Multilevel Modeling Methods for E-Collaboration Data

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INTRODUCTION

By design, most e-collaboration research has multilevel structures where e-collaboration groups of individuals may be created for different purposes (e.g., productivity improvements, or organizational decision-making). E-collaboration data usually has multilevel structures such as individuals (e-collaboration group members) are nested within groups and we have variables describing the individuals as well as the groups are an example of multilevel design.

Over the course of the past few decades, the multilevel modeling (hierarchical linear modeling, mixed-effects, random coefficients, variance components) methods have been developed (Hedeker & Gibbons, 1996; Longford, 1993; Rasbash et al., 2000; Raudenbush & Bryk; 2002). As a result of computer advances, the use of the multilevel methods to examine the effects of groups or contexts on individual outcomes has simply exploded across all disciplines (e.g., business, medicine, psychology, social and behavioral science).

E-collaboration data usually consists of multiple groups and levels, for example, individual-level data (micro-level), which consists of the characteristics of the individuals within e-collaboration groups and group-level data (macro-level), which consists of the characteristics of the e-collaboration groups. However, many E-collaboration theories center on the presumption that individual measurements at one level are usually influenced by the group dynamics. Yet, despite the multilevel structure of the e-collaboration data, the multilevel statistical methods have not been used in e-collaboration research to address questions of critical significance for decision-making purposes. Gallivan and Benbunan-Fich (2005) reviewed 36 e-collaboration empirical studies published from 1999 to 2004 in six IS journals and found that over two-thirds of these studies contained one or more problems of levels of analysis that cast doubts about the validity of the results of these studies. They stated in their article that one methodological issue of particular concern in e-collaboration research seems to be the researchers' decision to analyze data at either the individual level or the group level, even when the theory that provides the basis for the research is formulated at both the individual and group levels and the research setting featured individuals working in e-collaboration groups. In such settings, the observations for individuals within the same group are correlated to some extent because these individuals share the same experiences and environments.

One of the common mistreatments of e-collaboration multilevel data in e-collaboration research is to disaggregate the data to the individual-level (micro-level) and ignore the existence of group-level (macro-level). Ignoring the multilevel structure and the grouping structure of the e-collaboration data has serious methodological consequences. Inaccurate and biased parameter estimates and biased standard errors of these estimates are examples of such methodological problems.

The other mistreatment of the e-collaboration multilevel data is to aggregate the individual-level (micro-level) to the group-level (macro-level) by using aggregated outcome and explanatory measurements such as the mean or the total values of these measurements. Similar to the disaggregation treatment of the multilevel data, the aggregation practice will lead to serious methodological problems. One of the significant problems is biased results and inaccurate conclusions because the analysis results of the aggregated measurements are different from the analysis results of the original individual-level measurements. Also, these biased results from analyzing the aggregated data leads to "ecological fallacy" (Robinson, 1950) where correlations between aggregated variables at the group level are used to make conclusions about individual level relationships.

Thus, one of the primary advantages of multilevel models is that they allow one to simultaneously investigate relationships within a particular hierarchical level as well as relationships between variables across hierarchical levels. This leads to valid and unbiased results and conclusions.

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Multilevel modeling methods can be applied to different kinds of hierarchically structured e-collaboration data. E-collaboration data with continuous, binary, ordinal, or count outcomes are a few examples of such different applications. However, the two-level multilevel e-collaboration data with continuous outcomes (dependent variables) and individuals are clustered (nested) within e-collaboration groups is one of the most basic and common applications in e-collaboration research. Thus, the field of e-collaboration research that deals with using e-collaboration and virtual teams needs special and rigorous research methods to meet the challenges and the complexities of the multi-group e-collaboration data.

The present article aims to (1) conceptualize and present the two-level multilevel model for e-collaboration research, (2) conceptualize the Intra-Class Correlation Coefficient (ICC), (3) conceptualize R^2 in e-collaboration multilevel modeling, (4) present centering methods that can be used in e-collaboration multilevel modeling, (5) present parameter estimation and hypothesis testing methods for e-collaboration multilevel modeling, and (6) list some of the existing commercial software packages that can be used for analyzing the e-collaboration multilevel data.

TWO-LEVEL MULTILEVEL MODEL

The two-level multilevel model is characterized as having two levels where individuals (e-collaboration group members) are nested within e-collaboration groups and there are predictors for each of the two levels. Hence, in multilevel modeling with two levels, each level is represented by its own regression equation. In this multilevel modeling application, e-collaboration researchers are primarily interested in assessing the effects of the individual characteristics (e.g., experience, age, education) within e-collaboration groups as well as e-collaboration group characteristics (e.g., location, size) on the continuous outcome variable (e.g., performance, accomplishment) and the interactions between the individual and group characteristics. Thus, these multilevel models express relationships among variables within each of the levels and specify how variables at one level influence relations occurring at another level (cross-level interaction).

It is important to note that understanding the technical conceptualization of the two-level model as presented below is needed for multilevel data analysis purposes using multilevel software packages. For example, this technical presentation clarifies the need for two data files to be inputted to the HLM software package. One is the Individual-Level (Level-1, Micro-Level) data file and the other is the Group-Level (Level-2, Macro-level) data file.

Individual-Level (Level-1) Model

The Individual-Level, Level-1, or Micro-level model specifies the relationships among various individual characteristics as independent explanatory variables (predictors), X_{ij}, for each of the j e-collaboration groups and the dependent variable, Y_{ij}. This Level-1 model takes the form of:

$$Y_{ij} = \beta_{oj} + \beta_{pj} X_{pij} + r_{ij}, \qquad (1)$$

where, $i = 1, 2, 3, \ldots, n_j$ individuals within E-collaboration group j. $j = 1, 2, 3, \ldots J$ E-collaboration groups. β_{oj} represents the intercept for the individual and β_{pj} represents p regression coefficients (slopes) capturing the effect of the p predictors X_{ij} on the outcome, Y_{ij}. In multilevel modeling, these Individual-Level (Level-1, Micro-Level) regression coefficients are assumed to be random and vary from one e-collaboration group to another. r_{ij} represents the Level-1 random error and assumed to be normally distributed with mean zero and a common variance, σ^2. These errors are assumed to be uncorrelated with the Level-1 predictor variables. Also, the variances of the random errors (σ^2) are assumed to be equal (homogeneous) across the e-collaboration groups. Thus, Individual-Level (Level-1) model yields j separate set of regression estimates for the intercept and each of the p slopes.

Group-Level (Level-2) Model

In multilevel modeling, the intercept and the slopes (regression coefficients) estimates from the Individual-Level (Level-1) model are conceived as outcome (dependent) variables in Group-Level (Level-2, Macro-Level) model. These Level-2 dependent variables (intercept and slopes) from Level-1 are modeled by the q Group-Level (Level-2) characteristics (predictors). The Group-Level (Level-2) intercept and slope models (Equations 2 and 3) take the form of:

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