DOCUMENT RESUME

ED 257 881 TM 850 351

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TITLE Coding and Commonality Analysis: Non-ANOVA Methods for Analyzing Data from Experiments.

PUB DATE Nov 84

NOTE 21p.; Paper presented at the Annual Meeting of the Mid-South Educational Research Association (New Orleans, LA, November, 1984).

PUB TYPE Speeches/Conference Papers (150) -- Reports - Research/Technical (143)

EDRS PRICE MF01/PC01 Plus Postage.

DESCRIPTORS Analysis of Variance; Aptitude Treatment Interaction; Comparative Analysis; *Educational Research; Regression (Statistics); *Research Methodology; *Statistical Analysis

IDENTIFIERS Coding Theory; *Commonality Analysis

ABSTRACT

The advantages and disadvantages of three analytic methods used to analyze experimental data in educational research are discussed. The same hypothetical data set is used with all methods for a direct comparison. The Analysis of Variance (ANOVA) method and its several analogs are collectively labeled OVA methods and are evaluated. Regression coding analysis is conducted by entering the five coding column predictor variables into a stepwise multiple regression analysis to predict the dependent variable. Regression coding represents OVA analyses a a regression equation. Commonality analysis focusses attention on effect size estimates for experimental, aptitude, and other independent variables. Results suggest that commonality analysis can be usefully employed in research studies in education, especially when aptitude-treatment interaction studies are involved. (DWH)

Coding and Commonality Analysis: Non-ANOVA Methods for Analyzing Data from Experiments

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Paper presented at the annual meeting of the Mid-South Educational Research Association, New Orleans, LA, November, 1984.

ABSTRACT

The importance of experiments in educational research is widely recognized, but methods used to analyze experimental data may not always be fully appropriate. Advantages and disadvantages of three analytic methods are discussed. A hypothetical data set is employed to make the discussion concrete. It is suggested that commonality analysis can be usefully employed in research studies in education, particularly when aptitude-treatment interaction studies are involved.

Researchers have long recognized the importance of experimental designs in social science. As Wundt observed in 1904, "The experimental method is of cardinal importance; it and it alone makes a scientific introspection possible" (p. 4). However, as Winer (1962, p. 2) noted, the design of an experiment can make or break a study:

> Two experiments having identical objectives may be designed in quite different ways; at the same cost in terms of experimental effort, one design may lead to unambiguous results no matter what the outcome, whereas the second design could potentially lead to ambiguous results no matter what the outcome.

It was this recognition that some 60 years ago prompted McCall (1923) to publish his text, How to Experiment in Education. Continuing concerns regarding the importance of designs have stimulated more recent works as well (Campbell & Stanley, 1966; Cook & Campbell, 1971).

Concerns regarding the analysis of experimental data also have their own long history. In 1925, in a work titled Statistical Methods for Research Workers, Sir Ronald Fisher presented the analysis of variance (ANOVA) techniques that he had developed. Today ANOVA methods and their analogs (ANCOVA, MANOVA, and MANCOVA--collectively here labelled OVA methods) are among the most commonly applied methods in the social sciences (Edgington, 1974; Wick & Dirkes, 1973; Willson, 1980).

Unfortunately, although design and analysis were initially conceptualized as discrete issues, it has now become quite common to confuse design with analysis. Specifically, OVA techniques have become somewhat equated with experimental design, and vice versa. Hicks (1973) provides a classic example of this confusion in his fine book, Fundamental Concepts in the Design of Experiments. The book is entirely about OVA analysis rather than about design. Thompson (1981) explores the etiology of this confusion.

The purpose of this paper is to point out that data from experiments can be profitably analyzed in a number of related but distinct ways. The advantages and limits of both OVA and non-OVA techniques are discussed. One hypothetical data set is analyzed throughout the presentation in order to make the discussion more concrete. Although the data set and the analyses are presented as a one dependent variable, or "univariate" case, it can be shown that the discussion generalizes to the multivariate case as well.

Method One: ANOVA

Table 1 presents data from a hypothetical experiment involving 24 subjects. The data are presented in some detail and using variable names accepted by several computer packages in case readers wish to verify or explore certain results using their own computers. Twelve subjects each were assigned to either a control condition (EXPERGRP=1) or an experimental condition (EXPERGRP=2). The hypothetical study also involves a measure of the subjects' aptitudes for mastering the dependent variable task. In this case both the aptitude variable and the dependent variable were cognitive tasks, i.e., respectively performance on an IQ test and standardized (Z) scores on an achievement posttest (ZDV) administered at the completion of the experiment.

INSERT TABLE 1 ABOUT HERE.

This is an example of the classic aptitude-treatment interaction (ATI) design that Cronbach (1957, p. 681) touted so convincingly in his 1957 presidential address to the American Psychological Association:

> Ultimately we should design treatments, not to fit the average person, but to fit groups of students with particular aptitude patterns... [Such efforts] will carry us into an educational psychology which measures readiness for different types of teaching and which invents teaching methods to fit different types of readiness.

Notwithstanding both the limits and the advantages of ATI designs (Cronbach, 1975), as Kerlinger (1973, p. 257) notes, "in the opinion of some behavioral researchers, especially in education, the study of interactions is becoming increasingly important and should become a central concern of researchers."

All independent variables or "ways" must be converted to nominal scale in order to perform OVA analyses. In this case the IQ data were converted into a trichotomy (IQGRP) in the usual manner. Table 2 presents conventional ANOVA results associated with the 3 X 2, six cell design.

INSERT TABLE 2 ABOUT HERE.

Method Two: Regression Coding

Cohen (1968) and others recognized quite some time ago that multiple regression analysis can readily be employed to perform OVA analyses. However, the widespread use of regression approaches to OVA analyses has been a more recent phenomenon (Willson, 1982). All that is required is that information about design cells be converted into "coding" variables, as illustrated in Table 1. Although discussion of the several methods for accomplishing this conversion is beyond the scope of this report, the conversion is clearly presented in several widely available texts (Edwards, 1979; Kerlinger & Pedhazur, 1973, pp. 116-153) and in practice is a straightforward matter.

But it should be noted that the coding variables (IQ1 through EXPBYIQ2) represent exactly the same information as presented for the ways in the OVA analysis (IQGRP and EXPERGRP), albeit in a different form. For example, note that all subjects in the "low IQ" cells of the IQ way (IQGRP=1) receive coding scores of -1-1 for the IQ coding variables, and that subjects in the other cells of the way receive different scores (0+2 or +1-1) on the two IQ coding variables. Note also that each of the six design cells receive a unique set of coding scores. For example, only the high IQ, experimental group subjects receive the coding score set: +1-1+1+1-1.

The analysis is conducted by entering the five coding column predictor variables into a stepwise multiple regression analysis to predict the dependent variable, ZDV. The sum of squares (SOS) regression on any given step, minus the SOS regression on any previous step (if any), is the SOS for the hypothesis associated with the coding variable entered on the given step. The remainder of the keyout presented in Table 3 is derived by then manipulating these sum of squares using a calculator.

INSERT TABLE 3 ABOUT HERE.

The only difference in the results when compared with the ANOVA analysis is that the coding results partition the total SOS of the dependent variable into smaller parts using one degree of freedom hypotheses. But this difference can be important whenever any way has more than two levels or cells. The coding analysis provides more specific information about from where the effects of independent variables on the dependent variable arise.

In the hypothetical example the coding column IQ1 tests the null hypothesis that the mean ZDV score of the eight "low IQ" subjects equals the mean ZDV score of the eight "high IQ" subjects. The IQ2 coding column tests the null hypothesis that the mean ZDV score of the eight "medium IQ" subjects equals the mean ZDV score of the remaining 16 subjects. Note in the example that the SOS for the IQ way in the Table 2 OVA analysis was .010. The coding analysis breaks this effect into two smaller components (IQ1 SOS = .00000 and IQ2 SOS = .00968) and indicates that almost all of the effect of IQ (although very minimal) arises from differences between the "medium IQ" subjects when compared with the other subjects.

Of course, more specific information about where differences occur within an OVA analysis can also be determined by conducting post hoc tests after the analysis is completed. Examples of OVA post hoc methods include the Scheffe test or a multiple range test. However, a priori hypothesis specification via coding still may be preferred because, as Kerlinger and Pedhazur (1973, p. 131) note:

> The tests of significance for a priori, or planned, comparisons are more powerful than those for post hoc comparisons. In other words, it is possible for a

specific comparison to be not significant when tested by post hoc methods but significant when tested by a priori methods.

Method Three: Commonality Analysis

Regression coding represents OVA analyses as a regression equation. The use of regression coding to analyze data from experimental designs suggests the intriguing possibility that multiple regression could be employed to analyze experimental data without having to reduce ordinal or interval independent variable data, e.g., aptitude data, to the nominal level of scale. It is recognized (e.g., Nie, Hull, Jenkins, Steinbrenner & Bent, 1975, pp. 372-373), although perhaps not widely, that interaction can still be represented in the analysis by computing what Kerlinger and Pedhazur (1973, p. 414) have termed "product variables." A product variable is created by multiplying any two variables times each other. Thus, the last three columns of Table 1 present all the independent variables necessary to conduct an analysis of experimental data without having to convert the IQ data into the nominal level of scale.

Cohen (1968) has implied that OVA methods have been attractive to social scientists because partitioning the dependent variable's variance into uncorrelated portions provides "computational simplicity"--this may have been particularly important in the era preceeding widespread availability of computers. However, use of regression with data at the level of scale at which the data are originally collected also has advantages. For example, as Darlington (1968, p. 166) notes:

> In analysis-of-variance designs, the complete independence

> of all the independent variables is assured by the requirement of equal or proportional cell frequencies... In multiple regression, however, there is no requirement that predictor variables be uncorrelated. This property gives regression analysis a substantial element of flexibility lacking in analysis of variance.

It has also been observed (Cohen, 1968; Thompson, 1981) that the use of non-OVA methods does not: 1) reduce reliability of aptitude and non-experimental variables; 2) inflate the Type II error probability; 3) discard substantively important information; or 4) distort the distribution shapes of or relationships among certain variables.

Although beta weights and structure coefficients (Thompson & Borrello, in press) can be consulted to evaluate "main effects" and the "interaction effects" represented by product variables, commonality analysis, also called "element analysis" (Newton & Spurrell, 1967) and "components analysis" (Mayeske, Wisler, Beaton, Weinfield, Cohen, Okada, Proshek & Tabler, 1969), can also be conducted if the researcher wants estimates of the uniqueness of each effect. For each independent variable, commonality analysis indicates how much of the variance of the dependent variable is "unique" to the predictor, and how much of the predictor's explanatory or predictive power is "common" to or also available from one or more of the other predictor variables. Mood (1969) presents an algebraic rule for computing these variance partitions for any number of independent variables, and Cooley and Lohnes (1976, p. 222) have tabled the required computational methods for studies involving as many as four independent variables. In addition to tabling the computational procedures for studies involving up to five independent variables (p. 358), Seibold and McPhee (1979) provide a brief and understandable introduction to this method of analysis.

In the present study the squared multiple correlation between ZDV and the predictor variables, ZIQ, ZEXPGRP, and ZIQBYEXP, was .23708. Table 4 illustrates the computations of the partitions of the unique and common predictive ability of the three independent variables to explain 23.708 percent of the variance in ZDV. Table 5 summarizes the commonality and regression results.

INSERT TABLES 4 AND 5 ABOUT HERE.

Two aspects of the commonality analysis merit further explanation. First, the interaction effect represented by the product variable, ZIQBYEXP, should not be confused with the commonality involving the two main effect variables, ZIQ and ZEXPGRP (Seibold & McPhee, 1979, p. 365). Interaction is the unique effect of two or more independent variables which in combination affect the dependent variable. Commonality indicates the proportion of predictive ability of a single variable that also happens to reside in another single predictor variable too; no unique effect of the predictors acting in combination is involved.

Second, negative commonalities (never negative uniqueness partitions) can occur, as with the "a,b,c" commonality in the present analysis. This is counterintiutive since the result could be taken to mean that each of the three predictor variables have in common the ability to explain less than zero percent of the variance in ZDV. Instead, negative commonalities frequently indicate the presence of a suppressor effect (DeVito, 1976, p. 12). As Craeger (1971, p. 675) notes:

> This [a negative commonality variance partition] is more

> likely to occur in higher order partitions obtained by subtraction and is more likely where some regression weights are negative (either by suppressor effects or from bipolar relations which cannot be removed by reflecting vectors). Negative partitions may also result from sampling errors in the correlation matrix.

Beaton (1973, p. 22) provides an illustration of how a negative commonality can have important substantive implications:

> Both weight and speed are important to success as a professional football player and each would be moderately correlated with a measure of success in football. Weight and speed are presumably negatively correlated and would have a negative commonality in predicting success in football. If both weight and speed are known, one would expect to make a much better prediction of success using both variables to select fast, heavy men rather than just selecting the fastest regardless or weight or heaviest regardless of speed. Thus the negative commonality indicates that explanatory power of either is greater when the other is used.

Seibold and McPhee (1979, pp. 364-365) report results of a cancer study that may well have been grossly misinterpreted if a commonality analysis detecting suppressor effects had not been conducted.

Discussion

The three techniques for analyzing data from experiments each have both advantages and disadvantages. For example, with respect to significance testing for the variance partitions from commonality analysis, "for the unique parts, and the unique parts only, one can make the usual F test of whether additional regression terms have contributed significantly to the regression if he is willing to overlook the logical difficulties arising from the fact that the tests are not independent" (Mood, 1971, pp. 196-197). However, with respect to the commonalities themselves, as Newton and Spurrell (1967, p. 61) note that "it is difficult to see that statistical theory will be able to give sampling errors which can be used in meaningful tests for secondary elements [commonalities] since they are obviously not independent statistical quantities."

Still, commonality analysis does inherently focus attention on effects size estimates for experimental, aptitude, and other independent variables. This emphasis is consistent with the recognition that statistical significance is primarily a function of sample size (Carver, 1978), and that estimates such as Hays' (1963, p. 382) omega squared are important adjuncts to OVA analyses. The focus is also consistent with emphasis on effect sizes in meta-analysis (Glass, McGaw & Smith, 1981).

As a practical matter, the advantages of commonality analysis accrue in most research examples because so many experiments involve aptitude or other intervally scaled independent variables. In fact, most variables other than experimental manipulation are higher than nominally scaled. Probably the most notable exception is sex of the subjects in a study. Although in exceptional areas of inquiry such as math anxiety (Aiken, 1976, p. 302) the use of sex as an independent variable may be warranted, as a general rule the use of even this variable may stem more from ease of measurement than from theoretical justification.

The compelling advantage of commonality analysis of experimental data is that the analysis does not require that all independent variables be converted to the nominal level of scale. It is this "squandering [of] much information" (Cohen, 1968, p. 441) that causes the previously mentioned difficulties with OVA methods. For example, it is this feature that distorts relationships among the independent variables, and as Seibold and McPhee (1979, p. 355) argue:

> Advancement of theory and the useful application of research findings depend not only on establishing that a relationship exists among predictors and the criterion, but also upon determining the extent to which those independent variables, singly and in all possible combinations, share variance with the dependent variable. Only then can we fully know the relative importance of independent variables with regard to the dependent variable in question.

Commonality analysis of data from experiments is attractive because the method honors the reality to which the researcher is purportedly trying to generalize. As Mood (1969, p. 480) notes, "The independent variables in any social process, and certainly in education, are highly correlated among themselves, and this kind of partition of variance [commonality analysis] provides measures of the extent to which they overlap each other in their association with the dependent variable." Thus, perhaps commonality analysis of data from experiments should be considered more frequently in contemporary practice in educational research.

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Table 1

Example Data Set for Three Related Analyses

Case	OVA Data: IQ	IQGRP	EXPERGRP	ZDV	Coding Data: IQ1	IQ2	EXP	EXPBYIQ1	EXPBYIQ2	Commonality Data: ZIQ	ZEXPGRP	ZIQBYEXP
1	68	1	1	-0.952	-1	-1	[illegible]1	+1	+1	-1.464	-0.979	+1.433
2	84	1	1	-0.270	-1	-1	[illegible]1	+1	+1	-0.793	-0.979	+0.776
3	88	1	1	-0.611	-1	-1	-1	+1	+1	-0.625	-0.979	+0.612
4	89	1	1	-0.952	-1	-1	-1	+1	+1	-0.583	-0.979	+0.571
5	50	1	2	+0.412	-1	-1	+1	-1	-1	-2.218	+0.979	-2.171
6	74	1	2	+1.434	-1	-1	+1	-1	-1	-1.212	+0.979	-1.186
7	76	1	2	+1.434	-1	-1	+1	-1	-1	-1.128	+0.979	-1.104
8	85	1	2	-0.611	-1	-1	+1	-1	-1	-0.751	+0.979	-0.735
9	95	2	1	-1.292	0	+2	-1	0	-2	-0.332	-0.979	+0.325
10	99	2	1	-0.270	0	+2	-1	0	-2	-0.164	-0.979	+0.161
11	103	2	1	-1.292	0	+2	-1	0	-2	+0.003	-0.979	-0.003
12	108	2	1	+1.094	0	+2	-1	0	-2	+0.213	-0.979	-0.208
13	102	2	2	+0.071	0	+2	+1	0	+2	-0.038	+0.979	-0.038
14	106	2	2	+1.094	0	+2	+1	0	+2	+0.129	+0.979	+0.126
15	107	2	2	-0.611	0	+2	+1	0	+2	+0.171	+0.979	+0.168
16	107	2	2	+1.434	0	+2	+1	0	+2	+0.171	+0.979	+0.168
17	111	3	1	+1.434	+1	-1	-1	-1	+1	+0.339	-0.979	-0.332
18	115	3	1	+0.071	+1	-1	-1	-1	+1	+0.506	-0.979	-0.496
19	133	3	1	-1.633	+1	-1	-1	-1	+1	+1.261	-0.979	-1.234
20	140	3	1	+1.094	+1	-1	-1	-1	+1	+1.554	-0.979	-1.522
21	120	3	2	-0.270	+1	-1	+1	+1	-1	+0.716	+0.979	+0.701
22	132	3	2	+0.412	+1	-1	+1	+1	-1	+0.412	+0.979	+1.193
23	135	3	2	+0.071	+1	-1	+1	+1	-1	+1.345	+0.979	+1.316
24	143	3	2	-1.292	+1	-1	+1	+1	-1	+1.680	+0.979	+1.645

Note: "ZDV" is the dependent variable for all three analyses. "ZIQBYEXP" is the product of "ZIQ" times "ZEXPGRP" (respectively, the Z score versions of "IQ" and "EXPERGRP").

Table 2

ANOVA Analysis

Source	Sum of Squares	df	Mean Square	Fcalc	Effect Size
IQGRP	.010	2	.005	<1	.010/23 = .000
EXPERGRP	2.135	1	2.135	2.262	2.135/23 = .093
2 Way Interaction	3.863	2	1.932	2.046	3.863/23 = .168
Error	16.992	18	.944		
Total	23.000	23	1.000		

Note: "Effect Size" is an r squared analog.

Table 3

Regression Coding Analysis

Source	Sum of Squares	df	Mean Square	Fcalc	Effect Size
IQ Group					
Low vs. High (IQ1)	.00000*	1*	.00000**	<1**	.00000**
Medium vs. Other (IQ2)	.00968*	1*	.00968**	<1**	.00042**
EXP	2.13492*	1*	2.13492**	2.26154**	.09282**
Interaction	3.86320	2	1.93160**	2.04616**	.16796**
EXPBYIQ1	3.51464*	1*	3.51464**		
EXPBYIQ2	.34856*	1*	.34856**		
Error	16.99221	18	.94401		
Total	23.00001	23	1.00000		

*By subtraction of one step's results from following step listed on the printout.
**By division using previously obtained tabled results.

Table 4

Commonality Computations of Variance Partitions

Unique to ZIQ (a)	$-R^2_{y.bc} + R^2_{y.abc}$ $-.23618 + .23708 = .00090$
Unique to ZEXPGRP (b)	$-R^2_{y.ac} + R^2_{y.abc}$ $-.14440 + .23708 = .09268$
Unique to ZIQBYEXP (c)	$-R^2_{y.ab} + R^2_{y.abc}$ $-.09995 + .23708 = .13713$
Common to a,b	$-R^2_{y.c} + R^2_{y.ac} + R^2_{y.bc} - R^2_{y.abc}$ $-.14335 + .14440 + .23618 - .23708 = .00015$
Common to a,c	$-R^2_{y.b} + R^2_{y.ab} + R^2_{y.bc} - R^2_{y.abc}$ $-.09282 + .09995 + .23618 - .23708 = .00623$
Common to b,c	$-R^2_{y.a} + R^2_{y.ab} + R^2_{y.ac} - R^2_{y.abc}$ $-.00677 + .09995 + .14440 - .23708 = .00050$
Common to a,b,c	$+R^2_{y.a} + R^2_{y.b} + R^2_{y.c} - R^2_{y.ab} - R^2_{y.ac} - R^2_{y.bc} + R^2_{y.abc}$ $+.00677 + .09282 + .14335 - .09995 - .14440 - .23618 + .23708 = -.00051$

Note: The sum of the unique and common predictive abilities of the three independent variables, represented by the seven partitions, equals the squared multiple correlation (.23708) obtained when the three independent variables are used to predict the dependent variable, ZDV.

Table 5

Commonality and Regression Results

Unique to ZIQ (a)	.090%		
Unique to ZEXPGRP (b)		9.268%	
Unique to ZIQBYEXP (c)			13.713%
Common to a,b	.015%	.015%	
Common to a,c	.623%		.623%
Common to b,c		.050%	.050%
Common to a,b,c	-.051%	-.051%	-.051%
Sum of the Partitions	.677%	9.282%	14.335%
r^2 of predictor with ZDV	.00677	.09282	.14335
Beta weight	.03151	.30444	-.38804
Structure Coefficient	-.16896	.62572	-.77760