Emperical Methods for Marketing Research and Analytics Using R

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About Me

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Using R for Scaling and Factor Analysis

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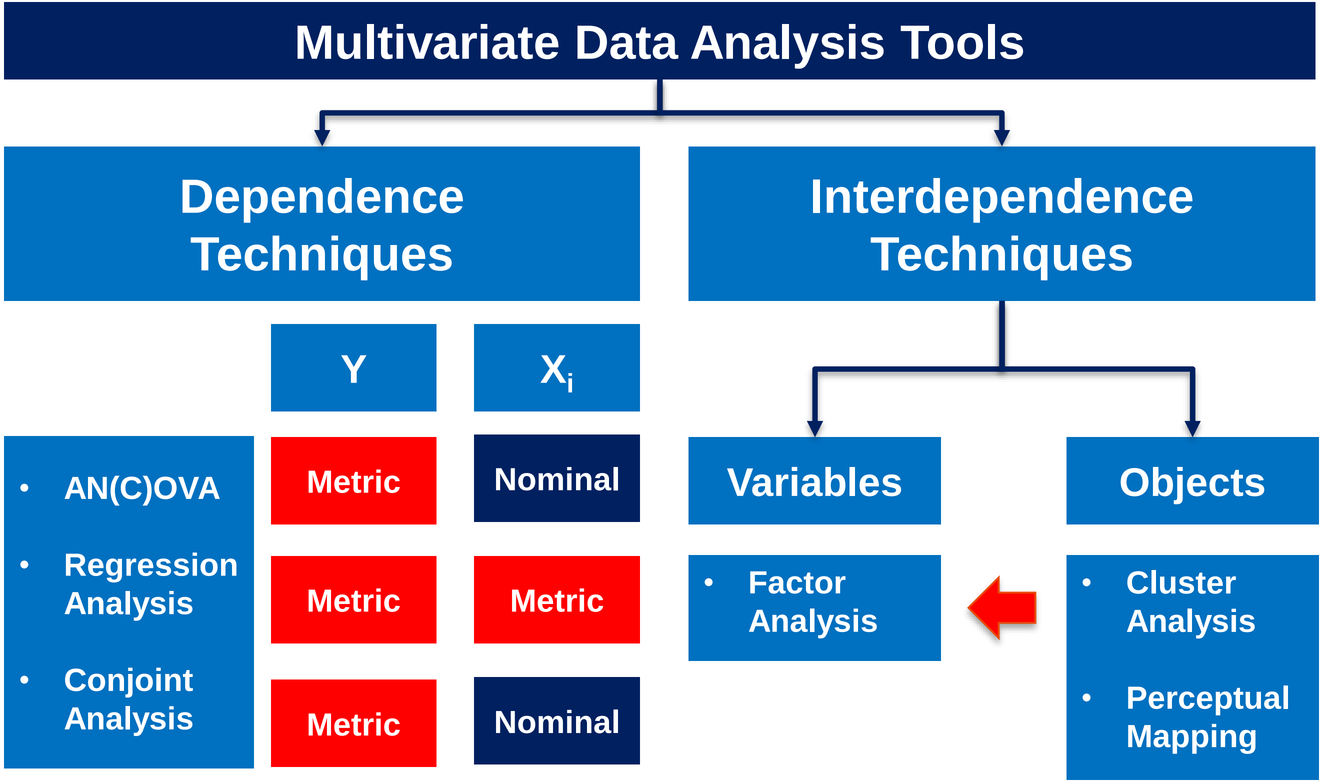
Course Outline

Session:	TOPIC:
DAY 1	
Session 1	INTRODUCING MULTIVARIATE ANALYSIS AND R
Session 2	USING R FOR BASIC ANALYSIS
DAY 2	
Session 3	USING R FOR AN(C)OVA
Session 4	USING R FOR REGRESSION ANALYSIS
DAY 3	
Session 5	USING R FOR SCALING AND FACTOR ANALYSIS
Session 6	USING R FOR SEM and PLS PATH MODELING

Exploratory Factor Analysis

Hair et al. (2018); Malhotra (2010); Pallant (2016)



Correlation Analysis

Hair et al. (2018); Malhotra (2010)

- The **(Pearson) product moment correlation, ρ,** summarizes the strength of association between two **metric** (at least **interval**) variables [-1, 1].

- Assumptions
  - **Metric** (at least **interval**) variables
  - Independent, random sample
  - Linearity
  - (Bivariate) Normal distribution
  - Homoscedasticity
  - No causality!
  - Outliers!

Correlation Analysis

Hair et al. (2018); Malhotra (2010)

- Covariance [-∞, + ∞]

$$COV_{XY} = \sum_{i=1}^{n} \frac{(X_i - M_X) * (Y_i - M_Y)}{n - 1}$$

- (Pearson Product-Moment) Correlation Coefficient [-1, 1]

$$r_{XY} = \frac{COV_{XY}}{S_X S_Y}$$

Correlation Analysis

Hair et al. (2018); Malhotra (2010)

- Hypotheses
  - H_0: correlation coefficient (ρ) = 0
  - H_1: correlation coefficient (ρ) ≠ 0

- Test statistic

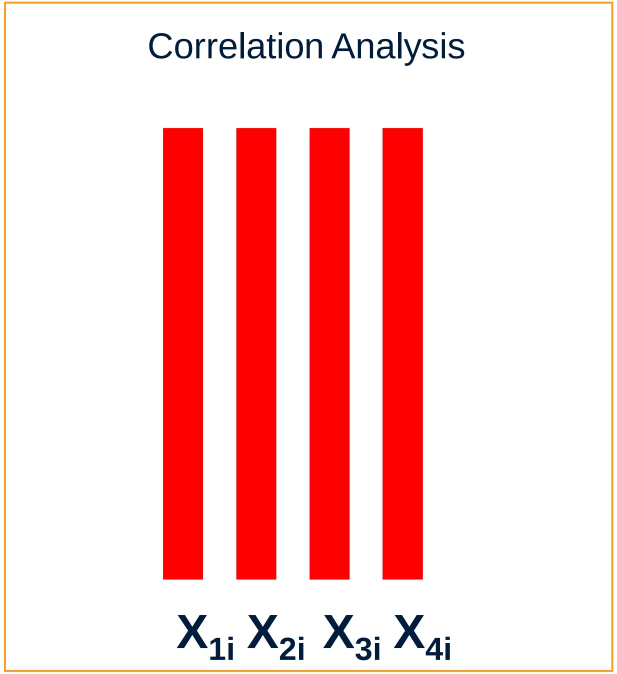
$$t = r * \sqrt{\frac{n-2}{1-r^2}}$$

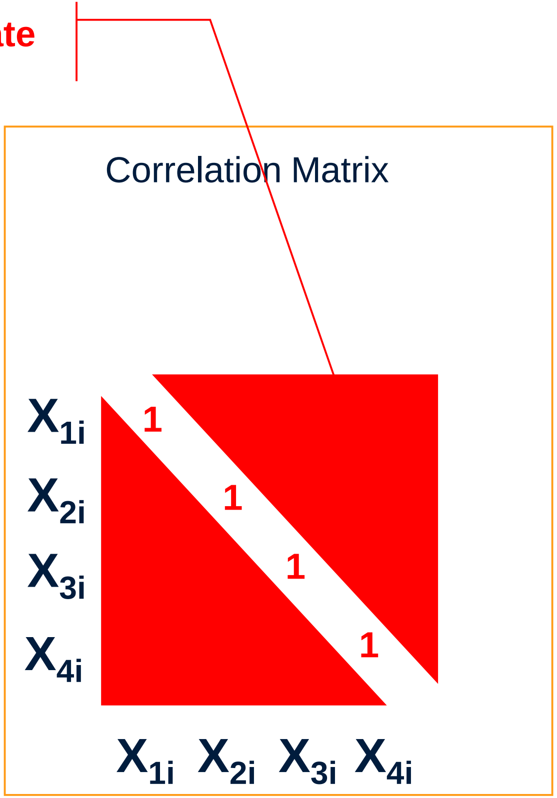
$$df = n - 2$$

Effect Size (r)	Effect Size (R^2)	
0.10	0.02	small
0.30	0.13	medium
0.50	0.26	large

Correlation Analysis

Hair et al. (2018); Malhotra (2010)





SPSS Application

TAM Data

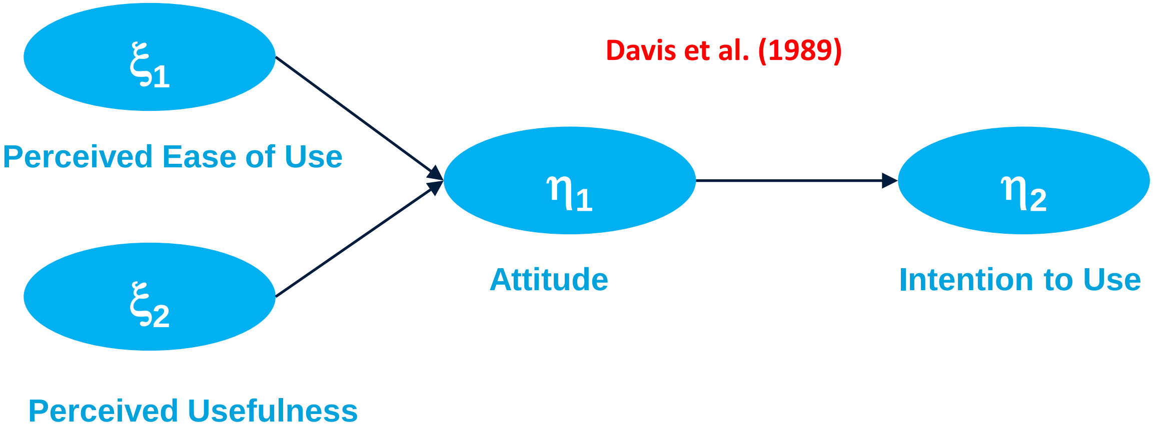
- Data Set *Data-01.sav* (n=439)

- Constructs and Items
  - Perceived Ease of Use (PEU, Q1-Q3)
  - Perceived Usefulness (PU, Q4-Q6)
  - Attitude (ATT, Q7-Q9)
  - Intention (INT, Q10-Q12)

- Reliability Analysis (Coefficient α)
  - PEU 0.93
  - PU 0.92
  - ATT 0.92
  - INT 0.87

SPSS Application

TAM Data



Construct	Items
PEU	Q1, Q2, Q3
PU	Q4, Q5, Q6
ATT	Q7, Q8, Q9
INT	Q10, Q11, Q12

Davis et al. (1989)

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USER ACCEPTANCE OF COMPUTER TECHNOLOGY: A COMPARISON OF TWO THEORETICAL MODELS*

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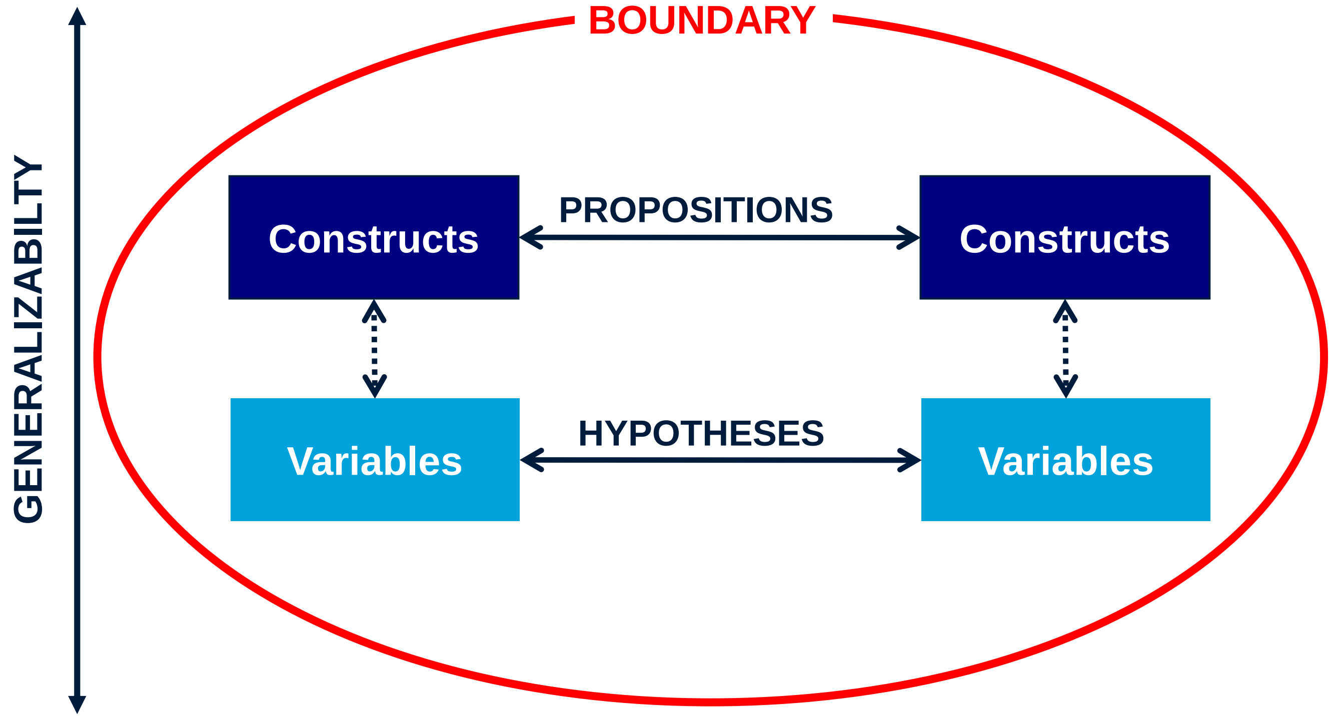
Computer systems cannot improve organizational performance if they aren't used. Unfortunately, resistance to end-user systems by managers and professionals is a widespread problem. To better predict, explain, and increase user acceptance, we need to better understand why people accept or reject computers. This research addresses the ability to predict peoples' computer acceptance from a measure of their intentions, and the ability to explain their intentions in terms of their attitudes, subjective norms, perceived usefulness, perceived ease of use, and related variables. In a longitudinal study of 107 users, intentions to use a specific system, measured after a one-hour introduction to the system, were correlated 0.35 with system use 14 weeks later. The intention-usage correlation was 0.63 at the end of this time period. Perceived usefulness strongly influenced peoples' intentions, explaining more than half of the variance in intentions at the end of 14 weeks. Perceived ease of use had a small but significant effect on intentions as well, although this effect subsided over time. Attitudes only partially mediated the effects of these beliefs on intentions. Subjective norms had no effect on intentions. These results suggest the possibility of simple but powerful models of the determinants of user acceptance, with practical value for evaluating systems and guiding managerial interventions aimed at reducing the problem of underutilized computer technology.

(INFORMATION TECHNOLOGY; USER ACCEPTANCE; INTENTION MODELS)

The Relevance of Theory…

Bacharach (1989, p. 499)



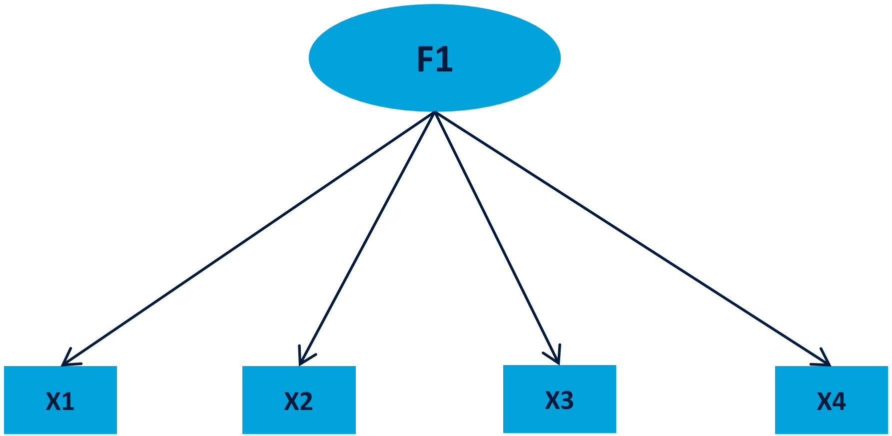
Psychometric Properties

Netemeyer et al. (2003)

- **(Uni)Dimensionality**
  - *A unidimensional measure underlies a single construct or factor*
- **Reliability**
  - *The portion of measurement that is due to permanent effects that persist from sample to sample*
- **(Construct) Validity**
  - *How well does a measure actually measure the construct it is intended to measure*

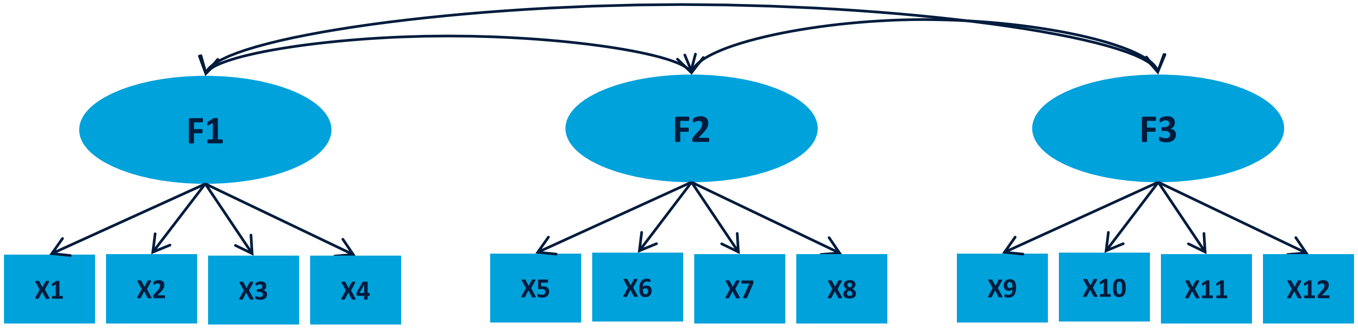
Unidimensionality

Netemeyer et al. (2003)



Multidimensionality

Netemeyer et al. (2003)



Hierarchical Model

Netemeyer et al. (2003)

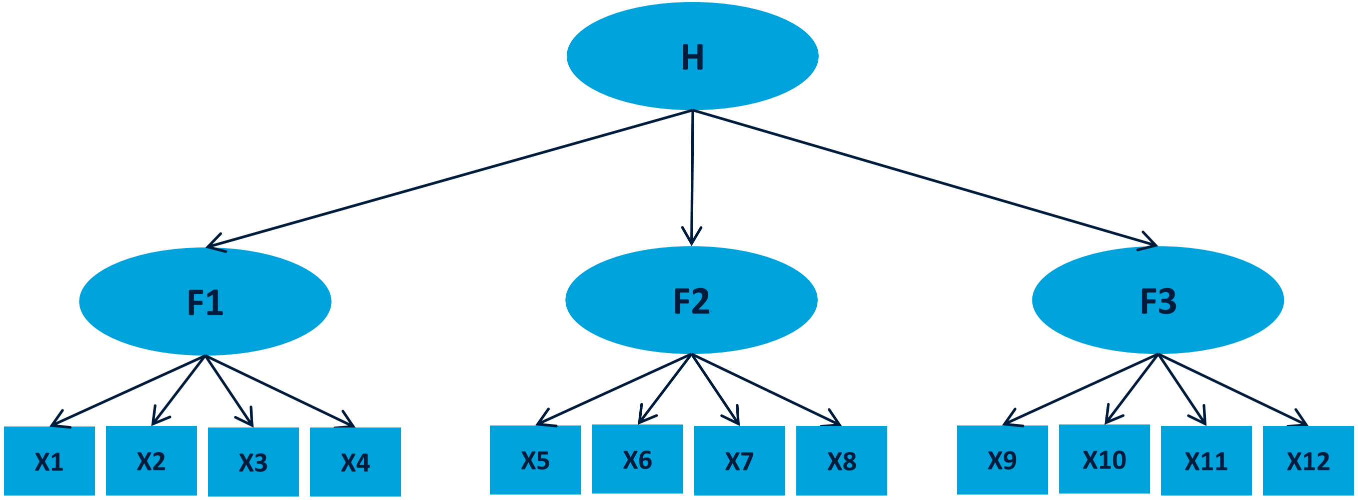


Illustration: Model

Netemeyer et al. (2003)

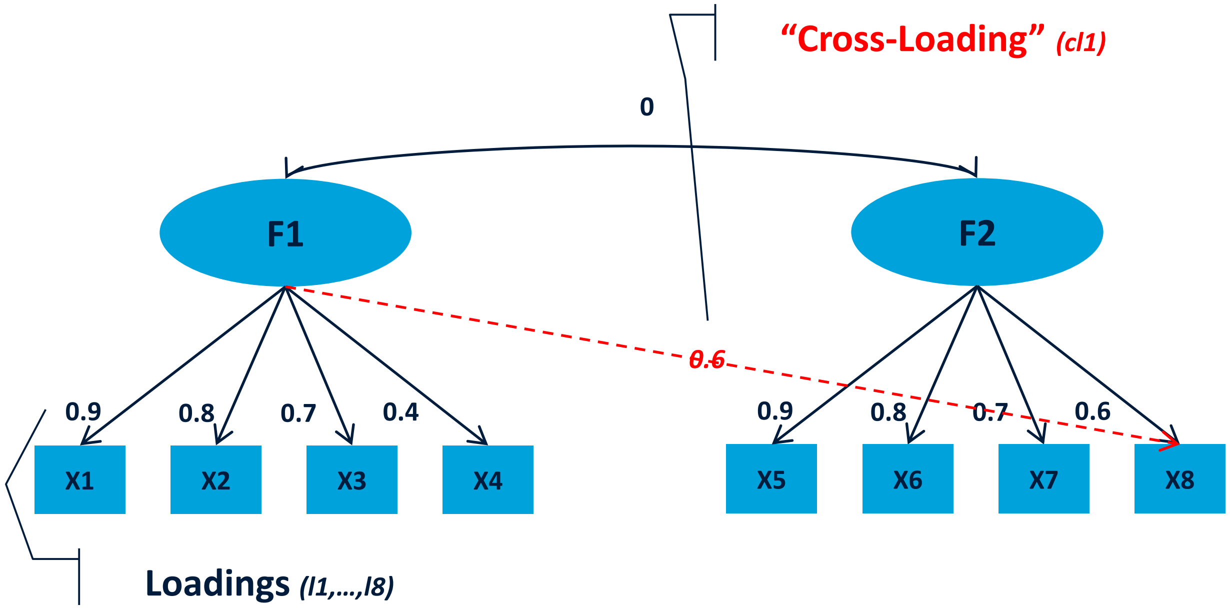


Illustration: Obtaining Correlations

Netemeyer et al. (2003)

Cor(X1,X2)=l1*l2=0.9*0.8=0.72
Cor(X1,X3)=l1*l3=0.9*0.7=0.63

…

Cor(X1,X8)=l1**cl1*=0.9*0.6=0.54

…

Cor(X7,X8)=l7*l8=0.7*0.6=0.42

Illustration: Correlation Matrix

Netemeyer et al. (2003)

Correlations

Control Variables			X1	X2	X3	X4	X5	X6	X7	X8	F1	F2
-none-[a]	X1	Correlation	1.000	.720**	.630**	.360**	.000	.000	.000	.540**	.900**	.000
	X2	Correlation	.720**	1.000	.560**	.320**	.000	.000	.000	.480**	.800**	.000
	X3	Correlation	.630**	.560**	1.000	.280**	.000	.000	.000	.420**	.700**	.000
	X4	Correlation	.360**	.320**	.280**	1.000	.000	.000	.000	.240**	.400**	.000
	X5	Correlation	.000	.000	.000	.000	1.000	.720**	.630**	.540**	.000	.900**
	X6	Correlation	.000	.000	.000	.000	.720**	1.000	.560**	.480**	.000	.800**
	X7	Correlation	.000	.000	.000	.000	.630**	.560**	1.000	.420**	.000	.700**
	X8	Correlation	.540**	.480**	.420**	.240**	.540**	.480**	.420**	1.000	.600**	.600**
	F1	Correlation	.900**	.800**	.700**	.400**	.000	.000	.000	.600**	1.000	.000
	F2	Correlation	.000	.000	.000	.000	.900**	.800**	.700**	.600**	.000	1.000

a. Cells contain zero-order (Pearson) correlations.

**. Correlation is significant at 0.01 level

Illustration: SPSS Input

Netemeyer et al. (2003)

Illustration.PPT.sav [DataSet1] - PASW Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Add-ons Window Help

	ROWTYPE_	VARNAME_	X1	X2	X3	X4	X5	X6	X7	X8	F1	F2	var
1	N		500.0000	500.0000	500.0000	500.0000	500.0000	500.0000	500.0000	500.0000	500.0000	500.0000	
2	CORR	X1	1.0000	.7200	.6300	.3600	.0	.0	.0	.5400	.9000	.0	
3	CORR	X2	.7200	1.0000	.5600	.3200	.0	.0	.0	.4800	.8000	.0	
4	CORR	X3	.6300	.5600	1.0000	.2800	.0	.0	.0	.4200	.7000	.0	
5	CORR	X4	.3600	.3200	.2800	1.0000	.0	.0	.0	.2400	.4000	.0	
6	CORR	X5	.0	.0	.0	.0	1.0000	.7200	.6300	.5400	.0	.9000	
7	CORR	X6	.0	.0	.0	.0	.7200	1.0000	.5600	.4800	.0	.8000	
8	CORR	X7	.0	.0	.0	.0	.6300	.5600	1.0000	.4200	.0	.7000	
9	CORR	X8	.5400	.4800	.4200	.2400	.5400	.4800	.4200	1.0000	.6000	.6000	
10	CORR	F1	.9000	.8000	.7000	.4000	.0	.0	.0	.6000	1.0000	.0	
11	CORR	F2	.0	.0	.0	.0	.9000	.8000	.7000	.6000	.0	1.0000	
12													
13													

ROWTYPE_
VARNAME_

Illustration: Exploratory Factor Analysis

Netemeyer et al. (2003)

```
FACTOR
    /MATRIX=IN(COR=*)
    /MISSING LISTWISE
    /ANALYSIS X1 X2 X3 X4 X5 X6 X7 X8
    /PRINT UNIVARIATE INITIAL KMO REPR AIC EXTRACTION ROTATION
    /PLOT EIGEN
    /CRITERIA MINEIGEN(1) ITERATE(25)
    /EXTRACTION PAF
    /CRITERIA ITERATE(25)
    /ROTATION VARIMAX
    /METHOD=CORRELATION.
```

Illustration: SPSS Output

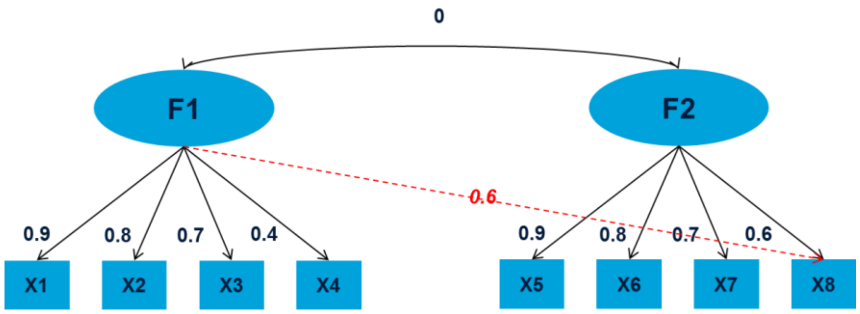
Netemeyer et al. (2003)

Rotated Factor Matrix[a]

	Factor	
	1	2
X1	.899	.009
X2	.800	.008
X3	.700	.007
X4	.400	.004
X5	-.009	.899
X6	-.008	.800
X7	-.007	.700
X8	.594	.606

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.



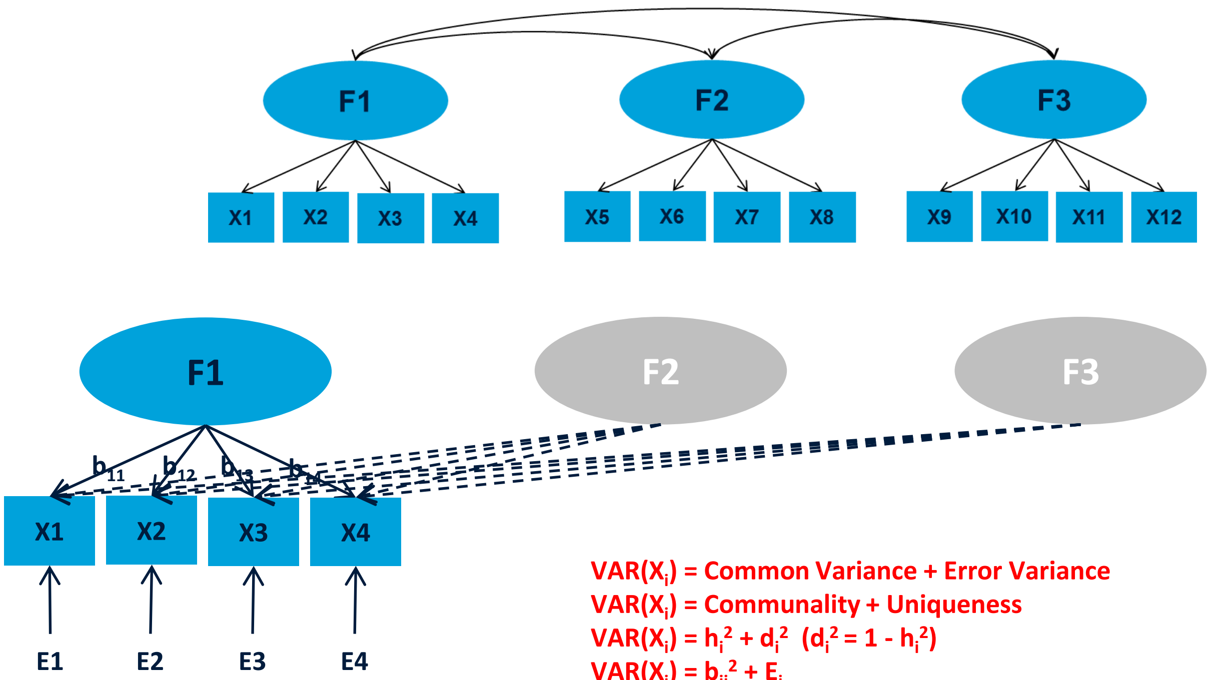
Exploratory Factor Analysis (EFA)
Introduction

- **Exploratory Factor Analysis**
  “Factor analysis is one of the more frequently used procedures in marketing research and, in fact, it has been cited as the most widely applied multivariate technique in the social sciences (Acito and Anderson 1980, 228).”

- **Modes of (Exploratory) Factor Analysis (Stewart, 1981):**
  - R Factor Analysis $\rightarrow$ Variables by Persons
  - Q Factor Analysis $\rightarrow$ Persons by Variables $\rightarrow$ Cluster Analysis

- **Types of Factor Analysis (Stewart, 1981):**
  - Exploratory Factor Analysis (EFA)
  - Confirmatory Factor Analysis (CFA)

Exploratory Factor Analysis (EFA)
Graphical Representation of Model



$VAR(X_i)$ = Common Variance + Error Variance

$VAR(X_i)$ = Communality + Uniqueness

$VAR(X_i) = h_i^2 + d_i^2 \quad (d_i^2 = 1 - h_i^2)$

$VAR(X_i) = b_{ij}^2 + E_i$

Exploratory Factor Analysis (EFA): Analysis Approach

Hair et al., 2018; Malhotra, 2010; Pallant, 2016

1	Objectives of Factor Analysis
2	Designing Factor Analysis
3	Assumptions for Factor Analysis
4	Deriving Factors and Assessing Overall Fit
5	Interpreting Factor Analysis

1. Objectives of Exploratory Factor Analysis

Hair et al. (2018); Malhotra (2010); Pallant (2016)

- Identifying an Underlying Causal Structure (Understanding Latent Constructs)
- Data Reduction

SPSS Application

TAM Data

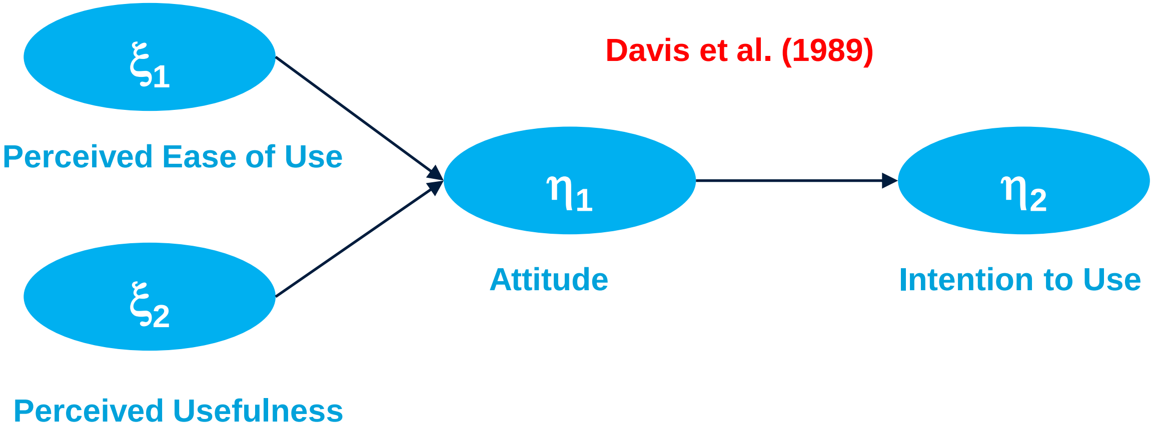
- Data Set *Data-01.sav* (n=439)

- Constructs and Items
  - Perceived Ease of Use (PEU, Q1-Q3)
  - Perceived Usefulness (PU, Q4-Q6)
  - Attitude (ATT, Q7-Q9)
  - Intention (INT, Q10-Q12)

- Reliability Analysis (Coefficient α)
  - PEU 0.93
  - PU 0.92
  - ATT 0.92
  - INT 0.87

SPSS Application

TAM Data



Construct	Items
PEU	Q1, Q2, Q3
PU	Q4, Q5, Q6
ATT	Q7, Q8, Q9
INT	Q10, Q11, Q12

2. Designing Exploratory Factor Analysis

Hair et al. (2018); Malhotra (2010); Pallant (2016)

n <
"Strong Data": high loadings, no (substantial) cross-loadings, multiple variables per factor

- Measurement Level
  - Metric (At Least Intervally Scaled → Correlations)

- Variables
  - At Least Three Manifest Variables (Indicator) per Latent Variable (Factor)

- Sample Size
  - n > 50 [100] (At Least 5 [10] Observations per Manifest Variable)
  - Random Sampling

SPSS Application

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
q1	439	1	6	3.39	.944
q2	439	1	6	3.65	.956
q3	439	1	6	3.52	1.009
q4	439	1	6	3.35	.965
q5	439	1	6	3.59	1.010
q6	439	1	7	4.15	.997
q7	439	2	7	4.22	.975
q8	439	1	7	3.24	.947
q9	439	1	7	3.85	.970
q10	439	1	7	4.14	1.239
q11	439	1	6	3.49	.931
q12	439	1	7	3.83	.959
Valid N (listwise)	439				

3. Assumptions for Exploratory Factor Analysis

Hair et al. (2018); Malhotra (2010); Pallant (2016)

- Normality
- Linearity
- No outliers
- Substantial Number of Correlations > 0.30
  - Visual Inspection
  - Bartlett’s Test of Sphericity
  - Measure of Sampling Adequacy

SPSS Application

Correlation Matrix

		q1	q2	q3	q4	q5	q6	q7	q8	q9	q10	q11	q12
Correlation	q1	1.000	.810	.814	.293	.343	.325	.397	.365	.390	.259	.315	.314
	q2	.810	1.000	.817	.306	.324	.347	.369	.352	.346	.259	.316	.314
	q3	.814	.817	1.000	.324	.353	.368	.374	.353	.356	.269	.334	.320
	q4	.293	.306	.324	1.000	.801	.797	.292	.246	.301	.315	.418	.402
	q5	.343	.324	.353	.801	1.000	.812	.298	.260	.324	.323	.384	.377
	q6	.325	.347	.368	.797	.812	1.000	.248	.243	.269	.332	.386	.371
	q7	.397	.369	.374	.292	.298	.248	1.000	.803	.806	.257	.316	.337
	q8	.365	.352	.353	.246	.260	.243	.803	1.000	.773	.233	.290	.318
	q9	.390	.346	.356	.301	.324	.269	.806	.773	1.000	.273	.368	.392
	q10	.259	.259	.269	.315	.323	.332	.257	.233	.273	1.000	.681	.674
	q11	.315	.316	.334	.418	.384	.386	.316	.290	.368	.681	1.000	.786
	q12	.314	.314	.320	.402	.377	.371	.337	.318	.392	.674	.786	1.000

SPSS Application

in the .90s	marvelous,
in the .80s	meritorious,
in the .70s	middling,
in the .60s	mediocre,
in the .50s	miserable,
below .50	unacceptable.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.853
Bartlett's Test of Sphericity	Approx. Chi-Square	4076.927
	df	66
	Sig.	.000

≥0.6

H_0: Identity Matrix

4. Deriving Factors and Assessing Overall Fit

Hair et al. (2018); Malhotra (2010); Pallant (2016)

- Criteria for the Number of Factors to Extract
  - Latent Root or Kaiser Criterion (Eigenvalues > 1)
  - Scree Test Criterion
  - A Priori Criterion
  - Proportion of Variance Accounted for (e.g., > 60%)
  - More Advanced Methods (Conway and Huffcutt, 2003):
    - Parallel Analysis
    - Minimum Average Partial Method

Common Factor Analysis (PAF) vs. Principal Components (PC) Analysis

- PC is based on a correlation matrix as input with “1”’s on the diagonal (all variance is redistributed over the components)

- PAF is based on a correlation matrix as input with common variance (<1) on the diagonal (only the shared variance is redistributed over the components). SMC (squared multiple correlation) of each variable with all other variables is used as starting value

SPSS Application

PC

Communalities

	Initial	Extraction
q1	1.000	.873
q2	1.000	.877
q3	1.000	.878
q4	1.000	.865
q5	1.000	.873
q6	1.000	.872
q7	1.000	.877
q8	1.000	.857
q9	1.000	.858
q10	1.000	.769
q11	1.000	.836
q12	1.000	.832

Extraction Method: Principal Component Analysis.

PAF

Communalities

	Initial	Extraction
q1	.736	.808
q2	.733	.812
q3	.741	.822
q4	.718	.790
q5	.734	.815
q6	.731	.810
q7	.737	.834
q8	.695	.769
q9	.713	.786
q10	.522	.584
q11	.674	.793
q12	.669	.782

Extraction Method: Principal Axis Factoring.

SPSS Application

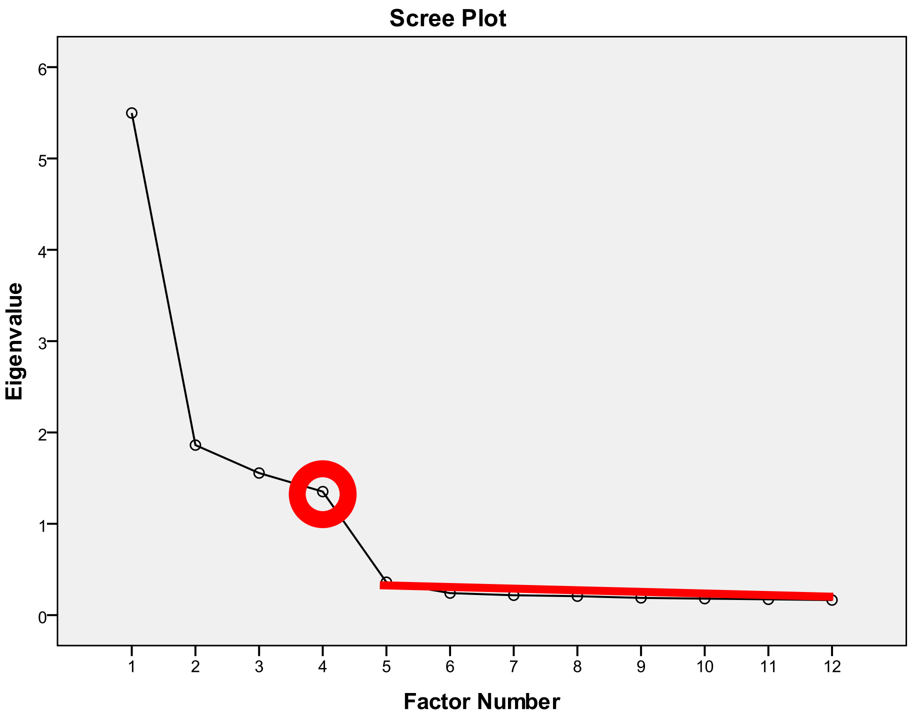
Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.498	45.814	45.814	5.287	44.058	44.058	3.660
2	1.862	15.513	61.327	1.655	13.788	57.845	3.604
3	1.556	12.963	74.290	1.349	11.241	69.086	3.537
4	1.352	11.269	85.559	1.117	9.306	78.392	3.492
5	.360	3.003	88.562				
6	.241	2.008	90.571				
7	.218	1.813	92.383				
8	.207	1.727	94.111				
9	.189	1.572	95.682				
10	.180	1.504	97.186				
11	.173	1.442	98.627				
12	.165	1.373	100.000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

SPSS Application



SPSS Application

Reproduced Correlations

		q1	q2	q3	q4	q5	q6	q7	q8	q9	q10	q11	q12
Reproduced Correlation	q1	.808[a]	.810	.814	.297	.329	.335	.398	.375	.381	.259	.317	.313
	q2	.810	.812[a]	.817	.302	.334	.342	.368	.346	.353	.260	.318	.312
	q3	.814	.817	.822[a]	.324	.356	.364	.373	.350	.359	.270	.330	.323
	q4	.297	.302	.324	.790[a]	.801	.797	.283	.254	.303	.334	.408	.395
	q5	.329	.334	.356	.801	.815[a]	.811	.298	.268	.315	.317	.390	.377
	q6	.335	.342	.364	.797	.811	.810[a]	.256	.227	.275	.319	.391	.376
	q7	.398	.368	.373	.283	.298	.256	.834[a]	.800	.807	.248	.318	.343
	q8	.375	.346	.350	.254	.268	.227	.800	.769[a]	.774	.228	.294	.318
	q9	.381	.353	.359	.303	.315	.275	.807	.774	.786[a]	.287	.362	.385
	q10	.259	.260	.270	.334	.317	.319	.248	.228	.287	.584[a]	.680	.674
	q11	.317	.318	.330	.408	.390	.391	.318	.294	.362	.680	.793[a]	.787
	q12	.313	.312	.323	.395	.377	.376	.343	.318	.385	.674	.787	.782[a]
Residual[b]	q1		.000	.000	-.004	.014	-.010	-.001	-.010	.010	.000	-.002	.001
	q2	.000		.000	.004	-.010	.006	.001	.006	-.006	-.001	-.001	.003
	q3	.000	.000		.000	-.004	.004	.000	.003	-.003	-.001	.004	-.003
	q4	-.004	.004	.000		.000	.000	.009	-.007	-.002	-.019	.011	.006
	q5	.014	-.010	-.004	.000		.001	.000	-.008	.009	.006	-.006	-.001
	q6	-.010	.006	.004	.000	.001		-.008	.016	-.006	.013	-.005	-.006
	q7	-.001	.001	.000	.009	.000	-.008		.002	-.001	.009	-.002	-.006
	q8	-.010	.006	.003	-.007	-.008	.016	.002		-.001	.005	-.004	-.001
	q9	.010	-.006	-.003	-.002	.009	-.006	-.001	-.001		-.014	.006	.007
	q10	.000	-.001	-.001	-.019	.006	.013	.009	.005	-.014		.001	.001
	q11	-.002	-.001	.004	.011	-.006	-.005	-.002	-.004	.006	.001		-.001
	q12	.001	.003	-.003	.006	-.001	-.006	-.006	-.001	.007	.001	-.001	

Extraction Method: Principal Axis Factoring.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 0 (.0%) nonredundant residuals with absolute values greater than 0.05.

Advanced Methods to Determine the Number of Factors in EFA

- Parallel Analysis (Horn, 1965)
- MAP test (Velicer, 1976)
- Maximum Likelihood (ML) Factor Analysis (χ^2 test)

O’Connor (2000)

Behavior Research Methods, Instruments, & Computers
2000, 32 (3), 396-402

SPSS and SAS programs for determining the number of components using parallel analysis and Velicer’s MAP test

BRIAN P. O’CONNOR
Lakehead University, Thunder Bay, Ontario, Canada

Popular statistical software packages do not have the proper procedures for determining the number of components in factor and principal components analyses. Parallel analysis and Velicer’s minimum average partial (MAP) test are validated procedures, recommended widely by statisticians. However, many researchers continue to use alternative, simpler, but flawed procedures, such as the eigenvalues-greater-than-one rule. Use of the proper procedures might be increased if these procedures could be conducted within familiar software environments. This paper describes brief and efficient programs for using SPSS and SAS to conduct parallel analyses and the MAP test.

Parallel Analysis: SPSS Application

O’Connor (2000)

Active Data File!

```
* DATA ==============================================================>.
* Open the SPSS data file and enter the variable names on the variables line, e.g. "/VAR= q1 to q10".


GET raw /FILE = *
/ missing=omit
/ VAR =q1 to q12. /*Enter variable names here!.

* ENTER OPTIONS! ========================================>.
```

Variable Names!

Parallel Analysis: SPSS Application

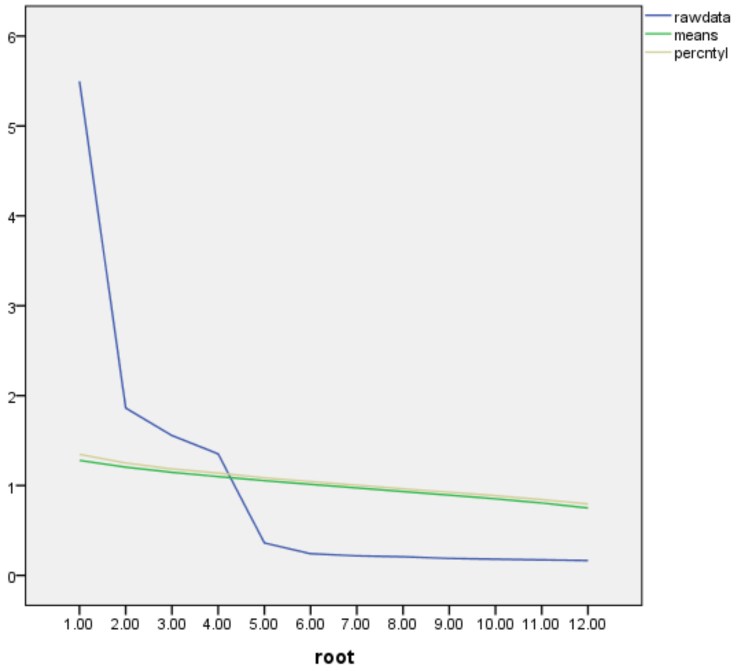
O'Connor (2000)

```
Run MATRIX procedure:

PARALLEL ANALYSIS:

Principal Components & Random Normal Data Generation

Specifications for this Run:
Ncases      439
Nvars        12
Ndatsets   1000
Percent      95

Raw Data Eigenvalues, & Mean & Percentile Random Data Eigenvalues
         Root      Raw Data         Means      Prcntyle
     1.000000      5.497684      1.278902      1.346217
     2.000000      1.861609      1.203786      1.250480
     3.000000      1.555539      1.146351      1.184455
     4.000000      1.352225      1.099147      1.138645
     5.000000       .360418      1.053659      1.085723
     6.000000       .241010      1.013332      1.044202
     7.000000       .217518       .973233      1.004229
     8.000000       .207260       .932973       .962753
     9.000000       .188616       .892773       .925738
    10.000000       .180428       .851332       .886614
    11.000000       .172986       .805433       .842883
    12.000000       .164708       .749077       .794979

------ END MATRIX -----
```

EV > Random Data

MAP Test: SPSS Application

O’Connor (2000)



MAP Test: SPSS Application

O'Connor (2000)

Variable Names!

```
* DATA ===========================================================>.
* Open the SPSS data file and enter the variable names on the variables line, e.g. "Variables= q1 to q10".

Correlation
Variables= q1 to q12 /*Enter variable names here!.
      /matrix out (*)  /missing = listwise.


* ===========================================================>.
```

Active Data File:
Matrix Data!

MAP Test: SPSS Application

O'Connor (2000)

```
Velicer's Average Squared Correlations
        .000000       .199559
       1.000000       .119585
       2.000000       .141272
       3.000000       .144236
       4.000000       .048378
       5.000000       .073491
       6.000000       .097302
       7.000000       .152419
       8.000000       .204150
       9.000000       .304644
      10.000000       .481952
      11.000000      1.000000

The smallest average squared correlation is
        .048378

The number of components is
   4
```

smallest average squared correlation

4 Factors!

ML Factor Analysis (χ^2 test): SPSS Application

H_0: F=4

Goodness-of-fit Test

Chi-Square	df	Sig.
23.313	24	.501

5. Interpreting Exploratory Factor Analysis

Hair et al. (2018) ; Malhotra (2010); Pallant (2016)

- Rotation
  - Orthogonal Rotation (No Interfactor Correlation Allowed)
  - Oblique Rotation (Interfactor Correlation Allowed)
    - Factor Pattern Matrix (Loadings)
    - Factor Structure Matrix (Correlations)
- Significance of Factor Loadings
  - $\pm$ 0.50 (n=120, α=0.05, 1-β (power)=0.80)
  - $\pm$ 0.70 (n=60, α=0.05, 1-β (power)=0.80)

5. Interpreting Exploratory Factor Analysis

Hair et al. (2018) ; Malhotra (2010); Pallant (2016)

- Interpretability
  - Inspect Factor Pattern Matrix (Using Orthogonal Rotation the Factor Pattern and Structure Matrix are Equivalent!) and Communalities
  - Are There At Least Three Manifest Variables (Indicators) Loading on a Latent Variable Factor?
  - Do These Manifest Variables (Indicators) Share Some Conceptual Meaning?
  - Do the Manifest Variables (indicators) that Load on Different Factors Seem to be Measuring Different Constructs

SPSS Application

Structure Matrix

	Factor			
	1	2	3	4
[illegible]	[illegible]	.387	[illegible]	.361
q2	[illegible]	.362	[illegible]	.348
q1	[illegible]	[illegible]	[illegible]	.348
q5	[illegible]	[illegible]	[illegible]	.425
q6	[illegible]	[illegible]	.282	.426
q4	[illegible]	[illegible]	.313	.446
q7	[illegible]	[illegible]	.913	.358
q9	[illegible]	[illegible]	[illegible]	.406
q8	[illegible]	[illegible]	[illegible]	.330
q11	[illegible]	.440	[illegible]	.891
[illegible]	[illegible]	.425	[illegible]	.883
[illegible]	[illegible]	.359	[illegible]	[illegible]

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

Pattern Matrix[a]

	Factor			
	1	2	3	4
q2	.907	-.004	-.011	.003
q3	.900	.023	-.013	.007
q1	.890	-.016	.035	-.004
q5	.005	.901	.026	-.020
q6	.037	.900	-.041	-.003
q4	-.039	.884	.016	.030
q7	.014	.003	.915	-.022
q8	.011	-.017	.889	-.028
q9	-.016	.017	.866	.051
q11	.008	.015	-.006	.883
q12	-.007	-.004	.039	.872
q10	.005	-.005	-.034	.778

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Factor Correlation Matrix

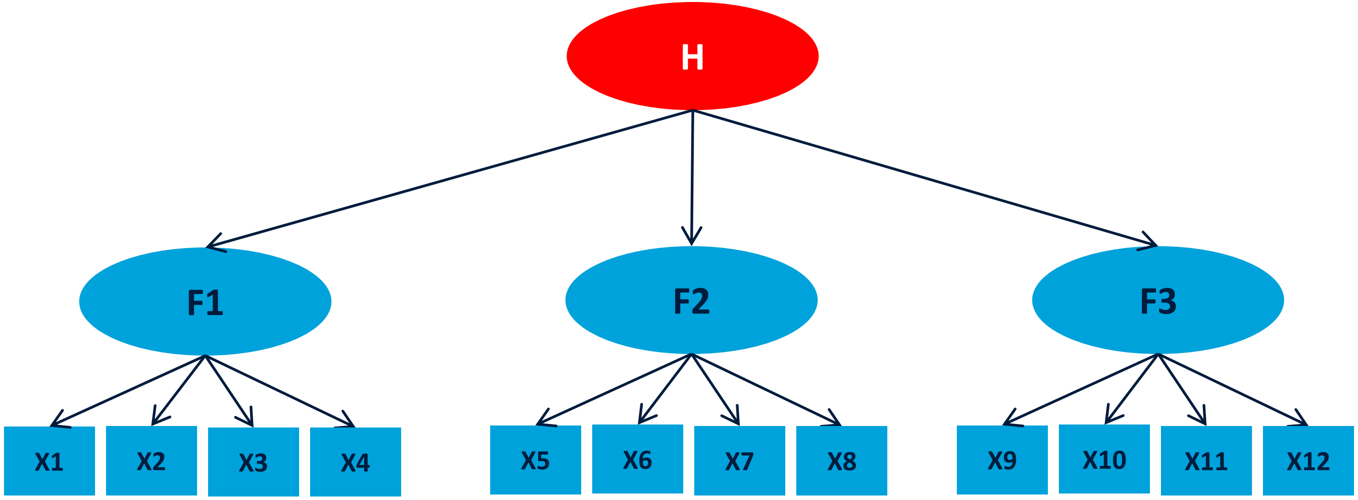
Factor	1	2	3	4
1	1.000	.406	.450	.387
2	.406	1.000	.341	.480
3	.450	.341	1.000	.408
4	.387	.480	.408	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

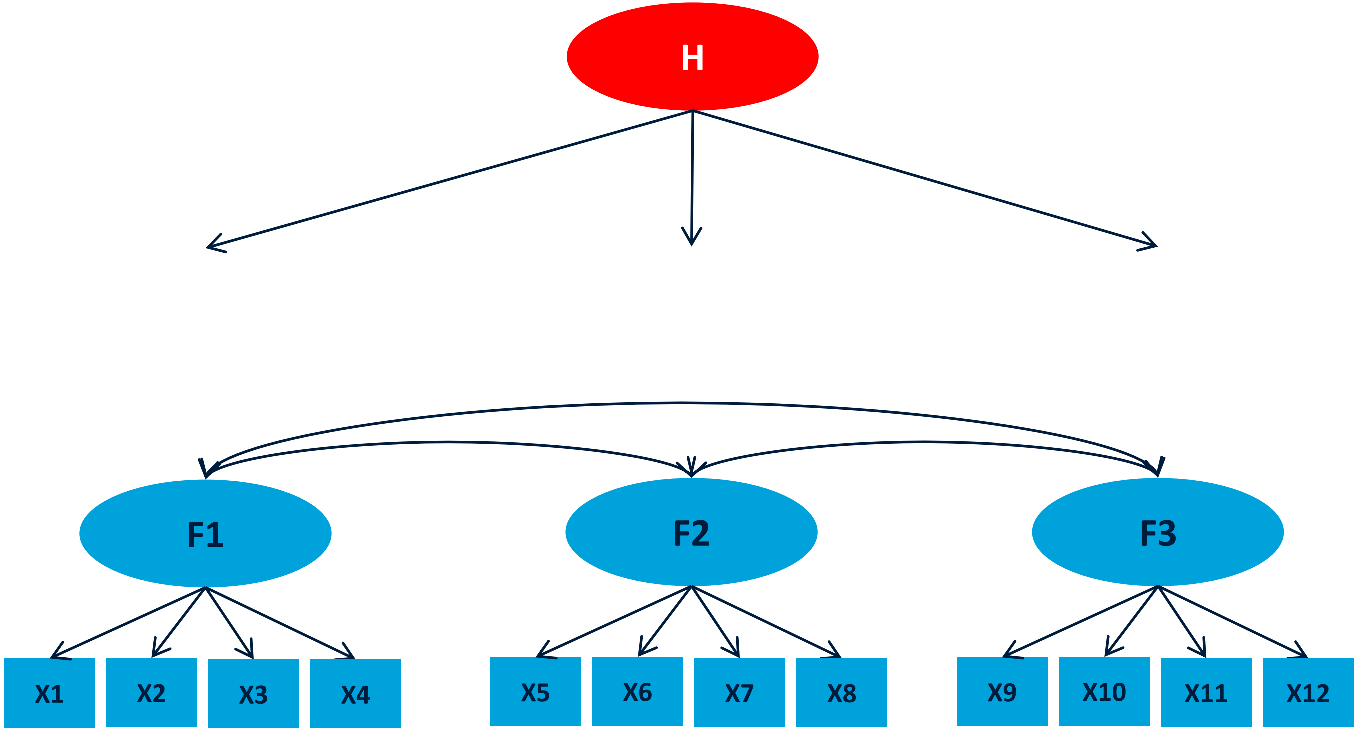
Exploratory Factor Analysis (EFA): High Quality EFA Decisions? (Conway and Huffcutt, 2003)

1. **Factor Extraction Model**
   - Common Factor Analysis Model
2. **Number of Factors**
   - Multiple Methods
3. **Type of Rotation**
   - Oblique Rotation, PROMAX
4. **Reporting**
5. **Sample size, sample-to-variable ratio and variable-to-factor ratio**
   - Large samples (> 400)
   - 5:1 (Sample-to-variable ratio)
   - 4:1 (variable-to-factor ratio)

Higher-Order Factor Analysis



Higher-Order Factor Analysis



Higher-Order Factor Analysis: SPSS Application

Wolff and Preising (2005)

Pattern Matrix[a]

	Factor			
	1	2	3	4
q1	.890	-.016	.035	-.004
q2	.907	-.004	-.011	.003
q3	.900	.023	-.013	.007
q4	-.039	.884	.016	.030
q5	.005	.901	.026	-.020
q6	.037	.900	-.041	-.003
q7	.014	.003	.915	-.022
q8	.011	-.017	.889	-.028
q9	-.016	.017	.866	.051
q10	.005	-.005	-.034	.778
q11	.008	.015	-.006	.883
q12	-.007	-.004	.039	.872

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

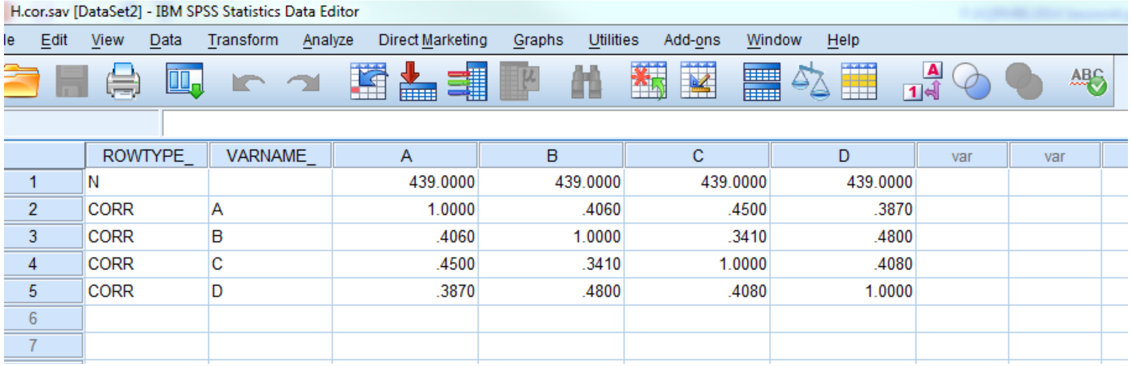
Factor Correlation Matrix

Factor	1	2	3	4
1	1.000	.406	.450	.387
2	.406	1.000	.341	.480
3	.450	.341	1.000	.408
4	.387	.480	.408	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

Higher-Order Factor Analysis: SPSS Application

Wolff and Preising (2005)



	ROWTYPE_	VARNAME_	A	B	C	D	var	var
1	N		439.0000	439.0000	439.0000	439.0000		
2	CORR	A	1.0000	.4060	.4500	.3870		
3	CORR	B	.4060	1.0000	.3410	.4800		
4	CORR	C	.4500	.3410	1.0000	.4080		
5	CORR	D	.3870	.4800	.4080	1.0000		
6								
7								

Higher-Order Factor Analysis: SPSS Application

Wolff and Preising (2005)

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.236	55.911	55.911	1.650	41.254	41.254
2	.698	17.457	73.368			
3	.576	14.406	87.774			
4	.489	12.226	100.000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor
	1
A	.644
B	.638
C	.614
D	.672

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 6 iterations required.

Higher-Order Factor Analysis: SPSS Application

Wolff and Preising (2005)

```
* Schmid-Leiman Solution for 2 level higher-order Factor analysis.
Matrix.
* ENTER YOUR SPECIFICATIONS HERE.
* Enter first-order pattern matrix.
Compute F1=
{.890,  -.016,  .035,   -.004;
.907,   -.004,  -.011,  .003;
.900,   .023,   -.013,  .007;
-.039,  .884,   .016,   .030;
.005,   .901,   .026,   -.020;
.037,   .900,   -.041,  -.003;
.014,   .003,   .915,   -.022;
.011,   -.017,  .889,   -.028;
-.016,  .017,   .866,   .051;
.005,   -.005,  -.034,  .778;
.008,   .015,   -.006,  .883;
-.007,  -.004,  .039,   .872}.
* enter first-order variable names.
compute varname={"q1"; "q2"; "q3"; "q4"; "q5"; "q6"; "q7"; "q8"; "q9"; "q10"; "q11"; "q12"}.
*enter first-order factor names.
compute f1name={"F1", "F2", "F3", "F4"}.
* enter second-order factor loadings.
Compute F2={0.644; 0.638; 0.614; 0.672}.
*enter second.order factor names.
compute f2name={"General1"}.
* END OF INPUT.
```

First-order loadings (PAF, Promax)!

Second-order loadings!

Higher-Order Factor Analysis: SPSS Application

Wolff and Preising (2005)

factor loadings of Schmid-Leiman Solution and h^2

	General1	F1	F2	F3	F4	H^2 total	H^2 G	H^2 1st
q1	.582	.681	-.012	.028	-.003	.803	.338	.465
q2	.577	.694	-.003	-.009	.002	.814	.333	.482
q3	.591	.689	.018	-.010	.005	.824	.349	.475
q4	.569	-.030	.681	.013	.022	.789	.324	.465
q5	.581	.004	.694	.021	-.015	.819	.337	.482
q6	.571	.028	.693	-.032	-.002	.808	.326	.482
q7	.558	.011	.002	.722	-.016	.833	.311	.522
q8	.523	.008	-.013	.702	-.021	.767	.274	.493
q9	.567	-.012	.013	.684	.038	.790	.321	.469
q10	.502	.004	-.004	-.027	.576	.585	.252	.333
q11	.604	.006	.012	-.005	.654	.793	.365	.428
q12	.603	-.005	-.003	.031	.646	.781	.363	.418

sum of squared loadings

	General1	F1	F2	F3	F4	total
H^2	3.894	1.421	1.426	1.485	1.179	9.406
%	.414	.151	.152	.158	.125	1.000

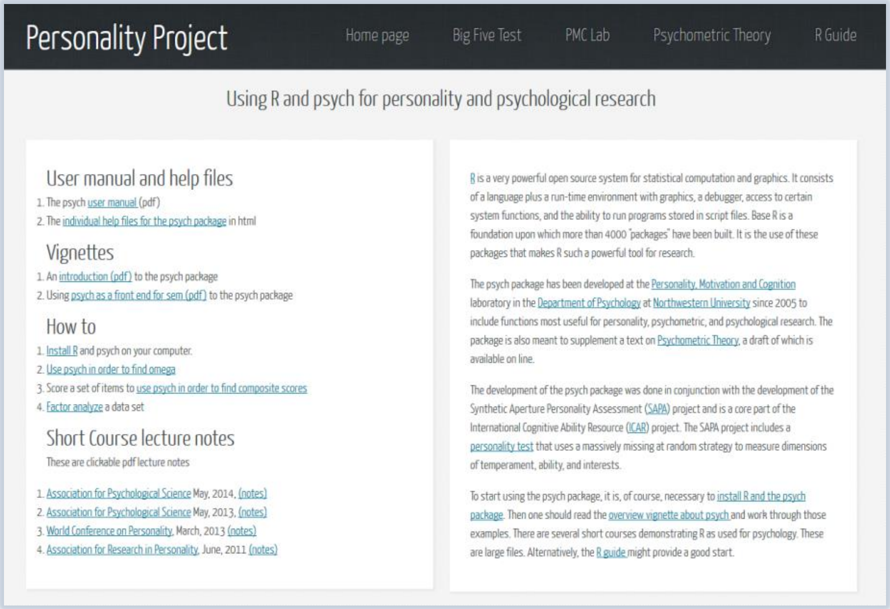
percentage of exracted variance explained by general factors (%)
.414

percentage of extracted variance explained by first order factors (%)
.586

------ END MATRIX -----

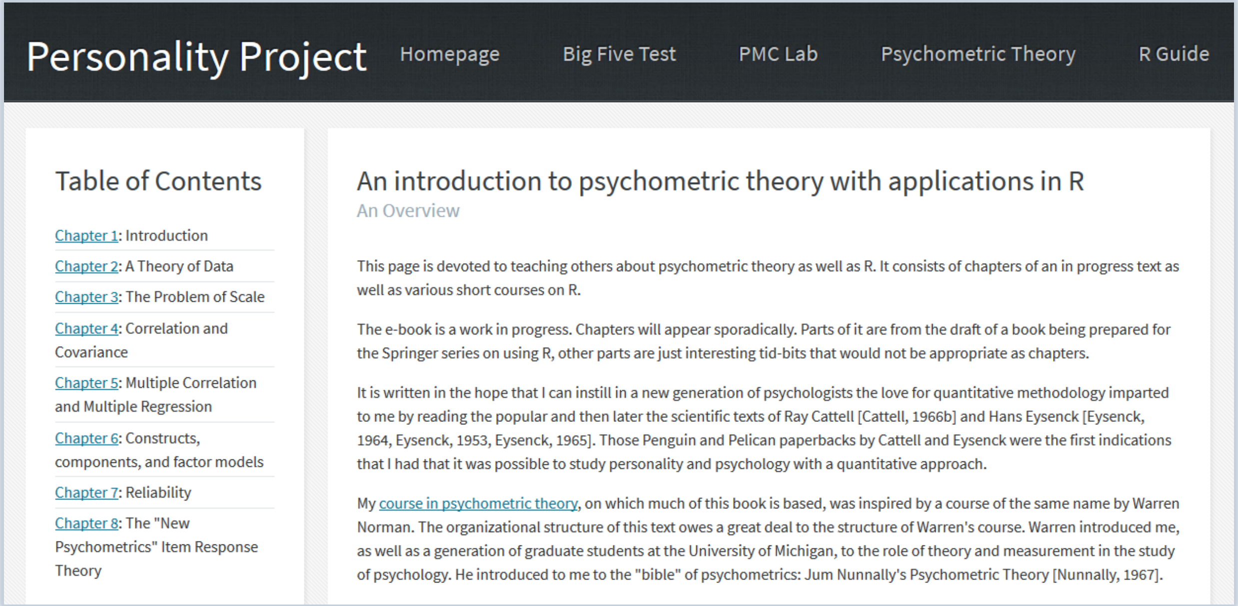
AlteRnative…

- EFA in R: package psych (http://personality-project.org/)



Alte R native…

- Book (http://www.personality-project.org/r/book/)


Personality Project Homepage Big Five Test PMC Lab Psychometric Theory R Guide

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Chapter 1: Introduction
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Chapter 6: Constructs, components, and factor models
Chapter 7: Reliability
Chapter 8: The "New Psychometrics" Item Response Theory

An introduction to psychometric theory with applications in R

An Overview

This page is devoted to teaching others about psychometric theory as well as R. It consists of chapters of an in progress text as well as various short courses on R.

The e-book is a work in progress. Chapters will appear sporadically. Parts of it are from the draft of a book being prepared for the Springer series on using R, other parts are just interesting tid-bits that would not be appropriate as chapters.

It is written in the hope that I can instill in a new generation of psychologists the love for quantitative methodology imparted to me by reading the popular and then later the scientific texts of Ray Cattell [Cattell, 1966b] and Hans Eysenck [Eysenck, 1964, Eysenck, 1953, Eysenck, 1965]. Those Penguin and Pelican paperbacks by Cattell and Eysenck were the first indications that I had that it was possible to study personality and psychology with a quantitative approach.

My course in psychometric theory, on which much of this book is based, was inspired by a course of the same name by Warren Norman. The organizational structure of this text owes a great deal to the structure of Warren's course. Warren introduced me, as well as a generation of graduate students at the University of Michigan, to the role of theory and measurement in the study of psychology. He introduced to me to the "bible" of psychometrics: Jum Nunnally's Psychometric Theory [Nunnally, 1967].

Factor Analysis

Editor

```r
library(psych)

# PAF

PAF<-fa(Data.01.PPT[,1:12], fm="pa", nfactors=4, rotate="promax")
PAF

cortest.bartlett(cor(Data.01.PPT[,1:12]), n=439)

# cortest.bartlett(Data.01.PPT[,1:12])

KMO(Data.01.PPT[,1:12])
```

Factor Analysis

Console

```
> PAF<-fa(Data.01.PPT[,1:12], fm="pa", nfactors=4, rotate="promax")
> PAF
Factor Analysis using method =  pa
Call: fa(r = Data.01.PPT[, 1:12], nfactors = 4, rotate = "promax",
    fm = "pa")
Standardized loadings (pattern matrix) based upon correlation matrix
      PA3   PA2   PA1   PA4   h2   u2 com
q1   0.89 -0.01  0.04  0.00 0.81 0.19   1
q2   0.91  0.00 -0.01  0.00 0.81 0.19   1
q3   0.90  0.02 -0.01  0.01 0.82 0.18   1
q4  -0.04  0.88  0.02  0.03 0.79 0.21   1
q5   0.01  0.90  0.03 -0.02 0.82 0.18   1
q6   0.04  0.90 -0.04  0.00 0.81 0.19   1
q7   0.01  0.00  0.91 -0.02 0.83 0.17   1
q8   0.01 -0.02  0.89 -0.02 0.77 0.23   1
q9  -0.02  0.02  0.86  0.06 0.79 0.21   1
q10  0.00 -0.01 -0.03  0.78 0.58 0.42   1
q11  0.01  0.01 -0.01  0.88 0.79 0.21   1
q12 -0.01  0.00  0.04  0.87 0.78 0.22   1

                       PA3  PA2  PA1  PA4
SS loadings           2.44 2.41 2.39 2.17
Proportion Var        0.20 0.20 0.20 0.18
Cumulative Var        0.20 0.40 0.60 0.78
Proportion Explained  0.26 0.26 0.25 0.23
Cumulative Proportion 0.26 0.52 0.77 1.00

 With factor correlations of
     PA3  PA2  PA1  PA4
PA3 1.00 0.40 0.45 0.39
PA2 0.40 1.00 0.34 0.48
PA1 0.45 0.34 1.00 0.40
PA4 0.39 0.48 0.40 1.00
```

Factor Analysis

Console

```
> cortest.bartlett(cor(Data.01.PPT[,1:12]), n=439)
$chisq
[1] 4076.927

$p.value
[1] 0

$df
[1] 66

>
> # cortest.bartlett(Data.01.PPT[,1:12])
>
> KMO(Data.01.PPT[,1:12])
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = Data.01.PPT[, 1:12])
Overall MSA =  0.85
MSA for each item = 
  q1   q2   q3   q4   q5   q6   q7   q8   q9  q10  q11  q12 
0.86 0.86 0.86 0.86 0.85 0.84 0.83 0.85 0.86 0.88 0.84 0.84 
```

Factor Analysis

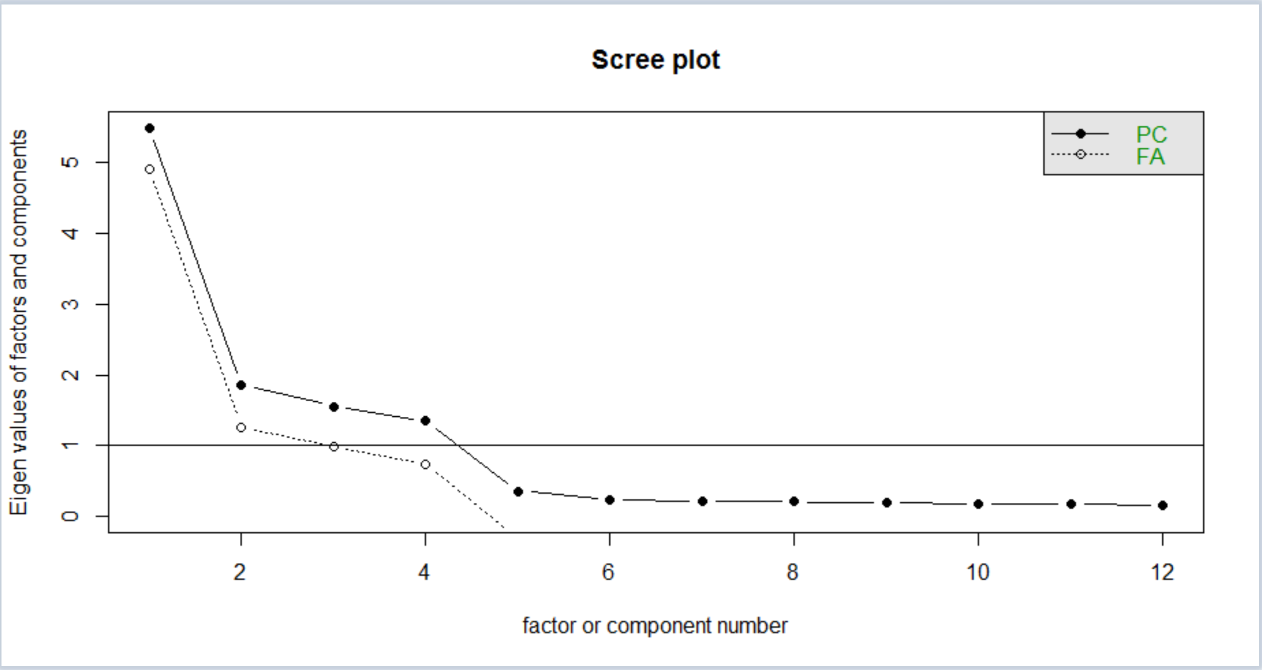
Console

```
> cortest.bartlett(Data.01.PPT[,1:12])
R was not square, finding R from data
$chisq
[1] 4076.927

$p.value
[1] 0

$df
[1] 66

> KMO(Data.01.PPT[,1:12])
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = Data.01.PPT[, 1:12])
Overall MSA =  0.85
MSA for each item =
  q1   q2   q3   q4   q5   q6   q7   q8   q9  q10  q11  q12
0.86 0.86 0.86 0.86 0.85 0.84 0.83 0.85 0.86 0.88 0.84 0.84
>
```

Factor Analysis

Graphics

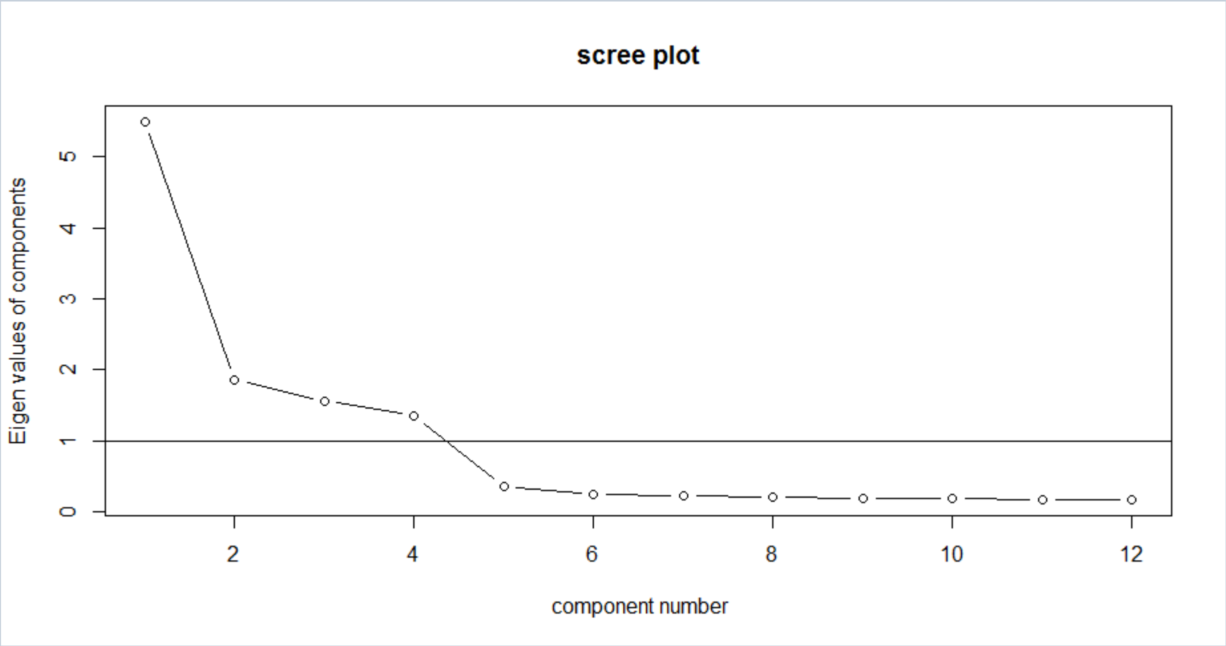
```
scree(Data.01.PPT[,1:12])
```



Factor Analysis

Graphics

```
27  VSS.scree(Data.01.PPT[,1:12])
```



Factor Analysis

Console

```
> PC<-principal(Data.01.PPT[,1:12], nfactors=4, rotate="promax")
> PC
Principal Components Analysis
Call: principal(r = Data.01.PPT[, 1:12], nfactors = 4, rotate = "promax")
Standardized loadings (pattern matrix) based upon correlation matrix
      PC3   PC2   PC1   PC4   h2   u2 com
q1   0.93 -0.02  0.03  0.00 0.87 0.13   1
q2   0.94  0.00 -0.01  0.00 0.88 0.12   1
q3   0.93  0.02 -0.01  0.01 0.88 0.12   1
q4  -0.04  0.93  0.02  0.03 0.87 0.13   1
q5   0.01  0.93  0.03 -0.02 0.87 0.13   1
q6   0.04  0.93 -0.04  0.00 0.87 0.13   1
q7   0.02  0.00  0.93 -0.01 0.88 0.12   1
q8   0.01 -0.02  0.94 -0.03 0.86 0.14   1
q9  -0.02  0.02  0.91  0.05 0.86 0.14   1
q10 -0.01 -0.04 -0.06  0.91 0.77 0.23   1
q11  0.01  0.03  0.01  0.89 0.84 0.16   1
q12  0.00  0.01  0.05  0.89 0.83 0.17   1

                       PC3  PC2  PC1  PC4
SS loadings           2.63 2.61 2.60 2.43
Proportion Var        0.22 0.22 0.22 0.20
Cumulative Var        0.22 0.44 0.65 0.86
Proportion Explained  0.26 0.25 0.25 0.24
Cumulative Proportion 0.26 0.51 0.76 1.00

 With component correlations of
     PC3  PC2  PC1  PC4
PC3 1.00 0.38 0.42 0.35
PC2 0.38 1.00 0.32 0.43
PC1 0.42 0.32 1.00 0.37
PC4 0.35 0.43 0.37 1.00
```

Factor Analysis

Console

```
> ML<-factanal(Data.01.PPT[,1:12], factors=4, rotation="promax")
> ML

Call:
factanal(x = Data.01.PPT[, 1:12], factors = 4, rotation = "promax")

Uniquenesses:
   q1    q2    q3    q4    q5    q6    q7    q8    q9   q10   q11   q12 
0.192 0.187 0.178 0.210 0.184 0.189 0.164 0.231 0.215 0.418 0.205 0.219 

Loadings:
    Factor1 Factor2 Factor3 Factor4
q1   0.890                         
q2   0.906                         
q3   0.900                         
q4           0.880                 
q5           0.901                 
q6           0.900                 
q7                   0.915         
q8                   0.887         
q9                   0.862         
q10                          0.776 
q11                          0.885 
q12                          0.873 

               Factor1 Factor2 Factor3 Factor4
SS loadings      2.426   2.399   2.373   2.155
Proportion Var   0.202   0.200   0.198   0.180
Cumulative Var   0.202   0.402   0.600   0.779

Factor Correlations:
        Factor1 Factor2 Factor3 Factor4
Factor1   1.000   0.338   0.448  -0.404
Factor2   0.338   1.000   0.404  -0.479
Factor3   0.448   0.404   1.000  -0.388
Factor4  -0.404  -0.479  -0.388   1.000
```

```
Test of the hypothesis that 4 factors are sufficient.
The chi square statistic is 23.31 on 24 degrees of freedom.
The p-value is 0.501
```

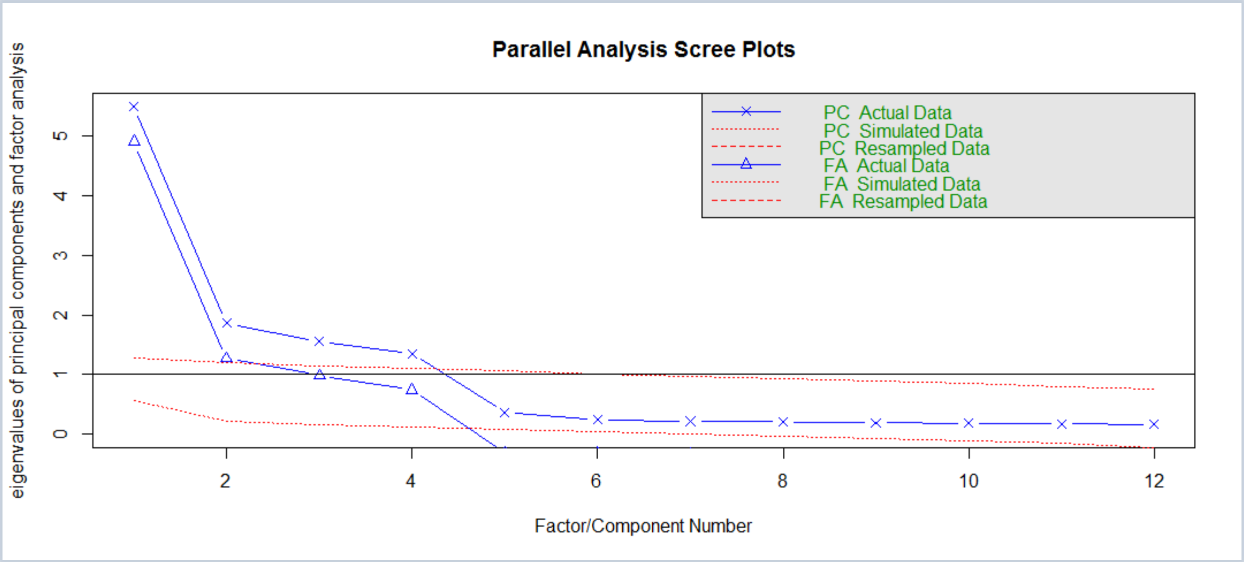
Factor Analysis

Editor

```
# Parallel Analysis and MAP test

fa.parallel(Data.01.PPT[,1:12], fa="both")

vss(Data.01.PPT[,1:12], n=12, rotate="promax")
```

Factor Analysis

Graphics



Factor Analysis

Console

```
The Velicer MAP achieves a minimum of NA  with  4  factors
BIC achieves a minimum of  NA  with  4  factors
Sample Size adjusted BIC achieves a minimum of  NA  with  4  factors
```

Factor Analysis

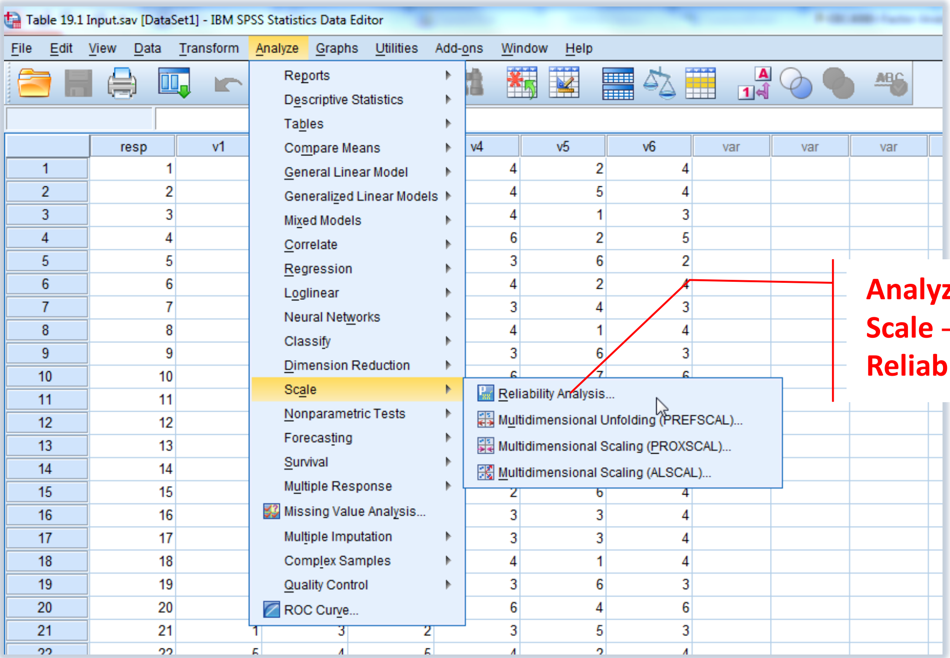
Console

```
> # Schmid Leiman Solution
>
> SL<-schmid(Data.01.PPT[,1:12], fm="pa", nfactors=4, rotate="promax")
Loading required namespace: GPArotation
> SL
Schmid-Leiman analysis
Call: schmid(model = Data.01.PPT[, 1:12], nfactors = 4, fm = "pa",
    rotate = "promax")

Schmid Leiman Factor loadings greater than  0.2
       g   F1*   F2*   F3*   F4*   h2   u2   p2
q1  0.58  0.68                   0.81 0.19 0.42
q2  0.58  0.69                   0.81 0.19 0.41
q3  0.59  0.69                   0.82 0.18 0.43
q4  0.57        0.68             0.79 0.21 0.41
q5  0.58        0.69             0.82 0.18 0.41
q6  0.57        0.69             0.81 0.19 0.40
q7  0.56              0.72       0.83 0.17 0.37
q8  0.52              0.70       0.77 0.23 0.35
q9  0.57              0.68       0.79 0.21 0.41
q10 0.50                    0.58 0.58 0.42 0.43
q11 0.60                    0.66 0.79 0.21 0.46
q12 0.60                    0.65 0.78 0.22 0.46

With eigenvalues of:
  g F1* F2* F3* F4*
3.9 1.4 1.4 1.5 1.2

general/max  2.61   max/min =   1.26
mean percent general =  0.41    with sd =  0.03 and cv of  0.08
```

Reliability: Cronbach's Alpha

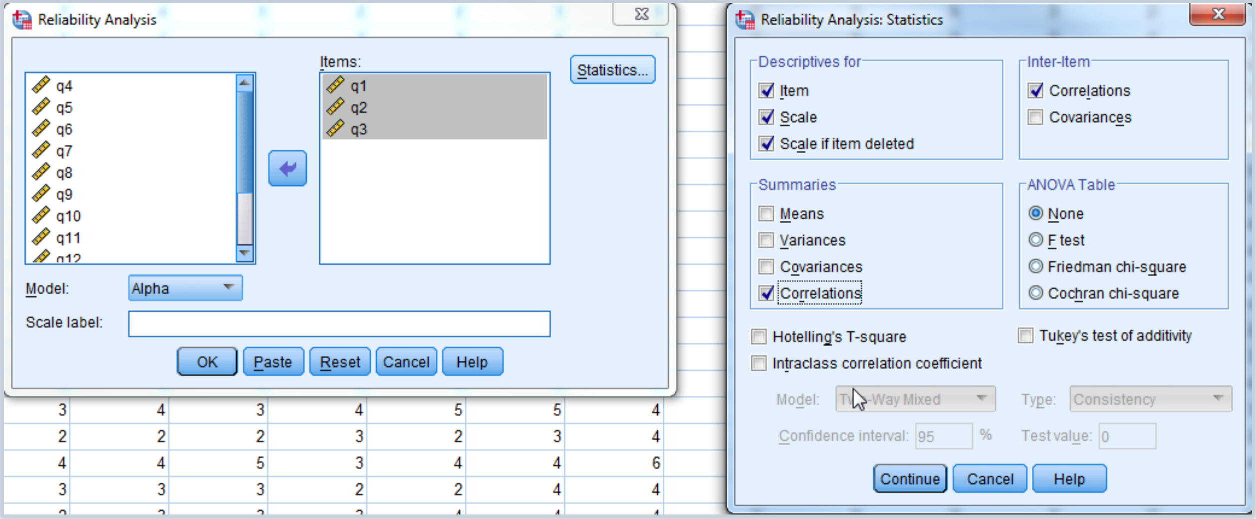
- Coefficient (Cronbach's) Alpha (ranges: 0-1, cut-off value: **0.7** [0.6 or 0.8])
  - Multiple Items
  - Additive = recode reverse-scored items (MEAN SCORES!)
- Key Assumption: **UNIDIMENSIONALITY** (Cortina, 1993)

Reliability: Coefficient Alpha



Analyze →
Scale →
Reliability Analysis

Reliability: Coefficient Alpha



Reliability: Coefficient Alpha

Reliability Statistics

Cronbach's Alpha[a]	Cronbach's Alpha Based on Standardized Items[a]	N of Items
-1.297	-1.550	3

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

What happened here?

Inter-Item Correlation Matrix

	v1 Prevents Cavities	v3 Strengthen Gums	v5 Tooth Decay Unimportant
v1 Prevents Cavities	1.000	.873	-.858
v3 Strengthen Gums	.873	1.000	-.778
v5 Tooth Decay Unimportant	-.858	-.778	1.000

Inter-Item Correlation Matrix

	v1 Prevents Cavities	v3 Strengthen Gums	v5r
v1 Prevents Cavities	1.000	.873	.858
v3 Strengthen Gums	.873	1.000	.778
v5r	.858	.778	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.938	.939	3

Reliability: Coefficient Alpha

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.929	.929	3

Cronbach's α

=k/(k-1)*("shared"/"shared" + "unique")

=3/(3-1) * (4.882/4.882+3)
=1.5*0.619=0.929

Inter-Item Correlation Matrix

	q1	q2	q3
q1	1.000	.810	.814
q2	.810	1.000	.817
q3	.814	.817	1.000

"Shared"= 2*(0.810 + 0.814 + 0.817) = 4.882

"Unique"= 1 + 1+ 1 = 3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
q1	7.17	3.506	.852	.726	.898
q2	6.91	3.457	.854	.729	.896
q3	7.03	3.266	.857	.734	.895

Reliability: Coefficient Alpha

Perceived Ease of Use

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.929	.929	3

Attitude

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.920	.920	3

Intention to Use

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.869	.882	3

Perceived Usefulness

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.924	.924	3

Reliability Analysis

Console

```
> # Coefficient Alpha
>
> alpha(Data.01.PPT[,1:3])

Reliability analysis
Call: alpha(x = Data.01.PPT[, 1:3])

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd
      0.93      0.93     0.9      0.81  13 0.033  3.5 0.91

 lower alpha upper     95% confidence boundaries
0.86 0.93 0.99

 Reliability if an item is dropped:
   raw_alpha std.alpha G6(smc) average_r S/N alpha se
q1      0.90      0.90    0.82      0.82 8.9    0.057
q2      0.90      0.90    0.81      0.81 8.7    0.057
q3      0.89      0.89    0.81      0.81 8.5    0.057

 Item statistics
     n raw.r std.r r.cor r.drop mean   sd
q1 439  0.93  0.93  0.88   0.85  3.4 0.94
q2 439  0.93  0.94  0.89   0.85  3.6 0.96
q3 439  0.94  0.94  0.89   0.86  3.5 1.01

Non missing response frequency for each item
      1    2    3    4    5    6 miss
q1 0.02 0.15 0.39 0.33 0.10 0.01    0
q2 0.01 0.11 0.31 0.41 0.15 0.02    0
q3 0.02 0.13 0.35 0.36 0.12 0.03    0
```

Kelly and Pornprasertmanit (2016)

Psychological Methods
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1082-989X/16/$12.00 http://dx.doi.org/10.1037/a0040086

Confidence Intervals for Population Reliability Coefficients: Evaluation of Methods, Recommendations, and Software for Composite Measures

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Texas Tech University

A composite score is the sum of a set of components. For example, a total test score can be defined as the sum of the individual items. The reliability of composite scores is of interest in a wide variety of contexts due to their widespread use and applicability to many disciplines. The psychometric literature has devoted considerable time to discussing how to best estimate the population reliability value. However, all point estimates of a reliability coefficient fail to convey the uncertainty associated with the estimate as it estimates the population value. Correspondingly, a confidence interval is recommended to convey the uncertainty with which the population value of the reliability coefficient has been estimated. However, many confidence interval methods for bracketing the population reliability coefficient exist and it is not clear which method is most appropriate in general or in a variety of specific circumstances. We evaluate these confidence interval methods for 4 reliability coefficients (coefficient alpha, coefficient omega, hierarchical omega, and categorical omega) under a variety of conditions with 3 large-scale Monte Carlo simulation studies. Our findings lead us to generally recommend bootstrap confidence intervals for hierarchical omega for continuous items and categorical omega for categorical items. All of the methods we discuss are implemented in the freely available R language and environment via the MBESS package.

Keywords: reliability, confidence intervals, composite score, homogeneous test, measurement

Supplemental materials: http://dx.doi.org/10.1037/a0040086.supp

R Package MBESS

References

Acito, F. and Anderson, R.D. (1980). A Monte Carlo Comparison of Factor Analytic Methods. *Journal of Marketing Research*, 17 (2), 228-236.

Bacharach, S.B. (1989). Organizational Theories: Some Criteria for Evaluation. *Academy of Management Review*, 14 (4), 496-515.

Conway, J.M. and Huffcutt, A. I. (2003). A Review and Evaluation of Exploratory Factor Analysis Practices in Organizational Research. *Organizational Research Methods*, 6 (2), 147-168.

Cortina, J.M. (1993). What is Coefficient Alpha? An Examination of Theory and Applications. *Journal of Applied Psychology*, 78 (1), 98-104.

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Management Science, 35*, 982-1003.

Gorsuch, R.L. (1983). *Factor Analysis*. Hillsdale, NJ: Lawrence Erlbaum & Associates.

Hair, J.F., Jr., Black, W.C., Babin, B.J, and Anderson, R.E. (2018). *Multivariate Data Analysis.* Cengage.

Netemeyer, R. G., Bearden, W. O., & Sharma, S. (2003). *Scaling Procedures: Issues and Applications*. Sage Publications.

Malhotra, N. (2010). *Marketing Research: An Applied Orientation*. Upper Saddle River: Pearson/Prentice-Hall.

References

O'Connor, B.P. (2000). SPSS and SAS Programs for Determining the Number of Components Using parallel Analysis and Velicer's Map Test. *Behavior Research Methods, Instruments & Computers*, 32 (3), 396-402.

Stewart, D.W. (1981). The Application and Misapplication of Factor Analysis in Marketing Research. *Journal of Marketing Research*, 18 (1), 51-62.

Tabachnick, B.G. & Fidell, L.S. (2007). *Using Multivariate Statistics.* Boston: Allyn and Bacon.

Wolff, H.-G. and Preising, K. (2005). Exploring Item and Higher Order Factor Structure with the Schmid-Leiman Solution: Syntax Codes for SPSS and SAS. *Behavior Research Methods*, 37 (1), 48-58.

References

Beaujean, A. A. (2013). Factor Analysis Using "R". *Practical Assessment*, *18*(4), 1-11.
Chapman, C., & Feit, E. M. (2015). *R for Marketing Research and Analytics.* New York, NY: Springer.
Crawley, MJ (2013). *The R Book.* Chichester, UK: John Wiley and Sons.
Everitt, BS and Hothorn, T (2006). *A Handbook of Statistical Analysis Using R.* Boca Raton, FL: Chapman and Hall/CRC.
Faraday, J.A. (2015). *Linear Models with R*. Boca Raton, FL: CRC Press.
Field, A, Miles, J and Field, Z (2012). *Discovering Statistics Using R.* Los Angeles, CA: Sage Publications.
Kabacoff, RI (2011). *R in Action*. Shelter Island, NY: Manning.
Kelley, K. & Pornprasertmanit, P. (2016). Confidence Intervals for Population Reliability Coefficients: Evaluation of Methods, Recommendations, and Software for Homogeneous Composite Measures. *Psychological Methods, 21*(1), 69-92.
Muenchen, RA (2009). *R for SAS and SPSS Users.* New York, NY; Springer Science and Business Media.
Revelle, W, *Psychometric Theory*. [http://www.personality-project.org/r/book/]

Thank you for Your Attention!