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ABSTRACT

Appropriate use of exploratory factor analysis (EFA) requires a series of thoughtful analytical decisions. Adequate reporting of an EFA would allow external evaluation of the decisions made by the analyst. This paper briefly reviews some of the decisions necessary in an EFA. It provides an empirical review of reporting practice in three educational research journals, and notes several errors in both EFA use and reporting. Three journals were identified for the study: (1) "American Educational Research Journal"; (2) "Journal of Educational Research"; and (3) "The Elementary School Journal." Examination of 14 total volumes across the journals resulted in the coding of 49 EFAs for the current study. Several errors of use and reporting omissions were noted in the study, and recommendations for improved practice are presented. (Contains 4 tables and 59 references.) (SLD)

Running head: EFA REPORTING PRACTICES



# Reporting Practice and Use of Exploratory Factor Analysis in Educational Research Journals

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## Abstract

Appropriate use of exploratory factor analysis (EFA) requires a series of thoughtful analytical decisions. Adequate reporting of an EFA would allow external evaluation of the decisions made by the analyst. The present paper (a) briefly reviews some of the decisions necessary in an EFA, (b) provides an empirical review of reporting practice in three educational research journals, (c) notes several errors in both EFA use and reporting, and (d) provides recommendations for improved practice.

# Reporting Practice and Use of Exploratory Factor Analysis in Educational Research Journals

Factor analysis is commonly employed in social science research to reduce many variables into a smaller set of factors or constructs, which theoretically "can be seen as actually causing the observed scores on the measured variables" (Thompson & Daniel, 1996, p. 202). As Kerlinger (1979) observed, factor analysis is "one of the most powerful methods yet for reducing variable complexity to greater simplicity" (p. 180). Because constructs are unobserved but really are the very things many researchers wish to study, "factor analysis is intimately involved with questions of validity. . . [and] is at the heart of the measurement of psychological constructs" (Nunnally, 1978, pp. 112-113).

The overarching goal of a factor analysis is relatively straightforward. As Henson and Roberts (in press) explained:

> Factor analysis is often used to explain a larger set of $j$ measured variables with a smaller set of $k$ latent constructs. It is hoped, generally, that the $k$ constructs will explain a good portion of the variance in the original $j$ x $j$ matrix of associations (e.g., correlational matrix) so that the constructs, or factors, can then be used to represent the observed variables.

More pragmatically, Tabachnick and Fidell (1996) suggested the

> specific goals of [factor analysis] are to summarize patterns of correlations among observed variables, to reduce a large number of observed variables to a smaller number of factors, to provide an operational definition (a regression equation) for an underlying process by using observed variables, or to test a theory about the nature of underlying processes. (p. 636)

Researchers can also use the factors derived from the analysis as variables in subsequent substantive analyses (e.g., McLeod, Brown, & Becker, 1977).

Although the theoretical framework for factor analysis is a century old (Pearson, 1901; Spearman, 1904), the frequent use of factor analysis is a rather recent phenomenon due to the advent of computers. However, frequency of use is not necessarily an indication of appropriate use. Indeed, although the goals of the method may be apparent, factor analysis requires a series of thoughtfully determined decisions that cannot be fully automated by statistical software and require researcher judgment.

Henson and Roberts (in press) examined the use of exploratory factor analysis across four psychological journals and noted several serious problems in how the method was being used and reported. Hetzel (1996) reported a similar, albeit less comprehensive, review. However, no known studies have explicitly examined the use of exploratory factor analysis in educational research journals. Therefore, the purpose of the present article was to evaluate the use and reporting practice of exploratory factor analysis within the educational research literature. We also present recommendations for improved practice for the analytical decisions required as well as for more accurate and comprehensive reporting of factor analysis results.

## Exploratory Versus Confirmatory Factor Analysis

A distinction must be made between exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The two methods are thoroughly discussed elsewhere (see e.g., Gorsuch 1983; Stevens, 2002; Tabachnick & Fidell, 1996) and so are only briefly mentioned here. Henson and Roberts (in press) explained the difference between EFA and CFA:

> As its name implies, EFA is an exploratory method [often] used to *generate* theory; researchers use EFA to search for the smaller set of *k* latent factors to represent the larger set of *j* variables. . . . On the other hand, confirmatory factor analysis (CFA) is used to *test* theory when the analyst has sufficiently strong rationale regarding what factors should be in the data and what variables should define each factor. (italics in original)

Gorsuch (1983) also noted, "Whereas the former [EFA] simply finds those factors that best reproduce the variables under the maximum likelihood conditions, the latter [CFA] tests specific hypotheses regarding the nature of the factors" (p. 129).

Because of its exploratory nature, EFA requires the researcher to make myriad analytical decisions during the analysis process in order to "find" the factors present in the data rather than "test" the expected factors as one would do with CFA. Accordingly, conducting an EFA is an inherently subjective process necessitating thoughtful and informed judgments. Tabachnick and Fidell (1996) noted that "One of the problems with [principal components analysis] and [factor analysis] is that there is no criterion variable against which to test the solution" (p. 636).

Furthermore, "Because the differences [between factor solutions] cannot be resolved by appeal to objective criteria, arguments over the best solution sometimes become vociferious" (Tabachnick & Fidell, 1996, p. 636). Cronkhite and Liska (1980) provided one perspective:

> Apparently, it is so easy to find semantic scales which seem relevant. . ., so easy to name or describe potential/hypothetical sources, so easy to capture college students to use the scales to rate the sources, so easy to submit those ratings to factor analysis, so much fun to name the factors when one's research assistant returns with the computer printout, and so rewarding to have a guaranteed

> publication with no fear of nonsignificant results that researchers, once exposed to the pleasures of the factor analytic approach, rapidly become addicted to it. (p. 102)

Nevertheless, thoughtful use of factor analysis can be a valuable analytic tool. As Pedhazur and Schmelkin (1991) noted, "of the various approaches to studying the internal structure of a set of variables or indicators, probably the most useful is some variant of factor analysis" (p. 66).

The issue is that EFA "can be conceptualized as a series of steps which require that certain decisions be addressed at each individual stage" (Kieffer, 1999, pp. 76-77). Furthermore, because "there are many different ways in which to conduct an EFA,. . . each different approach may render distinct results when certain conditions are satisfied" (Kieffer, 1999, pp. 77).

## Analytical Decisions

The various decisions necessary and the options possible in an EFA are thoroughly discussed elsewhere (Gorsuch, 1983; Stevens, 2002; Tabachnick & Fidell, 1996). Kieffer (1999) provided a user-friendly primer of the methods. However, several key decisions are noted here to provide context for the current study.

### Matrix of Association

Factor analysis essentially attempts to reproduce the relationships between many variables with a fewer number of factors. Accordingly, the researcher must begin with deciding what type of matrix of association (e.g., correlation, variance/covariance) will be submitted to analysis. Most statistical packages (e.g., SPSS) analyze the correlation matrix as the default option.

If the variables used in the analysis are arbitrarily scaled, the correlation matrix is often desired due to its standardized nature. If the variables are meaningfully scaled in some fashion, the variance/covariance matrix might be used. The decision is important because, as Stevens (2002) observed, "The components obtained from the correlation and covariance matrices are, in general, not the same" (p. 388, italics in original).

Factor Extraction

Most statistical packages provide a variety of options regarding how to extract the factors from the matrix of association. The first extracted factor attempts to explain the most variance in the matrix, leaving a residual matrix behind. Additional factors, uncorrelated with the previous factors, are then extracted to reproduce the variance in each subsequent residual matrix.

Principal components analysis (PCA) and principal axis factoring (PAF) are the most common strategies used and researchers at times "differ quite heatedly" over the relative merits of each approach (Thompson & Daniel, 1996, p. 201). The fundamental difference between PCA and PAF regards the matrix of associations examined. When a correlation matrix is analyzed, PCA uses ones on the diagonal of the matrix. PAF replaces the ones on the diagonal with estimates of reliability of the variables due to the assumption that error variance should not be analyzed as part of the analysis. Communality ($\underline{h}^2$) coefficients, or the percent of variance in the variable that is reproducible by the factors, are used on the diagonal after being derived in an iterative process.

Gorsuch (1983) suggested that researchers should carefully consider which approach to employ because differences in results could be meaningful. Thompson (1992) argued that the practical ramifications regarding different interpretations between PCA and PAF is often negligible. Indeed, differences between the approaches are likely to be reduced when (a) the variables are measured with high reliability, because the estimates on the diagonal would approach one and (b) there are many variables to be factored, because the number of entries on the diagonal relative to the number of entries in the entire matrix would have proportionately less impact on the analysis.

Deciding How Many Factors to Extract

Perhaps one of the more important decisions in an EFA concerns the number of factors to retain. Factor definition/interpretation can vary considerably depending on the number of factors kept for the final solution. The number of possible factors in the analysis equals the number of variables factored. However, many of these factors may not reproduce enough variance to matter or simply may not be interpretable. Therefore, only a smaller set of factors are extracted with the intent to maximize the interpretability and variance explained.

Several factor retention rules are available but the most commonly employed (Henson & Roberts, in press; Hetzel, 1996) tend to be the eigenvalue greater than one rule (EV > 1; Kaiser, 1960) and the scree test (Cattell, 1966). The Kaiser's EV > 1 rule is the default option in some statistical packages, and therefore leads the way in frequency of use. Other options include minimum average partial (MAP, Velicer, 1976), Barlett's chi-square test (Bartlett, 1950, 1951), and parallel analysis (Horn, 1965; Turner, 1998). Thompson (1988) suggested using the bootstrap to determine the number of factors. These various rules do not necessarily lead to the same conclusions as regards the number of factors to retain.

The EV > 1 rule increases in accuracy when the number of variables is small to moderate (10 to 30 or so) and when the communalities are high (> .70), but can grossly overestimate the number of factors in many conditions (Browne, 1968; Cattell & Jaspers, 1967; Linn, 1968). Zwick and Velicer (1986) demonstrated that the EV > 1 rule almost always overestimates the number of reliable factors, making use of this rule problematic, especially as the default option in some statistical packages. The scree plot was more accurate despite the subjectivity of interpretation with this graphical method.

In Zwick and Velicer's (1986) study, parallel analysis and MAP were the most accurate decision rules. Unfortunately, Henson and Roberts (in press) also noted that these rules are almost never employed in published research.

Factor Rotation

Most factor analysts rotate their extracted factors to facilitate interpretability, or the ability to recognize which variables define which factors (Gorsuch, 1983). Many rotation strategies are possible and can generally be grouped into orthogonal (uncorrelated) and oblique (correlated) categories. Others have delineated these strategies (cf. Gorsuch, 1983; Keiffer, 1999; Stevens, 2002; Tabachnick & Fidell, 1996).

It is worth noting, however, that in EFA the rotation strategy used generally should balance interpretability with the correlation between the factors. Orthogonal solutions tend to facilitate interpretability because the factors are forced to be uncorrelated. Oblique solutions honor possible intercorrelation between the factors but the shared variance between the factors can (a) reduce interpretability and (b) limit generalizability due to the fact that two matrices of parameters must be estimated, thereby hindering parsimony. Because orthogonal solutions tend to be the default in statistical packages, they also tend to be the most frequently employed.

Factor Pattern and Factor Structure Matrices

A factor is defined by what variables share the most variance with the factor (and thereby share variance among themselves). In order to determine what variables are related to what factors in EFA, one must consult factor pattern and factor structure coefficients. The factor pattern matrix consists of coefficients indicating the unique contribution of each variable to each factor. These coefficients are directly analogous to standardized regression coefficients (i.e., beta weights). Throughout the general linear model, a structure coefficient is a correlation between an observed variable and a synthetic/latent variable, and so the factor structure matrix consists of bivariate correlations between each factored variable and each latent factor.

It is unfortunate that these two sets of coefficients are often ambiguously called "loadings" without clarification of which type of coefficient is being referenced in the literature. Stevens (2002, p. 393) indicated "that a loading is simply the Pearson correlation between the variable and the factor (linear combination of the variables)," which would indicate structure coefficients. Tabachnick and Fidell (1996), however, suggested that a "loading" in an orthogonal solution is the correlation between a variable and a factor (i.e., structure coefficient) but a "loading" in an oblique solution is a pattern coefficient. A perusal of published articles would easily reveal additional ambiguous use of the term.

For orthogonal rotations, the distinction between pattern and structure coefficients is perhaps less important because both matrices will be identical. For example, the structure matrix is found by multiplying the factor pattern matrix ($\mathbf{P}_{VxF}$) by the factor correlation matrix ($\mathbf{R}_{FxF}$). When rotating orthogonally, the factor correlation matrix is an identity matrix with ones on the diagonal and zeros off. In matrix algebra, multiplication by an identity matrix is analogous to multiplying by one, which would leave the structure matrix to be identical to the pattern matrix. In this case, the pattern matrix should be called the "factor pattern/structure matrix" to clarify the unity between the two important matrices.

For oblique solutions, both matrices "are usually essential to interpretation" (Thompson & Daniel, 1996, p. 199). Because the factors will be correlated, the factor correlation matrix will <u>not</u> be an identity matrix and the pattern and structure matrices will <u>not</u> be the same. In this case, it is important to interpret <u>both</u> matrices when defining factors. As is true in regression analysis (cf. Courville & Thompson, 2001), examination of only the pattern coefficients (or beta weights in regression) can lead to errant conclusions about variable importance due to multicollinearity. Structure coefficients, then, are critical in oblique solutions and should be both reported and interpreted.

## Reporting Practices in Published Research

Science largely progresses through discovery of phenomena that are shown to be replicable. Within the published research literature, sufficient information should be reported to allow reasoned critical evaluation of the study's methods, results, and conclusions. For studies invoking EFA, this point is particularly relevant as EFA methods can vary depending on the aforementioned researcher decisions. As Henson and Roberts (in press) argued,

> Regarding factor analysis, it is very important that researchers be able to independently evaluate the results obtained in an EFA study. This can, and should, occur on two levels. Given the myriad subjective decisions necessary in EFA, independent researchers should be able to evaluate the analytic choices of authors in the reported study. Second, independent researchers should be able to replicate accurately the study on new data, perhaps via a CFA.

This expectation is often not met in the published EFA literature due to either (a) authors failing to document their procedures and decisions or (b) editors cutting relevant information due to limited signature space in journals (cf.

Comrey, 1978; Henson & Roberts, in press; Hetzel, 1996; Tinsley & Tinsley, 1987). Consequently, many have called for more detailed analytic information in EFA articles (cf. Comrey, 1978; Gorsuch, 1983; Henson & Roberts, in press; Kline, 1984; Thompson & Daniel, 1996; Tinsley & Tinsley, 1987; Weiss, 1971).

Most reviews of EFA practice, however, have occurred in the psychological literature. Our purpose was to extend the examination to the educational literature and evaluate whether educational research suffers from the same ailments or if the literature has responded to previous calls for improvement. Paralleling the coded information in the Henson and Roberts (in press) study, we explored a broader range of practices and decisions than most other prior studies.

## Method

### Selection of EFA Applications

Three journals were identified for the study: *American Educational Research Journal* (*AERJ*), *Journal of Educational Research* (*JER*), and *The Elementary School Journal* (*ESJ*). The journals were selected for their different levels of focus in research application, moving from more general to specific, respectively. We examined 14 total volumes across the journals (*AERJ*: Vol. 33-36, *JER*: Vol. 89-93, *ESJ*: 96-100). Each application of EFA was coded for decisions made during the analysis and information reported. For articles employing more than one EFA, each was coded resulting in 49 EFAs for the current study.

## Results and Discussion

Table 1 presents descriptive statistics for six continuously scored variables. Sample sizes tended to be large (Md = 515), but the distribution was positively skewed by several studies utilizing large national databases. One quarter of the studies had samples of less than 100. According to the general standards presented by Comrey and Lee (1982), the median sample size could be considered very good. However, 37% of the samples would be considered no better than fair (18 EFAs with samples less than 200). Tabachnick and Fidell (1996) offered $n$ = 300 as a minimum rule of thumb. Forty-one percent of the EFAs failed to meet this criterion.

INSERT TABLE 1 ABOUT HERE

Importantly, Stevens (1996) correctly proposed that it is more accurate to speak of the ratio of subjects to variables rather than general rules of thumb for sample sizes, and recommended a minimum ratio of five subjects per variable. The median ratio for the present data was a healthy 22.06:1, but this finding was again positively biased by several massive sample sizes. For EFAs with sample sizes of 1000 (still a large $n$ by most standards) or less, the median ratio was a more marginal

7.86:1. Fourteen percent of the EFAs had ratios less than 5:1, and two studies had fewer participants than variables! (Note: One article failed to report the number of items being factored leaving $n$ = 48 for this variable.)

Guadagnoli and Velicer (1988) argued that component saturation (i.e., the strength and number of variables weighting on a factor) was more important for identification of reliable factors rather than sample size directly. Although this point is well-made, saturation is a post-hoc determination which may not inform data collection in a purely exploratory context.

The average "cutoff" used for noteworthy pattern or structure coefficients was around .40 with extracted factors accounting for an average of 45% of the matrix of association variance. However, more than half (57%) of the EFAs did not report the total variance explained, leaving the reader to simply guess as to the overall ability of the factor solution to represent the variance in the original variables. The average variance explained is considerably short of Stevens' (2002, p. 390) recommendation of "at least 70%" and Gorsuch's (1983) claim that investigators typically "stop the factoring process when 75, 80, or 85% of the variance is accounted for" (p. 165). The average is also slightly less than the 52% observed by Henson and Roberts' (in press) review of psychological journals. However, the present data combined with the Henson and Roberts study represent a review of 109 EFAs in seven prominent journals, suggesting that the practical realization of explaining 70% or better of the matrix of association variance is a rarity in much of the published literature. Nevertheless, many EFAs in the present study failed to account for even a reasonable amount of variance (i.e., 28.6% of articles reporting variance-accounted-for explained less than 30% of the matrix variance).

Table 2 presents frequencies and percentages for many other EFA features examined. The EFAs were fairly evenly split regarding substantive or measurement applications and all involved a first order analysis. Unfortunately, almost all (93.9%) failed to report the matrix of association analyzed.

INSERT TABLE 2 ABOUT HERE

PCA was more popular than PAF with about a quarter of the EFAs employing some other method (e.g., maximum likelihood factoring) of extraction. About a third did not indicate what method was used.

One of the more striking, albeit expected, findings concerned the strategies employed to determine the number of factors to retain. The EV > 1 rule was more popular (16.3%) than any other traditional statistical method followed closely by the scree plot (12.2%). About a third used *a priori* theory to set the number of factors. This percentage begs the question of why CFA was not used rather than EFA if theory was sufficiently strong to declare the expected factors (Daniel, 1989; Kieffer, 1999). A fair number (22.4%) of other miscellaneous approaches were also employed (e.g., an item response theory approach).

Parallel analysis and minimum average partial were never used in the EFAs examined, despite their tendency to yield more accurate conclusions about the presence of reliable factors (Zwick & Velicer, 1986). Furthermore, fully 22.4% of EFAs failed to report what retention rules were used and only 8.2% of EFAs employed more than one rule. None used more than two rules.

These findings are troublesome as they prevent independent evaluation of results in many cases due to lack of reporting. Sole use of the EV > 1 rule may suggest that too many factors were extracted in some cases, resulting in poorly defined and unreliable factors. Most EFAs (69.4%) only used one retention rule although the "simultaneous use of multiple decision rules is appropriate and often desirable" (Thompson & Daniel, 1996, p. 200). Use of multiple criteria allows researchers to examine their data from more than one perspective, and perhaps overcome the weaknesses of any one approach.

Orthogonal (34.7%) and oblique (40.8%) rotations were fairly evenly split. This finding differs from prior reviews in which the orthogonal approach tended to be more frequently used. However, 75.5% never provided justification for why one rotation approach was used over the other. As previously noted, rotation procedures in EFA must balance interpretability with replicability and honor the relationship between the factors in the data. As Pedhazur and Schmelkin (1991) noted,

> From the perspective of construct validation, the decision whether to rotate factors orthogonally or obliquely reflects one's conception regarding the structure of the construct under consideration. It boils down to the question: Are aspects of a postulated multidimensional construct intercorrelated? The answer to this question is relegated to the status of an assumption when an orthogonal rotation is employed. . . . The preferred course of action is, in our opinion, to rotate both orthogonally and obliquely. When, on the basis of the latter, it is concluded that the correlations among the factors are negligible, the interpretation of the simpler orthogonal solution becomes tenable. (p. 615)

Unfortunately, rotating without justification of the procedure provides no information as to the rationale for the procedure and limits external critique.

Varimax, the default in many statistical packages, was the only specific orthogonal rotation reported (32.7%). There was an even split between Oblimin (14.3%) and Promax (16.3%) for oblique rotations. Again, 36.7% failed to indicate the specific rotation used.

For the 20 oblique EFAs, one-half reported only the factor pattern matrix and the other half reported coefficients in a manner sufficiently ambiguous as to prevent determination of whether they were pattern or structure coefficients. The factor structure matrix was never clearly reported, and therefore never clearly interpreted as we can only assume the authors used the matrices reported for interpretation. This deficit is troubling as structure coefficients are almost always necessary for interpretation in the presence of correlated factors (Gorsuch, 1983; Henson & Roberts, in press; Kieffer, 1999; Thompson & Daniel, 1996).

None of the EFAs included communality coefficients. None reported the variance explained by each factor <u>after</u> rotation. Post-rotation variance is the variance of interest given that interpretation typically is post-rotation as well. (Note that many researchers are also not aware that the first factor may not account for the most variance after rotation.)

Most EFAs (79.6%) did not include eigenvalues for retained factors, limiting the application of an external parallel analysis to evaluate the number of factors and the calculation of variance explained by a third party. We also would argue that the inclusion of the eigenvalue of at least one factor <u>not</u> retained is important for evaluating the break point for factor retention decisions. There also exists ambiguity in the literature concerning whether the eigenvalues reported are pre- or post-rotation. If post-rotation, the eigenvalues are appropriately called "trace" as they are no longer eigenvalues per se. Again, it is the post-rotation trace that are of primary interest given that interpretation occurs at this point. Trace in an orthogonal solution are readily calculated by summing the squared entries in the pattern/structure matrix down each factor column. In an oblique solution, trace are the sum of the products of each pattern coefficient with its respective structure coefficient down each factor column.

Table 3 presents additional descriptive statistics concerning the number of factors extracted, the percentage of variance explained, and the number of items used to define each factor. Because of the ambiguity whether the variance explained was pre- or post-rotation, we collapsed the EFAs together for this table. However, given the tendencies in reporting, we would expect that most of the EFAs reported variance prior to rotation. One additional point stemming from Table 3 concerns factor saturation. Across all factors, the minimum number of variables used to define a factor was just one or two variables. This finding strongly suggests the retention of unreliable factors in the literature and "seems to contradict the basic idea of a factor as a latent construct" that summarizes the variance in several variables (Henson & Roberts, in press).

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INSERT TABLE 3 ABOUT HERE

We also examined whether CFA may have been warranted over EFA in situations when sufficient theory existed to test hypotheses. The value of using CFA when applicable is noted by Thompson and Daniel (1996),

> . . . CFA can readily be used to test rival models and to quantify the fit of each rival model. Testing rival models is usually essential because multiple models may fit the same data. Of course, finding that a single model fits data well, whereas other plausible models do not, does not "prove" the model, since untested models may fit even better. However, testing multiple plausible models does yield stronger evidence regarding validity. (p. 204)

In our review, we roughly operationalized "sufficient theory" in terms of whether the instrument had been used previously or if the authors reported having *a priori* theory regarding the outcome. For 15 EFAs, it appeared that CFA may have been warranted. However, in 9 of these cases at least justification was given as to why CFA was not used due to a small *n* or insufficient theory.

## Recommendations for EFA Practice

Several errors of use and reporting omission were noted in the current review. We therefore present several recommendations to facilitate improved EFA use and reporting. Our recommendations echo some of those proffered by other authors (cf. Comrey, 1978; Gorsuch, 1983; Henson & Roberts, in press; Kline, 1994; Thompson & Daniel, 1996; Tinsley & Tinsley, 1987; Weiss, 1971).

1. As a general guideline, authors should report sufficient information to allow external evaluation of their decisions and results. Decisions should be justified and not assumed.
2. Report which matrix of association was analyzed. It is preferred to actually report the matrix, but if space disallows, at least the make matrix available upon request for external evaluation.
3. Always report the factor extraction method.
4. Using (and reporting) multiple criteria for determining the number of factors to retain is almost always a good idea. Increased use of parallel analysis and minimum average partial is clearly needed. Caution should be exercised with employing the EV > 1 rule.
5. Report trace (i.e., the transformed eigenvalues) and variance explained for factors post-rotation. We also recommend that authors report the eigenvalue for at least once factor not retained.

6. Justify the use of an orthogonal or oblique rotation strategy. This typically can be done by conducting an oblique rotation. If the factors are not sufficiently correlated then interpret the orthogonal approach (Pedhazur & Schmelkin, 1991). Also indicate the specific rotation used (e.g., Varimax, Oblimin, Promax).

7. Always report the full factor pattern and structure matrices. Of course, for orthogonal rotations, report the pattern/structure matrix. Do not "blank out" entries in the matrix as this prevents others from rotating the matrix to a different criterion. The full matrices also allows for meta-analysis of factor structures for instruments across studies.

8. For oblique rotations, always consider both the pattern and structure coefficients for interpretation.

9. Always report communality coefficients ($h^2$) as they indicate the percent of variance for each variable reproduced in the factors. Of course, $h^2$ can be readily calculated from a factor pattern/structure matrix (orthogonal rotation) or both the pattern and structure matrices (oblique rotation), but their inclusion eases digestion of EFA results for the reader.

10. Ensure that proper factor saturation is present before retaining or interpreting factors. Guadagnoli and Velicer (1988) provided some applied guidelines. At a minimum, however, factors should be defined by more than a couple of variables and with sufficiently large pattern and/or structure coefficients.

Interpreting a factor with poor saturation equates to interpreting a factor that is unlikely to be replicable in future samples.

Importantly, these expectations are readily met within the typical reporting framework already employed in most journals, and so their inclusion is not likely to suffer the wrath of a space-conscious editor. We present hypothetical EFA results in Table 4 as a guide for reporting. The example is an oblique solution, and thus includes both the pattern and structure coefficients. Although the table does not meet all the expectations above, it does provide a typical reporting strategy that captures most of the recommendations. The other recommendations could be readily included in the narrative with little space required.

INSERT TABLE 4 ABOUT HERE

Note that trace are calculated by multiplying the pattern and structure coefficients for a variable and summing down the column. Communality [$h^2$] is calculated by multiplying the pattern and structure coefficients for a factor and summing across the row. For orthogonal solutions, trace and communalities are the sum of the squared pattern/structure coefficients down the columns and across the rows, respectively. Post-rotation variance-accounted-for is found by dividing the trace by the number of variables (and multiplying by 100).

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Table 1

Descriptive Statistics for Exploratory Factor Analysis (n = 49) Reporting Practices

| Variable | n | Median | M | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| Sample size | 49 | 515.00 | 3517.29 | 7021.31 | 31.00 | 33244.00 |
| Ratio of no. of participants to no. of variables factored | | | | | | |
| All articles | 48 | 22.06[a] | 153.92 | 284.28 | 0.78 | 1072.00 |
| n < 1001 | 31 | 7.86 | 18.13 | 22.11 | 0.78 | 85.00 |
| No. of variables factored | 48 | 20.00 | 25.94 | 15.75 | 4.00 | 70.00 |
| No. of factors extracted | 49 | 3.00 | 4.16 | 2.92 | 1.00 | 17.00 |
| Cutoff used to determine which coefficients were "weighted" on a factor | 17 | 0.40 | 0.39 | 0.10 | 0.26 | 0.60 |
| Total variance explained by extracted factors | 21 | 49.00% | 44.92% | 16.55% | 12.80% | 70.20% |

Note. n = number of uses of exploratory factor analysis reporting the relevant information.

[a] Indicates that there were 22.06 participants per one variable factored.

Table 2

Frequencies and Percentages of Exploratory Factor Analysis (n = 49) Reporting Practices

| Variable | n | % |
|---|---|---|
| Article type | | |
| Measurement | 20 | 40.8 |
| Substantive | 29 | 59.2 |
| Level of analysis | | |
| First order factoring | 49 | 100.0 |
| Higher order factoring | 0 | 0.0 |
| Matrix of association analyzed | | |
| Correlation | 3 | 6.1 |
| Not reported | 46 | 93.9 |
| Factor extraction method used | | |
| Principal components | 14 | 28.6 |
| Principal axis | 7 | 14.3 |
| Other | 12 | 24.5 |
| Not reported | 16 | 32.7 |
| Strategies used for factor retention | | |
| Eigenvalue greater than 1 | 8 | 16.3 |
| Scree plot | 6 | 12.2 |
| Minimum average partial | 0 | 0.0 |
| Parallel analysis | 0 | 0.0 |
| Bartlett's chi-square | 0 | 0.0 |
| No. set *a priori* | 17 | 34.7 |
| Other | 11 | 22.4 |
| Number of strategies used for factor retention decisions | | |
| None reported | 11 | 22.4 |
| One | 34 | 69.4 |
| Two | 4 | 8.2 |
| General rotation strategy | | |
| Orthogonal | 17 | 34.7 |
| Oblique | 20 | 40.8 |
| No rotation used | 5 | 10.4 |
| Not reported | 7 | 14.4 |
| Justification for rotation strategy given | | |
| Yes | 12 | 24.5 |
| No | 37 | 75.5 |

| Variable | $n$ | % |
|---|---|---|
| Specific type of rotation used | | |
| Varimax | 16 | 32.7 |
| Oblimin | 7 | 14.3 |
| delta value given ($n$ = 7) | | |
| Yes | 0 | 0.0 |
| No | 7 | 100.0 |
| Promax | 8 | 16.3 |
| pivot given ($n$ = 8) | | |
| Yes | 0 | 0.0 |
| No | 8 | 100.0 |
| Not reported | 18 | 36.7 |
| If oblique rotation, coefficients reported ($n$ = 20) | | |
| Factor pattern only | 10 | 50.0 |
| Factor structure only | 0 | 0.0 |
| Both | 0 | 0.0 |
| Can't tell | 10 | 50.0 |
| Reported communality coefficients ($h^2$) | | |
| Yes | 0 | 0.0 |
| No | 49 | 100.0 |
| Reported variance explained for each factor after rotation | | |
| Yes | 0 | 0.0 |
| No | 6 | 12.2 |
| Can't tell | 16 | 32.7 |
| Not reported | 27 | 55.1 |
| Named factors with other than a variable name | | |
| Yes | 49 | 100.0 |
| No | 0 | 0.0 |
| Reported eigenvalues for factors retained | | |
| Yes | 10 | 20.4 |
| No | 39 | 79.6 |
| Reported eigenvalue for at least one factor not retained | | |
| Yes | 0 | 0.0 |
| No | 49 | 100.0 |
| Initial eigenvalue interpreted as applying postrotation | | |
| Yes | 7 | 14.3 |
| No (interpreted correctly) | 2 | 2.0 |
| No reference | 41 | 83.7 |
| Confirmatory factor analysis (CFA) warranted | | |
| Yes, not a new measure | 15 | 30.6 |
| No, new measure | 34 | 69.4 |

| Variable | n | % |
|---|---|---|
| If CFA warranted, reasons given for not using CFA (n = 15) | | |
| Sample size too small | 3 | 20.0 |
| No strong theory | 6 | 40.0 |
| Not addressed | 6 | 40.0 |

Table 3

Percentage of Variance Explained and Number of Items for Extracted Factors

| | % Variance Explained | | | Number of Items | | | | |
|---|---|---|---|---|---|---|---|---|
| Factor | n | M | SD | n | M | SD | Min. | Max. |
| I | 18 | 25.29 | 11.26 | 45 | 7.42 | 4.93 | 2 | 30 |
| II | 16 | 11.58 | 6.75 | 39 | 6.13 | 4.69 | 1 | 25 |
| III | 9 | 7.69 | 2.82 | 30 | 4.70 | 2.45 | 1 | 12 |
| IV | 6 | 6.02 | 1.58 | 20 | 3.95 | 2.24 | 1 | 9 |
| V | 4 | 5.03 | 1.25 | 14 | 4.21 | 2.19 | 2 | 8 |
| VI | 2 | 3.55 | 2.19 | 10 | 4.30 | 2.26 | 2 | 8 |
| VII | 1 | 4.90 | -- | 9 | 4.56 | 2.35 | 2 | 8 |
| VIII | 1 | 4.70 | -- | 7 | 3.29 | 1.38 | 2 | 5 |
| IX | 1 | 3.30 | -- | 1 | 2.00 | -- | 2 | 2 |

Note. Variance explained by the factors is given for both pre- and post-rotation estimates, combined. These were not separated due the to ambiguity in the literature as to whether the variance explained by each factor was pre- or post-rotation.

Table 4

Hypothetical Factor Pattern (P) and Structure (S) Matrices Rotated to the Direct Oblimin Criterion (delta = 0)

| | I | | II | | III | | |
|---|---|---|---|---|---|---|---|
| Variable | P | S | P | S | P | S | $\underline{h}^2$ |
| X1 | <u>.890</u> | .455 | .230 | .123 | .312 | .404 | .559 |
| X2 | <u>.634</u> | .700 | .111 | .320 | .210 | .077 | .495 |
| X3 | <u>.750</u> | .450 | .300 | .301 | .289 | .250 | .500 |
| X4 | <u>.590</u> | .676 | .114 | .203 | .034 | .035 | .423 |
| X5 | .237 | .128 | <u>.659</u> | .349 | .007 | .032 | .261 |
| X6 | .100 | .234 | <u>.802</u> | .539 | .222 | .360 | .536 |
| X7 | .298 | .004 | <u>.595</u> | .601 | .033 | .154 | .365 |
| X8 | .009 | .022 | .213 | .034 | <u>.500</u> | .450 | .232 |
| X9 | .302 | .255 | .210 | .209 | <u>.667</u> | .543 | .483 |
| X10 | .220 | .104 | .002 | .090 | <u>.497</u> | .320 | .182 |
| Trace | 1.741 | | 1.249 | | 1.047 | | |
| Variance | 17.41% | | 12.49% | | 10.47% | | |

<u>Note</u>. I = Verbal, II = Mathematical, III = Spatial, P = pattern coefficient, S = structure coefficients, $\underline{h}^2$ = communality coefficient.

Pattern coefficients greater than |.45| are underlined. Percent variance is post-rotation. The fourth, unretained eigenvalue was .893.

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