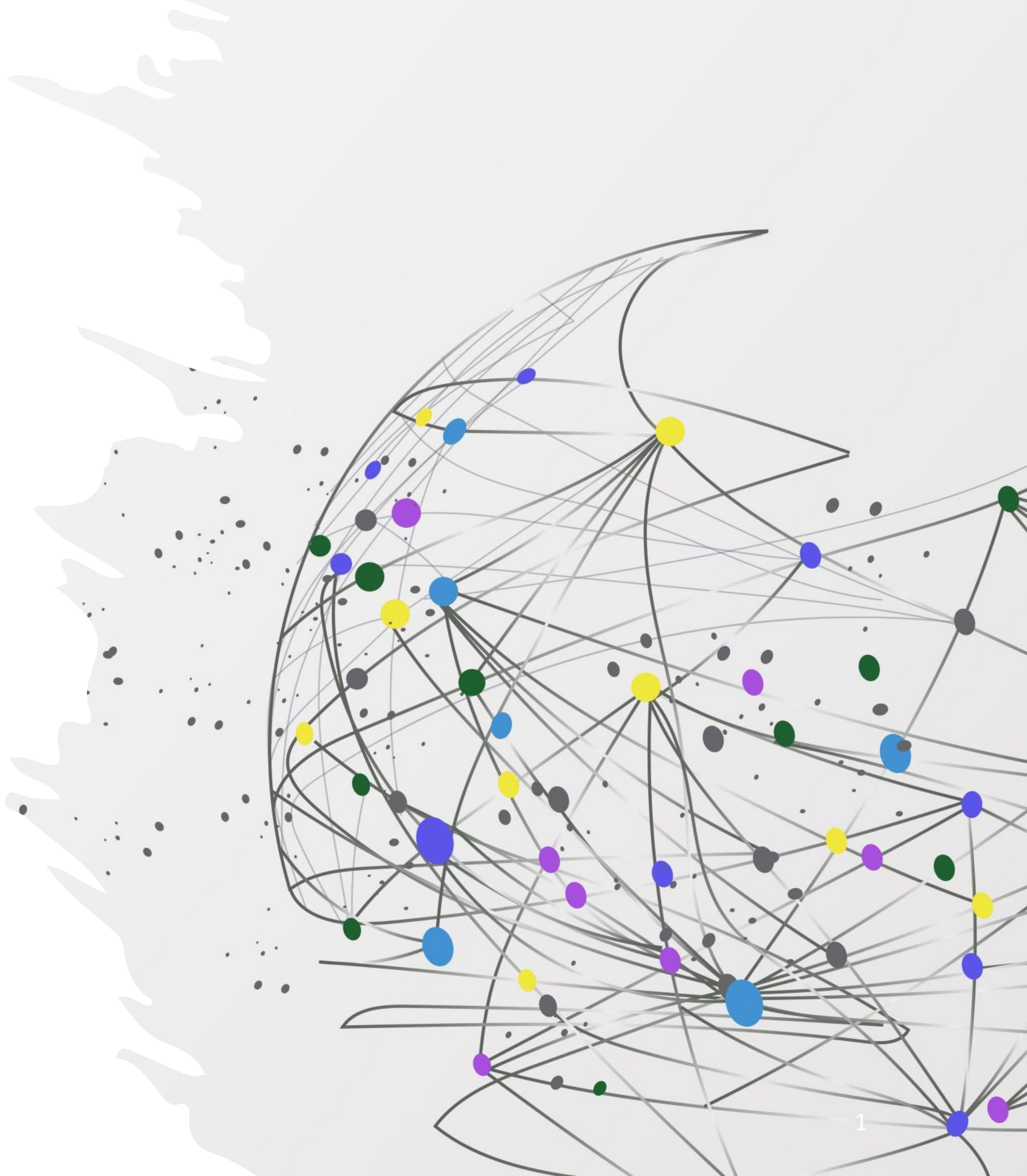
Workshop Construction and Analysis of Tests & Questionnaires



Day 2: Validity (Factor analysis)
Part 2: Factor analysis in practice

Simulated data for illustrative purposes

Generated/fictitious dataset with six items (X1 up to and including X6)
Depression-scale

N respondents = 300

Correlation matrix:

Correlation Matrix

		Anxious	Tense	Restless	Depressed	Useless	Unhappy
Correlation	Anxious	1,000	,449	,443	,296	,314	,326
	Tense	,449	1,000	,446	,312	,264	,250
	Restless	,443	,446	1,000	,279	,258	,282
	Depressed	,296	,312	,279	1,000	,467	,516
	Useless	,314	,264	,258	,467	1,000	,497
	Unhappy	,326	,250	,282	,516	,497	1,000

Correlation Matrix

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	Useless	,314	,264	,258	,467	1,000	,497
	Unhappy	,326	,250	,282	,516	,497	1,000

Based on the correlations, above - can you see a pattern?

Are there multiple **dimensions** underlying the depression questionnaire?

Correlation Matrix

		X1: Anxious	X2: Tense	X3: Restless	X4: Depressed	X5: Useless	X6: Unhappy
Correlation	X1: Anxious	1,000	,449	,443	,296	,314	,326
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	X4: Depressed	,296	,312	,279	1,000	,467	,516
	X5: Useless	,314	,264	,258	,467	1,000	,497
	X6: Unhappy	,326	,250	,282	,516	,497	1,000

- For now: we just assume that we have two factors.
  We will learn later how we can <u>determine</u> the number of factors

- Two factors -> 2 dimensions -> 2 scales
  - Factor 1: Accounts for most of the variance seen in the six items
  - Factor 2: **given the first factor and in addition to this factor** accounts for most of the ***remaining*** variance of the six items

Factor loadings

Factor Matrix [a]

	Factor	
	1	2
X1: Anxious	,610	,274
X2: Tense	,583	,345
X3: Restless	,575	,327
X4: Depressed	,642	-,261
X5: Useless	,616	-,268
X6: Unhappy	,665	-,337

Extraction Method: Principal Axis Factoring.

a. 2 factors extracted. 10 iterations required.

- Here, in this table we see the factorloadings for every item on factor 1 and factor 2
- Note that the second factor accounts for unexplained var/correlation *on top* of the 1st factor

- The loadings on the first and second factor are equal to the **correlation** of an item with these factors (dimensions):

- $a_{j1} = r_{X_j F_1}$
- $a_{j2} = r_{X_j F_2}$

- For example: the correlation of the item 'Anxious' with the second factor = 0,274:

- $r_{Anxious,F2} = a_{12} = 0{,}274$

Communality

Factor Matrix [a]

	Factor	
	1	2
X1: Anxious	,610	,274
X2: Tense	,583	,345
X3: Restless	,575	,327
X4: Depressed	,642	-,261
X5: Useless	,616	-,268
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Extraction Method: Principal Axis Factoring.

a. 2 factors extracted. 10 iterations required.

- The communality h_j^2 of X_j is the amount of variance of X_j accounted for by *both* factors

- $h_j^2 = r^2_{X_j F_1} + r^2_{X_j F_2} = a^2_{j1} + a^2_{j2}$

- For example: the factors account for 0,447 of the variance in the scores on $X1$: 'Anxious'

- $h_1^2 = a^2_{11} + a^2_{12} = (0{,}610)^2 + (0{,}274)^2 = 0{,}447$

Variance accounted for ('eigen value'):

Factor Matrix [a]

	Factor	
	1	2
X1: Anxious	,610	,274
X2: Tense	,583	,345
X3: Restless	,575	,327
X4: Depressed	,642	-,261
X5: Useless	,616	-,268
X6: Unhappy	,665	-,337

Extraction Method: Principal Axis Factoring.

a. 2 factors extracted. 10 iterations required.

- The variance accounted for by a factor
- $VAF_2 = a_{12}^2 + a_{22}^2 + a_{32}^2 + a_{42}^2 + a_{52}^2 + a_{62}^2$
- For example: the **second** factor accounts for 0,554 variance in total
- $VAF_2 = 0{,}554$

And in SPSS:

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,802	46,700	46,700	2,276	37,937	37,937
2	1,081	18,015	64,715	,554	9,228	47,165
3	,578	9,639	74,354			
4	,560	9,335	83,690			
5	,522	8,693	92,382			
6	,457	7,618	100,000			

Extraction Method: Principal Axis Factoring.

Total variance accounted for by PAF

- So, how do we know how many factors we need?!
- Are there any rules to decide on the number of factors?

How do we decide how many factors we have?

- How can you determine the number of factors underlying the data?

  - Option 1: Common sense
  - Option 2: Rules based on eigenvalues: Kaiser’s criterion and scree test
  - Option 3: Theory

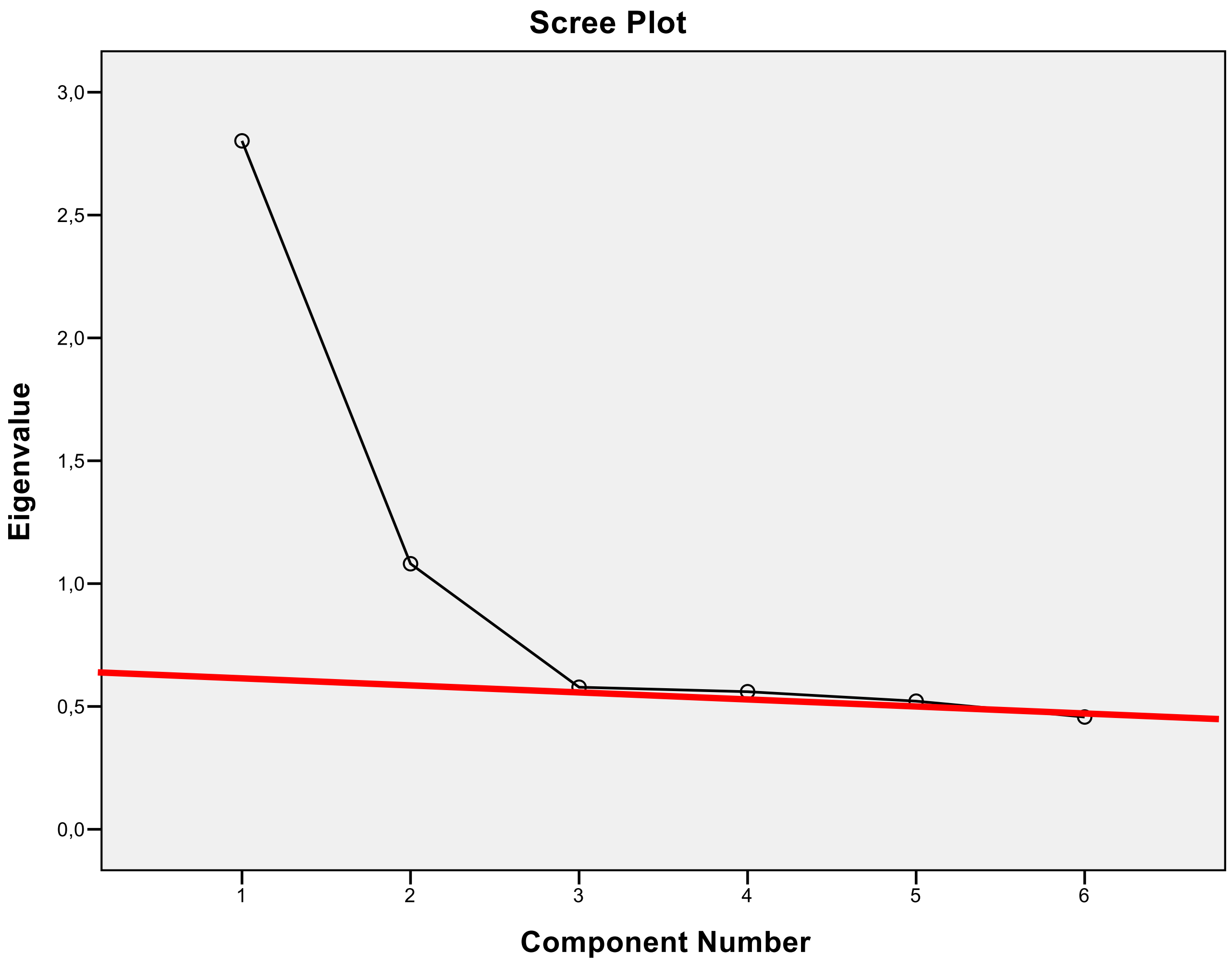
(1) Common sense

- $K \leq J/3$
- Intuition: a factor with less than three items cannot be reliable
- For the example: $K \leq J/3 = 6/3 = 2$
  (K = total number of factors, J = total number of items)

(2) Kaiser's criterion

- "Greater-than-one" rule
- Number of factors = number of factors having an eigenvalue larger than one

(3) Scree test (Catell)



- Choose the number of factors for which the eigenvalue is above the line that goes true the “scree”
- Often very subjective
- Here: indicates a solution with 2 factors

(4) Theory

- Often there is some theoretical knowledge about the number of constructs/dimensions underlying the data

- Eg, NEO big five

- Use this knowledge to further support other indications of that number of factors or to choose between several options (in case one rule or different rules do not result in a unique number)
    - eg, scree test: often ‘different levels of scree’, or different number of factors based on Kaiser’s criterion and the scree plot

Methods to find easier solutions for a factor analysis

Loading: what dimension does an item measure?

- Results can be used to determine, per item, to which dimension this item “belongs” (based on factor loadings)

- So: to determine the internal structure: Which loading is the highest? Highest loading indicates to which this item belongs

- However, this is not always as easy as it sounds..

FA results in the perfect world

- What would be ideal would be that we don't have any doubts to which dimension an item belongs to

- E.g., perfect correlation/loading 1 on only ONE dimension + rest of the loadings = 0

- Immediately clear to what dimension an item belongs
- *=> easy interpretation!*

- *But in practice, we don't get that (to the right: hypothetical example!)*

Factor Matrix[a]

	Factors		
	Factor 1	**Factor 2**	**Factor 3**
Item 1	1	0	0
Item 2	1	0	0
Item 3	1	0	0
Item 4	0	1	0
Item 5	0	1	0
Item 6	0	1	0
Item 7	0	0	1
Item 8	0	0	1
Item 9	0	0	1

… in real life: interpetation of the output can be difficult:

Component Matrix[a]

	Component		
	1	2	3
+ situatie denk	.837	-.258	
- situatie denk	.819	-.245	
- denk	.762	-.230	
+ denk	.744	-.260	-.106
verkeer	.687		
controleer	.370	.761	
voor mezelf	.265	.745	.133
- uitdrukking	.279	.658	.324
+ uitdrukking	.253	.413	-.721
stressvol	.373		.580

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

b. Values < 0.2 have been left blank (not shown in the table)

Component Matrix [a]

	Component	
	1	2
X1: Anxious	,687	,375
X2: Tense	,654	,467
X3: Restless	,651	,464
X4: Depressed	,708	-,385
X5: Useless	,688	-,415
X6: Unhappy	,710	-,432

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Factor Matrix

	Factor		
	1	2	3
ACT1	.321	-.221	.689
ACT2	.587	.103	.132
ACT3	.623	.589	-.536
ACT4	.214	-8.75E-02	.379
ACT5	.709	.563	-.221
ACT6	-.240	.426	4.446E-02
ACT7	.549	-.191	.361
ACT8	.327	.307	1.874E-02
ACT9	-.215	.380	.144

Extraction Method: Principal Axis Factoring.

- “Perfect” loadings of 0/1 => unfortunately, utopic..

- In practice: Realistic aim:
  - as simple as possible (-> easier interpretation!)
  - We try to get as close as possible to a “**simple structure**” **:**

- **Rules of thumb for a simple structure**
  - Every item (variable) measures only ONE subconstruct (dimension) = every item has a loading of >**|**,30**|** with only **one** factor

How do we get close(r) to a simple structure?

- The solution we get from a factor analysis is an *estimation* and therefore **not unique**:

  - There are endless possible combinations of factorloadings that are all equally good
    - The different solutions explain the same amount of variance & reproduce the same residual correlations
    - Compare with: different regression equations that explain the same amount of variance

  - Simply put: 5 + 5 = 10, but 4 + 6 also equals 10.

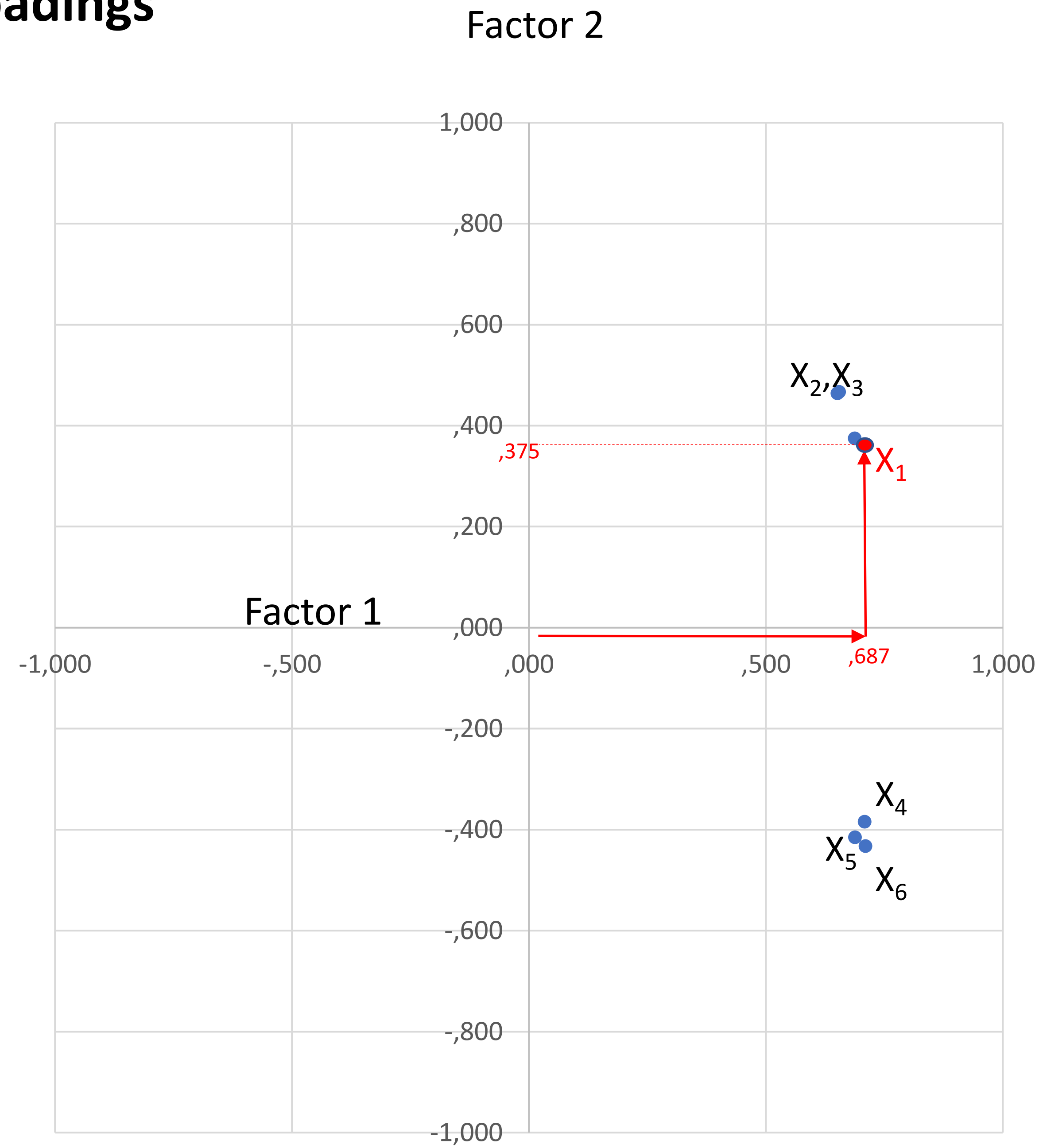
Get closer to a simple structure: <u>ROTATION</u>

- So we are looking for an *alternative combination* of factorloadings that
  - Are of the same quality (explain equal amount of variance)
  - But: are *<u>easier to interpret</u>*

How?? -> Statistical trick ☺: **<u>ROTATION</u>**

Figure of the loadings

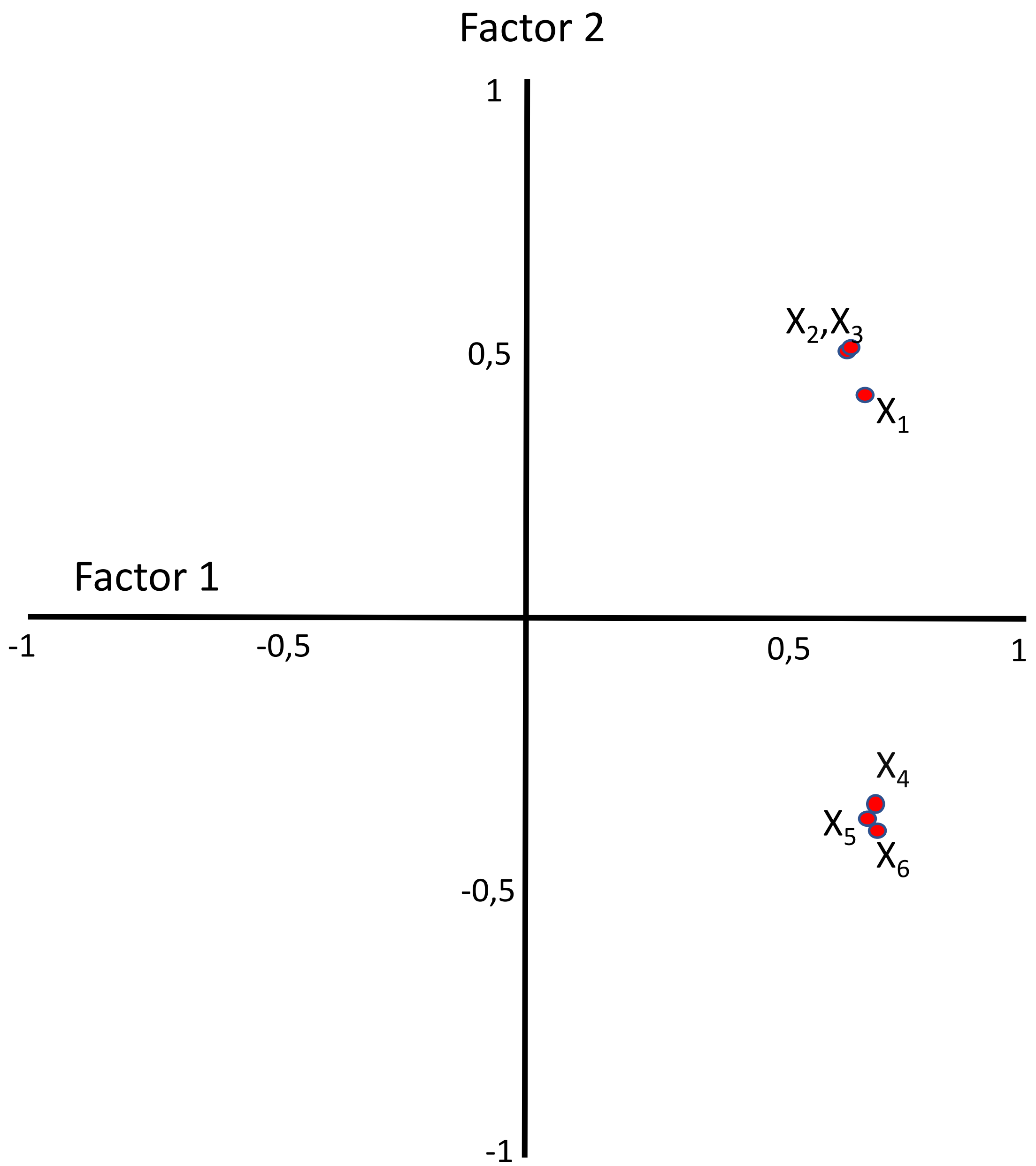
	Factor 1	Factor 2
X_1	0.687	0.375
X_2	0.654	0.467
X_3	0.651	0.464
X_4	0.708	-0.385
X_5	0.688	-0.415
X_6	0.710	-0.432



- Factor analysis with 2 factors, based on a dataset with 6 variables ($X_{1,}$ $X_{2,}$ $X_{3,}$ $X_{4,}$ X_5 & X_6)

- X axis = loading of every variable on the first factor (factor 1)

- Y axis = loading of every variable on the second factor (factor 2)

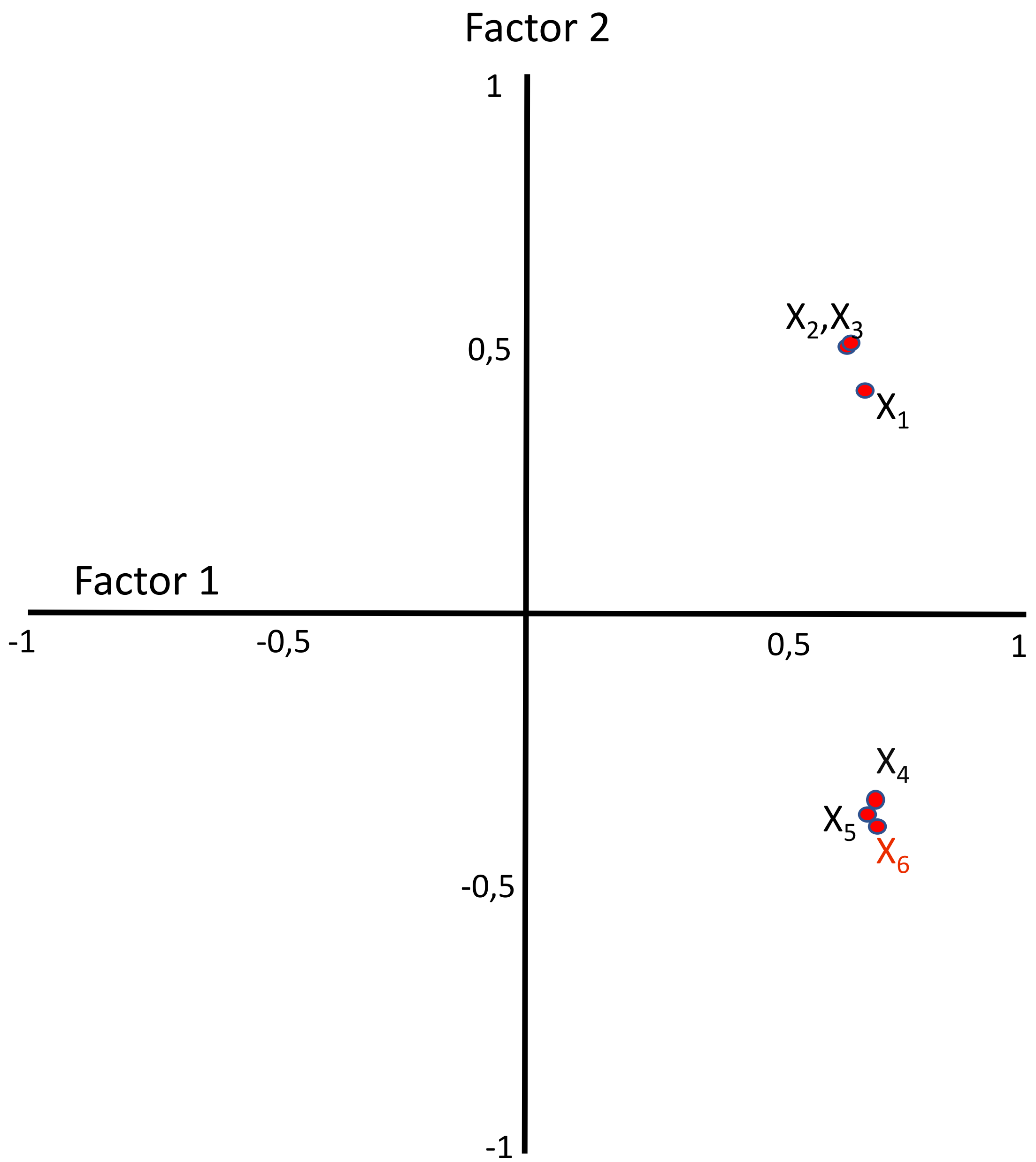


- Now: high loadings (in the absolute sense) on both factors

- For example:

- Item $X_{6:}$ loading of ~ -.432 on factor 2 and loading of .710 on factor 1

-> difficult interpretation



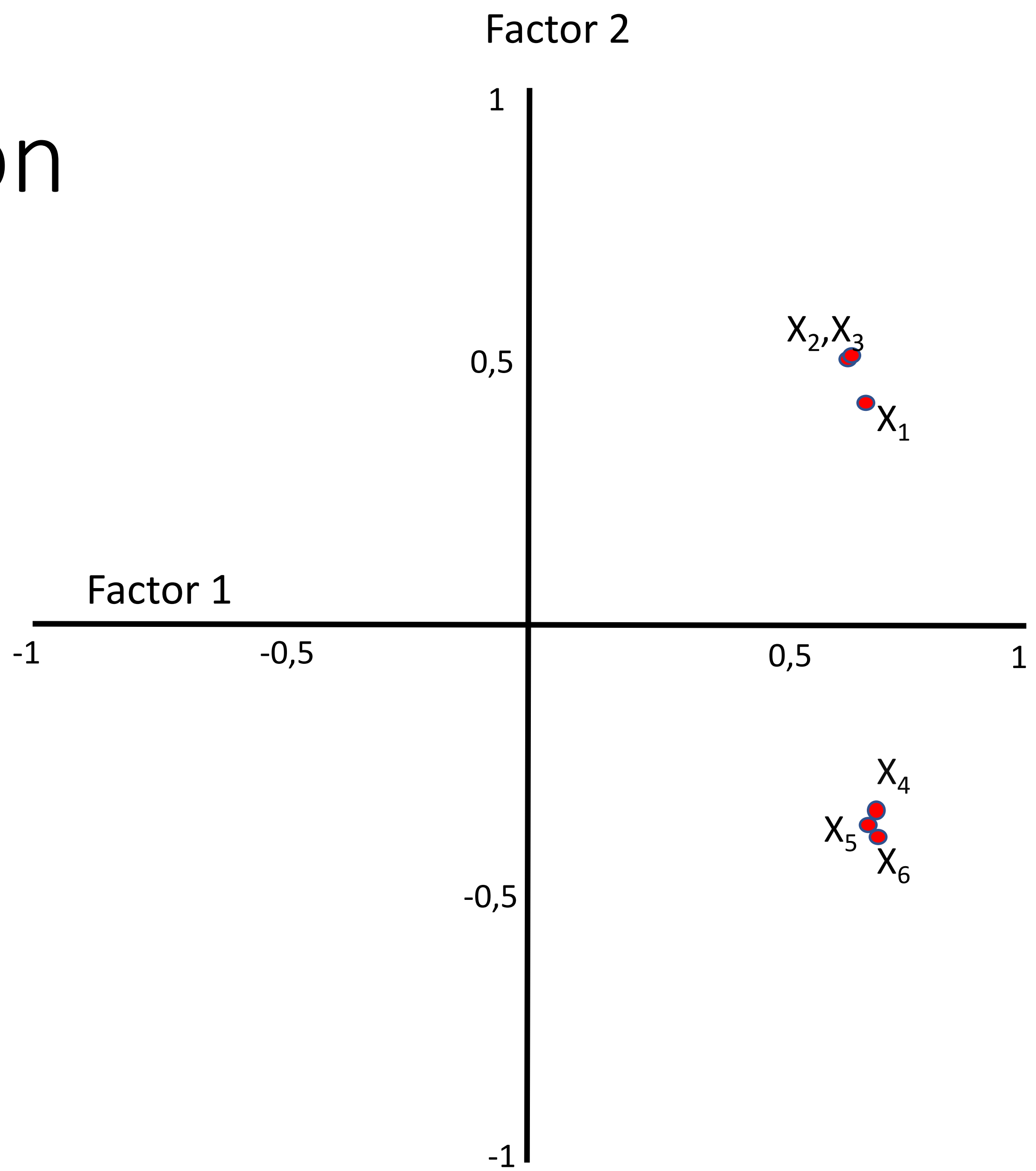
Rotation: demonstration

Rotation

= changing the orientation of the X axis and Y axis

This changes the loadings

The quality of the solution remains the same, but the interpretation gets easier.

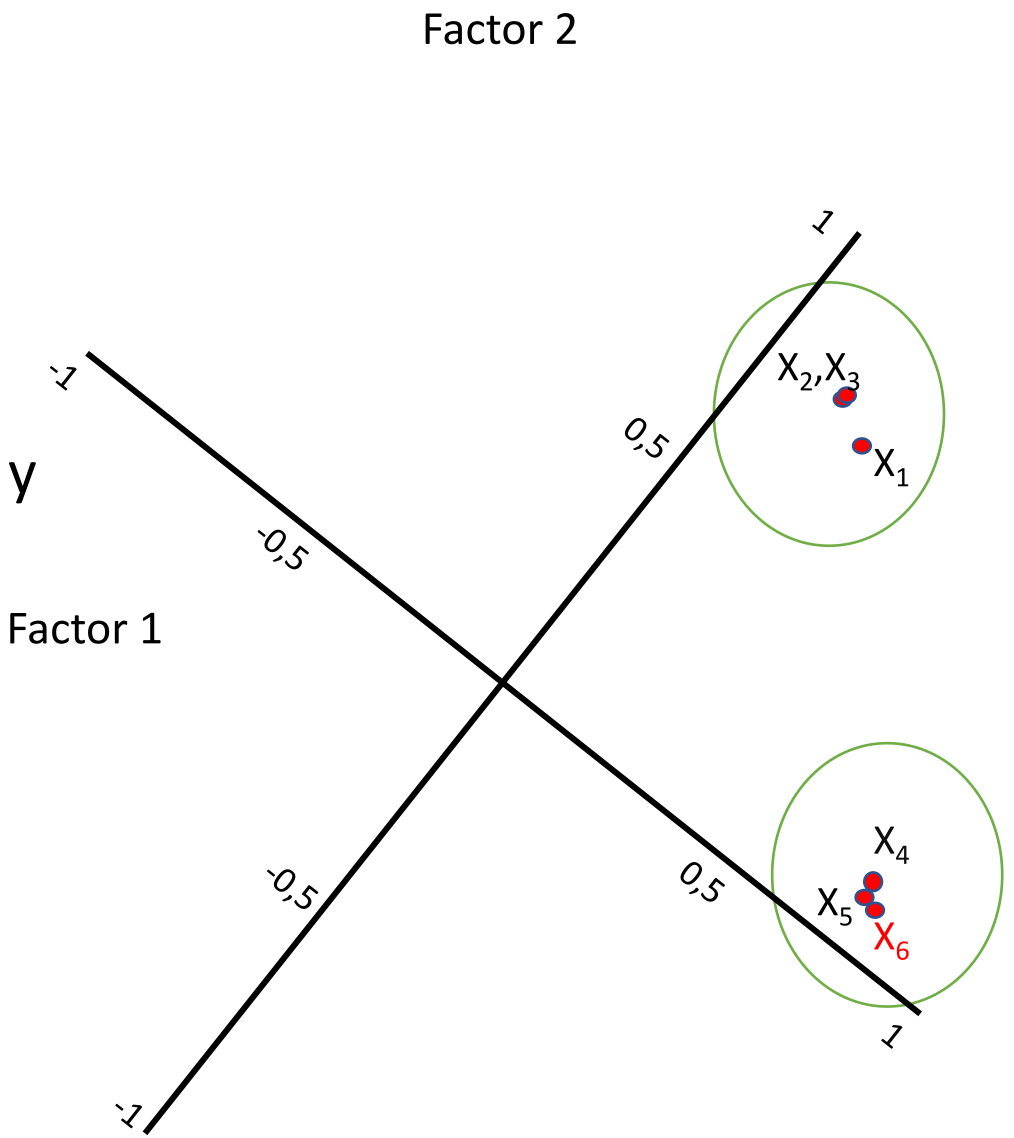


Rotation:demonstration

Rotation

= changing the orientation of the x axis and y axis

-> nou we can clearly see **2 groups of items** e.g., loadings of ~ .8 on factor 1 and .1 on factor 2 for item 6



Rotation: Summary of what happens

Question: I am confused, what is this rotation about?

Answer: We are interested in another/alternative (easier to interpret) solution.

We want items that follow a **simple structure,** meaning that an item loads strongly only on **one** factor (rule of thumb: loading of >|,30| with only *one* factor)

Through rotation, the loadings change such that we get closer to a simple structure, but the quality of the solution (the results of the analysis) remain the same (we still explain as much of the variance as we did before)

Pragmatically said:
Rotation = "***Changing" the loadings such that we can interpret the results easier***

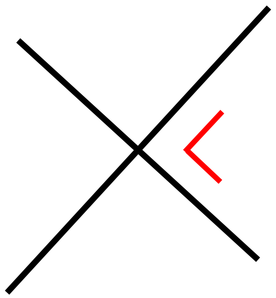
Different sorts of rotations:

Orthogonal rotation (“VARIMAX” rotation)
Oblique rotation (“OBLIMIN” rotation)

Two types of rotation:

- **Orthogonal**:
  Factors *cannot* correlate with each other: $r_{F_m F_n} = 0$
  Many different techniques, but most commonly used: **VARIMAX** rotation

Two types of rotation:



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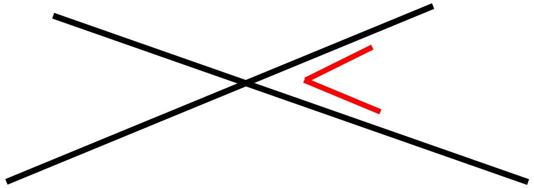

- **Oblique**:
  Factors *can* correlate with each other: $r_{F_m F_n} \neq 0$
  Many different techniques, but most commonly used: **OBLIMIN** rotation

1. VARIMAX

In SPSS: VARIMAX

Component Matrix [a]

	Component	
	1	2
X1: Anxious	,687	,375
X2: Tense	,654	,467
X3: Restless	,651	,464
X4: Depressed	,708	-,385
X5: Useless	,688	-,415
X6: Unhappy	,710	-,432

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Rotated Component Matrix [a]

	Component	
	1	2
X1: Anxious		,745
X2: Tense		,789
X3: Restless		,784
X4: Depressed	,779	
X5: Useless	,785	
X6: Unhappy	,813	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

**Note that I am using PCA here as an example – this is just of illustrative purposes*

*** loadings <.2 are suprressed on the right (often done because it makes it easier to see patterns immediately*

- Simple structure?
- Easier interpretation than before rotation
- Reflects also what we expected from the correlation matrix (2 groups of items that have high inter-correlations and not very correlated with items of other group)

Rotated Component Matrix [a]

	Component	
	1	2
X1: Anxious		,745
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Extraction Method: Principal Component Analysis.
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a. Rotation converged in 3 iterations.

Does varimax rotation always make sense?

- Varimax rotation assumes that there is no correlation – does that make sense to you?
- Example: mathematics test

2. OBLIMIN

In SPSS: OBLIMIN

Pattern Matrix [a]

	Component	
	1	2
X1: Anxious	,076	,747
X2: Tense	-,030	,816
X3: Restless	-,030	,812
X4: Depressed	,792	,030
X5: Useless	,808	-,010
X6: Unhappy	,837	-,014

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 5 iterations.

- Loadings are now in ***pattern* matrix** instead of (rotated) factor matrix
- Stronger *simple structure* than with VARIMAX (loadings are more extreme / closer to one and zero)

**loadings < .2 are shown here to clearly show how close loadings are to 0 after using OBLIMIN rotation*

In SPSS: OBLIMIN

Component Correlation Matrix

Component	1	2
1	1,000	,438
2	,438	1,000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

- An assumption of the Oblimin rotation is that there is also a correlation between factors.

  So this correlation will be estimated (see table on the left side):

$r_{F1F2} = 0{,}438$

- Which solution to choose?
  - Simple structure => *always rotate*
  - VARIMAX or OBLIMIN? Choose OBLIMIN if
    - Simple structure better attained by OBLIMIN
    - OR, if the correlation between at least one pair of factors is ≥ |0,30|
    - Else VARIMAX (easier to work with uncorrelated/unrelated dimensions)
  - What kind of rotation would we choose for our example data?

- Ok, so now we know how to interpret the output of a factor analysis in SPSS.

- But, since we are performing a statistical technique, aren’t there assumptions we have to check first?!

- -> Yes!

When is it allowed to perform FA?

- If
  - 1) the assumptions are met
  - 2) *N* and *J* satisfy some rules (*N* = total participants, *J* = total items)
  - 3) *R* satisfies some rules (*R* = correlation matrix of items)

- 1) **Assumptions FA**
  - Linear relation between the item pairs
  - Each item is of (at least) ordinal measurement level with at least 5 answer categories

- 2) ***N* and *J* (*N* = total participants, *J* = total items)**
  - $N \geq 100$
  - $N \geq 5J$

- 3) **Correlation matrix *R***

- Items have to correlate sufficiently

  - (a) Bartlett's sphericity test must be signifcant ($p < 0,05$)

  - (b) KMO index must be larger than 0,6   ***This is the most important rule!***

Recap of our example data:

- Measuring depression
- 6 items: *Anxious*, *tense*, *restless*, *depressed*, *useless* & *unhappy*
- 300 respondents
- Likert items with 7 answer categories

Applied to our example data

- 1) Assumptions FA
  - Items have scores ranging from 1 upto and including 7
  - Relations are linear (or, they are not of another form): Check scatter plots!!

  $\Rightarrow$Correlation is a good measure of association

- 2) Assumptions *N* and *J*
  - $N = 300 \geq 100$
  - $N = 300 \geq 5*J = 30$

- 3) R
  - $p < 0{,}05$
  - KMO = 0,794

Correlation Matrix

		X1: Anxious	X2: Tense	X3: Restless	X4: Depressed	X5: Useless	X6: Unhappy
Correlation	X1: Anxious	1,000	,449	,443	,296	,314	,326
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	X5: Useless	,314	,264	,258	,467	1,000	,497
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KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,794
Bartlett's Test of Sphericity	Approx. Chi-Square	430,306
	df	15
	Sig.	,000

Very important!

- Factor analysis <u>only</u> works well if all assumptions are met & your sample size is big enough. Otherwise, <u>you might get results, but they can be biased</u>
- Hence, check your data for the assumptions

- If the assumptions are not met => do not trust results of FA blindly

- We’ve heard so many things about reliability and validity…

How, and in what order, are all these steps applied in research practice?

- -> Step by step guide for the complete procedure of exploratory contruction of sclaes

-> Use of all methods in practice

-> Step by step:
What do we do in research practice?

Overview of all steps

Determine validity

Overview of all steps

Determine validity

1)How many dimensions?
2) Which items belong to what dimension?

-> By using factor analysis, we know which items belong to what dimension

The items that measure together one dimension (e.g., a certain aspect of the construct) form together <u>a scale</u>

Overview of all steps

Determine validity → **Calculate scale scores separately for every dimension**

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The items that measure together one dimension (e.g., a certain aspect of the construct) form together <u>a scale</u>

Per *dimension* we calculate, for every respondent, a scale score. We do this by using sumscores*.

The sumscore is based on the answers of a respondent to all items that belong to the dimension (the scale).

**default in research practice. You can also use 'factor scores' – if you want to Know more about this let me know*

Overview of all steps

Determine validity → **Calculate scale scores separately for every dimension** → **Determine reliability separately for every dimension** (Based on sumscores)

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The items that measure together one dimension (e.g., a certain aspect of the construct) form together a scale

Per *dimension* we calculate, for every respondent, a scale score. We do this by using sumscores.

The sumscore is based on the answers of a respondent to all items that belong to the dimension (the scale).

The scale scores are then used to, per dimension, estimate the reliability

Based on the reliability analysis, we can further select items/improve the quality of the scale.

Focus of today: Factor analysis

Determine validity

1)How many dimensions?
2) Which items belong to what dimension?

-> By using factor analysis, we know which items belong to what dimension

The items that measure together one dimension (e.g., a certain aspect of the construct) form together <u>a scale</u>

Factor analysis: all steps

- 1) Are the assumptions met?
- 2) Rotation: VARIMAX or OBLIMIN?
- 3) Interpretation of the factors
  - E.g., factor 1: Which dimension is that? –
    -> Look at the content of the items & choose a label based on that

Exploratory FA: Complete procedure

- For a complete FA, we need to perform 5 steps:
  - (i) **Check if the association between items is linear**

Exploratory FA: Complete procedure

- Five steps / analyses:
  - (i) **Check if the association between items is linear**
  - (ii) **First FA: does it make sense to perform FA + how many factors/components?**
    - KMO & Bartlett’s sphericity test – assupmtions met?
    - How many factors do we choose? (How many dimensions?)

Exploratory FA: Complete procedure

- Five steps / analyses:
  - (i) **Check if the association between items is linear**
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    - KMO & Bartlett's sphericity test – assupmtions met?
    - How many factors do we choose? (How many dimensions?)
  - (iii) **Second FA: VARIMAX**
  - (iv) **Third FA: OBLIMIN**

Exploratory FA: Complete procedure

- Five steps / analyses:
  - (i) **Check if the association between items is linear**
  - (ii) F**irst FA: does it make sense to perform FA + how many factors/components?**
    - KMO & Bartlett's sphericity test – assupmtions met?
    - How many factors do we choose? (How many dimensions?)
  - (iii) **Second FA: VARIMAX**
  - (iv) **Third FA: OBLIMIN**
  - (v) **Choose a solution between (iii) & (iv) and interpret it**
    - Which solution is easier to interpret? + is there a correlation between factors?
    - After choosing: Interpretation of the dimensions -> look at content of the items

Once we have determined the internal structure, we have to calculate scale scores

Determine validity

Calculate scale scores separately for every dimension

1)How many dimensions?
2) Which items belong to what dimension?

-> By using factor analysis, we know which items belong to what dimension

The items that measure together one dimension (e.g., a certain aspect of the construct) form together a scale

Per *dimension* we calculate, for every respondent, a scale score. We do this by using sumscores.

The sumscore is based on the answers of a respondent to all items that belong to the dimension (the scale).

Calculation of a sumscore in practice

- Sum score => sum up only those items that form one scale (= that belong to the same dimension)

- For example thus, for a questionnaire consisting of 10 items :
  Dimension 1 -> Item 1,2,4,5,7 = SCALE 1 -> sumscore 1
  Dimension 2 -> Item 3,6,8,9,10 = SCALE 2 -> sumscore 2

From where can we get this information??!!

-> last step of the FA-steps that we just dicussed:
the output gives us information on which items form together one scale (e.g. – decide for every item to which dimension/scale this item belongs - based on the loadings)

- Imagine that we have applied the 5 steps plan and conducted a PCA.

- To the right: componentloadings

⇒Dimension 1: X4, X5, X6 = SCALE 1

⇒ Dimension 2: X1, X2, X2 = SCALE 2

⇒So:
X4 + X5 + X6 = SUMSCORE 1,
X1 + X2 + X2 = SUMSCORE 2

For every respondent, we then calculate 2 sumscores.

Rotated Component Matrix [a]

	Component	
	1	2
X1: Anxious		,745
X2: Tense		,789
X3: Restless		,784
X4: Depressed	,779	
X5: Useless	,785	
X6: Unhappy	,813	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Based on the scale scores (sumscores), we determine the reliability of every separate scale

Determine validity → **Calculate scale scores separately for every dimension** → **Determine reliability separately for every dimension**

1)How many dimensions?
2) Which items belong to what dimension?

-> By using factor analysis, we know which items belong to what dimension

The items that measure together one dimension (e.g., a certain aspect of the construct) form together <u>a scale</u>

Per *dimension* we calculate, for every respondent, a scale score. We do this by using sumscores.

The sumscore is based on the answers of a respondent to all items that belong to the dimension (the scale).

The scale scores are then used to, per dimension, estimate the reliability

Based on the reliability analysis, we can further select items/improve the quality of the scale.

Based on the sumscores: determine reliability

- So we have to calculate 2 sumscores for every respondent.
- Then, we perform for every scale, based on the sumscores that belong to that particular scale, a reliability analysis
- *Thus, per scale* we run one analysis and one Cronbach's alpha
- This is what you have done/learned yesterday

For the example data: X1,X2 en X3 form together one scale and X4, X5 and X6

Reliability Statistics

Cronbach's Alpha	N of Items
,706	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X1: Anxious	7,8967	3,003	,524	,615
X2: Tense	8,0300	3,073	,527	,611
X3: Restless	8,1400	3,365	,522	,620

Reliability Statistics

Cronbach's Alpha	N of Items
,745	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X4: Depressed	7,9267	3,239	,569	,663
X5: Useless	7,8867	3,499	,553	,681
X6: Unhappy	7,8933	3,206	,592	,635

All steps: see next slide

Determine validity → **Calculate scale scores separately for every dimension** → **Determine reliability separately for every dimension**

1)How many dimensions?
2) Which items belong to what dimension?

-> By using factor analysis, we know which items belong to what dimension

The items that measure together one dimension (e.g., a certain aspect of the construct) form together <u>a scale</u>

Per *dimension* we calculate, for every respondent, a scale score. We do this by using sumscores.

The sumscore is based on the answers of a respondent to all items that belong to the dimension (the scale).

The scale scores are then used to, per dimension, estimate the reliability

Based on the reliability analysis, we can further select items/improve the quality of the scale.

And these are all steps: Exploratory construction of scales

1. Check if the association between items is linear

2. First FA: does it make sense to perform PFA + how many factors/components do we have?

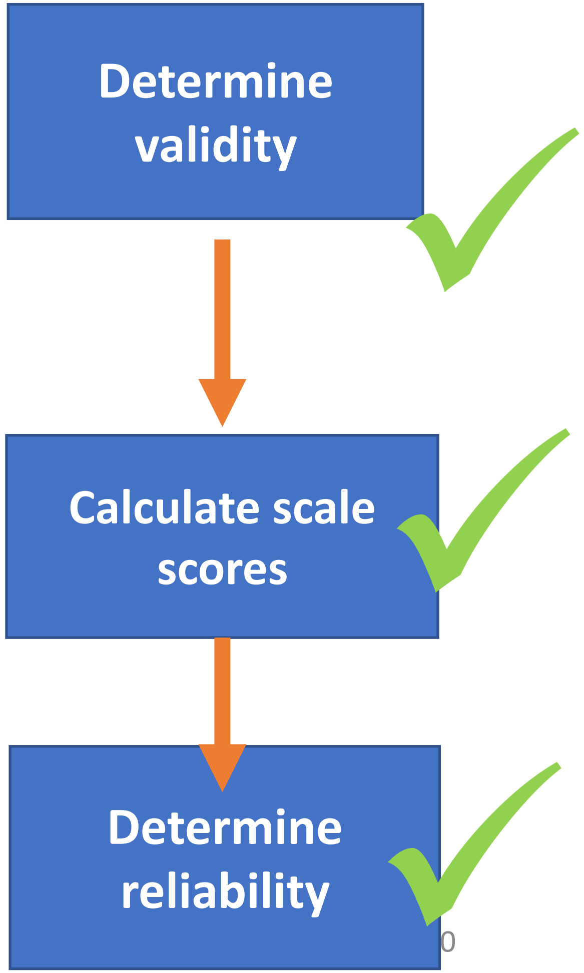
3. Second FA: VARIMAX

4. Third FA: OBLIMIN

5. Choose a solution between 3 & 4 and interpret it

6. Calculate sum scores for each scale / dimension

7. Evaluate **reliability** of every scale, the item contributions to the reliability (per scale), and report Cronbach's alpha per scale



Advanced topics

- Some more advanced analyses are not possible in SPSS

  - **Test internal structure that is known beforehand**
    (*Confirmatory factor analysis*) -> see example R script on github

  - **Test for measurement invariance**
    Compare multiple groups (e.g., companies/countries)
    (*Multiple group analysis*)
    Not possible by (only) conducting separate factor analyses!!!