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ABSTRACT

This introduction to confirmatory factor analysis presents an overview of its basic concepts and processes. Conventional factor analysis can be described as set of analytic techniques designed to examine the covariance structure of a set of variables and to provide an explanation of the relationships among those variables in terms of a smaller number of unobserved latent variables called factors. Confirmatory factor analysis offers the researcher a more viable method for evaluating construct validity than conventional (exploratory) factor analysis. In confirmatory factor analysis, a model positing the number and composition of the factors is determined prior to the analysis and tested against the data in hand. The basic procedures are illustrated through the confirmatory factor analysis of the Bem Sex-Role Inventory (BSRI) conducted by T. C. Campbell, J. A. Gillaspy, and B. Thompson (in press). An appendix presents an annotated LISREL Syntax File for the BSRI. (Contains 1 figure, 3 tables, and 24 references.) (SLD)

Running Head: FACTOR ANALYSIS

A Primer on Confirmatory Factor Analysis

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Abstract

The present paper provides a primer on confirmatory factor analysis. An overview of the basic concepts and processes of confirmatory factor analysis will be presented. Finally, Campbell, Gillaspy, and Thompson's (in press) confirmatory factor analysis of the Bem Sex-Role Inventory (BSRI) (Bem, 1981) will be used to illustrate the application of CFA in the behavioral sciences.

A Primer on Confirmatory Factor Analysis

Conventional factor analysis can be defined as a set of analytic techniques, "designed to examine the covariance structure of a set of variables and to provide an explanation of the relationships among those variables in terms of a smaller number of unobserved latent variables called factors" (Daniel, 1988, p. 2). As such, factor analysis provides the researcher a means of reducing large numbers of variables to a more manageable size and of investigating the latent constructs underlying the variables. Kerlinger (1986) explained that:

> Factor analysis serves the cause of scientific parsimony. It reduces the multiplicity of tests and measures to greater simplicity. It tells us, in effect, what tests or measures belong together...It thus reduces the number of variables with which the scientist must cope. (p. 569)

Factor analytic methods have long been used to examine the validity of psychological constructs and the psychometric instruments used to measure those constructs. Nunnally (1978, p. 111) noted that construct validity has often been referred to as factorial validity." Thus, Nunnally (1978, pp. 112-113) argued that "factor analysis is intimately involved with questions of validity," and that "Factor analysis is at the heart of the measurement of psychological constructs. This proposition is echoed by Kerlinger (1986, p. 468), who stated that, "Factor analysis is perhaps the most powerful method of construct validation." Thompson and Daniel (in press) review the history of applications of factor analysis in validity studies, and recommend selected best practices.

Exploratory Factor Analysis (EFA)

There are two major types of factor analytic techniques; conventional or exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The distinction between exploratory and confirmatory factor analysis is based on the purpose of the data analysis. As implied by the name, exploratory factor analysis is used to explore the data when the researcher does not have sufficient evidence to form a hypothesis about the number or nature of the factors underlying the data. Confirmatory factor analysis, on the other hand, is a technique in which the number and the composition of factors are specified prior to the analysis or extraction of factors. Historically, the majority of factor analytic studies have been exploratory (Gorsuch, 1983; Kim & Mueller, 1978). Exploratory factor analytic methods have primarily been used in the development of theory or in the definition of theoretical constructs.

Unfortunately, the use of exploratory factor analysis as a means of evaluating the construct validity of test scores or of serving the purposes of scientific parsimony is inappropriate in some circumstances. Mulaik (1988) argued that the extraction of factors does not provide "justified or authenticated knowledge" (p. 267).

There are several features of exploratory factor analysis that inherently limit its usefulness for evaluating construct validity. First, the factor structures yielded in exploratory factor analysis are determined by the mechanics of the method. For example, different extraction procedures, such as Cattell's scree test (Cattell, 1966) or Guttman's eigenvalue greater than one rule (Guttman, 1954), can produce different numbers of factors (Zwick & Velicer, 1986).

Even in exploratory methods, researchers impose certain assumptions on the data that do not always honor the relationships between the variables. For example, orthogonal rotations require that the factors be perfectly uncorrelated, while oblique rotations require that the factors be correlated with one another. In other words, when using either orthogonal or oblique rotation methods, the researcher a priori may impose potentially mistaken assumptions onto the data. Thus, it should be clear that the factors obtained during an exploratory factor analysis are very much dependent on specific theories and mechanics of extraction and rotation procedures. Despite misconceptions to the contrary, exploratory factor analysis does not simply allow the data to "speak for themselves."

How to interpret the factors once they have been extracted during EFA is another problem. Nunnally (1978) noted that interpretation of factors measured by few variables is often complicated. Mulaik (1972) also raised concern about interpreting the results of exploratory factor analysis:

This difficulty most often comes about because the

> researcher lacks even tentative prior knowledge about the processes which produce covariation among the variables studied and has no basis on which to make his interpretations. In these circumstances the interpretations given the factors may be nothing more than tautological transformations of the names of the original variables. Difficulty is also encountered when the factors obtained represent confounded effects and the researcher is unable to decide which of these effects is unique to the factor--a problem which may come about from random selection of variables. (p. 363)

Due to these and other shortcomings, Mulaik (1987, p. 301) cautions that "It is we who create meanings for things in deciding how they are to be used. Thus we should see the folly of supposing that exploratory factor analysis will teach us what intelligence is, or what personality is."

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis offers the researcher a more viable method for evaluating construct validity. In confirmatory factor analysis, a model positing the number and the composition of the factors is determined prior to the analysis and tested against the data in hand. Thus, confirmatory factor analysis enables the researcher to explicitly test hypotheses concerning the factor structure of the data. For this reason, Gorsuch (1983, p. 134) stated that, "Confirmatory factor analysis is the more theoretically important-and should be the much more widely used-of the two major factor analytic approaches."

Basic Procedures of Confirmatory Factor Analysis

Confirmatory factor analyses can be conducted using computer programs such as LISREL VII (Joreskog & Sorbom, 1989). The first step in a confirmatory factor analysis is to propose competing models or hypotheses about the factor structure of variables based on theory or existing data. Different models of the data are proposed by "fixing" and "freeing" specific parameters, i.e., the factor coefficients, the factor correlation coefficients, and the variance/covariance of the error of measurement. Fixing a parameter refers to setting the parameter at a specific value based on one's expectations. Thus, in fixing a parameter the researcher does not allow that parameter to be estimated in the analysis. Within the command computer file, such as the one presented in Appendix A, fixed variables are indicated by being zero values.

Freeing a parameter refers to allowing the parameter to be estimated during the analysis by fitting the model to the data according to some theory about the data. The competing models or hypotheses about the structure of the data are then tested against one another.

The confirmatory factor analysis yields several different statistics for determining how well the competing models explained the covariation among the variables or fit the data. These statistics are referred to as "fit statistics." These indicators of model fit include the chi square/degrees of freedom ratio, the Bentler Comparative Fit Index (CFI) (Bentler, 1990), the parsimony ratio, and the Goodness-of-fit Index (GFI) (Joreskog & Sorbom, 1989). Using the chi square/degrees of freedom ratio, a model is considered to have a better fit with the data when the ratio is 2-to-1 or lower. Using the GFI, better models are those in which the GFI approaches 1.00.

The parsimony ratio is also important when interpreting the data. This ratio takes into consideration the number of parameters estimated in the model. The fewer number of parameters needed to specify the model, the simpler or more parsimonious is the model. In science, parsimony is sought to explain phenomena because more parsimonious solutions are more likely to be true and thus typically more generalizable. The parsimony ratio can also be multiplied by a fit statistic to produce an index of both the overall efficacy of the model to explain the covariance among the variables and the parsimony of the proposed model. With the variety of fit statistics available to the researcher for evaluating model fit, Campbell, Gillaspy, and Thompson (1995, p. 6) advocated that "fit should be simultaneously evaluated from the perspective of multiple fit statistics."

An Example of Confirmatory Factor Analysis

To illustrate the basic concepts and procedures of confirmatory factor analysis, Campbell, Gillaspy, and Thompson's (in press) study of the covariance structure of the scores of the

Bem Sex-Role Inventory (BSRI) (Bem, 1981) is reviewed. The Bem Sex-Role Inventory is a popular measure of androgyny. The development of the BSRI can be traced to Constantinople (1973) who argued that persons could possess stereotypically masculine and stereotypically feminine psychological traits in any combination, regardless of physical gender. For example, persons who are both masculine and feminine in their psychological outlook are termed "androgynous". In the BSRI, masculinity and femininity are considered to be two separate constructs. Prior to Constantinople's work, masculinity and femininity were considered to be opposite poles of a single construct.

The BSRI yields scores on a masculine (M) and feminine (F) scale. These scores are then dichotomized, creating a 2X2 contingency table with four cells: (a) masculine (high M, low F); (b) feminine (high F, low M); (c) androgynous (high M, high F); and (d) undifferentiated (low M, low F). Figure 1 presents the BSRI 2X2 contingency table. This scoring implies a model in which the two constructs or factors, masculine and feminine, are uncorrelated.

INSERT FIGURE 1 ABOUT HERE

The structure underlying responses to the Bem Sex-Role Inventory has been investigated using various analytic methods across diverse samples (see Thompson, 1989). Thompson and Melancon (1986) provide an example of the use of exploratory methods with scores from the measure. Confirmatory methods have been applied to BSRI data from adolescents (Thompson & Melancon, 1988). Second-order confirmatory methods have also been used (Marsh, 1985).

The present study investigated the covariance structure associated with the BSRI data provided by 791 graduate and undergraduate students enrolled at a large university. The sample was predominately white (82.9%), though the sample also included Hispanics (9.5%), and African-Americans (4.2%). There were slightly more women (50.9%) in the sample. The mean age was 20.23 (SD=4.04).

Three completing models of the factors underlying the BSRI were evaluated:

Model #1a (v=40). This model posited a single bipolar factor defined by the 40 variables or items of the BSRI. This model tested the plausibility of the view of masculinity and femininity prior to Constantinople (1973). The expectation was that 20 items measuring M (or F) should have positive factor parameters, while the remaining 20 items should have negative parameters.

Model #2a (v=40). This model posited two uncorrelated factors defined by the 40 variables--20 items per factor. This was the model implied by conventional scoring of the BSRI that creates the four-fold classification typology.

Model #3a (v=40). This model posited two correlated factors defined by the 40 variables--20 items per factor. This model presumed that there are two discernable M and F dimensions, but either (a) that the dimensions may have a stable but non-zero correlation or (b) that the correlation of the dimensions may vary over samples or time, even though the M and F constructs themselves remain invariant.

As noted by Thompson (1994) the characteristics of reliability and validity inure to scores and not to tests. In fact, sometimes scores from shorter tests are more reliable than scores from longer tests (Thompson, 1990, p. 586). The scores on the BSRI provide a powerful example of this situation. Specifically, the 20-item short-form of the BSRI generally yields comparable or more reliable scores (α_M ranging from .84 to .86; α_F ranging from .84 to .87) than does the 40-item long-form (α_M ranging from .86 to .87; α_F ranging from .75 to .78), especially on the Feminine scale (Bem, 1981, p. 14). Therefore, parallel models of the structure underlying only the responses to the subset of the 20 BSRI short-form were also evaluated:

<u>Model #1b</u> (<u>v</u>=20). This model posited a single bipolar factor defined by the 20 variables.

<u>Model #2b</u> (<u>v</u>=20). This model posited two uncorrelated factors defined by the 20 variables--10 items per factor.

<u>Model #3b</u> (<u>v</u>=20). This model posited two correlated factors defined by the 20 variables--10 items per factor.

Each model was specified by freeing (a) one factor parameter per variable, (b) the factor correlation coefficients, and (c) the measurement error variance for each variable. All other parameters were fixed. Table 1 presents a comparison of exploratory vs confirmatory models as regards the parameters that are estimated.

INSERT TABLE 1 ABOUT HERE

Confirmatory factor analyses were conducted using LISREL covariance structure analyses (Joreskog & Sorbom, 1989). Bivariate correlation matrices were used as the basis for each analysis, to produce "scale-free" parameters. Correlation matrices could be used because all the models involved variables correlating with only one factor, and each factor had factor variance fixed to one (Cudeck, 1989). For most other CFA applications, the variance/covariance matrix must be analyzed, as Cudeck (1989) explained.

Table 2 presents the fit statistics (Bentler, 1990, 1994) for the six models. Table 3 presents the maximum-likelihood parameter estimates for Model #3b.

INSERT TABLES 2 AND 3 ABOUT HERE

Several features of this analysis are noteworthy. First, neither a model positing no factors nor a model positing a single bipolar factor fit the data, as indicated by the various fit statistics reported in Table 2. The failure to fit a bipolar single factor supports Constantinople's (1973) original theory as regards these constructs.

Second, the correlation (r = -.076) between the two factors in Model #3b (v=20) was negligible, as reported in Table 3. The correlation between the two factors in Model #3a (v=40) was -022. These results suggest that the two constructs may be essentially orthogonal, at least in the present study, as implied by a classification scheme presented as the 2X2 contingency table typically employed by researchers using the Bem Sex-Role Inventory.

Third, the fit statistics presented in Table 2 would not make one completely sanguine about the validity of scores from the long form of the measure, or at least of scores computed using conventional scoring keys. Models #2a and #3a fit the data equally well, but neither provided a particularly good fit.

The Table 2 fit statistics also suggest the superiority of scores from the short form. Again, researchers can not simply assume that scores from long forms inherently have better measurement characteristics than scores from shorter test versions. Consistent with previous literature (cf. Bem, 1981), the 20-item short-form of the Bem yielded comparable or more reliable scores (α_M = .82, α_F = .89) for our data than did the 40-item long-form (α_M = .85, α_F = .81), especially on the Feminine scale.

Models #2b and #3b fit the data reasonably well. Therefore, given both the CFA and alpha coefficients, it is suggested that scores on the short-form of the BSRI may have more utility for the purposes of future research.

Summary

The present paper has attempted to demonstrate that confirmatory factor analysis is, in most cases, the tool of choice for evaluating construct validity. Confirmatory factor analysis holds a distinct advantage over exploratory factor analytic methods in that CFA enables the researcher to test competing hypotheses about the number and composition of the factors underlying the data. Exploratory methods, through the use of specific extraction and rotation methods, impose certain assumptions on the data that may not honor the nature and relationship among the variables. An example of a confirmatory factor analysis of the Bem Sex-Role Inventory (Bem, 1981) was used to illustrate the basic concepts and procedures of CFA.

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Figure 1
Bem Sex-Role Inventory 2X2 Contingency Table

		Feminine: High	Feminine: Low
Masculine	High	Androgynous	Masculine
	Low	Feminine	Undifferentiated

Table 1
Factor Matrices of (a) Exploratory Factor Analysis and (b) Confirmatory Factor Analysis for the Two Factor Hypothesis of the Short-form of the Bem Sex-Role Inventory

(a) Exploratory Factor Analysis

Items Dimension	I	II
1	λ_{11}	λ_{12}
2	λ_{21}	λ_{22}
3	λ_{31}	λ_{32}
4	λ_{41}	λ_{42}
5	λ_{51}	λ_{52}
6	λ_{61}	λ_{62}
7	λ_{71}	λ_{72}
8	λ_{81}	λ_{82}
9	λ_{91}	λ_{92}
10	λ_{101}	λ_{102}
11	λ_{111}	λ_{112}
12	λ_{121}	λ_{122}
13	λ_{131}	λ_{132}
14	λ_{141}	λ_{142}
15	λ_{151}	λ_{152}
16	λ_{161}	λ_{162}
17	λ_{171}	λ_{172}
18	λ_{181}	λ_{182}
19	λ_{191}	λ_{192}
20	λ_{201}	λ_{202}

(b) Confirmatory Factor Analysis

Items	I	II	
1	λ_{11}	0	M
2	λ_{21}	0	M
3	λ_{31}	0	M
4	λ_{41}	0	M
5	λ_{51}	0	M
6	λ_{61}	0	M
7	λ_{71}	0	M
8	λ_{81}	0	M
9	λ_{91}	0	M
10	λ_{101}	0	M
11	0	λ_{112}	F
12	0	λ_{122}	F
13	0	λ_{132}	F
14	0	λ_{142}	F
15	0	λ_{152}	F
16	0	λ_{162}	F
17	0	λ_{172}	F
18	0	λ_{182}	F
19	0	λ_{192}	F
20	0	λ_{202}	F

λ = the factor pattern/structure coefficients; M: masculine items; F: feminine items.

Table 2
Fit Statistics for Six Models
(n = 791; v = 40 or 20)

	Model					
Statistic	#1a	#2a	#3a	#1b	#2b	#3b
v	40	40	40	20	20	20
Null chi sq	12628.22	12628.22	12628.22	6093.77	6093.77	6093.77
Null df	780	780	780	190	190	190
Noncentrality	11848.22	11848.22	11848.22	5903.77	5903.77	5903.77[a]
Model chi sq	8891.26	5415.64	5415.35	2636.03	926.40	922.96
Model df	740	740	739	170	170	169
Noncentrality	8151.26	4675.64	4676.35	2466.03	756.40	753.96[a]
NC / df	11.01522	6.31843	6.32794	14.50606	4.44941	4.46130[b]
GFI	0.482	0.728	0.728	0.627	0.884	0.884
Pars Ratio	0.90244	0.90244	0.90122	0.80952	0.80952	0.80476[c]
GFI*Pars	0.43498	0.65698	0.65609	0.50757	0.71562	0.71141[d]
CFI	0.31203	0.60537	0.60531	0.58230	0.87188	0.87229[e]
Pars Ratio	0.94872	0.94872	0.94744	0.89474	0.89474	0.88947[f]
CFI*Pars	0.29503	0.57433	0.57349	0.52100	0.78010	0.77588[g]

[a] Noncentrality = χ^2 - df

[b] Noncentrality / df

[c] Parsimony Ratio = Model df / [(variables * (variables + 1)) / 2]

[d] GFI * Parsimony Ratio

[e] $$\text{CFI} = \frac{[(\text{Null } \chi^2 - \text{Null df}) - (\text{Model } \chi^2 - \text{Model df})]}{(\text{Null } \chi^2 - \text{Null df})}$$

[f] Parsimony Ratio = Model df / [(variables * (variables - 1)) / 2]

[g] CFI * Parsimony Ratio

Note. These fit statistics are described by Bentler (1990, 1994) and by Mulaik, James, van Alstine, Bennett, Lind, and Stilwell (1989). Both #1 models ("a" and "b") posited a single bipolar dimension; the #2 models posited two uncorrelated factors; the #3 models posited two correlated factors.

Table 3
Correlated Two-Factor Model
Maximum Likelihood Parameter Estimates

LAMBDA X

	MASCULIN	FEMININE
DEFENDMY	0.469	0.000
INDEPEND	0.394	0.000
ASSERTIV	0.700	0.000
STRONGPE	0.640	0.000
FORCEFUL	0.474	0.000
LEADERSH	0.591	0.000
TAKERISK	0.479	0.000
DOMINANT	0.663	0.000
TAKESTAN	0.614	0.000
AGRESSIV	0.628	0.000
AFFECTIO	0.000	0.651
SYMPATHE	0.000	0.677
SENSITIV	0.000	0.684
UNDERSTA	0.000	0.635
COMPASSI	0.000	0.771
SOOTHEHU	0.000	0.649
WARM	0.000	0.770
TENDER	0.000	0.794
LOVECHIL	0.000	0.383
GENTLE	0.000	0.757

PHI

	MASCULIN	FEMININE
MASCULIN	1.000	
FEMININE	-0.076	1.000

Appendix A
Annotated LISREL Syntax File for BSRI Confirmatory Factory Analysis

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SUBTITLE 'A      CREATE CORR MATRIX N=791 V=20'
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  /"0.  null model                **VCOV MATRIX**  UNCOR  FACTORS"
  /DA NI=20 NO=791 MA=KM
  /MATRIX=IN(COR)
  /MO NX=20 NK=20 PH=ZE LX=SY TD=ZE
  /FR LX(1,1) LX(2,2) LX(3,3) LX(4,4) LX(5,5)
  /FR LX(6,6) LX(7,7) LX(8,8) LX(9,9) LX(10,10)
  /FR LX(11,11) LX(12,12) LX(13,13) LX(14,14) LX(15,15)
  /FR LX(16,16) LX(17,17) LX(18,18) LX(19,19) LX(20,20)
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