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An Overview of the Logic and Rationale of Hierarchical Linear Models

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Due to the inherently hierarchical nature of organizations, data collected in organizations consist of nested entities. More specifically, individuals are nested in work groups, work groups are nested in departments, departments are nested in organizations, and organizations are nested in environments. Hierarchical linear models provide a conceptual and statistical mechanism for investigating and drawing conclusions regarding the influence of phenomena at different levels of analysis. This introductory paper: (a) discusses the logic and rationale of hierarchical linear models, (b) presents a conceptual description of the estimation strategy, and (c) using a hypothetical set of research questions, provides an overview of a typical series of multi-level models that might be investigated.

Hierarchically ordered systems are an integral and defining aspect of organizations. For example, Hall (1987) defined organizations as follows:

> An organization is a collectivity with a relatively identifiable boundary, a normative order, ranks of authority, communication systems, and membership-coordinating systems; this collectivity exists on a relatively continuous basis in an environment and engages in activities that are usually related to a set of goals; the activities have outcomes for organizational members, the organization itself, and for society. (p. 40).

Even in this broad definition, a hierarchical ordering is evident. Individuals are organized into a collective that exists in an environment thereby resulting in three hierarchical levels: individual, collective/organization, and environment. Although these three levels would exist for any organizational investigation, there are likely to be several intermediate hierarchical levels. For example, a typical organization may have individuals nested within work groups, work groups nested in departments, departments nested in organizations, and organizations

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nested in environments. To investigate these various levels, one must measure variables and constructs that describe each of these levels.

How to investigate hierarchically ordered systems, such as organizations, has been a concern for a number of disciplines for quite some time. For example, researchers in sociology (e.g., Blalock, 1984; Mason, Wong & Entwistle, 1983), economics (e.g., Hanushek, 1974; Saxonhouse, 1976), education (Burstein, 1980), biology (e.g., Laird & Ware, 1982), marketing (e.g., Wittink, 1977), statistics (e.g., Longford, 1989), and management/organizational behavior (e.g., Mossholder & Bedeian, 1983) have all discussed issues, problems, and solutions surrounding research conducted within hierarchically ordered systems. From an organizational science perspective, two themes have dominated the discussion: (a) issues surrounding the aggregation of data, and (b) how to investigate relationships between variables residing at different hierarchical levels.

With regard to aggregation, the discussion has focused on whether it is appropriate to aggregate data, as well as the types of inferences that can be made from aggregated data. James (1982), Rousseau (1985) and others (e.g., Dansereau, Alutto, & Yammarino, 1984; James, Demaree & Wolf, 1984, 1993; Joyce & Slocum, 1984; Klein, Dansereau & Foti, 1994; Kozlowski & Hattrup, 1992) have discussed both the theoretical and statistical issues surrounding the use of aggregate measures to investigate higher level units. Likewise, Robinson (1950) and others (e.g., Burstein, 1978; Firebaugh, 1978; Hannan & Burstein, 1974; Thorndike, 1939) have discussed the inferences that one can draw from aggregated data.

Although aggregation issues are certainly an important aspect of organizational research, they are not the focus of this paper. The focus of the current paper is to address the second major theme; namely, how to investigate *relationships* between variables that reside at *different* hierarchical levels (e.g., Bryk & Raudenbush, 1992; Mossholder & Bedeian, 1983).

Relationships that Cross Hierarchical Levels

Given the nature of organizations, it is clear that variables at one hierarchical level can influence variables at another hierarchical level. In fact, numerous theoretical discussions and empirical investigations have identified relationships between variables that reside at different levels. For example, researchers have discussed the relationships between: organizational environmental factors and organizational structures (e.g., Aldrich & Pfeffer, 1976; Pfeffer & Salancik, 1978), organizational technologies and organizational structures (e.g., Comstock & Scott, 1977; Fry & Slocum, 1984; Thompson, 1967; Woodward, 1965), organizational/subunit technologies and individual attitudes (Hulin & Roznowski, 1985), group norms/stimuli and individual behavior (Hackman, 1992), departmental characteristics/structure and individual attitudes (Brass, 1981; James & Jones, 1976; Oldham and Hackman, 1981; Rousseau, 1978), and climate/culture and individual behavior (James, James & Ashe, 1990; Martocchio, 1994). All of these examples describe hierarchical *relationships* which occur when variables at one level of analysis influence, or are influenced by, variables at another level of analysis.

These examples notwithstanding, House, Rousseau and Thomas-Hunt (1995; see also Tosi, 1992) recently observed a distinct separation between macro and micro organizational theory. Specifically, they noted that macro researchers tend to,

> make predictions of organizational functioning and performance while treating individuals and groups as 'black boxes' whose functioning they do not explain (p. 76)

while micro researchers tend to "apply general psychological theories to the study of behavior [in organizations] as though behavior is context-free" (p. 77). House, et al. (1995) argue quite convincingly that in order to develop more comprehensive theories of organizations, researchers need to adopt a meso paradigm which consists of linking macro and micro concepts to form integrated theories of organizations.

Hierarchical Data: Three Possible Options

The meso paradigm (House, et al., 1995) suggests that researchers need to investigate variables that span multiple levels of analysis. Thus, to study individual behavior within organizations, one needs not only to measure individual attributes but also to measure aspects of the environment within which they are performing (see Pervin, 1989). Similarly, in order to investigate the behavior of organizations as a whole, one needs to measure attributes of the organizations as well as their environments. In either case, the resulting data will include variables that reside at different levels of analysis (i.e., variables describing the lower level units as well as the higher level contexts). Typically, researchers are interested in investigating the influence of both lower level and higher level influences on a lower level outcome variable. This type of investigation has been referred to as either a cross-level (Rousseau, 1985) or mixed determinant (Klein, et al., 1994) model.

In cases where variables exist at more than one level of analysis (e.g., a lower level outcome and both lower level and higher level predictors), there are three main options for data analysis. First, one can disaggregate the data such that each lower level unit is assigned a score representing the higher level unit within which it is nested. The data analysis for this option, therefore, would be based on the total number of lower level units included in the study. For example, all individuals might receive a score representing their work group's cohesion, with the investigation between cohesion and satisfaction carried out at the individual level. The problem with this solution is that multiple individuals are in the same work group and, as a result, are exposed to similar stimuli within the group. Thus, one cannot satisfy the independence of observations assumption that underlies traditional statistical approaches (Bryk & Raudenbush, 1992). In addition to violating this assumption, the disaggregation approach results in another problem. Statistical tests involving the variable at the higher level unit are based on the total number of lower level units (e.g., the effect of group cohesion is assessed based on the number of individuals, not the number of groups) which can influence estimates of the standard errors and the associated statistical inferences (Bryk & Raudenbush, 1992; Tate & Wongbundit, 1983). Incidentally, this approach has been traditionally used within the organizational sciences for investigations of cross-level effects (see, e.g., Baratta & McManus, 1992; Martocchio, 1994; Mathieu & Kohler, 1990; Mellor, Mathieu & Swim, 1994; Mossholder & Bedeian, 1983; Ostroff, 1993; Rousseau, 1978).

The second major approach is to aggregate the lower level units and investigate relationships at the aggregate level of analysis. For example, one could investigate the relationship between group characteristics and individual outcomes by aggregating the individual outcomes to the group level. The disadvantage of this approach is that potentially meaningful individual level variance in the outcome measure is ignored. In summary, the traditional choice has been between a disaggregated model that violates statistical assumptions and assesses the impact of higher level units based on the number of lower level units, or an aggregated model that discards potentially meaningful lower level variance. Neither of these two options seem to be satisfactory.

Hierarchical linear models represent the third major approach to dealing with hierarchically nested data structures. These models are specifically designed to overcome the weakness of the disaggregated and aggregated approaches discussed above. First, these models explicitly recognize that individuals within a particular group may be more similar to one another than individuals in other groups and, therefore, may not provide independent observations. More specifically, these approaches explicitly model both individual and group level residuals, therefore, recognizing the partial interdependence of individuals within the same group (this is in contrast to OLS approaches where individual and group level residuals are not separately estimated). Second, these models allow one to investigate both lower level unit and higher level unit variance in the outcome measure, while maintaining the appropriate level of analysis for the independent variables. Therefore, one can model both individual and group level variance in individual outcomes while utilizing individual predictors at the individual level and group predictors at the group level. Thus, hierarchical linear models overcome the disadvantages of the previous two approaches because one can model explicitly both within and between group variance (i.e., one is not forced to discard potentially meaningful within group variance), as well as investigate the influence of higher level units on lower level outcomes while maintaining the appropriate level of analysis.

Hierarchical Linear Models: Background

As noted above, one of the primary advantages of hierarchical linear models is that they allow one to simultaneously investigate relationships *within* a particular hierarchical level,—as well as relationships *between* or across hierarchical levels. In order to model both within level and between level relationships, one needs to simultaneously estimate two models: one modeling relationships within each of the lower level units, and a second modeling how these relationships within units vary between units. This type of two level modeling approach defines hierarchical linear models (Bryk & Raudenbush, 1992).

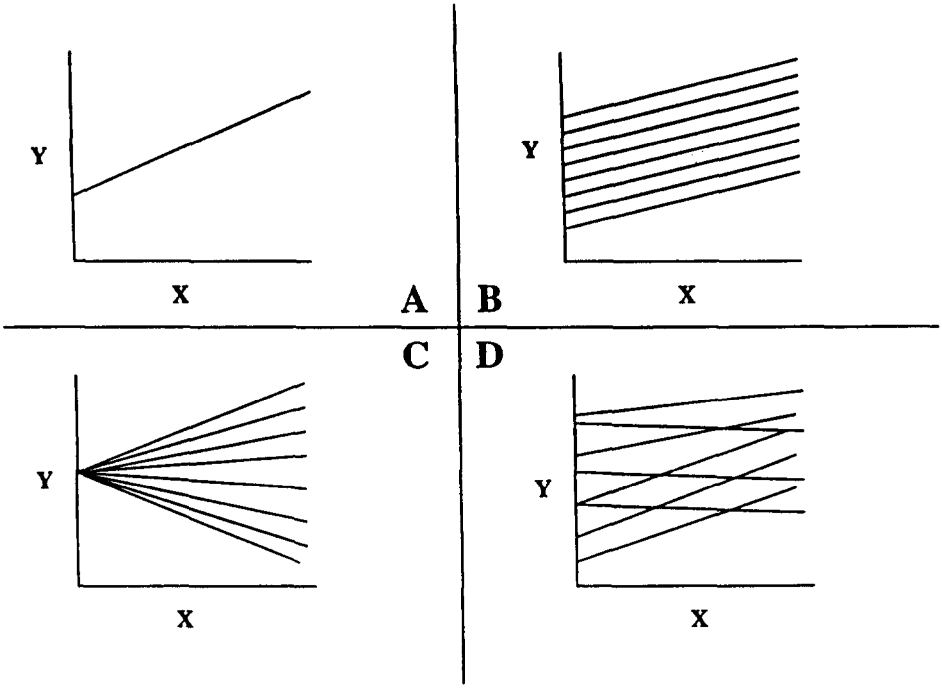

Figure 1. Four possible patterns for intercepts and slopes when level-1 models are estimated separately for each group.

Conceptually, hierarchical linear models are relatively straightforward. For clarity, I will be referring to the two levels as individuals and groups, however, the methods apply to any situation within which there are lower-level units nested within higher-level units. These models adopt a two level approach to cross-level investigations where the level-1 model is estimated separately for each group. This model typically takes the form of a regression based model such as:

$$\text{Level-1: } Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij} \tag{1}$$

where Y_{ij} is the outcome measure for individual i in group j, X_{ij} is the value on the predictor for individual i in group j, β_{0j} and β_{1j} are intercepts and slopes estimated separately for each group (as noted by the subscript j), and r_{ij} is the residual.

To illustrate the nature of these equations, I will use an example consisting of several different groups. When separate regression equations are estimated for each group, four different patterns can emerge. Figures 1a, 1b, 1c, and 1d illustrate these four possible options. In Figure 1a, each of the groups in the sample have identical regression lines. Therefore, each group has identical intercepts and slopes. In Figure 1b, the groups still have identical slope terms, but now the intercept terms vary significantly across groups. Thus, even though the relationship between X_{ij} and Y_{ij} is equivalent across groups, the initial "location" (i.e., intercept) of this relationship varies across groups. In Figure 1c, the groups have similar intercept terms, but the relationship between X_{ij} and Y_{ij} varies significantly across groups. In Figure 1d, both the initial location and the relationship between X_{ij} and Y_{ij} vary significantly across groups (i.e., both the intercepts and slopes vary across groups).

Three of these figures display systematic patterns or differences across the groups. These differences raise the question of whether there are group level variables associated with the variation across the groups. For example, group level variables may be associated with varying intercepts in Figures 1b and 1d and varying slopes in Figures 1c and 1d. This is precisely the question that the level-2 analysis in hierarchical linear models answers. The level-2 analysis uses the intercepts and slopes from the level-1 analysis as dependent variables. For example, a typical level-2 model may take the following form:

$$\text{Level-2:} \quad \beta_{0j} = \gamma_{00} + \gamma_{01}G_j + U_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}G_j + U_{1j} \tag{3}$$

where G_j is a group level variable, γ_{00} and γ_{10} are the second stage intercept terms, γ_{01} and γ_{11} are the slopes relating G_j to the intercept and slope terms from the level-1 equation, and U_{0j} and U_{1j} are the level-2 residuals. Depending on the pattern of variance in the level-1 intercepts and slopes, different level-2 models would be required. For example, in situations such as 1b, where there is no slope variance, the inclusion of G_j in equation 3 would not be meaningful given that β_{1j} is identical for all groups. Similarly, in situations like 1c, where there is no intercept variance, the inclusion of G_j in equation 2 would not be very meaningful because there is no variance in β_{0j} across groups.

The set of three equations above are not new approaches to investigating relationships occurring across hierarchical levels. Some fifteen years ago, Burstein (1980) discussed this same type of approach under the label of "intercepts-as-outcomes" and "slopes-as-outcomes." Conceptually, this is a very appropriate description since the regression parameters (i.e., intercepts and slopes) estimated for each group at level-1 are used as outcome measures (i.e., dependent variables) in the level-2 model (see also Boyd & Iversen, 1979).

Although the conceptual approach has been understood for a number of years, statistical concerns about adequacy of the level-1 intercept and slope estimates as well as the estimation of the variance components hindered the full development of these models (see Burstein, Kim & Delandshere, 1987). Throughout the 1980's, however, a number of separate statistical advances greatly improved the estimation strategy for intercepts- and slopes-as-outcome models. Burstein, et al. (1989), as well as Bryk and Raudenbush (1992), outlined the specific statistical advances and their relationship to hierarchical models (see also Raudenbush, 1988). These advances have resulted in the development of several different software packages designed specifically for hierarchical linear models (e.g., HLM, Bryk, Raudenbush & Congdon, 1994; Mln, Rasbash & Woodhouse, 1995; VARCL, Longford, 1990; see Kreft, de Leeuw & Van Der Leeden, 1994).

Hierarchical Linear Models: Estimation of Effects

In estimating the level-1 and level-2 models discussed above, a distinction is made between fixed effects, random coefficients, and variance components. Fixed effects are parameter estimates that do not vary across groups, for example, the γ's from equations 2 and 3. Alternatively, random coefficients are parameter estimates that are allowed to vary across groups such as the level-1 regression coefficients (e.g., β_{0j} and β_{1j}). In addition to these level-1 and level-2 regression coefficients, hierarchical linear models also include estimates of the variance components which include: (1) the variance in the level-1 residual (i.e., r_{ij} referred to as σ^2), (2) the variance in the level-2 residuals (i.e., U_{0j} and U_{1j}), and (3) the covariance of the level-2 residuals [i.e., cov (U_{0j} , U_{1j})]. The variance-covariance matrix of the level-2 residuals is referred to in the hierarchical linear modeling literature as τ, therefore, element τ_{00} represents the variance in U_{0j}, element τ_{11} represents the variance in U_{1j} and element τ_{10} represents the covariance between U_{0j} and U_{1j}. Obviously, the number of elements in the τ matrix will depend on the number of level-2 equations estimated.

Fixed Effects

The γ's in equations 2 and 3 represent fixed effects in hierarchical linear models. Although these level-2 regression weights could be estimated using an Ordinary Least Squares (OLS) regression approach, this is not appropriate given that the precision of the level-1 parameters will most likely vary across groups. Given this varying precision, an OLS approach is not appropriate due to the violation of the homoscedasticity assumption. Hierarchical linear models use a Generalized Least Squares (GLS) estimate for the level-2 parameters which provide a weighted level-2 regression such that the groups with more precise level-1 estimates (i.e., more precise estimates of the dependent variable; that is, intercepts and slopes) receive more weight in the level-2 regression equation.

Variance-covariance Components

The variance-covariance components in hierarchical linear models represent the variance of the level-1 residuals (i.e., the variance in the r_{ij}'s) and the variance-covariance of the level-2 residuals (i.e., the variance-covariance of U_{0j} and U_{1j}). These variance components are estimated using a Maximum Likelihood function and the the EM algorithm (see Bryk & Raudenbush, 1992 for more details; also Raudenbush, 1988).

Level-1 Random Coefficients

Oftentimes, especially in the context of educational research, a researcher is interested in obtaining the best estimate of a particular level-1 random coefficient (cf. Raudenbush, 1988). In the educational context, this might be when a researcher is interested in an estimate of a particular school's effectiveness where effectiveness is conveyed via a level-1 slope coefficient. One of the simplest ways to estimate the level-1 coefficient for a particular group or school is to compute an OLS regression equation for that particular unit (e.g., equation 1). Assuming large sample sizes within each group, this analysis would provide relatively precise estimates. When groups are smaller, however, these estimates will not be stable (Burstein, 1980). Inspection of level-2 equations (i.e., equations 2 and 3) reveal, however, that there are actually *two* estimates of the level-1 intercepts and slopes. The first estimate comes from an OLS regression equation estimated for a particular unit (i.e., equation 1) whereas the second estimate comes from the level-2 regression model (i.e., the predicted values of β_{0j} and β_{1j} from equations 2 and 3). In other words, for any particular unit, two predicted intercept and slope values can be estimated: one from the level-1 regression equation, and the second from the level-2 regression model. The question now becomes which of these estimates provide a more accurate assessment of the population intercept and slope parameters for that particular unit.

Instead of forcing a choice between these two estimates, hierarchical linear models (and the HLM software program; Bryk & Raudenbush, 1992) compute an optimally weighted combination of these two estimates using an empirical Bayes estimation strategy (see, e.g., Morris, 1983). In other words, HLM computes an empirical Bayes estimate of the level-1 intercepts and slopes for each unit which optimally weights the OLS level-1 estimates (equation 1) and the level-2 predicted values for these same estimates (equations 2 and 3). These empirical Bayes estimates are contained in the residual file generated by the HLM software. Raudenbush (1988) provides proofs demonstrating that this composite estimate produces a smaller mean square error term than either the level-1 estimate or the level-2 predicted value. Thus, when one is interested in obtaining the best estimate of the level-1 coefficient for a particular unit, the empirical Bayes estimate will meet this criteria. This is, of course, assuming that both the level-1 and level-2 models are correctly specified (Raudenbush, 1988).

The empirical Bayes estimates are a weighted composite of the two estimates discussed above where the weight is based on the precision, or reliability, of the OLS estimate. HLM provides an estimate of the "reliability" of the OLS level-1 regression coefficients by first partitioning the variance in the OLS regression parameters for each group into maximum likelihood estimated *true* parameter variance and *error* variance (e.g., variance in β_{0j} = true variance in β_{0j} + error variance in β_{0j}). After obtaining these estimates, one can compute a "reliability coefficient" for each group's OLS parameters via the ratio of true parameter variance to the total parameter variance (i.e., reliability = true variance/total variance). The HLM software reports the reliability of each level-1 random coefficient averaged across groups. This reported reliability can be interpreted as the amount of *systematic* variance in the parameter across groups (i.e., the variance that is available to be modeled by between group variables).

Statistical Tests

HLM provides a variety of statistical tests for hypothesis testing. Specifically, HLM provides *t*-tests for all of the fixed effects (i.e., the second level regression parameters; e.g., γ's) which test whether these parameter estimates significantly depart from zero. Chi-square tests are provided for the level-2 residual variance (e.g., variance in the U's; e.g., τ_{00} and τ_{11}) indicating whether the residual variance significantly departs from zero. In addition to these basic statistical tests, there are more complicated tests available (see Bryk & Raudenbush, 1992), however, for the majority of hierarchical models, these basic tests should suffice.

The above introduction reviewed the background, logic, rationale, and estimation approach of hierarchical linear models. The next section explores how these models can be applied to answer questions relevant to organizational researchers. To further illustrate the hierarchical linear modeling approach, I will first present a hypothetical set of research questions and then discuss the sequence of models that would be used to investigate these questions.

Hierarchical Linear Models: A Conceptual Illustration and Application to Organizational Research

Suppose that a researcher is interested in predicting helping behavior at the individual level. Also suppose that he/she has identified mood (an individual level variable) and proximity (a group level variable) as potential predictors of helping behavior. Table 1 specifies three, rather straightforward,—hypotheses regarding the relationship between helping behavior, mood, and group member proximity. In order for these hypotheses to be supported, there are a number of necessary conditions that must be met. These conditions are listed in the bottom half of Table 1.

Hypothesis 1 and 2 suggest that helping behavior will be significantly related to both an individual level variable (i.e., mood), as well as group level variable (i.e., proximity). Thus, one should expect meaningful within and between group variance in helping behavior (condition 1). Hypothesis 2 proposes that, after controlling for

Table 1. Hypotheses and Necessary Conditions: Helping Behavior, Mood, and Proximity

	Hypotheses
H1.	Mood is positively related to helping behavior.
H2.	Proximity is positively related to helping after controlling for mood (i.e., on average, individuals who work in closer proximity are more likely to help; a group level main effect for proximity after controlling for mood).
H3.	Proximity moderates the mood—helping behavior relationship (i.e., the relationship between mood and helping behavior is stronger in situations where group members are in closer proximity to one another).
	Necessary Conditions
1.	Systematic within and between group variance in helping behavior.
2.	Significant variance in the level-1 intercept.
3.	Significant variance in the level-1 slope.
4.	Variance in the intercept significantly predicted by proximity of group members.
5.	Variance in the slope significantly predicted by proximity of group members.

mood, helping behavior will be significantly associated with proximity. In this example of a hierarchical linear model, the variance in the level-1 intercept term represents the between group variance in helping behavior after controlling for mood.[1] Thus, for hypothesis 2 to be supported there needs to be significant variance in the intercept term (condition 2), and this variance needs to be significantly related to the proximity of group members (condition 4 and hypothesis 2). Hypothesis 3 proposes that the relationship between mood and helping will vary as a function of the proximity of group members. Therefore, for this hypothesis to be supported, there would need to be significant variance in the level-1 slope coefficient across groups (i.e., the relationship between mood and helping behavior; condition 3), and this variance would have to be significantly related to the proximity of group members (condition 5 and hypothesis 3). The following section outlines a typical sequence of models that would allow one to assess the viability of each of these necessary conditions as well as the three hypotheses listed in Table 1.

One-way Analysis of Variance

The first condition specifies systematic within and between group variance in helping behavior. The investigation of within and between group variance suggests that one needs to partition the variance in helping behavior into its within and between group components. To accomplish the variance partitioning in hierarchical linear models, the following set of equations can be estimated:

$$\text{Level-1:} \quad \text{Helping}_{ij} = \beta_{0j} + r_{ij}$$

$$\text{Level-2:} \quad \beta_{0j} = \gamma_{00} + U_{0j}$$

where:

β_{0j} = mean helping for group j

γ_{00} = grand mean helping

Variance $(r_{ij}) = \sigma^2$ = within group variance in helping

Variance $(U_{0j}) = \tau_{00}$ = between group variance in helping

In this set of equations, the level-1 equation includes no predictors and, therefore, the regression equation includes only an intercept estimate. In order to compute intercept terms in regression, the analysis includes a unit vector as a predictor in the equation. The parameter associated with this unit vector represents the intercept term in the final regression equation. In regression software packages, this is typically done implicitly such that the researcher does not have to explicitly model the unit vector. Hierarchical linear modeling is no different. Thus, when a researcher specifies no predictors in a level-1 or level-2 equation, the variance in the outcome measure is implicitly regressed onto a unit vector producing a regression-based intercept estimate. In the level-1 equation above, helping behavior is, therefore, regressed onto a constant unit vector which is implied when one chooses no predictors. Since there are no additional predictors in the model, the β_{0j} parameter will be equal to that group's mean level of helping behavior (i.e., if a variable is regressed only onto a constant unit vector, the resulting parameter is equal to the mean).

The level-2 model regresses each group's mean helping behavior onto a constant; that is, β_{0j} is regressed onto a unit vector resulting in a γ_{00} parameter equal to the grand mean helping behavior (i.e., the mean of the group means, β_{0j}). Given that each of the respective dependent variables is regressed onto a constant, it follows that any within group variance in helping behavior is forced into the level-1 residual (i.e., r_{ij}) and any between group variance in helping behavior is forced into the level-2 residual (i.e., U_{0j}).

Although HLM does not provide a significance test for the within group variance component (i.e., σ^2), it does provide a significance test for the between group variance (i.e., τ_{00}). In addition, the ratio of the between group variance to the total variance can be described as an intra-class correlation. In the model above, the total variance in helping behavior has been decomposed into its within and between group components [i.e., Variance (Helping$_{ij}$) = Variance ($U_{0j} + r_{ij}$) = $\tau_{00} + \sigma^2$]. Therefore, an intra-class correlation can be computed by investigating the following ratio: ICC = $\tau_{00}/(\tau_{00} + \sigma^2)$. This intra-class correlation represents a ratio of the between group variance in helping behavior to the total variance in helping behavior (i.e., the percentage of variance in helping behavior that resides between groups). In summary, the one-way analysis of variance provides the following pieces of information regarding the helping behavior measure: (1) the amount of variance residing within groups, (2) the amount of variance residing between groups, and (3) the intra-class correlation specifying the percentage of the total variance residing between groups.

Random Coefficient Regression Model

After assessing the degree of within and between group variance in helping behavior, one can now investigate whether there is significant variance in the intercepts and slopes across groups (conditions 2 and 3). In other words, for hypothesis 2 to be supported, there needs to be significant variance across groups in the intercepts, and for hypothesis 3 to be supported, there needs to be significant variance across groups in the slopes. In addition to providing evidence in support of necessary conditions 2 and 3, this model will also directly test hypothesis 1. The random coefficient regression model takes on the following form:

$$\text{Level-1: } \text{Helping}_{ij} = \beta_{0j} + \beta_{1j}(\text{Mood}_{ij}) + r_{ij}$$
$$\text{Level-2: } \beta_{0j} = \gamma_{00} + U_{0j}$$
$$\beta_{1j} = \gamma_{10} + U_{1j}$$

where:

γ_{00} = mean of the intercepts across groups
γ_{10} = mean of the slopes across groups (Hypothesis 1)
Variance (r_{ij}) = σ^2 = Level-1 residual variance

Variance (U_{0j}) = τ_{00} = variance in intercepts
Variance (U_{1j}) = τ_{11} = variance in slopes

Because there are no level-2 predictors of either β_{0j} and β_{1j}, the level-2 regression equation is simply equal to an intercept term and a residual. In this form, the γ_{00} and the γ_{10} parameters represent the level-1 coefficients averaged across groups (i.e., they represent the pooled β_{0j} and β_{1j} parameters). Similarly, given that β_{0j} and β_{1j} are regressed onto constants, the variance of the level-2 residual terms (i.e., U_{0j} and U_{1j}) represent the between group variance in the level-1 parameters.

HLM provides a *t*-test related to the γ_{00} and γ_{10} parameters where a significant *t*-value indicates that the parameter departs significantly from zero. In the case of the γ_{10} parameter, this *t*-test provides a direct test of hypothesis 1. In other words, this tests whether mood is significantly related to helping behavior. Note that this test is actually assessing whether the pooled level-1 slope between mood and helping behavior differs significantly from zero. Thus, this test investigates whether, on average, the relationship between mood and helping is significant.

HLM also provides a chi-square test for the two residual variances (i.e., τ_{00} and τ_{11}). These chi-square tests indicate whether the variance components differ significantly from zero and provide a direct test of necessary conditions 2 and 3. In other words, these tests determine whether the variance in the intercepts and slopes across groups is significantly different from zero. Thus, the random regression model provides two primary pieces of information: (1) it tests the significance of the pooled level-1 slopes which are used to test level-1 hypotheses, and (2) whether there is significant variance surrounding the pooled level-1 intercepts and slopes. In other words, the random regression model provides a significance test for the mean of the level-1 regression coefficients (i.e., is the mean significantly different from zero?) as well as the variance in the level-1 regression coefficients.

In addition to estimating the fixed (γ's) and random (τ's) effects, HLM also estimates the level-1 residual variance (i.e., the variance in r_{ij} or σ^2). Remember in the one-way analysis of variance model, σ^2 was equal to the within group variance in helping behavior. Since the random regression model adds a level-1 predictor, σ^2 is now equal to the level-1 residual variance. Comparing these two values of σ^2 can, therefore, provide an estimate of the level-1 variance in helping behavior accounted for by mood. More specifically, one can obtain the R^2 for helping behavior by computing the following ratio:

$$R^2 \text{ for level-1 model} = (\sigma^2_{\text{oneway ANOVA}} - \sigma^2_{\text{random regression}})/\sigma^2_{\text{oneway ANOVA}}$$

This ratio compares the amount of variance accounted for by mood in the numerator (i.e., the total variance – the variance unrelated to mood = variance attributable to mood) to the total within group variance in helping in the denominator. Thus, this ratio represents the percentage of the level-1 variance in helping accounted for by mood.[2]

Intercepts-as-outcomes

Assuming that condition 2 was satisfied in the random regression model (i.e., there was significant variance in the intercept term), the intercepts-as-outcomes model assesses whether this variance is significantly related to the proximity of group members. Thus, this model directly tests condition 4 which is also a test of hypothesis 2.

The HLM model would take the following form:

$$\text{Level-1: } \text{Helping}_{ij} = \beta_{0j} + \beta_{1j}(\text{Mood}_{ij}) + r_{ij}$$

$$\text{Level-2: } \beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Proximity}_j) + U_{0j}$$

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

where:

γ_{00} = Level-2 intercept
γ_{01} = Level-2 slope (Hypothesis 2)
γ_{10} = mean (pooled) slopes
Variance (r_{ij}) = σ^2 = Level-1 residual variance
Variance (U_{0j}) = τ_{00} = residual intercept variance
Variance (U_{1j}) = τ_{11} = variance in slopes

This model is similar to the random regression model discussed above with the addition of proximity as a level-2 predictor of β_{0j}. Therefore, the t-test associated with the γ_{01} parameter provides a direct test of hypothesis 2; that is, the relationship between proximity and helping after controlling for individual level mood. Given that the level-2 equation for β_{0j} now includes a predictor (i.e., proximity), the variance in U_{0j} parameter (i.e.,τ_{00}) represents the residual variance in β_{0j} across groups. If the chi-square test for this parameter is significant, it indicates that there remains systematic level-2 variance that could be modeled by additional level-2 predictors. If the chi-square test of this residual variance is not significant, the researcher may use an option within HLM to fix this variance component to zero (i.e., implying that all of the systematic between group variance in β_{0j} has been accounted for by proximity). All other parameters take on the same meaning as they did under the estimation of the random regression model (i.e., the chi-square for τ_{11} provides an assessment of necessary condition 3).

To obtain information regarding the percentage of variance accounted for by proximity, the same type of procedure described above can be invoked. Remember in the random regression model, τ_{00} was equal to the between group variance in the intercept term (i.e., β_{oj}). In this intercepts-as-outcomes model, a level-2 predictor (proximity) has been added to the equation rendering τ_{00} equal to the residual between group variance in the intercept term. Thus, by comparing these two τ's, one can obtain the R^2 for proximity. The R^2 would be computed as follows:

$$R^2 \text{ for level-2 intercept model} = (\tau_{00\text{-random regression}} - \tau_{00\text{-intercepts-as-outcomes}}) / \tau_{00\text{-random regression}}$$

Once again, this ratio compares the amount of intercept variance accounted for by proximity (i.e., the numerator) to the total intercept variance (i.e., the denominator).

Slopes-as-outcomes

Assuming condition 3 was supported in the preceding model, then one can investigate whether the variance in the slope across groups is significantly related to the proximity of group members. Therefore, this model provides a direct test of condition 5 which is also a test of hypothesis 3.

The HLM model would take the following form:

$$\text{Level-1: } \text{Helping}_{ij} = \beta_{0j} + \beta_{1j}\,(\text{Mood}) + r_{ij}$$
$$\text{Level-2: } \beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{Proximity}_j) + U_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}\,(\text{Proximity}_j) + U_{1j}$$

where:

γ_{00} = Level-2 intercept
γ_{01} = Level-2 slope (Hypothesis 2)
γ_{10} = Level-2 intercept
γ_{11} = Level-2 slope (Hypothesis 3)
Variance $(r_{ij}) = \sigma^2$ = Level-1 residual variance
Variance $(U_{0j}) = \tau_{00}$ = residual intercept variance
Variance $(U_{1j}) = \tau_{11}$ = residual slope variance

The differences between this model and the intercepts-as-outcomes model above are that proximity is now included as a predictor of the β_{1j} parameter and, as a result, the U_{1j} variance is now the residual variance in the β_{1j} parameter across groups, instead of the total variance across groups. Once again, if the chi-square test associated with this parameter variance is significant it indicates that there remains systematic variance in the β_{1j} parameter that could be modeled by additional level-2 predictors. In addition, the t-test associated with the γ_{11} parameter provides a direct test of hypothesis 3. This hypothesis represents a *cross-level moderator* or *cross-level interaction* because a group level variable is hypothesized to moderate the *relationship* between two individual level variables.

It is also possible, as before, to compute the R^2 for proximity as a level-2 moderator of the relationship between individual level mood and helping behavior. Using the value of τ_{11} from the intercepts-as-outcomes model (i.e., the total between group variance in β_{1j}) and the value of τ_{11} from the slopes-as-outcomes model, one can obtain the R^2 as follows:

$$R^2 \text{ level-2 slope model} = (\tau_{11\text{-intercept-as-outcomes}} - \tau_{11\text{-slopes-as-outcomes}}) / \tau_{11\text{-intercepts-as-outcomes}}$$

This ratio compares the percentage of variance accounted for by proximity to the total variance in the mood-helping behavior slope across groups.

The preceding sequence of models provides a general introduction to hierarchical linear models and the HLM software. The extension of these models to include more level-1 and level-2 predictors is relatively straightforward. The purpose of this overview is to provide a *general* introduction to the way in which researchers might ask and answer multi-level questions within the hierarchical modeling framework. Additional details regarding more complex estimation strategies and the statistical intricacies of hierarchical linear models can be found in Bryk and Raudenbush (1992), Goldstein (1995), and Longford (1993).

Hierarchical Linear Models: Additional Issues

Before concluding, there are several additional issues that are worth mentioning: the application of hierarchical linear models to longitudinal data, centering issues, expanding the models to include additional levels, statistical assumptions, and sample size requirements.

Longitudinal Data

Although it might not be apparent, virtually all longitudinal investigations conducted by organizational scientists are hierarchical in nature (see Bryk & Raudenbush, 1987). The nested nature of these data would include multiple observations within a unit and a sample of multiple units. Thus, one would have a within unit level-1 model, and a between unit level-2 model. From a theoretical perspective, one is essentially investigating inter-unit differences in intra-unit change (see Nesselroade, 1991).

Several researchers in the organizational sciences have discussed and demonstrated the hierarchical, nested nature of longitudinal data. Hofmann and colleagues, for example, discussed and demonstrated significant inter-individual differences in intra-individual change for both a sample of professional baseball players (Hofmann, Jacobs, & Gerras, 1992) and insurance sales agents (Hofmann, Jacobs & Baratta, 1993). Similarly, Deadrick, Bennett and Russell (1997) have investigated individual difference predictors of individual patterns of performance change for a sample of sewing machine operators.

At a more macro level, these nested longitudinal models might include investigations of organizational growth and decline (Child, 1974, 1975; Lenz, 1978; Mintzberg & Waters, 1982), organizational/group learning (Argote, 1993), and the survival and growth of new ventures (e.g., Cooper, Gimeno-Gascon & Woo, 1991). In each of these cases, the resulting data structure is one where a time series of data is nested within a larger number of units, thus allowing for an investigation of inter-unit differences in change or growth.

Centering Issues

Since hierarchical linear models use the level-1 regression parameters (i.e., intercepts and slopes) as outcome variables in the level-2 equation, it is imperative that researchers fully understand the specific interpretation of these parameters. As noted in basic regression texts (e.g., Cohen & Cohen, 1983), the slope parameter represents the expected increase in the outcome variable for a unit increase in the predictor variable, while the intercept parameter represents the expected value of the outcome measure when all the predictors are zero. In the ongoing example used in this paper, the slope simply represents the predicted increase in helping behavior given a unit increase in mood. The intercept term represents the predicted level of helping for a person with zero mood. An obvious question regarding the meaning of the intercept, however, seems to emerge: "How can someone have zero mood?"

Like the mood example above, a value of zero is not particularly meaningful for many of the constructs studied in the organizational sciences (e.g., mood, commitment, satisfaction, structure, technology, formalization, centralization). For example, what does it mean for an organization to have zero formalization or centralization, or for an individual to have zero commitment, satisfaction or mood. In order to make intercepts more interpretable, a number of researchers have discussed different ways in which to rescale the level-1 predictors. "Centering" describes the rescaling of the level-1 predictors for which three primary options have emerged: (1) raw metric approaches where no centering takes place and the level-1 predictors retain their original metric, (2) grand mean centering where the grand mean is subtracted from each individual's score on the predictor (e.g., $\text{mood}_{ij} - \text{mood}_{\text{grand mean}}$), and (3) group mean centering where the group mean is subtracted from each individual's score on the predictor (e.g., $\text{mood}_{ij} - \text{mood}_{\text{group mean}}$). With grand mean centering, the intercept represents the expected level of the outcome for a person with an "average" level on the predictor. In the current case, it would be the expected helping behavior for a person in an average mood. With group mean centering, the intercept represents the expected helping behavior for a person with his/her group's average mood. In both cases, the intercept is somewhat more interpretable than the raw metric alternative, however, centering issues do not begin and end with intercept interpretation.

Recently, several researchers have discussed how the various centering options can change the estimation and meaning of the hierarchical linear model as a whole (see Kreft, de Leeuw, & Aiken, 1995; Longford, 1989; Plewis, 1989; Raudenbush, 1989a, 1989b). Hofmann and Gavin (in press) have reviewed these discussions and presented both the theoretical and methodological implications of centering decisions as they relate to research in the organizational sciences. In summary, the choice of centering options goes well beyond simply the interpretation of the intercept term. A researcher must primarily consider their overarching theoretical paradigm and from that discern what centering option best represents their paradigm. Hofmann and Gavin (in press) concluded that different centering options are preferred when researchers are operating under alternative theoretical perspectives (e.g., contextual/ main effect models or cross-level moderation models).

Expanding to Include Additional Levels

Although the discussion thus far has focused on two-level models, it is quite obvious that organizations usually represent more than two hierarchical levels. The extension of the two-level model to higher-level models is relatively straightforward. For example, if in the current example individuals were sampled across different departments, then a three level model could be easily estimated where the level-1 model would be within groups, the level-2 model would be groups within departments, and the level-3 model would be a between departments model. The HLM software is currently available for up to three levels, whereas a new version of the Mln (Rasbash & Woodhouse, 1995) software program will handle a number of hierarchical levels (i.e., up to 15).

Statistical Assumptions

As with any statistical technique, there are certain assumptions required for statistical inference. The HLM software for two-level models assumes (Bryk & Raudenbush, 1992; p. 200): (1) level-1 residuals are independent and normally distributed with a mean of zero and variance σ^2 for every level-1 unit within each level-2 unit; (2) the level-1 predictors are independent of the level-1 residuals; (3) the random errors at level-2 are multivariate normal, each with a mean of zero, a variance of τ_{qq}, and a covariance of $\tau_{qq'}$, and are independent among level-2 units; (4) the set of level-2 predictors are independent of every level-2 residual (similar to assumption 2, but for level-2); and (5) the residuals at level-1 and level-2 are also independent.

Using the ongoing example of helping behavior and the slopes-as-outcomes model (i.e., level-1: helping predicted by mood; level-2: intercept and slope predicted by proximity), these assumptions mean (Bryk & Raudenbush, 1992): (1) after taking into account the effect of mood, the within group errors are normal and independent with a mean of zero in each group and equal variances across groups (assumption 1); (2) if any addition level-1 predictors of helping are excluded from the model—and thereby their variance is forced into the level-1 residual—they are independent of individual mood (assumptions 2); (3) the group effects (i.e., the level-2 residuals) are assumed bivariate normal with variances τ_{00} and τ_{11} and covariance τ_{01} (assumption 3); (4) the effects of any group level predictors excluded from the model for the intercept and mood slope are independent of proximity (assumption 4); and (5) the level-1 residual r_{ij} is independent of the residual group effects U_{0j} and U_{1j}.

Although Bryk and Raudenbush (1992; Chapter 9) discuss these assumptions and the influence of possible violations, James (1995) noted several issues not discussed by Bryk and Raudenbush. First, hierarchical linear models assume multivariate normality and, based on this assumption, proceed with maximum likelihood estimation. The multivariate normality assumption, however, can be problematic, especially in the presence of interactions which is clearly the case when level-1 slopes are predicted with level-2 variables. Second, hierarchical linear models treat independent variables as random variables; that is, processes beyond the control of the researcher determine the level of an individual's value on the independent variable (this is contrasted to fixed variables where individuals are randomly assigned to particular levels of the independent variable). Given this assumption, it is possible that the independent variables will be correlated with the associated residuals. This could occur if an omitted variable is both correlated with the predictor variable included in the model as well as the dependent variable (James, 1980). Finally, with regard to longitudinal data (see Bryk & Raudenbush, 1987), HLM assumes that the level-1 residuals are independent, which is not likely to be the case when one is modeling time series data. Given the relative newness of hierarchical linear models, it is still yet to be seen how robust these techniques are to violations of these assumptions and, therefore, the robustness of this approach to multilevel analysis.

Sample Size Requirements

Although it is difficult to provide specific guidelines on sample size requirements for hierarchical linear models, several general recommendations have been discussed. Bryk and Raudenbush (1992), drawing on the OLS regression rule of thumb of 10 observations per predictor, mentioned that analogous rules for hierarchical linear models can be developed. For predicting any single level-2 outcome (e.g., the level-1 intercept term), the 10-to-1 rule of thumb applies. With multiple level-2 outcomes (e.g., level-2 intercepts and slopes), however, the guidelines offered by Bryk and Raudenbush (1992) become less clear.

Recent simulation studies have provided additional evidence regarding power issues and appropriate sample sizes. Kim (1990) and Bassiri (1988), as discussed by Kreft (1996), both conducted simulation studies investigating the power of hierarchical linear models. The conclusions of both investigations were the same. With regard to level-2 effects, more power is gained by increasing the number of groups as opposed to the number of individuals per group, whereas the power of level 1 effects depends more on the total sample size (i.e., the total number of observations). After reviewing a number of simulation studies, Kreft (1996) concluded that, in general, relatively large sample sizes are required. With regard to specific numbers, two studies have indicated that to have adequate power (i.e., .90) to detect cross-level interactions (i.e., level-2 slope relationships, a sample of 30 groups with 30 individuals is necessary (Bassiri, 1988; Van Der Leeden & Busing, 1994), although there does seem to be a tradeoff among between and within unit observations. For example, if a large number of groups is present, then the number of observations required per group is reduced (e.g., 150 groups requires only five persons per group to obtain a power estimate of .90). Conversely, with fewer groups, one needs more individuals within each group to obtain sufficient power. Bassiri (1988) found that collecting data over many groups, as opposed to sampling more individuals per group, is preferred for detecting cross-level interactions (Kreft, 1996). When considering main effects models (i.e., level-2 intercept models), it is likely that the sample size requirements will be reduced to some degree given the increased precision afforded in estimating intercepts as opposed to slopes.

Conclusions

As the call for developing multi-level theories of organizations continues (House, et al., 1995), it is important to acknowledge and utilize methodological advances from other disciplines to begin testing hypothesized relationships across levels. Although hierarchical linear models have been discussed for a number of years in education and other disciplines, they have only recently been gaining attention within the organizational sciences (see Bennett, 1995; Hofmann, Jacobs & Baratta, 1993; Hofmann & Griffin, 1992; Hofmann & Stetzer, 1996; Hofmann & Gavin, in press; Scandura & Williams, 1995;

Vancouver, Millsap & Peters, 1994). I believe that hierarchical linear models, however, represent an avenue by which these more complex theories of organizations can be further developed and tested, such as those examples that follow in this volume (Deadrick et al, 1997; Griffin, 1997: Kidwell, Mossholder, & Bennett, 1997, Vancouver, 1997). Although hierachical linear models, given their infancy, are far from perfect, they represent a great technical leap forward and can provide a mechanism for adequately testing relationships between variables that cross hierarchical levels. The continuing calls for the integration of macro and micro concepts into *organizational* theories, coupled with these technical advancements, should lead to a better understanding of organizations in all of their complexity.

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Notes

1. This assumes either raw metric or grand mean centering of the level-1 predictors. Hofmann and Gavin in press provide more details regarding the implications of different centering options for organizational research.
2. See Snijders and Bosker (1994) for alternative R^2 estimates.

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