Improving Your Exploratory Factor Analysis for Ordinal Data: A Demonstration Using FACTOR

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Exploratory factor analysis (EFA) methods are used extensively in the field of assessment and evaluation. Due to EFA's widespread use, common methods and practices have come under close scrutiny. A substantial body of literature has been compiled highlighting problems with many of the methods and practices used in EFA, and, in response, many guidelines have been proposed with the aim to improve application. Unfortunately, implementing recommended EFA practices has been restricted by the range of options available in commercial statistical packages and, perhaps, due to an absence of clear, practical 'how-to' demonstrations. Consequently, this article describes the application of methods recommended to get the most out of your EFA. The article focuses on dealing with the common situation of analysing ordinal data as derived from Likert-type scales. These methods are demonstrated using the free, stand-alone, easy-to-use and powerful EFA package FACTOR (http://psico.fcep.urv.es/utilitats/factor/, Lorenzo-Seva & Ferrando, 2006). The demonstration applies the recommended techniques using an accompanying dataset, based on the Big 5 personality test. The outcomes obtained by the EFA using the recommended procedures through FACTOR are compared to the default techniques currently available in SPSS.

Exploratory factor analysis (EFA) is a cluster of common methods used to explore the underlying pattern of relationships among multiple observed variables. EFA is useful for assessing the dimensionality of questionnaire scales that measure underlying latent variables. Researchers use EFA to hypothesise and, later, confirm, through replication or confirmatory factor analysis (CFA), the model that gave rise to the interrelationships among the scale's variables. From a practical standpoint, a researcher might want to know if a new scale can be considered uni- or multi-dimensional. Responding to this can help researchers reduce the total number of variables into a smaller number of factors, which are composed of highly related variables. EFA remains a very popular data analysis technique. However, criticisms of conventional EFA practices have frequently been cited (see Fabrigar, Wegener, MacCallum, & Strahan, 1999). EFA requires subjective input from the researcher and making poor decisions at each EFA stage can have a substantial impact on results. The main areas of concern include deciding on the following: an

appropriate extraction method, the number of factors to retain, and the factor rotation technique (Costello & Osborne, 2005)

Many researchers have attempted to improve the practice of EFA by publishing useful recommendations, many of which appear in PARE (Beavers et al., 2013; Costello & Osborne, 2005; Courtney, 2013; DiStefano, Zhu, & Mindrilla, 2009; Osborne & Fitzpatrick, 2012). The authors of these articles should be commended for presenting clear and practical guidelines for EFA practitioners. Unfortunately, many of the recommendations are challenging to implement using mainstream statistical software such as IBM SPSS Statistics (IBM Corp, 2012). Commercial statistical packages, textbooks and instructors appear to be lagging behind recommended practices. Clear practical demonstrations for improving EFA are needed. Basto and Pereira (2012) and Courtney (2013) discuss the use of the R-Menu plugin for IMB SPSS Statistics (IBM Corp, 2012) for implementing judicious factor retention methods. The R plugins for SPSS substantially improve EFA

functionality, but the installation process can be burdensome and the very idea of using free EFA tools through a commercial package will seem nonsensical to some. Using the EFA packages directly through the free statistical package R (R Core Team, 2013) requires familiarity of the open source software and a moderate level of programming knowledge required may be off-putting to some. As such, the aim of this paper is to demonstrate a viable alternative for implementing recommended EFA methods.

Specifically, this article will demonstrate how to apply recommended EFA methods using the freely available PC software package FACTOR (http://psico.fcep.urv.es/utilitats/factor/, Lorenzo-Seva & Ferrando, 2006). FACTOR is an easy to use, standalone EFA package with many powerful and cutting-edge features. It runs directly from an executable file and does not require installation. The demonstration, using an accompanying dataset, will focus on the analysis of ordinal variables created through the use of Likert-type rating scales. Ordinal variables are the norm for most EFAs. Research shows that the common use of Pearson correlations for EFA models can substantially underestimate the strength of the relationship between ordinal variables. This can lead to spurious factors in EFA outcomes (Garrido, Abad, & Ponsoda, 2013; Holgado–Tello, Chacón–Moscoso, Barbero–García, & Vila–Abad, 2008; Olsson, 1979b).

Improving Your EFA

Prior to demonstrating the use of FACTOR, methods for improving your EFA practices will be briefly summarised. The reader is directed to excellent articles in PARE by Costello and Osborne (2005) and Beavers et al. (2013) for more comprehensive treatments. At the outset, the decision faced by the practitioner during EFA is choosing between EFA and principal components analysis (PCA). Both EFA and PCA are used to reduce the number of dimensions inherent in the data. However, both make very different assumptions. Factor analysis is concerned with identifying the underlying factor structure that explains the relationships between the observed variables. On the other hand, PCA is used to reduce a large number of interrelated variables into a smaller set of "components" with minimal loss of information. For example, a researcher with multicollinearity issues in a multiple regression model might use PCA to cluster highly related variables into a single predictor to

avoid biased parameter estimates. PCA does not attempt to explain the underlying population factor structure of the data and makes the often, unrealistic, assumption that each variable is measured without error. EFA, on the other hand, is based on the common or shared variance between variables, which is partitioned from the left-over variance unique to each variable and any error introduced by measurement. Hence, EFA is more theoretically aligned to the goals of exploring the dimensionality of a scale proposing to measure a latent variable. The researcher must also decide between EFA vs. confirmatory factor analysis (CFA). Generally speaking, CFA is selected when a researcher has a hypothesised structure explaining the relationship between variables and wishes to validate the fit of a model using data taken from a sample (Note. CFA can still be used in an exploratory manner, see Schmitt, 2011). On the other hand, EFA is chosen when the researcher cannot assume, a priori, a structure to the variable's relationships and must rely on the sample to estimate it (Matsunaga, 2010). This commonly occurs when new assessment instruments or scales are developed and tested for the first time.

Another related issue is the type of correlation matrix to be analysed. Conventional EFA is based on the Pearson correlation matrix. Pearson correlations assume data have been measured on, at least, an equal interval scale and a linear relationship exists between the variables. These assumptions are typically violated in the case of variables measured using ordinal rating scales (Timmerman & Lorenzo-Seva, 2011). Pearson correlations have been found to underestimate the strength of relationships between ordinal items (Olsson, 1979a). In relation to EFA procedures, studies have observed Pearson correlation matrices used on ordinal data giving rise to spurious multidimensionality and biased factor loadings (Bernstein & Teng, 1989). Acknowledging the limitations of the Pearson correlation, researchers have investigated the use of an alternate measure of correlation known as the polychoric correlation. The polychoric correlation, which is an extension of the tetrachoric correlation, is a technique for estimating the correlation between two bivariate normally distributed continuous variables measured using an ordinal scale (Olsson, 1979a).

To demonstrate the performance of the Polychoric correlation, a simple simulation was performed using R (R Core Team, 2013, contact author for the simulation script). First, a bivariate normal population distribution was generated with a population Pearson correlation of

r = .557 (Figure 1a). Next, 1000 random samples of size n = 30 from the bivariate data, x,y, were taken from the population. For each sample, the normally distributed bivariate data were converted to ordinal data measured on a five-point Likert-type scale using
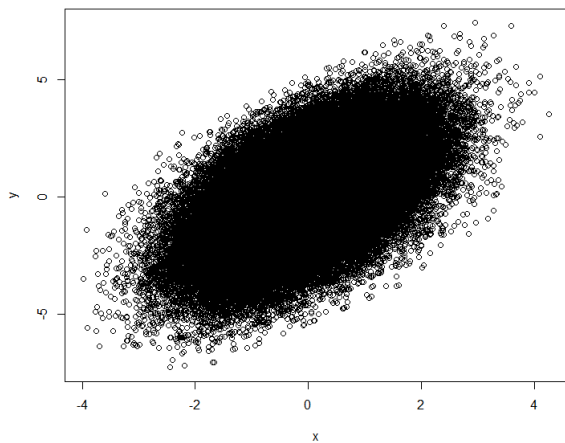

Figure 1a. Bivariate normal distribution, Pearson r = .557.

arbitrary and unequal splits in the distribution (Figure 1b). These splits were determined subjectively and should only be considered one hypothetical example of an infinite number of ways to split a continuous scale. Even though an underlying bivariate normal distribution was used, the resulting ordinal conversion resulted in highly skewed distributions. The simulation involved calculating a Pearson correlation and a Polychoric correlation for each sample of the ordinal data. The mean Pearson correlation for the 1000 simulated samples resulted in Pearson's r = 0.462, which was a substantial underestimation. On the other hand, the Polychoric correlation was able to recover the population's true correlation closely by returning a sampling mean of r = 0.560. This very simple simulation demonstrates that the polychoric correlation is an unbiased estimate of the population Pearson correlation for bivariate normally distributed variables which have been measured using an ordinal scale. Therefore, it's not surprising that researchers recommend the use of polychoric correlations for EFA performed on data from ordinal variables (Garrido et al., 2013; Holgado–Tello et al., 2008; Timmerman & Lorenzo-Seva, 2011).

The next major decision faced by a researcher during EFA is deciding on the extraction method. Common examples include unweighted least squares,

generalised least squares, maximum likelihood, principal axis factoring, alpha factoring and image factor to name a few (Costello & Osborne, 2005). The
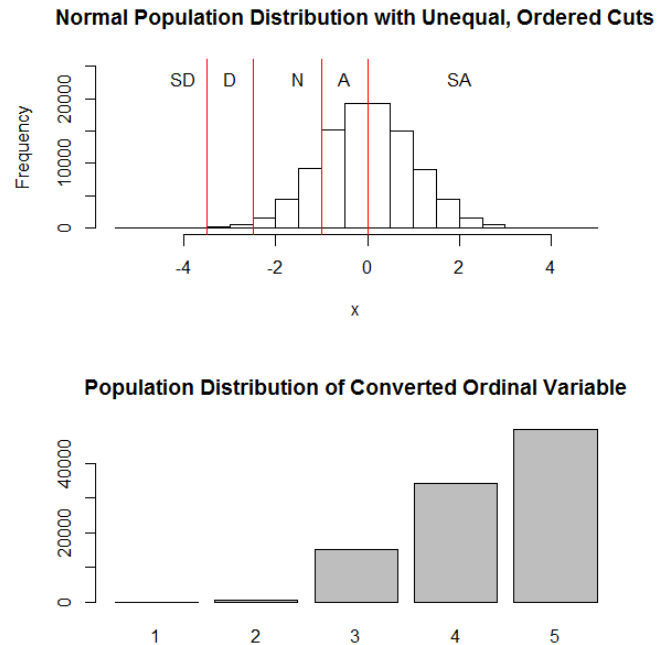

Figure 1b. A normally distributed random variable is arbitrarily converted to an ordinal random variable measured on a five-point Likert scale (ranging from strongly disagree to strongly agree). Even though the variable is normally distributed in the population, the ordinal conversion results in a highly skewed distribution.

method selected should be based on the nature of the underlying distribution of the data. For example, maximum likelihood is recommended when data are multivariate normally distributed, while principal axis factoring makes no distributional assumptions (Fabrigar et al., 1999). For other methods, clear guidelines are lacking. A common problem with EFA extraction methods concerns the reporting of indices of model fit including the amount of variance explained by an EFA model. PCA allows a researcher to report the total variance explained as a measure of goodness of fit. PCA is able to do this because it only has to distinguish between the explained variability of the components and the total variability inherent in all the observed variables. EFA can produce a measure of goodness of fit based only on the common variance, after error and unique variance is partitioned out, but there are challenges with this computation for regular EFA methods including principal axis factoring,

unweighted least squares and maximum likelihood EFA (Lorenzo-Seva, 2013). Minimum rank factor analysis (MRFA, Shapiro & ten Berge, 2002; ten Berge & Kiers, 1991), as currently implemented only in FACTOR, is able to estimate the percentage of common variance explained by an EFA model. This is an attractive property for an EFA extraction method.

Deciding how many factors to retain following extraction has received substantial attention in the literature. While researchers can use their own judgement to decide on the number of factors to retain, more often than not, researchers revert to conventional guidelines, including the Kaiser criteria (eigenvalue > 1) and scree plot. Unfortunately, the Kaiser criteria and scree plot have been shown to overestimate the number of dimensions in the data (Hubbard & Allen, 1987; Ruscio & Roche, 2012; Zwick & Velicer, 1986). While the scree plot is substantially more accurate than the Kaiser criteria (Zwick & Veliver, 1986), ambiguous scree plots suffer from issues with subjectivity as evidence by poor inter-rater reliability (Crawford & Koopman, 1979). Parallel analysis (PA, Horn, 1965) is a commonly recommended method for factor retention (Fabrigar et al., 1999). Horn's original PA works by generating many (e.g. 500) random parallel datasets, with the same number of variables and cases as the sample dataset. Each of these parallel datasets, which are filled with independent randomly generated data, is analysed using PCA. The mean eigenvalues of the factors extracted from the random parallel datasets are compared to the samples' eigenvalues. All factors where the sample's eigenvalues are greater than the means of the random parallel datasets are retained. PA has been found to be superior to conventional methods for correctly identifying the true number of dimensions (Hubbard & Allen, 1987; Ruscio & Roche, 2012; Zwick & Velicer, 1986). PA analysis was second only to the comparison data (CD) method in simulation studies performed by Ruscio and Roche (2012). In FACTOR, a powerful variation of PA using MRFA and polychoric correlations is available. Timmerman and Lorenzo-Seva (2011) found PA-MRFA, which is based on random permutation of the sample data and comparing the percentage of common variance extracted by MRFA, outperformed Horn's PA and PA based on principal axis factoring (Humphreys & Ilgen, 1969).

Assuming a scale is multidimensional, factor rotation will be necessary to aid the interpretation of the model. There are two main classes for rotation, orthogonal and oblique. Orthogonal rotation seeks to find a solution that minimises the relationship between factors. This method has been criticised as most factors that make up a latent variable are expected to share some degree of relationship (Gaskin & Happell, 2013). Costello and Osborne (2005) also demonstrated that an oblique rotation could be used to estimate an orthogonal model, but not vice versa. Therefore, oblique rotation, which allows relationships between factors, should be preferred in most situations, unless a strong argument can be made as to why the factors should not be correlated (Beavers et al., 2013; Costello & Osborne, 2005; Gaskin & Happell, 2013; Matsunaga, 2010). In FACTOR, many common and advanced methods for oblique and orthogonal rotation are available. For example, FACTOR provides the option to use the oblique Promin rotation method which has been found to perform comparably to direct oblimin for recovering a true rotated solution and to slightly outperforms it when fewer complex variables (variables that load highly onto more than one factor) are present (Lorenzo-Seva, 1999).

The following recommendations can be made based on this brief summary on how to improve your EFA for ordinal data:

- EFA is theoretically based on exploring the underlying relationship among variables that comprise a scale used to measure a latent variable.

- Polychoric correlations are preferred in place of Pearson correlations when variables are measured using an ordinal scale. However, polychoric correlations still make the assumption that the ordinal variables are derived from a bivariate normal population distribution.

- Decisions about the extraction method to be used for EFA should be based on the scale and shape of the data's distribution.

- The Kaiser criteria and scree plot should be avoided for factor retention decisions. Scree plots are suitable for getting a sense of the number of dimensions, but ambiguities can arise. Parallel analysis-based methods are recommended as they outperform both the Kaiser criteria and scree plot.

- By default, oblique rotation methods should be chosen as most factors in a multidimensional scale will share some degree of relationship. Orthogonal rotation should only be used when

there is a strong justification to assume no relationship between factors.

Each of these recommendations will be met in the following sections by using FACTOR. The demonstration will use a motivating example. The options available and output generated by FACTOR are substantial. The aim of this article is to demonstrate and discuss the most pertinent for getting the most out of your EFA for ordinal data.

Demonstrating FACTOR

The Example

The example data was downloaded from the Online Personality Tests website (http://personality-testing.info/). This website stores the responses from over half a million online anonymously completed personality tests. The tests and data are made freely available to the public for educational purposes. The test chosen was the well-known Big 5 Personality Test based on the Big-Five markers reported by Goldberg (1992). According to Big 5 theory, personality is comprised of five main traits including extraversion (E), agreeableness (A), conscientiousness (C), emotional stability (N) and intellect/imagination (O). While the Big 5 has generated substantial evidence of construct validity through previous factor analytic studies, it was interesting to investigate if EFA performed in FACTOR using the recommend methods could extract the theoretically proposed factor structure and compare these results to what would have been obtained using a default approach in SPSS. The Big 5 dataset contained the results of more than 11,000 tests. Computationally, this was very large for the PA procedure that would be implemented. Therefore, a random sample of 500 tests was analysed, which was considered a more representative sample size used in EFA studies. The Big 5 test used by the Online Personality Tests website included 50 self-reported personality items, for example, "I get stressed out easily", which were rated on an ordinal five-point scale ranging from (1) disagree to (5) agree. The dataset used in the following demonstration can be obtained by contacting the author.

Preparation

The first step is to download and open FACTOR (http://psico.fcep.urv.es/utilitats/factor/).

Unfortunately, FACTOR is only available for PCs. FACTOR runs directly from an executable file and does not require installation. FACTOR requires the data to be in a simple format using the .dat file extension. The data file must have no labels and no extra variables, just the variables to be included in the EFA. No missing values are permitted. If participants have missing values, the participant must either be removed entirely (case-wise deletion) or an appropriate missing value imputation implemented (see Shrive, Stuart, Quan, & Ghali, 2006). A file with descriptive variable labels can be attached separately. The easiest way to create a .dat file is to export your data from the statistical package in the .dat format. Packages such as SPSS will have built-in options for this purpose. You can also convert common dataset formats using Excel, but not directly. To do so, use Excel to save the dataset as a plain text file, .txt, in a tab delimited format. Find the dataset saved on your computer and change its extension from .txt to .dat. A tab delimited .txt file and a .dat file are equivalent. The file is now ready to be used in FACTOR.

A label file can also be created to accompany the dataset. Open a plain file in a text editor and type the labels for the variables in column order. Each row corresponds to a column label. Save this file as a simple .txt file. Figure 2Figure displays an example. The Big 5 items were labelled using an item number, 0 – 49 and a letter corresponding to the theoretically aligned trait.
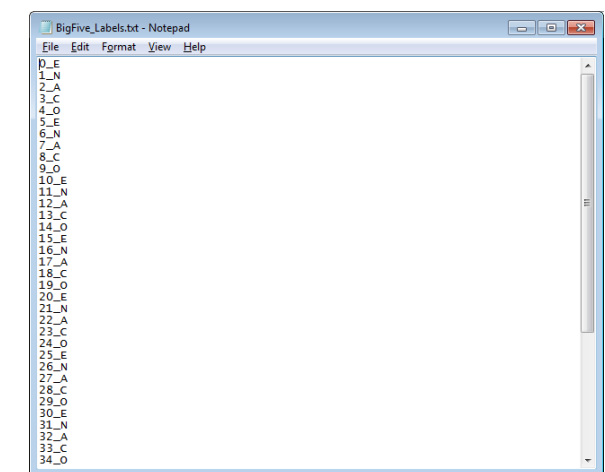

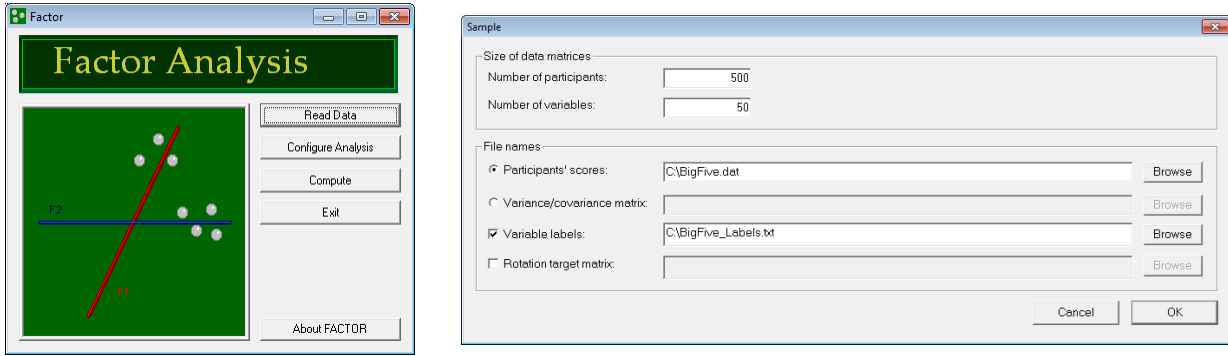
Figure 2. FACTOR label file example.

Figure 3. FACTOR's Main window and Read Data window.

Extraction and Retention

The EFA demonstration will be broken into two major steps: 1) Extraction and Retention and 2) Rotation. To begin, open FACTOR and click on the read data button (**Figure 3**). Set the number of participants and number of items. You will also need to locate the file with the participants' scores (the *.dat* dataset) and the variables' labels file if you have one. Click OK and select the Configure Analysis button.
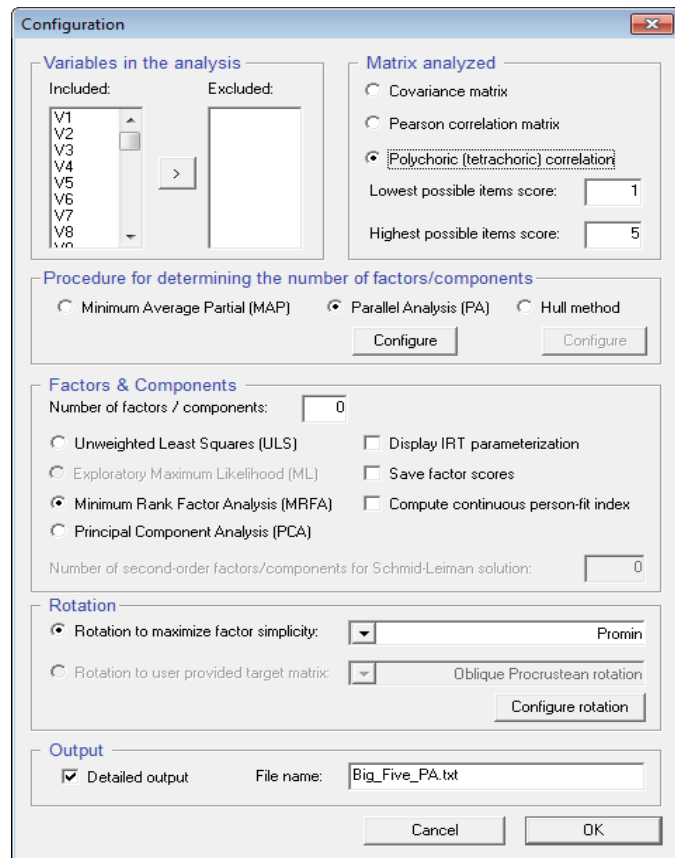
Figure 4a. Main FACTOR Configuration window

The configuration window is where the many features of FACTOR become apparent (Figure 4a). The practitioner has access to many powerful EFA

methods including the option to analyse polychoric correlations, perform parallel analysis and execute advanced extraction and rotation methods such as MRFA and Promin. In the configuration menu, select the option to analyse polychoric correlations, due to the ordinal nature of the data. PA should also be selected and based on the minimum rank factor analysis (MRFA, Timmerman & Lorenzo-Seva, 2011). Note that Horn's method is available as a configurable option (Figure 4b). The PA-MRFA is advised based on simulation studies which have found it to outperform Horn's PA (Timmerman & Lorenzo-Seva, 2011). Other conventional extraction methods, including PCA are also available in addition to the useful option to save factor scores (see DiStefano et al., 2009). In the first step, it's not important to specify the correct rotation
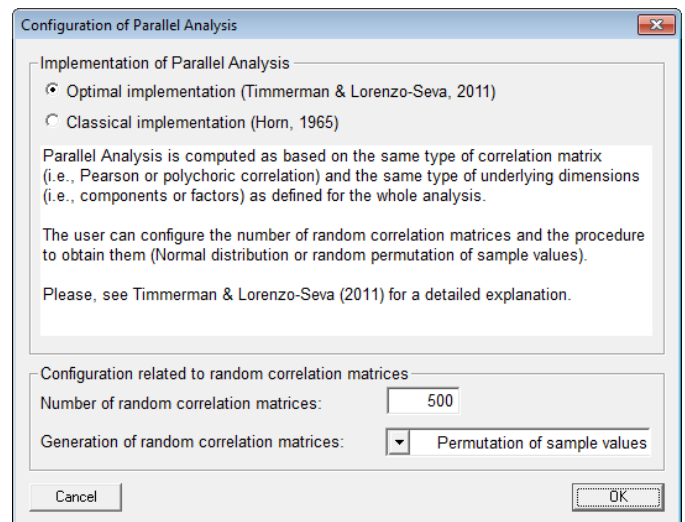
Figure 4b. Main FACTOR PA Configuration window

method or the number of factors to be retained. The number of factors to be extracted and rotation method can be specified in the second step once the PA has advised the number of dimensions to retain. You can also specify the name of the output file from the

analysis to be saved in a .txt file. Click OK and hit the compute button to run the PA. FACTOR will give you a warning before proceeding if you specify zero number of factors. Ignore this message and proceed. The author advises that separate files be saved for each step of the EFA. This enables the practitioner to separate the results of the PA from the rotation.

PA is a simulation method and, as such, can take considerable computational time depending on the sample size and number of variables. For some perspective, the PA for the Big 5 data took 16 minutes on a Core I7 Intel processor with 8 GB RAM. It's also common for Windows to report FACTOR to be non-responsive even though the simulation is correctly running in the computer's memory (Figure 5). Once the PA is complete you will be presented with a comprehensive output file. The most pertinent output will now be presented and discussed.
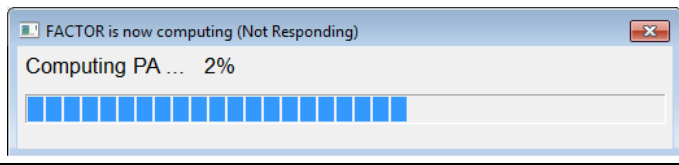

Figure 5. Parallel analysis will take some time. Be patient. FACTOR is still responding despite the warning.

The first part of the output lists the details of the analysis. The log includes the data file location, number of participants, variables, factors extracted, factor retention method, type of correlation matrix analysed, and the factor extraction and rotation method. The second important table presents the item's univariate statistics (**Table 1**). FACTOR recommends the use of polychoric correlations when either the skewness or kurtosis statistics are higher than one in absolute value. Items 6 and 8 in Table 1 exhibit kurtosis in excess of this threshold. While such rules of thumb may be convenient, the author advises that the decision to use either polychoric or Pearson correlations be based on the level of the item's measurement. Also, recall that polychoric correlation assume variables represent bivariate normal distributions measured using an ordinal scale. Multivariate tests for skewness and kurtosis proposed by Mardia (1970) are also reported. For the Big 5 data, the test for skewness was not statistically significant, $p = 1.00$. However, there was evidence of excessive kurtosis, $p < .001$. Mardia's test result can be used for supporting the decision to us polychoric correlations.

Common methods for determining the suitability of the data for factor analysis are also reported by FACTOR. Check the polychoric correlation matrix for evidence of non-zero correlations, a statistically significant Bartlett's test and a Kaiser-Meyer-Olkin (KMO) statistic above .80 (Beavers et al., 2013). The Big 5 example satisfied all these checks with evidence of substantial correlations between items, Bartlett's statistic = 11497.3 (df = 1125), $p < .001$, and KMO = 0.88. On a practical note, estimating the polychoric

Table 1. FACTOR's Univariate Descriptive Statistics Output for the First 10 Big 5 Items

Var	Mean	Confidence Interval		Variance	Skewness	Kurtosis
V1	2.494	(2.36	2.63)	1.406	0.350	-0.742
V2	2.118	(1.98	2.26)	1.480	0.915	-0.214
V3	3.276	(3.15	3.40)	1.228	-0.243	-0.769
V4	3.166	(3.02	3.31)	1.578	-0.164	-0.973
V5	3.918	(3.80	4.04)	1.107	-0.785	-0.017
V6	2.916	(2.76	3.07)	1.841	0.061	-1.177
V7	3.850	(3.73	3.97)	1.135	-0.851	0.136
V8	3.010	(2.85	3.17)	1.874	-0.027	-1.259
V9	3.268	(3.13	3.41)	1.488	-0.278	-0.942
V10	1.944	(1.83	2.06)	1.013	0.891	0.047

correlation requires the convergence of an iterative maximum likelihood algorithm. Researchers have noted that the polychoric correlation estimation commonly fails to converge (Babakus, Ferguson, & Jöreskog, 1987; Timmerman & Lorenzo-Seva, 2011). When this occurs in FACTOR, the pair of variables responsible for non-convergence will be reported and the Pearson correlation inserted into the correlation matrix instead. Therefore, the correlation matrix may be a polychoric and Pearson correlation matrix. For the Big 5 example, all polychoric correlations converged. Once the suitability of the data for EFA has been satisfied, it's time to interpret the results of PA-MRFA.

FACTOR will report the advised number of dimensions based on the PA-MRFA. You will notice that PA-MRFA is based on the random explained common variance, and not eigenvalues as proposed by Horn (1965). The method also uses random permutation of the data instead of purely randomly generated data. There are two criteria that FACTOR will apply to make the decision for how many factors to retain. One method is based on the mean of random variance extracted and the other on the 95th percentile of random percentage of variance. Simulation studies

suggest that the 95th percentile criteria is more accurate (Timmerman & Lorenzo-Seva, 2011). FACTOR compares the mean or the 95th percentile of the factor's percentage of common variance explained from the randomly permutated data to the observed explained common variance from the sample. If a factor's observed percentage exceeds the random percentage, the factor is retained. This occurred five times in the case of the Big 5 example (Table 2). The real data percentage of variance for the first five factors exceeded the 95th percentile of the random common variance extracted. For factor 6, the common variance from the 95th percentile of random variance, 3.6 exceeded the real-data percentage, 2.7, hence five factors were retained.

Table 2. Parallel Analysis Based On Minimum Rank Factor Analysis of Polychoric Correlations (Timmerman & Lorenzo-Seva, 2011) for the Big-5 Example

Var	Real-data % of variance	Mean of random variance	95 percentile of random % of variance
1	20.0*	4.2	4.5
2	11.8*	4	4.2
3	9.6*	3.8	4
4	8.6*	3.7	3.9
5	5.8*	3.6	3.8
6	2.7	3.5	3.6
7	2.6	3.4	3.5
8	2.2	3.3	3.4
9	2	3.2	3.3
10	1.9	3.1	3.2

Note. Only the first 10 factors are shown. Percentage of variance relates to common variance. The factors with stars are retained as the real-data percentage of common variance is higher than the 95th percentile of the PA-MRFA's random datasets

Factor Rotation

Once the PA has advised the number of dimension supported by the data, the next step is to extract the number of advised dimensions and select a rotation option to aid in factor interpretation. To save time, ensure you don't select the PA option in the second step or else the PA will be run again, wasting time. Instead, select the Minimum Average Partial (MAP) option as this is a non-simulation method. Set

the number of advised dimensions to five, select the MRFA option for extraction, and select a rotation method. The oblique rotation method is recommended for EFA. Promin (Lorenzo-Seva, 1999) rotation is the advised option by the developers of FACTOR. However, other more familiar oblique rotation methods are available including the commonly used direct oblimin method. Save the output file using a different file name to the PA output. These options are summarised in Figure 6.
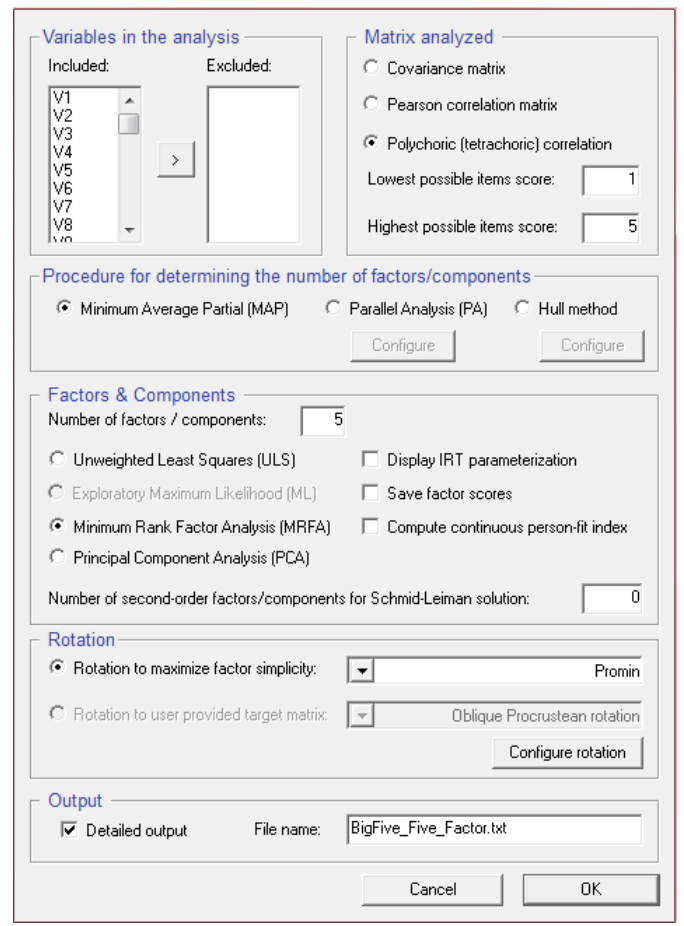
Figure 6. FACTOR Rotation Configuration for the second step of the Big 5 example.

The overall fit of the five factor model can be expressed by reporting the overall percentage of common variance explained. This estimate was made possible with the use of MRFA. For the five factor model of the Big 5 data, the overall percentage of common variance explained was 63.03%. The output also reports the unrotated loading matrix, structure matrix, communalities and rotated (pattern) matrix. The rotated (pattern) loading matrix, structure matrix and communalities are reported in Appendix A. All communalities were above the minimum of .4 as

Table 3. A Comparison of the Big 5 Rotated Factor Solutions for FACTOR and SPSS

Item	FACTOR[a] F1	F2	F3	F4	F5	SPSS[b] F1	F2	F3	F4	F5
16_N	0.796							0.755		
41_N	0.695							0.649		
26_N	0.662							0.621		
36_N	0.661							0.609		
6_N	0.611					-0.316		0.592		
46_N	0.399							0.377		
11_N	-0.437							-0.380		
1_N	-0.596							-0.555		
31_N	-0.641							-0.594		
21_N	-0.726							-0.678		
20_E		0.791				-0.766				
0_E		0.769				-0.742				
30_E		0.758				-0.728				
40_E		0.684				-0.662				
10_E		0.653				-0.642				
25_E		-0.541				0.538				
35_E		-0.651				0.609				
45_E		-0.720				0.689				
5_E		-0.802				0.761				
15_E		-0.808				0.766				
38_C			0.843							0.812
28_C			0.795							0.779
33_C			0.787							0.757
43_C			0.784							0.736
3_C			0.690							0.677
48_C			0.657							0.636
13_C			0.610							0.580
23_C			0.597							0.551
18_C			-0.395							-0.373
8_C			-0.628							-0.609
2_A				0.726			-0.700			
22_A				0.702			-0.686			
42_A				0.661			-0.617			
32_A				0.617			-0.569			
47_A				0.575			-0.542			
12_A				0.468			-0.437			
37_A				-0.414			0.396			
7_A				-0.588			0.549			
17_A				-0.593			0.577			
27_A				-0.719			0.697			
4_O					0.704				0.654	
49_O					0.683				0.659	
39_O					0.666				0.619	
24_O					0.642				0.619	
34_O					0.555				0.496	
14_O					0.548				0.491	
44_O					0.457				0.424	
19_O					-0.479				-0.465	
29_O					-0.513				-0.481	
9_O					-0.666				-0.616	
Reliability[c]	0.896	0.931	0.923	0.879	0.873	.816	.849	.911	.888	.839
% Variance[d]	23.1	13.5	10.7	8.9	6.7	-	-	-	-	-

Note. Rotated loading with values < .3 suppressed. [a] Matrix: Poloychoric correlations , Extraction: MRFA , Retention: PA, Rotation: Promin, [b] Matrix: Pearson correlations, Extraction: Principal Axis Factoring, Retention: Scree plot, Rotation: Direct oblimin. [c] Factor: Mislevy and Bock (1990), SPSS: Cronbach's α. [d] Percentage of common variance explained based on MRFA.

suggested by Costello and Osbourne (2005). The rotated (pattern) matrix, with loading below .3 suppressed is reported in Table 3. All items load onto their theoretical personality dimension. All loadings are checked to be above the minimum of .32 as advised by Tabachnick and Fidell (2001). No complex or cross-loading items are present.

FACTOR also reports reliability estimates based on Mislevy and Bock (1990) and the McDonald's Omega statistic (Table 3). The Mislevy and Bock reliability estimate reflects the proportion of variance in a group of items' factor score accounted for by the underlying common latent variable that drives the item scores. In other words, imagine for each person in the population, there was a factor score (summed or average scores across items that compose a factor) and an individual's true score on a latent variable. A correlation is calculated between the factor scores and the true latent variable. If this correlation is squared you obtain the reliability estimate proposed by Mislevy and Bock, which reflects the proportion of variability in the factors scores explained by the latent variable. The Miselvy and Bock estimate is different to the McDonald estimate as it is based on the standardised factor scores, whereas the McDonald estimate is based on the unstandardised factor loadings (Zinbarg, 2006). FACTOR does not report conventional Cronbach's alpha statistics as estimates of internal consistency for each factor. These estimates would need to be obtained through another statistical package such as SPSS.

SPSS

The EFA for the Big 5 data was performed in SPSS using principal axis factoring. This allowed a comparison using the standard methods available in SPSS. Had the conventional Kaiser Criteria been followed, the practitioner would have extracted 9 factors (Table 4). The scree plot suggested the correct five factors (Figure 7), however, such an unambiguous plot shouldn't be expected in practice. Ambiguities are common. Scree plots may provide an initial idea of the number of dimensions, but PA analysis should be preferred. PA has been shown to be more accurate and avoids issues with subjectivity. The five factor solution is presented alongside the five factor model discovered using FACTOR in Table 3 (Appendix B contains the complete results including the rotated loading matrix, structure matrix and communalities). The major difference between the two solutions concerns the factor loadings. The EFA in SPSS was based on

Table 4. Eigenvalues from EFA Extracted using Principle Axis Factoring for the Big 5 Data

| Factor | Initial Eigenvalues | | | Rotation Loadings |
	Total	% of Variance	Cumu-lative %	Total
1	8.748	17.497	17.497	6.382
2	5.222	10.444	27.941	4.181
3	4.226	8.452	36.393	4.520
4	3.553	7.106	43.499	2.573
5	2.752	5.503	49.002	5.781
6	1.320	2.641	51.643	3.293
7	1.305	2.611	54.254	1.116
8	1.126	2.252	56.506	.920
9	1.004	2.007	58.513	2.227
10	.946	1.893	60.406	
11	.921	1.841	62.247	
12	.915	1.830	64.076	
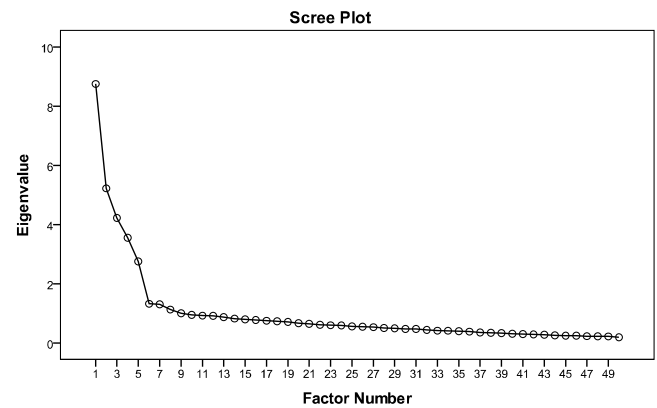
Figure 7. Scree plot of factor eigenvalues for EFA using principal axis factor for factor extraction. The eigenvalues drop-off substantially after the fifth factor, therefore, five factors are advised. This was an example of an unambiguous scree plot, however, in practice, ambiguities can arise. Scree plots may be suitable for getting an idea of the number of dimensions, but PA should be preferred

Pearson correlations and as a result the resulting factor loadings are systematically lower than the factor loadings based on the polychoric correlations matrix analysed in FACTOR. A cross-loading also appears for item 6_N. In conclusion, it was interesting to note that both FACTOR and SPSS EFAs arrived at the correct theoretical model. Therefore, a practitioner might consider what was gained by performing the recommended EFA practices through FACTOR. The EFA performed in FACTOR provided objective evidence to retain five factors, demonstrated

systematically higher factor loadings, contained no complex factors and provided an overall indicator of model fit.

Conclusions

A major barrier to the implementation of recommended EFA practices relates to a lack of features in major software, particularly SPSS, and, perhaps, a lack of clear how-to demonstrations. While SPSS's EFA features can be greatly enhanced with the R-menu plugin, alternatives are available. This paper demonstrated recommended methods for improving your EFA for ordinal data using FACTOR, a free, powerful and standalone EFA package for the PC. FACTOR provides the practitioner with a powerful arsenal of EFA options including the use of polychoric correlations, parallel analysis and minimum rank factor analysis. This demonstration concentrated on the salient features of FACTOR that are most likely to assist the EFA practitioner. FACTOR includes other advanced options including semi-specified target matrices of the factor loadings, second order factors and advanced output for evaluating EFA models. Despite these features there are some minor limitations of the current version. FACTOR will run only on PC, does not accept many standard data formats, the PA procedures take a long time to simulate and the very promising comparison dataset (CD) method (Ruscio & Roche, 2012) for factor retention is yet to be implemented. Yet, FACTOR's benefits far outweigh its' caveats. FACTOR is free, packaged with many powerful and cutting edge EFA procedures and is relatively easy to use. It is hoped that this demonstration helps other researchers to improve their EFA for ordinal data by implementing recommended procedures that are commonly inaccessible.

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Appendix A: Complete EFA Results for Big 5 Example Analysed Using FACTOR

Variable	Rotated (Pattern) Matrix[a]					Structure Matrix[a]					Communality
	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	
0_E	-0.033	0.769	0.031	-0.018	0.052	0.215	0.761	-0.200	-0.027	0.225	0.765
1_N	-0.596	0.078	-0.036	0.037	-0.086	-0.574	-0.121	0.001	-0.040	-0.152	0.608
2_A	-0.026	-0.034	0.022	0.726	0.018	0.075	-0.038	-0.158	0.715	-0.034	0.715
3_C	0.122	-0.095	0.690	-0.119	-0.098	-0.010	-0.288	0.749	-0.278	-0.178	0.805
4_O	-0.039	-0.047	-0.049	-0.047	0.704	0.046	0.120	-0.102	-0.077	0.696	0.838
5_E	-0.048	-0.802	-0.100	0.043	0.050	-0.281	-0.776	0.129	0.052	-0.135	0.860
6_N	0.611	0.268	0.007	-0.022	0.069	0.702	0.477	-0.137	0.069	0.221	0.791
7_A	0.067	0.034	0.055	-0.588	0.095	-0.004	0.056	0.182	-0.597	0.137	0.680
8_C	-0.027	0.065	-0.628	-0.096	0.018	0.044	0.249	-0.622	0.065	0.109	0.609
9_O	0.010	0.092	0.181	0.066	-0.666	-0.066	-0.114	0.214	0.055	-0.668	0.853
10_E	0.110	0.653	-0.229	0.018	-0.045	0.338	0.747	-0.437	0.103	0.150	0.825
11_N	-0.437	0.265	0.208	-0.115	0.144	-0.370	0.095	0.185	-0.242	0.124	0.645
12_A	0.007	-0.067	0.063	0.468	0.253	0.088	-0.020	-0.071	0.438	0.207	0.550
13_C	0.201	-0.129	0.610	0.057	0.025	0.111	-0.242	0.611	-0.075	-0.051	0.678
14_O	-0.013	0.067	0.159	-0.072	0.548	0.061	0.143	0.094	-0.144	0.547	0.809
15_E	0.074	-0.808	0.008	-0.005	0.095	-0.172	-0.765	0.235	-0.007	-0.084	0.802
16_N	0.796	-0.112	0.025	0.046	-0.020	0.762	0.130	-0.030	0.161	0.064	0.802
17_A	-0.036	-0.002	0.264	-0.593	0.088	-0.141	-0.078	0.415	-0.673	0.082	0.744
18_C	-0.097	0.208	-0.395	0.055	-0.114	0.001	0.270	-0.450	0.152	-0.035	0.668
19_O	-0.048	0.076	0.108	0.171	-0.479	-0.077	-0.082	0.102	0.161	-0.489	0.561
20_E	0.115	0.791	0.109	0.079	-0.020	0.366	0.791	-0.160	0.076	0.164	0.860
21_N	-0.726	0.019	0.025	0.121	-0.003	-0.705	-0.220	0.061	0.003	-0.114	0.764
22_A	0.018	0.077	0.024	0.702	-0.028	0.143	0.075	-0.183	0.701	-0.046	0.673
23_C	-0.067	0.093	0.597	0.005	-0.143	-0.117	-0.142	0.591	-0.154	-0.202	0.751
24_O	-0.076	0.161	-0.042	0.181	0.642	0.101	0.301	-0.207	0.149	0.664	0.748
25_E	-0.183	-0.541	0.011	0.011	-0.191	-0.384	-0.648	0.212	-0.014	-0.346	0.777
26_N	0.662	-0.083	0.145	-0.014	-0.127	0.601	0.055	0.122	0.055	-0.067	0.663
27_A	0.078	0.029	0.072	-0.719	0.058	-0.022	0.039	0.238	-0.729	0.105	0.739
28_C	0.057	0.032	0.795	0.011	-0.090	-0.024	-0.211	0.787	-0.185	-0.169	0.794
29_O	-0.148	-0.013	-0.018	-0.011	-0.513	-0.227	-0.175	0.064	-0.003	-0.535	0.674
30_E	0.043	0.758	0.005	-0.044	0.034	0.283	0.778	-0.221	-0.034	0.219	0.848
31_N	-0.641	-0.237	0.006	0.063	0.024	-0.705	-0.438	0.123	-0.040	-0.129	0.895
32_A	-0.008	-0.025	0.165	0.617	0.017	0.065	-0.067	0.008	0.571	-0.042	0.649
33_C	-0.115	0.150	0.787	-0.006	-0.004	-0.147	-0.125	0.756	-0.230	-0.079	0.814
34_O	-0.047	-0.019	-0.069	0.155	0.555	0.058	0.118	-0.165	0.137	0.544	0.765
35_E	0.062	-0.651	-0.040	0.038	0.022	-0.133	-0.614	0.138	0.051	-0.118	0.653
36_N	0.661	-0.031	-0.050	0.045	-0.056	0.655	0.183	-0.112	0.162	0.036	0.747
37_A	-0.117	-0.026	0.057	-0.414	-0.047	-0.201	-0.095	0.191	-0.445	-0.055	0.503
38_C	-0.083	0.112	0.843	0.040	0.011	-0.124	-0.166	0.805	-0.194	-0.077	0.867
39_O	-0.075	-0.070	-0.055	-0.128	0.666	-0.015	0.077	-0.071	-0.160	0.652	0.810
40_E	-0.050	0.684	-0.029	0.005	0.058	0.180	0.691	-0.239	0.008	0.214	0.664
41_N	0.695	0.025	0.091	0.060	0.071	0.713	0.236	-0.010	0.139	0.164	0.799
42_A	0.082	0.005	0.050	0.661	-0.094	0.166	0.000	-0.123	0.665	-0.121	0.745
43_C	-0.178	0.123	0.784	0.005	0.027	-0.213	-0.164	0.760	-0.229	-0.063	0.894
44_O	0.117	-0.201	0.199	0.044	0.457	0.106	-0.116	0.182	-0.016	0.401	0.574
45_E	0.075	-0.720	0.014	-0.018	0.011	-0.158	-0.698	0.227	-0.017	-0.147	0.684
46_N	0.399	0.264	-0.189	0.031	0.065	0.517	0.464	-0.325	0.141	0.206	0.766
47_A	-0.004	0.009	0.122	0.575	0.158	0.098	0.013	-0.050	0.534	0.116	0.574
48_C	0.026	-0.185	0.657	-0.059	0.113	-0.092	-0.349	0.713	-0.236	-0.002	0.797
49_O	-0.045	0.162	0.069	0.082	0.683	0.112	0.288	-0.078	0.023	0.702	0.771

Note. a Matrix: Poloychoric correlations, Extraction: MRFA, Retention: PA, Rotation: Promin

Appendix B Complete EFA Results for Big 5 Example Analysed using SPSS

Variable	Rotated (Pattern) Matrix[a]					Structure Matrix[a]					Communality
	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	
0_E	-0.742	0.016	0.000	0.064	0.004	-0.752	0.035	0.148	0.187	-0.184	0.570
1_N	-0.013	-0.025	-0.555	-0.096	-0.030	0.104	0.050	-0.556	-0.146	-0.004	0.320
2_A	0.030	-0.700	-0.027	-0.011	-0.011	0.048	-0.699	0.074	-0.044	-0.148	0.491
3_C	0.102	0.132	0.112	-0.105	0.677	0.267	0.251	0.027	-0.145	0.731	0.573
4_O	0.006	0.039	-0.035	0.654	-0.060	-0.112	0.056	0.024	0.655	-0.086	0.434
5_E	0.761	-0.044	-0.082	0.033	-0.068	0.755	-0.060	-0.217	-0.098	0.118	0.584
6_N	-0.316	0.012	0.592	0.087	-0.013	-0.449	-0.071	0.661	0.198	-0.126	0.551
7_A	-0.039	0.549	0.062	0.114	0.079	-0.061	0.561	-0.007	0.142	0.175	0.340
8_C	-0.074	0.078	-0.022	0.036	-0.609	-0.232	-0.044	0.015	0.084	-0.612	0.389
9_O	-0.040	-0.051	0.011	-0.616	0.177	0.106	-0.037	-0.041	-0.620	0.191	0.413
10_E	-0.642	-0.025	0.132	-0.026	-0.246	-0.725	-0.085	0.271	0.107	-0.419	0.604
11_N	-0.197	0.123	-0.380	0.128	0.187	-0.100	0.229	-0.358	0.118	0.175	0.232
12_A	0.050	-0.437	0.007	0.221	0.030	0.028	-0.424	0.083	0.196	-0.062	0.229
13_C	0.120	-0.038	0.185	0.009	0.580	0.230	0.053	0.139	-0.028	0.593	0.395
14_O	-0.084	0.071	-0.004	0.491	0.127	-0.134	0.118	0.043	0.500	0.092	0.276
15_E	0.766	0.004	0.037	0.082	0.033	0.753	-0.007	-0.106	-0.044	0.221	0.577
16_N	0.036	-0.053	0.755	-0.006	0.014	-0.105	-0.166	0.755	0.058	-0.026	0.575
17_A	0.012	0.577	-0.033	0.101	0.281	0.061	0.644	-0.128	0.101	0.401	0.500
18_C	-0.187	-0.060	-0.075	-0.094	-0.373	-0.251	-0.127	-0.019	-0.051	-0.424	0.219
19_O	-0.038	-0.153	-0.040	-0.465	0.103	0.076	-0.142	-0.059	-0.474	0.090	0.251
20_E	-0.766	-0.076	0.143	-0.009	0.072	-0.773	-0.067	0.299	0.125	-0.144	0.628
21_N	0.053	-0.100	-0.678	-0.025	0.027	0.198	0.006	-0.677	-0.104	0.055	0.473
22_A	-0.081	-0.686	0.017	-0.051	-0.007	-0.064	-0.690	0.133	-0.061	-0.170	0.486
23_C	-0.048	0.021	-0.054	-0.148	0.551	0.127	0.140	-0.090	-0.176	0.555	0.334
24_O	-0.180	-0.178	-0.063	0.619	-0.071	-0.284	-0.156	0.062	0.640	-0.186	0.484
25_E	0.538	-0.007	-0.197	-0.197	0.040	0.620	0.013	-0.322	-0.308	0.196	0.465
26_N	0.027	0.009	0.621	-0.113	0.136	-0.041	-0.062	0.597	-0.065	0.120	0.393
27_A	-0.030	0.697	0.077	0.085	0.099	-0.048	0.710	-0.020	0.118	0.229	0.527
28_C	-0.014	0.008	0.056	-0.105	0.779	0.189	0.159	0.008	-0.142	0.780	0.621
29_O	0.055	0.015	-0.138	-0.481	0.001	0.162	0.018	-0.197	-0.503	0.053	0.278
30_E	-0.728	0.040	0.073	0.050	-0.023	-0.757	0.041	0.215	0.181	-0.205	0.582
31_N	0.285	-0.044	-0.594	-0.002	0.020	0.407	0.044	-0.644	-0.109	0.113	0.499
32_A	0.027	-0.569	-0.004	-0.013	0.122	0.072	-0.544	0.069	-0.046	0.010	0.313
33_C	-0.112	0.027	-0.102	-0.021	0.757	0.102	0.203	-0.125	-0.054	0.740	0.568
34_O	-0.013	-0.141	-0.037	0.496	-0.087	-0.108	-0.135	0.039	0.495	-0.147	0.277
35_E	0.609	-0.037	0.029	0.011	-0.017	0.598	-0.057	-0.082	-0.088	0.127	0.361
36_N	-0.035	-0.055	0.609	-0.037	-0.056	-0.160	-0.160	0.623	0.028	-0.105	0.399
37_A	0.041	0.396	-0.112	-0.034	0.079	0.081	0.427	-0.188	-0.042	0.181	0.209
38_C	-0.080	-0.018	-0.076	-0.008	0.812	0.142	0.165	-0.099	-0.050	0.792	0.637
39_O	0.034	0.113	-0.069	0.619	-0.058	-0.073	0.134	-0.031	0.615	-0.058	0.399
40_E	-0.662	-0.008	-0.022	0.068	-0.051	-0.682	0.001	0.117	0.178	-0.224	0.472
41_N	-0.092	-0.065	0.649	0.080	0.071	-0.213	-0.144	0.681	0.151	-0.004	0.483
42_A	-0.009	-0.617	0.079	-0.115	0.013	0.010	-0.630	0.163	-0.129	-0.116	0.415
43_C	-0.073	0.024	-0.157	0.005	0.736	0.142	0.204	-0.183	-0.039	0.730	0.560
44_O	0.159	-0.038	0.101	0.424	0.179	0.115	-0.004	0.108	0.396	0.181	0.230
45_E	0.689	0.018	0.042	0.002	0.037	0.689	0.005	-0.096	-0.110	0.213	0.478
46_N	-0.297	-0.043	0.377	0.081	-0.196	-0.432	-0.133	0.459	0.176	-0.305	0.381
47_A	-0.015	-0.542	-0.001	0.130	0.084	-0.004	-0.519	0.092	0.107	-0.041	0.292
48_C	0.186	0.073	0.015	0.093	0.636	0.327	0.204	-0.056	0.030	0.692	0.517
49_O	-0.182	-0.081	-0.035	0.659	0.039	-0.273	-0.040	0.074	0.681	-0.061	0.497

Note. a Matrix: Pearson correlations, Extraction: Principal Axis Factoring, Retention: Scree plot, Rotation: Oblique

Citation:

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