A COMPARISON OF AN ACTUARIAL AND A LINEAR MODEL FOR PREDICTING MANAGERIAL BEHAVIOR

A Dissertation

Presented to

the Faculty of the Department of Psychology

University of Houston

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

By

Blake A. Frank

May 1976

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ABSTRACT

The objective of the current research was to compare an actuarial and a linear model for predicting criteria related to managerial success. Two subject samples were involved, both of which contained managers and potential managers who were current or past employees of a large petrochemical company. Each sample contained 2,899 individuals, who had been tested in the company's ongoing managerial assessment program, and each sample was predominantly white and male, although females and minorities were present in both samples. One sample was a validation sample; the other served as a cross-validation sample.

In the first step of the actuarial analysis, twelve homogeneous subgroups of employees were identified through the hierarchical and convergent clustering of the validation sample subjects on thirteen scores available from the company's managerial assessment battery. In the cross-validation sample the twelve subgroups were replicated through a minimum distance comparison of each subject and the twelve validation sample subgroup centroids. Cross-validation subjects were assigned to the subgroup they most closely resembled.

In the second step of the analysis, the twelve subgroups were cross-tabulated against various descriptive and predictive criteria. In both samples subgroup membership was found significantly associated with ethnic group, age, education,

occupation, manpower classification, employment status, and two factor analytically derived job performance scores. Descriptions of the subgroups were developed in terms of the thirteen assessment scores and the various descriptive criteria. In terms of the predictive criteria, despite the significant association, it was found that subgroup membership could not be used to predict employment status better than the base rate of the high frequency criterion category. However, knowledge of subgroup membership could be used to influence the base rate of the criterion. The job performance variables were observed to have differential affinity for the subgroups in both samples, and, thus, knowledge of subgroup membership could be used to predict job performance at better than the base rate levels.

In the analysis of the linear model, the thirteen assessment scores were used as independent variables in predicting employment status and the job performance scores. Multiple group discriminant analysis was employed to predict employment status. Statistically significant results were observed; however, in both samples the model could not develop better than base rate predictions of the criterion and could not be used to influence the base rate of the high frequency category. Multiple regression analysis was employed to predict the job performance scores. In both samples significant multiple R's and better than base rate predictions of job performance were observed.

In comparing the models the actuarial model was slightly superior to the linear model in predicting employment status since the model could be used to influence the employment status base rate and the linear model could not. In terms of predicting job performance, the models were found equal in the validation sample. On cross-validation the linear model was observed to be significantly more accurate than the actuarial model. However, this superiority was traced to an artifact of the coarse grouping of job performance, which was done to facilitate the presentation of the data. Therefore, the models were ultimately found equal in accuracy in predicting job performance.

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CHAPTER I

INTRODUCTION

Toops (1948, 1959) contended that the whole of society consisted of an array of homogeneous, statistically sorted groups of people called ulstriths. Toops believed that ulstriths could be identified by gathering and sorting vast amounts of data on individuals. Once identified, these ulstriths could be related to any external criteria, and predictions of an individual's behavior could be made based on the relationship or his/her ulstrith to the external criteria. In summary, Toops believed that

> 1. Like-traited, like-minded people think alike, act alike, and perhaps even emote alike...
>
> 2. To know the ulstrith, the pattern, is virtually to know the behavior.
>
> 3. That a man reacts as a whole personality, as a member, as a first approximation, of an ulstrith population. It follows that any member thereof, is, presumably, almost as good a representation of an ulstrith as any other. (p. 193, 196)

In essence, Toops described a model for the actuarial prediction of behavior. Actuarial prediction, as used here, refers to procedures that involve the derivation of probability estimates from contingent-frequency tables (Wiggins, 1973). The actuarial prediction problem takes the form: Given several patterns of data (R_1, R_2, ..., R_k), what is the probability that an individual with a particular pattern will be a member of a given criterion group (C_1, C_2, ..., C_j). Sines (1966) referred to this strategy as prediction from taxonomic classes.

An actuarial prediction system has three basic components: (1) Identification of data patterns or taxonomic classes, (2) Specification of criteria of interest, and (3) Relating the taxonomic classes to the criteria of interest in a contingent-frequency fashion. The basic assumption underlying an actuarial prediction system is that by knowing the class or group an individual belongs to, the type of behavior likely to be emitted by that person can be predicted.

Proponents of this basic approach argue that it affords an opportunity to better understand and describe the individual and will result in more accurate predictions of relevant criteria. Tyler (1959) suggested that if a workable psychology of individuality is to be developed a model which recognizes significant, discrete patterns of individual "choice" behavior will have to be developed, and that some statistic, not a correlation coefficient, leading to a statement of probabilities must be developed. Owens (1969, 1971) argued that in assessing individuals a model which makes predictions based on homogeneous subgroups of individuals can lead to a fuller, more complete, and more meaningful characterization of individuals and provide a very efficient method of measurement. Sines (1964, 1966) proposed that the actuarial method provides the true test of an instrument's validity. That is, the usefulness or diagnostic efficiency of an instrument should be studied by examining the behavior of groups of people clustered on the basis of similarity of test scores.

The actuarial model has implications for the assessment and prediction of behavior in organizations. Contemporary organizational theorists have argued that the traditional linear model approach to the prediction of complex behavior in organizations is inadequate and that a model which accounts for configurations of individuals and their unique interactions with task demands and the organizational environment should be adopted (Dunnette, 1963; Campbell, Dunnette, Lawler, and Weick, 1970). In a similar vein Owens (1971) has suggested that the behavior of individuals may be predicted from subgroups homogeneous with respect to antecedent life-history experiences. Inherent in these suggestions is the concept of ulstriths and their concomitant behaviors. Thus, in an organizational context, knowing the ulstrith of a person would allow the prediction of the managerial behavior unique to the ulstrith, as well as the development of a better understanding of the behavior in terms of the characteristics of the ulstrith.

However, before it can be taken seriously such a system must be shown to be at least as effective in predicting criteria relevant to managerial success as the traditional linear model. The purpose of this study was to develop an actuarial model for predicting a managerial behavior and to compare this model with the linear model for effectiveness in predicting various criteria.

CHAPTER II

REVIEW OF THE LITERATURE

Of the two models studied in this research, the linear model has been widely discussed in terms of methodology and results. However, relatively little has been written about the methodology, predictive efficiency, or comparative utility of the actuarial model. Therefore, this review will consider only studies which are actuarial in nature. It is organized by the following general topic areas: Clinical Psychology and Psychiatry, Criminology, Academia, and Industrial/Organizational Psychology.

Clinical Psychology and Psychiatry

Meehl (1956) described one of the first applications of the actuarial method to a clinical prediction problem. Average Q-sort descriptions, based on nine randomly selected subjects, were developed for each of four frequently appearing MMPI (Minnesota Multiphasic Personality Inventory) score profiles. Independently, and without reference to MMPI data, therapists developed Q-sort descriptions of a second sample of eight subjects. Then, the eight subjects were assigned the Q-sort descriptions found associated with the MMPI profiles in the original sample. These "cookbook" predicted Q-sort descriptions were Q-correlated with the therapist-derived descriptions and compared to the Q-correlation of clinical predictions and therapist-derived Q-sorts. None of the correlations derived from the clinical predictions was as high as the correlations derived from the actuarial predictions. The average correlation based on the actuarial method was .78 compared to .48 for the clinical method, a difference of about 38% in predicted variance.

In another study Meehl (1959) compared clinicians' judgments, linear discriminant analysis, and four configurational methods in terms of success in identifying psychotics from MMPI score profiles. The prediction in each configurational method was based on the presence or absence of an MMPI score configuration; therefore, the configurations were analogous to the person clusters used in predicting from taxonomic classes. One of the configurational methods was based on a frequency of occurrence of MMPI elements; the other methods were derived from a subjective combination of MMPI scores.

The predictions resulting from the discriminant analysis and the four configurational methods were cross-validative, each having been developed on previous samples. In the analysis, which covered several samples and approximately 860 subjects, predictions made from the configurational methods resulted in the most accurate predictions. Individual predictions made by 21 clinicians were next in accuracy of prediction, followed by the linear discriminant analysis. However, these results were clouded by criterion contamination in more than half the sample. In a subsequent analysis using uncontaminated subjects, one of the configurational methods was as accurate as the pooled clinicians' judgments. The other configurational methods ranked next, followed by the individual clinicians, with the linear discriminant analysis last. The percentage correct classification, or "hit rate," of the methods varied from a high of 73% for one of the configurational methods to a low of 59% for the discriminant analysis (Lykken and Rose, 1963).

Using MMPI profiles, Marks and Seeman (1963) developed an actuarial prediction system. Sixteen profile types, based on MMPI score elevations, were clinically developed over several years from the records of more than 1,400 psychiatric patients. The profiles were cast into actuarial tables consisting of the cross-tabulation of profile type by a categorical representation of various criteria. The criteria were quantified as a percentage of each criterion category associated with each profile type. These percentages were further quantified as to their deviation from the base rate of the criterion category.

Use of the system requires a clinician to match a patient profile to one of the sixteen profile types. When a match is found, the clinician consults the actuarial table to determine the significant characteristics associated with the profile type. Using their classification rules, Marks and Seeman reported a "hit rate" of approximately 80% in their original sample. However, subsequent application of these rules by others has resulted in much lower classification rates (Wiggins, 1973).

Gilberstadt and Duker (1965) devised an actuarial prediction system based on a classic case concept. Using the case histories of 266 patients, they clinically developed 19 MMPI profile types unique in the characteristics they possessed. As in the Marks-Seeman system, the profile types were cross-tabulated against a categorical representation of various clinical criteria.

Application of the system requires a clinician to match a patient profile to one of the profile types. Once a match is found the clinician consults a table to determine the significant characteristics of the profile type. As with the Marks-Seeman system, subsequent use of the system has resulted in low classification rates (Wiggins, 1973).

Also using MMPI profiles, Sines (1966) constructed an actuarial prediction system based on empirically derived clusters of profiles. Employing the method suggested by Sawrey, Keller, and Conger (1960), Sines identified 11 person clusters in his patient sample. The Sawrey _et al_. method generated the person clusters in an iterative procedure using a Euclidean distance function. Wiggins (1973) reported that the Sines system was still in its developmental stages, and in a search of the literature only one additional reference was located. Gynther, Altman, Warbin, and Sletten (1972) reported that Sines had successfully developed only two of his person clusters.

Sines (1966), Gilberstadt and Duker (1965), and Marks and Seeman (1963) have developed actuarial prediction systems. All have identified homogeneous MMPI profile types in their respective populations and have related these profile types to various clinical criteria. The adequacy of these systems for predicting clinical criteria is difficult to evaluate. While all of the researchers reported initially promising results, subsequent attempts to apply the systems have yielded disappointing results. Moreover, none of the systems have been compared to other methods of prediction. Therefore, it is difficult to assess the relative merit of the systems.

Harman and Raymond (1970) conducted a study to evaluate a computer based method for empirically identifying person clusters from which predictions could be made. First, the ratings and test variables for 356 patients were clustered and cluster scores were calculated for each patient on the five resulting clusters. Second, person clusters were formed by a convergent means clustering technique applied to the cluster scores (Tryon and Bailey, 1970). In essence, an arbitrary number of clusters was pre-specified and subjects were assigned to clusters on the basis of an Euclidean distance function. Ten clusters were identified and cross-tabulated against a five category outcome rating. The statistical significance of this relationship was evaluated by a homogeneity coefficient calculated for each cluster (Tryon and Bailey, 1970). The homogeneity coefficient is a measure of within-cluster similarity with reference to criterion categories; the higher the coefficient, the more alike the cluster members are with respect to the criterion. Six of the ten clusters had homogeneity coefficients significant at the .05 level or less. The authors concluded that the feasibility and value of computerized clustering techniques for deriving patient clusters of significant prognostic value had been demonstrated. However, it should be pointed out that their procedure was not cross-validated or compared with other methods of prediction. Until that is done, the results can only be considered tentative.

Overall (1971) identified five phenomenological subtypes, or person clusters, in a sample of 350 patients who had been rated on a target symptom rating scale. The five clusters were identified from a Q-type factor solution computed on the correlation of patients over the rating scale items. In a subsequent study Overall, Henry, and Markett (1972) assigned 1,032 new patients to the five clusters on the basis of a similarity coefficient between the patient rating profile and the original cluster profile. Patients were assigned to the cluster they most closely resembled.

Contingency tables relating the clusters to background factors, treatment assignment, and outcome and prognosis ratings were developed on this cross-validation sample. Chi square tests indicated that the clusters were related to nine of fifteen background factors at the .05 level or less, to five treatment variables at the .001 level, and to five of seven post-treatment ratings at the .05 level or less. The authors concluded that the observed relationships appeared to support the utility of the classification scheme, and that the cluster content lent support to the notion that the clusters corresponded to primary syndromes of psychotherapy.

Paykel, Prusoff, Klerman, Haskell, and Dimascio (1973) compared a linear regression prediction strategy and a cluster based strategy. Each of 165 subjects in a validation sample was rated on 35 clinically oriented variables. A multivatiate cluster technique described by Friedman and Rubin (1967) was used to develop four clusters. The technique assigned individuals to clusters based on canonical variates that best discriminated the clusters. Subsequently, in a cross-validation sample 85 patients were assigned to the four groups on the basis of the canonical variates.

One-way analyses of variance were used to compare the four clusters on several demographic characteristics, pre-treatment ratings, and a global rating of illness severity. The clusters were significantly different on 17 of the 28 comparisons made. In addition, a comparison of a post-treatment rating and rating change score across clusters indicated differences significant at the .01 and .05 levels.

The 29 ratings which were used to assign the cross-validation subjects to their clusters were then used as independent variables in a multiple regression equation to predict the post-treatment rating and rating change score in the cross-validation sample. Multiple correlations of .75 and .72, significant at the .01 level were observed.

In comparing the two methods the authors pointed out that the multiple regression approach accounted for more criterion variance than the cluster analytic approach, but that the two approaches differed little in terms of statistical significance and confidence. However, the comparison was not strictly fair since the cluster analytic results were based on a cross-validation sample while the regression results were not. Moreover, the high multiple correlations may in part be explained by the high variables to subjects ratio. Having too few subjects relative to the number of independent variables tends to inflate the observed multiple correlation. Until a direct comparison of the methods is made in a cross-validation sample, the claim that the methods are equivalent is not justified.

Table 1 presents a summary of the Clinical Psychology and Psychiatry studies reviewed. In general, the studies suffered from one or more methodological flaws which rendered their results ambiguous. For example, in four of the studies no cross-validation of results was reported, and in five of the studies no comparison of the actuarial methodology with other prediction methods was made. Other problems noted were a comparison of a cross-validated and noncross-validated model (Paykel, et al., 1973), criterion contamination (Meehl, 1959), and results based on very small samples (Meehl, 1956).

TABLE 1

Summary of the Literature in Clinical Psychology and Psychiatry

Study	Clustering Technique	Predictors	Criteria	Cross-Validation	Comparison With Other Methods	Superior Method
Meehl (1956)	Empirical	MMPI	Q-sort Description	Yes	Clinical	Actuarial
Meehl (1959)	Empirical/ Subjective	MMPI	Rating	Yes	Clinical Linear	Actuarial
Marks and Seeman (1963)	Subjective	MMPI	Multiple	No	No	--
Gilberstadt and Duker (1965)	Subjective	MMPI	Multiple	No	No	--
Sines (1966)	Empirical	MMPI	Multiple	No	No	--
Harman and Raymond (1970)	Empirical	Ratings/ Tests	Treatment Outcome	No	No	--
Overall (1971); Overall, et al. (1970)	Empirical	Ratings	Multiple	Yes	No	--
Paykel, et al. (1973)	Empirical	Ratings	Treatment Outcome	Yes	Linear[1]	Equal

[1]Linear model not cross-validated.

Nevertheless, in the three studies where a comparison of the actuarial and other methods was made, the results tended to favor the actuarial model. However, the reliability of this trend remains doubtful in light of the inadequacies previously noted.

Criminology

Glaser (1962) examined the accuracy of two subjective and one empirical clustering techniques for predicting post-release behavior of convicted felons. In the subjective methods sociologists and psychiatrists assigned approximately 2,600 prisoners to prediction categories on the basis of an interview or case reading. The clusters of prisoners were then cross-tabulated against parole behavior. No significance tests were reported, and better than base rate predictions of parole success were made for prediction categories encompassing 20 and 55 percent of the subjects in the two studies.

Employing a configurational model suggested by Stuckert (1958)[1], Glaser empirically developed person clusters using 63 types of information from the case records of approximately 1,000 prisoners. The resulting 12 subgroups were cross-tabulated against post-release behavior. No significance tests

[1]Stuckert's method is discussed in the next section of this review.

were presented, and better than base rate predictions were made for only 45% of the subjects in the sample.

Neither of the methods were cross-validated. Therefore, no conclusions concerning the stability or utility of the results can be drawn. In addition, since different samples and types of information were used in the two methods to develop the prediction clusters, no accurate comparison of the results of the methods can be made.

Wilkins and MacNaughton-Smith (1964) compared clusters derived by association analysis and predictive attribute analysis for accuracy in predicting prisoner reconviction rate. Both methods used 13 variables reduced to attribute form (i.e., yes or no answers) to cluster 937 English convicts.

Association analysis is a multistage, hierarchical cluster procedure which formed clusters by combining individuals or clusters having several attributes in common that were strongly associated with one another (MacNaughton-Smith, 1965). Ten clusters were identified and cross-tabulated against reconviction status. The cross-tabulation yielded a contingency coefficient of .38, and although the authors regarded this as "encouraging," no significance level was reported.

Predictive attribute analysis is similar to association analysis in that clusters were formed on the basis of commonly held attributes. However, in predictive attribute analysis the attribute on which cluster membership depended was that attribute which was most strongly associated with some external criterion variable (MacNaughton-Smith, 1965). Eleven clusters were identified and cross-tabulated against reconviction status. This cross-tabulation yielded a contingency coefficient of .45. As before, no significance level was reported.

Although the magnitude of the contingency coefficient calculated for the predictive attribute analysis was greater than the coefficient calculated for the association analysis, it cannot be said that the relationship was stronger for predictive attribute analysis. Contingency coefficients can be compared only when they result from contingency tables with equal rows and columns (McNemar, 1969). Since the number of rows and columns differed, the contingency coefficients were not comparable. Moreover, no cross-validation was conducted. Therefore, the utility and stability of the observed relationships remain uncertain.

Babst, Gottfredson, and Ballard (1969) compared configuration analysis and regression analysis for predicting the probability of parole violation in validation and cross-validation samples of paroled convicts. For both samples prediction tables for fourteen and eight clusters of individuals based on arrest record data were developed. In addition, prediction tables based on a regression analysis which used the same arrest record data plus several additional variables were also constructed.

No overall measures of association were reported for the configurational analysis prediction tables, and no multiple correlation was reported for the regression analysis. However, other measures of predictive efficiency showed the two approaches yielded similar results. For example, on cross-validation violation rates for the fourteen and eight homogeneous person configurations varied from about 20 to 70 percent, while violation rates for eight score groupings based on regression analysis varied from about 20 to 60 percent. Significance tests comparing the proportion of violators in each person configuration and regression score grouping from validation to cross-validation sample indicated nonsignificant differences for both methods. Additional comparisons examining the degree of differentiation between violators and nonviolators, and the risk of violation rankings from validation to cross-validation sample revealed only minor differences that did not consistently favor either method.

Fildes and Gottfredson (1972) compared association analysis and modified association analysis for defining clusters to predict parole performance. Modified association analysis is similar to association analysis with the exception that clusters were based on a combination of attributes which maximized the within cluster multiple correlation of attributes already in the cluster with attributes being considered for inclusion (Gower, 1967).

Each method was applied to a sample of more than 4,000 subjects, and examined for replication of subgroups in a second, equally large sample. Replicability was defined as the overlap of identical subgroups (i.e., defined by the same attributes) found in the separate analyses. None of the clusters were replicated in the association analysis, and only 39% of the clusters identified in the modified association analysis were found in both samples.

As a next step, four prediction tables were constructed by cross-tabulating the clusters from each analysis against parole success. The prediction tables were compared for their efficiency in differentiating parole violators and nonviolators. The tables developed by the modified association analysis predicted the criterion more accurately than the tables developed from the association analysis. In addition, the results showed the modified association analysis to be comparable to the methods examined by Babst, et al. (1968). However, it should be noted that the Babst, et al. results were based on a cross-validation study while Fildes and Gottfredson's results were not.

With reconviction rate as the criterion, Simon (1972) compared the following methods for predictive accuracy: multiple linear regression, association analysis, predictive attribute analysis, configuration analysis, mean cost rating analysis, centroid predictive analysis and point scores. The mean cost rating is a configurational method similar to

Stuckert's (1958) method. In the centroid predictive analysis centroids were computed for each criterion category, and success or failure was predicted on the basis of an individual's similarity to the centroids. The point score systems were based on points accrued for possessing attributes assumed to be related to reconviction rate.

The analyses used various subsets of 62 variables from prisoner case records, and each analysis was developed on a validation sample and applied to a cross-validation sample. Significance of results was evaluated by multiple correlations for the regression analysis and phi coefficients and mean cost indexes for the prediction tables based on person clusters and point scores.

Two significant findings resulted. First, nearly all of the methods suffered severe shrinkage on cross-validation, and second, eleven of seventeen cross-validated multiple correlations and phi coefficients were significant at the .05 level or less. Moreover, the various methods differed little from one another in level of significance.

Simon pointed out that these comparisons were restricted in that the various analyses used differing subsets of the 62 predictor variables. Thus, another analysis using the same set of variables to compare multiple regression and predictive attribute analysis was conducted. On cross-validation results significant at the .01 level for the regression analysis, and significant at the .001 level for predictive attribute analysis were observed.

Simon concluded that, for practical purposes, there was little difference in the power of the various methods of combining variables for purposes of prediction.

Table 2 summarizes the Criminology studies reviewed. As with the Clinical Psychology and Psychiatry studies, several methodological inadequacies made their interpretation difficult. Three of the five studies attempted no cross-validation of results or comparison of models. Babst, et al. (1968) cross-validated their results and presented a comparison of models. However, their comparison was not based on the same set of predictor variables. Therefore, the conclusion that the actuarial and linear models were equal in predictive power is questionable. Simon (1972) presented the most methodologically sound study. In it the results of prediction by an actuarial and linear model were cross-validated and compared. The models were found to be equivalent in predictive power.

<u>Academia</u>

Stuckert (1958) compared a configurational method with multiple regression analysis and two point scoring methods for predicting grade point average of college freshmen. The configurational method was designed to predict a criterion with discrete categories from a set of attributes which were used to form homogeneous person clusters. Individuals were combined into groups on the qualification that their particular

TABLE 2

Summary of the Literature in Criminology

Study	Clustering Technique	Predictors	Criteria	Cross-Validation	Comparison With Other Methods	Superior Method
Glaser (1962)	Empirical/ Subjective	Ratings/ Case Hist.	Parole Behavior	No	No	--
Wilkins and MacNaughton-Smith (1964)	Empirical	Person Attributes	Reconvic. Rate	No	No	--
Babst, et al. (1968)	Empirical	Person Attributes	Parole Behavior	Yes	Linear[1]	Equal
Fildes and Gottfredson (1972)	Empirical	Person Attributes	Parole Behavior	No	No	--
Simon (1972)	Empirical	Person Attributes	Parole Behavior	Yes	Linear	Equal

[1]Linear model not developed on the same set of variables as the actuarial model.

configuration of attributes maximized the probability that the person possessed a specified external criterion. Each of the point score methods assigned numerical weights to the various attributes studied. The weights were summed, and the sums were used to predict the criterion (Burgess, 1928; Glueck and Glueck, 1950).

Two studies were conducted and in each study the methods were developed on a validation sample (N = 568), applied to two cross-validation samples (N's = 499 and 498), and assessed for accuracy and efficiency of prediction. Accuracy was the proportion of the samples predicted correctly by the method (i.e., hit rate); efficiency was the proportional reduction in error of prediction over the base rate prediction.

In the first study the four methods were used to predict grade point average divided into two categories. In the validation sample all methods were essentially equivalent in accuracy of prediction. In the two cross-validation samples the configurational, regression, and one point score method were equivalent in accuracy. The other point score method was significantly inferior to the other methods.

All methods were equivalent in efficiency of prediction in the validation sample. In the first cross-validation sample three methods were equivalent in efficiency, with the point score method which was inferior in the accuracy analysis also inferior in the efficiency analysis. In the second cross-validation sample the configurational method was significantly superior in efficiency to the other methods.

In the second study only the configurational and regression methods were compared in the prediction of a trichotomized grade point average covering the entire grade range. The configurational method was significantly superior to the regression procedure in accuracy in the validation sample, but was statistically equivalent to the regression method in both cross-validation samples. For predictive efficiency the configurational method was statistically superior to the regression procedure in the validation and one cross-validation sample. In the other cross-validation sample both methods were equal in predictive efficiency.

Considering only the configurational and regression procedures, essentially no differences were found between them in accuracy of prediction. Of the six comparisons made, the configurational method significantly differed from the regression method only once. In terms of predictive efficiency, the configurational method was significantly more efficient than the regression approach in three of six comparisons. In the remaining comparisons both methods were equivalent in predictive efficiency. The results led Stuckert to conclude that the configurational method was superior to the other methods.

Forehand and McQuitty (1959) evaluated two configurational methods and multiple regression for predicting grade point average. Eleven subscores from several tests were factor analyzed. Factor scores were computed and trichotomized for a validation sample (N = 183) and a cross-validation sample (N = 183) of college freshmen. Subjects in each sample were assigned factor standings based on their position within the trichotomized factor score distributions.

Three analyses were conducted. First, grade point average was regressed on the factor standings, and the results were applied to the cross-validation sample. Second, an analysis based on the method suggested by Lubin and Osburn (1957) was made. Groups of subjects with identical factor standing configurations were formed. The mean grade point average for each of the subgroups served as the predicted grade point average in the validation and cross-validation samples, and zero order correlations were calculated between predicted and actual grade point average for each sample. Third, the various factor score standings configurations were isolated, and those patterns with a greater than chance probability of occurrence were retained. Subjects not having configurations that were retained were assigned to the configuration most similar to their pattern. Predicted grade point average and correlations were obtained in the manner of the previously described configuration analysis.

The correlations between predicted and actual grade point average in both the validation and cross-validation samples were significant at the .01 level for all methods. In the validation sample the first configurational method yielded a correlation significantly higher than the regression procedure and the second configurational method. The regression approach was also superior to the second configurational method. However, the cross-validation correlations shrank considerably, and the strength of the relationships also changed. The linear model yielded correlations significantly higher than both configurational methods which were equivalent.

The authors concluded that the configurational methods were potentially more useful than the regression approach. However, in practical terms, these methods may not be applicable due to their severe shrinkage upon cross-validation.

Using Strong Vocational Interest Blank (SVIB) data, Collins and Taylor (1963) identified 28 clusters in a sample of 1,169 college freshmen. SVIB profiles were grouped employing a method suggested by Darley and Hagenah (1955). The subgrouping procedure formed clusters based on the occurrence of high and low scores on the SVIB scales as they related to various occupational groups.

Each person cluster was compared to the total sample on various ability, personality, socioeconomic, and academic variables. Each comparison was expressed as a positive or negative deviation from the total sample base rate. However, no estimate of the significance of the deviation was made, and no cross-validation was attempted. Nonetheless, the authors suggested that the configurational approach might provide counselors with useful descriptions of clients and enchance SVIB profile interpretation.

In a series of studies Schoenfeldt (1970a, 1970b, 1974) described an ongoing project aimed at actualizing the model suggested by Toops (1948, 1959) and formalized by Owens (1968). Life history factor score profiles were developed for males ($N \doteq 1,000$) and females ($N \doteq 900$) from a 389 item biographical information blank. With the life history profile as input data, person clusters for each sex group were developed by the method of Ward and Hook (1963). Clusters were formed by successively combining individuals or clusters of individuals into groups on the basis of an objective function. That is, clusters were formed under the condition that the combination of individuals or clusters to form a new cluster resulted in the minimum increase in the within cluster sum of squares. Twenty-three male and fifteen female homogeneous life-history subgroups were identified. These subgroups accounted for approximately 75% of the original sample, with the remaining subjects not fitting any of the clusters, or, alternatively, matching two or more of the clusters.

Differences between the person clusters on the biodata factor scores were highly significant. In addition, significant cluster differences were observed on a variety of tests (e.g., Scholastic Aptitude Test, SVIB, Purdue Values Inventory) (Owens, 1971). Significant cluster differences were also observed for educational criteria such as major, dean's list membership, and academic probations.

The stability of the subgroups was examined in three subsequent samples containing more than 6,000 subjects. On the basis of estimated factor scores, new subjects were classified to the clusters they most closely resembled by means of a discriminant function analysis. The percentage of new subjects assigned to the clusters was approximately the same as the percentage of the original subjects in the clusters. Thus, Schoenfeldt concluded that the original subgroup structure was applicable to all samples studied.

The grade point average for each of the original person clusters was compared to the grade point average of one subsequently developed sample of person clusters as a measure of the cross-validity of the groups as predictors. Rank order correlations of .89 and .73, significant at the .01 level, were observed for males and females, respectively.

Finally, Schoenfeldt (1974) suggested implementation of an assessment-classification model with person clusters as predictors. For example, person clusters are developed, and concurrently, jobs are clustered into families. The probability of success in job families given membership in person clusters is estimated with a discriminant analysis. Subsequently, new individuals are classified to person clusters, and then assigned to the job family in which they are most likely to succeed. Schoenfeldt's research indicated that person clusters were related to job families represented by "path walked in working toward a baccalaureate degree." However, this result was not cross-validated. Nor was it extended to job families more relevant to industrial organizations. Therefore, the applicability of the results to industrial organizations remains uncertain.

A summary of the literature in Academia is shown in Table 3. Only the Collins and Taylor (1973) study did not present cross-validation results. Two studies presented a comparison of models. Forehand and McQuitty (1959) found the linear model superior to the actuarial model, while Stuckert (1958) found the actuarial model superior to the linear model. However, Stuckert's models were based on differing numbers of predictors; therefore, his comparison reamins tenuous.

Industrial/Organizational Psychology

Taylor (1968) made the first application of the Toops (1948, 1959) model in an organizational environment. Nine clusters of individuals, accounting for approximately 75% of a validation sample of 200 salesmen and engineers were identified by applying the Ward and Hook (1963) procedure to

TABLE 3

Summary of the Literature in Academia

Study	Clustering Technique	Predictors	Criteria	Cross-Validation	Comparison With Other Methods	Superior Method
Stuckert (1958	Empirical[1]	Education Data	Grade Point	Yes	Linear	Actuarial
Forehand and McQuitty (1959)	Empirical	Test Data	Grade Point	Yes	Linear	Linear
Collins and Taylor (1973)	Empirical	SVIB	Multiple	No	No	--
Schoenfeldt (1970a, 1970b, 1974)	Empirical	Biodata	Multiple Education	Yes	No	--

[1]The clustering technique developed clusters containing different numbers of predictors; therefore, the comparison between the actuarial and linear models was not necessarily based on the same set of predictors.

biodata factor scores. Individuals in a second sample of 244 salesmen and engineers were then assigned to the cluster to which the Euclidean distance of their biodata profile was a minimum. Both sets of clusters were examined in light of three hypotheses.

First, the hypothesis that "co-existing similarities in background pattern and job behaviors would be found" was tested by comparing cluster variance to total sample variance on several performance variables. Significant differences were found for several clusters, but these relationships did not show general support for the hypothesis (Taylor, 1968).

Second, Taylor hypothesized that "an affinity would be observed between life-history subgroup membership and job assignment." The results showed that job assignments associated with subgroups in the original sample were also significantly related to the subgroups in the second sample. Thus, Taylor's hypothesis was supported.

Finally, Taylor hypothesized that "individuals matched to existing subgroups for pattern of background behavior would tend to exhibit the characteristic industrial behavior of their subgroup." The hypothesis was evaluated by testing the difference between an individual's performance and the performance of individuals in and not in his subgroup. Results showed that there was a tendency for a person within a given cluster to exhibit the median potential of his group, but this tendency was not found for the two remaining performance measures - appraisal and job grade. Thus, only partial support was found for this hypothesis (Taylor, 1968).

In summary, Taylor found only partial support for his hypotheses, and those hypotheses relating to his original goal of developing a useful individual assessment technique were not substantiated.

Using biodata factor scores and the Ward and Hook (1963) procedure, Ruda (1970) identified thirteen person clusters from a sample of 458 individuals. Each cluster was compared to overall success rankings. Two of the clusters showed high positive relationships to success while two clusters were highly negatively related to success in both a validation and cross-validation sample.

Pinto (1970) examined three methods of prediction. First, using biodata factor scores and the Ward and Hook (1963) technique, he identified 21 person clusters on a sample of 915 salesmen. Second, 1,145 salesmen in a cross-validation sample were assigned to the clusters on the basis of a discriminant analysis. In his first prediction study Pinto used the 21 person clusters as moderators. Within each of the original subgroups, termination rate was regressed on ability and personal profile test scores. Only three of the 21 multiple correlations were significant, and when the regression weights were applied to the second sample of 21 clusters, no significant correlations were observed. The lack of cross-validation was attributed to the restriction in range of both test scores and the criterion resulting from the clustering. That is, clusters homogeneous with respect to biodata would likely be homogeneous with respect to other behavioral indices, thus restricting the range of the data.

Second, the original 21 clusters were examined for use as predictors. They were cross-tabulated with termination status. The resulting Chi square, significant at the .01 level, indicated the clusters had differential affinity for the criterion categories. However, a similar cross-tabulation of the 21 cross-validation clusters resulted in a nonsignificant Chi square. On the other hand, the rank order correlation of percentage of termination between the two samples was significant. Thus, it was concluded that the affinity of the criterion for the clusters had been demonstrated in both samples.

Finally, without reference to cluster membership, the termination criterion was regressed on the ability and personal profile test scores for the validation sample. The obtained correlation of .13 was significant; however, the validity shrank to a nonsignificant .02 on cross-validation. As a follow-up, the biodata factor scores were added to the ability and profile scores, and all were used to predict the criterion. The resulting multiple correlations of .24 and .12 were significant, though not of great magnitude.

Using SVIB total profile scale scores and item responses, Suziedelis and Lorr (1973) employed typological analysis to develop two sets of person clusters from a sample of 560 individuals representing artist, farmer, minister, physicist, purchasing agent, real estate salesman, and newsman occupational groups. The typological analysis employed a congruency coefficient (a normalized cross-product of profile scores) in an iterative process of cluster formation (Lorr and Radhakrishman, 1967). The total profile scale score analysis resulted in six person clusters accounting for approximately 50% of the subjects analyzed, while the item response analysis yielded five person clusters accounting for slightly more than 25% of the subjects.

The total profile scale score analysis yielded clusters that contained more subjects and subjects from all six occupational groups, while the item response analysis resulted in smaller clusters representing only five of the occupational groups. Only F tests showing that the profile total scores were significantly different across the six clusters on the SVIB variable scores were reported. Although the clusters were found to differ, these differences were not cross-validated. Therefore, conclusions concerning the utility and stability of the results cannot be drawn.

Using the Ward and Hook procedure and in-basket scores, Pinder and Pinto (1974) identified three person clusters in a sample of 200 managers. The clusters were cross-tabulated against twelve organizationally relevant criteria. Significant Chi squares were observed for the criteria of age and organizational department. The authors concluded that the results suggested that managerial styles represented by the three clusters may be associated with various organizational variables, but that further longitudinal research was needed to validate this conclusion.

Welches, Dixon, and Stanford (1974), using the Tryon and Bailey (1970) cluster routines and factor scores covering various individual attributes, identified twelve person clusters in a sample of 650 nurses. Approximately 95% of the sample was classified into one of the clusters. The twelve clusters were examined for differences in an independently derived performance rating. Only two of the twelve clusters had mean ratings significantly different from the grand mean of the sample. In addition, the results of the study were not cross-validated; therefore, the utility and stability of the results remain uncertain.

The results of the Industrial/Organizational literature review are summarized in Table 4. Three of the studies attempted no cross-validation of results, and no study presented a comparison of the actuarial model with any other prediction model. Pinto (1970) presented results

TABLE 4

Summary of the Literature in Industrial/Organizational Psychology

Study	Clustering Technique	Predictors	Criteria	Cross-Validation	Comparison With Other Methods	Superior Method
Taylor (1968)	Empirical	Biodata	Pot./App./ Job Grade	Yes	No	--
Ruda (1970)	Empirical	Biodata	Perform.	Yes	No	--
Pinto (1970)	Empirical	Biodata	Term. Rate	Yes	No[1]	--
Suziedelis and Lorr (1973)	Empirical	SVIB	Occupation	No	No	--
Pinder and Pinto (1974)	Empirical	In-basket	Demograph. Variables	No	No	--
Welches, et al., (1974)	Empirical	Multiple	Rating	No	No	--

[1]Although predictions were made from several models, no direct comparison of results was presented.

from several models. However, the same set of predictors was not common to two or more of the models, and no direct comparison of the results was presented. Thus, considering all of these studies, little can be said about the effectiveness of the actuarial model for predicting industrial variables.

Summary

Considering all of the studies reviewed, the following was observed:

1. The majority of studies employed some empirical method of identifying person clusters. The favored technique involved some variation of the hierarchical procedure described by Ward and Hook (1963).
2. A variety of predictor variables was used to identify person clusters. In clinical studies the MMPI was most often used; in the remaining studies no one type of data was used consistently across areas.
3. Multiple criteria were used in the studies. Only in the criminology area, where parole behavior was the criterion, was the criterion consistent across studies.
4. Cross-validation of results was carried out in approximately 50% of the studies reviewed.

5. The actuarial model was compared with other models in seven of the twenty-three studies reviewed. The results of these comparisons were equivocal since, in many cases, the models were based on different sets of variables. However, if the comparisons are assumed accurate, the actuarial model was more accurate than the other models in three comparisons, equal to the other models in three comparisons, and inferior to another model in one comparison.
6. Little or nothing was said about the practical utility versus the statistical significance of predictions generated by the models. Only two authors (Meehl, 1956, 1959; Stuckert, 1958) made any mention of the predictive utility of the models versus base rate predictions.
7. Although not specifically mentioned in the review, one final important issue concerns whether or not person clusters were formed independently of criterion measures. In some cases (e.g., configurational analysis and predictive attribute analysis) the formation of clusters hinged on the relationship of an analysis variable to some

external criterion. In other methods (e.g., association analysis and hierarchical cluster analysis) the generation of clusters depended on the relationships among analysis variables without reference to an external criterion. The criterion dependent methods are, in essence, "fitted" models which are analogous to the linear model which is also criterion dependent. Since they are criterion dependent, the methods do not fit well the concept of the actuarial model as used in this research. By virtue of their criterion dependent nature, these methods are applicable only to criteria similar to those on which the model was developed, and, therefore, accrue none of the advantages associated with the criterion independent model. That is, since they are criterion dependent, the composition of the subgroups change from criterion to criterion, and the efficiency of having unique, unchanging subgroups is lost. The ultimate result would be the loss of the opportunity to develop a taxonomy centered on unique, unchanging subgroups of individuals.

CHAPTER III

PROCEDURE

Subjects

The goal of this research was to compare two approaches for predicting criteria relevant to managerial performance. To this end 5,798 managers, or potential managers, in a large petroleum firm were selected for study. This sample represented all individuals who had been tested in the company's ongoing managerial assessment program and who were employed, or had been employed, in one of five broad manpower categories: management, supervisory professional-technical, supervisory professional, professional-technical, and professional.

The sample consisted of 87 females and 5,711 males, and 249 minorities and 5,549 nonminorities. The average age of the subjects was 38.22, with a standard deviation of 7.31. The sample averaged 11.13 years of company service, with a standard deviation of 7.64, and 2.75 years of service in their current job, with a standard deviation of 1.72.

For purposes of cross-validation, the sample was divided into two samples of 2,899 subjects. The individuals were ordered according to social security number. From this ordering, each even-positioned individual was assigned to the validation sample, and each odd-positioned individual was assigned to the cross-validation sample. Chi square and

and t-tests were used to determine whether significant differences existed between the two samples on various demographic and analysis variables. No significant differences were observed between the samples on any of the variables available for study.

Criteria

Approximately 33% of the individuals tested had left the company. In light of this rather substantial turnover rate, employment status was designated as one criterion for analysis. Employment status was divided into the following categories: currently employed or retired, gone regretted, and gone without regret. Subjects in the validation and cross-validation samples were assigned to one of these categories on the basis of data in their personnel files.

The second criterion was a performance measure consisting of the first factor score from a factor analysis of age, total company service, job grade, performance appraisal, and an estimate of career potential. Job grade, performance appraisal, and potential estimate were taken as the average of the last three available values for each variable. Table 5 presents the varimax rotated factor matrix which resulted from this analysis. As indicated by the low loadings of age and company service, the resulting factor scores were relatively free of age and tenure bias. Thus, although this criterion was a global measure of performance, it was developed from an array of performance

TABLE 5

Rotated Factor Matrix: Job Performance

Variable	Factor[1]	
	I	II
Appraisal[2]	.84	-.12
Potential	.94	.01
Job Grade	.76	.52
Total Service	.11	.94
Age	-.10	.94

[1]The factors accounted for approximately 43% and 41% of the variance.

[2]Appraisal was reflected. The scale was reversed; low ratings indicated high performance.

related variables from which contamination due to nonperformance measures was largely eliminated.

Criteria such as this, however, have been criticized as being contaminated by the inclusion of an estimate of potential in their development in that the estimate may be influenced by prior knowledge of the assessment data (Wallace, 1974). However, on a subset of the individuals in this study on whom performance data were available for two separate occasions, Sparks (1976) has shown that inclusion of potential in the criterion does not result in contamination. Several scores, developed from the tests also used in this study, were correlated with two performance measures, the first of which was developed prior to the test administration, and the second of which was developed two years later. Only two of eight test-criterion correlations increased in magnitude, and then from .34 to .38, and .33 to .39. The remaining correlations remained the same or decreased slightly. Therefore, it appears that, for these data, the threat of contamination is not great. Nevertheless, since the scores and subjects used by Sparks were not identical to those used in this study, a performance measure excluding potential was developed in the same manner as the previously described measure. Table 6 presents the varimax rotated factor matrix which resulted from the factor analysis of age, company service, job grade, and appraisal.

TABLE 6

Rotated Factor Matrix: Job Performance with Potential Excluded

Variable	Factor[1]	
	I	II
Appraisal[2]	.92	-.15
Job Grade	.71	.53
Total Service	-.07	.94
Age	.14	.94

[1]The factors accounted for approximately 35% and 52% of the variance.

[2]Appraisal was reflected. The scale was reversed; low ratings indicated high performance.

For the purpose of analysis, each of the performance criteria was dichotomized at the mean for both the validation and cross-validation samples. Thus, predictions for this variable were made in terms of scoring above or below the mean of the group.

Analysis Variables

Scores or subscores available from the firm's managerial assessment test battery were used as analysis variables. Complete data on thirteen scores were available on the 5,798 subjects. The following is a description of the analysis variables stated in terms of high scorers:

Developmental Influences. Developed a high degree of self-reliance early in life; Parents provided a supportive and emotionally comfortable family atmosphere; Parents encouraged independence; Related to others and controlled emotions; Involved in many activities; In summary, circumstances of youth and early adulthood encouraged the development of a wide range of personal skills, independence and self-reliance.

Achievement: Academic Years. Attained high level of formal education and scholastic success; Held positions of leadership in school; Gained membership in school related clubs; Desired and received recognition of accomplishments; In summary, adapted well to the prevailing academic environment, and achieved a high level of scholarship, leadership and social success.

Present Self-Concept. Confident of ability and capacity to develop new skills; Feels that given proper training and support can do any job well; Has feeling of self-worth; Does not feel need for continual approval of others; Is independent; Satisfied with current life situation; In summary, has the image of self as worthy, capable, and possessing the potential to take on any job, given the proper preparation.

Staff Communication, Participation. Ideas and decisions need to be sold, not just announced; Staff should be depended on to help formulate ideas and explain them to other employees; Conferences should be held to facilitate upward communication; Differences in responsibility should be clear to employees. In summary, believes in involving subordinates in developing and implementing new procedures, communicating with employees on a regular basis, and clearly delineating lines of responsibility.

Employee Selection-Development. Select and advance employees on ability and merit; Use objective setting and performance review procedures; Hold employees accountable for their objectives; Managerial and supervisory skills best taught in context of actual job; Supervisory skills not common sense; In summary, believes in using ability and merit as basis for organizational rewards, involving employees in procedures relevant to their performance and teaching the skills necessary to manage and supervise.

Employee Motivation-Labor Relations. Nonfinancial rewards useful in recognizing employee contributions; Employee motivation enhanced by resolving problems at lowest organizational level possible; Employees should be allowed to increase competence and knowledge; Organization should be responsive to employee complaints, and ready to help solve problems. In summary, believes rewards other than pay can motivate individuals, motivation is enchanced by the self solution of problems, and the organization has a responsibility to listen to its employees.

Management Style, Decision-Making. Managers should not be constrained by historical precedent; Calculated risks necessary; Managers should challenge superiors when necessary; Managers should be responsible for own decisions; Managers should not continually depend on superiors; In summary, feels managers should not be constrained by the past or the decisions of superiors, and that independence should be exercised in making decisions.

Behavioral Consistency. Maintains consistent temperament and avoids behavioral extremes; Thinks before acting; Not easily upset; Not influenced by moods of others; Controls behavior when irritated; In summary, is even tempered and self-controlled.

Energy Level, Time Use. Consistently full of energy; Sets fast work pace; Gets a lot of work done; Is impatient when delayed; Does not like to be mired in detail; Spends little time meditating and daydreaming; In summary, is an on-the-go person, conscious of time, and a hard worker.

Confidence, Conviction. Has confidence in own ideas and plans; Is willing to persuade others; Listens to new ideas; Pursues own objectives; Accepts competition; Worries little; Has received deserved recognition; In summary, feels comfortable with self in terms of ideas and plans.

Behavior Understanding, Tolerance. Avoids conflict over minor issues; Is not petty; Not cynical about human nature; Is considerate; Recognizes and accepts limitations of others; Tries to understand behavior of others; In summary, attempts to understand the behavior of others on their terms, and accepts people for what they are.

Verbal Reasoning. Possesses a high level of cognitive skill as measured by the ability to evaluate analogies.

Nonverbal Reasoning. Possesses a high level of cognitive skill as measured by the ability to evaluate similarities or differences among drawn figures.

The first three variables were subscores developed from a biographical information blank. Scales four through seven were derived from a test of managerial judgment, and scores eight through eleven were developed from a temperament survey. The verbal reasoning score is the Miller Analogies Test, and the nonverbal reasoning score is the RBH Test of Nonverbal Reasoning.

Prior to use in any analysis, the thirteen variables were standardized on the entire sample of 5,798 subjects. Each variable was transformed to have a mean of 20.0 and a standard deviation of 5.0.

Development of the Actuarial Model

The development of the actuarial model followed four successive steps: (1) Initial formation of person clusters through a hierarchical clustering routine; (2) Reallocation of individuals improperly placed in clusters; (3) Validation of the final array of person clusters; and (4) Cross-validation on a second sample.

Hierarchical Clustering. The initial array of person clusters was identified by a hierarchical clustering procedure described by Ward (1963) and Ward and Hook (1963). This procedure began by considering each individual as a unique cluster described by a p-dimensional vector of variable scores. In successive steps clusters were combined until only one cluster containing all individuals remained. At each step of the clustering process, two clusters were merged so as to maximize an objective function. In this study the objective at each stage of clustering was to find those two clusters whose merger minimized intracluster variation while maximizing intercluster variation. That is, clusters were combined to give the minimum increase in the total within group sum of squares, called error sum of squares, E. In essence, the change in E was determined by computing the sum of the Euclidean distances (D^2) of all variables in each cluster with all the variables in all other clusters, and combining the two clusters whose D^2 was the minimum. The combining of the two clusters whose D^2 is the minimum results in the minimum increase in E.

The typical hierarchical clustering procedure involves computing a matrix of intersubject D^2's and searching the matrix for the minimum D^2 for cluster combinations. However, in the case where there is a large number of subjects, this procedure becomes unworkable because of computer storage limitations. Thus, in this study where the objective was to cluster a very large sample (N = 2,899), a hierarchical clustering procedure presented by Anderberg (1973) was used in order to circumvent the computer storage limitation problem. The procedure, which is equivalent to the D^2 matrix scanning approach, stores only the raw data in the computer's memory. The clustering statistics are generated by scanning the raw data list rather than a D^2 matrix. The result is a capability of clustering many more subjects than could be clustered with the usual procedure.

There are, unfortunately, two problems inherent in the hierarchical clustering procedure. First, there is no unambiguous answer for the problem of when to stop clustering. Logically, the answer is related to the amount of increase in the error sum of squares, E, calculated at each clustering stage. As the clustering proceeds, and more and more dissimilar clusters are combined, the rate of increase in the error sum of squares must accelerate. Thus, clustering should be terminated when an unacceptable increase in E has occurred. However, the determination of what constitutes an unacceptable increase remains subjective. In this study, as in others (Taylor, 1968; Pinto, 1970), the rate of change in E was plotted, and the number of clusters retained for analysis was pinpointed at a stage in the clustering which preceded the first inordinately large increase in E.

<u>Convergent Clustering</u>. The second problem with hierarchical clustering is that once an individual joins a cluster that person becomes "locked" into that cluster. The hierarchical clustering procedure provides no way for an individual to be removed from a cluster should the cluster subsequently change in such a way that the person is no longer most similar to the cluster. Therefore, as an adjunct to the hierarchical clustering procedure, those clusters selected for further study were subjected to a convergent means cluster analysis (Anderberg, 1973). In this procedure an individual's Euclidean distance was computed between his/her parent cluster centroid and the centroids of all other clusters. If the distance to the parent cluster was the minimum, no changes were made. If the distance to a nonparent cluster was the minimum, the individual was moved to that cluster, and the old parent and new parent cluster centroids were changed to reflect the move. The procedure is iterative, and terminated when no moves were made; that is, when all individuals were in the cluster they most closely resembled.

<u>Validation</u>. After final cluster membership was determined in the convergent clustering procedure, clusters were cross-tabulated against the three pre-specified criteria. The relationship between the clusters and the criteria was analyzed as follows: First, a Chi square was computed to measure the statistical significance of the relationship

between the variables. Second, the degree of association between the clusters and the criteria was estimated by Cramer's Statistic (Hays, 1963). This statistic measures the relationship between two variables in a correlational sense. If there is no relationship Cramer's Statistic has a value of zero; if there is a perfect relationship it has a value of 1.0. Third, lambda, or the Index of Predictive Association, was computed to assess the practical utility of the association between the variables (Hays, 1963). Lambda is a measure of the percentage reduction in the probability of error in predicting the criteria from the clusters. The statistic varies from zero, when knowing cluster membership results in no reduction in error of prediction, to 1.0, when knowing cluster membership results in 100% reduction in error of prediction. Finally, a "hit rate" for predicting the criterion categories was calculated. For each criterion in the validation sample, this represented the sum over clusters of the number of people in the most frequently appearing criterion categories divided by the total sample size.

<u>Cross-validation</u>. Two steps were involved in the cross-validation of the actuarial model. First, the 2,899 cross-validation sample subjects were assigned to one of the clusters developed in the cluster analysis by means of a minimum distance qualifier. The Euclidean distance of

each sample member to each of the previously developed cluster centroids was calculated, and individuals were assigned to the cluster to which their distance was the minimum. The only qualification to this rule was that an individual would not be assigned to any cluster if two or more of his/her distance functions were equal. However, this rule did not disqualify anyone in the cross-validation sample from cluster membership. Second, cross-validation clusters were cross-tabulated against the three pre-specified criteria. The Chi square, Cramer's and lambda statistics were calculated as in the validation analysis. The "hit rate" was calculated as the sum over clusters of the number of people in the most frequently appearing criterion categories identified in the validation sample analysis divided by the total sample size.

<u>Development of the Linear Model</u>

<u>Discriminant Analysis</u>. In the validation sample a multiple group discriminant analysis was performed on the employment status criterion categories using the thirteen analysis variables as discriminating variables. The objective of the analysis was to develop a set of classification function for predicting criterion category membership. The classification functions were derived from the pooled within-groups covariance matrix and the centroids of the discriminating variables in the criterion categories (Overall and Klett, 1972). The analysis resulted in a series of

discriminating variable weights and a constant term for each criterion category. A predicted criterion category was developed for each subject by applying the classification weights to his/her analysis variable scores and adjusting the resulting value by the a-priori probability of criterion category membership. A classification table was generated by cross-tabulating actual by predicted criterion category, and a "hit rate" was calculated as the number of classifications where predicted category was identical to actual category divided by the total number of classifications.

The results of this procedure were essentially equivalent to developing classifications based on all discriminant functions available from the analysis (Tatsuoka, 1971). Thus, this classification procedure was an empirical test of the adequacy of the linear discriminant analysis. In addition to this empirical test, multivariate and univariate F tests comparing each analysis variable across criterion categories, and Mahalanobis D^2 were calculated as a test of the statistical significance of the discriminant analysis.

In the cross-validation sample predicted criterion category membership was derived by applying the validation sample classification function weights to the analysis variable scores of the subjects and adjusting the resulting value by the prior probability of criterion category membership. As in the validation analysis, a classification table and "hit rate" were generated.

Regression Analysis. In the validation sample the two factor analytically derived performance criteria were regressed on the thirteen analysis variables. For each criterion the resulting multiple correlation coefficient was tested for statistical significance, and the regression weights from the regression equation were used to calculate a predicted score for each sample member. Both the predicted and actual scores were dichotomized at their respective means and cross-tabulated against one another. Chi square, phi (Cramer's statistic for two by two tables), and lambda were calculated for the tables. The "hit rate" was calculated as the numbers of comparisons where the predicted and actual criterion categories were the same divided by the total number of comparisons.

In the cross-validation sample a predicted criterion score was computed by applying the regression weights developed in the validation analysis to the analysis variable scores of each sample member. A cross-validated multiple correlation was calculated by correlating these predicted scores with the actual scores of the sample members. Then, both the predicted and actual scores for each criterion were dichotomized at their respective means and cross-tabulated against one another. As in the validation analysis, a Chi square, phi, lambda, and "hit rate" were computed on the cross-tabulations.

<u>Comparison of Models</u>

In the actuarial analysis the person clusters were cross-tabulated against the various criterion categories, and in the linear analysis a predicted criterion category was cross-tabulated against actual criterion category. For both models association statistics relevant to contingency tables were employed: Chi square, Cramer's statistic or phi, and lambda. For these statistics an empirical comparison of the cluster and linear models was made for each criterion. In addition, a "hit rate" for making predictions was computed for each model. The significance of the difference in "hit rates" between the models was determined using the McNemar (1969) test for correlated proportions.

CHAPTER IV

RESULTS

Cluster Analysis

At each stage of the hierarchical cluster procedure, the within-group error sum of squares, E, was computed. Figure 1 shows the increase in E associated with the reduction of clusters from 45 to one. The increase in E was fairly uniform going from 45 to 12 clusters. However, there was a large inflection in E with the reduction of clusters from 12 to 11. Therefore, 12 clusters (homogeneous subgroups) were retained for further analysis. Selecting more than 12 subgroups would have resulted in analyzing two or more subgroups very similar to one another since the step-by-step increase in E prior to this stage was fairly small. Conversely, selecting fewer than 12 subgroups would have resulted in analyzing two or more very hetereo-geneous subgroups since E increased rather drastically following this step.

The 12 subgroups were then analyzed by the convergent clustering technique. In this iterative procedure all subjects were compared to all subgroup centroids and reassigned to the subgroup they most closely resembled if different from their parent subgroup. This adjustment process required 12 iterations before subgroup membership stabilized. The following numbers of subjects were moved

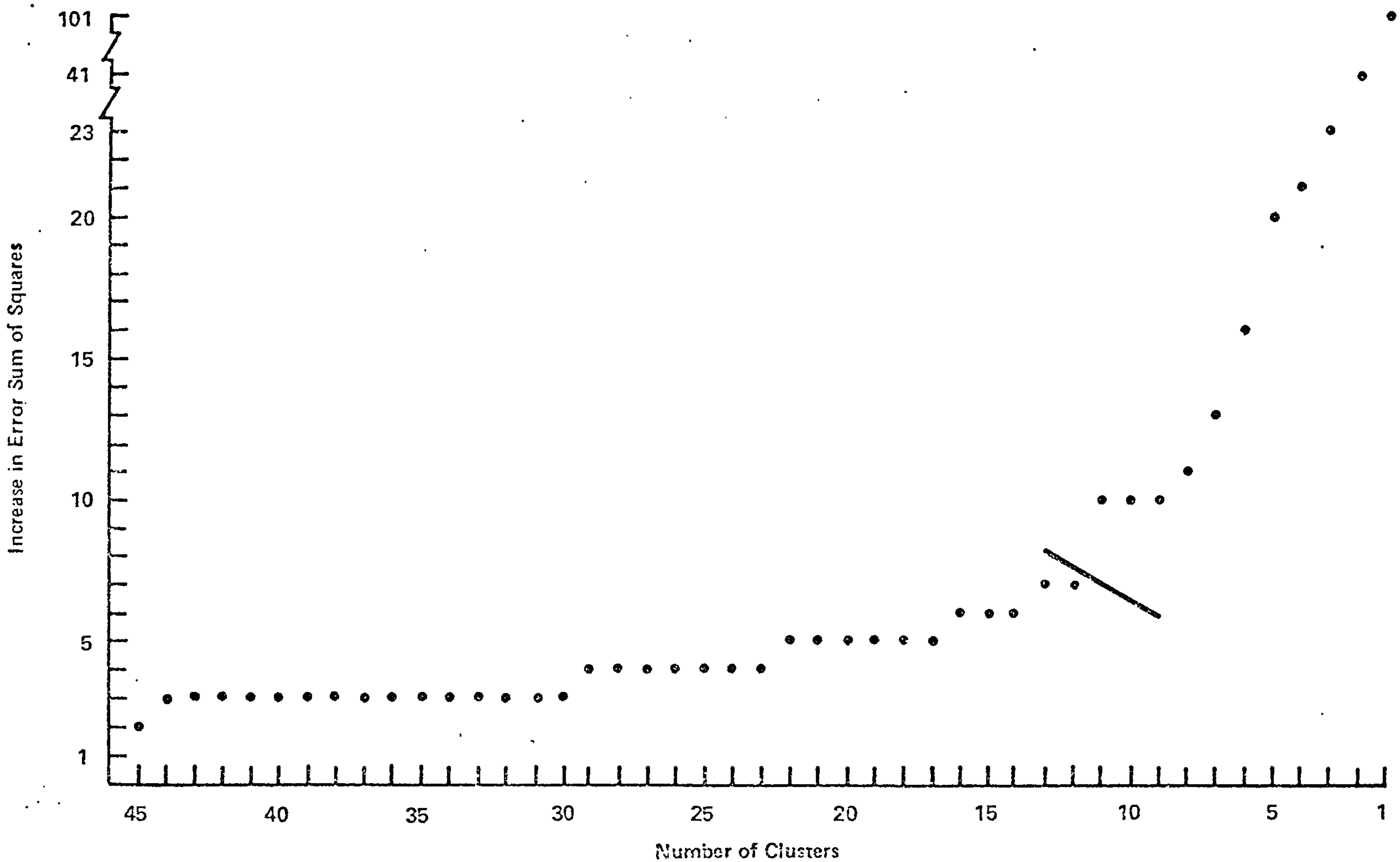


Figure 1

Increase in Error Sum of Squares Associated with the Reduction in Number of Clusters in each iteration: (1) 1,123; (2) 253; (3) 126; (4) 88; (5) 78; (6) 63; (7) 35; (8) 21; (9) 27; (10) 13; (11) 1; (12) 0. The convergent clustering reduced the error sum of squares calculated for the 12 subgroups in the hierarchical procedure by approximately 10.7%. Thus, the convergent clustering technique produced subgroups more homogeneous than the original array of subgroups.

Next, subjects in the cross-validation sample were assigned to the subgroup they most closely resembled. Subjects were assigned to the subgroup yielding the minimum D^2 between their 13 analysis variable scores and the 12 subgroup centroids computed on the validation sample. The centroids for the validation and cross-validation samples are presented in Appendix A. Figure 2 graphically displays the centroids for both samples. Each analysis variable mean is shown as a deviation from the variable mean for the sample. Since the variables were standardized, all variables had a mean of 20.0 and a standard deviation of 5.0 in both samples. From left to right the variables are as follows:

1. Developmental Influences
2. Achievement: Academic Years
3. Present Self-Concept
4. Staff Communication, Participation
5. Employee Selection-Development
6. Employee Motivation, Labor Relations

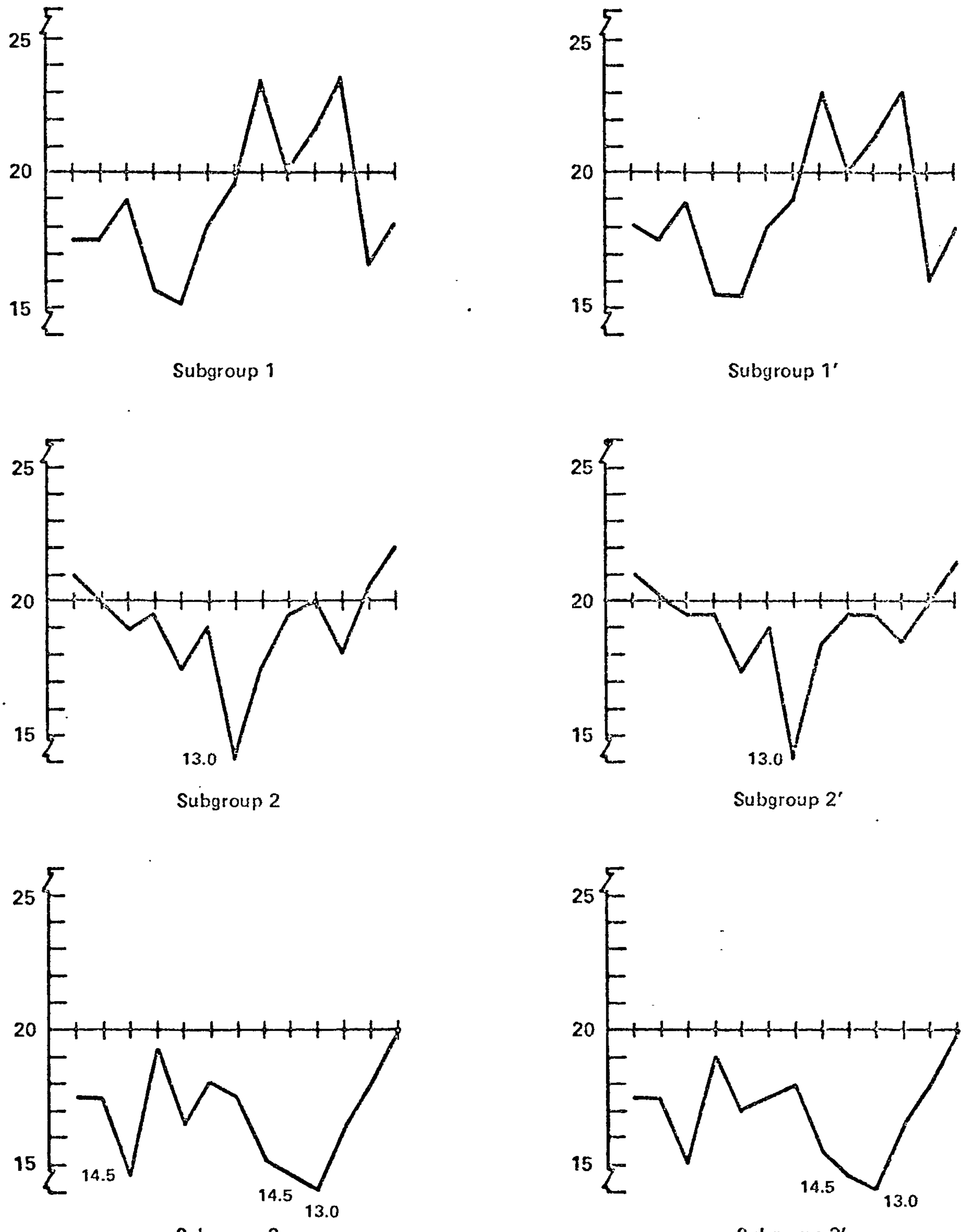


Figure 2

Analysis Variable Profiles for the Employee Subgroups:
Validation and Cross-Validation Samples

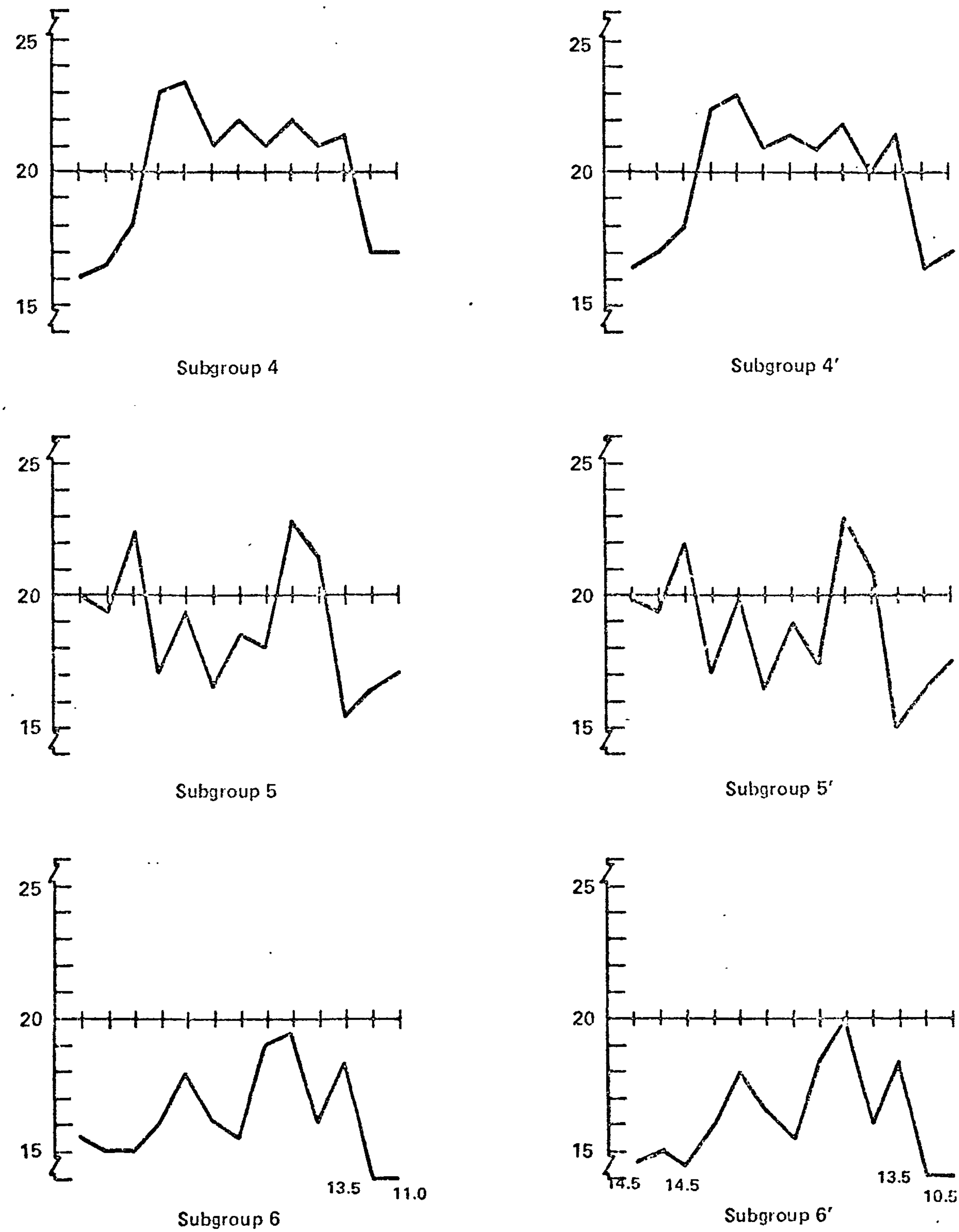


Figure 2

(Continued)

Analysis Variable Profiles for the Employee Subgroups:
Validation and Cross-Validation Samples

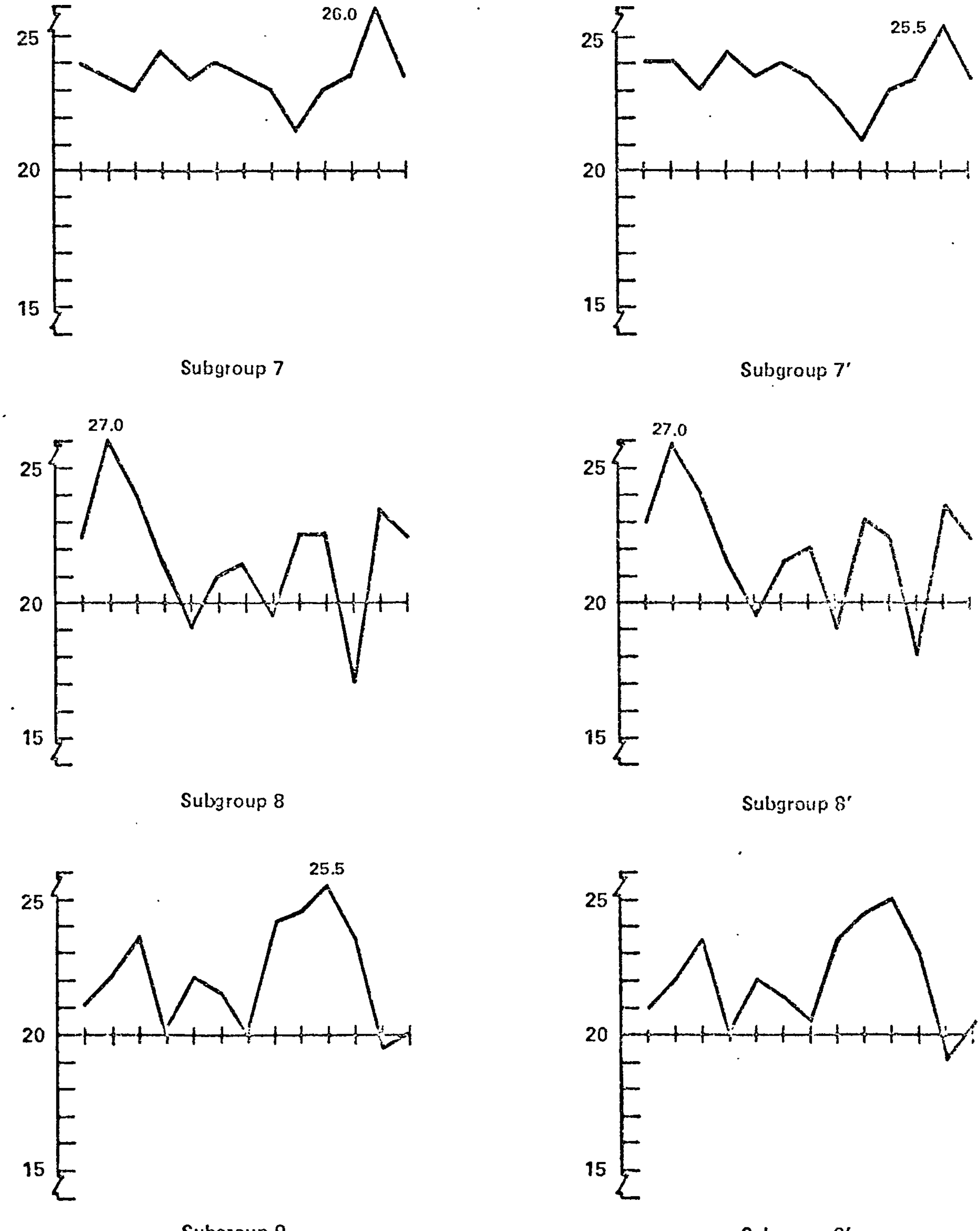
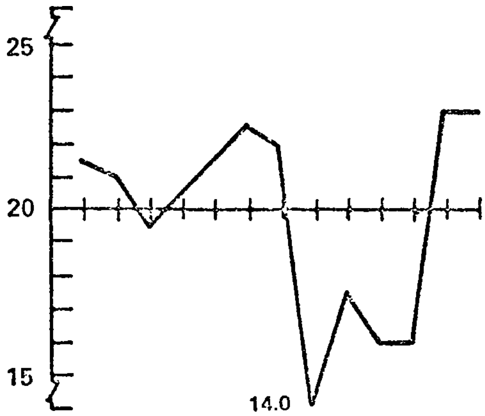


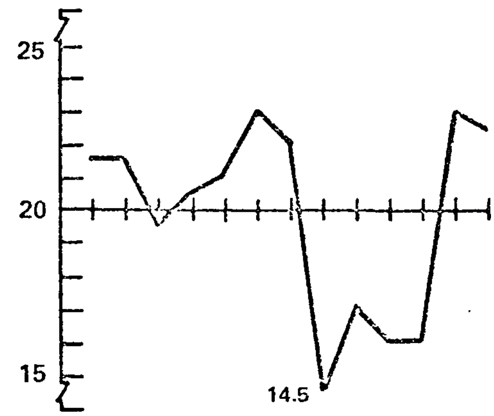
Figure 2

(Continued)

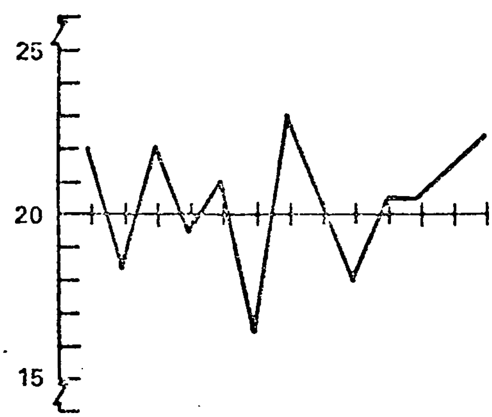
Analysis Variable Profiles for the Employee Subgroups: Validation and Cross-Validation Samples



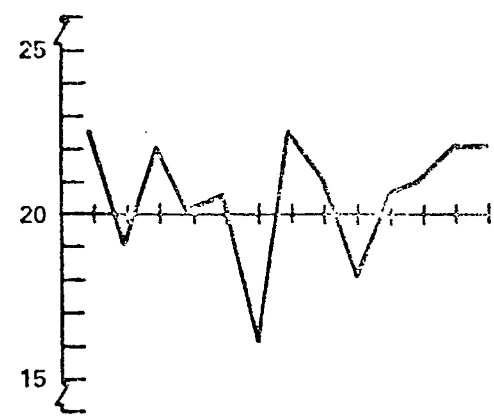
Subgroup 10



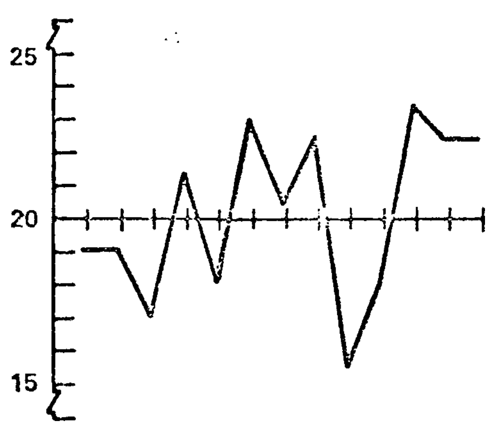
Subgroup 10′



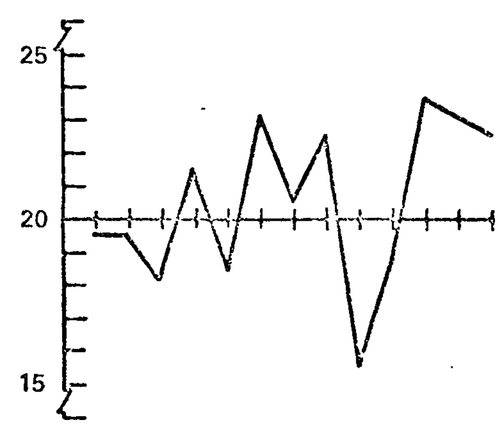
Subgroup 11



Subgroup 11′



Subgroup 12



Subgroup 12′

Figure 2

(Continued)

Analysis Variable Profiles for the Employee Subgroups:

Validation and Cross-Validation Samples

7. Management Style, Decision-Making
8. Behavioral Consistency
9. Energy Level, Time Use
10. Confidence, Conviction
11. Behavior Understanding, Tolerance
12. Verbal Reasoning
13. Nonverbal Reasoning

It is apparent that the minimum distance assignment of the cross-validation subjects to the subgroups resulted in the replication of the validation sample subgroups. In each case the validation sample profile and the cross-validation sample profile (designated by a prime symbol, ') are virtually identical. In general, the mean values of the variables between samples deviated from one another by no more than one-half point (.10 standard deviation). Additionally, the number of subjects in each subgroup differed from sample to sample by no more than one percent.

Description of the Subgroups

The following is a description of the twelve homogeneous employee subgroups in terms of the thirteen analysis variables. Where no specific mention is made of an analysis variable characteristic, it may be assumed that the subgroup mean was near the total sample mean. It should also be noted that references to above and below average in the following descriptions refer only to comparisons within the research samples and do not reflect comparisons with the general population from which these samples were taken.

Subgroup 1. Subgroup 1 is below average in intelligence and academic achievement. The members had a nonnurturing family background. They tend to be rigid and authoritarian in their dealings with employees. They are consistent in their behavior and exhibit an understanding and tolerance of the behavior of others.

Subgroup 2. This group is average to slightly above average in intelligence and academic achievement. They tend to be rigid and authoritarian with their subordinates and are especially deferent to superior authority and precedents set in the organization.

Subgroup 3. These individuals are average or slightly below average in intelligence and academic achievement. They come from non-nurturing family backgrounds. They are very slow workers, have little confidence in themselves, and have a poor self-concept. The individuals tend to be rigid and authoritarian with their subordinates.

Subgroup 4. This subgroup is well below average in intelligence and academic achievement. Their family background was nonnurturing, and they have poor self-concepts. On the other hand, they believe in communicating with their employees and developing and selecting employees on merit and skill. They believe in autonomy of decision-making, and they tend to be energetic, hard workers.

<u>Subgroup 5</u>. Subgroup 5 is well below average in intelligence, but average in academic achievement. Subgroup members have a positive self-concept, are confident in themselves, and tend to be energetic, hard workers. However, they are conflict prone and intolerant of others. These individuals also tend to be more rigid and authoritarian with their subordinates and tend toward behavioral extremes.

<u>Subgroup 6</u>. Subgroup 6 is below average on all analysis variables. The subgroup members are well below average in intelligence and academic achievement. The members had many negative family experiences. They have poor self-concepts and lack confidence in themselves and conviction in their ideas. These individuals tend to be rigid and authoritarian in dealings with their employees.

<u>Subgroup 7</u>. Subgroup 7 is the opposite of Subgroup 6; this subgroup is above average on all analysis variables. Subgroup members are well above average in intelligence and academic achievement. They had many positive family experiences and have a positive self-concept,

with confidence in themselves and conviction in their ideas. They tend to be participative and flexible with their subordinates, believing in advancement due to ability and the rights of individuals in organization.

Subgroup 8. This subgroup is above average in intelligence and demonstrated extremely high academic achievement. These individuals had nurturing family backgrounds. Subgroup members are energetic, hardworking employees who have a positive self-concept and confidence in themselves. However, they tend to be conflict prone and intolerant of others.

Subgroup 9. This subgroup is average in intelligence, but above average in academic achievement. The subgroup members come from families providing positive developmental influences, possess a positive self-concept, and are extremely confident in themselves and their ideas. They exhibit behavioral consistency, are hard workers, and show an understanding of the behavior of others. They tend to believe in employee development and selection based on ability and the obligation of an organization to interact with its employees.

Subgroup 10. Members of this subgroup are above average in intelligence and slightly above average in academic achievement. This subgroup had more positive than negative family experiences. The subgroup members tend toward inconsistency of temperament and extremes of behavior. They use time and energy well, but tend to lack confidence in themselves. However, they tend to be flexible and participative in their dealings with subordinates.

Subgroup 11. This subgroup shows great variation across the analysis variables. Subgroup members are above average in intelligence, but below average in academic achievement. The individuals come from nurturing families and exhibit a positive self-concept. They believe in the monetary motivation of employees and do not necessarily believe the organization has a responsibility to listen to its employees. They believe that managers should be responsible for their decisions and that decisions should not hinge on precedent.

Subgroup 12. Subgroup 12 also shows great variation over the analysis variables. Subgroup members are above average in intelligence, but below average in academic achievement. Their family backgrounds had more negative than positive experiences.

> They have a poor self-concept and lack confidence and conviction. They tend to use their time and energy poorly. On the other hand, they exhibit an understanding of the behavior of others and tend to be participative and employee oriented, though not necessarily believing the development and selection of employees should be based on merit and skill.

As a further test of the adequacy of the clustering procedure, one-way analyses of variance were performed to compare the thirteen analysis variables across subgroups. In the validation and cross-validation samples all F-values were statistically significant, indicating mean differences on the analysis variables between subgroups. Each sample was then examined for subgroup differences on sex, ethnic group identification (minority versus nonminority), education, occupation, and manpower category. For all comparisons the general results are reported for the validation and cross-validation samples. However, where further illustrations are shown in tabular form, only the cross-validation results are reported in the text in order to facilitate presentation of the data. All corresponding validation sample data, which are essentially equivalent to the cross-validation results, are presented in Appendix B.

The subgroup by sex cross-tabulation yielded nonsignificant Chi squares in both samples. Thus, sex was not significantly associated with subgroup membership. The subgroup by ethnic group cross-tabulation resulted in significant Chi squares ($p < .001$) in both samples. However, since the majority of individuals in each subgroup were nonminorities, knowing an individual's subgroup would not allow the differential prediction of ethnic group. On the other hand, each subgroup could be characterized as having more, the same number, or fewer minorities than the base rate of minorities in each sample as a whole. In the validation sample Subgroups 3 and 6 had significantly more minorities than the total minority base rate, while Subgroups 7, 11, and 12 had significantly fewer. In the cross-validation sample Subgroups 3, 5, and 6 had significantly more minorities than the sample base rate, while Subgroups 7 and 12 had significantly fewer.

Age was compared across subgroups by a one-way analysis of variance. In both samples, the computed F-values were significant at the .001 level, indicating age differences between the subgroups. Subgroups 4 and 6 contained the oldest individuals, averaging 42 and 43 years in the validation sample and 42 and 44 years in the cross-validation sample. Subgroups 2, 5, 8, and 10 contained the youngest individuals, averaging 35 and 36 years in both samples. The average age for all individuals was approximately 38 years.

Next, subgroup membership was cross-tabulated by college major in the validation and cross-validation samples. The resulting Chi squares of 403.42 and 395.52 were significant at the .001 level. Since the association was significant, the subgroups could be differentiated in terms of college major. Table 7 presents the cross-tabulation of subgroup and major, showing the relative frequency of each major for each subgroup, and the deviation of the frequency from the base rate in the cross-validation sample. The data show that Subgroups 2, 3, 7, 8, 10, 11, and 12 had more technical engineering majors than other majors, while Subgroups 1, 4, 5, 6, and 9 had more business administration majors than other majors. The over-representation of these majors may in part be explained by their relatively large base rates as compared to the other majors. However, when the deviation of frequency from the base rate was examined, the same general pattern was found. Subgroups 7, 8, 10, 11, and 12 had significantly more technical engineering majors than the technical engineering base rate, while Subgroups 1, 4, 5, 6, and 9 had significantly more business administration majors than the business administration base rate. Even though the other majors are underrepresented when compared to the technical engineering and business administration majors, each subgroup may be described by the amount of deviation from the sample base rates. For example, Subgroups 11 and 12 have significantly more earth science majors than the earth science base rate. Other deviations are noted in Table 7.

TABLE 7

Homogeneous Employee Subgroup by College Major:
Cross-validation Sample

Subgroup	Major[1]							N
	Technical Engineer.	Physical Sciences	Earth Sciences	Account.	Business Adminis.	Liberal Arts	Law	
Subgroup 1	14-	4	14	6	47+	13	2	132
Subgroup 2	37	5	12	4	31	8	3	147
Subgroup 3	33	4	14	8	32	10	0	161
Subgroup 4	16-	3	5-	14+	49+	11	2	244
Subgroup 5	16-	4	4-	9	50+	16+	2	171
Subgroup 6	6-	3	5	11+	59+	13	4	109
Subgroup 7	49+	4	9	5	25-	7	1	221
Subgroup 8	50+	4	8	2-	26-	7	3	207
Subgroup 9	31	3	5-	4	43+	12	2	212
Subgroup 10	58+	7	5-	3	21-	4-	2	185
Subgroup 11	43+	5	16+	3	22-	9	2	181
Subgroup 12	50+	3	21+	4	17-	5-	2	200
Total Group	35	4	10	6	34	9	2	2170

[1]Data in the tables are row percents.

+The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

-The row percent of this category for this subgroup is significantly ($p < .05$) below the category base rate.

The homogeneous subgroups were then cross-tabulated against the occupation of the subgroup members. Occupation consisted of nine categories derived from a subjective grouping of the company's various departments according to the duties and job skills required in them. For example, marketing sales consisted of departments such as retail sales, industrial sales, and reseller sales. Appendix C presents a detailed breakdown of each occupation by its component departments.

The cross-tabulations in the validation and cross-validation samples yielded Chi squares of 681.84 and 627.12, both significant at the .001 level. Table 8 presents the cross-tabulation for the cross-validation sample. At least 50% of the individuals in Subgroups 1, 4, 5, and 6 worked in marketing sales, and although marketing sales had the largest base rate (38%) relative to the other occupations, the representation of this category for these subgroups was significantly above the base rate. Subgroups 7, 8, 10, and 12 had significantly fewer individuals than the base rate of marketing sales. These groups tended to be significantly overrepresented in production, refining, and other occupations. Conversely, the subgroups overrepresented in marketing sales tended to be significantly underrepresented in exploration/minerals, refining, and other occupations.

In general, the nontechnical occupations were concentrated in Subgroups 1, 3, 4, 5, and 6, whereas the more technically

TABLE 8

Homogeneous Employee Subgroup by Occupation:

Cross-validation Sample

Subgroup	Occupation[1]				
	Accounting/ Systems Controllers	Marketing Sales	Marketing Nonsales	Production	Exploration/ Minerals
Subgroup 1	5	55+	10+	8	10
Subgroup 2	5	41	5	12	15+
Subgroup 3	13+	33	9	14	11
Subgroup 4	11+	50+	7	8	3-
Subgroup 5	5	69+	6	5-	6-
Subgroup 6	7	65+	8	5-	7
Subgroup 7	7	17-	4	13	10
Subgroup 8	5	22-	3-	17+	9
Subgroup 9	6	41	10+	10	6-
Subgroup 10	8	24-	3-	17+	9
Subgroup 11	4	33	7	14	13
Subgroup 12	10	15-	3-	25+	18+
Total Group	7	38	6	12	10

TABLE 8

(Continued)

Subgroup	Occupation				N
	Law/ Tax/ Treasury	Employee Relations	Refining	Other	
Subgroup 1	1	1	2-	8-	204
Subgroup 2	2	1	9	11	205
Subgroup 3	1	0	10	10	210
Subgroup 4	4+	3	3-	12	319
Subgroup 5	1	2	2-	4-	220
Subgroup 6	2	0	3-	4-	193
Subgroup 7	4+	7	15+	24+	279
Subgroup 8	3	3	16+	22+	253
Subgroup 9	3	3	10	12	269
Subgroup 10	3	2	19+	17	242
Subgroup 11	2	2	10	16	236
Subgroup 12	3	2	12	14	248
Total Group	2	2	9	13	2878

[1]Data in the table are row percents.

[+]The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

[-]The row percent of this category for this subgroup is significantly ($p < .05$) below the category base rate.

oriented occupations were concentrated in Subgroups 7, 8, 10, and 12. These results are consonant with those observed for college major. In general, nontechnically oriented subgroups had nontechnical college majors, while the technically oriented subgroups had technical majors.

Finally, the homogeneous subgroups were cross-tabulated against a broad manpower category designation used by the employer of the subjects. The manpower categories are roughly defined by the type of work performed by the subjects. The categories and an example of a typical job within each category are as follows: (1) Management - department head; (2) Supervisory professional-technical - supervisor of a geologist, engineer, etc.; (3) Supervisory professional - supervisor of an accountant, lawyer, etc.; (4) Professional-technical - engineer, geologist, etc.; (5) Professional - accountant, lawyer, etc. Chi squares of 546.45 and 561.10, significant at the .001 level, were observed for the cross-tabulations. Table 9 presents the cross-tabulation for the cross-validation sample. Since the professional-technical and professional categories had large base rates (36%) relative to the other manpower categories, these categories were predominant in all subgroups. However, significant deviations from these base rates were observed. Subgroups 2, 3, 8, 10, 11, and 12 were significantly overrepresented in the professional-technical category; Subgroups 1, 4, 5, and

TABLE 9

Homogeneous Employee Subgroup by Manpower Classification:

Cross-validation Sample

Subgroup	Manpower Classification[1]					N
	Management	Supervisory-Professional Technical	Supervisory-Professional	Professional Technical	Professional	
Subgroup 1	6	8	7	23-	57+	145
Subgroup 2	4	8	8	46+	34	154
Subgroup 3	2-	9	5	45+	38	166
Subgroup 4	13+	4-	17+	14-	52+	256
Subgroup 5	5	2-	14+	19-	60+	169
Subgroup 6	2-	0-	11	12-	75+	137
Subgroup 7	19+	16+	9	38	19-	248
Subgroup 8	10	19+	7	45+	19-	219
Subgroup 9	15+	9	12	26-	39	214
Subgroup 10	5	17+	5-	54+	19-	197
Subgroup 11	7	11	7	47+	28-	192
Subgroup 12	4-	11	5-	62+	17-	207
Total Group	8	10	9	36	36	2304

[1]Data in the table are row percents.

+The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

-The row percent of this category for this subgroup is significantlu ($p < .05$) below the category base rate.

6 were significantly overrepresented in the professional category. In general, for both of these categories, the subgroups not overrepresented were underrepresented. Managerial and supervisory classifications occurred in greater than base rate frequencies in Subgroups 4, 5, 7, 8, 9, and 10. Subgroups 3, 6, and 12 tended to be significantly underrepresented in these categories. Supervisors of professional-technicals tended to come from technically oriented occupational and educational backgrounds, and supervisors of professionals tended to come from nontechnical occupational and educational backgrounds.

Prediction of Employment Status

Actuarial Model. Table 10 presents a cross-tabulation of cluster membership by employment status. The Chi square of 95.12 computed on the table shows that there was a very significant association ($p < .001$) between subgroup membership and employment status. However, Cramer's Statistic (.14) indicated the strength of association to be slight despite statistical significance. In a statistical sense the criterion had differential affinity for the subgroups; however, in practical terms the subgroups contributed nothing to the prediction of the criterion since lambda was zero. That is, if one were to predict employment status as a function of subgroup membership, the prediction would be the same for each subgroup. In this case

TABLE 10

Homogeneous Employee Subgroup by Employment Status: Validation Sample

Subgroup	Employment Status: With Company f	With Company Row %	Gone Regretted f	Gone Regretted Row %	Gone Not Regretted f	Gone Not Regretted Row %
Subgroup 1	86*	53-	51	31+	26	16
Subgroup 2	98*	61	34	21	28	18
Subgroup 3	119*	69	30	17	24	14
Subgroup 4	175*	71	46	19	26	11
Subgroup 5	118*	50-	74	32+	43	18
Subgroup 6	125*	65	26	14-	41	21+
Subgroup 7	215*	78+	42	15-	19	7-
Subgroup 8	146*	68	49	23	21	10
Subgroup 9	170*	66	58	23	29	11
Subgroup 10	153*	72	39	18	20	9
Subgroup 11	145*	68	45	21	23	11
Subgroup 12	164*	74+	37	17	22	10
Total Group	1714	67	531	21	322	13

*The most frequently occurring criterion category for this subgroup.

+The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

-The row percent of this category for this subgroup is significantly ($p < .05$) below the category base rate.

one would achieve a "hit rate," or percentage correct prediction, equal to the base rate of the most frequently appearing criterion category (67%).

Although the practical utility of the actuarial model for predicting employment status could not be demonstrated, a cross-validation of the results was done to see if the relationship observed was stable. The subgroups developed on the cross-validation sample were cross-tabulated by employment status. Table 11 presents these data. The Chi square of 107.64 computed on the table was significant at the .001 level. As in the validation sample, Cramer's Statistic (.15) indicated only a slight degree of association between the variables. The practical utility of making predictions from subgroup membership was zero (lambda = 0). Therefore, predicting from the subgroups would yield a "hit rate" equal to the base rate of the most frequently appearing criterion category (68%).

On the other hand, in both samples an examination of the subgroup-employment status relationship showed that some of the criterion category frequencies significantly deviated from the sample base rates for several subgroups. For example, the frequencies of Subgroups 1 and 5 were significantly below ($p < .05$) the "With Company" category base rate of 67%. This suggests that if these subgroups were not hired or never considered for promotion, the base rate of the "With Company" category would increase for the remaining subgroups. Table 12 presents the cross-

TABLE 11

Homogeneous Employee Subgroup by Employment Status

Cross-validation Sample

Subgroup	Employment Status					
	With Company		Gone Regretted		Gone Not Regretted	
	f	Row %	f	Row %	f	Row %
Subgroup 1	98*	57-	43	25	31	18+
Subgroup 2	98*	58-	50	30+	21	12
Subgroup 3	114*	66	38	22	22	13
Subgroup 4	207*	74+	57	20	16	6-
Subgroup 5	86*	47-	58	31+	41	22+
Subgroup 6	116*	69	24	14	28	17+
Subgroup 7	204*	78+	40	15	17	7-
Subgroup 8	164*	70	53	23	16	7
Subgroup 9	160*	65	56	23	29	12
Subgroup 10	152*	75+	33	16	19	9
Subgroup 11	151*	75+	31	15-	19	10
Subgroup 12	156*	70	43	19	24	11
Total Group	1706	68	526	21	283	11

*The criterion category the subgroup members were predicted to occupy.

+The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

-The row percent of this category for this subgroup is significantly ($p < .05$) below the category base rate.

TABLE 12

Below the Base Rate Subgroups Versus Other Subgroups by Employment Status: Validation and Cross-validation Samples

Subgroup	Employment Status[1]		
	With Company	Gone Regretted	Gone Not Regretted
Validation			
Subgroups 1 & 5	51	31	17
Other Subgroups	70	19	12
Cross-validation			
Subgroups 1 & 5	52	28	20
Other Subgroups	71	20	10

[1]Data in the table are row percents.

tabulation of Subgroups 1 and 5 versus the remaining subgroups against employment status for the validation and cross-validation samples. The resulting Chi squares of 51.78 and 56.50 indicated a significant association ($p < .001$) between the two combinations of subgroups and employment status. The data show that by eliminating Subgroups 1 and 5 the odds of selecting or promoting individuals that will stay with the company are improved. Therefore, despite the fact that the actuarial model cannot be used to predict employment status, the company could minimize the attrition rate of its managerial personnel by selecting or promoting only individuals in subgroups where the likelihood of staying with the company equals or exceeds the base rate of the "With Company" criterion category.

Linear Model. A multiple group discriminant analysis was performed to develop predictions of employment status as a function of the linear combination of the thirteen analysis variables. A Mahalanobis D^2 was calculated to test the hypothesis that the mean values of the analysis variables were the same in all criterion categories. The resulting D^2 of 165.78 ($p < .001$) permitted rejection of this hypothesis. In addition, two sets of F-values were computed comparing the analysis variables across criterion categories. First, univariate F-values were calculated to test the hypothesis that the mean for each analysis variable was the same in all categories. With one exception

(Confidence, Conviction) all F-values were significant at the .05 level or less. Second, stepdown multivariate F-values were calculated. These are the likelihood ratio tests of equality, over all criterion categories, of the conditional distribution of a specific analysis variable, given the other variables (Dixon, 1972). If the stepdown F for a variable is low that variable could be deleted with very little loss of discriminating power. The F values for four variables (Employee Motivation, Labor Relations; Management Style, Decision-Making; Energy Level, Time Use; and Behavior Understanding, Tolerance) were not significant. Nevertheless, all variables were retained for analysis since all were used in developing the subgroups for the actuarial analysis.

The discriminant analysis results were then used to develop classification functions to predict criterion category membership in the validation and cross-validation samples. The classification weights and constant term were applied to the analysis variable scores of each subject. From these scores a predicted criterion category, adjusted by the base rate of each category, was determined. Predicted criterion category was then cross-tabulated by actual criterion category to yield a percentage of correct classification. For practical purposes the predictions equaled the base rate of the "With Company" criterion category. In the validation sample the correct classification rate was 67% versus the "With Company" base rate of 67%; in the cross-validation sample the correct classification rate was 68% versus the "With Company" base rate of 68%. Therefore, despite the statistical significance of the linear discriminant model, it contributed nothing to the prediction of employment status. In addition, unlike the actuarial analysis, where knowledge of subgroup membership could be used to modify the criterion category base rates, knowledge of predicted criterion category could not be used to better the original base rate predictions.

Prediction of Job Performance

Actuarial Model. Table 13 presents the cross-tabulation of subgroup membership by job performance dichotomized at the mean. The Chi square of 216.95 was significant at the .001 level, and Cramer's Statistic (.32) showed a moderate degree of association between the variables. Lambda indicated that predicting from the subgroups reduced the probability of error of prediction by approximately 26%. The "hit rate" of 64% was approximately 13% higher than the base rate of the high performance category (51%). Subgroups 2 and 7 through 12 contained the highest percentage of high performers.

Table 13 also presents the subgroup by job performance cross-tabulation for the cross-validation sample. The most frequently appearing criterion category for each subgroup in the validation sample was taken as the predicted criterion.

TABLE 13

Homogeneous Employee Subgroup by Job Performance

Subgroup	Job Performance							
	Validation Sample				Cross-Validation Sample			
	Below Mean		Above Mean		Below Mean		Above Mean	
	f	Row %	f	Row %	f	Row %	f	Row %
Subgroup 1	88*	67	44	33	102*	67	50	33
Subgroup 2	67	49	69*	51	78	53	68*	47
Subgroup 3	95*	59	66	41	113*	68	54	32
Subgroup 4	127*	58	91	42	130*	50	128	50
Subgroup 5	117*	60	77	40	99*	61	64	39
Subgroup 6	147*	83	30	17	129*	86	21	14
Subgroup 7	54	27	149*	73	43	21	160*	79
Subgroup 8	49	29	117*	71	50	28	131*	72
Subgroup 9	81	39	127*	61	83	43	112*	57
Subgroup 10	72	40	107*	60	72	39	111*	61
Subgroup 11	63	37	109*	63	63	37	108*	63
Subgroup 12	81	42	113*	58	91	47	104*	53
Total Group	1041	49	1099	51	1053	49	1111	51

*Validation Sample: The most frequently occurring criterion category for the subgroup.
Cross-validation Sample: The criterion category the subgroup members were predicted to occupy.

Only the prediction for Subgroup 2 was in error, a result due to a shift of only 4% in criterion category membership. In the validation sample the majority of subjects (51%) were above the criterion mean for this subgroup, while the majority (53%) were below the mean in the cross-validation sample. Nevertheless, the computed Chi square of 252.25 was very significant ($p < .001$), and Cramer's Statistic (.34) revealed a moderate degree of association between the variables. Lambda denoted a 25% reduction in the probability of error of prediction. The "hit rate" of 63% was about 12% higher than the base rate of the high performers (51%).

Thus, in terms of both statistical and practical significance, use of the actuarial model resulted in predictions of job performance considerably more accurate than the base rate of the most frequently occurring criterion category.

Linear Model. Job performance was regressed on the thirteen analysis variables. The resulting multiple R of .45 was significant at the .001 level. Table 14 displays both the raw score and standard score regression weights for all variables. These weights were applied to the analysis variables to yield a predicted criterion score for each subject. Both the actual and predicted scores were dichotomized at their respective means, and cross-tabulated against one another. Table 15 presents this cross-tabulation. A Chi square of 159.90 showed a very significant association

TABLE 14

Regression Weights for Predicting Job Performance

Analysis Variable	Regression Weight	
	Raw Score	Standard Score
Developmental Influences	.012	.061
Achievement: Academic Years	.036	.188
Present Self-Concept	.018	.096
Staff Communication, Participation	.017	.090
Employee Selection-Development	.011	.056
Employee Motivation, Labor Relations	.004	.021
Management Style, Decision-Making	.013	.068
Behavioral Consistency	.008	.041
Energy Level, Time Use	.000	-.001
Confidence, Conviction	-.012	-.062
Behavior Understanding, Tolerance	.004	.022
Verbal Reasoning	.015	.081
Nonverbal Reasoning	.025	.133
Constant	2.024	----

TABLE 15

Cross-tabulation of Predicted and Actual Job Performance

Predicted Job Performance	Actual Job Performance							
	Validation Sample				Cross-validation Sample			
	Below Mean		Above Mean		Below Mean		Above Mean	
	f	Row %	f	Row %	f	Row %	f	Row %
Above Mean	368	35	689	65	328	31	736	69
Below Mean	673	62	410	38	725	66	375	34
Total	1041	49	1099	51	1053	49	1111	51

($p < .001$) between the score levels of the variables. The phi coefficient (.27), developed from the Chi square, denoted a moderate degree of relationship between the dichotomized variables. Lambda indicated that knowing the predicted score level reduced the probability of error in predicting the actual score by 25%. The "hit rate" computed as the percentage of correct prediction was 64%, approximately 13% higher than the base rate of the high performers.

In the cross-validation sample the regression weights were used to develop a predicted criterion score for each subject. The actual and predicted scores were correlated, yielding a cross-validated multiple R of .45 ($p < .001$). The scores were then dichotomized and cross-tabulated. Table 15 also presents these data. The Chi square of 266.45 was significant at the .001 level. The phi coefficient of .35 represented a substantial increase from the validation sample value of .27. As shown by lambda, knowing the predicted criterion score level reduced the probability of error in predicting the actual criterion by 33%. This, too, represented a substantial improvement over the validation sample. The observed "hit rate" of 68% was approximately 17% higher than the high performer base rate.

<u>Comparison of Models</u>. Table 16 presents a comparison of the actuarial and linear model contingency table statistics. In terms of significance and degree of

TABLE 16

Comparison of Actuarial and Linear Models for Predicting Job Performance

Comparison Statistic	Validation Sample		Cross-Validation Sample	
	Actuarial	Linear	Actuarial	Linear
Chi Square	216.95*	159.90*	252.25*	266.45*
Cramer's Statistic/Phi	.32	.27	.34	.35
Lambda	.26	.25	.25	.33
Hit Rate	64%	64%	63%	68%
McNemar Test	-.15		4.69*	

* $p < .001$

association, the two models were similar. In the validation sample the two models had essentially equivalent lambda values and "hit rates." The McNemar test comparing "hit rates" was not significant. However, in the cross-validation sample, the linear model was clearly superior to the actuarial model. As indicated by the lambda values, the linear model was approximately eight percent better than the actuarial model in reducing error in prediction. In addition, the 4.5% difference in "hit rates" in favor of the linear model was highly significant ($p < .001$).

Prediction of Job Performance with Potential Excluded

Actuarial Model. Job performance without potential consisted of the performance score developed from the factor analysis of job grade, appraisal, age, and tenure. An estimate of potential was excluded from the analysis to guard against the possibility of criterion contamination. Table 17 displays the cross-tabulation of subgroup by this job performance measure dichotomized at its mean. The Chi square of 154.43 computed on the table was significant at the .001 level. Cramer's Statistic (.26) revealed a moderate degree of association between the variables. As shown by lambda, knowing cluster membership reduced the probability of error in prediction of the criterion by approximately 20%. The "hit rate" of 61% was about 9% higher than the base rate of the high performers (52%).

TABLE 17

Homogeneous Employee Subgroup by Job Performance with Potential Excluded

Subgroup	Job Performance							
	Validation Sample				Cross-validation Sample			
	Below Mean		Above Mean		Below Mean		Above Mean	
	f	Row %	f	Row %	f	Row %	f	Row %
Subgroup 1	86*	64	49	36	93*	61	60	39
Subgroup 2	72*	52	67	48	82*	55	68	45
Subgroup 3	94*	58	68	42	111*	66	57	34
Subgroup 4	116*	52	108	48	125	48	133	52
Subgroup 5	116*	58	83	42	88*	54	75	46
Subgroup 6	139*	78	40	22	116*	77	34	23
Subgroup 7	63	29	155*	71	59	28	151*	72
Subgroup 8	63	36	113*	64	62	33	129*	67
Subgroup 9	84	38	135*	62	78	38	125*	62
Subgroup 10	73	41	107*	59	91	49	93*	51
Subgroup 11	73	40	108*	60	67	37	112*	63
Subgroup 12	85	43	114*	57	95	47	105*	53
Total Group	1064	48	1147	52	1067	48	1142	52

*Validation Sample: The most frequently occurring criterion category for the subgroup.
Cross-validation Sample: The criterion category the subgroup members were predicted to occupy.

In the cross-validation sample the Chi square of 156.05, computed on the cross-tabulation in Table 17, was significant at the .001 level, and Cramer's Statistic (.27) indicated a moderate degree of association between the two variables. Lambda showed an 18% reduction in the error of prediction when subgroup membership was taken into account. The "hit rate" of 60% was approximately 8% higher than the high performer base rate.

Linear Model. Table 18 presents the raw score and standard score regression weights derived by regressing job performance with potential excluded on the thirteen analysis variables. The observed multiple R of .38 was significant at the .001 level. The raw score regression weights were used to develop a predicted score for each subject. Predicted and actual scores were then dichotomized and cross-tabulated. A Chi square of 121.74 ($p < .001$) and a phi coefficient of .23 were observed for this cross-tabulation shown in Table 19. Lambda indicated a 20% reduction in the probability of error in prediction when predicted criterion score level is taken into account. The "hit rate" of 62% was about 10% higher than the base rate of the high performers.

The correlation of actual and predicted scores in the cross-validation sample yielded a multiple R of .37 ($p < .001$). Table 19 also presents the cross-tabulation of the dichotomized scores for the cross-validation sample. A Chi square of

TABLE 18

Regression Weights for Predicting Job Performance with Potential Excluded

Analysis Variable	Regression Weights	
	Raw Score	Standard Score
Developmental Influences	.010	.052
Achievement: Academic Years	.029	.153
Present Self-Concept	.016	.087
Staff Communication, Participation	.016	.082
Employee Selection-Development	.013	.069
Employee Motivation, Labor Relations	.002	.011
Management Style, Decision-Making	.010	.055
Behavioral Consistency	.011	.059
Energy Level, Time Use	.003	.016
Confidence, Conviction	-.011	-.059
Behavior Understanding, Tolerance	.004	.022
Verbal Reasoning	.004	.023
Nonverbal Reasoning	.035	.131
Constant	2.651	----

TABLE 19

Cross-tabulation of Predicted and Actual Job Performance with Potential Excluded

Predicted Job Performance	Actual Job Performance							
	Validation Sample				Cross-validation Sample			
	Below Mean		Above Mean		Below Mean		Above Mean	
	f	Row %	f	Row %	f	Row %	f	Row %
Above Mean	406	36	707	64	391	35	729	65
Below Mean	658	60	440	40	676	62	413	38
Total	1064	48	1147	52	1067	48	1142	52

163.16 ($p < .001$) and a phi coefficient of .27 were observed for these data. Lambda indicated a 25% reduction in error of prediction. The "hit rate" of 64% was approximately 12% higher than the base rate.

Comparison of Models. Table 20 displays a summary of the contingency table statistics comparing the actuarial and linear models across the validation and cross-validation samples. In both models the predictors and criterion were significantly associated. Both lambda values and "hit rates" were essentially equivalent in the validation sample. However, as in the previous analysis of job performance, the linear model was superior to the actuarial model in the cross-validation sample. The linear model was approximately 7% better than the actuarial model in reducing the probability of error in prediction, and the 4% difference in "hit rates" in favor of the linear model was significant at the .001 level.

TABLE 20

Comparison of Actuarial and Linear Models for Predicting Job Performance with Potential Excluded

Comparison Statistic	Validation Sample		Cross-validation Sample	
	Actuarial	Linear	Actuarial	Linear
Chi Square	154.43*	121.74*	156.05*	163.16*
Cramer's Statistic/Phi	.26	.23	.27	.27
Lambda	.20	.20	.18	.25
Hit Rate	61%	62%	60%	64%
McNemar Test	.52		3.84*	

* $p < .001$

CHAPTER V

DISCUSSION AND CONCLUSIONS

Introduction

Aside from the specific results, two issues were highlighted by this study. In previous studies severe shrinkage on cross-validation has been observed for both actuarial and linear models (Forehand and McQuitty, 1959; Simon, 1972). In a regression study shrinkage may be attributed to a large independent variable to subject ratio which tends to result in overestimation of the multiple correlation in the validation sample (Kerlinger and Pedhazur, 1973). In an actuarial study shrinkage may result from subgroup profiles based on too few cases to reliably establish the profile shape. Excessive shrinkage was not a factor in this study, a result due to the large sample sizes. For example, in the regression analysis of the job performance criteria, validation and cross-validation sample multiple correlations were .45 and .45 for job performance and .38 and .37 for job performance with potential excluded. In the actuarial analysis of these variables, Cramer's Statistic was .32 and .34 for job performance and .26 and .27 for job performance with potential excluded.

Another important issue concerns the influence of criterion category base rates on the predictive utility of the models. It is well known that the higher the base rate of a "success" group, the stronger the predictor-criterion association must be for the relationship to be useful; and, an association that is statistically significant does not necessarily mean that the relationship is useful in a predictive sense. These facts were emphasized by the failure of both the actuarial and linear models to successfully predict employment status. Although the predictor-criterion relationships were highly significant, predictions made by the models were no better than the base rate of the "success" category. This comment is made to emphasize the necessity of evaluating the effect of criterion base rates on the efficiency of any model designed to be used predictively - an emphasis that is frequently overlooked in the reporting of many validity studies (Meehl and Rosen, 1955).

Cluster Procedure Results

The first step in the development of the actuarial prediction model was the development of the homogeneous employee subgroups. From a sample of 2,899 individuals, twelve subgroups were identified and retained for analysis. Relative to other studies in industrial environments, twelve is representative of the median number of subgroups identified. In the second step of the analysis, the twelve subgroups were subjected to a convergent clustering procedure which reassigned individuals who had been inappropriately "locked" into a subgroup. In the twelve iterations of the cluster procedure, 1,828 moves were made. It is not known how many moves are typical since such information has not been presented in the previous studies. It is clear, however, that the convergent clustering procedure is needed as an adjunct to the hierarchical cluster analysis.

The minimum distance assignment of the cross-validation subjects to the homogeneous subgroups resulted in a near perfect replication of the subgroups. The number of subjects in the subgroups varied no more than one percent from the validation to cross-validation sample. The comparison with other studies where percentages deviated as much as four to six percent (Pinto, 1970; Schoenfeldt, 1974), this deviation seems negligible.

In several studies subjects not fitting any subgroup well (in a minimum distance sense) were dropped from the analysis (e.g., Taylor, 1968; Harman and Raymond, 1970; Schoenfeldt, 1974). This typically resulted in the elimination of 20 to 30 percent of the sample. A similar elimination of subjects was not considered in this study since the purpose of the research was to compare two prediction models developed on identical samples. It was felt that the elimination of subjects from one model and not the other would not allow a fair comparison. Moreover, in a practical situation the elimination of misfits would not be possible. Thus, retaining all subjects was more representative of a "real life" organizational environment.

Comparison of Actuarial and Linear Models

Employment Status. In terms of statistical significance and efficiency in predicting the criterion, both models were equally valid. The majority of all subgroup members in the validation and cross-validation samples were in the high frequency, "With Company" category, and therefore, predictions resulting from the actuarial model were equal to the base rate of this category. For the linear model the predicted criterion category was identical to the actual criterion category 67 and 68 percent of the time. This was equal to the base rates in both samples. However, it was noted that several of the subgroups developed for the actuarial analysis had significantly greater or fewer members than the base rate. It was demonstrated that if subgroups significantly below the base rate were not hired or promoted the attrition rate would decrease for the remaining subgroups considered as a whole. Similar results were not found for the linear model. For example, in the validation and cross-validation samples only 67 and 68 percent of those predicted to stay with the company were actually with the company. Therefore, the actuarial model was superior to the linear model for making decisions which maximize the percentage of correct "With Company" predictions, provided, of course, the elimination of one or more subgroups from the manpower pool is tenable.

Job Performance. Since the results for job performance and job performance without potential were highly similar, the following discussion will be in terms of job performance only. It is noteworthy that the results of the actuarial and linear models were essentially equal in the validation sample since the linear model is a "fitted" model. That is, the choice of a set of regression weights is designed to yield the highest possible correlation between the independent variables and the criterion. On the other hand, the actuarial model is not "fitted." The subgroups were developed independently of the criterion. The fact that both models were equal in significance and practical utility (as indicated by essentially equivalent "hit rates" and lambdas) despite their different theoretical relationships with the criterion, provides sound support for the equivalence of the models.

However, the cross-validation results presented an aberration which, taken at face value, questions the equivalence of the models. The cross-validation actuarial results were essentially the same as the validation sample results. However, the efficiency of the linear model improved on cross-validation. Lambda increased from .25 to .33 and the "hit rate" improved from 64 to 68 percent. The result was that the linear model was significantly more accurate than the actuarial model in predicting the criterion.

This is unusual in that, due to the nature of the linear model, results on cross-validation are nearly always poorer than validation results (Kerlinger and Pedhazur, 1973).

It was hypothesized that the linear model's improvement on cross-validation was an artifact resulting from the dichotomization of the continuous job performance score. Kerlinger and Pedhazur (1973) have pointed out that categorization of continuous data may lead to a loss of information and a less sensitive analysis. One consequence is that rather small differences on the continuous variable may result in labeling a subject as high or low - a labeling that may not reflect a true difference. To test the hypothesis that the coarse grouping procedure produced the improvement on cross-validation, job performance in both samples was cast into five categories, each containing approximately 20% of each sample, and ten categories, each containing approximately 10% of each sample. Table 21 presents a comparison of "hit rates" for the linear and actuarial models for each categorization. "Hit rates" were lower due to the increase in number of categories which resulted in a lower probability of obtaining a correct prediction. For the linear model although the improvement on cross-validation did not completely disappear, the degree of improvement was substantially less than in the two category case. The cross-validation results were only .7% and .4% higher than the validation results. This finding, in addition to the fact that the multiple correlation did not

TABLE 21

Comparison of Actuarial and Linear Model Hit Rates for Two Categorizations of Job Performance

Model	Five Category		Ten Category	
	Validation	Cross-Validation	Validation	Cross-Validation
Linear	30.0%	30.7%	15.7%	16.1%
Actuarial	31.9%	30.2%	18.2%	16.4%

increase on cross-validation, suggests that the observed improvement in the original analysis was an artifact of the coarse grouping procedure. Moreover, a comparison of results shows the actuarial model to be essentially equivalent to the linear model in accuracy of prediction in these analyses. On cross-validation the maximum difference in "hit rates" between the models was .5%. In the five category analysis the linear model "hit rate" was .5% higher than the actuarial model "hit rate." In the ten category analysis the actuarial model "hit rate" was .3% higher than the linear model "hit rate." Thus, these results indicate that the superiority of the linear model for predicting job performance in the original analysis was due to the coarse grouping of job performance and that the models are actually equal in terms of accuracy in predicting job performance.

Description of Subgroups

One of the purported advantages of the actuarial model is that greater understanding of human behavior is possible through the analysis of subgroup score profiles and subgroup correlates. Thus, the task of defining what it means to be a member of a particular subgroup remains. For the sake of brevity, only four of the twelve subgroups (Subgroups 1, 6, 7, and 12) were selected for analysis.

Subgroup 1. In terms of the analysis variables, this subgroup was characterized as below average in intelligence and academic achievement, coming from a nonnurturing family background, rigid and authoritarian with their subordinates, consistent in their behavior, and tolerant of others. Subgroup members were significantly overrepresented by business administration majors and significantly underrepresented by technical engineering majors. In addition, this subgroup was significantly overrepresented in nontechnical jobs such as marketing sales and significantly underrepresented in professional-technical jobs.

In terms of the performance related criteria, this subgroup was rather unsuccessful. For example, significantly fewer of this subgroup's members were still with the company compared to the total sample base rate. In addition, a majority of subgroup members had performance scores below the sample average. An examination of the subgroup's score profile shows that subgroup members tend to score low on many variables, such as intelligence, supervisory ability, and self-concept, found to be positively related to managerial success in organizations. Members of Subgroup 1 tended to score low in intelligence, presented a rigid, authoritarian supervisory style, and had a poor self-concept. Thus, the profile scores were consonant with previous research which has found similar patterns associated with poor managerial performance (Campbell, et al., 1970; Korman, 1971).

Subgroup 6. Subgroup 6 was characterized by below average scores on all analysis variables. A majority were business administration majors, and the subgroup had significantly more business administration and technical engineering majors than sample base rates. Most subgroup members were in marketing sales, and were underrepresented in production and other occupations. The subgroup was significantly underrepresented in managerial and supervisory professional-technical manpower classifications. The great majority were classified as professionals. In terms of employment status, these individuals stayed with the company at the overall base rate, but were the worst performers of all subgroups. Once again their profile scores were consonant with other research on the correlates of managerial success.

Subgroup 7. This subgroup was characterized by above average scores on all analysis variables. Most of this subgroup's members were technical engineering majors, and the representation of this major was significantly above the sample base rate. This subgroup also had significantly fewer business administration majors than the base rate. Subgroup members were significantly underrepresented in marketing sales and significantly overrepresented in law/tax/treasury. Subgroup 7 had significantly fewer professionals than the sample base rates.

Regarding employment status, this subgroup contained significantly more individuals than the base sample rate and contained more successful performers than any other subgroup. Thus, the successful nature of the subgroup was consistent in terms of profile score levels with previous managerial research.

<u>Subgroup 12</u>. This subgroup was characterized as high in intelligence, low in academic achievement, coming from a nurturing family background, lacking confidence, having a poor self-concept, and using their time poorly. They also tended to be employee centered, but in a paternalistic way. A majority were technical engineering or earth science majore, both majors being significantly over-represented in the subgroup. These individuals were concentrated in production and exploration/minerals jobs, and a majority were classified as professional-technicals. Managers and supervisors of professionals were significantly underrepresented in this subgroup.

There were significantly more individuals in this subgroup than the sample base rate of the "With Company" employment status. However, only slightly more than 50% of the individuals were above the mean on job performance.

It appears that subgroup profile score levels were logically related to various descriptive and predictive criteria and that different aspects or levels of these criteria were associated with different subgroups. Therefore, being a member of one subgroup rather than another has a unique meaning determined by which criteria are significantly associated with subgroup membership. The uniqueness of subgroup membership represents an advantage inherent in the actuarial approach to prediction. Since the subgroups remain constant over criteria, an understanding of what it means to be a member of a particular subgroup may be developed by analyzing the subgroup-criterion relationships over many criteria. Consequently, one can build a picture of what is and is not related to subgroup membership, and since a basic assumption of the actuarial model is that the characteristics of the subgroup can be attributed to each member, the model provides for the description of individual behavior in terms of all criteria found associated with subgroup membership.

Compare the above to the linear model. If one were interested in predicting several criteria, a separate regression equation or discriminant analysis would have to be developed for each criterion. While within each regression equation or discriminant analysis, the differential weighting of the analysis variables may provide some insight into the nature of the predictor-criterion relationship, on different criteria the same independent variable may have weights different in sign and/or magnitude. Therefore, any understanding of the predictor-criterion relationship is in terms of the different regression or discriminant variable weights for a specific criterion - not several criteria and not the individuals whose scores are being analyzed. Thus, the actuarial model appears to provide for a greater understanding of human behavior by allowing the development of a descriptive and behavioral taxonomy centered on stable, homogeneous subgroups.

Conclusions

The objective of this research was to compare an actuarial and linear model for effectiveness in predicting criteria related to managerial performance. In predicting employment status both models performed equally well. Overall, neither model yielded predictions of the criterion better than the base rate of the high frequency criterion category. However, it was shown that under certain circumstances the actuarial model could be used to increase the percentage of correct "With Company" predictions. Therefore, in terms of this capability, the actuarial model was superior to the linear model.

In predicting job performance both models performed equally well in the validation sample. However, on cross-validation the linear model was significantly superior to the actuarial model. This result was traced to an artifact resulting from the coarse grouping on the continuous criteria. When the coarse grouping was corrected, the difference between the models disappeared. Therefore, in terms of predicting job performance, the models were equal.

Finally, an analysis of several descriptive variables showed subgroup membership to be significantly related to education, occupation, and manpower classification. These associations, in addition to the performance criterion relationships clearly suggest that subgroup membership can be described in terms of many criteria. The result is that a better understanding of what it means to be a member of a specific subgroup can be developed. Once subgroups have been identified and described in terms of an array of organizationally relevant criteria, the subgroups become identifiable target groups for procedures designed to modify the subgroup-criterion relationships, or for some type of special treatment relevant to the subgroup. One example has already been cited in the discussion of employment status. Other examples are easy to imagine. Suppose there were a subgroup whose attrition rate was high, but whose performance was outstanding. This group could become the target for an analysis of attrition rate, with the purpose of identifying and solving the attrition problem in the subgroup. Suppose there were an individual from a subgroup whose success rate was high in some departments but not others. When considering this individual for promotion, the organization could steer him/her toward departments where probability of success was maximized. The point is that an organization can use the fact of subgroup membership and what it represents in terms of organizationally relevant criteria to effectively and fairly interact with its employees.

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APPENDIX A

Analysis Variable Means:

Validation and Cross-validation samples

TABLE A

Analysis Variable Means by Employee Subgroup: Validation Sample

Analysis Variable	Subgroup					
	1	2	3	4	5	6
Developmental Influences	17.47	20.77	17.56	16.13	20.02	15.59
Achievement: Academic Years	17.31	20.22	17.47	16.66	19.42	15.01
Present Self Concept	19.01	19.09	14.51	18.19	22.46	14.82
Staff Communication, Participation	15.43	19.35	19.37	22.81	16.97	15.81
Employee Selection-Development	15.22	17.61	16.41	23.44	19.61	17.92
Employee Motivation, Labor Relations	18.16	19.05	17.96	20.85	16.31	15.82
Management Style, Decision-making	19.27	12.81	17.43	21.76	18.59	15.41
Behavioral Consistency	23.67	17.64	15.18	21.15	17.78	18.85
Energy Level, Time Use	20.09	19.40	14.52	21.96	23.00	19.37
Confidence, Conviction	21.60	20.14	13.04	20.84	21.38	16.22
Behavior Understanding, Tolerance	23.64	18.02	16.33	21.70	15.57	18.51
Verbal Reasoning	16.41	20.29	18.24	16.79	16.46	13.32
Nonverbal Reasoning	17.99	22.20	19.88	16.86	17.00	11.04
Subgroup Size (N)	194	182	201	276	261	218

TABLE A

(Continued)

Analysis Variable	Subgroup					
	7	8	9	10	11	12
Developmental Influences	24.01	22.63	21.19	21.36	22.15	19.15
Achievement: Academic Years	23.55	27.06	21.92	21.21	18.64	18.78
Present Self-Concept	22.96	23.84	23.70	19.58	21.96	17.21
Staff Communication, Participation	24.30	21.31	19.75	20.29	19.50	21.45
Employee Selection-Development	23.69	19.17	21.90	21.45	20.92	17.77
Employee Motivation, Labor Relations	24.09	21.22	21.43	22.49	16.43	22.93
Management Style, Decision-Making	23.47	21.70	20.24	21.85	22.91	20.52
Behavioral Consistency	23.04	19.73	23.90	14.04	20.43	22.73
Energy Level, Time Use	21.25	22.68	24.57	17.39	17.92	15.67
Confidence, Conviction	23.00	22.51	25.28	15.92	20.36	18.08
Behavior Understanding, Tolerance	23.59	17.12	23.37	15.88	20.51	23.38
Verbal Reasoning	26.07	23.42	19.64	23.23	21.71	22.48
Nonverbal Reasoning	23.54	22.40	20.19	22.92	22.70	22.54
Subgroup Size (N)	299	245	286	239	241	257

TABLE B

Analysis Variable Means by Employee Subgroup: Cross-validation Sample

Analysis Variable	Subgroup					
	1	2	3	4	5	6
Developmental Influences	17.85	20.96	17.42	16.43	20.07	14.61
Achievement: Academic Years	17.43	19.83	17.41	17.05	19.37	15.03
Present Self Concept	18.77	19.65	15.20	17.93	21.85	14.63
Staff Communication, Participation	15.68	19.65	19.08	22.48	17.15	16.05
Employee Selection-Development	15.69	17.56	17.11	23.24	20.19	18.06
Employee Motivation, Labor Relations	18.13	19.00	17.72	21.06	16.51	16.25
Management Style, Decision-making	19.03	12.99	17.85	21.27	18.75	15.44
Behavioral Consistency	23.33	18.63	15.53	20.82	17.49	18.71
Energy Level, Time Use	20.12	19.55	14.47	21.80	23.16	19.85
Confidence, Conviction	21.25	19.72	13.00	20.14	21.15	16.16
Behavior Understanding, Tolerance	23.24	18.37	16.46	21.59	14.76	18.60
Verbal Reasoning	16.17	20.14	18.04	16.59	16.33	13.62
Nonverbal Reasoning	17.88	21.55	19.77	16.98	17.50	10.62
Subgroup Size (N)	204	205	211	320	220	193

TABLE B

(Continued)

Analysis Variable	Subgroup					
	7	8	9	10	11	12
Developmental Influences	23.92	22.83	21.07	21.66	22.56	19.49
Achievement: Academic Years	23.96	27.03	21.76	21.27	19.12	19.32
Present Self Concept	22.82	23.83	23.59	19.63	21.89	17.76
Staff Communication, Participation	24.30	21.43	19.89	20.44	19.77	21.33
Employee Selection-Development	23.60	19.57	22.14	21.12	20.73	18.39
Employee Motivation, Labor Relations	23.88	21.44	21.56	22.75	16.21	22.83
Management Style, Decision-making	23.40	21.86	20.62	22.13	22.71	20.48
Behavioral Consistency	22.46	19.21	23.63	14.35	20.92	22.36
Energy Level, Time Use	21.04	22.86	24.27	17.15	18.11	15.49
Confidence, Conviction	22.75	22.28	24.87	15.90	20.38	18.39
Behavior Understanding, Tolerance	23.47	17.92	22.98	15.95	20.85	23.58
Verbal Reasoning	25.69	23.36	19.23	23.16	21.83	22.84
Nonverbal Reasoning	23.56	22.53	20.30	22.30	22.12	22.38
Subgroup Size (N)	284	254	273	242	238	255

APPENDIX B

Homogeneous Subgroups by Education, Occupation, and Manpower Classification: Validation Sample

TABLE A

Homogeneous Employee Subgroup by College Major:

Validation Sample

Subgroup	Major[1]							N
	Technical Engineer.	Physical Sciences	Earth Sciences	Account.	Business Adminis.	Liberal Arts	Law	
Subgroup 1	16-	5	9	8	44+	14	5+	134
Subgroup 2	37	4	13	6	30	11	1	142
Subgroup 3	33	4	16+	11+	26	9	1	153
Subgroup 4	20-	4	6	11+	43+	13	4+	213
Subgroup 5	13-	3	4-	5	55+	19+	1	198
Subgroup 6	8-	4	4-	9	51+	22+	3	115
Subgroup 7	51+	4	11	3-	24-	5-	3	240
Subgroup 8	56+	4	8	3	21-	7	3	182
Subgroup 9	32	3	8	4	40+	11	3	216
Subgroup 10	55+	5	7	3	23-	5-	2	192
Subgroup 11	41	1-	16+	4	31	6	1	185
Subgroup 12	42+	5	20+	6	18-	6	3	203
Total Group	35	4	10	6	33	10	2	2173

[+]The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

[-]The row percent of this category for this subgroup is significantly ($p < .05$) below the category base rate.

[1]Data in the table are row percents.

TABLE B

Homogeneous Employee Subgroup by Occupation:

Validation Sample

Subgroup	Occupation[1]				
	Accounting/ Systems/ Controllers	Marketing Sales	Marketing Nonsales	Production	Exploration/ Minerals
Subgroup 1	6	56+	7	9	10
Subgroup 2	4	35	6	14	15+
Subgroup 3	13+	30	4	17+	17+
Subgroup 4	10	51+	11+	6-	6-
Subgroup 5	6	68+	8	3-	5-
Subgroup 6	7	67+	6	5-	1-
Subgroup 7	6	17-	4	14	12
Subgroup 8	7	26-	3-	14	6-
Subgroup 9	5	38	9+	11	7
Subgroup 10	9	23-	5	17+	7
Subgroup 11	5	31-	4	16	17+
Subgroup 12	7	17-	5	21+	21+
Total Group	7	38	6	12	10

TABLE B

(Continued)

Subgroup	Occupation: Law/ Tax/ Treasury	Employee Relations	Refining	Other	N
Subgroup 1	1	2	3-	6-	194
Subgroup 2	3	2	13	9	182
Subgroup 3	1	1	10	9-	201
Subgroup 4	2	4	3-	9-	275
Subgroup 5	1	2	2-	6-	261
Subgroup 6	1	1	3-	5-	218
Subgroup 7	3	3	14+	27+	297
Subgroup 8	2	2	19+	22+	243
Subgroup 9	1	7+	5-	18	285
Subgroup 10	2	1	17+	21+	235
Subgroup 11	1	2	9	16	237
Subgroup 12	4+	2	12	12	255
Total Group	2	3	9	14	2883

[1] Data in the table are row percents.

[+] The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

[-] The row percent of this category for this subgroup is significantly ($p < .05$) below the category base rate.

TABLE C

Homogeneous Employee Subgroup by Manpower Classification

Validation Sample

Subgroup	Manpower Classification[1] Management	Supervisory-Professional Technical	Supervisory-Professional	Professional Technical	Professional	N
Subgroup 1	2-	5-	9	30	55+	132
Subgroup 2	3-	7	6	51+	33	146
Subgroup 3	2-	11	4	45+	38	168
Subgroup 4	10	5-	18+	18-	48+	225
Subgroup 5	6	4-	15+	16-	60+	200
Subgroup 6	1-	3-	10	12-	74+	178
Subgroup 7	19+	16+	3-	41	22-	263
Subgroup 8	9	17+	4-	49+	21-	201
Subgroup 9	16+	13	10	24-	37	233
Subgroup 10	7	15	1-	56+	22-	198
Subgroup 11	8	19+	8	40	25-	193
Subgroup 12	5	10	5	59+	21-	212
Total Group	8	11	8	36	37	2349

[1]Data in the table are row percents.

+The row percent of this category for this subgroup is significantly ($p < .05$) above the category base rate.

-The row percent of this category for this subgroup is significantly ($p < .05$) below the category base rate.

APPENDIX C

Derivation of Occupation from Organizational Departments

OCCUPATION BY DEPARTMENT BREAKDOWN

Accounting/Controllers/Systems

- Controllers
- Accounting
- Math, Computers, and Systems

Marketing Sales

- LPG
- Retail Oil Heat Sales
- Retail Sales
- Industrial Sales
- Reseller Sales
- Marketing

Marketing Nonsales

- Economic and Business Analysis
- Credit
- Marketing Development
- Distribution and Engineering
- Financial and Business Advisor

Production - Production

Exploration/Minerals

- Exploration
- Minerals

Law - Law

Employee Relations/Public Affairs

- Employee Relations

Public Affairs

Refining

Refining

Technical

Mechanical

Process

Tax/Treasury

Tax

Treasury

Other Occupations

Staff

Corporate Planning

General Services

Natural Gas

Operations

Secretary's

Supply

Oil Movements

TOA

Marine

Land Development

Claims and Insurance

Administrative

Subsidiary Companies (4)

Travel Club

Business Services

Mechanical and Services