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IDENTIFICATION OF MODERATOR VARIABLES BY DISCRIMINANT ANALYSIS IN A MULTI-PREDICTABLE GROUP VALIDATION MODEL

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ABSTRACT

A moderator variable is a quantitative or qualitative variable which improves the usefulness of a predictor by isolating subgroups of individuals for whom a predictor or set of regression weights is especially appropriate. Sequential prediction techniques have been used to determine the existence of moderator variables. Two problems exist with the present moderator variable techniques: (1) differences between unpredicted individuals (overpredicted and underpredicted individuals) generally have been ignored, and (2) there is no efficient objective method available that readily identifies moderator variables.

The purpose of this dissertation was to use a discriminant analysis procedure for the systematic identification of moderator variables in a multi-predictable group validation (MPGV) model. "Prediction" groups; i.e., groups differing in degree of predictability, in MPGV were formed based on the algebraic difference scores between standardized criterion and standardized predictor scores. In addition, results from MPGV were compared to those of simple algebraic (±D) and absolute difference (/D/) techniques.

Seven problems differing in *a priori* intervals for "prediction" groups (underpredicted, predicted, and overpredicted) and/or number of levels of underpredicted and overpredicted individuals were analyzed. Subjects were 418 undergraduate students randomly assigned to the experimental group, Sample A (N=209), and to the cross-validation group, Sample B (N=209). The predictor was the composite score on the American College Test (ACT) and the criterion was grade point average (GPA). Seventeen variables, including personality and intelligence measures, were investigated as potential moderator variables.

In 6 of 7 problems the one-way multivariate analysis of variance (MANOVA), with the 17 potential moderator variables as the dependent vector variable, indicated a significant ($p < .01$ in each case) "prediction" group main effect. To identify potential moderators, the discriminant function (with standardized coefficients) provided by MANOVA for each problem was analyzed by stepwise multivariate analyses of covariance (MANOCOVA). The initial MANOCOVA treated the variable associated with the highest coefficient as the covariate and the remaining 16 as dependent. Succeeding MANOCOVA's added the variable with the next highest weight to the set of covariates. The procedure was repeated until

the dependent set did not result in a significant main effect. Results of the MANOCOVA's revealed different moderators for the different problems.

Assessment of the effectiveness of the moderator in discriminating "prediction" groups was based on two techniques for classifications of Ss. First, Ss in Sample B were placed into "prediction" groups according to the correspondence of their discriminant scores with the cutoff discriminant scores established in Sample A. Second, a chi-square classification technique (Cooley & Lohnes, 1962) provided for placement of Ss in Sample B into a group depending on the deviation of their discriminant scores from the appropriate group mean discriminant score determined in Sample A. Results of both classification techniques revealed significant amounts of misclassification.

To assess the effectiveness of the moderators on validity, validity coefficients of ACT were computed for each "prediction" group in Sample B. The correlation coefficients for the different "prediction" groups in Sample B were not significantly higher than the coefficient (.52, $p < .01$) for the total group in Sample A.

The $\pm D$ and /D/ techniques, in Sample A, revealed moderators different from each other and from those of MPGV. The results were not substantiated in Sample B.

Problems in the use of discriminant analysis for the purpose of identifying moderator variables are discussed. In addition, the psychological composition of underpredicted, predicted, and overpredicted groups was examined in the light of the importance of maintaining differences between unpredicted groups. Suggestions are offered for future research.

To The Memory Of My Father

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IDENTIFICATION OF MODERATOR VARIABLES BY DISCRIMINANT ANALYSIS IN A MULTI-PREDICTABLE GROUP VALIDATION MODEL

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In an effort to increase predictive efficiency, investigators have modified the classic prediction model. In particular, Dunnette's (1963) model gives considerable attention to interactions which may occur between several factors - predictors, individuals, behaviors in the situation, and consequences of these behaviors relative to the goals of the group. The classic validation model provides a simple index of the relationship between predictor and criterion, whereas Dunnette's model implies that prediction and understanding of the situation are increased by examining the operation of the above-named factors in given situations. In Dunnette's model, it is necessary to identify relatively homogeneous subsets of predictors, individuals, behaviors, and situations in an examination of the interactions between predictors and criteria. This dissertation concerns a systematic identification of homogeneous subsets of individuals in a multi-predictable group validation model.

Review of the Literature

The basic approach to the identification of homogeneous sets of individuals has involved the discovery and use of moderator variables. Banas (1964) defined a general "moderator variable" as a quantitative or qualitative variable which improves the usefulness of a predictor by isolating subgroups of individuals for whom a predictor or set of regression weights are especially appropriate. More specific definitions of such variables are:

<u>Population control variable</u> (Gaylord & Carroll, 1948): A variable which identifies subpopulations in which the application of a multiple regression equation, optimal for the entire population, is inappropriate. A multiple regression equation is derived which includes cross products of the variables in a multivariate analysis. The assumption is that any variable in the analysis may have population control as well as predictor effects.

<u>Moderator variable</u> (Saunders, 1955, 1956): A continuous variable which influences the predictive effectiveness of the predictor variable. A multivariate curvilinear regression equation involving cross products is used in which the beta weights, instead of being constant, are linear functions of moderator variables.

<u>Predictability variable</u> (Ghiselli, 1956, 1960c): A variable which is correlated with an absolute difference score between standardized predictor and

standardized criterion scores. The predictability variable identifies those subjects in the sample who deviate from the line of relations (regression line) and for whom the predictor is inappropriate.

Referent variable (Toops, 1959): A variable which modifies the meaning of other variables. The weight of a predictor variable is not constant, but rather a mathematical function of a referent variable. Toops proposed analyzing relationships in terms of homogeneous groups or "ulstriths," the members of which tend to behave in a similar manner.

Modifier variable (Grooms & Endler, 1960): An independent variable which when dichotomized or trichotomized leads to differential subgroup relationships between a predictor and a criterion variable. A modifier variable is not to be confused with Saunders' (1956) moderator variable which is a continuous independent variable that influences the relationship between another independent variable and a dependent variable.

The common meaning emerging from the alternative definitions is the notion of dividing a heterogeneous population into homogeneous subgroups on the basis of the variables affecting the relationship between predictor and criterion. Thus, the definitions imply some form of interaction among variables. Another implication is that homogeneous subgroups, showing differential patterns of validity, may be isolated.

Techniques involving sequential prediction have been used to determine the existence of moderator variables. In particular, prediction techniques involving subgroup analysis, differential prediction of predictability, moderated regression, and recently, quadrant analysis, have been used. These techniques involve the prediction of future behavior only after some preliminary prediction or measurement for purposes of classification is made (Guion, 1965).

Sequential Prediction Techniques

Subgroup analysis. The technique of subgroup analysis has been investigated in studies pertaining to education as early as 1926 when Scates found that grades of college students graduated from certain high schools were more predictable than others. Similar results were obtained by Wagner and Strabel (1935).

In a frequently cited study of subgroup analysis, Frederiksen and Melville (1954) hypothesized that the usefulness of an interest test can be improved by identifying subgroups of engineering students for whom the test was especially appropriate as a predictor; specifically, the usefulness of interest measures would be limited to a relatively noncompulsive group. A measure of reading speed and an unspeeded vocabulary test were used to identify compulsive and noncompulsive subjects. In 5 of 10 interest scales on the Strong Vocational Interest Blank, correlations between interest scores and grade point averages were significantly higher for the noncompulsive group than for the compulsive group. One replication by Frederiksen and Gilbert (1960) yielded similar results, but only for the occupational keys most logically related to engineering.

The above-mentioned compulsivity studies were conducted with male engineering students. Stricker (1966) examined the generality of the findings with liberal arts and science students of both sexes. Results indicated that the compulsivity scales were not operating as moderators in this population.

Additional studies in which subgroup analyses were attempted demonstrate the diverse characteristics of moderator variables. Personality variables such as personal adjustment (Hoyt & Norman, 1954; Stagner, 1933) and anxiety (Grooms & Endler, 1960; Pervin, 1967), used as bases for subgrouping, have resulted in differential validities for various predictor-criterion combinations. Self-report personality variables, particularly with respect to motivation, have also afforded meaningful subgrouping and differential predictive validities of academic predictors

(Brown, 1968).

Other variables which have shown subgrouping or moderating characteristics include demographic factors, biographical information blanks (Baker, 1967; Medvedeff, 1964; Rock, 1965; Tesser, Starry, & Chaney, 1967), problem-solving styles (French, 1961b), knowledge and aptitude tests (Pervin, 1967; Steinemann, 1964), and job characteristics (Peterson, 1964). Job satisfaction operated as a moderator in a study by Dawis, Weiss, Lofquist, and Betz (1967). Banas and Moore (1968) demonstrated, however, that there were no differences between validity patterns for subgroups which were randomly formed and those which were based on job satisfaction scores. The latter study indicated the necessity for cross-validation of results in moderator research.

Berdie (1961) used a measure of intra-individual variability (scores on 10 mathematics subtests) as a basis for subgrouping. The hypothesis was that first year engineering students whose variability of behavior was greater while taking a test used for predictive purposes would be less predictable than persons whose behavior was less variable. Results indicated that the low variance group was more predictable than the high variance group, but only for the group having the high test scores.

<u>Saunders' (1955, 1956) moderated multiple regression</u>.

The moderator variable is a means of maintaining the integrity of the total population while still maintaining a statistical control on each individual's membership in one of a continuous, infinite series of subpopulations defined by his score on the moderator (Saunders, 1955). Saunders (1956) treats the cross product of the moderator and predictor scores as a new predictor in any standard multiple regression technique. The regression equation is: $y = \bar{y} + \Sigma a_i x_i + \Sigma b_j z_j + \Sigma c_{ij} x_i z_j$, where a, b, and c are weights, x_i the predictors, and z_j the moderators.

Saunders (1956) reanalyzed the Frederiksen and Melville (1954) data using the moderated regression technique. In 5 of 10 comparisons, moderated regression resulted in increases in predictive validity over the multiple correlation method.

Parrish (1959) compared the predictive efficiency of the moderated regression technique with that of the linear multiple regression method. Aptitude, interest, and personality scales were used as predictors and combat efficiency ratings were used as a criterion. Results indicated that the moderated regression technique was not more effective than the linear multiple regression analysis.

Kirkpatrick, Ewen, Barrett, and Katzell (1968) investigated "race" and "cultural deprivation," measured by factor scores, as moderators of success in various occupations. The data did not support their hypothesis that tests are differentially valid for different ethnic groups.

Cleary (1966) presented a generalized moderated regression technique which allows individual differences to emerge without the constraints of a priori conceptions. One set of weights is derived for each person and a second set for each predictor. The two sets of weights are combined into a composite weight for each dimension in the combined predictor-criterion matrix. This individual differences model showed improvement of prediction over the regular multiple regression technique.

Differential predictability. Ghiselli's (1956, 1960c) technique involves obtaining absolute difference scores (/D/) between standardized criterion (Z_c) and standardized predictor (Z_p) scores. Algebraic difference scores are not used since the model is concerned with accuracy of prediction and overprediction and underprediction of the same degree are considered equal errors. The magnitude of /D/ serves as an index of predictability; the smaller the /D/, the better the relation between criterion and predictor. Figure 1 illustrates the concept. The performance of A, an individual close to the line of relations (line of perfect correlation) is more predictable than that of an individual farther away, B.

Correlates of the /D/ scores are subsequently identified and used as "predictors of predictability." A high

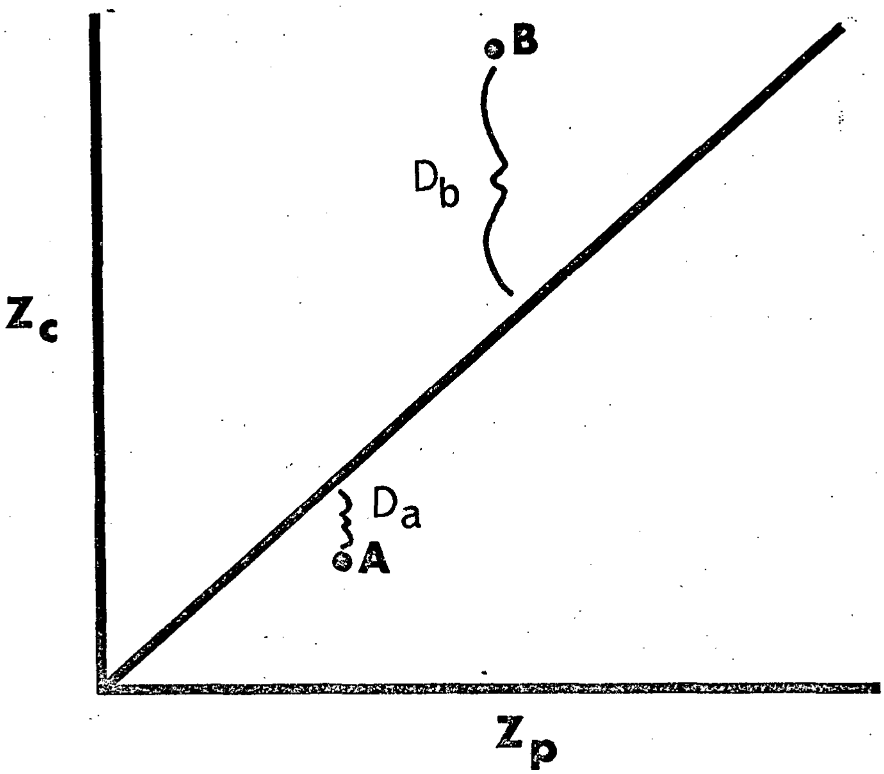

Fig. 1. Determination of /D/ values as indices of the predictability of performance.

positive correlation indicates that the validity should be higher for those scoring low on the "predictor of predictability" than for the entire group. The difference between the validity coefficients for the 1/3 (or 2/3) lowest and 2/3 (or 1/3) highest scorers on the predictability test is then tested for significance. A significant difference indicates that the predictor should be used only for the low scorers and a different predictor should be used for the remaining subjects.

Ghiselli (1956) demonstrated the potential usefulness of the technique in a study involving prediction of job proficiency of taxicab drivers. An occupational inventory identified those individuals for whom a tapping-and-dotting test was a good predictor of job proficiency. The occupational inventory itself had a negligible correlation with the criterion.

Ghiselli (1960c) also demonstrated that scales of an inventory used as a predictor could serve as its own predictability test. In this technique, /D/ scores are obtained for each individual in an experimental group. The original items of the predictor are then reanalyzed to determine which items discriminate those individuals with large /D/ scores from those with small /D/ scores. Low scores on the resulting predictability scales imply small differences between Z_c and Z_p, and high scores imply large differences. In the Ghiselli study, the predictability scales were applied to a cross-validation group for which the hypothesized relationships held.

In addition to moderating validity of predictors, Ghiselli and Sanders (1967) developed a moderator based on a self-analysis inventory which moderated heteroscedasticity. The moderator differentiated two subgroups which displayed different patterns of heteroscedasticity.

Ghiselli (1963) found that his technique resulted in the identification of moderators which are highly situation-specific. Banas (1964), however, found that transsituational moderators (moderators which function to identify more and less predictable subgroups when applied in different situations) obtained by Ghiselli's technique do exist in the prediction of performance of three classes of workers in a rehabilitation center.

Quadrant analysis. Hobert and Dunnette (1967) claimed that there is practical value in identifying overpredicted (individuals whose Z_p scores exceed their Z_c scores) and underpredicted (individuals whose Z_p scores are below their Z_c scores) individuals as separate groups rather than treating them as an aggregate of unpredictables. Underpredicted and overpredicted individuals are identified by examining a scatter diagram depicting the bivariate distribution of a predictor test and the corresponding criterion scores. Both the predictor and criterion scores are divided at the median to yield the following classifications of individuals: high hits (high predictor-high criterion), low hits (low predictor-low criterion), overpredicted (high predictor-low criterion), and underpredicted (low predictor-high criterion). The approach is depicted in Figure 2.

Hobert and Dunnette (1967) developed two moderators: one for the underpredicted and low hits, and the other for the high hits and overpredicted. Moderators were developed through an analysis of the items used to form the predictor composite; i.e., those items which discriminated significantly between criterion score levels within a given predictor score level; e.g., between the low hits and underpredicted groups, were used. The approach succeeded in identifying two moderators, one for each level of predictor score, which enhanced the prediction of managerial effectiveness.

Abrahams (1965), in a comment on quadrant analysis, stated that mean differences on the predictor composite; e.g., low hits and underpredicted, are ignored. Since the moderator is composed of items from the predictor composite, differences found in item analyses reflect to some degree these predictor mean differences. The developed moderator variable may be predictive only of differences on the

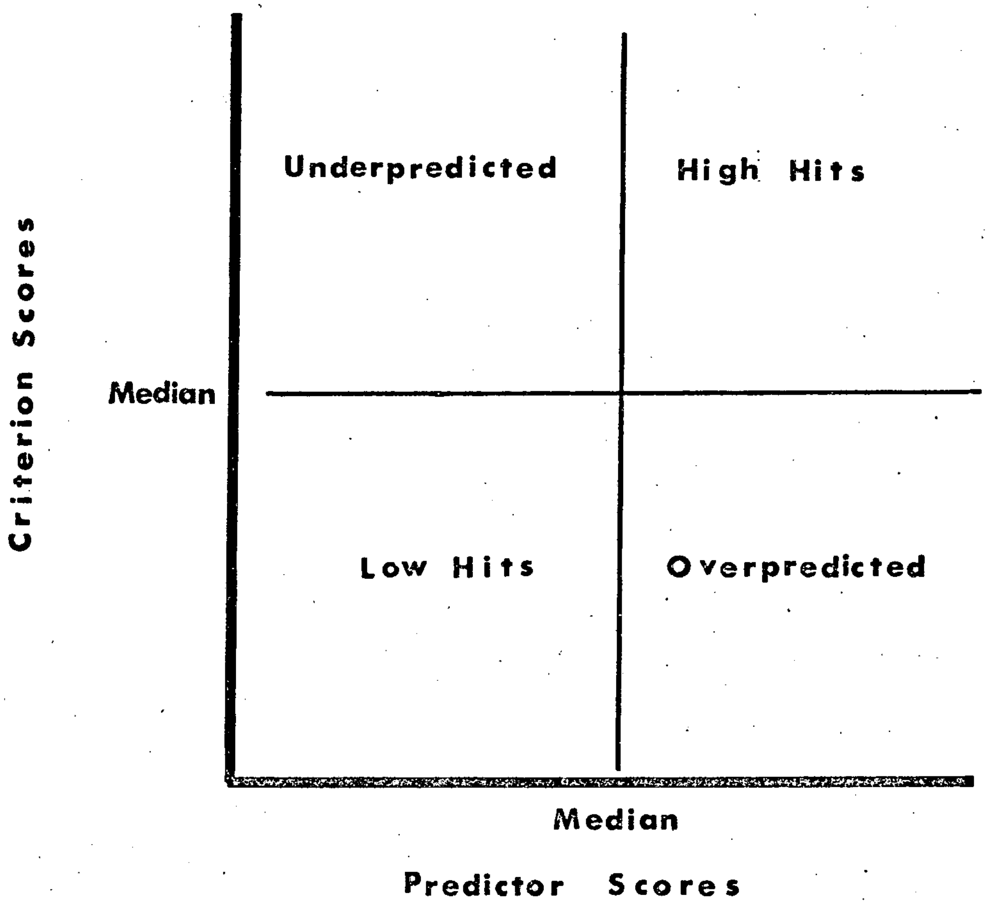

Fig. 2. General diagram of subgroups resulting from quadrant analysis.

predictor variable itself. At best, the components of the moderator variable would reflect a combination of differences; i.e., actual differences between hits and misses and spurious differences due to predictor-score differences. Thus, quadrant analysis insures finding differences between hits and unpredicted individuals. The items and variables showing such differences will be related to the predictor and it is doubtful that such a moderator will have value beyond that already shown in the predictor-criterion relationship.

McNemar (1969) demonstrated that not only do the two predictor groups on one side of the predictor median differ with respect to their mean criterion scores, but they also differ with respect to their mean predictor scores. Thus, discriminating items for a moderator test need not be uncorrelated with the predictor variable. McNemar showed that the predictor itself is a moderator variable which results in increased predictive efficiency, increased hit rate, and decreased percentage of overlap between low and high criterion groups. Furthermore, though the validity coefficient of the predictor increases, the error of estimate remains unchanged if cases are screened out from the central portion of the distribution on the predictor variable. If the gain in hit rate is based on the total sample rather than on the sample after screening, the actual result will be a loss in hit rate.

Operation of Moderator Variables

Most of the literature on moderator variables is concerned with demonstrating that they do operate rather than with explaining how they operate. The common notion held is that moderators operate by sorting heterogeneous aggregates of individuals into homogeneous subgroups (Johnson, 1960; Saunders, 1956). The subgroups are intended to be homogeneous with respect to error and psychological structure, with the magnitudes and patterns of reliability and validity coefficients varying from group to group (Baker, 1967). Banas (1964), however, stated that subgrouping is not simply homogeneous grouping, but is grouping restricted usually to the extreme scores on the moderator variable.

According to Ghiselli (1963), evidence indicates that moderators differentiate those individuals in a group for whom error of measurement or prediction is small from a group for whom it is large. This explanation presumes that individuals can be divided into clear and distinct classes. Ghiselli claimed that, in actual practice, moderators distribute individuals along a continuum. Individuals are sorted into separate classes and a group consists of individuals who fall at the same point on the continuum.

Another possible explanation of moderator effects is that the common elements which account for the correlation between two variables differ from individual to individual rather than from group to group (Ghiselli, 1963). Rather than sorting into classes or groups each falling at a single point on the continuum, there is sorting into class intervals. Such a notion presumes that error of measurement varies from small for some individuals to large for others. Consequently, error scores would carry less weight in determining observable scores for some individuals than for others. However, a necessary condition is that individual differences in error scores possess reliability over parallel tests.

Likewise, error of prediction is smaller and test validity higher for individuals at one extreme on the moderator continuum, and, at the other extreme, error of prediction is larger and test validity lower (Ghiselli, 1963). Consequently, the weight a test carries in prediction varies from individual to individual. With respect to validity, the function of the moderator is to predict for a given individual the weight a test carries in determining criterion performance. However, nothing in the concept indicates the relationship of the individual's weights to the criterion and/or test scores.

Lykken and Rose (1963) suggested that the predictability of the criterion (Y) from the predictor (X) varies as a function of a moderator (Z) which may be uncorrelated with either Y or X. The function relating Y to X differs among individuals in the sample. One equation; e.g., $Y = aX$, is appropriate for the group close to the line of relations whereas another equation; e.g., $Y = b/X$, is appropriate for those further from the line of relations. The predictability of Y from X varies as a function of Z. Z is a function of the likelihood that an individual belongs to the $Y = aX$ group; i.e., Z is a discriminant function.

Hobert and Dunnette (1967) applied the Lykken and Rose (1963) explanation to the quadrant analysis approach. Hobert and Dunnette (1967) claimed that equation $Y = aX$ is appropriate for the low hits and high hits whereas the underpredicted and overpredicted are described by $Y = b/X$. However, Z is correlated with Y as a result of developing two moderators (one for the low hits and underpredicted, and the second for the high hits and overpredicted) instead of only one.

<u>Usefulness of Moderator Variables</u>

The moderator variable concept is particularly useful in situations in which a validity coefficient is low but, at least with certain individuals, reasonably accurate prediction of criterion performance may be made from scores on the test. Applying the moderator concept allows the investigator to identify those individuals for whom more accurate predictions can be made. The practical implications of the moderator techniques are the increased flexibility in the use of predictors and the increased efficiency of selection models.

Ghiselli (1960b) extended the concept and demonstrated that it is possible to differentiate which of two tests gives better prediction for a given individual. For two tests, 1 and 2, $/D_1/$ and $/D_2/$, between Z_c and Z_p scores, are obtained, respectively. For all individuals for whom $/D_1/ < /D_2/$, scores on test 1 predict criterion scores more accurately than do scores on test 2; for all individuals for whom $/D_1/ > /D_2/$, scores on test 2 predict criterion scores more accurately than do scores on test 1. Consequently, we obtain $/D_2/ - /D_1/$ for each individual and thereby have a set of scores such that positive values indicate individuals for whom test 1 gives better predictions and negative values indicate individuals for whom test 2 gives better predictions.

Richardson (1965), in three studies, examined the utility of the above described approach in an educational situation. In all three studies, the technique failed to be effective in improving prediction of college grade point average. Richardson suggested that the failure was due to the complexity of the factors involved in grade point average.

Problems

Quadrant analysis (Hobert & Dunnette, 1967) or any model involving off-quadrant consideration (Marks, 1964) is a logical extension of Ghiselli's (1956, 1960c) technique. Emphasis on underpredicted and overpredicted individuals, as opposed to combining these individuals into an unpredictable group, has practical implications. Maintaining differences among unpredictable groups provides enhancement of the understanding of the psychological composition of groups. For example, Hobert and Dunnette (1967) found that the overpredicted were characterized as lacking the same traits which typified the underpredicted.

A problem with quadrant analysis, in addition to that specified by Abrahams (1969) and McNemar (1969), is that an individual whose /D/ score is small can be placed in an unpredicted group, whereas an individual whose /D/ score is larger can be placed in a hit group. For example (see Figure 3), individual A is closer to the line of relations than is individual B, but A is in the overpredicted group and B is in the high hit group.

<u>Multi-predictable Group Validation Model</u>

Hence, a different extension of Ghiselli's (1956, 1960c) model is proposed. A multi-predictable group validation (MPGV) model involves algebraic differences (considers

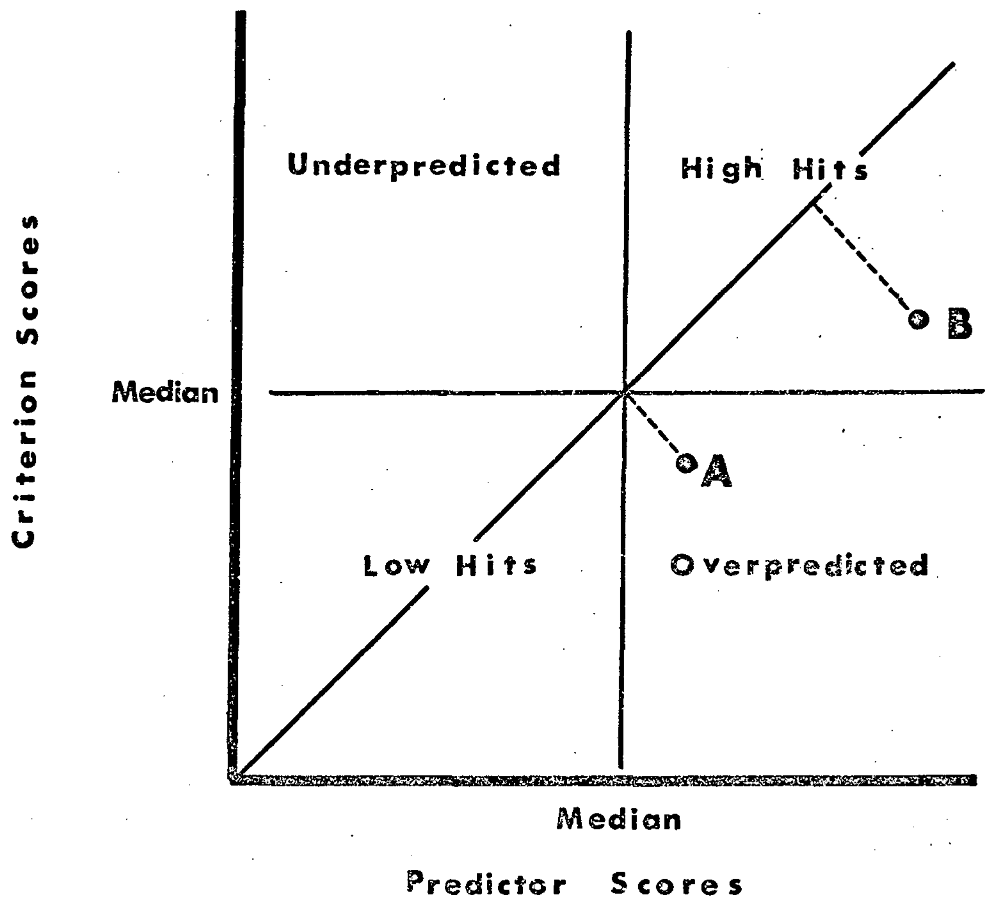

Fig. 3. Comparison of classifications in quadrant analysis and difference score techniques.

underpredicted, overpredicted, and predicted individuals) and deviations from the line of relations. The simplest form of the proposed model, in which we have one overpredicted, one predicted, and one underpredicted group, is depicted in Figure 4.

"Prediction" groups are formed by taking the algebraic difference ($\pm D$) between an individual's standardized criterion score and standardized predictor score, $\pm D = Z_c - Z_p$. The underpredicted group is composed of individuals with D greater than some _a priori_ value; e.g., >+1. The overpredicted group is composed of individuals with D <-1. The predicted group is composed of individuals with $-1 \leq D \leq +1$. Size of the predicted region and number of levels of underpredicted and overpredicted groups could vary depending on the situation.

Hobert and Dunnette (1967) mentioned several advantages of quadrant analysis. First, since overpredicted and underpredicted groups differ from each other both on predictor scores and criterion scores, it seems reasonable that they are two distinct groups differing in certain characteristics important in the predictive situation. The MPGV model shares this advantage.

Second, in quadrant analysis two moderators are developed; one for the low hit and underpredicted groups and the other for the high hit and overpredicted groups.

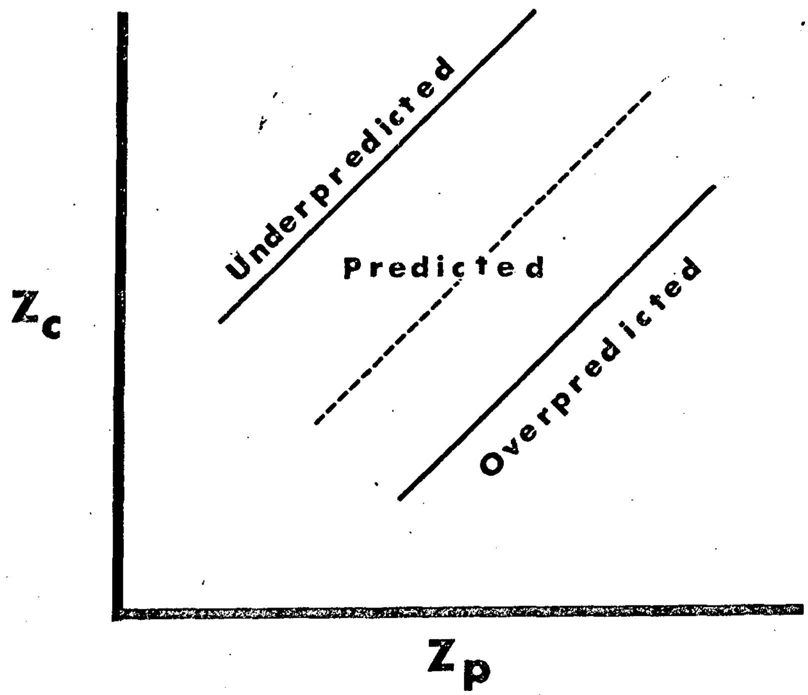

Fig. 4. General diagram of subgroups resulting from MPGV.

Since they are two distinct groups, two separate moderators should eliminate the possibility of masking the important differences as would happen in the /D/ technique. In MPGV, however, the differences between the unpredicted groups are maintained while only one moderator needs to be determined. As will be discussed below, the difficulty in discovering or developing moderators supports a procedure that requires one moderator rather than two moderators.

Third, Hobert and Dunnette (1967) claimed that quadrant analysis provides for a more complete analysis of the criterion. This advantage is also true of the MPGV model. In comparing individuals with different predictor scores but the same criterion score, various hypotheses can be formed as to the differences among groups.

Identification of Moderator Variables by Discriminant Analysis

Regardless of the validation model used -- absolute difference, algebraic difference, quadrant analysis, or MPGV -- there still exists the problem of systematically identifying moderator variables. Moderator variables can be uncorrelated with both the predictor and criterion. There is no efficient objective method available that readily identifies moderator variables. Ghiselli's (1956, 1960c) technique approaches objectivity, but since one variable at a time has to be investigated, it is not very efficient.

Moderator variables are usually discovered by intuition, hypothesis-forming, or accident; or are developed by item analysis and then investigated to determine whether the resulting variable is moderating the relationship between the predictor and criterion.

Frederiksen and Melville (1954) examined compulsiveness as a moderator for it "appeared to be useful" as the basis for an hypothesis about types of students. They concluded that better methods of "discovering" subgrouping variables are necessary. Other investigators have used item analysis procedures to develop moderators. Ghiselli (1960b) derived moderator scales based on the selection of items which correlated most highly with /D/.

Banas (1964) reviewed the literature on moderator variables and concluded that a substantial body of evidence exists which indicates that certain scales and variables function as moderators. However, the problem of readily identifying a moderator variable still remains unsolved. The method of trying out specific hypotheses is slow and expensive because of the tremendous number of possibilities that exist. Also, the development of moderator scales through item analyses is no more satisfactory. There are no statistics that mechanically identify moderators. Furthermore, not enough evidence has accumulated to make it possible to state any general principles about the nature of items or traits that function as moderators. Unless a systematic and objective technique is developed to identify moderators from massive data, the utility of moderator variables will be limited. As Ghiselli (1963) cautioned, the time and effort required to develop moderators might be more fruitfully spent seeking improvement in reliability and validity of the sort that follow from classic theory.

French (1961a) attempted to develop a program for the selection of moderator variables from a large number of variables. The program was designed to identify moderators from 42 potential moderator variables without taking time to compute actual correlations. Indices, based on the joint distribution, in 3 x 3 contingency tables, of predictor and criterion scores which had been trichotomized, were used in place of correlation coefficients. The technique was unsuccessful because of distortion of the indices.

Hence, a second purpose of this dissertation is to investigate a method for identifying moderator variables in the MPGV model. Since moderator variables discriminate between those close to the line of relations and those farther away, it is conceivable that the statistical method of discriminant analysis will identify the variables that contribute to the discrimination of overpredicted, predicted, and underpredicted individuals in the MPGV model.

Discriminant analysis is a technique for estimating categorical criteria from metrical data (Rozeboom, 1966). In a discrimination analysis problem we have a set of *a priori* classification categories among which are partitioned the members of a population. The purpose of the analysis is to determine the likelihood of the individual's belonging to each category based on a linear combination of his metrical scores.

In summary, the purpose of this dissertation is to use a discriminant analysis procedure for the systematic identification of moderator variables, single or joint (Zedeck, 1969), in a multi-predictable group validation model. In addition, results from MPGV are compared with that of simple algebraic and absolute difference techniques. To achieve these ends, several variables are examined to determine their moderator effects on prediction of college grade point average.

Method

Subjects

Subjects were 500 undergraduate students at Bowling Green State University (BGSU) fulfilling a research participation requirement of an Introductory Psychology course. Because of incomplete predictor and criterion information, sample size was reduced to N = 418. Subjects were randomly assigned to the experimental group, Sample A (N = 209), and to the cross-validation group, Sample B (N = 209).

Criterion

The criterion measure was student's accumulative grade point average (GPA) compiled prior to the Winter 1969 quarter.

Predictor

The predictor was the composite score obtained on the American College Test (1965) - (ACT) - administered prior to admission to BGSU.

Potential Moderator Variables

Six tests, administered to *Ss* in one session, were examined to determine their effects on the relationship between ACT and GPA. The tests and subtests are presented in Table 1. These tests and subtests provided scores for 17 potential moderator variables.

Procedure

Multi-predictable group validation model. All scores (predictor, criterion, and potential moderators) were converted to standardized Z-scores. Overpredicted, predicted, and underpredicted groups were formed based on the algebraic difference score, $\pm D = Z_{GPA} - Z_{ACT}$. Seven problems differing in *a priori* intervals for "prediction" groups and/or number of levels of underpredicted or overpredicted individuals were analyzed in Sample A. The parameters differentiating

Table 1

Potential Moderator Variables

Analysis of Relationships (Ghiselli, 1960a) -(A-R)

Bell Adjustment Inventory (Bell, 1962)

- Emotionality (E)
- Health Adjustment (He)
- Home Adjustment (Ho)
- Hostility-Friendliness (H-F)
- Masculinity-Femininity (M-F)
- Submissiveness (S)

Culture Fair Intelligence Test ("g") (Cattell, 1963)

Mandsley Personality Inventory (Eysenck, 1962)

- Neurotocism (N)
- Extroversion-Introversion (E-I)

Multiple Affect Adjective Check List (Zuckerman & Lubin, 1963) - (MAACL)

- Anxiety (A)
- Depression (D)
- Hostility (H)

Survey of Study Habits and Attitudes (Brown & Holtzmen, 1965)

- Delay Avoidance (DA)
- Work Method (WM)
- Teacher Approval (TA)
- Education Acceptance (EA)

the problems are presented in Table 2.

For each problem, a one-way multivariate analysis of variance (MANOVA), with the 17 potential moderators used as the dependent vector random variable, was performed in Sample A. A significant "prediction" group main effect, tested by Wilks' lambda criterion, indicates that at least one of the discriminant functions (with standardized coefficients) is significant.

To identify potential moderators within each problem, a stepwise application of multivariate analysis of covariance (MANOCOVA) was used. The initial MANOCOVA treated the variable associated with the highest discriminant function coefficient as the covariate and the remaining 16 as dependent. A significant main effect indicated that some discriminating power still remained among the 16 dependent variables. Each succeeding MANOCOVA added the variable with the next highest weight to the set of covariates and removed it from the dependent set. The procedure was repeated until the dependent set no longer produced a significant main effect.

Once the moderators were identified, a new discriminant function using only those moderators was found and a discriminant score for each S was computed; $DS_i = \Sigma w_j x_{ij}$, where the discriminant score for individual i is DS_i, w_j is the coefficient of the jth variable, and x_{ij} is individual i's

Table 2

"Prediction" Group Intervals

	Problem 1	2	3	4	5	6	7
Over-predicted				(1) D<-1.4	(1) D<-1.1	(1) D<-1.4	(1) D<-.7
				(2) -1.4≤D<-.8	(2) -1.1≤D<-.4	(2) -1.4≤D≤-.9	
	(1) D<-.5	(1) D≤-1.0	(1) D≤-1.5				(2) -.7≤D≤-.4
				(3) -.8≤D<-.5	(3) -.4≤D≤-.1	(3) -.9≤D<-.5	
				(4) -.5≤D<-.2		(4) -.5≤D<-.2	
Predicted	(2) -.5≤D≤+.5	(2) -1.0<D<+1.0	(2) -1.5<D<+1.5	(5) -.2≤D≤+.2	(4) -.1<D<+.1	(5) -.2<D<+.2	(3) -.4<D<+.4
Under-predicted				(6) +.5≥D>+.2	(5) +.4≥D≥+.1	(6) +.5≥D≥+.2	(4) +.7≥D≥+.4
				(7) +.8≥D>+.5	(6) +1.1≥D>+.4	(7) +.9≥D>+.5	
	(3) D>+.5	(3) D≥+1.0	(3) D≥+1.5	(8) +1.4≥D>+.8	(7) D>+1.1	(8) +1.4≥D>+.9	(5) D>+.7
				(9) D>+1.4		(9) D>+1.4	

Note:— Levels within problems indicated in parentheses.

score on the *jth* variable.

Classification of individuals in Sample B was established in two ways. First, cutoff discriminant scores were obtained for each *a priori* "prediction" group in Sample A based on England's (1961) Index of Differentiation which minimizes the number of misclassifications. Thus, in Classification Method I, an *S* in Sample B was placed in a "prediction" group based on cutoff scores established in Sample A. Tetrachoric correlation coefficients were computed between observed and predicted group classification of *S*s. For computational purposes, "prediction" groups were dichotomized as indicated in the Results section.

The second classification method was based on a chi-square technique suggested by Cooley and Lohnes (1962). The procedure, applied to *S*s in Sample B, places an individual into a group depending on the deviation of his discriminant score from the appropriate group mean discriminant score determined in Sample A. Again, tetrachoric correlation coefficients were computed to assess the effectiveness of the moderator in discriminating multi-predictable groups in the cross-validation sample.

To assess the effectiveness of the moderators on validity, validity coefficients of the predictor, ACT, were computed for each "prediction" group in Sample B for both classification techniques. It was hypothesized that validity coefficients of ACT would be higher for the "prediction" groups in Sample B than the overall coefficient in Sample A.

Absolute difference model. Each potential moderator was correlated with the absolute difference (/D/) between the criterion, GPA, and the predictor, ACT. If a significant correlation was obtained in Sample A, then the sample was split into 1/3 (and 2/3) high scorers and 2/3 (and 1/3) low scorers on the potential moderator variable, and validity coefficients were obtained for each fractionated group. Significantly different coefficients indicated the existence of a moderator. Results were cross-validated in Sample B.

Algebraic difference model. Each potential moderator was correlated with the algebraic difference ($\pm$D) between the criterion, GPA, and the predictor, ACT. If a significant correlation was obtained in Sample A, then the sample was trichotomized. Differential validity coefficients of the predictor for the subgroups indicated the existence of a moderator variable. Results were cross-validated in Sample B.

Results

The validity coefficient of ACT as a predictor of GPA was .52 ($p < .01$) and .51 ($p < .01$) for Sample A (N = 209) and Sample B (N = 209), respectively. Tables 3 and 4 present the intercorrelations among all variables (predictor, criterion, and potential moderators) and difference scores

Table 3

Correlation[a] Matrix[b] for Sample A[c]

	GPA	ACT	E-I	N	DA	WM	TA	EA	"g"	Ho	He	S	E	H-F	M-F	A	D	H	A-R	/D/	±D
GPA		52	-15	-16	32	37	43	46	23	-09	08	-03	-13	-16	-12	02	-06	-11	42	-05	49
ACT			-26	-23	25	34	39	35	38	-11	-09	08	-19	-17	10	-09	-08	-06	71	-06	-49
E-I				-15	-16	-01	-07	-17	01	-02	02	-64	-24	-07	-16	-16	-28	-07	-11	-08	10
N					-33	-30	-35	-31	-17	36	48	34	76	61	-07	46	46	39	-20	04	06
DA						49	47	64	14	-16	-12	-12	-25	-23	-06	-14	-15	-24	18	05	07
WM							51	59	24	-08	01	-23	-26	-23	-11	-20	-19	-22	25	-08	04
TA								73	16	-21	-16	-17	-36	-35	-12	-24	-22	-25	32	-17	04
EA									18	-23	-08	-06	-27	-29	-17	-16	-20	-24	29	-15	12
"g"										-15	-09	-02	-18	-13	-02	-09	-09	-12	42	-13	-15
Ho											33	10	43	46	00	31	38	33	-05	06	02
He												16	51	45	-06	36	34	21	-11	00	01
S													52	34	10	30	36	20	-09	-02	-11
E														66	-17	56	51	36	-23	05	06
H-F															04	42	47	48	-24	10	01
M-F																-10	01	08	08	10	-22

Table 3 (continued)

	GPA	ACT	E-I	N	DA	WM	TA	EA	"g"	Ho	He	S	E	H-F	M-F	A	D	H	A-R	/D/	±D
A																	78	60	-16	08	11
D																		67	-17	07	02
H																			-14	03	-05
A-R																				-04	-29
/D/																					01
±D																					

[a]*r* of .14 is significant at .05 level;

r of .18 is significant at .01 level.

[b]Decimals omitted.

[c]N = 209.

Table 4

Correlation[a] Matrix[b] for Sample B[c]

	GPA	ACT	E-I	N	DA	WM	TA	EA	"g"	Ho	He	S	E	H-F	M-F	A	D	H	A-R	/D/	±D
GPA		51	-16	00	19	28	17	23	18	-08	-04	07	08	-08	-08	06	04	-01	34	-03	49
ACT			-12	02	-03	31	19	12	39	12	00	07	-04	-03	08	03	07	00	62	-11	-50
E-I				-31	-05	07	-03	-10	-12	-12	-20	-68	-38	-10	05	-30	-27	-13	-06	00	-05
N					-17	-18	-11	-18	-03	42	51	38	75	43	-12	50	49	31	-01	-06	-02
DA						50	35	64	-04	-22	-07	-15	-11	-20	-20	-11	-10	-14	-07	10	23
WM							43	55	08	-08	-09	-23	-16	-17	-23	-24	-21	-21	23	-06	-03
TA								61	10	-14	-11	-09	-08	-21	-08	-12	-10	-15	21	00	01
EA									08	-19	-12	-07	-09	-27	-16	-09	-12	-22	10	03	12
"g"										08	02	12	08	-05	-14	14	09	07	33	-10	-22
Ho											25	16	42	39	-09	26	25	12	11	07	-20
He												26	49	20	-05	30	26	14	01	05	03
S													55	21	00	31	26	20	01	-13	01
E														38	-26	53	44	26	-08	-09	12
H-F															11	16	22	18	-10	-04	-05

Table 4 (continued)

	GPA	ACT	E-I	N	DA	WM	TA	EA	"g"	Ho	He	S	E	H-F	M-F	A	D	H	A-R	/D/	±D
M-F																-06	02	14	05	12	-15
A																	80	63	-02	-08	02
D																		72	08	04	02
H																			-05	-06	-01
A-R																				-02	-28
/D/																					08
±D																					

[a] *r* of .14 is significant at .05 level;

r of .18 is significant at .01 level.

[b] Decimals omitted.

[c] N = 209.

(algebraic and absolute) for Sample A and Sample B, respectively.

Multi-predictable Group Validation Model

Assessment of potential moderator variables. Seven one-way MANOVA's were computed for the problems outlined in Table 2. The main effect was "prediction" group and the levels within the factor varied according to the problem. Scores for the 17 potential moderator variables constituted the dependent vector variable in the analyses. Results of MANOVA for the seven analyses are presented in Table 5. A significant ($p < .01$ in each case) main effect was found in Problems 1-6; Problem 7 did not yield a significant main effect and thus was excluded from further examination.

For each problem, the first discriminant function was analyzed by MANOCOVA's to determine which variables were contributing significantly to the discrimination. In Table 6, an asterisk (*) indicates the significant variables.

To confirm the significance of the contributing variables, one-way MANOVA's were conducted for each problem with all significant variables treated as the dependent vector variable. Results demonstrated that all main effects were significant (Table 7, $p < .01$ in each case).

Table 8 presents the mean and standard deviation of each significantly contributing variable within each level

Table 5

Summary of Results of MANOVA

Problem	df_{HYP}	df_{ERR}	F	p
1	34	380	1.74	<.01
2	34	380	2.06	<.01
3	34	380	1.73	<.01
4	136	1354.47	1.36	<.01
5	102	1067.37	1.57	<.01
6	136	1354.47	1.40	<.01
7	68	740.08	1.29	<.10

Table 6

Discriminant Weights for the 17 Potential Moderator Variables in Each Problem

	Problem					
Variable	1	2	3	4	5	6
E-I	.031	-.076	.243	.106	.606*	.363
N	-.445	.090	.398	.131	.340	.290
DA	-.398	.251	-.103	-.082	-.036	.082
WM	-.297	-.145	-.044	-.263	-.034	-.159
TA	.138	-.032	-.164	.219	.293	.346
EA	-.078	.243	.626*	.554*	.493*	.366
"g"	.475*	-.334	.016	.138	-.037	.064
Ho	-.158	.116	.084	-.004	-.182	-.014
He	.484*	-.374	-.143	-.068	-.055	-.002
S	.138	-.644*	-.494	-.294	.162	-.008
E	.291	-.091	-.016	.176	-.227	-.038
H-F	-.465*	.297	-.078	.086	.047	-.089
M-F	.058	-.099	-.189	-.425	-.347	-.409*
A	-.630*	.923*	.395	.236	.071	.182
D	.064	-.165	.316	-.221	.418	.131
H	.641*	-.486*	-.478	-.167	-.146	-.255
A-R	.353	-.380*	-.593*	-.753*	-.664*	-.737*

*Significant weights of the discriminant function for the problem as determined by MANOCOVA's.

Table 7

Summary of Results of MANOVA with Significantly Weighted Variables as Dependent

Problem	df_{HYP}	df_{ERR}	F	p
1	10	404	2.52	<.01
2	8	406	4.12	<.01
3	4	410	3.84	<.01
4	16	398	2.56	<.01
5	18	566.17	3.17	<.01
6	16	398	2.70	<.01

Table 8

Means (M) and Standard Deviations (S) of

Significantly Contributing Variables

Level[a]		Variable				
Problem 1:		"g"	He	H-F	A	H
1 (N=54)	M	.041	-.069	.143	-.022	.128
	S	.863	1.100	1.086	.986	1.175
2 (N=101)	M	.148	.053	-.164	-.077	-.027
	S	.993	1.010	.985	.953	.965
3 (N=54)	M	-.319	-.031	.164	.167	-.077
	S	1.091	.892	.912	1.102	.885

Problem 2:		S	A	H	A-R
1 (N=27)	M	.055	-.065	.119	.502
	S	1.124	.838	1.058	.770
2 (N=155)	M	.065	-.061	-.016	-.019
	S	.963	.976	.999	1.015
3 (N=27)	M	-.428	.417	-.027	-.391
	S	1.031	1.221	.995	.959

Problem 3:		EA	A-R
1 (N=16)	M	-.387	.531
	S	1.159	.541

Table 8 (continued)

Level		EA	A-R
2 (N=177)	M	.047	.002
	S	.980	1.015
3 (N=16)	M	-.136	-.557
	S	1.056	.960
Problem 4:		EA	A-R
1 (N=16)	M	-.387	.531
	S	1.159	.541
2 (N=17)	M	-.336	.246
	S	.992	1.046
3 (N=21)	M	-.087	.159
	S	.852	.943
4 (N=20)	M	-.271	.048
	S	.927	1.099
5 (N=59)	M	.244	.197
	S	1.126	.859
6 (N=22)	M	.041	-.558
	S	.765	.938
7 (N=19)	M	-.034	-.205
	S	.940	1.280

Table 8 (continued)

Level		Variable		
		EA	A-R	
8 (N=19)	M	.348	-.185	
	S	.803	1.058	
9 (N=16)	M	-.136	-.557	
	S	1.056	.960	
Problem 5:		E-I	EA	A-R
1 (N=22)	M	-.388	-.345	.651
	S	1.090	1.148	.591
2 (N=42)	M	.093	-.265	.009
	S	1.063	.867	1.047
3 (N=36)	M	-.225	.143	.247
	S	.895	1.047	.754
4 (N=16)	M	.145	.004	.244
	S	1.101	1.192	.855
5 (N=32)	M	.375	.329	-.312
	S	.921	1.005	1.049
6 (N=39)	M	-.170	.133	-.203
	S	.963	.854	1.126
7 (N=22)	M	.229	-.101	-.436
	S	.908	1.002	1.027

Table 8 (continued)

Level		Variable	
Problem 6:		M-F	A-R
1 (N=16)	M	.784	.531
	S	1.175	.541
2 (N=11)	M	-.147	.460
	S	.611	1.048
3 (N=27)	M	.189	.091
	S	1.238	.946
4 (N=29)	M	.026	.136
	S	.926	1.013
5 (N=39)	M	.127	.229
	S	.920	.778
6 (N=33)	M	-.475	-.381
	S	.858	1.035
7 (N=27)	M	.004	-.214
	S	.774	1.250
8 (N=11)	M	-.412	-.149
	S	.897	.948
9 (N=16)	M	-.100	-.557
	S	1.159	.960

[a]Level number corresponds to number in Table 2.

for all problems. The weights of the new discriminant function for each problem are presented in Table 9.

Effectiveness of moderators in discriminating "prediction" groups: Classification Method 1. In Sample A, a distribution of discriminant scores was obtained for each level within a problem. Examination of the distributions resulted in two modifications of procedure. First, for problems with more than one level of overpredicted or underpredicted intervals there was considerable overlap between groups. Thus, Ss within all levels of underpredicted groups were combined into a single underpredicted group and, similarly, all levels of overpredicted groups were combined into a single overpredicted group. Second, for several problems with only three groups, there still existed considerable overlap between groups. Hence, to use England's (1961) Index of Differentiation, the "predicted" group was combined with one of the unpredicted groups in Problems 1, 2, 3, and 6.

Based on the cutoff discriminant scores obtained in Sample A, Ss in Sample B were placed into "prediction" groups. Contingency tables with their corresponding tetrachoric correlation coefficients are presented in Table 10. There were significant relationships for Problems 3 and 6 ($p < .01$ and $p < .05$, respectively).

Table 9

Discriminant Weights for Sets of Contributing Variables in Each Problem

Problem	Variables				
1	"g"	He	H-F	A	H
	.636	.580	-.725	-.633	.751
2	S	A	H	A-R	
	.664	-.892	.568	.593	
3	EA	A-R			
	-.599	1.004			
4	EA	A-R			
	-.699	.993			
5	E-I	EA	A-R		
	.491	.730	-.870		
6	M-F	A-R			
	.708	.701			

Table 10

Tetrachoric Correlation Coefficients for Contingency Tables: Observed vs. Classification Group Based on Index of Differentiation[a] in Sample B

Problem 1:

		Classified: 1 & 2	Classified: 3	
Observed	3	29	7	r_t = -.11
	1 & 2	126	47	

Problem 2:

		Classified: 1 & 2	Classified: 3	
Observed	3	48	14	r_t = .16
	1 & 2	125	22	

Problem 3:

		Classified: 1 & 2	Classified: 3	
Observed	3	50	12	r_t = .43*
	1 & 2	140	7	

Problem 4:

		Classified: 1 & 3	Classified: 2	
Observed	2	79	28	r_t = -.02
	1 & 3	77	25	

Table 10 (continued)

Problem 5:

Observed		Classified 1 & 3	Classified 2	
	2	26	4	r_t - .10
	1 & 3	161	18	

Problem 6:

Observed		Classified 1 & 2	Classified 3	
	3	42	43	r_t = .29**
	1 & 2	85	39	

*$p < .01$.

**$p < .05$.

[a] 1=Overpredicted, 2=Predicted, 3=Underpredicted.

Effectiveness of moderators in discriminating "prediction" groups: Classification Method 2. The chi-square technique (Cooley & Lohnes, 1962) resulted in a second set of discriminant cutoff scores. The tetrachoric correlation coefficients for the contingency tables for observed vs. classified group are presented in Table 11. None of the problems contained a significant relationship.

Effectiveness of moderators on validity: Groups based on Index of Differentiation. Table 12 presents the correlation coefficients between ACT and GPA for the "prediction" groups within each problem. None of the coefficients for the "prediction" groups within any problem differed significantly from .52 (overall validity coefficient for Sample A).

Effectiveness of moderators on validity: Groups based on chi-square classification. Table 13 presents the correlation coefficients between ACT and GPA for the "prediction" groups within each problem. Again, none of the coefficients for the "prediction" groups within any problem differed significantly from .52.

Absolute Difference Technique

Table 3 shows that the correlations between /D/ and TA ($-.17$, $p < .05$) and /D/ and EA ($-.15$, $p < .05$) were significant in Sample A. For each of the two potential moderator variables (TA and EA), two fractionations were

Table 11

Tetrachoric Correlation Coefficients for Contingency Tables: Observed vs. Classification Group Based on Chi-square[a] in Sample B

Problem 1:

		Classified: 1 & 3	Classified: 2	
Observed	2	54	44	r_t = .05
	1 & 3	65	46	

Problem 2:

		Classified: 1 & 3	Classified: 2	
Observed	2	12	36	r_t = -.14
	1 & 3	54	107	

Problem 3:

		Classified: 1 & 3	Classified: 2	
Observed	2	5	44	r_t = -.20
	1 & 3	27	133	

Problem 4:

		Classified: 1 & 3	Classified: 2	
Observed	2	13	6	r_t = .13
	1 & 3	144	46	

Table 11 (continued)

Problem 5:

		Classified	
		1 & 3	2
Observed	2	26	3
	1 & 3	161	19

$r_t = .01$

Problem 6:

		Classified	
		1 & 3	2
Observed	2	19	5
	1 & 3	153	32

$r_t = .09$

[a]1=Overpredicted, 2=Predicted, 3=Underpredicted.

Table 12

Correlations between GPA and ACT for "Prediction" Groups in Sample B Based on Index of Differentiation

Problem	Prediction Group[a]		
1		1 & 2	3
		.49 (N=173)	.63 (N=36)
2		1 & 2	3
		.51 (N=147)	.50 (N=62)
3		1 & 2	3
		.49 (N=147)	.53 (N=62)
4	1	2	3
	.55 (N=44)	.51 (N=107)	.55 (N=58)
5	1	2	3
	.51 (N=114)	.57 (N=30)	.50 (N=65)
6		1 & 2	3
		.53 (N=124)	.49 (N=85)

[a]1=Overpredicted, 2=Predicted, and 3=Underpredicted.

Table 13

Correlations between GPA and ACT for "Prediction" Groups in Sample B Based on Chi-square Classification

Problem	"Prediction" Group[a]		
	1	2	3
1	.50 (N=30)	.56 (N=98)	.47 (N=81)
2	.55 (N=85)	.52 (N=48)	.43 (N=76)
3	.55 (N=81)	.59 (N=49)	.45 (N=79)
4	.52 (N=101)	.61 (N=19)	.48 (N=89)
5	.50 (N=100)	.61 (N=29)	.51 (N=80)
6	.47 (N=78)	.62 (N=24)	.53 (N=107)

[a]1=Overpredicted, 2=Predicted, and 3=Underpredicted.

made: (1) 1/3 low and 2/3 high scorers, and (2) 2/3 low and 1/3 high scorers. Table 14 presents the correlations between GPA and ACT for each of the fractionated groups. The difference between validity coefficients for the 1/3 low and 2/3 high TA scorers and for the 1/3 low and 2/3 high EA scorers was significant ($p < .05$ in both cases).

Table 15 shows the corresponding correlation coefficients in the cross-validation group, Sample B. Neither of the differences in correlations between fractionated groups were significant.

<u>Algebraic Difference Technique</u>

Table 3 shows that the correlations between $\pm$D and "g" (-.15, $p < .05$), $\pm$D and M-F (-.22, $p < .01$), and $\pm$D and A-R (-.29, $p < .01$) were significant. For each of the three potential moderators ("g", M-F, and A-R) trichotomizations were made. Table 16 presents the correlations between GPA and ACT for each of the "prediction" groups with respect to the three potential moderators. The difference between the predicted and both the overpredicted and underpredicted groups was significant ($p < .05$) when the trichotomization was based on M-F.

Table 17 shows the correlation coefficients for each of the "prediction" groups based on M-F in Sample B. The differences were not significant.

Table 14

Correlations between GPA and ACT for

Fractionated Groups in Sample A

Variable	Fractionated group	$\underline{r}$
TA	1/3 low (N=72)	.31*
	2/3 high (N=137)	.56
	2/3 low (N=138)	.41
	1/3 high (N=71)	.57
EA	1/3 low (N=67)	.28*
	2/3 high (N=142)	.57
	2/3 low (N=137)	.44
	1/3 high (N=72)	.56

*Significantly different at $\underline{p} < .05$.

Table 15

Cross-validation: Correlations between GPA and ACT

For Fractionated Groups in Sample B

Variable	Fractionated group	r
TA	1/3 low (N=69)	.45
	2/3 high (N=140)	.52
EA	1/3 low (N=68)	.49
	2/3 high (N=141)	.51

Table 16

Correlations between GPA and ACT for "Prediction" Groups in Sample A Based on ±D Correlation with Moderator

Variable	"Prediction" Group	*r*
"g"	Overpredicted (N=62)	.49
	Predicted (N=91)	.42
	Underpredicted (N=56)	.59
M-F	Overpredicted (N=53)	.35
	Predicted (N=107)	.66*
	Underpredicted (N=49)	.49*
A-R	Overpredicted (N=67)	.42
	Predicted (N=84)	.39
	Underpredicted (N=58)	.35

*Predicted is significantly different from both Overpredicted and Underpredicted at $p < .05$.

Table 17

Cross-validation: Correlations between GPA and ACT For "Prediction" Groups in Sample B Based on $\pm D$ Correlation with Moderator

Variable	"Prediction" Group	r
M-F	Overpredicted (N=63)	.46
	Predicted (N=84)	.61
	Underpredicted (N=62)	.54

Discussion

This dissertation concerns the use of discriminant analysis for the systematic identification of moderator variables in a multi-predictable group validation model. In addition, results from MPGV are compared with those of simple algebraic and absolute difference techniques. The results of this dissertation did not support the use of any of the moderator variable techniques because of the problems and inconsistencies within each method.

Multi-predictable Group Validation Model

As Tables 10 through 13 indicate, the variables discriminating the groups in Sample A were not effective in Sample B. The ineffectiveness of discriminant analysis in this situation is due to several problems. First, the discriminant weights obtained in the initial MANOVA's were not different enough to lend themselves to an "eye-ball" analysis for extracting significant contributors. Hence, MANOCOVA was necessary; the selection of the potential moderator variables was based on the *a priori* notion that the largest weights indicate the most important variables. It is possible that the selection of a different set of variables; e.g., those that are significant in a univariate analysis of variance, would also provide a significant main effect. The necessity for using MANOCOVA limits the facility of using discriminant analysis to identify moderators.

Second, a significant discriminant function does not mean that all levels within a factor are discriminable. It is possible (e.g., Table 8, Problem 4) that the means for one set of levels (1-4, 7, and 9) are similar as are the means for a second set of levels (5, 6, and 8); however, the first set of levels is different from the second set. Discriminant analysis does not necessarily provide a discrimination between all levels, but distinguishes between sets of levels.

Overlap or similarity of levels necessitated modification of the proposed procedure. For most problems studied, a discrimination between all levels of the "prediction" group was difficult. As a result, levels within a "prediction" group were combined. For some problems, it was further necessary to combine to the extent that the three basic "prediction" groups (overpredicted, predicted, and underpredicted) could not be maintained. The inability to maintain all levels and/or groups was due to the small amount of between group variance accounted for by the moderators. For the six problems, the proportion of between group variance accounted for by the set of moderators was .09, .12, .05, .14, .19, and .16, respectively.

Third, if two variables are highly correlated, they provide redundant information for discriminating among the groups. Thus, if a set of subtests are significantly correlated (see, for example, SSHA subtests, Table 3), only one need be retained in the analysis. The procedure and interpretation would thus be facilitated.

Fourth is the problem of misclassification. The Index of Differentiation, a crude estimate of classification, provided largely non-significant associations. The chi-square technique, derived from a discriminant analysis system, maximizes the probability of correct classification. With both techniques, there was considerable misclassification as evidenced by the lack of many significant tetrachoric correlation coefficients. Examination of the contingency tables (see Tables 10 and 11) revealed that there was a tendency to place less than the actually observed number of Ss into the "predicted" group.

Fifth, the non-significant results may be a function of the value of initial validity coefficient and sample size. It is difficult and perhaps impractical to attempt to improve upon a validity coefficient that is relatively high. In this study, the correlation coefficient (.52) between GPA and ACT was adequate. The basic purpose of any moderator variable approach is to improve validity in situations in which predictors are poor. The higher the coefficient, the more difficult and less necessary it is to improve validity. Whether the slight gain possible is practically significant is a matter to be decided by the individual making the selection decisions. However, improvement can be obtained in situations which have high original validity coefficients. For example, Hobert and Dunnette (1967) found a moderator that improved the validity coefficient from .65 to .73.

Sample size is a related problem. Sample sizes of the "prediction" groups depend on three factors: (1) validity coefficient for the entire sample, (2) $\pm$D interval for the predicted group, and (3) number of levels within the overpredicted and underpredicted groups. The higher the validity coefficient for the total sample and the greater the $\pm$D interval for the predicted group, the more unequal are the "prediction" group sample sizes. In addition, if more than one level of underpredicted or overpredicted is used, the sample sizes of the levels within the unpredicted groups, especially the more extreme levels, become smaller. With relatively small and unequal sample sizes among groups, the test for significance between coefficients loses power.

Psychological Composition of "Prediction" Groups

Examination of the mean and standard deviation of each of the discriminating variables, in conjunction with the interpretation of test scores provided by the test manuals, reveals the following characteristics of the "prediction" groups.

Problem 1. The predicted group is composed of individuals with relatively high general intelligence, moderate anxiety, and friendly disposition. The underpredicted group has relatively lower general intelligence and is more hostile and anxious. The overpredicted individuals have relatively average general intelligence and moderate hostility.

Problem 2. The predicted group is characterized by moderate intelligence, anxiety, hostility, and submissiveness. The overpredicted tend to be higher and the underpredicted lower on the same variables.

Problem 3. The predicted group has moderate intelligence and is relatively moderate in acceptance of educational objectives. In contrast, the overpredicted group has relatively high intelligence but little acceptance of educational objectives. The underpredicted are characterized by relatively low intelligence and low educational acceptance.

Problem 4. Again, the predicted group is characterized by moderateness; moderate educational acceptance and moderate intelligence. The overpredicted and underpredicted groups have low educational acceptance, but the latter has lower intelligence than the former.

Problem 5. The predicted group is characterized by relatively moderate educational acceptance and intelligence, but is slightly extroverted. The overpredicted are characterized by introversion, relatively higher intelligence, but relatively lower educational acceptance. The underpredicted are extroverted, high in educational acceptance, and low in intelligence.

Problem 6. The predicted group is again characterized by moderateness; moderate intelligence and no maladjustment with regard to preference for activities of either sex. The overpredicted are similar to the predicted with regard to masculinity-femininity, but have higher intelligence. In contrast, the underpredicted have more of a preference for feminine activities than is typical of their sex and also have lower intelligence.

In summary, predicted subjects are consistent and moderate on the relevant variables. In contrast, the underpredicted, with lower intelligence, possibly compensate by being higher in other variables; e.g., educational acceptance. The overpredicted in general have higher intelligence, but their abilities are not fully realized because of their hostility and lower acceptance of educational objectives.

Absolute Difference Technique

Educational acceptance (EA) and teacher approval (TA) were identified as moderators in Sample A. Results indicated that subjects were more predictable if they had relatively higher acceptance of educational objectives and higher approval of their teachers' methods and classroom behaviors. The results did not hold up in cross-validation in Sample B, thus supporting the need for verifying moderator results prior to making decisions (Banas & Moore, 1968).

Algebraic Difference Technique

M-F, "g", and A-R were identified through their correlation with $\pm D$ as possible moderators in Sample A. The only variable that provided differential validities was M-F. The failure of "g" and A-R to yield differential patterns of validity may be due to restriction of range. Moderator variables are usually uncorrelated with predictors or criteria (Zedeck, 1969). In this study, M-F was uncorrelated with GPA and ACT (Table 3) whereas "g" was correlated with GPA (.23, $p < .01$) and ACT (.38, $p < .01$) and A-R was correlated with GPA (.42, $p < .01$) and ACT (.71, $p < .01$). Consequently, subgrouping on the latter two potential moderator variables was equivalent to restricting the range on both the predictor and the criterion, resulting in lower validity coefficients.

With regard to M-F, differential validities appeared in Sample A; for those subjects with normal masculine-feminine tendencies the validity coefficient was highest. The problem of cross-validation is evident in this technique as in the /D/ technique.

Implications

The data of this research do not confirm the use of discriminant analysis to identify moderators in a multi-predictable group validation model. Likewise, the data do not support the use of the algebraic difference or absolute difference (Ghiselli, 1956, 1960c) techniques. However, a consideration of the problems of discriminant analysis and those of cross-validation suggests further research.

First, future research should be conducted on larger sample sizes thus limiting the effect of sampling error. Second, to facilitate procedure and interpretation, no more than one level within a "prediction" group is necessary.

Third, when potential moderator variables in a matrix are significantly and highly intercorrelated, only one variable of the set needs to be employed in the discriminant analysis. If the number of variables is extremely large, factor scores derived from a factor analysis can be used as the dependent variables in the discriminant analysis.

Fourth, since some evidence does exist that effective moderator variables may be uncorrelated with predictors and criteria, all potential moderator variables highly correlated with the predictor and/or criterion can be eliminated prior to subsequent investigation in a discriminant analysis.

Fifth, once the moderators are determined, differential patterns of validity can be ascertained by considering the variables independently, one at a time. Thus, a simple analysis would be possible without interaction effects. Joint moderators were not found in academic situations in studies by Zedeck (1969) and Stricker (1966). In addition, the procedure would be easier since raw scores would be used in classification as opposed to discriminant scores.

Sixth, different classification procedures from the ones in this study might be tried. In addition, using more than one discriminant function for classification may account for more of the variance and result in better outcomes.

The use of a technique such as discriminant analysis in conjunction with MPGV does have some advantages. First, if variables could be found to identify the "prediction" groups, then greater emphasis in the future will be placed on reliability of instruments. Second, maintaining differences among unpredictable individuals enhances psychological understanding and leads to different priorities of selection. For example, suppose two individuals had the same acceptable predictor score but different moderator scores. On the basis of moderator scores, if one individual was placed in the underpredicted group and the other in the predicted group, then the MPGV concept suggests hiring the former before the latter. In essence, MPGV reduces the amount of "misses" more than does the absolute difference technique.

Finally, a systematic technique for selection of moderator variables would allow us to examine larger masses of data and select those variables which serve as moderators. A systematic technique is more efficient than intuition for discovering or developing moderator variables.

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