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ABSTRACT

Research has suggested that important research questions can be addressed with meaningful interpretations using hierarchical linear modeling (HLM). The proper interpretation of results, however, is invariably linked to the choice of centering for the Level-1 predictor variables that produce the outcome measure for the Level-2 regression analysis. In this study, three centering methods (uncentered, group mean, and grand mean) were compared using Read93 and Lunch Status as Level-1 predictor variables of Iowa Tests of Basic Skills (ITBS) 1994 reading test scores (for 5,638 ninth graders enrolled in 26 high schools within a large urban school district). The reliability estimates, or how accurately the sample estimate represents the population value differed among the three centering methods. It was found that the group mean centering method provided the best reliability estimate. When using outcome measures based on these three centering methods in a Level-2 analysis using two predictors, graduation rate (Gradrate) and percent in advanced diploma plans (%Advdip), the group mean centering method indicated a more reliable estimate, but the grand mean centering method explained more between-school variance. In fact, the gamma coefficients were markedly different, and the amount of variance explained was no longer consistent across the centering methods. These findings indicate that centering effects in Level-1 predictor variables can affect both theoretical and empirical findings in HLM. Five tables present study findings. (Contains 11 references.) (Author/SLD)

Centering Effects in HLM Level-1 Predictor Variables

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Paper presented at the American Educational Research Association annual meeting
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ABSTRACT

Research has suggested that important research questions can be addressed with meaningful interpretations using hierarchical linear modeling. The proper interpretation of results, however, is invariably linked to the choice of centering for the Level-1 predictor variables which produce the outcome measure for the Level-2 regression analysis. In this study, three centering methods (uncentered, group mean, and grand mean) were compared using Read93 and Lunch Status as Level-1 predictor variables of ITBS94 reading test scores. The reliability estimates, or how accurately the sample estimate represents the population value differed between the three centering methods. It was found that the group mean centering method provided the better reliability estimate. When using outcome measures based upon these three centering methods in a Level-2 analysis using two predictors, Gradrate and %Advdip, the group mean centering method indicated a more reliable estimate, but the grand mean centering method explained more between school variance. In fact, the gamma coefficients were markedly different and the amount of variance explained was no longer consistent across the centering methods. These findings indicate that centering effects in Level-1 predictor variables can affect both theoretical and empirical findings in HLM.

CENTERING EFFECTS IN HLM LEVEL-1 PREDICTOR VARIABLES

In quantitative research, it is essential that the variables under study are meaningful and interpretable so that statistical results can be related to theoretical concerns (Arnold, 1992). This principle is especially meaningful in analyses with multiple levels of variables such as hierarchical linear modeling (HLM). In hierarchical linear modeling, the Level-1 variable's intercepts and slopes become outcome variables at Level-2. Because of this potentially complex "nested" design, it is important that each variable's value be clearly understood and specifically articulated (Bryk & Raudenbush, 1992).

Hierarchical linear modeling can be used to investigate many of the research questions in education that involve at least two levels of variables. Samples of such questions include: Do schools with a high percentage of students with limited English proficiency also have high achievement scores? Is the relationship between student SES and achievement invariant across schools? In fact, several studies investigating teacher effect eness, school effectiveness, and student change and growth have been conducted using HLM (Bryk & Raudenbush, 1987 & 1988, Raudenbush, 1988, Lee & Bryk, 1989, Mendro et al. 1994, Webster et al, 1994). These studies recognize the nested design structure of students within classrooms, classrooms within schools, and schools within districts which produce different variance components for variables at each level.

In multi-level analyses, variables measured at the different levels provide different variance estimates (Bock, 1989). For example, school level variables do not vary for students in a particular school. These school-level variables instead help to explain between-school variance rather than within-school variance. Likewise, students in the same classroom or school tend to be more alike than in other classrooms or schools; hence, the variance between students is not constant. Student level data, however, measures the within-school variance, conditioned by school-level effects. These research characteristics, until recently, have been overlooked with most analyses being done in multiple regression using a single-level model.

One critical aspect in conducting HLM analyses is the centering of Level-1 predictor variables that produce the outcomes used in Level-2 analyses as dependent variables. The interpretation of these outcomes is critical to the meaningfulness of results since centering changes, not only the coefficient values, but also the research questions being answered by the statistical analysis (Burton, 1993). Theory should drive the decision to center any Level-1 variable as indicated by the research questions included in the investigation. This policy is in keeping with appropriate multiple linear regression procedures. With the introduction of HLM, however, the effect of one level of variables on another introduces several areas for further investigation (see last section paper). The focus of this paper is on one such area, namely, centering effects of Level-1 variables.

Four possibilities exist for centering Level-1 predictor variables in HLM: X metric, grand mean, group mean, and user defined location, such as a cut-off score (Bryk & Raudenbush 1992). This study included the first three centering methods to determine whether the Level-1 centering decision affects the reliability estimates in the HLM analysis. This investigation further examined how centering decisions made for Level 1 variables affect the amount of between-school variance explained by Level-2 variables.

METHODOLOGY

Data Set

The research questions posed for this study were investigated using data from ninth grade students (n = 5638) who were continuously enrolled in 26 high schools within a large urban school district. The Level-1 variables in this study were defined as student level variables [some examples of potential student-level variables are: gender, achievement measures, socio-economic status, ethnicity, and level of English proficiency]. Level-2 variables were defined as school-level variables [some examples of school level variables are: attendance rates, graduation rates, number of students in advanced courses, and mobility and crowdedness].

The student level variables selected for this study included the individual reading test scores from the Iowa Test of Basic Skills (ITBS94) for 1994 as the dependent variable; the 1993 individual reading scores (Read93) and an individual student socio-economic indicator identifying free-lunch status (Lunch Status) as the two independent predictor variables.

The school level variables from the twenty-six high schools selected for the study were the graduation rate for each high school (Gradrate) and the percent of the students in advanced diploma plans within each school (%Advdip). The Level-2 variables used in the study were not aggregates of any individual Level-1 variables.

Research Questions

A typical research question for the analysis of this data in an HLM framework would be: **What is the effect of a school's graduation rate and percent students in** advanced diploma plans on the mean reading test scores of 9th graders? In HLM terminology, this is a "means as outcomes" approach which involves an examination and use of the intercept values as cutcomes (dependent variable) for Level-2 variable analysis.

In our investigation, we were concerned with the questions: Does the choice of centering method affect the reliability estimates at Level-1? and Is the amount of between-school variance explained the same at Level-2?. Prior research has indicated that both an interpretation of intercept outcome values and a change in the research question occurs based upon a choice of centering method. Are concern therefore was not only with these theoretical issues, but with the empirical issues surrounding the reliability estimates which reflect how well the sample mean indicates the population mean and whether the amount of between-school variance predicted at Level-2 would be the same.

Analysis

An initial analysis established a "fully unconditional" model or a model without Level 1 or Level 2 predictors (Bryk & Raudenbush, 1992). The model is as follows:

Student level (Level 1) $Y_{ij} = \beta_{0j} + r_{ij}$

where
Y_{ij} = ITBS 94 reading score for student I in school j
β_{0j} = mean reading score in school j
r_{ij} = Level-1 error, assumed $N(0,\sigma^2)$, σ^2 = student level variance

School level (Level 2)

$\beta_{0j} = \gamma_{00} + u_{0j}$

where

γ_{00} = grand mean of the district (N=26 schools)

u_{0j} = random effect school j, assumed $N(0,\tau_{00})$,

τ_{00} = school level variance

Results from the "fully unconditional" intercept (means as outcomes) ANOVA analysis are listed in Table 1.

Table 1. ANOVA Intercept Model[a] for 1994 ITBS Reading Outcomes (N=26 schools)

Centering Method	β_0[c]	$SE\beta_0$	Reliability Estimate
Fully unconditional model[b]	16.85	.67	.98

a No predictors specified at Level-1

[b] Intraclass correlation coefficient = $\tau_{00}/(\tau_{00} + \sigma^2) = 11.60/(11.60 + 36.08)$ = 24% of variance in 1994 ITBS Reading outcomes between schools explained.

c t=25.15, p=.0001

This initial "fully unconditional" model allows us to partition the total variance in reading into a between school variance component . It also establishes an estimate for the grand mean (β_0) , a confidence interval (β_0 +/- $SE\beta_0$), and establishes the parameters for within-school variability (σ^2) and between school variability (τ_{00}). The reliability estimate indicates how well each school's sample average in reading achievement estimates their true mean (Bryk & Raudenbush, 1992). In this case, the reliability estimate was .98, indicating that the school's sample means are quite reliable as indicators of their true school means. The significant t-value indicates that the schools do not have the same mean ITBS 1994 reading average.

In the next two analyses, the Level-1 predictors, Read93 and Lunch, were added separately to the "fully unconditional" model.

Reading 1993 as predictor:

$Y_{ij} = \beta_{0j} + \beta_{1j}(READ93) + r_{ij}$

where
Y_{ij} = ITBS 94 reading score for student I in school j
β_{0j} = intercept for school j
β_{1j} = slope for school j
r_{ij} = Level-1 error

$\beta_{0j} = \gamma_{00} + u_{0j}$

where
γ_{00} = average intercept in N=26 schools
u_{0j} = random effect for school j

$\beta_{1j} = \gamma_{10} + u_{1j}$

where
γ_{10} = average slopes in N=26 schools
u_{1j} = random effect for school j

Lunch Status as predictor:

$Y_{ij} = \beta_{0j} + \beta_{1j}(LUNCH) + r_{ij}$

where
Y_{ij} = ITBS 94 reading score for student I in school j
β_{0j} = intercept for school j
β_{1j} = slope for school j
r_{ij} = Level-1 error

$\beta_{0j} = \gamma_{00} + u_{0j}$

where
γ_{00} = average intercept in N=26 schools
u_{0j} = random effect for school j

$\beta_{1j} = \gamma_{01} + u_{1j}$

where

γ_{10} = average slope in N=26 schools

u_{1j} = random effect for school j

For each Level-1 variable, three analyses were run. These analyses involved either an uncentered predictor, a predictor centered on the grand mean, or a predictor centered on the group mean. The results of the three analyses for each Level-1 variable are included in Tables 2 and 3, respectively, which are presented and discussed in the Results section of the paper.

In a subsequent analysis, both Level-1 predictor variables were included and the three analyses run again with predictors uncentered, centered on the grand mean, or centered on the group mean.

Two Level I predictors -- Read93 and Lunch Status

$Y_{ij} = \beta_{0j} + \beta_{1j}(READ93) + \beta_{2j}(LUNCH) + r_{ij}$

where
Y_{ij} = ITBS 94 reading score for student I in school j
β_{0j} = intercept for school j
β_{1j} = slope of READ93 for school j
β_{2j} = slope of LUNCH for school j
r_{ij} = Level-1 error

$\beta_{0j} = \gamma_{00} + u_{0j}$

where
γ_{00} = average intercept in N=26 schools
u_{0j} = random effect for school j

$\beta_{1j} = \gamma_{10} + u_{1j}$

where
γ_{10} = average READ93 slope in N=26 schools
u_{1j} = random effect for READ93 in school j

$\beta_{2j} = \gamma_{20} + u_{2j}$

where
γ_{20} = average LUNCH slope in N=26 schools
u_{2j} = random effect for LUNCH in school j

Results of these analyses are included in Table 4 which is also presented and discussed later in the Results section of the paper.

A final analysis included both Level-1 predictors (READ93, LUNCH) and the two Level-2 predictors (AdvDip, Gradrate). This analysis was also run three times using the Level-1 predictors as either uncentered, centered on the grand mean, or centered on the group mean. The Level-two predictors were not centered. The equations were as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{READ93}) + \beta_{2j}(\text{LUNCH}) + r_{ij}$$

where
Y_{ij} = ITBS 94 reading score for student I in school j
β_{0j} = intercept for school j
β_{1j} = slope for READ93 in school j
β_{2j} = slope for LUNCH in school j
r_{ij} = Level-1 error

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{AdvDip}) + \gamma_{02}(\text{Gradrate}) + u_{0j}$$

where
γ_{00} = average intercept for N=26 schools
u_{0j} = random effect for school j

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{AdvDip}) + \gamma_{12}(\text{Gradrate}) + u_{1j}$$

where
γ_{10} = average READ93 slope for N=26 schools
u_{1j} = random effect for school j

$$\beta_{2j} = \gamma_{20} + \gamma_{21}(\text{AdvDip}) + \gamma_{22}(\text{Gradrate}) + u_{2j}$$

where
γ_{20} = average LUNCH slope for N=26 schools
u_{2j} = random effect for school j

Results of these analyses are included in Table 5 and discussed in the Results section.

RESULTS

Centering Effects of Level-1 Predictors

The meaningfulness of the intercept and slope values in a Level-1 (student level) model depends upon the centering of the Level-1 predictor variables. In raw metric form, the equation $Y_{ij} = \beta_{0j} + \beta_1 X_{ij} + r_{ij}$, yields intercept values, β_{0j}, which are interpreted as an outcome measure for a student attending school j who has a 0 (zero) on X_{ij}. Obviously this causes a problem in the interpretation of student achievement using these raw metric intercept values because the lowest score on the test will not be zero.

When centering Level-1 predictor variables around the grand mean, they are determined by: $(X_{ij} - X_{..})$. The intercept, β_{0j}, can now be interpreted as an outcome measure for a student in school j whose value on X_{ij} is referenced to the grand mean. This permits a useful interpretation of the intercept as an adjusted mean for school j: in this case, $\beta_{0j} = \mu_{Yj} + \beta_{1j}(X_{.j} - X_{..})$. These intercept values can now represent a specific interpretation of the outcome measures for each school in the Level-2 analysis. The intercept variance term reflects the variation in the adjusted means for the set of schools.

If the Level-1 predictor variables are centered around the group mean, they are determined by $(X_{ij} - X_{.j})$. Now the intercept, β_{0j}, represents the unadjusted outcome measure for a student in school j. In this instance, $\beta_{0j} = \mu_{Yj}$. The intercept variance, Var (β_{0j}), is now the variance around these Level-2 unit means, μ_{Yj} . This permits an examination of the sampling distribution of school means or slopes around a population mean value.

HLM users typically center some or all student-level predictors at either the grand mean or group mean to add stability to the estimation process and provide for intercepts that can be meaningfully interpreted. Centering, however, also has the effect of changing the coefficients that are estimated and altering the research question(s) being asked (Burton, 1993). In fact, Burton (1993) indicated, using a NELS88 data set (outcome=mathematics achievement test; student-level variables=minority status, socio-economic status, and absenteeism; school-level variables=percent minority; location of school, and percent low SES), that uncentered and grand mean centering indicated only significant Level-1 coefficients while group mean centering indicated significant Level-2 coefficients (school level). This implied two different interpretations of results: at the student level, individual status affected achievement, while in contrast, at the school level, average school status affected achievement. It is troublesome that a choice between these two centering methods could result in two different interpretations. Which is the correct interpretation of the results?

In practical applications, Level-1 predictor variables appear to become more stable when they are centered on either the group mean or grand mean. In our study, the initial sample estimate (intercept, β_0) was close to the population value in the fully unconditional model, as indicated by the reliability estimate of .98 (Table 1). This finding is expected in any initial null model.

The reliability estimates, or how accurately the sample estimate represents the population value, however, differed between the three centering methods when centering the Level-1 predictor Read93 (Table 2). The reliability estimates were .76 for uncentered,

.90 for grand mean centering, and .98 for group mean centering. The intercept and the reliability estimate values were the same in the initial fully unconditional model and the Level-1 Read93 prediction equation using the group-mean centering method. These values differed for the grand mean centering and uncentered methods, although they were more approximate when using grand mean centering. As expected, the amount of within school variance explained remained the same regardless of which centering method was used (45%).

Table 2

Level-1 predictor Read93 for 1994 ITBS Reading Outcomes (N=26 schools)

Centering Method[a]	β_0	$SE\beta_0$	r.	β_1	$SE\beta_1$	r.
Uncentered	7.41	.36	.76	.23	.004	.28
Centered: Group Mean	16.85	.67	.98	.22	.004	.37
Centered: Grand Mean	16.78	.27	.90	.22	.004	.28

[a] Intraclass correlation the same for each centering method [σ^2 (ANOVA) - σ^2(Read93)/ σ^2 (ANOVA) = 36.08-20.00/36.08 = 45%]

Table 3 indicates the results of the three centering methods when using Lunch Status as a Level-1 predictor variable. Once again, the group mean centering method yielded results identical to the initial fully unconditional model, and the grand mean centering method more closely approximated the initial model than the uncentered approach. The amount of within school variance explained was small (3%), and as expected the same regardless of choice of centering method.

Table 3

Level 1 predictor Lunch Status for 1994 ITBS Reading Outcomes (N=26 schools)

Centering Method[a]	β_0	$SE\beta_0$	r.	β_1	$SE\beta_1$	r.
Uncentered	13.85	.55	.69	1.87	.33	.67
Centered: Group Mean	16.85	.67	.98	1.82	.33	.67
Centered: Grand Mean	16.74	.62	.97	1.87	.33	.67

[a] Intraclass correlation the same for each centering method [σ^2 (ANOVA) - σ^2(Lunch)/ σ^2 (ANOVA) = 36.08-35.05/36.08 = 3%]

Table 4 indicates the effect of each centering method when both Read93 and Lunch Status were used in a Level-1 prediction equation for 1994 ITBS Reading outcomes. The results indicated that 45% of the between school variance was explained when using both predictors, which was the same amount indicated when using Read93 alone. Moreover, the sample mean intercept value using the group mean centering method was the same as in the initial fully unconditional model (Table 1), with only a slight improvement in the reliability estimate (.98 to .99). The reliability estimate for the grand mean centering method was more approximate to these values than the uncentered method, especially when using Read93 as the only predictor (see Tables 2 and 3, respectively). The group mean centering method was therefore the most stable of the three centering methods.

Table 4

Two Level-1 predictors: 1993 ITBS Reading and Lunch Status for 1994 ITBS Reading Outcomes (N=26 schools).

	Null			Read93			Lunch Status		
Centering Method[a]	β_0	$SE\beta_0$	r	β_1	$Se\beta_1$	r	β_1	$Se\beta_1$	r
Uncentered	6.46	.34	.47	.22	.004	.30	.69	.15	.25
Centered: Group Mean	16.85	.68	.99	.22	.004	.37	.69	.16	.28
Centered: Grand Mean	16.77	.26	.89	.22	.004	.29	.69	.15	.26

a Intraclass correlation the same for each centering method | σ^2 (ANOVA) - σ^2 (Read93 & Lunch) / σ^2 (ANOVA) = 36.08 - 19.88/36.08 = 45%

From a research standpoint, the choice of Level-1 predictor will impact the amount of within school variance explained. In our study, the preference would be given to using only Read93 as a Level-1 predictor since Lunch Status didn't add any additional significant variance explained. For our purposes, however, we continued to use both Level-1 predictor variables in the Level-2 equation. More importantly, we would choose a group mean centering approach for the predictor variables because it reflected similar values to those in the fully unconditional model.

Centering Level-1 variable effects on Level 2 analysis

The different centering effects on Level-1 predictor variables indicates the importance of being able to meaningfully interpret outcomes. The choice of centering method also indicates a different interpretation for β_{0j}, its variance, and any covariances involving β_{0j}. The prediction of any outcome measure, given Level-2 predictor variables, should provide additional information for considering these centering effects.

When introducing the Level-2 school-level predictor variables, AdvDip and Gradrate, the combined equation for the full model becomes:

$$
\begin{aligned}
Y_{ij} = \; & [\gamma_{00} + \gamma_{01}(\text{AdvDip}) + \gamma_{02}(\text{Gradrate}) + u_{0j}] \; + \\
& [\gamma_{10} + \gamma_{11}(\text{AdvDip}) + \gamma_{12}(\text{Gradrate}) + u_{1j}] \, (\text{READ93}) \; + \\
& [\gamma_{20} + \gamma_{21}(\text{AdvDip}) + \gamma_{22}(\text{Gradrate}) + u_{2j}] \, (\text{LUNCH}) \; + \\
& r_{ij}
\end{aligned}
$$

Table 5 indicates each type of centering method and the associated summary statistics from this Level-2 prediction equation.

Table 5

Two Level 2 predictors: Graduation Rate and % Advanced Diploma Conditioning the 1994 ITBS Reading Outcomes of READ93 and Lunch Intercept Only (N=26 schools)

Centering Method	γ_{00}	$SE\gamma_{00}$	γ_{01}	$SE\gamma_{01}$	γ_{02}	$SE\gamma_{02}$	r.
Uncentered[a]	4.17	1.11	.003	.02	.04	.03	.43
Centered: Group Mean[b]	8.76	1.19	.030	.02	.13	.03	.96
Centered: Grand Mean[c]	14.15	.68	.004	.01	.05	.02	.84

[a] Intraclass correlation = τ_{00} (ANOVA) - τ_{00} (Gradrate & %Advdip)/ τ_{00}(ANOVA) = 11.60 - 1.22/ 11.60 = 89%; t = 3.75, p > .002.
[b] Intraclass correlation coefficient =τ_{00} (ANOVA) - τ_{00} (Gradrate & %Advdip)/ τ_{00}(ANOVA) = 11.60 - 3.46/ 11.60 = 70%; t = 7.36, p > .0001.
[c] Intraclass correlation coefficient =τ_{00} (ANOVA) - τ_{00} (Gradrate & %Advdip)/ τ_{00}(ANOVA) = 11.60 - .97/ 11.60 = 92%; t = 20.87, p > .00001.

Table 5 reveals two very important findings. First, the amount of variance explained is no longer consistent across the centering methods. The amount of variance explained using uncentered Level-1 variables was 89%; with group mean centering it was 70 %; and with grand mean centering it was 92%. Secondly, the reliability estimates, or how well the sample estimates indicate the true population values, also fluctuated. The group mean centering method yielded the highest reliability estimate (.96), but indicated very different coefficients for the variables than the other two centering methods, and had the lowest percent variance explained (70%). This leads to conflicting results since the group mean centering method was preferred at Level-1, but the grand mean centering method explains more between-school variance at Level-2.

CONCLUSIONS

The reliability estimates, or how accurately the sample estimate represents the population value, differed between the three centering methods, especially in the case of the Read93 Level-1 predictor variable. In further examining the centering effects in Level-1 predictor variables, it was found that the group mean centering method provided the better reliability estimate. When using outcome measures based upon these three centering methods in a Level-2 analysis using two predictors, Gradrate and %Advdip, the group mean centering method indicated a more reliable estimate, but the grand mean centering method explained more between school variance. The gamma coefficients were markedly different and the amount of variance explained was no longer consistent across the centering methods. These findings indicate that the centering of Level-1 variables empirically effects the variance estimation.

Research has suggested that important research questions can be addressed with meaningful interpretations using hierarchical linear modeling (Raudenbush, Rowan, & Cheong, 1993). For practical applications, the unconditional model allows partitioning of variance into within-school and between-school components for the outcome measure. The choice of variables at Level-1 impacts the amount of within-school variance (student-level) that can be explained, and the choice of variables at Level-2 impacts the amount of between-school variance (school-level) that can be explained given the outcome measures provided from the Level-1 equation. The proper interpretation of results, however, is invariably linked to the choice of centering for the Level-1 predictor variables which produces the dependent measures for Level-2 regression analyses. Studies which examined organizational level school effectiveness and teacher effectiveness variables using hierarchical linear models have provided more appropriate variance estimates and means as outcomes than previous single level data analyses. The proper interpretation and accuracy of estimation , however, requires that a researcher pay special attention to the centering effects in Level-1 student-level variables upon Level-2 analyses when conducting hierarchical linear models.

OTHER CONSIDERATIONS

For many researchers, multiple regression has become a valuable data analytic tool because many of the issues related to using multiple regression have been investigated. For example, normality, heterogeneity, number of predictors, ratio of sample size to predictors, multi-collinearity, use of composite variables, and interaction effects. We believe that many of these concerns need to be restated in the context of hierarchical linear modeling. Once case in point is the effect of centering when including an interaction term. Aiken & West (1993) have indicated that centering variables in the presence of an interaction term in multiple regression changes the value of the regression coefficients. In HLM, this would also probably follow as a dictum, especially in light of the findings by Burton (1993). Additional examination of the other factors will determine what effect, if any, they have upon hierarchical linear analyses.

REFERENCES

Aiken, L. S. & West, S. G. (1991). Multiple Regression: Testing and Interpreting Interactions. Newbury Park, CA: Sage Publications.

Arnold, C. L. (1992). An introduction to hierarchical linear models. Measurement and Evaluation in Counseling and Development, 25, 58-90.

Bock, R. Darrell. (1989). Multilevel Analysis of Educational Data. San Diego, CA: Academic Press.

Bryk, A. S. & Raudenbush, S. W. (1992). Hierarchical Linear Models: Applications, and Data Analysis Methods. Newbury Park, CA: Sage Publications.

Bryk, A. S. & Raudenbush, S. W. (1988). Toward a more appropriate conceptualization of research on school effects: A three-level hierarchical linear model. American Journal of Education, November, 65-108.

Bryk, A. S. & Raudenbush, S. W. (1987). Application of hierarchical linear models to assessing change. Psychological Bulletin, 101, 147-158.

Burton, Bob. (1993, April). Some observations on the effect of centering on the results obtained from hierarchical linear modeling. (Paper presented at the Annual Meeting of the American Educational Research Association, Atlanta, GA).

Lee, V. E. & Bryk, A. S. (1989). A multilevel model of the social distribution of high school achievement. Sociology of Education, 62, 172-192.

Mendro, R. L., Webster, W. J., Bembry, K. L. & Orsak, T. H. (1994, October). Applications of Hierarchical Linear Models in Identifying Effective Schools. (Paper presented at the Annual Meeting of the Rocky Mountain Educational Research Association, Tempe, AZ).

Raudenbush, S. W. (1988). Educational applications of hierarchical linear models: A review. Journal of Educational Statistics, 13, 85-116.

Webster, W. J., Mendro, R. L., Bembry, K. L. & Orsak, T. H. (1994, October) Alternative methodologies for identifying effective schools (Paper presented at the Annual Meeting of the Rocky Mountain Educational Research Association, October, Tempe, AZ).