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Hierarchical Linear Modeling in Park, Recreation, and Tourism Research

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Myriad research contexts in parks, recreation, and tourism are characterized by the existence of effects "nested" within other effects, but only very rarely are these effects acknowledged and incorporated into designs. Failure to account for these effects not only prevents researchers from assessing effects of nested variables, but it also creates a violation of the assumption of independence of observations that is fundamental to most such commonly used sampling distributions as *t* and *F*. Hierarchical linear modeling (HLM) is a statistical technique that provides a solution to this problem. HLM allows researchers to account for nested effects in studies that use unbalanced designs (unequal sample sizes per group), studies that use repeated measures, or other designs that create linear dependency among observations. In this paper, we review the nested effects problem and illustrate applications of HLM using a set of experience sampling data and a set of evaluation data in which intact groups are nested within a treatment variable.

KEYWORDS: *Hierarchical linear modeling, leisure research.*

Investigating many facets of parks, recreation, and tourism involves units of analysis in which effects are "nested" within other effects. An effect is nested if all levels of one factor in a design do not occur under all levels of a second factor. For example, if data are collected at four different trailheads at two different parks, trailhead might be treated as a factor that is nested within a "park" factor. Much more familiar "crossed" designs transpire when all levels of one factor of a design occur under all levels of another factor. Such a design might occur if we collected data under two different experimental conditions at each of two trailheads. Figures 1a and 1b contrast these two designs in two different types of studies. In the nested design in Figure 1a, each of four courses (i.e., four different groups of participants) is only present under a single program type (e.g., land-based vs. water-based adventure). In the crossed design (Figure 1b), each of the two instructors is present within both of the program types. Although myriad research contexts in parks, recreation, and tourism give rise to the recognition and modeling of nested effects, only very rarely are they acknowledged and incorporated into

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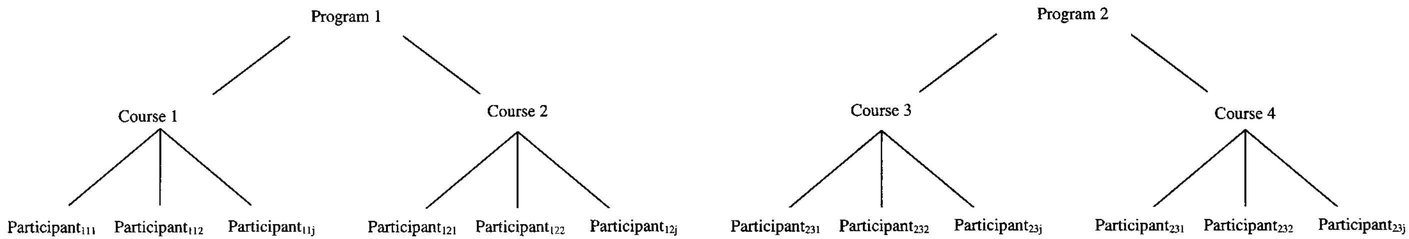

Figure 1a. Example 1 Random effect nested design—The factor "Course" is nested within the factor "Program."

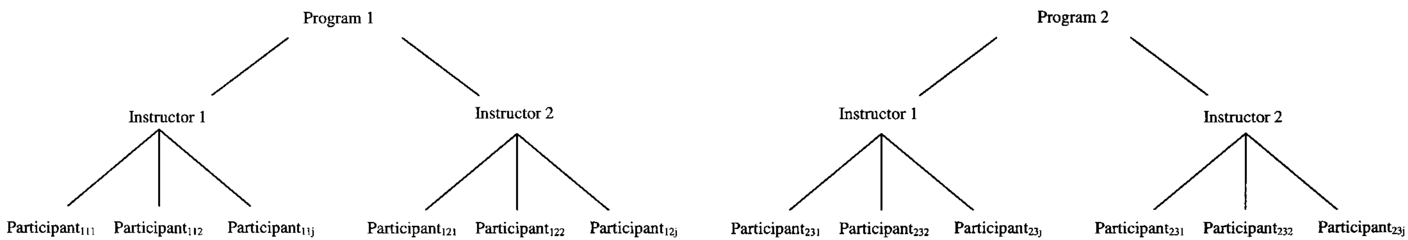

Figure 1b. Random effect crossed design—The factor "Instructor" is crossed with the factor "Program."

research designs (e.g., Caldwell, Darling, Payne, & Dowdy, 1999; Long, Ellis, Trunnell, Tatsugawa, & Freeman, 2001).

A few examples provide evidence of the great breadth of these applications. A recreation researcher investigating natural resource settings who samples visitors at multiple park sites within different parks might incorporate "site" as a factor nested within the independent variable that is of interest (e.g., ethnicity, outdoor recreation behavior; Carr & Williams, 1993). Nesting might also be inherent in certain studies of employees in recreation management contexts. An investigator studying the effects of different management strategies, for example, might collect data from various work groups, such as park maintenance, recreation center managers, special services employees, and others. In this example, work group would be nested within management strategy because each work group would be exposed to only one management strategy. A study of effects of a specific therapeutic recreation intervention might involve clients nested within cohorts or assigned treatment groups, diagnostic groups, or therapists (Wells, 2001).

Experience sampling studies and studies that use time diary methods (e.g., Caldwell et al, 1999; Csikszentmihalyi & Csikszentmihalyi, 1988; Ellis, Voelkl, & Morris, 1994) provide yet another example of nested effects. Daily experiences of participants in these studies, may be sampled on numerous occasions over the course of two or more days. The effects of daily experience predictor variables that are of interest are thus nested within "participant" and "day" variables. In some instances of time diary and ESM research, predictor variables are of interest at both the level of the experience and at the level of the individual. Caldwell, et al. (1999), for example, conducted a time diary study to examine the relationship between select situational (daily experience) variables, individual difference variables (intrinsic motivation, parental monitoring, and gender), and boredom. That design allowed testing the effects of the situational variables that were nested within participants as well as testing the effects of the individual differences variables. A substantial potential exists for incorporating nested effects into park, recreation, and tourism research designs and for understanding these predictors at different, hierarchically arranged levels.

Neglecting to include nested effects in designs creates a number of undesirable consequences. Two of the most notable of these are failure to account for important sources of variance and violation of the statistical assumption of independence of observations. With respect to the first of these issues, variance that could be explained by the nested effects is unaccounted for and is relegated to error terms. The result is a design that is less than optimal in efficiency (i.e., statistical power is compromised) and does not provide insight into the role of the nested variable in influencing the dependent variable of interest. Further, in many instances, failure to incorporate the nested effect into the design is a direct violation of the independence assumption that underlies key test statistics such as the *F* ratio and the *t* ratio. Individuals who are part of a single group that receives treatment collectively influence one another's experiences. In such circumstances, observations are not independent and traditional linear modeling procedures such as ordinary least squares regression and analysis of variance (ANOVA) produce standard errors that are too small. These biased estimates lead to a higher probability of inappropriately rejecting the null hypothesis than if observations were truly independent (Osborne, 2000).

The problem of modeling nested effects was a focus of research by Dempster, Laird, and Rubin (1977), who developed a covariance component estimation method for hierarchical designs. This work allowed the development of data analysis software that could handle nested data structures. One popular example of such software is the "Hierarchical Linear Modeling" (HLM) program (Raudenbush, Bryk, Cheong, & Congdon, 2001). HLM, and similar programs, now provide behavioral scientists with access to this statistical method. The purpose of this paper is to illustrate utilization of hierarchical linear modeling procedures to problems associated with nested effects designs in park, recreation, and tourism research.

Past Approaches

Prior to HLM, approaches to solve the problem of nested effects involved disaggreation of data, aggregation of data, two-stage sampling, and hierarchical ANOVA. Disaggregating data may not be an appropriate solution because a nesting factor is ignored and, therefore, a valuable piece of the equation is lost. For example, in a therapeutic setting, analyzing data at the level of treatment type while ignoring the impact of therapists, a nesting factor, would not allow the assignment of variance attributable to differences in therapists' skills. This analysis would also violate the assumption of independence because each therapist provides a shared experience with their patients that is different from other therapists (Raudenbush & Bryk, 2002). Aggregating individual observations into their respective nested groups provides another approach to addressing the nested effects problem. Visitor scores might, for example, be averaged to represent typical scores per trailhead. That approach, however, results in a dramatic decrease in degrees of freedom. Data from large numbers of visitors are reduced to a single data point when trailhead becomes the unit of analysis (reducing sample size from number of respondents to the number of trailheads). Another possible solution is two-stage hypothesis testing. Two-stage hypothesis testing seeks to pool error terms by incorporating error variance associated with the nested effects variable, which is assumed to be a nuisance variable, into the test of a factor of interest. Researchers cannot plan, a priori, to pool error terms because a nonsignificant F ratio must exist for the nested effects variable and the chance of a type I error increases. Lastly, hierarchical ANOVA and HLM will lead to the same results when there is a sufficient and even number of cases within each nested group. HLM is a more powerful tool, however, under conditions of dependency in the design, lack of balance in the design, small numbers of cases per group, or repeated measures.

Fundamentals of HLM

At the most basic level, HLM is a regression equation; HLM is based on a simple linear regression structure where a single dependent variable depends on a series of independent variables. In HLM, however, regression sub-models are built at each level of nesting, within a single overall model. Each model is thus associated with a particular "level" in an analysis. If, for example, only one variable is nested within a factor, regression models at two levels are estimated within HLM (a "level 2 model"). Standard HLM notation uses "level 1" in reference to the lowest level of observation with "level 2" being a nesting factor above level 1 and "level 3" being a nesting variable above level 2. For example, level 1 might be participant, level 2 might be course, and level 3 might be program. Alternatively, level 1 might be time, level 2 might be participant, and level 3 might be course. These sub-models may provide important insight into effects of variables that would otherwise be neglected in the analysis. Further, HLM is not dependent on the assumption of independence, which is often violated when nested, or multilevel, data structures are analyzed with techniques based on the General Linear Model (Raudenbush & Bryk, 2002).

In HLM, sample size and statistical power are dependent on the overall size of the sample, the number of groups, and the number of observations per group (Hofmann, 1997). The power of level 1 effects depends more on the total sample size while the power of level 2 (and subsequent level) effects depends more on the number of groups at that level, because the degrees of freedom are dependent on the number of groups. When a design has fewer groups, a larger sample size is needed to gain sufficient power. The guidelines for sample size recommend 10 observations per predictor, but when there is more than one predictor the guidelines become more ambiguous. Thus, the overall sample size requirements, number of necessary groups, and the number of individuals per group are all important in the analysis, but the relative importance depends largely on the desired contrasts (i.e., main effects vs. cross level interactions).

It is perhaps easiest to understand what HLM can and cannot offer through an example. Assume that a researcher is interested in studying the effects of two different adventure program types on a developmental outcome of participants. Participants are organized into four distinct courses, with two courses receiving program one and two courses receiving program two. This three-level model is illustrated in Figure 1a. In this example, variables associate with participants in an adventure program are nested within a "course" factor and course level variables are nested within a "program" factor. It would be inappropriate to assume that individual development while participating on the adventure program is independent of course level variables such as instructor and dynamics of the respective groups. With traditional approaches, a single unit of analysis, most likely the participants, would be chosen and ANOVA procedures would be used to test the hypothesis that no significant difference exists between means of the different programs. This type of analysis would not allow the researcher to discern differences attributable to course level variables. The assumption of independence would be violated as subjects within a specific course will likely have been influenced by some common factors not shared between courses. If traditional approaches are used to analyze the data, these common experiences result in correlated error components and biased estimates. In addition, measures of change or growth are commonly addressed through the calculation of change or difference scores (i.e., use of a t-test); such indices of change are commonly considered problematic (Nunnally, 1983). In HLM, change can be handled through the inclusion of time as a level in the analysis and, thus, more appropriately modeled.

The three-level model in Figure 1a is built from a basic level 1 model. The level 1 equation is simply:

$$Y_{ij} = \beta_{0j} + r_{ij} \tag{1}$$

Where Y_{ij} is the dependent variable, β_{0j} is the level 1 coefficient, and r_{ij} is the level 1 error. When we add a second level, $\beta_{0j} = \gamma_{00} + \mu_{0j}$ where γ_{00} is the grand mean outcome of the population (estimated from the sample), and μ_{0j} is the random effect associated with level 2. τ_{00} is the variance attributable to the level 2 random effect (Variance of μ_{0j}) and σ^2 is the variance attributable to the level 1 random effect (Variance of r_{ij}). So, in short, τ_{00} (associated with the μ_{0j} term) represents the amount of variance between level 2 groups, and σ^2 (associated with the r_{ij} term) represents the amount of variance within groups, or attributable to level 1. Using our example from above, Y_{ij} might be a programmatic outcome variable such as social self-efficacy, τ_{00} would represent the amount of variance accounted for between course groups, σ^2 would represent the amount of variance attributable to individual differences plus error variance, and γ_{00} would equal the grand mean of the social self-efficacy measure.

To this point, the analysis is not much different than a traditional ANOVA with a single random level factor (course). Adding a predictor variable at level 1 creates a regression function that parallels an analysis of covariance (ANCOVA) with random effects. For example, suppose participant age (X_i) is a viable covariate for social self-efficacy.

$$Y_{ij} = \beta_{0j} + \beta_1 X_i + r_{ij} \tag{2}$$

with $\beta_1 = \gamma_{10}$

The only difference between this and a traditional analysis of covariance is that the group effect, μ_{0j}, is considered random.

Next, a level 2 covariate may be added to the equation. A course level variable, such as a report on instructor rapport with the group, might be included as W_j below.

$$Y_{ij} = \gamma_{00} + \gamma_{01} W_j + \gamma_{10} X_i + \mu_{0j} + r_{ij} \tag{3}$$

Thus, the above equation may be considered an analysis of social self-efficacy.

The equation includes the inherent benefits of (a) partialing of variance at both the participant and course level, (b) appropriate handling of the assumption of independence, (c) inclusion of the course level variable as a random effect, and (d) the ability to include predictor variables (covariates) at each of the two levels (participant and course). Subsequent additions to the above equation could offer more analysis options. For example, a level 3 random effect, such as program type, with its own predictors might be added; or a linear growth model might be incorporated by adding time as a new level 1 unit of analysis (participant would then become level 2 and course would become level 3), which would eliminate the need of difference calculations to measure change in the dependent variable. To follow the above example further, it is useful to examine some output from HLM 5.03.

Example 1: Courses Nested within Programs

For the first example, data were collected from a commercial adventure education program that conducts three week long courses for adolescents involving sailing and scuba diving. Data from 168 respondents were collected from 20 different courses and 2 program types. Thus, level 1 is participant level or within group variance, level 2 represents the variance between courses, and level 3 would represent the amount of variance attributable to the program type. A traditional random effects ANCOVA could be used to analyze the first two levels of these data if the cell sizes were equal and no level 2 covariates were of interest. However, this is not the case with this data set where complete course level cell sizes range from 5 to 11 responses and the researchers wanted to include a course level predictor variable (level 2 covariate).

Following the example above, a 2 level model was calculated to see if the "course" effect explains a significant amount of the variance in the dependent variable of group functioning. The initial HLM equation can be seen below.

$$Y_{ij} = \gamma_{00} + \mu_{0j} + r_{ij} \quad (4)$$

Where Y_{ij} represents the dependent variable of interest (group functioning in this example), γ_{00} represents the grand mean of the dependent variable, μ_{0j} represents the course level effect, and r_{ij} represents the effect not accounted for by course.

The initial results (see Table 1) support the premise that the random effect of course explains a significant portion of the variance in the dependent variable. With a σ^2 value of 8.44 and a τ_{00} value of 3.10, it is evident that the course level variable (μ_{0j}) accounts for approximately 27% of the variance in this sample [$\tau_{00}/(\tau_{00} + \sigma^2)$ or $3.10/(3.10 + 8.44)$]. Because a significant amount of variance is attributable to the level 2 variable, predictors, or covariates may be added to the equation to better discern the precise reason for differences at level 2. This would add an additional term to our equation ($\gamma_{01} W_j$) to represent a course level variable of instructor support.

TABLE 1
Example 1 Final Estimation of Variance Components: Participants Nested within Courses

Random Effect	Standard Deviation	Variance Component	df	Chi-square	*p*-value
μ_{0j}	1.76	3.10 (τ_{00})	19	79.9	<.001
r_{ij}	2.90	8.44 (σ^2)			

μ_{0j} = the unique increment associated with course level effect
r_{ij} = the participant level random effect

$$Y_{ij} = \gamma_{00} + \gamma_{01} W_j + \mu_{0j} + r_{ij} \quad (5)$$

The results of this second HLM analysis (Table 2) show that a course level rating of instructor support is a significant predictor of group functioning ($t = 3.81$, $p < .01$), and that the instructor support variable accounts for approximately 44% [(τ random − τ predictor)/τ random, or (3.10-1.75)/3.10] of the variance explained by the random effect of course, or approximately 12% of the variance in the sample (.44 × .27).

A level 1 predictor could also be included in the model, such as participant age. This adds another term to our equation ($\gamma_{10}X_i$), and we get Equation 3 above. However, these data did not support the inclusion of age as a level 1 predictor as the Maximum Likelihood iterations would not easily converge. Subsequent analysis might include additional level 2 predictors, or explore the effects of the level 3 variable of program type.[1]

In summary, these data show that course, a random level factor, explains 44% of the variance in perceived group functioning and that the group's

TABLE 2
Example 1 Final Estimation of Variance Components: Participants Nested within Courses with Instructor Support as a Level 2 Predictor Variable

Random Effect	Standard Deviation	Variance Component	df	Chi-square	*p*-value
μ_{0j}	1.32	1.75 (τ_{00})	18	50.2	<.001
r_{ij}	2.90	8.42 (σ^2)			

μ_{0j} = the unique increment associated with course level effect controlling for student perceptions of instructor support
r_{ij} = the participant level random effect

[1]When using HLM, it is best to include the highest level variable (e.g., program type) in the initial analysis and then to remove it from further analyses if it does not offer a significant explanation of variance, which was the case with this data set. However, because of the pedagogical purpose of this paper, a simplified explanation of only the 2 level analysis (without the prior level 3 analysis) was considered appropriate.

perceived instructor support accounts for 27% of this 44%, or 12% of the total variability in perceived group functioning.

Example 2: Experiences Nested within Individual Respondents

For the second example, participants were undergraduate students at a university located in the Midwest (Voelkl & Ellis, 2002). Participants ranged in age from 19 to 50, with a mean age of 21.4 years. Participation involved carrying a "beeper" watch for four days that was programmed to "beep" the participant at five random times each day between the hours of 9:00 am and 11:00 pm. Upon hearing the "beep," participants were instructed to complete a self-report form that contained items on current activity and the characteristics of flow. For the purpose of the current paper, data from 719 experience sampling forms from 55 students were available, with 5 to 22 responses per person. In this example, experiences, the level 1 variable, are nested within individuals, the level 2 variable (see Figure 2). As in the above example, HLM offers several benefits over the traditional analysis strategies of double standardization and ordinary least squares regression (Ellis, et al., 1994). Both of those techniques fail to account for the lack of independence among experiences that results from the fact that numerous experiences are sampled from each participant.

As in the previous example, an initial 2 level HLM analysis is used to determine if a significant amount of variance in the dependent variable (affect) is accounted for by the level 2 variable (individual respondents). Our equation is the same as Equation 1 above, but Y_{ij} represents reported affect, γ_{00} represents the grand mean of affect, μ_{0j} represents the effect of the individual respondent, and r_{ij} represents the effect of the discreet experiences and error variance. This initial analysis shows that the individual respondent is responsible for a significant portion (~24%) of the variance in the sample (see Table 3).

While it appears that individuals vary on level of affect, supporting the premise of an autotelic personality (e.g., Csikszentmihalyi & Csikszentmihalyi, 1988), the researchers were interested in the impact of the ratio of challenge and skills on affect. That ratio was operationalized through a dummy variable in which experiences that were characterized by both high challenge and high skills were coded "1" (flow state) while all other experiences received a "0" (non-flow state). Flow state was the level 1 predictor

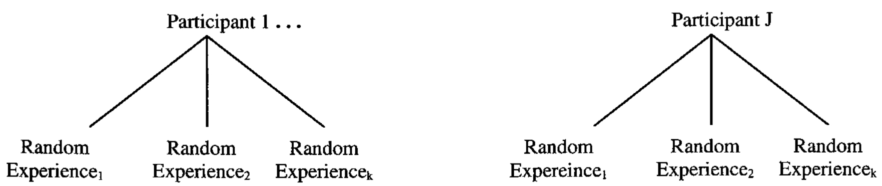

Figure 2. Example 2 random effect design—The factor "Experience" is nested within the factor "Participant."

TABLE 3
Example 2 Final Estimation of Variance Components: Participants Nested within Individual Respondents

Random Effect	Standard Deviation	Variance Component	df	Chi-square	p-value
μ_{0j}	2.11	4.49 (τ_{00})	54	254.36	<.001
r_{ij}	3.75	14.05 (σ^2)			

μ_{0j} = the unique increment associated with course level effect
r_{ij} = the participant level random effect

in the model. In this analysis, since $\tau_{11} = 5.72$ (the variance component of the flow state variable), we may conclude that it is different than 0 ($p < .001$) and infer that the relationship between flow and affect within persons does indeed vary significantly across the population of people (see Table 4). In addition, by comparing the experience level variance (σ^2) between the alternative models, an index of the proportional reduction in variance at level 1 can be obtained. The proportion of variance explained at level 1 by inclusion of the flow predictor variable is equal to 7.6% ((σ^2 − σ^2 predictor)/σ^2 or (14.05-12.98)/14.05). Thus, flow accounts for about 7.6% of the experience level variance in affect, after partialing the effects of individual differences.

In summary, the random factor of individual respondent accounts for 24% of the variance in affect in this data set. Flow state (as defined above) can reduce the amount of unexplained variance (variance at the experience level) in affect by 7.6%.

Discussion

As with any statistical method, the research question and context remain the most important considerations in determining if HLM is appropriate.

TABLE 4
Example 2 Final Estimation of Variance Components: Participants Nested within Individual Respondents with Flow State as a Level 1 Predictor

Random Effect	Standard Deviation	Variance Component	df	Chi-square	p-value
μ_{0j}	2.26	5.11 (τ_{00})	51	231.54	<.001
μ_{1j}	2.39	5.72 (τ_{11})	51	106.63	<.001
r_{ij}	3.60	12.98 (σ^2)			

μ_{0j} = the unique increment associated with individual level effect intercept
μ_{1j} = the unique increment associated with individual level effect slope
r_{ij} = the experience level random effect after controlling for Flow State

HLM can be applied in park, recreation, and tourism research with nested or hierarchical data structures. It offers an alternative to collapsing variables or analyzing data at individual levels, which can lead to the loss of important sources of variation by ignoring units of analysis or can violate statistical assumptions. HLM also accounts for effects at different levels of a model, providing the researcher with a better understanding of the phenomenon and can be used to model growth and change over time without using difference scores. The most recent developments include the analysis of multiple dependent variables. Another advantage of this procedure over traditional inferential statistical methods commonly employed in recreation and tourism research is the ability to better handle unbalanced designs through the use of Restricted and Maximum Likelihood (ML) estimation.[2]

Despite some inherent advantages, HLM has limitations and a hierarchical data structure does not necessarily justify the use of HLM. Traditional regression analyses with the use of dummy variables and hierarchical ANOVA work well in a fixed-effects model if the number of subjects in each nested group is equal (Raudenbush & Byrk, 2002). If the effect of the nested variable is insignificant, two-stage hypothesis testing may be appropriate. These techniques are well documented and easily accessible. In addition, lack of institutional support (e.g., consulting, software) and a lack of familiarity among researchers regarding HLM techniques and assumptions will create a reluctance to use HLM. However, when random factors exist at more than one level of the data hierarchy, HLM affords greater flexibility, statistical power, and provides a more appropriate analysis.

HLM presents another analytic technique that can be useful in park, recreation, and tourism research. This is especially important in a field where applied research is common, resulting in less than optimal study designs. Unequal sample sizes, small numbers of cases per group, repeated measures, and dependency are often logistically unavoidable and, under these circumstances, HLM may provide benefits over alternative approaches. Adding HLM to a researcher's statistical repertoire allows him or her to choose a form of analysis that is appropriate to both the research question and context and to resist employing a less powerful analytic technique to hierarchical data.

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[2]A two-level HLM model uses restricted ML approach, in which the variance-covariance components are estimated by means of ML. The fixed effects (level two) are then estimated via generalized least squares given those variance-covariance estimates (Raudenbush & Bryk, 2002). Full ML is employed in the three level HLM, rather than the restricted ML used in the two level model. In a model with three levels both the fixed effects (level three) and the variance-covariance components are estimated by means of ML. This is particularly important because ML is more effective than ordinary least squares estimates when the n's are unequal and will give appropriate weights to groups with differing numbers of subjects. It computes precision-weighted means, sums of squares, and sums of cross products. This weighted-precision is a powerful tool and more accurately helps determine if the results are significant and increases the amount of variance explained.

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