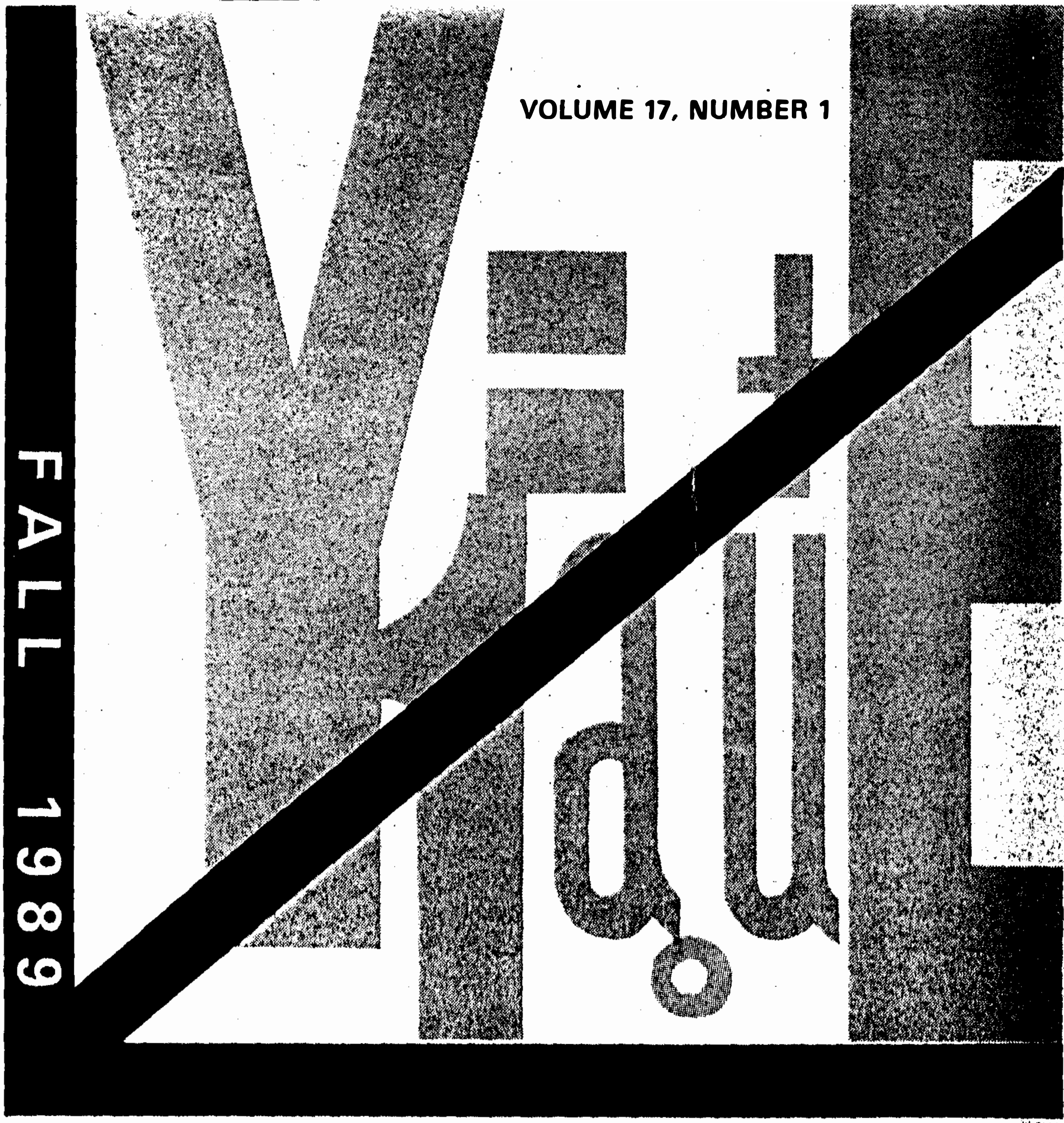

MULTIPLE LINEAR REGRESSION VIEWPOINTS

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Use of Linear Models vs. Multiple Discriminant Analysis with Three Groups

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ABSTRACT

It is well known that the three-group oiscriminant function cannot be expressed as a specialized case of the general linear model or multiple linear regression. However, researchers should be alert to the possibility that the set of three-group membership vectors might be adequately representeo by an unidimensional bipolar variable of three points thus permitting the use of regression techniques.

A research example is presented in which data were examined both on the basis of the three-group multiple discriminant function as well as by regression procedures. Results of the comparative analysis were such that regression techniques furnished an accurate picture of the finoings. The obvious implication is to suggest that researchers consider using a three-point dependent variable and regression techniques when it makes theoretical or logical sense to conceptualize the three-group membership vectors as a single variable.

In the case of the two-group discriminant function it is well known that the discriminant weights are proportional to the weights for a multiple regression equation of a dichotomous criterion group-membership variable on a set of predictor variables. Thus, discriminant analysis for two groups is a special case of multiple linear regression in which all Group 1 members are assigned the score "1," and all Group 2 members the score "0," on a "dummy" criterion variable Y. Many early writers such as Garrett (1943) and Wherry (1947), as a result of the two-group relationship between the discriminant function and multiple linear regression, stated falsely that discriminant analysis, in general, was nothing more than a special case of multiple linear regression. It should be emphasized, at this point, that the relationship between the discriminant function and multiple linear regression holds only in the case of two groups. When there are more than two groups under investigation, the discriminant function reduces, not to multiple linear regression, but to canonical correlation analysis.

In a doctoral dissertation completed at the University of Northern Colorado, Marcantonio (1977) explored the relationships between selected demographic and personality characteristics as they relate to the variable of the Divorce Initiating Party (I, Both, H/She). The author utilized multiple linear regression techniques as he conceptualized the criterion variable of the Divorce Initiation Party to represent a three-point bipolar vector. In order to make more meaningful the comparison between the three-group discriminant function with a specialized example in which the criterion variable was scored on a three-point scale, it should be helpful to review the main findings of Marcantonio (1977) derived primarily from correlational and regression procedures.

The _Ss_ in the original study by Marcantonio (1977) consisted of 101 formerly-married individuals who had participated in a divorce adjustment seminar presented by a trained psychologist in Colorado during the Fall Quarter, 1977. All the _Ss_ were tested prior to the start of the seminar. The tests included the Tennessee Self Concept Scale, the revised edition of the Fisher Divorce Adjustment Scale (1976), and the demographic questions. Below are presented a list and description of the variables.

Description of the Variables

1. Tennessee Self Criticism Score
2. Tennessee Total Score
3. Tennessee Row 1 Score - Identity
4. Tennessee Row 2 Score - Self Satisfaction
5. Tennessee Row 3 Score - Behavior
6. Tennessee Column A - Physical Self
7. Tennessee Column B - Moral Ethical Self
8. Tennessee Column C - Personal Self
9. Tennessee Column D - Family Self
10. Tennessee Column E - Social Self
11. Tennessee Total Variability
12. Fisher Divorce Adjustment Scale Symptoms-of-Grief Factor

Variable 12 was the Symptoms-of-Grief Factor score obtained on the revised edition of the Fisher Divorce Adjustment Scale. The revised edition utilized items for this factor on the original Fisher Divorce Adjustment Scale (1976). For his study, Marcantonio selected out only those test items or questions which had factor loadings in excess of 0.40 and were of complexity one. This variable measures the extent to which a person mourns the death of the love relationship.

13. Fisher Divorce Adjustment Scale Disentanglement of the Love-Relationship Factor

Variable 13 was the Disentanglement of the Love-Relationship Factor score obtained on the revised edition of the Fisher Divorce Adjustment Scale. This variable measures the extent to which the person dissipates the strong emotional feelings that he/she had for the former love-object person.

14. Fisher Divorce Adjustment Scale Feelings-of-Anger Factor

Variable 14 was the Feelings-of-Anger Factor score obtained on the revised edition of the Fisher Adjustment Scale. This variable measures the anger level of the divorced party.

15. Fisher Divorce Adjustment Scale Rebuilding Social Relationships Factor

Variable 15 was the Rebuilding Social Relationships Factor score obtained on the revised edition of the Fisher Adjustment Scale. This variable measures the extent to which a person has learned to build new friendships and to feel comfortable with friends.

16. Time Separated from One's Spouse

Variable 16 was scored on a four-point scale:

1 identifying a S separated between zero and six months;

2 identifying a person separated between six and 12 months;

3 identifying a person separated one to three years;

4 identifying a person separated more than three years.

17. Age of the Divorced Party

Variable 17 was scored on a five-point scale: 1 identifying a person who is between 20 and 29; 2 identifying a person who is between 30 and 39; 3 identifying a person who is between 40 and 49; 4 identifying a person who is between 50 and 59; 5 identifying a person who is 60 or older.

18. Sex Status of the Divorced Party

Variable 18 was binary coded: 1 identifying a female S; 2 identifying a male S.

19. Divorce Initiating Party

Variable 19 (the criterion variable) was trinary coded: 1 identifying the situation in which S who was tested also initiated the divorce; 2 identifying the situation in which both formerly-married parties initiated the divorce; 3 identifying the situation in which the S who was tested did not initiate the divorce. Since the variable of Divorce Initiating Party was essentially a bipolar concept, it was felt that a three-point numeric scale could be utilized to represent it as a one-dimensional vector.

Multiple Regression Analysis

A list of the variables and their abbreviations are presented in Table 1. In Table 2 are presented the means and standard deviations for the 19 variables studied. The intercorrelation coefficients among the 19 variables are product-moment coefficients and are presented in Table 3. Because one of the variables is binary-coded, some of the coefficients are point-biserial's. In the Marcantonio study there was an attempt to measure both the total or absolute contribution of a predictor variable to the criterion variable as well as the unique contribution of a variable or set of variables to the criterion variable. The total or absolute contribution of a predictor variable is measured by the square of the correlation coefficient between the predictor variable and the criterion variable. The unique contribution of a variable or a set of variables to the criterion variable was determined by methods described in Schmid and Reed (1966). The authors explain that the unique contribution of a predictor variable to the prediction of a criterion

TABLE 1

LIST OF VARIABLES

Number	Variable	Abbreviation
1	TSCS Self Criticism Score	SC-T
2	TSCS Total Score	TOT-T
3	TSCS Row 1 Score - Identity	R1-T
4	TSCS Row 2 Score - Self Satisfaction	R2-T
5	TSCS Row 3 Score - Behavior	R3-T
6	TSCS Column A - Physical Self	CA-T
7	TSCS Column B - Moral Ethical Self	CB-T
8	TSCS Column C - Personal Self	CC-T
9	TSCS Column D - Family Self	CD-T
10	TSCS Column E - Social Self	CE-T
11	TSCS Total Variability	TV-T
12	FDAS Symptoms-of-Grief Factor	SOG-F
13	FDAS Disentanglement of the Love-Relationship Factor	DLR-F
14	FDAS Feelings-of-Anger Factor	FOA-F
15	FDAS Rebuiling Social Relationships Factor	RSR-F
16	Time Separated from One's Spouse	TIME
17	Age of the Divorced Party	AGE
18	Sex Status of the Divorced Party	SEX
19	Divorce Initiating Party (criterion variable)	DIP

TABLE 2

MEANS AND STANDARD DEVIATIONS (N=101)

Variable	Mean	Standard Deviation
1 SC-T	35.56	5.53
2 TOT-T	264.48	12.71
3 R1-T	82.56	5.93
4 R2-T	88.25	7.08
5 R3-T	92.70	5.33
6 CA-T	55.83	4.11
7 CB-T	51.87	4.25
8 CC-T	47.86	5.11
9 CD-T	55.00	5.40
10 CE-T	53.31	3.98
11 TV-T	36.79	10.17
12 SOG-F	49.67	8.91
13 DLR-F	51.06	13.71
14 FOA-F	24.46	6.22
15 RSR-F	23.86	6.34
16 TIME	2.911	1.04
17 AGE	2.17	0.76
18 SEX	1.38	0.48
19 DIP	2.02	0.92

TABLE 3

INTERCORRELATION MATRIX*

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
SC-T	1																		
TOT-T	2	-08																	
R1-T	3	-05	58																
R2-T	4	-03	67	37															
R3-T	5	-05	54	10	20														
CA-T	6	04	14	38	23	12													
CB-T	7	-02	54	47	54	38	17												
CC-T	8	-16	39	35	44	15	-04	23											
CD-T	9	-07	65	45	49	43	-08	41	17										
CE-T	10	04	33	23	28	16	10	07	-00	10									
TV-T	11	01	-06	-16	-18	19	09	05	-28	-01	22								
SOG-F	12	-03	-18	-15	-18	-09	-02	-15	-17	-18	-02	-10							
DLR-F	13	25	-00	06	-02	-06	00	-04	-11	03	08	-16	49						
FOA-F	14	03	12	10	14	05	-00	-00	-02	18	-01	-14	39	42					
RSR-F	15	-16	13	14	20	07	17	12	08	13	-02	-22	17	19	47				
TIME	16	08	07	10	-09	-00	-06	08	-15	18	03	10	13	28	21	-06			
AGE	17	-12	11	19	-02	10	14	-02	17	01	02	-02	-17	-12	-00	01	21		
SEX	18	-06	-12	-18	04	-09	-14	06	-02	-20	-12	-07	-01	-26	07	06	-16	-11	
DIP	19	-20	04	-02	17	-00	-03	12	09	10	-06	04	-18	-46	-10	13	-08	-18	16

variable may be interpreted in a couple of ways. If a predictor variable is making a unique contribution, then knowledge of that variable furnishes information about the criterion. Secondly, if a variableis making a unique contribution, then two Ss, who are different on the variable but who are alike on the other predictor variables, will differ on the criterion. Thus, according to Schmid and Reed, the magnitude of the unique contribution of a set of variables to prediction may be measured by the difference between two squares of multiple correlation coefficients (RSs), one obtained for a linear regression model in which all predictors are used, called the full model (FM), and the other obtained for a linear regression equation in which the proper subset of variables under consideration have been deleted; this model is called the restricted model, (RM). The RS for the RM can never be larger than the RS for the FM. The difference between the two RSs may be tested for statistical significance with the variance-ratio or F test. The formula for this test is as follows:

$$F = \frac{(RS_{FM} - RS_{RM}) \,/\, (DF_{FM} - DF_{RM})}{(1 - RS_{FM}) \,/\, (N - DF_{FM})}$$

in which N = the size of the sample,

RS_{FM} = the square of the multiple correlation coefficient for the full model,

RS_{RM} = the square of the multiple correlation coefficient for the restricted model,

DF_{FM} = the degrees of freedom associated with the full model, that is, the number of parameters to be estimated in the full model, and

DF_{RM} = the degrees of freedom or number of parameters to be estimated in the restricted model.

For a determination of which variables made a significant total or unique contribution, see Tables 3 and 4. Marcantonio's major findings include:

1) There was found to be a negative significant correlation between the Tennessee Self Criticism (TSC) scores and the Divorce Initiating Party (DIP) scores. This indicates that Ss with a healthy openness and a higher capacity for self-criticism tend to be the initiating party in the divorce procedure.

2) There was found to be a positive significant correlation between the Row 2 TSC scores and the DIP scores. This indicates that Ss with a lower self-satisfaction score tend to be the initiating party in the divorce procedure.

3) There was found to be a negative significant correlation between the Fisher Divorce Adjustment Scale (FDAS) Symptoms-of-Grief Factor scores and the DIP scores. This indicates that Ss with high grief scores tend to be the initiating party in the divorce procedure.

4) There was found to be a negative significant correlation between the FDAS Disentanglement of the Love-relationship Factor scores and the DIP scores. This indicates that SS with high disentanglement scores tend to be the initiating party in the divorce procedure.

5) There was found to be a negative significant correlation between the Age of the Divorced Party scores and the DIP scores. This indicates that Ss who were older tend to be the initiating party in the divorce procedure.

6) The variables of the Age of the Divorced was found to be making a significant unique contribution to the explanation of the DIP scores.

7) The variable of the FDAS Disentanglement of the Love-relationship Factor was found to be making a significant unique contribution to the explanation of the DIP scores.

8) The variable of the FDAS Rebuilding Social Relationship Factor was found to be making a significant unique contribution to the explanation of the DIP scores.

9) The set of 11 TSC Scales was not found to be making a significant unique contribution to the explanation of the DIP scores.

TABLE 4

SUMMARY TABLE OF LINEAR MODELS TESTED

Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--18	2.68	0.001*
0	0.0000	19	None	Denominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--1	0.05	0.83
2	0.3703	19	1-17	Denominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--1	7.22	0.01*
3	0.3152	19	1-16,18	Denmominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--1	2.50	0.11
4	0.3514	19	1-15,17-18	Denominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--1	4.43	0.04*
5	0.3367	19	1-14,16-18	Denominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--1	0.04	0.84
6	0.3704	19	1-13,15-18	Denominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--1	21.43	0.001*
7	0.2062	19	1-12,14-18	Denominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--1	0.03	0.86
8	0.3705	19	1-11,13-18	Denominator--82		
Model	RS Values	Y-Variable	X-Variables	Degrees of Freedom	F	P
1	0.3707	19	1-18	Numerator--11	0.35	0.97
9	0.3410	19	12-18	Denominator--82		

*Significant beyond 5% level.

Multiple Discriminant Analysis

The problem of studying the direction of group differences is essentially a problem of finding a linear combination of the original set of predictor variables that shows large differences in group means or centroids. Discriminant Analysis is such a method for determining the linear combinations. A very readable and mathematical treatment of discriminant analysis may be found in Tatsuoka (1970). In addition, a mathematical proof that the discriminant analysis and canonical correlational approaches yield identical results was given also by Tatsuoka (1953).

In Table 5 are presented the actual classification results for N = 101, derived by the multiple discriminant function for three groups when the 18 variables are used. From Table 5 it can be seen that 70 (69.31%) of the cases

TABLE 5

DISCRIMINANT CLASSIFICATION RESULTS ON ALL VARIABLES
WITH ACTUAL PRIOR PROBABILITIES

Actual Group	Number of Cases	Predicted Group Membership 1	2	3
Group 1	42	34 (83.3%)	1 (2.4%)	6 14.3%)
Group 2	15	6 (40.0%)	6 (40.0%)	3 (20.0%)
Group 3	44	11 (25.0%)	4 (9.1%)	29 (65.9%)

were correctly classified. The numbers along the diagonals represent correct classifications, while the off-diagonal numbers represent misclassifications. The discriminant function was especially accurate for Group 1 (83.3%) and Group 3 (65.9%).

In a forward-selection procedure it was found that Variables 13, 15 and 17 were sufficient variables contributing to group separation in reduced space with alpha = 0.05. It is interesting to observe in Table 4 that the unique contributions of Variables 13, 15 and 17 were also significant beyond the 0.05 level when multiple linear regression procedures were employed. The classification results based on the use of Variables 13, 15 and 17 in reduced space with the prior probabilities the actual probabilities are presented in Table 6. From an analysis of Table 6 it can be seen that 65 (64.4%) of the cases are now correctly classified. Again, the most accurate predictions are

TABLE 6

DISCRIMINANT CLASSIFICATION RESULTS ON THREE VARIABLES
WITH ACTUAL PRIOR PROBABILITIES

Actual Group	Number Of Cases	Predicted Group Membership 1	2	3
Group 1	42	34 (81.0%)	1 (2.4%)	7 (16.7%)
Group 2	15	8 (53.3%)	0 (0.0%)	7 (46.7%)
Group 3	44	11 (25.0%)	2 (4.5%)	31 (70.5%)

associated with Group 1 (81.0%) and with Group 3 (70.5%). In Table 7 are presented the classification results based on the use of Variables 13, 15, and 17 in reduced space with the prior probabilities for each group set at one-third. From the results of Table 7 it can be seen that 62 (61.4%) are now correctly classified. It is interesting to observe that by setting each of the prior probabilities to one-third for each of the three groups, the accuracy associated with predicting membership to Group 2 has increased from 0.0% (Table 6) to 53.3% (Table 7) even though the overall accuracy has slipped from 64.4% (Table 6) to 61.4% (Table 7).

TABLE 7

DISCRIMINANT CLASSIFICATION RESULTS ON THREE VARIABLES WITH EQUAL PRIOR PROBABILITIES

Actual Group	Number Of Cases	Predicted Group Membership 1	2	3
Group 1	42	29 (69.0%)	12 (28.6%)	1 (2.4%)
Group 2	15	3 (20.0%)	8 (53.3%)	4 (26.7%)
Group 3	44	6 (13.6%)	13 (29.5%)	25 (56.8%)

In an attempt to produce a classification via multiple linear regression models alone, a series of binary-coded criterion variables were generated in which "1" designated membership in a particular group and "0" represented membership in one of the other two groups. Using this procedure repeatedly, the researchers produced a classification table which is presented in Table 8. The three variables used as predictors for Table 8 include Variables 13, 15 and 17. From Table 4 it was determined that each of them was making a significant unique contribution beyond the 0.05 level. From Table 8 it can be seen that 69 (68.3%) of the individuals were correctly classified by means of the series of binary-coded multiple linear regression models. The square of the multiple correlation coefficient for the series of binary-coded regression models ranged from 0.266 to 0.366.

TABLE 8

MULTIPLE LINEAR REGRESSION CLASSIFICATION RESULTS ON THREE VARIABLES

Actual Group	Number Of Cases	Predicted Group Membership 1	2	3
Group 1	42	35 (83.3%)	0 (0.0%)	7 (16.7%)
Group 2	15	7 (46.7%)	5 (33.3%)	3 (20.0%)
Group 3	44	14 (31.8%)	1 (2.3%)	29 (65.9%)

Summary Comments

While it is well known that the three-group discriminant function is not a specialized case of multiple linear regression, researchers should consider the possibility that the three groups might form three points on a bipolar continuum. If the set of three-group membership vectors can be captured by a one-dimensional vector, then multiple regression techniques certainly would be appropriate in the analysis of the data. Results from this study furnish an example in which the ability to classify correctly increased from 68.3% to just 69.31% by using the discriminant function instead of multiple linear regression. The slight increase incorrect classification hardly justifies the use of the discriminant function in this case.

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The Meta-Analysis of the Effect of Class Size on Achievement: A Secondary Analysis

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Abstract

One of the first examples of the use of Gene Glass' meta-analysis was the Glass and Smith studies of the effect of class size on achievement in school. It was concluded that "a clear and strong relationship between class size and achievement has emerged" (Glass & Smith, 1979). This paper presents the reanalysis of the Glass and Smith data, removing small classes of five or less, which are virtually tutorial sessions. The results show a greatly reduced effect on achievement for small classes.

An earlier version of this paper was presented at the annual meeting of the Mid-Western Educational Research Association in Chicago, Sept. 27-29, 1984.

Introduction

If teachers were asked if they favored smaller classes over larger ones, the vast majority would probably respond that they favored smaller classes (Bain & Achilles, 1986). The rationale for this might be expressed in the following ways: the teacher-student rapport is better in smaller classes, teachers can individualize instruction to a greater extent resulting in greater learning in smaller classes, and the attitudes of both teachers and students improve in smaller classes. The importance of small classes can be underscored by noting that this topic is often an issue in teacher contract negotiations. The opposing position, usually held by school administrators, is that the achievement of students in larger classes is equivalent to that of students in smaller classes and the larger classes are more cost-effective.

Although a considerable number of research studies have compared student achievement in small versus large classes, a representative sampling of the literature would lead to inconclusive findings: studies can be found that favor large classes and other studies can be found that indicated an advantage to small classes. Therefore, this topic is an ideal one for the application of a statistical technique called meta-analysis.

Meta-analysis, pioneered by Gene V Glass, is a statistical methodology for integrating a large number of individual studies. Glass (1976) divided research into two types: primary analysis and secondary analysis. He defined primary analysis as "original analysis of data in a research study," while secondary analysis is defined as "re-analysis of the data for the purpose of answering the original research question with better statistical techniques or answering new questions with old data" (p. 3). He continued to propose a new type of analysis, meta-analysis, which "refers to the analysis of analyses...[or] the statistical analysis of a large collection of analyses results from individual studies for the purpose of integrating the findings" (p. 3).

The results of a meta-analysis are often presented in terms of mean effect size and its place on the normal distribution. Effect size is usually defined either as the difference between means of experimental and control groups divided by a standard deviation:

$$ES = \frac{(\bar{X}_E - \bar{X}_C)}{s}$$

where s = either the standard deviation of the control group or a pooled estimate of the standard deviation

or as a correlation coefficient:

$$ES = r.$$

Glass and Smith's Original Meta-analysis

Glass and Smith (1976) performed a meta-analysis on the relationship between class size and achievement. Their estimate of effect size was given by:

$$ES_{SL} = \frac{(\bar{X}_S - \bar{X}_L)}{s}$$

where $\bar{X}_S$ = the mean achievement for the smaller class,

$\bar{X}_L$ = the mean achievement for the larger class, and

s = the estimated pooled, within-class standard deviation

After a careful search of the previous studies of the class size literature, the document retrieval and abstracting resources, and the bibliographies of the studies which were found, 77 studies were identified which yielded 725 effect sizes. Glass and Smith (1979) reported that the mean of the 725 effect sizes was .088 and the median was .050. The standard deviation was .401, the skewness 1.151 and the kurtosis 7.461. The effect sizes ranged from -1.98 to 2.54, and 40% were negative while 60% were positive (i.e. favoring smaller classes).

Glass and Smith (1979) fit the following quadratic least squares regression model to the data:

$$ES_{S\text{-}L} = \beta_0 + \beta_1 S + \beta_2 S^2 + \beta_3 (L - S) + \varepsilon$$

where S = the size of the smaller class,
L = the size of the larger class,
β_0, β_1, β_2, β_3 = the population regression weights, and
ε = the error of estimate

Glass and Smith (1979) obtained the following summary table:

Source of Variation	df	MS	F
Regression	3	6.684	50.636
Residual	721	.132	

The multiple R for the model was .426. Substituting the estimated regression weights in the model yielded the following regression equation:

$$\hat{ES}_{S\text{-}L} = .57072 - .03860\,S + .00059\,S^2 + .00082\,(L - S)$$

A graph of the regression line for achievement in percentile ranks on class size for all data appears in Figure 1 (Note from Glass & Smith, 1979).

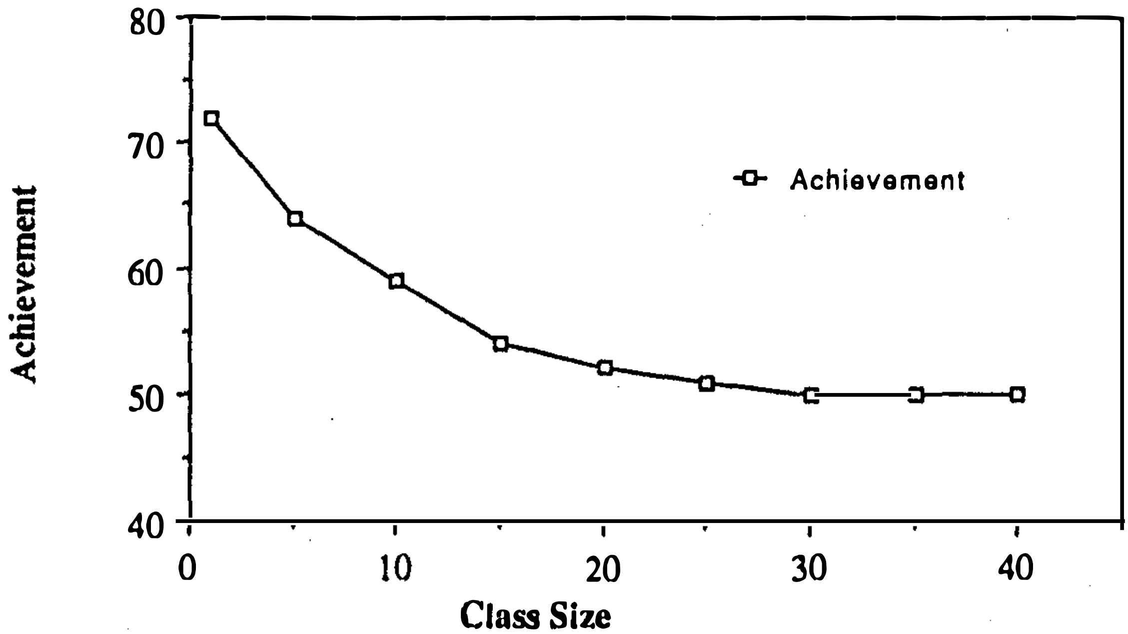

Figure 1. Regression Line for Achievement

A number of other variables were also analyzed in this meta-analysis. Included among these were year of the study, duration of instruction, pupil/instructor ratio, pupil ability, age, assignment of pupils and teachers, type of achievement measure and quantification of outcomes. However, of all the regression analyses performed on the data, only two analyses provided any meaningful information. These analyses were based on two comparisons: elementary vs. secondary students and well-controlled vs. poorly-controlled studies.

Students were sorted by age into two groups: those who were 11 years old or younger (elementary students) and those who were 12 years old or older (secondary). Separate regression analyses using the model given earlier yielded the following results for elementary school-aged children:

ELEMENTARY (N=342)

Source of Variation	df	MS	F
Regression	3	1.898	38.735
Residual	338	.049	

The multiple R for this model was .505. Substituting the estimated regression-weights into the model yielded the following equation:

$$\hat{ES}_{S\text{-}L} = .38503 - .02995\,S + .00052\,S^2 + .00344\,(L - S)$$

The following results were obtained for secondary school-aged pupils:

SECONDARY (N=349)

Source of Variation	df	MS	F
Regression	3	5.667	27.377
Residual	345	.207	

The multiple R for this model was .439 and the regression equation was given by the following:

$$\hat{ES}_{S\text{-}L} = .75539 - .05024\,S + .00071\,S^2 + .00111\,(L - S)$$

A graph of the regression lines for both the elementary and secondary groups for achievement in percentile rank on class size appears in Figure 2 (Note from Glass & Smith, 1979). The graph indicates that the relationship between small class size and higher achievement is more pronounced in the secondary grades than in the elementary grades.

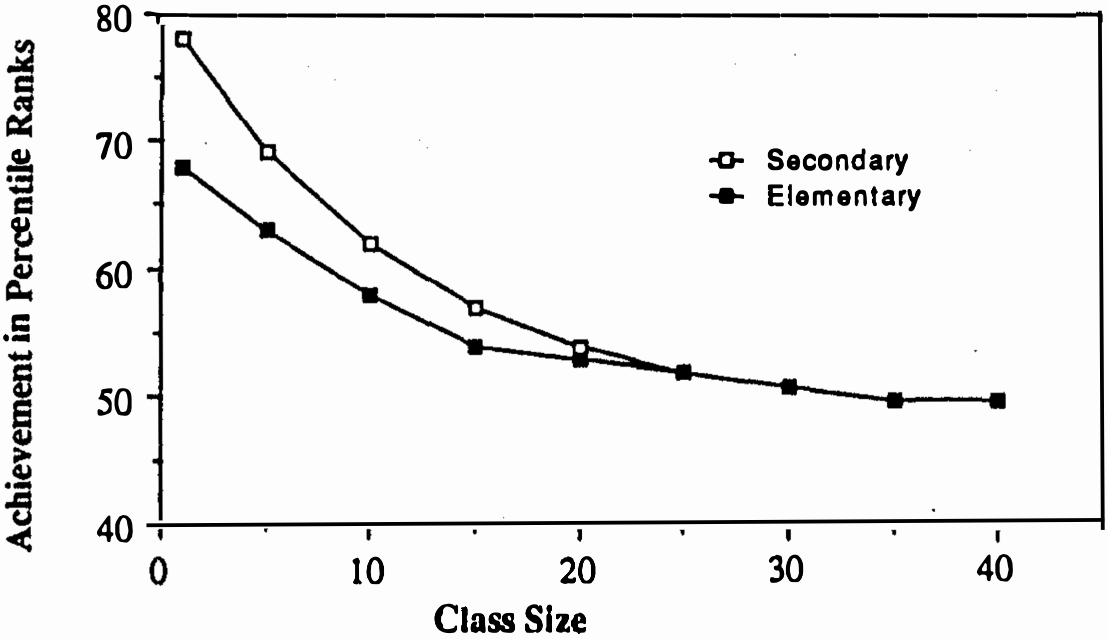

Figure 2. Regression of Achievement onto Class Size by Grade Level

Finally, comparable regression analyses were done on groups of studies classified as well-controlled versus studies classified as poorly controlled. In well-controlled studies, students were randomly assigned to large and small classes, while intact classes were used in the poorly-controlled studies.

The analysis of well-controlled studies provided the following results:

WELL-CONTROLLED (N=108)

Source of Variation	df	MS	F
Regression	3	4.226	21.784
Residual	104	.194	

The multiple R for this model was .621. Substituting the estimated regression weights into the model yielded the following equation:

$$\hat{ES}_{S\text{-}L} = .69488 - .06334\,S + .00128\,S^2 + .00783\,(L - S)$$

The analysis of the poorly-controlled studies yielded the following results:

POORLY-CONTROLLED STUDIES (N=334)

Source of Variation	df	MS	F
Regression	3	.263	3.985
Residual	330	.066	

The multiple R for this model was .187 and the regression equation was given by:

$$\hat{ES}_{S\text{-}L} = .07399 - .00587\,S + .00009\,S^2 + .00376\,(L - S)$$

A graph of the regression lines for both the well-controlled and poorly-controlled studies for achievement in percentile ranks appear in Figure 3 (Note from Glass & Smith, 1979). For studies using random assignment of student, the achievement in small classes was markedly higher than in the poorly controlled studies where random assignment was not used.

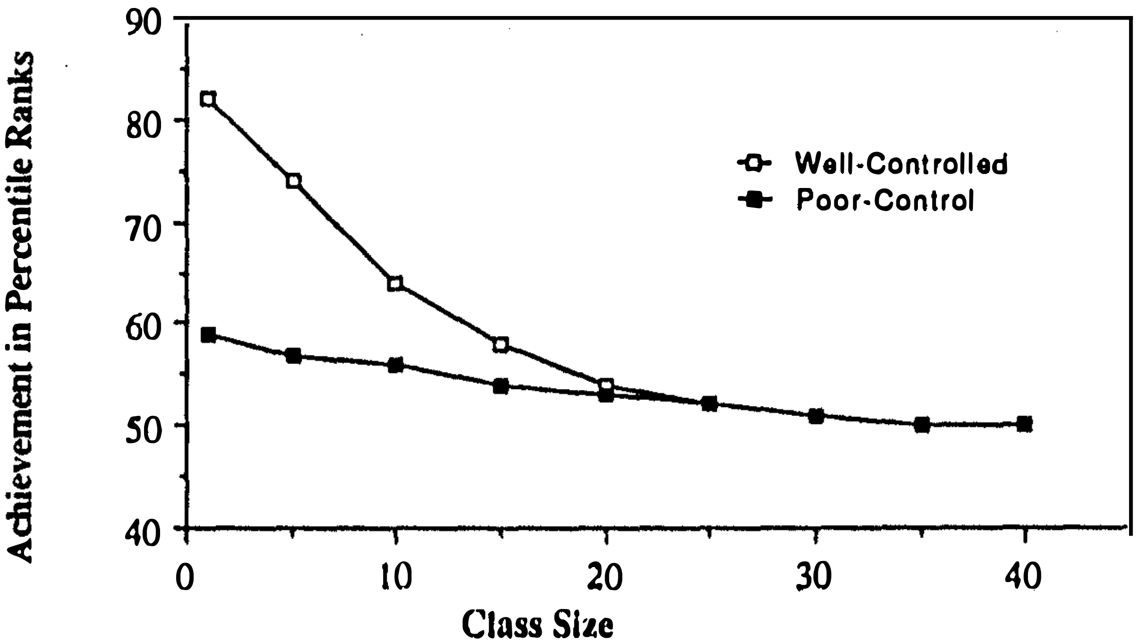

Figure 3. Regression of Achievement onto Class Size by Control

Glass and Smith (1979) concluded that:

> "a clear and strong relationship between class size and achievement has emerged. The relationship seems slightly stronger at the secondary grades than the elementary grades, but it does not differ appreciably across different schools subjects, level of pupil IQ, or several other obvious demographic features on classrooms. The relationship is seen most clearly in well-controlled studies in which pupils were randomly assigned to classes of different sizes" (p. 15).

Criticisms of the Glass and Smith Meta-analysis

Although the work of Glass and Smith appears to be quite conclusive, it has not gone without criticism. First, one contradiction in their findings is that only 60% of the effect sizes were positive although they claim a "clear and strong relationship between class size and achievement" exists. This means that, in nearly half (40%) of the effect sizes, the achievement of the larger class exceeded the achievement of the smaller class. In addition, an R^2 of .181 leaves almost 82% of the variance of achievement unexplained by variation in class size. Even though a highly significant proportion of variance is accounted for, there is much room for improvement.

Another criticism, presented by the Educational Research Service (1980), was that the graph of achievement regressed on class size for well-controlled studies vs. poorly-controlled studies was based on only 14 studies. Of these 14 studies, a mere six studies were conducted in situations that are typical of elementary and second school.

Perhaps the most telling criticism of all pertains to the range of class sizes where the largest increments in achievement occur. As all the graphs presented illustrate, the most pronounced change in the rate of achievement occurs in classes smaller than 15 in number. Only minimal differences in achievement can be seen in the range of 20 to 40 students, which are the more typical sizes of classes.

Reanalysis Eliminating Tutorials

A large number of the small classes had only one to five students enrolled. These classes could more accurately be called "tutorial sessions." The purpose of this study was to reanalyze the Glass and Smith data eliminating the very small, atypical, class sizes and observing the resulting effect sizes to see the impact of the "tutorial sessions." The data reported by Glass and Smith (1978) were entered into the computer for this reanalysis. The results appear in Table 1.

Table 1. Means and Standard Deviations of models of Effect Sizes for Original and Successively Reanalyzed Data from Glass and Smith (1978)

Study	N	Mean	St. Dev.	R^2	p <
Glass and Smith	725	.088	.401	.181	.0001
Tracz and Leitner	662	.091	.406	.180	.0001
Eliminating effect sizes based on small class of					
1	609	.046	.356	.060	.0001
1-2	607	.045	.356	.058	.0001
1-3	601	.033	.332	.017	.0176
1-4	599	.031	.330	.013	.0493
1-5	598	.031	.330	.012	.0609

Although Glass and Smith (1978) appear to have presented their entire data set, the listing omits 63 effect sizes. For the available data, the mean was .091. The standard deviation of the two data sets was almost identical as was the multiple R^2 for our reanalysis. This gave us confidence, that while some studies were missing, our reanalysis was not substantively affected.

When the 53 effect sizes that included the small classes with only one student were removed from the analysis, the mean effect size dropped from .091 to .046 - a decrease of nearly 50%. The standard deviation dropped from .406 to .356 and the R^2 dropped from .180 to .060 - leaving 94% of the variance unaccounted for! The 53 effect sizes were from 8 studies, averaged .608 with a standard deviaiton of .566 and ranged from -.44 to 2.52.

When an additional nine effect sizes were eliminated, representing small classes with two through five students, the mean decreased even further to .031, approximately one-third of what it was for the full data set. The model involving the three variables used in all analyses accounts for slightly more than 1% of the variance in Effect Size and is no longer significant at the .05 level.

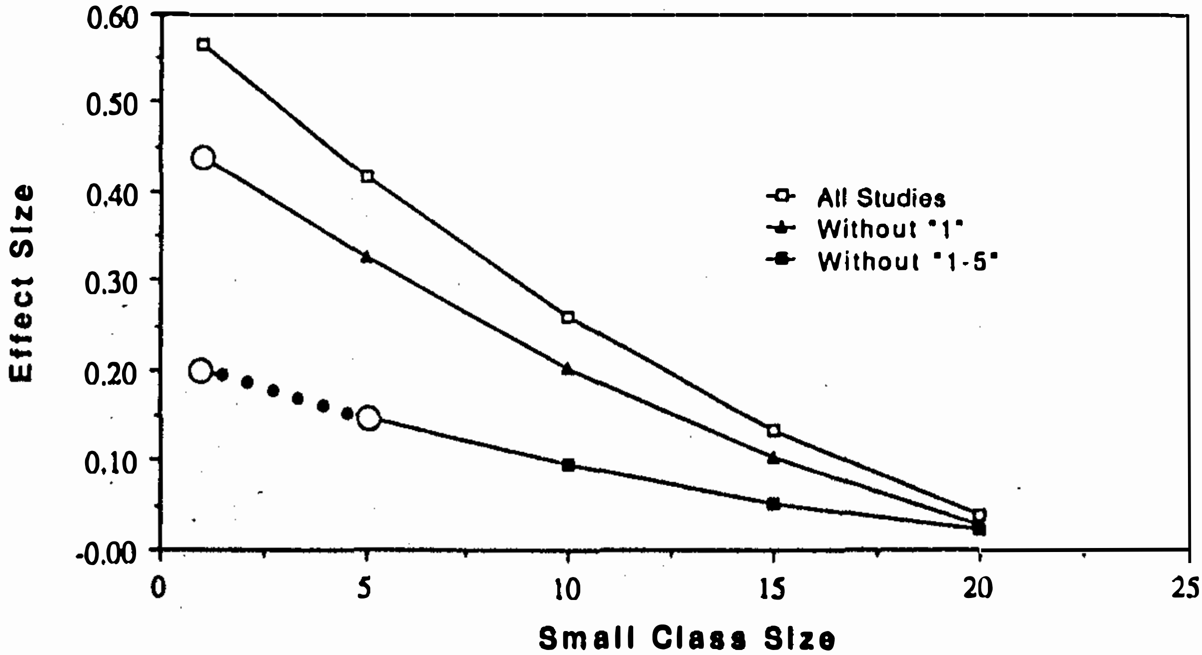

Figure 4. Effect Sizes With and Without Small Classes

Figure 4 is a graph of the three regression of effect size on class size, plotted for the small class sizes of 1 to 20 (assuming a large class size of 38, which is the average large class size for all studies). The general regression equation is:

$$ES_{S\text{-}L} = \beta_0 + \beta_1 S + \beta_2 S^2 + \beta_3 (L - S) + \varepsilon$$

Looking at the left side of the graph, the top line represents the regression line for all the data, the middle line represents the regression line with the small classes of one student eliminated from the analysis, and the bottom line represents the regression with small classes of fewer than six pupils eliminated from the analysis. Empty circles and dotted lines depict projected information where data were eliminated (i.e., studies with small class sizes of 1-5 removed). When the unrealistically small classes are removed, the predicted effect size dramatically decreases. The predicted effect size for a class of one student drops from approximately .58 to .21, from what one, using Cohen (1977), might call a drop from a medium to a small effect size. When the small class consists of about 20 students, the effect size is about .05. If the average of a class of 38 were considered to fall at the 50 percentile, a class of 20 would fall at the 52nd percentile (which is the percentile rank of a z-score of .05).

The fact that class sizes for five or fewer students are virtually impossible for the vast majority of school districts is underscored by the tenor of the major longitudinal research study conducted in and partially funded by the state of Tennessee. The researchers conducting this study, Whittington, Bain and Achilles (1985) state that

> ...class size studies have often investigated the wrong sizes, studying reductions from 36 to 25 pupils are various grade levels. Perhaps the real payoffs are achieved by reducing class size significantly — to 15 pupils per classroom teach in the primary grades. (p. 33)

This rigorously conducted, three-year study followed students from kindergarten, compared achievement in classes of 15 and 25 students and found significantly higher achievements in the smaller classes (Bain, Achilles, & Witherspoon-Parks, 1988). However, those smaller classes were much larger than many included in Glass and Smith's meta-analysis, and it is the effect sizes from these extremely small classes that drastically inflate the mean effect size they report.

In conclusion, the increased achievement that Glass and Smith attributed to small classes may be substantially less than claimed after deleting the effect sizes based on atypically small classes of one to five students. However, other positive by-products of small but feasible class sizes may still be found.

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Prediction of Academic Success in Computer Programming and Systems Design Course Work

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ABSTRACT

The study investigated the ability of 17 intuitively selected cognitive and affective variables to differentiate between the academically successful and unsuccessful subject in regard to computer programming and system design course performance. Furthermore, the ability of Computer Programmers Aptitude Battery (CPAB) to predict academic success in programming and systems design was explored. The analysis, which employed factor analysis, stepwise regression and MANOVA, revealed that two variables--recognition of assumptions and diagramming --differentiated between the successful and unsuccessful system design students, whereas three variables--diagramming, test anxiety-worry and embedded figures ability--differentiated between the successful and unsuccessful programming student. The results suggested that the CPAB is a predictor of academic performance in programming and systems design. However, the factors identified herein as good differentiators not contained in the CPAB may merit consideration in the development of future standardized computer programming/systems design aptitude tests.

Note: This article is based on a paper originally presented at the first Data Con Educator Conference, St. Louis, MO, September 24, 1985.

INTRODUCTION

With accelerating usage of computers in both educational and business environments, providing effective instruction to potential data processing users is increasingly important. Unfortunately, not everyone may be suited to perform some of the high level tasks associated with the upper strata professional job titles within the computer science industry. Therefore, the ability to predict success in data processing training based on a number of cognitive and affective abilities could be helpful in screening potential applicants for computer science academic programs.

However, much of the research to date focuses upon prediction of achievement only in programming classwork (Burns, 1973; Williams, 1976; McLaughlin, 1981; Irons, 1982). Thus, systems analysis, an area critical to the provision of efficient computer systems is often overlooked from a measurement standpoint. This may be due to the fact that systems analysis is often viewed as an extension of programming since historically people filling systems design positions began their careers as programmers.

Furthermore, in regard to skills required in these job titles there appears to be a certain degree of differentiation. The programmer often works on a specific program that makes up only a small portion of the entire system, whereas the system analyst must have a more global orientation in that he/she must design a system that will be made up of a multiple programs that interact with each other. This trend of giving priority to prediction of success in programming has appeared in the business environment as well. For example, one of the more widely used standardized instruments in the prediction of vocational success in data processing, the Computer Programmers Aptitude Battery (Palormo, 1974), presents adequate technical data in regard to prediction of success in the field of programming. However, since this instrument has been validated as a predictor of programming potential primarily in a business environment, its relative predictive power in an academic environment has not been totally established. In addition, the test battery assumes an overlap between the skills required for systems analysis and programming, meaning that the instrument's ability to predict success in systems analysis requires further validation.

Therefore, the present study was designed to validate empirically which of a number of intuitively selected cognitive and affective abilities are required for success in second year academic computer programming and system analysis courses. More specifically, an attempt was made to determine the relationship between and among cognitive and affective variables required for achievement in both a computer programming course (Advanced COBOL) and a systems analysis course (Advanced Systems Analysis and Design). Furthermore, an attempt was made to ascertain the ability of the Computer Programmers Aptitude Battery to predict academic success in computer programming and systems analysis.

Procedure

In the summer of 1984 a meeting of instructors in a data processing program revealed that the high achievers in the systems analysis courses were not necessarily the same students that performed well in the programming courses. To analyze the cause of this situation properly a two-prong approach was used in selecting variables for the study. First, some of the instructors felt that differences in achievement were due to factors in the cognitive domain, particularly those abilities associated with the analysis and synthesis levels. Second, some of the committee suggested the differences might be related to affective considerations, especially in regard to anxiety resulting from course expectations. The major class requirement that was contained in the system design classes and not in the programming courses was a written document that suggested a solution to a given system design case study. This report was to be compiled over the entire semester and was weighted 25% in regard to final semester grade determination.

The instructors then reviewed a list of both cognitive and affective

variables that had proved pertinent in previous research designed to select items related to success in academic computer science related courses. From this list the group of instructors selected a number of both cognitive and affective factors that they felt might clarify the differences observed between programming and system design performance. The success that Beleutz, 1975 had in the validation of cognitive style as a predictor of success in mastering computer programming led to the inclusion of cognitive style. To ascertain differences in cognitive style the Group Embedded Figures Test (GEFT) (Witkin, Oltman, Raskin and Karp, 1971) was employed due to its ease of administration and adequate reliability and validity data. The work of Hunt and Randhawa, 1973 that ascertained a relationship between some of the subtest of the Watson Glaser Critical Thinking Appraisal (WGCTA) and performance in an academic computer science training situation prompted the group to include all five subtests of the WGCTA (Watson and Glaser, 1980). In addition to these cognitive factors, the Computer Programmers Aptitude Battery (CPAB) (Palormo, 1974) was included to ascertain its validity in predicting success in academic computer programming and systems analysis courses. Lastly, a number of members in the group felt that creativity was a variable that should be added since systems analysis often requires the generation and evaluation of several alternate designs before an effective solution can be reached. Thus, the Test of Creative Potential (TCP) (Hoepfner and Hemenway, 1973) was used to determine the relative degree of creativity within the sample of subjects.

Regarding affective factors the committee discerned that a high level of persistence is required on the job as well as the ability to reach a high level of technical achievement, both characteristics associated with an individual that displays a task-orientation. Therefore, the task-orientation scale of the Orientation Inventory (ORI) (Bass, 1977) was brought into the study. Furthermore, the instructors voiced a concern regarding anxiety interfering with individual performance in evaluative situations in both the programming and systems analysis academic environments. To ascertain the degree of this anxiety the results of the Test Anxiety Inventory (TAI) (Spielberger, 1980) were added to the data analyzed. The final affective factor included by the group was attitude toward systems design. Several instructors stated that rumors circulating on campus concerning the difficulty and workload of the course may have predisposed certain students to enter the class with a bit of apprehension that may have affected their performance. A Scale To Measure Attitude Toward Any School Subject (SMATSS) (Remmers, 1960) was employed to measure attitude toward systems analysis.

The selected instruments were given, one instrument a week, starting with the second week of the semester. The order of administration was
(1) SMASS, (2) ORI, (3) TAI, (4) GEFT, (5) TCP, (6) WGCTA, and (7) CPAB. By employing this strategy it was hoped that reliability would be enhanced since the maximum testing period was limited to the longest of the instruments, reducing subject fatigue. Furthermore, this situation allowed only one test to be administered per class period which limited the possibility of contamination occurring as a result of interaction between the material contained on the instruments.

<u>Sample</u>

The subjects were 106 students enrolled in one of three sections of Systems Analysis and Design II (DP 242) at St. Louis Community College at Maramec, Kirkwood, Missouri. Enrollees in this class are typically near completion of an Associates in Applied Science in Data

Processing or a Certificate of Proficiency in Data Processing. The composition of the sample was 45 male and 61 female. The average age was 28.5.

Analysis

The raw scores for all the standardized instruments and the final course grades in both Systems Analysis and Design II and COBOL II programming were obtained. In addition, the project grade assigned to the students in Systems II was included. This addition brought to 19 the number of variables utilized in the study. Descriptive statistics using the entire sample as a data base were generated. The intercorrelational matrix computed by the Pearson product-moment procedure containing 19 variables was further analyzed using the common factor model (Nie, Hull, Jenkins, Steinbrenner, and Bent, 1975; Gorsuch, 1974). After eigenvalues for the reduced correlation were calculated, a criteria of an eigenvalue > 1 was set for inclusion. Next the main diagonal of the correlation matrix was replaced with commonality estimates. These estimates were ascertained as a result of the multiple correlations obtained for each variable. Thus the factors were extracted from the reduced correlation matrix and the respective amounts of variance accounted for by these factors were replaced in the matrix as the current estimates of commonality. It took six iterations to reach the model's maximum allowable absolute difference between successive commonality estimates, which was a value less than .001. Five factors were extracted using the SPSS routine for principal component factor analysis. Then each structure was rotated to obtain a normalized varimax solution (Nie, Hull, Jenkins, Steinbrenner and Bent, 1975). Loadings that contained values equal to or exceeding .30 were considered significant.

Two different stepwise regression equations were formulated employing all variables in the study as predictors except the two course final grades which were used as criteria. The first analysis was designed to ascertain which variables could be considered predictors of academic performance in programming course-work while the second computation was devised to determine the potential predictive variables in a formula employing academic performance in systems analysis as the criterion. The probability of F-to-enter (PIN) for both of these equations was set at .1. The results of the step-wise regression analyses identified five potential predictors of academic performance in computer programming and two predictors of academic success in systems design.

One of the charges of the present study was to identify cognitive and affective abilities displayed by the successful and unsuccessful students regarding their achievement in two distinctly different types of data processing courses. To meet this charge two different analyses were undertaken to validate the predictors obtained from the regression analysis. First, the subjects were divided into two groups based upon the final grade they received in COBOL programming. Those students with a B or above were considered the high group (PHI). Subjects that received a C or below were deemed the low group achievement group in regard to programming (PLO). A one-way multivariate analysis of variance (MANOVA) was then performed on the five variables selected by step-wise regression. The second leg of the analysis was similar in structure except the grouping was based upon the final grade the subjects obtained in the Advanced Systems Analysis and Design course. Students who received an A or B in systems were classified high (SHI), while a subject receiving a grade of C or less were characterized as low (SLO). A one-way MANOVA was then applied to the two variables identified by the regression equation to be predictors of achievement in systems design. The MANOVA technique was utilized due to its ability to allow the researcher to view differences among groups of subjects on several variables simultaneously (Jones, 1966). In this case an analysis involving five variables was possible on the programming split, while two variables were analyzed in relation to the system design groups.

RESULTS AND DISCUSSION

The results of the descriptive statistic analysis and intercorrelation matrix are presented in Table 1. Factor analysis using the principal components method was undertaken utilizing the intercorrelation matrix as the data source. On examination of the results the varimax rotation procedure was employed. The varimax rotated factor matrix is included in Table 2.

Outcome for Factor I - General Knowledge

As can be seen from Table 2, eight variables had loadings greater than .30 on Factor I. Four of these items in the form of the subtests inference, deduction, interpretation, and evaluation of arguments came from the WGCTA. In light of the fact that the WGCTA has been found to correlate with general intelligence (Watson and Glaser, 1980) it would seem prudent to have portions of WGCTA included as a portion of this factor. In addition, three of the subtests of CPAB were represented in Factor I. Those measures were verbal meaning, reasoning and number ability. The correlations obtained between these subtests and the Thurstone Test of Mental Alertness (TMA) (Palormo, 1974) would seem to support their addition to the general knowledge factor. Given the acceptance of the supposition that the TMA is actually a test of verbal and mathematical abilities (North, 1972), the correlations (.74 between the TMA and verbal ability, .78 between the TMA and reasoning, .66 between the TMA and number ability) support the inclusion of these abilities in Factor I. The final variable that loaded within the general knowledge factor was the TCP score. Although the TCP loaded higher on Factor II, its inclusion in the factor might be explained by the fact that two of its three subtests use a structure that may be based on one's general knowledge. For example, the writing words exercise requires the subject to generate as many synonyms as he/she can for a given word. Certainly a strong verbal individual would have a broader base from which to proceed than a person with weak verbal skills. The License Plate Words subtest may also relate to verbal ability since the subject is expected to develop words using the letters appearing in the license number and use them in a given sequence.

Outcome for Factor II - Analytic Ability

Five variables loaded within Factor II and in regard to commonality among these variables the ability to disembed material was required. The first variable, the GEFT, measures the degree of field dependence/
independence displayed by a subject. This cognitive style construct has loaded in factor-analytic studies with the analytical factor of the Wechsler intelligence tests (Goodenought and Karp 1961; Karp, 1963). The placement of the GEFT within the analytic factor in this study would be consistent with this prior research. The letter series subtest from the CPAB was the second variable that loaded on Factor II. In this test one series of letters with an embedded pattern is presented to the subject to serve as the criterion. The subject must then analyze the letters and determine the next letter that would occur in the pattern. Therefore, the abilities needed for success in this test would fit into the mold set by the analytic ability factor. Diagramming, also a subtest of CPAB, was the third variable to load on Factor II. Since this test is designed to examine the participants analytical ability to effect a solution to a problem presented in flow chart form in regard to logical sequence of steps, it would seem appropriate for this variable to be included in Factor II. The TCP appeared again as the fourth loading in Factor II. Perhaps it is the test structure that places this variable in Factor II. The License Plate Words subtest, for example, would

require an analysis of letter patterns. In this analytical task, the license number would serve as the embedded portion to a number of surrounding fields; those surrounding fields, of course, would be all the words the subject could devise. Therefore, the presence of the TCP in Factor II can be explained if the assumption regarding the test's structure, which appears to route its placement outside of a single creative factor, is accepted. The last variable to load on Factor II was the course grade in COBOL programming. Being able to write programs from scratch based upon several paragraphs of specifications would undoubtedly require analytical skills. Furthermore, the debugging of these programs after their development would involve a high degree of disembedding skills, since a very minute hidden detail within the program can cause an execution failure.

Outcome for Factor III - Academic Success

Three variables loaded on Factor III; all were either a course grade or a project grade assigned to the subjects by their respective professors in programming and systems design. In one respect this factor might be an indication of the subject's ability to function in an academic environment. However, both courses require a substantial workload either through design projects or programs. Furthermore, there is no set temporal pattern regarding completion of the activities in either course. Both types of activities require persistence on the part of the students to make sure that they complete the assignments and complete them correctly. For example, a program written in COBOL may not execute properly on the first, second, or even the third try. In fact, it may take several more analysis, correction, and resubmission cycles before the desired results are obtained. Therefore, an underlying component of the academic success factor may be persistence.

Outcome for Factor IV - Test Anxiety

Within the fourth factor, loadings occurred on three variables. The two variables that displayed the strongest loadings were the two subtests contained in the TAI. The third variable identified in the anxiety factor was the interpretation subtest from the WGCTA. This same variable loaded at .530 on Factor I, meaning that its loading on Factor IV of .307 might be considered to be of secondary importance to its contribution to the general knowledge factor. Therefore, its appearance, although not expected of a variable generally considered to be related to knowledge, may not be totally inconsistent with relationships observed between TAI subscales and instruments that are dependent on reading comprehension. For example, the correlation presented in the TAI manual between the Nelson-Denny (ND) comprehension subtest and TAI total score for males was -.20 and -.25 for females (Spielberger, 1980).

Outcome for Factor V - Prior Experience

An interesting combination of three variables was obtained from the loadings of Factor V. The highest loading occurred on attitude toward system design, while lesser loadings were recorded for the recognition of assumptions and deduction subtests for the WGCTA. In the case of the deduction appraisal, the loading obtained in Factor V was secondary in magnitude to its loading on the general knowledge factor. However, recognition of assumptions loaded only on Factor V. Although the relationship among deduction, recognition of assumptions and attitude toward systems design cannot be explained with the clarity of some of the other factors obtained in the present study, perhaps there is some relationship among the variables due to the subject's prior experiences. Interestingly, a negative relationship was obtained between recognition of assumptions and attitude toward systems design. It may be that in this study the subject's attitude, if negative or suspicious of new experiences, influenced his/her performance on other variables contained in Factor V. The fact that attitude loaded negatively on the other variables in this factor would tend to support this assertion. However, similar negative relationships have been found in other studies (Defleur, and Westie, 1958). Perhaps this negative relationship is due to a lack of direct relevant experiences. According to Regan and Fazio, 1976, direct experience is a crucial factor in the development of an attitude which is consistent with behavior. In the case of the two variables that loaded only on Factor V, prior direct experience could influence the magnitude of the scores obtained.

However, to prove or disprove this assertion, additional research needs to be undertaken to ascertain whether lack of direct experience in system design related functions is responsible for the negative relationship obtained between recognition of assumptions and attitude toward system design. It could be hypothesized that applying the same measure of attitude to the subjects after completion of the course would yield a more favorable attitude score if, in fact, the course provides direct relevant experiences. Furthermore, if direct experiences related to the development of assumption recognition skills were provided to the subjects, it could be hypothesized that the subject's scores would increase as well. How developing a positive attitude toward system design would influence performance in recognition of assumptions is a question that will have to be answered by further research. Whether a lack of related direct experiences in systems design inhibits one's ability to recognize assumptions would be the critical question to be studied in further research in this area.

Regression Analysis

With the relationship among the various cognitive and affective variables by means of factor analytic methods complete, the next phase of the investigation was carried out using regression analysis on the 19 cognitive and affective variables recorded. Two separate analyses were carried out. The first employed final grade in systems design as the criterion and all but one (final grade in COBOL) of the remaining 18 variables as predictors, while the second equation used final grade in COBOL programming as the criterion and the remainder of the 18 variables minus final grade in systems design as the predictors.

The results of the stepwise regression analysis in which systems design performance was the criterion yielded two predictor which combined to account for 16.8 percent of the variance. Of the two predictors, diagramming accounted for 12.2 percent of the variance while the remaining portion of the 16.8 percent was attributed to recognition of assumptions. In the other analysis, which employed COBOL programming performance as the criterion, five variables were included in the equation before the PIN = 0.100 limit was reached. The variable that made the major contribution regarding variance accounted for was diagramming. This variable, by itself, accounted for 21.0 percent of the variance. In a somewhat surprising development, attitude toward systems design was the second variable selected as a predictor for the equation. This variable, when coupled with diagramming, accounted for 24.4 percent of the variance. The next two variables added to the formula were the two TAI subscales, worry and emotion. Their addition increased the accumulative variance accounted for to 31.5 percent. The final predictor included in the equation was the GEFT score. Its inclusion raised the total accumulative variance explained to 34.0 percent.

The fact that diagramming was picked as the main predictor in each of the equations would tend to indicate that there is some overlap of skills required for success in the two disciplines. Furthermore, it seems logical to expect that the major predictor in each analysis would come from the analytic ability factor. A second variable (GEFT) from this factor appeared in the programming performance analysis reinforcing the importance of factor analytic ability. In all 23.5 percent of the variance was explained by variables that loaded on Factor II in the programming performance prediction equation. Variables from Factor V appeared as predictors in both equations. Recognition of assumptions was selected as a predictor in the formula that employed systems design performance as the criterion. While attitude toward systems design appeared as a predictor of COBOL programming performance in the other analysis.

The other factor represented in the regression analyses was the anxiety factor. Variables that loaded on this factor were included only in the equation employing programming performance as the criterion. In this step-wise regression equation both subscales from the TAI were identified as predictors.

Validation of Predictors (HI-LO) MANOVA

The two potential predictors of academic achievement in systems design having been determined, the answer of whether the abilities identified did indeed differentiate between the successful and unsuccessful systems design student was sought. Table 3 presents the means and standard deviations for the SHI-SLO groups in systems design regarding performance on the predictors diagramming and recognition of assumptions. In terms of magnitude, the SHI group mean exceeded the SLO group mean on both predictors. However, to strengthen the analysis, a MANOVA was performed on both predictors to ascertain if there was any significant difference between the SHI-SLO groups on either predictor. The average F-test with ($F(2,208)=1807.20$ was significant well beyond the .05 level. Furthermore, the univariate F-test with 1 and 104 degrees of freedom revealed a value of 2420.00, $p < .05$ for recognition of assumptions and a magnitude of 1685.54, $p < .05$ for diagramming. Therefore, it would appear that diagramming and recognition of assumptions are not only good predictors of academic success in systems design, but also significantly differentiate between successful and non-successful students.

A similar strategy was used to analyze the ability of the predictors of COBOL programming performance to differentiate between successful and non-successful students. In this analysis the average F-test for the five variables identified as being predictors of success in COBOL programming was ($F(5,520) = 10.14$, $p < .05$. However, in this case there was not the clear difference in the magnitude of the means particularly in the variables: attitude toward systems design and TAI-emotion as is illustrated in Table 4. The results of the univariate F-tests confirmed that significant differences occurred on only three of the five predictors: GEFT score ($F(1,104)$, $p < .05$; TAI-worry ($F(1,104)$, $p < .05$; and diagramming ($F(1,104$, $p < .05$. The other two predictors: TAI-emotion ($F(1,104)$, $p > .05$ and attitude toward systems design ($F(1,104)$ $p > .05$ did not significantly differentiate between the PHI-PLO groups. In regard to diagramming and the GEFT the difference, which would be expected, was in favor of the PHI group. However, in the case of the TAI-worry, the scoring difference was in favor of the PLO group, which would indicate an inverse relationship between TAI-worry and COBOL programming performance.

Summary

In the empirical validation attempts to identify variables related to academic success in both COBOL programming and systems design, the original list of variables was significantly reduced after the MANOVA treatment. The variables found to be predictors of course performance in system design and differentiate between high and low achievers in regard to course grade were diagramming and recognition of assumptions, whereas the predictive variables that differentiated between high and low achievement in the COBOL course were diagramming, TAI-worry, and the GEFT. The results of these findings are mixed in regard to the validation of the CPAB as a predictor of academic achievement in data processing related courses. First, on the positive side the diagramming subtest of the CPAB was the major contributor in the prediction of success in both courses. However, variables from factors not included in the coverage of the CPAB were identified as part of the academic success formula. For example, recognition of assumptions was included from the prior experience factor, a factor which contained no loadings from CPAB variables. Furthermore, TAI-worry was a predictive variable that loaded on the anxiety factor, a second factor that did not include variables from the CPAB subtests. Therefore, based on the results of this study one could conclude that there are one or more important factors missing from the measurement ability of the CPAB in regard to the prediction of academic success in both programming and systems design courses. Whether or not the importance of the missing factors could be substantiated in regard to vocational success is a question for further research which would have to focus upon two questions. First, is there a difference in the ability of successful versus non-successful systems analysts to recognize assumptions? Second, is the anxiety worry level of successful programmers less than that of non-successful programmers? Obtaining the appropriate data sample to determine this information may be difficult, since only the people that complete company training programs in these respective areas are normally appointed to these positions. Therefore, the successful/non-successful split might be undertaken based on a subject's ability to successfully complete company training in programming or systems design.

Lastly, the results of the study suggest that a reduction in administration time, as compared with the total CPAB, could be realized if testing was limited to the variables selected as good differentiators. To measure potential in programming the administration time would drop to 63 minutes (diagramming = 35, TAI-worry = 8, GEFT = 20). Also, the time required for administration of a systems design oriented predictive instrument would be less than the whole CPAB> The time required to administer this instrument would be 45 minutes (diagramming = 35, recognition of assumption = 10). If an instrument was desired that would provide broader coverage, recognition of assumptions could be added to the academic programming prediction instrument, thereby, increasing its predictive potential in the area of systems design. The time required for this testing device would be 73 minutes (diagramming = 35, TAI-worry = 8, GEFT = 20, recognition of assumptions = 10). However, the testing time requirements for this comprehensive evaluation exercise would be in the same range as the total CPAB. This development would mean that this comprehensive evaluation exercise would be in the same range as the total CPAB. This development would mean that reduction of administration time could be realized only on the two specific suggested measurement devices, programming and systems design. Therefore, the advantage of the comprehensive instrument would be that an increase in breath of coverage could be obtained while maintainingan administration time in the seventy minute range.

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Table 1

Means, Standard Deviations, and Intercorrelation Matrix Among 19 Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
GEFT	1.00	.04	-.22	-.22	.24	.23	.31	.25	.23	.31	.30	.26	.18	.44	.21	.00	.17	-.19	.29
ORI-Task	.04	1.00	-.16	-.04	.10	.04	.15	.14	.22	.23	.18	.13	.15	.18	.09	.03	.14	.00	.19
TAI-Worry	-.22	-.16	1.00	.76	-.40	-.30	-.33	-.46	-.31	-.41	-.30	-.29	-.22	-.38	-.33	.02	-.19	.14	-.33
TAI-Emotion	-.22	-.04	.76	1.00	-.29	-.11	-.20	-.32	-.17	-.31	-.18	-.11	-.11	-.17	-.15	.15	.02	.09	-.09
WGCTA-Inference	.24	.10	-.40	-.29	1.00	.31	.47	.45	.38	.49	.51	.28	.17	.34	.28	.01	.21	-.03	.24
WGCTA Recognition of Assumptions	.23	.04	-.30	-.11	.31	1.00	.36	.32	.28	.29	.33	.19	.00	.26	.15	.13	.29	-.14	.22
WGCTA-Deduction	.31	.15	-.33	-.20	.47	.36	1.00	.36	.48	.46	.41	.20	.35	.34	.27	.02	.21	-.21	.28
WGCTA-Interpretation	.25	.14	-.46	-.32	.45	.32	.36	1.00	.31	.53	.44	.21	.23	.30	.37	-.02	.14	-.16	.12
WGCTA-Evaluation of Arguments	.23	.22	-.31	-.17	.38	.28	.48	.31	1.00	.40	.37	.31	.26	.34	.25	.02	.13	-.13	.20
CPAB-Verbal Meaning	.31	.23	-.41	-.31	.49	.29	.46	.53	.40	1.00	.53	.19	.40	.28	.43	.10	.24	-.02	.19
CPAB-Reasoning	.30	.18	-.30	-.18	.51	.33	.41	.44	.37	.53	1.00	.45	.54	.42	.29	.12	.19	-.09	.17
CPAB-Letter Series	.26	.13	-.29	-.11	.28	.19	.20	.21	.31	.19	.45	1.00	.33	.55	.46	.04	.23	-.11	.34
CPAB-Number Ability	.18	.15	-.22	-.11	.17	.00	.35	.23	.26	.40	.54	.33	1.00	.24	.26	.11	.21	.04	.19
CPAB-Diagramming	.44	.18	-.38	-.17	.34	.26	.34	.30	.34	.28	.42	.55	.24	1.00	.38	.19	.35	-.07	.45
TCP	.21	.09	-.33	-.15	.28	.15	.27	.37	.25	.43	.29	.46	.26	.38	1.00	.00	.28	.11	.35
System Design Project Grade	.00	.03	.02	.15	.01	.13	.02	-.02	.02	.10	.12	.04	.11	.19	.00	1.00	.71	-.02	.28
Final Grade Systems Design	.17	.14	-.19	.02	.21	.29	.21	.14	.13	.24	.19	.23	.21	.35	.28	.71	1.00	.06	.63
Attitude Toward Systems Design	-.19	.00	.14	.09	-.03	-.14	-.21	-.16	-.13	-.02	-.09	-.11	.04	-.07	.11	-.02	.06	1.00	.15
Final Grade COBOL Programming	.29	.19	-.33	-.09	.24	.22	.28	.12	.20	.19	.17	.34	.19	.45	.35	.28	.63	.15	1.00
MEAN	14.1	32.9	13.5	15.3	9.4	12.9	11.3	12.8	12.2	16.6	9.5	13.5	12.5	24.3	63.7	153.1	2.6	7.8	2.9
dard Deviation	4.3	6.1	5.0	5.3	2.7	2.8	2.4	2.3	2.4	6.1	4.3	4.4	5.0	6.5	19.2	39.5	1.0	0.8	1.1

Table 2

Varimax Rotated Factor Solution
For 19 Variables*

Variables	I	II	III	IV	V	Estimated Commonality: Principal Components	Estimated Commonality: Interactive
T		.334				.34	.26
-Task						.14	.07
-Worry				-.839		.74	.86
-Emotion				-.795		.66	.68
TA-Inference	.525					.48	.42
TA-Recognition of Assumptions					.420	.36	.32
TA-Deduction	.529				.363	.48	.46
TA-Interpretation	.530			.307		.44	.43
TA-Evaluation of Arguments	.452					.34	.34
B-Verbal Meaning	.781					.57	.68
B-Reasoning	.693					.61	.59
B-Letter Series		.710				.50	.57
B-Number Ability	.542					.47	.37
B-Diagramming		.644				.52	.61
	.387	.435				.45	.40
tem Design Project Grade			.717			.63	.53
al Grade Systems Design			.951			.75	.97
itude Toward Systems Design					-.511	.27	.26
al Grade Cobol Programming		.482	.520			.58	.55

adings Less than .30 have been omitted

Table 3

Means and Standard Deviations for the SHI and SLO System Design Groups

Variable	Mean		SD	
	SHI(N=65)	SLO(N=41)	SHI	SLO
Diagramming	26.2	21.2	5.7	6.5
Recognition of Assumptions	13.5	11.9	2.4	3.0

Table 4

Means and Standard Deviations for the
PHI and PLO COBOL Programming Groups

Variable	Mean PHI(N=79)	Mean PLO(N=27)	SD PHI	SD PLO
Diagramming	25.7	19.9	5.7	6.8
Attitude Toward System Design	7.9	7.7	0.7	1.0
TAI - Worry	12.8	15.8	4.4	6.0
TAI - Emotion	15.1	15.7	5.0	6.3
GEFT	14.9	11.7	3.7	4.9

Occupational Stress among Physicians: Some Coping Mechanisms

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Abstract

Impairment among physicians due to high stress levels has been documented in the past, but little research has been conducted concerning the coping mechanisms physicians use to reduce their stress level. The present study analyzed responses from 377 physicians across the country to determine what methods were most effective. It is concluded that prediction of stress level on the basis of employment of 15 coping mechanisms is not possible, but that physicians with lower stress levels use 6 of the methods more than their high stress counterparts. Other demographic differences are also analyzed, and implications for the training of medical students are discussed.

OCCUPATIONAL STRESS AMONG PHYSICIANS: SOME COPING MECHANISMS

Counselors and counseling psychologists are becoming increasingly aware of occupational stress among professionals, including physicians. Pfifferling (1980) indicates that the modern profession is intensely concerned with problems of impaired physicians, many of whom are under severe pressure and suffer from a number of stress-related disorders as they attempt to reconcile the often heroic image of physicians with their individual deficiencies. The pressures that come as a result of heavy workloads, complex schedules, coping with difficult clients, maintaining currency in the profession, and preserving a satisfactory personal life increase the probability that physicians will continue to be prime victims of stress-related disorders (McCue, 1982).

Selye (1976) concluded that medical interns in many U.S. hospitals endanger both their performance and their health as a result of excessive stress. He noted that radio-telemetric observations on both medical students and physicians, taken while the subjects were performing stressful tasks, almost always revealed tachycardia, which roughly paralleled urinary catecholamine excretion.

Krakowski (1982) noted that most studies of physicians reveal a greater incidence of affective disorders, suicide, divorce, and alcohol and other drug dependence, than for the general public. Numerous authors offer support for this statement (deSole, Singer &

Arons, 1969; Sargent, Tensen, Petty & Raskin, 1977; Vaillant, Brington & McArthur, 1970; Williams, 1980). Relatedly, Selye (1974) commented that the incidence of coronary artery disease is correlated with stress, and suggested that the high percentage of A type personalities among physicians may be responsible.

Reasons for the high level of stress among physicians, as well as the nature of that stress, are varied. Numerous researchers have assessed causal factors and how such factors turn into emotional problems (Bates, 1982; Krakowski, 1982; London, 1981).

The present research, however, focuses on how physicians cope with stress. The authors believe that individuals do have the capacity to deal effectively with stress. Research on this topic has been much more limited, and is more related to conjecture or open-ended questions than to empirical methods. Marmor (1953) suggested contact with colleagues and members of other professions could be useful measures to alleviate stress. Bellak (1974) mentioned physical activity and mixing the caseload as coping mechanisms. Guggenbuhl-Craig (1971) added the need for cultural activities. London (1981) found family, hobbies, and religion to be three additional stress relievers that some physicians find helpful.

Unfortunately, none of these studies deals exclusively with physicians, thus raising the possibility that physicians may employ different coping mechanisms, or employ similar mechanisms with different frequencies. The purpose of the present study is to look at how physicians cope with stress, and to attempt to differentiate between those reporting high stress and those believing they have low stress, on the basis of their use of various coping mechanisms. Through these results, it is hoped that counselors and medical educators can suggest coping techniques to their students and encourage the use of such techniques in the attempt to deal positively with stress.

Procedure

A total of 1,000 physicians was randomly selected from across the United States via an APA listing and sent a one-page questionnaire asking them to rate their use of 15 coping mechanisms on scales of 1 to 4. In addition, they were asked to rate how stressful they perceived the practice of medicine to be on a scale of 1 to 10, what their specialty was, and what type of practice (e.g. office, hospital, research, etc.) they maintained.

After follow-up procedures, there were 377 usable replies to the questionnaire. The resulting data were analyzed by multiple regression and multivariate analysis of variance (MANOVA) to look for differences in the use of coping mechanisms among those with high versus low self-reported stress.

Results

A forward stepwise multiple regression was used to determine how much overall stress level could be accounted for by the 15 coping mechanisms. The optimum equation yielded an R^2 of .119, indicating that overall stress level cannot be adequately predicted by the extent to which physicians use the 15 coping strategies. As a group, the 377 physicians reported a mean overall stress level of 5.92, with a standard deviation of 2.15.

A reviewer of a previous version of this article suggested that a matrix be obtained of the correlation of the items with each other, and that negatively correlated items be eliminated on the grounds that they do not measure the coping concept. When this was done, there were only two negative correlations, and it was believed that the advantages of re-analyzing the data were not enough to justify disruption of the integrity of the questionnaire. Cronbach's alpha was .74, giving further indication that the measure is reasonably internally consistent.

The physicians were put into two groups based on a median split of their overall stress level. A one-way MANOVA (Stress Level) using all 15 questions as dependent variables was performed to determine what coping mechanisms low stress physicians employ that their high stress colleagues do not. The overall MANOVA was significant (T^2 = .12, $p < .001$), allowing subsequent analyses of the univariate cases, a procedure seen as viable by Tabachnick and Fidell (1983), among others. The risk of an inflated Type I error rate does exist, encouraging caution in interpretation. Lower-stressed physicians engaged in six coping strategies more than higher-stressed doctors, as indicated in Table 1.

Table 1

Means, Standard Deviations, and Differences in High Versus Low Stressed Physicians for 15 Coping Mechanisms

	Item	$\bar{X}$	SD
1.	I cultivate non-medical interests.	3.10	.75
*2.	I distribute my workload evenly in terms of time.	2.67	.73
3.	I set realistic goals for myself.	2.89	.67
*4.	I derive professional satisfaction from my medical specialty.	3.36	.58
5.	I share coverage of my patients with other physicians.	3.16	.89
6.	I take frequent vacations.	2.41	.84
7.	I develop my professional competence.	3.41	.60
8.	I maintain effective communication and good rapport with other physicians.	3.36	.58
*9.	I distinguish my personal responsibilities from my professional responsibilities.	3.28	.66
*10.	I engage in physical exercise.	2.83	.87
11.	My office staff is effective with patients.	3.24	.56
12.	I give my patients educational information about their medical conditions.	3.12	.80
*13.	I receive adequate rest and relaxation.	2.66	.71
14.	I strive to develop a strong family life.	3.34	.66
*15.	I maintain a sense of humor.	3.24	.60

*statistically significant ($p \leq .05$)

Males and females did not differ in overall stress level t = .57, NS), or in their responses to the 15 questions (T^2 = .05, NS). It should be noted, however, that only 28 subjects identified themselves as female.

No differences were found when looking at the geographic region in which the physicians practice. This was true both for the stress level (F = .26, NS) and for their employment of the coping mechanisms (T^2 = .22, NS).

Different specialties did not differ in their overall stress level (F = 1.78, NS), but a significant MANOVA (Specialty) allowed analysis of the 15 coping questions. The only significant difference was in the amount a physician shares patient coverage with other physicians, and a Newman-Keuls post-hoc test showed that psychiatrists utilize this mechanism less than seven other specialties. This seems to be due less to any intrinsic characteristics of psychiatrists than to the nature of their practice.

Physicians were asked whether their practice was private, hospital based, a combination of private and hospital work, administrative, teaching and research, or other. There were no significant differences in the overall stress level of practitioners in different types of practices (F = 2.19, p < .055). Because of the closeness to significance of this statistic, however, it can be noted that those combining hospital work and a private practice had the highest level of stress, and those in administration the lowest. A

MANOVA looking for differences in the use of coping mechanisms among those with different types of practice was significant (T^2 = .34, $p < .01$), and subsequent analyses and Newman-Keuls' post-hoc tests showed that physicians combining a hospital and private practice felt that they maintained communication and rapport with other physicians more than did doctors working either in a hospital or in a private practice. It also showed that private practitioners reportedly give their patients more educational information than those combining private practices and hospital work.

Discussion

On a scale of 1 to 10, where 1 represented a value of not stressful and 10 was labeled extremely stressful, the national group of physicians reported a mean stress level of just more than the median value possible. This result indicates that physicians do believe that the practice of medicine is stressful, and corroborates the finding of Walton, Walton and Zook (1986). Following this finding, which held true for all specialties, types of practice, regions of the country, and sexes, the present study attempted to find what coping mechanisms physicians found useful in the reduction of stress.

An attempt to predict stress level by the rate of use of 15 coping mechanisms accounted for less than 12% of the total variance. This supports the authors' supposition that coping mechanisms are an individual attribute. A method or combination of methods that helps alleviate stress in one physician may be ineffective for a second doctor. Each physician must find the factors that seem to alleviate stress most effectively for him or her.

It is possible, however, to determine if those with a lower stress level use the coping mechanisms to a different extent than those reporting more stress. In other words, it is relevant to determine if some coping mechanisms are more related to stress level than are others.

The lower stress group used six coping mechanisms more than did their more stressed counterparts. First, they engage in more physical exercise. In light of the recent exercise emphasis and reports of its healthiness, this is not surprising. At the same time, physicians reporting lower stress stated that they received more rest and relaxation. The ability to relax is apparently important, and is corroborated by the finding that they also take pains to distinguish their personal lives from their professional responsibilities. Also related is the finding that those with lower stress report that they distribute their workloads evenly in terms of time more frequently than their more stressed colleagues. All of those suggest that lower stressed physicians recognize their limits, and know when to disengage themselves.

The fifth significant factor is satisfaction with medical specialty. It appears as if those who had the foresight or good fortune to select a specialty with which they would be satisfied, or who have adjusted their cognitions to ensure satisfaction, have less total stress. It is important, then, for medical students to choose carefully what specialty they will enter.

Finally, physicians who believe they maintain more of a sense of humor report lower stress levels. This coping mechanism was not expected to be one of the most effective methods, but was highly significant.

The finding that no differences are present for geographic location or gender, either in stress level or in employment of the coping mechanisms, suggests that the data has external validity. The same finding was true for the specialty factor, with the exception that psychiatrists were less likely to share patient coverage than seven other specialties. Because of the especially sensitive nature of doctor-patient relationships in psychiatry, as well as ethical and legal considerations, this is an expected finding.

Physicians who combined hospital work and a private practice had a higher stress level than other specialties, although this finding did not attain statistical significance. The present authors suggest that those physicians combining these practices may be overworking themselves, thus causing excessive stress. One thing that may help this dual practice bind from being even more stressful is that these doctors are reportedly more likely to maintain effective and good rapport with other physicians than those in either practice alone.

The other difference in the use of coping mechanisms by type of practice was that those in private practice were more likely to report that they give their patients more educational information than those combining a private practice with hospital work. Reasons for this finding are unclear.

The authors suggest that individuals who wish to help physicians or future physicians reduce their stress levels can use the present study as a guide. Suggesting coping mechanisms which the present study showed to be effectively employed by lower-stressed physicians will help doctors and medical students lower their stress level. The present authors suggest that a unit on stress and coping mechanisms be included in medical schools' curricula, possibly as part of a course on ethics or human behavior. If students can learn early how to deal with stress and gain knowledge of some coping mechanisms that seem to work, prognosis for their future stress level should be improved.

Several considerations should be kept in mind when using the information in this study. First, the authors used a self-report inventory, with neither the overall stress level nor the coping mechanisms reported by an external source, and neither was covertly obtained. Also, a finite number of coping methods was presented. It is likely that some physicians find other coping techniques more useful than those given. While most common methods were covered, others do exist.

Second, individual differences are relevant. While the findings reported here are true for physicians as a group, each doctor is a separate individual. He or she has interests, a background, and capabilities which may be different than physicians as a whole. Whenever possible, individual coping mechanisms should be used.

Thirdly, the return of usable questionnaires (37.7%), while considered good for physicians, does place limitation on the ability to generalize their results. Although the present findings are not definitive, they do provide a starting place which medical educators can use to help medical students reduce their level of professionally-related stress. The alternative, as noted in the literature review, may make itself evident with continued high levels of impairment among physicians.

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Multiple Linear Regression Viewpoints: An Index of Abstracts from 1986-1988

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Volume 14, No. 2

Lynch, R. M. (1986). Regression surfaces for suppression effects in multiple linear regression, Viewpoints, 14(1), 1-12.

In multiple linear regression suppression effects occur when the coefficient of determination is greater than the sum of zero order correlations squared. In this paper, regression surfaces which can give rise to classical, net and cooperative suppression are illustrated. Each case presented has the condition that a regression coefficient, b, has a sign contradictory to a zero-order correlation, r.

Houston, S. R., & Stutier, D. L. (1986). Comparable worth and salary allocation models: A proposed strategy using judgment analysis. Viewpoints, 14(2), 13-32.

Judgment analysis (JAN) was utilized as a technique for measuring comparable worth in a job description. Eighty hypothetical profiles were each generated on eight job factors or profile dimensions deemed essential for success. Seven administrators were requested to assign each potential applicant to a specific salary category. Each of the policies by the seven administrators serving as decision makers or judges was captured by multiple linear regression techniques. Results of the hierarchical grouping of captured policies suggested that three different policies were in operation. Strategies for setting a single policy as well as assigning appropriate salaries were proposed.

Ward, J. H., Roecks, A., Powell, G., & Dyas, F. (1986). Matching pupils and teachers to maximize expected outcomes. Viewpoints, 14(2), 33-50.

The purpose of this project was to demonstrate some procedures that can be used to supply information that can help match pupils to teachers to maximize learning outcomes. Use of the procedures will allow educators to estimate the potential effect of focusing on teacher-pupil match. The analysis will give an indication of the extent of teacher-pupil match effects; however, the results should be applied to new pupils to gain confidence in the results.

Thayer, J. D. (1986). Applications of multiple regression: Violations of assumptions. Viewpoints, 14(2), 51-56.

This paper presents the author's comments on three general issues raised by the following three papers:

McNeil, K. A., & Smith, G. (1985). Significant interaction: I got what I needed. Viewpoints, 14(1), 107-111.

Tracz, S. M., & Elmore, P. B. (1985). The effect of the violation of the assumption of independence when combining correlation coefficients in a meta-analysis. Viewpoints, 14(1), 61-80.

Brown, R. (1985). Multiple linear regression viewpoints: An index of abstracts from 1982-1985. Viewpoints, 14(2), 57-70.

The author presents abstracts of all articles published in Multiple Linear Regression Viewpoints 1982-1985, a publication of the special interest group on multiple linear regression of the American Educational Research Association.

Multiple Linear Regression Viewpoints:
An Index of Abstracts from 1986-1988

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The University of Akron

Volume 15, No. 1

Ward, J. H., & Sorenson, R. C. (1986). Catalytic variables for improving personnel classification and assignment. Viewpoints, 15(1), 1-36.

The authors contend that there is no interaction between people characteristics and jobs in the prediction of job performance, then it makes no different in overall system performance which people are assigned to which jobs. To increase interaction (and, therefore, differential assignment potential), it is usually necessary to add new variables to the operational variables in the prediction system. The addition of new variables can be costly, time consuming, and frequently controversial. The approach described herein suggests adding predictor variables in a noninteractive way to the operational (interacting) predictors to increase the possibility of more interaction between people and jobs. If these additional noninteractive variables can increase interaction, they are called catalytic variables. Catalytic variables (which enter the prediction system in an additive way) are not required for use in the assignment of people to jobs to maximize overall system performance.

Thayer, J. D. (1986). Testing different model building procedures using multiple regression. Viewpoints, 15(1), 37-52.

The author indicates that one of the most appealing aspects of multiple regression to beginning multiple regression students is the amazing feat performed by a stepwise regression computer program. The process of selecting the "best" combinations of predictors so effortlessly and efficiently creates an overwhelming urge to use this procedure and the computer program that accomplishes it for a multitude of tasks for which it is ill suited. The author identifies the strengths, dangers, and limitations of this process.

Morris, J. D. (1986). Microcomputer selection of a predictor weighting algorithm. Viewpoints, 15(1), 53-68.

An empirical method (PRESS) for examining and contrasting the cross-validated prediction accuracies of some popular algorithms for weighting predictor variables was advanced and examined. The weighting methods that were considered were ordinary least squares, ridge regression, regression on principal components, and regression on an equally weighted composite. PRESS was executed on several data sets having varied characteristics, with each of the weighting techniques obtaining the greatest accuracy under some conditions. The degree of advantage or disadvantage offered by these alternate weighting algorithms relative to ordinary least squares was considered. As it was not possible to determine a priori which weighting technique would be most accurate for a particular data set from theoretical knowledge or from simple sample data characteristics, the sample specific PRESS method was proffered as possibly most appropriate when the researcher wishes to select from among the several alternate predictor weighting algorithms in order to achieve maximum cross-validated prediction accuracy. The feasibility of the use of a microcomputer for the computation intensive PRESS algorithm was also considered.

Rogers, B. G. (1986). Discussion of AERA 1986 Session 21.25 applications of multiple linear regression. Viewpoints, 15(1), 69-74.

The author presents his critique of the session 21.25 AERA conference presentations by Joe Ward, Jerome Thayer, and John Morris on multiple linear regression applications.

Smith, G., McNeil, K., & Mitchell, N. (1986). Regression and model c for evaluation. Viewpoints, 15(1), 75-89.

This paper presents an overview of the symposium on regression and Model C for evaluation. The objectives of this symposium are to:

1. Provide a rationale for using regression analysis (specifically Model C) to evaluate educational programs.
2. Provide one example of an extensive Model C evaluation report.
3. Discuss assumptions of Model C and ways to deal with those assumptions.
4. Share examples of disseminating Model C results to decision makers.
5. Identify and resolve additional technical issues that evaluators need to be concerned about when implementing Model C.

Thayer, J. D. (1986). Using multiple regression with dichoto mous dependent variables. Viewpoints, 15(1), 9-98.

This paper concludes that tests of significance are identical whether the dichotomous variable is an independent variable or a dependent variable. It appears, therefore, that if the critics of using multiple regression with a dichotomous dependent variable are to be taken serious, they must also deal with all significance testing with t tests, analysis of variance, analysis of covariance, discriminant analysis, and any use of dummy variables in multiple regression. There may be other statistics reported in a multiple regression analysis, such as the standard error of estimate or predicted values for which the interpretations may not be appropriate when dichotomous dependent variables are used, but this paper did not deal with these issues.

Blumenfeld, G. J., Newman, I., Johnson, A., & Taylor, T. (1986). Relationship of student characteristics and achievement in a self-paced CMI application. Viewpoints, 15(1), 99-107.

Learner control of CBE applications has been an enticing topic of research. Reviews by Steinberg (1977) and Taylor (1976) indicate that effects upon achievement are equivocal when learner control has been compared with program or instructor control. The mixed results suggest the possibility of an interaction between certain aspects of instruction and characteristic of the learner, when the learner is permitted to control the program.

When trying to identify the relevant learning characteristics in a natural setting, the potential interactions and the types of relationships between variables are enormous. What may be needed to map out many of these possible relationships, develop a matrix, and systematically develop studies to investigate the relationship between these variables and learning. One may take a particular model such as suggested by McGuire (1960) and Whiteside (1964) which takes the position that when one is trying to account for complex behavior, one has to look at at least three classifications of behavior. One is the person variables which include things such as personality, intelligence, sex roles, learning characteristics, etc. The second is the characteristic of what is to be learned. Suppes (1966) and Gagne (1965) have given excellent examples of how to delineate the component of what is to be learned through a task or job analysis. The third is the environmental of context variables. These would include such things as the structure as well as the environment of the learning situation, interactions with peers, expectations produced by the environment (significant other within the environment). This three dimensional matrix may facilitate the identification and systematic investigation of the variables which may influence and/or "cause" the differential effectiveness of "learning" as reported in the literature.

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Volume 15, No. 2

Searls, D. T. (1987). Using diagnostics for identification of biased test items. Viewpoints, 15(2), 1-28.

This paper demonstrates how recent developments in the analysis of regression models may prove useful in the identification of atypical and potentially biased test items. Regression diagnostics studied are based on analysis of the sensitivity of leverage points, studentized residuals, and ratios of covariances due to the sequential deletion of each test item from the analysis. These procedures appear to offer a substantial refinement over existing approaches.

Williams, J. D. (1987). The use of nonsense coding the ANOVA situations. Viewpoints, 15(2), 29-39.

Nonsense coding systems can be constructed that retain outcomes regarding R^2 values, F values, and multiple comparison tests. Nonsense coding highlights the flexibility of coding ANOVA problems to be analyzed by multiple linear regression procedures; however, no additional analytic power appears to be gained from their use.

Strube, M. J. (1987). A general model for estimating and correcting the effects of nonindependence in meta-analysis. Viewpoints, 15(2), 40-47.

This paper describes a general meta-analysis model that can be used to represent the four types of meta-analysis commonly conducted. The model explicitly allows for nonindependence among study outcomes, providing exact statistical solution when the nonindependence can be estimated. Alto discussed are the directional biases that result if nonindopendence is ignored.

Houston, S. R. (1987). The use of judgment analysis and a modified canonical JAN in evaluation methodology. Viewpoints, 15(2), 48-84.

Judgment Analysis is presented as a technique for capturing and clustering unidimensional policies among a group of judges or evaluators. JAN utilizes a multiple linear regression model to represent each policy and then cluster evaluators together who are expressing similar policies. JAN is extended to a multid mensional situation in which a modified and simplified Canonical JAN (C-JAN) procedure for capturing policies on more tha two criteria is described. Both unidimensional and multidime sional JAN procedures should be of general interest o the evaluation methodologist.

Fraas, J. W., & Drushal, M. E. (1987). The use of MLR models to analyze partial interaction: An educational applicatior Viewpoints, 15(2), 85-96.

Certain research questions found in educational studies requir partial interaction effects to be tested. This paper presents an application of the method of using MLR models to test a partial interaction hypothesis.

Schonfeld, I. S., & Erickson, C. (1987). Conducting an 86-variable factor an analysis on a small computer and preserving the mean substitution option. Viewpoints, 15(2), 97-105.

The paper shows how we overcame limitations imposed on us by the memory capacity of the relatively small mainframe we used in conducting a factor analysis in which means are substitute for missing values. Insufficient memory did not permit us to employ SPSSX, with its mean substitution feature, in conductin a factor analysis of 86 variables reflecting ways in which parents cope with the hospitalization of their children. Instead, we employed a two-step solution: (1) we ran SPSSX Condescriptive to create z-score equivalents of the 86 variables and recoded the z variable's system missing values to zeros; (2) the output of the Condescriptive run constituted th input of a BMDP P4M factor analysis run.

Blumenfeld, G. J. (1987). The use of multiple regression in evaluating alternative methods of scoring multiple choice tests. Viewpoints, 15(2), 106-133.

In this study, an attempt was made to develop a multi-variable approach for improving item validities via multiple regression procedures.

Colliver, J. A., Verhulst, S. J., & Kolm, S. J. (1987). A simple multiple linear regression test for differential effects of a given independent variable on several dependent measures. <u>Viewpoints, 15(2),</u> 134-141.

Multiple linear regression may be used to determine whether an independent variable of interest has a differential effect on two or more dependent variables. The initial step involves the separate standardization of each dependent variable. The values of the standardized dependent variables are pooled and treated for purposes of the analysis as constituting a single dependent variable. A within subjects independent variable is created and the levels of the variable are used to denote the different dependent variables. The data are analyzed with a split-plot analysis of variance for which the independent variables of interest is the between groups factor and the independent variables which distinguishes the dependent variables is the within subjects factor. The test of the interaction of these two factors provides a statistical determination of whether the independent variable of interest ha a differential effect on the two or more dependent variables.

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Volume 16, No. 1

Bush, A. J. (1988). A perspective on applications of maximum likelihood and weighted least squares procedures in the context of categorical data analysis. Viewpoints, 16(1), 1-35.

The author presents a case for embracing both the ML and GSK technologies and for appreciating that both are fundamentally regression based strategies. Further, he hopes that the point has been adequately made that to argue which is better is, at best, a contextually bound issue which begs the question for a universal answer.

Presley, R. J., & Huberty, C. (1988). Predicting statistics achievement: A prototypical regression analysis. Viewpoints, 16(1), 36-77.

The purposes of the current study are: (a) to demonstrate a viable approach to the conduct of a multiple regression/ correlation analysis; and (b) to illustrate the approach in the context of predicting achievement in an introductory statistical methods course. The analysis is proposed as being appropriate if the basic intent of a study is that of prediction as opposed to that of explanation. That is, the intent is to arrive at a model for predicting a criterion in as efficient a manner as the data on hand will allow. No model, causal or otherwise, is being posited or verified.

Morris, D., & Huberty, C. (1988). Some parallels between predictive discriminant analysis and multiple regression. Viewpoints, 16(1), 78-90.

The purpose of this paper is to outline some important similarities in, and differences between, predictive discriminant analysis (DA) and multiple regression (MR). The areas covered are estimates of model accuracy, hypothesis testing, and non-least squares models. Some of the parallels are well know, some are less well known, and some appear to have not yet been considered at all.

Williams, J. D., Williams, J. A., & Roman, S. J. (1988). A ten-year study of salary differential by sex through a regression methodology. Viewpoints, 16(1), 91-107.

A ten-year study of salary differential by sex was completed, using a multiple regression methodology, with rank, discipline, degree, years in department, years in current rank, and sex as predictors, focusing on the change in the value of the sex variable. The sex variable evidenced lower salaries for women when controlling for the other variables throughout the study period for both proposed and actual salaries from $341 in 1978-79 (proposed salary) to $1675 for 1981-82 (actual salary) to $504 for 1986-87 (proposed salary). This apparent drop in discrimination by sex in salary at each rank was accompanied by increasing differences in pay. The change is in the direction of "market adjustments," i.e., paying lower salaries to those in disciplines with higher proportions of women.

Huberty, C. J., & Morris, J. D. (1988). Multivariate analysis versus multiple univariate analyses. Viewpoints, 16(1), 108-127.

The argument for preceding multiple ANOVAs with a MANOVA to control for Type I error is challenged. Several situations are discussed in which multiple ANOVAs might be conducted. Three reasons for considering a multivariate analysis are discussed: to identify outcome variable system constructs, to select variable subsets, and to determine variable relative worth.

Thompson, B., & Melancon, J. G. (1988). Developmental trends in androgyny: Implications for measurement. Viewpoints, 16(1), 128-148.

The present study was conducted to investigate differences in item performance, reliability, and scale means of the Bem Sex-Role Inventory when comparisons are made across developmentally different groups. Analyses were conducted comparing results for adolescents with results for adults, and further analyses were conducted comparing results for the adolescents across various adolescent gender and age groups. The results tend to support the conclusion that the BSRI has reasonable measurement integrity when used with adolescents, and thus indicates that the measure may be useful in exploring developmental changes in sex-role perceptions as they occur during adolescence.

Multiple Linear Regression Viewpoints: An Index of Abstracts from 1986-1988

Adria Karle-Weiss
The University of Akron

Volume 16, No. 2

McNeil, K. (1988). "Notes" covariance as the basis for all research questions and tests of significance. Viewpoints, 16(2), 2-9.

The author contends that the covariance straitjacket makes us think of certain limited possibilities regarding: (a) the order to tests of significance, (b) all adjustments based on rectilinear lines of best fit, (c) the number of covariates-one, (d) the covariate being a continuous variable, (e) R^2, and (f) "the big picture."

Sidhu Pittenger, K. K., & Fraas, J. W. (1988). The use of LISREL VI to test a management model. Viewpoints, 16(2), 10-32.

LISREL VI is used to test a relatively complex model of management which suggests a relationship between Leader-Member Exchange, Job Scope, and career outcomes of a young professional. The model if modified to improve the goodness of fit of the original model. The need to validate the reconstructed model has been acknowledged. Also, caution is urged in the use of path analysis as assessment of fit alone may not indicate misspecifications related to the model. The article demonstrates the use of LISREL in building and testing models in management theory.

Byrne, B. M. (1988). Testing the factorial validity and invariance of a measuring instrument using LISREL confirmatory factor analyses: A reexamination and application. Viewpoints, 16(2), 33-80.

The paper identifies and addresses four methodological weaknesses common to most previous studies that have used LISREL confirmatory factor analysis to test for the factorial validity and invariance of a single measuring instrument. Specifically, the paper demonstrates the steps involved in (a) conducting sensitivity analyses to determine a statistically best-fitting, yet substantively most meaningful baseline model; (b) testing for partial measurement invariance; (c) testing for the invariance of factor variances and covariances, given partial measurement invariance; and (d) testing of the invariance of test item and subscale reliabilities. These procedures are illustrated with item response data from normal and gifted children in grades 5 and 8, based on the Perceived Competence Scale for Children.

Hu, M., Fisher, S. A., & Fisher, D. M. (1988). Effect of sample size on the MLE and WLS approaches to solving logit models: An empirical example. Viewpoints, 16(2), 81-92.

Logit is frequently used in education, business, and economics to model qualitative choice situations. Maximum likelihood estimation (MLE) and weighted least squares (WLS) are alternative approaches to solving logit models. WLS has been touted as computationally simpler and easier to interpret than MLE. Using economic data, this study compares the relative variability in parameter estimates between the MLE and WLS procedures as sample size changes. The results indicated that with reductions in sample size there are increasing differences in the coefficients provided by the alternative procedures. Additionally, both MLE and WLS exhibit instability at the smallest sample sample sizes.

Levine, D. U., & Stephenson, R. S. (1988). Differing policy implications of alternate multiple regressions using the same set of student background variables to predict academic achievement. Viewpoints, 16(2), 94-104.

The purpose of this paper is to utilize actual data sets in illustrating how substantially and sometimes radically different conclusions and implications can be drawn from alternate multiple regressions predicting academic achievement from the same set of variables measuring student background.

If you are submitting a research article other than notes or comments, I would like to suggest that you use the following format if possible:

Title
Author and affiliation
Indented abstract (entire manuscript should be single spaced)
Introduction (purpose—short review of literature, etc.)
Method
Results
Discussion (conclusion)
References

All manuscripts should be sent to the editor at the above address. (All manuscripts should be camera-ready.)

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