

LCDB7011 Quantitative Research Methods

Week 6&7 – Moving beyond the Basics

Validity and Reliability

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Agenda

Upon completion of the class, you should be able to understand

➤ Reliability

Cronbach's Alpha

➤ Validity

- Criterion validity
- Construct validity

A magnifying glass with a black frame and handle is positioned over a lush green field of grass. The lens of the magnifying glass is centered on the word "RELIABILITY", which is written in a bold, black, sans-serif font. The background is a soft-focus green field with some dew drops visible on the grass blades. The entire image has a white, torn-paper-like border on the right side.

RELIABILITY

Reliability (Consistency)



- To measure the internal consistency of a scale or test
- Cronbach's Alpha is adopted to reflect the level of internal consistency.

α

Reliability (Internal Consistency)

Reliability (internal consistency) is not sufficient in confirming a good measurement, because a reliable measure may not necessarily be valid. If an instrument shows satisfactory reliability, then it would be expected that satisfactory validity estimates would also be achievable. So, it is important to ensure validity of data (Froman, 2000; Hair et al, 2003)

Reliability

- Once you have created your summative or composite variables, check for reliability using the **Cronbach Alpha** score $\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}}$

- Where:

N = the number of items.

$\bar{c}$ = average covariance between item-pairs.

$\bar{v}$ = average variance.

Reliability

Covariance vs. Variance

- Covariance and variance are used to measure the distribution of points in a data set.
- However, variance is typically used in data sets with **only one variable** and indicates how closely those data points are clustered around the average.
- Covariance measures the direction of **the relationship between two variables**. A positive covariance means that both variables tend to be high or low at the same time. A negative covariance means that when one variable is high, the other tends to be low.

Reliability

Reliability in SPSS

- Step 1: Click “Analyze,” then click “Scale” and then click “Reliability Analysis.”
- Step 2: Transfer your variables (q1 to q5) into “Items,”. The model default should be set as “Alpha.”
- Step 3: Click “Statistics” in the dialog box.
- Step 4: Select “Item,” “Scale,” and “Scale if item deleted” in the box description. Choose “Correlation” in the inter-item box.
- Step 5: Click “Continue” and then click “OK”.

Reliability test

The screenshot shows the SPSS 'Analyze' menu. The 'Scale' option is highlighted with a red oval. A sub-menu is open for 'Scale', and the 'Reliability Analysis...' option is also highlighted with a red oval. The background shows a data table with columns EP2, EP3, AC1, EP4, and JS2.

	EP2	EP3	AC1	EP4	JS2
	0	5	1	6	4
	0	10	2	7	4
	0	10	1	7	2
	0	9	2	7	5
	9	10	1	6	4
	0	7	1	7	6
	9	9	2	6	3
	0	10	1	7	2
	3	8	3	3	5
	0	8	2	7	3
	0	9	4	7	7
	0	9	4	7	4
	9	8	1	5	4
	3	8	1	5	4
	9	9	2	6	4
	0	10	4	7	4

Cronbach's alpha	Internal consistency
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

<https://www.statisticshowto.datasciencecentral.com/cronbachs-alpha-spss/>



Prifysgol Cymru
Y Drindod Dewi Sant
University of Wales
Trinity Saint David

Reliability Test

3 OC4 EP2 EP3 AC1 EP4 JS2 JS3 AC2

Reliability Analysis

Items:

JS2 [JS2]
JS3 [JS3]
AC2 [AC2]
SI1 [SI1]
JS4 [js4]
SI2 [SI2]
JS5 [JS5]
AC3 [AC3]
SI3 [SI3]
AC4 [AC4]
SI4 [SI4]
C1 - Gender Class [C1]
C2 - Employee Type Cl...

JS1 [JS1]
JS2 [JS2]
JS3 [JS3]
JS4 [js4]
JS5 [JS5]

Ratings:

Model: Alpha

Scale label: JS1-5

OK Paste Reset Cancel Help

Statistics...

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
JS1	64.92	518.873	.586	.448	.230
JS2	64.91	517.287	.598	.453	.226
JS3	65.90	523.897	.511	.384	.240
JS4	66.45	522.507	.551	.411	.237
JS5	14.28	17.988	.653	.433	.811

Exercise time

- Please run Reliability Test for the following items
- OC1-4
- EP1-4
- AC1-4

EP1-4

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.823	.832	4

OC1-4

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
OC1	25.48	27.067	.561	.317	.831
OC2	21.95	26.707	.739	.598	.732
OC3	21.71	32.808	.612	.384	.797
OC4	21.96	28.234	.721	.585	.744

EP1-4

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.848	.857	4

EP1-4

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
EP1	23.61	14.465	.640	.417	.839
EP2	23.29	14.906	.729	.535	.788
EP3	23.21	17.336	.685	.506	.813
EP4	26.30	16.472	.735	.560	.791

AC1-4

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.891	.894	4

AC1-4

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
AC1	9.54	17.788	.764	.586	.860
AC2	8.75	15.382	.764	.585	.861
AC3	9.53	17.493	.775	.602	.856
AC4	9.09	16.291	.756	.572	.861

JS1-5

CR <0.7

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.281	.844	5

JS1-5

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
JS1	64.92	518.873	.586	.448	.230
JS2	64.91	517.287	.598	.453	.226
JS3	65.90	523.897	.511	.384	.240
JS4	66.45	522.507	.551	.411	.237
JS5	14.28	17.988	.653	.433	.811

How to present the Cronbach's Alpha ?

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<http://myjms.mohe.gov.my/index.php/ijssr>

4. Results and Discussion

4.1 Reliability and Validity

The construct reliability and validity values are presented in Table 2. Cronbach's α is widely used for testing the internal consistency and thus the reliability of the result. The indicator reliability ranged from 0 to 1, and the acquired constructs should be beyond the recommendation of 0.7 (Cronbach, 1951; Sarstedt, Ringle, & Hair, 2017). Table 2 shows that the Cronbach's α value ranged from 0.936 to 0.965. All data exceeded the criteria. The results indicate the high level of reliability of the study.

To assess the convergent validity of the constructs, factor loadings, composite reliability (CR), and average variance extracted (AVE) were tested to demonstrate the degree to which a metric correlate positively with alternative means of the same construct. The factor loading and CR of each item were greater than the threshold value of 0.70. AVE was used to evaluate the convergent validity. An acceptable variance for AVE is 0.5 or higher (Bagozzi & Yi, 1988). In this study, factor loading ranged from 0.895 to 0.956, the CR values ranged from 0.954 to 0.971, and the AVE ranged from 0.828 to 0.886. All data meet the standard.

Table 2: Reliability and Validity of the Construct

Constructs	Loading	Alpha	CR	AVE
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Table 2: Reliability and Validity of the Construct

Constructs	Loading	Alpha	CR	AVE
Green Corporate Image				
GI1	0.945			
GI2	0.910			
GI3	0.911			
GI4	0.898	0.965	0.971	0.828
GI5	0.900			
GI6	0.895			
GI7	0.909			
Warm Glow				
WG1	0.948			
WG2	0.934	0.928	0.954	0.874
WG3	0.923			
Self-expressive Benefits				
SB1	0.956			
SB2	0.939	0.936	0.959	0.874
SB3	0.928			
Nature Experience				
NE1	0.953			
NE2	0.928	0.934	0.958	0.883
NE3	0.938			
Green Experimental Satisfaction				
GS1	0.934			
GS2	0.932			
GS3	0.919	0.958	0.968	0.856
GS4	0.916			
GS5	0.925			
Green Switching Intention				
SI1	0.955			
SI2	0.937	0.936	0.959	0.886
SI3	0.933			

Chan, et al (2021). <https://myjms.mohe.gov.my/index.php/ijssr/article/view/16701/8789>

Activity

VALIDITY



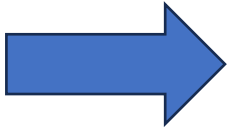
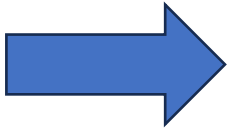


Ensuring Validity in Qualitative Research

Qualitative Research – Researcher Subjectivity Concern

- Use a robust analysis and explain that clearly in your research.
- Share some conclusions with some interview participants to ensure that your conclusions do not deviate from their described experiences .
- When interviews were conducted in languages other than English, validity concerns must be addressed.

Types of Validity

- 
- **Construct Validity** - evaluates whether a **measurement tool** really represents the thing we are interested in measuring. It's central to establishing the overall validity of a method (Factor Analysis, Correlation) e.g. measurement of job satisfaction
 - Content Validity – assesses whether a test is representative of all aspects of the construct (Critical value or Content validity index)
 - Face Validity - evaluates the suitability of the content of a test superficially. It's similar to content validity, but face validity is a more informal and subjective assessment. (Questionnaire design)
- 
- **Criterion Validity** - evaluates how well a test can **predict** a concrete outcome, or how well the results of your test approximate the results of another test. (Correlation)

Construct Validity

- Factor Analysis (KMO)

Criterion Validity

- Pearson's coefficient (r)
- Critical values for Pearson's coefficient

VALIDITY (Accuracy)

We do **Criterion Validity**

Type of validity	Definition
Face	Does it make sense to use the measure for the construct?
Content	Does the measure sufficiently cover the phenomenon that it is intended to cover
Criterion	Does the measure (<i>predictor</i>) correctly predict an outcome (<i>criterion</i>)?

Data Validity

“Validity determines whether the research truly measures what it was intended to measure or how truthful the research results are. In other words, does the research instrument allow you to hit “the bull’s eye” of your research object?” (Joppe, 2000, p.1).

To achieve validity, two forms of analyses would be carried out:

- Correlation Analysis (for Construct validity), and
- Factor Analysis

Correlation Analysis

- Understanding how to run Correlation Analysis
- Correlation ranges between -1 and +1
 - +ve correlation = X correlates positively with Y
 - ve correlation = X correlates negatively with Y

Correlation Analysis

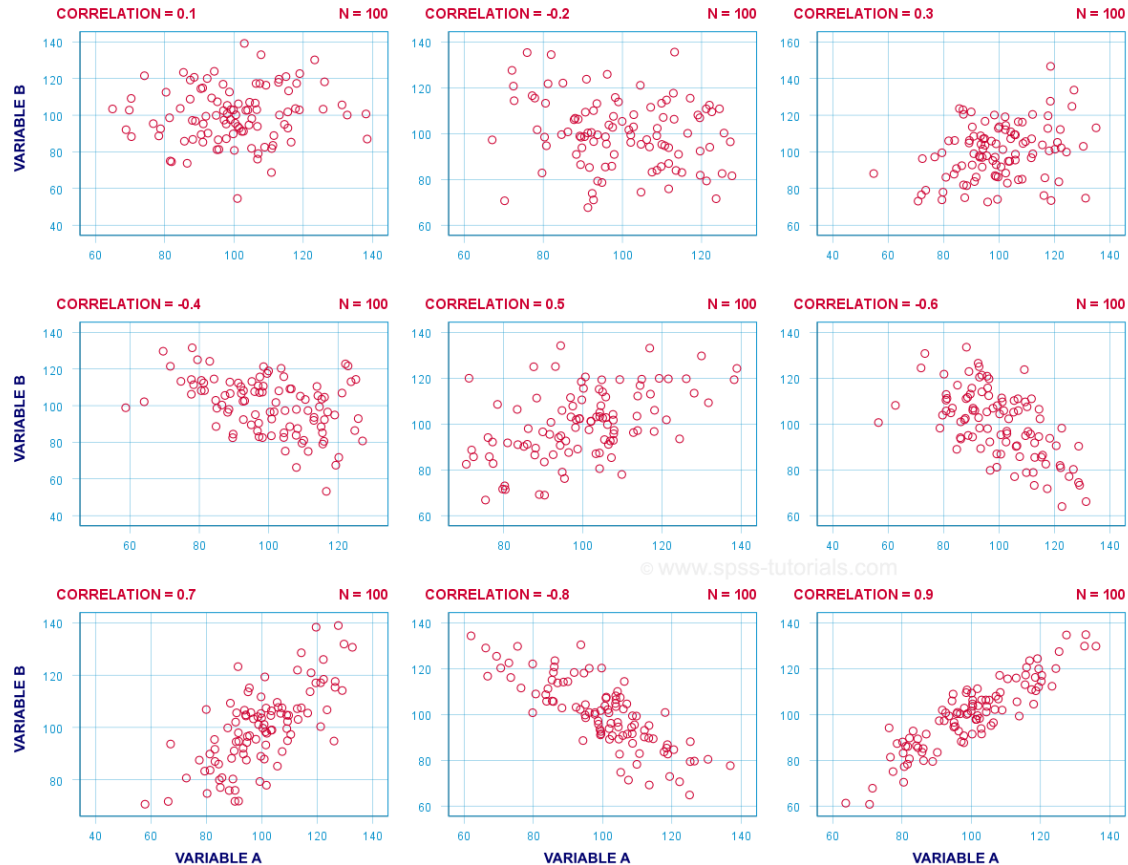
- Correlation Analysis can be used to:
 1. Understand inter-item correlation of measurement items (or variables) for a construct. Checking the commonality between the items (variables) for a construct (factor).
 2. To understand the degree of correlation between the constructs.

Correlation Analysis

- Correlation analysis of the measurement variables should be done before doing the factor analysis (Rummel, 1970; Rietveld & Van Hout, 1993).
- The correlation technique should be used to check the strength and direction of associations between variables, and validate data to ensure parsimony towards (Hair et al, 1992):
 - ❑ Checking the strength of the relationships,
 - ❑ Examining the statistical significance of the relationships
- Near zero values indicate weak relationships, while values nearer to +1 or -1 suggest stronger relationship (Field, 2005)

Correlations

(PEARSON CORRELATIONS) VISUALIZED AS SCATTERPLOTS



- A Pearson correlation is a number between -1 and +1 that indicates to what extent 2 metric variables are linearly related.
- A Pearson's correlation coefficient (r) is a **measure of the strength of the association** between the two variables.
- It does not matter which measuring units the variables are in (can be different scales) as long as the relation is linear

<https://www.spss-tutorials.com/spss-correlation-analysis/>

Correlations

The correlation between two variables X and Y is defined as the **covariance** of X with Y (covarXY) divided by the product of the standard deviation of X (stdevX) and the standard deviation of Y (stdevY):

$$r = \text{covarXY} / (\text{stdevX} \cdot \text{stdevY}).$$

$$r = \text{covarX,Y} / \sigma_X \sigma_Y$$

- Variance: the mean value of all the differences from the mean multiplied by themselves (=squared)
- Covariance: The mean value of all the pairs of differences from the mean for X multiplied by the differences from the mean for Y.
- If X and Y aren't closely related to each other, they don't *co-vary*, so the covariance is small, so the correlation is small.

Correlations

		Wechsel IQ Test Score	Depression Test Score	Anxiety Test Score	Social Functioning Test Score	Ge Beir
Wechsel IQ Test Score	Pearson Correlation	1	.121	.152	-.151	
	Sig. (2-tailed)		.194	.110	.104	
	N	122	116	112	117	
Depression Test Score	Pearson Correlation	.121	1	.282**	-.328**	
	Sig. (2-tailed)	.194		.003	.000	
	N	116	122	112	116	
Anxiety Test Score	Pearson Correlation	.152	.282**	1	-.534**	
	Sig. (2-tailed)	.110	.003		.000	
	N	112	112	117	111	
Social Functioning Test Score	Pearson Correlation	-.151	-.328**	-.534**	1	
	Sig. (2-tailed)	.104	.000	.000		
	N	117	116	111	122	
Generall Well Being Test Score	Pearson Correlation	-.080	-.801**	-.296**	.333**	
	Sig. (2-tailed)	.393	.000	.001	.000	
	N	117	117	113	117	

The correlations on the main diagonal are the correlations between each variable and itself - which is why they are all 1 and not interesting at all.

The 10 correlations *below* the diagonal are what we need. As a rule of thumb, **a correlation is statistically significant if its “Sig. (2-tailed)” < 0.05.**

You would report a correlation like this:

**. Correlation is significant at the 0.01 level (2-tailed). © 2017 www.spss-tutorials.com Table X. Pearson Correlations Among Psychological Test Scores

	1	2	3	4	5
1. Wechsel IQ Test Score	-				
2. Depression Test Score	.082	-			
3. Anxiety Test Score	.378**	.222*	-		
4. Social Functioning Test Score	-.077	-.328**	-.405**	-	
5. General Well Being Test Score	-.037	-.801**	-.226*	.333**	

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

Correlation Analysis can also be used to:

To gauge relationship (association) between two factors. In other words, to test hypotheses.

- Correlation Analysis is not adequate for testing hypotheses because it does not consider associated multi-collinearity factors. Thus, discriminant validity cannot be ensured.

Factor Analysis



Factor Analysis

- As Gorsuch (1983) commented, “all scientists are united in a common goal: they seek to summarise data so that the empirical relationships can be grasped by the human mind” (p. 2).
- Factor Analysis:
 1. Analytical approach designed to analyze interrelationships (Reyment & Joreskog, 1993),
 2. a number of related statistical techniques which help determine characteristics that go together (Bryman & Cramer, 1990).

Factor Analysis

- In other words, factor analysis involves a set of procedures, and enables the reduction of number of variables into a smaller set of factors. It involves determining the latent variables for a factor (Field, 2009)
- Factor analysis enables the researcher: (1) gain a clear view of the data, and (2) use the output in subsequent analyses (Rummel, 1970; Field, 2000; Rietveld & Van Hout, 1993; Field, 2005).

Types of Factor Analysis

- **Confirmatory Factor Analysis (CFA)** - a quantitative data analysis method that assesses the fit between observed data and a theoretically grounded model specifying the causal relations between latent factors and their observed variables.
- **Exploratory factor analysis (EFA)** - a statistical method used to identify the underlying relationships between a large number of observed variables by reducing them into fewer latent factors. EFA aims to clarify the structure of data, helping to explain variance and revealing meaningful patterns among correlated variables.

Principal Component Analysis

- A technique to **reduce dimensionality** without loss of important information (variance)
- To identify the directions (principal components) of maximum variance, while capturing the remain orthogonal (uncorrelated) variance.
- **Eigenvector** (The directions of Max. var of PC) and **Eigenvalues** (Amount of variance each component explains)

Factor Analysis

The screenshot shows the SPSS software interface. The 'Analyze' menu is open, and the 'Dimension Reduction' option is highlighted with a red circle. A sub-menu is also open for 'Dimension Reduction', with the 'Factor...' option highlighted by another red circle. The background shows a data table with columns 'id', 'JS1', 'OC1', 'EP2', 'EP3', 'AC1', 'EP4', and 'JS2'.

id	JS1	OC1	EP2	EP3	AC1	EP4	JS2
1	5	3	0	5	1	6	4
2	3	0	0	10	2	7	4
3	4	6	0	10	1	7	2
4	4	7	0	9	2	7	5
5	5	2	9	10	1	6	4
6	6	5	0	7	1	7	6
7	2	6	9	9	2	6	3
8	2	4	0	10	1	7	2
9	4	9	3	8	3	3	5
10	5	5	0	8	2	7	3
11	4	9	0	9	4	7	7
12	5	4	0	9	4	7	4
13	2	1	9	8	1	5	4
14	4	0	3	8	1	5	4
15	4	7	?	?	?	?	4
16	4	4					4
17	3	4					4
18	5	7					6
19	3	7					2
20	5	6	0	9	1	7	4

Statistics

- ☐ Univariate descriptives
☒ Initial solution

Correlation Matrix

- ☒ Coefficients ☐ Inverse
☒ Significance levels ☐ Reproduced
☒ Determinant ☐ Anti-image
☒ KMO and Bartlett's test of sphericity

☐ Covariance matrix

Continue

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: 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

Determinant
>.000001

Correlation Matrix ^a																								
	JS1	OC1	OC2	EP1	OC3	OC4	EP2	EP3	EP4	JS2	JS3	JS4	JS5	SI3	SI4	AC1	AC2	SI1	SI2	AC3	AC4	EXP - Experience in Years	JP - Performance	
Correlation	JS1	1.000	.063	.142	.065	.159	.162	.123	.104	.094	.557	.514	.511	.550	.046	.141	.041	.003	.114	.114	-.019	.020	.045	.037
	OC1	.063	1.000	.524	.111	.444	.484	.229	.122	.229	.055	.075	.059	.083	.136	.176	.056	.104	.183	.190	.093	.128	.010	.205
	OC2	.142	.524	1.000	.251	.558	.738	.373	.348	.332	.089	.132	.101	.188	.363	.459	.264	.211	.432	.473	.272	.288	.085	.239
	EP1	.065	.111	.251	1.000	.236	.279	.596	.504	.567	.167	.146	.114	.159	.330	.377	.140	.159	.342	.371	.156	.153	-.020	.205
	OC3	.159	.444	.558	.236	1.000	.566	.370	.315	.370	.110	.084	.130	.140	.202	.261	.134	.089	.226	.281	.121	.161	.061	.239
	OC4	.162	.484	.738	.279	.566	1.000	.378	.290	.328	.091	.112	.095	.173	.304	.414	.151	.170	.379	.387	.206	.243	.049	.225
	EP2	.123	.229	.373	.596	.370	.378	1.000	.614	.649	.168	.120	.115	.140	.347	.452	.173	.175	.349	.390	.164	.226	.019	.251
	EP3	.104	.122	.348	.504	.315	.290	.614	1.000	.666	.157	.148	.113	.209	.299	.363	.186	.131	.293	.323	.151	.186	-.010	.240
	EP4	.094	.229	.332	.567	.370	.328	.649	.666	1.000	.162	.149	.124	.153	.360	.391	.136	.158	.396	.369	.125	.201	.031	.267
	JS2	.557	.055	.089	.167	.110	.091	.168	.157	.162	1.000	.498	.524	.559	.105	.151	-.004	-.015	.124	.126	-.027	.008	.057	.130
	JS3	.514	.075	.132	.146	.084	.112	.120	.148	.149	.498	1.000	.509	.473	.161	.180	.044	.011	.150	.105	-.008	.068	.066	.135
	JS4	.511	.059	.101	.114	.130	.095	.115	.113	.124	.524	.509	1.000	.513	.146	.168	.047	.013	.119	.090	.047	.051	.069	.143
	JS5	.550	.083	.188	.159	.140	.173	.140	.209	.153	.559	.473	.513	1.000	.130	.213	.110	.078	.179	.171	.050	.115	.082	.141
	SI3	.046	.136	.363	.330	.202	.304	.347	.299	.360	.105	.161	.146	.130	1.000	.670	.203	.166	.580	.625	.200	.195	.087	.107
	SI4	.141	.176	.459	.377	.261	.414	.452	.363	.391	.151	.180	.168	.213	.670	1.000	.203	.205	.670	.725	.246	.254	.135	.092
	AC1	.041	.056	.264	.140	.134	.151	.173	.186	.136	-.004	.044	.047	.110	.203	.203	1.000	.673	.230	.200	.691	.670	.061	.045
	AC2	.003	.104	.211	.159	.089	.170	.175	.131	.158	-.015	.011	.013	.078	.166	.205	.673	1.000	.196	.192	.690	.671	.070	.015
	SI1	.114	.183	.432	.342	.226	.379	.349	.293	.396	.124	.150	.119	.179	.580	.670	.230	.196	1.000	.733	.206	.207	.124	.071
	SI2	.114	.190	.473	.371	.281	.387	.390	.323	.369	.126	.105	.090	.171	.625	.725	.200	.192	.733	1.000	.211	.225	.141	.093
	AC3	-.019	.093	.272	.156	.121	.206	.164	.151	.125	-.027	-.008	.047	.050	.200	.246	.691	.690	.206	.211	1.000	.675	.079	.045
	AC4	.020	.128	.288	.153	.161	.243	.226	.186	.201	.008	.068	.051	.115	.195	.254	.670	.671	.207	.225	.675	1.000	.212	.117
	EXP - Experience in Years	.045	.010	.085	-.020	.061	.049	.019	-.010	.031	.057	.066	.069	.082	.087	.135	.061	.070	.124	.141	.079	.212	1.000	.107
	JP - Performance	.037	.205	.239	.205	.239	.225	.251	.240	.267	.130	.135	.143	.141	.107	.092	.045	.015	.071	.093	.045	.117	.107	1.000
Sig. (1-tailed)	JS1		.106	.002	.096	<.001	<.001	.007	.019	.031	<.001	<.001	<.001	<.001	.178	.002	.209	.475	.012	.011	.349	.345	.183	.229
	OC1	.106		.000	.013	.000	.000	.000	.007	.000	.138	.067	.122	.049	.003	.000	.132	.019	.000	.000	.031	.005	.424	.000
	OC2	.002	.000		.000	.000	.000	.000	.000	.000	.037	.004	.022	.000	.000	.000	.000	.000	.000	.000	.000	.000	.045	.000
	EP1	.096	.013	.000		.000	.000	.000	.000	.000	.000	.002	.011	.001	.000	.000	.003	.001	.000	.000	.001	.001	.345	.000
	OC3	.001	.000	.000	.000		.000	.000	.000	.000	.014	.047	.005	.002	.000	.000	.004	.037	.000	.000	.008	.001	.113	.000
	OC4	.001	.000	.000	.000	.000		.000	.000	.000	.035	.012	.029	.000	.000	.000	.001	.000	.000	.000	.000	.000	.166	.000
	EP2	.007	.000	.000	.000	.000	.000		.000	.000	.000	.008	.011	.003	.000	.000	.000	.000	.000	.000	.001	.000	.356	.000
	EP3	.019	.007	.000	.000	.000	.000	.000		.000	.001	.002	.012	.000	.000	.000	.000	.005	.000	.000	.001	.000	.419	.000
	EP4	.031	.000	.000	.000	.000	.000	.000	.000		.001	.001	.006	.001	.000	.000	.003	.001	.000	.000	.006	.000	.266	.000
	JS2	.000	.138	.037	.000	.014	.035	.000	.001	.001		.000	.000	.000	.018	.001	.471	.383	.007	.006	.297	.436	.128	.005
	JS3	.000	.067	.004	.002	.047	.012	.008	.002	.001	.000		.000	.000	.001	.000	.192	.413	.001	.018	.435	.087	.096	.004
	JS4	.000	.122	.022	.011	.005	.029	.011	.012	.006	.000	.000		.000	.002	.000	.176	.395	.009	.037	.176	.156	.085	.002
	JS5	.000	.049	.000	.001	.002	.000	.003	.000	.001	.000	.000	.000		.005	.000	.014	.060	.000	.000	.160	.011	.051	.002
	SI3	.178	.003	.000	.000	.000	.000	.000	.000	.000	.018	.001	.002	.005		.000	.000	.000	.000	.000	.000	.000	.041	.016
	SI4	.002	.000	.000	.000	.000	.000	.000	.000	.000	.001	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000	.003	.033
	AC1	.209	.132	.000	.003	.004	.001	.000	.000	.003	.471	.192	.176	.014	.000	.000		.000	.000	.000	.000	.000	.111	.184
	AC2	.475	.019	.000	.001	.037	.000	.000	.005	.001	.383	.413	.395	.060	.000	.000	.000		.000	.000	.000	.000	.081	.381
	SI1	.012	.000	.000	.000	.000	.000	.000	.000	.000	.007	.001	.009	.000	.000	.000	.000	.000		.000	.000	.000	.007	.079
	SI2	.011	.000	.000	.000	.000	.000	.000	.000	.000	.006	.018	.037	.000	.000	.000	.000	.000	.000		.000	.000	.002	.032
	AC3	.349	.031	.000	.001	.008	.000	.001	.001	.006	.297	.435	.176	.160	.000	.000	.000	.000	.000	.000		.000	.058	.187
	AC4	.345	.005	.000	.001	.001	.000	.000	.000	.000	.436	.087	.156	.011	.000	.000	.000	.000	.000	.000	.000		.000	.010
	EXP - Experience in Years	.183	.424	.045	.345	.113	.166	.356	.419	.266	.128	.096	.085	.051	.041	.003	.111	.081	.007	.002	.058	.000		.016
	JP - Performance	.229	.000	.000	.000	.000	.000	.000	.000	.000	.005	.004	.002	.002	.016	.033	.184	.381	.079	.032	.187	.010	.016	
a. Determinant = 1.091E-5																								

Factor Analysis

KMO is used to measure the proportion of variance among variables SHOULD BE GREATER THAN 0.7

KMO and Bartlett's Test

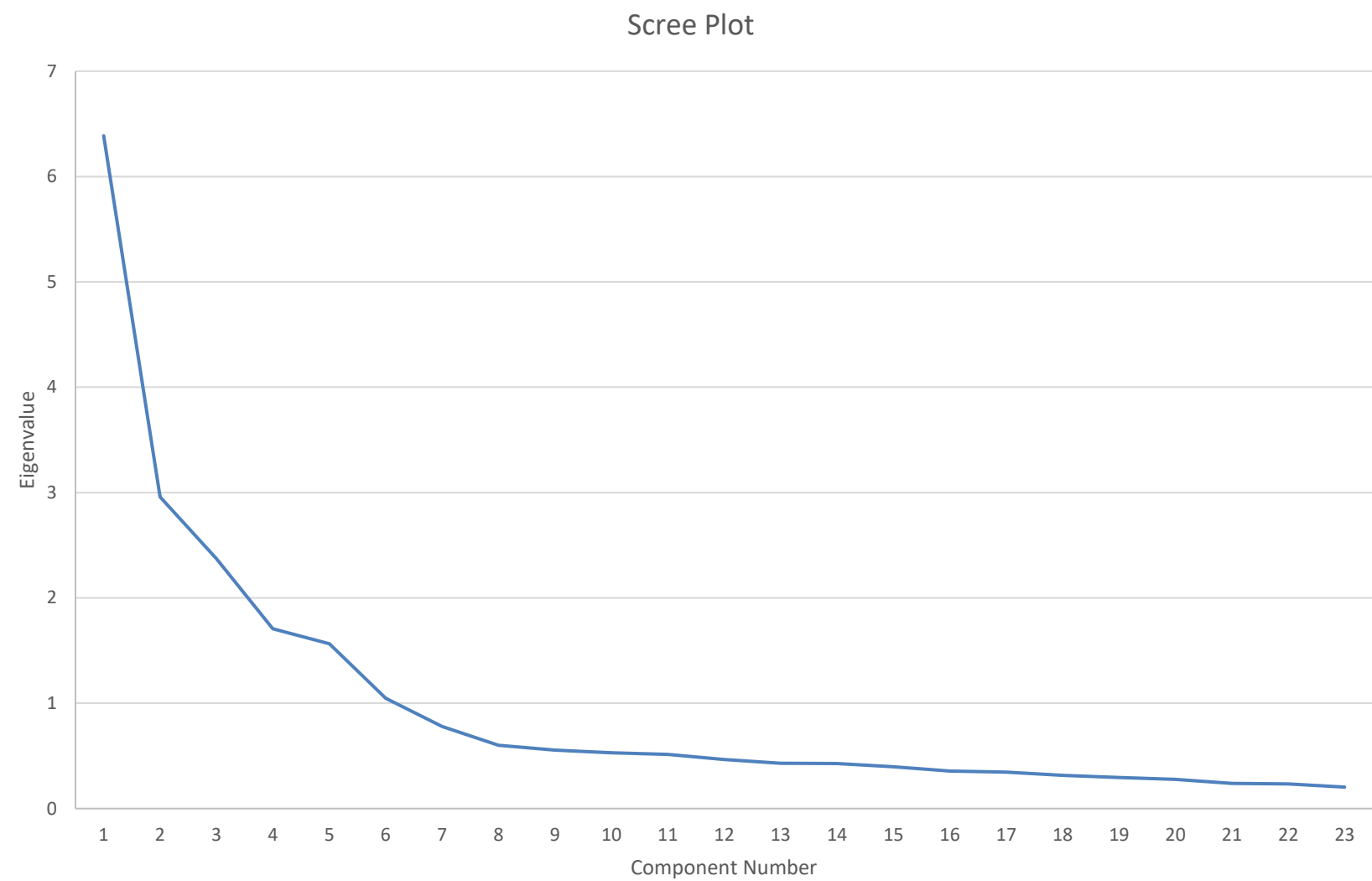
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.877
Bartlett's Test of Sphericity	Approx. Chi-Square	4354.035
	df	210
	Sig.	<.001

No. of factor groupings
By eigenvalues

Component	Total Variance Explained								
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.386	27.767	27.767	6.386	27.767	27.767	3.124	13.584	13.584
2	2.959	12.865	40.632	2.959	12.865	40.632	3.121	13.569	27.152
3	2.371	10.311	50.943	2.371	10.311	50.943	3.086	13.418	40.570
4	1.708	7.425	58.367	1.708	7.425	58.367	2.919	12.691	53.261
5	1.563	6.798	65.165	1.563	6.798	65.165	2.680	11.650	64.911
6	1.046	4.547	69.712	1.046	4.547	69.712	1.104	4.801	69.712
7	.780	3.392	73.104						
8	.600	2.607	75.711						
9	.556	2.417	78.128						
10	.529	2.299	80.427						
11	.515	2.240	82.666						
12	.467	2.029	84.695						
13	.430	1.871	86.566						
14	.427	1.857	88.423						
15	.397	1.727	90.150						
16	.356	1.550	91.700						
17	.345	1.499	93.199						
18	.315	1.368	94.567						
19	.296	1.286	95.853						
20	.276	1.202	97.054						
21	.240	1.043	98.097						
22	.234	1.016	99.113						
23	.204	.887	100.000						

Extraction Method: Principal Component Analysis.

No. of Groupings by screen plot



Factor Analysis

Component Matrix
Loading factor should
be greater than $>.4$

Component Matrix^a

Component
1

Salary	.794
Job Satisfaction	.927
Motivation	.562

Extraction Method: Principal
Component Analysis.

a. 1 components
extracted.

Component Matrix loading
factor indicates relationship
between observed variable
and the principal component

Factor Analysis

How many factor groups should
be categorized ?
Initial Elgenvalues >1

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings ^a
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %	
1	6.280	29.904	29.904	6.280	29.904	29.904	4.487
2	2.947	14.033	43.937	2.947	14.033	43.937	3.408
3	2.350	11.191	55.127	2.350	11.191	55.127	3.600
4	1.667	7.936	63.063	1.667	7.936	63.063	3.575
5	1.491	7.098	70.161	1.491	7.098	70.161	4.188
6	.615	2.930	73.091				
7	.563	2.683	75.774				
8	.529	2.519	78.293				
9	.517	2.463	80.757				
10	.482	2.294	83.051				
11	.431	2.055	85.105				
12	.430	2.047	87.152				
13	.398	1.894	89.046				
14	.374	1.779	90.825				
15	.348	1.656	92.481				
16	.317	1.510	93.992				
17	.304	1.445	95.437				
18	.278	1.324	96.761				
19	.241	1.150	97.911				
20	.234	1.114	99.025				
21	.205	.975	100.000				

Extraction Method: Principal Component Analysis.

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

Factor Analysis

How many factor groups should
be categorized ?
Initial Elgenvalues >1

Total Variance Explained

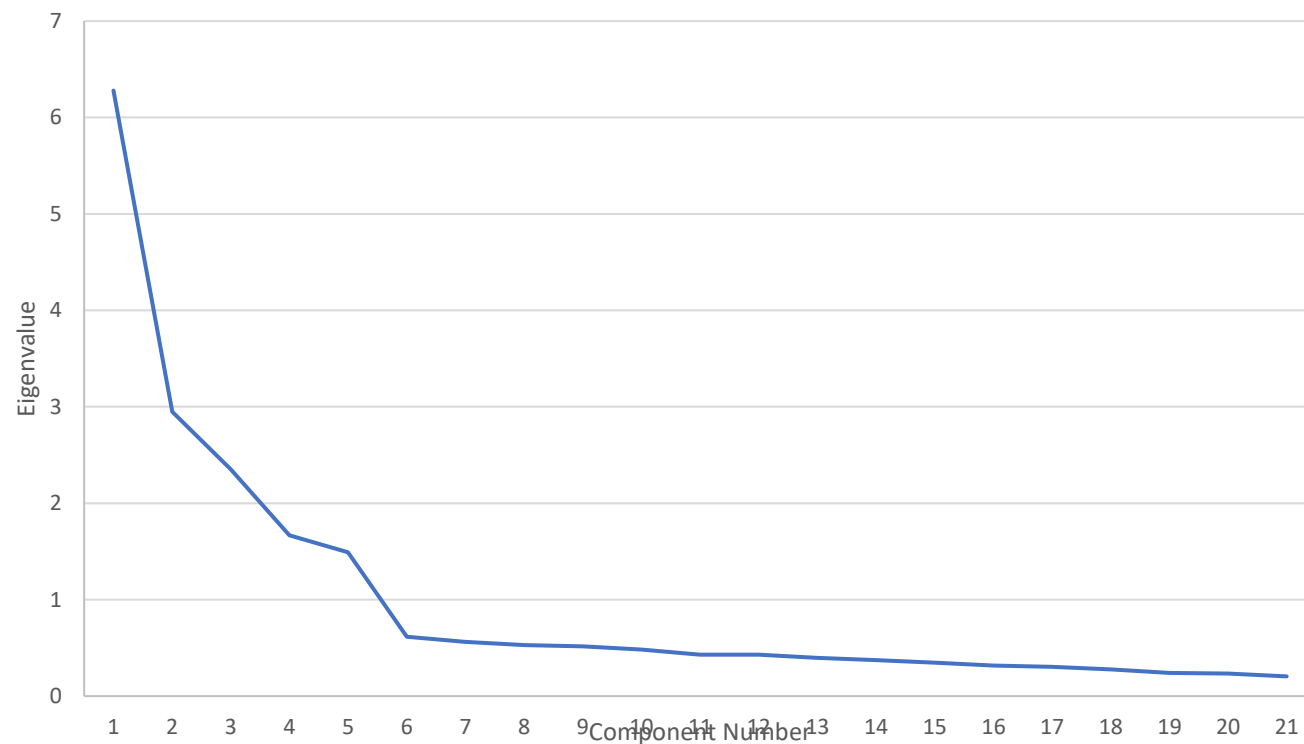
Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings ^a
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %	
1	6.280	29.904	29.904	6.280	29.904	29.904	4.487
2	2.947	14.033	43.937	2.947	14.033	43.937	3.408
3	2.350	11.191	55.127	2.350	11.191	55.127	3.600
4	1.667	7.936	63.063	1.667	7.936	63.063	3.575
5	1.491	7.098	70.161	1.491	7.098	70.161	4.188
6	.615	2.930	73.091				
7	.563	2.683	75.774				
8	.529	2.519	78.293				
9	.517	2.463	80.757				
10	.482	2.294	83.051				
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19	.241	1.150	97.911				
20	.234	1.114	99.025				
21	.205	.975	100.000				

Extraction Method: Principal Component Analysis.

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

How many factor groups should
be categorized ?
Initial Eigenvalues >1

Scree Plot



Component Matrix^a

	Component					
	1	2	3	4	5	6
SI4	.733	-.035	-.149	-.374	-.282	-.011
OC2	.706	-.090	-.158	.395	-.290	-.070
SI2	.704	-.077	-.197	-.366	-.339	.000
EP2	.680	.007	-.270	-.035	.423	-.004
SI1	.678	-.061	-.155	-.376	-.330	-.027
EP4	.662	.036	-.291	-.058	.452	.046
OC4	.651	-.040	-.206	.438	-.254	-.100
SI3	.628	-.062	-.161	-.415	-.257	.001
EP3	.614	.044	-.224	-.059	.507	-.009
EP1	.586	.029	-.228	-.186	.448	-.041
OC3	.550	.031	-.223	.514	-.070	-.024
JS2	.320	.668	.311	-.031	.056	-.022
JS1	.301	.643	.361	.063	-.076	-.141
JS4	.316	.607	.371	-.003	-.012	.007
JS3	.330	.598	.328	-.031	-.009	-.002
JS5	.396	.573	.376	.012	-.013	-.026
AC1	.442	-.480	.568	.014	.094	-.086
AC2	.418	-.514	.554	.022	.103	-.086
AC3	.440	-.532	.536	.036	.056	-.065
AC4	.489	-.471	.531	.082	.078	.126
OC1	.408	-.018	-.198	.592	-.230	-.080
EXP - Experience in Years	.152	-.018	.147	-.049	-.227	.846
JP - Performance	.318	.117	-.105	.315	.239	.498

Extraction Method: Principal Component Analysis.

a. 6 components extracted.

Rotated Component Matrix^a

	Component					
	1	2	3	4	5	6
JS1	.803	.038	-.007	-.014	.112	-.071
JS2	.793	.042	-.047	.129	.004	.029
JS5	.774	.088	.077	.083	.079	.042
JS4	.772	.050	.022	.049	.028	.067
JS3	.748	.083	.001	.075	.024	.054
SI2	.059	.836	.102	.194	.191	.047
SI4	.127	.813	.129	.239	.167	.038
SI1	.088	.813	.115	.174	.160	.019
SI3	.065	.772	.098	.212	.083	.034
AC3	-.021	.119	.865	.054	.087	-.005
AC2	-.003	.086	.864	.075	.049	-.031
AC1	.038	.102	.862	.077	.052	-.026
AC4	.028	.098	.837	.102	.117	.192
EP4	.075	.222	.061	.800	.182	.057
EP3	.103	.154	.096	.794	.130	-.001
EP2	.072	.232	.100	.773	.218	.014
EP1	.083	.249	.080	.744	.042	-.042
OC4	.078	.276	.113	.161	.783	.005
OC1	.024	.033	.027	.040	.782	.013
OC2	.077	.344	.187	.146	.770	.040
OC3	.087	.074	.043	.256	.733	.064
EXP - Experience in Years	.050	.181	.091	-.121	-.036	.869
JP - Performance	.101	-.141	-.012	.376	.281	.529

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Identify those factors
with low factor
loadings

Rotated Component Matrix^a

	Component					
	1	2	3	4	5	6
JS1	.803	.038	-.007	-.014	.112	-.071
JS2	.793	.042	-.047	.129	.004	.029
JS5	.774	.088	.077	.083	.079	.042
JS4	.772	.050	.022	.049	.028	.067
JS3	.748	.083	.001	.075	.024	.054
SI2	.059	.836	.102	.194	.191	.047
SI4	.127	.813	.129	.239	.167	.038
SI1	.088	.813	.115	.174	.160	.019
SI3	.065	.772	.098	.212	.083	.034
AC3	-.021	.119	.865	.054	.087	-.005
AC2	-.003	.086	.864	.075	.049	-.031
AC1	.038	.102	.862	.077	.052	-.026
AC4	.028	.098	.837	.102	.117	.192
EP4	.075	.222	.061	.800	.182	.057
EP3	.103	.154	.096	.794	.130	-.001
EP2	.072	.232	.100	.773	.218	.014
EP1	.083	.249	.080	.744	.042	-.042
OC4	.078	.276	.113	.161	.783	.005
OC1	.024	.033	.027	.040	.782	.013
OC2	.077	.344	.187	.146	.770	.040
OC3	.087	.074	.043	.256	.733	.064
EXP - Experience in Years	.050	.181	.091	-.121	-.036	.869
JP - Performance	.101	-.141	-.012	.376	.281	.529

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Factor analysis

How to facilitate the groupings ?

Exclude those factor loadings and re-run the factor analysis again.

Factor analysis

Groupings after
excluding those factor
loadings below 0.4

Rotated Component Matrix^a

	Component					
	1	2	3	4	5	6
JS1	.803					
OC1					.782	
OC2					.770	
EP1				.744		
OC3					.733	
OC4					.783	
EP2				.773		
EP3				.794		
EP4				.800		
JS2	.793					
JS3	.748					
JS4	.772					
JS5	.774					
SI3		.772				
SI4		.813				
AC1			.862			
AC2			.864			
SI1		.813				
SI2		.836				
AC3			.865			
AC4			.837			
EXP - Experience in Years						.869
JP - Performance						.529

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

- C) Or we can run a Principal Component Analysis (PCA)

A PCA reduces a larger set of variables to one or more index variables which are called components

In essence it extracts a linear composite variable from observed variables.

PCA tries to achieve the optimal number of components, the optimal choice of measured variables for each component, and the optimal weights.

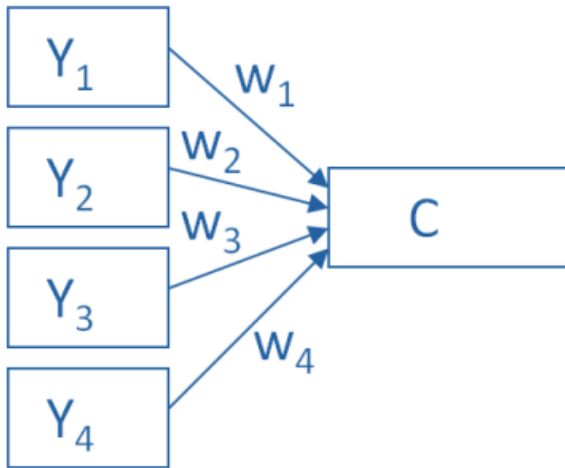
Principal Components are the underlying structure in the data. They are the directions where there is the most variance, the directions where the data is most spread out.

PCA requires a large sample size, 200 upwards for good results

If different scales, use the correlation matrix.

Use Kaiser-Meyer-Olkin (KMO) Measure to establish sample adequacy (value should be larger than 0.6 and as close to one as possible)

Use Bartlett's test to reject the null hypothesis that the correlation matrix is an identity matrix, i.e. all diagonal elements are 1 and all of diagonal elements are 0. To reject this your p value should be significant.

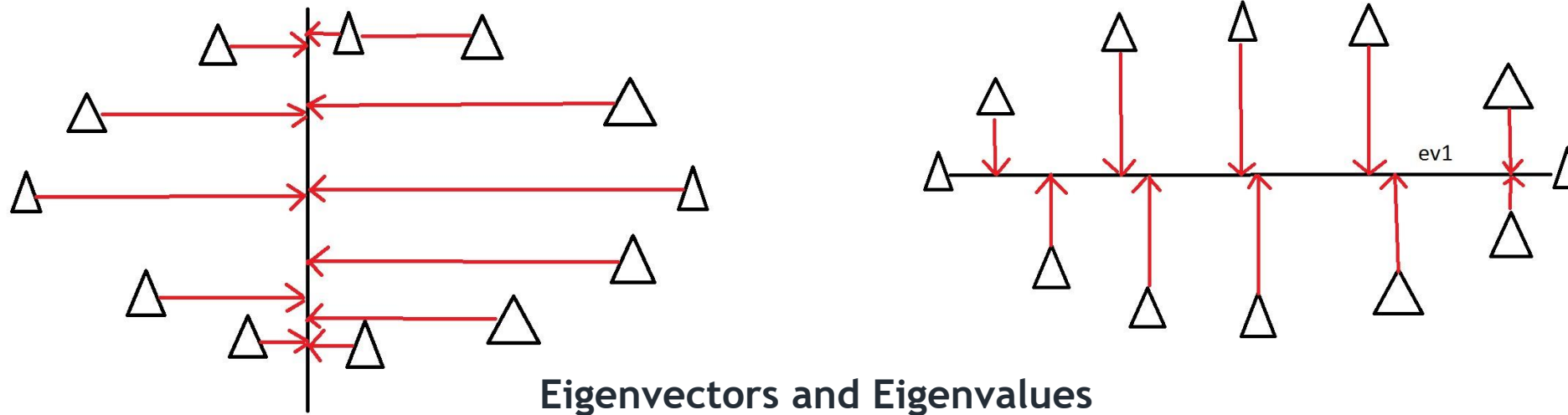


- Run a PCA on the HBAT data set. Include all metric (interval) variables
- Use the correlation matrix as not all scales are the same.
- Ensure you tick the box for Scree plot
- Use Direct Oblim as a rotation method (as in the social sciences we need to assume that constructs are to some extent interrelated)
- Save components with Eigenvalues over 1

Interpreting Output

Adapted from:
<https://georgemdallas.wordpress.com/2013/10/30/principal-component-analysis-4-dummies-eigenvectors-eigenvalues-and-dimension-reduction/>

Principal Component Analysis looks for the axis in data where the variance is highest, i.e. data is most spread out



Eigenvectors and Eigenvalues

The axis with the widest variance is called the **Eigenvector**. It is a direction, and does not change even if the data is transformed, e.g. scaled. Each Eigenvector has an **Eigenvalue** which shows how much variance there is in the data in that direction (how spread out the data is on the line). The eigenvector with the highest eigenvalue is therefore the principal component.

Interpreting Output

The number of components extracted is equal to the number of variables

- Kaiser suggested that only components with eigenvalues of 1 and above are retained.
- Also look the scree plot of the eigenvalues and identify points of inflection
- To look at the total variance explained by the retained factors (should be about 70%)

Activity

Way forward T-Test and ANOVA



