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ABSTRACT

The appropriate use of exploratory factor analysis (EFA) necessitates thoughtful researcher judgment concerning a number of analytic decisions. This paper reviews some of the fundamental decisions necessary to conduct an EFA and examines reporting practice in published research across four journals. In general, insufficient information was given in published applications of EFA (n=60) to allow external verification of the results. Researchers often used poor strategies to determine the number of factors to retain. In one-third of the cases, a confirmatory factor analysis was warranted rather than EFA. Other errors in reporting and practice were noted. Several recommendations for improved EFA reporting practice are given. (Contains 4 tables and 105 references.) (Author/SLD)

Running Head: EFA REPORTING PRACTICES

A Meta-analytic Review of Exploratory Factor Analysis Reporting Practices in Published Research

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Abstract

Appropriate use of exploratory factor analysis (EFA) necessitates thoughtful researcher judgment concerning a number of analytic decisions. The present paper reviewed some of the fundamental decisions necessary to conduct an EFA and examined reporting practice in published research across four journals. Largely, insufficient information was given in published applications of EFA (n = 60) to allow external verification of the results. Researchers often utilized poor strategies to determine the number of factors to retain. In one-third of the cases, a confirmatory factor analysis was warranted over EFA. Other errors reporting and practice errors are noted. Several recommendations for improved EFA reporting practice are given.

A Meta-analytic Review of Exploratory Factor Analysis Reporting Practices in Published Research

Researchers commonly attempt to explain the most with the least. For example, because all classical parametric analyses are part of a broader general linear model, these analyses are all correlational, yield $\underline{r}^2$ type effect sizes, and maximize the shared variance between variables (e.g., regression) or between sets of variables (e.g., canonical correlation) (Bagozzi, Fornell & Larcker, 1981; Cohen, 1968; Henson, 2000; Knapp, 1978; Thompson, 1991). In fact, classical parametric analyses (e.g., ANOVA, $\underline{r}$, MANOVA, DDA) can all be performed with canonical correlation analysis, and thus are special cases of canonical analysis (Fan, 1996, 1997; Thompson, 2000a).

Because implicit within canonical correlation analysis itself is a principal components analysis (Thompson, 1984, pp. 11-14), all classical parametric analyses also invoke principal components analyses. This truism suggests the importance of factor analysis within statistics.

In the interest of parsimony, researchers often strive to explain the most shared variance of measured variables using the fewest possible latent or synthetic variables. Such parsimonious solutions are generally considered to have greater external validity and, as such, are more likely to replicate. Thus, Kerlinger (1979) argued that factor analysis is "one of the most powerful methods yet for reducing variable complexity to greater simplicity" (p. 180).

Factor analysis is often used to explain a larger set of $\underline{j}$

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., correlation matrix) so that the constructs, or factors, can then be used to represent the observed variables. These constructs can be used as variables in subsequent analyses and "can be seen as actually causing the observed scores on the measured variables" (Thompson & Daniel, 1996, p. 202). In short, "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).

Historically, the theoretical framework for factor analysis is credited to Pearson (1901) and Spearman (1904), but practical application of the method is a modern phenomenon. As Kieffer (1999) noted:

> Spearman, through his work on personality theory, provided the conceptual and theoretical rationale for both exploratory and confirmatory factor analysis. Despite the fact that the conceptual bases for these methods have been available for many decades, it was not until the wide-spread availability of both the computer and modern statistical software that these analytic techniques were employed with any regularity. (p. 75)

Thanks to the advent of technology, factor analysis is now frequently employed in both measurement and substantive research.

Given the proliferation of factor analysis applications in the literature, the purpose of the present paper was to examine the utilization of factor analysis in current published research. Notwithstanding ease of analysis due to computers, the appropriate use of factor analysis requires a series of thoughtful researcher judgments. These judgments directly impact results and interpretations.

Specifically, we examined across studies (a) the decisions made while conducting exploratory factor analyses and (b) the information reported from the analyses. In doing so, we present here the current status of factor analytic reporting practices and make recommendations for future practice as regards analytic decisions and reporting in empirical research.

Exploratory Factor Analysis

Modern conceptualizations of factor analysis include both exploratory and confirmatory methods, as well as the hybrid invoking exploratory factor extraction followed by confirmatory rotation (Thompson, 1992). Exploratory factor analysis (EFA) is used to "identify the factor structure or model for a set of variables" (Bandalos, 1996, p. 389). As its name implies, EFA is an exploratory method 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. 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).

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. A fundamental and critically important difference between EFA and CFA is that results of an EFA are a sole function of the "mechanics and mathematics of the method" (Kieffer, 1999, p. 77). EFA <u>does not</u> consider <u>a priori</u> theory held by the researcher (Daniel, 1989). CFA, on the other hand, is driven by theoretical expectations regarding the structure of the data.

As Gorsuch (1983) noted, "Whereas the former [EFA] simply finds those factors that best reproduce the variables under the maximum likelihood conditions, the latter [CFA] tests specific hypothesis regarding the nature of the factors" (p. 129). The reader is referred to Gorsuch (1983), Stevens (1996), and Tabachnick and Fidell (1996) for extensive treatments of these approaches. The present chapter is concerned with EFA.

<u>Purposes of Factor Analysis</u>

Because the latent constructs, or factors, are thought to cause and summarize responses to observed variables, theory development and score validity evaluation are both closely related to factor analysis. As Hendrick and Hendrick (1986, p. 393) emphasized, "theory building and construct measurement are joint bootstrap operations." Factor analysis at once both tests measurement integrity and guides further theory refinement.

As noted by Kieffer (1999), "[t]he utilization of factor analytic techniques in the social sciences has been indelibly intertwined [both] with developing theories and evaluating the construct validity of measures [i.e., scores]" (p. 75). Regarding construct validity, Gorsuch (1983) noted,

> Research proceeds by utilizing operational referents for the constructs of a theory to test if the constructs interrelate as the theory states.... A prime use of factor analysis has been in the development of both the operational constructs for an area and the operational representatives for the theoretical constructs. (p. 350)

Factor analysis can be used to determine what theoretical constructs underlie a given data set and the extent to which these constructs represent the original variables. Of course, the meaningfulness of latent factors is ultimately dependent on researcher definition. As Mulaik (1987) suggested, "It is we who create meanings for things in deciding how they are to be used. Thus we should see the folly of supposing that EFA will teach us what intelligence is, or what personality is" (p. 301). However, Thompson and Daniel (1996) noted that

> analytic results can inform the definitions we wish to create, even though we remain responsible for our elaborations and may even wish to retain the definitions that have not yet been empirically supported or that limited empirical evidence may even contradict. (p. 202)

<u>(Thoughtful) Researcher Judgment in EFA</u>

Despite its utility in both measurement and substantive research contexts, factor analysis has been criticized. Cronkhite and Liska (1980) observed,

> 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 [sic] results that researchers, once exposed to the pleasures of the factor analytic approach, rapidly become addicted to it. (p. 102)

Much of the criticism centers on the inherent subjectivity of the decisions necessary to conduct an exploratory factor analysis. Tabachnick and Fidell (1996) stated that "[o]ne 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). Interpretation of results largely hinges on (hopefully) reflective researcher judgement. Tabachnick and Fidell also noted that after factor extraction,

> there is an infinite number of rotations available, all accounting for the same amount of variance in the original data, but with factors defined slightly differently. The final choice among alternatives depends on the researcher's assessment of its interpretability and scientific utility. In the presence of an infinite number of

> mathematically identical solutions, researchers are bound to differ regarding which is best. Because the differences cannot be resolved by appeal to objective criteria, arguments over the best solution sometimes become vociferous. (p. 636)

Because EFA "can be conceptualized as a series of steps which require that certain decisions be addressed at each individual stage... there are many different ways in which to conduct an EFA, and each different approach may render distinct results when certain conditions are satisfied" (Kieffer, 1999, pp. 76-77). Therefore, appropriate use of EFA necessitates thoughtful and informed researcher decision making.

EFA Decisions

A complete review of the steps and possible decisions necessary to conduct an EFA is beyond the scope of this chapter. However, a brief review is given here to place the current study in context. A comprehensive treatment is provided by Gorsuch (1983). Hetzel (1996) and Kieffer (1999) presented briefer user-friendly primers on factor analysis.

Matrix of Associations

Because all classical statistical analyses are fundamentally correlational (cf. Cohen, 1968; Knapp, 1978), all analyses focus on a matrix of associations that describes the relationships between the variables in question. To conduct an EFA, the researcher must decide which matrix of associations (e.g., correlation, variance/ covariance) to analyze. Most statistical packages use the correlation matrix (with 1.0 on the diagonal) as the default option in EFA. Subsequently, researchers tend to use the correlation matrix.

Method of Factor Extraction

There are multiple ways to extract factors. Principal components analysis (PCA) and principal axis factoring (PAF) tend to be the most common. Factor extraction attempts to remove variance common to sets of variables from the original matrix of association. After the first factor (or common variance for a set of variables) has been extracted, a residual matrix remains. A second factor, which is orthogonal to the first, is then extracted from the residual matrix to explain as much of the remaining variance among the variables as possible. The process continues until noteworthy variance can no longer be explained by factors.

The application of PCA as against PAF has been hotly debated. As Thompson and Daniel (1996) noted,

> Analysts differ quite heatedly over the utility of principal components as compared to common or principal factor analysis [i.e., PAF].... The differences between the two approaches involves the entries used on the diagonal of the matrix of associations that is analyzed. When a correlation matrix is analyzed, principal components analysis uses ones on the diagonal whereas common factor analysis uses estimates of reliability, usually estimated through an iterative process. (p. 201)

Gorsuch (1983) suggested that the researcher consider carefully which method to use, because differences can be meaningful.

Thompson (1992) argued, however, that the practical difference between the methods is often negligible in terms of interpretation. Differences in results will decrease as (a) the measured variables have greater score reliability or (b) the number of variables measured increases. Regarding (a), the higher the score reliability for a variable, the closer the PAF entry on the diagonal is to one, which is what is used by PCA.

Regarding (b), as the number of variables increases, so does the total number of entries on the matrix of association. The influence of the diagonal entries then has less influence on the solution, because the proportion of entries on the diagonal decreases exponentially as more variables are measured (cf. Snook & Gorsuch, 1989). For examples, with 10 measured variables there are 10 diagonal entries out of 100 total entries (i.e., 10.0%), but with 30 measured variables there are 30 diagonal entries out of 900 total entries (i.e., 3.3%), and with 50 measured variables there are 50 diagonal entries out of 2500 total entries (i.e., 2.0%).

<u>Factor Retention Rules</u>

When variables are factored (see Campbell (1996) and Thompson (2000b) for a discussion of factoring people), the total number of possible factors equals the number of variables factored. However, because many of these factors may not contribute substantially to the overall solution or be interpretable, some factors are not useful to retain in the analysis and generally represent noise or error in the variables. The goal of EFA is to retain the fewest possible factors while explaining the most variance of the observed variables. It is critical that the researcher extract the correct number of factors because this decision will impact results directly.

Many rules can be used to determine the number of factors to retain (cf. Zwick & Velicer, 1986), including the eigenvalue greater than one rule (EV > 1; cf. Kaiser, 1960), scree test (Cattell, 1966), minimum average partial correlation (Velicer, 1976), Bartlett's chi-square test (Bartlett, 1950, 1951), and parallel analysis (Horn, 1965; Turner, 1998). Thompson and Daniel (1996) and Zwick and Velicer (1986) elaborated these approaches. The most frequently used method is the EV > 1 rule. As Thompson and Daniel noted, "This extraction rule is the default option in most statistics packages and therefore may be the most widely used decision rule, also by default" (p. 200).

Importantly, these rules do <u>not</u> necessarily lead to the same decision regarding the number of factors to retain. For example, in a Monte Carlo evaluation, Zwick and Velicer (1986) found that the EV > 1 rule almost always severely overestimated the number of factors to retain. Their findings were consistent with those of Cattell and Jaspers (1967), Linn (1968), Yeomans and Golder (1982), and Zwick and Velicer (1982), but contrary to Humphreys (1964) and Mote (1970), who noted that the EV > 1 rule may underestimate the number of factors.

Bartlett's chi-square test was very inconsistent. The statistical significance test is heavily influenced by sample size. Because EFA studies typically involve large sample, the test may have little utility.

Despite its subjective nature in interpretation, the scree test was much more accurate but also tended to overextract factors. Importantly, parallel analysis was the most accurate procedure, followed closely by minimum average partial method. Unfortunately, these methods are seldom employed in published research. As an additional option, Thompson (1988) suggested using a bootstrap method to determine the number of factors and provided a program to automate the process.

Because the factor retention decision directly impacts the EFA results obtained, researchers are advised to use both multiple criteria and reasoned reflection. Researchers should also explicitly inform readers about the strategies used in making factor retention decisions.

Factor Rotation and Coefficient Interpretation

Rotation strategies are numerous and can be classified into two broad categories: orthogonal and oblique. Almost all researchers rotate their EFA results to facilitate interpretation of their factors. Discussion of the various rotation strategies is dealt with elsewhere (cf. Gorsuch, 1983; Kieffer, 1999; Stevens, 1996) and will not be addressed here. However, one point will be made regarding the coefficients used when interpreting EFA results.

In EFA, the contribution of a variable to a given factor is indicated by <u>both</u> factor pattern coefficients (sometimes ambiguously called "loadings") and factor structure coefficients (also sometimes ambiguously called "loadings"). Thompson and Daniel (1996) noted that structure coefficients, or correlations between observed and latent variables, "are usually essential to interpretation" (p. 199). Their sentiment applies not only to factor analysis but also to other general linear model analyses (cf. Thompson & Borrello, 1985).

In factor analysis, the factor structure matrix gives the correlations between all observed variables and all extracted (latent) factors. When factors are orthogonally rotated, they remain uncorrelated and the factor structure matrix will exactly match the factor pattern matrix. Mathematically, the structure matrix is obtained by multiplying the factor pattern matrix ($\underline{P}_{VxF}$) by the factor correlation matrix ($\underline{R}_{FxF}$), which is an identity matrix (i.e., ones on diagonal, zeros off diagonal) after orthogonal rotation. The resulting structure matrix ($\underline{S}_{VxF}$) will match the original factor pattern matrix (cf. Gorsuch, 1983, p. 52) whenever the factor correlation matrix is an identity matrix. In such cases, the pattern matrix should be called the "factor pattern/structure matrix" to facilitate clarity. Because "loading" is used ambiguously in the literature, use of this term is proscribed by some editorial policies (Thompson & Daniel, 1996).

When an oblique rotation is utilized, the factors are allowed to correlate with each other. In such cases, the factor correlation matrix will not be an identity matrix, and the structure matrix will not equal the pattern matrix. Appropriate interpretation, then, must invoke both the factor pattern and factor structure matrices. Because all analyses are correlational and belong to the general linear model, the problem of only interpreting the factor pattern coefficients is analogous to only interpreting beta weights in regression when the predictors are correlated. As illustrated by Thompson and Borrello (1985), consideration of structure coefficients is critical in such cases.

EFA Reporting Practices

Replication is a foundational principle of science (Henson & Smith, in press; Thompson, 1999). Findings in a single study seldom "prove" anything, but confidence in results increases when independent researchers externally evaluate the validity of previously reported research. 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.

Unfortunately, such practices are not possible for most applications of EFA. Tinsley and Tinsley (1987) noted that most applied uses of factor analysis do not provide sufficient information to allow others to make independent interpretations. Too often, authors only report the final results of their factor analysis, thereby eliminating the possibility of external evaluation of EFA decisions (cf. Comrey, 1978). Additionally, some authors do not report sufficient information to even allow independent interpretation of the final results, such as only giving part of the factor pattern matrix or excluding the factor structure matrix for oblique solutions (Thompson & Daniel, 1996; Tinsley & Tinsley, 1979). Many authors have called for more detailed factor analytic information in published research (cf. Comrey, 1978, Gorsuch, 1983; Kline, 1994; Thompson & Daniel, 1996; Tinsley & Tinsley, 1987; Weiss, 1971). According to Hetzel (1996),

> It is generally agreed that the following information should be included when reporting a factor analysis: (a) background information, such as sample size, sample composition, method of selecting the subjects, and method of selecting the variables; (b) matrix of association used; (c) method of factor extraction; (d) initial communality estimates used; (e) the criteria used for determining the number of factors to retain; and (f) the method of rotation used. In addition, the following basic data should be included when reporting a factor analysis: (a) the means and variances of the items; (b) the matrix of associations among the items; (c) the rotated factor pattern and structure matrices; and (d) the final communality coefficients, eigenvalues, and

proportion of variance explained by each rotated factor. (pp. 198-199)

However, in a review of 13 factor analysis articles in the Journal of Counseling Psychology, Hetzel (1996) found that much of this information was not reported by authors. Of course, precious journal space may limit information given, but critical decisions should nevertheless be explicitly addressed (e.g., the rule(s) used to determine the number of factors to retain) and complete information should be made available to interested persons (cf. Tinsley & Tinsley, 1987).

As noted, the purpose of the present chapter was to examine the EFA decisions and reporting practices in published EFA research. Although Hetzel (1996) characterized basic patterns of reporting in the counseling literature, the present review (a) broadened the literature studied to include both measurement and substantive articles and (b) considerably expanded the reporting practices and decisions examined.

Method

Journal and Article Selection

Journals frequently employing factor analytic studies were identified from a search of the ERIC and PsycLIT databases using the keywords "factor analysis". Although many journals publish articles using EFA, the following four journals were selected for investigation because of their greater reporting frequency as regards EFA applications: Educational and Psychological Measurement (EPM), Journal of Educational Psychology (JEP), Personality and Individual Differences (P&ID), and Psychological Assessment (PA). These journals also reflect both substantive and measurement applications of EFA.

Fifteen uses of EFA were examined from each of the journals, resulting in 60 total EFAs studied. Articles were selected if they employed EFA; articles only using CFA were not examined. Additionally, if one article included more than one EFA, all EFAs was coded if they were substantively different in terms of the information reported. We began examining articles from the end of 1999 (except for P&ID, for which only articles from volume 26, June 1999, and earlier were available) and worked backwards until 15 applications of EFA from each journal were identified. A total of 432 articles were examined. Forty-nine articles were identified that used one or more EFAs, giving a total EFA sample of 60. These EFAs were coded on multiple criteria to assess the information reported and the analytic decisions made by authors.

Results and Discussion

Table 1 presents descriptive results for six global EFA variables. The sample size distribution was quite variable and positively skewed (coefficient of skewness = 3.07). The median sample size (267) would be classified as somewhere between fair and good according to Comrey and Lee (1992), who portrayed as a guide sizes of 50 as very poor, 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 as excellent. Tabachnick and Fidell (1996) noted that, "As a general rule of thumb, it is comforting to have at least 300 cases for factor analysis" (p.

640).

INSERT TABLE 1 ABOUT HERE

Stevens (1996) suggested that the number of participants per variable is a more appropriate way to determine sample size (ranging from five to 20 participants per variable). Fewer participants are needed when component saturation is high. In the current sample, the median ratio of number of participants to variables was 11:1 (coefficient of skewness = 4.67), suggesting that most sample sizes were marginal to sufficient, depending on component saturation. However, seven EFAs (11.86%) had ratios less than Stevens' (1996) minimum of 5:1. One study failed to report sample size.

The extracted factors explained, on average, 52.03% of the total variance in the original variables. This amount is drastically less than the "75% or more" recommended by Stevens (1996, p. 364). It is also inconsistent with Gorsuch's (1983) claim that "[u]sually, investigators compute the cumulative percentage of variance extracted after each factor is removed from the matrix [of association] and then stop the factoring process when 75, 80 or 85% of the variance is accounted for" (p. 165). Only the most effective EFAs in the current study met these criteria for variance-accounted-for. It is unclear whether the modest explained variance was due to researchers failing to extract meaningful factors in their data or that their instruments failed to yield data with clear internal structure that can be represented by latent constructs. This question is worthy of further empirical investigation. If analysts are not extracting the correct number of factors, subsequent results can be adversely impacted. If analysts' instruments are not yielding scores with factorial "simple structure" (Thurstone, 1935), the construct validity of scores may be questionable.

Table 2 presents frequency counts and percentages of articles reporting a various information. Table 2 presents both overall frequencies as well as those for each journal examined. For the sake of brevity, only the overall results will be summarized here. However, it should be noted that, in general, the outcomes for the individual journals were similar to the overall results, with the marked exception of article type. Article type varied considerably due to the different objectives, both substantive and measurement, of the journals examined.

INSERT TABLE 2 ABOUT HERE

Careful examination of Table 2 highlights many of the typical decisions made by researchers when conducting EFAs. Careful review also reveals some egregious errors concerning appropriate reporting practice. For example, the majority (65.0%) of authors failed to note what matrix of association they analyzed. Authors also failed to indicate their factor extraction method on eight occasions (13.3%). Among those reporting the extraction method used, most (56.7%) used principal components analysis, which is the default option in most statistical packages.

Regarding strategies used to determine the number of factors to retain, the EV > 1 rule was most common (56.7%). Interestingly, the EV > 1 rule is also the default in most statistical packages, and its frequency of use mirrors that for principal components analysis. The scree test was frequently used (35.0%) as well. Largely, the other rules were ignored (or at least not reported, and so assumed ignored) by authors. For 10 uses of EFA, the authors noted that they set the number of factors to extract based on *a priori* theory. As Daniel (1989) and Kieffer (1999) noted, this approach is generally not appropriate for EFA, given that EFA does not consider the *a priori* considerations of the researcher in the analyses. A CFA would likely be more appropriate in these circumstances.

Although Zwick and Velicer (1986) demonstrated that minimum average partial and parallel analysis were among the most accurate methods for determining the number of factors, most authors failed to use either of these methods. Minimum average partial was never used and parallel analysis (Turner, 1998) was used on four occasions (6.7%). Given the problems with the EV > 1 rule, and less so with the scree test, these findings are troublesome and call into question whether the authors extracted the correct number of factors from their matrices. It is in cases such as these that independent evaluation of results is critical; however, few articles reported enough information to allow for such an investigation.

Furthermore, despite Thompson and Daniel's (1996, p. 200) recommendation that "[t]he simultaneous use of multiple decision rules is appropriate and often desirable," most authors in the current study (n = 33, 55.0%) only used (or at least only reported using) one rule. Of these, 18 invoked the EV > 1 rule, 6 used the scree test, 2 used parallel analysis, and 7 made decisions based on a priori theory. Two decision rules were explicitly considered in 11 EFAs and three rules were used in 7 EFAs. No authors reported using more than three rules. Unfortunately, authors of 9 EFAs (15%) failed to give any indication of how they determined the number of factors to extract.

Regarding factor rotation, orthogonal rotations were most common (55.0%), although rotation strategy was not explicitly justified in 61.7% of the EFAs. Varimax was the most commonly used specific method (51.7%). The most common oblique strategy was oblimin (21.7%), although the exact delta value used was not given in almost all of these cases (n = 10). Gorsuch (1983) discussed the potential differences from using varied delta values. When delta was reported (n = 3), it was always zero, the default in most statistical packages.

Thirteen percent of cases did not report their specific rotation strategy and three failed to even indicate whether the rotation was orthogonal or oblique. Again, this lack of information severely limits external evaluation of others' work. The reader is left to accept the authors' findings on faith, a noble virtue in some contexts, but not in EFA.

Furthermore, when oblique solutions were used (n = 23), only

5 EFAs included either the factor structure matrix (n = 4) or both the factor pattern matrix and the structure matrix (n = 1). The rest either erroneously reported only the factor pattern matrix (n = 11, which is insufficient for the reasons noted previously), none of the matrices (n = 5), or presented the matrix ambiguously so as to prevent the reader from knowing what matrix was given (n = 2). It can only be assumed that authors used the matrices reported to make substantive interpretations of the factor structure. When only the factor pattern matrix is consulted in oblique solutions, incorrect interpretations are very possible (Gorsuch, 1983; Kieffer, 1999; Thompson & Daniel, 1996). Structure coefficients are also almost always necessary for interpretation when factors are correlated.

Additional errors of omission included failure to report communality coefficients (83.4%), variance explained for each factor (63.3%), and eigenvalues for each factor prior to rotation (51.7%). We would also suggest that external evaluation would be facilitated by reporting the eigenvalue for at least the first factor not retained. This eigenvalue would be particularly relevant when only the EV > 1 rule is used for extraction. Only 5.0% of the EFAs reported this information.

Thompson and Daniel (1996) noted that "factors should be given names that do not invoke the labels of observed variables because the latent constructs are not observed variables themselves" (p. 202). Seventy-five percent of the EFAs met this expectation. Another aspect of factor interpretation involves how many and how strongly observed variables weight on a given factor. At least two variables are necessary to define a factor, otherwise the factor would be little more than the observed variable itself. Although multiple items were used to define factors in most all cases, six of the EFAs involved factors that were defined by only one variable, which seems to contradict the basic idea of a factor as a latent construct.

Table 3 presents descriptive information regarding the variance explained by extracted factors and the number of salient items per factor. The data are presented based on whether the authors reported the variance explained before or (appropriately) after rotation. The average number of salient items for a given factor was around six.

INSERT TABLE 3 ABOUT HERE

Finally, we also examined whether CFA was warranted as a potentially more appropriate analysis when the authors held *a priori* expectations concerning the factor structure. In general, we considered *a priori* theory tenable when the instrument was not new and when the authors had knowledge of the factor structure of scores from a previous administration of the instrument. In these cases, CFA is arguably a preferred method given its ability to falsify theoretical expectations (Thompson & Daniel, 1996). EFA use is more appropriate during instrument development.

In our sample, CFA was warranted, but not used, in one-third of the cases. Some authors (11.7%) conducted an EFA when they had theoretical expectations but then appropriately followed up the EFA with a CFA on an independent sample. Although CFA may not be tenable in some instances (e.g., small sample size), this finding reflects a tendency to underutilize CFA, despite its ability to explicitly test hypotheses and build theory.

In EFA, only one model is tested; in CFA, multiple models can be pitted against each other in an attempt to falsify the theoretical constructs that are tested. This falsification potential is fundamental to construct validity and theory development. As 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)

We contend that CFA should be used with greater frequency, and if it were, theory development would likely proceed at a faster pace. As Long and Brekke (1999) argued:

> Longitudinal factorial invariance has been examined with both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Of the two

approaches, CFA is preferred because it emphasizes a priori model testing (Bartko, Carpenter, & McGlashan, 1988) and avoids the factor selection and rotation problems of EFA (McDonald, 1985). (p. 498)

Recommendations for Practice

Based on the results obtained in the present study and the pleas of numerous researchers (cf. Comrey, 1978, Gorsuch, 1983; Kline, 1994; Thompson & Daniel, 1996; Tinsley & Tinsley, 1987; Weiss, 1971), we suggest the following recommendations for practice when conducting and reporting an EFA. In general, sufficient information should be presented to allow external evaluation of the analysis and all analytic decisions should be explicitly noted. Unfortunately, these expectations were often unmet in the articles examined here.

1. When prior theory exists regarding the structure of the data, CFA should probably be used over EFA.
2. Always report which matrix of association was analyzed and the method of factor extraction used. Furthermore, the actual matrix of association should be reported (or made available upon request) to allow others to replicate the analysis.
3. Use and report multiple criteria when determining the number of factors to retain. Avoid overdependence on the EV > 1 rule. Parallel analysis and minimum average partial are grossly underutilized in published research and should be employed with greater frequency, given their utility (cf.

Zwick & Velicer, 1986). Thompson and Daniel (1996) provided a program to conduct parallel analysis for interested readers. We also suggest that authors report the eigenvalue for the first factor <u>not</u> retained.

4. Explicitly indicate which specific rotation strategy was used (e.g., varimax, promax). Furthermore, explicitly justify why an orthogonal or an oblique solution was selected. In general, as is the case throughout the general linear model, because oblique rotation requires the estimation of more parameters, an oblique structure will usually fit sample data better than will an orthogonal rotation. However, as Hetzel (1996) noted,

   > Some researchers have argued that, all things being equal, orthogonal solutions are desirable. Since the factor pattern and the factor structure matrices are identical, and the factor correlation matrix is an identity matrix, fewer parameter matrices are estimated. In theory, the resulting parsimony should lead to more replicable results. (p. 194)

5. Always report the full factor pattern/structure matrix. All factored items should be included. This information is needed to allow (a) external evaluation of analytic decisions, (b) others to rotate reported results to alternative rotation criteria, and (c) also allows for important meta-analyses of factor structure invariance across studies. When oblique

solutions are used, always report and interpret both the factor pattern and factor structure matrices.

Table 4 illustrates a recommended reporting method when presenting orthogonal factor pattern/structure coefficients. Although this table does not list the justification for the rotation strategy or the eigenvalues of non-retained factors, it does present all pertinent information concerning results from the EFA. While this table alone would not allow an external researcher to reproduce a presented study, it should help readers understand the general design of the study and relevant outcome information concerning the results.

INSERT TABLE 4 ABOUT HERE

6. Always report communalities, the total variance explained by the factors, initial eigenvalues, and the variance explained by each factor <u>after</u> rotation or final traces (i.e., the transformed eigenvalue variance-accounted-for statistic after rotation).
7. Never name a factor with the label used for an observed variable. Such practice is potentially confusing and does not honor the fact that the factor is a latent, unobserved variable. Additionally, do not define a factor with only one item. Sufficient component saturation is needed to warrant factor interpretation and to assume some level of replicability.

Conclusion

Appropriate use of EFA necessitates thoughtful researcher judgment concerning a number of analytic decisions. The present chapter reviewed some of the fundamental decisions necessary to conduct an EFA and examined reporting practice in published research. Largely, the information presented in published applications of EFA results tended to be too insufficient to allow external verification of the EFA results and researcher decisions. In addition, the results suggest that researchers often simply use the default options in common statistical packages, which may lead to errant results. For example, when determining the number of factors to retain, the default option (usually EV > 1) is among the weakest methods available.

Multiple deficits in reported information were noted. Several recommendations for improved EFA reporting practice were also given, including the overall recommendation of providing sufficient information to allow external verification of one's EFA results and decisions. Historically, factor analytic techniques have been very useful in theory development and assessing construct validity (cf. Nunnally, 1978, p. 112). The future value of EFA would be enhanced by (a) careful consideration of the choices made in the analysis and (b) reporting more complete information in published research.

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Table 1

General Descriptive Results of Exploratory Factor Analysis Reporting Practices

Variable	n	Median	M	SD	Min.	Max.
Sample size	59	267.00	436.08	540.74	42	3113
Ratio of no. of participants to no. of variables factored	59	11.00[a]	26.86	52.79	3.25	348.40
No. of variables factored	60	20.00	23.73	16.70	5	110
No. of factors extracted	60	3.00	3.48	1.46	1	7
Cutoff used to determine what coefficients were meaningfully weighted on a factor	37	.40	.40	.07	.30	.50
Total variance explained by extracted factors	43	51.70%	52.03%	14.48%	16.70%	87.50%

Note. n = number of articles reporting the relevant information.

[a] Indicates that there were 11 participants per one variable factored.

Table 2

Frequencies and Percentage of Articles Reporting Exploratory Factor Analysis Information

Variable	EPM (n=15) n	EPM (n=15) %	JEP (n=15) n	JEP (n=15) %	PA (n=15) n	PA (n=15) %	P&ID (n=15) n	P&ID (n=15) %	Overall (n=60) n	Overall (n=60) %
Article type										
Measurement	15	100.0	--	--	14	93.3	7	46.7	36	60.0
Substantive	--	--	15	100.0	1	6.7	8	53.3	24	40.0
Level										
First order	15	100.0	14	93.3	15	100.0	14	93.3	58	96.7
Higher order	--	--	1	6.7	--	--	1	6.7	2	3.3
Matrix analyzed										
Correlation	5	33.3	6	40.0	3	20.0	5	33.3	19	31.7
Variance/covariance	--	--	--	--	--	--	2	13.3	2	3.3
Not reported	10	66.7	9	60.0	12	80.0	8	53.3	39	65.0
Extraction method										
Principal components	11	73.3	6	40.0	10	66.7	7	46.7	34	56.7
Principal axis	1	6.7	5	33.3	5	33.3	2	13.3	13	21.7
Other	--	--	1	6.7	--	--	4	26.7	5	8.3
Not reported	3	20.0	3	20.0	--	--	2	13.3	8	13.3
Strategies used for factor retention										
EV > 1	9	60.0	9	60.0	7	46.7	9	60.0	34	56.7
Scree plot	6	40.0	1	6.7	9	60.0	5	33.3	21	35.0
Min. average partial	--	--	--	--	--	--	--	--	0	0.0
Parallel analysis	1	6.7	1	6.7	1	6.7	1	6.7	4	6.7
Bartlett's chi-square	--	--	--	--	--	--	--	--	0	0.0
No. set *a priori*	3	20.0	2	13.3	2	13.3	3	20.0	10	16.7
Other	--	--	1	6.7	2	13.3	4	26.7	7	11.7
General rotation strategy										
Orthogonal	6	40.0	9	60.0	7	46.7	11	73.3	33	55.0

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Oblique	7	46.7	5	33.3	8	53.3	3	20.0	23	38.3
No rotation used	--	--	1	6.7	--	--	--	--	1	1.7
Not reported	2	13.3	--	--	--	--	1	6.7	3	5.0
Rotation justification presented										
Yes	6	40.0	4	26.7	8	53.3	5	33.3	23	38.3
No	9	60.0	10[a]	66.7	7	46.7	10	66.7	37	61.7
Rotation type										
Varimax	6	40.0	8	53.3	6	40.0	11	73.3	31	51.7
Oblimin	3	20.0	2	13.3	5	33.3	3	20.0	13	21.7
delta value given										
Yes (delta=0)	1	33.3	--	--	2	40.0	--	--	3	23.1
No	2	66.7	2	100.0	3	60.0	3	100.0	10	76.9
Promax	3	20.0	1	6.7	--	--	--	--	4	6.7
pivot given										
Yes	--	--	--	--	--	--	--	--	0	0.0
No	3	100.0	1	100.0	--	--	--	--	4	100.0
Procrustes	--	--	--	--	1	6.7	--	--	1	1.7
Other	1	6.7	2	13.3	--	--	--	--	3	5.0
Not reported	2	13.3	1[a]	6.7	3	20.0	1	6.7	8	13.4
If oblique, coefficients reported (n=23 total)										
Factor pattern only	3	42.9	1	20.0	4	50.0	3	100.0	11	47.8
Factor structure only	1	14.3	1	20.0	2	25.0	--	--	4	17.4
Both	1	14.3	--	--	--	--	--	--	1	4.3
Can't tell	1	14.3	1	20.0	--	--	--	--	2	8.7
None reported	1	14.3	2	40.0	2	25.0	--	--	5	21.7
Reported communalities										
Yes	2	13.3	2	13.3	2	13.3	4	26.7	10	16.7
No	13	86.7	13	86.7	13	86.7	11	73.4	50	83.4
Reported variance explained/factor										
Yes	5	33.3	3	20.0	9	60.0	11	73.3	22	36.7
No	10	66.7	12	80.0	6	40.0	4	26.7	38	63.3
Named factors other than variable name										
Yes	10	66.7	9	60.0	15	100.0	11	73.3	45	75.0
No	5	33.3	6	40.0	--	--	4	26.7	15	25.0

Reported EV for factors retained										
Yes	6	40.0	6	40.0	7	46.7	10	66.7	29	48.3
No	9	60.0	9	60.0	8	53.3	5	33.3	31	51.7
Reported EV of at least one factor not retained										
Yes	--	--	--	--	2	13.3	1	6.7	3	5.0
No	15	100.0	15	100.0	13	86.7	14	93.3	57	95.0
Initial EV interpreted as applying postrotation										
Yes	--	--	--	--	3	20.0	7	46.7	10	16.7
No	6	40.0	6	40.0	3	20.0	3	20.0	19	31.7
No reference	9	60.0	9	60.0	9	60.0	5	33.3	31	51.7
CFA warranted										
Yes, not new measure	7	46.7	3	20.0	4	26.7	6	40.0	20	33.3
No, new measure	5	33.3	11	78.3	8	53.3	9	60.0	33	55.0
Yes, but both EFA and CFA done	3	20.0	1	6.7	3	20.0	--	--	7	11.7
If CFA warranted, reasons given for not using CFA (n=20 total)										
Sample size	--	--	--	--	--	--	--	--	0	0.0
No strong theory	--	--	--	--	--	--	--	--	0	0.0
Other	--	--	--	--	--	--	--	--	0	0.0
Not addressed	7	100.0	3	100.0	4	100.0	6	100.0	20	100.0

[a] *n* does not sum to 15 because only one factor was extracted in one case. No rotation was necessary or possible.

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Table 3

Variance Explained and Number of Items for Reported Factors

	% Variance Expl.			Number of Items				
Factor	n	M	SD	n	M	SD	Min.	Max.
Reported Before Rotation								
I	17	31.18	11.06	24	7.54	3.41	3	17
II	16	10.60	5.86	23	5.09	2.70	2	12
III	9	7.52	3.54	15	4.73	2.34	2	9
IV	7	7.42	2.01	12	5.67	3.26	2	13
V	1	5.20	--	4	7.00	1.83	5	9
VI				2	10.50	.71	10	11
VII				1	7.00	--	7	7
Reported After Rotation								
I	4	29.75	30.56	6	7.67	3.67	4	14
II	4	11.45	1.66	6	6.67	3.78	1	10
III	3	10.00	1.05	5	5.60	2.88	2	8
IV	3	8.00	.10	4	5.00	2.94	1	8
V	1	10.00	--	2	6.50	.71	6	7

Table 4

Heuristic Factor Pattern/Structure Matrix
Rotated to the Varimax Criterion

Variable	Factor I Mechanical	Factor II Spatial	Factor III Verbal	$\underline{h}^2$
X1	.685	.133	.168	.515
X2	.005	.070	.832	.697
X3	.625	.280	.032	.470
X4	.101	.688	-.110	.496
X5	.035	.003	.850	.724
X6	.489	.358	.252	.431
X7	.822	.085	.008	.683
X8	.006	-.002	.780	.608
X9	.285	.589	.056	.431
X10	.100	.785	.021	.627
Trace	1.841	1.673	2.132	5.646
% of Variance	18.4	16.7	21.3	56.4

Note. Coefficients greater than |.40| are _underlined_ and retained for that factor. Percent variance is post-rotation; because here there were 10 measured variables, "% of Variance" is trace divided by 10 times 100 (or trace times 10).

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