Principal Components (PCA) & Exploratory Factor Analysis (EFA) with SPSS

IDRE Statistical Consulting

https://stats.idre.ucla.edu/spss/seminars/efa-spss/

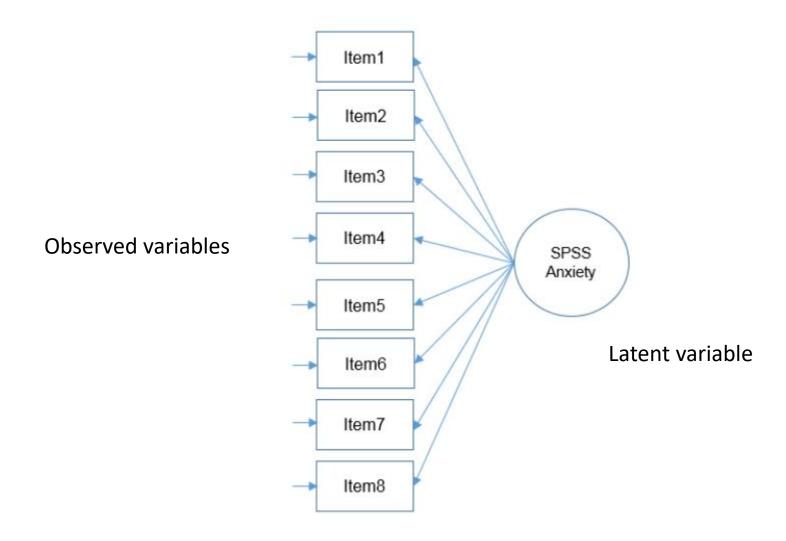
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Introduction

- Motivating example: The SAQ
- Pearson correlation
- Partitioning the variance in factor analysis

Factors (latent) and Items (observed)



Assumption: the correlations among all observed variables can be explained by latent variable

SPSS Anxiety Questionnaire (SAQ-8)

- 1. I dream that Pearson is attacking me with correlation coefficients
- 2. I don't understand statistics
- 3. I have little experience with computers
- 4. All computers hate me
- 5. I have never been good at mathematics
- 6. My friends are better at statistics than me
- 7. Computers are useful only for playing games
- 8. I did badly at mathematics at school

Pearson Correlation of the SAQ-8

Correlations

My friends will

There exist varying magnitudes of correlation among variables

| des of | | think I'm | | Pearson is | | | | |
|---|--------------|-----------------|------------|--------------|------------|---------------|---------------|--------------|
| on among | | stupid for not | | attacking me | | | | |
| | | being able to | Standard | with | I don't | I have little | | I have never |
| • | Statistics | cope with | deviations | correlation | understand | experience of | All computers | been good at |
| | makes me cry | SPSS | excite me | coefficients | statistics | computers | hate me | mathematics |
| Statistics makes me cry | 1 | | | | | | | |
| My friends will think I'm stupid for not being able to cope with SPSS | 099 | 1 | | | | | | |
| Standard deviations excite me | 337 | .318 | 1 | | | | | |
| I dream that Pearson is attacking me with correlation coefficients | .436 | 112 | 380 | 1 | | | | |
| I don't understand statistics | .402 | 119 | 310 | .401 | 1 | | | |
| I have little experience of computers | .217 | 074 Large ne | 227 | .278 | .257 | 1 La | irge positiv | ve |
| All computers hate me | .305 | 159 | 382 | .409 | .339 | .514 | 1 | |
| I have never been good at mathematics | .331 | 050 | 259 | .349 | .269 | .223 | .297 | 1 |

Partitioning the variance in factor analysis

Common variance

- variance that is shared among a set of items
- Communality (h²)
 - common variance that ranges between 0 and 1

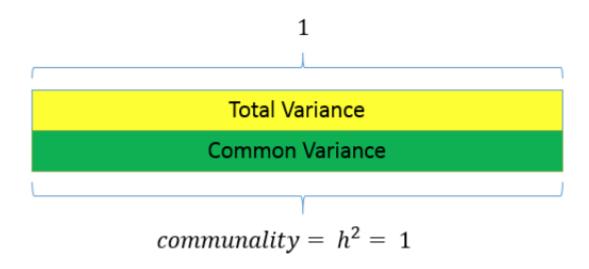
Unique variance

- variance that's not common
- Specific variance
 - variance that is specific to a particular item
 - Item 4 "All computers hate me" → anxiety about computers in addition to anxiety about SPSS

Error variance

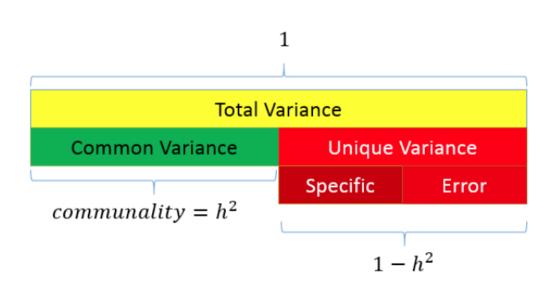
- anything unexplained by common or specific variance
- e.g., a mother got a call from her babysitter that her two-year old son ate her favorite lipstick).

Variance Partitioning in PCA

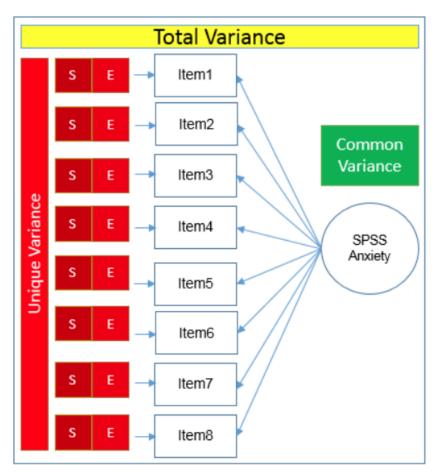


In PCA, there is no unique variance. Common variance across a set of items makes up total variance.

Variance Partitioning in an EFA



Total variance is made up of common and unique variance



Common variance = Due to factor(s)

Unique variance = Due to items

Factor Extraction + Factor Rotation

Factor Extraction

- Type of model (e.g., PCA or EFA?)
- Estimation method (e.g., Principal Axis Factoring or Maximum Likelihood?)
- Number of factors or components to extract (e.g., 1 or 2?)

Factor Rotation

- Achieve simple structure
- Orthogonal or oblique?

Extracting Factors

- Principal components analysis
 - PCA with 8 / 2 components
- Common factor analysis
 - Principal axis factoring (2-factor PAF)
 - Maximum likelihood (2-factor ML)

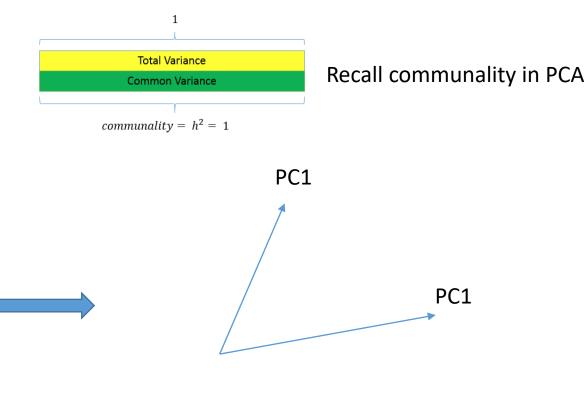
PCA

Principal Components Analysis (PCA)

• Goal: to replicate the correlation matrix using a set of components that are fewer in

number than the original set of items

| | Correlations | | | | | | | |
|--|----------------------------|--|-------------------------------------|--|-------------------------------------|---------------------------------------|---------------|---|
| | Statistics makes me cry | My friends will think I'm stupid for not being able to cope with SPSS | Standard deviations excite me | I dream that Pearson is attacking me with correlation coefficients | I don't understand statistics | I have little experience of computers | All computers | I have never been good at mathematics |
| Statistics makes me cry | 1 | | | | | | | |
| My friends will think I'm stupid for not being able to cope with SPSS | 099 | 1 | | | | | | |
| Standard deviations excite me | 337 | .318 | 1 | | | | | |
| I dream that Pearson is attacking me with correlation coefficients | .436 | 112 | 380 | 1 | | | | |
| I don't understand statistics | .402 | 119 | 310 | .401 | 1 | | | |
| I have little experience of computers | .217 | 074 | 227 | .278 | .257 | 1 | | |
| All computers hate me | .305 | 159 | 382 | .409 | .339 | .514 | 1 | |
| I have never been good at mathematics | .331 | 050 | 259 | .349 | .269 | .223 | .297 | 1 |



8 variables 2 components

PCA: Eigenvalues and Eigenvectors

Eigenvalues

- Total variance explained by given principal component
- Eigenvalues > 0, good
- Negative eigenvalues → ill-conditioned
- Eigenvalues close to zero → multicollinearity

Eigenvectors

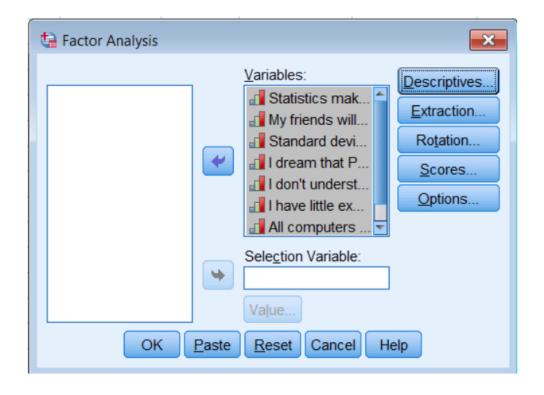
- weight for each eigenvalue
- eigenvector times the square root of the eigenvalue \rightarrow component loadings

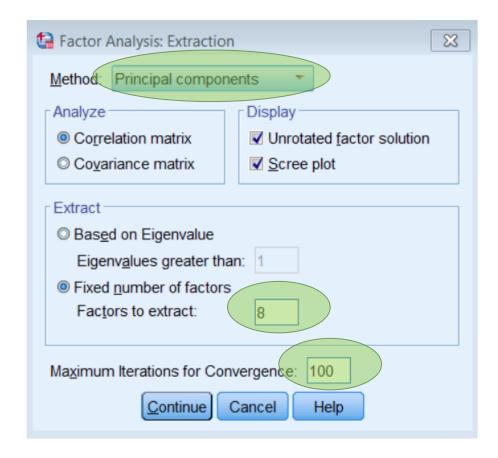
Component loadings

- correlation of each item with the principal component
- *Eigenvalues* are the sum of squared component loadings across all items for each component

Running a PCA with 8 components

Analyze – Dimension Reduction – Factor





Note: Factors are NOT the same as Components 8 components is NOT what you typically want to use

Component Matrix of the 8-component PCA

Component loadings

Component Matrix^a

correlation of each item with the principal Component component

| component | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|------|------|------|------|------|------|------|------|
| Statistics makes me cry | .659 | .136 | 398 | .160 | 064 | .568 | 177 | .068 |
| My friends will think I'm stupid for not being able to cope with SPSS | 300 | .866 | 025 | .092 | 290 | 170 | 193 | 001 |
| Standard deviations excite me | 653 | .409 | .081 | .064 | .410 | .254 | .378 | .142 |
| I dream that Pearson is attacking me with correlation coefficients | .720 | .119 | 192 | .064 | 288 | 089 | .563 | 137 |
| I don't understand statistics | .650 | .096 | 215 | .460 | .443 | 326 | 092 | 010 |
| I have little experience of computers | .572 | .185 | .675 | .031 | .107 | .176 | 058 | 369 |
| All computers hate me | .718 | .044 | .453 | 006 | 090 | 051 | .025 | .516 |
| I have never been good at mathematics | .568 | .267 | 221 | 694 | .258 | 084 | 043 | 012 |

Sum of squared loadings across components is the communality

 $0.659^2 = 0.434$ 1

1

1

1

1

43.4% of the variance explained by first component (think R-square)

 $0.136^2 = 0.018$

1.8% of the variance explained by second component

Q: why is it 1?

Excel demo

Sum squared loadings down each column (component) = eigenvalues

Extraction Method: Principal Component Analysis.

1.067 a. 8 components extracted. 3.057

0.958

0.736

0.622

0.571

0.543

0.446

Total Variance Explained in the 8-component PCA

3.057 1.067 0.958 0.736 0.622 0.571 0.543 0.446

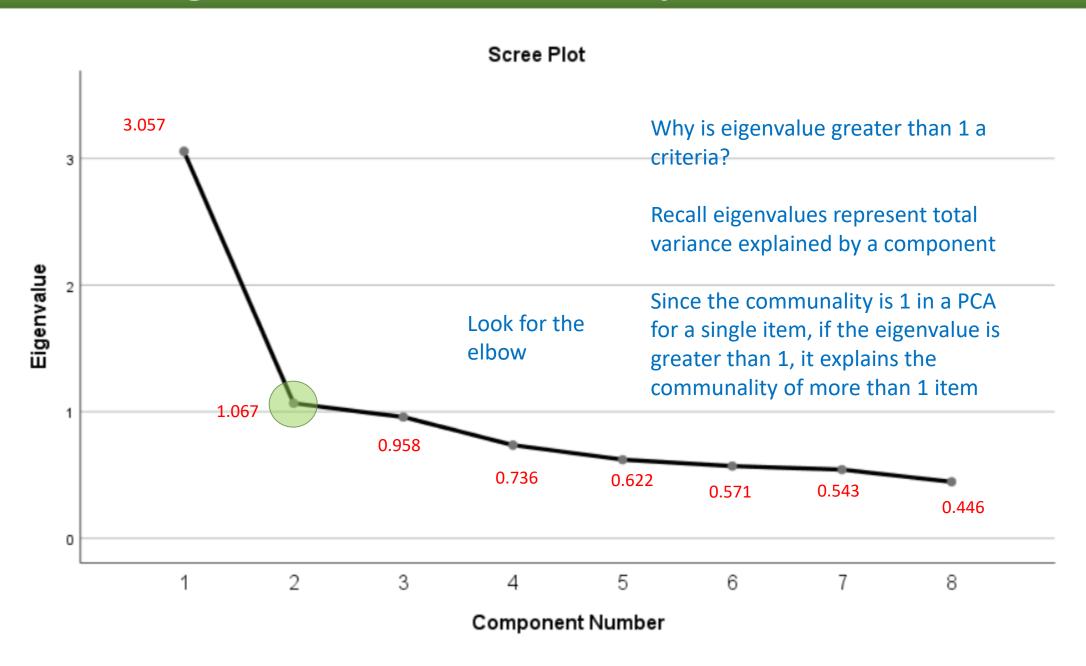
Total Variance Explained

| Initial Eigenvalues | | | | | | Extraction Sums of Squared Loadings | | | |
|---------------------|------|-----|---------------|--------------|-----|-------------------------------------|---------------|--------------|--|
| Component | Tota | al | % of Variance | Cumulative % | Tot | tal | % of Variance | Cumulative % | |
| 1 | 3/.(| 057 | 38.206 | 38.206 | 3 | 3.057 | 38.206 | 38.206 | |
| 2 | 1.0 | 067 | 13.336 | 51.543 | | 1.067 | 13.336 | 51.543 | |
| 3 | _(| 958 | 11.980 | 63.523 | | .958 | 11.980 | 63.523 | |
| 4 | - | 736 | 9.205 | 72.728 | | .736 | 9.205 | 72.728 | |
| 5 | _(| 622 | 7.770 | 80.498 | | .622 | 7.770 | 80.498 | |
| 6 | _ : | 571 | 7.135 | 87.632 | | .571 | 7.135 | 87.632 | |
| 7 | | 543 | 6.788 | 94.420 | | .543 | 6.788 | 94.420 | |
| 8 | \ | 446 | 5.580 | 100.000 | | .446 | 5.580 | 100.000 | |

Extraction Method: Principal Component Analysis.

Why is the left column the same as the right?

Choosing the number of components to extract

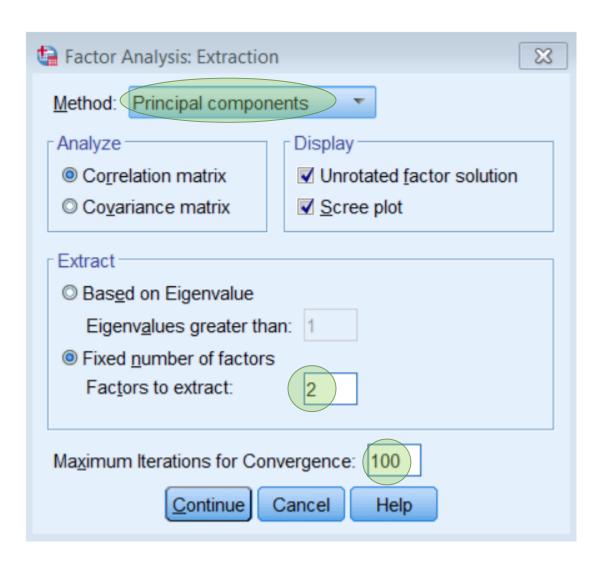


Running a PCA with 2 components

Analyze – Dimension Reduction – Factor

Goal of PCA is dimension reduction

This is more realistic than an 8-component solution



Output from 2-Component PCA

Recall these numbers from the 8-component solution

3.057 1.067 0.958 0.736 0.622 0.571 0.543 0.446

Total Variance Explained

| | | Initial Eigenvalu | Extraction Sums of Squared Loadings | | | |
|-----------|-------|-------------------|-------------------------------------|-------|---------------|--------------|
| Component | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 3.057 | 38.206 | 38.206 | 3.057 | 38.206 | 38.206 |
| 2 | 1.067 | 13.336 | 51.543 | 1.067 | 13.336 | 51.543 |
| 3 | .958 | 11.980 | 63.523 | | | |
| 4 | .736 | 9.205 | 72.728 | Noti | ce only two | eigenvalues |
| 5 | .622 | 7.770 | 80.498 | | | |
| 6 | .571 | 7.135 | 87.632 | | | |
| 7 | .543 | 6.788 | 94.420 | | | |
| 8 | .446 | 5.580 | 100.000 | | | |

Extraction Method: Principal Component Analysis.

Notice communalities not equal 1

Communalities

| | Initial | Extraction | |
|---|---------|------------|--|
| Statistics makes me cry | 1.000 | .453 | |
| My friends will think I'm stupid for not being able to cope with SPSS | 1.000 | .840 | |
| Standard deviations excite me | 1.000 | .594 | |
| I dream that Pearson is attacking me with correlation coefficients | 1.000 | .532 | |
| I don't understand statistics | 1.000 | .431 | |
| I have little experience of computers | 1.000 | .361 | |
| All computers hate me | 1.000 | .517 | |
| I have never been good at mathematics | 1.000 | .394 | |

Extraction Method: Principal Component Analysis.

Quick Check 1

- 1. The elements of the Component Matrix are correlations of the item with each component. (Single Choice)
 - Answer 1: T
 - Answer 2: F
- 2. The sum of the squared eigenvalues is the proportion of variance under Total Variance Explained. (Single Choice)
 - Answer 1: T
 - Answer 2: F
- 3. The Component Matrix can be thought of as correlations and the Total Variance Explained table can be thought of as R-square. (Single Choice)
 - Answer 1: T
 - Answer 2: F

Extracting Factors

- Principal components analysis
 - PCA with 8 / 2 components
- Common factor analysis
 - Principal axis factoring (2-factor PAF)
 - Maximum likelihood (2-factor ML)

Factor Analysis

Factor Analysis (EFA)

• Goal: also to reduce dimensionality, BUT assume total variance can be divided into

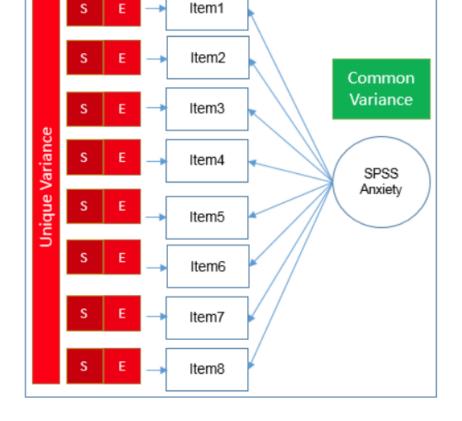
common and unique variance

 Makes more sense to define a construct with measurement error

| | | | Correla | tions | | | | |
|-----------------------------|--------------|-----------------|------------|--------------|------------|---------------|---------------|--------------|
| | | My friends will | | I dream that | | | | |
| | | think I'm | | Pearson is | | | | |
| | | stupid for not | | attacking me | | | | |
| | | being able to | Standard | with | I don't | I have little | | I have never |
| | Statistics | cope with | deviations | correlation | understand | experience of | All computers | been good at |
| | makes me cry | SPSS | excite me | coefficients | statistics | computers | hate me | mathematics |
| Statistics makes me cry | 1 | | | | | | | |
| My friends will think I'm | 099 | 1 | | | | | | |
| stupid for not being able | | | | | | | | |
| to cope with SPSS | | | | | | | | |
| Standard deviations | 337 | .318 | 1 | | | | | |
| excite me | | | | | | | | |
| I dream that Pearson is | .436 | 112 | 380 | 1 | | | | |
| attacking me with | | | | | | | | |
| correlation coefficients | | | | | | | | |
| I don't understand | .402 | 119 | 310 | .401 | 1 | | | |
| statistics | | | | | | | | |
| I have little experience of | .217 | 074 | 227 | .278 | .257 | 1 | | |
| computers | | | | | | | | |
| All computers hate me | .305 | 159 | 382 | .409 | .339 | .514 | 1 | |
| I have never been good at | .331 | 050 | 259 | .349 | .269 | .223 | .297 | 1 |
| mathematics | | | | | | | | |



8 variables

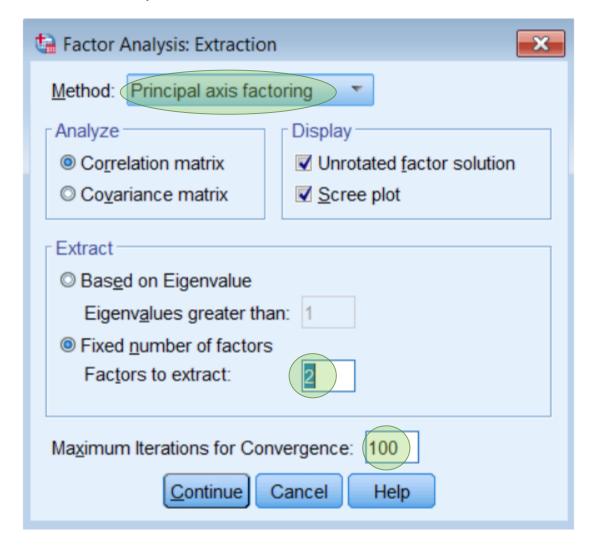


Total Variance

1 variable = factor

Common Factor Analysis with 2 factors (PAF)

Analyze – Dimension Reduction – Factor



SPSS does not change its menu to reflect changes in your analysis. You have to know the idiosyncrasies yourself.

Make note of the word eigenvalue it will come back to haunt us later

Communalities of the 2-factor PAF

Communalities

Initial communalities are the squared multiple correlation coefficients controlling for all other items in your model

Q: what was the initial communality for PCA?

| | Initial | Extraction |
|--|---------|------------|
| Statistics makes me cry | .293 | .437 |
| My friends will think I'm | .106 | .052 |
| stupid for not being able to cope with SPSS | | |
| Standard deviations excite me | .298 | .319 |
| I dream that Pearson is attacking me with correlation coefficients | .344 | .460 |
| I don't understand statistics | .263 | .344 |
| I have little experience of computers | .277 | .309 |
| All computers hate me | .393 | .851 |
| I have never been good at mathematics | .192 | 236 |

Extraction Method: Principal Axis Factoring.

Sum of communalities across items = 3.01

Total Variance Explained (2-factor PAF)

Unlike the PCA model, the sum of the initial eigenvalues do not equal the sums of squared loadings

Sum eigenvalues = 4.124

The reason is because Eigenvalues are for PCA not for factor analysis! (SPSS idiosyncrasies)

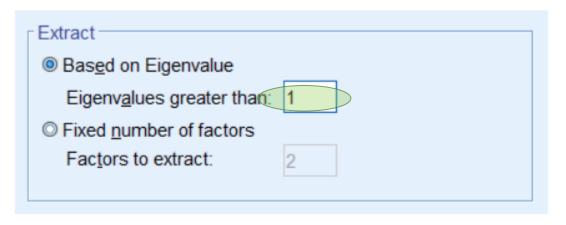
Total Variance Explained

| | | Initial Eigenvalu | ies | Extraction | on Sums of Squar | ed Loadings | |
|--------|-------|-------------------|--------------|------------|------------------|-----------------|-----------------|
| Factor | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | |
| 1 | 3.057 | 38.206 | 38.206 | 2.511 | 31.382 | 31.382 | |
| 2 | 1.067 | 13.336 | 51.543 | .499 | 6.238 | 37.621 | |
| 3 | .958 | 11.980 | 63.523 | 2.510 | 0.499 | | |
| 4 | .736 | 9.205 | 72.728 | Sum of | squared loadi | ngs Factor 1 = | 2.51 |
| 5 | .622 | 7.770 | 80.498 | Sum of | squared loadi | ngs Factor 2 = | 0.499 |
| 6 | .571 | 7.135 | 87.632 | (recall) | Sum of comm | unalities acros | ss items = 3.01 |
| 7 | .543 | 6.788 | 94.420 | | | | |
| 8 | .446 | 5.580 | 100.000 | | | | |

Extraction Method: Principal Axis Factoring.

Eigenvalues do not belong in EFA!

Analyze – Dimension Reduction – Factor



Caution!

Eigenvalues are only for PCA, yet SPSS uses the eigenvalue criteria for EFA



When you look at the scree plot in SPSS, you are making a conscious decision to use the PCA solution as a proxy for your EFA

Quick Check 2

- 1. In the Total Variance Explained table, the percent of variance in the Initial column equals the Extraction column when... (Single Choice)
 - Answer 1: You run a factor analysis.
 - Answer 2: There is no error variance.
 - Answer 3: There is no unique variance.
- 2. In SPSS when you use the Principal Axis Factor method the scree plot uses the final factor analysis solution to plot the eigenvalues. (Single Choice)
 - Answer 1: T
 - Answer 2: F

Factor Matrix (2-factor PAF)

Factor Matrix^a

These are analogous to component loadings in PCA

Squaring the loadings and summing up gives you either the Communality or the Extraction Sums of Squared Loadings

Summing down the communalities or across the eigenvalues gives you total variance explained (3.01)

| | ' | 2 | |
|---|---------------------|-------|-------|
| Statistics makes me cry | .588 | 303 | 0.438 |
| My friends will think I'm stupid for not being able to cope with SPSS | 227 | .020 | 0.052 |
| Standard deviations excite | 557 | .094 | 0.319 |
| I dream that Pearson is attacking me with correlation coefficients | .652 | 189 | 0.461 |
| don't understand | .560 | 174 | 0.344 |
| have little experience of omputers | .498 | .247 | 0.309 |
| All computers hate me | .771 | .506 | 0.850 |
| I have never been good at mathematics | .470 | 124 | 0.236 |
| Extraction Method: Principal | Axis Factorir 2.510 | o.499 | 3.01 |

a. 2 factors extracted. 79 iterations required.

Sum of squared loadings across factors is the communality

$$0.588^2 = 0.346$$

34.5% of the variance in Item 1 explained by first factor

$$(-0.303)^2 = 0.091$$

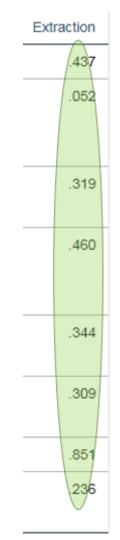
9.1% of the variance in Item 1 explained by second factor

$$0.345 + 0.091 = 0.437$$

43.7% of the variance in Item 1 explained by both factors = COMMUNALITY!

Sum squared loadings down each column = Extraction Sums of Square Loadings (not eigenvalues)

Communalities



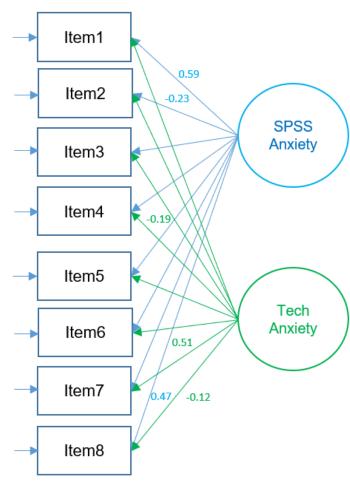
Path Diagram

Communalities

Factor Matrix^a

| | | Fac | tor |
|------------|---|------|------|
| Extraction | | 1 | 2 |
| .437 | Statistics makes me cry | .588 | 303 |
| .052 | My friends will think I'm stupid for not being able to cope with SPSS | 227 | .020 |
| .319 | Standard deviations excite me | 557 | .094 |
| .460 | I dream that Pearson is attacking me with correlation coefficients | .652 | 189 |
| .344 | I don't understand statistics | .560 | 174 |
| .309 | I have little experience of computers | .498 | .247 |
| .851 | All computers hate me | .771 | .506 |
| 236 | I have never been good at mathematics | .470 | 124 |

Extraction Method: Principal Axis Factoring.



Note: only selected loadings shown

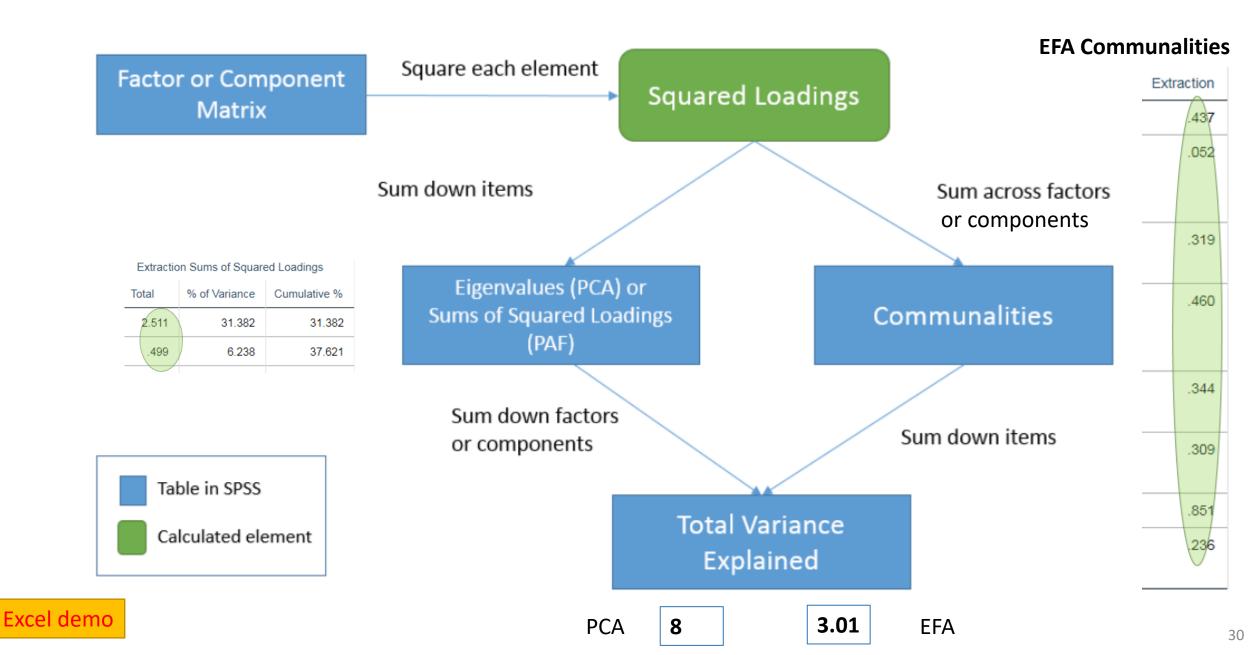
Extraction Sums of Squared Loadings

| Total | % of Variance | Cumulative % |
|-------|---------------|--------------|
| 2.511 | 31.382 | 31.382 |
| .499 | 6.238 | 37.621 |

Caution when interpreting unrotated loadings. Most of total variance explained by first factor.

a. 2 factors extracted. 79 iterations required.

The relationship between the three tables

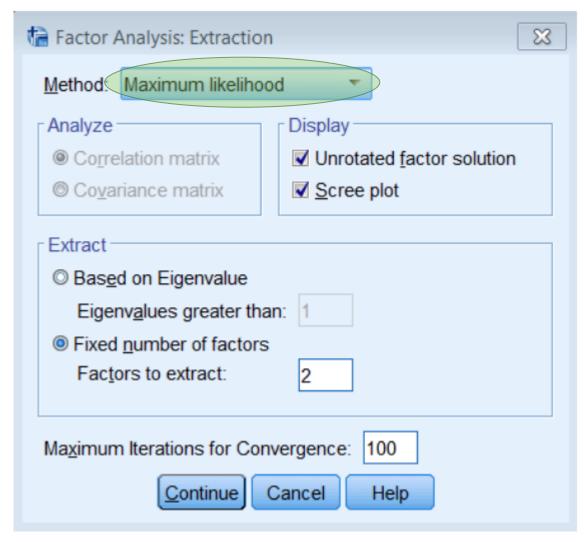


Quick Check 3

| . The eigenvalue represents the communality for each item. (Single Choice) |
|--|
| Answer 1: T |
| Answer 2: F |
| . For a single component, the sum of squared component loadings across all items represents the eigenvalue for that omponent. (Single Choice) |
| Answer 1: T |
| Answer 2: F |
| . The sum of eigenvalues for all the components is the total variance. (Single Choice) |
| Answer 1: T |
| Answer 2: F |
| . The sum of the communalities down the components is equal to the sum of eigenvalues down the items. (Single Choice |
| Answer 1: T |
| Answer 2: F |
| |

Maximum Likelihood Estimation (2-factor ML)

Analyze – Dimension Reduction – Factor



New output

A significant chisquare means you reject the current hypothesized model

Goodness-of-fit Test

| Chi-Square | df | Sig. |
|------------|----|------|
| 198.617 | 13 | .000 |

This is telling us we reject the two-factor model

Chi-square Comparison Table

Chi-square and degrees of freedom goes down

The three factor model is preferred from chi-square

| Number of Factors | Chi- square | Df | p-value | Iterations needed |
|-------------------|----------------|-----|---------|-------------------|
| 1 | 553.08 | 20 | <0.05 | 4 |
| _ | | | | · |
| 2 | 198.62 | 13 | < 0.05 | 39 |
| 3 | 13.81 | 7 | 0.055 | 57 |
| 4 | 1.386 | 2 | 0.5 | 168 |
| 5 | NS | -2 | NS | NS |
| 6 | NS | -5 | NS | NS |
| 7 | NS | -7 | NS | NS |
| 8 | N/A | N/A | N/A | N/A |

Want NONsignificant chisquare

Iterations needed goes up

Warnings

You cannot request as many factors as variables with any extraction method except PC. The number of factors will be reduced by one.

An eight factor model is not possible in SPSS

The number of degrees of freedom (-7) is not positive. Factor analysis may not be appropriate.

Quick Check 4

| 1. Since they are both fac | ctor analysis methods, | Principal Axis | Factoring and the | e Maximum | Likelihood method | will result in th | ne |
|----------------------------|------------------------|----------------|-------------------|-----------|-------------------|-------------------|----|
| same Factor Matrix. (Sin | gle Choice) | | | | | | |

Answer 1: T

Answer 2: F

2. In SPSS, both Principal Axis Factoring and Maximum Likelihood methods give chi-square goodness of fit tests. (Single Choice)

Answer 1: T

Answer 2: F

3. When looking at the Goodness-of-fit Test table, a p-value less than 0.05 means the model is a good fitting model. (Single Choice)

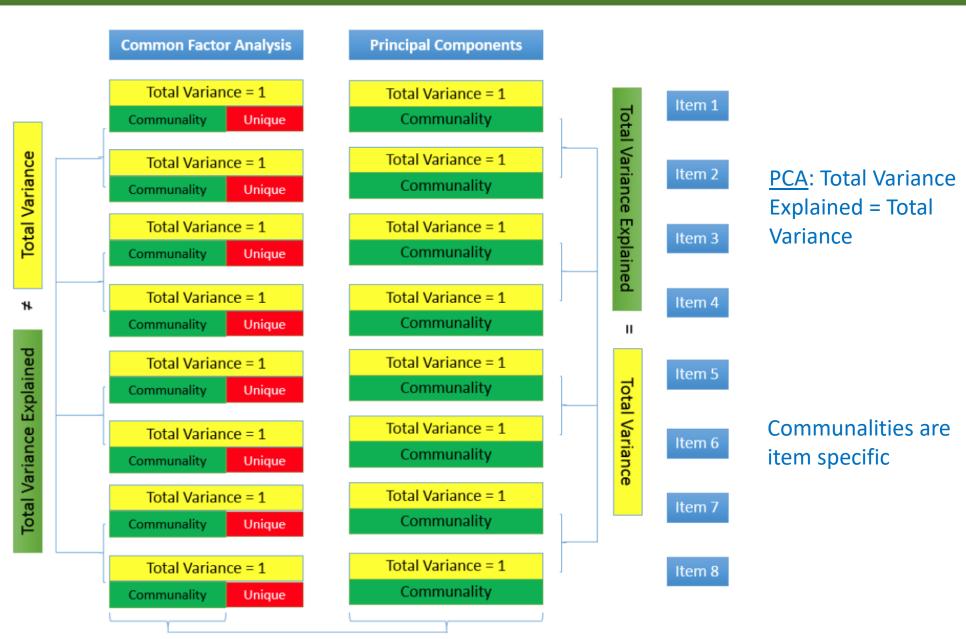
Answer 1: T

Answer 2: F

Comparing EFA with PCA

EFA: Total VarianceExplained = TotalCommunalityExplained NOTTotal Variance

For both models, communality is the total proportion of variance due to all factors or components in the model



Quick Check 5 (optional)

1. In Principal Axis Factoring, the elements of the Factor Matrix represent correlations of each item with a factor. (Single Choice)

Answer 1: T

Answer 2: F

2. In common factor analysis, the Sums of Squared loadings is the same as the eigenvalue. (Single Choice)

Answer 1: T

Answer 2: F

3. In EFA, the Sum of Squared Loadings across all items in the Factor Matrix represents the communality. (Single Choice)

Answer 1: T

Answer 2: F

Quick Check 6

1. In common factor analysis, the communality represents the common variance for each item. (Single Choice) Answer 1: T Answer 2: F 2. For both PCA and common factor analysis, the sum of the communalities represent the total variance explained. (Single Choice) (across all items) Answer 1: T Answer 2: F 3. For PCA, the total variance explained equals the total variance, but for common factor analysis it does not. (Single Choice) Answer 1: T Answer 2: F

Rotation Methods

- Simple Structure
- Orthogonal rotation (Varimax)
- Oblique (Direct Oblimin)

Simple structure

- 1. Each item has high loadings on one factor only
- 2. Each factor has high loadings for only some of the items.

Pedhazur and Schemlkin (1991)

| Item | Factor 1 | Factor 2 | Factor 3 |
|------|----------|----------|----------|
| 1 | 0.8 | 0 | 0 |
| 2 | 0.8 | 0 | 0 |
| 3 | 0.8 | 0 | 0 |
| 4 | 0 | 0.8 | 0 |
| 5 | 0 | 0.8 | 0 |
| 6 | 0 | 0.8 | 0 |
| 7 | 0 | 0 | 0.8 |
| 8 | 0 | 0 | 0.8 |

The goal of rotation is to achieve simple structure

NOT simple structure

- 1. Most items have high loadings on *more* than one factor
- 2. Factor 3 has high loadings on 5/8 items

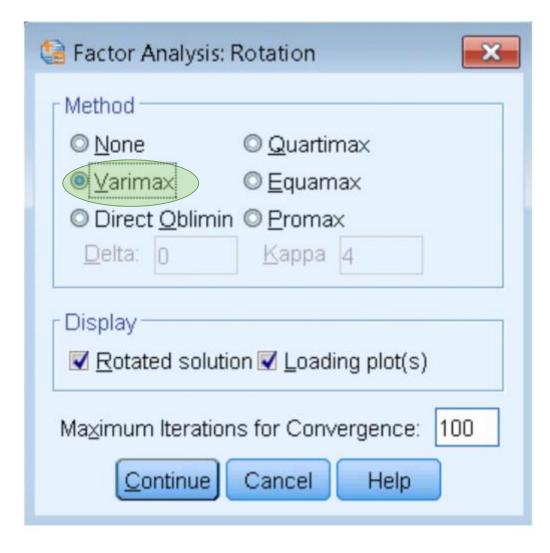
| Item | Factor 1 | Factor 2 | Factor 3 |
|------|----------|----------|----------|
| 1 | 0.8 | 0 | 0.8 |
| 2 | 0.8 | 0 | 0.8 |
| 3 | 0.8 | 0 | 0 |
| 4 | 0.8 | 0 | 0 |
| 5 | 0 | 0.8 | 0.8 |
| 6 | 0 | 0.8 | 0.8 |
| 7 | 0 | 0.8 | 0.8 |
| 8 | 0 | 0.8 | 0 |

Running a 2-factor solution (PAF Varimax rotation)

Without rotation, first factor is the most general factor onto which most items load and explains the largest amount of variance

Varimax: orthogonal rotation

maximizes
variances of the
loadings within the
factors while
maximizing
differences
between high and
low loadings on a
particular factor



Orthogonal means the factors are uncorrelated

Factor Transformation Matrix



The factor transformation matrix turns the regular factor matrix into the rotated factor matrix

Factor Transformation

Matrix

| Factor | 1 | 2 |
|--------|------|------|
| 1 | .773 | .635 |
| 2 | 635 | .773 |

Extraction Method: Principal

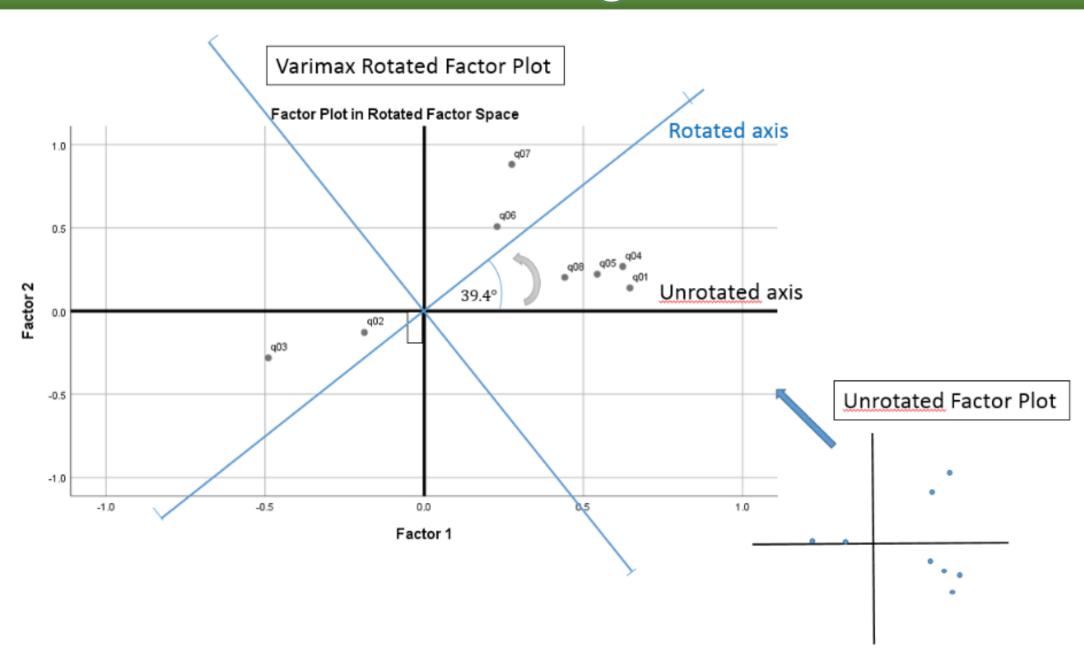
Axis Factoring. Rotation

Method: Varimax with Kaiser

Normalization.

The amount of rotation is the angle of rotation

Factor Loading Plot



Rotated Factor Matrix (2-factor PAF Varimax)

Factor Matrix^a

Rotated Factor Matrix^a

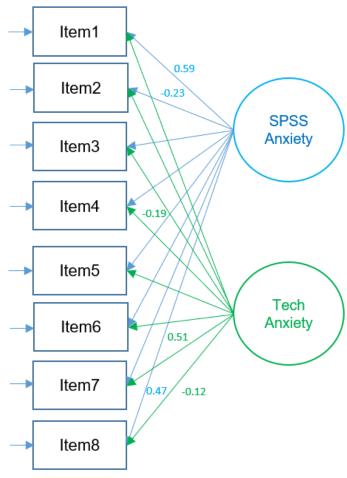
| | Fac | tor | |
|---|------|------|---------------|
| Unrotated solution | 1 | 2 | Communalities |
| Statistics makes me cry | .588 | 303 | 0.438 |
| My friends will think I'm stupid for not being able to cope with SPSS | 227 | .020 | 0.052 |
| Standard deviations excite me | 557 | .094 | 0.319 |
| I dream that Pearson is attacking me with correlation coefficients | .652 | 189 | 0.461 |
| I don't understand statistics | .560 | 174 | 0.344 |
| I have little experience of computers | .498 | .247 | 0.309 |
| All computers hate me | .771 | .506 | 0.000 |
| I have never been good at mathematics | .470 | 124 | 0.236 |

a. 2 factors extracted. 79 iterations required.

| | Fac | tor | | |
|---|------|------|-------|----------------------------------|
| Varimax rotation | 1 | 2 | Commu | nalities |
| Statistics makes me cry | .646 | .139 | 0.437 | maximizes sum of |
| My friends will think I'm stupid for not being able to cope with SPSS | 188 | 129 | 0.052 | the variance of squared loadings |
| Standard deviations excite me | 490 | 281 | 0.319 | within each factor |
| I dream that Pearson is attacking me with correlation coefficients | .624 | .268 | 0.461 | |
| I don't understand statistics | .544 | .221 | 0.344 | |
| I have little experience of computers | .229 | .507 | 0.309 | |
| All computers hate me | .275 | .881 | 0.850 | |
| I have never been good at mathematics | .442 | .202 | 0.236 | |
| Extraction Method: Principal A | | ng. | 0.230 | communalities are the same |
| Normalization. | | | | |

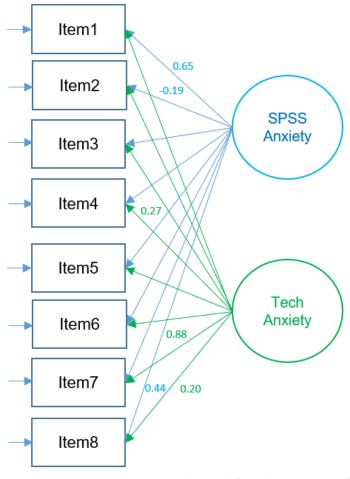
Comparing path diagrams

Unrotated Solution



Note: only selected loadings shown

Varimax Solution



Varimax Rotation with Kaiser Normalization Note: only selected loadings shown

Total Variance Explained (2-factor PAF Varimax)

True or False: Rotation changes how the variances are distributed but not the total communality

Total Variance Explained

| | Extraction Sums of Squared Loadings | | | Rotation | Sums of Square | ed Loadings |
|--------|-------------------------------------|----------|--------------|----------|----------------|--------------|
| | | % of | | | % of | |
| Factor | Total | Variance | Cumulative % | Total | Variance | Cumulative % |
| 1 | 2.511 | 31.382 | 31.382 | 1.521 | 19.010 | 19.010 |
| 2 | .499 | 6.238 | 37.621 | 1.489 | 18.610 | 37.621 |

maximizes variances of the loadings

Extraction Method: Principal Axis Factoring.

3.01

3.01

Even though the distribution of the variance is different the total sum of squared loadings is the same

Answer: T

Varimax vs. Quartimax

Quartimax: maximizes the squared loadings so that each item loads most strongly onto a single factor. Good for generating a single factor.

Total Variance Explained

| Rotation Sums of Squared Loadings (Varimax) | | | Rotation Sums | of Squared Loadin | igs (Quartimax) | |
|---|-------|----------|---------------|-------------------|-----------------|--------------|
| | | % of | | | | |
| Factor | Total | Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 1.521 | 19.010 | 19.010 | 2.381 | 29.760 | 29.760 |
| 2 | 1.489 | 18.610 | 37.621 | .629 | 7.861 | 37.621 |

Extraction Method: Principal Axis Factoring.

Varimax: good for distributing among more than one factor

The difference between Quartimax and unrotated solution is that maximum variance can be in a factor that is not the first

Oblique Rotation

factor pattern matrix

- partial standardized regression coefficients of each item with a particular factor
 - Think (P)artial = Pattern

factor structure matrix

- simple zero order correlations of each item with a particular factor
 - Think (S)imple = Structure

factor correlation matrix

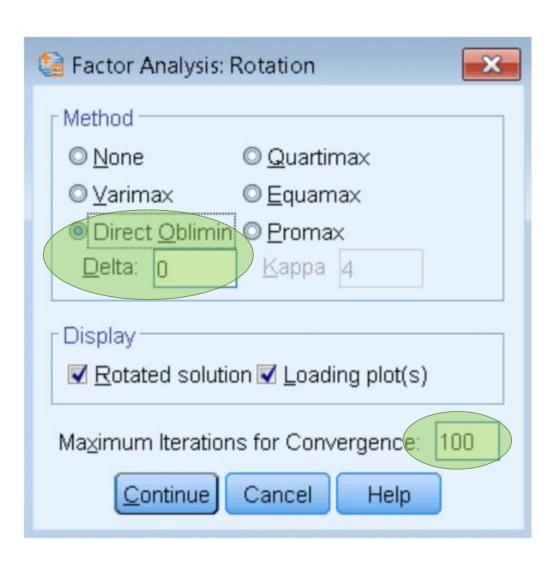
matrix of intercorrelations among factors

Running a two-factor solution (PAF) with Quartimin

When Delta =0 → Direct Quartimin

Larger delta increases correlation among factors

Negative delta increases makes factors more orthogonal

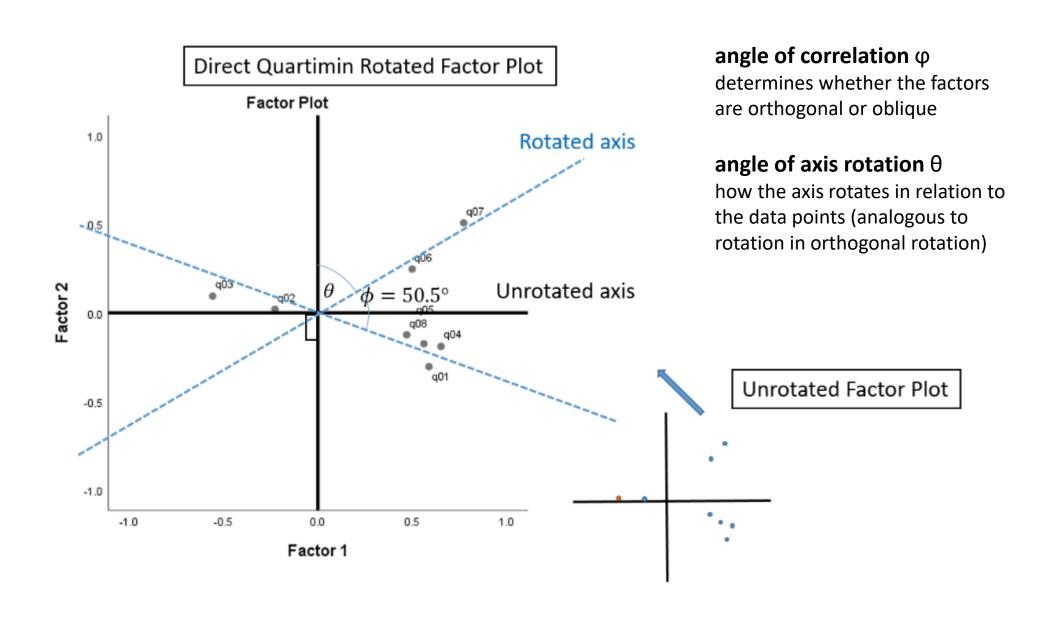


Oblique rotation means the factors are correlated

Quick Check 7

- 1. When selecting Direct Oblimin, delta = 0 is actually Direct Quartimin. (Single Choice)
 - Answer 1: T
 - Answer 2: F
- 2. Smaller delta values will increase the correlations among factors. (Single Choice)
 - Answer 1: T
 - Answer 2: F

Factor plot of Direct Quartimin Rotation



Factor Correlation Matrix (2-factor PAF Quartimin)



The more correlated the factors, the greater the difference between pattern and structure matrix

Factor Correlation

Matrix

| Factor | 1 | 2 |
|--------|-------|-------|
| 1 | 1.000 | .636 |
| 2 | .636 | 1.000 |

Extraction Method: Principal

Axis Factoring. Rotation

Method: Oblimin with Kaiser

Normalization.

orthogonal, the correlations between them would be zero, then the factor pattern matrix would EQUAL the factor structure matrix.

Structure & Pattern Matrix (2-factor PAF Direct Quartimin)

| | Pattern M regression coefficie | | or |
|--|---|---------------|------|
| can exceed one) | | 1 | 2 |
| | Statistics makes me cry | .740 | 137 |
| 0.740 is the effect of Factor 1 on | My friends will think I'm stupid for not being able to cope with SPSS | 180 | 067 |
| Item 1 controlling for Factor 2 | Standard deviations excite me | 490 | 108 |
| | I dream that Pearson is attacking me with correlation coefficients | .660 | .029 |
| There IS a way to make the | I don't understand statistics | .580 | .011 |
| sum of squared loadings equal to the communality. Think back to Orthogonal | I have little experience of computers | .077 | .504 |
| | All computers hate me | 017 | .933 |
| | I have never been good at mathematics | .462 | .036 |
| Rotation. | Extraction Method: Principal | Axis Factorin | g. |
| | Deteller Meller tracking | | |

Rotation Method: Oblimin with Kaiser

Normalization.

Dattern Matriva

Structure Matrix Factor 2 0.537 Statistics makes me cry .653 .333 0.566 My friends will think I'm -.222 -.181 0.082 stupid for not being able 0.037 to cope with SPSS 0.489 -.559 -.420 Standard deviations excite me 0.252 0.661 .449 I dream that Pearson is .678 attacking me with 0.436 correlation coefficients .587 .380 0.489 I don't understand statistics 0.337 I have little experience of .553 0.464 .398 computers 0.260 1.185 All computers hate me .923 .577 I have never been good at .485 .330 0.871 0.344 mathematics 0.215 Extraction Method: Principal Axis Factoring.

Simple zero order correlations (can't exceed one)

> **0.653** is the simple correlation of Factor 1 on Item 1

Note that the sum of squared loadings do NOT match communalities

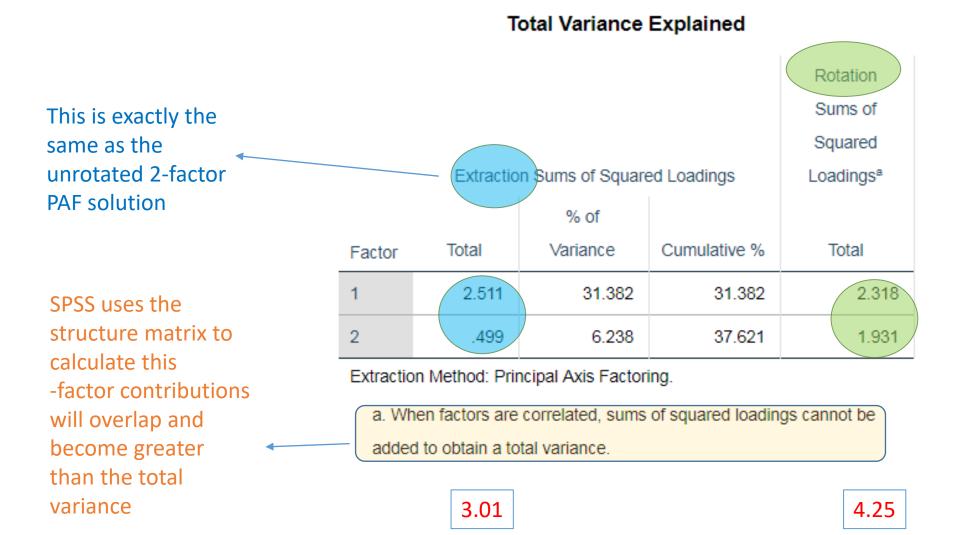
Communalities

| | Initial | Extraction | | | |
|---|---------|------------|--|--|--|
| Statistics makes me cry | .293 | .437 | | | |
| My friends will think I'm stupid for not being able to cope with SPSS | .106 | .052 | | | |
| Standard deviations excite me | .298 | .319 | | | |
| I dream that Pearson is attacking me with correlation coefficients | .344 | .460 | | | |
| I don't understand statistics | .263 | .344 | | | |
| I have little experience of computers | .277 | .309 | | | |
| All computers hate me | .393 | .851 | | | |
| I have never been good at mathematics | .192 | .236 | | | |
| Extraction Method: Principal Axis Factoring. | | | | | |

Rotation Method: Oblimin with Kaiser

Normalization.

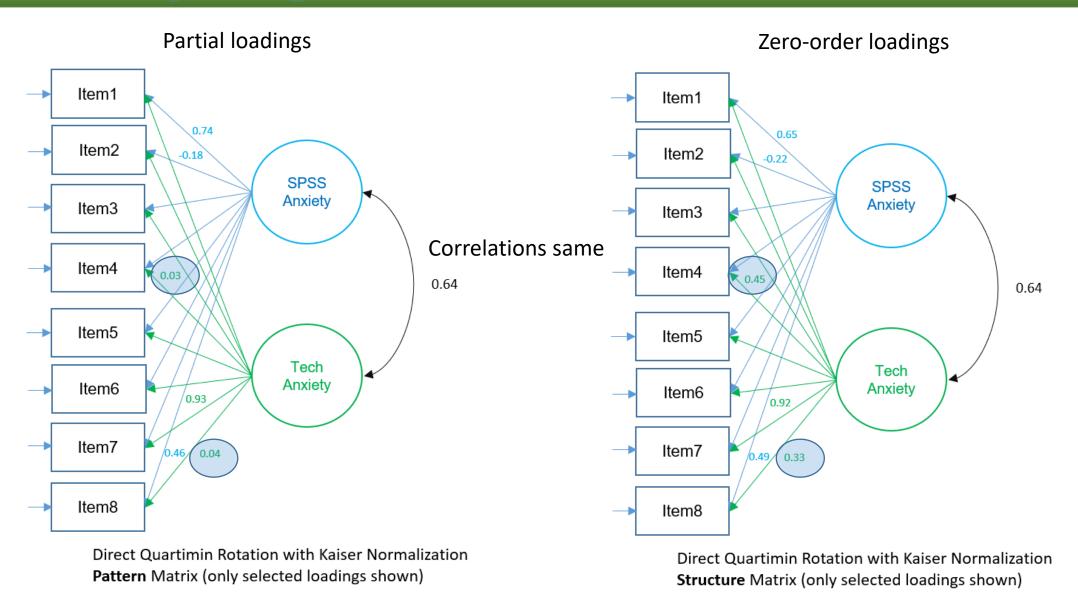
Total Variance Explained (2-factor PAF Quartimin)



Note: now the sum of the squared loadings is HIGHER than the unrotated solution

SPSS uses the structure matrix to calculate this -factor contributions will overlap and become greater than the total variance

Comparing Pattern to Structure Matrix



Lower absolute loadings of Items 4,8 onto Tech Anxiety for Pattern Matrix

Interpreting loadings (2-factor PAF Quartimin)

Factor

| Structure Matr | ix s | tructure Matrix | c Pattern Matri | _{ix} Pat | tern Matrix |
|---|------|-----------------|-----------------|-------------------|--------------|
| | 1 | 2 | 1 | 2 | |
| Statistics makes me cry | .653 | .333 | .740 | 137 | |
| My friends will think I'm stupid for not being able to cope with SPSS | 222 | 181 | 180 | 067 | W |
| Standard deviations excite me | 559 | 420 | 490 | 108 | lo |
| I dream that Pearson is attacking me with correlation coefficients | .678 | .449 | .660 | .029 | M to M |
| I don't understand statistics | .587 | .380 | .580 | .011 | |
| I have little experience of computers | .398 | .553 | .077 | .504 | |
| All computers hate me | .577 | .923 | 017 | .933 | |
| I have never been good at mathematics | .485 | .330 | .462 | .036 | |

Why do you think the second loading is lower in the Pattern Matrix compared to the Structure Matrix?

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

Factor or Pattern Matrix?

- There is no consensus about which one to use in the literature
- Hair et al. (1995)
 - Better to interpret the pattern matrix because it gives the unique contribution of the factor on a particular item
- Pett et al. (2003)
 - Structure matrix should be used for interpretation
 - Pattern matrix for obtaining factor scores
- My belief: I agree with Hair

Quick Check 8

1. In oblique rotation, an element of a factor pattern matrix is the unique contribution of the factor to the item whereas an element in the factor structure matrix is the non-unique contribution to the factor to an item. (Single Choice)

Answer 1: T

Answer 2: F

2. In the Total Variance Explained table, the Rotation Sum of Squared Loadings represent the unique contribution of each factor to total common variance. (Single Choice)

Answer 1: T

Answer 2: F

3. If the factors are orthogonal, then the Pattern Matrix equals the Structure Matrix (Single Choice)

Answer 1: T

Answer 2: F

4. Varimax, Quartimax and Equamax are three types of orthogonal rotation and Direct Oblimin, Direct Quartimin and Promax are three types of oblique rotations. (Single Choice)

Answer 1: T

Answer 2: F

Factor Analysis: Rotation

Direct Oblimin ○ Promax

Rotated solution Loading plot(s)

Maximum Iterations for Convergence: 100 Cancel

Quartimax

Equamax

Kappa 4

Help

Method

Display

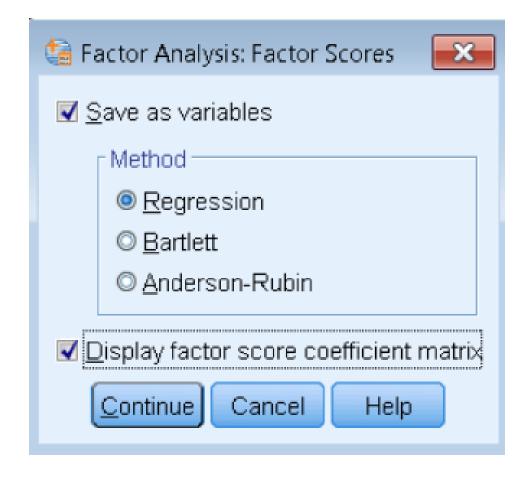
O None

Generating Factor Scores

- Regression
- Bartlett
- Anderson-Rubin

Generating factor scores (Quartimin, Reg Method)

Analyze – Dimension Reduction – Factor – Factor Scores



What it looks like in SPSS Data View

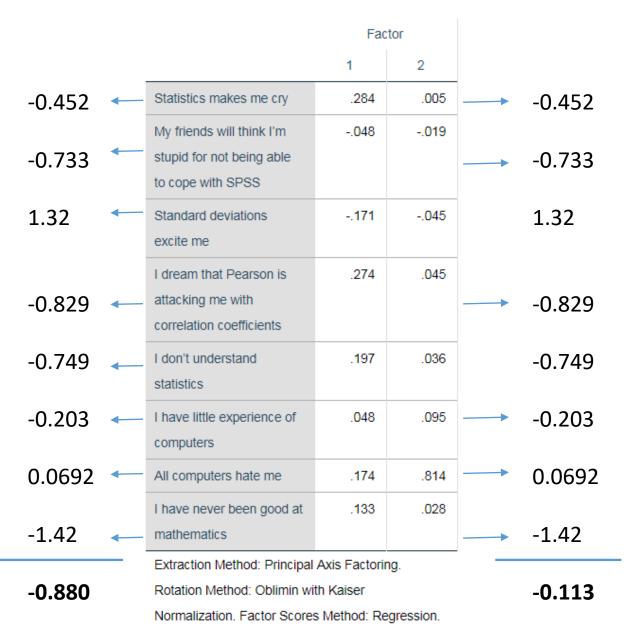
| ₫ q08 | | |
|-------|---------|---------|
| 1 | 87974 | 11277 |
| 2 | 93859 | 77805 |
| 2 | 31326 | 79102 |
| 2 | 1.07582 | 1.00312 |
| 2 | 52530 | .04489 |

Factor Score Coefficient Matrix (Direct Quartimin)

Factor Score Coefficient Matrix

This is how the factor scores are generated

SPSS takes the standardized scores for each item Then multiply each score



Factor Score Covariance (Direct Quartimin)

Covariance matrix of the **true** factor scores

Covariance matrix of the **estimated** factor scores

Factor Score

Covariance Matrix

| Factor | 1 | 2 |
|--------|-------|-------|
| 1 | 1.897 | 1.895 |
| 2 | 1.895 | 1.990 |

Extraction Method: Principal

Axis Factoring. Rotation

Method: Oblimin with Kaiser

Normalization. Factor Scores

Method: Regression.

Correlations

| | | REGR factor | REGR factor |
|------------------------------------|------------|-------------|-------------|
| | | score 1 for | score 2 for |
| | | analysis 1 | analysis 1 |
| REGR factor score 1 for analysis 1 | Covariance | .777 | .604 |
| REGR factor score 2 for analysis 1 | Covariance | .604 | .870 |

Notice that for Direct Quartimin, the raw covariances do not match Regression method has factor score mean of zero, and variance equal to the squared multiple correlation of estimated and true factor scores

Factor Score Covariance (Varimax)

Factor Score

Covariance Matrix

| Factor | 1 | 2 |
|--------|------|------|
| 1 | .831 | .114 |
| 2 | .114 | .644 |

Extraction Method: Principal

Axis Factoring.

Rotation Method: Varimax

without Kaiser Normalization.

Factor Scores Method:

Regression.

Correlations

| | | REGR factor score 1 for analysis 2 | REGR factor score 2 for analysis 2 |
|------------------------------------|------------|--|--|
| REGR factor score 1 for analysis 2 | Covariance | .831 | .114 |
| REGR factor score 2 for analysis 2 | Covariance | .114 | .644 |

Notice that for Direct Quartimin, the raw correlations *do* match (property of Regression method)

However, note that the factor scores are still correlated even though we did Varimax

Comparing score methods

1. Regression Method

- Variance equals the square multiple correlation between factors and variables
- Maximizes correlation between estimated and true factor scores but can be biased

• 2. Bartlett

- Factor scores highly correlate with own true factor and not with others
- Unbiased estimate of true factor scores

• 3. Anderson-Rubin

- Estimated factor scores become uncorrelated with other true factors and uncorrelated with other estimated factor scores
- Biased especially if factors are actually correlated, not for oblique rotations

Correlations between estimated factors

| Correlations | | | |
|-------------------------|---------------------|--|--|
| | | REGR factor score 1 for analysis 1 | REGR factor score 2 for analysis 1 |
| REGR factor score 1 for | Pearson Correlation | 1 | .765** |
| analysis 1 | Sig. (2-tailed) | | .000 |
| | N | 2571 | 2571 |
| REGR factor score 2 for | Pearson Correlation | .765** | 1 |
| analysis 1 | Sig. (2-tailed) | .000 | |
| | N | 2571 | 2571 |

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

Correlations

| | | BART factor score 1 for analysis 2 | BART factor score 2 for analysis 2 |
|------------------------------------|---------------------|--|--|
| BART factor score 1 for analysis 2 | Pearson Correlation | 1 | .475** |
| | Sig. (2-tailed) | | .000 |
| | N | 2571 | 2571 |
| BART factor score 2 for analysis 2 | Pearson Correlation | .475** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 2571 | 2571 |

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

Correlations

| | | | A-R factor score 1 for analysis 3 | A-R factor score 2 for analysis 3 |
|-----------------------------------|---------------------|---------------------|---|---|
| A-R factor score 1 for analysis 3 | 1 for | Pearson Correlation | 1 | .000 |
| | | Sig. (2-tailed) | | 1.000 |
| | | N | 2571 | 2571 |
| A-R factor score 2 for analysis 3 | Pearson Correlation | .000 | 1 | |
| | | Sig. (2-tailed) | 1.000 | |
| | | N | 2571 | 2571 |

Direct Quartimin

Quick Check 9

- 1. If you want the highest correlation of the factor score with the corresponding factor (i.e., highest validity), choose the regression method. (Single Choice)
 - Answer 1: T
 - Answer 2: F
- 2. Bartlett scores are unbiased whereas Regression and Anderson-Rubin scores are biased. (Single Choice)
 - Answer 1: T
 - Answer 2: F
- 3. Anderson-Rubin is appropriate for orthogonal but not for oblique rotation because factor scores will be uncorrelated with other factor scores. (Single Choice)
 - Answer 1: T
 - Answer 2: F