The Advantages of Using Multilevel Modeling to Address Institutional Research Questions

By:

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Why Use Multilevel Modeling (MLM)?

From the perspective of a robustnik like myself, Multilevel Modeling (called by many different names), has a lot to recommend it, including, but not limited to:

- First, it can be used for a very wide variety of different purposes, and all with far fewer and less restrictive assumptions than OLS. It can be used in place of the following, just to name a few: Meta analysis, repeated measures analysis, multiple regression, and logistic regression.
- MLM treats the world as it exists, taking contextual influences into account when computing statistical estimates.
- I really "like" predictive type statistical methods (Regression, Hotellings T, etc.) because through my many years of applied statistics, I have frequently found them to give me useful information (I frequently use rank-based Regression). Multilevel Modeling is rooted in Multiple Regression, but rests upon far less restrictive assumptions than the OLS method, and can produce pretty darn accurate predictive models. Also, because Maximum Likelihood (ML) estimates are used to estimate both fixed and random effects, and because test statistics based on robust variance estimates are included in HLM 6 outputs, and because covariance estimates derive from Empirical Bayes (EB) residuals, the validity of output is surely more robust to violations of the underlying normality assumptions than are OLS estimates.
- Almost all who teach or write about Multilevel Modeling and anyone decent teaching about Regression, make it a point to emphasize how important it is to check the underlying distributional assumptions, and particularly, to conduct analysis of Residuals' distributional characteristics (We Robustniks just love this.).
- Most who use Multilevel Modeling use graphs/charts to better see what's occurring. This is, from my perspective, such a very good idea that I can't even begin to say how enthusiastic I am about this emphasis.
- Multilevel modeling allows one to readily estimate Intraclass Correlation Coefficients (ICC), which can substantially alter error terms in analyses and thereby create false positives. A common rule of thumb is to use multilevel modeling when ICC is greater than 0.05.
- It treats the open systems in which research is almost always conducted as open, rather than closed. The traditional Experimental Paradigm is based upon 19th Century, reductionist, closed system thinking, which really only applies to a few things like the movement of planetary bodies, and to absolutely nothing in the Social and Behavioral Sciences. Because everything nests within a larger context, it makes perfect sense to use a technique for analysis that can take this nesting into account.
- Following on the preceding, Multilevel Modeling nests dependent variables within contexts which exert influence on those dependent variables in the real world. A summary of Kreft, de Leeuw & Aiken (1995) says it well:

  > In multilevel models, micro-level units, such as workers or students, are nested within macro-level units, such as industries or schools. In multilevel models, separate predictors characterize the micro-level units,

the *individuals,* and the macro-level units, the *groups* or *contexts*. The assumptions regarding the coefficients of the model depend upon the level of the predictors. The coefficients of all but the highest level predictors may be treated as random; hence the name *random coefficient models,* while those of the highest level are always treated as fixed.

- The process of building Multilevel Models makes perfect sense to an experienced empirical researcher, because you first construct an unconditional model (like a ONEWAY ANOVA), see if it makes sense to use Multilevel Modeling given the nature of the data relative to the question, and advance step-by-step through the process of model development to a final point, checking in multiple ways at each step to see whether what you are doing is a good idea or not, until you finally have a full model, which, hopefully, provides a reasonably accurate prediction for your dependent variable.
- Because all social science contexts are complex, only analyses that can isolate the unique impact (unique variation) of specific factors at their various levels, such as multilevel modeling, are appropriate. Effectively, Multilevel Modeling uses Backward Elimination rather than Stepwise to model equations thereby primarily unique rather than shared variance to determine a variables contribution to a model.
- Multilevel modeling can allow one to develop a regression (prediction) model for each context separately rather than assuming that a single average prediction model applies to all disciplines.

The Simplest Arguments for Using Multilevel Modeling

It is widely applicable in situations that many wish to analyze, as Raudenbush & Byrk (2002, p. 142) note: "One of the most common applications of HLM in organizational research is simply to estimate the association between a level-II predictor (*in this case, sex*) and the mean of Y, adjusting for one or more level-I covariates."

Luke (2004, p. 7) makes the simplest argument:

> The simplest argument, then, for multilevel modeling techniques is this: Because so much of what we study is multilevel in nature, we should use theories and analytic techniques that are also multilevel. If we do not do this, we can run into serious problems like the Ecological Fallacy. Where relationships observed in groups are assumed to hold for individuals (Robinson, 1950). The Atomistic Fallacy, in which inferences about groups are incorrectly drawn from individual-level information (Hox, 2002)...fallacies are a problem of inference, not of measurement. That is, it is perfectly admissible to characterize higher-level collective using information obtained from lower-level members. The types of fallacies described above come about when relationships discovered at one particular level are inappropriately assumed to occur in the same fashion at some other (higher or lower) level.

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Key Issues Regarding Handling Data in HLM 6

http://www.ssicentral.com/hlm/downloads.html

Categorical Predictor Variables

In Multilevel Modeling in general, categorical predictor variables must be converted to a dichotomous form, preferably in an ordinal form where the advantaged group receives a value of one (1) and the disadvantaged zero (0).

The preceding provides you with an estimate of the influence of a single level change in the predictor on the outcome variable.

For example, sex, for standardized multiple choice test scores or salaries would be coded
Male=1, Female=0.
Sex for any other education or performance variable (outside of sports) would be coded
Female=1, Male=0

Multichotomous data can be classified into multiple dichotomous forms. Take for example Race/Ethnicity.

A dichotomous form would be:
White (perhaps add Asian)=1, Non-White=0
Or to evaluate specific subgroups:
Asian=1, nonAsian=0
Black=1, nonBlack=0
Hispanic=1, nonHispanic=0,
Etc.

HLM 6 requires a source data file for each level

- Level I data should include all of your predictor variables and be sorted by your nesting (grouping) variable.
- Level II data should include one case for each combination of your nesting variable and your level II variable (e.g. Male or Female). In SAS, when nesting within discipline and using sex as your Level II variable it would be: **Proc sort nodupkey; by discip sex**;
- Level II data is like level II, only with your next level variable added to the sort (say race/ethnicity): **Proc sort nodupkey; by discip sex race;**

Some Requirements for Handling Data for HLM 6

- I recommend converting data to STATA 6 versions (.dta) before importing to HLM 6. The current version of HLM 6 does not properly import SPSS 14 data files.
- Data **must be sorted** by your nesting variable in all files (Level I, Level II and Level III), otherwise HLM 6 will give you an error message.

Missing Data in HLM6

- When making the MDM file, click "yes" under "missing data?" and right next to that click "delete when running analyses"

- You have to re-save the MDM file (at the top right) and then re-make it (bottom left) after you change those inputs.

HLM Student Edition Stuff

The free student edition of HLM 6 is available as a single, self-extracting executable **hlm602_student.exe for Windows users.**

Download this file to a temporary folder (for example **C:\tempfiles**).

Run **hlm602_student.exe** from the **Start** Menu or Program Manager.

Default installation will be to a new folder "**C:\Program Files\HLM6S**". You may change the name and location of this folder. After successful installation the downloaded file **hlm602_student.exe** may be deleted.

Data Points (from Ted)

I recommend converting data to STATA 6 versions (.dta) before importing to HLM 6.
Data **must be sorted** by your nesting variable in all files (Level I, Level II and Level III

The student edition contains the following:

- All the examples distributed with the full HLM 6 version. These examples may be run with the student edition.
- An on-line helpfile, as provided for the full version too. The helpfile includes most of the new HLM 6 manual and a complete tutorial showing the use of HLM.

The student edition can run all the analyses the full version can in terms of models selected, statistical options and output. Restrictions are, however, placed on the data used and the size of the model selected. The following restrictions apply in this edition:

- The STAT/Transfer utility used for the importation of data is not included. The student edition will only accept ASCII, SYSTAT, SPSS for Windows or SAS transport data files.
- For a level-3 model, the maximum number of observations that may be used at levels 1, 2 and 3 are approximately 7500, 1700 and 60 respectively. Note that the restriction applies to observations in the case of the level-2 file, for example, and not to actual number of level-2 units to be included in the analysis.
- For a level-2 model, the maximum number of observations at the two levels are 7200 at level-1 and 350 at level-2 of the hierarchy.
- No more than 5 effects may be included in any HLM equation at any level of the model, and the grand total of effects can not be 25 or higher.

When these limitations are exceeded, an appropriate error message will automatically be displayed.

For more information on how to set up these models and how to interpret the output, please see the Help file that comes with the program. Also (partially) available on this website.

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