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Multilevel Methods: Emergent Issues and Future Directions in Measurement, Longitudinal Analyses and Non-Normal Outcomes

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Multilevel Methods

Future Directions in Measurement, Longitudinal Analyses, and Nonnormal Outcomes

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The study of multilevel phenomena in organizations involves a complex interplay between methods and statistics on one hand and theory development on the other. In this introduction, the authors provide a short summary of the five articles in this feature topic and use them as a platform to discuss the broad need for work in the two areas of (a) multilevel construct validation and measurement and (b) statistical advances in variance decomposition. Within these two broad frameworks, the authors specifically discuss, first, the need to continue moving beyond notions of isomorphism in developing and testing aggregate-level constructs. Second, they discuss the potential value of using discontinuous growth models to understand transitions in longitudinal studies. Finally, they discuss some of the issues surrounding the ability to decompose variance in multilevel modeling of dichotomous and other nonnormal outcome data.

Keywords: *multilevel; discontinuity; transition; construct validation; agreement*

Progress in science involves a complex interplay between specification of theoretical propositions and tests of these propositions using appropriate methods and statistics. Although virtually all researchers would profess that data analyses should be driven by substantive theoretical propositions, the reality is more complex; in some cases, advancements in methods and statistics may be the impetus that drives or guides theory development. The study of multilevel phenomena in organizational research represents a good example. In multilevel research, the concurrent advancement of theory and methodology is evident in two areas. First, it is evident in the theory-based specification of multilevel constructs and associated methodological issues surrounding multilevel measurement. Second, it is evident in the articulation of progressively more complex multilevel theories as well as the associated methodological advances in variance decomposition and data analysis that

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Authors' Note: The views expressed in this article are those of the authors and do not necessarily represent the official policy or position of the U.S. Army Medical Command or the Department of Defense. Correspondence regarding this article can be addressed to Paul Bliese (paul.bliese@us.army.mil); David Chan (davidchan@smu.edu.sg) or Robert Ployhart (Ployhart@moore.sc.edu). The authors would like to thank Herman Aguinis and Amy B. Adler for constructive comments on earlier drafts of the article.

support testing these theories. In both of these areas, the substantive theory and the corresponding methods continue to develop; however, it is not always clear whether theory is driving the methods and statistics or vice versa (a concern not unique to multilevel research; Ployhart, in press). What is clear, however, is that concurrent developments of theory and methods in multilevel research have allowed organizational researchers to more accurately and realistically model organizational phenomena.

The five articles in this feature topic represent a good selection of state-of-the-art multilevel research where the complex interplay between theory and statistical methods is evident. The articles address theoretical, methodological, and statistical issues surrounding (a) the choices and validity of measures for assessing higher level constructs (Quigley, Tekleab & Tesluk, 2007 [this issue]; Roberson, Sturman & Simons, in press); (b) methods of handling level-2 missing data in longitudinal studies (Cheung, in press); (c) identification and prediction of unobserved subpopulations in longitudinal studies (Wang & Bodner, in press) and (d) the degree to which individual-level item properties affect group-level correlations (Beal & Dawson, in press).

In this introduction, we use these studies as a platform to delineate three areas for future multilevel research. The first topic area focuses on the challenges associated with multilevel construct validation and measurement in situations where isomorphism across lower-level and aggregate-level variables cannot be assumed. The second topic area focuses on the theoretical implications of being able to decompose variance from longitudinal designs into studies of discontinuous change processes. The third topic area focuses on the challenges surrounding variance decomposition in multilevel models of dichotomous and other nonnormal outcome data.

Aggregate Variable Measurement

Two of the articles in the feature topic (Quigley et al., 2007, and Roberson et al., 2007) focus on properties of group-level measures and/or the links between individual and group-level measures. As evident in these articles, and many of the submissions to this feature topic, measurement issues surrounding what happens when lower-level variables are aggregated to represent higher level constructs continue to remain a central theme in multilevel organizational methods research. This is not surprising because aggregation issues play a central role in how we specify and test the functional relationships between constructs at different levels of analysis (Bliese, 2000; Chan, 1998b).

Roberson et al. (2007) fill an important gap by examining via simulation how a variety of measures such as $r_{wg.j}$ and the standard deviation perform when used as indices of dispersion. Dispersion studies explicitly test the idea that variability around a construct of interest is an important predictor of organizational outcomes (e.g., Bliese & Halverson, 1998), and although a number of indices are used to measure dispersion, there has been a knowledge gap in terms of understanding the relative strengths and weaknesses of the various indices. The article by Quigley et al. (2007) focuses more on the measurement properties associated with group-level constructs. Specifically, Quigley et al. consider whether team-level variables are best measured using consensus or aggregation-based methods. Both studies fill important voids in the literature.

It is encouraging that studies in this feature topic are directed toward the substantive meaning of group-level constructs and the recognition that aggregation often results in changes in meaning across levels. This change in meaning is obvious when measures of dispersion are created from individual-level constructs; however, we contend that change in meaning also frequently occurs when higher level constructs are aggregated using summary statistics such as means. Until recently, there has been a tendency in organizational research to consider aggregated higher level variables as faithful representations of the lower-level variables used in the composition. That is, conceptual content has been thought to essentially remain identical across levels as the researcher composes the higher level variable from the lower-level counterparts. This idea is typically referred to as "isomorphism"—defined as similarity or one-to-one correspondence between two or more elements.

Bliese (2000), Chan (1998b, 2005), and Kozlowski and Klein (2000) among others have pointed out that aggregation may result in isomorphic constructs in some instances but not in others. Therefore, it is critical to approach aggregation from one or more specific composition models that provide the conceptual and organizing framework for specifying and testing the functional relationships between the aggregated (higher level) variable and its lower-level units.

The idea of isomorphism is most useful when the construct of interest can reasonably be assumed to be determined by (a) a single lower-level attribute or (b) a combination of lower-level attributes where all but one determinant can be considered randomly distributed across groups. For instance, individual disease is often assumed to be determined by the two individual attributes of biological predisposition and exposure to pathogens. Thus, in an occupational health study of cancer rates, it would be reasonable to assume an isomorphic link between individual cancer and average rates of cancer in a work group as long as it were also reasonable to assume that biological predispositions were randomly distributed across work groups. In this example, average rates of cancer would reflect a central tendency presumably driven by the presence or absence of pathogens causing individual cancer.

Although the isomorphic conceptualization may appear useful, in practice, it tends to be hard to support in organizational research for two reasons. First, individuals are not randomly assigned to work groups in organizations; consequently, personality, intelligence, and other attributes often cluster by group. Second, many constructs of interest to organizational researchers (commitment, job satisfaction, ratings of well-being, power, etc.) have both group-based and individual-based determinants (Bliese, 2000, 2006; Fiol, O'Connor, & Aguinis, 2001). Individual reports of job satisfaction, for instance, cannot be traced back to a single "pathogen" such as a disease; rather, individual reports of job satisfaction are influenced by (a) an individual's job experiences and job attributes and (b) shared experiences and perceptions among work group members. The multifaceted determinants of job satisfaction raise the possibility that the group mean reflects shared group properties such as cohesion, group morale, or collective efficacy. Because of nonrandom distribution of personnel across work groups, the group mean may also serve as a proxy for an attribute such as average work group intelligence (particularly because intelligence appears to be related to ratings of job satisfaction; see Ganzach, 1998).

Figure 1
Factors Affecting the Lack of Isomorphism in the Link Between Individual and Aggregate Ratings of Job Satisfaction

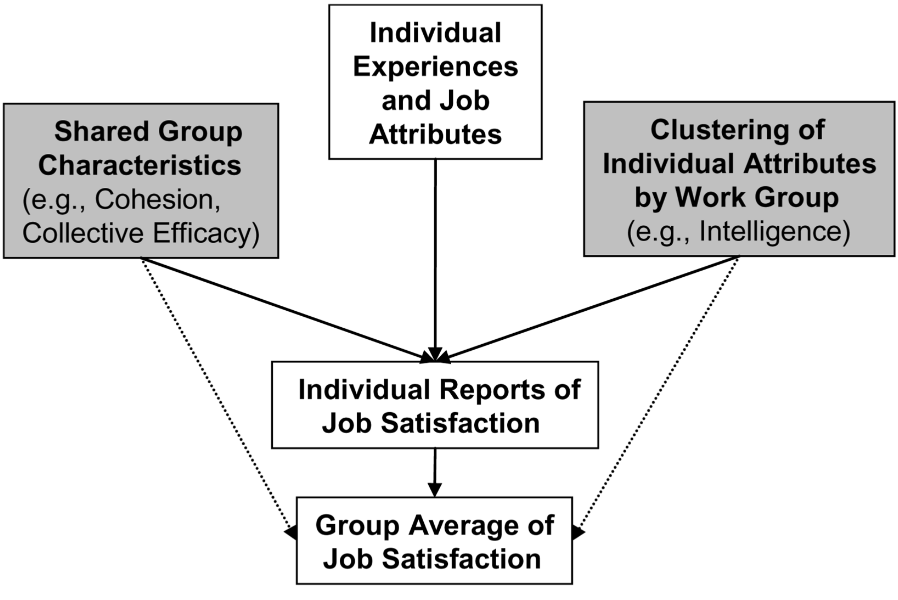


Figure 1 illustrates the factors affecting the aggregate rating of job satisfaction. For the link between individual ratings of job satisfaction and average group job satisfaction to be isomorphic, a researcher must assume that neither of the gray boxes exerts influence on individual reports of job satisfaction. Assumptions of this nature are rarely empirically supported (Bliese, 2000). As Bliese (2000) noted, many seemingly individual-level variables have intraclass correlation (ICC[1]) values greater than zero. Nonzero ICC(1) values provide evidence of group effects, but they do not identify whether these effects are due to group characteristics such as collective efficacy or from clustering of individual attributes in work groups.

In short, the clustering of individual attributes among work groups and the inability to tie an aggregated central tendency back to a single determinant raises the possibility that the central tendency is a proxy for some other variable. In our example, the group mean of individual measures of job satisfaction is probably not a simple summary of individual tendencies; instead, it most likely reflects some property of the entire group. This lack of isomorphism has been noted in several disciplines to include sociology (Firebaugh, 1976) and is well articulated in organizational theory by Morgeson and Hofmann (1999), who observed that "measures of an individual-level construct cannot always simply be aggregated and assumed to be a veridical representation of its collective counterpart" (p. 260).

The lack of isomorphism between lower-level and aggregate-level constructs is important because it leads directly to issues of measurement and construct validation of aggregate-level variables (Chen, Mathieu, & Bliese, 2004). The work of Sampson and colleagues

(Sampson, 2003; Sampson, Raudenbush, & Earls, 1997) provides an excellent illustration. Sampson and colleagues (1997, 2003) observed (as had others) that health-related problems in geographic communities correlate with a number of aggregate social characteristics (poverty rates, child density, home ownership rates, etc.). Not only do social characteristics of a community correlate with rates of health problems; they also contribute unique variance in predicting health over and above individual risk factors (Robert, 1999). For instance, average poverty rates in a community may predict health in statistical models that already contain individual income as a predictor.

A central premise underlying the work of Sampson and colleagues is that aggregate community variables such poverty, child density, and home ownership are nonisomorphic with their lower-level counterparts. That is, the meaning of these variables at the community level differs from the meaning at the individual level. One significant scientific contribution of Sampson and colleagues' work centers on the theoretical exploration of the meaning of the aggregate community variables. Sampson (2003) wrote, "If 'neighborhood effects' of concentrated poverty on health exist, presumably they stem from social processes that involve collective aspects of neighborhood life, such as social cohesion, spatial diffusion, local support networks, informal social control and subcultures of violence" (p. S56). In short, Sampson and colleagues propose that aggregated individual variables such as poverty are more than central tendencies; rather, they are proxies for important social processes such as community collective efficacy (Sampson et al., 1997).

The challenges faced by Sampson and colleagues are the same challenges faced by multilevel organizational researchers. These challenges include, first, the need to identify the underlying theoretical group-level processes reflected in aggregate individual-level variables and, second, the need to identify ways to measure these organizational- and group-level processes directly. In particular, we see a need to address the measurement of aggregate-level constructs. Sampson (2003) wrote,

> As interest in the behavioral sciences turns increasingly to an integrated scientific approach that emphasizes individual factors in social context, a mismatch has arisen in the quality of measures. Standing behind individual measurements are decades of psychometric and biological research, producing measures that often have excellent statistical properties. (p. S56)

Sampson argues, in contrast, that much less is known about measures in aggregate settings. He states, "The basic idea is to take the measurement of ecological properties and social processes as seriously as we have always taken individual-level differences" (p. S57).

Using the structure–function distinction in the framework of collective constructs proposed by Morgeson and Hofmann (1999), we contend researchers must begin by focusing on the "functional" aspect of the construct. Once the functional aspect of the construct has been explicated, the "structural" measurement of the construct can be considered. In construct validation work for aggregate variables, the theoretical challenge is to clearly define the higher level construct, and the measurement challenge is to develop a strategy for assessing this construct that fully captures the elements of the higher level construct (Chen et al., 2004). Hence the need to integrate theory with alternate measurement options for assessing higher level constructs (e.g., Quigley et al., 2007).

Multilevel analysis techniques such as random coefficient modeling (RCM), latent growth modeling, and multilevel structural equation modeling provide ways to empirically demonstrate "emergent" effects where aggregate-level variables explain unique variance above their individual-level counterparts. Emergent relationships provide strong evidence that lower-level and aggregate-level constructs lack isomorphism. To fully capitalize on findings from tests of emergent effects, however, researchers must develop the supporting theoretical framework that explains the nature of the aggregate-level variables. Therefore, we encourage researchers to begin by identifying the fundamental social and organizational processes reflected in emergent relationships and to then extend this work by refining and developing measures of the aggregate-level variables (see also Chan, 2005; Chen, Bliese, & Mathieu, 2005; Chen et al., 2004; Kozlowski & Klein, 2000).

An organizational illustration of the changing nature of variables across levels is provided by Ployhart, Weekley, and Baughman (2006). They predicted individual job performance and job satisfaction using the Five Factor Model of personality in a manner typical of single-level research. However, they also demonstrated that personality was more than an individual-level phenomenon. Using the theoretical tenets of attraction–selection–attrition processes, they maintained that personality displays both consensus (composition) and dissensus (compilation) elements (Bliese, 2000). Consequently, the *structure* of higher level personality constructs differs somewhat across levels. Furthermore, application of a three-level random coefficient model demonstrated that higher level personality composition and compilation exhibited different *functional* relationships with individual-level performance and satisfaction. Thus, careful specification of the structure and function of higher level constructs is necessary to articulate theoretically meaningful multilevel and cross-level relationships.

In summary, there have been important advancements in understanding the structure and function of aggregate constructs and processes. The articles in this feature topic help with understanding composition and compilation measurement issues, but considerably more research must be conducted on this topic. Addressing the issues will require careful integration of both theory and methods. As this section has implied, we see the theoretical specification of aggregate-level constructs as being one of the largest challenges in this area. Future work directed toward developing theoretically and empirically sound aggregate-level constructs is a necessity in multilevel organizational research.

Although our first focus for future research has centered on measurement issues, the second area focuses more directly on model testing and variance decomposition. Specifically, we examine the theoretical and practical implications of being able to decompose variance in longitudinal designs into studies of discontinuous change.

Longitudinal Studies

Cross-sectional multilevel models examine individual (or lower-level) responses nested within higher level entities such as work groups. In longitudinal analyses, the models examine patterns of repeated measures nested within individuals. In other words, instead of focusing on interindividual differences in contexts of group membership, the application of a multilevel framework to longitudinal data focuses on modeling intraindividual changes over time (Bliese and Ployhart, 2002; Chan, 2005; Singer & Willett, 2003).

Issues with describing and predicting intra individual changes over time are often complex and distinct from typical cross-sectional research (Bliese & Ployhart, 2002; Ployhart, Holtz, & Bliese, 2002). These issues involve various facets of change over time such as conceptual changes in the constructs and changes in calibration of measurement (Chan, 1998a). Developments in latent variable analysis, particularly structural equation modeling, have been successfully applied to modeling the complexities involved in a variety of these changes (see Chan, 1998b, 2002a, 2002b, 2005; Singer & Willett, 2003).

Two articles in this feature topic (Cheung, 2007; Wang & Bodner, 2007) focus on methodological issues associated with analyzing longitudinal data using advanced structural equation modeling techniques. Cheung (2007) uses simulations and a structural equation approach to illustrate the robustness of multilevel models in cases where level-2 data are missing. Wang and Bodner (2007) illustrate how growth mixture models can be used to identify and predict unobserved subpopulations in longitudinal data. These articles contribute important information about the robustness and versatility of multilevel longitudinal models.

We anticipate that theoretical and methodological advances in longitudinal modeling such as subpopulation identification will continue to play an increasingly important role in understanding organizational phenomena. For example, Chan and Schmitt's (2000) application of latent growth modeling to longitudinal data on organizational newcomers addressed a variety of important substantive research questions that were not examined in previous newcomer adaptation research. Detailed discussions on applications of latent growth modeling and its extensions to organizational research are available in Chan (1998a, 2002a, 2002b). Of course, random coefficient models have also been widely applied to longitudinal research and growth modeling. Although many of the same issues with latent growth modeling apply to RCM, there are some unique differences between the two approaches (for details, see Bliese & Ployhart, 2002; Chan, 1998a; Ployhart et al., 2002). For instance, random coefficient models can easily be applied to data where individuals are measured on different time schedules.

In addition to subpopulation identification, one particularly new development important for understanding organizational phenomena involves growth modeling for discontinuous change. Discontinuous growth modeling provides a way to conceptualize and assess discontinuities (i.e., transitions) in longitudinal data (Singer & Willett, 2003). Given that this technique is likely to be unfamiliar to many organizational researchers, we illustrate its application with several examples. In the first example, Bliese, Wesensten, and Balkin (2006) applied a discontinuous growth model to a 10-day study where the first 7 days involved sleep restriction and the last 3 days involved recovery. The transition from sleep restriction to recovery was a distinct point presumably predictive of improvements in reaction time on a vigilance task. To capture this design aspect of the study, it was necessary to include a discontinuity in the growth model—fitting a smooth growth function to the data would have failed to capture the underlying process. The inclusion of the discontinuity allowed the entire experiment to be divided into three periods: the trend leading to the transition, the transition itself, and the trend following the transition. The nature of the change at each period could be examined, each period could be examined for individual differences, and individual characteristics (e.g., participant age) could be used as predictors of individual differences within periods.

Although this example is from a laboratory experiment involving sleep and cognitive performance (an area arguably tangential to organizational behavior), the basic model is clearly applicable to understanding individual and organizational phenomena. For instance, Lang (2007) applied the model to a study of adaptation. In the design, participants learned a complex task, and performance was recorded. After an initial period of task mastery, the rules underlying the task changed (the transition point) and performance continued to be assessed. The discontinuous approach allowed Lang to model trends and individual differences during three periods: (a) initial task mastery, (b) reactions to the transition, and (c) posttransition trends. The application of the discontinuous growth model in this context provided a way for Lang to focus on the transition (the point in time requiring adaptation) and determine how responses to the change were related to individual characteristics such as intelligence.

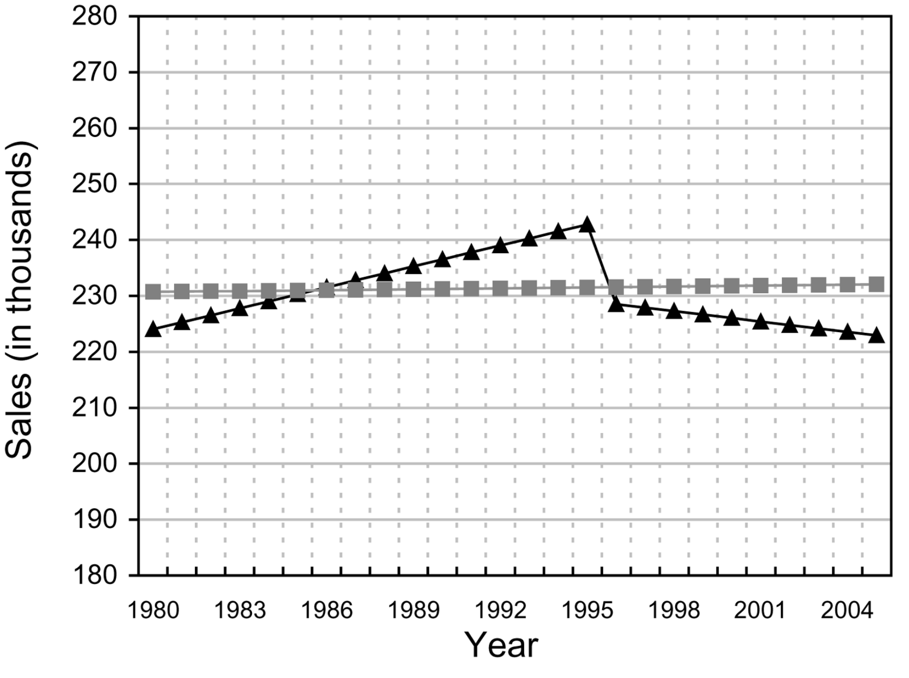
Another example of the value of focusing on transitions is illustrated in Bliese, McGurk, Thomas, Balkin, and Wesensten (2007). In this study, the researchers examined average daily sleep during 26 days among a group of 77 participants in an assessment center. The overall linear sleep trend was basically flat—that is, there was no indication that time was significantly related to sleep. In a growth model, a flat line typically limits subsequent analysis options because there is no change to model. In this case, however, the participants in the study had transitioned at Day 17 from sleeping in barracks to sleeping in tents as part of a field exercise. Once this change was included, individual reactions to the transition could be analyzed along with patterns pre- and posttransition, and age was found to be related to adjusting to the transition.

The Bliese et al. (2007) study illustrates the potential value of examining transitions using discontinuous growth modeling in situations where data have no obvious overall trends. Traditional growth models are well suited to situations where an outcome is expected to either increase or decrease over time—skill acquisition among new hires is a good case in point (e.g., Deadrick, Bennett, & Russell, 1997; Thoresen, Bradley, Bliese, & Thoresen, 2004). In a number of settings, however, there may be no reason to assume increases or decreases over time. In these situations, change associated with transitions may reveal both practical and theoretical insight. For instance, in established fast-food restaurants, one might reasonably expect sales to be flat; therefore, modeling change over time would reveal little. As an illustration, notice that Figure 2 predicts a flat line (boxes) when a linear growth model is applied to hypothetical sales data over time.

If one considers the possibility that the flat line is composed of a transition (rival restaurant opening, new manager, etc.), then it becomes clear that the flat line is actually composed of segments that contain considerable information. In Figure 2, a transition is modeled at the year 1996 using the same data as those used to estimate the linear line. Basically, the linear model eliminates time-related variability surrounding the transition, and including the transition uncovers a key source of variability that may differ across individuals or other Level-2 entities in the sample.

There is considerable flexibility in modeling transitions. Transitional events can be either planned (introduce new product, change the rules in a study of adaptability) or unplanned (Hurricane Katrina). In addition, within a RCM framework, there is no need for transitions to occur at a set time for all participants. Indeed, transitions might not even occur for some groups. Singer and Willett (2003) detailed methodological options for modeling discontinuities.

Figure 2
Example of How a Discontinuous Transition Can Be Masked in a Linear Growth Model



In summary, in addition to considering how longitudinal analyses might be used to identify subpopulations (Wang & Bodner, 2007), we also encourage organizational researchers to consider how discontinuities might be included in longitudinal analyses to help understand the complexities of how individuals and organizations respond to change. We anticipate organizational research can benefit from both theoretical advances in considering how individuals and organizations respond to discontinuous transitions and that empirical tests of these theoretical advances using the methods of discontinuous growth models.

Future research should also consider the possibility of change occurring simultaneously at multiple levels with potential time asymmetries across levels (see Kozlowski & Klein, 2000). We have not seen many applications of multiple-level growth models where, for example, change patterns in organizations are modeled simultaneously with change patterns in departments. Repeated measure observations of department data nested within organizations could test whether growth patterns at each level were similar (e.g., department change might be characterized by a linear pattern, whereas organizational change might be quadratic). In addition, studies of this nature could examine whether predictors of rate of change differ across levels. Indeed, it would potentially be possible for the rate of change at one level to be a predictor of change at another level. For instance, given a sample with a sufficient number of departments and organizations, one could potentially test whether the rate of change in the R&D department of an organization was a predictor of the rate of change in the organization.

Simultaneously studying change at multiple levels adds methodological complexity; however, it also provides opportunities to refine and test theoretical propositions and to ultimately add fidelity to models of organizational behavior. We recommend future methodological research focus on improving our ability to develop and test longitudinal models across multiple levels. Finally, recent methodological research on growth modeling/longitudinal modeling has begun to move beyond simply describing forms of change to modeling and testing specific dynamic functions. Doing so may present a better test of theory than more exploratory approaches (Ployhart, in press).

Nonnormal Outcomes

The ability to decompose variance not only allows one to test complex models as in the case of discontinuous growth models; it also ensures that relatively simple models appropriately account for variance and provide correct standard errors (Bliese & Hanges, 2004). The third and final area we address for future multilevel research concerns issues of variance decomposition in nonnormally distributed data. Beal and Dawson's (2007) study addresses the importance of normality in a simulation study of the degree to which using single-item measures on 5-, 6-, 7-, and 9-point Likert-type scales leads to biases in ICC values and relationships among group-level variables across a variety of group size and variance conditions. Because of the focus on nonnormal data in multilevel research, we think this work and its future extensions are important to organizational research.

Organizational researchers tend to assume multilevel models will be robust to a number of violations of normality. This assumption, however, may not be well-founded. For example, many of the outcomes available to organizational researchers have distributions that severely violate the assumptions of normality. Specifically, organizational researchers often contend with dichotomous outcomes such as turnover and absenteeism or with Poisson distribution data such as health outcomes and deviant behaviors. Presumably, many of the constructs measured with nonnormally distributed data will have the same group-level influences as do normally distributed data. For instance, absenteeism might be expected to be partially influenced by group membership (e.g., Mathieu & Kohler, 1990). Likewise, one might expect individual reports of deviant behaviors to be influenced by characteristics of the group.

Tools to analyze nonnormal data outside of a multilevel framework are well developed. The statistical framework of the generalized linear model (GLM), for instance, can be used to model a wide variety of outcomes from dichotomous to overdispersed Poisson data (McCullagh & Nelder, 1989). Harrison (2002) provided a nice overview of such models. In terms of statistical tools, many multilevel programs now provide options for examining dichotomous and other nonnormally distributed outcomes. By providing this option, researchers can control for nonindependence among responses and can also include aggregate-level predictors.

To a large degree, however, there exists a lack of practical knowledge surrounding the implementation of these techniques. For instance, programs are capable of estimating longitudinal growth models where the dependent variable is dichotomous (e.g., generalized RCM with a binomial link). A model of this nature might be useful, for instance, in a situation where individuals pass or fail some performance measure over successive days. In practice, however, the application of such a model is complicated by the nature of the outcome. When responses are normally distributed, one has the potential to detect relatively small changes over time (e.g., a 100-point performance measure may change from 89 to 92). In contrast, if responses are dichotomous, it may require a large impetus for an individual to change his or her state from 0 to 1 or vice versa (e.g., task success to task failure). Consequently, one may have a large proportion of the data where individuals simply do not change. Thus, the effective sample size for detecting changes over time may be driven only by a small percentage of individuals who do, in fact, show variability.

Our point is that although we see a large potential to model nonnormally distributed data and applaud the inclusion of this ability in multilevel software, we also see the need to address a number of practical questions surrounding the relative utility of such models. We anticipate that during the next few years, these issues will emerge as important topics in organizational methods research.

Concluding Thoughts

When we accepted the role of guest editors for this feature topic, we expected to see excellent submissions resulting in publications that would contribute to the advancement of multilevel methods and statistics. Our expectations were more than exceeded by the high quality of the numerous submissions. In the end, we were only able to select the five excellent articles in this feature topic. The articles advance the field in terms of the two broad issues of (a) multilevel construct measurement and validation and (b) methods for variance decomposition and data analysis. We have no doubt that these articles will prompt advances and refinements in both theoretical specification and testing of theoretical propositions.

The issues addressed in these five articles have also set the foundation for us to identify areas for future work. Consequently, this introductory article has argued for the need to continue both the theoretical and methodological advancement of multilevel construct measurement and has explored the areas of discontinuous growth modeling and nonnormal outcome data modeling. As a whole, we hope this introduction and the five articles will provide a comprehensive and thought-provoking resource for researchers interested in modeling organizational phenomena.

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