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Comparison of Factor Analysis Options Using the Home/ Employment Orientation Scale

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Factor analysis is a commonly used technique for evaluating the strength of the relationship of individual items of a scale with the latent concept, assessing content or construct validity of an instrument, determining plausible structures underlying a set of variables, and combining a set of variables into one composite score. In using the technique, the analyst must make decisions about the type of extraction and rotation to request and about the number of factors to retain. The purposes of this paper are to compare the results obtained with each of the rotation and extraction methods in traditional factor analysis and with LISREL (Joreskog & Sorbom, 1988), and to explore how these results influence the decisions one makes regarding the structure and item composition of a scale.

The decision regarding which type of extraction to use can be based on one's theoretical expectation about the type of error that is present in the scores obtained. The classic model assumes that all error is random where the neoclassic acknowledges both a random and a systematic component (Ferketich & Muller, 1990). Choosing the classic model necessitates principal components (PC) extraction; whereas, principal axes factoring (PAF), image factoring (IF), alpha factoring (AF), generalized least squares (GLS), and unweighted least squares (ULS) are representative of the neoclassic model.

The method of extraction also reflects the analyst's assumptions about the factors obtained (Nunnally, 1978). Principal components extracts "real" factors in the sample, those that are due to optimization of the data at hand. Because these factors are "real" rather than hypothetical, some sources refer to them as components or component factors rather than as factors (Kim & Mueller, 1978; Nunnally, 1978). Maximum likelihood (ML) extracts "real" factors in the population, using the sample correlation matrix to predict the population matrix. In contrast, the PAF, IF, and AF extractions seek to uncover hypothetical factors that are estimated from the observed data but that are not completely defined by those data.

Each of these extraction methods differ mathematically, based on manipulations of the correlation matrix to be analyzed. The PC and PAF methods differ because of the value placed on the diagonal of the correlation matrix. Principal components places a "1" in each of the diagonal spots, whereas PAF places squared multiple correlations on the main diagonal. The IF, AF, GLS, and ULS methods manipulate the off-diagonal elements before extraction. ML adjusts the correlation matrix after each iteration, so that more weight is given to correlations with less unique variance (Kim & Mueller, 1978). In addition, each subsequent factor is tested for significance before extraction (Nunnally, 1978). Thus, nonsignificant factors are not extracted and interpretation is simplified.

The second decision to be made is whether to rotate the extracted factors. Nunnally (1978) recommends that the analyst rotate the factors in order to simplify the interpretation of the factor structure. However, if one chooses PC extraction, rotation may not be theoretically appropriate (Ferketich & Muller, 1990). If rotation is desired, the analyst must decide whether the factors should be orthogonal (uncorrelated) or oblique (correlated).

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A third decision in factor analysis is the number of factors to extract. There are many rules of thumb that the analyst may use to guide the decision, or the number of factors may be decided on the basis of the structure that the analyst expects theoretically. Frequently, the number of factors extracted on the first factor analysis is decided either by the analyst theoretically or by the computer empirically. On subsequent factor analyses, the analyst changes the number of factors based either on the values or patterns of the eigenvalues or on the clarity of the factor loadings. For example, if several variables load strongly on two factors, the analyst may decrease or increase the number of factors by one to see if the loadings are cleaner.

Many other technical decisions must be made so that the computer can carry out the procedure. Default settings are usually written into the computer program; however, the analyst can override most of them if necessary. For example, in the SPSS FACTOR procedure, the number of iterations, the convergence criterion for extraction and for rotation, and the minimum eigenvalue can be controlled with the /CRITERIA subcommand. In the SAS FACTOR procedure, the subcommands are MAXITER, CONVERGE, and MINEIGEN, respectively.

Despite the many available options and the degree of flexibility, traditional factor analysis does not allow the analyst to specify the exact factor structure of the variables. The analyst may specify only the number of factors to be extracted, not which variables should load on which factors. Looking at the pattern of factor loadings provides an indirect test of the expected model. Unfortunately, problems that affect the interpretation of the factor analysis are often encountered. Variables that are expected to load together, i.e. to represent a particular concept, do not load together. When this happens, the analyst can change the number of factors extracted and hope for the best. Frequently, the analyst runs several factor analyses, manipulating the number of factors extracted and perhaps dropping items that do not load strongly. When several different underlying structures are possible, the analyst is left with the difficult decision of choosing the “best” or “right” solution, often by weighing the positives and the negatives of each.

Confirmatory factor analysis (CFA) with programs such as LISREL (Joreskog & Sorbom, 1988) or EQS (Bentler, 1989) provides the needed control over the analysis in order to directly test the analyst’s theoretical expectations about the underlying structure of a scale (Long, 1983). With CFA, the analyst specifies which variables belong to which latent concepts or factors. The program then calculates the parameters based on the hypothesized model and provides measures of fit that help the analyst to see whether the hypothesized model adequately represents the relationships among the variables.

Faced with all the options in traditional factor analysis, Ferketich and Muller (1990) suggest that the analyst try several extractions and rotations. They reason that if the scale holds up under several methods, one can be more confident in the structure of the relationships among the variables. Nunnally (1978) also states that the results obtained with different extraction methods often are remarkably similar.

Instrument

The Home/Employment Orientation (HEO) Scale (Youngblut, Loveland-Cherry, & Horan, 1990) was part of a battery of instruments completed by mothers (N=110) in a large, longitudinal study of parents’ reactions to the premature birth of an infant. The original scale contained 10 items that mothers rated on an 8-point Likert scale ranging from 1 (strongly agree) to 8 (strongly disagree). Word anchors were not provided for the other six points on the scale. Coefficient alpha for the 10-item scale was .76.

The original scale was designed to measure two related, but distinct, concepts: the mother's orientation toward being employed and her orientation toward staying home with her children. It was expected that these two concepts did not lie on opposite ends of the same continuum, but rather that each was a separate continuum ranging from low to high. Thus, two factors (subscales) with 5 items each were hypothesized for the 10-item scale.

Analysis Procedures

Each of the extraction methods were used in turn in order to see if the different extraction and rotation methods provided different information about the structure of the scale, the relative strength of the relationship between the items and the underlying concept, and the stability of the items' loadings. Two factors were specified in the procedure since that was the a priori expectation. Varimax rotation was used with all extraction methods. A second PC extraction was done with oblique rotation (oblimin). Since the results obtained with oblique and varimax rotations with PC extraction were identical, other extractions with oblique rotation were not done. Nunnally (1978) suggests that loadings of < .40 are small and warrant caution in interpretation. Thus, items were considered to load strongly on a particular factor if the loading was ≥ 40. Items were considered to load on both factors if the absolute difference between the loadings was less than .20. Items that did not reach the .40 criterion were considered not to load on either factor. Finally, a one factor solution with PC extraction was requested in order to further assess the strength of each item (see Table 1).

Comparison of Methods

Only PC supported the extraction of two component factors. The other six methods supported only one factor. For PC, one item did not load cleanly on one factor and one item did not load strongly on either factor. For AF, two items did not load strongly and one did not load cleanly. For the remaining five methods (PAF, ML, IF, ULS, GLS), there were two items that did not load cleanly and three that did not load strongly. Finding that half of the scale's items did not load strongly and cleanly on a factor suggests that the analyst might consider a one-factor solution.

Factor analysis can be used to identify psychometrically weak items, i.e., those that do not load strongly in a one-factor solution. Items 4, 8, and 10 did not perform well on many of the extractions. These same three items did not load strongly in the one-factor solution.

LISREL VII (Joreskog & Sorbom, 1988) was used to test the proposed theoretical structure of the HEO. Results of the LISREL test are presented in Figure 1. Although the chi-square is significant, the goodness-of-fit index of .89 is very close to the recommended .90 criterion for good fit of the model to the data (Boyd, Frey & Aaronson, 1988). However, inspection of the parameters raises some questions about the adequacy of the theoretical model. First, the residuals for five indicators are high (> .60) and all are significant ($p < .01$). Thus, the factor to which the indicator is tied does not account for a major part of the variance in these indicators. Second, three of the indicators are not tied strongly to the theorized factor. Since the parameters on the arrows between the factor and the indicator are analogous to factor loadings, criteria established to evaluate strength of a loading in factor analysis can be used to evaluate the tie between the factor and the indicator (Long, 1983). Thus, items 4, 8, and 10 do not load strongly. Finally, the strength of the correlation ($r = .82$) between the two latent factors indicates that the two concepts are redundant. Perhaps a one-factor solution would be more suitable in this case.

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Conclusions

The patterns of loadings were remarkably similar across the different types of extractions and rotations available in traditional factor analysis. Items that were strong with one extraction tended to be strong across methods. The same was true for weaker items. In addition, confirmatory factor analysis supported the results of the traditional factor analysis. While this may be unique to the scale used, it is likely that these similarities indicate that the HEO scale has a strong factor structure (Nunnally, 1978).

Factor analysis often is used to provide information about the composition of a scale. In order to decide which items to keep and which items to drop from a particular scale, the researcher generally combines the information obtained from a factor analysis and a reliability analysis. This study indicates that the researcher's decision may be facilitated by comparing an item's performance on several factor analyses with different extractions. In addition, CFA with programs such as LISREL or EQS can further substantiate the researcher's ideas about scale composition and factor structure.

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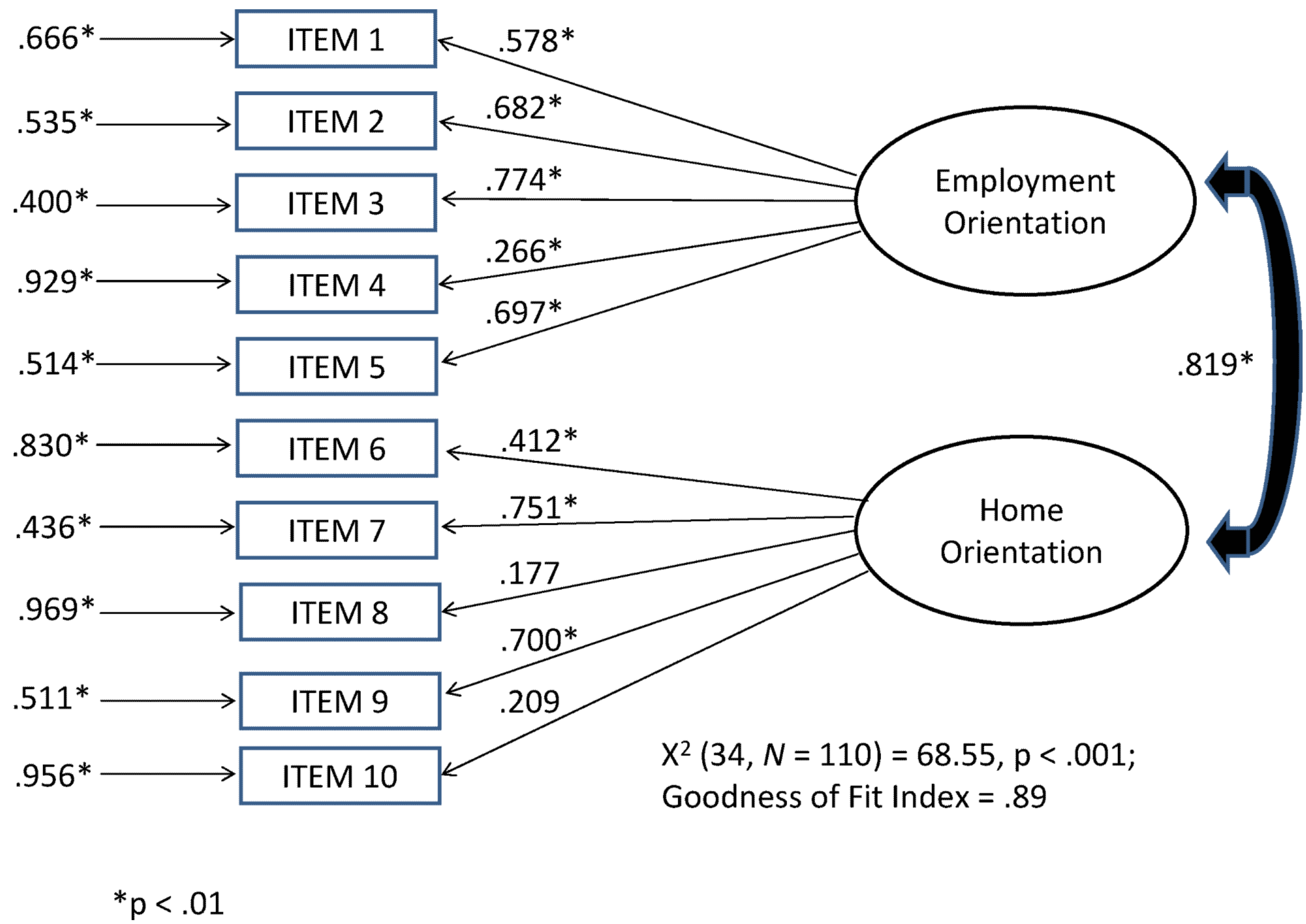

Figure 1.
Testing Factor Structure with LISREI.

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Table 1

Comparison of Factor Loadings

Item	Principal Components	Maximum Likelihood	Principal Axis	Alpha	Image	Unweighted Least Squares	Generalized Least Squares	Principal Components	Principal Components
# Factors	2	2	2	2	2	2	2	2	1
Rotation	Varimax	Varimax	Varimax	Varimax	Varimax	Varimax	Varimax	Oblimin	Varimax
Item 1	F1	F1	F1	F1	F1	F1	F1	F1	F1
Item 2	F1	F1	F1	F1	F1	F1	F1	F1	F1
Item 3	F1	B	B	F1	B	B	B	F1	F1
Item 4	F1	N	N	F1	N	N	N	F1	N
Item 5	F1	F1	F1	F1	F1	F1	F1	F1	F1
Item 6	F2	F2	F2	F2	F1	F2	F2	F2	F1
Item 7	B	F2	F2	B	F2	F2	F2	B	F1
Item 8	N	N	N	N	N	N	N	N	N
Item 9	F1	B	B	F1	B	B	B	F1	F1
Item 10	F2	N	N	N	N	N	N	F2	N

Note: F1= Factor #1; F2 = Factor #2; B = Both Factors; N = Neither Factor.