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AUTHOR Elterich, Kenneth W.; And Others
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ABSTRACT

The predictive validity of the Comparative Guidance and Placement Program (CGP) tests for two diverse curricular groups was examined. Three methods for developing predictive equations were compared. The CGP was administered to 417 Liberal Studies and 316 Business Technical students at a New England community college. Principal component analyses and varimax rotations were employed for each curricular group. Three multiple regression procedures were run to predict end-of-freshman year grades. Predictors were component, scale, and raw scores. or both groups, R's near .50 were found; cross-validation R's near .53 and .43 were found for the two groups. Incremental validity associated with adding high school grades to the equations is presented. The predictive equations are compared in light of comments by Darlington (1968) and Rozeboom (1966). (Author)

The Use of the Comparative Guidance and Placement Test in Predicting School Achievement: Three Models[1]

Kenneth W. Elterich

Manchester Community College

Robert K. Gable
Steven V. Owen

University of Connecticut

In an age of accountability, it becomes increasingly important to identify present student competencies and interests in order to predict, as accurately as possible, later student achievement. With accurate identification of students who are likely to do poorly, it is possible to establish preventive or remedial programs before failure becomes a fact. For example, in specific freshman courses, Miller (1974) incorporated prediction of low achievement and failure with remediation in small-group tutorial sessions. SHe reported improved achievement for those students predicted to fail. In community colleges the heterogeneous background of the non-traditional student calls for precise academic prediction, intensive admissions counseling, and the establishment of preventive or remedial programs. In most Connecticut community colleges, guidance services and remedial programs are inadequate (Connecticut General Assembly, 1974).

Several of the community colleges are using the Comparative Guidance and Placement Program (CGP) developed by the Educational Testing Service (ETS) in conjunction with the College Entrance Examination Board (CEEB) to estimate initial student achievement levels. The CGP is an integrated battery of tests and interest scales designed to assist the two-year college student, faculty,

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counselors, and administrators. The primary purpose of the CGP is to assist admission's counselors in their efforts at helping students make sound educational and career decisions (CEEB, 1969). The CGP facilitates entering students realization of their academic and career plans. These tests also aid in the placement of students into proper course levels and curricula.

Purpose

The main emphasis of this research is to examine the predictive validity of the CGP for two diverse curricular groups. This examination is important for generating optimal predictions using a guidance and placement instrument like the CGP. In admissions counseling it is necessary to know the probable performance of students seeking and entering the various curricula. This type of information helps the counselor guide and place the student into an appropriate program of study. Studies by CEEB (1970, 1973) indicate reasonable predictive validity coefficiants obtained from a central prediction analysis for the standard CGP curricula areas using grades as the criterion. The median validity coefficients in their 1973 study for four curricula areas were: Liberal Arts (.38), Occupational-Technical careers (.40), Occupational-Vocational careers (.42), and Developmental Programs (.31). Data pooled in a particular school may differ in basic ways from those in a national sample. Thus, the predictive validity of the CGP should also be examined for individual institutions.

A second purpose of this study is to compare the relative usefulness of three methods for developing predictive equations. Establishing stable regression weights for use on subsequent samples, while simultaneously maximizing the multiple correlation between the predictors and criterion, is a methodological dilemma in prediction problems (Burket, 1964; Herzberg, 1969). Adding predictors to a regression equation will increase the multiple correlation. However, a greater number of predictors leads to more unstable sample regression weights and a lower sample cross-validity. A possible solution to this problem is to determine a method that selects an optimal subset of predictors which maximizes the predictability of the criterion in future samples, i.e., to grnerate more stable regression weights and a higher cross-validity.

Several ways have been suggested to select such a subset of predictors. The most popular method is stepwise regression (Darlington, 1969). In this method, predictors are added to the equation until there is no significant increase in the ability of the predictor to explain criterion variance; the variable entered in the equation provides the greatest increase in the multiple correlation (Kerlinger, 1973). Darlington, (1968) has found this an effective method with raw scores when the variables are highly reliable. The desirable property of this strategy is that the contribution of each predictor to the equation is considered.

Herzberg, (1969), Burket, (1964), and others, have investigated a second method of reducing the original number of predictors. Rather than using the predictors themselves, a fewer number of linear combinations or composites (principal components) of the predictors are used. Thus, the information contained in the original set of predictors is retained in a fewer set of variables. This procedure should technically increase the stability of the resulting prediction equation.

Herzberg, (1969) studied prediction from the full set of predictors and two reduced-rank models. Results indicated that using the largest principal components of the predictors was superior to the other methods.

Herzberg concluded that, in order to maximize cross-validity, predictors should be chosen independently of the criterion. These results parallel those . Burket (1964) who investigated five predictor selection methods. The largest principal components were consistently superior in prediction in future samples to those methods which utilized the highest multiple correlation with the criterion. The present study will capitalize on these research findings to investigate the combination of stepwise regression (Darlington, 1968; Kerlinger, 1973) with the largest principal components (Herzberg, 1969; Burket, 1964) in an attempt to establish an optimal prediction method.

In this study, the largest-principal component reduced-rank method will be used to construct factor scores for two regression models. The derived scores will be referred to as: component scores (Kaiser, 1962) and scale scores (Cattell, 1957). Component scores are obtained by first computing a principal component analysis followed by a varimax rotation of components with eigenvalues greater than one. Scores are then computed for each subject directly from the varimax model (Jennrich, 1966; Kaiser, 1970). The component scores are computed orthogonally, thus representing unrelated sources of information (Glass and McGuire, 1966).

A second method of constructing "factor" scores is recommended by Cattell (1957) and Cooley and Lohnes (1962). The procedure involves selecting a group of variables to represent a component and summing their values for each case. The sum is the "factor" score estimate or <u>scale</u> score. Herzberg (1969, p. 6) states that selection of "predictors loading highly on the components as a sublet to use in future prediction" is a possible method of constructing score estimates. However, in an investigation by Glass and McGuire (1966) composite scale scores were found to produce high intercorrelations and erratic correlations with the orthogonally computed varimax factor scores. Glass and McGuire state that unwary researchers might treat correlated factor scores as if they were uncorrelated. Thus, this study will properly refer to summed raw scores as scale scores. The phrase "factor scores" will be used to represent factor scores as defined by Kaiser (1962).

Procedures

In light of the above studies three methods of constructing an optimal predictor set will be investigated. The methods will utilize stepwise regression on the raw score variables and stepwise regression on the largest principal components. The composite principal component variables will be represented by component scores and scale scores.

Predictors. Table 1 contains a listing of the 19 measures that are included in the CGP battery. Accompanying the names of the measures are the scale reliabilities. Appendix A contains a brief description of the CGP test content.

Insert Table 1

Criterion. The criterion employed in this research was the end-of-year grade point average (GPA). Academic success is most commonly measured in terms of course grades and grade averages. In addition, grades are generally accepted by administrators, counselors, teachers, students and parents as the standard measure for achievement. The GPA for the subjects of this study was compiled by transforming individual course grades to a numerical scale (A=4, B=3, C=2, D=1, F=0). By adding all the grade-numerials multiplied by the course hours taken in a semester, the GPA is derived.

Sample. The Comparative Guidance and Placement exam was administered to all incoming Freshman students at Manchester Community College during the Springs of 1971 and 1972. From this initial population, complete sets of data were identified and extracted for investigation for two curricular groups: Liberal Studies and Business Technical career programs.

Liberal Studies. The first area, Liberal Studies, were composed of students from the Liberal Arts and General Studies programs (N=397). The data from these two programs were combined based on results of a previous study (Elterich and Gable, 1972). The analysis indicated comparable factor structures for the two groups on the CGP dimensions. Course content and a common preference for continuing their education beyond the two year level are also similar in the two programs.

Business Technical. The second area, Business Technical career programs, consists of those students enrolled in a two year business program (N=291). The sub-curricula included were Business Administration, Data Processing, Hotel-Restaurant Management, Accounting, Marketing, and Secretarial programs. The students in these programs have similar career goals and in similar course content. All the programs listed in this group follow the CGP curriculum classification suggested by the College Board (CEEB, 1973).

Statistical Analyses. For the two curricular groups, principal component analyses and varimax transformations were performed on the 19 variable intercorrelation matrix; component scores were generated. The decision to submit the samples to separate analyses was based on results obtained in the previous study (Elterich and Gable, 1972). The earlier results identified different factor structures for the two curricula on the CGP dimensions.

For each curricular group, the total sample was randomly split into validation and cross-validation samples. Validation equations using three multiple regression procedures were developed on the first half of each samples; these equations were then used to predict achievement for the second half. The predicted averages for the complete and reduced predictor sets were then correlated with the subjects actual grade averages to obtain a cross-validation coefficient. The reduction in the multiple correlation from the first to the second sample is an estimate of the amount of shrinkage (Herzberg, 1969). Cross-validation coefficients for the total predictor sets and those developed on optimal-reduced predictor sets were compared. The optimal predictor sets were selected using a test of significance for the beta weights at the .05 level as the criterion.

Results

Principal Components of the Predictors. The principal component analysis and varimax rotation resulted in the six meaningful factors for the Liberal Studies curricula which accounted for 69% of the total variation. These components, listed in order of their importance, were Scholastic Aptitude, Science Technology, Biology-Academic Motivation, Business Interest, Social Science, and Fine Arts. For the Business Group, six components were also derived which account for 70% of the total variance; these were named Scholastic Aptitude, Biology Interest, Business-Academic Motivation, Business Social Science, Engineering Technology, and Fine Arts. The previous study on a similar sample (Elterich and Gable, 1972) derived a CGP factor structure nearly identical to that found in the present research. The earlier study presents a detailed description of the factors.

Table 2 contains the test names and component loadings for the principal component analysis and varimax rotation for the Liberal Studies and Business groups.

Insert Table 2

Regression Analyses: Liberal-Studies. Table 3 contains a listing of the complete predictor sets for the raw scale, and component score regression models. Also included are the multiple correlations and standard errors of estimate. For the Liberal-Studies group, five raw score predictors generated an optimal prediction battery. Table 4 contains the validation and cross-validation multiple correlations for the total and reduced predictor sets for each curricula group. The amount of shrinkage in each model is also indicated. Inspection of the table entries indicates that a multiple correlation of .53 and a cross-validity coefficient of .48 was obtained for the total raw score battery. The optimal predictor set generated a multiple correlation of .50 and a cross-validity coefficient of .48. For the scale score analyses, four predictors defined the optimal battery for the six scale scores; mutiple correlations of .50 and cross-validation coefficients of .45 and .46 were obtained for the total and optimal predictor sets respectively.

Finally, the component score analysis revealed four optimal predictors and developed multiple correlations of .49 and cross-validates of .48 for both predictor sets. Shrinkage for the three regression equations in the Liberal Studies group for both the total and reduced optimal predictor set was small and similar, with the least amount of the shrinkage occurring in the raw and component score models for the optimal predictor sets.

Insert Table 3

Insert Table 4

Regression Analyses: Business-Technical. Table 5 contains a listing of the total predictors for the raw, scale, and component score regression models. Also included are multiple correlations and standard errors of estimates. For the Business-Technical group, six raw score predictors provided an optimal prediction battery. Multiple correlations of .61 and .53 and cross-validation coefficients of .31 and .35 were obtained for the total and optimal predictor sets respectively (see Table 4). For the scale score model, four predictors

Insert Table 5

defined the optimal battery for the six scale scores; multiple correlations of .46 were obtained for both predictor sets. Cross-validation coefficients of .36 and .38 were obtained for the total and optimal predictor sets. The component score analysis provided an optimal battery of three predictors from the original six component scores; multiple correlations of .45 and .44, and cross-validation coefficients of .35 and .37 were generated for the total and optimal predictor sets respectively. Considerable shrinkage occured within all three regression models, particularly for the total predictor set. The two reduced-rank models contained the least amount of shrinkage when the optimal predictor sets were used.

Discussion

It was found that a moderate amount of variation in grade point average could be explained by the CGP scores for Ss in this study. Thus, the predictive validity of the CGP for both curricular groups is moderately supported. It should be pointed out that the "worth" of a predictive battery depends, ultimately, on the amount of <u>systematic</u> criterion variance accounted for. Since the reliability of the criterion automatically sets an upper limit for prediction (Cureton, 1965, p. 344) the "variance accounted for" is actually the following proportion:

$$\frac{R^2 \text{ (coefficient of determination)}}{\text{reliability of criterion}}$$

Reliability estimates were generated for the criterion following Humphrey's (1970) suggestion of using the correlation of adjacent semester GPA's. Correlations of .71 and .70 were generated for a random sample of the Liberal Studies (N=101) and Business-Technical (N=69) groups respectively. These correlations were then used in computing the systematic criterion variance accounted for by the present study's predictors. Table 6 presents a summary of the systematic criterion variance predicted within the several analyses. It can be seen that the predictor batteries accounted for roughly 30 percent of the predictable criterion variance in Liberal Studies and 20 percent in the Business Technical group.

- - Insert Table 6 - -

When the three regression models were compared it was found that the raw score regression model for the total and optimal predictor sets had the highest multiple correlation; the two reduced rank methods were associated with multiple correlations close to the raw score model but used fewer number of predictors. Shrinkage in the multiple correlations for the Liberal Studies group was quite small and similar for all three models; the least amount of shrinkage occured for the component score model.

Cross-validations of the Business Technical regression models suffered large shrinkage in the raw score model, .30 for the total and .18 for the optimal predictor set. The two reduced-rank models contained substantially less shrinkage, especially for the optimal predictor sets. The large shrinkage in the cross-validation coefficients for the Business Technical group may be explained by sampling error. That is, when a random hold-out sample is used for cross-validation, the sampling distribution of predictor score differences between the validation and various cross-validation samples will vary from very small to very large (Owen, 1970). In the case of the Business Technical regression models the differences may have been very large. If random fluctuation is large, and it occurs with an important predictor variable, then the reliability of the validation regression will be weakened, and the cross-validation of that equation will show a relatively large amount of shrinkage. Another perspective may be found in the work of Burket (1964) and Herzberg (1969). Results of these studies indicate when the sample size is relatively small and the number of predictors large the generated regression equation would be the least stable, thus a reduced-rank model might be more effective in such cases. This conclusion was substantiated with the Business-Technical group in which the two reduced-rank models showed less shrinkage than the raw score model.

For the practitioner, the findings of this validation study suggests several possibilities. From a counseling viewpoint it may be more beneficial to consider the meaningful derived dimensions from the CGP when counseling Ss with respect to curriculum decisions. In both curricular samples, the optimal predictor sets for the two reduced-rank models are composed of dimensions which rationally appear to be most meaningful for each separate group. For example, the optimal predictor set for Liberal Studies was defined by the dimensions called Scholastic Aptitude, Biology/Academic Motivation, Scientific Technology, and Fine Arts which are meaningful dimensions to students within this curriculum. Thus, it may not be efficient to spend time discussing several test scores on the CGP when the scores from a fewer number of meaningful composites, which have almost equal predictive validity.

It should be pointed out, however, that a concern for efficiency may moderate the suggestion to use component scores as predictors. Because component scores are based on the entire array of original predictors, it is clear that the use of component scores would not reduce time spent in testing. By contrast, the use of the optimum raw scores as predictors (especially for the Liberal Studies group in this research) implies that fewer subtests need be administered to students, permitting increased efficiency in data gathering procedures.

The results of this study partially support some of the theoretical literature which suggests the use of the component scores as predictor variables (see, for example, Darlington, 1968; Herzberg, 1969). This relative usefulness of component or raw scores may depend upon the nature of criterion. That is, for certain criteria, the use of component scores as predictors may provide a decided advantage. This issue has not been investigated, and seems to be fertile ground for future research.

Finally, the use of component or raw scores must depend in part upon the context of the research. It seems reasonable that if the purpose of prediction is simply to develop the most efficient, valid equation possible, then raw scores as predictors might be most useful. If, however, the purpose of the research is to gain a better understanding of why certain things predict certain other things, the use of component scores, by virtue of their data-reduction attributes, may provide more insight than economy.

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Appendix A

Comparative Guidance and Placement Battery Scales

The CGP battery includes 11 interest measures, six aptitude measures, and an academic motivation score. The scores on the six ability tests are reported on a 20 to 80 scale, with a mean of 50 and a standard deviation of 10. The Interest Index scores are obtained by using the formula Likes-Dislikes + 16.

Aptitude Scales

Reading Test. Measures a student's comprehension of ideas and specific details, ability to make inferences, and ability to extract the meaning of vocabulary from context.

Verbal. The verbal score is obtained by combining scores received on the reading test and a short vocabulary test. A separate vocabulary score is not reported. The vocabulary test consists of synonym questions that can be answered by someone who has a general knowledge of the meaning of a word.

Sentence Test. Measures mastery of standard written English by asking students to recognize errors in grammar, usage, choice of words, idiom, capitalization, and punctuation.

Mathematics Test. The student takes one of two measures: one consists of general mathematics and algebra; the other consists of the algebra test and trigonometry. The latter is taken only by students who have had a course in trigonometry.

Year 2000. Measures integrative reasoning. The students are asked to follow a set of increasingly complex directions for locating certain dates on the calendar of the year 2000.

Mosaic Comparisons. A perceptual speed and accuracy measure. The student is asked to identify differences in pairs of tile-like patterns. There are three parts to this highly speeded test.

Letter Groups. A test of inductive reasoning in a non-verbal context where each item consists of five groups of four letters each. A student must determine which set of letters does not share the characteristics common to the other four by trying out various hypotheses.

Interest Scales

Mathematics. The scale indicates whether a student is interested in business math, algebra, geometry and in the practical applications of mathematics.

Physical Sciences. High scores suggest an interest in geology, electricity, optics, chemestry, and special emphasis on discovery and interest in laboratory work.

Engineering Technology. Interests in drafting, architecture, and home repairs in the construction of gadgets and small machines are measures in this sc e.

Biology. High scores in this scale indicate a general interest in discovery, operations of the natural world, genetics, and preventive medicine as well as laboratory research, classification, and scientific theory.

Health. High scores on this scale indicate an interest in those duties performed by nurses, medical technicians, and laboratory assistants.

Home Economics. This scale measures an interest in thrift and economy dealing in cooking, sewing, gardening, and home decorating. Interest in restaurant cooking, decorating, and retail buying is also measured.

Secretarial. High scores indicate an interest in the business world, in procedural details, and in the establishment of an efficient routine. Practical interests in operations of business machines and proficiency in shorthand, typing, filing, and the handling of formal correspondence.

Business. High scores indicate an interest in the executive role in business and in the practical aspect of business life.

Social Science. Interest in politics, news reporting, current events and possibly history is indicated by high scores.

Fine Arts. An enjoyment of all crafts, commercial drawing, and an appreciation of art and art history as well as a desire to paint, draw, or sculpt is measured.

Music. The scale measures a student's interest in classical and popular music, solo and group, participation in an appreciation of conducting, composition, and theory.

Academic Motivation

Academic motivation scores are obtained from the last 10 items of the CGP's Biographical Inventory. The score is reported on a 20-80 scale and is based on the student's perception of his high school efforts.

Table 1

CGP Scale Names and Reliabilities[a]

CGP Scale Names	Reliability	CGP Scale Names	Reliability
Aptitude Scales:		Interest Scales:	
Reading	.88	Mathematics	.95
Verbal	.90[b]	Physical Sciences	.95
Sentences	.84	Engineering Technology	.94
Math	.90	Biology	.93
Year 2000	.73	Health	.90
Mosaic Comparisons	.77	Home Economics	.94
Letter Groups	.75	Secretarial	.91
Academic Motivation	.74	Business	.91
		Social Sciences	.94
		Fine Arts	.92
		Music	.93

a. Reliabilities are KR20 estimates except where indicated

b. The verbal score is an equally weighted composite of two separately timed tests - vocabulary and reading - measures of speededness are not available.

Table 2

Component Loading Matrix for
Principal Component Analysis and Varimax Rotation:
Liberal-Studies and Business-Technical Programs[1]

VARIABLE NAMES	LIBERAL-STUDIES Component						BUSINESS-TECHNICAL Component					
	I	II	III	IV	V	VI	I	II	III	IV	V	VI
Interest Scales												
Mathematics		70									73	
Physical Science		78						51			61	
Engineering		75									73	
Biology			81					86				
Health			85					87				
Home Economics			51	44					72			
Secretarial				89					80			
Business				85					40	79		
Social Science					57					77		
Fine Arts						83						76
Music						79						70
Aptitude Scales												
Reading	87						85					
Verbal	90						85					
Sentences	77						71					
Math	67						63			44		
Year 2000	73						76					
Mosaic Comparisons					75		36					
Letter Groups	49				62		62					
Academic Not.			40						69			

[1] All decimals have been omitted

Table 3

Total Predictor Set for the Step-wise
Multiple Regression Analyses Using the
Raw, Scale, and Component Score Regression Models:
Liberal - Studies

Raw Scores					Scale Scores					Component Scores				
Step Number	Variable	R	R^2	S.E. Est.	Step Number	Variable	R	R^2	S.E. Est.	Step Number	Variable	R	R^2	S.E. Est.
1 *	Sentences	.36	.13	.61	1 *	Scholastic Apt.	.32	.10	.62	1 *	Scholastic Apt.	.35	.12	.61
2 *	Home Economics	.43	.19	.59	2 *	Biology/Acad. Mot	.43	.18	.59	2 *	Bio./ Acad. Mot.	.42[c]	.18	.59
3 *	Verbal	.46	.21	.58	3 *	Scientific Tech.	.47[b]	.22	.58	3 *	Scientific Tech.	.46	.21	.57
4 *	Eng. Tech.	.48[a]	.23	.58	4 *	Fine Arts	.49	.24	.57	4 *	Fine Arts	.49	.24	.57
5 *	Biology	.50	.25	.57	5	Social Science	.50	.25	.57	5	Business Int.	.49	.24	.57
6	Fine Arts	.50	.25	.57	6	Business - Int.	.50	.25	.57	6	Social Science	.49	.24	.57
7	Academic Mot.	.51	.26	.57										
8	Mosaic	.51	.26	.57										
9	Letter	.52	.27	.57										
10	Phy. Science	.52	.27	.57										
11	Year 2000	.52	.27	.57										
12	Music	.53	.28	.57										
13	Math Aptitude	.53	.28	.57										
14	Secretarial	.53	.28	.57										
15	Social Science	.53	.28	.57										
16	Business	.53	.28	.58										
17	Health	.53	.28	.58										
18	Math Interest	.53	.28	.58										
19	Reading	.53	.28	.58										

* Optimal Predictor Sets

a. F= 12.32, DF= 5/188, $p < .01$

b. F= 12.54, DF= 4/188, $p < .01$

c. F= 14.9, DF= 4/189, $p < .01$

Table 4

Multiple Correlations and Cross Validates for the Three Regression Models: Liberal-Studies – Business-Technical Samples

Regression Model	Total # of Predictors	Validation R	X Validation	Shrinkage	Optimum[1] # of Predictors	Validation R	X Validation	Shrinkage
Liberal Studies N = 194								
Raw	19	.53	.48	.05	5	.50	.48	.02
Scale	6	.50	.45	.05	4	.50	.46	.04
Component	6	.49	.48	.01	4	.49	.48	.01
Business Technical N = 156								
Raw	19	.61	.31	.30	6	.53	.35	.18
Scale	6	.46	.36	.10	4	.46	.38	.08
Component	6	.45	.35	.10	3	.44	.37	.07

[1] Criterion for selection of predictors was test of significance for b's at .05 level with df = 1, n-k-1.

Table 5

Total Predictor Set for the Step-wise
Multiple Regression Analyses Using the
Raw, Scale, and Component Score Regression Models:
Business

Raw Scores Step Number		Variable	R	R^2	S.E. Est.	Scale Scores Step Number		Variable	R	R^2	S.E. Est.	Component Scores Step Number		Variable	R	R^2	S.E. Est.
1	*	Verbal	.31	.09	.65	1	*	Scholastic Apt.	.29	.08	.65	1	*	Scholastic Apt.	.30	.09	.65
2	*	Acad. Mot.	.41	.17	.62	2	*	Bus.Int/Aca. Mot.	.41	.17	.62	2	*	Bus./Sec. Sci.	.37	.14	.63
3	*	Business	.46	.22	.61	3	*	Engr. Tech.	.44	.19	.61	3	*	Bus./Acad. Mot.	.44[c]	.19	.62
4	*	Math Apt.	.49	.24	.60	4	*	Fine Arts	.46[b]	.21	.61	4		Eng. Tech.	.45	.20	.61
5	*	Eng. Tech.	.51	.26	.59	5		Bus./Soc. Sci.	.46	.21	.61	5		Fine Arts	.45	.20	.62
6	*	Phy. Sci.	.54[a]	.29	.59	6		Biology Int.	.46	.21	.61	6		Biology Int.	.45	.20	.62
7		Letter Groups	.54	.30	.58												
8		Year 2000	.56	.31	.58												
9		Health	.57	.32	.57												
10		Secretarial	.58	.34	.57												
11		Math Int.	.59	.34	.57												
12		Home Econ	.59	.35	.57												
13		Fine Arts	.60	.35	.57												
14		Mosaic	.60	.36	.57												
15		Soc. Sci.	.60	.36	.57												
16		Reading	.60	.36	.57												
17		Sentences	.61	.37	.57												
18		Biology	.61	.37	.58												
19		Music	.61	.37	.58												

* Optimal Predictor Sets

a. F= 9.98, DF= 6/149, p .01

b. F= 10.06, DF= 4/151, p .01

c. F= 12.22, DF= 3/152, p .01

Table 6

Criterion Variance Predicted in all Analyses

Analyses	Total Predictor Set Shrunken R^2	Total Predictor Set Proportion of Variance	Optimal Predictor Set Shrunken R^2	Optimal Predictor Set Proportion of Variance
Liberal Studies				
Raw	.23	.32	.23	.32
Scale	.20	.28	.20	.28
Component	.23	.32	.23	.32
Business-Technical				
Raw	.09	.13	.12	.17
Scale	.13	.19	.14	.20
Component	.12	.17	.14	.20