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Effects of Physical Activity on Psychological Change in Advanced Age: A Multivariate Meta-Analysis

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An example of multivariate meta-analysis is demonstrated by synthesizing the treatment effects of exercise of 15 groups on six mood state changes in elders measured by the Profile of Mood States (POMS) scale. Two different methods were used to analyze this multivariate dataset. The SAS codes for two set of the analyses were provided. Results showed that exercise has a modest and positive impact on elders mood change.

Key words: multivariate meta-analysis, mood state, POMS, Psychological change, exercise

Introduction

In this article, an application of meta-analysis to multivariate data is demonstrated. The eight primary studies included in the current meta-analysis are a subset of studies from a larger meta-analysis of the impact of exercise on psychological change in the elderly. The full list of studies on this topic, the search process, and study selection criteria can be found in Netz, Wu, Becker, and Tenenbaum (2005). This meta-analysis includes studies examining the treatment effects of exercise on mood change in the elderly, published between 1993 and 2001. Outcomes for participants in 15 treatment groups from these studies were measured by the Profile of Mood States (POMS; McNair, Lorr, & Droppleman, 1971), before and after exercise. Six identifiable mood states are measured in the POMS: Tension-Anxiety, Depression-Dejection, Anger-Hostility, Vigor-Activity, Fatigue-Inertia, and Confusion-Bewilderment, however, not all 15 groups provide measures of all six outcomes. (Below each scale is referred to using the first word of its label.) The numbers of mood states measured range from 4 to 6 in these groups. The 15 independent treatment groups in this meta-analysis produced 71 effect sizes.

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Calculation of the Effect Size

The effect size in this synthesis is the standardized mean-change measure (Becker, 1988), which represents the magnitude of the

difference between the pretest and the posttest means for each outcome. It is defined as $g = \dfrac{\bar{Y}^{trt} - \bar{X}^{trt}}{S_X^{trt}}$, where $\bar{Y}^{trt}$ denotes the posttest mean of the treatment group, $\bar{X}^{trt}$ denotes the pretest mean of the treatment group, and S_X^{trt} denotes the standard deviation of the pretest in the treatment group. The effect size g represents change from pretest to posttest in pretest-standard-deviation units. A g value of 1.0 for a treatment group indicates the participants' mean level of the outcome after exercise improved one standard deviation relative to their initial level.

All gs were corrected for bias due to small sample sizes. The unbiased effect size, denoted d, was obtained by correcting g via $d = (1 - \dfrac{3}{4n-5})g$, where n is the sample size for which g is computed. The variance of d is defined as $\mathrm{var}(d) = \dfrac{4(1-r)+d^2}{2n}$, where r is the pretest-posttest correlation. Because r is not reported in any of the studies, it is assumed to be 0.7 in this meta-analysis.

The signs of effect sizes for all outcomes except vigor (which is scored positively) were reversed; therefore, all positive d values in the dataset indicate improved mood status.

Methodology

Several approaches to synthesizing multivariate data in meta-analysis are discussed and summarized in Becker (2000). Here, two methods are presented: One commonly used approach creates independent subgroups for analysis; the other is more sophisticated, yet requires more assumptions. The latter approach uses generalized least squares (GLS) to take dependence among the outcomes into account while analyzing multivariate data (Raudenbush, Becker, & Kalaian, 1988). The two methods are used to calculate the mean effects of exercise (and associated standard errors) for each of the six mood states.

Method I: Creating Independent Subgroups

The 71 effect sizes were first categorized into six subgroups based on what mood state was measured. Effect sizes within each of the six sets of outcomes are independent, because each treatment group had at most one effect size for each mood state.

The mean effect size for each mood status can then be calculated separately. Each mean effect size is calculated by weighting each individual effect by its associated variance. The variance used for weighting was estimated based on the random-effects model, in which between-samples variation was accounted for, producing more conservative results. The variance of each effect was computed as $\mathrm{var}(d) + S_\delta^2$, where $\mathrm{var}(d)$ is defined above and S_δ^2 is a method-of-moments estimator of between-studies variation given in formula 18 of Shadish and Haddock (1994). More details on random-effects modeling can be found in Shadish and Haddock (1994, pp. 273-275).

Below is the SAS macro for calculating the mean effects and their standard errors for the six outcomes. The remarks in the right hand column document each of the steps.

```
%MACRO random(outcome);                          /*Start the macro;*/
DATA &outcome;
      SET exercise.dat;                          /*Call in the data with the outcome
      IF outcome="&outcome"; RUN;                of interest;*/
DATA &outcome; SET &outcome;                      /*Calculate the sums of v (sv), d
      dd=d*d;                                     (sd), and d² (sdd) for later
PROC MEANS N SUM;                                 calculation;*/
      VAR v d dd;                                 /*v is variance of d; k is number of
      OUTPUT OUT=randeff N=k SUM=sv sd sdd;       effect sizes;*/
DATA randeff; SET randeff;
      svar=(sdd-sd*sd/k)/(k-1)-sv/k; RUN;         /*Estimate between-group variation
DATA RANDOM;                                      (svar)based on random-effects
      IF _N_=1 then set randeff;                  model;*/
      SET &outcome;
      IF svar lt 0 then svar=0;
      vstar=v+svar;                               /*Calculate the new weight (vstar)
      wstar=1/vstar;                              that incorporates the between-group
      wdstar=wstar*d;                             variation;*/
PROC MEANS NOPRINT N SUM;
      VAR wstar wdstar;
      OUTPUT OUT=sumup N=k
      SUM=swstar swdstar; RUN;
DATA final; SET sumup;
      d_dot=swdstar/swstar;                       /*Calculate the mean effect(d_dot)
      se_d_dot=SQRT(1/swstar);                    and its standard error (se_d_dot);*/
PROC PRINT DATA=final;
VAR k d_dot se_d_dot; RUN;
%MEND random;                                     /*End of the macro;*/

%random(anger);%random(confus);                   /*Run the macro for each outcome;*/
%random(dep); %random(fatigue);
%random(tens); %random(vigor);
```

Method II: Accounting for Dependence among the Outcomes

To use the generalized least squares (GLS) method to model the dependence among outcomes and calculate the mean effects of exercise on each mood state, a vector $\mathbf{d}$ is created, containing all 71 effect sizes and a 71*71 variance-covariance matrix among the effects is obtained.

Let $\mathbf{d}_i$ represent the vector effect size for group i (i=1 to 15); d_{ij} in the vector represents the effect size from group i on measure j (j= 1 to 6 for tension, depression, anger, vigor, fatigue, confusion). As noted earlier, not every study measured all six outcomes. Therefore, for example, the first group had only measures of tension (j=1), depression (j=2), anger (j=3), and vigor (j=4), and $\mathbf{d}_1$=(d_{11}, d_{12}, d_{13}, d_{14})'; The fifteenth group measured all six outcomes and $\mathbf{d}_{15}$=($d_{(15)1}$, $d_{(15)2}$, $d_{(15)3}$, $d_{(15)4}$, $d_{(15)5}$, $d_{(15)6}$)'.

The linear model that can be used to represent variation in effect sizes is:

$$\mathbf{d} = \mathbf{X} \times \boldsymbol{\delta} + \mathbf{e}$$

$$\begin{bmatrix} d_{11} \\ d_{12} \\ d_{13} \\ d_{14} \\ d_{21} \\ \vdots \\ d_{(15)6} \end{bmatrix}_{71\times1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{71\times6} \times \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \end{bmatrix}_{6\times1} + \begin{bmatrix} e_{11} \\ e_{12} \\ e_{13} \\ e_{14} \\ e_{21} \\ \vdots \\ e_{(15)6} \end{bmatrix}_{71\times1}$$

where the matrix $\mathbf{X}$ contains six columns to indicate which one of the six outcomes each effect size measured (e.g., a one in the first column means the effect was a measure of tension). The δs, the regression coefficients for the dummy variables, represent the estimated mean effects, and e_{ij} is the corresponding residual for outcome j for group i.

The δs can be estimated using GLS estimation, assuming the errors $\mathbf{e}$ have a mean vector of 0 and a known variance-covariance matrix $\boldsymbol{\Sigma}$. The matrix $\boldsymbol{\Sigma}$ can be estimated by $\mathbf{S}$, which is the 71*71 variance-covariance matrix among the d_{ij} values, with the variance-covariance for each treatment group ($\mathbf{S}_i$) on the diagonal. Other elements in the matrix $\mathbf{S}$ are all 0 assuming the 15 treatment groups are independent of each other.

In each $\mathbf{S}_i$, the diagonal elements are the variances of each effect size, the var(d_{ij}) for $j = 1$ through 6 as defined above, plus the between studies variance. The off-diagonal elements in $\mathbf{S}_i$ are the covariances between pairs of effect sizes d_{ij} and d_{ij} for study i, each of which is defined as $S(d_{ij}, d_{ij'}) = r_{ijj'} S(d_{ij}) S(d_{ij'})$. The $S(d_{ij})$ and

$S(d_{ij'})$ are the square roots of var(d_{ij}) and var($d_{ij'}$). The $r_{ijj'}$ are the correlations between outcomes j and j', which unfortunately often are not reported and have to be assumed. In the current study, the correlations reported in the POMS manual (McNair et al., 1971) were used, which ranged from .13 between anger and vigor to .77 between tension and depression.

The mean effect for each outcome can be estimated by solving

$$\hat{\boldsymbol{\delta}} = (\mathbf{X'S}^{-1}\mathbf{X})^{-1}\mathbf{X'S}^{-1}\mathbf{d}.$$

The variance-covariance matrix of the estimated mean effects is

$$\mathrm{Var}(\hat{\boldsymbol{\delta}}) = (\mathbf{X'S}^{-1}\mathbf{X})^{-1}.$$

An easy way to obtain the estimates is to set up the values in $\mathbf{d}$, $\mathbf{X}$ and $\mathbf{S}$ in Excel, and then call them into SAS in the form of a vector ($\mathbf{d}$) and matrices ($\mathbf{X}$ and $\mathbf{S}$). That is, in the Excel spreadsheet the 71 effect sizes are in one column. Six more columns, each with 71 values, indicate the outcome(s) represented by each of the 71 effect sizes. Each column indexes one of the 6 outcomes, and each column contains a 1 in row r if the effect size in row r measured that specific outcome. The 71*71 variance-covariance matrix can be computed and saved in 71 columns, each with 71 values. The SAS IML code used to retrieve the data from Excel and to compute the estimates of mean effect for the outcomes and their standard errors are shown below.

```
DATA exercise.varcov;                    /*Save variance-covariance spreadsheet
     SET work.varcov;                     imported from Excel (work.varcov)as SAS
PROC IML;                                 dataset;*/
     USE exercise.varcov;                /*Save the data in the form of matrix S;*/
     READ all var _num_ into S;
     STORE S; RUN;
PROC IML;
     USE exercise.data;                  /*Read in the six dummy coded outcomes
     READ all var {Danger Dconfuse Ddepress   in the SAS and form the (71*6) matrix X;*/
     Dtension  Dfatigue Dvigor} INTO X;  /*Read in the (71*1) effect size vector d ;*/
     READ all var {d} INTO d;
     STORE X d; RUN;
PROC IML;
     LOAD X d S;                         /*Estimate the means for each outcome
     d_hat=inv(X`*inv(S)*X)*X`*inv(S)*d;  (d_hat) and their standard errors (se_d);*/
     se_d=SQRT(inv(X`*inv(S)*X));
     PRINT d_hat Vd; RUN;
```

Results

The estimated mean effects of exercise on six mood states in the elderly are shown in Table 1. Under both methods, almost all mood states show significant improvement after the exercise intervention, except tension estimated using method I ($\bar{d}$=0.12) and vigor under both methods. Using method I, fatigue ($\bar{d}$=0.30), anger ($\bar{d}$=0.29), and depression ($\bar{d}$=0.29) improve the most; under method II, tension ($\bar{d}$=0.28), anger ($\bar{d}$=0.27), and depression ($\bar{d}$=0.26) improve the most.

The standard errors for outcomes based on method I are larger than those computed based on method II. This occurs in part because the intercorrelations among the outcomes allow estimates of each mean to borrow strength from other outcomes and thus precision is increased. Also, Table 1 shows the correlations among the group means. Although none of the entries is large, some are moderate in size suggesting that it would be wrong to treat the means as if they were independent, as one would if tests to compare means were conducted using method I.

Table 1. Results

Outcome	k	Method I		Method II						
		$\bar{d}$	SE	$\bar{d}$	SE	Correlations				
						C	D	T	F	V
Anger (A)	13	0.29*	0.076	0.27*	0.068	.34	.30	.28	.20	.02
Confusion (C)	12	0.15*	0.065	0.14*	0.053		.44	.40	.38	.08
Depression (D)	13	0.29*	0.084	0.26*	0.075			.35	.28	.07
Tension (T)	8	0.12	0.115	0.28*	0.065				.30	.06
Fatigue (F)	14	0.30*	0.072	0.13*	0.063					.09
Vigor (V)	11	0.20	0.243	0.17	0.204					

Note. The "*" indicates the mean effect size is significantly different from 0 at the .05 level

Conclusion

Exercise has a positive impact on elders' mood change, though all changes are modest (at most three tenths of a standard deviation). However, the magnitudes of the impact on different mood states are varied. Additional analyses would examine this variation among effect sizes, which can be quantified using Q statistics (Shadish & Haddock, 1994). Further investigation could focus on moderators such as type of exercise or participant age which might explain the variation in effects.

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