

**Multilevel Modeling: Foundations and Opportunities in Agricultural Communications,  
Education, and Extension**

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## Introduction

People function within social contexts where they are part of a hierarchical system, nested within groups (Kwok, 2022a), and the system can be observed at different hierarchical levels. For example, students are nested within schools, farmers are nested within formal and informal associations, and consumers are nested within countries. Repeated measures in a longitudinal study are also considered a nested data structure because multiple observations are nested within individuals (Peugh, 2010). Multilevel modeling (MLM) allows researchers to preserve the hierarchical population structure itself in the analysis (Goldstein, 1991). The term *multilevel* “refers to the random variables in the model which are defined as varying between units at different levels of the hierarchy” (Goldstein, 2021). Therefore, researchers would use a two-level model if, for example, there was random variation between students (level 1) and between schools (level 2; Goldstein, 2021). MLM was developed to extend regression modeling. Traditional multiple regression techniques only allow researchers to model variable variance at one unit of analysis (e.g., student level or school level, but not both; Peugh, 2010). Kwok (2022a) explained three reasons why researchers need multilevel analysis techniques: 1) To obtain correct standard error estimates of model parameters; 2) to allow variables (or predictors) at different hierarchical levels to be included in the same model; and 3) to determine how relationships between level 1 (e.g., student level) variables vary across level 2 (e.g., school level) variables and what level 2 (e.g., school level) variables can explain variation in the dependent variable. After searching the *Journal of Applied Communications* and the *Journal of Agricultural Education*—the designated journals for agricultural communications and education research—we found no studies that used MLM. Because research conducted by scholars in the discipline often lends to nested data, we believe MLM provides a rigorous approach to analyzing the data through a novel lens.

## How It Works

Usually, researchers pose research questions focusing primarily on a level 1 (e.g., student level) variable, a level 2 (e.g., school level) variable, or an interaction between variables (Peugh, 2010). MLM can be conducted when independent variables are continuous or categorical. Dependent variables can also be continuous or categorical; however, we limit our explanation of this analysis method to datasets with continuous dependent variables because additional complexities are involved when the dependent variable is categorical. Basic requirements associated with MLM include a clear grouping criterion (i.e., each level 1 variable should have a clear group membership to a level 2 variable), and variables should be unequivocally assigned to one level (Kwok, 2022a). The four basic models include the random intercept model, the means-as-outcomes model, the random coefficients model, and the intercept- and slopes-as-outcomes model (Kwok, 2022b). To fit a model, researchers tend to start with the random intercept model, also considered the baseline model, to determine how much variance is at each level (Centre for Multilevel Modeling, n.d.; Kwok & Chang, 2022). Results from a random intercept model also allow researchers to calculate the intra-class correlation, which is the proportion of variance explained in the dependent variable attributable to the level 2 variable (Kwok, 2022c; Stawski, 2013). After fitting the random intercept model and calculating the intra-class correlation, the next step or model involves adding the predictor(s). The appropriate model is determined based on the research question. For example, researchers would fit a means-as-outcomes model if they sought to explain the variance in the dependent variable as a function of a level 2 predictor, or they would fit a random coefficients model if they sought to explain the variance in the

dependent variable as a function of a level 1 predictor (Lee & Sbarra, 2010). Of course, there are other important considerations researchers must address when conducting MLM (e.g., choosing an estimation method, centering continuous predictors).

### Results to Date

We used MLM to determine how gender affected critical thinking style scores between agricultural students in the U.S. and China. Critical thinking style was measured using the University of Florida Critical Thinking Inventory (Lamm, 2015). We collected online survey data from Texas Tech University students in the U.S. ( $n = 104$ ) and Hebei Agricultural University students in China ( $n = 103$ ). Most U.S. students identified as female (64.4%) and most Chinese students identified as male (67%). Students were nested within two countries—the U.S. and China. We first fit a random intercept model with *critical thinking style* as the dependent variable and no predictor. The mean of *critical thinking style score* was 79.27 and statistically significantly different from zero ( $p < .001$ ). The between country variance was 1.73 and the within country variance was 25.07. Country accounted for 6.4% of the variance in students' critical thinking style scores. We then fit a random coefficients model with *critical thinking style* as the dependent variable and *gender* as the predictor. The mean critical thinking style score was .64 lower for female students compared to males students ( $t(206) = -0.82, p = .414$ ). Only .16% of the variance in students' critical thinking style scores between countries could be accounted for by adding *gender* to the model, which could be because students were nested within a small number of groups. These results indicate gender does not influence the variation between U.S. and Chinese agricultural students' critical thinking style scores.

### Advice to Others

We believe there are significant opportunities for scholars to use MLM in agricultural communications, education, and Extension research contexts. For example, agricultural communications scholars may be interested in investigating how consumers' trust in the agricultural industry (level 1 variable; predictor) influences their frequency of purchasing locally produced food (dependent variable). By collecting data from consumers in various states (level 2 variable), they could fit a random coefficients model (since the predictor is at the level 1) to determine the amount of variation in the relationship between trust in the agricultural industry and purchasing frequency across states. As another example, Extension services use programming to support farmers with their mental health and stress levels. Therefore, agricultural Extension scholars may be interested in exploring how environmental risk factors (level 2 variable; predictor) influence farmers' willingness to participate in mental health programming (dependent variable). If data are collected from farmers in various agricultural production sectors (level 2 variable), it could be analyzed using a means-as-outcomes model (since the predictor is at the level 2) to determine if there is a significant difference between farmers' willingness to participate in mental health programming between production sectors.

### Costs & Resources Needed

The only resource, and associated cost, required to conduct MLM is a general purpose statistical software (e.g., Stata, SAS, SPSS, R). For our applications of MLM, we use Stata.

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