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ABSTRACT

Arguments which suggest that improved prediction of multiple criteria can be achieved employing pattern scoring of responses, as opposed to conventional methods, are examined. Models for improving prediction of single and multiple criteria were examined. The findings are: (1) simple linear combinations of predictor variables perform as well predicting single criterion as do nonlinear combinations of the variables; and (2) for predicting multiple criteria, the most appropriate model also appears to be simple linear combinations of the predictor variables. It is suggested, however, that when a number of measures, multifactor in nature, are to be predicted, the model used in the present study may be appropriate for improving predictability. (CK)

THE USE OF PATTERN ANALYSIS FOR THE
PREDICTION OF ACHIEVEMENT CRITERIA

BY

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CHAPTER I

INTRODUCTION

Advances have been made in recent years in the direction of improving the methodology of achievement measurement. The pattern or configural model designed to treat data so as to yield a higher degree of predictive ability, has been one of the products of these efforts. Evidence has been presented that increased accuracy of prediction may be obtained if the predictor variables are treated as patterns of scores rather than as linear combinations or averages of separate independent scores.

If the criterion is a single composite index, the researcher's problem involves finding that combination of variables which yield the best prediction of the criterion involved. For most studies, pattern analysis as applied to item responses within a single test yield no better discriminations than the more usual additive techniques which ignore inter-item relationships. Many times, however, we are interested in predicting success on a number of performance measures at once. The present study is important because it examines arguments which suggest that improved prediction of multiple criteria can be achieved employing pattern scoring of responses as opposed to conventional methods.

CHAPTER II

REVIEW OF THE LITERATURE

Simple weighted addition has been the traditional method of combining scores to predict achievement criteria. However, this linear assumption does not always yield the best prediction of criterion scores (Cronbach, 1970). Tyler (1956) has pointed out that the limit to the predictive accuracy achieveable for most criteria is, in general, a multiple correlation of about 0.6.

Horst (1941) presented a theoretical solution designed to increase predictability, but its usefulness was limited by the complexity of the calculations involved. He pointed out that a general polynomial regression equation using non-linear combinations of variables was probably the best multivariate predictor of criterion measures. The equation may be represented as in (1):

$$\Sigma Y_i = \beta_o + \Sigma \beta_i X_i + \Sigma \beta_{ij} X_i X_j + \Sigma \beta_{ijk} X_i X_j X_k + \ldots \quad (1)$$

where,

Y_i is the predicted criterion scores for variable i

X_i is the predictor variable i,

X_j is the predictor variable j, etc.,

and, β_o, β_i, β_j, etc., are the best fitting regression coefficients.

Another solution to the predictability problem was presented in Meehl's (1950) discussion of what seemed a paradoxical prediction phenomenon. Meehl demonstrated that although two binary measures each had a zero correlation with a dichotomous criterion, perfect prediction of the criterion was possible by scoring the patterns of response to the items rather than linearly combining them as would normally be done.

A generalization of the pattern scoring approach was presented by Lubin and Osburn (1957). Given a quantitative criterion, the mean criterion score for those subjects having a particular pattern of responses constituted a least-square error of estimate score. The vector of criterion means was called the configural scale. The approach emphasized the unique assignment of each individual to one pattern. The single, most congruent pattern was then substituted for the original variables as the basis for prediction. The configural scale approach, however, suffered from severe shrinkage in cross-validation.

Horst(1954) prompted considerable interest in a second approach to pattern analysis which was considered a more effective way of scoring a given set of variables. He demonstrated that configural or pattern scores were a straightforward application of a nonlinear combination of measures. Through the use of multivariate polynomial techniques, which had been proposed earlier, individuals could be assigned a multitude of scores, each based on a subpattern. He further suggested that these subpattern scores could then be used with the original variables as a set of predictors for the criterion.

Lunneborg and Lunneborg (1967b) attempted to extend this latter approach to the problem of estimating student success in each of a number of academic areas. They reasoned that ordinary multiple regression techniques provided the means for linearly weighting several measures in the prediction of some attribute or performance. However, this technique fell short of utilizing pattern information because the weights assigned any particular variable remained fixed, independent of the level of other variables. Consequently, new routines were developed to make use of subpattern responses in the multiple regression solution. Nevertheless, the study failed to demonstrate that patterns were any more valid predictors of success than linear functions of the original variables.

In summary, two points can be made: Attempts to improve prediction by nonlinear methods have failed in the past because the pattern relations did no better than linear combinations in prediction of the criterion (Lunneborg and Lunneborg, 1967a,b); nor do the relations tend to hold up from one sample to another (Ghiselli, 1964). It is possible that when single criterion variables are predicted, simple linear combinations of predictor variables will do as good a job as nonlinear combinations of the variables. However, when we are interested in predicting a number of measures of success, other models may provide a better set of predictor variables. One of these models, the nonlinear pattern scoring procedure, is suggested as being appropriate. Consequently, the contribution of pattern analysis toward increased predictability of multiple criteria is worthy of consideration.

CHAPTER III

STATEMENT OF THE PROBLEM

As Horst (1954) has pointed out, the pattern method of scoring tests proposed by Meehl (1950) is a special case of a nonlinear combination of item scores. The formulation of the multivariate polynomial prediction equation yields, in addition to directly measured variables, certain systematically derived products of the original variables. Each of the derived variables represents a possible source of variance not accounted for by variables preceding them. To the extent that traditional approaches fail to yield multiple correlations with criteria as high as the correlations using pattern formulations, can it be said that these derived variables add information?

To demonstrate that pattern analysis procedures increase prediction of differentiated criteria, it is only necessary to present a model which includes derived variables that yield a multiple correlation coefficient higher and as stable as those of other models. When a single criterion is to be predicted, it is probably accurate to assume that simple linear combinations of the variables are the best set of predictors (Lunneborg and Lunneborg, 1967b). When multiple criteria are to be predicted, however, simple linear combinations of the variables may not yield the largest and most stable correlation coefficients. An alternative model using pattern scoring procedures is likely to be the more appropriate for the latter condition.

It is not known whether there will be a significantly greater correlation coefficient for derived variables used in combination with variables preceding them than with derived variables alone, but both should be models which have greater stability when predicting multiple criteria as shown in Figure 1.

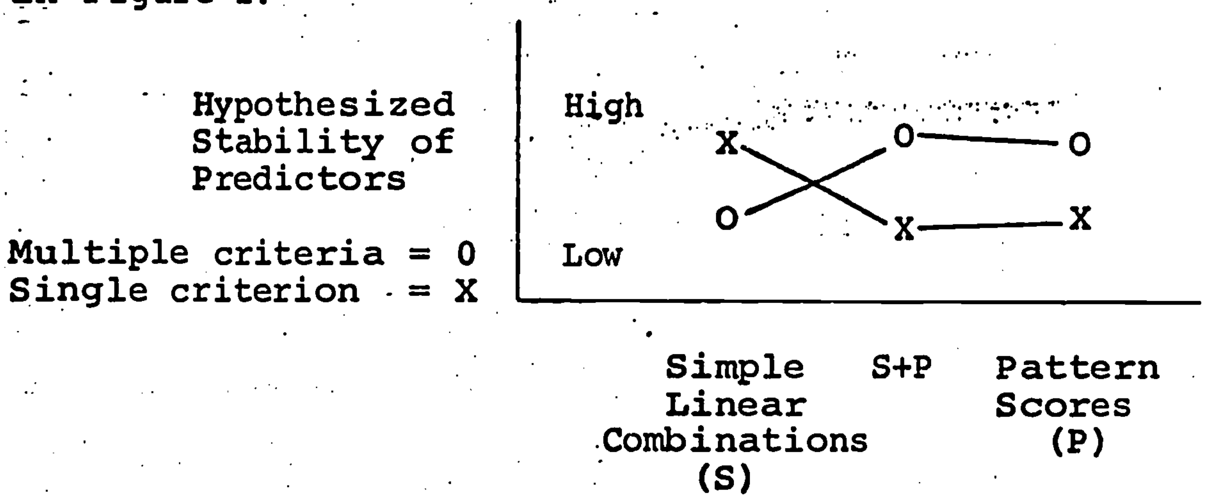

Fig. 1.--Hypothesized stabilities of predictors as a function of criteria to be predicted and predictors

Two predictions are made for the study:

Prediction 1. Simple linear combinations of variables will yield multiple correlation coefficients that are not significantly lower than pattern score variables combined with preceding linear variables when a single criterion of achievement is predicted.

Prediction 2. Derived variables or derived variables used in combination with preceding variables will tend to yield greater correlation coefficients which are more stable than simple linear combinations of variables when multiple criteria of achievement are predicted.

CHAPTER IV

METHOD

Subjects.--Approximately seven hundred, eighth-grade students from four Escambia County, Florida, schools served as subjects. The students, all white, represented a wide-range of social, economic and cultural backgrounds.

Procedure.--Each student was administered the Parent-Child Relations Questionnaire (PCR) (Roe and Siegelman, 1963). Responses were made directly in questionnaire booklets, and subsequently were recorded on machine-scoreable answer sheets. The answer sheets were processed to yield ten scale scores for each subject. These scores served as the variables used in creating the predictors for the study.

Six achievement test scores were obtained for each subject. The achievement scores were the variables used as the criteria for the study. These variables came from the California Achievement Test, Form C, 1957 edition, 1963 norms (Tiegs and Clark, 1957). The six standardized scores represented three areas: Two reading, two arithmetic, and two language achievement.

Analysis of the data.--Derivation of all possible subpatterns of independent variables for the ten PCR scale scores was computationally infeasible. For the ten scores, the total number of patterns possible would have been 2^{10} or 1024 patterns. In order to make the analysis possible, the number of independent variables was reduced using a technique which made the patterns and variables derived practicable for predicting the criteria.

It has been demonstrated that the weights computed when the number of predictor variables is reduced do not undergo as severe shrinkage typical in cross-validation as when any large number of variables entered into a multiple regression analysis (Lunneborg and Lunneborg, 1967b). Therefore, all attempts at the subpattern approach have included techniques for reducing the number of patterns studied (Alf, 1956; Horst, 1957; and Wainwright, 1965). Reduction techniques probably involve the loss of some information, but it has not been considered serious enough to affect the results of the analyses.

To reduce the number of variables and, hence, patterns, the ten scale scores of the PCR were factor analyzed. Using a modified version of the Biomedical Computer Program X-72, designed to produce punched standardized factor scores, three analyses were performed: One on the total group (N=682); one on the males only (N=346); and one on the females only (N=336). Orthogonal rotation yielded three factors with eigenvalues greater than one. The criterion scores for each subject were merged with his factor scores.

The next step in the procedure examined the appropriateness of the data, especially the predictors, for use in the study. Recall the purpose of using derived variables: To increase the size of the multiple correlation coefficient significantly above the one calculated using simple linear combinations of the original variables. Stated mathematically, the prediction formulation for a single criterion using simple linear combinations of say, two variables would be:

$$Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 \qquad (2)$$

And, similarly, for multiple criteria:

$$\lambda_1 Y_1 + \lambda_2 Y_2 = \beta_o + \beta_1 X_1 + \beta_2 X_2 \qquad (3)$$

Now, if the derived predictor variables were multiplicative combinations of the previous variables, the $\underline{Y}$'s would then be predicted by:

$$Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 \; ; \qquad (4)$$

and

$$\lambda_1 Y_1 + \lambda_2 Y_2 = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 \qquad (5)$$

with the assumption being that the interaction term was not zero and contributed a significant effect. To the extent that such an interaction term did not fulfill these requirements, then equations 4 and 5 would be no better than equations 2 and 3 in predicting the criterion. Therefore, to discover whether the data would meet the assumptions needed

for 4 and 5, the three derived PCR factor scores were dichotomized at the mean and cast into a given cell of a 2 X 2 X 2 design. The sums of squares for the main effects, interaction and error were calculated, using each of the six criterion scores as a dependent variable. Significant interactions resulted from the analysis.
Thus, the data were considered appropriate for testing the predictions in the study.

At this step in the procedure, those subjects with missing criteria data were eliminated from the study, leaving a total subject pool of 605 (300 males and 305 females).

All subpatterns of the factor scores were derived using two methods: Multiplication of the factor scores to form derived continuous variables; and dichotomization of the scores at the mean and multiplication of the resulting binary scores to form derived discrete variables. A random selection of half the subjects was made for purposes of cross-validation.

Analysis procedure for single criterion prediction.--The continuous variables (factor scores) and their multiplicative combinations (derived continuous variables) were used to predict each of the single criterion variables in turn employing multiple regression techniques. Using a FORTRAN program, Linear C, analyses were performed for each group (males, females, and total). F tests of significance were conducted to determine the contribution of the various combinations of the variables toward predicting each of the criterion. The formula used to perform these tests is as follows:

$$F_{\alpha;p-m;n-p-1} = \frac{R_F^2 - R_R^2}{1 - R_F^2} \cdot \frac{n-p-1}{p-m} \qquad (6)$$

where, R_F^2 is the multiple correlation coefficient for the full model

R_R^2 is the multiple correlation coefficient for the model containing the variables to be removed

n is the total number of subjects
p is the number of independent variables
and, m is the number of variables removed.

The value of *F* (with p-m and n-p-1 degrees of freedom) obtained was compared with the value in the *F* table with the appropriate α level and degrees of freedom. The calculated *F* values tested the significance of the contribution of the variables which remained in the prediction equation.

The multiple correlations obtained with the original sample data were cross-validated using a method suggested by Bashaw (1966). An estimate of the correlation between the predicted and actual values of each criterion is given by:

$$r_{pa}^2 = \frac{(B'V)^2}{B'RB} \qquad (7)$$

where
B is the vector of beta weights from the original sample

B' is the transpose of B
V is the vector of validity coefficients for the new sample, and
R is the matrix of the intercorrelations of the independent variables for the new sample

The multiple correlations obtained from the cross-validation sample were then compared to the correlation estimated from a shrinkage formula presented in Nunally (1967) for purposes of determining the stability of the weights obtained in the analysis. The formula for estimating the shrinkage is:

$$\hat{R}^2 = 1 - \left[(1 - R^2) \cdot \left(\frac{N - 1}{N - k} \right) \right] \qquad (8)$$

where
$\hat{R}^2$ is the unbiased estimate of the population multiple correlation coefficient
R^2 is the multiple correlation coefficient found in a sample of size N, and
k is the number of independent variables used as predictors

Analysis used in predicting multiple criteria.--The continuous variables and their multiplicative derivatives were used to predict the six criterion variables simultaneously by employing canonical correlation analysis techniques. The computer program used to perform the analyses yielded standardized canonical coefficients and canonical correlations. Three separate analyses were run on each of the three data groups: 1. Using the continuous variables (factor scores) combined with the derived continuous variables; 2. Using the continuous variables only as predictors; and, 3. Using the derived variables only as predictors. Each of the canonical correlation coefficients were tested for significance using Bartlett's (1948) test. The test is a χ^2 goodness-of-fit statistic where,

$$\chi^2_{df} = -C \cdot \log_e(1-\lambda_i) \qquad (9)$$

and, $C = N - \frac{1}{2}(p + q + 1)$

$df = p + q + 1 - 2i$

with,

N = the number of subjects
p = the number of predictor variables
q = the number of criterion variables
and λ_i = eigenvalue extracted at any particular point *i* in the analysis

Based on the results obtained from the tests of significance, the weights associated with the total group analysis were used for purposes of calculating correlation coefficients in cross-validation.

CHAPTER V

RESULTS

Preliminary treatment of the data.--A factor analysis was performed on each of the three groups of data: the male group, the female group and the total of the groups combined. From the ten scale scores, the analysis derived three factors whose eigenvalues were greater than one. A varimax rotation was performed on the three factors and the resulting rotated loadings along with their respective means, standard deviations, and communalities for each of the three groups are reported in Tables 1, 2, and 3.

The loadings after rotation appear to be consistent with those presented by Roe and Siegelman (1963). From these loadings, standardized factor scores were generated for each subject in each group. These factor scores and the resultant nonlinear combinations of the three variables gave a total of seven continuous predictor variables. Each linear variable and nonlinear combination was dichotomized at the mean and scores of 1 or -1 were assigned to each of the seven variables depending on whether the continuous variable was above or below the mean, respectively. These binary scores served as additional predictors for the study. All analyses of the data were computed using variables from this complete

Table 1.--Rotated factor loadings, communalities, means, and standard deviations for scores on the Parent-Child Questionnaire; male analysis only
(N=346)

Variable No.	Factor Loadings I	II	III	H^2	Mean	S.D.
1	.407	.537	.319	.556	38.098	8.493
2	.825	.151	-.024	.704	26.913	7.073
3	.734	-.386	.387	.837	28.702	9.951
4	-.082	.219	.895	.855	40.928	9.364
5	.120	.823	-.052	.694	33.295	7.671
6	.785	.294	.056	.706	43.945	10.839
7	.829	.169	-.169	.744	25.168	8.201
8	-.081	.851	.088	.738	55.176	12.409
9	.597	-.440	.485	.785	25.162	8.294
10	.192	.738	.081	.587	27.249	9.089

Table 2.--Rotated factor loadings, communalities, means, and standard deviations for scores on the Parent-Child Questionnaire; female analysis only
(N=336)

Variable No.	Factor Loadings I	II	III	H^2	Mean	S.D.
1	.293	.664	.332	.637	42.205	9.947
2	.840	.044	-.011	.708	26.735	6.874
3	.835	-.291	.251	.845	27.988	10.465
4	-.062	.213	.912	.881	42.033	9.821
5	.058	.859	-.057	.745	34.110	8.269
6	.796	.322	-.049	.740	43.656	11.059
7	.784	.253	-.264	.749	24.315	8.654
8	-.299	.796	.035	.723	58.949	12.051
9	.683	-.422	.428	.828	25.033	8.799
10	.159	.811	.106	.694	28.545	10.385

Table 3.--Rotated factor loadings, communalities, means, and standard deviations for scores on the Parent-Child Questionnaire; total group pooled analysis (N=682)

Variable No.	Factor Loadings I	II	III	H^2	Mean	S.D.
1	.325	.617	.339	.602	40.122	9.457
2	.831	.095	-.014	.699	26.826	6.971
3	.786	-.341	.323	.841	28.350	10.206
4	-.079	.220	.897	.860	41.472	9.601
5	.093	.842	-.061	.721	33.696	7.976
6	.794	.303	.006	.722	43.804	10.941
7	.811	.204	-.215	.746	24.748	8.432
8	-.188	.828	.062	.724	57.035	12.370
9	.637	-.430	.467	.809	25.098	8.540
10	.176	.777	.094	.645	27.887	9.763

set of information.

Results of the analyses for predicting single criteria.--One of the expected outcomes of the study was that simple linear combinations of the predictor variables would perform as well as these variables combined with nonlinear combinations when a single criterion was to be predicted. In order to demonstrate that such an outcome would occur, each criterion was predicted using original sample data. The contribution of the various combinations of linear and nonlinear variables toward increasing the multiple correlation coefficient between predictors and criterion was then examined.

Two prediction equations were used to generate the multiple R's, and both were used for the continuous and binary variables. They were: 1. A simple linear combination of the three derived factor scores and their respective pattern score equivalents, designated here as variables A, B, and C; and 2. Nonlinear combinations of the variables, given as AB, AC, BC, and ABC. (The binary variables were designated with a ' mark after the variable as in A'.) The full model against which tests of significance of the contributions of the reduced models were performed was a linear combination of the two prediction equations presented above.

Tables 4, 5, and 6 present the tests of significance of the multiple correlation coefficients for the various models.

In all but one instance, the *F* test for significance of the contribution of the model indicated that simple linear combinations of the variables for the original sample data did the best job of predicting the criterion. Thus, it would appear that prediction one is demonstrated.

In addition to substantiating this part of the prediction, it was also possible to examine the stability of the multiple correlation coefficients in cross-validation. To determine the stability of the coefficients, the estimated shrinkage of the multiple *R*'s in cross-validation was computed. Then the actual multiple correlation coefficients for each criterion using the continuous and pattern variables as predictors was calculated for each group.

The results of this analysis may be found in Tables 7, 8, and 9. It may be seen from the tables that the estimated *R*'s due to shrinkage and the calculated *R*'s using the method described by Bashaw (1966) are almost all significantly different from zero, though not always of the same order. Consequently, it would appear that the multiple correlation

Table 4.--Tests of significance of multiple correlation coefficients for male group using original sample data

Source	R^2	F	p
	Criterion 1 - Continuous Variables		
A+B+C	.102	4.931	<.05
AB+AC+BC+ABC	.042	1.220	N.S.
Full model	.132		
	Criterion 1 - Binary Variables		
A'+B'+C'	.076	3.778	<.05
A'B'+A'C'+B'C'+A'B'C'	.060	2.190	N.S.
Full model	.129		
	Criterion 2 - Continuous Variables		
A+B+C	.072	5.100	<.05
AB+AC+BC+ABC	.024	1.864	N.S.
Full model	.119		
	Criterion 2 - Binary Variables		
A'+B'+C'	.059	2.703	<.05
A'B'+A'C'+B'C'+A'B'C'	.043	1.423	N.S.
Full model	.095		
	Criterion 3 - Continuous Variables		
A+B+C	.062	4.871	<.05
AB+AC+BC+ABC	.009	1.543	N.S.
Full model	.101		

Table 4.--Continued

Source	R^2	F	p
Criterion 3 - Binary Variables			
A'+B'+C'	.057	2.667	<.05
A'B'+A'C'+B'C'+A'B'C'	.039	1.290	N.S.
Full model	.090		
Criterion 4 - Continuous Variables			
A+B+C	.048	4.526	<.05
AB+AC+BC+ABC	.025	2.455	<.05
Full model	.110		
Criterion 4 - Binary Variables			
A'+B'+C'	.081	4.270	<.05
A'B'+A'C'+B'C'+A'B'C'	.067	2.639	<.05
Full model	.144		
Criterion 5 - Continuous Variables			
A+B+C	.051	2.868	<.05
AB+AC+BC+ABC	.017	0.847	N.S.
Full model	.073		
Criterion 5 - Binary Variables			
A'+B'+C'	.073	3.371	<.05
A'B'+A'C'+B'C'+A'B'C'	.046	1.452	N.S
Full model	.109		
Criterion 6 - Continuous Variables			
A+B+C	.074	3.565	<.05
AB+AC+BC+ABC	.022	0.664	N.S.
Full model	.091		

Table 4.--Continued

Source	R^2	F	p
	Criterion 6 - Binary Variables		
A'+B'+C'	.065	2.928	<.05
A'B'+A'C'+B'C'+A'B'C'	.035	1.010	N.S.
Full model	.091		

Table 5.--Tests of significance of multiple correlation coefficients for female group using original sample data

Source	R^2	F	p
	Criterion 1 - Continuous Variables		
A+B+C	.131	7.176	<.05
AB+AC+BC+ABC	.038	1.376	N.S.
Full model	.163		
	Criterion 1 - Binary Variables		
A'+B'+C'	.154	9.008	<.05
A'B'+A'C'+B'C'+A'B'C'	.026	0.519	N.S.
Full model	.117		
	Criterion 2 - Continuous Variables		
A+B+C	.154	9.008	<.05
AB+AC+BC+ABC	.021	0.927	N.S.
Full model	.175		
	Criterion 2 - Binary Variables		
A'+B'+C'	.107	5.929	<.05
A'B'+A'C'+B'C'+A'B'C'	.012	0.543	N.S.
Full model	.120		
	Criterion 3 - Continuous Variables		
A+B+C	.046	2.473	<.05
AB+AC+BC+ABC	.020	0.840	N.S.
Full model	.067		
	Criterion 3 - Binary Variables		
A'+B'+C'	.069	3.359	<.05
A'B'+A'C'+B'C'+A'B'C'	.016	0.419	N.S.
Full model	.080		

Table 5.--Continued

Source	R^2	F	p
Criterion 4 - Continuous Variables			
A+B+C	.094	6.116	<.05
AB+AC+BC+ABC	.026	1.746	N.S.
Full model	.136		
Criterion 4 - Binary Variables			
A'+B'+C'	.089	5.355	<.05
A'B'+A'C'+B'C'+A'B'C'	.029	1.497	N.S.
Full model	.125		
Criterion 5 - Continuous Variables			
A+B+C	.049	2.606	<.05
AB+AC+BC+ABC	.057	2.268	.10<p<.05
Full model	.105		
Criterion 5 - Binary Variables			
A'+B'+C'	.053	2.931	<.05
A'B'+A'C'+B'C'+A'B'C'	.034	1.440	N.S.
Full model	.089		
Criterion 6 - Continuous Variables			
A+B+C	.028	1.108	N.S.
AB+AC+BC+ABC	.021	0.562	N.S.
Full model	.043		
Criterion 6 - Binary Variables			
A'+B'+C'	.026	1.255	N.S.
A'B'+A'C'+B'C'+A'B'C'	.011	0.359	N.S.
Full model	.036		

Table 6.--Tests of significance of multiple correlation coefficients for total group using original sample data

Source	R^2	F	p
	Criterion 1 - Continuous Variables		
A+B+C	.099	9.052	<.05
AB+AC+BC+ABC	.032	1.212	N.S.
Full model	.114		
	Criterion 1 - Binary Variables		
A'+B'+C'	.056	6.132	<.05
A'B'+A'C'+B'C'+A'B'C'	.014	1.315	N.S.
Full model	.072		
	Criterion 2 - Continuous Variables		
A+B+C	.082	8.372	<.05
AB+AC+BC+ABC	.019	1.158	N.S.
Full model	.096		
	Criterion 2 - Binary Variables		
A'+B'+C'	.061	6.251	<.05
A'B'+A'C'+B'C'+A'B'C'	.020	1.477	N.S.
Full model	.079		
	Criterion 3 - Continuous Variables		
A+B+C	.049	5.605	<.05
AB+AC+BC+ABC	.012	1.280	N.S.
Full model	.065		
	Criterion 3 - Binary Variables		
A'+B'+C'	.041	3.925	<.05
A'B'+A'C'+B'C'+A'B'C'	.015	0.961	N.S.
Full model	.053		

Table 6.--Continued

Source	R^2	F	p
	Criterion 4 - Continuous Variables		
A+B+C	.039	6.357	<.05
AB+AC+BC+ABC	.006	2.209	.10<p<.05
Full model	.067		
	Criterion 4 - Binary Variables		
A'+B'+C'	.043	4.337	<.05
A'B'+A'C'+B'C'+A'B'C'	.009	0.593	N.S.
Full model	.051		
	Criterion 5 - Continuous Variables		
A+B+C	.037	5.667	<.05
AB+AC+BC+ABC	.012	2.241	.10<p<.05
Full model	.066		
	Criterion 5 - Binary Variables		
A'+B'+C'	.035	3.611	<.05
A'B'+A'C'+B'C'+A'B'C'	.006	0.458	N.S.
Full model	.041		
	Criterion 6 - Continuous Variables		
A+B+C	.044	4.374	<.05
AB+AC+BC+ABC	.013	0.859	N.S.
Full model	.055		
	Criterion 6 - Binary Variables		
A'+B'+C'	.036	3.692	<.05
A'B'+A'C'+B'C'+A'B'C'	.022	1.711	N.S.
Full model	.058		

Table 7.--Multiple regression correlation coefficients, estimated shrinkage of coefficients in cross-validation, and correlation coefficients of cross-validation sample used to predict single criterion for male subject pool

Criterion No.	Original Sample R^2	Estimated R^2 Due to Shrinkage	Cross-validation Sample R^2	R_c^*
Continuous variables used as predictors				
1	.132	.096	.061	.247
2	.119	.082	.057	.238
3	.101	.063	.098	.312
4	.110	.072	.031	.175
5	.073	.034	.061	.296
6	.091	.089	.039	.199
N = 150				
Binary variables used as predictors				
1	.129	.093	.040	.200
2	.095	.057	.066	.257
3	.090	.052	.054	.233
4	.144	.108	.030	.172
5	.109	.072	.051	.225
6	.091	.053	.087	.223
N = 150				

*R_c is the square root of the calculated R^2 from the cross-validation sample. All R_c's are significantly different from zero at $p < .05$.

Table 8.--Multiple regression correlation coefficients, estimated shrinkage of coefficients in cross-validation, and correlation coefficients of cross-validation sample used to predict single criterion for female subject pool

Criterion No.	Original Sample R^2	Estimated R^2 Due to Shrinkage	Cross-validation Sample R^2	R_c^*
		Continuous variables used as predictors		
1	.163	.122	.116	.340
2	.175	.135	.078	.279
3	.067	.022	.043	.207
4	.136	.094	.023	.152 (N.S.)
5	.105	.062	.036	.188
6	.043	-.003	.041	.202
N = 153				
		Binary variables used as predictors		
1	.117	.074	.054	.232
2	.120	.078	.031	.177
3	.080	.035	.046	.214
4	.125	.083	.068	.261
5	.089	.045	.041	.203
6	.036	-.011	.029	.170
N = 152				

*R_c is the square root of the calculated R^2 from the cross-validation sample. All R_c's are significantly different from zero at $p <.05$, except where noted.

Table 9.--Multiple regression correlation coefficients, estimated shrinkage of coefficients in cross-validation, and correlation coefficients of cross-validation sample used to predict single criterion for total subject pool

Criterion No.	Original Sample R^2	Estimated R^2 Due to Shrinkage	Cross-validation Sample R^2	R_c^*
		Continuous variables used as predictors		
1	.114	.096	.108	.328
2	.096	.078	.094	.307
3	.065	.046	.069	.263
4	.067	.048	.053	.230
5	.066	.047	.051	.226
6	.055	.036	.043	.208
N = 302				
		Binary variables used as predictors		
1	.072	.053	.101	.319
2	.079	.060	.058	.241
3	.053	.034	.067	.248
4	.051	.031	.088	.296
5	.041	.022	.091	.302
6	.058	.039	.026	.160
N = 303				

*R_c is the square root of the calculated R^2 from the cross-validation sample. All R_c's are significantly different from zero at $p < .05$.

coefficients computed from the original sample data are stable in cross-validation.

Results of the analyses for predicting multiple criteria.--The study also proposed to examine the prediction stated that nonlinear combinations of variables when combined with simple linear combinations of predictor variables would yield a higher correlation coefficient when predicting multiple criteria than when simple linear combinations of the independent variables are used alone in making predictions. To demonstrate this, the continuous variables for the original sample data and their corresponding nonlinear combinations were used as predictors for all six criteria. A canonical analysis of the data was performed on all three groups using first all seven predictors, then only the three simple linear variables, and only the four nonlinear variables as predictors. The means, standard deviations, canonical coefficients, and canonical correlation coefficients for the various analyses are presented in Tables 10-18.

To test the significance of the canonical correlation coefficients for each set of canonical coefficients, the study employed Bartlett's (1948) test. The results of the tests are also presented in the tables. Of particular interest were the significant correlations found for the analysis of the total group of subjects in the original data set. Table 12 shows that when all seven variables are used as predictors, there are three canonical correlation

Table 10.--Means, standard deviations, and standardized canonical correlation coefficients for factor scores and derived variables used in predicting multiple criteria for original sample data male subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients					
Factor Scores			1	2	3	4	5	6
1	-.012	1.023	-.666	-.150	-.333	-.015	.077	-.060
2	-.064	1.026	.473	.098	-.269	.099	-.391	.013
3	-.065	0.974	-.123	.547	-.158	-.230	-.062	.085
4	.014	1.631	-.584	.006	-.442	.075	-.136	.181
5	.066	0.976	.169	.262	-.389	.217	.444	.072
6	-.034	0.989	.127	-.283	-.044	-.387	.145	.172
7	-.290	1.290	-.080	-.045	.273	.134	.438	.367
Criterion Scores								
1	49.427	10.003	.325	-.687	-.464	-.366	.261	-.486
2	49.433	10.313	.620	.583	-.541	.185	-.278	.294
3	49.907	9.532	-.221	-.042	.521	.637	-.101	-.513
4	43.667	9.488	.534	.130	.438	-.602	-.078	-.001
5	47.173	9.706	-.292	.065	.098	.251	.734	.505
6	48.007	11.333	-.302	-.047	.139	-.014	-.546	.400
Canonical Correlation			.379	.369	.241	.191	.110	.080
Bartlett's χ^2/df test of significance of canonical correlation coefficients			1.853*	2.090*	1.068	0.874	0.432	0.430

N = 150

*Indicates the canonical correlation coefficient is significant at $p < .05$.

Table 11.--Means, standard deviations, and standardized canonical correlation coefficients for factor scores and derived variables used for predicting multiple criteria for original sample data female subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients					
Factor Scores			1	2	3	4	5	6
1	-.082	0.981	-.398	-.040	.162	-.179	.186	-.134
2	.026	0.981	-.148	.042	-.435	.199	-.434	-.261
3	.054	1.046	-.594	.013	-.096	-.083	.018	.249
4	.078	1.530	-.169	-.183	.222	.029	-.218	.355
5	-.046	1.111	-.103	.773	-.099	-.047	-.148	.141
6	-.032	1.219	-.139	-.049	-.555	.114	.512	.065
7	-.288	1.806	-.086	.606	.405	.344	.265	.020
Criterion Scores								
1	49.909	9.320	.587	.437	-.218	-.714	-.043	.264
2	51.052	10.304	.508	.220	.088	.555	.519	-.199
3	48.536	9.653	-.333	.121	-.189	-.130	-.314	-.835
4	44.327	10.695	.274	-.272	.659	.175	-.545	.359
5	53.118	8.368	-.208	-.819	-.238	-.094	.441	.089
6	51.824	10.058	-.409	.035	-.647	.356	-.372	.237
Canonical Correlation			.544	.274	.193	.127	.113	.020
Bartlett's χ^2/df test of significance of canonical correlation coefficients			4.270*	1.138	0.688	0.392	0.478	0.073
N = 153								

*Indicates the canonical correlation coefficient is significant at $p < .05$.

Table 12.--Means, standard deviations, and standardized canonical correlation coefficients for factor scores and derived variables used for predicting multiple criteria for original sample data total subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients					
Factor Scores			1	2	3	4	5	6
1	-.007	0.975	-.575	.032	-.485	-.253	.044	-.092
2	-.010	1.010	.188	-.323	.072	.013	-.066	-.390
3	-.001	1.024	-.543	-.331	.058	.211	.025	-.095
4	-.002	1.392	.006	-.246	-.591	-.011	-.218	.044
5	-.003	1.191	.045	.347	-.074	.466	-.012	-.391
6	-.045	1.230	-.144	-.157	-.166	.043	.498	.091
7	-.363	2.062	-.220	.289	-.035	.475	-.110	.109
Criterion Scores								
1	49.967	9.963	.815	.152	-.638	-.499	-.090	.184
2	50.967	9.988	.446	-.484	.019	.511	-.345	-.411
3	49.702	9.808	-.245	.520	-.198	.464	.674	-.130
4	44.616	10.178	.074	.428	.406	-.044	-.560	.389
5	50.142	9.750	-.157	-.015	.582	-.503	.230	-.517
6	49.487	10.977	-.215	-.537	.224	.144	.228	.602
Canonical Correlation			.361	.221	.200	.109	.077	.043
Bartlett's χ^2/df test of significance of canonical correlation coefficients			3.424*	1.482*	1.505*	1.094	0.444	0.295
N = 302								

*Indicates the canonical correlation coefficient is significant at $p < .05$.

Table 13.--Means, standard deviations, and standardized canonical correlation coefficients for factor scores only used for predicting multiple criteria for original sample data male subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients		
Factor Scores			1	2	3
1	-.012	1.023	-.034	-.587	-.283
2	-.064	1.026	.134	.307	-.533
3	-.065	0.974	-.784	.125	-.080
Criterion Scores					
1	49.427	10.003	.813	-.190	.138
2	49.433	10.313	-.309	.776	-.693
3	49.907	9.532	.195	-.253	.078
4	43.667	9.488	-.295	.488	.548
5	47.173	9.706	-.084	-.167	.357
6	48.007	11.333	.336	-.179	-.258
Canonical Correlation			.341	.250	.110
Bartlett's χ^2/df test of significance of canonical correlation coefficients			2.235*	1.547*	0.438
N = 150					

*Indicates the canonical correlation coefficient is significant at $p < .05$.

Table 14.--Means, standard deviations, and standardized canonical correlation coefficients for factor scores only used for predicting multiple criteria for original sample data female subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients		
Factor Scores			1	2	3
1	-.082	0.981	-.295	-.353	-.370
2	.026	0.981	-.211	.604	-.162
3	-.054	1.046	-.533	-.062	.276
Criterion Scores					
1	49.909	9.320	.590	-.572	-.353
2	51.052	10.304	.532	.167	-.108
3	48.536	9.653	-.337	.123	-.512
4	44.327	10.695	.237	.115	.483
5	53.118	8.368	-.228	-.056	.607
6	51.824	10.058	-.383	.783	-.028
Canonical Correlation			.510	.137	.035
Bartlett's χ^2/df test of significance of canonical correlation coefficients			5.583*	0.498	0.047
N = 153					

*Indicates the canonical correlation coefficient is significant at $p < .05$.

Table 15.--Means, standard deviations, and standardized canonical correlation coefficients for factor scores only used for predicting multiple criteria for original sample data total subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients		
Factor Scores			1	2	3
1	-.007	0.975	-.550	.269	-.375
2	-.010	1.010	-.104	-.374	-.518
3	-.001	1.024	-.552	-.354	.248
Criterion Scores					
1	49.967	9.963	.817	.444	-.708
2	50.967	9.988	.453	-.561	-.009
3	49.702	9.808	-.195	.412	.325
4	44.616	10.178	.033	.226	.582
5	50.142	9.750	-.243	-.081	.046
6	49.487	10.977	-.174	-.510	.226
Canonical Correlation			.341	.199	.090
Bartlett's χ^2/df test of significance of canonical correlation coefficients			4.578*	2.021*	0.596
N = 302					

*Indicates the canonical correlation coefficient is significant at $p <.05$.

Table 16.--Means, standard deviations, and standardized canonical correlation coefficients for derived continuous variable scores used for predicting multiple criteria for original sample data male subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients			
Derived Scores			1	2	3	4
1	-.014	1.681	.063	.005	-.824	.036
2	-.066	0.976	.072	-.672	.016	.203
3	-.034	0.989	-.467	.141	.280	.201
4	-.290	1.290	.111	-.140	.435	.613
Criterion Scores						
1	49.427	10.003	-.737	-.060	-.111	-.489
2	49.433	10.313	.082	-.722	-.206	.123
3	49.907	9.532	.533	.101	.115	-.164
4	43.667	9.488	-.328	.239	.896	-.176
5	47.173	9.706	.232	-.212	-.056	.770
6	48.007	11.333	-.062	.603	-.355	.309
Canonical Correlation			.272	.209	.153	.086
Bartlett's χ^2/df test of significance of canonical correlation coefficients			1.234*	0.929	0.673	0.338
N = 150						

*Indicates the canonical correlation coefficient is significant at $p < .05$.

Table 17.--Means, standard deviations, and standardized canonical correlation coefficients for derived continuous variable scores used for predicting multiple criteria for original sample data female subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients			
Derived Scores			1	2	3	4
1	.078	1.530	.164	-.047	-.183	-.636
2	-.046	1.111	-.761	.120	-.099	-.154
3	-.032	1.219	.049	.436	.531	.038
4	-.288	1.806	-.613	-.524	.327	-.084
Criterion Scores						
1	49.909	9.320	-.448	.899	-.595	.282
2	51.052	10.034	-.227	.112	.443	-.382
3	48.536	9.653	-.109	-.096	-.068	.261
4	44.327	10.695	.264	-.403	-.473	-.636
5	53.118	8.368	.816	.089	.290	.402
6	51.824	10.058	-.003	.006	.370	-.375
Canonical Correlation			.273	.205	.138	.075
Bartlett's χ^2/df test of significance of canonical correlation coefficients			1.278*	0.904	0.566	0.296
N = 153						

*Indicates the canonical correlation coefficient is significant at $p < .05$.

Table 18.--Means, standard deviations, and standardized canonical correlation coefficients for derived continuous variable scores used for predicting multiple criteria for original sample data total subject pool

Variable No.	Mean	Standard Deviation	Canonical Coefficients			
			1	2	3	4
Derived Scores						
1	-.002	1.392	-.546	.048	-.163	-.264
2	-.003	1.191	.104	.758	.004	.046
3	-.049	1.230	-.174	-.092	.024	.468
4	-.363	2.062	.314	.427	-.658	.077
Criterion Scores						
1	49.967	9.963	-.720	.166	.310	-.256
2	50.967	9.988	-.436	-.014	-.317	-.193
3	49.702	9.808	.208	.687	-.031	.705
4	44.616	10.178	.323	.123	.202	-.544
5	50.142	9.750	.379	-.436	.784	.083
6	49.487	10.977	.011	-.543	-.383	.313
Canonical Correlation			.247	.158	.109	.075
Bartlett's χ^2/df test of significance of canonical correlation coefficients			2.074*	1.073*	0.716	0.595
N = 302						

*Indicates the canonical correlation coefficient is significant at $p < .05$.

coefficients which are significantly different from zero. When the simple linear combination of the variables is used as the predictor model (See Table 15.), two of the canonical correlation coefficients were found to be significantly different from zero. This finding also resulted when the model for prediction was a nonlinear combination of the variables, as in Table 18.

The purpose of these tests was to establish a basis for testing the various models to determine if the simple linear model was as effective in predicting the criteria as a combination of the linear and nonlinear variables. To show that one of the models was more appropriate than the other, the full model (simple linear variables and nonlinear variables combined) canonical regression coefficients were used in calculating correlation coefficients with the cross-validation sample. The same operation was performed on the cross-validation data using the regression coefficients of the model containing only the linear predictor variables. A correlation coefficient for the first and second set of regression coefficients using the full model, and the first set of regression coefficients only for the reduced model which was significantly different from zero would be considered sufficient evidence that the nonlinear variables were contributing to increasing the correlation, and thus, the predictability of multiple criteria.

Results of these computations are presented in Table 19. For the full model and the simple linear model ,

Table 19.--Cross-validation correlation coefficients using canonical coefficient sets predicting multiple criteria for the total group of subjects with the continuous variables and derived variables

	r	p
Continuous and derived variables as predictors (7 predictors)		
1st set of coefficients	.281	<.05
2nd set of coefficients	-.043	N.S.
3rd set of coefficients	-.018	N.S.
Continuous variables as only predictors (3 predictors)		
1st set of coefficients	.304	<.05
2nd set of coefficients	-.004	N.S.

only the first set of coefficients produced a correlation coefficient significantly different from zero. Consequently, it would appear that a simple linear combination of variables would do as good a job of predicting this multiple criteria set.

CHAPTER VI

DISCUSSION

Two experimental predictions were made about models for improving the prediction of single and multiple criteria. The results of the data analyses appear to support the prediction that simple linear combinations of variables do as good a job of predicting a single achievement criterion as nonlinear combinations of the variables. When put together with findings by Lunneborg and Lunneborg (1967b), Alf (1956), and others, it would seem that attempts to predict single criterion with more than simple linear combinations of variables have met with little or no success. Consequently, further research in this area would appear to be unwarranted.

When predicting multiple criteria, however, there would seem to be grounds for further exploration toward improving the prediction model. The results obtained in the present study might lead one to conclude that simple linear combinations of the variables were performing as the best predictors of the criteria. However, it might be premature to generalize this finding to other sets of predictors for other criteria.

The six achievement test scale scores were factor analyzed to determine if there was more than one factor actually contained in these dependent variables. Results of the analysis and varimax rotation extracted only one general factor which could be used to account for the criteria. Table 20 presents the results of the analysis.

This finding suggests that a single, composite score might have substituted for all six scores. Thus, the model appropriate for the prediction of single criterion probably would have been sufficient. The results of the analyses seem to bear out this assumption.

However, if one were concerned with multifactor measures of success it would seem possible that the prediction model for this set of variables might prove useful. Such measures might also be noncognitive in nature. Though not as easily predicted as grade-point average or achievement, these noncognitive criteria of success might provide information not normally obtained by our present assessment methods. To the extent that the prediction model increased the predictability of the criteria, it would appear useful in helping researchers reach more reliable decisions.

An example of noncognitive variables which might be used may be found in a study by Stakenas (1970). Multiple criteria were measured, but examined one at a time. Evidence was presented that the three suprascales (a developmental scale, a satisfaction scale, and an involvment scale) were measured by success on a number of subscales in each suprascale. Use of the model to increase the predictability of

Table 20.--Factor loadings, communalities, means, and standard deviations of criterion variables for total group of subjects

Criterion Variable Number	Factor Loading	H^2	Mean	S.D.
1	.870	.756	50.048	9.706
2	.872	.760	50.757	9.867
3	.879	.772	49.397	9.632
4	.838	.703	44.236	10.028
5	.857	.734	50.595	9.641
6	.797	.635	59.473	11.396
N = 605				

the various subscales at once would appear to be a useful application for future examination of its appropriateness.

CHAPTER VII

SUMMARY AND CONCLUSIONS

This study examined models for improving prediction of single and multiple criteria. Two predictions were made: 1. Simple linear combinations of predictor variables would perform as well predicting single criterion as would non-linear combinations of the variables. 2. Linear and non-linear combinations of predictor variables would yield the highest correlation with multiple criteria.

The results of the study support the first prediction. Taken together with outcomes of other efforts, it would seem that further attempts at trying to improve prediction of single criterion by other than linear models is unwarranted.

For predicting multiple criteria, the most appropriate model seemed to also be simple linear combinations of the predictor variables. However, based on results of a factor analysis of the criterion variables, one composite score (or a single criterion) could have been substituted for the six criteria. Consequently, it is suggested that when a number of measures, multifactor in nature are to be predicted, the model used in this study may indeed be appropriate for improving predictability.

If the multiple criteria are linearly related, it may well be that the best prediction of these criteria will rise from a simple linear combination of the predictors. If the multiple criteria include cognitive and noncognitive variables which exhibit nonlinear relationships, then further investigation is needed to determine whether the linear or nonlinear model is most appropriate for predicting the criteria.

REFERENCES

Alf, E. E. Configural scoring and prediction. Unpublished doctoral dissertation, University of Washington, 1956.

Bartlett, M. S. Internal and external factor analysis. Brit. Journ. Psychol. (Statistical Section), 1948, 1 (Part II), 73-81.

Bashaw, W. L. The application of regression weights to new data. J. Exp. Educ., 1966, 34, 69-70.

Cronbach, L. J. Essentials of Psychological Testing. New York: Harper & Row, Publishers, 1970, 3rd edition.

Ghiselli, E. E. (Comment.) Personnel Psychol., 1964, 17, 61-63.

Horst, P. et al. The prediction of personal adjustment. Soc. Sci. Res. Counc. Bull., 1941, 48.

Horst, P. Pattern analysis and configural scoring. J. Clinical Psychol., 1954, 10, 3-11.

Horst, P. The uniqueness of configural test item scores. J. Clinical Psychol., 1957, 13, 107-114.

Lubin, A. and Osburn, H. G. A theory of pattern analysis for the prediction of quantitative criterion. Psychometrika, 1957, 22, 63-73.

Lunneborg, C. E. and Lunneborg, P. W. EPPS patterns in the prediction of academic achievement. J. Counseling Psychol., 1967a, 14, 389-390.

Lunneborg, C. E. and Lunneborg, P. W. Pattern prediction of academic success. Educ. and Psychol. Meas., 1967b, 27, 945-952.

Meehl, P. E. Configural scoring. J. Consult. Psychol., 1950, 14, 165-171.

Nunnally, J. C. Psychometric Theory. New York: McGraw-Hill Book Company, 1967.

Roe, A. and Siegelman, M. A parent-child relations questionnaire. Child Development, 1963, 34, 355-369.

Stakenas, R. G. Student-faculty contact and attitude change: Results of an experimental program for college freshman. Paper presented at American Educational Research Association Annual Convention, Minneapolis, 1970.

Tiegs, E. and Clark, W. California Achievement Test. Monterey, California: California Test Bureau, 1957.

Tyler, L. E. The Psychology of Human Differences. New York: Appleton-Century-Crofts, Inc., 1956, 2nd edition.

Wainwright, G. E. Configural information in item responses. Unpublished doctoral dissertation, University of Washington, 1965.