Principal Component Analysis and Exploratory Factor Analysis

Module 3: Exploratory Factor Analysis

Karen Grace-Martin

Workshop Outline

Exploratory Factor Analysis

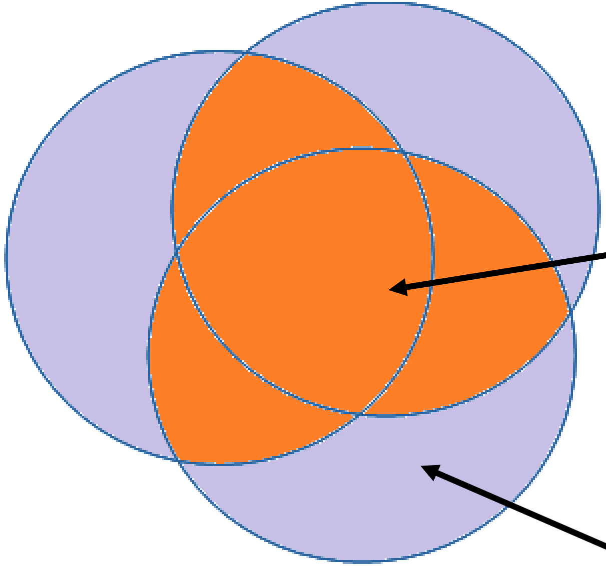
1. The Similarities and Differences between EFA and PCA
2. Methods of Initial Extraction for EFA
3. More on Factor Scores and Factor-Based Scores
4. Reporting Results

5. Example

The Similarities and Differences between EFA and PCA

PCA vs. (Common) Factor Analysis

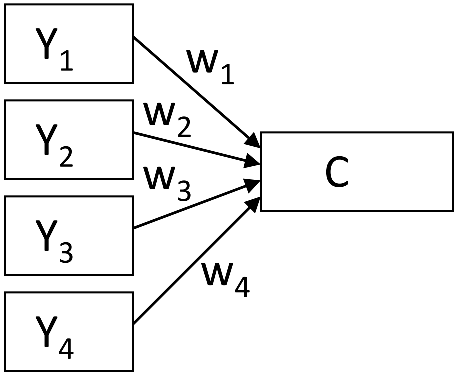
PCA	FA
Components are a linear function of Variables $C = w_1(Y_1) + w_2(Y_2) + w_3(Y_3) + w_4(Y_4)$	Variables are a linear function of Factors $Y_1 = b_1F_1 + b_2F_2 + u_1$
Explains *all* variance in variables, assumes no error variance	Explains *common* variance in variables, assumes error and specific variance
A Component is an *artificial* variable, a linear combination of observed variables	A Factor is a *latent* variable responsible for the correlation among observed variables
Calculated Component Scores are actual measures of the components	Calculated Factor Scores are *estimates* of the latent variable
Can only *reduce number* of variables	Can examine the *underlying structure* of factors that create correlations in the data



Common variance: h^2

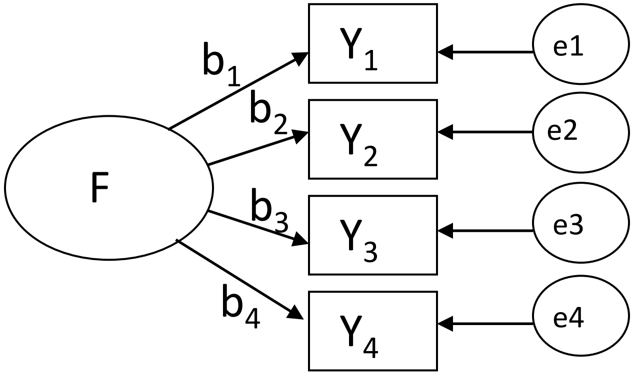
Unique variance: $1 - h^2$

Principal Component Analysis



$$C = w_1(Y_1) + w_2(Y_2) + w_3(Y_3) + w_4(Y_4)$$

Factor Analysis



$$Y_1 = b_1*F + e_1$$
$$Y_2 = b_2*F + e_2$$
$$Y_3 = b_3*F + e_3$$
$$Y_4 = b_4*F + e_4$$

Principal Component Analysis or Factor Analysis?

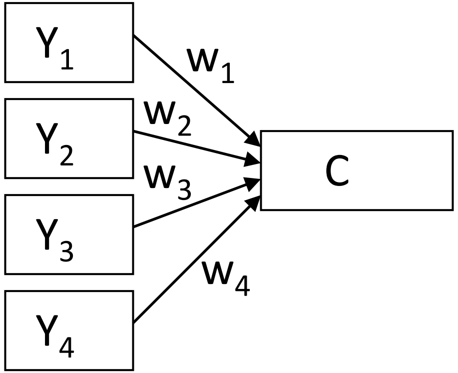
Animal Data Set:
- Weight
- Total Sleep
- Predation
- Exposure During Sleep

Breastfeeding Data Set:
- Breastfeeding intention
- Self-Efficacy to Resist Formula

Caregivers:
- Mutual Communal Behavior Scale
- CES-D

Psych Data:
- Life Orientation (Optimism)
- Social Anxiety
- Attitude toward counseling

PCA General Variable Reduction Process



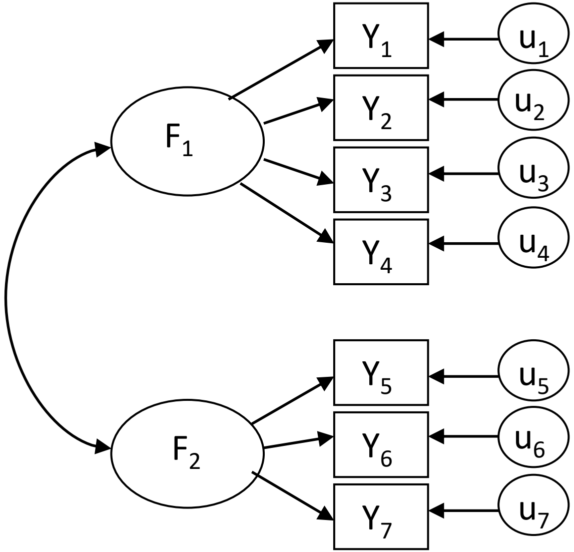
Have a set of correlated variables that you're using as predictors or outcomes

Combine them with a PCA

Use the component scores (index) in the analysis

Interpret results using this combination variable

Exploratory Factor Analysis General Measurement Model Process



Write a set of items for a scale designed to measure a latent construct or multiple related constructs

Run an EFA to see loadings on the intended scale or subscales

Iteratively rerun the EFA to get the optimal number of factors and cleanly loading items

If necessary, rewrite items and rerun on a new sample

Once you find a clean loading of items on subscales, collect a new data set and run a Confirmatory FA

Factor Analysis Steps

1. Initial Extraction of the Factors
2. Determine the Number of Factors to Retain
3. Rotation
4. Interpret the Rotated Solution
5. Create Factor Scores
6. Summarize the results in a Table
7. Write a formal description of results for a paper

Compared to PCA

1. Same step, different extraction method
2. Same
3. Same
4. Same, apply interpretation to latent variables
5. Maybe not in EFA
6. New
7. New

Methods of Initial Extraction for EFA

Initial Extraction of the Components in PCA

Correlation Matrix

	HospBf	HospF	ONEmosBf	ONEmosF	FIVEmosBf	FIVEmosF
HospBf	1.000	.305	.713	.085	.370	.080
HospF	.305	1.000	.331	.752	.259	.553
ONEmosBf	.713	.331	1.000	.159	.490	.172
ONEmosF	.085	.752	.159	1.000	.164	.665
FIVEmosBf	.370	.259	.490	.164	1.000	.470
FIVEmosF	.080	.553	.172	.665	.470	1.000

Two Component Extraction:

Communalities

	Initial	Extraction
HospBf	1.000	.778
HospF	1.000	.747
ONEmosBf	1.000	.827
ONEmosF	1.000	.847
FIVEmosBf	1.000	.506
FIVEmosF	1.000	.739

Six Component Extraction:

Communalities

	Initial	Extraction
HospBf	1.000	1.000
HospF	1.000	1.000
ONEmosBf	1.000	1.000
ONEmosF	1.000	1.000
FIVEmosBf	1.000	1.000
FIVEmosF	1.000	1.000

Initial Extraction of the Components in PCA

Correlation Matrix

	HospBf	HospF	ONEmosBf	ONEmosF	FIVEmosBf	FIVEmosF
HospBf	1.000	.305	.713	.085	.370	.080
HospF	.305	1.000	.331	.752	.259	.553
ONEmosBf	.713	.331	1.000	.159	.490	.172
ONEmosF	.085	.752	.159	1.000	.164	.665
FIVEmosBf	.370	.259	.490	.164	1.000	.470
FIVEmosF	.080	.553	.172	.665	.470	1.000

Two Component Extraction:

Communalities

	Initial	Extraction
HospBf	1.000	.778
HospF	1.000	.747
ONEmosBf	1.000	.827
ONEmosF	1.000	.847
FIVEmosBf	1.000	.506
FIVEmosF	1.000	.739

Six Component Extraction:

Communalities

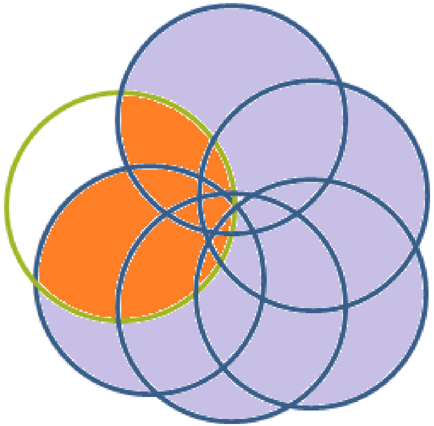
	Initial	Extraction
HospBf	1.000	1.000
HospF	1.000	1.000
ONEmosBf	1.000	1.000
ONEmosF	1.000	1.000
FIVEmosBf	1.000	1.000
FIVEmosF	1.000	1.000

Squared Multiple Correlation is One Estimate of Common Variance

SMC for HospBF is the R^2 from this model:

$$HospBf_i = \beta_0 + \beta_1 HospF_i + \beta_2 ONEmosBf_i + \beta_3 ONEmosF_i + \beta_4 FIVEmosBf_i + \beta_5 FIVEmosF_i + \varepsilon_i$$

HospBf



Initial Extraction of the Factors in Principal Axis Factoring

Correlation Matrix

	HospBf	HospF	ONEmosBf	ONEmosF	FIVEmosBf	FIVEmosF
HospBf		.305	.713	.085	.370	.080
HospF	.305		.331	.752	.259	.553
ONEmosBf	.713	.331		.159	.490	.172
ONEmosF	.085	.752	.159		.164	.665
FIVEmosBf	.370	.259	.490	.164		.470
FIVEmosF	.080	.553	.172	.665	.470	

Five Factor Extraction:

Communalities

	Initial	Extraction
HospBf	.534	.722
HospF	.630	.775
ONEmosBf	.578	.799
ONEmosF	.687	.898
FIVEmosBf	.446	.642
FIVEmosF	.596	.816

Two Factor Extraction:

Communalities

	Initial	Extraction
HospBf	.534	.586
HospF	.630	.638
ONEmosBf	.578	.865
ONEmosF	.687	.855
FIVEmosBf	.446	.311
FIVEmosF	.596	.562

Initial Extraction of the Factors in PAF

Correlation Matrix

	HospBf	HospF	ONEmosBf	ONEmosF	FIVEmosBf	FIVEmosF
HospBf	.534	.305	.713	.085	.370	.080
HospF	.305	.630	.331	.752	.259	.553
ONEmosBf	.713	.331	.578	.159	.490	.172
ONEmosF	.085	.752	.159	.687	.164	.665
FIVEmosBf	.370	.259	.490	.164	.446	.470
FIVEmosF	.080	.553	.172	.665	.470	.596

Five Factor Extraction:

Communalities

	Initial	Extraction
HospBf	.534	.722
HospF	.630	.775
ONEmosBf	.578	.799
ONEmosF	.687	.898
FIVEmosBf	.446	.642
FIVEmosF	.596	.816

Two Factor Extraction:

Communalities

	Initial	Extraction
HospBf	.534	.586
HospF	.630	.638
ONEmosBf	.578	.865
ONEmosF	.687	.855
FIVEmosBf	.446	.311
FIVEmosF	.596	.562

PCA

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.876	47.926	47.926	2.876	47.926	47.926
2	1.568	26.128	74.054	1.568	26.128	74.054
3	.803	13.375	87.430			
4	.293	4.889	92.319			
5	.277	4.622	96.941			
6	.184	3.059	100.000			

PAF

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.876	47.926	47.926	2.533	42.221	42.221
2	1.568	26.128	74.054	1.283	21.386	63.607
3	.803	13.375	87.430			
4	.293	4.889	92.319			
5	.277	4.622	96.941			
6	.184	3.059	100.000			

Extraction Techniques in Common Factor Analysis

1. **Principal Axis Factoring** (PAF): Squared Multiple correlations
2. **Maximum Likelihood** (ML): Iterative process that produces parameter estimates most likely to have resulted in the actual correlation matrix
3. **Unweighted Least Squares**: Minimizes the sum of the squared differences between observed and reproduced correlation matrices
4. **Generalized Least Squares**: Same as ULS, but correlations are weighted by the inverse of their uniqueness.
5. **Alpha Factoring**: uses and maximizes Cronbach's alpha (internal consistency). Generalizes to a population of measures, not a populatin of individuals (but only for unrotated solution)
6. **Image Factoring**: Common variance in a variable is defined as its linear regression on remaining variables in the correlation matrix, not the factors

PCA

Component	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.876	47.926	47.926
2	1.568	26.128	74.054

PAF

Factor	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.533	42.221	42.221
2	1.283	21.386	63.607

ML

Factor	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.333	38.883	38.883
2	1.479	24.651	63.534

GLS

Factor	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.362	39.374	39.374
2	1.546	25.764	65.138

AF

Factor	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.520	42.007	42.007
2	1.293	21.548	63.555

ULS

Factor	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.534	42.228	42.228
2	1.284	21.404	63.633

IF

Factor	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.106	35.093	35.093
2	.869	14.481	49.574

Which Extraction to use?

Similar results from all options if:

- basic assumptions are met
- the factor structure is clear

Recommendations

<u>Maximum Likelihood</u>

- Confirmatory models
- Normally distributed items
- Larger sample sizes

<u>Principal Axis Factoring</u>

- Less sensitive to non-normality

Factor Scores and Factor-Based Scores

Factor Scores and Factor Based Scores

Estimated Factor Scores

Theoretical model: $Y_1 = b_1F_1 + b_2F_2 + u_1$

Estimated Factor Scores:

$$F'_1 = b_{11}(Y_1) + b_{12}(Y_2) + b_{13}(Y_3) + b_{14}(Y_4)$$
$$F'_2 = b_{21}(Y_1) + b_{22}(Y_2) + b_{23}(Y_3) + b_{24}(Y_4)$$

Assumption: factor loadings are stable and generalizable

Estimated Factor-Based Scores

Estimated Factor Score: $FB'_1 = (Y_1 + Y_2 + Y_3)/3$

Assumption: all variables have equal contribution to the construct

Create Estimated Factor Scores

Regression: Standardized scores have a mean of 0 and a variance = squared multiple correlation between the estimated factor scores and the true factor values

Bartlett: lowers weight on variables with lower loadings

Anderson-Rubin: Modification of Bartlett. Standardized scores have a mean of 0 and a variance = 1

Factor Score Weightings

Factor Scores Method: Regression.

Factor Score Coefficient Matrix		
	Factor	
	1	2
HospBf	-.020	.199
HospF	.145	.073
ONEmosBf	-.117	.774
ONEmosF	.719	-.238
FIVEmosBf	.109	.005
FIVEmosF	.148	.107

Factor Scores Method: Bartlett.

Factor Score Coefficient Matrix		
	Factor	
	1	2
HospBf	-.038	.231
HospF	.225	.035
ONEmosBf	-.101	.846
ONEmosF	.754	-.160
FIVEmosBf	.026	.079
FIVEmosF	.191	-.008

Factor Scores Method: Anderson-Rubin.

Factor Score Coefficient Matrix		
	Factor	
	1	2
HospBf	-.034	.218
HospF	.213	.035
ONEmosBf	-.089	.798
ONEmosF	.711	-.145
FIVEmosBf	.025	.075
FIVEmosF	.180	-.006

Factor Based Scores

Create variables that are a mean of the variables that load on each factor:

FBS_1 = Mean(HospF, ONEmosF, FIVEmosF).
FBS_2 = Mean(HospBF, ONEmosBF, FIVEmosBF).

Correlations Among Various Scores for Factor 1

	FAC1_1 REGR factor score 1	FAC1_2 BART factor score 1	FAC1_3 A-R factor score 1 for	FBS_1 Factor based score
FAC1_1	1	.997	.997	.965
FAC1_2	.997	1	1.000	.966
FAC1_3	.997	1.000	1	.967
FBS_1	.965	.966	.967	1

Should you use Factor Scores on an Exploratory Data Set?

"EFA should be used as an exploratory technique only, and as prelude to follow-up with confirmatory methods…"

"The solutions that we often receive from EFA are highly unstable across samples, and thus factor scores would be highly unstable. This is not a good situation for scientific inquiry"

"EFA was not designed to produce highly refined estimates of latent variables for use in subsequent analyses"

- J. Osbourne, *Best Practices in Exploratory Factor Analysis 2014*

Replication and Confirmation

EFA is an exploratory technique

Best Practices include:

1. Avoid overfitting by replicating
   - If sample size is sufficient, split the sample
   - Run two EFAs on different samples and comparing number of factors, loading structures

2. Follow up with a new sample and use confirmatory factor analysis

Reporting Results

Reporting Results

Extraction method. The EFA was conducted with Principal Axis Factoring.

Determination of the number of factors. A series of criteria were taken into consideration in order to determine the number of factors (i.e. parallel analysis and simple structure).

Rotation method. The Factor Structure Loadings were interpreted using a Promax rotation.

Reporting Results

Factor summary. Factor 1 accounted for 42.2 % of variance with an eigenvalue of 2.53. Factor 2 accounted for 21.4% of variance with an eigenvalue of 1.28. The two-factor model accounted for 63.6% of variance. The factor analysis summary is shown in Table 1.

Table 1. ***Eigenvalues, Percentages of Variance, and Cumulative Percentages for Factors for the 6 Item Variable Set***

Factor	Eigenvalue	% of variance	Cumulative %
1	2.53	42.2%	42.2%
2	1.28	21.4%	63.6%

Reporting Results

Factor interpretation. The following variables had excellent loadings for Factor 1: HospF, ONEmosF, and FIVEmosF. Any other loadings were insignificant for Factor 1. The following variables had excellent loadings for Factor 2: HospBf and ONEmosBf. The following variables had fair loadings for Factor 2: FIVEmosBf. Any other loadings were insignificant for Factor 2. The factor analysis loadings are shown in Table 2. The factors were correlated at r = .30.

Table 2. *Promax Rotated Factor Structure Loadings From Exploratory Factor Analysis*

	Factor loading		
Variable	1	2	Communality
HospBf		0.76	0.59
HospF	0.78		0.64
ONEmosBf		0.93	0.87
ONEmosF	0.92		0.86
FIVEmosBf		0.52	0.31
FIVEmosF	0.75		0.56

Reporting Results

Evaluating the factor structure. According to Costello and Osborne (2005), examining the communality of each variable, checking for crossloadings across multiple factors, and inspecting the number of strong loadings for each factor are good ways to analyze the validity of the factor structure. Crossloadings occur when there are loadings (> .40) for a single variable across multiple factors.

There were no variables with crossloadings, which suggests a factor structure that is simple and easy to interpret. Each factor had at least three significant loadings (> .40), which is indicative of a strong and solid factor (Osborne & Costello, 2005). Costello and Osborne (2005) also suggest dropping variables with low communality, crossloadings, and any variable that is the only significant loading on a factor which may prevent a weak factor structure and alleviate these problems.

Example: Social Anxiety Scale

Example: Social Anxiety Scale

PrAnxAuth	I get nervous if I have to speak with someone in authority
PrAnxEye	I have difficulty making eye-contact with others
PrAnxStreet	I tense-up if I meet an acquaintance on the street
PrAnxMix	When mixing socially I feel uncomfortable
PrAnxOne	I feel tense if I am alone with just one other person
PrAnxTalk	I have difficulty talking with other people
PrAnxExp	I worry about expressing myself in case I appear awkward
PrAnxSay	I find myself worrying that I won't know what to say in social situations
PrAnxWell	I am nervous mixing with people that I don't know well
PrAnxEmbarr	I feel I'll say something embarrassing when talking
PrAnxIgn	When mixing in a group, I find myself worrying that I will be ignored
PrAnxTense	I am tense mixing in a group
PrAnxGreet	I am unsure whether to greet someone I know only slightly
PrAnxSelf	I have high self-esteem

1	Not at all
2	Slightly
3	Moderately
4	Very
5	Extremely

Exploratory Factor Analysis Steps

1. Initial Extraction of the Factors
2. Determine the Number of Factors to Retain
3. Rotation
4. Interpret the Rotated Solution
5. Create Factor Scores
6. Summarize the results in a Table
7. Write a formal description of results for a paper

Correlation Matrix

	PrAnxAuth	PrAnxEye	PrAnxStreet	PrAnxMix	PrAnxOne	PrAnxTalk	PrAnxExp	PrAnxSay	PrAnxWell	PrAnxEmbarr	PrAnxIgn	PrAnxTense	PrAnxGreet	PrAnxSelf
PrAnxAuth	1	0.346	0.329	0.43	0.257	0.384	0.465	0.428	0.464	0.493	0.354	0.359	0.284	-0.321
PrAnxEye	0.346	1	0.48	0.51	0.403	0.387	0.346	0.345	0.491	0.321	0.311	0.487	0.364	-0.284
PrAnxStreet	0.329	0.48	1	0.555	0.511	0.499	0.395	0.415	0.456	0.399	0.415	0.485	0.475	-0.221
PrAnxMix	0.43	0.51	0.555	1	0.501	0.63	0.614	0.608	0.713	0.587	0.573	0.727	0.474	-0.387
PrAnxOne	0.257	0.403	0.511	0.501	1	0.455	0.399	0.366	0.32	0.397	0.4	0.447	0.328	-0.239
PrAnxTalk	0.384	0.387	0.499	0.63	0.455	1	0.564	0.535	0.619	0.517	0.42	0.609	0.352	-0.285
PrAnxExp	0.465	0.346	0.395	0.614	0.399	0.564	1	0.733	0.641	0.7	0.567	0.615	0.437	-0.436
PrAnxSay	0.428	0.345	0.415	0.608	0.366	0.535	0.733	1	0.695	0.69	0.621	0.694	0.465	-0.373
PrAnxWell	0.464	0.491	0.456	0.713	0.32	0.619	0.641	0.695	1	0.63	0.565	0.71	0.521	-0.405
PrAnxEmbarr	0.493	0.321	0.399	0.587	0.397	0.517	0.7	0.69	0.63	1	0.568	0.621	0.398	-0.446
PrAnxIgn	0.354	0.311	0.415	0.573	0.4	0.42	0.567	0.621	0.565	0.568	1	0.634	0.4	-0.443
PrAnxTense	0.359	0.487	0.485	0.727	0.447	0.609	0.615	0.694	0.71	0.621	0.634	1	0.488	-0.457
PrAnxGreet	0.284	0.364	0.475	0.474	0.328	0.352	0.437	0.465	0.521	0.398	0.4	0.488	1	-0.237
PrAnxSelf	-0.321	-0.284	-0.221	-0.387	-0.239	-0.285	-0.436	-0.373	-0.405	-0.446	-0.443	-0.457	-0.237	1

Run an Initial Model

Options:

1. Four Factors
2. Principal Axis Factoring
3. Promax Rotation
4. Scree test, Parallel Analysis, MAP test, interpretability

Initial Extraction of the Factors

Total Variance Explained

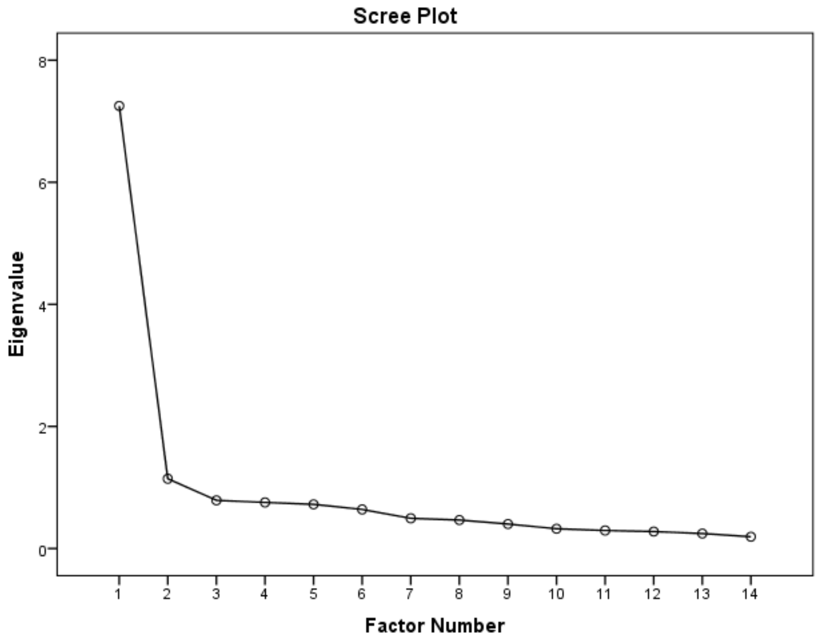
Factor	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %
1	7.252	51.797	51.797	6.886	49.188	49.188
2	1.143	8.168	59.964	.704	5.027	54.215
3	.789	5.639	65.603	.343	2.453	56.669
4	.755	5.392	70.995	.275	1.965	58.633
5	.723	5.168	76.162			
6	.640	4.570	80.732			
7	.495	3.536	84.268			
8	.466	3.328	87.596			
9	.401	2.867	90.463			
10	.324	2.314	92.777			
11	.295	2.107	94.885			
12	.278	1.985	96.869			
13	.245	1.752	98.621			
14	.193	1.379	100.000			

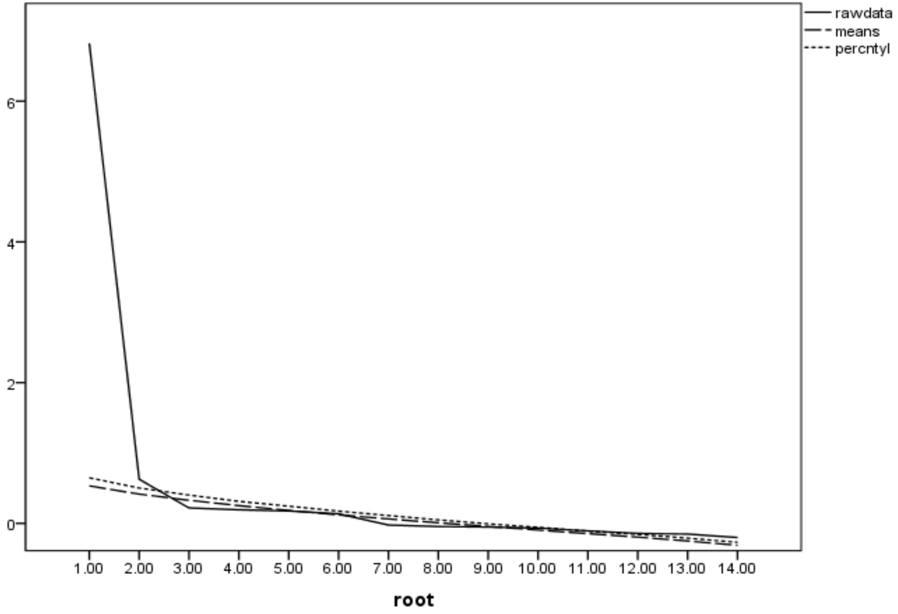
Extraction Method: Principal Axis Factoring.

Communalities

	Initial	Extraction
PrAnxAuth	.332	.435
PrAnxEye	.396	.435
PrAnxStreet	.472	.585
PrAnxMix	.678	.710
PrAnxOne	.405	.544
PrAnxTalk	.537	.506
PrAnxExp	.654	.709
PrAnxSay	.688	.712
PrAnxWell	.702	.876
PrAnxEmbarr	.619	.713
PrAnxIgn	.522	.561
PrAnxTense	.701	.794
PrAnxGreet	.371	.353
PrAnxSelf	.306	.276

Initial Extraction of the Factors





Warning: Parallel analyses of adjusted correlation matrices eg, with SMCs on the diagonal, tend to indicate more factors than warranted (Buja, A., & Eyuboglu, N., 1992, Remarks on parallel analysis. Multivariate Behavioral Research, 27, 509-540.).

Initial Extraction of the Factors

Velicer's Minimum Average Partial (MAP) Test:

Average Partial Correlations

	squared	power4
.0000	.2363	.0712
1.0000	.0211	.0012
2.0000	.0219	.0014
3.0000	.0322	.0047
4.0000	.0477	.0089
5.0000	.0649	.0139
6.0000	.0795	.0223
7.0000	.1019	.0399
8.0000	.1469	.0588
9.0000	.1987	.1050
10.0000	.2715	.1509
11.0000	.3812	.2485
12.0000	.4763	.3602
13.0000	1.0000	1.0000

The smallest average squared partial correlation is: .0211

The smallest average 4rth power partial correlation is: .0012

The Number of Components According to the Original (1976) MAP Test is: 1

The Number of Components According to the Revised (2000) MAP Test is: 1

Structure Matrix				
	Factor			
	1	2	3	4
PrAnxAuth	.499	.402	.457	.566
PrAnxEye	.410	.602	.572	
PrAnxStreet	.478	.757	.564	
PrAnxMix	.736	.735	.778	
PrAnxOne	.481	.717	.390	
PrAnxTalk	.623	.625	.639	.310
PrAnxExp	.825	.533	.621	.459
PrAnxSay	.837	.523	.682	.334
PrAnxWell	.759	.556	.916	.393
PrAnxEmbarr	.817	.517	.587	.489
PrAnxIgn	.739	.533	.570	
PrAnxTense	.815	.671	.794	
PrAnxGreet	.500	.519	.557	
PrAnxSelf	-.522	-.334	-.403	

The Interpretability criteria

☑ 1. Minimum of three items with high loadings on each

2. Items loading on same factor make sense

3. Items loading on different factors make sense

☒ 4. Simple structure

Factor Correlation Matrix

Factor	1	2	3	4
1	1.000	.645	.746	.363
2	.645	1.000	.676	.239
3	.746	.676	1.000	.305
4	.363	.239	.305	1.000

Structure Matrix		
	Factor	
	1	2
PrAnxAuth	.538	.450
PrAnxEye	.464	.640
PrAnxStreet	.505	.766
PrAnxMix	.771	.801
PrAnxOne	.465	.626
PrAnxTalk	.656	.675
PrAnxExp	.830	.589
PrAnxSay	.845	.598
PrAnxWell	.816	.700
PrAnxEmbarr	.814	.569
PrAnxIgn	.714	.570
PrAnxTense	.811	.738
PrAnxGreet	.529	.571
PrAnxSelf	-.524	-.372

The Interpretability criteria

☑ 1. Minimum of three items with high loadings on each

2. Items loading on same factor make sense

3. Items loading on different factors make sense

☒ 4. Simple structure

Factor Correlation Matrix		
Factor	1	2
1	1.000	.747
2	.747	1.000

Factor Matrix	
	Factor
	1
PrAnxAuth	.540
PrAnxEye	.553
PrAnxStreet	.616
PrAnxMix	.831
PrAnxOne	.548
PrAnxTalk	.706
PrAnxExp	.787
PrAnxSay	.800
PrAnxWell	.828
PrAnxEmbarr	.768
PrAnxIgn	.706
PrAnxTense	.839
PrAnxGreet	.578
PrAnxSelf	-.501

The Interpretability criteria

1. ☑ Minimum of three items with high loadings on each
2. ☑ Items loading on same factor make sense
3. Items loading on different factors make sense
4. ☑ Simple structure

Determine the Number of Factors to Retain

Criterion	Number of Factors Suggested
Kaiser	1
Total Variance Accounted for	4
Scree Plot	1
Parallel Analysis	1-2
MAP Test	1
Interpretability	1

One Factor Solution

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.252	51.797	51.797	6.788	48.487	48.487
2	1.143	8.168	59.964			
3	.789	5.639	65.603			
4	.755	5.392	70.995			
5	.723	5.168	76.162			
6	.640	4.570	80.732			
7	.495	3.536	84.268			
8	.466	3.328	87.596			
9	.401	2.867	90.463			
10	.324	2.314	92.777			
11	.295	2.107	94.885			
12	.278	1.985	96.869			
13	.245	1.752	98.621			
14	.193	1.379	100.000			

One Factor Solution

Factor Matrix

	Factor
	1
PrAnxAuth	.540
PrAnxEye	.553
PrAnxStreet	.616
PrAnxMix	.831
PrAnxOne	.548
PrAnxTalk	.706
PrAnxExp	.787
PrAnxSay	.800
PrAnxWell	.828
PrAnxEmbarr	.768
PrAnxIgn	.706
PrAnxTense	.839
PrAnxGreet	.578
PrAnxSelf	-.501

Communalities

	Initial	Extraction
PrAnxAuth	.332	.292
PrAnxEye	.396	.305
PrAnxStreet	.472	.380
PrAnxMix	.678	.691
PrAnxOne	.405	.301
PrAnxTalk	.537	.498
PrAnxExp	.654	.620
PrAnxSay	.688	.640
PrAnxWell	.702	.685
PrAnxEmbarr	.619	.590
PrAnxIgn	.522	.499
PrAnxTense	.701	.703
PrAnxGreet	.371	.334
PrAnxSelf	.306	.251

One Factor Solution: 12 Variables

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.691	55.757	55.757	6.251	52.088	52.088
2	1.085	9.045	64.802			
3	.729	6.075	70.877			
4	.662	5.514	76.391			
5	.558	4.653	81.044			
6	.484	4.030	85.074			
7	.426	3.549	88.623			
8	.325	2.708	91.331			
9	.298	2.485	93.816			
10	.292	2.433	96.249			
11	.252	2.100	98.349			
12	.198	1.651	100.000			

One Factor Solution: 12 Variables

Factor Matrix

	Factor 1
PrAnxEye	.548
PrAnxStreet	.625
PrAnxMix	.836
PrAnxOne	.555
PrAnxTalk	.712
PrAnxExp	.778
PrAnxSay	.802
PrAnxWell	.826
PrAnxEmbarr	.753
PrAnxIgn	.700
PrAnxTense	.845
PrAnxGreet	.586

Communalities

	Initial	Extraction
PrAnxEye	.380	.300
PrAnxStreet	.469	.391
PrAnxMix	.677	.699
PrAnxOne	.404	.308
PrAnxTalk	.534	.507
PrAnxExp	.645	.605
PrAnxSay	.684	.643
PrAnxWell	.700	.682
PrAnxEmbarr	.597	.567
PrAnxIgn	.508	.490
PrAnxTense	.688	.714
PrAnxGreet	.370	.343

One Factor Solution: 8 Variables

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.349	66.863	66.863	4.982	62.273	62.273
2	.647	8.091	74.955			
3	.519	6.484	81.439			
4	.375	4.690	86.129			
5	.323	4.032	90.161			
6	.299	3.741	93.901			
7	.275	3.432	97.334			
8	.213	2.666	100.000			

One Factor Solution : 8 Variables

Factor Matrix	Factor 1
PrAnxMix	.805
PrAnxTalk	.696
PrAnxExp	.806
PrAnxSay	.833
PrAnxWell	.835
PrAnxEmbarr	.780
PrAnxIgn	.699
PrAnxTense	.842

Communalities

	Initial	Extraction
PrAnxMix	.644	.649
PrAnxTalk	.491	.485
PrAnxExp	.640	.649
PrAnxSay	.678	.695
PrAnxWell	.659	.697
PrAnxEmbarr	.592	.608
PrAnxIgn	.486	.489
PrAnxTense	.678	.710

Two Factor Solution? 8 Variables

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.349	66.863	66.863	5.027	62.831	62.831
2	.647	8.091	74.955	.302	3.778	66.609
3	.519	6.484	81.439			
4	.375	4.690	86.129			
5	.323	4.032	90.161			
6	.299	3.741	93.901			
7	.275	3.432	97.334			
8	.213	2.666	100.000			

Two Factor Solution? 8 Variables

Factor Matrix		
	Factor 1	Factor 2
PrAnxMix	.820	
PrAnxTalk	.699	
PrAnxExp	.809	
PrAnxSay	.842	
PrAnxWell	.833	
PrAnxEmbarr	.784	
PrAnxIgn	.697	
PrAnxTense	.842	

Communalities		
	Initial	Extraction
PrAnxMix	.644	.760
PrAnxTalk	.491	.522
PrAnxExp	.640	.694
PrAnxSay	.678	.767
PrAnxWell	.659	.709
PrAnxEmbarr	.592	.657
PrAnxIgn	.486	.493
PrAnxTense	.678	.727

Reporting Results

Extraction method. The EFA was conducted with Principal Axis Factoring.

Determination of the number of factors. A series of criteria were taken into consideration in order to determine the number of factors (i.e. parallel analysis and simple structure).

Rotation method. The Factor Structure Loadings were interpreted using a Promax rotation.

Reporting Results

Factor summary. In the final model, eight of the original 14 variables were retained. A single factor accounted for 62.3% of the variance with an eigenvalue of 5.03. The factor analysis summary is shown in Table 1.

Table 1. ***Eigenvalues, Percentages of Variance, and Cumulative Percentages for Factors for the 8 Item Variable Set***

Factor	Eigenvalue	% of variance	Cumulative %
1	5.027	62.831	62.831

Reporting Results

Factor interpretation. All eight variables had excellent loadings on the single factor. The factor analysis loadings are shown in Table 2.

Table 2. *Factor Loadings From Exploratory Factor Analysis*

Variable	Factor Loading	Communality
PrAnxMix	.820	.760
PrAnxTalk	.699	.522
PrAnxExp	.809	.694
PrAnxSay	.842	.767
PrAnxWell	.833	.709
PrAnxEmbarr	.784	.657
PrAnxIgn	.697	.493
PrAnxTense	.842	.727

Reporting Results

Evaluating the factor structure. According to Costello and Osborne (2005), examining the communality of each variable, checking for crossloadings across multiple factors, and inspecting the number of strong loadings for each factor are good ways to analyze the validity of the factor structure. Crossloadings occur when there are loadings (> .40) for a single variable across multiple factors.

There were many variables with crossloadings on a four and two-factor solution. Parallel analysis and interpretability criteria both suggested a single factor. Costello and Osborne (2005) also suggest dropping variables with low communality, crossloadings and any variable that is the only significant loading on a factor which may prevent a weak factor structure and alleviate these problems. To strengthen the scale, four variables with low communalities were dropped and a final 8-item scale of a single factor representing social anxiety is presented.