# THE USE AND ABUSE OF FACTOR ANALYSIS IN COMMUNICATION RESEARCH

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This paper discusses several decisions that researchers must make in their application of factor analysis to data related to communication phenomena. Several suggestions are provided to aid researchers in reaching appropriate decisions.

Since the early 1960s, the use of factor analysis in communication research has consistently increased. Unfortunately, many of the factor analytic studies reported have been so seriously flawed that it is no exaggeration to state that the field would be far better off if the studies had never been reported. As recently as two decades ago, it was extremely difficult and time-consuming to conduct a factor analytic investigation at most universities. Many hours, even days, of hand computation were required. People who performed factor analyses had to have a thorough knowledge of the method as well as considerable stamina. With the advent of wide accessibility to electronic computers and packaged factor analysis programs, the method has become available with minuscule effort to anyone with access to a computation center, which means almost everyone in a university setting.

The flagrant abuse of factor analysis in published communication research led one critic to suggest (and we think not completely facetiously) that before anyone be allowed access to a factor analysis computer program, they must receive a "Certified Factor Analyst" card from some special agency created for this purpose. We find this suggestion appealing, but, pending the formation of the certifying agency, we believe that a discussion of some of the decisions that a person must confront when utilizing the factor analytic method might be useful. We will address some of these decisions in this paper.

### Factor Analysis: A Brief Overview

Factor analysis is one method of examining a correlation (or covariance) matrix. In effect, the procedure searches for groups of variables that are substantially correlated with each other, while not maintaining high correlations with other variables or groups of variables. Such groups of variables are called "factors" or "dimensions." The degree to which a given variable is associated with a particular factor is estimated by its "factor loading," a statistic analogous to a correlation which can range from -1.00 to +1.00. The closer the loading approaches -1.00 or +1.00, the greater the association between the variable and the factor.

The procedure will automatically (with currently available computer packages) extract as many factors as there are variables present in the matrix examined. Some of these will be "common" factors, which represent variability in the matrix associated with several variables. Others will be "specific" factors, which represent variability primarily associated with a single variable in the matrix. The usual goal of the researcher employing factor analysis is to isolate the common factors. Specific factors typically will not be of interest. When a researcher reports a three-factor solution when 30 variables have been analyzed, he or she is

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indicating that three of the 30 possible factors represent common variance in the matrix, while the other 27 represent specific variance. Methods for determining the number of common factors in a matrix are discussed later.

### Definition of Construct(s)

Although factor analysis can serve many other purposes, this method has been used most often in communication research for the purpose of investigating the dimensionality of constructs and the refinement of measuring instruments. In either instance, careful definition of the construct with which the researcher is concerned should be the first step in the research process. Later decisions depend on this step, and if the researcher is careless at this point, the product of the research may be of little value. We will use the factor analytic research on source credibility to illustrate the importance of decisions about the nature of the construct to be investigated, since this work has been seriously flawed as a result of a lack of careful definition of the construct to be investigated prior to conducting the research.

The factor analytic research on source credibility has been characterized by careless or nondefinition of the construct. As a result, factors of "credibility" have been reported that fail to correspond with the way the construct has been defined by scholars concerned with credibility theory. A good example is the "dynamism" or "extroversion" dimension originally reported by Berlo, Lemert, and Mertz (1961). Although the avowed purpose of the Berlo et al. research was to extend the work of Hovland (Hovland, Janis, & Kelley, 1953), at no point had the earlier research included nonevaluative elements in the definition of the credibility construct. Of additional note is the fact that Berlo et al. did not include nonevaluative elements in their definition either. In fact, they chose not to use "source credibility" as the label for their construct but to call it "dimensions for evaluating message sources'' (italics ours). In the two decades that have followed, the distinction between "source credibility" and "person perception" has become increasingly fuzzy.

The definition problem illustrated by the cred-

ibility research is a serious one, because many later decisions in factor analytic research must be based on the definition of the construct being studied. One of the basic requirements of measurement is the need for isomorphism between the constituent definition of the construct and the operational definition (the measure[s]) of the construct. If there is no clear constituent definition, this requirement cannot be met, as we will see in the next section.

## Item-Variable Selection

Once the construct to be studied is carefully defined, the next step in factor analytic research is the selection of the variables (or items, if we continue our credibility example) to be measured. The key to this process is the maintenance of isomorphism between the construct (as defined) and the measurement. If "source credibility" is defined as the "evaluation of a message source," then only evaluative scales should be chosen for use. If "person perception" is defined as "all of the ways one person can view another person," then both evaluative and nonevaluative scales should be included. If only evaluative scales are used for "person perception" or nonevaluative scales are used for "source credibility," isomorphism is sharply reduced and conclusions about the originally defined construct are negated.

There are many ways in which items may be generated for factor analytic work. The most commonly employed methods are surveying previous theoretical work, surveying previous factor analytic work, and obtaining free responses from research subjects. Any of these may be appropriate, given that each item is examined for its isomorphism with the constituent definition of the construct prior to use. Failing to apply this test to items is very likely to result in the "discovery" of a dimension that does not really exist. For example, we could add a "new" dimension of "source credibility" by including estimates of the person's height, weight, belt size, finger length, arm length, and inseam measure along with our other scales. These measures would be correlated with each other but probably not correlated with our other scales. We might call our new dimension "size," or even

"dynamism" if we prefer. In either event, we would be making a dubious knowledge claim.

## )etermining Sample Size

There has been considerable discussion in the iterature concerning the size of the sample necessary for conducting factor analytic research. Much of this has been less than useful. To understand the importance of sample size in factor analytic regearch, we should first recognize that factor analvsis, unlike most other statistical procedures, does not operate from raw data. The input to factor analysis is a correlation or covariance matrix (although most standard programs allow the user to input raw data, which is transformed to a correlation matrix prior to beginning factor analysis). Consequently, factor analysis itself is completely insensitive to sample size. It makes not one bit of difference whether the correlation matrix is based on N=3 or N=3000; if the correlation matrix is the same, the factor analytic output will be the same. The key to the sample-size question, then, is the correlation matrix. With small sample sizes, the individual correlations are accompanied by a wide margin of error. As sample size increases, the confidence interval around the individual correlations is narrowed and the probability that factor analysis will be working with true correlations is increased. Thus, as with most quantitative research, the larger the sample size the more confidence we can have in the factor analysis.

But what sample size is sufficient? There is no firm number that can be set as an absolute criterion. Rather, the researcher must determine the size of error with which he or she is willing to live. With as few as 11 items or variables, there are 100 nonunity correlations in the matrix. Using a conservative (p<.01) significance criterion, we would still expect one significant correlation to occur by chance. (With 40 items or variables (which is not an uncommonly large number), over 1500 correlations are included in the matrix, and 15 would be expected to be significant by chance alone-possibly enough for two or more factors by themselves. This probem, of course, cannot be completely overcome by (ncreasing sample size. However, much of the negaive impact can be overcome. With N=50, a Pearson r must exceed .353 to be significant. With N=200, r must exceed .180. With N=400, r must exceed .127, and with N=1000, r must exceed .080. Thus, the sample size is directly related to the severity of the problems introduced by the presence of chance correlations in the matrix. With small sample sizes, the factor analysis can be severely distorted by spurious correlations. (Correlations of .30 can have a major impact on factor structure.) But, with large sample sizes, such distortion will be greatly reduced because the spurious correlations are likely to be smaller.

Large samples not only help to protect against alpha error (obtaining factors produced by chance correlations), but also help to protect against beta error (missing factors which actually exist). Chance can operate in either direction, or even in both directions in the same investigation. As in any other quantitative analysis, other things being equal, the larger the sample the higher the power of the analysis.

While no firm sample size can be set for all factor analytic work, we recommend approximately 200 for any study which purports to produce generalizable findings. With N = 200 the correlations obtained are reasonably stable, and nonsignificant correlations can have little impact on the factor analysis. For less pretentious work that is extremely preliminary or exploratory (and not intended for publication prior to extensive replication), smaller samples may be appropriate. However, it should be recognized that this recommendation is only a "rule-ofthumb" to be applied during the planning stages of the study. Kaiser (1970) has noted that sampling adequacy is a function of number of common factors extracted, number of variables in the matrix, and number of subjects. His Measure of Sampling Adequacy (MSA) is the best available method of determining whether enough subjects have been included. Unfortunately, at the time of this writing, the only widely used computer package which includes Kaiser's MSA is the BIOMED package.

#### Insuring Adequate and Representative Variability

In most instances, factor analysis is conducted with the intention of generalizing the results beyond the narrow confines of the study itself. To make this possible, the researcher must insure adequate variability in his or her data and that the variability is representative of the population to which the results will be generalized.

The first and most obvious method of insuring adequate and representative variability is to select a large, random sample of subjects from the population to which the research will be generalized. If one wishes to generalize only to college sophomores, the sample should include college sophomores. However, if one should wish to generalize further, a more varied sample would be more appropriate.

In many cases, insuring adequate and representative variability in the subject sample is not enough. Let us again take the source credibility research to illustrate. This research has sought to determine generalizable dimensions which will apply to many different sources, or even different types of sources. The early work of Berlo et al. is exemplary in this regard in that 18 different sources were used in one study and 12 in another. It is not surprising, therefore, that later, well-conducted studies have generally obtained similar results. However, other studies which have not included sufficient numbers of sources generally have produced unreplicable results, and, in several instances, results that were not even internally consistent. Unfortunately, the latter type of research is much more common than the former.

Without sufficient variance in source, the unique relationships among perceptions of one or two sources may produce factor structures vastly different than would be representative of a generalized group of sources. Of course, if someone is interested only in the dimensions on which Richard Nixon is perceived, then that would be the only source used. But, if the construct defined is broader, there must be more sources employed. This same principle applies to many other factor analytic projects, such as rating scale development and any other concept based on multiple measurement of perceptions.

Although we have not yet said anything directly about factor analysis techniques, we will do so in a moment. But, before we do, we want to stress that the four decision points we have discussed thus far are crucial for competent use of any factor analytic technique. In fact, most abuses of factor analysis in communication research have stemmed from errors in these four areas. Nevertheless, there are a number of decisions that must be made about applying the techniques of factor analysis per se. Unless these decision points are addressed appropriately, the best data will not result in meaningful generalizations. We will now turn our attention to some of these decision points.

## Unity vs. Estimates of Communality

Recently, there has been a call for factor analysts to be more sensitive to the actual methods that are performed in determining various values for diagonal entries in factor analysis. This is not to suggest that this is somehow a "new" issue, nor is it to suggest that communication researchers have been unaware of its significance. But, because reporting a factor analytic investigation often leaves little room for a discussion of what diagonal entries were used (or even what they mean), a discussion of that issue will be offered.

Quite simply, diagonal entries in factor analysis are important because they can contribute to, or reduce, the error associated with any specific number of common factors. In any correlation matrix, we generally are not concerned with the diagonals, because we have specified that we are interested in obtaining the magnitude of a relationship that can be obtained from off-diagonal values. However, this is where correlation matrices and factor analysis conceptually split. When using factor analysis, we are concerned with values for all the variables in an N X N matrix. Diagonal values are important in determining the relative contribution of a variable to the common factor structure. This is where unity vs. estimates of communality placed in diagonals becomes a most controversial issue.

Placing a value of 1.0 in the diagonals in a correlation matrix will make the rank of a matrix equal to the number of variables. In other words, if we have 20 variables, making a 20 X 20 matrix, with 380 known off-diagonal values, and then insert unity into the diagonals, we are suggesting that from the outset we have at least 20 common factors, i.e., the common variance is accounted for, and no specific or error variance can enter the factor structure. The alternative is not to be so presumptuous, and enter

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only *estimates* of communality, thereby providing a truer estimate of the relative contribution diagonals play in factor structure. Of course, there are problems in doing this also. While many factor analysts have lamented the use of unity, Cattell goes so far as to say it is "barbarous"; little agreement exists as to what decision option a person should choose. These authors have encountered as many as 11 methods, but, for the sake of brevity, we will limit our discussion to the two most commonly used.

The first method is known as the "method of highest correlation." Quite simply, this means that the highest correlation found in a matrix should be at least equal to the diagonal value. Others have suggested that the squared multiple correlations serve as the best entry decisions. While diagonal estimation is an important issue in factor analysis, the severity of its importance has decreased substantially, as high speed computers have the ability to perform several iterations on diagonal entries. This procedure provides the researcher with the best estimate of communality. Most available standard programs include numerous iterations as a default option unless this option is suppressed. This has made the unity vs. communality controversy moot, unless the researcher forces retention of unity in the diagonals, as some suggest in research reports. But we doubt that this procedure is often, if ever, really employed.

### Oblique vs. Orthogonal Rotations

Our field, rightfully so, may be charged with a very suspicious ambition in determining the factor structure associated with the concept/construct credibility. This ambition relates to the issue of using orthogonally determined factors as the means of determining the dimensionality of the credibility construct. Only recently have communication researchers begun to utilize an alternate method of determining factors, that being oblique analysis.

As the name implies, orthogonality imposes independency on a structure, thus insuring that factors that are orthogonally determined are uncorrelated with one another. Oblique analysis, on the other hand, does not impose this requirement. Rather, it totates all factors in hyperspace with one another in search of the best hyperplanes describing a con-

struct, unlike orthogonal analysis that rotates factors at 90° angles from one another. The following example will illustrate this principle. If we have 10 factors that appear to operate in a given matrix. using orthogonal analysis will provide five shifts or rotations. Oblique analysis is capable of making 10 rotations. Independence is lost, but we feel that information is gained. Oblique analysis assumes that correlations exist among all phenomena; the issue at hand is whether or not those correlations are of sufficient magnitude to warrant a redefinition of the construct. We maintain that this is the only realistic way to look at communication phenomena. Clean, tidy, independent structures are elegant in a mathematical sense, but they may not be representative of reality. For example, research has found the construct of "interpersonal attraction" to be multidimensional, consisting of at least three dimensions-physical, social, and task. While it is possible to employ orthogonal rotation to generate factors for each of these three dimensions which are uncorrelated, common experience (as well as numerous research studies) tells us that, most commonly, when our physical attraction for a member of the opposite sex increases, so does our social attraction for that person.

The best argument for selecting orthogonal rotation over oblique rotation which we have seen is that this procedure will generate uncorrelated factor scores which, subsequently, may be used in multiple regression analyses without introducing the problem of multicolinearity of predictors. This is a distinct advantage. However, procedures for decomposing  $R^2$  are available which will negate this advantage (Siebold & McPhee, 1979). Generally, then, we believe that oblique rotation procedures are preferable for communication research.

#### Item on Factor Decision

Determining whether an item is on a factor is, on the one hand, a fairly obvious issue, but, on the other, a relatively complex issue. The most obvious basis for determination is that the factor that has the highest loading for an item across N factors is the factor upon which the item is loaded. However, items have loadings across all factors, and, in many instances, they contribute nearly equal variance on

several factors. We, and several other factor analysts, have been plagued with the issue of what to do with items that contribute significant variance on two or more factors. We have employed in many instances the a priori criterion that for the loading of an item to be considered significant it must have a primary loading on one factor of at least .60, and no secondary loading on another factor with a value above .40. It has been charged that this criterion for item significance is very conservative, for, in fact, we may be discarding items that are contributing variance to the factor model. We agree. In our use of factor analysis, we have been primarily interested in instrument development. We have sought items that were "pure" measures of a given factor and have used orthogonal (varimax) rotation procedures to increase the purity. If one has carefully chosen items, and if those items appear to be representative of the construct under investigation, then one must be careful to select only those items that will meet the demands of replicability. If, however, one has a priori grounds for hypothesizing that certain items will load on certain factors, or even that they will contribute variance to several factors, the .60-.40criterion would be of little value. In exploratory investigations of a construct, we would suggest the utilization of a more liberal criterion. Similarly, when any rotation method other than varimax is employed, the .60-.40 criterion is meaningless.

It is important to remember that all items are loaded on all factors, unless a given loading is actually 0.00. The issue of which factor has the "primary" loading is not important unless one plans to discard certain items or to score items on a priori criteria, rather than on the basis of factor weights. When developing measuring instruments, both of these practices are common. Thus, we would argue that very conservative criteria (such as the .60-.40 criterion) should be employed if the researcher expects her or his results to replicate in later studies.

## Determining the Number of Factors

Probably the most perplexing problem confronted by the factor analyst is determining how many common factors exist in his or her data. There have been a sizeable number of methods suggested for making this determination, but none of these guarantee that the researcher will make the right decision. Most of the packaged factor analysis programs have built-in decision-making parameters that the user must override to avoid solutions that may be completely inappropriate. The two most common rules that are included in packaged programs are: (1) extract as many factors as there are items or variables, and (2) terminate extraction when a factor accounts for less variance than would be expected for the total variance of a single item or variable (eigenvalue=1.0). Neither of these approaches is usually appropriate.

The task that the researcher faces is separating the factors that are based on common variance from those based on specific variance. Normally, one wishes to rotate all of the common factors, but exclude all of the specific factors. By common factors we mean those factors with which meaningful variance on more than one item/variable is associated. Specific factors are those with which meaningful variance on only a single item/variable is associated. However the decision about how many factors exist is made, the criteria to be applied must be determined in advance, much like the determination of alpha level before running an analysis of variance. We will consider some of the criteria that can be considered.

The first decision the researcher should make is whether there is more than one factor. In general, the law of parsimony applies to the interpretation of the factor analysis results-the fewer the factors, the better. While this law does not always apply (more factors may increase the heuristic value of the study), generally, the optimal solution is a singlefactor solution. To determine whether such a solution is appropriate, the unrotated factor structure should be examined. If all of the variables have their highest loadings (no matter of what absolute magnitude) on the first factor, the proper interpretation is that the variables form a single factor. If a relatively small proportion (as a rule of thumb we use 10 percent) of the variables does not have the highest loading on the first unrotated factor, the singlefactor solution still may be the best interpretation. The content of the deviant variables should be examined to see if they appear to be psychologically related. Such deviant variables may represent

specific factors or simply poor measures (e.g., bad items). In such cases, the variables can be excluded from future analysis. If it is determined that only one factor exists, the researcher has completed his or her task. If not, the researcher must determine how many factors to submit to rotation.

Probably the best means of determining how many factors to rotate is by considering prior research and theory, if any is available. If one is using a factor-based measure, one should rotate the number of factors previously observed on the instrument. If one is using a new instrument, the number of factors to rotate should be based upon the theory leading to the instrument. For example, if you write five items for each of four theoretical dimensions, four factors should be rotated. Examination of only this solution, however, may lead to a self-fulfilling prophecy. Thus, it is advisable also to examine rotations with both more and less factors than theoretically expected to see if some factors collapse together or split into two factors.

Many times, however, the researcher is in doubt about how many factors to expect. In this event, more mathematically based criteria should be employed. A common method is to rotate all factors with an eigenvalue>1.0. The eigenvalue for a factor represents an estimate of the variance associated with a factor. An eigenvalue of 1.0 indicates that there is variance associated with the factor equal to that potentially generated by a single variable across all factors. The higher the eigenvalue, the more likely the factor represents common, rather than specific, variance. The researcher can be reasonably certain that this procedure will include all common factors, but some specific factors may also be included. To protect against including specific factors, two additional criteria should be applied. The first is Cattell's "scree test." The "scree test" is not really a test, but simply a method eyeballing the raw factor analysis. The eigenvalues for the factors are plotted. The descending eigenvalue curve will be continuous to a point, then register a slight rise or hump, and then continue to decline slowly. The rise or hump on the curve marks the number of factors to rotate.

While the use of the scree test will probably exclude all of the specific factors, in some instances it will not. Thus, one should also include a second criterion based on the number of items with their highest (*how high* is a separate question) loading on a given factor. The common requirement employed is either two or three items, depending on the size of the original item/variable pool.

Our colleague, Lawrence Wheeless, in an unpublished study, tested the above criteria to determine their usefulness. He generated a factor analysis based on data taken from a table of random numbers. He then applied all of the criteria that have been used in published factor analytic research in communication to see which ones would correctly indicate that all of his obtained factors were based on specific variance. The only ones he found to work were the combination of scree and items-onfactor (specifically two items with loading>.60 and no secondary loading>.40 after varimax rotation). We have used these criteria subsequently in over 40 factor analytic investigations and believe they will usually accomplish their intended purpose.

Employing the above criteria requires the processing of multiple rotation analyses, so we need to clarify this procedure. We automatically process all possible rotations from two to the number of factors with eigenvalue 1.0. We then begin with the largest number of factors and "step down." Presume there are 11 factors. Presume, in addition, that the scree test suggests eight factors. We then examine the eight-factor rotation and apply the items-on-factor criterion. If all factors meet that criterion, we report the eight-factor solution and discard the rest. However, presume the sixth factor did not meet the items-on-factor criterion. In such event, we step down to the next solution (in this case the sevenfactor solution) and once again apply the items-onfactor criterion. We repeat this procedure until we find a solution that meets the criterion. Our experience indicates that this process works exceptionally well. By "works" we mean that the structure we finally accept is replicable in later research with different subjects.

#### The Use of Factor Scores

Once a factor structure is accepted as representative of the available data, the next question is what to do with it. Central to this question is how to score data collected subsequently on the same measure. Should the scores be totaled, based on the raw numbers originally assigned (e.g., 1-7 on bipolar scales) or should the scores be weighted by the factor loadings? The answer depends on criteria applied earlier in the process.

Our experience has been that if conservative criteria for item selection have been employed (the .60-.40 criterion, for example), both scoring methods are essentially equivalent—the correlation usually exceeds .95. However, if all items are retained, or if there is a major difference in the loadings of items on the same factor, or if some items have large secondary loadings, scores weighted by factor loadings should be employed to remove extraneous error.

#### Interstudy Factor Comparisons

Interstudy factor comparisons are probably the most crucial basis for determining factor generalizability. The necessity for replication, by the initial investigator and other investigators as well, is the most basic tenant in factor analytic research. However, when one scans the literature, one not only finds this basic tenant violated, but, when interfactor study comparisons are reported, they often do not represent a *true* replication of the construct originally factored.

Those researchers who report factor analytic results that have not as yet been replicated with different populations must be careful to spell out *exactly* the criteria utilized in determining their factor structure. Too often this is not done, and replication is virtually impossible. What items were factored, what means of analysis, and what criteria were specified for factor extraction and determination are all crucial details that need to be reported for factor replication.

Some researchers who have attempted replication of prior factor analytic research have neglected the criteria that were originally specified, and, perhaps most importantly, have paid little attention to the constituent and operational definitions that have been reported. We have mentioned earlier in this paper that the establishment of the isomorphism between these two is crucial. However, some researchers have neglected consideration of this relationship. For example, Anatol and Applebaum (1973) attempted replication of several factor analytic investigations of the source credibility construct. Many of the research investigations they attempted to replicate were investigations of *several* sources and *several* populations. Their analysis of one source was just not isomorphic with the prior investigations. Interstudy factor comparisons, when meaningful, are crucial, but only if done properly. Otherwise, they may make false knowledge claims and lead the unsuspecting or naive reader astray.

Our purpose in writing this paper has been to highlight some of the problems associated with conducting and interpreting factor analytic research. One of our colleagues once commented that factor analysis is "a blend of math, magic, and mischief." Indeed, as employed in previous communication research, elements of all three sometimes have been visible. We hope that the observations in this paper will help future researchers reduce reliance on the latter two elements.

#### NOTE

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