

## FACTOR ANALYSIS | SPSS ANNOTATED OUTPUT

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This page shows an example of a factor analysis with footnotes explaining the output. The data used in this example were collected by Professor James Sidanius, who has generously shared them with us. You can download the data set [here \(https://stats.idre.ucla.edu/wp-content/uploads/2016/02/M255.sav\)](https://stats.idre.ucla.edu/wp-content/uploads/2016/02/M255.sav).

Overview: The "what" and "why" of factor analysis

Factor analysis is a method of data reduction. It does this by seeking underlying unobservable (latent) variables that are reflected in the observed variables (manifest variables). There are many different methods that can be used to conduct a factor analysis (such as principal axis factor, maximum likelihood, generalized least squares, unweighted least squares). There are also many different types of rotations that can be done after the initial extraction of factors, including orthogonal rotations, such as varimax and equimax, which impose the restriction that the factors cannot be correlated, and oblique rotations, such as promax, which allow the factors to be correlated with one another. You also need to determine the number of factors that you want to extract. Given the number of factor analytic techniques and options, it is not surprising that different analysts could reach very different results analyzing the same data set. However, all analysts are looking for simple structure. Simple structure is pattern of results such that each variable loads highly onto one and only one factor.

Factor analysis is a technique that requires a large sample size. Factor analysis is based on the correlation matrix of the variables involved, and correlations usually need a large sample size before they stabilize. Tabachnick and Fidell (2001, page 588) cite Comrey and Lee's (1992) advice regarding sample size: 50 cases is very poor, 100 is poor, 200 is fair, 300 is good, 500 is very good, and 1000 or more is excellent. As a rule of thumb, a bare minimum of 10 observations per variable is necessary to avoid computational difficulties.

For the example below, we are going to do a rather "plain vanilla" factor analysis. We will use iterated principal axis factor with three factors as our method of extraction, a varimax rotation, and for comparison, we will also show the promax oblique solution. The determination of the number of factors to extract should be guided by theory, but also informed by running the analysis extracting different numbers of factors and seeing which number of factors yields the most interpretable results.

In this example we have included many options, including the original and reproduced correlation matrix, the scree plot and the plot of the rotated factors. While you may not wish to use all of these options, we have included them here to aid in the explanation of the analysis. We have also created a page of annotated output for a principal components analysis that parallels this analysis. For general information regarding the similarities and differences between principal components analysis and factor analysis, see Tabachnick and Fidell (2001), for example.

```
factor
/variables item13 item14 item15 item16 item17 item18 item19 item20 item21 item22 item23 item24
/print initial det kmo repr extraction rotation fscore univariate
/format blank(.30)
/plot eigen rotation
/criteria factors(3)
/extraction paf
/rotation varimax
/method = correlation.
```

## Descriptive Statistics

	Mean <b>a</b>	Std. Deviation <b>b</b>	Analysis N <b>c</b>
INSTRUC WELL PREPARED	4.46	.729	1365
INSTRUC SCHOLARLY GRASP	4.53	.700	1365
INSTRUCTOR CONFIDENCE	4.45	.732	1365
INSTRUCTOR FOCUS LECTURES	4.28	.829	1365
INSTRUCTOR USES CLEAR RELEVANT EXAMPLES	4.17	.895	1365
INSTRUCTOR SENSITIVE TO STUDENTS	3.93	1.035	1365
INSTRUCTOR ALLOWS ME TO ASK QUESTIONS	4.08	.964	1365
INSTRUCTOR IS ACCESSIBLE TO STUDENTS OUTSIDE CLASS	3.78	.909	1365
INSTRUCTOR AWARE OF STUDENTS UNDERSTANDING	3.77	.984	1365
I AM SATISFIED WITH STUDENT PERFORMANCE EVALUATION	3.61	1.116	1365
COMPARED TO OTHER INSTRUCTORS, THIS INSTRUCTOR IS	3.81	.957	1365
COMPARED TO OTHER COURSES THIS COURSE WAS	3.67	.926	1365

The table above is output because we used the **univariate** option on the **/print** subcommand. Please note that the only way to see how many cases were actually used in the factor analysis is to include the **univariate** option on the **/print** subcommand. The number of cases used in the analysis will be less than the total number of cases in the data file if there are missing values on any of the variables used in the factor analysis, because, by default, SPSS does a listwise deletion of incomplete cases. If the factor analysis is being conducted on the correlations (as opposed to the covariances), it is not much of a concern that the variables have very different means and/or standard deviations (which is often the case when variables are measured on different scales).

- a. **Mean** – These are the means of the variables used in the factor analysis.
- b. **Std. Deviation** – These are the standard deviations of the variables used in the factor analysis.
- c. **Analysis N** – This is the number of cases used in the factor analysis.

## Correlation Matrix<sup>a</sup>

a. Determinant = .002

The table above is included in the output because we used the **det** option on the **/print** subcommand. All we want to see in this table is that the determinant is not 0. If the determinant is 0, then there will be computational problems with the factor analysis, and SPSS may issue a warning message or be unable to complete the factor analysis.

**KMO and Bartlett's Test**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy. <b>a</b>		.934
Bartlett's Test of Sphericity <b>b</b>	Approx. Chi-Square	8676.712
	df	66
	Sig.	.000

a. **Kaiser-Meyer-Olkin Measure of Sampling Adequacy** – This measure varies between 0 and 1, and values closer to 1 are better. A value of .6 is a suggested minimum.

b. **Bartlett's Test of Sphericity** – This tests the null hypothesis that the correlation matrix is an identity matrix. An identity matrix is matrix in which all of the diagonal elements are 1 and all off diagonal elements are 0. You want to reject this null hypothesis.

Taken together, these tests provide a minimum standard which should be passed before a factor analysis (or a principal components analysis) should be conducted.

**Communalities<sup>a</sup>**

	Initial <sup>b</sup>	Extraction <sup>c</sup>
item13 INSTRUC WELL PREPARED	.564	.676
item14 INSTRUC SCHOLARLY GRASP	.551	.619
item15 INSTRUCTOR CONFIDENCE	.538	.592
item16 INSTRUCTOR FOCUS LECTURES	.447	.468
item17 INSTRUCTOR USES CLEAR RELEVANT EXAMPLES	.585	.623
item18 INSTRUCTOR SENSITIVE TO STUDENTS	.572	.679
item19 INSTRUCTOR ALLOWS ME TO ASK QUESTIONS	.456	.576
item20 INSTRUCTOR IS ACCESSIBLE TO STUDENTS OUTSIDE CLASS	.326	.369
item21 INSTRUCTOR AWARE OF STUDENTS UNDERSTANDING	.516	.549
item22 I AM SATISFIED WITH STUDENT PERFORMANCE EVALUATION	.397	.444
item23 COMPARED TO OTHER INSTRUCTORS, THIS INSTRUCTOR IS	.662	.791
item24 COMPARED TO OTHER COURSES THIS COURSE WAS	.526	.632

Extraction Method: Principal Axis Factoring.

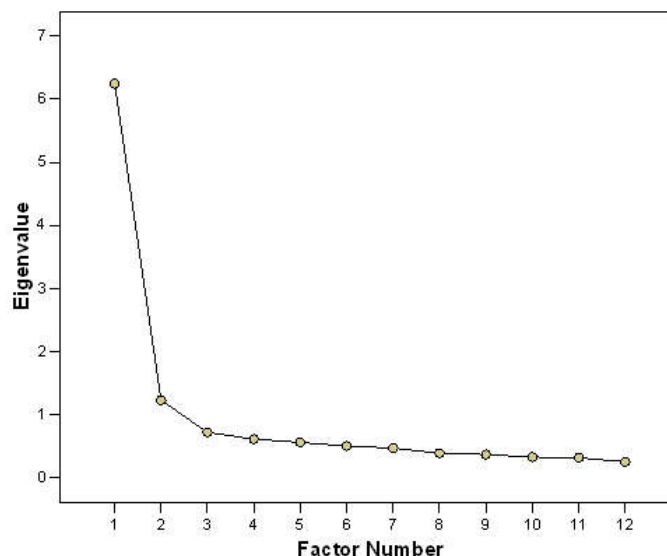
- a. **Communalities** – This is the proportion of each variable’s variance that can be explained by the factors (e.g., the underlying latent continua). It is also noted as  $h^2$  and can be defined as the sum of squared factor loadings for the variables.
- b. **Initial** – With principal factor axis factoring, the initial values on the diagonal of the correlation matrix are determined by the squared multiple correlation of the variable with the other variables. For example, if you regressed items 14 through 24 on item 13, the squared multiple correlation coefficient would be .564.
- c. **Extraction** – The values in this column indicate the proportion of each variable’s variance that can be explained by the retained factors. Variables with high values are well represented in the common factor space, while variables with low values are not well represented. (In this example, we don’t have any particularly low values.) They are the reproduced variances from the factors that you have extracted. You can find these values on the diagonal of the reproduced correlation matrix.

Factor <sup>A</sup>	Initial Eigenvalues <sup>B</sup>			Total Variance Explained			Rotation Sums of Squared Loadings <sup>C</sup>		
	Total <sup>F</sup>	% of Variance <sup>G</sup>	Cumulative % <sup>H</sup>	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
	1	6.249	52.076	52.076	5.951	49.598	48.759	2.950	24.563
2	1.229	10.248	62.322	.806	6.719	55.478	2.855	22.127	46.710
3	.719	5.992	68.313	.380	3.000	58.478	1.412	11.769	58.478
4	.613	5.109	73.423						
5	.561	4.676	78.099						
6	.503	4.192	82.291						
7	.471	3.927	86.218						
8	.389	3.240	89.458						
9	.368	3.066	92.524						
10	.328	2.735	95.259						
11	.317	2.645	97.904						
12	.252	2.098	100.000						

Extraction Method: Principal Axis Factoring.

- Factor** – The initial number of factors is the same as the number of variables used in the factor analysis. However, not all 12 factors will be retained. In this example, only the first three factors will be retained (as we requested).
- Initial Eigenvalues** – Eigenvalues are the variances of the factors. Because we conducted our factor analysis on the correlation matrix, the variables are standardized, which means that each variable has a variance of 1, and the total variance is equal to the number of variables used in the analysis, in this case, 12.
- Total** – This column contains the eigenvalues. The first factor will always account for the most variance (and hence have the highest eigenvalue), and the next factor will account for as much of the left over variance as it can, and so on. Hence, each successive factor will account for less and less variance.
- % of Variance** – This column contains the percent of total variance accounted for by each factor.
- Cumulative %** – This column contains the cumulative percentage of variance accounted for by the current and all preceding factors. For example, the third row shows a value of 68.313. This means that the first three factors together account for 68.313% of the total variance.
- Extraction Sums of Squared Loadings** – The number of rows in this panel of the table correspond to the number of factors retained. In this example, we requested that three factors be retained, so there are three rows, one for each retained factor. The values in this panel of the table are calculated in the same way as the values in the left panel, except that here the values are based on the common variance. The values in this panel of the table will always be lower than the values in the left panel of the table, because they are based on the common variance, which is always smaller than the total variance.
- Rotation Sums of Squared Loadings** – The values in this panel of the table represent the distribution of the variance after the varimax rotation. Varimax rotation tries to maximize the variance of each of the factors, so the total amount of variance accounted for is redistributed over the three extracted factors.

Scree Plot



The scree plot graphs the eigenvalue against the factor number. You can see these values in the first two columns of the table immediately above. From the third factor on, you can see that the line is almost flat, meaning the each successive factor is accounting for smaller and smaller amounts of the total variance.

Factor Matrix<sup>a</sup>

	Factor <sup>c</sup>		
	1	2	3
item13 INSTRUC WELL PREPARED	.713	-.398	
item14 INSTRUC SCHOLARLY GRASP	.703	-.339	
item15 INSTRUCTOR CONFIDENCE	.721		
item16 INSTRUCTOR FOCUS LECTURES	.648		
item17 INSTRUCTOR USES CLEAR RELEVANT EXAMPLES	.783		
item18 INSTRUCTOR SENSITIVE TO STUDENTS	.740	.345	
item19 INSTRUCTOR ALLOWS ME TO ASK QUESTIONS	.616	.415	
item20 INSTRUCTOR IS ACCESSIBLE TO STUDENTS OUTSIDE CLASS	.550		
item21 INSTRUCTOR AWARE OF STUDENTS UNDERSTANDING	.732		
item22 I AM SATISFIED WITH STUDENT PERFORMANCE EVALUATION	.613		
item23 COMPARED TO OTHER INSTRUCTORS, THIS INSTRUCTOR IS	.819		-.345
item24 COMPARED TO OTHER COURSES THIS COURSE WAS	.695		-.386

Extraction Method: Principal Axis Factoring.

a. 3 factors extracted. 7 iterations required.

b. **Factor Matrix** – This table contains the unrotated factor loadings, which are the correlations between the variable and the factor. Because these are correlations, possible values range from -1 to +1. On the **/format** subcommand, we used the option **blank(.30)**, which tells SPSS not to print any of the correlations that are .3 or less. This makes the output easier to read by removing the clutter of low correlations that are probably not meaningful anyway.

c. **Factor** – The columns under this heading are the unrotated factors that have been extracted. As you can see by the footnote provided by SPSS (a.), three factors were extracted (the three factors that we requested).

		Reproduced Correlations <sup>a</sup>											
		Item13 INSTRUC- TIVE WELL- PREPARED	Item4 INSTRUC- TIONAL COM- PREHENSIV- E	Item5 INSTRUC- TIVE COM- PREHENSIV- E	Item6 INSTRUC- TIVE COM- PREHENSIV- E	Item7 INSTRUC- TIVE COM- PREHENSIV- E	Item8 INSTRUC- TIVE COM- PREHENSIV- E	Item9 INSTRUC- TIVE COM- PREHENSIV- E	Item10 INSTRUC- TIVE COM- PREHENSIV- E	Item11 INSTRUC- TIVE COM- PREHENSIV- E	Item12 INSTRUC- TIVE COM- PREHENSIV- E	Item13 INSTRUC- TIVE COM- PREHENSIV- E	
Reproduced Correlation	Item13 INSTRUC- TIVE WELL- PREPARED	.676	.686	.622	.548	.584	.406	.268	.286	.475	.331	.583	.653
	Item4 INSTRUC- TIONAL COM- PREHENSIV- E	.646	.619 <sup>b</sup>	.601	.571	.562	.414	.288	.275	.479	.349	.581	.646
	Item5 INSTRUC- TIVE COM- PREHENSIV- E	.622	.601	.602 <sup>b</sup>	.578	.563	.461	.284	.288	.499	.378	.581	.646
	Item6 INSTRUC- TIVE COM- PREHENSIV- E	.548	.571	.578	.608 <sup>b</sup>	.529	.428	.278	.272	.452	.349	.487	.604
	Item7 INSTRUC- TIVE COM- PREHENSIV- E	.584	.562	.563	.529	.622 <sup>b</sup>	.563	.462	.479	.505	.479	.623	.617
	Item8 INSTRUC- TIVE COM- PREHENSIV- E	.406	.414	.461	.428	.461	.671 <sup>b</sup>	.518	.583	.552	.541	.583	.671
	Item9 INSTRUC- TIVE COM- PREHENSIV- E	.268	.288	.278	.278	.462	.518	.671 <sup>b</sup>	.493	.505	.493	.641	.574
	Item10 INSTRUC- TIVE COM- PREHENSIV- E	.286	.275	.288	.272	.479	.505	.493	.671 <sup>b</sup>	.491	.588	.612	.591
	Item11 INSTRUC- TIVE COM- PREHENSIV- E	.475	.479	.499	.452	.505	.552	.505	.491	.641 <sup>b</sup>	.479	.588	.571
	Item12 INSTRUC- TIVE COM- PREHENSIV- E	.331	.349	.378	.345	.479	.541	.483	.588	.479	.641 <sup>b</sup>	.583	.646
	Item13 INSTRUC- TIVE COM- PREHENSIV- E	.583	.581	.581	.607	.623	.588	.641	.612	.588	.583	.781 <sup>b</sup>	.583
	Item14 INSTRUC- TIVE COM- PREHENSIV- E	.653	.646	.658	.604	.617	.677	.678	.681	.611	.648	.782	.653 <sup>b</sup>
Residual <sup>b</sup>	Item13 INSTRUC- TIVE WELL- PREPARED		.016	-.022	-.018	-.017	.008	-.002	-.001	.008	.001	.001	.001
	Item4 INSTRUC- TIONAL COM- PREHENSIV- E	.016		.024	-.014	-.023	.018	.013	.008	-.006	-.007	.013	-.002
	Item5 INSTRUC- TIVE COM- PREHENSIV- E	-.022	.024		-.035	.023	-.004	.008	.009	.010	-.007	.022	-.023
	Item6 INSTRUC- TIVE COM- PREHENSIV- E	.018	-.021	-.020		.009	-.022	-.003	-.003	.003	.017	-.028	.028
	Item7 INSTRUC- TIVE COM- PREHENSIV- E	-.017	-.021	-.003	.028		.007	-.053	-.063	-.031	-.008	.087	-.003
	Item8 INSTRUC- TIVE COM- PREHENSIV- E	.008	.008	-.004	-.022	-.007		.018	.021	-.027	-.006	.013	-.003
	Item9 INSTRUC- TIVE COM- PREHENSIV- E	-.002	.013	.003	-.003	-.013	.018		-.008	.003	.003	.003	-.003
	Item10 INSTRUC- TIVE COM- PREHENSIV- E	-.001	-.006	.006	-.006	-.003	.021	-.008		-.006	-.016	.003	.003
	Item11 INSTRUC- TIVE COM- PREHENSIV- E	.003	-.028	.010	.008	.023	-.027	.008	-.009		.027	.001	-.011
	Item12 INSTRUC- TIVE COM- PREHENSIV- E	.001	-.007	-.007	.017	-.008	-.002	-.018	.027	.027		.013	.008
	Item13 INSTRUC- TIVE COM- PREHENSIV- E	.001	.013	.022	-.018	-.007	.012	.003	-.003	.001	-.018		.003
	Item14 INSTRUC- TIVE COM- PREHENSIV- E	.001	-.002	-.021	.028	.003	-.002	-.002	.007	-.011	.003	.003	

<sup>a</sup> Statistics are computed between observed and reproduced correlations. There are 1 (1) (1%) nonredundant residuals with absolute values greater than .055.  
<sup>b</sup> Residuals are nonredundant.

c. **Reproduced Correlations** – This table contains two tables, the reproduced correlations in the top part of the table, and the residuals in the bottom part of the table.

d. **Reproduced Correlation** – The reproduced correlation matrix is the correlation matrix based on the extracted factors. You want the values in the reproduced matrix to be as close to the values in the original correlation matrix as possible. This means that the residual matrix, which contains the differences between the original and the reproduced matrix to be close to zero. If the reproduced matrix is very similar to the original correlation matrix, then you know that the factors that were extracted accounted for a great deal of the variance in the original correlation matrix, and these few factors do a good job of representing the original data. The numbers on the diagonal of the reproduced correlation matrix are presented in the Communalities table in the column labeled Extracted.

e. **Residual** – As noted in the first footnote provided by SPSS (a.), the values in this part of the table represent the differences between original correlations (shown in the correlation table at the beginning of the output) and the reproduced correlations, which are shown in the top part of this table. For example, the original correlation between item13 and item14 is .661, and the reproduced correlation between these two variables is .646. The residual is .661 – .646 (with some rounding error).



Rotated Factor Matrix<sup>a</sup><sup>b</sup>

	Factor <sup>c</sup>		
	1	2	3
item13 INSTRUC WELL PREPARED	.771		
item14 INSTRUC SCHOLARLY GRASP	.726		
item15 INSTRUCTOR CONFIDENCE	.676		
item16 INSTRUCTOR FOCUS LECTURES	.591		
item17 INSTRUCTOR USES CLEAR RELEVANT EXAMPLES	.587	.446	
item18 INSTRUCTOR SENSITIVE TO STUDENTS		.739	
item19 INSTRUCTOR ALLOWS ME TO ASK QUESTIONS		.727	
item20 INSTRUCTOR IS ACCESSIBLE TO STUDENTS OUTSIDE CLASS		.540	
item21 INSTRUCTOR AWARE OF STUDENTS UNDERSTANDING	.402	.533	.321
item22 I AM SATISFIED WITH STUDENT PERFORMANCE EVALUATION		.559	
item23 COMPARED TO OTHER INSTRUCTORS, THIS INSTRUCTOR IS	.449	.377	.668
item24 COMPARED TO OTHER COURSES THIS COURSE WAS	.324	.321	.652

Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

b. **Rotated Factor Matrix** – This table contains the rotated factor loadings (factor pattern matrix), which represent both how the variables are weighted for each factor but also the correlation between the variables and the factor. Because these are correlations, possible values range from -1 to +1. On the **/format** subcommand, we used the option **blank(.30)**, which tells SPSS not to print any of the correlations that are .3 or less. This makes the output easier to read by removing the clutter of low correlations that are probably not meaningful anyway.

For orthogonal rotations, such as varimax, the factor pattern and factor structure matrices are the same.

c. **Factor** – The columns under this heading are the rotated factors that have been extracted. As you can see by the footnote provided by SPSS (a.), three factors were extracted (the three factors that we requested). These are the factors that analysts are most interested in and try to name. For example, the first factor might be called "instructor competence" because items like "instructor well prepare" and "instructor competence" load highly on it. The second factor might be called "relating to students" because items like "instructor is sensitive to students" and "instructor allows me to ask questions" load highly on it. The third factor has to do with comparisons to other instructors and courses.



The table below is from another run of the factor analysis program shown above, except with a promax rotation. We have included it here to show how different the rotated solutions can be, and to better illustrate what is meant by simple structure. As you can see with an oblique rotation, such as a promax rotation, the factors are permitted to be correlated with one another. With an orthogonal rotation, such as the varimax shown above, the factors are not permitted to be correlated (they are orthogonal to one another). Oblique rotations, such as promax, produce both factor pattern and factor structure matrices. For orthogonal rotations, such as varimax and equimax, the factor structure and the factor pattern matrices are the same. The factor structure matrix represents the correlations between the variables and the factors. The factor pattern matrix contain the coefficients for the linear combination of the variables.

**Structure Matrix**

	Factor		
	1	2	3
item13 INSTRUC WELL PREPARED	.816	.471	.585
item14 INSTRUC SCHOLARLY GRASP	.786	.488	.574
item15 INSTRUCTOR CONFIDENCE	.768	.547	.587
item16 INSTRUCTOR FOCUS LECTURES	.680	.507	.520
item17 INSTRUCTOR USES CLEAR RELEVANT EXAMPLES	.755	.672	.662
item18 INSTRUCTOR SENSITIVE TO STUDENTS	.564	.824	.605
item19 INSTRUCTOR ALLOWS ME TO ASK QUESTIONS	.430	.751	.478
item20 INSTRUCTOR IS ACCESSIBLE TO STUDENTS OUTSIDE CLASS	.427	.606	.446
item21 INSTRUCTOR AWARE OF STUDENTS UNDERSTANDING	.628	.701	.649
item22 I AM SATISFIED WITH STUDENT PERFORMANCE EVALUATION	.462	.656	.556
item23 COMPARED TO OTHER INSTRUCTORS, THIS INSTRUCTOR IS	.718	.669	.885
item24 COMPARED TO OTHER COURSES THIS COURSE WAS	.582	.573	.795

Extraction Method: Principal Axis Factoring.

Rotation Method: Promax with Kaiser Normalization.

**Pattern Matrix<sup>a</sup>**

	Factor		
	1	2	3
item13 INSTRUC WELL PREPARED	.900		
item14 INSTRUC SCHOLARLY GRASP	.829		
item15 INSTRUCTOR CONFIDENCE	.730		
item16 INSTRUCTOR FOCUS LECTURES	.632		
item17 INSTRUCTOR USES CLEAR RELEVANT EXAMPLES	.516		
item18 INSTRUCTOR SENSITIVE TO STUDENTS		.807	
item19 INSTRUCTOR ALLOWS ME TO ASK QUESTIONS		.877	
item20 INSTRUCTOR IS ACCESSIBLE TO STUDENTS OUTSIDE CLASS		.586	
item21 INSTRUCTOR AWARE OF STUDENTS UNDERSTANDING		.435	
item22 I AM SATISFIED WITH STUDENT PERFORMANCE EVALUATION		.547	
item23 COMPARED TO OTHER INSTRUCTORS, THIS INSTRUCTOR IS			.781
item24 COMPARED TO OTHER COURSES THIS COURSE WAS			.821

Extraction Method: Principal Axis Factoring.

Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

The table below indicates that the rotation done is an oblique rotation. If an orthogonal rotation had been done (like the varimax rotation shown above), this table would not appear in the output because the correlations between the factors are set to 0. Here, you can see that the factors are highly correlated.

**Factor Correlation Matrix**

Factor	1	2	3
1	1.000	.667	.750
2	.667	1.000	.727
3	.750	.727	1.000

Extraction Method: Principal Axis Factoring.

Rotation Method: Promax with Kaiser Normalization.

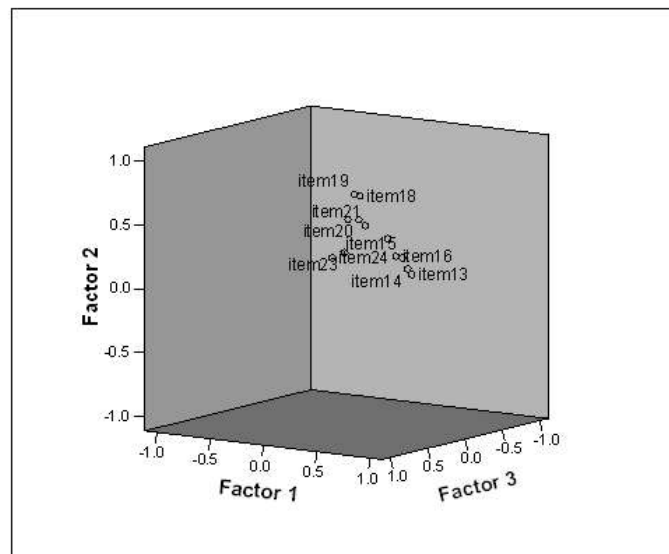
The rest of the output shown below is part of the output generated by the SPSS syntax shown at the beginning of this page.

**Factor Transformation Matrix<sup>a</sup>**

Factor	1	2	3
1	.659	.612	.438
2	-.684	.729	.009
3	.314	.305	-.899

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

a. **Factor Transformation Matrix** – This is the matrix by which you multiply the unrotated factor matrix to get the rotated factor matrix.

**Factor Plot in Rotated Factor Space**

The plot above shows the items (variables) in the rotated factor space. While this picture may not be particularly helpful, when you get this graph in the SPSS output, you can interactively rotate it. This may help you to see how the items (variables) are organized in the common factor space.

**Factor Score Coefficient Matrix<sup>a</sup>**

	Factor		
	1	2	3
item13 INSTRUC WELL PREPARED	.409	-.155	-.102
item14 INSTRUC SCHOLARLY GRASP	.309	-.095	-.096
item15 INSTRUCTOR CONFIDENCE	.248	-.021	-.106
item16 INSTRUCTOR FOCUS LECTURES	.152	.004	-.051
item17 INSTRUCTOR USES CLEAR RELEVANT EXAMPLES	.171	.072	-.055
item18 INSTRUCTOR SENSITIVE TO STUDENTS	-.093	.431	-.126
item19 INSTRUCTOR ALLOWS ME TO ASK QUESTIONS	-.097	.358	-.130
item20 INSTRUCTOR IS ACCESSIBLE TO STUDENTS OUTSIDE CLASS	-.023	.150	-.047
item21 INSTRUCTOR AWARE OF STUDENTS UNDERSTANDING	.006	.147	.015
item22 I AM SATISFIED WITH STUDENT PERFORMANCE EVALUATION	-.063	.157	.034
item23 COMPARED TO OTHER INSTRUCTORS, THIS INSTRUCTOR IS	-.076	-.107	.715
item24 COMPARED TO OTHER COURSES THIS COURSE WAS	-.093	-.056	.436

Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization.

- a. **Factor Score Coefficient Matrix** – This is the factor weight matrix and is used to compute the factor scores.

**Factor Score Covariance Matrix<sup>a</sup>**

Factor	1	2	3
1	.773	.088	.124
2	.088	.747	.114
3	.124	.114	.632

Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization.

- a. **Factor Score Covariance Matrix** – Because we used an orthogonal rotation, this should be a diagonal matrix, meaning that the same number should appear in all three places along the diagonal. In actuality the factors are uncorrelated; however, because factor scores are estimated there may be slight correlations among the factor scores.

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