Paper 274-28

Reliability, Exploratory & Confirmatory Factor Analysis
for the Scale of Athletic Priorities
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Abstract
The process of evaluating a measurement instrument for reliability and investigating the factor structure will be discussed using the Scale of Athletic Priorities (SAP) as an example. SAS® procedures served to provide an indication of the internal consistency (reliability with PROC CORR),to verify the factor structure (confirmatory factor analysis with PROC CALIS), and to explore the factor structure (with PROC FACTOR) of the measurement instrument.

Introduction
The Scale of Athletic Priorities (SAP) was developed to measure administrators' priorities related to inter-collegiate athletics. Division 1 university administrators completed the SAP in 1999 as part of a research study (Garrity, 2000). The sample included 69 women and 135 men with 50 university presidents, 55 athletic directors, 50 senior women administrators, and 49 faculty athletic representatives (n = 204). See Appendix A to review the SAP.

Respondents were instructed to rate each item of the 36-item scale on a 7-point Likert scale of 1=not important to 7=very important. The scale's introductory statement served to elicit the relative importance of administrators' goals for intercollegiate athletic teams.

Reliability
Reliability refers to the accuracy and precision of a measurement procedure (Thorndike, Cunningham, Thorndike, & Hagen, 1991). Reliability may be viewed as an instrument's relative lack of error. In addition, reliability is a function of properties of the underlying construct being measured, the test itself, the groups being assessed, the testing environment, and the purpose of assessment. Reliability answers the question, How well does the instrument measure what it purports to measure?

Some degree of inconsistency is present in all measurement procedures. The variability in a set of item scores is due to the actual variation across individuals in the phenomenon that the scale measures, made up of true score and error. Therefore, each observation of a measurement (X) is equal to true score (T) plus measurement error (e), or X = T + e. Another way to think about total variation is that it has two components: "signal" (i.e., true differences in the latent construct) and "noise" (i.e., differences caused by everything but true differences).

Sources of measurement inconsistency could be due to
1) a person changing from one testing to the next
   a. the amount of time between tests may have resulted in growth or change
   b. motivation to perform may be different at each testing
   c. the individual may be physically better able to perform, e.g., more rested
   d. the individual may have received tutoring between testings
2) the task being different from one testing to the next
   a. different environment
   b. different administrator
   c. different test items on parallel forms
3) the sample of behavior resulting in an unstable or undependable score
   a. the sample of behavior and evaluation of it are subject to chance or random influences
   b. a small sample of behavior does not provide a stable and dependable characterization of an individual

   c. for example, the average distance of 100 throws of a football would provide a more stable and accurate index of ability than a single throw.

Reliability may be expressed
1) as an individual's position in a group (correlation between first and second measurements; the more nearly individuals are ranked in the same order, the higher the correlation and the more reliable the test)
2) within a set of repeated measures for an individual (internal consistency, how consistency are items answered)

Reliability can be assessed by
1) repeating the same test or measure (test-retest)
2) administering an equivalent form (parallel test forms)
3) using single-administration methods
   a. subdividing the test into two or more equivalent parts
   b. internal consistency – measured with Cronbach's coefficient alpha.

Internal Consistency
Internal consistency is a procedure to estimate the reliability of a test from a single administration of a single form. Internal consistency depends on the individual's performance from item to item based on the standard deviation of the test and the standard deviations of the items.

$$\alpha = \frac{(n)}{(n-1)}\left(\frac{SD_t^2 - \Sigma SD_i^2}{SD_t^2}\right) \qquad (1)$$

where α is the estimate of reliability,
n is the number of items in the test,
SD_t is the standard deviation of the test scores
Σ means "take the sum" and covers the n items,
SD_i is the standard deviation of the scores from a group of individuals on an item.

KR20, Kuder-Richardson Formula 20, is a special form of coefficient alpha that applies when items are dichotomous (e.g., yes/no, true/false) or are scored as right or wrong.

Factors Influencing Reliability
Many factors can affect the reliability of a measurement instrument. They are the
   1) range of the group
      a. pooling a wider range of grades or ages produces a reliability coefficient of higher magnitude
      b. take into account the sample on which the reliability coefficient is based when comparing instruments
   2) level of ability in the group
      a. precision of measurement can be related to ability level of the people being measured
      b. report the standard error of measurement for different score levels
   3) methods used for estimating reliability
      a. amount of time between administrations
      b. method of calculating reliability
   4) length of the test
      a. when reliability is moderately high, it takes a considerable increase in test length to increase reliability

b. relationship of reliability to length of test can be expressed with

$$r_{kk} = \frac{kr_{tt}}{1 + (k-1)\, r_{tt}} \qquad\qquad (2)$$

where r_{kk} is the reliability of the test k times as long as the original test,
r_{tt} is the reliability of the original test, and
k is the factor by which the length of the test is changed.

For example, If reliability is .60 for a 10-item instrument, what is reliability for a 20-item instrument?
$r_{kk} = 2(.60) / (1 + (2 - 1)(.60)) = 1.20 / 1.60 = 0.75$

Levels of Reliability
Acceptable levels of reliability depend on the purpose of the instrument. Acceptable reliability of instruments developed for research purposes can be as low as 0.60. An acceptable reliability level of a diagnostic instrument used for making decisions about individuals (e.g., a psychological measure) should be much higher, e.g., 0.95.

Comparisions
The reliability coefficient provides a basis for assessment instrument comparison when measurement is expressed in different scales. The assessment with the higher reliability coefficient could provide a more consistent measurement of individuals.

Statistical Power
An often overlooked benefit of more reliable scales is that they increase statistical power for a given sample size (or allow smaller sample size to yield equivalent power), relative to less reliable measures. A reliable measure, like a larger sample, contributes relatively less error to the statistical analysis. The power gained from improving reliability depends on a number of factors including
1) the initial sample size
2) the probability level set for detecting a Type I error
3) the effect size (e.g., mean difference) that is considered significant
4) the proportion of error variance that is attributable to measure unreliability rather than sample heterogeneity or other sources.

To raise the power, substitute a highly reliable scale for a substantially poorer one. For example, when n = 50, two scales with reliabilities of 0.38 have a correlation of 0.24, p < 0.10, and would be significant at p < 0.01 if their reliabilities were increased to 0.90 or if the sample was more than twice as large (n > 100).

Confirmatory Factor Analysis
CFA allows the researcher to test the hypothesis that a relationship between the observed variables and their underlying latent construct(s) exists. The researcher uses knowledge of the theory, empirical research, or both, postulates the relationship pattern a priori and then tests the hypothesis statistically.

Exploratory Factor Analysis
Psychologists searching for a neat and tidy description of human intellectual abilities lead to the development of factor analytic methods. Galton, a scientist during the 19th and 20th centuries, laid the foundations for factor analytic methods by developing quantitative methods to determine the interdependence between 2 variables. Karl Pearson was the first to explicitly define factor analysis. In 1902, Macdonnell was the first to publish an application of factor analysis. His study compared physical characteristics of 3000 criminals and 1000 Cambridge undergraduates.

Factor analysis could be described as orderly simplification of interrelated measures. Traditionally factor analysis has been used to explore the possible underlying structure of a set of interrelated variables without imposing any preconceived structure on the outcome (Child, 1990). By performing exploratory factor analysis (EFA), the number of constructs and the underlying factor structure are identified.

Goals of factor analysis are
1) to help an investigator determine the number of latent constructs underlying a set of items (variables)
2) to provide a means of explaining variation among variables (items) using few newly created variables (factors), e.g., condensing information
3) to define the content or meaning of factors, e.g., latent constructs

Assumptions underlying EFA are
- Interval or ratio level of measurement
- Random sampling
- Relationship between observed variables is linear
- A normal distribution (each observed variable)
- A bivariate normal distribution (each pair of observed variables)
- Multivariate normality

Limitations of EFA are
- the correlations, the basis of factor analysis, describe relationships. No causal inferences can be made from correlations alone.
- the reliabilty of measurement instrument (avoid instrument with low reliability)
- sample size (larger sample → larger correlation)
  - minimal number for reliable results is greater than 100 and 5 times the number of items
  - since some subjects may not answer every item, a larger sample is desirable, e.g., for 30 items, at least 150 subjects (5*30), a sample of 200 subjects would allow for missing data.
- sample selection
  - Representative of population
  - Do not pool populations
- variables could be sample specific, e.g., a unique quality possessed by a group does not generalize to the population
- nonnormal distribution of data

Factor Extraction
Factor analysis seeks to discover common factors. The technique for extracting factors attempts to take out as much common variance as possible in the first factor. Subsequent factors are, in turn, intended to account for the maximum amount of the remaining common variance until, hopefully, no common variance remains.

Direct extraction methods obtain the factor matrix directly from the correlation matrix by application of specified mathematical models. Most factor analysts agree that direct solutions are not sufficient. Adjustment to the frames of reference by rotation methods improves the interpretation of factor loadings by reducing some of the ambiguities which accompany the preliminary analysis (Child, 1990). The process of manipulating the reference axes is known as rotation. The results of rotation methods are sometimes referred to as derived solution because they are obtained as a second stage from the results of direct solutions.

Rotation applied to the reference axes means the axes are turned about the origin until some alternative position has been reached. The simplest case is when the axes are held at 90° to each other, orthogonal rotation. Rotating the axes through different angles gives an oblique rotation (not at 90° to each other).

Criteria for Extracting Factors

Determining the number of factors to extract in a factor analytic procedure is dependent on meeting appropriate criteria. They are

1) Kaiser's criterion, suggested by Guttman and adapted by Kaiser, considers factors with an eigenvalue greater than one as common factors (Nunnally, 1978)

2) Cattell's (1966) scree test. The name is based on an analogy between the debris, called scree, that collects at the bottom of a hill after a landslide, and the relatively meaningless factors that result from overextraction. On a scree plot, because each factor explains less variance than the preceding factors, an imaginary line connecting the markers for successive factors generally runs from top left of the graph to the bottom right. If there is a point below which factors explain relatively little variance and above which they explain substantially more, this usually appears as an "elbow" in the plot. This plot bears some physical resemblance to the profile of a hillside. The portion beyond the elbow corresponds to the rubble, or scree, that gathers. Cattell's guidelines call for retaining factors above the elbow and rejecting those below it. This amounts to keeping the factors that contribute most to the variance

3) Proportion of variance accounted for keeps a factor if it accounts for a predetermined amount of the variance (e.g., 5%, 10%).

4) Interpretability criteria
   a. Are there at least 3 items with significant loadings (>0.30)?
   b. Do the variables that load on a factor share some conceptual meaning?
   c. Do the variables that load on different factors seem to measure different constructs?
   d. Does the rotated factor pattern demonstrate simple structure? Are there relatively
      i. high loadings on one factor?
      ii. low loadings on other factors?

Methods

As an aside, names given to factor extraction methods have some interesting origins.

- Procrustes was a highwayman who tied his victims to a bed and shaped them to its structure either by stretching them or by cutting off their limbs. In factor analysis, the Procrustes technique/method involves testing data to see how close they fit a hypothesized factor structure.

- The plasmode method is taken from well-established areas (e.g., physics, chemistry) so that the factor structure is predictable.

Statistical Analysis

With background knowledge of reliability, exploratory and confirmatory factor analysis, we're ready to proceed to the statistical analysis!

Reliability (9-factors)

Cronbach alpha for the 1999 study was calculated with PROC CORR using the factor structure suggested by Chelladurai, Inglis, & Danylchuck (1984). Reliabliity of the 9 factor structure in a previous study (n=141) ranged from 0.66 to 0.89 with a mean of 0.78 (Chelladurai, et al., 1984). Reliability in the 1999 study ranged from 0.70 to 0.90 with a mean of 0.81. Table 1 lists the 9 factors, items included in each factor, and factor alphas for the study sample (n=204).

The SAS code below calculates alpha for the "Entertainment" factor. NOCORR and NOSIMPLE options request no correlations and descriptive statistics be printed.

```
proc corr data=rawsub nocorr nosimple alpha;
var q10 q15 q17 q32;
```

Table 1. Scale of Athletic Priorities* Factor Structure and Reliability

Factor	Items	Alpha
Entertainment	10, 15, 17, 32	0.778
National Sport Development	9, 23, 25, 35	0.781
Financial	4, 19, 24, 34	0.837
Transmission of Culture	2, 5, 14, 18	0.704
Career Opportunities	6, 8, 11, 36	0.904
Public Relations	3, 12, 28, 29	0.827
Athlete's Personal Growth	1, 22, 31, 33	0.833
Prestige	7, 13, 20, 21	0.784
Achieved Excellence	16, 26, 27, 30	0.821
Total Scale	Items 1-36	0.925

(Chelladurai, et al., 1984)

Table 2 illustrates output from SAS's PROC CORR procedure (standardized variables not shown). Alpha for the "Entertainment" factor is 0.778. The results indicate that if Q32 were deleted, the alpha would increase to 0.826 for the remaining 3 items.

Table 2. SAP Entertainment Factor Reliability

```
The CORR Procedure
4 variables            Q10 Q15 Q17 Q32

Cronbach Coefficient Alpha

Variables              Alpha
Raw                    0.778372
Standardized           0.793011

                                    Raw Variables
Deleted                Correlation
Variable               With Total          Alpha
Q10                    0.637308            0.697541
Q15                    0.660060            0.689045
Q17                    0.663980            0.686724
Q32                    0.424596            0.826108
```

Confirmatory Factor Analysis (9 factor)

Factor scores (s1-s9) were created with the MEAN function, e.g., s1=mean(Q10, Q15, Q17, Q32). The factors were subjected to a confirmatory factor analysis (CFA) with PROC CALIS. Figure 1 illustrates the CFA model. The SAS code below tests the underlying factor structure.

```
proc calis data=rawsub cov stderr all kurtosis
modifications residual;
 lineqs
  S1 = ps1f1 F1 + e1,
  S2 = ps2f1 F1 + e2,
  S3 = ps3f1 F1 + e3,
  S4 = ps4f1 F1 + e4,
  S5 = ps5f1 F1 + e5,
  S6 = ps6f1 F1 + e6,
  S7 = ps7f1 F1 + e7,
  S8 = ps8f1 F1 + e8,
  S9 = ps9f1 F1 + e9;
 std
  e1-e9 = vare1-vare9,  F1 = 1;
 var s1-s9;
```

Results from the CFA analysis indicted lack-of-fit of the hypothesized model (chi-square = 427.051, df = 27, p < 0.0001, RMSEA = 0.266, CFI = 0.6018, NNFI = 0.469). Good fit is indicated by a chi-square close to zero, an RMSEA < 0.06, CFI and NNFI > 0.90 (Hu & Bentler, 1999).
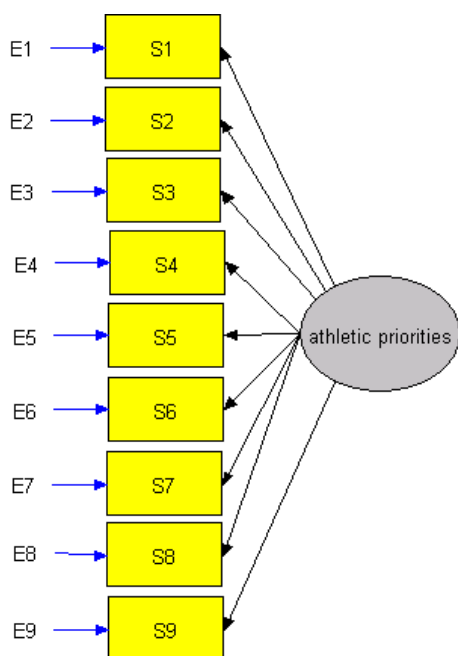

Figure 1. Confirmatory Factor Analysis

Another step that could be taken in the confirmatory approach is to test the structure for each of the 9 factors. The following SAS code would test a model for the Entertainment factor.

```
proc calis data=rawsub cov stderr all kurtosis
                        modifications residual;
lineqs
 q10 = ps10f1 F1 + e10,
 q15 = ps15f1 F1 + e15,
 q17 = ps17f1 F1 + e17,
 q32 = ps32f1 F1 + e32;
std
 e10 = vare10,
 e15 = vare15,
 e17 = vare15,
 e32 = vare32,
 F1 = 1;
var q10 q15 q17 q32;
```

If each factor can be confirmed, then a combined model is evaluated. If this model is confirmed, then a model including one latent construct (athletic priorities) with a direct relationship to each factor (e.g., entertainment, national sport development) is evaluated. Each factor influence responses to items. For example, the latent construct entertainment influences responses to items 10, 15, 17, and 32. The latent construct, athletic priorities, indirectly influences items 10, 15, 17, and 32.

Exploratory Factor Analysis
The next step in the analysis is to perform exploratory factor analysis (EFA) because the original factor structure could not be confirmed. The SAS code below provided a method of factor extraction.

```
proc factor data=rawsub reorder scree
        method=principal rotate=varimax;
var q1-q36;
```

According to Kaiser's rule, 7 factors were extracted. The the scree test (Cantell, 1966), indicates extracting 5 factors. Examining the eigenvalues and proportion of variance explained by each factor, indicates 3 or 4 factors be extracted. The next steps are to run PROC FACTOR for 3-7 factors, examine the results, and determine the number of factors. The following SAS code extracts 3 factors. Notice the scree option is removed and the n=3 is included to extract 3 factors. Table 3 shows 3 through 6 factor solutions and reliabilities. The 7-factor model was rejected because two factors had fewer than 3 items.

```
proc factor data=rawsub reorder n=3
        method=principal rotate=varimax;
var q1-q36;
```

Three-Factor Solution
After examining the alphas and the items grouped in each factor, a 3-factor solution was selected. Table 4 illustrates the rotated factor pattern. Items are placed in factors according to their factor loadings.

Using the REORDER option in PROC FACTOR sorts the loadings from largest to smallest values for each factor. Some items are considered as loading on more than one factor if their factor loadings are greater than or equal to 0.30. Item 26 is a potential problem because its factor loadings are 0.479 on factor 1 and 0.569 on factor3. Item 26 contributes a relatively large amount of variance to both factors 1 and 3.

Confirmatory Factor Analysis (3 factor)
CFA for the 3-factor structure was run with PROC CALIS using the following SAS code. Figure 2 illustrates the hypothesized model.

```
proc calis data=rawsub cov stderr all kurtosis
                        modifications residual;
lineqs
 n1 = ps1f1 F1 + e1,
 n2 = ps2f1 F1 + e2,
 n3 = ps3f1 F1 + e3;
std
 E1-e3 = vare1-vare3,
 F1 = 1;
var n1-n3;
```

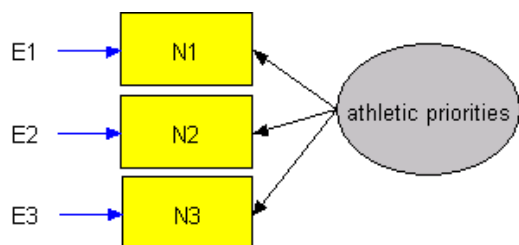Results indicated good model fit (chi-square = 0.000, df = 0, p < 0.0001, RMSEA = 0.000, CFI = 1.000, NNFI = 1.000).

Figure 2. Three-Factor Confirmatory Model

Table 3. Exploratory Factor Analysis

Factor	# Items	Items*	Alpha
3-factor solution			
#1	17	29, 20, 21, 28, 10, 13, 19, 15, 17, 3, 12, 4, 34, 24, 2, 7, 5	0.908
#2	9	33, 8, 22, 6, 11, 31, 36, 1, 32	0.923
#3	10	25, 35, 23, 9, 30, 27, 14, 18, 26, 16	0.882
4-factor solution			
#1	15	20, 29, 21, 13, 10, 28, 19, 15, 12, 17, 34, 4, 3, 24, 7	0.916
#2	10	33, 8, 22, 6, 11, 31, 36, 1, 32, 16	0.919
#3	9	25, 35, 23, 9, 30, 14, 27, 18, 26	0.878
#4	2	5, 2	0.774
5-factor solution			
#1	11	29, 28 13, 10, 12, 20, 21, 15, 3, 17, 19	0.922
#2	9	33, 8, 6, 11, 22, 36, 31, 1, 32	0.923
#3	10	25, 14, 35, 23, 18, 30, 9, 27, 26, 16	0.882
#4	4	24, 4, 34, 7	0.722
#5	2	2, 5	0.774
6-factor solution			
#1	10	29, 28, 10, 13, 12, 15, 17, 3, 20, 19	0.912
#2	9	33, 8, 11, 6, 22, 31, 36, 1, 32	0.923
#3	10	25, 14, 23, 18, 35, 30, 9, 27, 26, 16	0.882
#4	4	24, 4, 34	0.722
#5	2	2, 5	0.774
#6	2	7, 21	0.503

*items listed from largest to smallest values of factor loadings

Table 4. Rotated Factor Pattern for 3 factors

Item	Factor1	Factor2	Factor3
29	**0.810**	0.199	-0.019
20	**0.808**	0.036	0.151
21	**0.778**	0.066	0.120
28	**0.750**	0.233	0.049
10	**0.748**	-0.010	0.219
13	**0.740**	0.155	0.181
19	**0.721**	-0.124	0.276
15	**0.684**	0.166	0.244
17	**0.682**	0.000	*0.334*
3	**0.639**	*0.331*	-0.169
12	**0.634**	0.247	0.001
4	**0.627**	-0.212	0.271
34	**0.582**	0.021	*0.347*
24	**0.545**	-0.159	*0.371*
2	**0.343**	-0.044	0.207
7	**0.320**	0.101	0.221
5	**0.292**	0.109	0.021
33	0.060	**0.873**	0.095
8	0.069	**0.868**	-0.016
22	0.060	**0.849**	0.130
6	0.186	**0.837**	0.097
11	0.110	**0.829**	0.135
31	0.103	**0.739**	0.160
36	0.132	**0.715**	0.233
1	0.028	**0.661**	-0.196
32	0.293	**0.550**	0.281
25	0.091	-0.006	**0.748**
35	0.010	0.273	**0.747**
23	0.003	0.244	**0.682**
9	0.243	0.087	**0.680**
30	*0.404*	-0.056	**0.644**
27	*0.473*	-0.002	**0.638**
14	0.090	0.167	**0.621**
18	0.275	0.008	**0.593**
26	*0.479*	0.135	**0.569**
16	*0.347*	*0.372*	**0.379**

Note: values in bold indicate item loads on factor. Values in bold and italics indicate factor could load on more than one factor (loading >0.30 critera).

Confirmatory Factor Analysis (item level)

Results of CFA could be investigated at the item level using the SAS code below for factor 1.

```
proc calis data=rawsub COV stderr all
              kurtosis modification residual;
 lineqs
   q2  = pn2f1 F1 + e2,
   q3  = pn3f1 F1 + e3,
   q4  = pn4f1 F1 + e4,
   q5  = pn5f1 F1 + e5,
   q7  = pn7f1 F1 + e7,
   q10 = pn10f1 F1 + e10,
   q12 = pn12f1 F1 + e12,
   q13 = pn13f1 F1 + e13,
   q15 = pn15f1 F1 + e15,
   q17 = pn17f1 F1 + e17,
   q19 = pn19f1 F1 + e19,
   q20 = pn20f1 F1 + e20,
   q21 = pn21f1 F1 + e21,
   q24 = pn24f1 F1 + e24,
   q28 = pn28f1 F1 + e28,
   q29 = pn29f1 F1 + e29,
   q34 = pn34f1 F1 + e34;
 std
   e2 = vare2,   e3 = vare3,
   e4 = vare4,   e5 = vare5,
   e7 = vare7,   e10 = vare10,
   e12 = vare12, e13 = vare13,
   e15 = vare15, e17 = vare17,
   e19 = vare19, e20 = vare20,
   e21 = vare21, e24 = vare24,
   e28 = vare28, e29 = vare29,
   e34 = vare34,
   F1 = 1;
 var q2 q3 q4 q5 q7 q10 q12 q13 q15
       q17 q19 q20 q21 q24 q28 q29 q34;
```

Conclusion

Development of a measurement instrument is a complex process. Reliability assesses the accuracy and precision of the instrument. How well does the instrument measure what it purports to measure? Confirmatory factor analysis tests a hypothesized factor structure. Do relationships specified a priori exist between observed variables and their underlying latent construct(s)? Exploratory factor analysis identifies the possible underlying structure of a set of variables without imposing a preconceived structure on the outcome. Can the constructs and underlying factor structure of the measurement instrument be identified? You have the power to answer these questions with SAS® procedures (PROC CORR, PROC CALIS, PROC FACTOR). These procedures provide statistical analyses for the development and analysis of measurement instruments.

References

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research*, 1, 245-276.

Chelladurai, P., Inglis, S. E., & Danylchuck, K. E. (1984). Priorities in intercollegiate athletics: Development of a scale. *Research Quarterly for Exercise and Sport*, 55(1), 74-79.

Child, D. (1990). The essentials of factor analysis, second edition. London: Cassel Educational Limited.

DeVellis, R. F. (1991). Scale Development: Theory and Applications. Newbury Park, California: Sage Publications.

Garrity, K. S. (2000). A determination of the importance of the operative objectives of NCAA Division I-AAA intercollegiate athletics. Published Doctor of Education dissertation. University of Northern Colorado.

Hatcher, L. (1994). A step-by-step approach to using the SAS® System for factor analysis and structural equation modeling. Cary, NC: SAS Institute Inc.

Hu, L. & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6(1), 1-55.

Joreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis, *Psychometrika,* 34, 183-202.

Nunnally, J. C. (1978). Psychometric theory, 2nd edition. New York: McGraw-Hill.

SAS® Language and Procedures, Version 6, First Edition. Cary, N.C.: SAS Institute, 1989.

SAS® Procedures, Version 6, Third Edition. Cary, N.C.: SAS Institute, 1990.

SAS/STAT® User's Guide, Version 6, Fourth Edition, Volume 1. Cary, N.C.: SAS Institute, 1990.

SAS/STAT® User's Guide, Version 6, Fourth Edition, Volume 2. Cary, N.C.: SAS Institute, 1990.

Thorndike, R. M., Cunningham, G. K., Thorndike, R. L., & Hagen E. P. (1991). Measurement and evaluation in psychology and education. New York: Macmillan Publishing Company.

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Appendix A

Scale of Athletic Priorities

This questionnaire contains a list of 36 statements. Please read each statement carefully and **indicate the degree of importance** you would place on each statement for decisions regarding financial support for various sport teams. Rank each criterion by circling a number ranging from not important (1) to very important (7). Please assume that adequate coaching and athletic facilities are available for all sports. There are no right or wrong answers. Each person answers in his or her own way. Please be sure to answer all items.

A criterion to be considered in determining the degree of financial support for an intercollegiate athletic sport is that …

		not important					very important
1.	the student athletes enjoy the competitive experience.	1	2	3	4	5	6	7
2.	the sport has a long tradition at the college	1	2	3	4	5	6	7
3.	the sport fosters school spirit and is a unifying force.	1	2	3	4	5	6	7
4.	the port earns money through corporate advertising.	1	2	3	4	5	6	7
5.	the sport has an established tradition within the college.	1	2	3	4	5	6	7
6.	participation in the sport develops leadership qualities required in many jobs.	1	2	3	4	5	6	7
7.	the sport increases student enrollment at the college.	1	2	3	4	5	6	7
8.	participation in the sport develops skills required in many jobs.	1	2	3	4	5	6	7
9.	there are collegiate national champions in the sport.	1	2	3	4	5	6	7
10.	the sport attracts spectators from outside the college community.	1	2	3	4	5	6	7
11.	participation in the sport promotes the student-athlete's lifelong respect for authority and responsibility.	1	2	3	4	5	6	7
12.	the sport encourages alumni involvement in college affairs.	1	2	3	4	5	6	7
13.	the sport brings attention to the college.	1	2	3	4	5	6	7
14.	the sport is felt to be part of the national culture.	1	2	3	4	5	6	7
15.	the sport attracts spectators from on campus.	1	2	3	4	5	6	7
16.	the student-athletes exhibit a high level of excellence.	1	2	3	4	5	6	7
17.	the sport has spectator interest and appeal.	1	2	3	4	5	6	7
18.	the sport is popular in our American society.	1	2	3	4	5	6	7
19.	the sport promotes alumni and community donations to the college.	1	2	3	4	5	6	7
20.	the sport enhances the prestige of the college.	1	2	3	4	5	6	7
21.	the sport contributes to the status of the college.	1	2	3	4	5	6	7
22.	the sport develops the spirit of health competition.	1	2	3	4	5	6	7
23.	international competitions are available in the sport.	1	2	3	4	5	6	7
24.	the sport generates revenue.	1	2	3	4	5	6	7
25.	the student-athletes are often selected to represent the U.S. in international competition.	1	2	3	4	5	6	7
26.	the team has a favorable won-loss record in recent years.	1	2	3	4	5	6	7
27.	the student-athletes perform at or near all-conference or All-American standards.	1	2	3	4	5	6	7
28.	the sport enhances the quality of college-community relations.	1	2	3	4	5	6	7
29.	the sport produces a rallying point for the students, alumni, faculty, staff, and community.	1	2	3	4	5	6	7
30.	the team (or individual student-athletes) is (are) ranked high nationally.	1	2	3	4	5	6	7
31.	the sport promotes fitness.	1	2	3	4	5	6	7
32.	the action in the sport is stimulating and exciting to watch.	1	2	3	4	5	6	7
33.	the sport enhances the psychological well-being of the student-athlete.	1	2	3	4	5	6	7
34.	the support encourages businesses to make financial contributions to the college.	1	2	3	4	5	6	7
35.	support of the sport will contribute to the national sport development.	1	2	3	4	5	6	7
36.	participation in the sport enhances the student-athlete's career.	1	2	3	4	5	6	7