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ABSTRACT

Factor analysis is used frequently by researchers as a data reduction and summarization technique. Many analysts use exploratory factor analysis to search for underlying dimensions in attitudinal studies. Concern arises when novice researchers rely solely on information derived from computer printouts to factor analyze data, dismissing theoretical consideration of concepts underlying this analytical procedure. A primer on principal components exploratory factor analysis is presented, and five decision rules for selecting the number of principal components to retain are discussed: (1) the K1 rule; (2) the Scree test; (3) Bartlett's test; (4) the minimum average partial method; and (5) parallel analysis. A small data set, obtained in an actual exploratory study, was used to illustrate the discussion. The study addressed effects of preemployment tests on attitudes toward a firm formed by individuals outside that firm. In a pilot study, responses of more than 400 graduating seniors to three different preemployment tests were analyzed. In a second study, 249 graduating seniors and master's candidates responded to preemployment test scenarios. Dimensions of applicants' attitudes were examined through exploratory factor analysis. It is concluded that the results of different decision rules must be used when determining the number of principal components, and that factor analyses should be run with one or two components above and below those suggested with the five methods in order to avoid underextraction or overextraction. Analysts are cautioned to not rely on computer programs and preset default outputs as the "last word." Three figures and four tables supplement the discussion. A 35-item list of references is included. (Author/SLD)

EXPLORATORY FACTOR ANALYSIS: A REVIEW AND ILLUSTRATION OF FIVE PRINCIPAL COMPONENTS DECISION METHODS FOR ATTITUDINAL DATA

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ABSTRACT

Factor analysis is used frequently by researchers as a data reduction and summarization technique. A number of analysts use exploratory factor analysis to search for underlying dimensions in attitudinal studies. Concern arises that novice researchers might rely solely on information derived from computer printouts to factor analyze data, dismissing careful consideration of concepts underlying this analytical procedure. This paper presents a primer on principal components, exploratory factor analysis. In addition, five decision rules for selecting the number of principal components to retain are illustrated and discussed. A small, actual data set is employed throughout the discussion for heuristic purposes, to make the treatment more concrete.

"Because of its power, elegance, and closeness to the core of scientific purpose, factor analysis can be called the queen of analytic methods." (Kerlinger, 1986, p. 569)

Factor analysis was conceptualized before 1905, but was rarely used because of the vast number of calculations entailed in extracting and rotating factor pattern coefficients. This analytic technique is used much more frequently by today's researchers, largely because of the extensive capabilities of the modern computer (Kerlinger, 1986). However, the novice researcher might rely too heavily on computer printouts to analyze data and may dismiss careful consideration of the concepts which underlie such analytical procedures.

The purposes of this manuscript are (a) to serve as a "primer" on exploratory factor analysis; and (b) to illustrate principal components analysis with an illustrative attitudinal data set. Stewart (1981, p. 56) suggests that exploratory factor analysis is common in behavioral research and "appropriate when the underlying dimensions of a data set are unknown." An attitudinal data set (obtained in an actual exploratory study) is used to illustrate these analytic choices. Some theoretical considerations inherent in the determination of the appropriate number of factors to extract in a principal components, exploratory analysis, are also discussed.

Factor Extraction Types And Procedures

Factor Extraction Types

The researcher can choose between two types of factor analysis: exploratory or confirmatory. Each type uses different procedures of analysis. Trouble arises when exploratory factor analysis is performed in lieu of confirmatory factor analysis where previous like studies are ignored (Ehrenberg, 1968).

Confirmatory factor analysis is used to test whether a specific subset of variables actually define a factor that previous research proposed. Thus, confirmatory factor analysis differs from exploratory factor analysis in that specific hypotheses are tested (Gorsuch, 1983). Gorsuch reminds us (1983, p. 127) that "confirmatory factor analysis produces the solution directly, negating the need for rotation." Gorsuch (1983, p. 134) cautions that "confirmatory factor analysis is the more theoretically important--and should be the much more widely used--of the two major factor analytic approaches." Exploratory factor analysis should be used only when theories or prior analyses in that research area have not been reported.

The Research Study

The research project addressed the effects of three different pre-employment tests on the "company perception" (attitude toward the firm) formed by individuals outside the firm. The research design was exploratory, since a literature search revealed few studies concerning potential applicants' attitudes toward companies that require pre-employment tests.

A pilot study was conducted to investigate the dimensions of applicant attitudes toward companies that required as a condition of employment (1) a drug test; (2) a polygraph test; and (3) a medical (disease screening) test. More than 400 graduating seniors at a

Southeastern University participated in the pilot study, and their responses were utilized in scale development.

As a result of the pilot study, a multi-item scale was developed. The final scale reflected concepts presented in Crant and Bateman's (1989) "Employee Response Model" [to drug testing programs], and the pilot study results. The 14-item scale (presented in Figure 1) measures perceptions of fairness, justice, corporate image, similar job opportunities, need for the tests, legitimacy of the tests, confidence and anxiety regarding the test.

INSERT FIGURE 1 ABOUT HERE

A total of 249 graduating seniors and masters candidates at a Southeastern University participated in the second study (average age=26; number of men/women approximately equal). Each participant completed the scale after reading an employment scenario. One scenario example is presented in Figure 2. Each of the three employment scenarios dealt with either a commercial airline industry, health care industry, investments security industry, or university and each scenario required some type of pre-employment test (83 students were randomly assigned to each testing scenario). All data were collected in November, 1989.

INSERT FIGURE 2 ABOUT HERE

Because the design was exploratory, an exploratory factor analysis of the 14-item scale was appropriate to investigate the salient dimensions of the applicants' attitudes. This data set will be used to illustrate the use of exploratory principal components analysis.

Exploratory Factor Extraction Procedures

The purpose of exploratory factor extraction procedures "is to identify basic conceptual dimensions that can be examined in future research" (Gorsuch, 1983, p. 121)." Exploratory factor extraction procedures include principal components, principal axes and some maximum likelihood methods.

Principal components analysis forms linear combinations of the observed variables. The first principal component explains the greatest amount of sample variance. "Successive components explain progressively smaller portions of the total sample variance, and all are uncorrelated with each other" (Norusis, 1988, p. 130). Stewart cautions that the principal components procedure produces "inflated loadings in comparison with the other procedures but otherwise yields similar results" (1981, p. 56).

Principal axes analysis is similar, but utilizes communalities estimates other than ones on the diagonal of the correlation matrix. Using initial estimates of the communalities (typically squared multiple correlation coefficients), the first factors are extracted. As Norusis (1988, p. 137) explains, "the communalities are reestimated from the factor loadings, and factors are again extracted with the new communality estimates replacing the old. This continues until negligible change occurs in the communality estimates."

Maximum likelihood analysis produces parameter estimates that are "most likely to have produced the observed correlation matrix if the sample is from a multivariate normal distribution" (Norusis, 1988, p. 137). According to Gorsuch (1983, p. 117), "any factor solution that best reproduces the population values is a maximum likelihood analysis. Alone, the procedure is insufficient to establish a unique factor solution."

Principal components extraction was selected for analysis of the 14-item attitudinal scale. The choice of extraction method is subjective; however, Gorsuch (1983, p. 122) cautions "maximum likelihood procedures often result in problematic solutions." Stewart (1981, p. 56) suggests that when communalities are high, the procedure chosen "ultimately has little bearing on the results of an analysis."

Determining The Data's Appropriateness for Factor Analysis

Before a factor analysis, the researcher should check the factor model for appropriateness. A variety of indices provide this evidence. Although other matrices can be factored (e.g., variance/covariance) the correlation matrix can be examined to determine whether the variables have large correlations--denoting that they share common factors and that the factor model is appropriate. In the present example most scale items in the data set were moderately to strongly correlated with at least one other scale item (.4 to .7) as reported in Table 1. No scale item was unrelated to all other scale items (consistent correlations of .2 or less); two scale items (CARE, PROB) had the weakest pattern of correlations.

INSERT TABLE 1 ABOUT HERE

Bartlett's Test of Sphericity can be employed "to test the hypothesis that the correlation matrix is an identity matrix" (Norusis, 1988, p. 128). The test should be applied before factor analysis, for if this hypothesis cannot be rejected, factor analysis may be inappropriate. In other words, it is possible that each variable is a factor. However, Stewart (1981) advises that this hypothesis can be rejected when data are inappropriate (or when sample size is large); therefore, other methods should be utilized as well. The Bartlett test statistic for these data was 1096.27, significance = .00; therefore, the null that the correlation matrix was an identity matrix was rejected.

Two matrices can provide further evidence of the propriety of factor analysis: the anti-image correlation matrix and the inverse of the correlation matrix. The anti-image correlation is the negative of the partial correlation coefficient, and the proportion of large coefficients (below the diagonal) should be low for a good factor model. As reported in Table 2, only six percent of these correlations in the data set were larger than .20; most were .05 or smaller. Like the anti-image matrix, the inverse of the correlation matrix should approach a diagonal matrix if the data are appropriate, i.e., a matrix with ones on the diagonal and zeroes or near-zero values.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA) compares magnitudes of observed correlation coefficients to magnitudes of partial correlation coefficients (Kaiser, 1970). As Norusis (1988, p. 129) notes, "if the sum of the squared partial correlation coefficients between all pairs of variables is small when compared to the sum of the squared correlation coefficients, the KMO measure is close to 1. Small values for the KMO measure indicate that a factor analysis of the variables may not be a good idea, since correlations between pairs of variables cannot be explained by the other variables." Kaiser (1974) notes measures in the .90's are marvelous; 80's, meritorious; 70's, middling; 60's mediocre; 50's, miserable; and below .5 are unacceptable. The KMO was .88238 for the data set.

Item-level measures of sampling adequacy are printed on the diagonal of the anti-image correlation matrix reported in Table 2. For a good factor analysis, large values are needed, as with the KMO. These individual measures also provide assistance in identifying scale items for possible deletion. The item-level measures of sampling adequacy in the data set for this study ranged from .77 to .93. Therefore, at this point, all scale items were retained for the factor analysis.

INSERT TABLE 2 ABOUT HERE

Initial and final communalities provide additional evidence for the factor analyst. Although initial communalities in a principal components solution are always equal to 1.0, when other algorithms are utilized the initial communality estimate is the squared multiple correlation coefficient between a variable and all other variables. This provides measures of the strength of linear associations among variables. Stewart (1981, p. 57) states: "consistently small values may be an indication that factor analysis is inappropriate." A small communality would indicate a variable that needs to be dropped from the analysis (Norusis, 1983); this information can be helpful when making scale item deletion decisions. Final communalities document the variance explained by the factor solution. The final communalities for the four principal components that were extracted are presented in Table 3. All the values are reasonably large, suggesting once again that all of the variables should have been retained in the analysis.

INSERT TABLE 3 ABOUT HERE

Cautions When Determining The Appropriate Number of Factors To Extract In Principal Components Factor Analysis

Gorsuch (1974, p. 131) reminds analysts that "the major use of factor analysis is to find a limited number of factors which will contain the maximum amount of information." Others propose this "is one of the most critical decisions the applied researcher faces" (Zwick and Velicer, 1986, p. 432). Cliff (1988) considers the number of factors to retain the most difficult decision a factor analyst must make.

Several problems with using the incorrect number of factors have been cited, and illustrate the difficulty of this decision:

1. Comrey (1978) cautions that rotating the wrong number of factors can have a profound effect on the results if a computerized mathematical rotation algorithm is used.

2. Zwick and Velicer (1986) warn that underextraction results in a loss of information it a factor is either ignored or combined with another factor. Stewart (1981) suggests under extraction seriously distorts rotated solutions.

3. Comrey (cited in Zwick and Velicer, 1986, p. 432) indicates that overextraction may result in "minor factors being built up at the expense of major factors and/or the creation of factors with only one high loading and a few low loadings." Overextraction may result in factors that are hard to replicate and are uninterpretable, according to Zwick and Velicer (1986). Stewart (1981, p. 59) states: "too many factors will result in factor splitting." However, Cattell (1952) recommends the extraction of extra factors on the grounds that they become residual factors upon rotation and improve the interpretation of the solution.

Five Methods For Identifying The Number of Factors

Many methods are available to determine the correct number of factors to extract. This paper reports some theoretical considerations recommended for review by Zwick and Velicer (1986, p. 433) because of their "widespread use or their extensive theoretical justification." These five methods are (a) The K1 Rule; (b) The Scree Test; (c) Bartlett's Test; (d) The Minimum Average Partial (MAP); and (e) Parallel Analysis (PA).

Eigenvalue Greater Than 1.0 (K1)

At least in the principal components case, eigenvalues are the sums of the squared factor loadings on a given factor. The "Eigenvalue Greater Than 1.0 Rule" specifies that factors with eigenvalues of 1.00 (or more) should be retained in the factor analysis (Lawlis & Chatfield, 1974, p. 101). Each variable has a variance of 1.0; therefore, the logic is that factors with a variance less than 1.0 are no better than a single variable (Norusis, 1988).

The K1 method is very commonly used and is a default option on several statistical packages (i.e., SPSS*, SAS, BMDP), although Norusis (1988, p. 131) cautions it is not always a good solution. Kaiser (1960) elaborated Guttman's (1954) work that examined the lower bounds for the number of components in image analysis, and developed the K1 method by looking at component reliability, and pattern meaningfulness. Gorsuch (1983) suggests that many users follow Kaiser and use the K1 rule in deciding the exact number of components to extract rather than the minimum number of components to include, as Guttman intended.

Other researchers feel that the K1 rule leads to the retention of too few components (Humphreys, 1964; Mote, 1970). However, Zwick and Velicer (1986) agree with other researchers (Cattel & Jaspers, 1967; Lee & Comrey, 1979) who feel the K1 method is an overestimate of the number of factors. Zwick and Velicer (1986, p. 434) performed a Monte Carlo study (1982) which supported assertions by Gorsuch (1983) and Kaiser (1960) "that the number of components retained by K1 is commonly between one-third and one-fifth or one-sixth the number of variables included in the correlation matrix," and they find this relationship to be problematic. They do not support the K1 test as a primary, exclusive determinant of factor retention decisions.

Researchers new to factor analysis via commercial packages should be cognizant of the fact that the K1 rule is a default that must be consciously adjusted by changing the minimum eigenvalue. The K1 rule was applied to this data set. The first few eigenvalues of the correlation matrix for the attitudinal data set are presented in Table 4. Researchers must use judgment when deciding whether to literally apply Kaiser's rule, i.e., a theoretically meaningful factor may be associated with an eigenvalue of .95, while an ambiguous factor might have an eigenvalue of 1.05.

INSERT TABLE 4 ABOUT HERE

Scree Test

Typically, the scree plot shows a distinct break between the steep slope of the large factors and the gradual trailing off of the rest of the factors. This gradual trailing off is called the scree (Cattell, 1966) because it resembles the rubble (also called "scree") that forms at the foot of a mountain.

Cattell (1966) describes this rule, based on a graph of the eigenvalues, as an easy test: the eigenvalues are plotted, a straight line is fitted through the smaller values, and those falling above the line are retained. The scree plot is an option readily available in commercial statistical packages and is a visually appealing tool in factor selection. Zwick and Velicer (1986) found the scree test accurate, especially with larger samples and strong components. Other researchers (Crawford & Koopman, 1979) note interrater reliability as a controversial issue. Because the final decision of how many components to retain using the scree plot is made visually, different researchers might make different judgments even for the same data. Zwick and Velicer (1986, p. 441) report the scree procedure "to be relatively accurate" but the method is "too variable and too likely to overestimate to use as the sole decision method." They recommend it is a good complementary method to be used with other methods and "useful for initial estimates." The "scree" plot presented in Figure 3 corroborates the K1-based decision to extract four principal components.

INSERT FIGURE 3 ABOUT HERE

Bartlett's Test

Bartlett (1950, 1951) developed a statistical test to analyze the residual correlational matrix after each successive factor is extracted. This test is used to determine when the residual matrix is no longer significantly different from the identity matrix (meaning that all the diagonal terms are 1 and all off-diagonal terms are 0), indicating that factor extraction should be terminated. The test requires that the data be a sample from a multivariate normal population which can be assessed by using the computer program written and described by Thompson (1990).

Zwick and Velicer (1986) note that the Bartlett test appears more accurate with large sample sizes. Gorsuch (1974) proposes that using this method results in the retention of more components at larger sample sizes. Other researchers (Horn & Engstrom, 1979) suggest changing the alpha level at different sample sizes to compensate for this tendency to retain too many components when n is large.

It should be noted that this test is not accessible on SPSS* through principal components analysis. A somewhat similar chi-square statistic is only available through maximum likelihood extraction. For illustrative purposes, a maximum likelihood extraction was performed; the chi-square statistic indicated a four-factor solution (53.1150; 41 df; significance = .0973).

Two points should be made about this Bartlett test. First, this is not to be confused with Bartlett's Test of Sphericity which routinely follows the correlation matrix, or its inverse, in commercial packages. To obtain the chi-square statistic, a maximum likelihood extraction must be specified (in SPSS*). Second, some researchers believe that statistical significance is not a valuable criterion for evaluating the worthiness of a study (Carver, 1978; Rosnow & Rosenthal, 1989; Thompson, 1988). These analysts might agree that Bartlett's Test, which is based on statistical significance, might not be a viable criterion to use for establishing the correct number of factors to include in solution.

Statistical significance is largely an artifact of sample size. With a large sample size all or almost factors will be "significant," even though they may explain trivial amounts of variance and be uninterpretable. Thus, Kaiser (1976) was not happy when one of his doctoral students wanted to retain all but a couple of factors out of some size dozen factors. His student had a sample size of roughly 40,000 cases, so the significance was primarily informing the student that she had a large sample size, which she presumably already knew!

Minimum Average Partial (MAP)

Velicer (1976, p. 434) "suggested a method based on the matrix of partial correlations. The average of the squared partial correlation is calculated after each of the m components has been partialed out. When the minimum average squared partial correlation is reached, no further components are extracted." This occurs when the residual matrix most closely resembles an identity matrix.

Zwick and Velicer (1986) believe that the MAP rule is more accurate in identifying a known number of components than the K1 or the Bartlett test rule. They assert that the MAP method is "generally quite accurate and consistent when the component saturation is high or the component is defined by more than six variables" (p. 441). In their study of these five methods, the MAP was ranked second only to the parallel analysis method.

MAP calculations are performed in the following order:

1. Extract one factor from the original correlation matrix and obtain the reproduced correlation matrix (i.e., the difference between the observed correlation matrix and the residual correlation matrix).

2. Download the residuals to a spreadsheet and set formulas to square each residual. Sum the squared residuals, and divide by the total number of residual correlations. This yields the average partial correlation.

3. Repeat for two factors, then three, and so on to n factors.

4. Select the solution which yields the minimum average partial (MAP).

The average partials for the present data set were:

One Factor Average Partial = .006043
Two Factor Average Partial = .007076
Three Factor Average Partial = .006410
Four Factor Average Partial = .006087
Five Factor Average Partial = .005483

Results were conflicting; average partials were quite small for all solutions, comparable for a one or four factor solution, and minimum for a five factor solution. In the present study, the minimum average partial provided little assistance in the determination of the number of factors-- contrary to Zwick and Velicer's (1982, p. 434) contention "that the MAP rule was more accurate in identifying a known number of components than either the KJ or the Bartlett test rule."

This conflicting result may be explained in one of two ways. First, Zwick and Velicer's 1986 study involved four data sets: 36 variables with n=72, 36 variables with n=180, 72 variables with n=144, and 72 variables with n=360. In other words, their best scenario involved the use of five observations for each variable. Many factor analysts would consider a 5:1 ratio as minimum or inadequate for factor analysis. In the present "company image" study, there were 14 variables (scale items) and 250 observations, for a ratio of almost 18:1 (and the resulting KMO index of .88). Therefore, the ratio of observations to variables may greatly influence the utility of the MAP rule.

Second, the MAP may be least useful when the data set is well suited to factor analysis. Since the calculation is based on the residual, only ill-suited data sets are likely to generate noticeable differences in average partials.

Parallel Analysis (PA)

Some researchers (Horn, 1965) run a parallel factor analysis with identical numbers of variables and cases as the data matrix, using random numbers to represent the population. The factors of the real data matrix that have larger eigenvalues than those of the parallel factors of the random data matrix are considered to be real factors.

Zwick and Velicer (1986) found the PA method the most frequently accurate in their study of these five rules for determining the number of factors to retain in principal component factor analysis. Computer programs needed for its application are not widely available. Other researchers have used parallel analysis and found it did not work well with their data (Daniel, 1990).

To perform a parallel analysis, generate a random data set having the same matrix dimensions and size as the original data set. The random scores should also have the same range or variability as the real data set. Repeat the factor analysis, using the random data set. Compare the eigenvalues generated by the random data set to those of the "real" data set. If the "real eigenvalue" exceeds the "random eigenvalue" the factor should be retained. For the present example, A parallel analysis was performed and the eigenvalues for the real and the random data were:

FACTOR	REAL DATA	RANDOM DATA
ONE	5.08129	1.39185
TWO	1.27341	1.29400
THREE	1.13025	1.26214
FOUR	1.00039	1.17140
FIVE	.87330	1.11164

The parallel analysis suggested that a one-factor solution was appropriate. It should be noted that real data factors do not "behave" like random data factors in attitudinal research. It is not uncommon to find the first factor in an attitudinal study explaining a very large portion of the variance and having a high associated eigenvalue. Random data factors explain an approximately equal percent of variance; hence, no factor dominates the solution. It is possible that random eigenvalues are not as useful with attitudinal data, or data in which the first factor so dominates the factor space.

Additional Indicators

Percentage Of Variance Explained By The Solution. It is important to pay attention to the percentage of variance for individual factors, as well as the total percentage of variance for all extracted factors. Most researchers want a minimum of 50-60 percent total variance in their factor solution. However, this is a very subjective and arbitrary rule, even though frequently used.

Percentage of Variance Explained Before and After Rotation. With respect to the variance explained by individual factors (the eigenvalue divided by the number of factored entities multiplied by 100), it is vitally important to differentiate variance explained by a factor before rotation and variance explained after rotation, as Thompson (1989) emphasizes. Rotation redistributes the variance of the factors. Thus, the eigenvalues before rotation do not have much to do with related indices after rotation. For example, the prerotation eigenvalue for Factor I indicated that the factor was capable of reproducing 36.3% ((5.08129 / 14) x 100) of the variance in the correlation matrix. This does not mean that the first factor rotated after rotation still accounted for 36.3% of the variance among the variables. Yet this interpretation is probably the most common mistake in those published research reports including the presentation of a factor analysis (Thompson, 1990).

Summary

The purposes of this paper were to present and illustrate a variety of statistics and decision-making approaches for determining the number of principal components to extract. However, the final decision on how many factors to retain in exploratory factor analysis should be based on additional, more subjective, considerations, including the interpretability, and parsimony of rotated solutions.

Several conclusions regarding principal components analysis appear warranted. Careful analysis of the statistics that document whether the assumptions of factor analysis have been met is critical. It is important to utilize the results of different decision rules when determining the number of principal components. In the gestalt, what number is consistently indicated across methods? To avoid under or overextraction, run factor analyses with one or two components above and below those suggested with the five methods. Then examine the so'utions for interpretability.

Finally, don't rely on computer programs and preset default outputs as "the last word." Use the computer as an aid in your carefully planned study. Learn the default criteria and the reasons for adjusting defaults. Gorsuch (1974, p. 108) warns that "(w)hen a program does run and gives some output, there is a tendency to automatically assume the answers are correct. Unfortunately, this is often not the case."

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Figure 1

Pre-Employment Testing Scale

PROPOSED CONCEPT	STATEMENT/VARIABLE NAME
PERCEIVED NEED	"I understand the company's need to test applicants" (NEED).
	"I agree with the company's position regarding the testing of applicants" (COPOS).
JUSTICE	"I believe the company has violated my right to privacy by requiring me to take this test" (VIOL)*.
FAIRNESS	"I believe if I take this test the results will be accurate" (ACCUR).
JOB OPPORTUNITIES	"I would only apply for this job if I had no other job opportunities" (NOPRO)*.
	"I don't have to work for a company that requires this type of test" (DONT).
	"I would apply for this job even if there was another job opportunity with similar merits that did not require such a test" (MERITS).
COMPANY IMAGE	"This sounds like a good place to work" (GDPL).
	"I believe that any company that would ask an applicant to take such a test does not trust its employees" (TRUST)*.
	"I believe this company requires such a test in order to maintain a good working enviroment" (ENVIR).
	"I believe this company has experienced problems; therefore, they now require this type of test to select employees" (PROB)*.
APPLICANTS ANXIETY AND CONFIDENCE	"I don't care whether I take the test or not" (CARE).
	"The test doesn't bother me, because I know I could pass it" (NOBOT).
	"I believe this is the rule and there's nothing I can do about it" (RULE).

Note: * Reversed Scale

Figure 2

Example of Survey Employment Scenario

You are interviewing with a large and prestigious organization in the commercial airline industry. The position you are interviewing for has potential for advancement, and meets your expectations regarding salary and fringe benefits. In addition, the location appeals to you. The personnel manager has described the job duties and responsibilities to you, and the hiring process. As a part of the application/hiring process, you will be required to take a drug test.

Table 1

Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) GDPL	---													
(2) NEED	.42	---												
(3) NOPRO	.27	.13	---											
(4) TRUST	.33	.38	.41	---										
(5) COPOS	.41	.74	.22	.47	---									
(6) CARE	.25	.22	.13	.19	.21	---								
(7) ENVIR	.31	.57	.17	.35	.67	.14	---							
(8) DONT	.22	.22	.19	.27	.29	.03	.30	---						
(9) NOBOT	.34	.41	.26	.40	.53	.21	.50	.17	---					
(10) VIOL	.28	.46	.26	.45	.61	.15	.51	.41	.38	---				
(11) RULE	.14	.25	.04	.15	.23	.21	.26	.19	.10	.09	---			
(12) PROB	-.07	-.18	-.03	-.12	-.18	-.16	-.22	.05	-.17	-.01	-.14	---		
(13) MERITS	.39	.38	.24	.29	.48	.24	.47	.31	.41	.37	.16	-.14	---	
(14) ACCUR	.36	.47	.13	.29	.53	.16	.49	.25	.44	.43	.24	-.13	.46	---

Table 2

Anti-Image Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) GDPL	.91													
(2) NEED	-.18	.88												
(3) NOPRO	-.13	.08	.81											
(4) TRUST	-.08	-.05	-.29	.90										
(5) COPOS	-.03	-.49	.00	-.12	.87									
(6) CARE	-.13	-.06	-.01	-.05	.01	.81								
(7) ENVIR	.03	-.11	.06	.03	-.25	.10	.91							
(8) DONT	-.06	.02	-.05	-.07	.06	.09	-.08	.83						
(9) NOBOT	-.06	.03	-.10	-.14	-.17	-.08	-.20	.06	.92					
(10) VIOL	.06	.01	.08	-.16	-.29	-.06	-.14	-.26	.02	.87				
(11) RULE	.01	-.06	.02	-.05	-.04	-.17	-.13	-.16	.10	.15	.77			
(12) PROB	-.05	.05	-.01	.06	.02	.10	.13	-.10	.05	-.13	.06	.78		
(13) MERITS	-.15	.04	-.09	.05	-.11	-.13	-.15	-.16	-.09	.02	.03	.04	.91	
(14) ACCUR	-.11	-.08	.06	.03	-.07	.04	-.07	-.00	-.16	-.14	-.12	.01	-.18	.93

Table 3

Final Communality Estimates (Four Principal Components Extracted)

Variable	Communality
GDPL	.42
NEED	.63
NOPRO	.70
TRUST	.56
COPOS	.78
CARE	.60
ENVIR	.69
DONT	.65
NOBOT	.56
VIOL	.63
RULE	.76
PROB	.54
MERITS	.44
ACCUR	.52

Table 4

Eigenvalues In a Four-Factor Principal Components Solution

Factor	Eigenvalue	Cumulative % of Variance
1	5.08129	36.3
2	1.27341	45.4
3	1.13025	53.5
4	1.00039	60.6
5	.87330	66.8
6	.77145	72.4
7	.71251	77.4

Figure 3

"Scree" Plot of Eigenvalues

```
          +
          +
   5.081  +  *
          +
          +
          +
E         +
I         +
G         +
E         +
N         +
V         +
A         +
L         +
U         +
E         +
S         +
          +
          +
   1.273  +     *
   1.130  +        *
   1.000  +           *
    .771  +              *  *
    .657  +                    *  *
    .402  +                          *   *   *   *
    .211  +                                          *   *
    .000  +--+--+--+--+--+--+--+--+--+---+---+---+---+---+
             1  2  3  4  5  6  7  8  9  10  11  12  13  14
```