Multilevel Analysis

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3.5.10 Multilevel Analysis

Multilevel analysis (or multilevel model), also known by names such as hierarchical linear model (HLM), linear mixed model, mixed-effect model, and random effects model, is being increasingly used as an alternative to conventional analyses in the field of language testing and applied linguistics in general.

(1) Rationales behind using multilevel analysis

As the name suggests, multilevel analysis is used when data has a "nested," "clustered," or "grouped" structure (Robson & Pevalin, 2015, p. 2). Figure 3.5.10.1 shows an example of such a hierarchical data structure, in which students (Level 1) are nested within their classes (Level 2). It should be noted that because classes are nested within schools, multilevel analysis could include a higher level (i.e., Level 3). If we analyze the pooled data at Level 1, the dependency of data is ignored (i.e., students are nested in each class). Therefore, it is not possible to distinguish the results that are derived from the differences among students (Level 1) or from those among classes (Level 2). Furthermore, as the students nested within classes tend to have similar abilities, the assumption of independence, which is the prerequisite to the correct statistical inference, is violated and thus leads to an erroneous result. Multilevel analysis takes this type of hierarchical structure in data into consideration, and thus it is more appropriate than conventional analyses. More specifically, in multilevel analysis, the information about Level 1 and Level 2 is retained and "separate estimates are produced for both" (Robson & Pevalin, 2015, p. 7). As data obtained in education research are most likely have such a hierarchical structure, it is only natural that multilevel analysis has recently gained considerable attention in several fields.

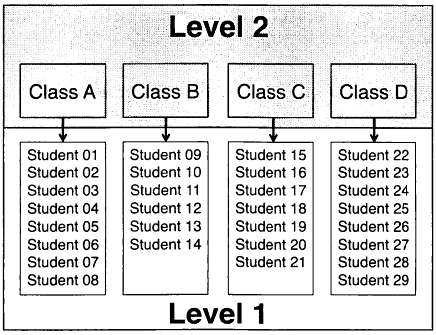

Figure 3.5.10.1. An example of two-level hierarchical data

(2) Types of multilevel analysis

Multilevel analysis can handle both cross-sectional and longitudinal data. Figure 3.5.10.2 displays two types of data structures to which multilevel analysis is often applied. The left panel shows learners (Level 1) who are nested within schools (Level 2). This is a cross-sectional data sample. On the other hand, in the right panel, time points of the measurement (Level 1) are nested within an individual learner (Level 2). As the right panel shows, multilevel analysis can be applied to longitudinal data analysis to investigate change over time (specifically called growth curve model in such application).

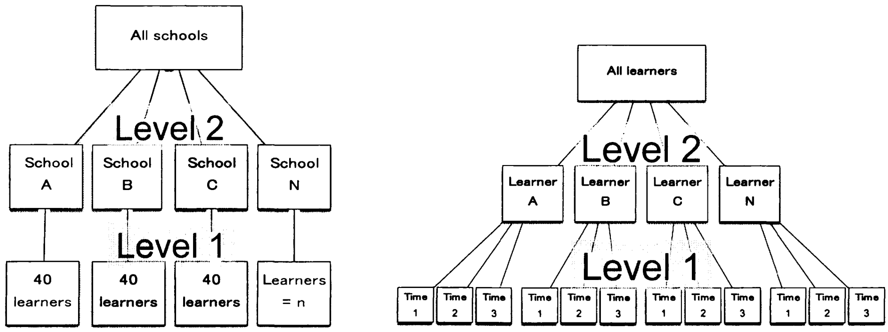

Figure 3.5.10.2. Types of multilevel analysis (cross-sectional and longitudinal data).

(3) Concepts

Multilevel analysis can be regarded as "basically just a posh regression" (Field, Miles, & Field, 2012, p. 866). As such, users of multilevel analysis should be familiar with the terns used in regression analysis such as intercept (切片 in Japanese) and slope (傾き in Japanese). In a very simplified formula without symbols, in the multilevel analysis for the left panel of Figure 3.5.10.2, a learner's dependent variable (i.e., an outcome variable such as a score) could be modeled as follows:

the intercept of level 2 + the slope of Level 2 × independent variable (of the learner) + error term

Although this formula looks exactly like the one for regression analysis, the key difference is that it includes the intercept and the slope of Level 2 in the formula for modeling a learner's dependent variable value (Level 1).

Other concepts central to multilevel analysis are "fixed effects" and "random effects." A fixed effect is one value (parameter) estimated from the sample. We are familiar with a fixed effect because it is the value we can obtain in ordinary regression (e.g., an intercept or a slope). For example, in an experiment, if all treatment conditions are in the design and no generalization is made beyond the experiment, it can be regarded as a fixed effect. On the other hand, if the conditions are random samples from a population, it is a random effect and we could generalize beyond the conditions within an experiment. Multilevel analysis is often referred to as a "mixed effects model" because it is a model that contains a mixture of fixed effects and random effects (Diez Roux, 2002, p. 591). The concept of random effects is of particular importance for language researchers as both participants and language stimuli (e.g., test items) are presumably sampled from a larger population (see Cunnings, 2012, for a more detailed description).

In the case of multilevel analysis, the intercept and the slope of Level 2 (or a higher level) can include both a fixed effect and a random effect. Since the combinations are (a) intercepts are random and slopes are fixed, (b) intercepts are fixed and slopes are random (which, in reality, is rarely assumed as a model), and (c) both intercepts and slopes are random, Figure 3.5.10.3 shows possible scenarios for such random effect models.

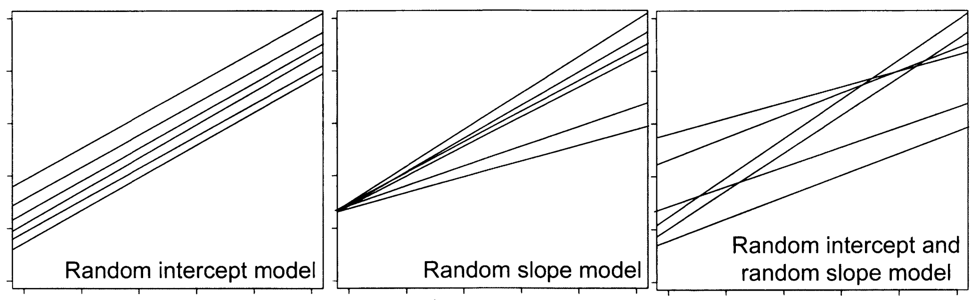

Figure 3.5.10.3. How intercepts or slopes could be random.

Multilevel analysis is interchangeably called multilevel model/modeling, wherein researchers compare different models similar to those seen above. For that purpose, model comparisons are made by assessing the goodness-of-fit indexes such as AIC, BIC, and log-likelihood.

(4) Benefits of using multilevel analysis

Multilevel analysis is not a completely new statistical approach, but rather, an extension of conventional linear models as shown in Figure 3.5.10.4. Multilevel analysis is a type of generalized linear mixed models.

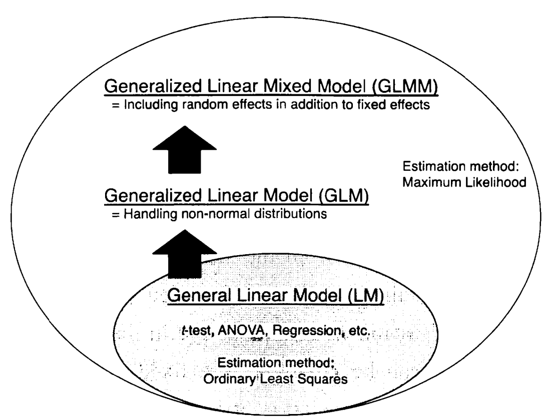

Figure 3.5.10.4. Extensions of linear models.

As it is an extension of conventional methods, additional benefits exist in using multilevel analysis in addition to the above-mentioned desirable characteristics. For example, it is robust against violations of assumptions such as homogeneity of variance and sphericity. Moreover, homogeneity of regression slopes in ANCOVA (analysis of covariance) is no longer a problem as such a variability can be included in the multilevel model. Another advantage of multilevel analysis is that it can model distributions other than the normal distribution, and both continuous and categorical variables can be included. Multilevel analysis is also suitable for longitudinal data analysis because it can factor in individually varying time points and better analyze dependent, repeated-measures data. Finally, multilevel analysis can handle unbalanced datasets and missing values without any loss of data.

(5) Conclusion

In recent years, L2 researchers have started utilizing multilevel analysis (e.g., Ardasheva & Tretter, 2013; Ardasheva, Tretter, & Kinny, 2012; Barkaoui, 2010, 2013; Kozaki & Ross, 2011; Sonbul & Schmitt, 2013) for various research purposes. Considering all the benefits of multilevel analysis, more researchers in the field of language testing will conduct multilevel analysis in their research. Mastering multilevel analysis has a steep learning curve, sometimes with complex mathematical equations. Thus, a hands-on approach with examples using software such as HLM, R, SPSS (SPSS Advanced Models), SAS, Mplus, and MLwiN will certainly be helpful for understanding the multilevel analysis more clearly and in greater depth.

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