

MULTIPLE LINEAR REGRESSION VIEWPOINTS

A publication of the Special Interest Group on Multiple Linear Regression of The American Educational Research Association.

Table of Contents

Acknowledgement	• •	I
Using Coefficients of Orthogonal Polynomials as Predictor Variables in Multiple Regression W.K. Brookshire and J.T. Bolding		1
Testing an Hypothesis About a Single Polulation Mean with Multiple Linear Regression - Keith A. McNeil		7
Identification of Significant Predictors of Children's Achievements and Attendance - Ofelia Halasa		15
Application of Multiple Regression Analysis In Invest- igating the Relationship Between the Three Com- ponents of Attitude in Rosenberg and Hobland's Theory for Predicating a Particular Behavior- Isadore Newman and Keith McNeil		23
Guidelines for Reporting Regression Analyses Joe H. Ward, Jr		40
Reaction to Ward's "Guidelines for Reporting Regression Analysis" and Some Alternatives - Keith McNeil		42
A Revised "Suggested Format for the Presentation of Multiple Regression Analyses" - Isadore Newman		45
Business Meeting - Judy McNeil		48
Announcement of A Multiple Linear Regression Symposium - Steve Spaner		51
1973 Membership List - Judy McNeil		52

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Isadore Newman, Editor Multiple Linear Regressive Viewpoints

USING COEFFICIENTS OF ORTHOGONAL POLYNOMIALS AS PREDICTOR VARIABLES IN MULTIPLE LINEAR REGRESSION

William K. Brookshire and J. T. Bolding

Coefficients of Orthogonal Polynomials are presented by some authors (Snedecor and Cochran) as a means of simplifying the computation required in trend analysis. Linear regression addicts who are computer oriented can still make good use of such coding in the analysis of complicated designs.

Consider a two factor design where the factors are assumed to be quantitative with levels selected at equal intervals. Testing for main effects and trend analysis can both be simplified by the use of coefficients of orthogonal polynomials as predictor vectors.

An example is presented where factor A has two levels and factor B has four equally spaced levels. The data is taken from Kirk (1969) chapter 7.

Table #1
Data From Kirk Page 175

	• B ₁	B ₂	B ₃	B ₄
A ₁	3	4	7	7
	6	5	8	8
	3	4	7	9
	3	3	6	8
A ₂	1	2	5	10
	2	3	6	10
	2	4	5	9
	2	3	6	11

Since factor A only has two levels there will only be a linear component and the two levels of factor A will be coded -1 and +1. The assignment $X_1 = +1$ is given for scores in A_1 . The assignment $X_1 = -1$ is given for scores in A_2 .

The four levels of factor B will give rise to three components - linear, quadratic, and cubic. The respective coefficients are found to be as follows:

	Linear Code	Quadratic Code	Cubic Code
Level 1	-3	+1	-1
Level 2	-1	-1	+3
Level 3	+1	-1	-3
Level 4	+3	+1	+1

Vector \mathbf{X}_2 is the linear component of factor \mathbf{B} and is coded as follows:

- -3 if the score is from B_1 (column 1),
- -1 if the score is from B_2 (column 2),
- +1 if the score is from ${\rm B_3}$ (column 3), and
- +3 if the score is from \mathbf{B}_4 (column 4).

Vectors \mathbf{X}_3 and \mathbf{X}_4 are similarly defined using the orthogonal ploynomial coefficients for the quadratic and cubic components respectively.

There are three degrees of freedom associated with the interaction mean square e.g., (2-1)(4-1). These three components are defined as follows:

 $X_{\varsigma} = A$ linear times B linear,

 $X_6 = A$ linear times B quadratic, and

 $X_7 = A$ linear times B cubic.

A condensed representative of the predictor vectors is given in Table 2. The sum of squares between rows, columns, or interaction can be partitioned into as many trend components as there are degrees of freedom for the respective variance estimate.

Table #2
Condensed Representation of Predictor Vectors

Cell			s for Facto Quadratic X ₃	Cubic	X ₅ =	iteraction Ter $X_6 = X_1$ times X_3	X ₇ =
A_1B_1	1	-3	1	-1	-3	1	-1
A_1B_2	1	-1	-1	3	-1	-1	. 3
A ₁ B ₃	1	1	-1	-3	1	-1	-3
A_1B_4	1	3	1	1	3	1	1
A_2B_1	-1	-3	1	-1	3	-1	1
A_2B_2	-1	-1	-1	3	1	1	-3
A_2B_3	-1	1	-1	-3	-1	1	3
A ₂ B ₄	-1	3	1	1	-3	-1	-1

With the predictor vectors defined as above the test for main effects, interaction, and trend analysis proceeds as outlined in Table 3.

Table #3--(Continued)

Testing Cubic Trend Component of B Restriction: $A_4=0$ Model 7 $Y=A_0U+A_1X_1+A_2X_2+A_3X_3+A_5X_5+A_6X_6+A_7X_7+E_7$	Restricted	.9146	1/24	2.08	.1594	194
Testing Linear X Linear Trend Component Restriction: A ₅ =0 Model 8 Y=A ₀ U+A ₁ X ₁ +A ₂ X ₂ +A ₃ X ₃ +A ₄ X ₄ +A ₆ X ₆ +A ₇ X ₇ +E ₈	Restricted	.8653	1/24	17.16	.0006	196
Testing Linear X Quadratic Trend Component Restriction: $A_6=0$ Model 9 $Y=A_0U+A_1X_1+A_2X_2+A_3X_3+A_4X_4+A_5X_5+A_7X_7+E_9$	Restricted	.9082	1/24	4.05	.0527	196
Testing Linear X Cubic Trend Component Restriction: $A_7=0$ Model 10 Y= A_0 U+ A_1 X $_1$ + A_2 X $_2$ + A_3 X $_3$ + A_4 X $_4$ + A_5 X $_5$ + A_6 X $_6$ + E_{10}	Restricted	.9086	1/24	3.92	.0563	196

 $\label{eq:Table #3} Table \ \mbox{\it \#3}$ Regression Analysis of Main Effect and Trend

Mode1	Mode1	R ²	df	F	P	Kirk's Page
Full Model for All F Test Model 1 Y=A ₀ U+A ₁ X ₁ +A ₂ X ₂ +A ₃ X ₃ +A ₄ X ₄ +A ₅ X ₅ +A ₆ X ₆ +A ₇ X ₇ +E ₁	Ful1	.9214				
Testing Interaction Effect Restriction: A ₅ = A ₆ = A ₇ =0 Model 2 Y=A ₀ U+A ₁ X ₁ +A ₂ X ₂ +A ₃ X ₃ +A ₄ X ₄ +E ₂	Restricted	.8392	3/24	8.38	.0008	176
Testing Column Effect Restriction: A ₂ =A ₃ =A ₄ =0 Model 3 Y=A ₀ U+A ₁ X ₁ +A ₅ X ₅ +A ₆ X ₆ +A ₇ X ₇ +E ₃	Restricted	.0955	3/24	84.11	.0000	176
Testing Row Effect Restriction: A ₁ =0 Model 4 Y=A ₀ U+A ₂ X ₂ +A ₃ X ₃ +A ₄ X ₄ +A ₅ X ₅ +A ₆ X ₆ +A ₇ X ₇ +E ₄	Restricted	.9082	1/24	4.05	.0527	176
Testing Linear Trend Component of B Restriction: $A_2=0$ Model 5 $Y=A_0U+A_1X_1+A_3X_3+A_4X_4+A_5X_5+A_6X_6+A_7X_7+E_5$	Restricted	.1363	1/24	239.87	.0000	193
Testing Quadratic Trend Component of B Restriction: A ₃ =0 Model 6 Y=A ₀ U+A ₁ X ₁ +A ₂ X ₂ +A ₄ X ₄ +A ₅ X ₅ +A ₆ X ₆ +A ₇ X ₇ +E ₆	Restricted	.8875	1/24	10.38	.0039	193

Draper and Smith (1966) discuss the use of orthogonal polynomials in curve fitting. Mendenhall (1968) devotes most of a chapter to the use of orthogonal predictors including a section on orthogonal polynomials, and their use in a "k-way classification" problem.

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Testing an Hypothesis About a Single Population Mean with Multiple Linear Regression

Keith A. McNeil Southern Illinois University at Carbondale

ABSTRACT

The recent emphasis on criterion referenced testing and on the explicit stating of objectives implies that more researchers will be testing hypotheses about a single population mean. The generalized regression procedure is one way to test such an hypothesis. The appropriate regression models are presented in this paper.

The multiple linear regression procedure has been shown to be an extremely flexible technique, encompassing both analysis of variance designs as well as correlational designs (Bottenberg and Ward, 1963; Kelly, Beggs, McNeil, Eichelberger and Lyon, 1969; Williams, 1970). Indeed, any hypothesis that requires a least squares solution can be tested with the multiple linear regression approach, with the exception of questions dealing with multiple dependent variables. Even some of the non-parametric techniques have been accomplished with the general linear model (McNeil and Morthland, 1971; Starr, 1971).

Of more importance though is the fact that multiple linear regression allows, indeed, demands that the researcher state his research hypothesis. The flexibility of the technique demands that the specific hypothesis be stated by the user. The specificity of the research hypothesis becomes quite clear when testing an hypothesis about a single population mean. For example, the researcher may suspect that the children in his school are, on the average, below the normal 10 mean.

Given that the "normal 10 mean" is 100, then the research hypothesis would be,

"The population of the school has a mean 10 lower than the normal mean 10."

Draper and Smith (1966) discuss the use of orthogonal polynomials in curve fitting. Mendenhall (1968) devotes most of a chapter to the use of orthogonal predictors including a section on orthogonal polynomials, and their use in a "k-way classification" problem.

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- Draper, N. R. and Smith H. Applied Regression Analysis. New York: John Wiley & Sons, Inc., 1966.
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The multiple linear regression procedure has been shown to be an extremely flexible technique, encompassing both analysis of variance designs as well as correlational designs (Bottenberg and Ward, 1963; Kelly, Beggs, McNeil, Eichelberger and Lyon, 1969; Williams, 1970). Indeed, any hypothesis that requires a least squares solution can be tested with the multiple linear regression approach, with the exception of questions dealing with multiple dependent variables. Even some of the non-parametric techniques have been accomplished with the general linear model (McNeil and Morthland, 1971; Starr, 1971).

Of more importance though is the fact that multiple linear regression allows, indeed, demands that the researcher state his research hypothesis. The flexibility of the technique demands that the specific hypothesis be stated by the user. The specificity of the research hypothesis becomes quite clear when testing an hypothesis about a single population mean. For example, the researcher may suspect that the children in his school are, on the average, below the normal 10 mean.

Given that the "normal 10 mean" is 100, then the research hypothesis would be,

"The population of the school has a mean 10 lower than the normal mean 10."

Stated symbolically, the research hypothesis would be: \mathcal{N}_{\parallel} < 100 where \parallel is the population mean of the school, and 100 is the normal 10 mean. The statistical hypothesis used to test this hypothesis is "The population of the school has a mean 10 equal to that of the normal mean 10," or symbolically: \mathcal{N}_{\parallel} = 100.

Another example may be of some assistance. Consider a project utilizing methods to reduce alienation. One of their objectives might be: After six weeks of participation, the alienation mean score of the children in the project will be less than five. Now if the project director is only interested in how the project works for the few children in the project, he simply needs to look at the sample alienation mean to see if it is less than five. But a more reasonable desire is to infer to the adequacy of the project, with the intent of adopting it in other schools. With this desire, the project director wants to infer to a population of children. The research hypothesis in this case would be: "After six weeks of instruction, the alienation mean score in the population will be less than five." Symbolically: $\mathcal{N}_1 < 5$. The statistical hypothesis is: "After six weeks of instruction, the alienation mean score in the population will be five." Symbolically, the statistical hypothesis is $\mathcal{N}_1 = 5$.

Traditional Solution

The traditional statistical solution to the kinds of hypotheses being discussed are presented as either a t test or a z test. Bloomers and Lindquist (1960) present a z test and their example is similar to the first example in this paper. Since a z test is presented, the authors indicate that the test is reserved for large samples.

Glass and Stanley (1970) present the technique in terms of a t test; and since the t test is sensitive to varying number of subjects, their formulation

provides the exact probability values, whereas a z test will provide only a close approximation. The data for the alienation research hypothesis discussed above is presented in Table 1 and tested in Table 2. The resulting t and related t values will be referred to later.

Regression Solution

The following regression solution also provides an exact probability value, but since the formulation is applicable to all least squares procedures, it can be argued that the regression formulation is preferred over the t test formulation.

To answer any research hypothesis on multiple linear regression, full and restricted models must be constructed. The same F test formula is applicable to all hypotheses, providing that the unit vector is in both the full and restricted models. If this is not the case, and the present solution is not, then an alternative formula for the F test must be used (Bottenberg and Ward, 1963):

$$F(m_1 - m_2), (N - m_1) = \frac{(ESS_r - ESS_t)/(m_1 - m_2)}{(ESS_t)/(N - m_1)}$$

where:

 ESS_{r} = error sum of squares in the restricted model

ESS_f = error sum of squares in the full mode!

 \mathbf{m}_{\parallel} = number of linearly independent vectors in the full model (number of pieces of information in the full model)

 $^{\rm m}_2$ = number of linearly independent vectors in the restricted model (number of pieces of information in the restricted model)

The alienation example will now be formulated in regression models. The research hypothesis: "After six weeks of instruction, the alienation mean score in the population will be less than five" dictates a full model which must allow the alienation mean to manifest itself:

 $Y_1 = a_0U + E_1$ where: $Y_1 = alienation scores$; U = ones for all subjects; and

 a_0 = regression coefficient chosen so as to minimize the error sum of squares, or the sum of the squared elements in E_{\parallel} , the error vector

Readers familiar with the regression technique will recognize this model as "the unit vector model" yielding no differential predictability ($\mathbb{R}^2=0$). The one regression coefficient that must be determined is \mathbf{a}_0 , and this will be the sample mean. The sum of the squared elements in \mathbb{E}_1 will be the EES $_f$. The statistical hypothesis implies the restriction that $\mathbf{a}_0=5$. Forcing this restriction on the full model results in the following algebraic gyrations:

full model: $Y_1 = a_0 U + E_1$ restriction: $a_0 = 5$ restricted model: $Y_1 = 5U + E_2$ but since U = 1 for all subjects, 5U is a constant, and subtracting . that constant from both sides yields the final form of the restricted model:

$$(Y_1 - 5) = E_2$$

The sum of the squared elements in E $_2$ (or Y $_1$ - 50) will be the ESS $_r$. Note that the full model utilizes one piece of information (the unit vector), whereas the restricted model utilizes no information, therefore, m_1 = 1 and m_2 = 0. The difference between m_1 and m_2 is one, being equal to the number of restrictions made, and also being the degrees of freedom numerator for the F test. Table I contains the intermediate values for the solution. The resultant F of 101.5 is within rounding error of the t 2 value of 102.4. The significance of the F must be judged by referring to tabled values, and since this was a directional

hypothesis, one must use the 90th percentile of F if his alpha was .05 <u>and</u> the sample mean is in the hypothesized direction. If the alienation sample mean was greater than 5, there would have been no need to go through the statistical gyrations; it would have sufficed to report "not significant," and then suggest dropping the project. More thorough discussion of directional hypothesis testing, within the context of multiple linear regression, can be found in McNeil and Beggs (1971) and McNeil (1971).

Summary

It would appear that with the recent emphasis on criterion referenced testing and on the explicit stating of objectives that more researchers will be turning to the single population mean hypotheses presented in this paper. It is hoped that the regression formulation is utilized since it is generalizable to other least squares procedures. Researchers having access to computing facilities can perform the required analysis quickly, as one computer run will provide all the component values of the F test. The substitution of the numerical values into the formula must be done by hand, but that is a small price to pay for the utilization of the flexible multiple linear regression technique. Hypotheses about a proportion could also be tested with the same full and restricted models. The criterion vector in this case would be a dichotomous vector rather than a continuous vector as in the alienation example.

Appendix A - Linear Setup to Achieve Intermediate Values

X(2) = (X(1)-2.5)**2.X(3) = (X(1)-5.0)**2.

The 2.5 in the first data transformation statement reflects the observed sample mean, while the 5.0 in the second reflects the hypothesized sample mean.

Mean for Variable 2 will be ESS /N Mean for Variable 3 will be ESS /N

Calculation of F can be accomplished by using from this output:

$$F_{1,N-1} = \frac{MEAN \ VAR \ 3 - MEAN \ VAR \ 2}{MEAN \ VAR \ 2/(N-1)}$$

Table !

Numerical Solution for Regression Testing of an
Hypothesized Population Mean

			Hy	pothes	ized Population	Mean	
Υ,	=	a ₀ U	÷	E	E2	(Y ₁ -	$(Y_1-5)^2$
[-				-1.5	2.25	Ī	16
1				-1.5	2.25	-4	16
1				-1.5	2.25	-4	16
ı		1		-1.5	2.25	-4	16
4		11		1.5	2.25	-1	
3		11		.5	.25	-2	4
3		1		.5	.25	-2	4
2				5	.25	-3	9
		1		-1.5	2.25	-4	. 16
4		1		1.5	2.25	-1	
2				5	.25	-3	9
1	=2.5			1.5	2.25	-4	16
3		1		.5	.25	-2	4
2				-,5	.25	-3	9
3		1	4	.5	.25	-2	4
				-1.5	2.25	-4	16
5		1		2.5	6.25	0	0
3	and the same of th	11		.5	.25	-2	4
2		1		5	.25	-3	9
3				.5	.25	-2	4
3		11		.5	.25	-2	4
3		11		.5	.25	-2	4
4			•	1.5	2.25	-1	
4_				1.5	2.25	-1	
_		_				- -	, <u>-</u>

 $F_{1, 23} = 101.5$

 $ESS_f = 34$

ESS_r = 184

Numerical Solution for Traditional Testing of an Hypothesized Population Mean

Formula from Glass and Stanley (1970, p. 293):

$$\uparrow_{(N-1)} = \frac{\overline{X} - \Lambda}{s_x / \sqrt{n}} \quad \text{where: } s_x = \sqrt{\frac{x X^2}{N-1}}$$

for the alienation data:

$$S_{\times} = 1.21$$
 $N = 24$
 $+ = \frac{2.5 - 5.0}{1.21} = -10.12$
 $t_{(N-1)}^2 = 102.4 = F_{1, N-1}$

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IDENTIFICATION OF SIGNIFICANT PREDICTORS OF CHILDREN'S ACHIEVEMENT AND ATTENDANCE

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The identification of variables other than the treatment process, which is affecting the criterion measure variance has always been a problem. Multiple regression techniques have been utilized to look at this problem through an efficient linear equation by which scores may be combined to predict one's level of performance on a criterion measure:

$$\hat{Y} = b_0 - b_1(X_1) + b_2(X_2) \dots b_k X_k$$

This is a fitted linear regression equation for a particular Y response in terms of the independent variables $X_1 \ X_2 \ \dots \ X_k$. It allows the investigator to extract from several variables the main features of the relationships hidden or implied.

To come up with reliable fitted values, it is necessary to include as many "predictors" or independent variables. However, it is not only realistically impossible in terms of cost and manpower, but the "overfitting" of the regression equation may stabilize the residual mean square (s^2) .

Paper presented at the 1971 National Council on Evaluation and Measurement Convention, February 5-7 at New York City.

Numerical Solution for Traditional Testing of an Hypothesized Population Mean

Formula from Glass and Stanley (1970, p. 293):

$$\uparrow_{(N-1)} = \frac{\overline{X} - h}{S_{X}/\sqrt{N}}$$
 where: $S_{X} = \sqrt{\frac{E X^{2}}{N-1}}$

for the alienation data:

$$S_{\times} = 1.21$$
 $N = 24$
 $+ = \frac{2.5 - 5.0}{1.21} = -10.12$
 $+ \frac{2}{(N - 1)} = 102.4 = F_{1.N - 1}$

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 Education. Boston: Houghton Mifflin Company, 1960.
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$$\hat{Y} = b_0 - b_1(X_1) + b_2(X_2) \dots b_k X_k$$

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To come up with reliable fitted values, it is necessary to include as many "predictors" or independent variables. However, it is not only realistically impossible in terms of cost and manpower, but the "overfitting" of the regression equation may stabilize the residual mean square (s^2) .

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The stepwise regression analysis (Draper and Smith, 1960) appears to represent a compromise between too many and too few variables, and allows for the selection of the best regression equation. It involves reexamination at entry stage of the regression of the variables incorporated into the model in previous stages. A variable which may have been the best single variable to enter at an early stage may be superflous because of the relationships between it and the variables now in regression. Thus, partial F criterion for each variable in the regression at any stage is evaluated and compared with a preselected percentage point of the appropriate F distribution. This provides a judgment on the contribution made by each variable as though it had been the most recent variable entered regardless of its point of entry into the model. Any variable which has a non-significant contribution is removed from the model. This process is continued until no more variables will be admitted or rejected.

The procedure may be briefly summarized as follows:

 The procedure starts with a simple correlation matrix and enters into a regression the variable most highly correlated with the criterion, and finds the first order linear regression equation:

$$\hat{Y} = f(X_1)$$

 Partial correlations of the other variables not in regression with the criterion are then calculated. Mathematically, the partial correlations represent correlations between the residuals from the first order linear regression and the residual from another regression not yet performed:

$$\hat{X}_{j} \approx f_{j}(X_{1})$$

The X_j with the highest partial correlation with Y (criterion) is now selected, e.g. X_2 , and a second regression equation is performed.

3. Given the regression equation of:

$${\stackrel{\wedge}{Y}} = f(X_1, X_2)$$

the procedure then examines the contribution X_1 would have made if X_2 had been entered first and X_1 entered second. If the partial F value exceeded the established level of significance, it is retained. This procedure is continued until contribution of other variables to the criterion variance becomes non-significant.

Results obtained from regression analysis take the form of correlation coefficients and regression coefficients along with standard errors of the regression coefficients. The regression coefficient gives the estimated effects of the independent variable which is significantly related to the criterion. A standard error estimated for each significant coefficient gives some indication of the confidence that can be placed in this coefficient. The multiple correlation coefficient (R) indicates how well the data fit the model. A square of this correlation (R²) indicates the per cent of variation of the dependent variable or criterion that could be attributed to the independent variable or variables.

The stepwise regression technique was utilized recently in the evaluation of a federally-funded project at first and second grades to answer the following question:

 Are there factors other than treatment effects which are influencing children's level of achievement and attendance? Ten regression analyses were run with the following dependent (criteria) and independent variables:

Dependent Variobles

At First Grade - COOP Primary (12B) Post Scores

Listening Word Analysis Math Reading

Attendance

At Second Grade - COOP Primary (23B) Post Scores

Listening Word Analysis Math Reading

Attendance

Independent Variables

Number of Children in the Family Ordinal Rank Mobility Rate Duration of Project Participation Pre-Test Score Attendance

Findings

Most of the regression coefficients which give the estimated effects of the different predictors failed a statistical test of significance. Of the six predictors, the pre-test score evidenced consistent significant contributions to the criterion variance. The per cent of predictable variance, however, indicates that a significant proportion of the variance remains unaccounted for (Tables 1 and 2):

- Pre-test score showed significant effects on achievement at first and second grades. The higher the initial score, the higher was the level of achievement at the end of the year. At first grade, criterion variable which may be attributed to this variable ranged from 5% to 29%. At second grade, predictable variance ranged from 7% to 29%.
- 2. Attendance of first grade children was a function of the Ordinal Rank, Mobility Rate, and Duration of Project Participation. The older, the less mobile the child, and the longer the duration of Project participation, the higher was his school attendance. Approximately 16% of variance of attendance may be attributed to the combined effects of these three variables.
- 3. Attendance of second grade children was a function of Number of Children and duration of Project Participation. The more children in the family, and the longer the Duration of Project Participation, the higher was the attendance. Predictable variance of attendance was 21%.

Implications

Identification of variables with significant influences on the criterion measures has the following advantages:

- Statements on treatment effects can be made with a higher level of confidence as they are less subject to contamination problems.
- Variables from a larger initial set can be reduced to a smaller but more meaningful set which has implications in terms of economy, time, manpower, and expenditures.
- Future data gathering procedures can result in higher predictive accuracy with subsequent sampling units.

STEPDOWN REGRESSION ANALYSIS OF SIX INDEPENDENT VARIABLES ON FIVE DEPENDENT VARIABLES

					Regression	Coefficients		
Dependent Variables	R ²	R	Children	Rank	Mobility Rate	Duration of Participation	Pre-Test Score (October)	Attendance (1969-1970)
COOP Primary Test (12B)								
Listening	0.26	0.51	-	-	-	-	0.49*	-
Word Analysis	0.17	0.41	-	-	-	-	0.54*	-
Mathematics	0.29	0.54	-	-	-	-	0.64*	0.04**
Reading	0.05	0.23	-	-	-	-	0.21**	-
Attendance	0.16	0.40	-	-1.55**	-2.21**	0.70**		

^{*} p<.001 ** p<.01 - p>.05

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Application of Multiple Regression Analysis in Investigating
the Relationship Between the Three Components of Attitude in
Rosenberg and Hovland's Theory for Predicting a Particular Behavior

Isadore Newman, University of Akron and Keith McWeil, Southern Illinois University

ABSTRACT

Multiple regression and factor analysis techniques were used to investigate the telationship between the components of attitude and their differential predictive power. It was found that the different components of attitude and the linear interaction are more likely to be predictive for intimate rather than non-intimate behaviors. The cognitive component was found to be significantly predictive of intrimate behavior but not predictive for non-intimate behaviors but not predictive for non-intimate behavior of having being the cognitive for non-intimate behavior and predictive for non-intimate behavior and intimate and non-intimate perfectly and the interactions in the interaction of an intimate and non-intimate behavior.

INTRODUCTION AND RATIONALE

Since La Pierre (1934) reviewed the attitude literature, there have been numerous efforts to demonstrate that attitude questionnaires can predict observable behavior. One major criticism of the La Pierre review, and others such as Kuthner (1952), was that an unidimensional definition of attitude was used.

Rosenberg and Hovland (1960) presented a theory that an attitude consists of at least three aspects: cognitive, affective and response disposition. The purpose of this investigation was to study the relationship of these components in the prediction of a particular behavior. The attitude chosen to be studied was racial prejudice.

TABLE 2
PDOWN REGRESSION ANALYSIS OF SIX INDEPENDENT VARIABLES
ON FIVE DEPENDENT VARIABLES

					Regression Coefficients	oefficients		
Dependent Variables	R ²	~	Children	Rank	Mobility Rate	Duration of Participation	Pre-Test Score (October)	Attendance (1969-1970)
OP Primary Test (23B)								
stening	0.22 0.47	0.47	1	ı	,	ı	*65.0	1
rd Analysis	0.07 0.26	0.26	1	1	1	ı	0,29**	1
thematics	0.29 0.54	0.54	ı	r	1	ı	0.55*	ı
ading	0.07 0.27	0.27	1	1	1	ı	0.40**	ŝ
tendance	0.21	0.21 0.46	1.71**	ı	1	0.22**		

* p<.01 - p>.05 Attendance Reading Word Analysis Listening Mathematics COOP Primary Dependent Variables 0.29 0.07 ₹2 .07 . 22 , 21 0.26 π Children Mobility Rate Regression Duration of Participation Pre-Test Score (October) 0.55* 0.29** 0.59* Attendance (1969-1970)

STEPDOWN REGRESSION ANALYSIS OF SIX INDEPENDENT VARIABLES ON FIVE DEPENDENT VARIABLES

2

Application of Multiple Regression Analysis in Investigating
the Relationship Between the Three Components of Attitude in
Rosenberg and Hovland's Theory for Predicting a Particular Behavior

Isadore Newman, University of Akron and Keith McNeil, Southern Illinois University

ABSTRACT

Multiple regression and factor analysis techniques were used to investigate the relationship between the components of attitude and their differential predictive power. It was found that the different components of attitude and the linear interaction are more likely to be predictive for intimate rather than non-intimate behaviors. The cognitive component was found to be significantly predictive of intimate behavior but not predictive for non-intimate behavior. Out of the three measures used, the behavioral differential was the most predictive scale for both intimate and non-intimate behavior.

INTRODUCTION AND RATIONALE

Since La Pierre (1934) reviewed the attitude literature, there have been numerous efforts to demonstrate that attitude questionnaires can predict observable behavior. One major criticism of the La Pierre review, and others such as Kuthner (1952), was that an unidimensional definition of attitude was used.

Rosenberg and Hovland (1960) presented a theory that an attitude consists of at least three aspects: cognitive, affective and response disposition. The purpose of this investigation was to study the relationship of these components in the prediction of a particular behavior. The attitude chosen to be studied was racial prejudice.

The theoretical model that is the basis of the three component theory of attitude infers that an individual interprets and gives meaning to a stimulus in reference to three aspects (factors); cognitive, affective and response disposition. These three dimensions are likely to interact with each other and take on differential weights in producing an individual's response. These weights should be thought of as being determined by the particular stimulus and the context in which the stimulus is presented. This model represents the position that a stimulus only acquires meaning through the individual's interpretation and that these three components may have different relationships for different stimuli.

METHOD

Sample: The Ss were 308 students from Southern Illinois University. Since 10% of the population of students at Southern Illinois University is black, the sample was chosen so that it would contain approximately the same racial proportions.

<u>Procedure and Design</u>: An attitude questionnaire was designed to measure the three components as defined. The definitions used in constructing the scales were:

cognitive component: consists of such things as thinking,
 perceiving, remembering and the beliefs that a person
 holds towards an object; including stereotypes.
 affective component: deals with the likes and dislikes
 a person has towards an object. Included would be
 his evaluation of an object and his emotional feelings
 towards that object.

response disposition: consists of all behavioral dispositions associated with the attitude. This component is usually operationally defined in terms of a social distance scale or a behavioral differential scale.

The percent of white Americans who are exploiting blacks

is: 0%, 5%, 10%, 20%, 25%, 30%, 35%, 40%, 45%,...100%.

Three scales were constructed to measure these components. The Subjective Perception Rating Scale (SPRS) was used to measure the cognitive dimension. Measurement was then based upon the subjective rating of items by Ss in the following examples:

The percent of blacks who are in favor of intermarriage between whites and blacks is: 0%, 5%, 10%, 15%...100%.

The above scales were constructed to measure the social perception of the Ss responding to it. The affective component was operationally defined by seven semantic differential (SD) scales, employing bipolar adjectives which loaded high on the evaluative factor of the SD.

Osgood, Suci and Tannenbaum (1957) presented evidence that the evaluative component of the SD is a measure of "Attitude." Williams and Robinson (1967) presented evidence that the evaluative factor of the SD was capable of assessing racial "attitudes" in children. The evaluative factor of the SD is very similar to what has been defined as the

The response disposition of an attitude was operationally defined by the use of four behavioral differential (BD) scales (Triandis, 1964).

Ostrom (1969) suggested that such a scale may be the most sensitive in measuring the response disposition component of an attitude (for a more detailed description of the scales and the rationale for their selection, see Newman, 1971).

affective component of an attitude.

The SPRS, SD and BD scales comprised the attitude questionnaire used in this study. The scales were then factor analyzed to make sure they were tapping separate components. The results of the factor analysis confirmed the belief that the three scales were measuring separate dimensions (see Tables 1 and 2).

The instrument used in the study consisted of two parts. Part I contained eight semantic differential scales, four behavioral differential scales, and a subjective perception rating scale. Part II, which was administered exactly one week later, consisted of three separate conditions. In Condition I, one third of the Ss were randomly chosen to receive an article entitled, "Militants Aren't the Brave Blacks," and were told that the author of the article was a prominent white statesman. After reading the article, the Ss were asked to rate the author on his fairness, whether or not they would elect him to political office, if they would want him as a roommate, etc. Another one third of the Ss were randomly chosen for Condition II. This condition was exactly the same as Condition I, except that the author was proported to be a prominent black statesman. The final one third of the Ss were given Condition III, which differed only in that the Ss were given no information concerning the author's race (see Newman, 1971, for a more detailed description of the scales used).

The ratings of the author of the article were factor analyzed using a principle component solution with 1's in the diagonal, a varimax rotation, which had an arbitrary cut off point of an eigenvalue > 1 (Nummally, 1967). Factor scores were computed for each S.

RESULTS

The ratings of the author of the article were factor anlayzed and resulted in a two factor solution. Factor I, Political-Evaluation (Y_1) , accounted for 23% of the trace and Factor II, Intimate-Social Response Tendency (Y_2) , accounted for 21% of the trace (see Table 3).

Twenty-two regression equations were calculated, eleven for each of these criterion, and are presented in Table 4. It was found that Model 1, using all available information -- knowledge of author's race, the Ss' factor scores on the semantic differential concepts, on the behavioral differential concepts and on the subjective perception rating scale, and the linear interaction between all of these variables -- was found to be significant at p=.00004, accounting for 11% of the criterion variance of Y_1 . However, the same variables, when used to predict the second criterion, Y_2 (Model 12), was found to be significant at p<.00001, accounting for 25% of the variance (see Tables 5 and 6).

It was found that knowledge of race did not account for a significant amount of variance in predicting Criterion 1, but was significant in predicting Criterion 2. The interaction between the components of attitudes was found to be nonsignificant in predicting Criterion 1, p=.634, while the interaction in predicting Criterion 2 just missed being significant, p=.056. It was also found that the SPRS accounted for a significant amount of variance in prediction \mathbf{Y}_2 (p<.001) above the other variable of Model 17, but found to be nonsignificant in predicting \mathbf{Y}_1 . The behavioral differential scale

was found to be the single best independent predictor for Criterion 1 and Criterion 2. The results of these and other questions are presented in Tables 5 and 6.

SUMMARY AND DISCUSSION

The purpose of this study was to investigate the predictive power of an attitude questionnaire which was constructed on the basis of Rosenberg and Hovland's (1960) three component theory of attitude, and to investigate some of the relationships between these components. The behavior predicted was an independent rating of an unnamed author whose one-page article was read by all Ss. The ratings of the author were factor analyzed, producing a two factor solution. The factor solution was used to obtain two factor scores, Y_1 and Y_2 .

Eleven regression models were calculated to predict each criterion. Model 1 was capable of accounting for 11% of the variance, which was significant. The component that accounted for the most independent amount of variance was response disposition (see Table 4).

Model 12 accounted for 25.1% of the variance, which was significant (p<0.00001) in predicting Y_2 . It was also found that in both cases response disposition (behavioral differential) was better able to predict the two criteria than the other two components.

In predicting Y_2 , knowledge of the author's race was found to account for a significant amount of the variance, however this information was not found to be significant in predicting Y_1 . The cognitive component accounted for 5.9% of the variance in predicting

 \mathbf{Y}_{2} , but was nonsignificant in predicting \mathbf{Y}_{1} .

Factor II (Intimate-Social Response Tendency), which was criterion \mathbf{Y}_2 , was more predictable and consistent with the Ss' responses to the rating of the author than was Factor I (\mathbf{Y}_1 , Political Evaluation). A possible explanation of this outcome is that there are different prejudices on some continuum of intimacy. It is likely that the less intimate prejudices are more susceptible to social pressure than the more intimate types of prejudice.

In general, it was found that the components of attitude differentially predicted behavior that may be classified as evaluative behavior and intimate behavior. It was also clearly demonstrated that multiple regression analysis has the desired flexibility to determine complex functional relationships.

This study confined itself to additive and multiplicative linear relationships. Another area of investigation is the nonlinear relationships between components of attitude and their predictive ability. For example, in addition to investigating the linear component of affect, one may be interested in looking at affect² or affect³ (the authors of this paper are now in the process of analyzing such data).

One major limitation of this study was that another questionnaire was used as the criterion behavior, rather than observation of actual behavior, and any inferences made from this study must keep this in mind.

TABLE #3

Varimax Factor Solution of the BD and SD Scales
Rating the Author of the Article

		I Political- Evaluation	
1.	Invite this person to my home	· · · · · · · · · · · · · · · · · · ·	66
2.	Defend his rights if they were jeopardized		48
3.	Admire the ideas of this person	73	
4.	Exclude from my neighborhood		66
5.	Take person into home if a riot victim		62
6.	Participate in a discussion with		57
7.	Want as a member of my church		57
8.	Elect this person to a political office	70	
9.	Accept as a close kin by marriage		69
10.	Want my child to go to school with		• 69
11.	Be alone with this person		65
12.	Want as a roommate	42	52
13.	Fair - Unfair	84	
14.	Worthless - Valuable	77	
15.	Good - Bad	82	
16.	Far - Near		
17.	Boring - Interesting	52	
18.	Unfamiliar - Familiar		
	Believable - Unbelievable	51	
20.	Important - Unimportant	63	
21.	Superficial - Profound	52	

NOTE: Only factor loading of an .40 and above have been reported and decimal points have been omitted. Factor I, which accounted for 23% of the trace was used to obtain the criterion factor scores (Y_1) . Factor II, which accounted for 21% of the trace was used to obtain the criterion factor scores (Y_2) .

TABLE #4

22 Regressions Models Used In This Study

Model 1	$Y_1 = a_0 u + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_1$
Model 2	$Y_1 = a_0 u + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + E_2$
Model 3	$Y_1 = a_0 u + a_1 x_1 + E_3$
Model 4	$y_1 = a_0 u + a_2 x_2 + E_4$
Model 5	$Y_1 = a_0 u + a_3 x_3 + E_5$
Model 6	$Y_1 = a_0 u + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_6$
Model 7	$Y_1 = a_0 u + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_7$
Model 8	$Y_1 = a_0 u + a_4 x_4 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_8$
Model 9	$Y_1 = a_0 u + a_4 x_4 + a_5 x_5 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_9$
Model 10	$Y_1 = a_0 u + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_8 x_8 + a_9 x_9 + E_{10}$
Model 11	$Y_1 = a_0 u + a_1 x_1 + \dots + a_7 x_7 + a_9 x_9 + E_{11}$
Model 12	$Y_2 = a_0 u + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_{12}$
Model 13	$Y_2 = a_0 u + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + E_{13}$
Model 14	$Y_2 = a_0 u + a_1 x_1 + E_{14}$
Model 15	$Y_2 = a_0 u + a_2 x_2 + E_{15}$
Model 16	$Y_2 = a_0 u + a_3 x_3 + E_{16}$
Model 17	$Y_2 = a_0 u + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_{17}$
Model 18	$Y_2 = a_0 u + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_{18}$
Model 19	$Y_2 = a_0 u + a_4 x_4 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_{19}$
Model 20	$Y_2 = a_0 u + a_4 x_4 + a_5 x_5 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_{20}$
Model 21	$Y_2 = a_0 w + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_8 x_8 + a_9 x_9 + E_{21}$
Model 22	$Y_2 = a_0 u + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_9 x_9 + E_{22}$
Model 99	= The model that accounts for zero variance
(cont.)	

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(Y₁)

TABLE #4 (cont.)

- Where: Y_1 = The lst principle factor scores of the author of the article.
 - \mathbf{Y}_2 = The 2nd principle factor scores of the author of the article.
 - $x_1 = 1$ if the author of the article was identified as black, 0 otherwise.
 - \mathbf{x}_2 = 1 if the author of the article was identified as white, 0 otherwise.
 - $x_3 = 1$ if no information was given about the race of the author, 0 otherwise.
 - x₄ = factor scores over the S.D. concept of federal enforcement of open housing, NAACP, bussing, white and black civil rights activists, of the Ss who took Part II, reading the article and rating the author.
 - x₅ = factor scores on the S.D. scale over the concepts of black Presidents and the Black Panthers, for those Ss who took Part II.
 - $\mathbf{x}_6^{} = \text{factor scores of those Ss on the SPRS who took Part II}$ of the questionnaire.
 - x₇ = factor scores on the BD scale over the concepts of black and white persons who favor civil rights, for those Ss who took Part II.
 - x_8 = factor scores on the BD scales over the concepts of black and white persons who oppose civil rights, for those who took Part II.
 - $x_9 = (x_4 * x_5 * x_6 * x_7 * x_8)$ interaction between the components of attitude.
 - u = Unit vector.
 - \mathbf{E}_1 through \mathbf{E}_{22} = Error terms for Model 1 through Model 22, respectively.
 - a_1, \dots, a_n = Partial regression weight.

energy where the second color and many of the forest and the second color and the second colo			-		
Models	Models	R2	df	143	P
Model 1 $Y_1 = a_0 u + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + a_5 x_5 + a_5 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_1$	Full	.11	-		
Restriction: a1=a2=a3=a4=a5=a6=a7=a8=a9 Model 99 Y1= a0u+E0	Restricted	.00	8/300	4.46	.00004
Model 1 $Y_1 = a_0 u + a_1 x_1 + \dots + a_9 x_9 + E_1$	Full	.11			
Model 2 $Y_1 = a_0 u + a_1 x_1 + a_2 x_2 + a_2 x_3 + a_4 x_4 + a_5 x_5 + a_$			1/300	. 22	.634
	Restricted	.10			
Model 3 $Y_1 = a_0 u + a_1 x_1 + E_3$	Full	.002	1/307	.64	.422
Model 99 Y1= a ₀ u+E ₀	Restricted	.000			Sometime and the state of the s
Model 4 $Y_1 = a_0 u + a_2 x_2 + E_4$	Full	.001	1/307	بد	, 555 5
Model 99 $Y_1 = a_0 u + E_0$	Restricted	.000			
Model 5 $Y_1 = a_0 u + a_3 x_3 + E_5$	Full	.001			
Model 99 $Y_1 = a_0 u + E_0$	Restricted	.000	1/30/	. 25	,619
(2017)					

 ${\tt TABLE~\#6}$ Models, F-Ratings and ${\tt R}^2$ For Predicting The Ratings Of The Author (Y_2)

- Models	Models	R ²	đf	F	Р
	Full Restricted	.251	8/300	102.9	.00001
Model 12 $Y_2 = a_0 u + a_1 x_1 + \dots + a_9 x_9 + E_{12}$ <u>Restriction</u> : $a_9 = 0$ (Interaction) Model 13 $Y_2 = a_0 u + a_1 x_1 + a_2 x_2 + \dots + a_8 x_8 + E_{13}$	Full Restricted	.251	1/300	3.66	.056
Model 14 $Y_2 = a_0 u + a_1 x_1 + E_{12}$ Restriction: $a_1 = 0$ (Black) Model 99 $Y_2 = a_0 u + E_0$	Full.	.021	1/307	6.5	.011
Model 15 $Y_2 = a_0u+a_2x_2+E_{15}$ Restriction: $a_2=0$ (White) Model 99 $Y_2 = a_0u+E_0$	Full Restricted	.025	1/307	7.88	.005
Model 16 $Y_2 = a_0 u + a_3 x_3 + E_{16}$ Restriction: $a_3 = 0$ (N-information) Model 99 $Y_2 = a_0 u + E_0$	Full Restricted	.003	1/307	.1	.73

(cont.)

TABLE # 5 (cont.)

Model 6	$Y_1 = a_0 u + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_6$ <u>Restriction</u> : $a_4 = 0$ (affect ₁)	Full	.099	1/303	3.119	.078
Model 7	$Y_1 = a_0 u + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_7$	Restricted	1,303	3.113		
Model 6	$y_1 = a_0 u + a_4 x_4 + \dots + a_9 x_9 + E_6$	Full	.099			
Model 8	Restriction: a ₅ =0 (affect ₂) · Y ₁ = a ₀ u+a ₄ x ₄ +a ₆ x ₆ +a ₇ x ₇ +a ₈ x ₈ +a ₉ x ₉ +E ₈	Restricted	.098	1/303	.243	.622
Model 6	$Y_1 = a_0 u + a_4 x_4 + \dots \cdot a_9 x_9 + E_6$	Full	.099			
Model 9	Restriction: $a_6=0$ (cognitive) $Y_1=a_0u+a_4x_4+a_5x_5+a_7x_7+a_8x_8+a_9x_9+E_9$	Restricted	.098	1/303	.045	.831
Model 6	Y ₁ = a _o u+a ₄ x ₄ +a ₉ x ₉ +E ₆	Full	.099			
Model 10	$\frac{\text{Restriction:}}{\text{Y}_{1}=\text{ a}_{0}\text{u}+\text{a}_{4}\text{x}_{4}+\text{a}_{5}\text{x}_{5}+\text{a}_{6}\text{x}_{6}+\text{a}_{8}\text{x}_{8}+\text{a}_{9}\text{x}_{9}+\text{E}_{10}}$	Restricted	.022	1/303	25.713	.001
Model 6	$Y_1 = a_0 u + a_4 x_4 + \dots \cdot a_9 x_9 + E_6$	Full	.099		·	
Model 11	Restriction: $a_8=0$ (response disposition ₂) $Y_1=a_0u+a_4x_4+a_5x_5+a_6x_6+a_7x_7+a_9x_9+E_{11}$	Restricted	.097	1/303	.614	.433

NOTE: The probability values (P) that are reported are for a two tail test of significance (see Table #4 for description of variables).

TABLE

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	two
	tail
	test
	οf
	The probability values (P) that are reported are for a two tail test of significance

	Mod	Мод	Mod	Mod	Mod	Mod	Mod	Mod	36.
Model 22	el 17	Model 21	Model 17	Model 20	Model 17	Model 19	Model 17	Model 18	el 17
Restriction: $a_8=0$ (Response tendency ₂)	Model 17 $Y_2 = a_0 u^+ a_4 x_4^+ \dots a_9 x_9 + E_1 7$	Restriction: $a_j=0$ (Response tendency ₁) $Y_2 = a_0u+a_4x_4+a_5x_5+a_6x_6+a_8x_8+a_9x_9+E_{21}$	$Y_2 = a_0 u + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_{17}$	Y ₂ = a ₀ u+a ₄ x ₄ +a ₅ x ₅ +a ₇ x ₇ +a ₈ x ₈ +a ₉ x ₉ +E ₂₀	$Y_2 = a_0 u + a_4 x_4 + \dots + a_9 x_9 + E_1 \gamma$ Restriction: $a_2 = 0$ (cognitive)	$Y_2 = a_0 u + a_4 x_4 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_{19}$	$Y2 = a_0 u + a_4 x_4 + \dots + a_9 x_9 + E_{17}$	Y ₂ = a ₀ uta5x5 ⁺ a6x6 ⁺ a7x7 ⁺ a8x8 ⁺ a9x9 ⁺ E ₁₈	Nodel 17 $Y_2 = a_0 u + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 + a_9 x_9 + E_1 7$ Restriction: $a_1 = 0$ (affect)
	Full	Restricted	Full	Restricted	Ful1	Restricted	Full	Restricted	Ful1
ນ ນ	.232	. 150	.232	.173	.232	.226	.232	.231	.232
1/303		1/303		j.	1/303	1/303		+/ 303	1 303
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.066		.001		, c	9	.131		940	613

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Guidelines for Reporting Regression Analyses by

Joe H. Ward, Jr.

Air Force Human Resources Laboratory Brooks Air Force Base, Texas

(With input from Earl Jennings and Bob Bottenberg)

The following items might be considered for inclusion in a report of regression analyses:

Title: Name of Analysis

General Comments

This section includes general information about the data and the analyses. (e.g. description of sample, population, number of observations) This can be whatever seems appropriate to the writer.

2. Regression Analysis Discussion

This section can include (1) natural language statements of the hypotheses, (2) identification of the assumed model, (3) hypotheses in terms of assumed model, (4) identification of the restricted model, and (5) results of the test. The numbering within this section (2.1, 2.2, . . .) should correspond to the model comparison in 4.2 below.

3. Vector Definitions

Vector Number	Definition
1 2	
•	
•	
•	
р	

4. Analyses

4.1 Model Specification and Summary of Results

Model Number	Criterion Vector(Y)	Predictor Vectors	SSE	\mathbb{R}^2	R	NIV	EMS	SEST
1								

4.2 Model Comparisons

Comparison Number

Assumed Restricted R²a R²r NIVA NIVR DF1 DF2 F P

5. Regression Computer Output

Contains detailed computer output of Models and F-Tests if appropriate for reporting. $% \label{eq:contains}%$

Notation:

SSE = Sum of Squares of Error Vector

R² = Squared multiple correlation coefficient

R = Multiple Correlation Coefficient

NIV = Number of linearly independent vectors in the predictor vectors (See Ward and Jennings - Introduction to Linear Models, Ch 5, p 77)

EMS = Error Mean Square = SSF.
[[Dimension of Vectors] - (NIV)]

SEST = Standard error of estimate = VEMS

 R^2 = Squared multiple correlation for assumed (or full) model

 R^2_r = Squared multiple correlation for restricted model

NIVA = Number of linearly independent vectors in the assumed model predictor vectors

NIVR = Number of linearly independent vectors in the restricted model predictor vectors

DF1 = NIVA - NIVR

DF2 = Dimension of Vectors (i.e. number of observations) - NIVA

F = F - statistic

P = Probability

Example of Guidelines for Reporting Regression Analyses

Analysis of Problems From Chapters 4 and 6 of Ward and Jennings

1. General Comments

The data are artificial, representing (N = 20) observations of typing - performance on students who are described as freshman, sophomore, junior, or senior. See p 58-59 of Ward and Jennings, Introduction to Linear Models.

2. Regression Analysis Discussion

- 2.1 (1) Is it appropriate to say that the levels of typing performance for freshman, sophomores, juniors, and seniors are equal?
 - (2) The assumed model is

$$\chi^{(1)} = a_1 \chi^{(2)} + a_2 \chi^{(3)} + a_3 \chi^{(4)} + a_4 \chi^{(5)} + E^{(1)}$$

(3) The hypothesis is

E (fr) = E (soph) = E (jr) = E (sr)
or

$$a_1 = a_2 = a_3 = a_4 = a_c$$

(4) The restricted model is

$$Y = a_c U + E^{(2)}$$

- (5) The result of the test (see Section 4.9) indicates that there is a statistically significant difference (p \angle .0006)between these four groups.
- 2.2 (1) Is the amount of change in typing performance for each year change in grade level constant for all grade levels?
 - (2) The assumed model is:

$$\chi(1) = a_1 \chi(2) + a_2 \chi(3) + a_3 \chi(4) + a_4 \chi(5) + E(1)$$

(3) The hypothesis is:

$$a_2 - a_1 = a_3 - a_2 = a_4 - a_3 = w_1$$
or
defining $a_1 = w_0 + 9w_1$ then the hypothesis is
 $a_1 = w_0 + 9w_1$
 $a_2 = w_0 + 10w_1$

$$a_3 = w_0 + 11w_1$$

$$a_4 = w_0 + 12w_1$$

(4) The restricted model is: $\chi^{(1)} = \psi_n \cup + \psi_1 \chi^{(6)} + E^{(3)}$

 $\mbox{(5)}$ The result of the test (see Section 6.7) indicates that the hypothesis is reasonable.

3. Vector Definitions

Vector Number	Definitions
1 2	Typing performance in words/min. 1 if student is freshman
3	l if student is sophomore
4	l if student is junior
5	l if student is senior
6	grade of student (9, 10, 11, 12)

4. Analyses

4.1 Model Specification and Summary of Results

Model Number	Criterion Vector(Y)	Predictor Vectors	SSE	<u>R</u> ²	R	NIV	EMS	SEST
1	1	2,,5	1996.8	.6554	.8096	4	124.80	11.17
2	1	U	5795.2	0	0	1	305.01	17.5
3	1	U,6	2000.6	.6548	.8092	2	111.15	10.54

4.2 Model Comparisons

Comparison Model	Assumed Model	Restricted Model	$\frac{R^2a}{}$	R^2 r	NIVA	NIVR	DF1	DF2	<u>F</u>	<u>P</u>
1	1	2	.6554	0	4	1	3	16	10.1	.0006
2	1	3	.6554	.6548	4	2	2	16	.015	.9847

5. Regression Computer Output

Results of detailed computer outputs (see p. 263 of Ward and Jennings).

Reactions to Ward's "Guidelines for Reporting Regression Analyses," and Some Alternatives

Keith McNeil

Ward's proposed guidelines need discussion by SIG members in a number of places:

- (1) There is not enough emphasis upon the statement of the question the researcher wants to establish, and the statistical hypothesis employed to test that question.
- (2) There is extraneous regression information, which is not desired by most researchers.
- (3) No allowance is made for alpha, and the decision regarding hypotheses is not given enough play—the guidelines make regression important for its own sake (rightfully so for SIG members, but not for common researchers) rather than as a tool for answering the researcher's question.
- (4) The encouragement of a "natural language statement," one that the researcher must state in his own language is welcomed, but the statement is nothing more than a "null hypothesis," which is usually not what the researcher is wanting to establish. The following guidelines I propose include <u>both</u> a research and a statistical hypothesis. (Those concerned about directional hypothesis testing realize that the same statistical (null) hypothesis serves both the directional and non-directional research hypotheses.)
- (5) Under Model Specifications, the criterion vector is referred to as "Y" when in fact it is an "X". SSE, R, NIV, EMS, SEST are all, with the possible exception of SEST, not usually of interest to researchers.
 - (6) Under Model Comparisons, NIVA and NIVR are excess information.

2

(4) The restricted model is:

$$\chi(1) = w_0 U + w_1 \chi^{(6)} + E^{(3)}$$

 $\ensuremath{(5)}$ The result of the test (see Section 6.7) indicates that the hypothesis is reasonable.

Vector Definitions

Vector Number	Definitions
1	Typing performance in words/min.
2	l if student is freshman
3	l if student is sophomore
4	l if student is junior
5	l if student is senior
6	grade of student (9 10 11 12)

4. Analyses

4.1 Model Specification and Summary of Results

Model Number	Criterion Vector(Y)	Predictor Vectors	SSE R ² R		SSE R ² R NIV EMS		<u>R N</u>		EMS SEST	
1	1	2,,5	1996.8	.6554	.8096	4	124.80	11.17		
2	1	U	5795.2	0	0	1	305.01	17.5		
3	1	U,6	2000.6	.6548	.8092	2	111.15	10.54		

4.2 Model Comparisons

Comparison Model	Assumed Model	Restricted Model	R^2	R ² r	NIVA	NIVR	DF1	DF2	<u>F</u>	<u>P</u>
1	1	2	.6554	0	4	1	3	16	10.1	.0006
2	1	3	.6554	.6548	4	2	2	16	.015	.9847

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Results of detailed computer outputs (see p. 263 of Ward and Jennings).

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 $\mbox{Ward's proposed guidelines need discussion by SIG members in a number of places:$

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 - (6) Under Model Comparisons, NIVA and NIVR are excess information.

2

Suggested Guidelines for Reporting Regression Analyses

Statement of the $\underline{\text{research}}$ $\underline{\text{hypothesis}}$ - that which the researcher is hoping to support.

Statement of the statistical hypothesis.

Statement of $\underline{\text{alpha}}$ - the risk (probability) the researcher is willing to make in rejecting a true statistical hypothesis.

Formulation of the $\underline{\text{full model}}$ - all variables must be implied unambiguously by the research hypothesis.

Statement of the restrictions implied by the statistical hypothesis.

Formulation of the $\underline{\text{restricted}}$ $\underline{\text{model}}$ - $\underline{\text{reflecting}}$ the statistical hypothesis.

Definition of the vectors.

Reporting of the probability (p) of calculated F occurring by chance alone and comparison of that p with the preset alpha level, in order for the researcher to make a <u>decision</u>:

- l. If $\mathbf{p} \not \leq \mathbf{alpha},$ then reject statistical hypothesis and accept research hypothesis.
- If p > alpha, fail to reject statistical hypothesis and fail to accept research hypothesis.

An Example Following the Above Guidelines

Directional Research Hypothesis: For some population, Method A is better than Method B on the criterion $\mathbf{Y}_1.$

Statistical Hypothesis: For some population, Method A and Method B are equally effective on the criterion Y_1 .

Full Model: $Y_1 = a_0 U + a_1 G_1 + a_2 G_2 + E_1$

Restrictions: $a_1 = a_2$

Restricted Model: $Y_1 = a_0U + E_2$

where: Y, = criterion

U = 1 for all subjects;

G₁ = 1 if subject in Method A, zero otherwise;

 $G_2 = 1$ if subject in Method B, zero otherwise; and

 $\mathbf{a}_0,\;\mathbf{a}_1,\;\mathrm{and}\;\mathbf{a}_2$ are least squares weighting coefficients calculated

so as to minimize the sum of the squared values in the error vectors,

 E_1 and E_2 .

F = 222 p < .0001

Decision: Since the weight $a_1 > a_2$ as hypothesized and p Z alpha, reject the statistical hypothesis and hold as tenable the research hypothesis.

A Revised Suggested Format for the Presentation of Multiple Regression Analysis

Isadore Newman University of Akron

In an earlier issue I suggested a format for presenting the results of multiple regression analysis. Since then, a committee, chaired by Joe Ward, was appointed by the Multiple Regression Special Interest Group. At the last meeting in New Orleans, Ward discussed his suggested guide lines. Keith McNeil has also made suggestions for the presentation of results of multiple regression analysis.

I have since revised my original format and I am now presenting it. All of these suggestions should be considered. I believe it is important to have a standard format which will reduce some ambiguity regarding the symbols used and the interpretation of multiple regression tables. This, I believe, will enhance our ability to promote further use of multiple regression through better communicating the results in the most concise and easily interpretable form.

TABLE II

THE COMPLETE REGRESSION MODEL

WHICH REFLECTS THE EMPIRICALLY TESTED FUNCTIONAL RELATIONSHIPS

$$Y_6 = a_0 U + a_1 X_1 + a_2 X_2 = a_3 X_3 + \dots + a_{10} X_{10} + E$$

where:

 Y_{6} = the criterion, posttest score in reading comprehension

 a_0 , a_1 , a_3 , ... a_{10} = partial regression weights;

U = the unit vector (a "1" for each sample);

 $X_1 = 1$ if S was in the Multi-Media Reading Program, zero otherwise:

 $X_2 = 1$ if S was in the traditional basal text reading program, zero otherwise;

 $X_3 = 1$ if S were male, zero otherwise;

 $X_h = 1$ if S were female, zero otherwise;

 X_{ς} = pretest raw score in reading comprehension measured by The Ohio Survey Test;

 $X_{\gamma} = 1$ if S were male and in the Multi-Media Reading Program, zero otherwise;

 $X_8 = 1$ if S were female and in the Multi-Media Reading Program, zero otherwise:

 $X_{Q} = 1 \text{ if } S \text{ were male and in the traditional basal text}$ reading program, zero otherwise;

 $X_{10} = 1$ if S were female and in the traditional basal text reading program, zero otherwise;

E = Error vector, difference between predicted score and

Newman, Isadore. Multiple Linear Regression Viewpoints. Vol. 2, No. 4, March 1972; Special Interest Group publication of AERA.

F-Ratios Predicting Posttest Scores of Students

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Hypothes1s £ N 9 Y 9_X , Y $Y_6 = a_0 U + a_1 X_1 + a_2 X_2 + a_3 X_3 + a_4 X_4 + a_5 X_5 + E$ - 81 11 11 a₀U+a₅X₅ a₀U+a₃X3+a4X4+a5X5 $\mathtt{a_0^{U+a_1X_1+a_2X}}$ a₀U+a₅X₅+a₇X₇+a₈X₈+a₉X₉+a₁₀X₁₀ a0U+a3X3+a4X4+a5X5+ : To determine if existed between when covarying p To determine if females differed significantly from males when covarying the pretest score. + P f interaction sex and treatment pretest scores. (**T**) H + [1] Restricted Restricted 50 . 50 50 1/145

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Note:

See

Table

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To determine if the Multi-Media program was significantly different from the traditional basal text program when covarying pretest scores. MODELS 121 1/145 ALPHA .05

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BUSINESS MEETING NOTES

The annual business meeting of the AERA Special Interest Group on Multiple Linear Regression was held on February 28, 1973 during the 1973 AERA Annual Meeting in New Orleans. 1972-73 Chairman Bill Connett presided.

Old business:

- A. Joe Ward, chairman of the committee to develop guidelines for reporting regression analyses, reported on a suggested format and invited comments on it from the Viewpoints readers.
- B. Dues were collected.

New business:

- A. The meeting was turned over to 1973-74 chairman, Judy McNeil.
- B. Election was held for the Office of Secretary, Chairman-elect. James Bolding of the University of Arkansas was elected.
- C. The membership expressed appreciation for the years of service given to the SIG by John Williams serving as editor and expressed a desire to find another individual and institution to take over the burden. Isadore Newman of the University of Akron accepted the position.
- D. The membership approved a proposal to combine the responsibilities of Chairman and program chairman beginning with this year.

Interaction Hours

A social interaction party was held for the SIG on the evening of February $28\ \text{in}$ New Orleans.

For Viewpoints

Membership:

Dues (\$1.00) for membership in the AERA Multiple Linear Regression Special Group were due as of the New Orleans Annual meeting (1973-1974). If you did not pay your \$1 at New Orleans send it to the new Secretary: James Bolding, Educational Foundations, University of Arkansas, Fayetteville, Arkansas, 72701

Since the paper presented by Keith and Judy McNeil at the AERA:SIG session was some 30 pages long, it will not be reprinted in Viewpoints.

Anyone desiring a copy should write to Keith McNeil, Department of Guidance and Educational Psychology, Southern Illinois University, Carbondale,
Illinois 62901.

Steve Spaner is proud to announce that his MLR symposium was accepted by Div. 5 (Measurement and Evaluation) of the APA for presentation Thursday, August 30, 1973 from 10-12 AM at the 1973 APA Convention in Montreal, Canada. The following is the list of participants and their presentations (abstracts are available from Steve):

The application of multiple linear regression (MLR) to research evaluation

Steven D. Spaner, University of Missouri-St. Louis, St. Louis, Mo.

Participants:

- Joseph Liftik, Services for Traffic Safety, Boston, Mass. The page application of MLR in alcoholism diagnosis.
- Jack Byrne, Westinghouse Research Laboratories, Pittsburgh, Pa. An evaluation of first grade reading: a multiple linear regression analysis.
- Judy T. McNeil and Keith A. McNeil, Southern Illinois University, Carbondale, Ill. A regression analysis of the functional relationship between mother-infant physical contact and infant development.
- Isadore Newman and Gerald J. Blumenfeld, The University of Akron, Akron, Ohio. The use of multiple regression in evaluating alternative methods of scoring multiple choice tests.
- Thomas E. Jordan and Steven D. Spaner, University of Missouri St. Louis, St. Louis, Mo. An AID-4 analysis of antecedents to internal locus of control at age 5.
- Samuel R. Houston and William E. Connett, University of Northern Colorado, Greeley, Col. The use of judgment analysis in capturing student policies of rated teacher effectiveness.

Discussants:

Francis J. Kelly, Southern Illinois University, Carbondale, Ill.

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