CHAPTER 12B

Principal Components and Factor Analysis Using SPSS

We begin our SPSS example using a principal components extraction analysis paired with a varimax rotation, one of the most popular factor analytic approaches. A second example using principal axis factoring and an oblique (direct oblimin) rotation follows. Both are described in some detail.

Preparing to Run a Principal Components Analysis With a Varimax Rotation

The present example is adapted from a larger study by Gamst et al. (2004) that explored the cultural competence of 1,244 mental health providers in California. Participants completed a number of instruments, including four self-report cultural competence questionnaires: the Multicultural Awareness, Knowledge, Skills Survey (MAKSS; D'Andrea, Daniels, & Heck, 1991), the Multicultural Counseling Awareness Scale (MCAS-B; Ponterotto & Alexander, 1996), the Cross-Cultural Counseling Inventory–Revised (CCCI–R; LaFromboise, Coleman, & Hernandez, 1991), and the Multicultural Competency and Training Survey (MCCTS; Holcomb-McCoy, 2000). The 157 items making up these four instruments were measured on a 4-point summative response scale ranging from *strongly disagree* (1) to *strongly agree* (4).

Begin by entering SPSS and open your SPSS save file by clicking **File → Open → Data** and selecting the SPSS data file you wish to analyze.

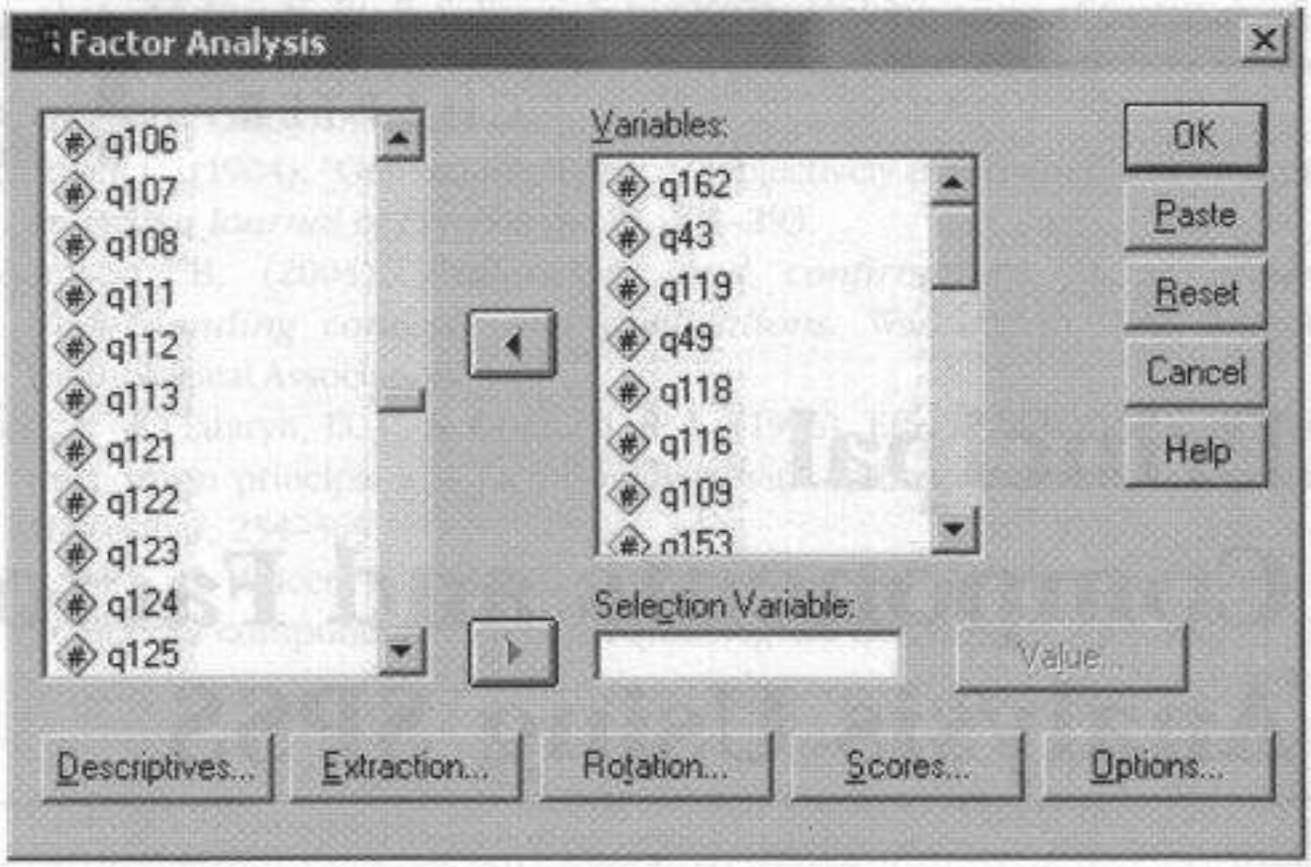


Figure 12b.1 Factor Analysis Main Dialog Box

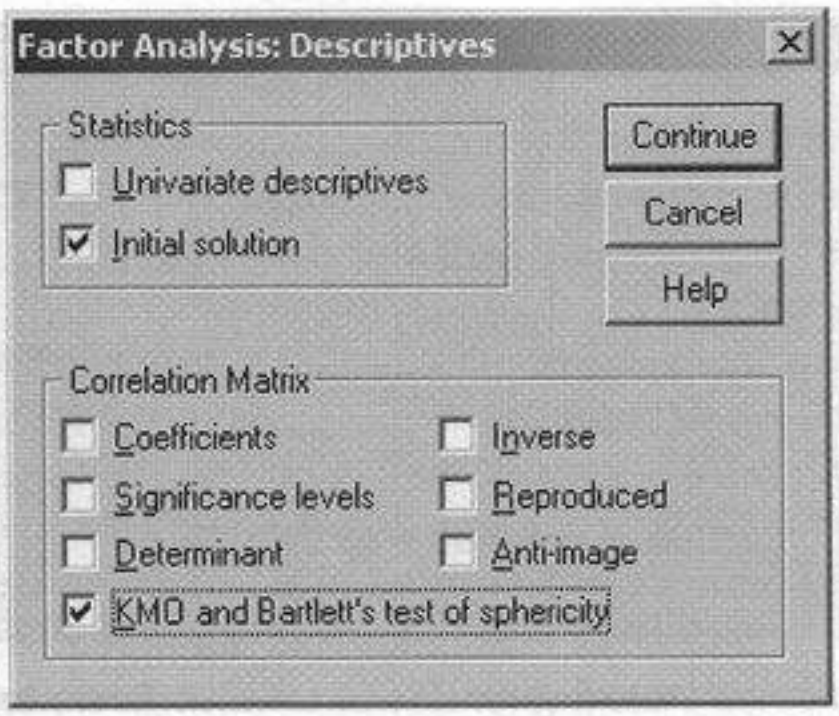
Getting to Factor Analysis

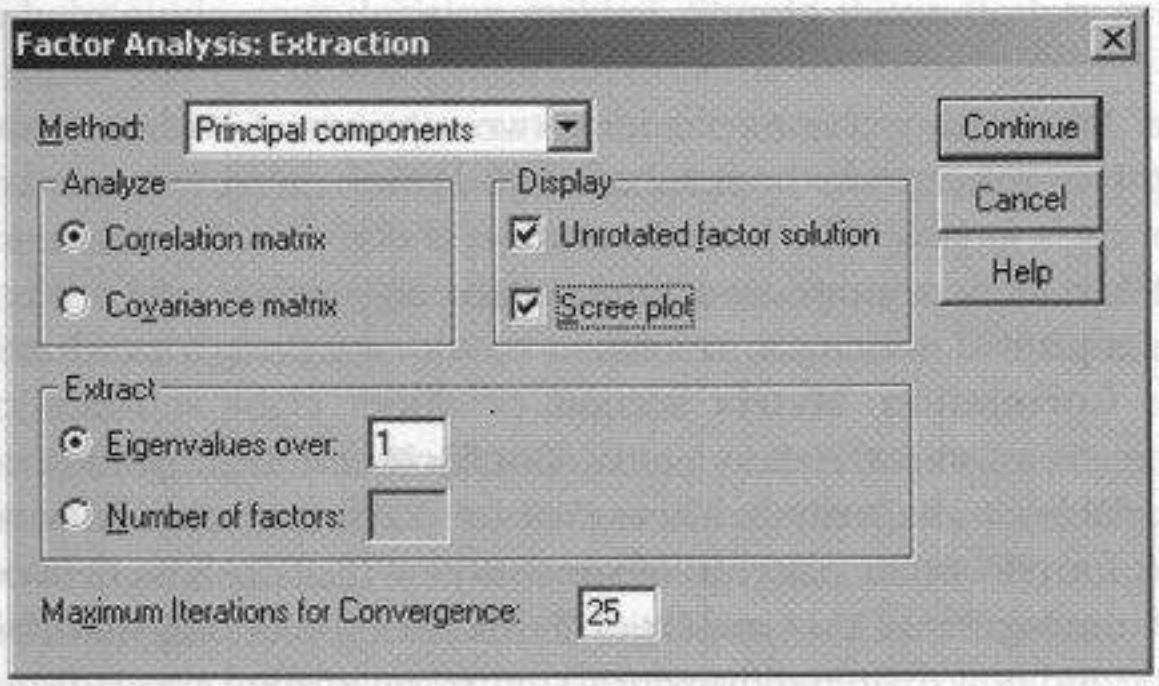
To begin our analyses we click **Analyze → Data Reduction → Factor.** This action produces our first SPSS dialog box: **Factor Analysis,** and we show this dialog box in Figure 12b.1.

The left panel of this box lists all the variables in our file. By successively clicking variables in the left panel and then clicking the right arrow, we can move the target variables (in the present example, individual cultural competence items) over to the variables list panel on the right side. For the present example, the 21 items we plan to factor analyze have been moved over. We did not select the variables in numerical order because we wanted to keep items from the same source together in our variable list; thus, our listing starts with **Q162**, then **Q43**, and so on. Variables can be selected in any order, and usually one selects variables from the first to the last as they appear in the data file.

The pushbuttons at the bottom of the dialog box (**Descriptives**, **Extraction**, **Rotation**, **Scores**, and **Options**) provide the researcher with a variety of procedural choices to which we will now turn our attention.

By clicking the **Descriptives** pushbutton, the **Factor Analysis: Descriptives** dialog box is produced. We reproduce this box in Figure 12b.2. This dialog box is composed of two sections: **Statistics** and **Correlation Matrix.**





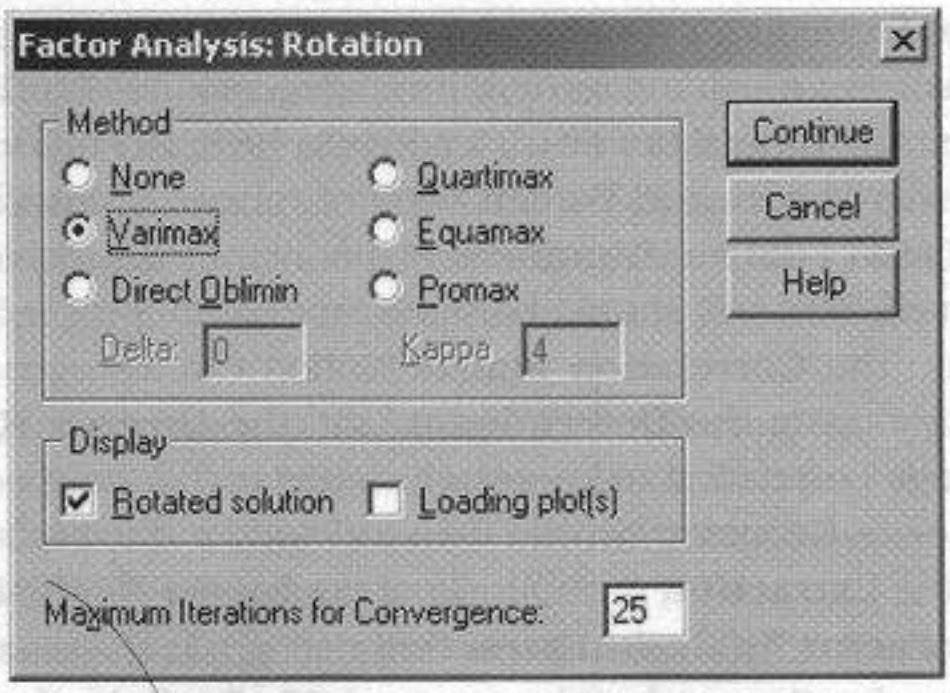


Figure 12b.2 Dialog Boxes for Descriptives, Extraction, Rotation, and Options From the Factor Analysis Main Dialog Box

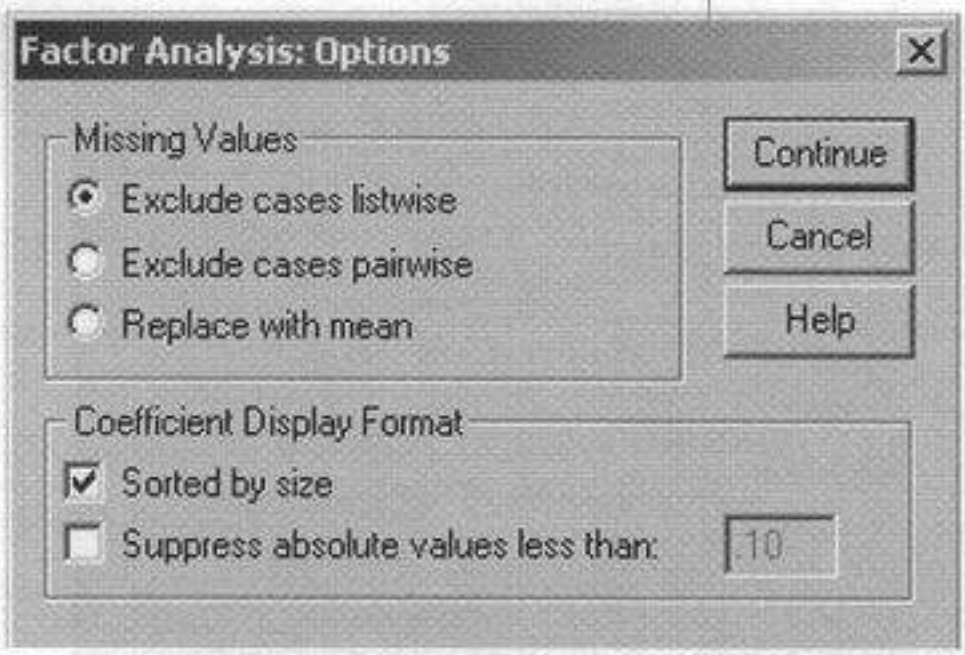


Figure 12b.2 (Continued)

The **Statistics** section provides two options. Clicking **Univariate descriptives** will provide the number of valid cases, mean, and standard deviation for each variable. The **Initial solution** checkbox will produce an initial (unrotated) solution, including communalities, eigenvalues, and percentage of variance explained, which can be compared with the final (rotated) solution.

The **Correlation Matrix** section produces eight separate options, including a Pearson correlation matrix (**Coefficients**) with significance levels for all variables in the analysis. These Pearson coefficients should be scanned to check for consistent patterns of variability or relationships between variables. We recommend this inspection be conducted during the initial data screening and univariate/multivariate assumption violation check discussed in Chapters 3A and 3B. Clicking on the **KMO and Bartlett's test of sphericity** checkbox produces the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, which is a rough indicator of how adequate the correlations are for factor analysis. As a general heuristic (see Kaiser, 1970, 1974), a value of .70 or above is considered adequate. Bartlett's test of sphericity provides the investigator with a test of the null hypothesis that none of the variables are significantly correlated. This test should be significant before proceeding with the factor analysis. The **Correlation Matrix** section can also generate several other items, including the **Determinant**, and the **Inverse**, **Reproduced**, and **Anti-image** correlation matrices, which are useful for specialized diagnostic considerations but are beyond the scope of our discussion.

Clicking the **Extraction** pushbutton of the **Factor Analysis** dialog box produces the **Factor Analysis**: **Extraction** dialog box shown also in Figure 12b.2. This box is composed of five sections: **Method**, **Analyze**, **Display**, **Extract,** and **Maximum Iterations for Convergence**.

The **Method** box allows the investigator to choose from one of seven methods of factor (or component) extraction. We have chosen to use the **Principal components** method (the default option) in this example.

The **Analyze** panel enables the investigator to produce either the **Correlation** or the **Covariance matrix**. We have chosen the correlation matrix here.

The **Display** panel allows the researcher to obtain an **Unrotated factor solution** and a **Scree plot**. The unrotated solution, although certainly optional, can be helpful to the investigator when it is compared with the final rotated solution. The **Scree plot** provides one source of information researchers generally use to determine the number of factors or components they will accept in the final solution.

The **Extract** panel defaults to selecting factors or components whose eigenvalues exceed 1. We encourage use of this default as well as the scree plot to help guide your decision making. Should theoretical or pragmatic circumstances dictate, investigators can override this constraint and provide their own selection criteria. Because we have a working familiarity with this data set, we can say in advance that the solution emerging from this analysis is the most viable one.

Last, the **Maximum Iterations for Convergence** section defaults at 25 iterations or algorithmic passes to achieve a solution. We have kept the default here.

The **Factor Analysis**: **Rotation** dialog box can be produced by clicking the **Rotation** pushbutton of the **Factor Analysis** dialog box. We present this also in Figure 12b.2. The **Rotation** dialog box consists of three sections: **Method, Display**, and **Maximum Iterations for Convergence**.

The **Method** section provides the researcher with a variety of factor rotation methods, including **Varimax**, **Direct Oblimin**, **Quartimax**, **Equamax**, and **Promax**. For this example, we have chosen the **Varimax** procedure. The **Display** section enables researchers to obtain the **Rotated solution** and the **Loading plot(s)** of the first two or three factors. We wish to take a look at the rotated solution but will bypass the loading plots.

Investigators can control the **Maximum Iterations for Convergence** (steps) needed for SPSS to perform the rotation. The default is set at 25 and we have left it at that.

Clicking the **Options** pushbutton of the **Factor Analysis** dialog box produces the **Factor Analysis**: **Options** dialog box also shown in Figure 12b.2. The **Options** dialog box has two sections: **Missing Values** and **Coefficient Display Format**.

The **Missing Values** section allows researchers to **Exclude cases listwise** (the default), **Exclude cases pairwise**, or **Replace with mean** of the particular variable. We have selected listwise deletion of cases.

The **Coefficient Display Format** section allows the investigator to sort the factor weightings by size and to suppress weightings with absolute values less than a specified value. Sorting coefficients by size usually makes it easier for researchers to comprehend the results, and we have chosen this form of display.

One other pushbutton (**Scores**) is available from the **Factor Analysis** dialog box. Clicking **Scores** produces a **Factor Analysis**: **Factor Scores** dialog box. This box allows researchers to create a new variable for each factor (component) derived from the analysis. Although this approach is both valid and legitimate, most researchers compute scale scores by taking the mean (or the sum) of the items that are "loaded" or relatively highly correlated with the factor. In the former procedure, each factor score is composed of all the variables; the factors are differentiated by the different weights assigned to each variable. In the latter procedure, variables received equal (unitary) weights regardless of their factor weights; each factor is ordinarily represented by a different and independent set of variables.

The Output From a Principal Components Analysis With a Varimax Rotation

We have now set up the parameters to run a principal components analysis with SPSS using data based on the self-reported cultural competency of 1,244 California mental health practitioners. Let's see what the analyses suggest.

Assume that prior to running our principal components analysis (i.e., during our data screening phase) we examined our descriptive statistics and our interitem correlations, and checked for assumption violations. Further assume that we noted during this initial assessment that our variables were all measured on a quantitative scale, that each pair of variables appeared to be bivariate normally distributed, and that each respondent or case was independent of one another. Assume that we also noted that the large sample size indicates that our variables-to-cases ratio is optimal. We are therefore now ready to look at the principal components output.

The first output table of Figure 12b.3 shows the results of the KMO and Bartlett's test of sphericity assessments by means of a **KMO and Bartlett's test** table. The results from both tests look good. A KMO coefficient in the high .8s suggests that the data are suitable for principal components analysis. Likewise, a significant Bartlett's test enables us to reject the null hypothesis of lack of sufficient correlation between the variables. These two results give us confidence to proceed with the analysis.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.854
Bartlett's Test of Sphericity	Approx. Chi Square	3225.584
	df	.210
	Sig.	.000

This KMO value exceeds the heuristic of .70, indicating that the correlations are adequate for factor analysis.

Communalities

	Initial	*Extraction*
Q162	1.000	.521
Q43	1.000	.605
Q119	1.000	.673
Q49	1.000	.676
Q118	1.000	.669
Q116	1.000	.576
Q109	1.000	.552
Q153	1.000	.621
Q53	1.000	.670
Q157	1.000	.515
Q167	1.000	.429
Q110	1.000	.679
Q115	1.000	.600
Q152	1.000	.557
Q185	1.000	.547
Q180	1.000	.413
Q191	1.000	.530
Q117	1.000	.709
Q144	1.000	.564
Q114	1.000	.599
Q120	1.000	.655

Extraction Method: Principal Component Analysis.

Four components with eigenvalues of 1 or greater were extracted and rotated.

These four components accounted for about 59% of the total variance.

Total Variance Explained

	Initial Eigenvalues			*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*		
Component	*Total*	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*
1	6.500	30.951	30.951	6.500	30.951	30.951	4.396	20.935	20.935
2	2.546	12.126	43.077	2.546	12.126	43.077	3.129	14.899	35.835
3	2.100	10.002	53.079	2.100	10.002	53.079	2.896	13.788	49.623
4	1.214	5.780	58.859	1.214	5.780	58.859	1.940	9.236	58.859
5	.970	4.617	63.476						
6	.855	4.071	67.548						
7	.736	3.506	71.054						
8	.696	3.313	74.367						
9	.600	2.859	77.225						
10	.588	2.800	80.025						
11	.542	2.581	82.606						
12	.502	2.392	84.998						
13	.471	2.245	87.243						
14	.447	2.130	89.373						
15	.434	2.069	91.441						
16	.407	1.939	93.380						
17	.359	1.709	95.090						
18	.346	1.646	96.736						
19	.314	1.495	98.230						
20	.242	1.155	99.385						
21	.129	.615	100.000						

Extraction Method: Principal Component Analysis.

Figure 12b.3 Selected Output Tables From the Principal Components Analysis

The next output table provides the communalities for the **Initial** and **Extraction** (i.e., final) principal components solution. As can be seen, in a principal components solution, the initial communalities are equal to 1.00. This means that all the variance is accounted for by each variable because principal components will create as many components as there are variables. Another way to think of this is to say that each variable is fully (1.00 or 100%) involved in the solution (because the solution goes to completion).

The **Extraction** (final) solution produces communalities that are less than 1.00 because the final solution retains only components that have eigenvalues greater than 1.00 (the SPSS default). Thus, less than the total amount of variance within the original items is captured. These communalities, sometimes symbolized as h^2, are based on the factor matrix (component matrix in this present analysis) that we discussed in Chapter 12A and will cover here in a moment. They are computed by summing the squared factor weights across each row of the matrix. Communalities at this stage of the analysis indicate the degree to which each variable is participating or contributing to (is captured by) the component solution. Researchers should inspect the **Extraction** communalities for any variables that appear to be particularly low. Such items may be candidates for removal from the analysis. After inspection of this table, we conclude that no such items are present, and proceed with the analysis.

The third output table of Figure 12b.3 summarizes the amount of variance accounted for by each component after the **Initial** part of the analysis, the **Extraction** phase of the analysis, and the **Rotation** phase of the analysis. Each row provides information on a component given the other components that have already been extracted. The left portion of the table labeled **Initial Eigenvalues** represents the solution having gone to completion. Thus, 21 components were extracted, accounting for 100% of the variance.

The default for SPSS, which we allowed to be in effect for this analysis, was to take seriously only those components with eigenvalues of 1.00 or greater. As can be seen in the portion labeled as **Extraction Sums of Squares Loadings,** only four factors reached this default criterion. The first component in an unrotated solution always accounts for the most variance—in this case, about 31%, followed by the second component, which accounted for about 12%, and so on. The total amount of variance accounted for by the first four principal components solution was about 59%. In practice, a robust solution should account for at least 50% of the variance (Tabachnick & Fidell, 2001b). The extraction and rotated cumulative percentage of variances accounted for (shown in the left portion of

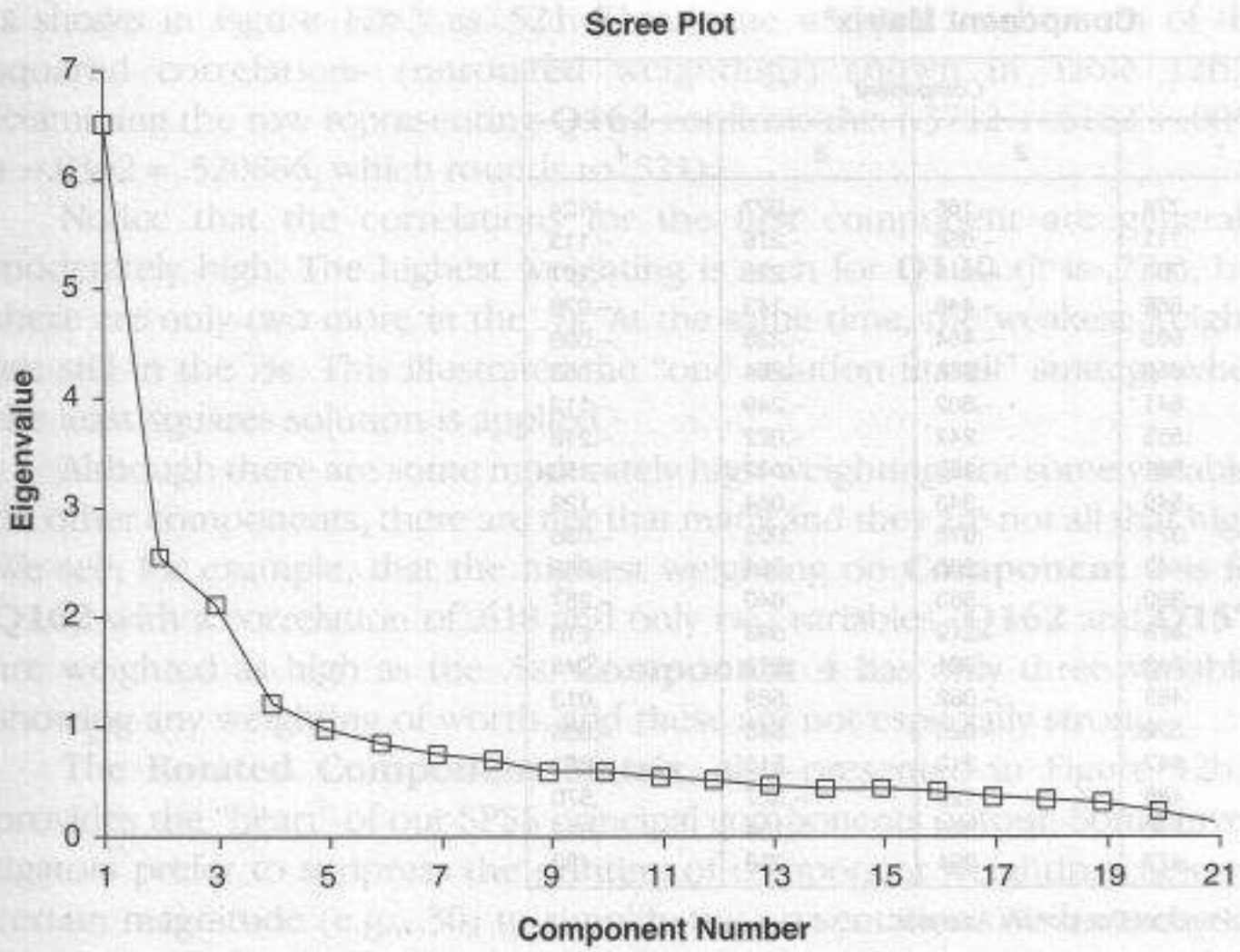


Figure 12b.4 Scree Plot of the Eigenvalues for the Principal Components Analysis

Figure 12b.3) will always be the same value. However, the rotated solution spreads the variability more evenly across the four components (factors).

Figure 12b.4 shows the **Scree Plot** for the initial (complete) solution. It is a graphical way of helping researchers determine how many components or factors to include in the solution that they will ultimately accept. This figure contains the eigenvalues on the Y (horizontal) axis and the component number on the X (vertical) axis. Researchers look to see where the curve turns or "flattens out" across the components. The scree plot takes its name from the debris that piles up on the sides of a volcano or a mountain. The turning point, in this case at Component 4, indicates a transition point between components with high and low eigenvalues. This plot confirms our previous observation derived from the **Total Variance Explained** table (Figure 12b.3) that four components best describes our principal components solution.

The **Unrotated Component Matrix** is shown in Figure 12b.5. Values in the array are correlations between the variables and the components. Thus, Variable **Q120** is correlated .774 with Component 1, −.186 with Component 2, and so on. This output is also the source of the communality results we showed in Figure 12b.3. For example, the communality of **Q162**

Component Matrix[a]

	Component			
	1	2	3	4
Q120	.774	−.186	−.077	−.124
Q114	.711	−.066	−.276	−.113
Q115	.703	−.213	−.225	−.101
Q119	.669	−.448	−.143	−.070
Q117	.663	−.454	−.238	−.088
Q118	.659	−.388	−.284	−.053
Q116	.641	−.302	−.249	−.112
Q180	.553	.242	−.022	−.218
Q152	.541	.489	.042	−.150
Q167	.540	.343	−.054	−.129
Q162	.371	.618	.005	−.036
Q153	.442	.586	.064	−.280
Q157	.360	.563	.040	−.257
Q110	.478	−.219	.598	.210
Q191	.443	−.061	.573	.045
Q185	.465	−.082	.569	.013
Q144	.520	−.026	.540	−.035
Q109	.447	−.212	.516	.203
Q53	.485	.128	−.307	.570
Q49	.490	.386	−.134	.519
Q43	.477	.294	−.238	.483

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Rotated Component Matrix[a]

	Component			
	1	2	3	4
Q117	.826	−.023	.146	.074
Q118	.801	.010	.099	.135
Q119	.783	−.021	.233	.067
Q116	.741	.096	.095	.092
Q115	.727	.189	.128	.141
Q120	.707	.257	.278	.112
Q114	.680	.312	.057	.189
Q153	.047	.780	.087	.052
Q157	.005	.715	.040	.045
Q152	.147	.694	.152	.174
Q162	−.052	.669	.042	.264
Q167	.257	.568	.098	.177
Q180	.326	.533	.135	.066
Q110	.157	−.026	.801	.108
Q109	.167	−.034	.714	.117
Q185	.133	.158	.710	−.019
Q191	.098	.151	.705	.007
Q144	.167	.247	.689	−.019
Q53	.276	.072	.020	.767
Q49	.085	.303	.114	.751
Q43	.175	.238	.030	.719

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

a. Rotation converged in 5 iterations.

We have highlighted the items that correlate most strongly with their respected factor.

Figure 12b.5 Component Matrix Summarizing the Extraction Phase and Varimax Rotated Component Matrix

is shown in Figure 12b.3 as .521. That value is equal to the sum of the squared correlations (unrotated weightings) shown in Table 12b.5. Examining the row representing **Q162** confirms this (.3712 + .6182 + .0052 + −.0362 = .520886, which rounds to .521).

Notice that the correlations for the first component are generally moderately high. The highest weighting is seen for **Q120** (it is .774), but there are only two more in the .7s. At the same time, the weakest weights are still in the .3s. This illustrates the "one solution fits all" strategy when the least squares solution is applied.

Although there are some moderately high weightings for some variables on other components, there are not that many and they are not all that high. We see, for example, that the highest weighting on **Component 2** is for **Q162** with a correlation of .618 and only two variables (**Q162** and **Q157**) are weighted as high as the .5s. **Component 4** has only three variables showing any weighting of worth, and these are not especially strong.

The **Rotated Component Matrix**, also presented in Figure 12b.5, provides the "heart" of our SPSS principal components output. Some investigators prefer to suppress the printing of component weightings below a certain magnitude (e.g., .30) to simplify the presentation. We have chosen to display all the coefficients. The "sorting by size" format that we checked in the **Options** dialog box, although operative in the previous table, can be best seen here. Variables are ordered by correlations within each of the components starting with **Component 1**. We see that **Q117** had the highest and **Q114** had the lowest correlation on the first component and so appear in order at the top of the list. **Q153** was the highest correlated variable on **Component 2** and so appears directly under **Q114**. A casual inspection of this rotated component matrix shows that the solution has moved in the direction of simple structure. Not only has the first component been somewhat "deflated," correlations on all components have been "sharpened" in that they are either relatively high or relatively low.

It is with respect to Figure 12b.5 that the science of objectively evaluating the dispersion of each variable's correlation on each component occurs. Conversely, the art of principal components (or factor) analysis occurs when researchers creatively decide the essence of each component by creating an identifying component name. Selecting a component name is typically driven by the nature of the most highly weighted items (e.g., items in the .7s or .8s) of the component. This information is found by inspecting each variable's correlation on each respective component. Ideally, investigators hope to find that each variable will have a relatively high correlation on one component (or factor) and relatively low correlations on the remaining components.

Careful inspection of Figure 12b.5 suggests that this is the case. For example, Variables **Q117** through **Q114** all have high correlations on **Component 1** and low correlations on **Components 2, 3,** and **4**. The researcher can then scrutinize these seven items to determine their underlying commonality or essential nature.

The content of the items are shown in Table 12b.1 toward the end of this chapter, ordered in the same way as the rotated components matrix. Interpretation of components or factors is based on item content. Researchers study what the items of a factor relate to and attempt to determine what they have in common—that is, what the underlying theme or dimension may be that ties them together. This theme is the label given to the variate (the component or factor).

The first seven items were found to correlate to the first component. From the item wording shown in Table 12b.1, these items all seem to be related to mental health practitioners' understanding of issues relating to sexuality, gender, aging, social class, and disability; thus, we refer to this component as non-ethnic ability. Variables **Q153** through **Q180** all correlate relatively highly and exclusively on **Component 2**. These six items deal with mental health practitioner multicultural awareness. The next five items (**Q110–Q144**) appear to be related to practitioners' multicultural knowledge. The last three items (**Q53, Q49,** and **Q43**) all have high correlations on **Component 4**. These last items encompass practitioner multicultural sensitivity to mental health consumers.

Our task was simplified (for presentation purposes) by the small number of variables (21) entered into the principal components analysis. In practice, researchers routinely factor analyze large numbers of variables (e.g., 30, 50, 100, or more) simultaneously. With large arrays of items, investigators should be deliberate in their inspection of the rotated component matrix. We encourage the adoption of this simple process. Line up a ruler underneath the first variable in the **Rotated Component Matrix**—in the present example, **Q117**. Using a highlight marker, underscore the highest weighting for that variable. If there happens to be more than one relatively high weighting, then highlight all of them for that variable. Repeat this process for each variable in turn. Through this process, the underlying structure should begin to emerge and then the more creative process of imposing meanings by labeling components (factors) can begin.

We have now achieved our goal of data reduction by reducing an array of 21 multicultural mental health practitioner statements into four orthogonal (uncorrelated) principal components. At this point, we can begin to use these components as "analytical devices" or composite variables where we average an individual respondent's scores on the items that compose each

of the four components. These new composite variables can then be used as dependent variables in subsequent statistical analyses.

Principal Axis Factoring With an Oblique Rotation

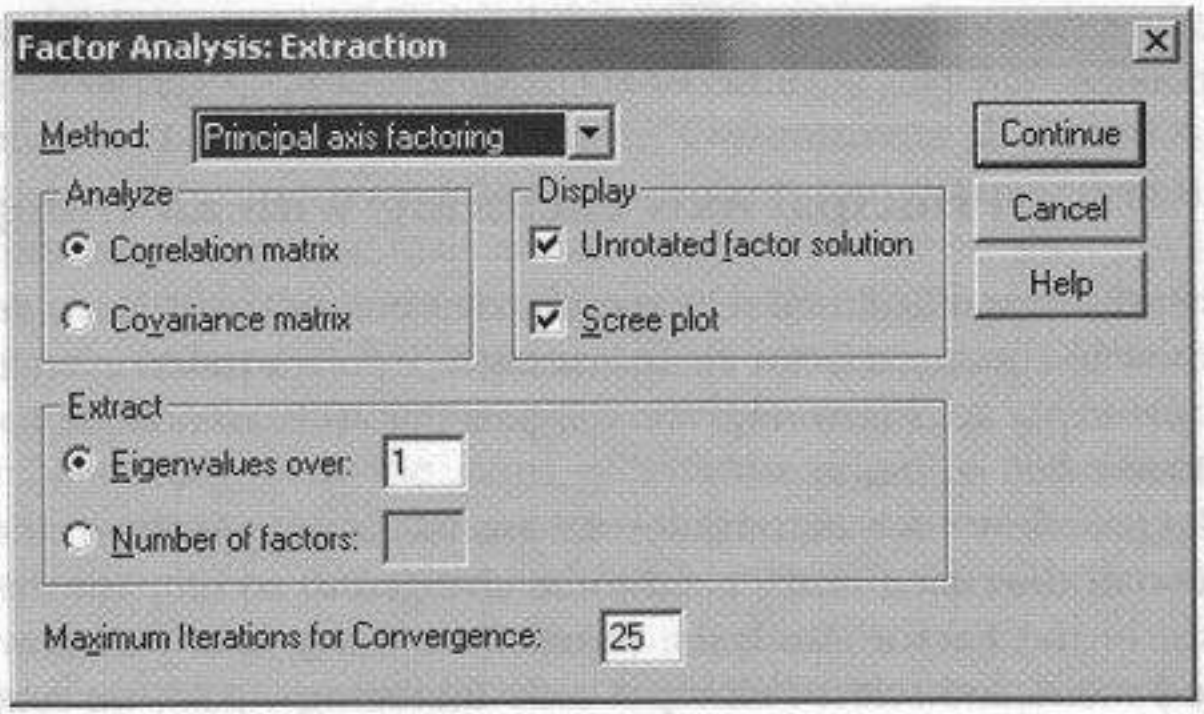
Using the same multicultural self-report data as before, we will now demonstrate how to conduct a factor analysis using a popular extraction technique called *principal axis* factoring. We will pair this with an oblique rotation technique called *oblimin*.

The process to now run the second analysis is very similar to the first. Only two of the dialog boxes need to be changed to accomplish this next analysis. In the **Factor Analysis**: **Extraction** dialog box, pull down the **Method** menu and select **Principal axis factoring**. Again, we request a **Correlation matrix**, an **Unrotated factor solution**, and a **Scree plot**. We will also ask for extraction of those factors whose **Eigenvalues** exceed 1.00. This is shown in Figure 12b.6.

Click the **Rotation** pushbutton to arrive at the **Factor Analysis**: **Rotation** dialog box (shown also in Figure 12b.6). Enter the **Method** section and click **Direct Oblimin.** Leave the **Delta** setting at **0** (the default). The delta setting is the way SPSS sets the limits on the degree of correlation it permits the factors to achieve. A delta value of 0 allows for a fair amount of correlation and can usually serve the purposes of most researchers most of the time. In the **Display** section of the **Rotation** dialog box we click the **Rotated solution** option.

The extraction phase is summarized in the **Total Variance Explained** table shown in Figure 12b.7. A quick inspection of this table is similar but not identical to what we found in our previous principal components analysis. The results labeled **Initial Eigenvalues** are the same as they were for the last analysis because in principal axis factoring, a principal components analysis is done initially. But then, as we have seen in Chapter 12A, the focus changed. Unlike principal components analysis, which analyzes the total variance, factor analysis deals with only the common variance. Principal axis factoring (also called principal factors analysis) substitutes commonalities for 1s on the diagonal of the correlation matrix and then extracts factors to account for the shared variance.

In its focus on the common variance, principal factors identified only three factors with eigenvalues over 1.00. These three factors cumulatively accounted for about 49% of the shared or common variance with this extraction method. This may be compared with the 59% of explained variance accounted for by the principal components analysis. Such a drop in explained variance occurs because variance not shared among the variables



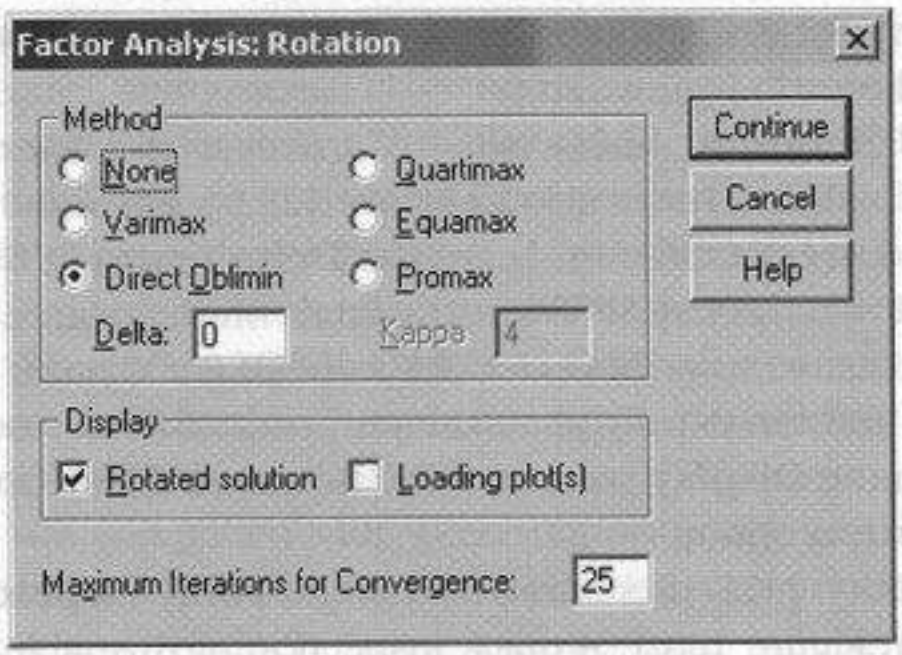


Figure 12b.6 Dialog Boxes for Extraction and Rotation From the Factor Analysis Main Dialog Box

is automatically not possible to be accounted for by the factor analysis procedures. Thus, principal axis (or any of the factor analyses) will therefore explain less variance than will be attributed to principal components.

The four-factor unrotated factor matrix is presented in Figure 12b.8 even though only three factors achieved eigenvalues over 1.00. We have done this for two reasons: (a) This allows us to contrast this outcome with the prior one, and (b) the three-factor solution was not nearly as interpretable as the four-component solution (that was ultimately selected by the researchers). Inspection of Figure 12b.8 suggests a pattern of results roughly similar to that found with the principal components solution. The first factor once again has relatively high to moderate correlations for all the variables, and

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	6.500	30.951	30.951	6.019	28.664	28.664	4.985
2	2.546	12.126	43.077	2.046	9.745	38.408	3.324
3	2.100	10.002	53.079	1.591	7.578	45.987	3.038
4	1.214	5.780	58.859	.705	3.356	49.343	3.436
5	.970	4.617	63.476				
6	.855	4.071	67.548				
7	.736	3.506	71.054				
8	.696	3.313	74.367				
9	.600	2.859	77.225				
10	.588	2.800	80.025				
11	.542	2.581	82.606				
12	.502	2.392	84.998				
13	.471	2.245	87.243				
14	.447	2.130	89.373				
15	.434	2.069	91.441				
16	.407	1.939	93.380				
17	.359	1.709	95.090				
18	.346	1.646	96.736				
19	.314	1.495	98.230				
20	.242	1.155	99.385				
21	.129	.615	100.000				

Extraction Method: Principal Axis Factoring.

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

The four factor principle axis solution accounted for about 49% of the common variance.

Figure 12b.7 Eigenvalues and Variance Accounted for by the Principal Axis Factoring

the correlations on the other factors are not very high. Notice that only three correlations on **Factor 4** are greater than .30 and that no variable showed its highest correlation on that factor. Such a result is not surprising given that the fourth factor did not reach an eigenvalue of 1.00.

Unlike orthogonal rotations such as varimax that produce one rotated solution matrix, oblique rotations such as oblimin produce two matrices: the **Pattern Matrix** and the **Structure Matrix** (both shown in Figure 12b.9). As we indicated previously, there has been a fair amount of discussion within the multivariate statistics literature as to which matrix to use. In practice, both often provide fairly comparable results; the main difference is that the pattern matrix reports the weightings in standardized

Factor Matrix[a]

	Factor			
	1	2	3	4
Q120	.759	–.159	–.054	–.107
Q114	.688	–.054	–.238	–.086
Q115	.681	–.185	–.183	–.082
Q117	.658	–.435	–.202	–.063
Q119	.658	–.413	–.106	–.049
Q118	.649	–.367	–.245	–.028
Q116	.616	–.261	–.193	–.076
Q152	.515	.450	.019	–.131
Q180	.513	.209	–.022	–.126
Q167	.502	.296	–.055	–.076
Q144	.495	.007	.467	–.030
Q49	.471	.365	–.131	.418
Q53	.464	.119	–.263	.442
Q43	.450	.261	–.203	.328
Q153	.423	.547	.033	–.251
Q162	.346	.536	–.018	–.034
Q157	.335	.481	.010	–.189
Q110	.467	–.171	.579	.176
Q185	.439	–.042	.481	.005
Q191	.417	–.022	.477	.025
Q109	.424	–.154	.451	.133

Extraction Method: Principal Axis Factoring.

a. 4 factors extracted. 7 iterations required.

Figure 12b.8 Factor Matrix for the Four-Factor Principal Axis Extraction

form (analogous to beta weights in multiple regression), whereas the structure matrix provides the structure coefficients representing the correlations of the variables to the factors.

As can be seen in both the **Pattern** and **Structure matrices**, fairly comparable correlations are found between the two. Generally, the pattern matrix produces slightly higher correlations for the more highly correlated items, and the structure matrix produces slightly higher correlations for the more weakly correlated items within each factor. This factor solution based on principal factors extraction and oblique rotation, although differing in the amount of explained variance and showing slightly different numerical correlations from the one derived based on principal components extraction and varimax rotation, nonetheless yielded very similar interpretations of the underlying structure of the variables. That is, exactly the same variables in virtually the same order correlated on the same factors. The only

Pattern Matrix[a]

	Factor			
	1	2	3	4
Q117	.835	-.115	.016	-.012
Q118	.789	-.088	-.028	.057
Q119	.758	-.109	.117	-.016
Q116	.693	.024	-.011	.014
Q115	.678	.108	.006	.039
Q120	.648	.168	.152	-.001
Q114	.628	.219	-.065	.089
Q153	-.005	.753	.015	-.045
Q157	-.032	.627	-.008	-.006
Q152	.062	.610	.074	.082
Q162	-.124	.558	.005	.191
Q167	.173	.441	.029	.115
Q180	.244	.410	.062	.028
Q110	-.020	-.145	.804	.081
Q109	.036	-.109	.645	.065
Q185	.018	.082	.629	-.049
Q191	-.017	.076	.622	-.025
Q144	.044	.164	.614	-.060
Q49	-.099	.117	.079	.698
Q53	.125	-.101	-.021	.687
Q43	.045	.095	-.014	.584

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 5 iterations.

The pattern matrix shows the standardized weights of the variables akin to multiple regression beta weights (pattern coefficients).

We have highlighted the items that correlate most strongly with their respective factor.

Structure Matrix

	Factor			
	1	2	3	4
Q117	.809	.082	.322	.281
Q118	.780	.117	.279	.335
Q119	.773	.095	.393	.268
Q120	.749	.362	.459	.368
Q115	.723	.288	.318	.366
Q116	.700	.192	.279	.306
Q114	.690	.391	.265	.432
Q153	.161	.735	.205	.292
Q152	.271	.681	.278	.394
Q162	.089	.616	.140	.391
Q157	.111	.615	.145	.259
Q167	.337	.541	.239	.389
Q180	.378	.498	.276	.324
Q110	.305	.102	.773	.161
Q144	.308	.312	.664	.148
Q185	.272	.232	.649	.114
Q109	.298	.101	.643	.153
Q191	.243	.227	.630	.120
Q49	.246	.426	.202	.725
Q53	.373	.229	.132	.689
Q43	.300	.362	.139	.641

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

The structure matrix shows the correlations of the variables with the factors (structure coefficients).

We have highlighted the items that correlate most strongly with their respective factor.

Figure 12b.9 Pattern Matrix and Structure Matrix for the Principal Axis Solution With an Oblique Rotation

exception can be seen on **Factor 4** where here **Q49** correlated more strongly than **Q53,** whereas the reverse was true on **Component 4**; however, the correlations are so close in both cases that the reordering is trivial. In the present example, the **Structure Matrix** also produced a pattern of moderate correlations on **Factor 3** and **Factor 4** that are not present in the **Pattern Matrix**. These correlations make the interpretation more ambiguous with the **Structure Matrix** and thus, we would encourage the use of the **Pattern Matrix** for this example.

As a conclusion to this analysis, consider Figure 12b.10, which depicts the **Factor Correlation Matrix** for this oblique rotation. As can be seen, all the factors show low to moderate correlations between factor pairs. Specifically, **Factor 1** seems to be moderately correlated with **Factor 3** and **Factor 4,** whereas **Factor 2** has a moderate correlation with **Factor 4** and low correlations with **Factor 1** and **Factor 3**.

Factor Correlation Matrix

Factor	*1*	*2*	*3*	*4*
1	1.000	.238	.406	.409
2	.238	1.000	.267	.447
3	.406	.267	1.000	.189
4	.409	.447	.189	1.000

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

Figure 12b.10 Correlations of the Principal Axis Factors

Results

An exploratory factor analysis using a principal component extraction method and a varimax rotation of 21 self-report cultural competence items was conducted on a random sample (n = 415) of 1,244 California mental health providers. Prior to running the analysis with SPSS, the data were screened by examining descriptive statistics on each item, interitem correlations, and possible univariate and multivariate assumption violations. From this initial assessment, all variables were found to be interval-like, variable pairs appeared to be bivariate normally distributed, and all cases were independent of one another. Because of the large sample size, the variables-to-cases ratio was deemed adequate. The Kaiser-Meyer-Olkin measure of sampling adequacy was .85, indicating that the present data were suitable for principal components analysis. Similarly, Bartlett's test of sphericity was significant ($p < .001$), indicating sufficient correlation between the variables to proceed with the analysis.

Using the Kaiser-Guttman retention criterion of eigenvalues greater than 1.0, a four-factor solution provided the clearest extraction. These four factors accounted for 59% of the total variance. Table 12b.1 presents the 21 items, the original scale and subscale they came from, their factor correlations, communality estimates, and item-total correlations. Communalities were fairly high for each of the 21 items, with a range of .51 to .71.

Factor 1: Non-Ethnic Ability (eigenvalue = 6.50) accounted for 31% of the variance and had seven items; Factor 2: Awareness of Cultural Barriers (eigenvalue = 2.55) and accounted for 12.1% of the variance and had six items; Factor 3: Multicultural Knowledge (eigenvalue = 2.10) accounted for 10% of the variance and had five items; and Factor 4: Sensitivity to Consumers (eigenvalue = 1.21) accounted for 5.8% of the variance and had three items. Corrected item-total correlation ranged from .33 to .70, and Cronbach's coefficient alpha ranged from .75 to .90 among the four factors, indicating good subscale reliability.

The rationale used in naming these four factors was guided in part by the recommendations of Comrey and Lee (1992) and Rummel (1970) in which sorted factor weights in excess of .65 were used to "drive" the process of labeling and interpreting each factor. The present four-factor model was deemed the best solution because of its conceptual clarity and ease of interpretability.

Table 12b.1 Summary of Items and Factor Loadings From Principal Components Analysis With Varimax Rotation ($N = 415$)*

Variable	*Scale Origin*	*Original Subscale Item Name*	*Component Loading* 1	2	3	4	*Communality*	*Corrected Item-Total Correlation*
Q117	MAKSS	I have an excellent ability to assess accurately the mental health needs of gay men.	**.83**	−.02	.15	−.07	.71	.55
Q118	MAKSS	I have an excellent ability to assess accurately the mental health needs of lesbians.	**.80**	**−.01**	−.09	.14	.67	.55
Q119	MAKSS	I have an excellent ability to assess accurately the mental health needs of persons with disabilities.	**.78**	−.02	.23	−.06	.67	.56
Q116	MAKSS	I have an excellent ability to assess accurately the mental health needs of older adults.	**.74**	.09	.09	.09	.58	.53
Q115	MAKSS	I have an excellent ability to assess accurately the mental health needs of men.	**.73**	.19	.13	.14	.60	.61
Q120	MAKSS	I have an excellent ability to assess accurately the mental health needs of persons who come from very poor socioeconomic backgrounds.	**.71**	.26	.28	.11	.66	.70

Variable	Scale Origin	Original Subscale Item Name	Component Loading 1	2	3	4	Communality	Corrected Item-Total Correlation
Q114	MAKSS	I have an excellent ability to assess accurately the mental health needs of women.	**.68**	.31	.06	.19	.60	.62
Q153	MCA-SB	I am aware that counselors frequently impose their own cultural values upon minority clients.	.05	**.78**	.09	.05	.62	.41
Q157	MCA-SB	I am aware that being born a White person in this society carries with it certain advantages.	.01	**.72**	.04	.05	.52	.33
Q152	MCA-SB	I am aware of institutional barriers that may inhibit minorities from using mental health services.	.15	**.69**	.15	.17	.56	.50
Q162	MCA-SB	I am aware that being born a minority in this society brings with it certain challenges that White people do not have to face.	.–05	**.67**	.04	.26	.52	.35
Q167	MCCTS	I am aware of how much my cultural background and experiences have influenced my attitudes about psychological processes.	.26	**.57**	.09	.18	.43	.48

(Continued)

Table 12b.1 (Continued)

Variable	Scale Origin	Original Subscale Item Name	Component Loading 1	2	3	4	Communality	Corrected Item-Total Correlation
Q180	MCCTS	I can identify my reactions that are based on stereo-typical beliefs about different ethnic groups	.33	**.53**	.14	.07	.41	.49
Q110	MAKSS	I have an excellent ability to critique multi-cultural research.	.16	−.03	**.80**	.11	.68	.45
Q109	MAKSS	I have an excellent ability to identify the strengths and weaknesses of psychological tests in terms of their use with persons of different cultural/ racial/ethnic backgrounds.	.17	−.03	**.71**	−.12	.55	.41
Q185	MCCTS	I can discuss within-group differences among ethnic groups (e.g., low socio-economic status (SES) Puerto Rican client vs. high SES Puerto Rican client).	.13	.16	**.71**	.02	.55	.43
Q191	MCCTS	I can discuss research regarding mental health issues and culturally different populations.	.09	.15	**.71**	.01	.53	.41

Variable	Scale Origin	Original Subscale Item Name	Component Loading 1	2	3	4	Communality	Corrected Item-Total Correlation
Q144	MCAS-B	I am knowledgeable of acculturation models for various ethnic minority groups.	.17	.25	**.69**	−.02	.56	.49
Q53	CCCI-R	My communication is appropriate for my clients.	.27	.07	.02	**.77**	.67	.41
Q49	CCCI-R	I am aware of institutional barriers that affect the client.	.09	.30	.11	**.75**	.68	.44
Q43	CCCI-R	I am aware of how my own values might affect my client.	.18	.24	.03	**.72**	.61	.42
Eigenvalues			6.50	2.55	2.10	1.21		
% of Variance			30.95	12.13	10.00	5.78		
Coefficient Alpha			.90	.78	.80	.75		

Notes. The variable names in the first column would not be part of the table placed into the manuscript; we included them here so that you may clearly see the inventory item that matches up with the variable names that were used in the analysis. Boldface indicates highest factor loadings. Component 1 = Non-Ethnic Ability, Component 2 = Multicultural Awareness, Component 3 = Multicultural Knowledge, Component 4 = Multicultural Sensitivity to Consumers. Corrected item-total correlations show the Pearson *r*s between the item and its subscale (the subscale score is "corrected" by excluding the particular item in computing the total score for the subscale).