AN EMPIRICAL INVESTIGATION COMPARING THE EFFECTIVENESS OF FOUR SCORING STRATEGIES FOR THE KUDER OCCUPATIONAL INTEREST SURVEY FORM DD

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ABSTRACT

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By

Stephen Olejnik

Objectives of the Inquiry

Improving the discriminatory accuracy of interest surveys has been a major concern of measurement theorists for many years. As a result, several quantitative scoring procedures have been developed but empirical studies comparing techniques on a given instrument have been lacking. The purpose of the present study was to compare the effectiveness of several scoring strategies for the Kuder Occupational Interest Survey form DD. Specifically the techniques compared included: lambda coefficients, the procedure currently used; chi-square weights as developed by Porter (1965) and discriminant analysis using occupational scores generated by (a) lambda coefficients and (b) chi-square weights.

Methods and/or Techniques

In 1958 Clemens had suggested that the relationship between an item and a criterion could be measured by a lambda coefficient which was defined as the ratio of the point biserial to the maximum

point biserial correlation. Several years later Kuder (1966) adopted the procedure of using the lambda coefficient as a measure of the relationship between an individual's responses to that of a specified criterion group on the Occupational Interest Survey form D. In computing the lambda ratio the selection or non-selection of a response pattern is considered the dichotomous variable while the continuous variable is the proportion of the criterion group selecting each of the possible response patterns. The individual is classified as belonging to the criterion group in which he has the highest lambda coefficient. Although the author retained the original items, his revision of the scoring technique resulted in the instrument being renamed the Kuder Occupational Interest Survey form DD, which is currently in use.

The second technique considered in the study was that suggested by Porter (1965) in which response weights are derived from the chi-square test statistic. Thus for each of the occupations considered, a fractional weight is calculated for each of the possible item responses. The similarity of an individual's interest to that of a certain group is simply the sum of the chi-square weights for the 100 items. The occupation in which an individual's total score is highest is designated as the most compatible group. In a study comparing this procedure with Kuder's earlier scoring technique prior to its revision, Porter showed the technique to be superior.

The third and fourth procedures considered, utilized the occupational scores generated by the lambda and chi-square procedures respectively and applied multiple discriminant analysis on each set of data. Discriminant analysis has been shown (Rao, 1948; Chappell, 1968) to be very successful in classifying both individuals and objects. The technique was therefore used here as an attempt to improve the accuracy of both the lambda and chi-square procedures.

In order to compare the accuracy of the four scoring techniques described above, nine occupational groups were selected for study: pediatricians, veterinarians, physical therapists, x-ray technicians, optometrists, clinical psychologists, social workers, foresters and auto mechanics. The first five groups were designated as Set I and were considered as similar occupations, while the last five groups were considered as dissimilar and labeled Set II. One occupational group, optometrists, appeared in both sets of data thus making the two sets non-independent. In addition, each criterion group was randomly divided into two halves A and B; thus two independent groups of data were available for each set. To obtain an estimate of the "true" effectiveness of each scoring procedure a double cross-validation technique as suggested by Moiser (1951) was followed.

To analyze the results of this comparison, an analysis of variance procedure for mixed models was utilized. The fixed variables being sets (similar-dissimilar), measures (lambda--chi-square) and discriminant analysis (discriminant function--non-discriminant function); all three of which were completely crossed. The random variable was occupations, having five levels and crossed with measures and discriminant analysis but nested within sets. To solve the problem of non-independence only the cross-validation results of half A were used for optometrists in Set I and the cross-validation results of half B were used with Set II. Although occupations were not actually selected at random it was felt that using the Cornfield-Tukey bridge argument, the results of this study could be generalized to all similar occupations. In addition, by assuming that occupations were randomly selected, the average percent correct identifications per group under each technique becomes the unit of analysis and the design is balanced.

Data Sources

The data used to develop and test the scoring keys in this study consisted of item responses made to the Kuder OIS by 3893 males from nine unequally sized occupational groups. These responses were originally collected by Kuder while developing the instrument and later obtained by Porter who identified the sets of similar and dissimilar occupations and randomly divided the groups into two subsets.

Results and/or Conclusions

The results of the study indicated that among similar occupations 56.37 percent of the individuals were correctly classified while among dissimilar occupations 68.41 percent correct classifications were made. This difference was not statistically significant at α=.05. The test for a difference between the use of discriminant analysis procedures against the non-use of this technique indicated that while 60.62 percent correct classifications were made by the former and 66.66 percent correct classifications were made by the latter, the null hypothesis of no difference was not rejected at α=.05. A comparison of the measures, lambda vs. chi-square indicated that an average of 61.29 percent correct classifications were made with the lambda technique while an average of 63.49 percent correct classifications were made with the chi-square procedure. This difference between between measures was not found to be statistically significant at α =.05. In addition 65.67 percent correct identifications were made with the discriminant analysis technique using the chi-square occupational scores; 55.56 percent of the individuals were correctly classified using the discriminant analysis technique with the lambda occupational scores; 61.32 percent correct classifications were made with the chi-square weights alone and 67.03 percent of the individuals were correctly classified using the lambda coefficients as the scoring technique. Although some differences seem to exist, the null hypothesis of no interaction between measures and discriminant analysis was not rejected at α=.05.

In conclusion the results of this study showed that no one scoring procedure offers significantly greater accuracy than the other three procedures for classifying individuals into their appropriate occupational group. The study suggested other aspects of classification which should also be considered in choosing the "best" scoring strategy for the Kuder OIS. One of these factors was the variability in the rate of correct classification across several occupations. Using Levene's test for equal variances it was pointed out that while no difference in variability of procedures was found with the homogeneous occupations; statistically significant differences in procedures were identified in the variability of correct classifications among heterogenous occupations. Post hoc tests indicated that of the four scoring strategies studied, the least variable procedure was the use of lambda coefficients and the most variable was the chi-square technique.

Based on the results of the study, it was concluded that of the four scoring strategies considered, the best technique for scoring and classifying individuals on the Kuder OIS was the use of the lambda coefficient. Although not having a statistically significant advantage in average accuracy over the other three strategies studied, the direction of difference in average accuracy favored the lambda technique in both sets. Furthermore, the rate of correct classifications using the lambda technique was remarkably stable across several occupations, especially in the heterogeneous set. Finally further research suggestions were presented.

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To Mom and Dad

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CHAPTER I

INTRODUCTION

Individual interests have long been considered by psychologists and educators as one of the prime factors in determining occupational success and satisfaction. This theory has been supported by several research findings which have indicated that the degree and direction of one's life accomplishments can be directly related to the individual's interests. Clark (1961) for example, has argued that occupational effectiveness is increased at least at the professional level when the person enters that field for which he is best fitted both intellectually and temperamentally. Moreover, extensive follow-up studies conducted by Lipsett and Wilson (1954) and McRae (1959) have indicated greater job dissatisfaction among individuals possessing the necessary mental ability but lacking in interest, than among individuals having the reverse characteristics.

Thus interests, as well as ability seem to play a significant part in defining the level of job success and satisfaction. The need for an accurate assessment of one's interests is, therefore, obvious. Such a technique could be a valuable tool in identifying occupations suitable in terms of satisfaction for the individual and efficiency for the employer. As a result, the development of instruments measuring interests has become an area of major significance within the field of psychological testing.

A major problem in the development of accurate interest inventories has been the evaluation of individual responses. These instruments consist primarily of questions related to personal feelings and attitudes which cannot be scored as either right or wrong. The effectiveness of such inventories in identifying suitable occupations is, therefore, directly dependent upon the scoring procedure which is used. Several techniques have been suggested, each promising to improve the accuracy of interest surveys. The question as to which procedure is the "best" is a difficult one that has merited considerable investigation. Kuder (1957) concluded that a number of factors were important for suggesting which approach would provide the greatest discriminatory power. He went on to suggest, "We need to build up an extensive background of experience and theory before it will be possible to make a good guess as to which technique will produce the best results in a specific situation." (p. 114)

Recently Loadman (1971) compared several methods for scoring the Kuder Occupational Interest Survey form DD (this instrument will for the remainder of this paper be referred to as the Kuder OIS) including the procedure currently used by the publisher referred to as lambda coefficients; chi-square weights based on the chi-square test statistic as suggested by Porter (1965); multiple discriminant analysis based on lambda occupational scores and a pattern analysis procedure based on a computer program developed by Clark (1969). The results of his study indicated that the procedure presently used to score the Kuder OIS (the lambda coefficient) offered the greatest differentiation among the occupations tested. In this study, however, two of the techniques, lambda and discriminant analysis, had non-cross-validated scoring keys, while the scoring keys developed using the chi-square and pattern analysis procedures were cross-validated. By comparing the effectiveness of the quasi-cross-validated techniques with the true cross-validated procedures, the author possibly gave an unfair advantage to the former, which had the opportunity to capitalize on chance factors. The results of his study are therefore questionable and a re-analysis of the scoring techniques was warranted. Furthermore, Loadman did not consider the use of multiple discriminant analysis based on occupational scores obtained using the chi-square weights.

It was the purpose of this investigation to compare the effectiveness of four scoring techniques including: lambda coefficients, chi-square weights and multiple discriminant analysis using occupational scores based on (a) the lambda coefficients and (b) chi-square weights; when used with the Kuder Occupational Interest Survey form DD. Scoring weights for each procedure were developed and cross-validated, thus an unbiased test comparing scoring strategies was conducted. As a measure of effectiveness, the percent of individuals in the cross-validated group correctly identified as belonging to his actual occupation was used. The conclusions from this study should either provide support for establishing a new scoring procedure for the Kuder OIS or a new rationale for using the present technique.

Description of the Occupational Interest Survey

The Kuder Occupational Interest Survey, which was used in this study, was developed by Fredric Kuder over a period of years.

During the early years of development, frequent changes in items and scoring techniques were made in attempts to improve the accuracy of the survey. The latest revision was made in 1966 when Kuder introduced a new scoring procedure and changed the name to the Kuder Occupational Interest Survey form DD. Except for scoring, the new survey is identical to the previous instrument, i.e., the same format is used for presenting the same one hundred triadic items describing some common activities. Kuder designed this test to be used with junior and senior high school students along with college freshmen and adults seeking employment counseling. The author warns that the use of this instrument with a younger group may provide erroneous information. The reading vocabulary for the survey's directions and items is fixed at the sixth grade level, thus making it easily understood. From each group of three activities, representing an item, the subject is instructed to select the activity he most prefers and that which he likes least. Testing time requires only about thirty minutes. The responses are scored using a complex procedure developed by the author for this instrument and will be described later.

A person who has taken the Kuder OIS ultimately receives a report indicating those occupations and college majors that the individual seems to be best suited for in terms of interests, but not necessarily ability. In total, there are 171 different scales available, all of which would not be reported to any one particular individual. Males do receive, however, scores on 77 occupations and 29 college majors while females are sent scores on 57 occupations and

27 college majors. A verification scale is also provided for each individual as a check on the confidence that can be placed in the subject's answers.

Scoring is problematic since every response is a "correct" answer if the individual answered the item sincerely. One of the possible solutions which has been proposed deals with the assigning of weights to individual item responses for each occupation. The occupation on which a subject scores relatively high is indicated as a suitable occupation for the subject in so far as interests are concerned. This is the approach followed by both Kuder and Strong in the scoring of their respective interest inventories. This solution, however, provides another problem, that of determining how many points should be given for a particular item response for a particular occupational group. A number of solutions to this issue have been proposed over the years, but as Berdie and Campbell (Whitla 1967) have indicated the problem is still unresolved. Recent contributions by Kuder (1966) and Porter (1965) have stimulated new interest in this area.

Still other proposals for the solution of the problem of interpreting responses are the use of pattern analysis and multiple discriminant analysis procedures. That is, for the former, investigators have looked at group responses to determine whether occupational groups display distinctive patterns in their answers. Patterns are then treated as items and are assigned weights. Multiple discriminant analysis on the other hand, is a technique used in studying the relationship or classification of individuals among several groups. The procedure results in the reduction of multiple measurements to one or more weighted combinations having a maximum potential for discriminating among members of the different groups. Both of these proposals have induced controversy and stimulated considerable research in their development.

Returning to the problem at hand, however, the question still remains; which of the several possible scoring strategies is the most effective in discriminating individuals from several criterion groups? Following a review of the history and description of the development of several proposals for scoring, an attempt will be made to answer the question for the four earlier proposed strategies in relation to the Kuder OIS.

CHAPTER II

DEVELOPMENT OF SCORING PROCEDURES

Historical Review

According to Fryer (1931) the earliest investigators of interest theory often relied upon responses made to direct questions concerning selected jobs as the basis for predicting occupational interests. It was quickly discovered, however, that such replies were usually unrealistic, superficial and unreliable. Anastasi (1968) has offered insufficient information on the part of the subject and prevailing stereotypes attached to certain occupations as the reasons for these results. Fryer further suggested that family and peer pressure may also influence individual responses, especially among young subjects. As a consequence, researchers turned to more subtle methods for assessing interests. Inquiries were made into attitudes toward a variety of activities which were scored and used as a basis for determining occupational interests. Scoring of these early inventories was very subjective, assigning item weights solely on an estimate of an item's significance by a group of "experts". A review of the literature shows, however, that the early researchers of interest inventories were concerned with the development of more objective scoring techniques.

The publication of Yule's Introduction to the Theory of Statistics, in 1919 provided a major breakthrough in the development of objective scoring procedures for interest inventories, by supplying a framework for dealing with percentage differences. Based upon this work, M. J. Ream (1924) introduced the first objective weighting technique for interest surveys in a study of the interests of successful and unsuccessful salesmen, using the Carnegie Interest Inventory (the first standardized interest inventory). Ream's procedure was rather simple. After administering the inventory to two homogeneous groups, the researcher assigned a weight of ± 1.0 when the difference between the groups was larger than one standard error; differences of lesser degree were not considered. This method was followed by subsequent investigators who modified and further developed the procedure (Freyd 1924, Kornhauser 1927).

A second major development in the construction of objective scoring techniques came in 1929 when Cowdery suggested a method for weighting all items, adjusting for size of group differences by giving larger weights to bigger differences. Although considerably more complex than Ream's method, it took into consideration all responses made by a subject and was therefore logically argued to be a more discriminating procedure. Cowdery took each item on the Interest Report Blank (1921 edition) and divided the responses into a 2 x 2 matrix:

	like	dislike
occupation in question	a	b
men in general	c	d

where the letters (a, b, c, d) indicate the number of responses per cell for a particular item. The weight for the item was then calculated using a formula devised by T. L. Kelley in 1923:

$$b = \frac{\Phi}{(1-\Phi^2)\sigma}$$

where b is the assigned weight, Φ is the coefficient of correlation derived from: $\Phi = \frac{ad-bc}{\sqrt{(a+c)(b+d)(a+b)(d+c)}}$ and σ is the standard deviation of the frequencies (a+b) and (b+d). The weight was given a positive or negative sign depending upon the direction of the percentage difference of the responses between the two groups.

Following a modified version of this scoring technique in which the method for calculating Φ and σ were changed, Strong eliminated all decimals in the weights by rounding the scores to the nearest whole number and multiplying by a factor of 10. The result of such a procedure was to generate scoring weights ranging as high as $\pm$ 30 which were undoubtedly difficult with which to work.

Kuder's Solution

As attempts to improve the accuracy of interest inventories continued, several researchers suggested and developed new procedures for the assigning of item weights. Among the leaders of this group of investigators was Fredric Kuder, who throughout the 50's and 60's published several papers on the weighting problem (1957, 1961, 1963, 1966). His interest in the scoring problem was necessitated by the development of the Preference Record-Occupational form D in 1956, when he was faced with the task of interpreting responses. Kuder realized that the theoretically best method of evaluating all possible combinations of responses in all items was impractical. Alternatively, he sought a procedure which was relatively simple and straightforward yet accurately discriminated between occupational groups. Kuder's research to find such a technique, through a comparison of several scoring procedures, resulted in the investigator concluding that "the effectiveness of any scoring key was contingent upon a number of variables including: the number of cases, the composition of the inventory, the content and type of items, the range of item validities, the homogeneity of the groups and the extent to which the items can be considered to be uniformly distributed in the domain represented." (1957, p. 114)

Kuder first used a technique which compared for each item the percentage of individuals from an occupation in question selecting a response to the analogus percentage of either a reference group of men in general or a contrasting occupational group. Utilizing Zubin's inverse arc sine transformation and a pre-established table, Kuder was able to assign item response weights ranging from ± 10 to -10 for each occupation.

The first solution to the scoring problem was not completely satisfactory, and thus Kuder continued his investigation into alternative scoring procedures. In 1963, he published a paper discussing the advantages and disadvantages of using Findley's (1956) formula for assigning occupational scores: $D = \Sigma P_A - \Sigma P_B$, where D is the occupational score, ΣP_A is the sum of the proportion of subjects in group A who selected each of the preferences marked by the subject, and ΣP_B is the sum of the proportions of group B who marked each of the preferences marked by the subject. Kuder applied Findley's technique to the data he had collected from the Preference Record, letting group B be men in general and group A be a particular occupation of interest. He found that such a procedure reduced the amount of overlapping between groups substantially and, therefore, improved the discriminatory accuracy of the test.

Kuder did not adopt Findley's procedure for scoring form D, but rather, he questioned the need for the reference group. He argued that instead of computing the difference in proportions between two groups, why not just consider the proportions of subjects which selected the same preferences as the subject. The major problem with such a procedure was that the more homogeneous groups would tend to reflect higher scores and, therefore, a comparison between occupations would not be possible. Kuder's solution to the differential problem associated with the homogeneity of groups was based on the work of Clemens (1958) who had suggested that the relationship between an item and a criterion could be measured by a lambda coefficient which was defined as the ratio of the point biserial to the maximum point biserial correlations. The use of the lambda coefficient, as a measure of the relationship between an individual's responses and those of a particular criterion group, represents the current procedure for scoring the Kuder OIS.

The development of the lambda coefficient can be described by considering the nature of a Kuder OIS test item. As noted earlier the instrument consists of 100 items having the format shown in Figure 1:

		most		least	
Activity	1	o	(1)	o	(4)
Activity	2	o	(2)	o	(5)
Activity	3	o	(3)	o	(6)

Figure 1. Item format for the Kuder Occupational Interest Survey form DD.

A subject is instructed to indicate the activity which he likes most and the activity which he likes least. Thus for the one hundred items, each subject selects a subset of 200 responses from the 600 possible. Furthermore an individual's two responses for any one item may be represented by one of the response patterns shown in Figure 2.

Response Pattern	Responses most likes		least likes
1	1	and	5
2	1	and	6
3	2	and	4
4	2	and	6
5	3	and	4
6	3	and	5

Figure 2. Response patterns utilized to represent selected item responses.

The subject's responses to the instrument may be represented by a total of 100 response patterns. To obtain a measure of the relationship between an individual's responses and those of a particular criterion group the lambda coefficient is computed. In calculating the point biserial correlation the dichotomous variable is the selection or non-selection of the 600 possible response patterns, while the continuous variable is the proportion of the criterion group selecting each of the 600 response patterns. It might be noted that in calculating the lambda coefficient, the responses made by one criterion group at a time are utilized. The point biserial formula used in computing the lambda coefficient may be written as: $r_{p.bis} = \frac{M_p - M_t}{\sigma_t}\sqrt{\frac{N_p}{N_q}}$ where M_p is the average value of the continuous variable associated with the 100 response patterns selected by the individual. That is $M_p = \sum_{i=1}^{100} \frac{p_{ij}}{100}$ where p_{ij} (the continuous variable) is the proportion of the criterion group selecting response pattern j for item i. M_t is the average value of the continuous variable across all 600 response patterns: $M_t = \frac{\sum_{i=1}^{100}\sum_{j=1}^{6} p_{ij}}{600} = .667$. σ_t is the standard deviation of the continuous variable. N_p is the number of response patterns selected by the individual; $N_p = 100$, while N_q is the number of response patterns not selected; $N_q = 500$. To compute the maximum point biserial correlation M_g is the average of the highest response pattern proportions for each item across all 100 items; thus $M_g = \frac{\sum_{i=1}^{100} \max_j p_{ij}}{100}$ where $\max_j p_{ij}$ is the highest response pattern proportion (j) for item i.

An individual's lambda coefficient for a particular occupational group is the ratio of the point biserial and the maximum point biserial correlation:

$$\lambda = \frac{\frac{M_p - M_t}{\sigma_t}\sqrt{\frac{N_p}{N_q}}}{\frac{M_g - M_t}{\sigma_t}\sqrt{\frac{N_p}{N_q}}} = \frac{\sum_{i=1}^{100} \frac{p_{ij}}{100} - .667}{\sum_{i=1}^{100} \frac{\max_j p_{ij}}{100} - .667}$$

Furthermore the lambda coefficient can be reduced to a subset of lambda weights:

$$\lambda_{ij} \qquad \frac{\frac{p_{ij}}{100} - .00667}{\sum_{i=1}^{100} \frac{\max_j p_{ij}}{100} - .667}$$

where λ_{ij} is the lambda weight associated with response pattern j for item i, such that the sum of 100 λ_{ij} gives the lambda coefficient. It might be noted that in calculating the lambda weights, the maximum point biserial correlation remains the same for all 600 weights for a particular criterion group but can vary across criterion groups.

Two advantages are associated with the use of the lambda coefficient as a measure of the similarity of interests between an individual and a particular occupational group. First the lambda coefficient is unaffected by the homogeneity of the criterion group and secondly it has an upper limit of 1.00. Kuder calculated the lambda coefficients for individuals from several occupational groups and compared the resultant discriminating accuracy against his then current method. The results indicated a sharp reduction in the degree of overlapping between occupations and therefore increased precision in occupational discrimination (Kuder, 1970). Kuder then revised all of his scoring keys using the technique for calculating the lambda coefficient and renamed his test the Occupational Interest Survey form DD, publishing it in 1966.

Porter's Proposal

At the same time that Kuder was developing his lambda weights, Porter (1965) was taking a different approach to the development of a scoring key for the same test. His proposal was to use the chi-square test statistic for assigning weights to individual item response patterns.

Defining response patterns identical to those shown in Figure 2 of the previous section, Porter constructed for each of the one hundred items on the test, a contingency table consisting of a simultaneous breakdown of subjects by occupations and by response patterns. An example is shown in Figure 3 below:

Item 1

Occupational Group	Pattern for Item 1	2	3	4	5	6	
n_1	z_{ij}						X_1
n_2							X_2
n_3							X_3
.							
.							
N_1							X_I
N	Y_1	Y_2	Y_4	Y_4	Y_5	Y_6	ΣX_i

Figure 3. Example of a contingency table used in computing chi-square item response weights.

For such a table the weights assigned per response pattern per occupation were calculated using the following formula:

$$W_{ij} = \frac{\left(Z_{ij} - \frac{X_i\,Y_j}{\Sigma X_i}\right)^2}{\frac{X_i\,Y_j}{\Sigma X_i}} \times \text{(sign of the unsquared numerator)}$$

where i = 1 . . . . I, and j = 1 . . . . J. I denotes the number of groups, and J denotes the number of response patterns. Z_{ij} is the number of observed responses made by i-th group to the j-th response pattern. X_i is the total number of subjects in the i-th group, Y_j is the total number of individuals selecting the j-th response pattern, and ΣX_i is the total number of subjects in the sample.

Thus for each of the occupations considered, a fractional weight was calculated for each of the possible response patterns. An individual's score for an occupation was simply the sum of the chi-square weights associated with the individual's responses to the 100 items. The occupation in which an individual's total score was highest was designated as the most compatible group.

In testing this technique against the one used by Kuder in the Preference Record form D (note this was Kuder's scoring procedure prior to the development of lambda coefficient scoring technique), the results indicated a significant improvement in discriminating among similar occupations, but inconclusive results were obtained concerning heterogeneous occupations.

It might be pointed out here, that in computing chi square weights for a given occupation, a set of other occupational groups are needed in order to compute the chi-square statistic. Furthermore, the numerical value assigned to the weights could vary with the number and type of occupations used in the computations. These characteristics are not present with the development of item weights using the lambda procedure. Thus there is a slight advantage to using the lambda technique in terms of convenience, since item weights are computed with one occupational group at a time and numerical values of the weights are not dependent upon other occupational groups.

Loadman (1971) compared Porter's procedure, to Kuder's new lambda weights and found the latter to be more discriminating. His lambda weights however were not cross-validated and the chi-square weights were. Loadman's results may therefore have been due to an unfair comparison of the two promising techniques. A re-analysis of the data was necessary in order to determine which of the two procedures is the most discriminating for the Kuder Occupational Interest Survey form DD.

Multiple Discriminant Analysis

Still another approach to the scoring problem, and one that has been used with considerable success in other scoring problems, is the application of the linear discriminant function. The earliest work utilizing this procedure was conducted in the area of biometry in studies concerned with such issues as the classification of hair color. Psychologists quickly adopted the technique, however, for problems dealing with classification or selection of individuals based on a number of measurements.

One of the first applications of multiple discriminant analysis was made by Barnard in 1935 when based on a suggestion by R. A. Fisher; the researcher used the procedure to classify a series of Egyptian skulls. Fisher himself later elaborated on the method (1936, 1938) proposing that "when two or more populations have been measured in several characteristics $n_1, n_2 \ldots n_x$, special interest attaches to certain linear functions of that measurement by which populations are best discriminated." (Fisher, 1936 p. 179) Rao calculated two discriminant functions and was able to achieve maximum classification of individuals into one of three Indian castes chosen for investigation. (Rao, 1948) Among the first psychological applications of the procedure was one made by Rao and Slater in 1949 in a study attempting to discriminate five groups of neurotics from one group of normals by using thirteen personality variables. (Rao and Slater, 1949) Their results indicated that only three discriminant functions were necessary to account for the significant variation in the means of the six groups.

In an unpublished doctoral dissertation, Bryan (1950) demonstrated a procedure which could identify all discriminant functions in a classification problem directly from the two matricies obtained from the original scores: the between groups deviation matrix and the within group deviation matrix. "The technique provides an exact determination of the characteristic equation and provides the latent vectors of matricies of a class to which those of discriminant analysis belong. Prior to this time lengthy iterative procedures have been required for these determinants." (Tiedeman 1951)

As an exercise illustrating the above procedure, Tiedeman and Bryan (1954) analyzed the responses made to the Kuder Preference Record by a group of Harvard students from five different areas of study. The responses were scored and each subject received nine scores to correspond to the categories of interest identified by the instrument. With these scores plus the information of the students' college major, the investigators computed the matrix of between groups sum of squares and cross products and the matrix of within groups sum of squares and cross products. Four discriminant functions were then identified but analysis showed that only two functions associated with the first and second latent roots were necessary to account for 91% of the total variance. The authors, however, did not cross-validate the computed discriminant functions and thus no measure of accuracy for predicting an individual's major was provided.

Finally, a recent study conducted by Chappell (1967) at the University of Purdue utilizing the discriminant function showed the usefulness and power of the procedure. The investigator was interested in studying personality and interest differences between veterinarians, electrical engineers and guidance counselors all of which were graduate students. The results indicated that the suspected differences did exist, and that the discriminant function based on the scores from the Guilford-Zimmerman Temperment Survey and the Strong Vocational Interest Blank was capable of identifying these differences. The author concluded by urging a wider application of the procedure in educational and psychological research.

Pattern Analytic Approach

While some researchers continued the work begun by Cowdery and Strong by investigating and developing new procedures for assigning individual response weights, other investigators began looking at different approaches to the scoring problem. Some members of this latter group suggested examining patterns in the responses to discriminate between groups. Evidence to support such a procedure was provided, at least at the theoretical level by Meehl (1950, 1954), who effectively argued that while two items taken separately may have predictive validity of zero, taken together the items could be perfect in prediction.

A problem with the technique, however, has been in identifying procedures which could isolate the particular response patterns unique to each group. Throughout the 50's and 60's McQuitty proposed several methods in which this problem could be resolved. (1957a, 1957b, 1961a, 1961b, 1963, 1966) The procedures which he suggested were based on isolating types or categories of individuals through a technique called elementary linkage analysis or some modification of it. In a study assessing levels of mechanical experience McQuitty (1958) showed the technique to be superior to some item scoring procedures when many subjects were used for each criterion group and when a number of criterion groups were to be discriminated. Clark (1968) developed a computer program, based on McQuitty's work and compared the discriminating power of the identified pattern responses to multiple regression analysis in predicting field dependency and U.N. row call voting behavior. The results indicated that Clark's procedure was superior in cross-validated data.

Based on the work of McQuitty and using the computer program developed by Clark, Loadman (1971) attempted to identify response patterns of several occupational groups to the Kuder OIS. The results of this study, however, indicated that the identified patterns did no better than chance in correctly discriminating individuals from the occupations studied. Thus while pattern analysis may provide a powerful method for discrimination among groups, researchers have been unsuccessful in defining workable procedures for identifying response patterns for use with the Kuder OIS.

Summary

The degree of job success and satisfaction has been shown to be highly related to an individual's interests. Since vocational counselors are interested in predicting job success and satisfaction, measurement practitioners have been concerned with the development of accurate instruments in this area. Early attempts, however, were often inaccurate and very subjective. Although vast improvements have been made, research continues in new attempts to achieve greater precision in the measurement of interests. As Nunnally (1970) has cautioned, "Even though interests are very important to consider in choosing an occupation, it does not necessarily follow that the available instruments are maximally effective measures of interests. As is true in most areas of testing, a great deal more research with interest inventories is needed." (p.48)

One of the more fruitful areas of research in which advancements have been made, has been the development of scoring techniques for interest surveys. A review of the literature shows that at least three major techniques have been considered as possible procedures to be used in interpreting individual responses: (1) assigning item weights, (2) application of multiple discriminant analysis and (3) the use of pattern analysis. While research findings with the first two techniques have indicated considerable success in classification problems, the third technique, pattern analysis, has appeared considerably less promising, at least as presently operationalized. In particular Loadman's (1971) study suggested that one pattern approach was not useful for the Kuder OIS. Thus further development in this latter procedure is needed before it can be considered as a possible procedure to follow.

The solution to the scoring problem of the Kuder OIS, at least for the present time, appears to be with item weighting techniques. It was the purpose of this investigation to determine which procedure offers the greatest accuracy in discriminating individuals among both similar and dissimilar occupations while using the Kuder OIS. More specifically, two item weighting procedures and two applications of multiple discriminant analysis were compared in an attempt to identify empirically which technique was best. The four scoring strategies which were considered include: (1) Kuder's adaption of the lambda coefficient--the procedure which is presently used, (2) chi-square weights as developed by Porter (1965) and discriminant analysis using occupational scores generated by (3) the lambda occupational scores and (4) the chi-square occupational scores. The most effective procedure was identified as that technique which correctly identified individuals to their corresponding occupation the greatest percentage of the time.

CHAPTER III

Method

The empirical investigation of the accuracy of the four scoring procedures for the Kuder OIS required the use of several techniques. It was necessary to first develop scoring keys using a sample of individuals from several occupational backgrounds by each of the methods considered (lambda coefficients, chi-square weights, and multiple discriminant analysis based on (a) lambda weights and (b) chi-square weights). Then to insure that the keys were not based on chance responses or some idiosyncrasies of the particular sample group, the scoring keys were applied to a new independent sample of individuals. The efficiency of each of the procedures was estimated by the percentage of correctly identified subjects into their respective occupations on the cross validation sample. To determine whether a statistically significant difference actually existed among the procedures considered, an analysis of variance for mixed models was computed.

Description of Data

The data used to develop and test the scoring keys consisted of responses made to the Kuder OIS by 3893 males from nine occupational groups. These responses were obtained from Porter, who had previously acquired the data from Kuder, the originator of the OIS. Since this comparative study required a large volume of data, without their assistance the investigation could not have been conducted.

The nine criterion groups were divided into two classifications: similar and dissimilar occupations, as suggested by Porter (1965) and were labeled Set I and Set II respectively. Each set then consisted of five occupational groups with one criterion group appearing in both sets. Set I consisted of 406 optometrists, 274 x-ray technicians, 455 pediatricians, 385 physical therapists and 396 veterinarians. Set II on the other hand was composed of 500 clinical psychologists, 300 auto mechanics, 346 foresters, 400 optometrists and 451 social case workers. Although optometrists in Sets I and II were the same individuals, six subjects were randomly deleted from set II as a partial effort to reduce the total number of subjects in set II to meet the restrictions imposed by the computer facilities. In addition, it should be noted that since optometrists appeared among both similar and dissimilar occupational groups, the two sets were non-independent of each other. Within each set, the individual occupations were randomly divided into two parts: subset A and subset B. Thus each set consisted of ten independent groups ranging in size from a low of 136 individuals to a high of 250 individuals. The purpose of having two subsets was to provide one sample from each occupation to derive a scoring key for all four techniques considered, and at the same time have a second independent sample of each occupation to test the efficiency of the derived keys.

Since the data must be considered as old, being collected originally in the mid 1950's, the responses made by individuals in the criterion groups may not accurately reflect the attitudes and interests of individuals involved in these occupations today. Nevertheless these responses did provide valuable data for comparing the effectiveness of each scoring strategy which was the purpose of this study.

Cross-Validation Procedures

In order to estimate the "true" effectiveness of the scoring strategies being considered, a double cross-validation technique as suggested by Moiser (1951) was followed. Separate scoring keys were developed for subset A and B for each occupational group for both sets. The keys from one half of an occupational set then applied to the other half of the occupational set. For example, a scoring key derived half A for clinical psychologists was applied to half B, and the derived key from half B was applied to the data in half A. The estimate of the effectiveness of the scoring technique for an occupation was computed by taking the average number of correct identifications made by the two derived keys. Thus each of the four scoring techniques was applied to both halves of each of the five occupational groups in both sets.

Kuder's Scoring Keys

In developing the lambda weights as the fractional components of the lambda coefficient, associated with the individual response patterns, Kuder utilized the knowledge he had gained from his research with scoring procedures. Although considerably more complex than the previous procedure used by Kuder, the increased discriminating accuracy of the method outweighed the inconvenience of its calculation. In addition the introduction of high speed computers made the task far less cumbersome. Thus in this study lambda weights were computed in the manner suggested by Kuder, on a sample of individuals from each of the occupational groups.

Each individual from subset A received five occupational scores based on the lambda weights calculated for each of the criterion groups in subset B. By summing for each criterion group the lambda value associated with the selected response patterns across all 100 items, the lambda coefficient was obtained for each of the occupations in subset B. Similarly, each individual in subset B received five occupational scores based on the lambda weights computed on the criterion groups in subset A. Individuals were then identified as belonging to the occupational group for which he had the highest lambda coefficient. The efficiency of this technique was estimated by the average percent of correct identifications of individuals to their corresponding occupational group across the two subsets.

Chi-Square Scoring Keys

As was mentioned earlier, Porter (1965) had suggested that item weights be computed using the chi-square test statistic. He further demonstrated that this procedure was superior, at least in discriminating among similar occupations, to Kuder's scoring technique used prior to the development of the lambda weights. Thus to compare the chi-square weights to Kuder's new scoring procedure, the former were calculated following the technique proposed by Porter and described earlier. The chi-square weights were assigned to each of the six response patterns per item for each occupational group. For each occupation in each subset, an individual's selected response patterns were matched with the chi-square weights calculated on the opposite subset and summed over the 100 items. The individual was then identified as belonging to the occupational group which produced the highest sum of weights. As with the lambda technique, the efficiency of this procedure was estimated by the average percent of individuals correctly identified as belonging to his actual occupational group across both subsets.

Discriminant Analysis

Fisher (1936) had suggested using discriminant analysis procedures in classification problems when measures on two or more predictor variables were available. This technique attempts to identify one or more sets of coefficients (vector weights) for linear combinations of the variables which will maximize the variance between occupations relative to the variance within occupations. Thus several measures on an individual or object are combined to produce one composite score. Since discriminant analysis has been shown to be successful in previous studies (Rao, 1948; Tiedeman and Bryan, 1954; Chappell, 1967) for classifying individuals, it was considered in this study as a possible solution to the scoring problem for the Kuder OIS.

However, in order to use the multiple discriminant analysis procedure, it was necessary that the predictor data be at least at the ordinal level. Since responses made to the Kuder were on the nominal level it was necessary to transform the data to meet the above restriction. This was done in two ways: (1) lambda coefficients (2) chi-square occupational score, both of which were described earlier. Although either procedure could have been used, it was decided that for this study both weighting methods would be tried. Thus two multiple discriminant analysis procedures were computed, one using the lambda occupation scores, and the other using the chi-square occupation scores as the predictor variables.

Utilizing the procedure described by Overall and Klett (1972), the discriminant functions were identified. Each half of each set was used separately to derive the discriminant functions. These vector weights were then applied in a double cross-validation procedure, which was described earlier, to obtain the individual's composite score on which classification was based.

To compute the vector weights, the total sums of products (SP) matrix was first calculated using the following equation: $X'X - \overline{X}'\overline{X}$; where X was a matrix consisting of five occupational scores on each individual in subset A; X' was the transpose of X. $\overline{X}$ was a matrix consisting of the five average occupational scores for each of the five criterion groups and $\overline{X}'$ was the transpose of $\overline{X}$. The results of this equation produced a 5 by 5 matrix. The within group SP matrix was then calculated for each criterion group separately in a manner similar to that described above. The matricies SP_1, SP_2, . . . SP_n

were then pooled together to form the within-group SP matrix for the entire set, i.e., $SP(W) = SP_1 + SP_2 + SP_3 + SP_4 + SP_5$, where the subscript indicates the criteria group. The between-group SP matrix (B) was then calculated by taking the difference of within group SP matrix from the total SP matrix: $SP(B) = SP(T) - SP(W)$. (Overall and Kleth, 1972, p. 45, ex. 2.29)

The elements of the within-group SP matrix were then divided by the degrees of freedom, N - I where N was the total number of individuals in a subset and I was the number of criterion groups in the subset. The new matrix W, was the within-group covariance matrix. The inverse of W was then computed by the square root method of matrix inversion. The results might be diagrammed as below:

W	I
V'	V^{-1}

where W is the within-group covariance matrix, I is the identity matrix, V' is the upper triangular factor of W such that $VV' = W$ and V^{-1} is the lower triangular square root inverse such that $V'V^{-1} = I$.

The between-group SP matrix B was then pre and post multiplied by its transpose: $V^{-1}BV'^{-1}$. The characteristic roots of this symmetric matrix were then identified, $\lambda_1, \lambda_2, \ldots \lambda_v$ and the associated vectors $Z^1, Z^2 \ldots Z^n$ were obtained using the iterative method of identifying the principal components. The discriminant function coefficients were obtained by pre-multiplying each of the Z vectors by the triangular square root matrix V'.

With the coefficients of the linear functions then identified, it was possible to classify an individual into one of the five criterion groups. For example if the following two linear functions were identified:

$$Y_1 = C_{11}X_1 + C_{12}X_2 + C_{13}X_3 + C_{14}X_4 + C_{15}X_5,$$
$$Y_2 = C_{21}X_1 + C_{22}X_2 + C_{23}X_3 + C_{24}X_4 + C_{25}X_5,$$

where Y_i is the composite score for the i-th function, C_{ij} is the linear coefficient computed for the i-th function and j-th measure, and X_j is the j-th occupational score derived from either the lambda weights or chi-square weights. Each individual receives two composite scores, Y_1 and Y_2, by summing the products associated with the individual's occupational scores and the corresponding vector weights. For example, a social worker will have an occupational score on the social worker measure plus a score on each of the four other occupations in Set I. Each of these scores is multiplied by the appropriate coefficient and summed to give composite scores Y_1 and Y_2. In addition, the average score on each function is computed for each of the criterion groups, i.e., μ_{ki} where k indicates the criterion group and i indicates the function.

To classify an individual, the simple d^2 function was utilized, i.e. the sum of the squared deviations of an individual's composite score from the mean composite score of each criterion group was computed. For example, if there were two functions identified and three criterion groups to discriminate then:

$$d_1^2 = (\mu_{11} - Y_1)^2 + (\mu_{12} - Y_2)^2,$$
$$d_2^2 = (\mu_{21} - Y_1)^2 + (\mu_{22} - Y_2)^2,$$
$$d_3^2 = (\mu_{31} - Y_1)^2 + (\mu_{32} - Y_2)^2,$$

where the subscript of d_1^2 indicates the associated criterion group.

The individual was classified as belonging to that criterion group corresponding to the smallest d^2 value.

Since the computations as described above would have been a monumental task if done by hand, the discriminant analysis procedure and classification of individuals was calculated by computer. The program by which the discriminant functions were calculated was written by Jeremy Finn, State University of New York at Buffalo, and modified for the computer facilities at Michigan State University by David Wright. The program to compute the d^2 function and classification of individuals was written by the author and is included in appendix A. As mentioned earlier, discriminant functions on lambda weights and chi-square weights were both analyzed for similar and dissimilar criterion groups.

Statistical Analysis

To compare the results of the four Kuder OIS scoring procedures, an analysis of variance for mixed models was utilized (see Figure 4). The dependent variable in the study was the average (across halves A and B) percent of correctly identified individuals for an occupation. The problem of non-independence between sets was solved by using the cross-validation results of half A for optometrists in Set I and the cross validation results of half B in Set II. Thus while the same occupational group, optometrists, appeared in both sets, a different group of individuals was used for respective cross validation studies, making the two sets independent. The fixed independent variables were: sets of similar and dissimilar occupations, S, lambda weights or chi-square weights, M, and discriminant analysis or not, D. All three fixed independent variables were completely crossed with each other. Occupations was treated as a random independent variable which was nested within S, with five levels per nest but crossed with the two scoring procedures D and M.

		D_1		D_2	
		M_1	M_2	M_1	M_2
S_1	O_1				
	O_2				
	O_3				
	O_4				
	O_5				
S_2	O_6				
	O_7				
	O_8				
	O_9				
	O_{10}				

Figure 4. Data matrix for a mixed model analysis of variance.

Although occupations were not actually selected at random from a larger pool of occupations, it was felt that by using the Cornfield-Tukey bridge argument (Cornfield-Tukey, 1956) the results of this study could be generalized to all similar occupations. Had occupations been treated as fixed, greater power would have resulted in the analysis since the individual test respondent would have been the unit of analysis rather than the occupation. The results of such a test, however, would have been limited to those occupations which were studied and thus would have had very little practical value. On the other hand, by treating occupations as random, some power was lost but the inferences which could be made were of greater interest.

The hypotheses which were considered in this design included testing for differences in the discriminating accuracy: between sets of occupational groups, between the measures chi-square and lambda techniques and differences between using discriminant analysis or not. In addition interaction effects between measures and discriminant analysis as well as interaction effects with sets were also tested. Each hypothesis considered was tested for statistical significance at $\alpha = .05$.

CHAPTER IV

RESULTS

Scoring keys, using the four strategies discussed in the previous chapter, were developed on both half A and half B for each set. Since the two subsets, A and B, were independent of each other, data were available for cross-validation purposes. The keys developed on half A were used to score the responses of individuals in half B, while the keys developed on half B were used to score the responses of individuals in half A. This procedure was followed with both sets of data and the effectiveness of each strategy was estimated from the cross-validated data.

For the multiple discriminant analysis procedure, coefficients for the best linear combination of the occupational scores were obtained by the procedure described in the previous chapter. Four latent roots were identified for each half of Set I and Set II, using the occupational scores based on lambda and on chi-square occupational scores separately. The associated eigenvectors were then utilized to compute the composite scores of individuals in the cross-validation sample of the data. Classification of these individual scores based on the simple d^2 statistic was then made for each half of both Set I and Set II.

The results of each cross-validated half of each set based on the four scoring techniques being considered are presented in Tables 1 through 16. For each criterion group (row) the percentage of individuals classified as belonging to each of the occupational groups (columns), is shown. The main diagonal elements of Tables 1 through 16, indicate the percentage of the individuals correctly identified as belonging to their occupational group. The off-diagonal elements, however, indicate the percentage of the particular criterion group who were classified as belonging to one of the four other occupational groups and are considered as errors.

These tables provide some interesting information on the stability of the four scoring procedures. Since half A and half B were obtained by randomly dividing each occupational group into two halves, the percentage of correct classifications for an occupation would be expected to be approximately equal across halves. Thus looking at the absolute values of the differences in the diagonals between halves gives some indication of the stability of each scoring strategy. The absolute values of the differences between subsets for the four scoring procedures are presented in Table 19 as well as the means, variances and standard deviations of the absolute values. Using these data as an estimate of the stability associated with each scoring strategy, an analysis of variance for mixed models was computed to test for differences between techniques, (see Figure 5). The dependent variable for the analysis was the absolute value of the differences between subsets. The fixed independent variable was the

Table 1. The percentage of males from each criterion group (row) in Set I half A classified into each of the five occupational groups (columns) using the lambda scoring key derived on half B of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	63.05	7.88	12.32	11.33	5.42
X-ray Technician	7.35	52.94	15.44	17.65	6.62
Pediatrician	3.21	8.72	71.56	11.47	5.05
Physical Therapist	11.73	26.26	12.85	45.81	3.35
Veterinarian	9.50	7.50	15.00	9.00	59.00

Table 2. The percentage of males from each criterion group (row) in Set I half B classified into each of the five occupational groups (columns) using the lambda scoring keys derived on half A of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	62.56	9.36	11.33	11.82	4.93
X-ray Technician	3.62	55.80	7.97	27.54	5.07
Pediatrician	6.91	11.98	63.59	13.36	4.15
Physical Therapist	12.14	18.45	13.59	53.88	1.94
Veterinarian	8.67	10.20	12.76	7.14	61.22

Table 3. The percentage of males from each criterion group (row) in Set I half A Classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on lambda scores derived on half B of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	54.19	6.40	9.85	9.36	20.20
X-ray Technician	8.09	23.53	3.68	33.09	31.62
Pediatrician	10.09	4.13	42.20	18.35	25.23
Physical Therapist	12.85	26.82	7.82	36.31	16.20
Veterinarian	8.50	8.50	8.00	3.50	71.50

Table 4. The percentage of males from each criterion group (row) in Set I half B classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on lambda scores derived on half A of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	50.74	4.93	5.91	16.26	22.17
X-ray Technician	5.80	37.68	5.80	31.88	18.84
Pediatrician	5.99	5.99	46.08	21.20	20.74
Physical Therapist	14.56	13.59	9.71	48.06	14.08
Veterinarian	8.67	3.02	7.14	8.67	72.45

Table 5. The percentage of males from each criterion group (row) in Set I half A, classified into each of the five occupational groups (columns) using the chi-square scoring keys derived on half B of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	60.10	4.43	18.23	6.90	10.34
X-ray Technician	10.29	44.12	16.18	11.76	17.65
Pediatrician	3.67	4.59	69.27	5.50	16.97
Physical Therapist	8.38	19.55	22.91	36.31	12.85
Veterinarian	3.00	1.00	7.50	1.50	87.00

Table 6. The percentage of males from each criterion group (row) in Set I half B, classified into each of the five occupational groups (columns) using the chi-square scoring keys derived on half A of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	60.10	4.43	14.78	9.36	11.33
X-ray Technician	10.14	42.03	7.97	17.39	22.46
Pediatrician	4.15	4.61	61.29	6.91	23.04
Physical Therapist	19.42	7.77	16.99	39.81	16.02
Veterinarian	6.12	0	3.06	1.02	89.80

Table 7. The percentage of males from each criterion group (row) in Set I half A, classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on the chi-square scores derived on half B of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	62.56	8.87	10.84	12.32	5.42
X-ray Technician	9.56	55.88	6.62	21.32	6.62
Pediatrician	5.05	9.17	57.80	15,60	12.39
Physical Therapist	7.26	23.46	10.06	54.75	4.47
Veterinarian	6.50	4.00	7.00	6.00	76.50

Table 8. The percentage of males from each criterion group (row) in Set I half B, classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on the chi-square scores derived on half A of Set I.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	67.00	5.91	9.36	9.36	8.37
X-ray Technician	13.04	50.00	9.42	15.94	11.59
Pediatrician	9.68	10.14	57.14	5.99	17.05
Physical Therapist	18.45	23.30	13.11	31.07	14,08
Veterinarian	8.16	3.06	6.12	2.04	80.61

Table 9. The percentage of males from each criterion group (row) in Set II half A, classified into each of the five occupational groups (columns) using the lambda scoring keys derived on half B of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optome-trist	Social Worker
Clinical Psychologist	70.00	.40	4.00	6.40	19.20
Auto Mechanic	.67	79.33	9.33	9.33	1.33
Forester	3.47	5.20	76.88	10.98	3.47
Optometrist	10.00	5.00	8.50	73.00	3.50
Social Worker	18.22	.44	2.67	12.44	66.22

Table 10. The percentage of males from each criterion group (row) in Set II half B, classified into each of the five occupational groups (columns) using the lambda scoring keys derived on half A of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optome-trist	Social Worker
Clinical Psychologist	72.40	0	2.40	10.40	14.80
Auto Mechanic	.67	82.67	10.00	5.33	1.33
Forester	6.36	6.36	79.19	5.20	2.89
Optometrist	5.00	4.50	5.00	75.00	10.50
Social Worker	14.16	2.21	1.33	8.41	73.89

Table 11. The percentage of males from each criterion group (row) in Set II half A, classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on the lambda scores derived on half B of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optometrist	Social Worker
Clinical Psychologist	46.80	.40	4.00	17.20	31.60
Auto Mechanic	0	86.00	8.00	4.00	2.00
Forester	5.20	10.40	76.30	5.20	2.89
Optometrist	15.50	6.00	4.00	70.00	4.50
Social Worker	21.25	3.98	1.77	6.64	66.37

Table 12. The percentage of males from each criterion group (row) in Set II half B, classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on lambda scores derived on half A of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optometrist	Social Worker
Clinical Psychologist	68.27	1.20	3.21	4.02	23.29
Auto Mechanic	.67	80.00	6.67	8.67	4.00
Forester	4.62	19.08	61.27	13.87	1.16
Optometrist	10.00	10.50	9.50	51.50	18.50
Social Worker	36.44	4.44	4.89	17.33	36.89

Table 13. The percentage of males from each criterion group (row) in Set II half A, classified into each of the five occupational groups (columns) using the chi-square scoring keys derived on half B of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optome-trist	Social Worker
Clinical Psychologist	86.80	4.40	1.60	.40	7.20
Auto Mechanic	.67	94.67	2.67	1.33	.67
Forester	9.83	43.35	42.77	3.47	.58
Optometrist	22.00	26.50	4.50	40.00	7.00
Social Worker	32.89	8.00	2.22	1.78	55.11

Table 14. The percentage of males from each criterion group (row) in Set II half B, classified into each of the five occupational groups (columns) using the chi-square scoring keys derived on half A of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optome-trist	Social Worker
Clinical Psychologist	86.80	4.00	2.00	1.60	5.60
Auto Mechanic	.67	97.33	1.33	.67	0
Forester	6.36	46.82	43.35	1.16	2.31
Optometrist	20.50	31.00	3.00	38.00	7.50
Social Worker	33.63	7.93	3.10	2.65	52.65

Table 15. The percentage of males from each criterion group (row) in Set II half A, classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on the chi-square scores, derived on half B of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optome-trist	Social Worker
Clinical Psychologist	66.80	.40	3.60	2.40	26.80
Auto Mechanic	0	82.00	6.67	7.33	4.00
Forester	1.73	8.67	76.30	8.67	4.62
Optometrist	2.50	5.00	7.50	69.50	15.50
Social Worker	34.67	1.33	3.56	11.11	49.33

Table 16. The percentage of males from each criterion group (row) in Set II half B, classified into each of the five occupational groups (columns) using the multiple discriminant analysis procedure based on the chi-square scores, derived on half A of Set II.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optome-trist	Social Worker
Clinical Psychologist	76.00	.40	1.60	6.40	15.60
Auto Mechanic	0	84.67	8.00	4.67	2.67
Forester	2.89	10.40	76.30	7.51	2.89
Optometrist	3.50	4.50	4.00	78.00	10.00
Social Worker	26.11	2.65	2.65	11.50	57.08

Table 17. The absolute value of differences between percent of individuals correctly identified as belonging to their actual occupational group in half A minus correctly classified in half B for each of the four scoring strategies studied in Sets I and II.

	Discriminant With Chi Square	Discriminant With Lambda	Chi Square	Lambda
Set I				
Optometrist	4.44	3.45	0	.49
X-ray Technician	5.88	14.15	2.09	2.89
Pediatrician	.66	3.88	7.98	7.97
Physical Therapist	23.68	11.75	3.50	8.07
Veterinarian	4.11	.95	2.80	2.22
Average Absolute Value of Differences	7.75	6.84	3.27	4.32
Variance of Absolute Values	82.94	32.12	8.64	25.24
Standard Deviation	9.11	5.76	2.94	5.02
Set II				
Clinical Psychologist	9.20	21.47	0	2.40
Auto Mechanic	2.67	6.00	.34	3.34
Forester	0	15.03	.58	2.31
Optometrist	8.50	18.50	2.00	2.00
Social Worker	7.75	29.48	2.46	7.67
Average Absolute Value of Differences	5.62	18.10	1.08	3.54
Variance of Absolute Values	26.40	74.21	3.32	12.28
Standard Deviation	5.14	8.61	1.82	3.50

four scoring strategies studied M, while the random independent variable was the five occupational groups in a set, O.

	M_1	M_2	M_3	M_4
O_1				
O_2				
O_3				
O_4				
O_5				

Figure 5. Data matrix for the test of equality of scoring consistency.

This model assumes no interaction between the random and fixed independent variables as well as an equal pairwise correlation for levels of the fixed independent variable. The computed F ratios were .33 and 17.13 for Set I and Set II respectively. Thus while differences in the stability of scoring strategies were not found to be statistically significant among homogeneous occupational groups, statistically significant differences in the stability of the scoring procedures among heterogeneous occupations were identified at $\alpha = .05$. Reviewing the mean absolute difference values for the scoring strategies in Set II, indicated that discriminant analysis with lambda occupational scores was the least stable scoring technique of the four procedures tested.

Moiser (1951) suggested that the average of the two cross-validated halves be used as an estimate of the "true" effectiveness of a particular scoring strategy. Following his suggestion, the average percent of individuals identified as belonging to each of the occupational groups was computed. The results of this computation are presented in Tables 18 through 25. The percent of individuals correctly identified using the lambda procedure ranged from 67.58 (pediatricians) to 49.85 (physical therapists) in Set I (see Table 18), and 81.00 (auto mechanics) to 70.06 (social workers) in Set II (see Table 22). Using the discriminant analysis technique based on the lambda scores, the percent correctly identified ranged from 71.98 (veterinarians) to 30.61 (x-ray technicians) in Set I (see Table 19) and 83.00 (auto mechanics) to 51.63 (social workers) in Set II (see Table 23). Based on the chi-square weights, however, the percent correctly identified ranged from 88.40 (veterinarians) to 38.06 (physical therapists) in Set I (see Table 20) and 96.00 (auto mechanics) to 39.00 (optometrist) in Set II (see Table 24). And finally, with the discriminant analysis procedure based on the chi-square weights the precentage of correct identifications ranged from 78.56 (veterinarians) to 42.91 (physical theratpsts) in Set I (see Table 21) and for Set II correct identifications ranged from 83.24 percent (auto mechanics) to 53.21 percent (social workers), see Table 25.

To facilitate a comparison of the effectiveness of the scoring strategies the elements on the main diagonals of Tables 18 through 25 were arranged together in one table. Since primary interest is with the number of correct identifications, the location of the main distractors for each technique is of little importance. Thus the

Table 18. Averages of percentages of males from each criterion group (row) in Set I half A and Set I half B classified into each of the five occupational groups (columns) in Set I using the lambda weights.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	62.81	8.62	11.83	11,58	5.18
X-ray Technician	5.49	54.37	11.71	22.60	5.85
Pediatrician	5.06	10.35	67.58	12.42	4.60
Physical Therapist	11.94	22.36	13.22	49.85	2.65
Veterinarian	9.08	8.85	13.88	8.07	60.11

Table 19. Averages of percentages of males from each criterion group (row) in Set I half A and Set I half B classified into each of the five occupational groups (columns) in Set I using the multiple discriminant analysis procedure based on lambda occupational scores.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	52.47	5.67	7.88	12.81	21.19
X-ray Technician	6.95	30.61	4.74	32.49	25.23
Pediatrician	8.04	5.06	44.14	19.85	22.99
Physical Therapist	13.71	20.21	8.77	42.19	15.14
Veterinarian	8.59	5.76	7.57	6.09	71.98

Table 20. Averages of percentages of males from each criterion group (row) in Set I half A and Set I half B classified into each of the five occupational groups (columns) in Set I using the chi-square weights.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	60.10	4.46	16.51	8.13	10.84
X-ray Technician	10.21	43.08	12.08	14.58	20.06
Pediatrician	3.91	4.60	65.25	6.21	20.01
Physical Therapist	13.90	13.66	19.95	38.06	14.44
Veterinarian	4.56	.50	5.28	1.26	88.40

Table 21. Averages of percentages of males from each criterion group (row) in Set I half A and Set I half B classified into each of the five occupational groups (columns) in Set I using the multiple discriminant analysis procedure based on chi-square occupational scores.

Actual Occupation	TEST INDICATED OCCUPATION				
	Optometrist	X-ray Technician	Pediatrician	Physical Therapist	Veterinarian
Optometrist	64.78	7.39	10.10	10.84	6.90
X-ray Technician	11.30	52.94	8.02	18.63	9.11
Pediatrician	7.37	9.66	57.47	10.80	14.72
Physical Therapist	12.86	23.38	11.59	42.91	9.28
Veterinarian	7.33	3.53	6.56	4.02	78.56

Table 22. Averages of percentages of males from each criterion group (row) in Set II half A and Set II half B classified into each of the five occupational groups (columns) in Set II using the lambda weights.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optometrist	Social Worker
Clinical Psychologist	71.20	.20	3.20	8.40	17.00
Auto Mechanic	.67	81.00	9.67	7.33	1.33
Forester	4.92	5.18	78.04	8.09	3.18
Optometrist	7.50	4.75	6.75	74.00	7.00
Social Worker	16.19	1.33	2.00	10.43	70.06

Table 23. Averages of percentages of males from each criterion group (row) in Set II half A and Set II half B classified into each of the five occupational groups (columns) in Set II using the multiple discriminant analysis procedure based on the lambda occupational scores.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optometrist	Social Worker
Clinical Psychologist	57.54	.80	3.61	10.61	27.45
Auto Mechanic	.34	83.00	7.34	6.34	3.00
Forester	4.91	14.74	68.79	9.54	2.03
Optometrist	12.75	8.25	6.75	60.75	11.50
Social Worker	28.85	4.21	3.33	11.99	51.63

Table 24. Averages of percentages of males from each criterion group (row) in Set II half A and Set II half B classified into each of the five occupational groups (columns) in Set II using the chi-square weights.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optometrist	Social Worker
Clinical Psychologist	86.80	4.00	1.80	1.00	6.40
Auto Mechanic	.67	96.00	2.00	1.00	.34
Forester	8.10	45.09	43.06	2.32	1.45
Optometrist	21.25	28.75	3.75	39.00	7.25
Social Worker	33.26	7.98	2.66	2.22	53.88

Table 25. Averages of percentages of males from each criterion group (row) in Set II half A and Set II half B classified into each of the five occupational groups (columns) in Set II using the multiple discriminant analysis procedure based on the chi-square occupational scores.

Actual Occupation	TEST INDICATED OCCUPATION				
	Clinical Psychologist	Auto Mechanic	Forester	Optometrist	Social Worker
Clinical Psychologist	71.40	.40	2.60	4.40	21.20
Auto Mechanic	0	83.34	7.34	6.00	3.34
Forester	2.31	9.54	76.30	8.09	3.76
Optometrist	3.00	4.75	5.75	73.75	12.75
Social Worker	30.39	1.99	3.11	11.31	53.21

results in Table 26 summarize the average percent correct identifications made by each of the four scoring strategies in each criterion group in both sets.

To evaluate these results an analysis of variance for mixed models was utilized. It should be recalled, however, that since optometrists appeared in both similar and dissimilar occupational groups, the two sets were non-independent. To resolve this problem only the cross-validated results of half A for optometrists, using each of the scoring strategies, were considered in Set I; while only the cross-validated results of half B for optometrists were considered in Set II. Thus rather than presenting the average correct identifications as found in Tables 18 through 25, Table 26 contains for optometrists the cross validated results of half A for Set I and half B for II.

The results of the mixed model analysis of variance are presented in Table 27. Although the unweighted average percent of individuals correctly classified in Set I was 56.37; while Set II had 68.41 percent correct classifications, no statistically significant difference between sets was identified, $p < .15$. The difference in percent correct identifications between sets was however, in the predicted direction. That is, a greater percentage of the individuals from the set of heterogeneous occupational groups were correctly classified than individuals classified among the homogeneous occupations. The unweighted average percent of individuals correctly identified when multiple discriminant analysis procedures were utilized was 60.62; while non-use of this technique produced 66.66 percent correct classifications. This difference, however, was not found to be statistically

Table 26. The average percent of individuals correctly classified into their actual occupational group from half A and half B for Set I and Set II.

	Discriminant Analysis		Non-Discriminant Analysis	
	Chi-Square Weights	Lambda Weights	Chi-Square Weights	Lambda Weights
Set I				
Optometrist	62.54	54.19	60.10	63.05
X-Ray Technician	52.94	30.61	43.08	54.37
Pediatrician	57.47	44.14	65.28	67.58
Physical Therapist	42.91	42.19	38.06	49.85
Veterinarian	78.56	71.98	88.40	60.11
Set II				
Clinical Psychologist	71.40	57.54	86.80	71.20
Auto Mechanic	83.34	83.00	96.00	81.00
Forester	76.30	68.79	43.56	78.04
Optometrist	78.00	51.50	38.00	75.00
Social Worker	53.21	51.63	53.88	70.06

Table 27. ANOVA table for mixed models, analyzing the data from Table 14.

Sources	Degrees of Freedom	Means Squares	F	P
S	1	1449.86	2.51	.15
O:S	8	578.07		
D	1	126.59	1.47	.26
M	1	48.44	.48	.52
SD	1	28.06	.33	.59
SM	1	85.73	.85	.39
DM	1	625.84	3.55	.10
SDM	1	76.95	.44	.53
OD:S	8	85.97		
OM:S	8	100.90		
ODM:S	8	176.51		

significant, $p < .26$. The difference in percent correct identifications between use and non-use of the discriminant analysis technique was in the opposite direction from what had been expected. These results may have been due, however, to the lack of stability of discriminant function in the cross-validated data as was presented earlier.

A comparison of the measures, lambda vs. chi-square showed that for the former an unweighted average of 61.29 percent of the individuals were correctly classified; while for the latter an average of 63.49 percent correct classifications were made. The null hypothesis of no difference between measures was not rejected, $p < .57$. Testing the interaction of discriminant analysis by measure indicated that an unweighted average of 65.67 percent correct classifications was made with the discriminant analysis based on chi-square scores; 55.56 percent correct classifications with discriminant analysis using lambda occupational scores, 61.32 percent correct classifications with the chi-square scoring technique used alone and 67.03 percent correct classifications when the lambda coefficients were used alone. Again the analysis did not indicate statistically significant differences, $p < .10$. Finally no interaction effects with sets, S, were identified for various levels of p as indicated in Table 27.

A further consideration in deciding which scoring technique was the most effective was consistency of accuracy with which the procedures correctly classified individuals across occupations. A technique which correctly classified individuals in one or two occupations at a very high rate but classified individuals in other occupational groups at low rates, may not, in the long run be as valuable

as a procedure which consistently classified individuals at a moderately high rate over all occupations. Thus variability in the rate of correct classifications might be an important aspect associated with a procedure when evaluating the scoring strategies. Using the data in Table 26, the equality of variance corresponding to each scoring procedure was tested using Levene's test of homogeneity of variances for both Set I and Set II. The means, variances, standard deviations and means of the absolute values of deviations from the means associated with Levene's test, for both sets of data are presented in Table 28. The null hypothesis of equality of variance among the four measures was not rejected for Set I at α=.05. Using the same test with Set II, however, the null hypothesis of equal variances was rejected at α=.05. In addition Scheffe's post hoc technique (see Table 28) indicated that the chi-square procedure was more variable than the lambda technique and the discriminant procedure with chi-square weights at α=.05. Thus, at least for dissimilar criterion groups, the chi-square technique seems to correctly identify individuals to their actual occupational group less consistently than the other techniques.

Table 28. The mean, variance, standard deviation and absolute error difference for each scoring strategy used in Levene's test for equality of variance across the four measures.

	Discriminant With Chi-Square	Discriminant With Lambda	Chi-Square	Lambda
		Set I		
Average	58.89	48.62	58.98	58.99
Variance	173.29	240.62	319.40	57.84
Standard Deviation	13.16	15.51	17.87	7.61
Average $\bar{e}$	9.33	11.57	14.73	5.51
		Set II		
Average	72.45	62.49	63.65	75.06
Variance	133.88	175.89	547.89	21.02
Standard Deviation	11.57	13.26	23.40	4.58
Average $\bar{e}$	8.12	10.72	22.20	3.57

Scheffé post hoc test statistic for comparing specific average error differences.

$$\psi \quad \pm\sqrt{(J-1)\ F_{J-1,(J-1)(I-1)}}\ \sqrt{MS_W\ \frac{1}{n} + \frac{1}{n}}$$

$$\sqrt{(3)\ (3.49)} \qquad \sqrt{(35.03)\ (\tfrac{2}{n})}$$

$$(3.24)\ \ (3.74)$$

$$\psi \quad \pm\ 12.13$$

CHAPTER V

DISCUSSION

The previous chapter presented the results of the development and cross-validation of several scoring keys for the Kuder OIS. The analysis of variance test which was computed failed to reject the null hypothesis of no difference between the four scoring strategies in discriminating individuals among both similar and dissimilar occupational groups. The lambda technique, however, had the highest percentage of correct classifications for optometrists, x-ray technicians, pediatricians and physical therapists among the similar occupational groups and among dissimilar occupations, the procedure had the highest rate of correct classification for foresters and social workers. On the other hand, the chi-square technique had the highest correct classification rate for veterinarians among the similar occupations and clinical psychologists and auto mechanics among dissimilar occupations. The discriminant analysis technique using the chi-square occupational scores had the highest rate of correct classification for optometrists among dissimilar occupations. The discriminant analysis technique using the lambda occupational scores had the lowest rate of correct classifications of the four techniques considered in four out of five occupations for the similar occupational groups and lowest rate of correct classifications in three out of five occupations among dissimilar occupations. Thus the lambda weighting procedure correctly identified individuals as belonging to their actual occupational group at the highest rate in six of ten occupations, the chi-square technique in three of ten, the discriminant analysis technique with chi-square occupational scores in one of ten, and the discriminant analysis technique with lambda occupational scores did not have the highest rate of correct classification in any of the occupations studied. Furthermore, Levene's test (for the equality of variance among j groups) indicated that while the null hypothesis of equal variances in percentage of correct classification was not rejected for I, there was a statistically significant difference in the variability of correct classification among the four scoring procedures with Set II. Using Scheffé's post hoc technique the lambda procedure was shown to be significantly less variable than the chi-square procedure at α =.05. Since the lambda and chi-square procedures did not differ on average accuracy, this greater uniformity across dissimilar occupations for the lambda technique is particularly important.

The conclusion of no difference between scoring procedures is in disagreement with that made by Loadman (1971) when a similar comparison was made. It should be recalled, however, that Loadman did not generate his own set of scoring keys, using the lambda procedure, but rather had obtained the item weights from SRA. These weights were derived from the total population of respondents on whom the researcher had hoped to classify. Thus an independent set of data for cross-validation purposes was not available which may have resulted in an inflated percentage of correct identifications. In addition, with twice as many individuals to build the scoring key another advantage was given to the Kuder lambda procedure in Loadman's study. Therefore, an undetermined level of bias could have entered the data in favor of the lambda technique, thus making the results of his study questionable.

An estimate of the bias which had entered Loadman's data is indicated in Tables 29 and 30. In these tables the average percent of individuals correctly classified in each occupational group, using the quasi-cross-validated scoring keys (Loadman 1971, p. 114) and the cross-validated scoring keys of the present study, are presented. The third column of each table shows the magnitude of the differences between the quasi and true cross-validation procedures for each occupation. The effect of quasi-cross-validation varied from one occupation to another, but in general the quasi-cross-validation percentages of correct classifications were considerably greater than the corresponding true cross-validation percentages. On two occasions however, the true cross-validated results produced considerably higher rates of correct classification than the quasi-cross-validated results: 1) Set I for physical therapists using the discriminant analysis technique (see Table 29), and 2) Set II for social worker using the lambda technique without the discriminant function (see Table 30). To explain these results, it might be suggested that since both of these occupational groups had a considerably lower rate of correct classification than the other occupations within the same set and scoring technique, it is possible that some error existed in the scoring keys used by Loadman. Loadman had indicated several problems in obtaining

Table 29. The average rate of correct identifications for each occupational group in Set I using the cross-validated and quasi-cross-validated data.

	Quasi-Cross-Validated Lambda	Cross-Validated Lambda	Difference
Optometrists	69.46	63.05	6.41
X-ray Technicians	66.78	54.37	12.41
Pediatricians	70.18	67.58	2.60
Physical Therapists	56.96	49.85	7.11
Veterinarians	59.75	60.11	-.36
	Quasi-Cross-Validated Discriminant Function With Lambda Scores	**Cross-Validated Discriminant Function With Lambda Scores**	**Difference**
Optometrists	67.98	52.47	15.51
X-ray Technicians	62.01	30.61	31.40
Pediatricians	66.98	44.14	22.84
Physical Therapists	20.99	42.19	-21.20
Veterinarians	79.75	71.98	7.77

Table 30. The average rate of correct identifications for each occupational group in Set II using the cross-validated and quasi-cross-validated data.

	Quasi-Cross-Validated Lambda	Cross-Validated Lambda	Difference
Clinical Psychologists	83.40	71.20	12.20
Auto Mechanics	80.98	81.00	-.02
Foresters	80.93	78.04	2.89
Optometrists	80.50	75.00	5.50
Social Worker	55.75	70.06	-14.21
	Quasi-Cross-Validated Discriminant Function With Lambda Scores	Cross-Validated Discriminant Function With Lambda Scores	Difference
Clinical Psychologists	80.60	57.54	23.06
Auto Mechanics	84.00	83.00	1.00
Foresters	81.50	68.75	12.71
Optometrists	75.50	51.50	24.00
Social Worker	64.38	51.63	12.75

the scoring keys from SRA, and these problems may not have been cleared up completely for his analysis.

A further indication of the effect of using quasi-cross-validated data on the results of the study might be to compare ANOVA table for the cross-validated results with the ANOVA table for the quasi-cross-validated results. Such a comparison is made in Table 31. It should be noted that the only difference in data which were used to produce the ANOVA tables was that Loadman's quasi-cross-validated results form the data for the other ANOVA table. In both analyses no statistically significant effects were identified, but a review of the p values in both tables (column 3) indicates that the quasi-cross-validated data produced significant levels considerably lower than the cross-validated data. In particular, the significance level for measures (lambda vs chi-square) which was the effect of prime interest in this study, was much lower for the quasi-cross-validated data than for the cross-validated data. Thus although in this present study the same conclusions would be drawn from either cross-validated or quasi-cross-validated data, the results of a comparison of the two ANOVA tables indicates that quasi-cross-validated data can inflate the actual differences which could, in some cases produce erroneous decisions.

It should be noted that in obtaining these results, the analysis of variance procedure for mixed models was utilized which is in one sense an extremely conservative test of the research findings. For the analysis, occupations were treated as random, but if occupations had been fixed the data would have been evaluated using

Table 31. ANOVA tables for cross-validated and quasi-cross-validated data.

ANOVA for Cross-Validated Data			
Sources	MS	F	P
S	1449.86	2.51	.15
O:S	578.07		
D	126.59	1.47	.26
M	48.44	.48	.52
SD	28.06	.33	.59
SM	85.73	.85	.39
DM	625.84	3.55	.10
SDM	76.95	.41	.53
OD:S	85.97		
OM:S	100.90		
ODM:S	176.51		
ANOVA for Quasi-Cross-Validated Data			
S	1468.10	2.33	.17
O:S	630.82		
D	24.07	.20	.67
M	397.09	2.70	.14
SD	151.44	1.27	.29
SM	90.21	.61	.46
DM	78.48	.46	.54
SDM	3.11	.02	.89
OD:S	118.97		
OM:S	146.83		
ODM:S	172.34		

individual respondents rather than occupations as the unit of analysis, resulting in a substantial increase in degrees of freedom. Furthermore, with occupations treated as random an additional source of variation is included in the E(MS) for both the numerator and denominator of the F ratio. The result produces a reduced quotient and thus a conservative estimate of the effect of the factor being tested. Had occupations been treated as fixed, greater power would have resulted in the analysis, but the findings would have been limited to those occupations which were studied and thus would have had very little practical value. On the other hand, by treating occupations as random some power was lost, but inferences which could be made were of greater interest.

It might be expected that individuals from similar occupations would make similar responses to the instrument, thus making discrimination among similar groups more difficult than among dissimilar groups where interests are likely to be completely different. The average percent of individuals correctly classified in Set I, the similar occupations, was 56.37 while in Set II, the dissimilar occupations, had an average rate of 68.41 percent correct classifications. Thus although the results indicated a higher rate of correct classifications among dissimilar occupations, the difference was not found to be statistically significant. The statistical conclusion then was that accuracy in discriminating individuals among similar occupations was as good as discrimination made among dissimilar occupations.

Although Loadman (1971) had cited a factor analytic study by Shutz and Baker (1962) to argue that the occupations selected were of two types: a group of similar occupations and a group of dissimilar occupations, the study's findings may have been due to the fact that the group of similar and dissimilar occupations selected were not actually representative of the total population of similar and dissimilar sets. In other words, several other explanations for the results may be offered: the similar occupations studied were unusually easy to discriminate for similar occupations; the dissimilar occupations were exceptionally difficult to discriminate for dissimilar occupations or a combination of both. Thus some confounding between sets may have caused the results of the study. A better test of the discriminating accuracy of the techniques between sets might be a comparison of the accuracy of discrimination for a single occupation that appears in both sets. Such a comparison was possible with optometrists. Among the homogeneous occupations, Tables 1 through 8, optometrists were correctly identified an average of 60.04 percent of the time, while among heterogeneous occupations, Tables 9 through 16, 61.87 percent were correctly identified. This comparison suggested that for the techniques investigated, discrimination among similar occupations was, practically speaking, as accurate as among dissimilar groups.

The use of multiple discriminant analysis was an attempt to improve upon the accuracy of both the lambda and chi-square techniques of scoring the Kuder OIS. The analysis of variance test computed indicated that there was no statistically significant difference between use or non-use of the discriminant function. Furthermore, the finding of no interaction between discriminant analysis or not and the measures, (lambda and chi-square), (DM), indicated that the effect of using discriminant functions was the same for both chi-square and lambda techniques. When the non-rejection to these two null hypotheses were considered together, the results indicated that there was no difference between the chi-square weights when used alone and when the chi-square weights are used with the discriminant functions. A similar conclusion can be drawn for the lambda weights. Although there was no statistically significant DM interaction, the means in Table 32 suggest some rather sizable differences. Virtually no difference was

Table 32. Averages of percent of individuals correctly identified in the two sets under each of the four scoring strategies considered.

	Discriminant Function		Non-Discriminant Function	
	Chi-Square	Lambda	Chi-Square	Lambda
Set I	59.89	48.62	58.98	58.99
Set II	73.45	62.49	63.65	75.07

found in Set I between the average correct identifications made by the chi-square weights alone and the chi-square weights used in the discriminant function. In Set II, however, an apparent improvement was shown when the discriminant function was used over the chi-square weights alone. With the lambda technique, a decrease in accuracy resulted from using the discriminant function in both Set I and Set II. These results seemed to indicate that among similar occupations the additional computations which are necessary when calculating the discriminant functions do not improve the accuracy of discrimination over that obtained when chi-square weights are used alone. Considerable improvement in accuracy was shown among dissimilar occupations, however, when the discriminant was used. The lambda technique on the other hand, was more effective in discriminating individuals in both sets when used alone rather than when using the discriminant function.

Summary and Conclusions

The measurement of interests has long been a major concern among both psychologists and educators. Although improvements have been made in the development and scoring of interest inventories, research continues in search of the optimal instrument. The quantitative scoring aspect of interest surveys has received a great deal of attention, but the best technique for a given instrument has yet to be identified.

The present study compared the effectiveness of four scoring strategies for the Kuder Occupational Interest Survey form DD: Lambda coefficients, the procedure currently used by the test publisher; chi-square weights for item responses as suggested by Porter; and two applications of multiple discriminant analysis procedures utilizing occupational scores generated by (a) lambda coefficients and (b) chi-square weights.

Scoring keys were developed on a set of similar and a set of dissimilar occupational groups following the procedures described by each technique. An independent set of data was used for cross-validation purposes. The accuracy of each scoring key was determined by the percent of the males in each criterion group that were correctly identified to their actual occupational group in the cross-validated sample. It should be pointed out that the data used in this study were old, (originally collected by Kuder for the development of the instrument in 1956) and the scoring keys developed may be meaningless for classifying individuals today. The data did provide the necessary information, however, for a valid test of the four scoring strategies considered.

A mixed model analysis of variance was used to test the hypothesis of no difference between scoring strategies on the dependent variable of percentage of correctly classified males. Independent variables were sets (similar-dissimilar), measures (lambda-chi-square), and discriminant analysis (discriminant analysis or not) which were fixed and completely crossed, and occupations which was random and nested within sets, but crossed with measures and discriminant analysis.

The results of the study indicated that among similar occupations 56.37 percent of the individuals were correctly classified while among dissimilar occupations 68.41 percent correct classifications were made. This difference was not statistically significant at α =.05. The test for a difference between the use of discriminant analysis procedures against the non-use of this technique indicated that while 60.62 percent correct classifications were made by the former and 66.66 percent correct classifications were made by the latter, the null hypothesis of no difference was not rejected at α =.05. A comparison of the measures, lambda vs chi-square indicated that an average of 61.29 percent correct classifications were made with the lambda technique while an average of 63.49 percent correct classifications were made with the chi-square procedure. This difference between measures was not found to be statistically significant at α = .05. In addition, 65.67 percent correct identifications were made with the discriminant analysis technique using the chi-square occupational scores; 55.56 percent of the individuals were correctly classified using the discriminant analysis technique with the lambda occupational scores; 61.32 percent correct classifications were made with the chi-square weights alone and 67.03 percent of the individuals were correctly classified using the lambda coefficients as the scoring technique. Although some differences seem to exist, the null hypothesis of no interaction between measures and discriminant analysis was not rejected at $\alpha = .05$.

In conclusion the results of this study showed that no one scoring procedure offered significantly greater accuracy than the other three procedures for classifying individuals into their appropriate occupational group. The study suggested other aspects of classification, however, which should also be considered in choosing the "best" scoring strategy for the Kuder OIS. One of these factors was the variability in the rate of correct classification across several occupations. Using Levene's test for equal variances it was pointed out that while no difference in variability of procedures was found with the homogeneous occupations, statistically significant differences in procedures were identified in the variability of correct classifications among heterogeneous occupations. Post hoc tests indicated that of the four scoring techniques studied, the least variable strategy was the use of lambda coefficients, and the most variable was the chi-square technique.

An additional factor to be considered before choosing which strategy to use is related to difficulty of computation. This aspect of developing scoring strategies has its biggest effect on the use of multiple discriminant analysis. Although the task has been made considerably easier with the introduction of high speed computers, the results of this study indicated that the extra effort is not worthwhile.

Finally, it was pointed out that a disadvantage of the chi-square technique is the fact that its scoring weights are dependent upon the group of occupations being considered. Thus it is possible to obtain different item response weights depending upon how many and which occupations are considered. For every set of occupations to be discriminated among a new set of item response weights must be generated even when occupations are common across sets.

Thus when all of these factors are taken into consideration in deciding which of the four techniques studied should be selected for scoring and classifying individuals on the Kuder OIS, the best decision appears to be the lambda technique. Although not having a statistically significant advantage in average accuracy over the other three strategies studied, the direction of difference in average accuracy favored the lambda technique in both sets. Furthermore, in developing the scoring keys only one occupational group is considered at a time. Thus once developed the item weights remain the same regardless of which occupations are being compared. Finally the rate of correct classifications using the lambda technique was remarkably stable across several occupations, especially in the heterogeneous set.

As far as future research is concerned it must be pointed out that the scoring problem has not yet been solved. Research should continue, attempting to improve the accuracy of occupational discrimination for interest surveys. While for the moment, Kuder's lambda technique seems to be the "best" of the four scoring strategies considered here, other techniques should be tested, most notably pattern analytic procedures. Investigations developing and improving this approach to the scoring problem of interest surveys are needed and would be considered as an important contribution to this area of measurement.

In addition to investigating different approaches to scoring the Kuder instrument, research should also turn to developing new more discriminating test items. Thus although the scoring procedure is an important factor in determining the effectiveness of the instrument, the items themselves should not be neglected.

An interesting study might be to look at the rate of correct classifications in a given occupation when it is considered with sets of similar and dissimilar occupations. The present study compared the rate of classification in Set I and Set II for optometrists but several more such comparisons are needed before the effect of similar and dissimilar sets can be determined.

Finally, further research with the lambda coefficient should be encouraged. While Kuder and SRA have chosen one technique for utilizing the lambda ratio, based on the 100 responses selected by an individual, other techniques may be possible. Another approach might be to calculate lambda coefficients for each of the 600 possible response patterns with an individual's similarity to a particular group estimated by the sum of the 100 lambda ratios associated with the individual's selected responses.

To calculate the lambda coefficient for each response pattern one criterion group at a time is considered. Each individual in the criterion group receives an agreement score based on the proportions of the total group selecting each of the response patterns. The individual's agreement score is simply the sum of the 100 proportions associated with his responses to the instrument. In computing the point biserial and maximum point biserial correlations, the continuous variable would be the agreement scores of the individuals in the criterion group. The dichotomous variable would be the selection or non-selection of a particular response pattern being considered. The lambda coefficient for a particular response pattern is calculated by computing the ratio of the point biserial to the maximum point biserial correlations. The point biserial correlation is calculated between the vector of N (the number of individuals in the criterion group) 1's and 0's, corresponding to selection or non-selection of the response pattern by the N individuals, and a vector of the N agreement scores. The maximum point biserial correlation is computed as if the n individuals (the number of individuals actually selecting the response pattern) having the highest or lowest agreement scores had selected the response pattern under consideration.

The computational formula for the lambda coefficient associated with a particular response pattern can be presented as:

$$\lambda_{ij} = \frac{\overline{X}_g - \overline{X}}{\overline{X}_t - \overline{X}}$$

where λ_{ij} is the computed lambda coefficient for item i and response pattern j, $\overline{X}$ is the overall average agreement score for the total criterion group, $\overline{X}_g$ is the average agreement score for those n individuals selecting response pattern j for item i, and $\overline{X}_t$ is the average agreement score for the n individuals having the highest or lowest agreement scores depending on whether the numerator is positive or negative respectively. The sign of the lambda coefficient would be that of the numerator positive if $\overline{X}_g$ is greater than $\overline{X}$ and negative if $\overline{X}_g$ is less than $\overline{X}$. Following this procedure then the weight for a particular response pattern for an item could range from +1.00 if those selecting the response pattern of interest had the highest agreement scores of the criterion group, and a lower limit of -1.00 if respondents selecting the response pattern had the lowest agreement scores of the criterion group. This procedure would then be used to calculate the lambda values for each of the 600 possible response patterns for the Kuder OIS and an individual's occupational score would be the sum of the 100 response pattern weights associated with the individual's selected responses. An individual could then be classified as belonging to that criterion group in which he had the highest occupational score.

Although Kuder's procedure is capable of accurately discriminating individuals at a fairly high rate, further research on improving the discriminating accuracy through item weights should continue. One procedure which may accomplish this task might be the new procedure for scoring individual responses through lambda coefficients as described above.

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APPENDICES

APPENDIX A

Computer program for calculating lambda coefficients.

```
      PROGRAM DRIVER(INPUT,OUTPUT,TAPE1,TAPE2,TAPE60=INPUT,TAPE61=OUTPUT
     +)
      COMMON /TOTALS/TOTALS(100,6,5)
      DO 10 I=1,4
      DO 5 J=1,5
    5 CALL LAMBDA(J)
      WRITE(1)TOTALS
 1000 FORMAT(10F8.5)
      ENDFILE 1
   10 CONTINUE
      ENDFILE 1
      END
      SUBROUTINE LAMBDA(NGROUP)
      REAL ISUM,ITOT
      INTEGER RESP
      DIMENSION RP(100,6),PI(100,6)
      DIMENSION ITOT(100,6)
      DIMENSION IRES(100),XN(250),L(6),H(6)
      COMMON /TOTALS/ TOTALS(100,6,5)
C
C     INITIALIZE ITOT
C
      DO 10 I=1,100
      DO 10 J=1,6
   10 ITOT(I,J)=0.0
C
C     READ IN DATA.
C
      NPEOPLE=0
   12 NPEOPLE=NPEOPLE+1
   13 CONTINUE
      READ(2,1000)IRES
 1000 FORMAT(6X,64I1/6X,36I1)
      IF(EOF(2))7,15
C
C     TOTAL IN THIS CARD'S DATA
   15 CONTINUE
        DO 18 J=1,100
        JJ=IRES(J)
        IF(JJ)16,17
   16 IF(JJ.LE.6) GO TO 18
   17   PRINT 999,NPEOPLE,NGROUP,J,JJ
  999 FORMAT(*9**LAMBDS PERSON*I4* OF GROUP*I3* HAS BAD DATA. RESPONSE (
     +*,I3,*)= *020)
      GO TO 13
   18 CONTINUE
      DO 50 J=1,100
   50   ITOT(J,IRES(J))=ITOT(J,IRES(J))+1
      GO TO 12
    7 CONTINUE
C
C   COMPUTE PROPORTIONS     PI1=ITOT(1,1)/SUM(ITOT(1J) (J=1,6*
C     AND CALCULATE RP'S
      SUM=0.0
      DO 530 J=1,100
      IF(J.GT.1)GO TO 505
      ISUM=0.0
      DO 500 K=1,6
      ISUM=ISUM+ITOT(J,K)
  500 CONTINUE
  505 DO 510 K=1,6
```

```
      PI(J,K)=(ITOT(J,K))/(ISUM)
  510 CONTINUE
      RP(J,1)=2*PI(J,1)+PI(J,2)+PI(J,6)
      RP(J,2)=2*PI(J,2)+PI(J,1)+PI(J,4)
      RP(J,3)=2*PI(J,3)+PI(J,4)+PI(J,5)
      RP(J,4)=2*PI(J,4)+PI(J,2)+PI(J,3)
      RP(J,5)=2*PI(J,5)+PI(J,3)+PI(J,6)
      RP(J,6)=2*PI(J,6)+PI(J,1)+PI(J,5)
C     COMPUTE MAX RP(J,I) FOR EVERY J AND SUM UP  JSUM=XT
      XMAX=0.0
      DO 520 K=1,6
      IF(K.EQ.1)GO TO 515
      IF(RP(J,K).GT.XMAX)GO TO 515
      GO TO 520
  515 XMAX=RP(J,K)
  520 CONTINUE
      SUM=SUM+XMAX
  530 CONTINUE
C    COMPUTE LAMBDA VALUES
      DO 550 J=1,100
      DO 540 K=1,6
      TOTALS(J,K,NGROUP)=(RP(J,K)-.667)/(SUM-66.7)
  540 CONTINUE
  550 CONTINUE
      RETURN
      END
```

APPENDIX B

Computer program for classifying individuals based on their Lamb a Coefficient total scores.

```
      PROGRAM DRIVER(INPUT,OUTPUT,TAPE1,TAPE2,TAPE3,TAPE60=INPUT,TAPE61=
     +OUTPUT)
      COMMON /TOTALS/TOTALS(100,6,5)
 1000 FORMAT(10F8.5)
      REWIND 2
      REWIND 1
      READ(1)TOTALS
      JK=3
      DO 60 I=1,5
   60 CALL CLASIFY(I,JK)
      REWIND 1
      READ(1)DUMMY
      READ(1)DUMMY
      Q=EOF(1)
      READ(1)DUMMY
      READ(1)DUMMY
      Q=EOF(1)
      READ(1)TOTALS
      JK=4
      DO 70 I=1,5
   70 CALL CLASIFY(I,JK)
      END
      SUBROUTINE CLASIFY(IGR,JK)
      COMMON /TOTALS/ TOTALS(100,6,5)
      DIMENSION M(100),SCORE(5)
      DIMENSION NN(21)
      DATA KT/1/
      DATA    NN/0,
     +          406,678,1114,1472,1872,2278,2554,2988,3400,3792,4292,4592,
     +  4938,5338,5790,6290,6590,6936,7336,7788      /
      I=0
      KT=KT+1
      KG=NN(KT)-NN(KT-1)
      KKK=KT-1
      PRINT 1,IGR
    1 FORMAT(*1GROUP NO.*I2/*0INDIVIDUAL*T35*GROUP1*T44*GROUP2*T53*GROUP
     +3*T62*GROUP4*T71*GROUP5*)
      WRITE(3,4)KG,KKK
    4 FORMAT(I6,I4)
      N1=0
      N2=0
      N3=0
      N4=0
      N5=0
      DO 10 I=1,1000
      READ(2,100)M
      IF(M(50).GE.7)GO TO 10
  100 FORMAT(6X,64I1/6X,36I1)
      IF(EOF(2))600,20
   20 DO 30 J=1,5
      SCORE(J)=0.
      DO 40 K=1,100
      SCORE(J)=SCORE(J)+TOTALS(K,M(K),J)
   40 CONTINUE
   30 CONTINUE
      IH=1
      HIGH=SCORE(1)
      DO 25 J=2,5
      IF(HIGH.GE.SCORE(J)) GO TO 25
      HIGH=SCORE(J)
      IH=J
```

```
   25 CONTINUE
      IF(IH.EQ.1)N1=N1+1
      IF(IH.EQ.2)N2=N2+1
      IF(IH.EQ.3)N3=N3+1
      IF(IH.EQ.4)N4=N4+1
      IF(IH.EQ.5)N5=N5+1
      PRINT 2, I,IGR,SCORE,IH
    2 FORMAT(*9INDV.*I4* OF GROUP NO.*I3*. SCORES=*5F9.4' HIGHEST CORRES
     +PONDENCE WITH GROUP ***'I2'***')
      WRITE(3,3)SCORE,I,IGR,JK
    3 FORMAT(5F9.4,5X,*INDIV.*I4* GROUP*I4* HALF*I2)
   10 CONTINUE
      CALL EXIT
  600 I=I-1
      PRINT 1600,I
 1600 FORMAT(*0*I4,* RESPONDENTS WERE FOUND*)
      PRINT 1601,N1,N2,N3,N4,N5
 1601 FORMAT(*0GROUP1*,I4,* GROUP2*,I4,* GROUP3*,I4,* GROUP4*,I4,* GROUP
     +5*,I4)
      END
```

APPENDIX C

Computer program for Calculating Chi Square weights.

```
      PROGRAM DRIVER(TAPE 33,INPUT,OUTPUT,PUNCH,TAPE60=INPUT,TAPE61=OUTP
     +UT,DISK,TAPE21=DISK)
      DIMENSION ANR(6,7,100), IDATA(100), NA(5)
      DO 999 NIM=1,4
      DO 60 K=1,100
      DO 60 J=1,7
      DO 60 I=1,6
   60 ANR(I,J,K)=0.0
C     PRESET ARRAY
C     I=PROFESSION, J=RESPONSE, K=ITEM
      DO 31 I=1,5
      READ(33,1492)NR
 1492 FORMAT(I3)
      DO 32 M=1,NR
      READ(33,18)(IDATA(K),K=1,100)
   18 FORMAT(6X,64I1/6X,36I1)
      DO 2 K=1,100
      J=IDATA(K)
    2 ANR (I,J,K)=ANR(I,J,K)+1.0
   32 CONTINUE
   31 CONTINUE
      READ(33,1492)DUMMY
      IF(EOF(33))1066,1067
 1067 PRINT 1068
 1068 FORMAT(* NO EOF FOUND*)
      STOP
 1066 CONTINUE
C     FOUND OBSERVED VALUES
   71 DO 5 K=1,100
      DO 5 J=1,6
      DO 5 I=1,5
    5 ANR(6,J,K)=ANR(6,J,K)+ANR(I,J,K)
      DO 6 K=1,100
      DO 6 I=1,5
      DO 6 J=1,6
    6 ANR(I,7,K)=ANR(I,7,K)+ANR(I,J,K)
C     ANR=MATRIX OF OBSERVED VALUES, ROW TOTALS,COLUMN TOTALS
      DO 7 K=1,100
      DO 7 I=1,5
    7 ANR(6,7,K)=ANR(6,7,K)+ANR(I,7,K)
C     COMPUTED TOTAL NUMBER RESPONDING
      DO 12 K=1,100
      DO 12 J=1,6
      DO 12 I=1,5
      SIGN=1.0
      EXP=(ANR(6,J,K)*ANR(I,7,K))/ANR(6,7,K)
      IF(EXP.EQ.0)GO TO 11
      IF(ANR(I,J,K)-EXP) 8,9,9
    8 SIGN=-1.0
    9 ANR(I,J,K)=(ANR(I,J,K)-EXP)**2/EXP
   10 ANR(I,J,K)=ANR(I,J,K)*SIGN
      GO TO 12
   11 ANR(I,J,K)=0.0
   12 CONTINUE
C     COMPUTED CHI SQUARE WEIGHTS WITH SIGN
C     PUT THEM BACK IN ANR
      DO 17 K=1,100
      PRINT 201 ,K
  201 FORMAT(1H0,6H ITEM ,I3)
      DO 16 I=1,5
      PRINT 53,I,(ANR(I,J,K),J=1,6)
   53 FORMAT(12H PROFESSION ,I1,2X,6F9.4)
      WRITE(21,301)(ANR(I,J,K),J=1,6),I,NIM
  301 FORMAT(6F9.4,20X,I1,3X,I1)
   16 CONTINUE
   17 CONTINUE
  999 CONTINUE
      END
```

APPENDIX D

Computer program for classifying individuals based on their Chi Square total scores.

```
      PROGRAM SCORE(INPUT,OUTPUT,PUNCH,TAPE 33,TAPE60=INPUT,TAPE61=OUTPU
     +T,TAPE62=PUNCH)
C     TOTAL SCORES FOR SET 2 HALF B USING WEIGHTS FROM HALF A
      DIMENSION ANRB(5,6,100),IDATA(100),TSA(5),NA(5)
      DO 2 K=1,100
      DO 2 I=1,5
    2 READ 72, (ANRB(I,J,K),J=1,6)
   72 FORMAT(6F9.4)
C WEIGHTS ARE IN
      PRINT 8
    8 FORMAT(12H PROFESSION ,3X3HONE,6X,3HTWO,5X,5HTHREE,4X,4HFOUR
     +5X,4HFIVE)
      DO 31 L=1,5
      READ(33,30)NR
   30 FORMAT(I3)
      PRINT 301,L
  301 FORMAT (/13H PROFESSION ,I1)
      KOUNT=0
      DO 32 M=1,NR
      DO 11 J=1,5
   11 TSA(J)=0.0
      READ(33,1)(IDATA(K),K=1,100)
    1 FORMAT (6X,64I1,10X/6X,36I1)
      DO 6 I=1,5
      DO 6 K=1,100
      J=IDATA(K)
    6 TSA(I)=TSA(I)+ANRB(I,J,K)
      KOUNT = KOUNT+1
      HIGH=-99999.
      DO 25 I=1,5
      IF(HIGH.GE.TSA(I))GO TO 25
      IH=I
      HIGH=TSA(I)
   25 CONTINUE
      PRINT 7, KOUNT,L,TSA,IH
    7 FORMAT(*9INDIVIDUAL*I4* OF GROUP NO.*I3*.  SCORES =*5F9.4* HIGHEST
     +CORRESPONDENCE WITH GROUP*5X,I2)
      PUNCH 9,(TSA(I),I=1,5),KOUNT,L
    9 FORMAT(5F9.4,5X,*INDIV.*I4* GROUP*I4)
   32 CONTINUE
   31 CONTINUE
      END
```

APPENDIX E

Computer program for computing the simple d^2 statistic and the classification of individuals based on discriminant-function scores.

```
      SUBROUTINE DSQUAR
      DIMENSION Z(5),C(5,4),Y1(250,5),Y2(250,5),Y3(250,5),Y4(250,5),MU(5
     +,4),S(5),KT(5)
      REAL MU
C     COMPUTE EACH PERSON'S SCORE FOR ALL 4 FUNCTIONS, THEN FIND MU FOR
C     EACH FUNCYION WHERE MY IS AVERAGE OF ALL PERSONS IN THE GROUP.  THIS
C     SUBROUTINF DOES 1 DATA SET (E.G. 2-A) AT A TIME
C
      READ 1,C
      DO 100 IGR=1,5
    1 FORMAT(5F9.4)
      DO 200 INDIV=1,1000
      READ 1,S
      IF(EOF(60))150,2
    2 Y1(INDIV,IGR)=C(1,1)*S(1)+C(2,1)*S(2)+C(3,1)*S(3)+C(4,1)*S(4)+C(5,
     +1)*S(5)
      Y2(INDIV,IGR)=C(1,2)*S(1)+C(2,2)*S(2)+C(3,2)*S(3)+C(4,2)*S(4)+C(5,
     +2)*S(5)
      Y3(INDIV,IGR)=C(1,3)*S(1)+C(2,3)*S(2)+C(3,3)*S(3)+C(4,3)*S(4)+C(5,
     +3)*S(5)
      Y4(INDIV,IGR)=C(1,4)*S(1)+C(2,4)*S(2)+C(3,4)*S(3)+C(4,4)*S(4)+C(5,
     +1)*S(5)
  200 CONTINUF
  150 CONTINUF
      INDIV=INDIV-1
      MU(IGR,1)=MU(IGR,2)=MU(IGR,3)=MU(IGR,4)=0
      KT(IGR)=INDIV
      DO 160 I=1,INDIV
      MU(IGR,1)=MU(IGR,1)+Y1(I,IGR)
      MU(IGR,2)=MU(IGR,2)+Y2(I,IGR)
      MU(IGR,3)=MU(IGR,3)+Y3(I,IGR)
      MU(IGR,4)=MU(IGR,4)+Y4(I,IGR)
  160 CONTINUE
      MU(IGR,1)=MU(IGR,1)/INDIV
      MU(IGR,2)=MU(IGR,2)/INDIV
      MU(IGR,3)=MU(IGR,3)/INDIV
      MU(IGR,4)=MU(IGR,4)/INDIV
  100 CONTINUF
C     WE HAVE NOW COMPUTED ALL 20 MU VALUES
      PRINT 2001, MU
 2001 FORMAT(*0THE AVERAGE SCORES OF THE 5 GROUPS APPEAR BELOW*/*9FUNCTI
     +ON 1* 5F10.4/*9FUNCTION 2* 5F10.4/*9FUNCTION 3*5F10.4/*9FUNCTION 4
     +*5F10.4)
```

```
C
C   COMPUTE Z SCORES FOR EACH PERSON
      DO 300 IGR=1,5
      PRINT 202,IGR
  202  FORMAT(*1Z VALUES FOR INDIVIDUALS OF GROUP* I2/*9PERSON* T20 *GRO
     + UP1*T35*GROUP2*T50*GROUP3*T65*GROUP4*T80*GROUP5*T90*BEST CORRESP.
     +*)
      N1=N2=N3=N4=N5=0
      KTIGR=KT(IGR)
      DO 290 INDIV=1,KTIGR
      DO 280 I=1,5
      Z(I)=(Y1(INDIV,IGR)-MU(I,1))**2 + (Y2(INDIV,IGR)-MU(I,2))**2 + (Y3
     +(INDIV,IGR)-MU(I,3))**2 + (Y4(INDIV,IGR)-MU(I,4))**2
  280 CONTINUE
      IH=1
      ZLOW=Z(1)
      DO 25 I=2,5
      IF(ZLOW.LE.Z(I))GO TO 25
```

```
      ZLOW=Z(I)
      IH=I
   25 CONTINUF
      IF(IH.EQ.1)N1=N1+1
      IF(IH.EQ.N2)N2=N2+1
      IF(IH.EQ.3)N3=N3+1
      IF(IH.EQ.4)N4=N4+1
      IF(IH.EQ.5)N5=N5+1
      PRINT 281, INDIV,IGR,Z,IH
  281 FORMAT(*9*I4*(*I1*)*5X,5F15.4,10X,I1)
  290 CONTINUF
      PRINT 1601, N1, N2, N3, N4, N5
 1601 FORMAT(*0GROUP1*,I4,* GROUP2*,I4,* GROUP3*,I4,* GROUP4*,I4,* GROUP
     +5*,I4)
  300 CONTINUF
      END
      PROGRAM DRIVER(INPUT,OUTPUT,TAPE60=INPUT)
      CALL DSQUAR
      END
```

APPENDIX F

DISCRIMINANT FUNCTION COEFFICIENTS BASED
ON LAMBDA OCCUPATIONAL SCORES FOR
SET I HALF A AND HALF B

Discriminant Function Weights Based on Set I-A

Variable	I	II	III	IV
Optometrist	-3.8020	24.5515	11.8603	5.2717
X-ray Technician	-12.9348	-2.3653	-7.4616	24.3207
Pediatrician	.1303	-19.1485	12.3645	8.8655
Physical Therapist	-6.3303	-5.2838	-12.6126	-34.3151
Veterinarian	23.1758	2.0519	-1.7843	-6.0631

Discriminant Function Weights Based on Set I-B

Variable	I	II	III	IV
Optometrist	-2.2039	-11.5293	21.0390	3.2611
X-ray Technician	-9.1794	5.6676	-1.5303	26.3915
Pediatrician	.6105	-15.7759	-14.3705	7.7153
Physical Therapist	12.8908	15.2085	-6.1785	-29.4697
Veterinarian	23.2791	2.8503	.0189	-7.6176

APPENDIX G

DISCRIMINANT FUNCTION COEFFICIENTS BASED ON LAMBDA OCCUPATIONAL SCORES FOR SET II HALF A AND HALF B

Discriminant Function Weights Based on Set II-A

Variable	I	II	III	IV
Clinical Psychologist	-.0232	-.0211	.0139	.1161
Auto Mechanic	4.4703	9.6291	-10.5210	-4.5558
Forester	2.5442	-2.6879	21.8326	-.1825
Optometrist	.9333	-19.9717	-15.8493	-1.6910
Social Worker	-9.0450	14.5850	4.8773	-4.7788

Discriminant Function Weights Based on Set II-B

Variable	I	II	III	IV
Clinical Psychologist	10.9216	-10.4250	15.5104	-22.9144
Auto Mechanic	1.5329	-17.3526	-1.0813	-7.7945
Forester	-10.5551	17.6540	13.1884	11.5552
Optometrist	1.3686	9.3011	-22.1827	-7.5960
Social Worker	-.4127	.3886	-4.3715	26.0036

APPENDIX H

DISCRIMINANT FUNCTION COEFFICIENTS BASED ON CHI-SQUARE OCCUPATIONAL SCORES FOR SET I HALF A AND HALF B

Discriminant Function Weights Based on Set I-A Data

Variable	I	II	III	IV
Optometrist	-.0011	-.0185	.0022	-.0029
X-ray Technician	-.0023	.0027	.0129	-.0198
Pediatrician	.0013	.0068	-.0028	-.0058
Physical Therapist	-.0025	.0013	.0142	.0014
Veterinarian	.0092	-.0033	.0038	.0014

Discriminant Function Weights Based on Set I-B Data

Variable	I	II	III	IV
Optometrist	-.0019	-.0014	.0141	.0055
X-ray Technician	-.0047	.0118	-.0007	-.0150
Pediatrician	-.0010	-.0068	-.0059	-.0009
Physical Therapist	-.0126	.0100	-.0053	.0269
Veterinarian	.0066	.0027	.0007	.0063

APPENDIX I

DISCRIMINANT FUNCTION COEFFICIENTS BASED ON CHI-SQUARE OCCUPATIONAL SCORES FOR SET II HALF A AND HALF B

Discriminant Function Weights Based on Set II-A Data

Variable	I	II	III	IV
Clinical Psychologist	.0021	-.0022	-.0005	-.0067
Auto Mechanic	-.0011	-.0022	-.0043	-.0025
Forester	-.0028	.0011	.0060	.0026
Optometrist	-.0028	.0148	-.0047	-.0020
Social Worker	.0012	.0004	-.0026	.0071

Discriminant Function Weights Based on Set II-B Data

Variable	I	II	III	IV
Clinical Psychologist	.0020	.0027	-.0031	-.0061
Auto Mechanic	-.0011	.0040	.0015	-.0016
Forester	-.0038	-.0044	-.0085	.0034
Optometrist	-.0001	-.0094	.0067	.0002
Social Worker	.0001	.0002	-.0019	.0095

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