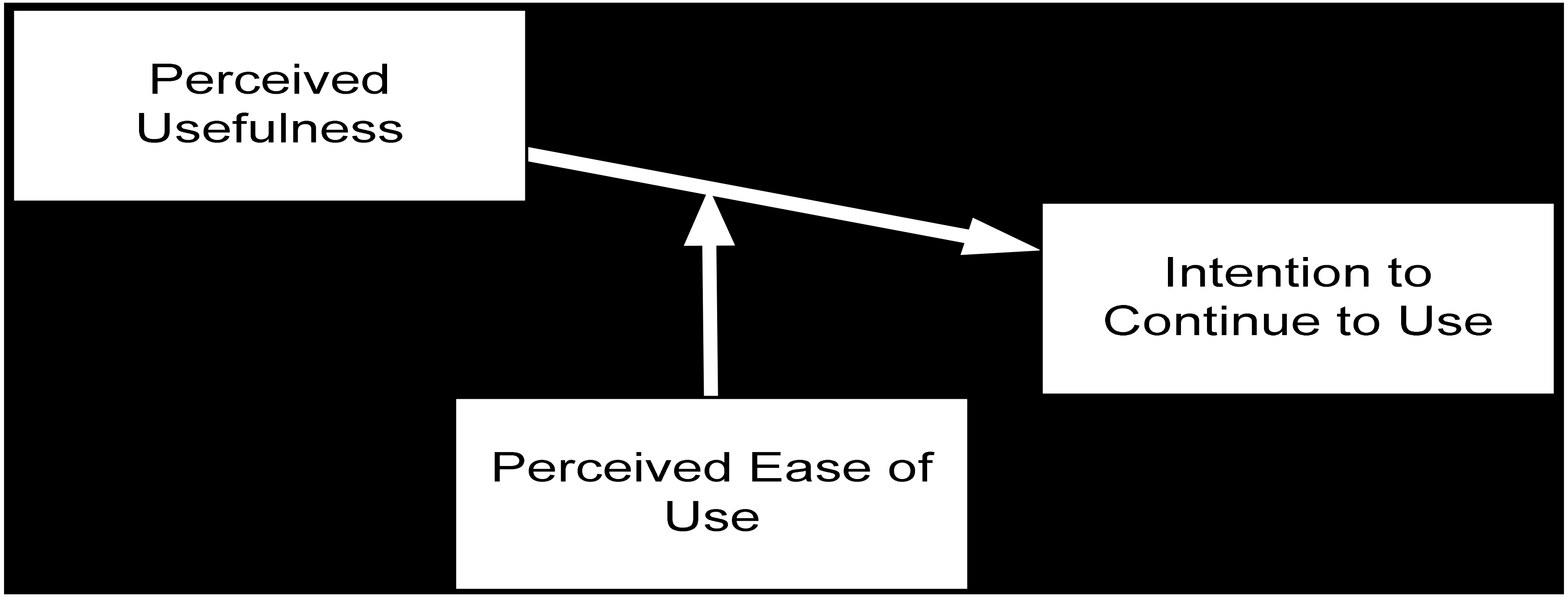
Table 5: Multi-group analysis results

Criterion variable	Predictor	Group 1 (academics) n = 55	group 2 (students) n = 53	group 3 (practitioners) n = 86	academics vs students	academics vs practitioners	students vs practitioners
ITU		R^2=0.72	R^2=0.68	R^2=0.51			
	PBC	0.53***	0.68***	0.18^{ns}	0.16	**0.01**	**0.00**
	MOT	0.39**	0.21**	0.57***	0.14	0.12	**0.00**
PBC		R^2=0.42	R^2=0.19	R^2=0.28			
	FC	0.65***	0.44***	0.53***	**0.04**	0.15	0.22
MOT		R^2=0.54	R^2=0.50	R^2=0.57			
	FC	0.41**	-0.07^{ns}	0.47***	**0.00**	0.36	**0.00**
	HELP	0.01^{ns}	0.47***	0.48***	**0.00**	**0.00**	0.48
	IMG	0.34**	0.61***	0.27*	**0.04**	0.30	**0.02**

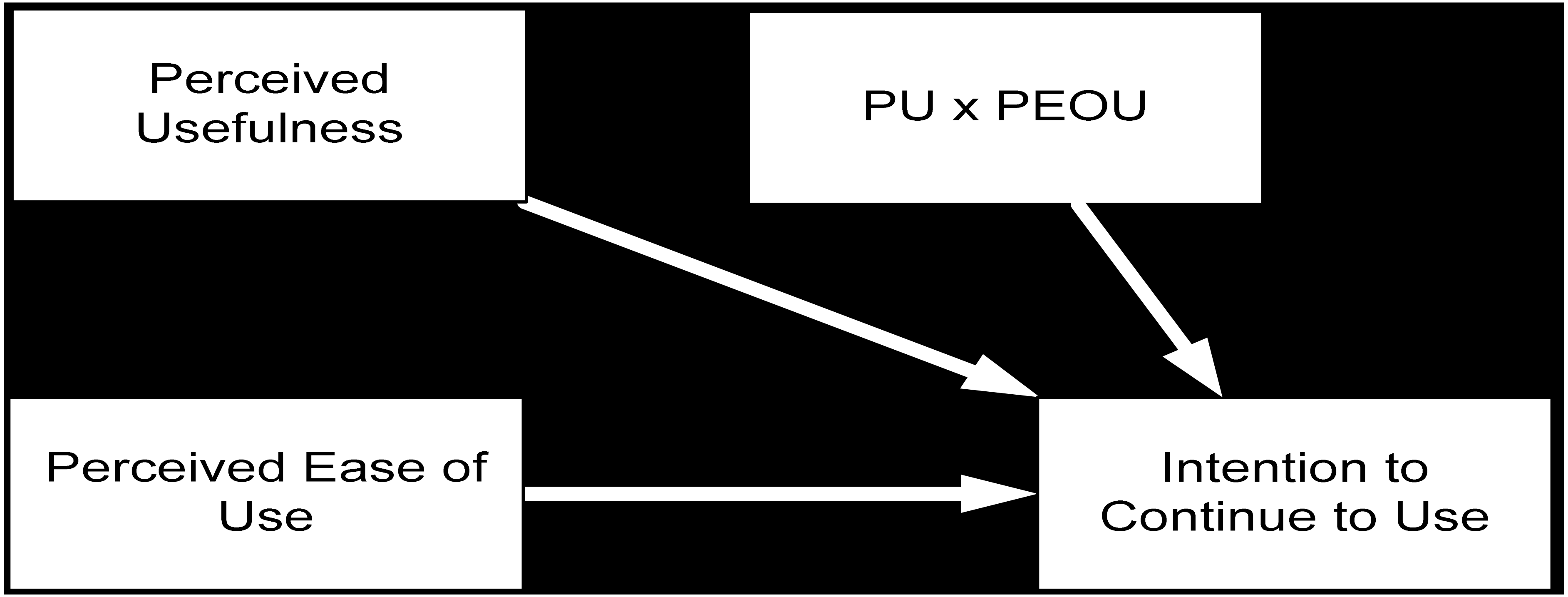
Figure 2. Structural model results (all groups)

Recker, Jan C. & La Rosa, Marcello (2012) Understanding user differences in open-source workflow management system usage intentions. Information Systems, 37(3), pp. 200-212.

Third approach to moderation analsyis: Interaction terms



Interaction Terms



The corresponding construct table

PU	PEOU	PU x PEOU	ITU
PU1	PEOU1	PU1 x PEOU1	ITU1
PU2	PEOU2	PU1 x PEOU2	ITU2
PU3	PEOU3	PU1 x PEOU3	ITU3
		PU2 x PEOU1	
		PU2 x PEOU2	
		PU2 x PEOU3	
		PU3 x PEOU1	
		PU3 x PEOU2	
		PU3 x PEOU3	

References - basic

- Gefen, D., D.W. Straub and M.-C. Boudreau, “Structural Equation Modeling and Regression: Guidelines for Research Practice,” *Communications of the Association for Information Systems, 2000, 4:7.*

- Straub, D.W., M.-C. Boudreau and D. Gefen, “Validation Guidelines for IS Positivist Research,” *Communications of the Association for Information Systems, 2004, 13:24, pp. 380-427.*

- MacKenzie, S.B., P.M. Podsakoff and N.P. Podsakoff, “Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques,” *MIS Quarterly, 2011, 35:2, pp. 293-334.*

- Im, K.S. and V. Grover, “The Use of Structural Equation Modeling in IS Research: Review and Recommendations” in Whitman, M.E. and A.B. Woszczynski (eds.) *The Use of Structural Equation Modeling in IS Research: Review and Recommendations, Idea Group Hershey, Pennsylvania, 2004, 44-65.*

- Vinzi, V.E., W.W. Chin, J. Henseler and H. Wang (eds.), *Handbook of Partial Least Squares: Concepts, Methods and Applications, Springer, New York, New York, 2010.*

- Jöreskog, K.G. and D. Sörbom, *LISREL 8: User's Reference Guide, Lincolnwood, Illinois: Scientific Software International, 2001.*

References – good examples

- Moderation/Multi-group analysis: example
  - Im, I., Y. Kim and H.-J. Han, “The Effects of Perceived Risk and Technology Type on Users’ Acceptance of Technologies,” *Information & Management, 2008, 45:1, pp. 1-9.*
  - Recker, J. and M. La Rosa, “Understanding User Differences in Open-Source Workflow Management System Usage Intentions,” *Information Systems, 2012, 37, pp. 200-212.*

- Mediation tests: example
  - Polites, G.L. and E. Karahanna, “Shackled to the Status Quo: The Inhibiting Effects of Incumbent System Habit, Switching Costs, and Inertia on New System Acceptance ” *MIS Quarterly, 2012, 36:1, pp. 21-42.*

- LISREL with missing data
  - Recker, J., M. Rosemann, P. Green and M. Indulska, “Do Ontological Deficiencies in Modeling Grammars Matter?,” *MIS Quarterly, 2011, 35:1, pp. 57-79.*

- LISREL vs PLS
  - Goodhue, D.L., W. Lewis and R.L. Thompson, “Statistical Power in Analyzing Interaction Effects: Questioning the Advantage of PLS With Product Indicators,” *Information Systems Research, 2007, 18:2, pp. 211-227.*
  - Ringle, C.M., Sarstedt, M., and Straub, D.W. "Editor's Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly," *MIS Quarterly (36:1) 2012, pp iii-xiv.*

References – further reading

- Straub, D.W., M.-C. Boudreau and D. Gefen, “Validation Guidelines for IS Positivist Research,” *Communications of the Association for Information Systems, 2004, 13:24, pp. 380-427.*

- MacKenzie, S.B., P.M. Podsakoff and N.P. Podsakoff, “Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques,” *MIS Quarterly, 2011, 35:2, pp. 293-334.*

- Wetzels, M., G. Odekerken-Schröder and C. Van Oppen, “Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration,” *MIS Quarterly, 2009, 33:1, pp. 177-195.*

- Ringle, C.M., M. Sarstedt and D.W. Straub, “Editor's Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly,” *MIS Quarterly, 2012, 36:1, pp. iii-xiv.*

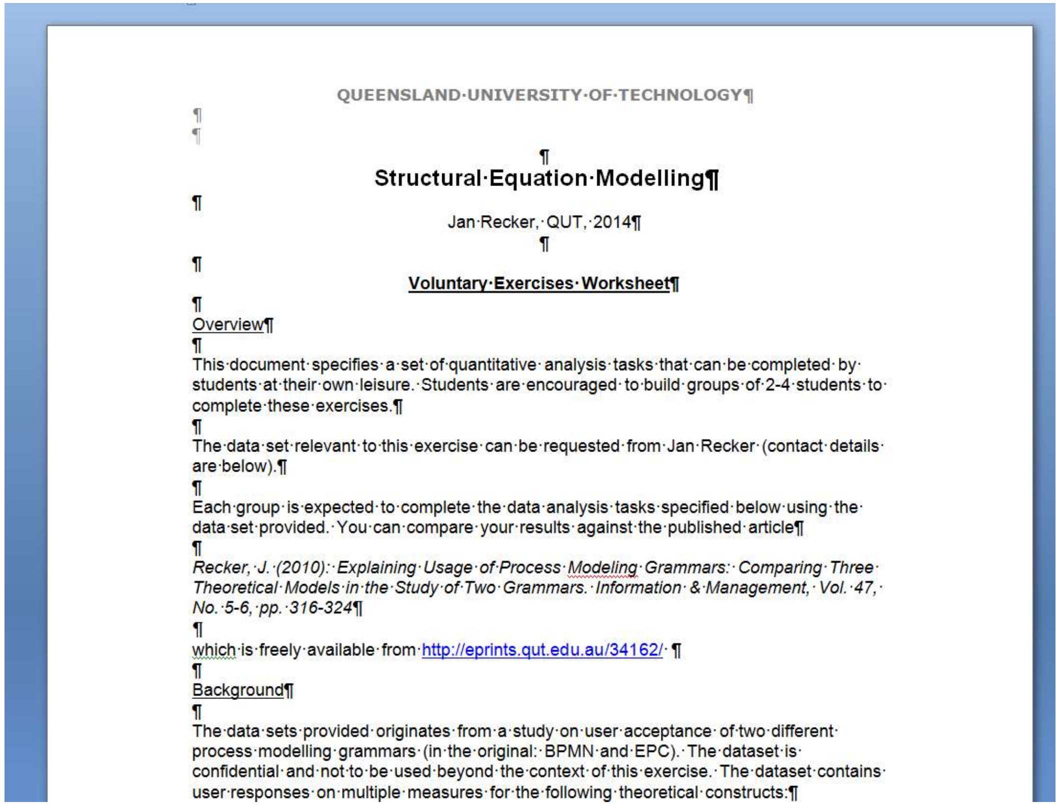
- Evermann, J. and M. Tate, “Fitting Covariance Models for Theory Generation,” *Journal of the Association for Information Systems, 2011, 12:9, pp. 632-661.*

- Evermann, J. and M. Tate, “Bayesian Structural Equation Models for Cumulative Theory Building in Information Systems—A Brief Tutorial Using BUGS and R,” *Communications of the Association for Information Systems, 2014, 34:77, pp. 1481-1514.*

Websites I use

- Online Statistics Textbook
  - http://www.statsoft.com/Textbook
- Statistical tables calculator
  - http://vassarstats.net/tabs.html
- Distribution tables for χ, t, F
  - http://www.medcalc.org/manual/chi-square-table.php
  - http://vassarstats.net/textbook/apx_d.html
  - http://www.psychstat.missouristate.edu/introbook/tdist.htm
- Interactive mediation tests
  - http://quantpsy.org/sobel/sobel.htm

Exercise – contact me



QUEENSLAND UNIVERSITY OF TECHNOLOGY

Structural Equation Modelling

Jan Recker, QUT, 2014

Voluntary Exercises Worksheet

Overview

This document specifies a set of quantitative analysis tasks that can be completed by students at their own leisure. Students are encouraged to build groups of 2-4 students to complete these exercises.

The data set relevant to this exercise can be requested from Jan Recker (contact details are below).

Each group is expected to complete the data analysis tasks specified below using the data set provided. You can compare your results against the published article

Recker, J. (2010): Explaining Usage of Process Modeling Grammars: Comparing Three Theoretical Models in the Study of Two Grammars. Information & Management, Vol. 47, No. 5-6, pp. 316-324

which is freely available from http://eprints.qut.edu.au/34162/

Background

The data sets provided originates from a study on user acceptance of two different process modelling grammars (in the original: BPMN and EPC). The dataset is confidential and not to be used beyond the context of this exercise. The dataset contains user responses on multiple measures for the following theoretical constructs:

End of Part 4