Multilevel Modeling

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Synonyms

Hierarchical linear modeling (HLM); Mixed-effects modeling; Random-coefficient regression modeling; Random-effects modeling

Definition

Multilevel modeling is a data analysis technique used to analyze nested data. Nested data refers to data wherein units of analysis at one level are nested within units of analysis at higher levels. Multilevel data are observed in cross-sectional designs which sample individuals nested within groups. An example of this type of multilevel data is patients (level 1) nested within hospitals (level 2). Multilevel data are also found in repeated measures designs (e.g., multiwave longitudinal or experience sampling designs) which sample repeated reports nested within individuals. An example of this type of multilevel data is an experience sampling study where repeated reports of pain (level 1) are nested within individuals (level 2). In multilevel modeling, *level* thus refers to the structure of the data. The lower level (level 1) represents the most detailed unit of analysis and has the greatest number of data points. Level 2 represents the higher level within which level 1 observations are nested.

Description

Why Is Multilevel Modeling Necessary?

Multilevel modeling is necessary because nested data structures violate the assumption of independence required by traditional, single-level data analysis techniques such as analysis of variance and ordinary least squares multiple regression. That is, in nested data, observations at the lower level (level 1) are not independent. For example, individuals (level 1) sampled from the same neighborhood (level 2) may be more similar than individuals sampled from a different neighborhood. Single-level data analysis techniques often fail to take into account such a nested data structure and either ignore the nested data structure (violating the assumption of independence) or collapse across the levels of the nested data structure (ignoring potentially meaningful variability in the data). Violating the assumption of independence may result in underestimation of standard errors and inflation of type I error rates.

In contrast, multilevel modeling allows for data to be analyzed at one level while accounting for variance at other levels. Maximum likelihood algorithms are typically used in multilevel analyses, which allow for simultaneous estimation of multiple error terms. As a result, standard errors are more accurate, and type I error rates are not inflated. In addition, multilevel modeling enables unique types of analyses. Multilevel analyses are similar to single-level regression analyses, where intercepts and slopes are calculated. However, unlike single-level regression analyses, multilevel modeling permits cross-level analyses, wherein a level 2 predictor is used to predict a level 1 outcome. For example, an investigator may test if the neighborhood people live in (level 2) predicts their obesity (level 1). Although such computations are complex, there are many software programs which perform multilevel modeling, including HLM, LISREL, MLwiN, MPlus, R, SAS, SPSS, and Stata.

Considerations When Using Multilevel Modeling

Power. Although sample sizes at both levels warrant consideration, in general, sample size at the higher level has a greater influence on power than sample size at the lower level. For example, in experience sampling studies, the number of participants (level 2) has a greater influence on power than the number of reports per participant (level 1).

Intraclass correlation. It is also necessary to test if multilevel modeling is even necessary. Multilevel modeling is not necessary if there is no variation at higher levels. Variation at higher levels may be computed using the intraclass correlation coefficient. The intraclass correlation coefficient measures the degree to which the lower level units (level 1) belonging to the same higher level unit (level 2) are dependent or clustered. Larger intraclass correlation coefficients indicate more dependence or clustering at higher levels. The occurrence of dependence or clustering at higher levels indicates it is important to use multilevel modeling to protect against inflation of type I error rates and to capture variability at higher levels of the nested data structure.

Missing data. Multilevel modeling is often used to analyze repeated measures data, where missing data are common. Because multilevel analyses typically use maximum likelihood algorithms, participants with missing data may be included in analyses. In multilevel modeling, results are weighted by the amount of data contributed by each participant. That is, participants who provide more data contribute more to the results than participants who provide less data.

Fixed and random effects. Another consideration in multilevel modeling is whether effects are fixed or random. With random effects, the outcome-predictor relationship varies across level 2 units. That is, the slope and the intercept of the regression line are assumed to vary across level 2 units. With fixed effects, the variables of interest do not vary across level 2 units; the slope and the intercept are the same for all level 2 units. If random effects are modeled, the results are assumed to generalize to the population from which cases were sampled, whereas, if fixed effects are modeled, the results are confined to the cases studied. However, random effects models typically require greater sample sizes and may be more complicated to interpret.

Centering. Variables in multilevel modeling may be centered around the group mean (i.e., the mean of each level 1 unit) or centered around the grand mean (i.e., the mean of all the level 2 units). For example, in an experience sampling study involving repeated reports (level 1) nested within individuals (level 2), group mean centering is conceptually equivalent to creating variables that are relative to the individual's own mean based on his/her repeated reports, whereas grand mean centering is conceptually equivalent to creating variables that are relative to the overall mean of all reports provided by all the individuals in the study. Centering aids in interpretation of the results and the choice of centering affects the estimates computed. Decisions regarding centering should be made on a theoretical basis.

Autocorrelation. In repeated measures designs, autocorrelation is an issue. Because of the repeated nature of the data, residual errors in repeated measures data may be correlated (i.e., autocorrelation). The simplest and the most common autocorrelation structure is the first-order autoregressive error structure in which reports closer together in time are more strongly correlated than reports further apart in time. Some software programs (e.g., MPlus or SAS) also model more complex error structures to better account for autocorrelation.

Advantages of Multilevel Modeling

Nested data commonly arises in the field of behavioral medicine. By taking into account the nested structure of the data, multilevel modeling provides more contextualized analyses. For example, multilevel modeling may be used to test neighborhood effects on individuals' obesity, partner effects on patients with cardiovascular disease, and peer influences on adolescents' risky health behaviors. Multilevel modeling may also be used in repeated measures designs, including multiwave longitudinal and experience sampling studies of health behaviors (e.g., smoking, diet, exercise, and medication adherence), chronic illnesses (e.g., pain, diabetes, and HIV), and physiological processes (e.g., cardiovascular reactivity and neuroendocrine levels).

There are several advantages to using multilevel modeling to analyze repeated measures data. Multilevel modeling is able to analyze unbalanced designs, including unequally spaced data and missing data. Using multilevel modeling, it is possible to simultaneously estimate within person and between persons effects. For example, a researcher could study if on days when a participant experiences more stress, he or she smokes more compared to days when he or she experiences less stress (a within person effect). This effect may then be tested to see if it generalizes across all participants in the study (a between persons effect) or to see whether between person differences, such as personality traits, moderate the relationship between stress and smoking (a cross level interaction).

Limitations of Multilevel Modeling

Multilevel modeling is an advanced statistical technique, which requires a solid grounding in statistics. Increasingly, resources are available to support researchers using multilevel modeling (e.g., Bickel, 2007; Field, 2009; Hox, 2010; Raudenbush & Bryk, 2002). Specialized software is also usually needed to conduct multilevel modeling. However, increasingly, mainstream software also performs multilevel analyses.

New Applications and Developments

Multilevel modeling is not limited to regression analyses. In recent years, researchers are combining multilevel modeling with other data analysis techniques. For example, multilevel modeling may be used in testing moderation, mediation, path models, structural models, growth curves, and meta-analyses. By integrating these data analysis techniques, multilevel modeling is able to analyze a wider variety of research questions.

Conclusion

Multilevel modeling is needed to appropriately analyze the nested data structures that often occur in research on behavioral medicine. Careful consideration of the above issues is critical to appropriately using this data analysis technique.

Cross-References

► Missing Data
► Multivariate Analysis
► Repeated Measures Design

References and Readings

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Field, A. (2009). *Discovering statistics using SPSS*. Thousand Oaks, CA: Sage.
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Multiple Regression

► Regression Analysis

Multiple Risk Factor Intervention Trial (MRFIT)

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Definition

The Multiple Risk Factor Interventional Trial (MRFIT) was a large, randomized primary prevention trial to test the effect of multiple interventions to reduce the risk of premature coronary heart disease (CHD) in 12,866 men, age 35–57, with one or more of three risk factors (hypertension, hyperlipidemia, or cigarette smoking) without a prior history of CHD. The trial was conducted in 22 clinical centers in the United States. MRFIT was conducted by the National Institutes of Health (NIH) and National Heart, Lung, and Blood Institute and was massive in scope, screening 356,222 men for the desired study population. These risk factors were chosen because they are modifiable, and there was an expectation (largely unproven at the time) that reduction of these factors should have beneficial results on the development of premature CHD. A subsample of 3,110 men was recruited to participate in the Behavior Pattern Study, which