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AUTHOR	Deeter, Thomas E.; Gill, Diane L.
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ABSTRACT

A two-step procedure is described and used to revise a multidimensional inventory in its developmental stages. First, the latent factors influencing the observed variables on the inventory are determined and justified using the following five methods: Kaiser's criterion, root staring, examination of difference values, examination of root mean square off-diagonal residuals and alpha coefficients. The second step, determining the factor pattern, consists of examining selected factor solutions for stability and simplicity of variables. Each of these methods is considered separately, and it is suggested that the conglomerate of methods be used in the initial stages of questionnaire development, with the final decision based on theoretical significance and parsimony. These procedures are illustrated with data from the initial form of the Competitiveness Inventory, a self-report, sport-specific achievement orientation inventory. The inventory was administered to physical education skills classes at the University of Iowa during spring semester 1984 (n=237), and again during spring semester, 1985 (n=218). Independent exploratory factor analyses were performed on each sample with the use of Statistical Analysis Systems (SAS) and Statistical Packages for the Social Sciences-X (SPSS-X). Results revealed a stable three-factor pattern across samples, and suggested that 25 of the original 32 items be retained for the revised version of the Competitiveness Inventory. (Author)

Determining Factor Structure in a Multidimensional inventory

Thomas E. Deeter and Diane L. Gill

The University of Iowa

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Abstract

A two-step procedure is described and used to revise a multidimensional inventory in its developmental stages. First, the latent factors influencing the observed variables on the inventory are determined and justified using the following five methods: Kaiser's criterion, root staring, examination of difference values, examination of root mean square off-diagonal residuals and alpha coefficients. The second step, determining the factor pattern, consists of examining selected factor solutions for stability and simplicity of variables. Each of these methods is considered separately, and it is suggested that the conglomerate of methods be used in the initial stages of questionnaire development, with the final decision based on theoretical significance and parsimony. These procedures are illustrated with data from the initial form of the Competitiveness Inventory, a self-report, sport-specific achievement orientation inventory. The inventory was administered to physical education skills classes at the University of Iowa during Spring semester 1984 (n = 237), and again during Spring semester, 1985 (n = 218). Independent exploratory factor analyses were performed on each sample with the use of SAS and SPSS-X. Results revealed a stable three-factor pattern across samples, and suggested that 25 of the original 32 items be retained for the revised version of the Competitiveness Inventory.

This presentation and the accompanying paper (Gill & Deeter, 1986) provide the first report of a long-term project on achievement orientation in sport, and specifically on the development of a multidimensional, sport-specific Competitiveness Inventory.

Recently, sport psychologists have increasingly advocated the use of sport-specific measures in both research and applied work. Martens' (1977) development and validation of the Sport Competition Anxiety Test (SCAT) demonstrated that a sport-specific measure predicted anxiety in competitive sport situations better than more general trait anxiety measures did. Currently, the SCAT measure is popular in both research and practice, and other sport psychologists have developed sport-specific measures that may well be equally valuable in such diverse areas as group cohesiveness (Carron, Widmeyer, & Brawley, 1985), confidence (Vealey, 1985), and intrinsic/extrinsic motivation (Weiss, Bredemeier and Shewchuk, 1985).

Typically, one of the earliest steps in the development of a sport-specific psychological measure involves determining the factor structure, either to identify underlying dimensions of a construct or to ensure that the questionnaire assesses a unidimensional construct. An investigator may use a number of methods to identify the underlying factor structure of a multidimensional measure and no single method is flawless. Even though the use of several methods may yield discrepancies, such a combination should permit a closer approximation of the number of significant factors than the use of any single method.

The development of a multidimensional instrument is a two step process. First, the number of factors assessed by the instrument must be determined and justified. Second, the factor pattern must be identified to modify the inventory for further validation and use.

These procedures are illustrated in this study with independent exploratory factor analyses performed on data gathered with an initial form of the Competitiveness Inventory (Gill, 1985), a self-report, sport-specific achievement orientation inventory. Development of the inventory stemmed from the earlier multidimensional assessment of general achievement motives by Spence and Helmreich (1978), and the demonstrated value of sport-specific constructs such as Martens' (1977) SCAT. Thus, the Competitiveness Inventory was designed as a sport-specific, multi-dimensional measure of achievement orientation.

Method

Subjects and Design

Two separate samples of male and female undergraduates enrolled in various physical education skills classes during Spring 1984 (n = 237) and Spring 1985 (n = 218) completed the inventory on the first day of their classes. Separate analyses were performed for each sample.

Questionnaire

The original form of the Competitiveness Inventory, described in more detail elsewhere (Gill, 1985), consists of 32 items rated on a 5-point Likert scale (strongly agree, slightly agree, neither agree nor disagree, slightly disagree, strongly disagree).

Factor Analysis Procedures

The data from both samples were analyzed with two computer packages, Statistical Packages for the Social Sciences - X (SPSS-X) (SPSS Inc., 1983) and Statistical Analysis Systems (SAS) (SAS Institute, Inc., 1982). An initial principal components analysis yielded six eigenvalues greater than 1.0 (Kaiser, 1960), which, according to Guttman (1958), is a strong lower bound estimate of the number of factors. Therefore, a maximum of six factors were subsequently extracted.

Several methods were used to extract two, three, four, five and six factors. Principal components analysis, unweighted least squares, maximum likelihood estimation, and alpha estimation were performed using the SPSS-X package, whereas principal factors, iterated principal factors, unweighted least squares, maximum likelihood estimation, and alpha estimation were

performed with the SAS package. Squared multiple correlations (SMCs) provided prior communality estimates for all SAS extractions. SMCs are lower-bound estimations (underestimates) of true communalities of a given variable (Dwyer, 1939), which have been recommended (Guttman, 1956) as the "best possible" estimate of communality. All factor solutions were subjected to both varimax rotation and oblique transformation to determine final solutions.

Results

Determining the Number of Factors

Five methods were used to determine and justify the number of latent factors influencing subject responses to the questionnaire items.

Kaiser Criterion. Kaiser (1960) assumes that the dimension of the common factor space is equal to the number of principal components having eigenvalues greater than 1.0 (see also Harman, 1976). Initial principal components analyses from SPSS-X showed that both data sets yielded six eigenvalues greater than 1.0 (see Table 1). However, initial principal factors extractions from SAS revealed that the reduced correlation matrices of both data sets yielded only three eigenvalues greater than 1.0 (see Table 2). These contradictory findings imply that additional criteria are needed to justify the number of factors.

Insert Tables 1 and 2 about here

Scree Test. This "root staring" method (Cattell, 1966) involves a visual examination of the plot of eigenvalues of the inter-item correlation matrix. To determine the number of latent roots, the investigator finds the point at which a break (or bend) in the eigenvalue plot appears. The number of latent roots is assumed to equal the number of points prior to the break/bend. The remaining components are assumed to be error components. Figures 1 and 2 depict the eigenvalue plots from SPSS-X principal components analyses for both data sets. Inspection of the figures reveals three latent roots in each data set. However, most investigators desire somewhat more objective methods of determining the number of latent roots.

Insert Figures 1 and 2 about here

Difference Values. The examination of differences between adjacent eigenvalues is related to the visual examination of the eigenvalue plot and may clear up any distortion created by computer printouts by clarifying the "break" between latent components and error components. A general rule is to locate the break between the eigenvalues that corresponds to the last difference markedly larger than all subsequent differences (Tucker, 1973). Both Tables 1 and 2 reveal obvious breaks between three and four factors. Thus, the three factor solution seems the most reasonable. This principle may also be applied to differences in the percent of variance accounted for by adjacent factors. Examination of these values in Tables 1 and 2 also implies that the three factor solution is the most appropriate.

Root Mean Square Residuals. Root mean square off-diagonal residual correlations indicate the average error of the estimated or reproduced correlation matrix when compared with the original correlation matrix. Examination of these values permits some intuitive insight into the reproducibility of correlation matrices based on specified numbers of factor solutions. Table 3 indicates that the three, four, five, or six factor solutions yield smaller residuals than the two factor solutions. Furthermore, the residuals are not reduced a great deal beyond the three factor solutions (varying in the thousandths between adjacent numbers of factor solutions). Keeping in mind that one of the goals of factor analysis is parsimony, any solution greater than the three factor solution would be difficult to justify, given the information presented thus far.

Insert Table 3 about here

Alpha Coefficients. The primary goal of determining coefficients of internal consistency is psychometric inference. In alpha factor analysis, variables included in the factor analysis are considered a sample from the universe of variables, observed over a population. Alpha coefficients, then, may be assumed to be generalizability values (Harman, 1976; Kim & Mueller, 1978). In the present study, alpha coefficients were determined for each number of factor subscales to determine the within-subscale stability for various factor solutions. For both data sets, the internal consistency of each subsequent factor decreases considerably after the third factor (see Table 4). These coefficients lend additional support for

a three factor solution.

Insert Table 4 about here

The conglomerate of aforementioned methods provides a solid basis for the selection of a specified number of latent factors assessed with a questionnaire. Analyses of the data in this study led to the conclusion that the Competitiveness Inventory had a three-dimensional factor structure. The next step, then, was identifying these factors by specifing the items associated with each factor or subscale. In addition, the inter-correlations of the factors (see Table 5), suggested that the oblique transformations be emphasized over the orthogonal rotations.

Insert Table 5 about here

Determining the Factor Structure

This second stage of questionnaire development consists of determining which items or variables cluster consistently to yield the designated factor structure. Subsequent revisions of the questionnaire may then exclude items that exhibit undesirable characteristics, such as factorial complexity and instability.

Factorial complexity occurs when a single variable loads on (or is predicted by, in a multiple regression framework) each of several

designated factors. Ideally, a single variable loads on only one factor. However, this simple structure (Harman, 1976) is rarely achieved, necessitating another means of judging factorial complexity. Because the chance for factorial complexity increases as the number of factors increases, especially for poor items, an arbitrary cutoff point of a factor loading greater than or equal to .50 was selected for inclusion within a cluster or factor.

This cutoff point decreases factorial complexity by requiring that a variable have the majority of its loading increment on only one factor, and also reduces the possibility of selecting variables whose complexity may be the result of chance. In addition, the closer each variable is to simple structure, the greater the internal consistency of the respective subscales in similar samples.

The stability of a variable refers to the consistency with which it loads on the same factor across different numbers of factor extractions. For example, from two to six extractions were performed on each of the current data sets. For a three-factor solution, variable (item) 14 loaded on the second factor; for the four-factor solution on the fourth factor; for the five-factor solution on the fifth factor; and for the six-factor solution on the sixth factor. Not only does this variable increase the chance of complexity, but it has very low stability, having failed to load consistently on one factor across different numbers of extractions. Such instability would lead an investigator to eliminate this variable from a revised questionnaire. The factor pattern for the revised Competitiveness Inventory was determined with the principles of simplicity and stability in mind, and using a minimum loading value of .50 for selection.

The most convenient procedure to consolidate the information from the multitude of program printouts and evaluate the simplicity and stability for each variable is to devise a tally system. Having completed this task, the stability of each item can be evaluated. For the purpose of this study, the following system was used:

1. Each line was reserved for a single item with the item numbers along the left margin.
2. The sheet was divided into six columns. The first five columns were headed with numbers (2, 3, 4, 5, or 6) to indicate the number of factors extracted. The last column was reserved for the final decision as to with which factor the item should be clustered for further testing, or deleted from the revised form.
3. Separate tally sheets were developed for SPSS-X and SAS extractions.
4. In recording tallies, it was necessary to examine each matrix of factor loadings (after rotation to final solutions) for each extraction method and for each number of factors extracted. For each factor solution, each item was tallied with a number representing the factor loaded on most heavily by that item, and meeting the cutoff criteria .50. For example, in a four-factor solution each item in the matrix was tallied (in the column headed "4") with a 1, 2, 3, or 4, identifying the factor on which it loaded greater than or equal to .50. If an item did not load greater than or equal to .50 on any factor, or if the item exhibited factorial complexity by loading substantially on two or more factors, it was tallied with a dash (-).
5. It should be mentioned that the investigator may wish to keep separate tally sheets for varimax (orthogonal) rotations and oblique transformations, because items may load onto different factors with

the two transformations. This should not present a great problem as the same items usually cluster together with both transformations even though the loadings may differ.

Factor Structure. Determination of the factor structure was based on the three-factor solution and on the general tendencies (stability) of factor loadings across other multi-factor solutions. Analyses of both data sets yielded virtually identical clusters of items. It should be noted that the order in which the second and third factors emerged was reversed from the 1984 data to the 1985 data, but this outcome had no effect on the clustering of the items. The items are listed below in their respective clusters:

Factor I:

1. I am a competitive person.
2. I try my hardest to win.
3. I am a determined competitor.
4. I want to be the best every time I compete.
6. I look forward to competing.
7. I thrive on competition.
8. My goal is to be the best athlete possible.
11. I enjoy competing against others.
13. I want to be successful in sports.
15. I work hard to be successful in sports.
18. The best test of my ability is competing against others.
29. I look forward to the opportunity to test my skills in competition.
31. I perform my best when I am competing against an opponent.

Factor II:

12. Winning is important.
25. Scoring more points than my opponent is very important to me.
26. I hate to lose.
27. The only time I am satisfied is when I win.
30. Losing upsets me.
32. I have the most fun when I win.

Factor III:

5. I set goals for myself when I compete.
10. I am most competitive when I try to achieve personal goals.
21. I try hardest when I have a specific goal.
22. Reaching personal performance goals is very important to me.
24. The best way to determine my ability is to set a goal and try to reach it.
28. Performing to the best of my ability is very important to me.

The items that were deleted due to not meeting the selection criteria were;

9. I like to show others that I am skilled.
14. I am determined to do my best every time I compete.
16. I feel great when I win.
17. I never give up, even when I'm losing.
19. Finishing the race is more important than winning.
20. I like to show others that I try hard.
23. Knowing that I performed well is a greater reward than the actual win.

Discussion

Use of the conglomerate of factor analysis methods revealed a consistent factor pattern in this study. The combined methods pointed to a three-factor latent structure and inspection of the various factor loadings revealed a consistent clustering of items across factor solutions. More important to most investigators, the clusters of items were conceptually logical. The items of Factor I seem to reflect the personality disposition of competitiveness as the desire to enter and strive for success in sport achievement situations. While Factor I emphasizes approaching achievement situations and effort within competition, Factors II and III reflect an orientation toward sport achievement <u>outcomes</u>. Specifically, the items of Factor II emphasize winning and successful social comparison within sport competition. In contrast, the items of Factor III focus on the achievment of noncompetitive, personal goals in sport. Thus, the three factors of the inventory are labeled as competitiveness, win orientation and goal orientation.

The two-stage process, using a conglomerate of factor analysis methods, effectively helped determine the factor structure of the Competitiveness Inventory in this illustration. The convergence of various methods in identifying a three-factor structure provided much stronger justification than any single method could. Also, examination of item loadings across several factor solutions with simplicity and stability in mind helps eliminate spurious items that might seem important with a single factor analysis. We suggest that investigators use a similar conglomerate of methods in the early stages of the development of other sport-specific psychological measures, with the final decision on factor structure based on conceptual significance and parsimony.

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Table 1

SPSS-X Principal Components Eigenvalues*

1984 DATA				1985 DATA			
λ	Δλ	% Var	Cum %V	λ	Δλ	% Var	Cum %V
11.161		34.9	34.9	11.253		35.2	35.2
	7.154				7.777		
4.007		12.5	47.4	3.476		10.9	46.0
	1.836				1.148		
2.171		6.8	54.2	2.328		7.3	53.3
	.832				1.196		
1.339		4.2	58.4	1.132		3.5	56.8
	.143				.026		
1.196		3.7	62.1	1.106		3.5	60.3
	.174				.070		
1.022		3.2	65.3	1.036		3.2	63.5
	.174				.082		
.848		2.6	67.9	.954		3.0	66.5
	.037				.092		
.811		2.5	70.5	.862		2.7	69.2

*Values shown are for the first eight characteristic roots.

Table 2

SAS Principal Factors Eigenvalues*

1984 DATA			1985 DATA		
λ	Δλ	% Var	λ	Δλ	% Var
10.814		57.5	10.878		60.6
	7.30			7.91	
3.511		18.7	2.970		16.6
	1.76			1.08	
1.749		9.3	1.887		10.5
	.80			1.21	
.948		5.0	.680		3.8
	.20			.05	
.752		4.0	.629		3.5
	.19			.09	
.562		3.0	.541		3.0
	.13			.06	
.434		2.3	.484		2.7

*Values shown are for the first seven characteristic roots.

Table 3

Root Mean Square Off-Diagonal Residuals

(From SAS)

1984 DATA

Number of Factors	Method*				
	PF	IPFA	Alpha	ULS	ML
2	.071	.071	.072	.071	.073
3	.049	.049	.049	.049	.050
4	.041	.041	.042	.041	.042
5	.034	.034	.035	.034	.036
6	.030	.030	.030	.030	.032

1985 DATA

Number of Factors	Method*				
	PF	IPFA	Alpha	ULS	ML
2	.072	.072	.074	.072	.072
3	.045	.044	.045	.044	.045
4	.040	.040	.042	.040	.041
5	.036	.036	.037	.036	.037
6	.032	.031	.033	.031	.033

* Method: PF = Principal Factors (w/ SMCs)
IPFA = Iterated Principal Factor Analysis
ALPHA = Alpha Factor Analysis
ULS = Unweighted Least Squares
ML = Maximum Likelihood Estimation

Table 4

Alpha Coefficients

(From SAS)

1984 Data

Solution	Factor 1	2	3	4	5	6
2	.987	.921				
3	.982	.904	.727			
4	.979	.899	.717	.426		
5	.976	.893	.710	.412	.282	
6	.974	.885	.700	.407	.271	.039

1985 Data

Solution	Factor 1	2	3	4	5	6
2	.989	.904				
3	.984	.883	.756			
4	.982	.872	.747	.263		
5	.980	.866	.738	.258	.176	
6	.978	.860	.731	.241	.171	.069

Table 5

Three Factor Intercorrelations

(From SPSS-X)

1984 Data

Principal Components

	1	2
2	.349	
3	.296	-.058

Maximum Likelihood

	1	2
2	.387	
3	.365	-.042

Unweighted Least Squares

	1	2
2	.380	
3	.340	-.066

Alpha

	1	2
2	.379	
3	.331	-.075

1985 Data

Principal Components

	1	2
2	.307	
3	.388	.017

Maximum Likelihood

	1	2
2	-.442	
3	.334	-.024

Unweighted Least Squares

	1	2
2	.336	
3	.430	.019

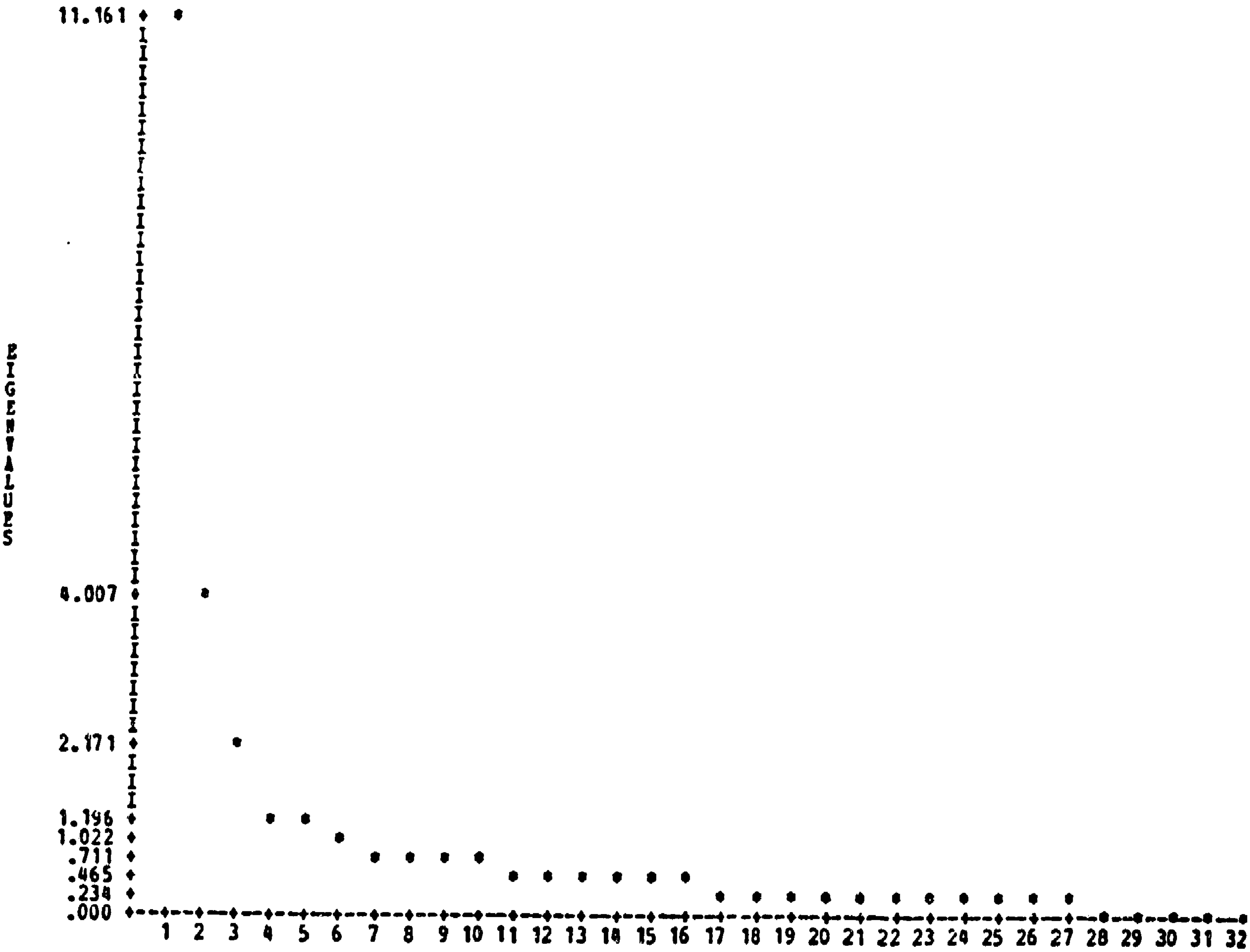
Alpha

	1	2
2	.343	
3	.420	.015

Figure Captions

Figure 1. Scree plot of eigenvalues for Spring 1984 data.

Figure 2. Scree plot of eigenvalues for Spring 1985 data.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2.171
1.196
1.022
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.465
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.000
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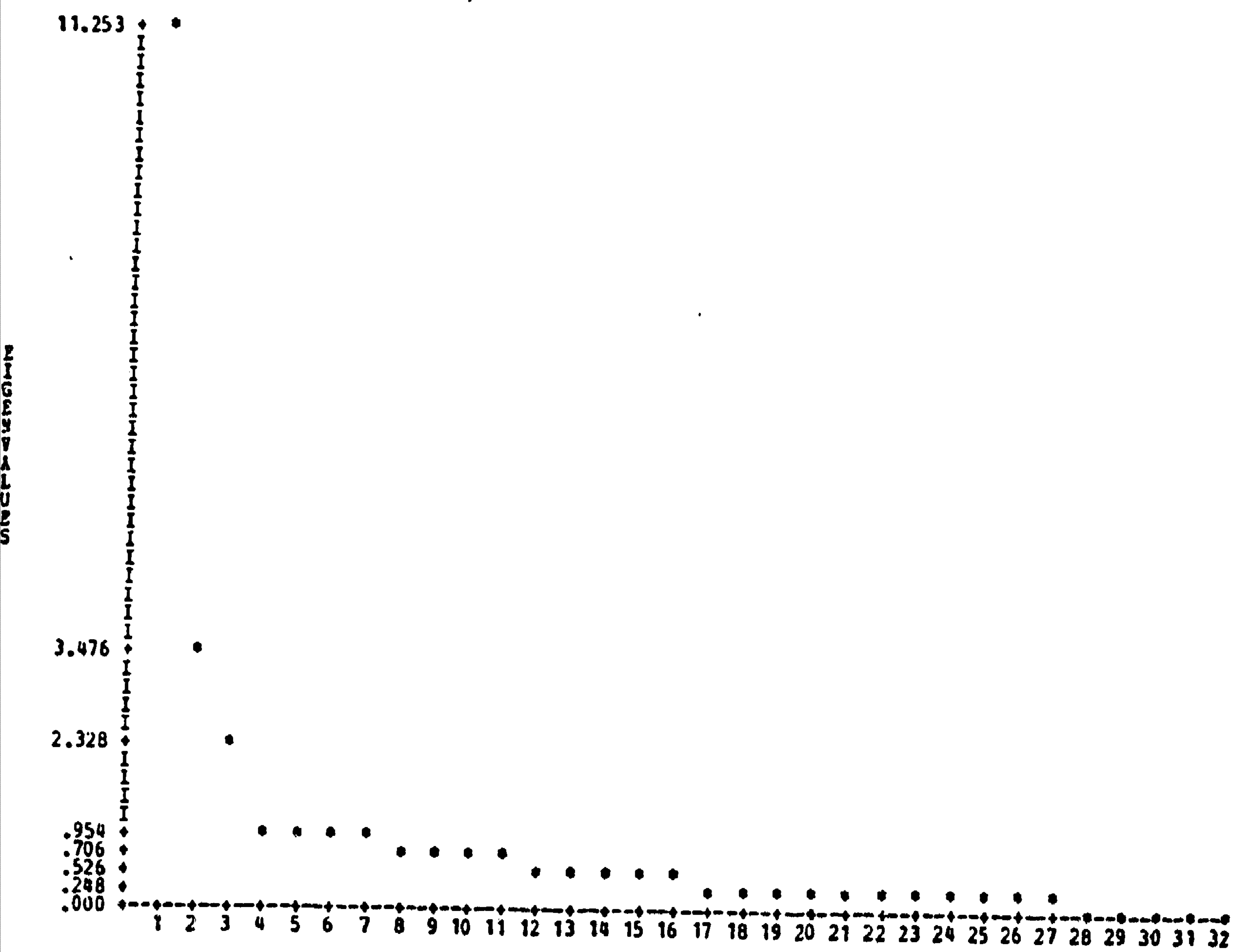
EIGENVALUES
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3.476
2.328
.954
.706
.526
.248
.000
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32