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# THE APPLICATION OF EXPLORATORY FACTOR ANALYSIS IN APPLIED PSYCHOLOGY: A CRITICAL REVIEW AND ANALYSIS

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Although factor analysis has been a major contributing factor in advancing psychological research, a systematic assessment of how it has been applied is lacking. For this review we examined the *Journal of Applied Psychology*, *Organizational Behavior and Human Performance*, and *Personnel Psychology* over a ten-year period (1975-1984) and located 152 studies that employed factor analysis. We then analyzed the choices made by the researchers concerning factor model, retention criteria, rotation, interpretation of factors and other issues relevant to factor analysis. The results indicate that choices made by researchers have generally been poor and that reporting practices have not allowed for informed review, cumulation of results, or replicability. A comparison of results by time interval (1975-1979; 1980-1984) revealed minimal differences in choices made or the quality of reporting practices. Suggestions for improving the use of factor analysis and the reporting of results are presented.

For more than 80 years, factor analysis (Spearman, 1904, 1927) has contributed to advancing psychological research. It has been used extensively as a data analytic technique for examining patterns of interrelationship, data reduction, classification and description of data, data transformation, hypothesis testing, and mapping construct space (Rummel, 1970). The journal *Psychometrika* has devoted more pages to factor analysis than to any other quantitative topic in the behavioral sciences (Nunnally, 1978), and the number of investigations ap-

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plying factor analysis has been on a geometric increase (Comrey, 1978).

While a large amount of information has been published on factor analysis, it is surprising that a systematic assessment of how factor analysis has actually been applied in empirical work is lacking. Such an assessment is critical for understanding how users have dealt with the complex issues of factor analytic methodology.

The purpose of the present paper is to review and critically evaluate current factor analytic practices in applied psychological research. The review focuses on exploratory rather than confirmatory approaches to factor analysis. While confirmatory techniques (Joreskog, 1974; Long, 1983) are becoming increasingly popular, the limited number of applications to date precludes any systematic review. Given that statistical procedures and techniques are becoming more complex, a review of exploratory factor analysis is not only overdue, it provides a unique view of how well psychometric theory has been translated into practice.

This paper first summarizes current perspectives relevant to some of the major issues in factor analysis application. Next, additional issues that affect the utility of factor analytic results are presented. Then research applying factor analysis over the last ten years in the industrial/organizational psychology literature is analyzed. Implications are drawn concerning the use of factor analysis in applied psychology. Finally, suggestions for improving the use and the reporting practices of factor analytic studies are presented.

### *Major Issues Considered*

A number of issues must be considered when conducting a factor analytic study. The present paper concentrates on four issues: (1) the choice of factor model to be used, (2) the decision about the number of factors to retain, (3) the methods or rotation, and (4) the interpretation of the factor solution. The decisions made at each choice point can have a substantial impact on the results of the factor analysis and on subsequent interpretation of those results (Armstrong & Soelberg, 1968; Comrey 1978; MacCallum, 1983; Weiss, 1976). Researchers must carefully review choice points, provide a rationale for each decision, and interpret results in accordance with those decisions (Weiss, 1976). Following is an overview of perspectives relevant to the four major issues defined above, as well as a number of less critical issues.

### *Factor Model*

The first decision the researcher faces when employing factor analysis is the choice of factor model. Most modern applications of factor analysis can be divided into two different approaches: common factor analysis and components analysis. Both approaches allow researchers to examine how variance for a given variable is distributed relative to other variables in the data set. The major assumption that distinguishes the two approaches concerns the nature of the variance in the variables.

The common factor model assumes that the variance of each measured variable can be decomposed into common and unique portions, where unique variance includes random error variance and systematic variance specific to the given measured variable. The common factor model analyzes the covariation among variables, as well as that portion of the total variability of each variable that is due to common factors. This requires the estimation of "communalities", which represent the common variance of each variable analyzed.

The components model does not differentiate between common, unique, and error variance. Instead, a set of observed variables is transformed into a new set of variables, which are linear composites of the observed variables (Kim & Mueller, 1978a). These composites are intended to account for covariation among variables as well as the total observed variance of each variable.

Critics charge that by mixing common, unique, and random error variance, the components model not only capitalizes on the analysis of unreliable variance (Weiss, 1976), it also results merely in convenient groupings of variables rather than theoretical constructs or latent variables (Hakstian & Muller, 1973). Supporters counter that, unlike common factor analysis, components analysis does not impose the potentially questionable assumption that a hypothetical causal model actually underlies the data (Kim & Mueller, 1978b; Nunnally, 1978). Researchers also point to the basic indeterminacy of the common factor model (estimated communalities and factor scores) as a major consideration in rejecting its use (Steiger, 1979).

Velicer, Peacock, and Jackson (1982) and Arrindell and van der Ende (1985) examined various sets of real data and found little substantial difference in results between the components and common factor analyses. Tucker, Koopman, and Linn (1969), though, found that the advantage of using common factor versus components analysis depends on the degree of correspondence between the data and the formal common factor model. Common factor analysis produced more accurate recovery of true factors than components analysis when the data closely corresponded to the common factor model.

The results by Tucker et al. (1969) suggest that researchers should give serious thought to the appropriate factor model during the design phase of the research. The components model is appropriate when a researcher is interested in maximizing the ability to explain the variance of the observed variables. Common factor analysis is more appropriate when measured variables are assumed to be a linear function of a set of unmeasured or latent variables. The use of components analysis when the researcher is interested in relationships among latent variables can lead to inappropriate solutions and weaken the contribution of factor analysis to substantive theory (Kenny, 1979).

*Number of Factors*

The outcome of a factor analysis heavily depends on how many factors are retained prior to rotation. Factoring should be stopped when additional factors are accounting for trivial variance (Rummel, 1970). Unfortunately, the criterion for retention of factors is uncertain (Humphreys, Ilgen, McGrath & Montanelli, 1967), and various rules of thumb used by researchers often lead to different solutions (Humphreys & Ilgen, 1969; Humphreys & Montanelli, 1974).

For components analysis, it has been argued that the Kaiser criterion of retaining factors with eigenvalues greater than one appears to be most appropriate (Kim & Mueller, 1978b; Weiss, 1976) especially when the sample to variable ratio is large (10:1) (Robbins, 1980). However, Tucker et al. (1969), in a large scale study using simulated population correlation matrices with a known factor structure, found this criterion often incorrectly estimated the number of factors.

Among the alternative criteria, the scree test and parallel analysis have the most support. With the scree test, the pattern of eigenvalues is examined for breaks or discontinuities. While some researchers have questioned the subjectivity of the scree criteria (e.g., Kaiser, 1970), the scree test is quite effective when strong factors are present (Zwick & Velicer, 1982). Monte Carlo studies by Tucker et al. (1969) also found the scree test performed consistently better than the eigenvalue-greater-than-one rule.

Parallel analysis is based on the assumption that some of the eigenvalues from real data with a valid underlying factor structure should be substantially larger than eigenvalues from random data where there are no underlying factors (Humphreys & Montanelli, 1974). Montanelli and Humphreys (1976) have provided an equation for determining eigenvalues that would be expected from random data for a given number of variables and sample size. The parallel analysis criterion for the number of factors is then defined as the number of real eigenvalues that are greater than the corresponding expected eigenvalues from random data.

The examination of eigenvalues also forces the researcher to consider the quality of the data used in the factor analysis. If the plot of observed eigenvalues closely resembles the plot of random eigenvalues, factor analysis of the data is not appropriate. The use of parallel analysis in conjunction with the scree criteria provides a most powerful strategy for researchers interested in making an informed choice as to the number of factors to retain. Parallel analysis, though, can only be used with the common factor model with squared multiple correlations (SMCs) as communality estimates. Results also suggest that the parallel analysis criterion should be considered an upper bound for the number of factors.

A good strategy is to use a number of decision rules and to examine a number of solutions prior to coming to a final conclusion on the retention issue (Comrey, 1978; Hakstian & Muller, 1973; Harris, 1967). Since evidence suggests that it is better to overestimate rather than to underestimate the number of factors (Guertin, Guertin, & Ware, 1981; Levonian & Comrey, 1966; Rummel, 1970), it is suggested that researchers examine the highest to the lowest number of factors until the most interpretable solution is found (Hakstian, Rogers, & Cattell, 1982).

### *Rotation*

Factor rotation is used to improve the psychological meaningfulness, reliability, and reproducibility of factors (Weiss, 1976). Because the number of different positions for the axis is unlimited, a unique solution to the rotation problem is not possible (Comrey, 1978). Simple structure (Thurstone, 1947), which has served as the major criterion for rotation, is achieved by rotating factors around the origin until each factor is maximally colinear with a distinct cluster of vectors (Rummel, 1970).

Orthogonal rotation produces factors that are statistically uncorrelated, while oblique rotation allows factors to be correlated. Proponents of orthogonal rotation cite its simplicity, conceptual clarity, and amenability to subsequent analysis (e.g., Nunnally, 1978). Oblique rotation adds statistical complexity by generating a pattern and structure matrix. This complexity requires greater user sophistication and care in interpretation. The value of this added complexity is the additional information obtained in the form of factor intercorrelations.

Oblique rotation more accurately represents the complexity of the examined variables because constructs in the real world are rarely uncorrelated (Harman, 1976).

While the varimax method of orthogonal rotation comes closest to satisfying the goal of simple structure when orthogonal simple structure is appropriate, other orthogonal rotations tend to produce similar results (Aleamoni, 1973). No type of oblique rotation clearly dominates the field in terms of acceptability, and each technique tends to give a slightly different solution (Harman, 1976). Oblique rotations considered to work well include the Harris-Kaiser othoblique approach (Harris & Kaiser, 1964), promax (Hendrickson & White, 1964), and direct oblimin (Jennrich & Sampson, 1966). Rummel (1970) suggests that different oblique rotations should be tried and the pattern of leadings examined to determine if a satisfactory (i.e., consistent) solution has been found.

*Interpretation*

In factor analysis, the ultimate goal is usually the identification of underlying constructs that summarize a set of variables. Interpretation, the process by which the results of the factor analysis are given meaning or labels, is clearly important. But this step is also highly subjective and dependent upon the choices made earlier in the factor analytic procedure.

To reduce subjectivity, researchers have established rules to guide interpretation. A commonly used rule specifies that only variables with loadings greater than .40 on a factor should be considered "significant" and used in defining that factor. If nothing beyond this is done, the value of the analysis is limited (Comrey, 1978). Factor labels are more meaningful when they reflect what is as well as what is not involved in a factor (Rummel, 1970). This strategy calls for an examination of the pattern of high and low loadings (and sign) across variables.

Users must also consider alternative constructs to reduce the danger of seeing what they expect to find. Tracy and Johnson (1981) reanalyzed the role conflict and ambiguity scales (Rizzo, House, & Lirtzman, 1970) and found that the scales corresponded more closely to a difference in the wording of items (stress or comfort) than to conflict and ambiguity. This example demonstrates that factor labels imply hypotheses that require further investigation (Comrey, 1978). One suggestion to minimize the subjectivity of the labeling process is to provide an independent panel with the results of a factor analysis and to use the panel's consensus judgment (Tracy, 1983).

Another problem with interpretation is that even when the factors appear to be clear and unambiguous, the factor structure may be unreliable because of sampling variability (Cliff & Pennell, 1967; Horn, 1967; Solomon, 1960). Armstrong and Soelberg (1968) have also demonstrated that variables with random numbers can be analyzed and "meaningful" factors interpreted. Therefore, the ability to interpret the results of a factor analysis may say little about the quality of the data or the validity of the results.

A number of approaches have been proposed to minimize the interpretation of meaningless factor solutions. Sampling error can be reduced by increasing sample size, lowering the ratio of factors to variables, and relaxing orthogonality restrictions (Cliff & Pennell, 1967). Factor reliability can be improved through cross validation and through Monte Carlo simulations using sets of random data chosen to conform to the actual data in terms of sample size, number of variables assumed to be underlying the distribution, and type of factor analysis (Armstrong & Soelberg, 1968).

### *Other Issues in Factor Analysis*

While the major decisions above can have a significant impact on results, other aspects affect the quality of a factor analytic study. Three specific issues include sample size, computer program package, and factor scores. A more general issue of concern is the reporting of factor analytic results.

Both theoretical rationale and Monte Carlo evidence (Archer & Jennrich, 1976; Cliff & Hamburger, 1967) show that the stability of factor loadings (and by implication the interpretation of factor solutions) is a direct function of sample size. A recent study by Arrindell and van der Ende (1985) suggests that stability can be achieved with smaller samples than previously acknowledged. The results, however, have limited generalizability, as the variation in factor solutions over repeated sampling for given sample sizes was not examined and the effects of sample size on the number of factors decision was not investigated. Large sample sizes are still considered highly desirable (Browne 1968). For example, Gorsuch (1974) has suggested at least five observations per variable, while Nunnally (1978) has argued for a 10:1 ratio.

With the advent of computer statistical packages, factor analysis has become a commonly used technique for the analysis of correlational data. Even users unfamiliar with factor analysis can conduct an analysis by using the default options available from the statistical packages. MacCallum (1983) has argued that default options of the widely used programs are generally inadequate and that high-quality application requires the user to make a series of careful and informed decisions. Therefore, it is important to examine the type of computer statistical package used and the options chosen by the researcher.

Although the factor solution is often the major goal of a research study, many studies transform observed data into factor scores for use in subsequent analyses. Factor scores represent individual differences on factors and can be determined by different methods, such as exact scores, regression estimates, and composite estimates (Rummel, 1970). Exact scores are obtainable for components analysis, while several types of factor score estimates (e.g., regression, least squares) are available in common factor analysis. These alternative methods for estimating common factor scores yield different factor score matrices for the same data, correlations, and factor loading matrices (McDonald & Burr, 1967). Because of this indeterminacy problem, Cattell (1958) and others have recommended the simple summing of variables salient to a particular factor. Tucker (1971), though, showed that least squares estimates are appropriate when factor scores are correlated with external variables, used as dependent variables in analysis of variance, or used as independent variables in regression analysis.

With regard to reporting factor analytic results, Rummel (1970) specified that published studies should contain the necessary information to allow for (a) critical evaluation of the research, (b) replication of the findings, and (c) advancement or cumulation of knowledge. Critical evaluation is possible only when information is clearly presented about the researcher's decisions in conducting the analysis. Replication and cumulation of knowledge require that the data input (correlation) matrix and results of the factor analysis (eigenvalues, communality estimates, factor loadings, percentage of variance accounted for) be provided (Hunter, 1979).

### *Overview of Research*

This review has highlighted most of the important issues a researcher faces when conducting a factor analytic study. Despite the large amount of literature devoted to issues and controversies in factor analysis, the actual practices used by researchers in the field have rarely been systematically examined and critiqued. The only review found on practices in factor analytic research was conducted by Glass and Taylor (1966). They reviewed three educational journals for three years and found 46 studies that used factor analysis. Ten studies were dropped from subsequent analyses because descriptions of the analyses were too vague to be categorized. Results revealed that 23 of 36 studies used the components model, and 16 of those used the Kaiser criterion for extracting factors with eigenvalues greater than one. Thirty-two studies used orthogonal rotation, with the major method ($N = 28$) being varimax. Glass and Taylor (1966) concluded that the most carefully designed studies used two or more techniques of factor extraction, multiple retention criteria, and various rotational strategies and examined multiple solutions prior to interpreting the results of the analyses.

The present research provides a more comprehensive and systematic assessment of current practices in factor analysis. Three journals of industrial/organizational psychology were reviewed for applications of factor analysis over a ten-year span (1975-1984). Decisions made by researchers relevant to the factor model, number of factors, rotation, and interpretation of results as well as information on sample/variable ratio, statistical package, factor scores, and presentation of the results were examined.

## *Method*

### *Sample*

The three major journals in industrial/organizational psychology, *Journal of Applied Psychology* (JAP), *Personnel Psychology* (PP), and *Organizational Behavior and Human Performance* (OBHP) were examined for studies that used factor analysis as an exploratory analytical technique. Every article in the three journals was reviewed for a ten-year period from 1975 to 1984 inclusive. Studies were eliminated from the sample if factor analysis was a very minor part of the overall analyses or if a study referred back to a factor analysis conducted previously that was used to support the present research endeavor.

A total of 152 studies were found from the review of the literature. Table 1 presents the sample of articles divided by type of journal (JAP, PP, OBHP) and by time of publication (1975-1979; 1980-1984). Results from Table 1 indicate that the majority of studies using factor analytic techniques were found in JAP ($N = 83$; 54.6%). Forty studies in the sample (26%) were from PP while 29 (19%) were from OBHP. The distribution of studies across journals is not surprising, given that JAP publishes a larger number of articles per year than PP and that PP publishes more articles than OBHP. Table 1 also indicates that applications of exploratory factor analysis were more

TABLE 1
*Sample of Factor Analysis Studies by Journal and Year*

| | OBHP | PP | JAP | Total | % |
|---|---|---|---|---|---|
| 1975-1979 | 12 | 19 | 34 | 65 | 42.8 |
| 1980-1984 | 17 | 21 | 49 | 87 | 57.2 |
| Total | 29 | 40 | 83 | 152 | |
| Percentage | 19.1 | 26.3 | 54.6 | | |

numerous in the last five years (1980-1984) than in the earlier five-year span (1975-1979) ($N$ = 87 to $N$ = 65, respectively).

### *Coding Procedure*

Each study in the sample was coded according to factor model, factor retention, rotational method, and interpretation. The studies were also coded for sample/variable ratio, statistical computer package, factor scores, and presentation of the correlation matrix, communality estimates, eigenvalues, factor loadings, and percentage of variance accounted for by the factors.

The choice-of-factor model was coded as (1) the common factor model (non-iterative principal axis, iterative principal axis or non-principal axis methods); (2) the components model; or (3) the model was not presented or type of model was indeterminant based on information provided in the study.

For the number-of-factors issue, studies were coded as to whether they (1) used the rule of eigenvalue greater than one (Kaiser, 1970), (2) retained the number of factors that corresponded to a priori reasoning of the authors, (3) rotated different numbers of factors to determine which solution best "fit" the data, or (4) used Cattell's (1958) scree criteria for examing the slope of the eigenvalue plot.

Additionally, studies that used two or more criteria for the retention of factors were placed in the "combination" category. Criteria such as Harman's (1976) residual criteria of factoring were placed into an "other" category, while studies not discussing the number-of-factors decision were placed in the "not presented" category.

The coding of rotational method consisted of determining whether orthogonal or oblique methods were used. Studies were also coded as not rotating factors or as not presenting information concerning rotational method.

For interpretation of factors, articles were coded into those that specified a minimum value for the significance of a factor loading, focused on unspecified "high loadings", or maintained a priori labels to factors. An "other" category was formed for studies that found one factor or for studies where interpretation was not an important component of the analysis. Studies that did not provide any discussion of factor interpretation were placed in the "not presented" category.

The studies in the sample were also coded for (1) sample/variable ratio size (above 5:1; below 5:1; information not presented); (2) statistical package employed, that is, SPSS (Hull & Nie, 1981), other [e.g., SAS (SAS Institute, Inc., 1982), BMDP (Dixon, 1981)], or information not presented; (3) the method of calculating factor scores (estimated true factor scores; composite scores; method of calculating scores indeterminant; factor scores not calculated); and, (4) presentation of results (coded yes or no for presenting the data input matrix, estimated communalities, eigenvalues obtained prior to rotation, factor loadings, and percentage of variance estimates for retained factors).

Operational problems in coding were found that required the authors to make minor changes in coding categories and to develop rules for uniform interpretation of the information presented. For example, it was difficult to determine whether high loadings were used in interpreting a factor or whether the interpretation strategy was not presented. A rule was enacted whereby a study was coded as using "high loadings" to interpret factors if the text specified that high loadings were used or if high loadings were italicized or underlined in the table of factor loadings.

*Coding Reliability*

Two authors independently coded each of the 152 studies in the sample. The reviewers met during the coding process to compare results and discuss disagreements. An average of two to three disagreements across the 12 dimensions were found for each study. Disagreements in coding resulted in both authors reviewing the article in question and coming to a joint decision. For studies with multiple disagreements, all decisions were reexamined and recoded if necessary.

The third author was given the coding scheme and the decision rules developed to aid accurate coding. Eighteen studies were randomly selected from the 152 studies in the sample for review. The results were compared to the consensus judgments of the other two authors. For the four major choice points, there were 72 possible comparisons. Of these 72 comparisons, 60 were matches resulting in an agreement percentage of 83.3%. Of the twelve disagreements, five had to do with the number-of-factors dimension. For the other variables coded (144 possible comparisons), the percentage of agreement was quite high (95%).[1]

## *Results*

The results for the four major decision variables of factor model, number of factors, rotation, and interpretation are presented in Table 2. The results are presented for the total sample and in five-year intervals (1975-1979; 1980-1984).

For the total sample of 152 studies, the components model ($N$ = 64; 42.1%) was the most popular factor model chosen. Of the 52 studies using some variant of the common factor model (34.2%), the majority ($N$ = 36) used non-iterative (with squared multiple correlations as communality estimates) principal axis. In 36 cases (23.7% of the total sample), it was impossible to determine which factor model was used. The indeterminancy was caused by two reporting problems described in the general discussion section. An examination of the results by time of publication indicated a slight increase in the use of the components model in the more recent publications (1980-1984).

A surprisingly large number of the total sample ($N$ = 47; 30.9%) failed to provide enough information to determine the decision rule for the number of factors. A higher percentage failed to present a decision rule for the number of factors in the more recent period (1980-1984) than in the 1975-1979 interval (34.5% to 26.2%, respectively). This result is especially problematic, given the importance of this decision on factor analytic results. The most popular decision rule was Kaiser's eigenvalues greater than one ($N$ = 33; 21.7%), which was mainly used in conjunction with the principal components model. Table 2 indicates the increased use of the eigenvalue rule in the last five-year period. The best fit criterion, a priori reasoning, and scree test were each used frequently ($N$ = 17; 11.2%).

Some studies ($N$ = 21; 13.8%) used more than one criterion for resolving the number-of-factors problem, with six studies employing three criteria, while 15 employed two. Fourteen used the "best fit" criterion, 12 used eigenvalues greater than one, and 8 used the scree test as one of the criteria. No evidence for greater use of multiple strategies with more recent studies was found.

Almost every study (91.7%) reported the rotational method used with the overwhelming majority using orthogonal rotation ($N$ = 125), with varimax as the most popular method ($N$ = 116). Five of the 15

[1]A list of the studies analyzed for this review and the final coding of each study is available upon request from the first author.

TABLE 2
*Summary of Decisions in The Application of Factor Analysis*

| | 1974-1979 | | 1980-1984 | | Total | |
|---|---|---|---|---|---|---|
| | *N* | % | *N* | % | *N* | % |
| Factor model | | | | | | |
| Common | 25 | 38.5 | 27 | 31.0 | 52 | 34.2 |
| Components | 25 | 38.5 | 39 | 44.8 | 64 | 42.1 |
| Not presented | 15 | 23.0 | 21 | 24.2 | 36 | 23.7 |
| Number of factors | | | | | | |
| Eigenvalue > 1.0 | 8 | 12.3 | 25 | 28.7 | 33 | 21.7 |
| A priori | 11 | 16.9 | 6 | 6.9 | 17 | 11.2 |
| Best fit | 10 | 15.4 | 7 | 8.0 | 17 | 11.2 |
| Scree test/Other | 9 | 13.8 | 8 | 9.2 | 17 | 11.2 |
| Combination | 10 | 15.4 | 11 | 12.6 | 21 | 13.8 |
| Not presented | 17 | 26.2 | 30 | 34.5 | 47 | 30.9 |
| Rotation | | | | | | |
| Orthogonal | 53 | 79.1 | 72 | 80.0 | 125 | 79.6 |
| Oblique/Unrotated | 8 | 11.9 | 11 | 12.2 | 19 | 12.1 |
| Not presented | 6 | 8.9 | 7 | 7.8 | 13 | 8.3 |
| Interpretation | | | | | | |
| Minimum value | 33 | 50.7 | 27 | 31.0 | 60 | 39.4 |
| High loadings | 5 | 7.7 | 12 | 13.8 | 17 | 11.2 |
| A priori | 5 | 7.7 | 12 | 13.8 | 17 | 11.2 |
| Other | 12 | 18.5 | 10 | 11.5 | 22 | 14.5 |
| Not presented | 10 | 15.4 | 26 | 29.9 | 36 | 23.7 |

studies using oblique rotation, also used an orthogonal rotation. Ten studies specified the type of oblique rotation used, with oblimin ($N$ = 4) the most popular. Five studies did not present factor loadings, while 3 studies specified that the loadings presented were from the pattern matrix. No studies presented results for the structure matrix, and only 4 of the 15 studies using oblique rotation presented factor intercorrelations.

Many studies ($N$ = 36; 23.7%) did not present enough information to determine how the factor solution was interpreted and factors labeled. Sixty studies (39.4%) presented a specific rule based on factor loading size. For example, 32 studies specified that interpretations were based on factor loadings greater than .40, while 28 studies specified a "significant" loading as either .35, .30, .20, or .15 and above. Several studies ($N$ = 17) specified that "high loadings" were used to label factors, while 17 studies based their interpretations on a priori expectations. Time of publication was related to the choices made, with more recent studies less likely to present the strategy used to interpret the factor solution and less likely to use the minimum value rule.

TABLE 3
*Summary of Information Presented in Factor Analytic Studies*

| | | 1974-1979 | | 1980-1984 | | Total | |
|---|---|---|---|---|---|---|---|
| | | *N* | % | *N* | & | *N* | & |
| Sample/Variable ratio | | | | | | | |
| > 5:1 | | 46 | 61.3 | 74 | 76.3 | 120 | 69.8 |
| < 5:1 | | 26 | 34.7 | 21 | 21.7 | 47 | 27.3 |
| Not presented | | 3 | 4.0 | 2 | 2.0 | 5 | 2.9 |
| Statistical package | | | | | | | |
| SPSS | | 12 | 18.5 | 12 | 13.8 | 24 | 15.8 |
| Other | | 4 | 6.1 | 1 | 1.1 | 5 | 3.3 |
| Not presented | | 49 | 75.4 | 74 | 85.1 | 123 | 80.9 |
| Factor scores | | | | | | | |
| Estimates | | 4 | 6.1 | 8 | 9.2 | 12 | 7.9 |
| Composites | | 18 | 27.7 | 26 | 29.9 | 44 | 29.0 |
| Indeterminant | | 26 | 40.0 | 25 | 28.7 | 51 | 33.5 |
| Not computed | | 17 | 26.2 | 28 | 32.2 | 45 | 29.6 |
| Presentation of results | | | | | | | |
| Data Matrix | Yes | 3 | 4.6 | 5 | 5.7 | 8 | 5.3 |
| Communalities | Yes | 18 | 27.7 | 7 | 8.0 | 25 | 16.4 |
| Eigenvalues | Yes | 16 | 24.6 | 26 | 29.9 | 42 | 27.6 |
| Variance | Yes | 50 | 76.9 | 59 | 67.8 | 109 | 71.7 |
| Factor loadings | All | 31 | 47.7 | 38 | 43.7 | 69 | 45.4 |
| | Part | 27 | 41.5 | 16 | 18.4 | 43 | 28.3 |
| | None | 7 | 10.8 | 33 | 37.9 | 40 | 26.3 |

Table 3 presents results for the sample/variable ratio, statistical package, factor scores, and presentation of results. Seventy percent of the studies had sample size to variable ratios of at least 5:1 (44.8% above a 10:1 ratio) with more recent studies having a higher sample/variable ratio. Only 29 studies (19%) presented the statistical package used with the majority citing SPSS.

Although most studies ($N$ = 107; 70.4%) calculated factor scores, it was impossible to determine how the factor scores were calculated in almost half the cases. Forty-five of the 57 studies that stated how factor scores were calculated derived pseudo-factor scores by summing across the variables having "significant" loadings on a given factor. Only 23 studies presented information on what was considered a high or significant loading. This procedure of summing variables yields composite scores rather than factor scores as defined in the common factor model. It is inappropriate to refer to such composites as factor scores. Only 12 studies calculated exact component scores or estimated true factor scores.

A final issue concerns the reporting of factor analytic results. Few studies presented the correlation matrix used as input for the factor analysis ($N = 8$). Only 12 of the 52 studies using the common factor model presented communalities. For three studies in which communality estimates were given, it was impossible to determine the factor model used. In addition, 10 studies that used the components model presented final communality estimates without any explanation.

Only 42 (27.6%) studies reported the eigenvalues used as a basis for the critical number-of-factors decision. Few studies provided eigenvalues beyond the ones for the factors retained. This reporting strategy does not allow for informed review of the criterion used to determine the number of factors.

Forty studies (26.3%) did not present factor loadings, while 43 studies left blank loadings that were not significantly related to a factor. The practice of presenting significant loadings has diminished in more recent studies. This decrease is balanced by an increase in the number of recent studies that did not present any factor loadings. It should be noted that a minority of the studies provided the actual items used in the factor analysis. Without the items and the factor loading matrix, it is impossible for others to provide their own interpretation of the research findings.

Almost 30% of the studies ($N = 43$) did not present the percentage of variance accounted for by each retained factor. The 109 studies that did present this information often used confusing terminology or presented inappropriate percentages.

## *General Discussion*

This review has examined the decisions made and results presented in applied factor analytic research. In this section, the major decisions made by applied researchers are critically analyzed. The comprehensiveness of information presented is then evaluated. The paper concludes with a list of criteria that should be considered whenever a factor analytic study is conducted.

### *Evaluation of Decisions*

A majority of the studies that identified a factor model chose the components model. This result supports previous statements that users have resolved the factor model problem by using components analysis and inserting "ones" for communality estimates (Comrey, 1978; Glass & Taylor, 1966; Velicer, Peacock, & Jackson, 1982). Since most researchers were interested in relationships among unmeasured latent variables, there appears to be an overreliance on the components model.

A surprisingly large number of studies did not present the criterion used for determining factor retention or used the eigenvalues greater than one rule of thumb. A problem with this rule is its arbitrary nature (e.g., Is an eigenvalue of 1.01 significant while one of .99 not?). Inflexible adherence to the rule can lead to underestimation or overestimation of the number of factors to retain (Tucker et al., 1969), which can severely distort the factor solution (Levonian & Comrey, 1966). A powerful but overlooked decision technique is parallel analysis (Humphreys & Ilgen, 1969). Although the importance of using multiple criteria of retention and of performing more than one factor analysis of the data has been emphasized (e.g., Kim & Mueller, 1978b), few studies mentioned the careful consideration of alternative solutions.

Most researchers used orthogonal rotation to "force" independence among the factors without conceptual justification. Other researchers used orthogonal rotation even though the interdependence of factors was recognized (e.g., see Rousseau, 1977). Since orthogonal rotation is a subset of oblique rotation, it is more sensible to rotate the factors obliquely and then determine the tenability of the orthogonality assumption. The use of orthogonal or oblique rotation affects conclusions drawn from data. For example, Dunham (1976) replicated a factor analytic study of the dimensionality of job characteristics (Sims, Szilagyi, & Keller, 1976) except for the choice of oblique rather than orthogonal rotation. Dunham found a more interpretable factor structure with more items loading on the appropriate a priori factors.

To interpret the factor solution, most studies set a minimum value above which the loading was considered significant. The use of a minimum score is arbitrary and can result in a loading of .31 being declared significant while a loading of .29 is ignored in defining a factor. Users also tended to force a variable to be related to one factor only. A variable with high loadings across multiple factors was "assigned" to the one factor to which it was related most closely. This approach ignores the fact that it is completely consistent with the common factor model and the principle of simple structure for a variable to have more than one high loading (i.e., to be affected by more than one factor). The result of using these rules of thumb is a reduction in the amount of information used for defining a factor.

The results for the major decisions indicate that users tended to favor (a) components analysis, (b) extracting factors with eigenvalues greater than one, (c) rotating the solution orthogonally, and (d) interpreting loadings above a minimum value. Few studies provided justification for their decisions or mentioned the careful consideration of alternative solutions. Such seemingly "automatic" decisions can result in misleading solutions. Armstrong (1967) made the above choices when analyzing an artificial data set. The lack of correspondence between the obtained and known solution led Armstrong to criticize the utility of factor analysis as a theory building tool. A reanalysis of the data by MacCallum (1983) with a more conceptually justifiable approach (common factor model, inspection of eigenvalue plot, oblique rotation) did recover the known structure in the data.

The reanalysis indicated that the findings of Armstrong were due to a series of poor methodological decisions. Given that this review reveals that the strategies used by Armstrong (1967) are quite typical in applied factor analysis, it is evident that many published applications are, unknown to their authors, characterized by distorted and potentially meaningless solutions.

*Reporting Practices*

A critical question posed by this review was the extent to which research studies have presented the amount and kind of information necessary for informed review, replication of results, and cumulation of knowledge. To meet these criteria, a study must provide (a) a clear presentation of the decisions made and (b) a comprehensive presentation of the results.

We found that information regarding the choices made at each decision point was often not presented. Information concerning factor model was absent in nearly a quarter of the cases. Over 30% of the studies did not present the rule used to determine the number of factors to retain, and a similar percentage failed to report the criteria used to interpret factor analysis solutions. Presentation of the statistical package used or descriptions of how factor scores were derived was more often the exception than the rule.

When factor analytic procedures were stated, the choices made were often presented in a confusing and contradictory manner. There were several instances in which the stated factor model was components analysis but the researcher declared inappropriately that communalities were estimated. Conversely, the common factor model was specified with unities in the diagonal. The factor model used in many studies was indeterminant, as users only reported that "factor analysis" or principal axis factoring was conducted. Since both components and the common factor model can be fit by the principal axis method, this information was uninformative.

The terminology of total and common variance observed was frequently misused. Researchers using the common factors model reported the percentage of total variance explained by the retained factors. Others reported percentage of variance obtained for unrotated factors as if they represented rotated factors. In some cases percentages of percentages were presented. For example, suppose two factors are extracted that account for 40% of the common variance, with the first factor accounting for 30% and the second factor accounting for 10% of the common variance. Instead of reporting these percentages, the researcher states that the first factor accounts for 75% of the variance while the second accounts for 25%. Some computer programs (e.g., SPSS) print out these statistics which are quite misleading as to the importance of the factors. It was apparent that some users had little knowledge of the relationship of factor model used and the variance accounted for by the factors.

Other problems included one researcher who stated that orthogonal factor analysis was used with oblique rotation while another researcher presented eigenvalues (actually the percentage of variance) for rotated rather than unrotated factors to justify the number of factors to retain. It is evident that the difficulty we had in understanding what the users actually did undoubtedly mirrors the confusion of anyone reading these studies and attempting to interpret or replicate results.

The presentation of factor analytic results was often incomplete. Few studies presented the intercorrelation of the variables (or even stated that the data matrix was available from the authors). While not surprising, given the premium for journal space, the lack of a correlation matrix (as well as descriptive statistics and the reliability of variables) does not allow for direct replication or the cumulation of results across studies through meta-analytic or other procedures. The absence of such information when the number of variables is small is especially disturbing.

Most studies that employed the common factor model failed to present communality estimates. Thus, it was impossible to determine the appropriateness of using factor analysis or to examine the amount of common variance associated with each variable. Most studies failed to present eigenvalues or provided eigenvalues only for the factors retained. Consequently, a reviewer could not plot the eigenvalues to determine the appropriateness of the number of factors retained. A majority of studies failed to provide information about the percentage of variance accounted for by the factors or presented inaccurate information.

More than half the studies either did not present factor loadings or only presented the "significant" loadings. While loadings can not be cumulated across studies, a complete presentation of loadings (and items) allows a reviewer to determine the appropriateness of the given factors and allows for comparison of results across studies. The practice of presenting only "significant" loadings is perplexing, given that it takes as much journal space to draw a line or leave blanks in the matrix as it does to provide "nonsignificant" loadings.

*Overall Analysis*

An overall impression gained from this review is that factor analysis in industrial/organizational psychology is often poorly applied. This is surprising, given these are recent studies employing a well-known, frequently used statistical procedure. The results are disturbing because they imply that users of factor analysis and other sophisticated statistical methodologies may have little understanding of techniques being used. This can result in meaningless solutions and erroneous conclusions.

The widespread availability of computer packages has been cited as a major reason for low quality applications of factor analysis (e.g., Comrey, 1978). Researchers without a firm background in factor analysis may be attempting to salvage poorly conceptualized and designed studies (Tucker et al., 1969). This attempt to "rescue" data through factor analysis is a contributing factor in the misuse of powerful analytic techniques (Comrey, 1978).

Problems in the application of factor analysis may be a function of researchers relying on default options. Acceptance of default options indicates a research orientation that is passive (or indecisive) rather than active. Factor analysis involves a series of subjective judgments that require careful consideration of alternative choices in order to link the technique with the goals of the research. Too few studies provided the statistical program used to test the hypothesis about the use of default values.

Inaccurate reporting may be a function of the blind acceptance of information presented on printouts from computer program packages. For example, SPSS prints eigenvalues and percentage of variance estimates that do not correspond to factors derived from fitting the data with the common factor model. BMDP provides percentages of total variance when data are fitted by the common factor model. Both SAS and BMDP print values for variance accounted for by oblique factors even though variance accounted for cannot be partitioned among oblique factors (see MacCallum, 1983 for a more complete discussion of logical flaws in computer program packages).

This review has examined the choices a user faces when conducting exploratory factor analysis that can affect the quality of a study. Researchers interested in exploring the relationships among latent factors should be especially attentive to conducting a high quality application of factor analysis. Practitioners should conduct factor analyses from a knowledge base of the limitations resulting from oversimplified or weak methodology. Special attention should be given to the number-of-factors decision and the type of rotation as they can have the greatest impact on the factor solution.

While the review has focused on choices rather than purposes (e.g., instrumentation, construct validation, factor congruency) for conducting factor analysis, it should be noted that applications of exploratory analyses to problems of multiple data sets (Skinner, 1978) and higher order factors (Thurstone, 1947) were rare. These data analytic strategies are quite appropriate during initial stages of a research program for explicating theory and generating testable hypotheses (Skinner, 1978). It should also be noted that a number of studies in this review had a priori notions of the number of factors to retain and a priori labels for the factor solution. Confirmatory factor analysis (see Joreskog, 1974; Long, 1983) is more powerful than are exploratory strategies for assessing factor structure when the researcher can make firm predictions based on theory and research. A recent study by Harvey, Billings, and Nilan (1985) demonstrates the power of confirmatory over exploratory approaches when belief in an a priori structure is high.

### *Conclusions*

The results of this review support the conclusion of an earlier review by Glass and Taylor (1966) that the applied literature demonstrates the use of relatively poor techniques in factor analysis. Glass and Taylor also noted that the descriptions of techniques used and the presentation of results were often given in a confusing or inaccurate manner. The reviewers' conclusion that editorial boards of journals publishing factor analytic studies could solve these problems quickly has not been realized.

Researchers in various areas of psychology have described the characteristics of a sound factor analytic study. This review indicates that the advice has not been heeded. Therefore, we provide the following recommendations regarding technique and presentation of factor analytic results:

*Technique*

1. Default options of computer packages are avoided unless justified by the researcher.
2. Factor analysis methodology is described completely with accurate terminology.
3. The factor model is related to the goal of the research.
4. Oblique rotation is used unless the orthogonality assumption is tenable.
5. Multiple solutions are examined prior to the decision on factor retention.
6. Factors are interpreted based on a knowledge of the variables and an examination of all factor loadings.

*Presentation*

1. Information about factor analytic procedures are presented clearly in enough detail for informed review, replication, and cumulation of knowledge.
2. Information that should be presented includes the
   a. factor model;
   b. method of estimating communalities (if applicable);
   c. method of determining the number of factors to retain
   d. rotational method;
   e. strategy of interpreting factors;
   f. eigenvalues for all factors (if applicable);
   g. percentage of variance accounted for (if using orthogonal rotation);
   h. complete factor loading matrix;
   i. descriptive statistics and correlation matrix if the number of variables is small;
   j. computer program package;
   k. method for computation of factor scores;
   l. pattern matrix and interfactor correlations when oblique rotation is used.

We strongly believe that adherence to these guidelines would dramatically improve both the quality of the applied factor analysis literature and the validity of the information obtained from applied factor analysis research.

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