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ABSTRACT

Although studies have succeeded in devising statistically sophisticated prediction schemes for use in screening or placing clients in rehabilitation programs, they typically lack comparison with simpler methods, e.g., the single best predictor method. In this study of 296 disabled clients referred to the St. Louis Jewish Employment Service for vocational evaluation, such a comparison was made. Variables included race, sex, age, education, 13 Wechsler Adult Intelligence Scale subtest and total scores, and 10 ratings of workshop performance. Employment status, assigned to the evaluated clients, was a further seven-categorized variable. Three prediction techniques were employed: (1) the multiple linear regression technique, (2) the multiple linear regression of factor scores, and (3) the single best predictor method. A cross-validation sample was utilized. The methodology was described and the results discussed. Two points were demonstrated: (1) the most useful prediction model may be the least statistically sophisticated model; and (2) shrinkage in predictive power upon cross-validation may be considerable, especially when regression models are used. Possible uses of prediction schemes were considered. (TL)

PREDICTING REHABILITATION SUCCESS

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Many attempts have been made to devise prediction schemes to be used in screening or placement of clients in various rehabilitation programs (Ayer, Thoreson, Butler, 1966; DeMann, 1963; Drasgow and Dreher, 1964; Norris, Marra, and Zadrozny, 1960; Perlman and Hylbert, 1969). Although these studies typically employ sophisticated statistical or configural techniques in developing prediction methods, they fail to compare the developed methods with simpler methods, e.g., using base rates, using the single best predictor, etc. In addition, some studies fail to crossvalidate prediction equations, and thus fail to take into account the shrinkage in predictive accuracy that almost always occurs upon crossvalidation. The purpose of this paper is to compare two statistically sophisticated prediction models with a simple model, to demonstrate the effects of the shrinkage phenomenon upon crossvalidation of each model employed, and finally to discuss the possible uses of such prediction schemes.

METHODOLOGY

The subjects for this study were 296 disabled clients of the St. Louis Jewish Employment Vocational Service (JEVS) who had been referred for vocational evaluation and who had complete data available on the variables of concern. The variables of concern included 27 predictor variables: race, sex, age, education, 13 WAIS subtest and total scores, and ten ratings of workshop performance. The workshop ratings were obtained from workshop counselors and supervisors after the client had completed three weeks of evaluation. Ratings were made on graphic rating scales in the following ten areas: productivity, ability to get along with others, motivation, ability to follow instructions, punctuality, reliability, judgement, social competence and communication skills, cooperativeness, and dress and appearance. The criterion, employment status, was a seven-categoried variable which was determined by the counselors after the evaluation program. Category one was assigned to clients who became competitively employed; category two, to clients whom the counselors judged were employable; category three, to those who were judged to need educational training; category four, to clients who were judged to need further work adjustment training; category five to those who were judged as employable only in sheltered settings; category six, to those who required further medical rehabilitation (e.g., psychotherapy); and category seven was assigned to those who were judged to be unemployable regardless of additional service.

First the 296 clients were randomly assigned to sample A (n = 151) or sample B (n = 145). Sample A was the sample used to develop the different prediction methods, and sample B was used as a crossvalidation sample. A stepwise multiple linear regression analysis of sample A (Veldman, 1967) was computed employing the 27 aforementioned variables as predictors, and the employability status variable as the criterion. The nine best predictors, i.e., those that contributed most of the variance to the predictor-criterion relationship, were selected. The selected predictors in the order of their relative contribution in predicting the criterion were:

1. The rating of Motivation
2. The rating of Productivity
3. The rating of Cooperativeness
4. The level of Education
5. The WAIS Picture Arrangement subtest
6. The WAIS Picture Completion subtest
7. The WAIS Comprehension subtest
8. The rating of Ability to Follow Instructions
9. The rating of Dress and Appearance

Three prediction techniques were used. The first method employed was the multiple linear regression technique. The nine selected predictors were used to predict the criterion for sample A. Regression weights and the cutoff score minimizing the number of errors for the predicted scores were determined (Helmstadter, 1964). Predicted scores for sample B were computed using the regression weights from sample A. By using the cutoff score from sample A and by comparing the predicted score with the criterion, the number of hits and misses in prediction were determined for both samples.

The second approach, multiple linear regression of factor scores, first necessitated a factor analysis of the nine predictors for sample A. Three factors were extracted and factor scores were computed for each of the factors (Veldman, 1967). The three factor scores then became the predictor variables in a multiple linear regression analysis of sample A. The remaining procedure involved determining the regression weights and cutoff score for sample A, applying these values to sample B, and counting the number of hits and misses in prediction for both samples.

Finally, the single best predictor, counselors' ratings of client motivation, was used in predicting the employment status criterion. A cutting score which minimized errors in prediction was computed on sample A and used on sample B. The number of hits and misses was also determined using this prediction technique.

RESULTS

The results comparing the three prediction models are presented in Tables 1 and 2. Table 1 shows that the technique using the single best predictor had the fewest number of total hits or correct predictions in the initial sample (sample A). However, on the crossvalidation sample (sample B) this technique had the greatest number of total correct predictions.

Table 2 shows the validity rate, base rate, improvement over the base rate, and shrinkage upon crossvalidation for each of the three prediction models. In terms of both improvement in prediction over the base rate and shrinkage in predictive power upon crossvalidation, the single best predictor model was superior to the regression of factor scores model which, in turn, was superior to the regression of raw scores model.

DISCUSSION

The results demonstrate two points:

1. The most useful prediction model may be the least statistically sophisticated model.
2. Shrinkage in predictive power upon crossvalidation may be considerable, particularly when regression models are used.

TABLE 1

Comparison of Prediction Models
on the Number of Hits and Misses
for Successful and Unsuccessful Clients*

		SAMPLE					
		Initial			Crossvalidation		
MODEL		Success	Fail	Total	Success	Fail	Total
Multiple Linear	Hits	47	62	109	30	53	83
Regression of	Misses	11	31	42	34	28	62
Raw Scores	Total	58	93	151	64	81	145
Multiple Linear	Hits	45	56	101	38	52	90
Regression of	Misses	13	37	50	26	29	55
Factor Scores	Total	58	93	151	64	81	145
Single	Hits	45	50	95	44	47	91
Best	Misses	13	43	56	20	34	54
Predictor	Total	58	93	151	64	81	145

*Success clients were those who were employed competitively or judges employable after evaluation. Unsuccessful clients (fail) were those judged as unemployable or as needing further rehabilitation services before they could be considered employable.

TABLE 2

Comparison of Prediction Models on Improvement over Base Rate and Shrinkage upon Crossvalidation

	MODEL					
	Multiple Linear Regression of Raw Scores		Multiple Linear Regression of Factor Scores		Single Best Predictor	
	SAMPLE					
MEASURE*	Initial	Crossvalidation	Initial	Crossvalidation	Initial	Crossvalidation
Validity Rate	72.2**	57.2	66.9	62.1	62.9	62.8
Base Rate	38.4	44.1	38.4	44.1	38.4	44.1
Improvement	33.8	13.1	28.5	18.0	24.5	18.7
Shrinkage		20.7		10.5		5.8

*Validity Rate = (# correct Predictions /N) X 100
Base Rate = (# successful /N) X 100
Improvement = Validity - Base Rate
Shrinkage = Initial Improvement - Improvement upon Crossvalidation

**All figures are percentages

These points suggest that an investigator should consider several models of different levels of complexity when attempting to formulate a prediction scheme. In addition, crossvalidation of the prediction equations is necessary to assess their "true" predictive power.

Even though these suggestions may be followed and the "best" of several models identified, the "best" model may still be inadequate for some purposes. For instance, the most adequate predictive model in this study had a validity rate of 62.8%. Using this model one might expect to correctly predict about 63% of the client outcomes. Predictions for about 37% of the clients would be in error. This level of error would seem to be too great for most selection or placement decisions within a rehabilitation program. However, such a model might be used to identify clients who are predictably unsuccessful in a particular rehabilitation program. Perhaps by intensive study of these client's characteristics one might identify new rehabilitation techniques to meet the special needs of this group. In addition, by studying the characteristics of those clients for whom predictions are in error, one might be able to develop new measurement instruments which would add to the accuracy of prediction models.

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