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ABSTRACT

This paper presents an example using university student satisfaction survey data to demonstrate how to address problems associated with the hierarchical or nested nature of the data. Massive large-scale secondary data have been used in higher education research, and ignoring hierarchically structured data may lead to inaccurate or misleading conclusions. Data for this example are from 1,187 students who completed a satisfaction survey. The paper illustrates the need for multilevel modeling, or hierarchical linear modeling, but does not provide an extensive description of the use of multilevel models. (Contains 18 references.) (Author/SLD)

Running head: HLM & HIGHER EDUCATION RESEARCH

A Hierarchical Linear Modeling Approach to Higher Education Research: The Influences of Student and Institutional Characteristics

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Abstract

The present study presents an example using a university student satisfaction survey data to demonstrate how to address problems associated with the hierarchical or nested nature of the data. Massive large-scale secondary data have been used in higher education research. Ignoring hierarchically structured data may lead to inaccurate or misleading conclusions.

A Hierarchical Linear Modeling Approach to Higher Education Research: The Influences of Student and Institutional Characteristics

The majority of educational data has the hierarchical multilevel character. It has been the methodological dilemmas to use the hierarchical nature of data in educational research (Burnstein, 1980; Burnstein et al., 1989; Murchan and Sloane, 1994). Burnstein (1980) argued that single level traditional linear OLS approaches are not adequate for estimating the effects of schooling on students. Since Burnstein's (1980) seminal paper, HLM has been used especially on the research on school effects at the elementary and secondary level. The researchers had acknowledged the hierarchical nature of the organization of schooling by gathering data on students, classes, and schools (Burnstein, 1980; Burnstein et al., 1989; Murchan and Sloane, 1994). Research in higher education had long been neglecting the hierarchical or nested nature of the data.

In fact, many higher education models for student learning or cognitive development include student background, structural, organizational, and environmental characteristics of the institution, the major department,

and peer groups (Pascarella, 1985; Weidman, 1989). The models reflect the hierarchical nature of the influences on college students' growth and development and research has involved data with nested structures (Ethington, 1997). Research utilizes either multi-institutional samples of students or single-institutional samples of students. In multi-institutional studies, both student and institutional measures are considered as factors impacting student outcomes. On the other hand, in single-institution studies, students are nested in classes, in majors, and in departments, schools or colleges within the institution.

Today, large-scale secondary data sets are available for research in higher education. The National Center for Education Statistics (NCES) in the U.S. Department of Education produces numerous surveys such as High School and beyond (HS & B), the National Postsecondary Student Aid Study (NPSAS), the National Study of Postsecondary Faculty (NSOPF), the beginning Postsecondary student Longitudinal Study (BPS), the Baccalaureate and Beyong Study (B & B), and the Integrated Postsecondary educational Data System (IPEDS). These large data are constructed using complex sample designs where the population is stratified on a number of dimensions (Thomas & Heck, 2001). These complex

sample designs often cluster lower level units (e.g., students) within higher-level units (e.g., colleges).

One of the key challenges for higher education institutions is to arrange their resources for learning so that students spend their time on the activities for their education. Higher education institutions can continually examine students' perceptions of campus life to identify their level of satisfaction with the campus (Astin, 1975; Pace, 1984; Tinto, 1993). Over the past few decades, a number of different tools have been developed and used to explore student perceptions of the quality of campus life (Austin, 1975; Pace, 1984). Upcraft and Schuh (1996) pointed out that measuring student satisfactions is a well-accepted practice in higher education. A university student survey is a useful data-gathering tool in that it provides institutions with valuable feedback regarding students' individual and collective impressions of the campus climate. Both individual and institutional factors are equally important. Identifying these characteristics helps administrators determine if institutions seek to improve the academic and student affairs in the higher education institution (Astin, 1993). Also, examining both individual and institutional factors that impact student satisfaction is critical to improving student retention.

Recent higher education research suggested the application of hierarchical linear modeling (HLM) to the research on college student (Ethington, 1997). HLM can allow the researchers to look at hierarchically structured data and interpret results without ignoring these structures (Roberts, 2000). Without considering the nature of nested data structure from multiple institutions (where students are nested within institutions), the conclusions from the conventional regression analysis could be inaccurate or even misleading.

The present study presents an example using a university student satisfaction survey data to demonstrate how to address statistical problems associated with the hierarchical or nested nature of the data. The purpose of this paper is simply to illustrate the need for multilevel modeling (or HLM), not to provide an extensive description of the usage of multilevel models. This study has two major limitations. First, only a few variables were included in the model. Second, very limited principles of the multilevel technique were engaged and described. For an extensive description of multilevel modeling procedures, see Snijders and Bosker (1999), Kreft and de Leeuw (1997), Goldstein (1995), and Bryk and Raudenbush (1992). Roberts

(in press) provides an excellent primer on multilevel modeling.

Conceptual Framework and Variables

This study is based on the belief that student satisfaction is understood best as a multilevel phenomenon of students and major/departments. Level-1 unit of students will be nested within level-2 unit of major/department. Because of the recognition of this nested structure, HLM rather than multiple regression analysis is the appropriate technique to use (Bryk & Raudenbush, 1992; Ethington, 1997).

Even within an institution, different majors/ departments may produce different influences on students. The environment within the major/department should have a more immediate influence on students than that of the institution as a whole. Holland (1966; 1985) suggested that individuals create their common environment as a function of their similar characteristics. This proximal environment of students can capture the immediate influences on students.

Student satisfaction at the individual level is a function of the characteristics and experiences of individual students within their majors/departments. Student satisfaction at the major/departmental level is a

function of the characteristics of the major/department and their impact on the individual experiences of the students within that major/department.

The dependent variable in this study is the student satisfaction of major faculty within a major/department. Because this study is a multilevel study, independent variables at both the individual and major/departmental levels were included since satisfaction is believed to be a function of both sources of variance. The individual-level variable was used to estimate the effects of student background characteristics on satisfaction within individual majors/departments. In this study, student's classification (i.e., undergraduate and graduate) is the individual-level (level-1) variable. An institution-level variable was used to estimate the effects of major/departmental-level characteristics on differences in satisfaction between majors/departments. In this study, the number of faculty members in each major/department was used.

Data Sources

In the present study, self-report survey data was analyzed as a multilevel or hierarchically structured dataset. The study included student-level data, reflecting student background and satisfaction information, and

institutional-level data, showing student composition, or size. The University Student Survey, developed by University Planning of the University of North Texas, provided the student-level data. The Vice President Office of Academic Affairs provided the department-level data.

Data Structure and Models

The level-1 units are individual students and the level-2 units are their departments. Such a hierarchy is described in terms of clusters of level-1 units within each level-2 unit. Ignored clustering may cause standard errors of regression coefficients to be underestimated (Hox, 1998). In the multilevel model, neither individual students nor individual departments are of primary interest. The main focus of this multilevel analysis is on estimating the pattern of variation in the underlying population (in this study, major or departments) (Rasbash et al., 2001).

Multilevel modeling is an extension of OLS regression. This study uses two HLM models: (1) random intercept model and (2) random slope model (Rasbash et al., 2001).

The random-intercepts model

This analysis includes both student-level and institutional-level variables. The student-level model (level-1) use the student's characteristics to predict

outcomes on the dependent variable. The following equation is estimated for each institution

$$y_{ij} = \beta_0 x_0 + \beta_1 x_{1ij} + u_{0j} + e_{0ij} , \quad (1)$$

which can also be written as

$$y_{ij} = \beta_{0ij} x_0 + \beta_1 x_{1ij} , \quad (2)$$

and

$$\beta_{0ij} = \beta_0 + u_{0j} + e_{0ij} , \quad (3)$$

where $\mathrm{var}(u_{0j}) = \sigma^2_{u0}$ and $\mathrm{var}(e_{0ij}) = \sigma^2_{e0}$. In this model, institutions vary only in their intercept. Thus, if x_0 is allowed to be random at both level-1 and level-2 in Equation 1, MLwiN added subscripts i and j to the coefficient β_0 in Equations 2 and 3. Each of the student-level predictors is centered about the institutional mean. The intercepts represent the institution mean dependent variable levels. The level-2 residual u_0 modifies the intercept term, but the slope coefficient β_1 is fixed (Rasbash et al., 2001, p. 33).

The random intercepts and slopes model

The random slopes model used in this study will be

$$y_{ij} = \beta_0 x_0 + \beta_1 x_{1ij} + u_{1j} + u_{0j} + e_{0ij} , \quad (4)$$

or

$$y_{ij} = \beta_{0ij} x_0 + \beta_{1j} x_{1ij} , \quad (5)$$

$$\beta_{0ij} = \beta_0 + u_{0j} + e_{0ij}, \tag{6}$$

and

$$\beta_{1j} = \beta_1 + u_{1j}, \tag{7}$$

where $\mathrm{var}(u_{0j}) = \sigma^2_{u0}$, $\mathrm{var}(u_{1ij}) = \sigma^2_{u1}$, $\mathrm{cov}(u_{0j}, u_{1j}) = \sigma_{u01}$, and $\mathrm{var}(e_{0ij}) = \sigma^2_{e0}$. If x_1 is random at level-2, the subscript "j" should be added to the coefficient for x_1. The level-2 residuals u_{0j} and u_{1j} modifies both the intercept term β_0 and the slope coefficient β_1 to vary (Rasbash et al., 2001, p. 36).

The random intercepts and slopes model is probably the most realistic model to consider in this type of analysis. Considering that it would be erroneous to conclude that the slopes and intercepts for each major/department would be the same, we must model in the data the perceived variability about each of these coefficients (Roberts, in press).

Intraclass correlation (ICC)

One of the important statistics in multilevel models is ICC. If ICC exists, the traditional OLS model must be abandoned because the assumption of independent observations has been violated (Kreft and de Leeuw, 1998). ICC is the proportion of total variance that is between the groups of the regression equation. ICC determines the amount of total variance due to the differences between

majors/departments in this study. The homogeineity of the clusters can be determined by partitioning the variance in the outcome measure into its within-cluster and between-cluster components (Thomas & Heck, 2001). The partitioning is accomplished using the equivalent of a one-way ANOVA with random effects where the sample cluster variable (in this study majors/departments) is treated as a random factor with the number of majors in the first-stage sample (Ethington, 1997, p.175; Thomas & Heck, 2001, p. 526). ICC (ρ) for a two-level model is the proportion of group level variance from the total variance, where σ^2_{u0} represents the level-2 variance and σ^2_{e0} represents the level-1 variance

$$\rho = \frac{\sigma^2_{u0}}{\sigma^2_{u0} + \sigma^2_{e0}}$$

As a result, as similarities among students within departments become more pronounced in the sample, estimate of variance and standard errors derived from the data become more biased (Muthen & Satorra, 1995). Ignoring clustering sampling leads to conservative estimates of standard errors and increase the possibility for committing Type I errors in hypothesis testing (Muthen & Satorra, 1995; Thomas & heck, 2001).

The presence of a high ICC would mean that the students within clusters tend to be homogeneous. If

students within departments are more similar than students in other departments, then the value of ICC will be high. If the ICC is high, the model should allow the explanatory variable to be random at level-2.

If the ICC is large, the impact of cluster sampling can be substantial. If the ICC coefficient is minimal, the observations are nearly independent and traditional multiple regression analysis will provide accurate estimates of the parameters and standard errors.

Findings

The data consist of 1,187 students (undergraduate: 79% and graduate: 21%) in 49 majors on both dependent and independent variables. The statistical package used was MLwiN Version 1.10 developed by the staff at the Multilevel Models Project, Institute of Education (Rasbash, Browne, Healy, Cameron, & Charlton, 2000). In order to compare results from the OLS regression and multilevel modeling, the data will be first fit with SPSS and then with MLwiN. The dependent variable used was the composite score measuring students' satisfaction on faculty in students' major. The independent variable used was a background variable—classification (i.e., undergraduate and graduate students) for the level-1 predictor and the number of

faculty members of each major/department for the level-2 predictor.

Multilevel models incorporate both random and fixed effects when nesting is an obvious consequence of multistage sampling or when nesting is a source of random variability (Bryk & Raudenbush, 1992; Raudenbush, 1988).

Using Equation 1, I specified that the coefficient of intercept is random at both level-1 and level-2. The model specified related student satisfaction to classification. The regression coefficients, β_0 and β_1, define the average line across all students in all major/departments. The model is made multilevel by allowing each major/ department's summary line to depart from the average line by an amount u_{0j}. The i'th student in the j'th major/department departs from its summary line by an amount e_{0ij}. This model fits a set of parallel straight lines for the different majors/departments. The slopes of the lines are all the same. The fitted value of the common slope is 1.291 with a standard error of 0.012 and it is highly significant. On the other hand, the intercepts of the lines vary. Their mean is 14.381 with a standard error of 0.162. The intercepts for the different majors/departments are the level-2 residuals u_{0j} and these are distributed

around their mean with a variance 0.510 (standard error 0.210). The simple comparison with the standard error and also the use of the "interval and tests" procedures provides approximations that can act as rough guides (Rasbash et al., 2000). The actual data points do not fit exactly on the straight lines; they vary about them with the level-1 residuals e_{0ij} 10.679 (standard error 0.447). In addition, when I added the 2-level predictor, the fitted value of the common slope was -0.026 with a standard error of 0.017 and it was not significant.

The homogeneity of clusters is measured by calculating an ICC coefficient. The degree of bias in estimating variance in the data collected through cluster samples is a function of the ICC present in the data:

$$\rho = \frac{0.511}{10.678 + 0.511} = 0.046(4.6\%) .$$

If students are taken at random from the population, their variance would be the sum of the level 2 and level 1 variances, 0.510 + 10.679 = 11.189. The between major/department variance makes up a population 0.046 of this total variance. The ICC in this dataset is not large. The presence of a small ICC means that there is a small dependence of context (in this case majors/departments) for individual student scores.

The ICC is examined in order to determine if further model modification needs to be made. A high correlation could indicate the need to free a variable at the highest level of the hierarchy (in this case level-2). That is, there is a possibility that the majors/departments lines may have different slopes (In fact, there is a very low chance of random slopes in this study because the ICC is a minimal value).

Using Equation 4, I specified a coefficient of classification, which is random at level 2. The coefficient of classification had a suffix j indicating that it varies from major/department to major/department. The mean is 1.290 (standard error 0.264), not far different from the model with a single slope. The individual major/department slopes vary about this mean with a variance estimated as 0.511 (standard error 0.211). The intercepts of the individual major/department lines also differ. Their mean is 14.381 (standard error 0.162). In addition there is zero covariance between intercepts and slopes. It suggests that major/department with higher intercepts has nothing to do with steeper slopes and this corresponds to zero correlation between the intercept and slope across majors/departments. As students' individual scores vary around their majors/departments lines by

quantities e_{0ij} and their variance is 10.678 (standard error 0.446).

The quantity of -2*log-likelihood can be used to make an overall comparison of this more complicated model with the previous one. It has remained the same. The new model involves two extra parameters; the variance of the slope residuals u_{1j} and their covariance with the intercept residuals u_{0j} and the change can be regarded as a χ^2 value with 2df under the null hypothesis that the extra parameters have population values of zero. It confirms no better fit of the more elaborate model to the data.

Table 1 presents the results from the simple bivariate regression for both OLS and multilevel cases. In an OLS equation, the unstandardized coefficient for the slope of

Table 1
Results comparing the ordinary least squares model and the multilevel model.

Variable	OLS Estimate	Mutilevel Estimate	Greater Value
Intercept	14.396 (0.109)	14.381 (0.162)	OLS
Dummy variable Undergraduate Vs. Graduate	1.418 (0.239)	1.290 (0.264)	OLS
Number of Fac	-0.0272 (0.012)	-0.026 (0.017)	Mult

Note: Multiple R^2 for the OLS model is 0.029.
Standard error in parenthesis

classification was 1.418. The results mean that students' satisfaction may vary across the classification of students (in this study, here undergraduate versus graduate students).

Contrasting with the OLS equation, a multilevel model was used to fit the data and to compare weights from the OLS regression and multilevel model. When solved for in the multilevel model equation, beta weight was 1.290. This is the interpretation of results from the OLS regression. The result from the multilevel model indicates that the these two procedures provided the similar coefficient of slope for the variable "classification." Therefore, both the OLS equation and the multilevel model may indicate that students' satisfaction scores is the function of the classification.

Conclusion

The purpose of this study is to illustrate the need for multilevel modeling in higher education research when the data are hierarchically structured or nested. Multilevel modeling is a relatively new technique in the higher education research. The results from this study have implications for the current issues on institutional quality and for the current movement of educational improvement in higher education institutions.

OLS techniques may provide incorrect estimates in some datasets. Multilevel modeling techniques are most useful when intraclass correlation is large. A large ICC does not mean that the parameter estimates obtained from multilevel modeling will be quite different from OLS estimates but that there is a greater dependence of context (in this study, majors/department) for individual student scores. However, multilevel techniques are often more difficult to interpret and thus less generalizable (Roberts, 2000).

This paper used very limited source of dataset. Beyond the statistical issues are data issues. Only a few variables from a limited dataset were included in the model. The multiple levels should be adequately reflected in the data gathered and the structure of data should be adequately addressed.

The special issue of the Journal of Educational and Behavioral Statistics (JEBS)(1995) provided problems and prospects of hierarchical linear models. In this special issue, Draper (1995) and de Leeuw and Kreft (1995) warned the uncritical use of modeling. Morris (1995) pointed out that when the number of level-2 units is small, the maximum likelihood methods do not provide better variance estimates. Raudenbush (1995) noted that even the level-2

coefficients can be misleading when the number of subjects varies substantially between units.

Goldstein (1995) summed up the future of multilevel modeling:

> There is a danger, and this paper reminds us of it, that multilevel modeling will become so fashionable that its use will be a requirement of journal editors, or even worse, that the mere fact of having fitted a multilevel model will become a certificate of statistical probity. That would be a great pity. These models are as good as the data they fit: they are powerful tools, not universal panaceas (p. 202).

Reference

Bryk, A.S., & Raudenbush, S.W. (1992). *Hierarchical linear models: Applications and data analysis methods.* Newbury Park: Sage.

Burnstein, L. (1980). The role of levels of analysis in the specification of education effects, In R. Dreeben and J.A. Thomas (ed.) *The analysis of Educational productivity*, Cambridge, MA: Ballinger publishing Company.

Burnstein, L., Kim, K.S., & Delandshere, G. (1989). Multilevel investigations of systematically varying slopes: issues, alternatives, and consequences, In *Multilevel Analysis of Educational Data.*

Draper, D. (1995). Inference and hierarchical modeling in the social sciences. *Journal of Educational and Behavirol Statistics, 20*, 115-148.

Ethington, C. (1997). A hierarchical linear modeling approach to studying college effects. In J.C. Smart (ed.), *Higher education: handbook of theory and research, Vol. 12*, New York: Agathon, 165-194.

Goldstein, H. (1995). Hierarchical data modeling in the social sciences. *Journal of Educational and Behavirol Statistics, 20*, 201-204.

Heck, R.H. & Thomas, S.L. (2000). *An introduction to*

multilevel modeling techniques. Lawrence Erlbaum Associates, Publishers. NJ: Mahwah.

Kreft, I, & De Leeuw, J. (1998). *Introducing multilevel modeling*. London: Sage Publications.

MLwiN Version 1.10. (2000). Multilevel Models Project, Institute of Education, Rasbash, J., browne, W., Healy, M., Cameron, B., & Charlton, C.

Morris, C. (1995). Hierarchical models for educational data: An overview. *Journal of Educational and Behavirol Statistics, 20*, 190-200.

Murchan, D.P., & Sloane, F.C. (1994). Conceptual and statistical problems in the study of school and classroom effects: An introduction to multilevel modeling techniques, In I. Westbury, C. Ethington, L. Sosniak, and D. Baker (ed.), In *Search of More Effective Mathematics Education*. NJ: ablex Publishing Corporation.

Pascarella, E.T., & Terenzini, P.T. (1991). *How college affects students: Findings and insights from twenty years of research*. San Francisco: Jossey-Bass.

Rasbash, J., Browne, W., Goldstein, H., Yang, M., Plewis, I., Healy, M., Woodhouse, G., Draper, D., Langford, I., & Lewis, T. (2001). *A user's guide to MlwiN*.

Multilevel Models Project, Institute of Education, University of London.

Raudenbush, S. (1995). Reexaming, reaffirming, and improving application of hierarchical models. *Journal of Educational and Behavirol Statistics, 20*, 210-220.

Raudenbush, S., & Bryk, A. (1986). A hierarchical model for studying school effects, *Sociology of Education*, 59, 1-17.

Roberts, J.K. (2000). An introductory primer on multilevel and hierarchical linear modeling. In B. Thompson (ed.), *Advanced in social science methodology, Vol. 6,* New Jersey: Mahwah.

Snijders, T., & Bosker, R. (1993). Standard errors and sample sizes for two-level research. *Journal of Educational Statistics, 18*, 237-259.

Thomas, S. L. & Heck, R. H. (2001). Analysis of large-scale secondary data in higher education research: Potential perils associated with complex sampling designs, *Research in Higher Education*, 42, 517-539.

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