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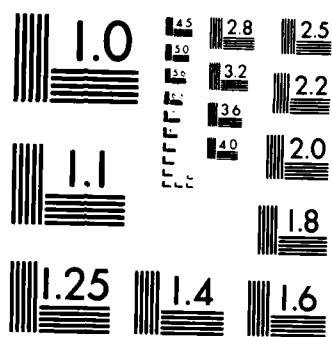
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Stephen B. Dunbar  
Shin-ichi Mayekawa  
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ONR Technical Report 85-1

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Simultaneous Estimation of Regression Functions  
for Marine Corps Technical Training Specialties\*

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Abstract

This paper considers the application of Bayesian techniques for simultaneous estimation to the specification of regression weights for selection tests used in various technical training courses in the Marine Corps. Results of a method for  $m$ -group regression developed by Molenaar and Lewis (1979) suggest that common weights for training courses belonging to certain general categories are justified in many cases. However, such commonality of regression weights does not appear to hold for all courses in these categories—weights for some training courses remain distinct even after the application of the simultaneous estimation procedure. Thus, a hypothesis of validity generalization across training courses in a given category would only be retained for a carefully selected subset of courses and not for all groups included in the analyses. — *ent Regress include: see 1473*

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Simultaneous Estimation of Regression Functions  
for Marine Corps Technical Training Specialties

The relative value of a regression function for predicting future performance is related to its consistency of prediction in important subgroups of examinees. When large differences between predictor-criterion relationships exist for distinct subpopulations of interest, the use of a common prediction equation is questionable for a variety of reasons. This perspective reiterates a historical concern for comparisons of more than overall predictor-criterion correlations in validation research. As noted by Humphreys (1952), useful subgroup comparisons must ask whether the same score has the same meaning in the groups being compared, i.e. whether the regression lines are identical or merely parallel (p. 134). One would only add to this an obvious concern for subgroup regressions that are neither identical nor parallel.

Empirical comparisons of regression equations for subgroups defined by demographic variables such as gender and race have generally followed procedures first outlined by Gulliksen and Wilks (1950) for statistical tests of the equality of errors of estimate, slopes and intercepts. When interest focuses on regions of the predictor space where the degree of differences between regressions is acute, the Johnson-Neyman technique has also been employed (see Gamache and Novick, 1985 and Dunbar and Novick, 1985 for some recent examples). Regression comparisons performed by these techniques are perhaps well suited for settings involving a small number of groups, although they are by no means limited to such settings.

An alternative approach to accommodating differences among subgroups in regression analysis is found in the literature on central prediction systems. Procedures such as those reviewed by Linn (1966) address the



problem of making adjustments to predictor and criterion scores for individuals of varying subgroups such that overall accuracy of prediction is increased upon cross-validation. A limiting case for approaches such as these is Cleary's (1966) individual differences model for multiple regression. As discussed by Linn (1966) and others, however, empirical studies of systems for central prediction have indicated little promise--perhaps because each classical procedure posits a particular model of group differences by the nature of the adjustments that are made to predictors and criteria. Model restrictions imposed by one central prediction system may not be justified for all groups belonging to the system (Novick and Jackson, 1974) and the effectiveness of the complete system is likely to be compromised as a result. In such cases a more flexible model for prediction in the multiple-group situation is advised.

The purpose of this paper is to describe the method of Bayesian simultaneous estimation of multiple regression in  $m$ -groups and to illustrate the application of this method to the problem of specifying prediction weights for subtests of the Armed Services Vocational Aptitude Battery (ASVAB), Forms 6 and 7, in a variety of technical training specialties in the military. The general approach to this problem was first developed by Lindley (1971) and Lindley and Smith (1972), and further refined and applied by Novick, Jackson, Thayer, and Cole (1972), who demonstrated empirically the effectiveness of this method in increasing predictability. The particular model adopted in this paper is due to Molenaar and Lewis (1979), who developed it as a refinement of earlier procedures noted above. Other approaches to the problem have been implemented by Rubin (1980) and Braun, Jones, Rubin, and Thayer (1982).

# Model Specification

The model for multiple regression in  $m$ -groups proposed by Molenaar and Lewis (1979), hereafter M-L, can be summarized as follows:

$$\tilde{Y}_k \sim N ( \tilde{X}_{Fk} \tilde{B}_F + \tilde{X}_{Gk} \tilde{B}_{Gk}, \sigma^2 \tilde{I}_{n_k} ),$$

$$k = 1, 2, \dots, m,$$

where  $\tilde{Y}_k = ( n_k \times 1 )$  vector of observed criterion scores for group  $k$ ,

$\tilde{X}_{Fk} = ( n_k \times F )$  matrix of predictor scores in a set  $F$ , described below,

$\tilde{X}_{Gk} = ( n_k \times G )$  matrix of predictor scores in a set  $G$ , described below,

$\tilde{B}_F = ( F \times 1 )$  vector of unknown regression parameters for set  $F$  predictors,

$\tilde{B}_{Gk} = ( G \times 1 )$  vector of unknown regression parameters for set  $G$  predictors in group  $k$ ,

$\sigma^2$  = unknown residual variance for all  $m$  groups,

$n_k$  = number of individuals in group  $k$ , and

$\tilde{I}_{n_k} = ( n_k \times n_k )$  identity matrix.

In addition, the unobserved parameters  $\tilde{B}_F$  are said to form an exchangeable sample from  $F$  independent uniform distributions for each variable in set  $F$ . The unobserved parameters  $\tilde{B}_{Gk}$  similarly form an exchangeable sample from a

$N(\underline{\mu}_G, \gamma_G \underline{I}_G)$  distribution. This model of prior information is further specified by designating hyperparameters  $\underline{\mu}_G$  and  $\gamma_G$  as exchangeable samples from  $U(-\infty, \infty)$  and inverse chi-square distributions with specified degrees of freedom, respectively, the latter in order to incorporate strength of prior information into the model. In the final prior specification for the M-L model,  $\ln \sigma^2$  is assumed to be uniform. With the above prior specifications the joint distribution of parameters and hyperparameters given the data is determined--integrating out hyperparameters yields an expression for the joint posterior density of  $\underline{B}_F$ ,  $\underline{B}_{Gk}$  and  $\sigma^2$  from which Molenaar and Lewis obtain joint modal estimates.

The M-L model for regression in m-groups represents a general simplification of previous Bayesian solutions to the problem developed by Lindley (1971) and Lindley and Smith (1972). In particular, the M-L specification differs from the original formulations in three important ways: (1) a partitioning of predictor variables into disjoint sets, (2) a restriction on the prior between-group covariance matrix of the regression parameters to diagonality, and (3) a specification of a non-informative prior distribution on a common residual variance for all groups. The implications of each difference for regression in m-groups are discussed below. These features and other numerical aspects of the M-L algorithm lead to an accurate and computationally efficient method for simultaneous estimation of multiple regression in m-groups.

Regression coefficients in the M-L model are of two types, common or fixed across groups (the  $\underline{B}_F$ ) and variable across the k groups (the  $\underline{B}_{Gk}$ ). Variables are assigned to sets F and G on the basis of the between-group

variances of their estimated regression coefficients. When prior information strongly suggests that between-group variability is negligible, a predictor is assigned to set F at the outset of the estimation procedure. Otherwise, predictors are initially assigned to set G and are transferred to set F only if the estimates of between-group variance fall below a threshold value during the iterative solution. Molenaar and Lewis (1979) describe how such estimates are obtained and used to partition predictors.

In addition to circumventing certain problems in estimation that have occurred with previous implementations of m-group regression models, the partition of predictors explicitly recognizes that some predictors perform in a virtually identical fashion across groups. Novick, Jackson, Thayer and Cole (1972) describe the Lindley-Smith model as one which seeks a compromise between within-group least squares and pooled least-squares analyses. Partitioning predictors into those with fixed and free parameters allows for pooling in a portion of the model when data and/or prior information suggest such pooling to be appropriate. Indeed, when predictor set G is empty, the model reduces to a pooled analysis, whereas when set F is empty the model is equivalent to that of Lindley and Smith (1972).

A second feature of the M-L model that distinguishes it from previous approaches is the assumption of independent prior distributions for the parameters  $\underline{B}_F$  and  $\underline{B}_{Gk}$ . Restricting the dispersion matrix for the  $\underline{B}_{Gk}$  to being diagonal places rather strong demands on the predictor set and is likely to be more appropriate for some predictor sets than for others. As noted by Molenaar and Lewis, however, prior knowledge about covariances is likely to be minimal in many practical situations - they also observe that their model allows for such covariances in the posterior distribution. A

consequence of this aspect of the model is that lack of shrinkage toward a common value across groups for, say,  $\beta_{1k}$  will not influence the degree of shrinkage that takes place for coefficients of other independent variables. This is perhaps reasonable for a selection battery that is heterogeneous with respect to the abilities required for test performance, such as the subtests of ASVAB.

The third aspect of the M-L model that distinguishes it from previous approaches is an assumption of between-group homoscedasticity of residual variances. This too places stronger demands on data, but for groups which are truly exchangeable such an assumption may be no less unreasonable than the usual assumption of homogeneity of variances within-groups. Indeed, it was observed by a reviewer that homogeneity of residual variances between groups in the M-L approach is likely to be a serious oversimplification in practice only when strong prior information for this aspect of the model is available. When the scaling of the dependent variable is arbitrary, simple standardization within groups, as is done in the following analysis, also helps to justify this aspect of the M-L model.

## Method

### Data Source

The M-L model for m-group regression was used to investigate predictor-criterion relationships in a set of technical training data from the Marine Corps. The particular data used were previously analyzed by Sims and Hiatt (1981) and consist of validation records for training courses taken from general categories of military job specialties. Of special interest is the

extent to which the regressions of final course grade (FCG) in training on a relevant set of predictors from ASVAB are similar for a group of training courses considered to be exchangeable. This is a special concern for a heterogeneous selection battery like ASVAB. A question that has plagued users of ASVAB over the years is whether common weights for subtests are justified for training programs with similar content. By initially considering such programs exchangeable, an alternative assessment of differences between regression equations for subgroups can be made. The general categories of specialties considered in this analysis are classified as Clerical, Electrical, and Mechanical. Individual recruits are assigned to training courses on the basis of ASVAB composite scores that are determined from the predictors used in each category of specialties.

#### Data Analysis

The training courses belonging to Clerical, Electrical and Mechanical specialty areas are presented in Table 1, along with sample sizes for each group. Preliminary inspections of bivariate scatterplots of course grades and ASVAB subtests were made for each training course in order to identify any serious departures from linearity and homoscedasticity within groups and to detect outliers. For several training courses, a small number of outliers were detected in the distribution of course grades--such observations were deleted in the ensuing analyses on the grounds that final grades for certain low-performing recruits were arbitrarily determined (see Sims and Hiatt, 1981).

For each category of training specialties, then, data analysis consisted of initial least-squares regressions of FCG on the relevant set of ASVAB predictor variables. These within-group least squares results were

then used as starting values in the M-L simultaneous estimation procedure. All courses listed in a given category in Table 1 were considered exchangeable in the Bayesian analysis. Thus, nine courses were analyzed simultaneously for the Clerical area, six for the Electrical area, and eleven for the Mechanical area.

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Insert Table 1 About Here

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The prior information required by the M-L model was specified in the same manner for the three types of specialties. In particular, prior estimates of the between-group variance of the parameters  $B_{Gk}$  were obtained from the so-called Model II analysis in a manner described by Jackson (1972). In essence, this method treats the  $\beta'_{gk}$  and their standard errors from the least squares analysis in a random-effects ANOVA manner in order to derive estimates of the between-group variance of  $\beta_{gk}$  for  $g = 1, 2, \dots, G$ . These values,  $\gamma'_g$ , were then treated as modal estimates from an inverse chi-square distribution, with degrees of freedom equal to 1 to indicate minimal prior information concerning between-group variability in the parameters.

In addition to the separate regression analyses described above, an attempt to understand the behavior of the M-L estimates in future samples was made through a cross-validation study of the Mechanical specialties. In this analysis, a 25 percent random sample was obtained from each training course and used to estimate parameters by least-squares and M-L methods. The estimates obtained from these samples were used in predicting course grades of recruits in the remaining 75 percent. It should be clear that this procedure does not mirror exactly an ideal cross-validation study.

Nevertheless, it does provide a beginning to understanding how the M-L estimation procedure might be expected to perform in practice, especially for training programs with sample sizes that would otherwise prohibit separate least-squares solutions.

### Results

The principal results presented are the estimates of regression parameters based on least-squares and M-L m-group analyses. The dependent variable, FCG, has been standardized within-groups to remove apparent differences between training courses in grading standards from the criterion distributions. The independent variables, ASVAB subtests, are typically reported on scales ranging from 20 to 80 and exceptions to this are noted in the description of results.

#### Clerical Specialties

ASVAB subtests used in the selection composite for clerical specialties include ability tests of Arithmetic Reasoning (AR), Word Knowledge (WK), Attention-to-Detail (AD), and an attitudinal measure called the Attentiveness Scale (CA). Unlike scores for the ability measures, observed scores on CA can range from 0 to 20. The results of within-group least-squares, pooled least-squares, and M-L analyses are summarized in Table 2. Estimates of coefficients for the four independent variables appear under the appropriate column heading. Rather than reporting the estimated intercept at 0, which is out of range on the joint predictor distribution, the intercept at the pooled centroid of the predictors is reported under the



heading Int(C). This value allows a more suitable comparison of any intercept differences that may exist among the groups. The residual standard deviations for the least-squares analysis appear in the column marked Res SD.

The within-group least-squares results in Panel (a) show clear differences among the groups, both with respect to intercept and slopes of the regression surfaces. Notable features of these results include the pattern of positive and negative intercepts across groups and the weights of relatively small magnitude for AD (recall AD is scaled in the same way as are AR and WK). In addition, coefficients estimated for the attitudinal measure, CA, display marked variation among the groups. However, when one considers that typical standard deviations on this measure are 2.5 to 3 points, the contributions made by it to prediction are quite small. Indeed, the usual significance tests failed to reject the null hypothesis that the coefficients for both AD and CA were zero at the .05 level for all Clerical specialties. Nevertheless, these variables were included in the m-group analyses in part to monitor the extent to which between-group differences on these variables were due to sampling fluctuations. Although not included in the table, multiple correlations in the least-squares analysis ranged from .40 to .79 within groups (.59 in the pooled sample).

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Insert Table 2 About Here

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The results of the M-L analyses in Panel (b) indicate a high degree of similarity among the Clerical training courses in terms of the slopes of regression surfaces using an equation with all four predictors when the courses are considered exchangeable and vague prior information is

specified. Estimates of coefficients for AR and WK do not differ to any important degree across the nine specialties and the apparently large differences observed for coefficients of CA in the least squares analysis are seen as a consequence of sampling variation through the eyes of the Bayesian approach. Though not reported here, results for the M-L model with predictors AD and CA removed were very similar to those in Panel (b), with only a small increase in the residual SD estimate caused by the reduced predictor set.

Where clerical specialties do differ, even in the M-L solution, is in their intercepts at the pooled centroid. Application of the M-L model didn't greatly influence the intercept differences noted in the least squares solutions. Aside from this factor, the ASVAB subtests used for clerical specialties perform quite consistently in predicting course grades. Justification for differential weighting of predictors among training courses would apparently have to come from an assumption that some courses are not exchangeable in the way specified by the M-L model.

#### Electrical Specialties

ASVAB subtests used in selection for courses classified as electrical specialties were AR, General Science (GS), Mathematics Knowledge (MK), and Electrical Information (EI). Results of regression analyses from the various approaches are given in Table 3, the contents of which parallel those of the previous table.

The least-squares estimates for Electrical specialties show greater variation among groups than was seen in the case of Clerical specialties. Multiple correlations for this group of specialties ranged from .15 to .58 (.37 in the pooled sample). Differences between groups are particularly

noticeable for coefficients of AR, which are relatively large for Avionics Repair, Basic Electrician and Basic Electronics, and near zero for the remaining courses. Moreover, the least-squares coefficient for MK in the Basic Electronics group is much larger (.047) than it is in any other group. In contrast to results from the Clerical specialties, no single predictor variable in the least-squares analysis appears less important than the others in predicting performance, at least based on the magnitudes of the regression weights. Again, because the immediate purpose here is not variable selection, all subtests are retained for the M-L analysis.

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Insert Table 3 About Here

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The M-L results in Panel (b) again show regression toward a common value for many of the coefficients in the model used with Electrical specialties. One predictor, AR, shows much greater homogeneity across groups--the Bayesian estimates of weights for this variable are also quite different in some cases from the pooled least-squares weights given in Panel (a). Note also that the weight for the Electrical Information test (EI) was judged constant across groups using the Model II prior estimates of between-group variances. A contrast to this degree of homogeneity is observed with respect to predictors GS and MK. Estimated weights of the former range from .014 to .021, while those of the latter are around .026 for all but the Basic Electronics course, whose estimated weight under the M-L model was .046. As seen in the results for Clerical specialties, intercepts for the six Electrical training courses are quite distinct when evaluated at the centroid of the pooled distributions. With small mean differences on the

predictors known to exist for these groups, this again is an unsurprising result.

Although estimates of slopes for the six Electrical specialties were quite similar for two predictors, even the M-L results fail to justify a single prediction equation for all specialties in this category. Predicting success for the Basic Electronics group using this set of predictors clearly requires heavier weight to be placed on MK. Whether such a result is taken to mean that Basic Electronics is not exchangeable with the other Electrical specialties is perhaps open to question. The M-L results indicate that even when exchangeability is assumed a priori, the data warrant that a prediction model for this course be considered separately from those of other Electrical specialties.

#### Mechanical Specialties

The ASVAB subtests that belong to the selection composite for mechanical specialties are again AR and GS, used previously, a test of Mechanical Comprehension (MC) and a test of Automotive Information (AI). Results of the regression analyses using these subtests as predictors are given in Table 4.

Variation from group to group in the magnitudes of least-squares regression weights is again the rule rather than the exception for the Mechanical specialties. With respect to GS, weights are near zero for the Aviation Crash Crew and Small Arms Repair courses, yet of substantial magnitude, relatively speaking, for ASM (Structures) and Tracked Vehicle Repair (.034 and .043, respectively). The other predictor in this set that displays marked variation in weights across groups is AI, which has a near zero weight for ASM (Safety) and a clearly non-zero weight for the two automotive

mechanics training courses. The magnitudes of weights assigned to AR and MC are much more homogeneous in the least-squares analyses -- indeed, the estimate given for MC the pooled sample is quite representative of nearly all within-group estimates. The pattern of positive and negative intercepts at the pooled centroid is again seen in the results for mechanical specialties, as is some variability in the size of the standard errors of estimate. Multiple correlations for these groups ranged from .34 to .67, with a value of .50 obtained in the pooled sample.

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Insert Table 4 About Here

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Shrinkage of parameter estimates toward common values in the M-L approach is again observed in the results in Panel (b) of Table 4. Two variables (AR and MC) were assigned to predictor set F on the basis of prior specifications determined from the Model II analysis. However, the M-L estimates of parameters for predictors GS and AI have only moderately approached a value that is common across groups. Although the coefficient for GS in the Tracked Vehicle Repair course has become closer in value to those of other courses, weights for GS are still comparatively small in the Crash Crew and Small Arms Repair courses. Moreover, GS appears to play a more prominent role in predicting course grades in the Advanced Auto course than it does in the Basic Auto course. These differences were still manifest when prior specifications were altered to indicate that more weight should be placed on the Model II analysis. Given the strong assumptions of the M-L model, differences like these would be difficult to ignore in future specifications of prediction equations for these courses. Other between-group differences that remain even after application of the M-L approach

involve estimates of intercepts and of weights for AI, which remain larger for the two automotive training courses.

### Cross Validation

An additional concern when results of a series of analyses like those in this report are to be used for future versions of an aptitude battery is the expected stability of regression coefficients on cross-validation. The issues relevant to this question have received much attention in the literature over the years and no review will be given here. Bayesian methods for simultaneous estimation of regression coefficients have been shown to cross-validate better than within-group least-squares (cf. Novick, Jackson, Thayer and Cole, 1972), particularly with small sample sizes. This result was confirmed for the Molenaar-Lewis approach with the limited cross-validation study performed on data from the Mechanical specialties. Table 5 contains mean-squared errors (MSE) and correlations (CORR) between observed and predicted criterion scores from the cross-validation analysis. The results in Table 5 are generally consistent with past comparisons of Bayesian m-group techniques and conventional methods -- a small yet consistent trend toward smaller errors of prediction on cross-validation using a Bayesian m-group model. Although the differences between least-squares and M-L errors given in Table 5 are quite small -- absolute differences between MSE's ranging from .001 to .043 -- this is perhaps to be expected when the cross-validation sample represents data from the same year as the calibration sample. If one goal of the Bayesian method is to smooth out minor temporal fluctuations in the parameter estimates that might otherwise be interpreted as differences between groups, then one would expect greater accuracy on cross-validation for the M-L estimates and data from a subsequent year.

That the results using a 25/75 split of data from one year are in the correct direction suggests some promise in further applications of the m-group approach to data of the type considered in this analysis.

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Insert Table 5 About Here

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### Discussion

Application of the M-L model for m-group regression to the prediction of success in technical training generally supports the use of common weights when ASVAB subtests are used to construct selection composites. If one were to place heavy reliance on the results of the within-group least-squares analyses, a different conclusion would certainly follow from a simple examination of estimated coefficients, even with sample sizes as large as those available in this data set. To the extent that the assumption of exchangeability is satisfied by the groups analyzed simultaneously, the M-L results provide a useful alternative assessment of the differences between specific training programs with similar content. These differences were found to be negligible for the group of Clerical training programs considered, but of sufficient magnitude for certain Electrical and Mechanical specialties to warrant more careful consideration when selection composites for future versions of ASVAB are developed.

A consideration of utmost importance in evaluating the appropriateness of the M-L model for developing prediction equations for technical training specialties in the military is the question of exchangeability. The approach to the question adopted in this paper has been to assume

exchangeability among training courses on the basis of course content and to allow results to point to groups which might well be distinct. Deletion of the few specialties in the Electrical and Mechanical areas that seem atypical of the area at large would no doubt produce even greater homogeneity of regression coefficients for predictors than has been reported here. However, more experience in applying the M-L method, or similar methods, to data from other recruiting years is likely to provide a better check on the extent to which exchangeability is justified for the groups studied in this analysis. In general, it seems that this type of assumption is properly evaluated over time rather than at a specific point in time.

The choice of the Molenaar-Lewis model for m-group regression also receives some support from the cross-validation results. As observed in the description of the model, M-L places greater restrictions on the specification of prior information, in part to increase computational efficiency and to avoid certain estimation problems (Molenaar and Lewis, 1979, pp. 6ff.). These restrictions do not appear to have compromised the effectiveness of the model for technical training specialties in the Marine Corps. Whether or not a model with more detailed prior specifications would yield results that differ perceptibly from those of the M-L approach is an open question - the extent of improvement would certainly be related to the strength of that additional prior information. It is far from obvious that strong prior information concerning, for example, between-group covariances of regression parameters or between-group variances of residual standard deviations is available for military training specialties at the present time. Further study of such specialties using m-group techniques should certainly consider applying more detailed prior specifications and methods of estimating the required hyperparameters. Some informal comparisons made with data of the



type used in this study indicate M-L yields results similar to those from a refinement of Rubin's (1980) empirical-Bayes approach when the M-L analysis is performed after standardizing the criterion variable within groups.

### Conclusion

Application of the Molenaar-Lewis model for regression in m-groups to the problem of predicting training success in various Marine Corps job specialties indicates some justification for limited use of common weights for predictor variables in training courses considered exchangeable on a priori grounds. All groups in the Clerical area were characterized by slopes of similar magnitude, although intercept differences were common. For both Electrical and Mechanical specialty areas, training courses were identified that had estimated slopes differing markedly with respect to at least one of the predictor variables included. Continued monitoring of such courses is important in judging the appropriateness of a common prediction equation for all training programs in these two areas.

The relevance of the methodology of m-group regression to predicting success in a variety of military training programs is an important outcome of this analysis. The extreme views of complete generalization of the criterion-related validity of ASVAB subtests across all courses and of entirely course-specific characterizations of subtest validity are equally unattractive. The model for m-group regression used in this study allows an assessment of exactly where between these two extreme positions an accurate characterization of criterion-related validity lies.

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Table 1  
Sample Sizes for Marine Corps  
Specialty Areas

Specialty Area	Sample Size
Clerical	
Basic Supply Stock	1238
Personal Financial Records	375
Administrative	1336
Personnel	176
Unit Diary	149
Communications Center	711
Aviation Operations	247
Aviation Maintenance Administration	215
Aviation Supply	496
Electrical	
Basic Electrician	223
Electrical Equipment Repair	215
Basic Electronics	1093
Radio Fundamentals	165
Field Radio Operator	1244
Avionics Repair	297
Mechanical	
Basic Auto Mechanic	1276
Advanced Auto Mechanic	618
Combat Engineer	934
Engineering Equipment Mechanic	691
Tracked Vehicle Repair	233
Basic Helicopter	801
ASM* (Safety)	124
ASM* (Hydraulics)	563
ASM* (Structures)	611
Aviation Crash Crew	295
Small Arms Repair	323

\*ASM = Aviation Structural Mechanics.

Table 2

Least-squares and M-L m-group Estimates of  
Regressions for Clerical Specialties

## Panel (a) - Least-squares

Training Course	Int(C)*	AR	WK	AD	CA	Res SD
Basic Supply	-.024	.048	.027	.004	.039	.862
Fin. Records	-.107	.050	.019	.002	.036	.620
Administrative	-.036	.032	.027	.009	.044	.754
Personnel	-.105	.043	.037	.003	.067	.869
Unit Diary	-.217	.026	.046	.003	.067	.908
Comm. Center	.152	.030	.027	.003	.031	.685
Av. Operations	.107	.036	.009	.017	.006	.928
Av. Maintenance	.088	.047	.027	.005	.016	.903
Av. Supply	.175	.039	.031	.015	.015	.890
Pooled	.000	.036	.026	.007	.033	.811

## Panel (b) - Molenaar-Lewis

Training Course	Int(C)*	AR	WK	AD	CA
Basic Supply	-.015	.041	.028	.006	.037
Fin. Records	-.089	.039	.026	.007	.034
Administrative	-.028	.036	.027	.008	.039
Personnel	-.052	.039	.027	.007	.037
Unit Diary	-.124	.038	.027	.007	.036
Comm. Center	.151	.036	.027	.006	.033
Av. Operations	.102	.038	.025	.008	.029
Av. Maintenance	.073	.039	.027	.007	.032
Av. Supply	.154	.039	.027	.009	.030

Modal Estimate of Res SD = .803

\*Int(C) represents the value of the regression intercept at the centroid of the predictors in the pooled sample.

Table 3

Least-squares and M-L m-group Estimates of  
Regressions for Electrical Specialties

## Panel (a) - Least-squares

Training Course	Int(C)	AR	GS	MK	EI	Res SD
Basic Electrician	.228	.019	.014	.023	.026	.930
Elec. Equip. Repair	-.113	.007	-.004	.031	.018	.968
Basic Electronics	-.354	.019	.022	.047	.021	.813
Radio Fundamentals	-.385	.009	.030	.026	.012	.965
Field Radio Operator	.299	.009	.017	.028	.017	.914
Avionics Repair	-.436	.035	.025	.012	.034	.922
Pooled	.000	.003	.013	.027	.014	.931

## Panel (b) - Molenaar-Lewis

Training Course	INT(C)	AR	GS	MK	EI*
Basic Electrician	.212	.015	.018	.026	.020
Elec. Equip. Repair	-.144	.014	.014	.026	.020
Basic Electronics	-.329	.015	.021	.046	.020
Radio Fundamentals	-.387	.014	.019	.027	.020
Field Radio Operator	.314	.014	.016	.026	.020
Avionics Repair	-.318	.015	.021	.025	.020

Modal Estimates of Res. SD = .888

\*EI was judged to belong to set F using the Model II prior estimate of between-group variance.

Table 4  
Least-squares and M-L m-group Estimates of  
Regressions for Mechanical Specialties

Panel (a) - Least-squares

Training Course	Int(C)	AR	GS	MC	AI	Res SD
Basic Auto	-.111	.028	.017	.018	.038	.788
Advanced Auto	-.134	.029	.028	.025	.034	.746
Combat Engineer	.265	.030	.021	.027	.017	.785
Eng. Equip. Mech.	.329	.022	.020	.019	.029	.861
Trk. Veh. Repair	.010	.028	.043	.017	.016	.831
Basic Helicopter	-.212	.022	.022	.020	.025	.872
ASM (Safety)	-.378	.032	.018	.020	.006	.942
ASM (Hydraulics)	-.122	.028	.029	.026	.019	.880
ASM (Structures)	-.180	.019	.034	.018	.013	.909
Av. Crash Crew	.091	.031	.004	.015	.018	.922
Small Arms	.113	.028	.002	.022	.015	.900
Pooled	.000	.020	.018	.020	.023	.868

Panel (b) - Molenaar-Lewis

Training Course	Int(C)	AR	GS	MC*	AI
Basic Auto	-.103	.026	.018	.021	.035
Advanced Auto	-.121	.026	.029	.021	.032
Combat Engineer	.256	.026	.024	.021	.020
Eng. Equip. Mech.	.342	.026	.019	.021	.026
Trk. Veh. Repair	-.015	.026	.032	.021	.020
Basic Helicopter	-.217	.026	.021	.021	.024
ASM (Safety)	-.334	.026	.018	.021	.017
ASM (Hydraulics)	-.113	.026	.028	.021	.021
ASM (Structures)	-.185	.026	.028	.021	.016
Av. Crash Crew	.090	.026	.010	.021	.018
Small Arms	.118	.026	.009	.021	.017
Modal Estimate of Residual SD = .841					

\*Variable assigned to set F on basis of Model II prior estimates of between-group variances.

Table 5

Mean Square Errors and Correlations from Cross-Validation  
Analyses for Mechanical Specialties

Training Course		MSE	CORR
Basic Auto	LS	.6272	.6111
	ML	.6282	.6103
Advanced Auto	LS	.6157	.6210
	ML	.6031	.6310
Combat Engineer	LS	.6081	.6268
	ML	.6010	.6324
Eng. Equip. Mech.	LS	.7535	.4979
	ML	.7385	.5127
Trk. Veh. Repair	LS	.7326	.5212
	ML	.6992	.5522
Basic Helicopter	LS	.7620	.4891
	ML	.7407	.5104
ASM (Safety)	LS	.8554	.3525
	ML	.8447	.4055
ASM (Hydraulics)	LS	.7876	.4630
	ML	.7698	.4818
ASM (Structures)	LS	.8663	.3682
	ML	.8395	.4027
Av. Crash Crew	LS	.8875	.3409
	ML	.8443	.3990
Small Arms	LS	.8404	.4036
	ML	.8326	.4132



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