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Exploratory factor analysis in validation studies: Uses and recommendations

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Abstract

Background: The Exploratory Factor Analysis (EFA) procedure is one of the most commonly used in social and behavioral sciences. However, it is also one of the most criticized due to the poor management researchers usually display. The main goal is to examine the relationship between practices usually considered more appropriate and actual decisions made by researchers. **Method:** The use of exploratory factor analysis is examined in 117 papers published between 2011 and 2012 in 3 Spanish psychological journals with the highest impact within the previous five years. **Results:** Results show significant rates of questionable decisions in conducting EFA, based on unjustified or mistaken decisions regarding the method of extraction, retention, and rotation of factors. **Conclusions:** Overall, the current review provides support for some improvement guidelines regarding how to apply and report an EFA.

Keywords: Exploratory Factor Analysis, factor extraction, number of factors retained, factor rotation.

Resumen

El análisis factorial exploratorio en estudios de validación: usos y recomendaciones. **Antecedentes:** la técnica del Análisis Factorial Exploratorio (AFE) es una de las más utilizadas en el ámbito de las Ciencias Sociales y del Comportamiento; no obstante, también es una de las técnicas más criticadas por la escasa solvencia con que se emplea en investigación aplicada. El objetivo principal de este artículo es describir y valorar el grado de correspondencia entre la aplicación del AFE en las publicaciones revisadas y las prácticas que habitualmente se consideran más adecuadas. **Método:** se analizan 117 estudios en los que se aplica la técnica del AFE, publicados en 2011 y 2012, en las tres revistas españolas de Psicología con mayor índice de impacto medio en los últimos cinco años. **Resultados:** se obtienen importantes tasas de decisiones injustificadas o erróneas respecto al método de extracción, retención y rotación de factores. **Conclusiones:** en conjunto, la presente revisión proporciona una guía sobre posibles mejoras al ejecutar e informar de un AFE.

Palabras clave: Análisis Factorial Exploratorio, extracción de factores, retención de factores, rotación.

After more than one hundred years of development, Exploratory Factor Analysis (EFA) has become one of the most extensively employed techniques in validation studies of psychological tests. In this sphere, the main goal of EFA is to determine the minimum number of common factors required to adequately reproduce the item correlation matrix.

In view of the enormous flexibility of possibilities of use provided by the technique, it is essential to acquire the necessary knowledge of EFA to make the best decisions to adapt to concrete measurement conditions; otherwise, a factorial study guided by the default options of the software employed may lead to incorrect decisions about the number and definitions of the factors. However, the necessary information to guarantee the replicability of the study must be included in the research report.

Accordingly, the goal of the present study article is twofold: a) to synthesize the most adequate recommendations for the correct application of EFA and the preparation of the report, and b) to review the use of EFA in the three Spanish Psychology journals with the highest impact factors. The main recommendations were taken from the reviews of Abad, Olea, Ponsoda, and García (2011), Bandalos and Finney (2010), Ferrando and Anguiano-Carrasco (2010), Henson and Roberts (2006), Thompson (2004), and Fabrigar, Wegener, MacCallum, and Strahan (1999).

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Decisions about the research design

The application of EFA will never resolve the problems or limitations committed in the research design phase. If relevant variables are omitted in the analysis, or groups of scarcely reliable or redundant items are included, the final solution of the number and composition of the factors will be seriously affected.

One of the first decisions to make is whether to apply EFA or Confirmatory Factor Analysis (CFA). The latter is recommended when the researcher, due to prior systematic results or the existence of solid theoretical previsions, can foresee the number of and relation among factors, as well as their loadings on the variables, some of which are assumed to be null. In any event, the reader is reminded that "exploratory" is not a synonym of not having any previsions or concrete hypotheses about the number of factors and their relations, and it is a bit "sneaky" (because of capitalizing on chance) to apply a CFA on the same sample after obtaining the results of an EFA. The degree of stability of the results obtained can be tested in other independent samples. For example, when the sample size allows it, it is habitual to conduct cross-validation studies to replicate the factor structure: applying EFA to one half of the sample and confirming the structure by means of CFA on the other half (Brown, 2006, p. 301).

With regard to sample size, there are no minimum recommended ratios between the number of subjects and variables because the demands are modulated by the communalities of the variables (proportion of variance explained by the common factors), the level of correlation among factors, and the number of variables that define each factor. At best, 100 or 200 subjects are usually sufficient if the communalities are higher than 0.5 and each factor is defined by a minimum number of 7 variables (MacCallum, Widaman, Zhang, & Hong, 1999; Mundfrom, Shaw, & Ke, 2005). When the communalities are low, no matter how large the sample size is, the estimation of the factor loadings (pattern/structure coefficients) will not be accurate.

In studies seeking evidence about the internal structure of a test, each factor should be defined by a high number of items, as a single item is usually a variable with low reliability. It is recommended to carry out a preliminary analysis of the metric quality of the items to subject the most adequate items to EFA. For this purpose, it is recommended to analyze and report the mean, standard deviation, and item-test correlation of each one of the items, as well as the Cronbach's alpha of the scales of the test. The researcher should decide whether to eliminate certain items and, if so, the EFA should be repeated in their absence because it may modify the initial solution. It is also appropriate to obtain different measures of sampling adequacy, such as KMO and Bartlett's sphericity test.

Other aspects to consider when designing the research are (Ferrando & Anguiano-Carrasco, 2010): (a) to define each one of the foreseeable factors with no less than 4 variables, (b) if possible, to include marker variables, for example, an item that obtained a relevant loading on the factor in prior studies, and (c) to employ representative and heterogeneous samples.

Decisions when running the program

A good software should at least allow to choose the best options regarding preliminary item analysis, the measure of association among variables, the factor extraction and rotation method, the criteria to decide the number factors to retain and to estimate the factor scores. Programs such as Factor, MPlus, or R provide a sufficiently broad array of options to be able to employ the different recommendations proposed in this article.

In EFA on items, it is essential to choose which type of correlation matrix to analyze. The technique assumes linear relations among the items and the latent factors, which is inappropriate for categorical variables. When the items have four or less response categories, it is recommended to start with tetrachoric or polychoric correlations (Finney & DiStefano, 2006). The Pearson correlation is normally used for items with 5 or more response categories. It is not advisable to apply an EFA with Pearson correlations if an important part of the items have asymmetric distributions because the items may group as a function of the mean of their distribution (Brown, 2006, p. 21).

Deciding how many factors to retain is one of the most relevant points in EFA which causes the majority of problems in the studies (Henson & Roberts, 2006). As most of the existing criteria to decide how many factors to retain are descriptive, it is recommended to use various strategies to make the decision, among them, to apply Parallel Analysis (Horn, 1965) or Minimum Average Partial (MAP, Velicer, 1976) along with a descriptive study of the residual correlations (e.g., standardized root mean square residual [SRMR]) and the inspection of the scree plot (Abad et al., 2011, p. 232). Garrido, Abad, and Ponsoda (2012) clearly describe the procedure of Parallel Analysis and recommend its application on the polychoric correlation matrix when analyzing categorical variables. It is not recommended to use Kaiser's K1 rule (retain factors with Eigenvalues higher than 1) because, compared with other procedures, it usually recommends retaining an excessive number of factors (Ruiz & San Martín, 1992). Lastly, obtaining weak or poorly identified factors (i.e., factors defined by one or two variables) should lead one to reconsider the number of factors extracted (Ferrando & Anguiano-Carrasco, 2010).

The factor extraction method allows us to estimate factor loadings and correlations between factors. The choice of any method will depend on the researcher's goal, the fulfillment of the distributional assumptions required by the method, and the researcher's interest in employing goodness-of-fit indices. In general, the Unweighted Least Squares (ULS), the Minimum Residuals (MINRES) or the Principal Axes procedures provide very similar results (Ferrando & Anguiano-Carrasco, 2010). With slight variations, they all attempt to estimate the weights that minimize the residual correlations (differences between the empirical correlations and those reproduced by the model) and they make similar estimations. The maximum likelihood (ML) method, which is an inferential method with the aim of minimizing the residual correlations in population rather than in the sample, is also recommendable (Bandalos & Finney, 2010, p. 98). The application of the ML method requires testing the assumption of multivariate normality in order to obtain goodness-of-fit indices of the model. The ML method is less robust (more convergence problems and incorrect estimations) if the sample is small and the factors are weak (Bandalos & Finney, 2010, p. 99). For categorical variables, the weighted least squares mean and variance adjusted (WLSMV) or the ULS methods are recommended (Forero & Maydeu-Olivares, 2009).

The reader is reminded that the Principal Components (PC) is not a method of factor analysis, but instead a method to reduce the dimensions that rejects measurement errors, something that is particularly serious when the analysis is carried out on the item scores. This practice frequently leads to overestimating factor loadings and the variance explained by the factors (Ferrando & Anguiano-Carrasco, 2010).

After deciding the number factors to retain and the extraction method, one must make decisions about the rotation method to use, taking into account the foreseen theoretical relations (for a review of the topic, see Browne, 2001). There is an (erroneous) tendency to consider a simple structure as a structure in which the factors are orthogonal, that is, independent. However, considering that in the Social and Health Science settings, the habitual tendency is for factors to correlate with each other, our recommendation is to begin testing an oblique rotation.

When oblique rotation is administered, three essential results are obtained: the factor pattern matrix, which includes the direct effect of the factors on the variables and is the most appropriate to interpret the obtained solution; the factor structure matrix, which includes the factor-variable correlations; and the factor correlation matrix. The loadings provided by the first two may differ notably if the factor intercorrelations are high, so, in this case, it is advisable to report both results and, otherwise, to explicitly state whether the reported loadings are factor pattern coefficients and/or factor structure coefficients (Thompson, 2004, p. 19).

Quite frequently, the rotated factor matrix does not optimally reflect a simple structure, because some items have loadings on more than one factor. If one proceeds to eliminate items, it is essential to carry out another EFA, report which variables were eliminated, as well as the criteria used to make the decision.

Decisions when preparing the report

It is not easy to incorporate all the necessary information for the application of an EFA in an article with a restricted number of words, as established in the journals (about 5,000 or 6,000 words). The report of the application of EFA should at least include information about the software used, the factor extraction method, the criteria employed to retain factors, the rotation procedure, the full rotated factor matrix (in oblique rotations, indicating whether it is the pattern matrix or the structure matrix), the correlations among factors (in the case of oblique rotations), and information about the importance of the factors (percentage of variance explained or the sum of squared factor loadings). With regard to the last point, when oblique rotations are carried out, the factors overlap, and their importance may be obtained by adding the squared factor structure coefficients. The reader is reminded that these summations are not the variances explained by the respective rotated factors. Following theoretical previsions, the factors should be justifiably interpreted and labeled, indicating which loading values (usually over 0.3 or 0.4) are considered in the interpretation.

If there is available space in the journal, it is recommended to include information about the descriptive statistics of the variables (correlation matrix, discrimination indexes, measures of central tendency and dispersion) and some measure of score reliability (e.g., Cronbach´s alpha). If these data cannot be included due to the available space, the researchers can provide an address where the information can be obtained.

There are various studies on the conditions of EFA application in diverse of research areas of Psychology. The reviews have been particularly prolific in the sphere of Organizational Psychology (e.g., Conway & Huffcutt, 2003; Ford, MacCallum, & Tait, 1986). Fabrigar et al. (1999) studied its use in two of the main journals of applied psychology. Park, Dailey, and Lemus (2002) summarized the options made in communication research. Henson and Roberts (2006) analyzed EFA applications in the four journals that include a larger number of works with this technique. Norris and Lecavalier (2010) studied the topic in five leading developmental disabilities journals. Frías-Navarro and Pascual (2012) evaluated EFA usage in five Spanish journals publishing works on consumer behavior and marketing.

Few of them (e.g., Conway & Huffcut, 2003) report a variable that is essential: the number of variables that define each factor. Practically none of them provide specific information about the type of variables, the measures of association, the criteria employed to eliminate variables, the software used, or the criteria employed to interpret the factors. These criteria, along with the more traditional ones, will be considered in the next review of studies.

Method

Sample

The selection of the journals was based on three criteria: Journal edited in Spain, with a generalist editorial trajectory and a high impact factor in the past 5 years. These journals are: *International Journal of Health and Clinical Psychology* (mean impact factor in 5 years: 2.039), *Psicothema* (1.178), and *Spanish Journal of Psychology* (0.951). Of the articles, 14.4% present at least one EFA. A total of 117 EFAs, published between 2011 and 2012, were examined. It must be noted that 112 of 117 EFA were EFA on item scores.

Instruments

Following the recommendations described, we designed a code to record the conditions in which the EFA was administered, the criteria of which are described in Tables 1, 2, and 3. Each EFA carried out in an article was encoded as a new unit of analysis.

Results

Decisions about the research design

Table 1 presents a detailed description of the results obtained. In most of the studies, EFA is used in order to validate the factor structure of other studies in a different sample or to perform an initial adaptation of a test to another language.

In one third of the works, both EFA and CFA were administered, using the same sample in 73.3% of these cases.

With regard to the sample size, in 80.4% of the articles, a sample larger than 300 participants was used, with a median of 554. The ratio between sample size and the number of variables was higher than 20:1 in more than one half of the cases. The mean number of items analyzed was 25, and the most frequent response format was a rating scale of 5 or more points.

The most frequently employed statistics in the preliminary analyses are: the means and the standard deviation (67.5%), the Cronbach's alpha (77.8%), and the item-test correlation (40.2%). The most extensively used procedures to determine whether the association matrix is factorizable are Bartlett's test (58.1%) and KMO (64.1%), the value of which ranges between .60 and .98, with a mean of .86.

Decisions when running the program

Table 2 shows that more than one third of the studies do not report the software employed. Among those that do report, the most frequently used is SPSS (65.3%), followed by Factor and MPlus.

Only one third of the studies that use items with four or fewer response categories make explicit the use of polychoric correlations. When analyzing items with 5 or more alternatives, they habitually do not report the type of matrix analyzed (95.2%), except when using polychoric correlations. In any case, almost one half of the studies that do not report this, use SPSS software for EFA, so it can be inferred that they use Pearson correlations.

By far, the most frequently used factor extraction method is Principal Components (58.1%), followed by Principal Axes, ULS, and ML, and the assumption of multivariate normality is only confirmed in one of the studies using this last method.

In approximately one half of the works, a single procedure was used to decide the number factors to be retained; the most frequently used are Kaiser's K1 rule (54.7%) and the scree plot (20.8%), and, to a lesser degree, Parallel Analysis and RMSR. When more than one procedure is used, approximately one half use Kaiser's K1 rule conjointly with the scree plot. One fourth of the studies do not report the criterion used.

Orthogonal and oblique rotation strategies are applied in a similar percentage. Both rotational procedures were only carried out on four occasions, first using oblique rotation. Varimax is the method employed almost exclusively when performing orthogonal rotation. Accordingly, oblique rotation presents more variability, and Oblimin and Promax are the most frequently used.

Table 1
Decisions about the research design

Variable	%	N
Initial goal of EFA		
Initial adaptation to another language	30.8	36
Application in a specific sample	21.4	25
Application in a nonspecific sample	25.6	30
New test	14.5	17
Short Test	6.8	8
Current review of a test	0.9	1
EFA and CFA		
Apply EFA and CFA	38.5	45
Uses the same sample	73.3	33
Sample size		
Less than 100	0.9	1
100 - 199	9.4	11
200 - 299	9.4	11
300 - 499	23.1	27
500 - 999	36.8	43
1,000 or more	20.5	24
Sample size-number of variables ratio		
5:1 or less	4.3	5
6:1 to 10:1	13.7	16
11:1 to 15:1	13.7	16
16:1 to 20:1	5.1	6
More than 20:1	61.5	72
Missing data	1.7	2
Description of the instrument		
Items (rating scale)	95.7	112
4 or less	24.1	27
5	55.3	62
7	14.3	16
Others (max 11)	4.5	5
Not reported	1.8	2
Scale or subscale scores	4.3	5
Preliminary analyses		
Descriptive statistics	67.5	79
Cronbach' s α	77.8	91
α if the item is eliminated	11.1	13
Item-test correlation	40.2	47
All the items	66.0	31
Only some items	34.0	16
KMO	64.1	75
Bartlett	58.1	68

Table 2
Decisions when running the program

Variable	%	N
Software		
Reported	64.1	75
SPSS	65.3	49
FACTOR	14.7	11
MPlus	9.3	7
Others	10.7	8
Not reported	35.9	42
Correlation matrix as a function of the number of alternatives (EFA on items, N = 112)		
4 or less		
Polychoric correlations	33.3	9
Not reported	66.7	18
5 or more		
Polychoric correlations	4.8	4
Not reported	95.2	79
Not reported		
Polychoric correlations	100.0	2
Factor extraction method		
Principal components	58.1	68
Principal axes	10.3	12
ULS	6.8	8
WLSMV	5.1	6
ML	5.1	6
Multivariate normality (assumed)	16.7	1
Others	4.4	5
Not reported	10.3	12
Selection of the number of factors		
A sole procedure	45.4	53
Kaiser's K1	54.7	29
Scree plot	20.8	11
Parallel Analysis	9.4	5
RMSR	7.5	4
Goodness-of-fit indices	3.8	2
Theoretical criteria	1.9	1
MAP	1.9	1
More than one procedure	32.2	37
Kaiser's K1 + Scree test	48.6	18
Others	51.4	19
Not reported	23.1	27
Rotation (two or more factors, N = 92)		
Orthogonal	46.7	43
Varimax	97.7	42
Others	2.3	1
Oblique	45.7	42
Oblimin	45.2	19
Promax	31.0	13
Others	23.8	10
Oblique-orthogonal	4.4	4
Not reported	3.3	3
Elimination of items		
Eliminates	26.5	31
Phase in which items are eliminated		
Before applying EFA	38.7	12
After applying EFA, EFA is repeated	19.4	6
After applying EFA, EFA is not repeated	25.8	8
Not reported when items are eliminated	16.1	5
Criteria employed		
Factor loading lower than a value	35.5	11
High loadings on more than one factor	6.5	2
Absence of theoretical coherence	6.5	2
Combination of various criteria	22.6	7
Low item-test correlation	22.6	7
Not reported	6.5	2
Definite factor solution		
Ratio of variables per factor		
Less than 3:1	1.7	2
3:1	6.8	8
4:1	5.1	6
5:1	13.7	16
6:1	7.7	9
7:1	57.3	67
Not reported	7.7	9
Number of variables that define the last factor		
2	10.3	12
3	8.5	10
4	11.1	13
5	2.6	3
6	12.0	14
7 or more	7.8	9
Not reported	47.9	56

In one fourth of the studies, items are eliminated, either before (38.7%) or after performing EFA (45.1%). Among studies that eliminate items afterwards, more than one half do not reapply EFA on the selected items. The criteria most frequently employed to justify the elimination of items are: loadings lower than a certain value (e.g., between .3 and .5) and low item-test correlation.

When analyzing the definite factor solution, we observed that in more than one half of the studies, the ratio of variables per factor is 7:1 or higher, although in 47.9% of the EFAs, the variables that define each factor are not reported, and in one fifth of the studies, the last factor is defined by two or three variables.

Decisions when preparing the report

Table 3 shows the results about the decisions when preparing the report. Almost one half of studies present the full matrix of factor loadings. The presentation of the incomplete matrix of factor loadings—with only those loadings higher than a certain value—is also a habitual practice.

In 94% of the cases, the total percentage of variance explained by extracted factors is reported, with an average percentage of 54% (*SD* = 19.64), and minimum and maximum values of 19.6% and 75.3%, respectively.

When orthogonal rotation is chosen, most of the times, the variance explained by each factor is included, whereas in 59.5% of the oblique rotations, the summation of the squared loadings of each factor is reported and, in all cases, it is called the "percentage of variance explained by the factor."

The most common practices in articles using oblique rotation are: to include a sole loading matrix without specifying whether it is a pattern matrix or structure matrix; or not to include any matrix. Of these studies, 57.1% do not report the correlations among factors.

When analyzing conjointly the main decisions made when applying EFA, we observe the following: when the factor extraction method is Principal Components, the most usual practice is to use Kaiser's K1 rule as the only criterion to make the decision about the number of factors to retain (39.7%), not to report the criterion used (26.5%), or to use the combination of Kaiser's K1 rule and the scree plot (20.6%). 30.2% of the studies performing orthogonal rotation apply Little Jiffy (Principal Components, Kaiser's K1 rule, and Varimax rotation), and it is most habitual to use SPSS analysis software (69%) or not to report the software used (23%).

Table 3
Decisions when preparing the report

Variable	%	N
Format of the loading matrix		
Full	46.1	54
Incomplete	29.9	35
Loadings higher than a value	80.0	28
Only if loads high on its theoretical factor	20.0	7
Not included	23.9	28
Explained variance		
Percentage of total explained variance	94.0	110
Importance of the factors (more than 1 factor)		
Percentage of explained variance (orthogonal)	86.0	37
Sum of squared loadings (oblique)	59.5	25
Not reported	11.8	5
Oblique rotation (N = 42)		
Loading matrix included		
Only pattern matrix	2.4	1
Only structure matrix	2.4	1
Pattern and structure matrix	2.4	1
Does not make explicit the matrix included	64.3	27
Not included	28.6	12
Correlation between factors		
Not reported	57.1	24

Discussion

Since Ford, MacCallum, and Tait (1986) published one of the first studies on good practices in the application of EFA, subsequent reviews have revealed that certain problems persist: choice of the Principal Components method, use of a single procedure to determine the number factors to be retained, extended use of Kaiser's K1 rule, and the unjustified application of orthogonal rotations. To this must be added the scarce information provided in the articles, which hinders their critical appraisal and replication. The results found in this review point in the same direction, although some improvements are observed.

In the present review, we observe an increase of some good practices in the design phase of the research: large sample sizes and high ratios of variables per factor are employed, and preliminary analyses of reliability and measures of sample adequacy are included. On the negative side, a recurring practice is to use the same sample to apply an EFA and a CFA.

With regard to the decisions when running the program, we observed that the most frequently employed software is SPSS, which might restrict the possibilities for adequate analysis (e.g., with items with four or fewer response categories, the polychoric correlations matrix should be used, which the software does not provide).

Table 4
General recommendations

Research design
- Apply EFA with theoretical previsions about the number of factors.
- Define each factor with a minimum number of items (i.e., four).
- Sample size: it is difficult to establish recommendations because the necessary sample may depend on the complexity of the model (e.g., number of factors) and on the communalities of the items. In any event, do not use samples of fewer than 200 subjects.
- If applying a CFA, use a different sample than the one employed for EFA.
- For unidimensional scales, items can be eliminated following the classic psychometric indicators (e.g., item-test correlation) as a step prior to EFA.

Running the program
- Report the software and the version used. Choose adequate software as a function of the requirements of the analysis.
- For items with four or fewer categories, analyze the polychoric correlation matrix.
- Do not use Principal Components as an extraction method.
- Use various procedures to decide the number of factors (e.g., Parallel Analysis and the MAP rule). Do not use Kaiser's rule. Be cautious if a factor is defined by only a few items (e.g., two).
- Use oblique rotation. Orthogonal rotation is only justified if the factors are independent.
- If items are eliminated in the EFA, repeat the analysis with the selected items.

Preparation of the report
- Report the criteria and decisions in the running phase (e.g., correlation matrix analyzed, extraction method, decision criterion about the number of factors, rotation method, and criteria to select the items).
- Interpret the factors with regard to the theoretical previsions.
- Include the full loading matrix (specifying whether it is the pattern matrix or the structure matrix), the total percentage of variance accounted for, measures of the importance of each factor, and the correlations among factors.

The results obtained in this study reveal persistence in the use of some not very recommendable criteria regarding the extraction method (Principal Components), the decision about the number of factors (K1 rule), and the rotation method (Varimax). Their concurrence may de due to the fact that they are the default options of the most extensively used software (i.e., SPSS). The extended use of the K1 rule is particularly serious.

Other aspects that could be improved in the phase of running the program are: eliminating items and not performing a new EFA on the remaining items nor making explicit the criteria employed for this purpose; not reporting the variables that define each factor, or defining factors with two or three variables, with the ensuing identification problems.

With regard to decisions in the report phase, the correlations among factors or the full factor loading matrix are frequently not reported, or if reported, the authors do not specify whether it is the pattern matrix or structure matrix Authors do not always inform about the decisions made when conducting EFA (the correlation matrix analyzed, extraction method, method to decide the number of factors, etc.).

We wish to underline that research of the methods to apply in an EFA, far from being a closed topic, represents a line of work that obliges us to update continually. To offer a few examples, extraction methods that allow reporting the proportion of common variance (Minimum Rank Factor Analysis, Ten Berge & Kiers, 1991), new rotation methods to use when testing complex items (Promin, Lorenzo-Seva, 1999), and efficient modifications of the Parallel Analysis method (Optimum Parallel Analysis, Timmerman & Lorenzo-Seva, 2011) have been proposed. The interested reader can apply these methods in the FACTOR program (Lorenzo-Seva & Ferrando, 2006), a free program that is easy to use, specific for EFA, and with flexible options.

As a synthesis, the main recommendations we propose are included in Table 4.

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