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Elements to Consider in Planning the Use of Factor Analysis

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Abstract

Factor analysis is a widely used and popular data reduction technique. Some have asserted that factor analysis is the most important statistical approach demonstrating factorial validity, and in turn, the construct validity and structure of measures of constructs, affect, perception, or opinion. There continues to be discussion over the decisions that need to be made once factor analysis is intended for use. Regardless of the ongoing debate, it is clear that some procedures can be employed in advance of factoring to help improve results. After summarizing some of the debated issues regarding factor analysis, a comparative description of exploratory and confirmatory factor analysis (EFA and CFA) is presented. That is followed by suggestions for preparation for factor analysis. Finally tips for identification of data appropriate for EFA are given, and a discussion of the points to consider in planning sample size is provided.

Key words: Factor analysis, instrument development, factorial validity

Elements to Consider in Planning the Use of Factor Analysis

Instrument development or validation is often the first step in a quantitative study. With a great deal of luck and significant perseverance in reviewing the literature, an inquisitive researcher might find exactly the scale needed to quantify a variable of interest. Unfortunately, this often is not the case. Frequently, precisely the right instrument is not available. In other cases, a promising instrument may be available but it may not have sufficient psychometric information available to argue for its use. In such instances, researchers are faced with either validating or possibly adapting an existing tool or developing a new one. These activities require the researcher to document the psychometric adequacy of existing, revised, or new instruments before getting on with study of the original research question. Sufficient defense of the measurement properties of any instrument worth using must address the issue of validity, particularly construct validity.[1] The intent of this article is to give a brief introduction to factor analysis (FA), including preparing data to be analyzed through FA, as one method to address the validity of instruments. The article is not an in-depth presentation, or exhaustive on the topic. It is merely an introduction to help the reader gain more familiarity with the popular

[1] Norbeck, J. (1985). What constitutes a publishable report of instrument development? *Image, 34*, 380-382.

procedure.

When reviewing a sample of published studies involving measurement of at least one construct, Goodwin and Goodwin[2] found the most popular method of documenting construct validity was the use of factor analysis techniques. They assert that "researchers commonly rely heavily, and sometimes exclusively, on factor analysis for obtaining evidence of the construct validity of their instruments."[3] Others claim "factor analysis is the most important statistical tool for validating the structure of our instruments."[4] Currently, popular as well as classic texts on psychometric theory,[5] instrument development,[6,7] and research, design, and statistics [8-10] devote multiple chapters to factor analytic procedures and their use in providing evidence of construct validity of measures. The interest in and use of factor analysis has been apparent since computers made the use of principal factor analysis (PFA) and principal components analysis (PCA) accessible to most researchers. With increased availability and easy use of procedures for confirmatory factoring, such as EQS, Linear Structural Relations (LISREL), and structural equation modeling (SEM), the entire family of analyses has enjoyed growing popularity.[11] It must be kept in mind that there are other components of construct validity that are not addressed by factor analysis. Some complain that researchers may rely too heavily upon factor analytic studies to the

[2]Goodwin, L., & Goodwin, W. (1991). Focus on psychometrics: Estimating construct validity. *Research in Nursing & Health, 14*, 235-243.

[3]ibid, p. 238

[4]Dixon, J. (1993). Grouping techniques. In B. Munro & E. Page, *Statistical Methods For Health Care Research (2nd. Ed)* (pp. 245- 274). Philadelphia: J. B. Lippincott.

[5]Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory (3rd Ed).* New York: McGraw Hill.

[6]DeVellis, R. (1991). *Scale development: Theory and Application.* Newbury Park, CA: Sage.

[7]Gable, R. K., & Wolf, M. B. (1993). *Instrument Development in the Affective Domain (2nd. Ed)* Boston: Kluwer.

[8]Munro, B. H. *(1997). Statistical Methods for Health Care Research (3rd Ed).* Philadelphia, Lippincott.

[9]Pedhazur, E., & Schmelkin, L. (1991). *Measurement, Design & Analysis*. Hillsdale, NJ: Erlbaum

[10]Tabachnick, B.G., & Fidell, L. S. (2001). *Using Multivariate Statistics (4rd Ed).* New York: Harper Collins.

[11]Kline, R. B. (1998) *Principles and Practice of Structural Equation Modeling.* New York: Guilford Press

exclusion of other means of assessing construct validity.[12] One should keep in mind that factor validity is but a single aspect of documenting accuracy in measuring a construct, albeit a powerful and widely used one.

[12] Goodwin, 1991

Ongoing debates regarding factor analysis

Debates on when to use each of the family of factoring procedures abound. The most ferocious debate surrounds the choice of PCA or PFA. Selective reading of the literature can argue for use of either PFA or PCA in the study of an instrument's construct validity.[13-16] Some authors suggest there is little difference between the results produced by the two approaches[17-19] although systematic studies have shown the two approaches to produce different results.[20] The underlying assumptions of PCA and PFA are not the same, leading to the debate. PCA assumes there is no error in measurement and all item variation is available for explanation and understanding. On the other hand, PFA assumes that there is error in measurement and only the systematic variation that is somehow common to the items on an instrument may be explained and understood. The discussion, tips, and recommendations presented here are specific to neither PCA or PFA but will be beneficial when applied in preparation for either.

[13] Ferketich, S. A., & Muller, M. (1990). Factor analysis revisited. *Nursing Research, 39*, 59-62.
[14] Gable, 1993
[15] Tabachnick, B. G., & Fidell, L. S. (1996). *Using Multivariate Statistics (3rd Ed)*. New York: Harper Collins
[16] Tabachnick, 2001
[17] Nunnally, 1994
[18] Stevens, J. (1996). *Applied Multivariate Statistics For The Social Sciences (3rd Ed).* Mahwah, NJ: Erlbaum.
[19] Tabachnick, 1996
[20] Borgatta, E. F., Kercher, K. & Stull, D. E. (1986). A cautionary note on the use of principal components analysis. *Sociological Methods and Research, 15*, 160-168

There are additional points of disagreement in the literature relevant to factor analysis (FA).

Often, the boundary between exploratory and confirmatory factoring is blurred or nonexistent.[21] Factor analysis suffers from inconsistent terminology, lack of uniformity in criteria or cutoff values for indicators, menus of rotations to select from, and variations in interpretations of the same results from one researcher to the next. It is easy to understand why some have described FA as confusing and complex[22] while others have been more blunt, referring to it with expletives.[23] The decisions you will have to make once you have gotten into FA will not be addressed in this article. Instead, a few simple precautions to take before engaging will be noted. None of the notions presented here are new. Certain points of preparation in advance of analysis, dubbed by statisticians as "data hygiene," have been recognized and promoted since the early 1950s.[24] Those that can help prepare for the most effective use of FA are reviewed.

[21] Goodwin, 1991

[22] Pedhazur, 1991

[23] Gould, S. J. (1981). *The Mismeasure of Man.* New York: Norton

[24] Guilford, J. P. (1952). When not to factor analyze. *Psychological Bulletin, 49*, 26-37

Exploratory and Confirmatory Factor Analysis

Having a healthy perspective about what to expect from FA can help one avoid disappointments. When used for instrument development, and particularly when applied to concerns about construct validity, FA is usually a two-stage process. The first stage of FA offers a systematic means of examining interrelationships among items on a scale. These

[25]DeVellis, 1991
[26]Nunnally, 1994

interrelationships are used to reveal the clusters of items that have sufficient common variation to justify their grouping as a factor. The factors, in turn, are frequently interpreted as indicators of the latent constructs underlying responses to the instrument as a whole.[25,26] The second stage of FA is used to test specific propositions about item groupings and the construct.

The first stage or initial application of FA to a set of items or variables making up an instrument is usually the first empirical exploration of what dimensions, or factors, contribute to the construct thought to underlie responses to items. This stage of FA is exploratory factor analysis (EFA). Although not technically conforming to all the requirements of rigorous hypothesis testing (i.e., providing a statistic that can be compared to tabled values of expected distributions to assess probability levels), this initial FA does test ideas. If one supposes a construct to be unidimensional, then an EFA showing a single factor grouping, where all items "hang together," is supportive. If the construct is theorized to have multiple facets or dimensions, a single factor solution on an EFA would not support the instrument's construct validity using that selection of measuring items. It is important to keep in mind that the EFA might not uncover the real dimensions underlying the construct, particularly when preparation of the item pool or preparation for the actual analysis has been sloppy. This undesirable outcome is a very likely one when items are included on an instrument without a well conceived theoretical basis. One needs a theoretical rationale for the use of FA (i.e., to detect an expected number of dimensions) derived from ideas about how the construct being explored should behave.[27] In the absence of theory about the dimensionality of constructs, and items derived from this theory, FA will only disappoint or confuse. But given sufficient theoretical preparation, EFA can provide the first objective test of an idea.

[27] Pedhazur, 1991

After the initial first stage EFA analysis, items are either discarded or retained and interpreted. At this time, many researchers progress to a subsequent stage of factor analysis. This stage, confirmatory factor analysis (CFA), is different from the EFA in both intent and actual analytic procedures used. CFA is best accomplished on a data set independent of the initial EFA. This data set might come from dividing the initial data pool into two: responses from one half of the subjects to be used for the EFA and the other half for the CFA. Such an arrangement requires a sizeable initial sample and data pool. A more common approach is to conduct the CFA on a set of data collected subsequent to the initial EFA. In this second data collection, adjustments to items or the instrument (revisions, deletions, or additions of new items made based upon the results of the initial EFA) may be included and their effect assessed.

CFA represents the actual testing of hypotheses about structures underlying responses to individual items on an instrument. In CFA, hypotheses about specified factors, parameter estimation, how the factors are arranged in a larger model, and how much of an underlying construct the factors can explain are tested. This more complex testing, using SEM, EQS or LISREL, is beyond the immediate concern of those preparing for the initial use of factor analysis. Considerations of specific importance to confirmation of expected factor structure are not presented here. Interested readers are urged to refer to sources such as Hayduk,[28] Kline,[29] Long,[30] Pedhazur and Schmelkin,[31] or Tabachnick and Fidell[32] for more information about CFA. For the remainder of this article, it will be assumed that the items responses providing the data for a factor analysis have not yet been subjected to empirical factoring procedures. This is always the case with a newly developed scale and, unfortunately, the case with many scales available in the literature.

[28]Hayduk, L. A. (1987). *Structural Equation Modeling with LISREL: Essentials and Advances*. Baltimore: Johns Hopkins Press.
[29]Kline, 1998
[30]Long, J. S. (1983). *ConfirmatoryFactor Analysis.* Newbury Park, CA: Sage.
[31]Pedhazur, 1991
[32]Tabachnick, 2001

Initial preparations and decisions for use of EFA

Data need to be available for an EFA. If an instrument exists in the literature, and factor analysis results have not yet been reported for it, its items may provide the vehicle for collecting data for an EFA. The Critical Care Family Needs Inventory (CCFNI)[33] provides an example of how

[33]Leske, J. S. (1991). Internal psychometric

a scale may come to be applied in research studies without a clear understanding of the instrument's structure. The initial development of the CCFNI was described by Molter.[34] The instrument was used subsequently in many nursing studies and responses were interpreted at either the item level[35] or in categories of intuitively derived item groupings.[36] The groupings suggested a multidimensional structure underlying the scale. In the absence of evidence that the measure was unidimensional, the internal consistency estimates for the full length 45 item scale were impressive.[37] It was not until twelve years after the CCFNI entered the literature that an actual factor analysis was conducted on responses to the items.[38] That analysis documented a five-factor structure underlying item responses, thus calling into question the previous scoring procedures for the CCFNI. Leske's[39] EFA on the CCFNI was an appropriate application of the procedure and represents a significant contribution to our understanding of how the scale operates.

In the case of either an existing, not yet factored instrument, or when a new instrument is being developed, items should only be selected or generated for inclusion in the analysis if there is a clear, explicit idea of what the domain of interest is. A specific conceptual definition of the construct is needed before item generation or inclusion. The need for an explicit definition might seem deceptively obvious. Unfortunately,

properties of the Critical Care Family Needs Inventory. *Heart & Lung, 20*, 236-243

[34]Molter, N. C. (1979). Needs of relatives of critically ill patients: A descriptive study. *Heart & Lung, 8*, 332-339.

[35]Rodgers, C. D. (1983). Needs of relatives of cardiac surgery patients during the critical care phase. *Focus on Critical Care, 10*(5), 50-55.

[36]Daley, L. (1984). The perceived immediate needs of families with relatives in the intensive care setting. *Heart & Lung 13*, 231-237.

[37]Leske, J. S. (1986). Needs of relatives of critically ill patients: A follow-up. *Heart & Lung, 15*, 189-193.

[38]Leske, 1991

[39]ibid.

this requirement may be overlooked in the rush of preparation of an instrument needed for a research opportunity immediately at hand. When that is the case, the omission may only be realized after time has been spent in generating items and collecting data, from either “expert judges” or actual subjects.[40]

[40]DeVellis, 1991

When measuring a construct, statement of a useful conceptual definition is sometimes difficult. Theories related to the concept should be considered. This can be accomplished through a thorough review of the literature. The approach used in developing items to measure nurses' attitudes toward patients with AIDS is an example of this.[41] A review of the literature suggested that theorists were then speculating about five types of attitudes toward these patients. Thus, an initial item pool of 83 items was generated to reflect the five dimensions needed to define the construct. Ultimately this pool was whittled down to 21 useable items, and the five theoretical dimensions were found to collapse into two measurable and meaningful ones when empirically tested in the EFA.

[41]Froman, R. D., Owen, S. V., & Daisy, C. (1992). Development of a measure of attitudes toward persons with AIDS. *Image, 24,* 149-152.

If there is no instrument in the literature reporting to measure the construct of interest, an entirely new set of items may need to be generated. In the case of new or emerging constructs, there may be little written to assist definition or speculation about the dimensionality underlying the items. In that event, qualitative study and interviews with individuals or focus groups composed of those familiar with the construct can prove immensely helpful. For example, when Lev began her study of strategies oncology patients use to promote health during cancer treatment,[42] there was little available in the literature on that specific topic. To help her refine her definition of the construct in advance of writing items for a scale, Lev met with 47 individuals who were adapting to cancer treatment. Following interviews and discussions with these individuals, Lev was able to develop a definition of her construct of interest, patients' confidence for a specific aspect of self-care, that included four dimensions. Given the multidimensional structure for the construct implied by the experienced persons in her focus groups, she knew the intended direction to take with item generation. Once a definition was in place, she could begin to write items to reflect the construct as specified by that definition.

[42] Lev, E. L., & Owen, S. V. (1996). A measure of self-care self-efficacy. *Research in Nursing & Health, 19,* 421-429.

Knowing how many dimensions are expected, based on your conceptual definition of the construct, gets you ready for item generation. At this point it is better to have the luxury of extra items in your initial pool than too few. It is not unusual to begin with as many as three to four times the number of items ultimately desired in the final scale.[43] For a construct initially theorized to have five dimensions, and with minimum requirement of at least three items per dimension in the final item pool to provide

[43] DeVellis, 1991

sufficient reliability,[44] between 45 and 60 items (5 dimensions X 3 items per dimension X 3 or 4 for initial pool) should be generated for the beginning item pool. The original pool of 83 items for the measure of attitudes towards AIDS patients[45] was larger than most for a similarly theorized five dimensional construct, but its size allowed flexibility in the content review process. Initial item pools may be reasonably and even considerably culled during review by expert judges.[46,47] The culling helps select the most salient items. It also helps avoid excess subject burden during pilot testing if an instrument is very lengthy.[48]

[44]Guilford, 1952

[45]Froman, 1992

[46]Gable, 1993
[47]Grant, J. S., & Davis, L. L. (1997). Focus on Quantitative Methods: Selection and use of content experts for instrument development. *Research in Nursing & Health, 20,* 269-274.
[48]DeVellis, 1991

After generating and culling an initial item pool, construction of a pilot instrument to use in collecting actual subjects' responses is necessary. At this stage it is important to consider that it is easier to remove or discard items from the pool after collection of data than to add items and have to capture a new sample to pilot additional items generated subsequently. It is a good idea to collect subject response data on at least five[49] but fewer than 10 items for each dimension theoretically postulated to define the construct. This recommendation is based on Guilford's rule,[50] that at least three variables (or in the case of instrument development, items) are needed to define a factor, balanced with what we know about reliability estimation. There are numerous formulas that demonstrate that the more items on a measure, all other things being equal, the

[49]Tabachnick, 2001

[50]Guilford, 1952

[51]Ferketich, S. (1991). Aspects of item analysis. *Research in Nursing & Health, 14*, 165-168.
[52]Gable, 1993

more reliable the measure.[51,52] Thus, it is preferable to have a bit of a surplus, rather than just the bare minimum of three items suggested by Guilford, to select from when calculating factor reliabilities after an EFA. If one initiates a pilot test with a minimum of five items for each theorized factor, there is some “wiggle room” to discard items that show low average inter-item correlation on a factor. The discard of such items would serve to increase an alpha estimate of internal consistency.[53] The effect of the discard can be estimated with extrapolation techniques available in most reliability calculation programs. The actual effect of item discard can only be accurately estimated with subsequent testing of a reduced item pool.

[53]Ferketich, 1991

One may seek to avoid collecting data on too many items for each expected factor, however, for practical as well as statistical reasons. An excess of items on a pilot tested instrument may demand a very large sample to allow a reasonable subject (N) to item (P), or N:P, ratio. Such samples may be difficult to access for EFA or could expend available subjects needed for an anticipated CFA. Additional practical concerns are that good items are difficult to write and long instruments are a “turn off" to subjects, presenting too great a subject burden or demand. When bored, subjects might discontinue the task or subvert a research effort, resulting in measurement error.[54] The following statistical limitations may also result from too many items

[54]Pedhazur, 1991

in an initial item pool. The excessive subject demands may result in many missing values from omitted items. This can lead to either reduction of sample size necessitated by casewise deletion or the necessity to use some form of missing data replacement procedure. Considering that factor analysis procedures rely on correlational analysis, and that in turn relies upon maximizing variance in a data set, need for replacement of missing values should be avoided if at all possible. Missing values replacement procedures (i.e., mean substitution, regressed score substitution) all have the effect of reducing variance. The outcome in that case may be an overfitting of data and a resultant creation of factors that are specific to the data set analyzed rather than being generalizable.[55] An over abundance of items, regardless of missing data, might also result in too complex a factor solution to achieve the goal of simple structure following rotation,[56] or a correlation matrix that does not meet minimum assumptions for any FA.[57,58] In short, a delicate balance between having too few and too many items should be sought before initiating an EFA.

[55]Tabachnick, 2001, pp. 587-589

[56]Thurstone, L. L. (1947). *Multiple Factor Analysis.* Chicago: University of Chicago Press.
[57]Guilford, 1952
[58]Tinsley, H. E., & Tinsley, D. J. (1987). Uses of factor analysis in counseling psychology research. *Journal of Counseling Psychology, 34*, 414-424.

In preparing your own, newly-generated item pool for an EFA, focal points (anticipated dimensions of a construct) should also be considered. Identifying focal points initially may help name factors that emerge after EFA procedures are used. These focal points may be achieved by identifying marker items, sometimes

[59]Tabachnick, 2001, pp. 587, 683

called marker variables[59] for each theorized dimension. These marker items are those you identify a priori as being the focus or essence of a theorized dimension. For example, agreement with the statement, "It is especially important to work with AIDS patients in a caring manner" was thought to capture the essence of a nurse's empathetic attitude toward caring for people with AIDS.[60] When this item showed the strongest contribution to one of the factors that emerged from an EFA of pilot tested items on the AIDS Attitude Scale, it was easy to name the factor it was associated with “Empathy.”

[60]Froman, 1992

Marker items might not be important when a construct is theorized as being unidimensional. In that case one would want to select items that all equally reflect the latent variable. The desired result from an EFA then would be the emergence of a single factor solution, indicating a homogeneous measure.[61]

[61]DeVellis, 1991

A final consideration before pilot testing a newly developed item pool is the selection of an item response scale. Certain response scales should not be used with factor analysis in any instance, while others require special procedures before use. For example, an ipsative scale, where each individual rank orders response options within an item, yields data inappropriate for factoring.[62,63] Dichotomous response scales (yes/no; agree/disagree) may be factored with popularly used methods like PFA or PCA only if

[62]Guilford, 1952
[63]Tinsley, 1987

responses to items approach a normal distribution for each item, a sizeable challenge for such response options.[64] If distributions are non-normal, data may require transformations or other special procedures to adjust data from dichotomous response scales before factor analysis can be accomplished. All of these “fix it” alternatives to adjust non-normal distributions pose their own set of problems in turn and may require statistical consultation. Discussion of these procedures is beyond the scope of this article.

[64]Tabachnick, 2001

Sample size considerations in preparing for EFA

There is continued discussion about how large a sample is needed for any meaningful FA. Before addressing that issue, review of the outcomes from using too small a sample might be helpful. In factor analysis, as in most statistical procedures built upon correlation matrices, small samples are likely to yield spurious results that elude replication. In FA these results frequently manifest themselves in the form of what some informally refer to as “rogue” or “splinter” factors. Rogues are those factors that are specific to one data set and may result from bias in a small sample limiting how representative it is of the larger population. Rogues can result from unique patterns of responding on even a single item. Splinter factors are smaller groupings of items that really constitute a larger factor that has “splintered” when tested on a sample with a small N:P ratio. Rogue or splinter factors may be discovered when a sufficiently large and representative sample is studied and yields fewer factors (with more items loading on each factor) than had occurred in a first round of FA on a small sample. In many cases these scoundrels are only discovered after an initial EFA has produced confusing, frustrating or misleading results. In any event, rogues and splinters are those factors to avoid in factor analysis.

Having a sufficiently large sample for an EFA helps avoid rogues and splinters. One can find a recommendation in the literature for sample size to fit almost any accessible sample. Lows range from 5 subjects per item with a minimum of 100 subjects regardless of the number of items,[65] through a minimum of 200,[66] up to 3 to 6 subjects per item with a minimum of 250.[67] Higher estimates for sample size recommend up to 10 subjects per item[68] or just a large sample, ideally several hundred.[69] Few have conducted systematic studies varying sample size to determine the minimum needed to avoid misleading results.[70] One such study, conducted by Arrindell and Van der Ende[71] looked at factorial stability as sample size varied. They considered the ratio of subjects to both the number of items included for factoring and the number of factors expected to explain the items. Based on results of these systematic, empirical analyses they rejected previous

[65]Gorsuch, R. L. (1983). *Factor Analysis (2nd. Ed).* Hillsdale, NJ: Erlbaum.
[66]Guilford, 1952
[67]Cattell, R. B. (1978). *The Scientific Use of Factor Analysis.* New York: Plenum.
[68]Nunnally, 1994
[69]Cureton, E. E. & D'Agostino, R. B. (1983). *Factor Analysis: An Applied Approach.* Hillsdale, NJ: Erlbaum.

[70]Tinsley, 1987
[71]Arrindell, W. A., & Van der Ende, J. (1985). An empirical test of the utility of the observation-to-variables ratio in factor and components analysis. *Applied Psychological Measurement, 9,* 165-178.

[72]Tinsley, 1987

recommendations about sample size. Arrindell and Van der Ende suggested necessary sample size for a meaningful analysis be estimated based upon the number of factors expected, with a minimum of 20 subjects desired per factor. Subsequently, Tinsley and Tinsley[72] noted that it is sometimes difficult to estimate the number of expected factors. In that event, they extended the recommendation to include 5 to 10 subjects per item for up to 300 subjects total.

The discussion in the literature described above might suggest that calculation of the size of the sample needed for a meaningful EFA is not a cut and dried decision. Keep in mind the earlier comments regarding insufficient samples: they may produce transient rogue or splinter factors. If data from a sample of modest size are subjected to an EFA and an uninterpretable factor structure results, consider whether inadequate sample size is the source of the problem. If this is the source of the problem, one should collect data from more people to increase sample size and representativeness, and rerun the EFA on the expanded sample.

Some final considerations in preparation for an EFA

Other matters of pre-analysis data hygiene can be employed to avoid frustrations resulting after an EFA. After data entry but before any FA, all data should be screened. One should remember that factor analysis is built upon correlations, so all the prerequisite assumptions associated with parametric analytic procedures apply. Screening should include at the least inspection for multivariate outliers, non-normal distributions of responses at the item level, and linear bivariate relationships between variables. Additionally, sufficient multicollinearity in the correlation matrix is needed to warrant a factor analysis, and redundancy or singularity of squared multiple correlations for each item with all other items should be avoided. These concerns reflect the “factorability” of the correlation matrix.[73] Sufficient multicollinearity can be actually tested through the use of a Box test or Bartlett’s test of sphericity, although both these tests are considered “notoriously sensitive” to correlations because of dependence on sample size and likely to be overly inclusive of factorable matrices. A more simple approach is to inspect the simple and squared multiple correlations (SMC) for the set of items. If no simple correlations exceed .30, the matrix probably has insufficient multicollinearity. If the SMC values are all in the high .90s or if any equal 1.0, then redundancy or singularity has probably been violated.[74] All of these reflect assumptions that need to be met before using any type of FA procedure. They are tedious procedures often not employed until after unsatisfactory results emerge. In some cases the procedures to ensure good data hygiene may never be applied at all. In those cases erroneous but interpretable results

[73]Tabachnick, 2001

[74]ibid, p. 589

may occur, only to be discovered at either the point of replication of an EFA or initiation of a CFA. Any good multivariate textbook can be consulted to identify procedures recommended for such data screening.[75,76] Once problems are found, repair or adjustment is possible, leading to more interpretable, rewarding and honest results from EFA procedures.

[75]Kline, R. B., 1998
[76]Tabachnick, 2001, pp. 587-590, 647

These preparatory considerations and procedures may sound elaborate, but the pay-off has the potential to be major. With a sound approach to the use of EFA for construct validation in instrument development or instrument adaptation, measurement of variables becomes more sound. All of the above help prevent falling into what Pedhazur and Schmelkin[77] describe as the "garbage in, garbage out trap" that "...is probably nowhere more evident than in applications of FA." With good preparation and appropriate use, the family of factor analysis procedures offers a powerful tool to researchers.

[77]Pedhazur, 1991, p. 591

This article is not meant to provide a detailed description of the many decisions an analyst must make in the actual course of using FA. Choices of extraction methods, how many factors to retain, what rotations to explore, and interpretation and naming of factors, are not addressed here. The interested reader is advised to consult any of the many more advanced articles and texts that speak to these and other more detailed content associated with factor

[78]Ferketich, 1990

analysis. Ferketich and Muller[78] provide an excellent summary overview of the family of factor analysis procedures. Sources such as Stevens'[79] and Tabachnick and Fidell's[80] multivariate statistics books, Kline's[81] SEM text, Pedhazur and Schmelkin's[82] text on measurement and design, as well as DeVellis'[83] instrument development book and finally Nunnally and Bernstein's[84] classic volume on psychometric theory all provide more in depth information than that presented here. This introduction has been meant to offer tips for preparation and should not be treated as any more than an introduction. The family of factor analysis procedures provides a variety of ways to study the underlying complexity of systematically collected indicators of constructs. FA offers one means to expand the repertoire of credible measurement instruments useful in advancing research more surely and speedily.

[79]Stevens, 1996
[80]Tabachnick, 2001
[81]Kline, 1998

[82]Pedhazur, 1991

[83]DeVellis, 1991

[84]Nunnally, 1994

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7 Essential Elements of Demand Forecasting, Planning & Replenishment. www.blueridgeglobal.com | 210 Interstate North Parkway SE Ste. 750 Atlanta, Georgia 30339 | O: 877-547-0346 Â© Blue Ridge Solutions, Inc. All rights reserved. Proprietary and confidential.Â Incomplete use or misuse of the principles makes it difficult to assess what factors lead to poor performance. Lack of clarity on cause, can leave companies scratching their heads in trying to get to the root of the problem, also making it nearly impossible to solve the problem.Â Some commonly used demand-forecasting approaches lead to inaccurate forecasts and improper levels of inventory: â€¢ Simple and moving average â€¢ Same period last year with a trending factor â€¢ Best-fit algorithms. Abstract Robin D. Froman, RN, Factor analysis is a widely used and popular data PhD, FAAN School of Nursing reduction technique. Some have asserted that factor University of Texas Medical Branch analysis is the most important statistical approach Galveston, Texas demonstrating factorial validity, and in turn, the construct validity and structure of measures of constructs, affect, perception, or opinion. There continues to be discussion over the decisions that need to be made once factor analysis is intended for use.Â Finally tips for identification of data appropriate for EFA are given, and a discussion of the points to consider in planning sample size is provided. Key words: Factor analysis, instrument. development, factorial validity p. 2. Elements to Consider in Planning. Finally, factor analysis is also employed to find out the most important factors of packaging. elements that are more important for consumers during the process of decision while buying. The data obtained rated the package design, printed information, and innovation and.Â In principle the primary purpose of packaging is to protect the product, but companies use the. packaging as an instrument for promoting their products, increasing sales, and attracting. customers.