A COMPARISON OF CANONICAL CORRELATION AND MULTIPLE REGRESSION IN THE ANALYSIS OF CHANGE

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The recognition that longitudinal data is a prerequisite for the analysis of change is now so widespread as to seem passe. It is less often recognized, however, that longitudinal data is in no sense a simple solution. The researcher must still decide how change as opposed to stability is to be defined, measured, and analyzed. The intuitive approach would appear to be a raw change score between the testing dates. Cronbach and Furby (1970), among others (cf. Bohrnstedt, 1969; Davidson, 1970), however, have argued persuasively on methodolofical grounds against the use of raw change scores.

A frequently suggested alternative method for the analysis of change is the use of residualized scores (Bohrnstedt, 1969; Cronbach and Furby, 1970). Mechanically this procedure involves a multiple regression technique in which the outcome measure of the variable of interest is the dependent variable. The baseline or initial level of that variable enters the regression equation first in order that the outcome level is residualized upon initial level. Other predictors may be entered into the equation in subsequent steps in order to assess the impact of those variables net of the impact of the baseline measure. The standardized regression coefficients may then be used to assess the relative importance of particular predictors, while the unstandardized or metric coefficients permit comparisons across different samples or populations (Duncan, 1975). In this way changes in a variable may be assessed without the use of raw change scores.

We agree with various researchers that the use of residualized scores and regression coefficients is one useful method of analyzing change and that it is methodologically superior to the use of individual change scores. However this technique addresses a very specific substantive question--namely, what causal factors predict change in a given measure over time. This is not the only type of question longitudinal analysis may wish to answer. Thus there is need for further specification concerning the purposes of various analytic techniques and their appropriateness to various substnative questions.

To this end we will compare the use of two different techniques--multiple regression and canonical correlation--in a longitudinal analysis of the same set of data. The techniques will be compared from both a substnative and methodological point of view. First, however, we will briefly describe our research problem and the data.

The Research Problem and the Data

The data used in this analysis are part of an ongoing longitudinal research project conducted by the Duke Center for the Study of Aging and Human Development. The basic research design involves four testing dates at two-year intervals. The first wave of data was collected between August, 1968 and April, 1969. There are currently three waves of completed data and our analysis utilizes measures from all three test dates.[2]

The 380 persons for whom there are three waves of completed data constitute the sample used in this analysis.[3] This sample includes 197 males and 183 females who range in age from 50-75 at the final test date.

The research problem is a social-psychological one concerning age identification or the individual's self-perception of himself in terms of age. Previous research has indicated that age identification is significantly associated with a variety of behavioral outcomes including such things as life satisfaction (Adams, 1971; Zola, 1962; Peters, 1971), general adjustment (Zola, 1962; Phillips, 1961; Mason, 1954), mental health status (Peters, 1971; Britton, 1963; Anderson, 1967), and feelings of anomie and alienation (Atchley and George 1973; Mason, 1954). More recent analysis indicates that these relationships remain net of the impact of chronological age (George, 1975), thus indicating that age identification may be an important predictor of various social-psychological states. In this analysis the emphasis is somewhat different however. We are interested in tracing the process of age identification--that is, in determining the causal factors which prompt a change in the individual's age identification over time.

Eight specific variables are used in this analysis. Age identification is operationalized here as the individual's perception as either middle-aged or old and is interpreted as a dimension of his self-concept. Although the age identification variable consists of nominal categories, because it takes on only two values, it is used as a 0-1 dummy variable. The time-three measure of age identification is used as the dependent variable, while the time-one measure serves as the baseline or initial level predictor.

The six additional variables are ones we would expect to be potentially significant causal factors in shifts in age identification over time and include chronological age, the occurrence or nonoccurrence of various events such as retirement and widowhood, objective health impairment (ie. clinically evaluated by a physician), self-perceived health status, the chronological age composition of the individual's group of significant others, and the individual's perceptions of the evaluations of others (ie. how old other people think he is). These six measures were taken from the second round of data. (The means, ranges and standard deviations of the variables as well as a correlation matrix of the variables are provided in Tables 1 and 2.

TABLE 1

MEANS, RANGES AND STANDARD DEVIATIONS OF VARIABLES

Variable	Potential Range	Actual Range	$\bar{X}$	S.D.
Baseline Age Identification	0-1	0-1	.256	.437
Chronological Age	NA	48-73	60.057	7.062
Objective Health Impairment	0-25	0-16	1.851	2.493
Self-Perceived Health	1-4	2-4	3.054	.652
Age Composition of Friendship Network	0-1	0-1	.217	.286
Cumulative Events	0-6	0-5	.475	.673
Individual's Perceptions of Evaluations of Others	0-1	0-1	.342	.475
Outcome Age Identification	0-1	0-1	.358	.480

Time limitations prohibit a more detailed presentation of the theoretical framework involved in the research problem. We will merely add that these specific variables were chosen to represent sources of standards and types of referents which the self-concept literature suggest as important in the dynamics of self-perception. This specific problem, while of interest to social-psychologists froma theoretical perspective, is used here for purposes of illustration. Our interpretive emphasis will be upon the implications of the two analytic techniques used and the types of questions they may be appropriately used to address.

TABLE 2

CORRELATION MATRIX OF MAJOR VARIABLES

	1	2	3	4	5	6	7	8
1. Baseline Age Identification	1.000	.5000	.0376	-.2441	.3309	.0636	.5091	.6206
2. Chronological Age		1.000	.1315	-.0765	.5597	.0577	.5099	.5821
3. Objective Health Impairment			1.000	-.3213	.1490	.1135	.1656	.1961
4. Self-Perceived Health				1.000	-.1137	-.0616	-.1927	-.2441
5. Age Composition of Friendship Network					1.000	.0252	.3027	.3905
6. Cumulative Events						1.000	.0919	.1014
7. Individual's Perceptions of Evaluations of Others							1.000	.5900
8. Outcome Age Identification								1.000

Results of the Multiple Regression

The multiple regression technique was outlined at the beginning of the paper. To briefly recap, the time-three measure of age identification is the dependent variable. The baseline (time-one) measure of age identification is entered into the regression first in order to residualize outcome level upon initial level. The predictors are entered into the equation in subsequent steps in order that their impact may be assessed net of the influence of initial level. In this way the independent variables are used to predict changes in age identification without the use of individual change scores.

Table 3 presents the regression equation for our data. The baseline measure of age identification has a large impact, in terms of both total and direct effects upon the outcome measure. This indicates that age identification is relatively stable in terms of the rank ordering of individuals over time in this sample. The difference in the value of the standardized coefficients for the baseline measure of age identification in the various steps indicates the degree to which the baseline measure is intercorrelated with the other predictors. Had the baseline measure not been included in the equation this shared variance would have been assigned to the other independent variables and the sizes of their coefficients would have been inflated. Substantively, had the baseline measure not been included, the regression technique would have shown how well the various independent variables predict age identification at a given point in time. It is the inclusion of the baseline measure which enables the researcher to assess how well the independent variables predict changes in age identification over time.

The independent variables vary widely in terms of their relative importance as predictors of changes in age identification. Along with the baseline level, chronological age and the individual's perceptions of the evaluations of others are relatively strong predictors of age identification at time-three, net of the other variables in the equation. Self-perceived health and the age composition of the individual's significant others are statistically significant predictors also, although their relative importance is considerably less. Finally the events measure and the objective health impairment variable are relatively unimportant predictors of changes in age identification.

The baseline measure of age identification, by itself, explains about 38% of the variance in age identification at time-three. The final equation which includes all of the variables explains about 59% of the variance in the outcome measure of age identification. Thus, as a set, the independent variables do significantly increase our ability to predict changes in age identification. Further discussion of the implications of the results of this analytic technique will follow presentation of the results of the canonical correlation procedure.

Thus a multiple regression technique in which outcome level of age identification was residualized upon a baseline measure was used to determine how well particular independent variables predict changes in age identification over time.

TABLE 3

LONGITUDINAL REGRESSION EQUATION FOR PROCESS OF AGE IDENTIFICATION*

STANDARDIZED COEFFICIENTS

Dependent Variable	Independent Variables: AGEIDA	AGE	EVENTS	IMPAIR	AGEFREN	SELFHELTH	OTHERS	R^2
AGEIDC	.62055							.38508
	.43691	.36056	.05280					.48634
	.45589	.34358	.04360	.08340				.49289
	.40753	.32861	.04231	.05101	.04922	-.10829		.50538
	.32556	.24172	.03175	.03706	.05249	-.08719	.25822	.54806

UNSTANDARDIZED COEFFICIENTS

Dependent Variable	AGEIDA	AGE	EVENTS	IMPAIR	AGEFREN	SELFHELTH	OTHERS	Constant
AGEIDC	.68161							.1835
	.47963	.02451	.02625					-1.3099
	.47851	.02336	.02168	.08387				-1.2636
	.44738	.02234	.02104	.00982	.08387	-.07968		- .9552
	.35739	.01643	.01579	.00714	.08818	-.06415	.26094	- .6934

* Key to variable names:
AGEIDC=time-three age identification
AGEIDA=time-one age identification
AGE=chronological age
EVENTS=cumulative events measure
IMPAIR=objective health impairment
AGEFREN=age composition of friendship network
SELFHELTH=self-perceived health
OTHERS=individual's perceptions of evaluations of others

Another and different question is to ask whether different patterns of age identification over time can be predicted using the same independent variables. In this case, initial, as well as outcome, level of age identification is important and a part of the dependent variable. Canonical correlation will be used to address this question.

Canonical correlation analysis is not as familiar to many social scientists as multiple regression, therefore we will present a brief description of the technique. Canonical correlation is the most general of the techniques encompassed by the general linear model as it can accomodate multiple or single independent or dependent variables and can be used with either nominal or scale data (Darlington et. al., 1973). Although canonical correlation analysis assumes linearity between the dependent and independent variables, techniques similar to conventional dummy variable analysis in multiple regression are available which enable the researcher to circumvent this assumption rather easily (cf. Campbell and Evers, 1974; Hope, 1972).

In situations where the dependent variables are categorical or constitute groups, canonical correlation is an exact identity with multiple discriminant analysis (Tatsuoks, 1971; Van de Geer, 1971). Such is the case in the current example.

Canonical correlation analysis is used to assess the relationship between two sets of variables where each set may be characterized by more than one dimension. Theoretically there are a potential of G-1 significant canonical variates, where "G" represents the number of dependent variables. Weights are attached to each variable on each side of the equation. The values of the weights on the predictor side indicate the relative importance of each variable, net of all the others in the equation. In the case of categorical dependent variables, the weights associated with each category indicate the scaling of groups on the basis of the linear composites determined by the independent variables.

The canonical correlation is analogous to the multiple correlation in regression analysis, and the canonical R^2 represents the amount of variance (in a given dimension) in the dependent variables explained by that weighted linear combination of independent variables. The statistical significance of the entire scaling equation is assessed via a Wilkes Lambda statistic which is distributed as chi-square.

One rather persistent problem remains in the use of canonical correlation analysis. There is no simple way to assess the significance of a single independent variable in a scaling equation. It is possible, however, to rerun the analysis, omitting a variable, then compare the overall significance of the two scaling equations to see whether that variable has a significant contribution to the equation (ie. the difference between two chi-square values is distributed as chi-square) and how much the weights of the remaining variables shift as a result.

Results of the Canonical Correlation

We can now turn to the analysis at hand. Cross-tabs based upon age identification at two points in time serve as an easy method to form groups which exhibit different patterns of age identification over time. Test dates one and three are used in order to maximize the equality of cell frequencies, although in spite of this the cell sizes are grossly unequal. The cross-tabular analysis of time-one age identification with time-three age identification yields four groups:

1. subjects who shift their age identification from old to middle-aged (OLD-MID, n = 15),
2. subjects who classify themselves as middle-aged at both test dates (MID-MID, n = 222),
3. subjects who shift their age identification from middle-aged to old (MID-OLD, n = 50),
4. subjects who classify themselves as old at both test dates (OLD-OLD, n = 86).

These four groups represent four distinct patterns of change and stability in age identification over time. Canonical correlation will be used to see how well our set of independent variables can distinguish among the four groups.

Table 4 presents the conditional group means for the four patterns of age identification on the independent variables. These means will aid in the interpretation of the subsequent canonical correlation analysis, but are also very interesting in their own right. We would expect that for all the variables except self-perceived health status that the rank order of the group means would be as follows (from highest to lowest): OLD-OLD, MID-OLD, OLD-MID, MID-MID. Thus to take the chronological age structure of the friendship network as an example, we would expect the mean value of this variable to be highest for the group that said they were old at both times (OLD-OLD), next highest for the group that had changed their age identification to old over time (MID-OLD), next highest for the group that had changed their age identification to middle-aged (OLD-MID), and lowest for the MID-MID group. For the self-perceived health variable, which is back-coded as compared to the other variables, we would expect the same pattern but in opposite order in terms of the absolute values of the conditional means.

TABLE 4

CONDITIONAL MEANS ON MAJOR VARIABLES FOR FOUR PATTERNS OF AGE IDENTIFICATION*

FIRST WAVE VARIABLES	MID-MID (n=222)	OLD-MID (n=15)
AGE	54.770	61.333
IMPAIR	1.604	1.821
SELFHELTH	2.986	2.600
AGEFREN	.077	.106
OTHERS	.050	.538
SECOND WAVE VARIABLES		
AGE	56.770	63.333
IMPAIR	1.467	2.733
SELFHELTH	3.164	2.933
AGEFREN	.133	.189
OTHERS	.130	.333
THIRD WAVE VARIABLES		
AGE	58.700	65.333
IMPAIR	1.400	1.833
SELFHELTH	3.140	3.071
AGEFREN	.126	.188
OTHERS	.082	.214
EVENTS	.833	.467
FIRST WAVE VARIABLES	MID-OLD (n=50)	OLD-OLD (n=86)
AGE	61.600	64.930
IMPAIR	3.112	2.482
SELFHELTH	2.860	2.651
AGEFREN	.174	.332
OTHERS	.327	.857
SECOND WAVE VARIABLES		
AGE	63.600	66.930
IMPAIR	2.612	2.787
SELFHELTH	2.857	2.798
AGEFREN	.263	.393
OTHERS	.510	.831
THIRD WAVE VARIABLES		
AGE	65.600	68.930
IMPAIR	2.969	3.145
SELFHELTH	2.673	2.826
AGEFREN	.294	.420
OTHERS	.755	.793
EVENTS	.880	1.081

* Key to variable names:
AGE=chronological age
IMPAIR=objective health impairment
SELFHELTH=self-perceived health
AGEFREN=age composition of friendship network
OTHERS=individual's perceptions of evaluations of others
EVENTS=cumulative events measure

In general the expected patterns are observed to a remarkable degree in the data. The differences between the MID-MID and OLD-OLD groups are always in the predicted direction. The distinctions between OLD-MID and MID-OLD are less clear-cut, but a majority of the variables rank order in the predicted direction across all four groups.

In addition, looking at the crosswave means (ie. down the columns) for the two groups which have experienced a change in age identification over time (OLD-MID and MID-OLD), we find expected patterns also. The OLD-MID group typically shows decreases in the mean values of the various measures (with the obvious exception of chronological age) which would be consistent with a shift in age identification from old to middle-aged. Likewise the MID-OLD group exhibits expected increases in the mean values of the various measures which are compatible with a change in age identification from middle-aged to old.

Table 5 presents the canonical correlation and scaling equation which resulted from our analysis. The independent variables included in the equation are the same ones which were used in the multiple regression analysis presented earlier. A single significant canonical variate emerged in this analysis.

Examining the weights associated with the dependent variables, we see that the four age identification patterns rank order as would be expected: MID-MID, OLD-MID, MID-OLD, OLD-OLD. In addition, as would be expected on the basis of the conditional means, the distinction between OLD-MID and MID-OLD is not as clear-cut, although they do rank order in the expected direction.

Turning to the canonical weights for the independent variables we find that chronological age and the individual's perceptions of the evaluations of others are the most important predictors. Objective health impairment and the events measure were relatively weak predictors of these age identification patterns. This is the same pattern, in terms of the relative importance of particular predictors, seen in the multiple regression analysis, although this is not necessarily always the case. It would also be possible for one set of independent variables to be important predictors of changes over time while another set were important predictors of different patterns exhibited over time (cf. George and Maddox, 1975).

Finally, the canonical variate explains a high proportion of the variance in the four age identification patterns—about 64%. This analysis indicates that the set of independent variables does a good job of predicting the four patterns of age identification both in terms of discriminating and scaling the groups and in terms of the amount of variance explained.

Discussion

Before making a comparison of the two analytic techniques, we should consider

TABLE 5

CANONICAL CORRELATION AND SCALING EQUATION OF AGE IDENTIFICATION. DEPENDENT VARIABLES ARE THE FOUR PATTERNS OF AGE IDENTIFICATION.

Independent Variables:	Canonical Variate*
Individual's Perceptions of the Evaluations of Others	-.71289
Chronological Age	-.31669
Self-Perceived Health	.11518
Age Composition of Friendship Network	-.10530
Objective Health Impairment	-.01602
Cumulative Events	-.04836
Groups:	
MID-MID	1.18389
OLD-MID	.44064
MID-OLD	.22067
OLD-OLD (omitted category)	.00000
Canonical R	.79869
Canonical R^2	.63791
Chi Square	358.99595
d.f.	18
p	.0001

* Canonical weights are reported in standardized form.

the methodological consequences of using change-stability groups such as those used in the canonical correlation analysis. In fact these groups representing patterns of change are grouped change scores and may be subject to the same methodological criticisms involved in the use of individual change scores. We began this paper by agreeing with criticisms of the use of individual change scores and have ended up using grouped change scores. We do not believe, however, that the use of grouped change scores poses the methodological problems which are found in the use of individual change scores.

There are three major difficulties in the use of individual change scores. The first is that combining a series of individual change scores into a change score variable results in a blurring of individual scores and the directions of individual change scores. For example, a difference of -2 is treated the same, whereas in one case it represents the difference between 20 and 18 and in another case it represents the difference between 3 and 1—thus the metric values associated with change are ignored. These individual change scores are summed and averaged to form a mean change score and analysis proceeds to attempt to explain variance about this mean change score. All patterns of change are lost and one aggregate statistic remains. This leads to the second problem with change scores: analysis based on change scores is difficult to interpret (Cronbach and Furby, 1970; Davidson, 1972). Because the mean change score is so far removed from individual scores and metric data, interpretation is highly problematic.

We feel that the type of change versus stability groups used in this analysis avoids both of these problems. These groups are built upon both direction of change and the original, metric values of the variables used. Patterns of change are not lost or blurred together. Interpretation remains easy because the groups involve metric levels (ie. old versus young, high versus low). Not only are metric directions of change specified, but so are metric levels of stability.

The third problem with the use of individual change scores involves the potential for confusing true change with the effects of unreliability (Bohrnstedt, 1969). This problem is also relevant to the groups constructed in the manner we have suggested, although it does appear manageable. First of all when the variables used to construct the groups are categorical as in the present example, group construction is simple. Cross-tabulation of the variables results in discrete cells in a contingency table which are easily assignable. If the variables used to construct the groups are not categorical, the situation is more difficult. In that case the investigator must decide upon the cut-off points for the groups. In this case, one might very legitimately wonder whether a change score of plus or minus two points reflects true change or the effects of unreliability in the measure. However, the researcher can impose a more conservative definition of true change. For example, positive change could be defined as an increase of four or more points over time in the metric value of the variable, while negative change would be defined as a decrease of four or more points. Thus while the true change versus unreliability issue remains unresolved, steps can be taken to act against the effects of unreliability to some degree. The only true solution is the use of reliable measures. And after all, unreliability takes its toll on any statistical technique, not only the measurement of change.

In general then we would argue that the construction of change versus stability groups is a legitimate enterprise. Patterns of change and stability remain clear, interpretation is relatively easy and can be tied to the metric of the measure, and the effects of unreliability can be mitigated to some degree by a conservative definition of change. On the basis of this analysis which yielded very useful information we would argue that the discrimination among patterns of change and stability using canonical correlation analysis is a profitable method of longitudinal analysis, deserving of increased attention and utilization.

An additional warning would be prudent at this point. The interpretation of the weights in canonical correlation analysis must proceed very carefully. In some cases exact inferences about the nature of the groups (ie. the dependent variables) can be problematic (Campbell and Evers, 1974). For example, if two independent variables have relatively large weights it is not immediately obvious whether it is the combination of the two variables that predicts group membership or whether the presence of one of the two variables is a sufficient condition for prediction. Another problem is that it is not immediately discernable whether a given predictor is discriminating between all the groups or is only important in distinguishing between two of the groups. In our analysis, these problems were clarified by carefully examining the patterns of group means on the independent variables. This is usually sufficient to clarify interpretation, but in cases where it is not, a revised canonical approach is available (Campbell and Evers, 1974; George and Maddox, 1975). This technique consists of canonical decomposition of the rows and columns of a table of the independent variables--this is equivalent to coding each cell of the table as a dummy variable.

Conclusions

In this paper we have compared multiple regression and canonical correlation in a longitudinal research design. The two techniques may be used to answer different types of substantive questions. The distinction we have made between predicting change and discriminating among patterns of change is, we believe, a useful one and each is a legitimate but different question.

Multiple regression was used to predict changes in age identification over time. In this analysis a baseline measure of age identification was entered in the equation prior to the other predictors. Thus the outcome measure is residualized upon initial level and the other independent variables are entered as predictors of these residualized scores. In this case the researcher is interested in predicting the outcome measure net of initial level or with the effects of initial level partialled out. In effect the baseline measure is a covariate, although the adjusted mean is not readily available without the application of additional analytic techniques.

A different research question is: given patterns based on certain baseline levels and certain outcome levels how well can a particular set of independent variables predict these patterns. In this case the object is not to partial out or control on initial level of the variable in question, but rather to use initial level as part of the dependent variable. Given that individuals start at and end at different places over time in regard to a particular variable, how well can a set of predictors account for these different patterns. Canonical correlation analysis seems to be an appropriate technique for this research question.

FOOTNOTES

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2. For a more thorough description of the data set and the strategies used in the cata collection process, see Appendix A of Normal Aging II edited by Erdman Palmore (1974).

3. At the end of the first round of data collection a total of 502 white males and females, aged 46-71 had been interviewed. By the end of the second wave there were 443 subjects and this number had decreased to 380 by the end of the third wave. Mortality records indicate that about 30% of the sample attrition had been due to death of the respondents. Surprisingly, however, chi square comparisons of dropouts to the final sample indicate that dropouts were neither significantly older nor in significantly poorer health as judged by a physician than the final sample. Dropouts were significantly more likely to view themselves as in relatively poor

health and to be retired from employment.

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