©Academy of Management Review, 1983, Vol. 8, No. 4, 547-558.

Cross-Level Inference and Organizational Research: Perspectives on Interpretation and Application[1]

KEVIN W. MOSSHOLDER
ARTHUR G. BEDEIAN
Auburn University

In a discussion of the concept of cross-level inference as it relates to organizational research, emphasis is placed on a description of basic issues and multilevel analytical approaches related to cross-level concerns. A focused review is provided of several substantive organizational research areas for which multilevel logic is relevant. It is suggested that in certain areas—organizational climate, leadership, job design, and organizational properties—multilevel conceptualizations provide a more expansive, integrative perspective of organizational phenomena.

Cross-level inference has been the subject of a growing number of research studies and reviews (Burstein, 1980; Lincoln & Zeitz, 1980; Roberts & Burstein, 1980; Roberts, Hulin, & Rousseau, 1978). Broadly defined, cross-level inference occurs when relations among variables at one level are inferred from analyses performed at a different level. A straightforward example would be the use of departmental indices of work satisfaction and absenteeism in making inferences about relations between individual satisfaction and absence from work. To the extent that the departmentally deduced relationship is not isomorphic with the true individual satisfaction-absenteeism relationship, cross-level bias would exist in the estimation of this relationship. Regardless of the direction in which an inference is drawn, there always is danger of fallacious reasoning when the unit to which an inference refers is smaller or larger than the unit of analysis. This peril generally has been labeled the "fallacy of the wrong level"—that is, "making direct translation of properties or relations from one level to another" (Galtung, 1967, p. 45). The attempt to infer individual (macro) level relationships from higher (lower) level analyses is known specifically as downward (upward) cross-level inference.

Multilevel analysis generally refers to analytical procedures that seek to partition effects at one level of analysis among variables belonging to separate levels of analysis (e.g., individual and supraindividual units). That there are multilevel influences on individuals within organizations of appreciable size is a point that few theorists would dispute. Nevertheless, organizational analysts only recently have shown a concern for separating the effects of individual and supraindividual variables within the same study. Situations in which only supraindividual measures are available are the most problematical with respect to cross-level issues because one cannot directly estimate potential cross-level bias under such conditions. However, as within the more traditional (micro) perspective of behavioral research in organizations, it is more typical for individual response data to be accessible and used in aggregate form as an approximation of a higher level construct. With the use of such aggregates, multilevel analysis procedures may afford a more judicious approach to addressing cross-level issues, especially when one is interested in how variables at different levels of analysis influence or covary with individual behavior and attitudes.

Use of aggregate responses in multilevel analysis can be illustrated in the combination of individual satisfaction assessments to represent group morale. Assume that one has an interest in the simultaneous influence of group morale *and* individual job satisfac-

[1]The authors wish to express their appreciation to Lawrence R. James and Denise M. Rousseau for comments on an earlier draft of this manuscript.

tion on individual absenteeism. To determine the existence of multilevel effects would require a three-step process: (1) construction of an aggregate morale measure (e.g., average group satisfaction); (2) statistically controlling variance in absenteeism attributable to individual satisfaction; and (3) determining what percentage of the remaining variance in absenteeism is associated with the aggregate measure. The presence of multilevel effects would be supported if both individual and aggregate components contributed significantly to the explanation of individual absenteeism. Of course, the use of such individual level surrogates is advisable only to the degree that individual responses are homogeneous within the level (unit) of measurement defined by the macro construct of interest. That is, if individual satisfaction is to be aggregated to represent group morale across groups being studied, there should be some degree of within-group agreement vis-à-vis satisfaction. Lack of homogeneity may result in what has been identified as one form of aggregation bias (Hammond, 1973; James, 1982). Bias results in that the aggregate measure (typically represented by the group mean) is taken as an isomorphic representation of a macro construct when actually there exists within-group variation that is not captured by the surrogate macro measure. James (1982) underscored this problem by illustrating misinferences that may occur when aggregations of micro-level responses are used as substitutes for more macro-oriented constructs. Focusing on individuals' climate perceptions, he demonstrated how the inappropriately aggregated climate perceptions can result in biased estimates of perceptual agreement.

The purpose of this paper is to examine the broad notion of cross-level inference as it applies within the confines of organizational research. Although a brief discussion of concepts fundamental to cross-level inference is necessary to provide a foundation from which to work, attention is directed primarily toward (a) presenting two general analytical approaches for addressing cross-level questions and (b) illustrating, through a focused review of several substantive areas, the growing awareness and epistemological relevance of cross-level logic to organizational understanding.

Data Analytic Approaches to Multilevel Analysis

Because organizational researchers typically have used aggregate measures to study individuals (Roberts et al., 1978), the following discussion principally focuses on such measures in discussing cross-level inference procedures. This is not meant to imply that aggregation is the only means of tapping supraindividual constructs; rather, that aggregates (as opposed to "global" measures) may serve a useful role in the partitioning of individual and macro effects (Roberts et al., 1978). Before considering general analytical approaches for addressing cross-level questions, several qualifications should be noted. First, the use of aggregate measures is in itself neither good nor bad. How and why they are used is of concern. Not all phenomena can be easily separated into different levels of meaning. Consequently, it is important that a sound rationale exist for interpreting individual measures as functional surrogates of macro constructs. By way of analogy, job satisfaction usually is defined as an individual sentiment, and only with ample theoretical justification should individual satisfaction scores be aggregated to represent a related but more encompassing construct such as group morale. Aggregating individual level responses may provide a practical means of access in measuring macro level effects and also may be useful for handling very large data sets and securing individual respondent anonymity. However, convenience and practicality should *not* be the prime factors determining the use of aggregate measures.

A second point to note is that general problems involving cross-level issues have been recognized for quite some time. Both Thorndike (1939) and Robinson (1950) discussed the fallacy of inputing the correlations found for groups to the individuals or smaller groups composing them. A third and related point is that cross-level issues are not unique to any particular field of research. Perhaps because they deal with a mixture of micro and macro issues, sociologists and economists have more actively engaged conceptual and analytical procedures basic to multilevel considerations. In contrast, organization researchers more micro in orientation only recently have begun to confront cross-level problems in such areas as leadership and organizational climate. Thus, though the general analytic approaches to be presented have been discussed in some fields (Burstein, 1980; Firebaugh, 1978, 1979), it is doubtful that their epistemological substantive focus are known to a sizeable segment of organization researchers. The utility of multilevel analysis should be considered by those seeking to understand organizational complexities, irrespective of its disciplinary origin. This paper represents an attempt to synthesize work in various disciplines to acquaint organization researchers more fully with cross-level inference procedures.

Finally, a focus on analytical approaches potentially useful for addressing cross-level questions does not deny the existence of as yet unresolved methodological problems in this area. For example, as noted earlier, the impact of a shift in level can cause ambiguities in the meaning of a measured variable (James, 1982; Jones & James, 1979). It is incumbent upon researchers employing cross-level inference procedures to consider the theoretical soundness of their efforts regardless of the substantive area in which the procedures are used.

The two most commonly cited general analytic approaches for addressing cross-level inference procedures are (1) regression analysis and (2) analysis of covariance. Both are variants of the general linear model. Throughout the following presentation, it is assumed that individual level and appropriate aggregate level measures are available. Because in most instances aggregate measures are represented in terms of the mean response of each aggregate unit, this practice is followed for illustrative purposes.

Regression Analysis Approach

When used in cross-level inference contexts, regression analysis procedures have been referred to as contextual or group effects analysis (Firebaugh, 1979). Although a univariate version is illustrated, a multiple regression approach applies by simple extension. The basic model that would be established in partitioning individual and aggregate level effects is:

$$Y_{ij} = \beta_1 X_{ij} + \beta_2 X_j + e_{ij} \text{ where } (i = 1, 2, \ldots k;\ j = 1, 2, \ldots m) \quad (1)$$

$Y_{ij}(X_{ij})$ refers to the response on Y (X) for the ith person in the jth group and X_j is the group mean of the jth group. This model makes the usual regression assumptions (e.g., linearity of relationships and independence of the error term, e). Operationally, the coefficient of the X_{ij} term indicates the degree to which variance in Y is explained by individual level responses. (See Firebaugh, 1978, for a more precise delineation of this component.) The coefficient of the X_j term indicates the degree to which variance is accounted for by supraindividual influences. Although the entry order of individual and group variables into the regression is conditional on the theoretical context, individual components most likely would be entered first.

An illustration of how the regression paradigm may be useful in partitioning individual and more macro (aggregate) level effects is presented briefly. Assume that research exists suggesting that a perceptual work group-based variable, social interaction (SI), has an impact on group members' satisfaction such that higher quality interacation leads to increased satisfaction. Further, assume that there is reason to hypothesize that this variable's influence does not operate totally through its impact at the individual level. Implicit in this notion is the idea that much of what takes place in groups occurs because of forces generated by no single individual. For example, there may be a synergistic effect such that individuals in groups with higher (or lower) SI exhibit satisfaction in higher (or lower) amounts than could be explained by individual variation in SI. Given theoretical justification and homogeneity of within-group variance, it would be possible to test for "group" effects by first regressing satisfaction on individual SI perceptions and then on mean SI for each group involved. Operationally, this is done by assigning the mean SI of the jth group to each member of the jth group and analyzing their responses by normal regression methods. If the aggregate term adds significantly to the variance accounted for by the SI individual level treatment, preliminary evidence exists that the processes at the aggregate level have an impact on individual satisfaction.

The procedural simplicity of this regression paradigm belies the summative complexity comprising cross-level issues. First of all, some researchers—for example, Irwin and Lichtman (1976)—feel that aggregate effects occur due to the omission of relevant explanatory variables at the individual level of analysis. When a theoretically important individual level variable related to Y_{ij} (controlling for X_{ij}) has been omitted, its insertion in the regression equation may reduce variance explained by an aggregate measure. In the above example, if perceived task importance explained satisfaction beyond that accounted for by SI, entering this variable into the regression equation before the aggregate measure could possibly reduce the amount of variance available for explanation by aggregated SI responses.

Aggregate effects will not occur unless an aggregate unit's composition is related to whatever else about the unit affects the dependent variable (Hauser, 1970, 1974). In essence, the regression paradigm evokes the problem of defining a construct (at the aggregate level) partially in terms of residual variance. Given such conditions, it is tempting for a researcher interested in supraindividual effects to ensure their validity by entering plausible individual level variables into the regression equation before aggregate measures. Ultimately, viewing aggregate effects simply in terms of model misspecification is shortsighted. Granted, because individual difference variation generally is larger than group difference variation, one eventually may find individual level variables to explain portions of group variation. To do so unquestioningly, though, ignores the potentially important role that aggregate level constructs may play in individual behavior (Roberts et al., 1978). Researchers should be willing to acknowledge this potentiality if a solid reason exists to anticipate aggregate level effects.

In using the regression approach, it is advisable to obtain an independent assessment of the aggregate constuct being measured—see, for example, Rousseau (1978). This normally would entail a global measurement such as a supervisor's evaluation of how well a group interacts interpersonally. If supraindividual effects are supported by aggregate and global measures, one may be more confident in the multilevel process hypothesized for the phenomenon under investigation. It should be stressed that finding different effects for aggregate or global measures does not necessarily reflect the innate superiority of one type of measure over the other. Some aggregate measures may be deficient in measuring the essence of the macro construct for which they substitute; however, the same is true of global measures. Thus, which type is of greater relevance is not determined simply by the manner in which the measure is formed (Lincoln & Zeitz, 1981).

Finally, complications in estimating true aggregate level effects may occur when certain assumptions are untenable. For instance, in field situations in which regression procedures most likely would be applied, random assignment to units of investigation is an exception. If nonrandom factors influence unit composition such that they systematically increase or decrease detected common variance between aggregate and dependent measures (after controlling for individual level variables), aggregate effects will be biased accordingly. Using the previous illustration, if persons with high SI needs were attracted to groups that had strong SI to begin with (or vice versa), there would be a higher probability, ceteris paribus, of finding "group" effects. Another complication in the estimation of aggregate level effects concerns the problem of homogeneity of within-group variance. It is unrealistic to expect perfect agreement within aggregate units. Consequently, to the degree that heterogeneity exists, the possibility of biased inferences increases (James, 1982). An acceptable level of heterogeneity will depend on the theoretical context of the research effort (Jones & James, 1979).

Analysis of Covariance Approach (ANCOVA)

The correspondence of regression and ANCOVA models is well known (Werts & Linn, 1971). ANCOVA typically is used to measure the impact of a nonmetric variable on the metric dependent variable, controlling for other metric variables. This approach is suited for multilevel analysis because the nonmetric (independent) variable can be an aggregate and the metric (dependent) variable can be an individual level characteristic (Firebaugh, 1979). The basic model for detecting aggregate level effects is:

$$Y_{ij} = \mu + \beta_1(X_{ij} - \overline{X}) + \alpha_j + e_{ij} \text{ where } (i = 1, 2, \ldots k;\ j = 1, 2, \ldots m) \quad (2)$$

With respect to the component terms, μ is common to all individuals, Y_{ij} (X_{ij}) refers to the response on Y (X) for the ith person in the jth group, $\overline{X}$ is the grand mean of X, α_j is common to individuals in the jth group. This model incorporates normal ANCOVA assumptions. Again, the estimation of within-group (individual level) and between-group (aggregate level) effects demands adequate theoretical specification at both levels lest explained variance be misattributed to either level (Alwin, 1976). The rationale underlying the ANCOVA approach to cross-level inference is straightforward: If after adjusting initial aggregate effects for individual level variates there remains a significant amount of variance explained by the aggregate measure, one has evidence that a supraindividual process has influenced individual level activity. This is tantamount to finding significant differences in adjusted Y means in normal ANCOVA.

Several characteristics of the aggregate effect in this approach are noteworthy. This effect is the sum of all relevant aggregate effects (Alwin, 1976; Firebaugh, 1979). In some cases, the effect may be accounted for entirely by one variable; in the earlier SI example the synergy of such interaction may explain all between-group differences. However, in different cases, other unmeasured aggregate characteristics may contribute to the "group" effect (e.g., group organizational status or group norms). The ANCOVA approach does not identify specific constructs that affect individual behavior. Regression analysis is better suited for this purpose. According to Firebaugh (1979), the aggregate effect of *X* is that portion of the total aggregate effect explained by *X*. Thus, variance accounted for by the regression approach always will be less than or equal to that accounted for by the ANCOVA approach. This allows determination of an upper limit on the amount of variance potentially attributable to aggregate effects. The ANCOVA approach may be a useful preliminary to regression analysis and the regression approach a useful follow-up to ANCOVA (assuming aggregate effects are found).

Regardless of what combination of variables is responsible for a total aggregate effect, it is assumed in a multilevel analysis that the effect has the same (within certain errors of measurement) impact within units of investigation. This is equivalent to the normal homogeneity of within-group regressions requirement of ANCOVA. The casual acceptance of this requirement in field contexts has led to some controversy (Cronbach, 1976; Dretzke, Levin, & Serlin, 1982). When the process underlying the formation of aggregate units is systematically related to (directly or indirectly) variables that also influence the dependent variable in question, ANCOVA models yield misleading results. For a discussion of available analytical alternatives in the heterogeneous condition, the reader is referred to Burstein, Linn, and Capell (1978).

Cross-Level Issues and Organizational Research

The analytical approaches presented represent the most common approaches for conducting multilevel analysis. A more conceptual rather than a purely mathematical exposition of the major approaches has been purposely employed in order to communicate the essence of multilevel techniques. Although mathematical treatments of cross-level inference procedures are available, it is felt that establishing an awareness of major procedures and their potential relevance to organizational research is of greater importance at this time. To this end, areas in which cross-level inference issues are pertinent are now highlighted. In some instances, variants of cross-level inference procedures have been employed; in other cases, the nature of the phenomenon under examination suggests that such procedures may be of use. This review is not intended to provide in-depth treatment of cross-level issues in all areas. Rather, it will serve to illustrate the increasing importance of cross-level thinking *as a whole* in understanding organizational phenomena.

Climate

Because the issue of cross-level inference perhaps has generated the largest amount of discussion in the area of perceived (psychological) climate, greater attention is accorded this area. The climate literature displays a lack of consensus about the proper level of measurement (James, 1982; Jones & James, 1979; Payne, Fineman, & Wall, 1976; Powell & Butterfield, 1978). Some researchers argue that climate is an organizational characteristic, but others feel that climate is more an individual attribute. This feeling most likely has arisen because of the mode of measurement used to assess climate. Typically, climate is measured by assessing individuals' perceptions of organizational processes and situations. As James (1982) notes, such assessments do not purport to capture veridical descriptions, but to tap psychological meanings of situations and processes as interpreted by each individual respondent. There is no argument here for or against a particular unit of analysis. Given the current state of climate research, it may be prudent simply to suggest that choice of a unit of analysis is not an either-or decision, but one of determining the problem in question and then selecting an appropriate perspective.

Though in the opinion of some the individual is the appropriate unit of analysis for climate research, this in and of itself does not prevent the use of aggregated measures in addressing the question of climate's impact beyond the individual level of analysis. "This is because describing an environment in psychological terms such as autonomy and equity may enhance, in comparison to situational descriptors such as size and salary structure, the understanding of how individuals in general impute meaning to environments and, especially, how individuals in general will respond to environments" (James, 1982, p. 220). The major concern in using aggregate climate measures is the extent of agreement that individuals exhibit in their climate perceptions. There must be some amount of agreement (Jones & James, 1979) among individuals in an aggregate level unit before one can attribute supraindividual meaning to aggregated scores. How to ascertain the amount of agreement required has provoked some disagreement. In a recent review of this topic, James (1982) has demonstrated that many estimates of agreement in climate perceptions are biased because they improperly delete within-group variance in indices purporting to assess the degree of within-group agreement. This treatment was concerned more with defining the proper interpretational level for perceived climate and did not focus on the simultaneous impact that individual or aggregate versions of climate may have on other individual level "dependent" variables such as performance or satisfaction.

Elsewhere, James, Demaree, and Hater (1980) have presented a statistical rationale for relating situational variables and individual level person variables that overlaps conceptually with the logic underlying multilevel analysis techniques. Briefly, their procedure determines the degree to which the magnitude of a specific situational variable-person variable relationship approximates the magnitude of the relationship between the person variable and total between-group variation. To do this, one computes the correlation between the person variable and situational variable after first assigning the *j*th group mean value of the situational variable to the *i*th member of each *j*th group. The square of this value yields the proportion of variance in the person variable associated with the situational variable. Next, a correlation ratio is computed with the *j* groups serving as the dependent variable. The square of this value yields an estimate of the total amount of variation in the person variable that is accounted by group differences. Dividing the squared person-situation correlation by the squared correlation ratio indicates the proportion of between-group varince accounted for by the situational variable.

This approach is similar to the previously discussed multilevel procedures in that it supplies information analogous to what one would obtain by first conducting ANCOVA and then regression procedures to determine the comparative amount of variance explained by aggregate unit differences and an aggregate vari[illegible] ames et al. (1980) procedure does not directly consider the influence of individual level effects on the person variable. (Note the use of ANOVA, not ANCOVA, to determine the correlation ratio.) In fairness, the James et al. (1980) approach was developed more for use with global as opposed to aggregate measures of situational variables and thus does not consider partitioning data responses into individual and aggregate level components.

Despite interest in level of analysis issues related to climate, there has been little concern with testing for cross-level effects. A number of studies have used aggregate climate measures and related them to aggregate outcome measures (Lawler, Hall, & Oldham, 1974; Schneider & Snyder, 1975), but none has directly entertained cross-level possibilities. Even Jones and James (1979) used climate perceptions aggregated at the subunit (division) level to predict subunit performance but did not disaggregate their data into individual and aggregate components. Perhaps the lack of cross-level studies in an area that has debated multilevel issues more than other substantive areas reflects a heightened concern about misspecifying the nature of the level and causal process underlying climate constructs (James, Hater, Gent, & Bruni, 1978). Regardless, it is cautiously suggested that some consideration of cross-level effects may add to the understanding of climate by showing if and how it impacts individual attitudes and behaviors.

Leadership

There is increasing controversy concerning two different perspectives underlying leadership phenomena. The traditional or average leadership style (ALS) approach holds that a leader displays the same style toward each subordinate. Assuming that leader behavior is similar for all group members, "differences in subordinate descriptions of the same leader were therefore attributable to measurement error, which could be minimized by the averaging method" (Schriesheim, House, & Kerr, 1976). Given the assumption of behavioral homogeneity, certain analytical procedures follow logically (Dansereau & Dumas, 1977). Measures are constructed to tap the leader's general behavior toward all subordinates; subordinate responses are sampled within units as being representative of the leader's behavior toward that unit; and inferences based on correlations of raw scores are seen as equal to correlations based on unit mean scores. In essence, the ALS model suggests that leadership is a group level phenomenon. A contrasting approach, the vertical dyad linkage model (VDL), assumes that a leader's behavior may vary with each subordinate (Dansereau, Graen, & Haga, 1975; Graen & Cashman, 1975). The VDL model argues that a more appropriate unit of analysis is the dyadic relationship existing between the leader and each subordinate and thus views leadership style as an individual level phenomenon. The mutual consideration of apparently contradictory positions suggests that multilevel analysis techniques may be of value, especially for determining the impact that leader influence as specified by the VDL and ALS models has on subordinate attitudes and behaviors.

Dansereau and colleagues (Dansereau & Dumas, 1977; Markham, Dansereau, & Alutto, 1979) proposed partitioning individual and aggregate level components of perceived leader behavior in order to compare the ALS and VDL models. The gist of their proposal recently has been used to determine the effects of within- and between-group variation in leadership styles (Katerberg & Hom, 1981; Vecchio, 1982). These multilevel analyses appear to support the notion that leadership influences function at both the individual and the aggregate levels. Thus, as with climate, the unit of analysis issue may not be an either-or issue but may be viewed from one or both perspectives depending on the theoretical context supporting a specific empirical effort.

It should be noted that the homogeneity of within-group perceptions requirement (James, 1982) necessary for considering leadership at the aggregate level typically has been assumed (Katerberg & Hom, 1981; Vecchio, 1982) or examined using ANOVA mean differences procedures (Graen, Dansereau, & Minami, 1972). This perhaps is a result of the conditions under which leadership studies often are conducted (i.e., clearly delineated leader-subordinate ties and the notion of leader behavior consistency). Regardless, greater awareness of the homogeneity requirement as reflected in the methodological suggestions of James et al. (1980) should be shown in multilevel leadership studies. To the degree that heterogeneity exists, findings may be subject to aggregation bias.

A final point concerning VDL versus ALS comparisons is that because the ALS model traditionally has considered leadership to be a group level phenomenon, researchers using regression procedures have entered aggregate mean data in their regression equation first and individual level variables second. This contrasts with the general regression approach of controlling for individual level variables before considering aggregate level effects. It would appear beneficial to use the individual, then the group ordering to determine if leadership has surplus meaning (i.e., accounts for variance not explained by VDL) at the group level.

The area of leadership should prove to be a fertile area for multilevel analyses because of the two competing views of the leadership process. At the very least, such analyses should permit greater insight into an important organizational phenomenon.

Task Characteristics—Job Design

In a recent review, Roberts and Glick (1981) noted that a critical weakness of the job characteristics approach to job design (Hackman & Oldham, 1976) is that it confuses the distinction between within-person and person-situation relations. That is, task perceptions often have been assumed to be equivalent to objectively defined tasks, and correlations between perceived task characteristics and individual outcomes have been accepted as indicating veridical individual responses in reaction to objectively defined tasks. In essence, Roberts and Glick suggest that the most supportive studies in the job characteristics literature make cross-level inferences, extrapolating from strictly individual level findings to aggregate level constructs. [It is assumed here that a job entails a group of similar positions at which more than one person is employed (McCormick & Tiffin, 1974) and that an objective situation entails supraindividual meaning.]

If, as theorized, jobs (and not just job perceptions) have an effect on individuals, one would expect that aggregate job measures would possess "surplus" meaning (Roberts et al., 1978) beyond that defined by individual level responses. This is testable through multilevel analysis. First, it would be necessary to demonstrate that perceived task characteristics were acceptably homogeneous within-groups across job categories (James, 1982). If this were shown, multilevel procedures could be employed to ascertain if aggregate job perceptions possessed significant explanatory power after controlling for within-job variation in perceptions. The use of global measures paralleling the aggregate perceptual measures would be beneficial as a check to insure the viability of the theoretical rationale underlying the job characteristics model (Rousseau, 1978). If supraindividual effects were found using aggregated individual job perceptions, but not found using suitable global measures collected independently of social interactional influences, one could not be certain that job (vs. social) influences were responsible for the effects (Blau & Katerberg, 1982).

The use of multilevel analysis in the job design area has not advanced as far as in the climate or leadership areas, even though fallacies of the wrong level have shaped ideas that are at the foundation of the job characteristics approach (Roberts & Glick, 1981). However, some of the same theoretical problems exist for job design as for these areas; thus, multilevel procedures would appear to have some potential for utilization by job design researchers. Although not focused on the job design area per se, some efforts have been made to demonstrate that greater explanation of situational effects on individual attitudes and behavior is afforded through multilevel considerations (Pugh, 1977). If theorists using the job characteristics approach intend to maintain person-situation relations as a meaningful aspect of job design theory, it seems imperative that multilevel considerations be confronted.

Organizational Properties

For the most part, macro-oriented organization researchers have not viewed the issue of cross-level inference as problematic. They typically have accommodated the question of cross-level considerations by simply assuming (a) knowledge of variables affecting *Y*, (b) that unknown sources of variation in *Y* are uncorrelated with known sources, and (c) that the conditional variance of *Y* given *X* is independent of different levels of *X*. These assumptions imply that organizations differ only in their relative level of *X*, not in the amount of variability of *X* within organizations. However, it has become increasingly evident that uniformity of structural forms across individuals and departments is atypical of complex organizations (Bedeian, 1980). This has raised major concerns about the proper unit of analysis and potential for cross-level effects (Freeman, 1978, 1980).

In cases in which theoretical rationale is sufficiently founded, multilevel procedures offer certain advantages. For instance, Lincoln and Zeitz (1980) developed a model of organizational properties in which decentralization and administrative intensity were conceptualized as relevant to both individual and organiza[redacted]y effects that would not have been revealed without using aggregate measures were found for each construct at different levels of analysis. Nevertheless, few studies of organizational properties have incorporated multilevel analysis procedures. The failure to do so often has led to questionable results. As clearly demonstrated in the Bidwell-Kasarda (1975, 1976) and Hannan-Freeman-Meyer (1976) exchange, selection of an inappropriate level of analysis can greatly influence a study's conclusions. Bidwell and Kasarda attempted to examine the effect of different organizational level properties on school system effectiveness. They defined effectiveness in terms of the average achievement score of students in selected grade levels. They found that such organizational properties as system level student/teacher ratios and the proportion of employees in administrative roles had significant effects on achievement. Taking exception to Bidwell and Kasarda's operationalization of achievement at a supraindividual level of analysis, Hannan et al. (1976) demonstrated the influence of cross-level bias on the obtained estimates of organizational effects. Viewing student achievement as an individual-level variable, and controlling for such factors as student ability and social background, their reanalysis of the Bidwell and Kasarda data yielded smaller or nonsignificant estimates of organizational level effects. This exchange clearly suggests that the theoretical mechanisms driving variables potentially involved in cross-level influences must be explicitly stated so that their interrelationships can be properly assessed.

Other organizationally relevant examples relating to cross-level bias could easily be cited. One area that would seem to benefit particularly from the application of cross-level techniques is the study of the relationship between technology and different organizational properties. With the exception of a few notable instances (Comstock & Scott, 1977; Rousseau, 1978), the issue of cross-level inference has received little attention. As Fry's (1982) review suggests, many of the apparently contradictory conclusions concerning the meaning and influence of technology may be a result of the tendency for researchers to fail in providing a multilevel rationale for the models they construct. Technology has been specified at the individual, group, and organization levels of analysis, with little but passing justification. Hickson, Pugh, and Pheysey (1969) studied the relationship between technology and structure using such organization level dimensions as ownership and total number of employees. Other researchers, recognizing that different work groups within the same organizations may have different technologies, have employed subunit or workflow level analysis. For example, Grimes and Klein (1973), as well as Van de Ven and Delbecq (1974), measured technology at the work flow level using such variables as subunit task variability and subunit task difficulty. A final group of researchers, showing a concern with the characteristics of the tasks performed by individual employees, have operated at the individual level of analysis. Illustrative of this approach, technology has been conceptualized at the individual level using such variables as task interdependence, task predictability, and task manageability (Comstock & Scott, 1977; Reimann, 1980; Rousseau, 1978).

The obvious point is that although all three approaches are similar in treating technology as an independent variable affecting specific dependent variables, the relationships suggested may very well be different. Only by using multilevel procedures will a researcher be able to determine if variations at one level are explainable by influences from more than a single level. This argues for the use of cross-level conceptualizations to provide a more expansive, integrative perspective of organizational phenomena. Of course, not all inquiries concerning organizational properties are of a multilevel nature. However, multilevel logic is relevant when theory suggests unique influences among constructs belonging to different levels of analysis.

Summary

The role that multilevel analysis can play in furthering the understanding of organizational phenomena has been emphasized. This limited survey should not be taken as a full explication of issues that must be confronted for optimal use of multilevel procedures in specific areas. For example, in the leadership and job design areas, concern has been expressed over the common method variance problem occurring when independent (e.g., JDS, LBDQ responses) and dependent (e.g., job outcomes) measures are collected from the same individuals (Rousseau, 1978; Vecchio, 1982). Control over nonrandom errors of measurement is important in any research effort and is crucial in multilevel analysis if one wants to avoid overestimating or underestimating individual and aggregate level effects (Hauser, 1974).

As analyses become more involved, more is demanded in terms of instrument validity and reliability. It is imperative that efforts to detect multilevel effects employ measures whose meaning is well defined vis-à-vis the nomological net of a specific substantive theory. For example, finding multilevel effects with an ad hoc measure of climate would call into question the nature of the measure as much as the nature of the process it putatively taps. This is not to suggest that measures that are judged to be more amenable to multilevel procedures should not be developed, but that researchers doing so take care to insure that minimal slippage occurs between a measure and the construct it represents. Essentially, the multilevel perspective may be viewed as a tool for testing alternative explanations if multilevel effects are tenable. The meaning or construct validity of an aggregate term ultimately will be determined by its relation with and impact on other variables. Such meaning can be only hypothesized until empirical research is conducted. For various substantive areas (e.g. leadership, job design), it is necessary to begin conducting such validational work, defining variables in terms of what is known, and then demonstrating the place of these varibles in the context of the particular substantive area.

Another point to be emphasized is the empirical nature of the causal process(es) linking individual and aggregates. Though the approaches considered in this paper are presented such that organizational phenomena (e.g., climate, leadership) explain variance in individual response variables (e.g., satisfaction, performance), this is not to imply that causal processes are recursive (James & Singh, 1978; James et al., 1978). Extreme caution should be used in designing loci confirmatory of causality in multilevel data. This is especially true for the researcher interested in a confirmatory (structural equations) approach to multilevel analysis rather than an exploratory (multiple regression) approach.

Finally, because of space limitations, only selected areas of organizational psychology have been reviewed. Other areas could have been chosen. For example, small group research would be a natural area for application of such analyses (Hill, 1982; Webb, 1980). Various group processes have been explained through synergistic effects (Cummings, 1981). Such processes by definition involve group level phenomena that may be isolated and examined through multilevel procedures.

Conclusions

A review of selected studies from within several substantive areas of organizational research indicates that cross-level inference and multilevel analysis increasingly are being recognized as matters that concern a wide range of research. Although knowledge of cross-level issues has existed for some time, until recently organization researchers have tended to ignore such knowledge in developing their theory and research. Organizational studies for too long have been separated into micro and macro perspectives, even while both perspectives commonly acknowledged the reciprocity of influences linking the two. Researchers now are beginning to recognize the diminishing utility of maintaining this dichotomy. Multilevel research has potential for integrating micro and macro components within a common framework.

Scattered use of multilevel analysis in the organizational literature may belie somewhat its epistemological importance in furthering general understanding of organizational pehenomena. Quite properly, use of multilevel techniques thus far has been embedded within the context of particular theoretical issues relevant to specific substantive areas (e.g., ALS and VDL models of leadership). The application of multilevel procedures should not be misconstrued as applying only to the particular content areas in which they have been introduced.

The philosophy underlying multilevel analysis conceptually extends to any instance involving attempts to move from lower to higher level abstractions or vice versa. Although not of direct relevance here, this interpretation suggests that multilevel issues may be pertinent even when subindividual inferences are made. Cross-level bias can occur as easily with regard to trait-individual inferences as for individual-aggregate inferences. Because certain behavioral elements are found within a specific individual does not mean that they will be found within the same behavioral and mental contexts into which an individual may be subdivided (Galtung, 1967). By way of conceptual analogy, traits are to individuals as individuals are to aggregates. Some attitude/personality theorists—for example, Mischel (1968)—have discussed inferential problems involved in predicting individual behavior from component traits, noting that response consistencies often attributed to trait constructs may be quite situationally specific. Thus inferring that the relationship between a trait and a specific response is isomorphic with relations between a trait and an individual's total behavior often may be fallacious or, at best, misleading.

This type of problem may be relevant for organizational phenomena as it is the attitudinal/personality literature. Fisher (1980) suggests that such cross-level bias (in the form of mixed levels of specificity) may account to some degree for the infamously low relationship found in studies of satisfaction and performance. She notes that general attitudes (satisfaction) too frequently are used to explain specific types of behavior (work performance) and calls for recognition that satisfaction and performance should coincide in their levels of specificity. In other words, ignoring level of analysis (specificity) and/or cross-level inference issues may hinder understanding of relations among organizationally important variables.

In the long run it may be more beneficial to view multilevel analysis as simply reflecting a higher order, more encompassing realization of the complexity comprising organizational science. Such a perspective would permit researchers not only to employ multilevel analysis in examining specific content issues, but perhaps also to reshape theories concerning organizational phenomena to be more consistent with the complexity they entail.

References

Alwin, D. F. Assessing school effects: Some identities. *Sociology of Education,* 1976, 49, 294-303.

Bedeian, A. G. *Organizations: Theory and analysis.* Hinsdale, Ill.: Dryden Press, 1980.

Bidwell, C. E., & Kasarda, J. D. School district organization and student achievement. *American Sociological Review,* 1975, 40, 55-70.

Bidwell, C. E., & Kasarda, J. D. Reply to Hannan, Freeman, and Meyer, and Alexander and Griffin. *American Sociological Review,* 1976, 41, 152-160.

Blau, G. J., & Katerberg, R. Toward enhancing research with the social information processing approach to job design. *Academy of Management Review,* 1982, 7, 543-550.

Burstein, L. The analysis of multilevel data in educational research and evaluation. In L. Schulman (Ed.), *Review of research in education.* Itasca, Ill,: Peacock, 1980, 158-233.

Burstein, L., Linn, R. L., & Capell, F. J. Analyzing multilevel data in the presence of heterogeneous within-class regressions. *Journal of Educational Statistics,* 1978, 3, 347-383.

Comstock, D. E., & Scott, W. R. Technology and the structure of subunits: Distinguishing individual and workgroup effects. *Administrative Science Quarterly,* 1977, 22, 177-202.

Cronbach, L. J. *Research on classrooms and schools: Formulation of questions, designs, and analysis.* Stanford, Cal.: Stanford University, Stanford Evaluation Consortium, July 1976.

Cummings, T. G. Designing effective workgroups. In P. C. Nystrom & W. H. Starbuck (Eds.), *Handbook of organizational design* (Vol. 2). New York: Oxford University Press, 1981, 250-271.

Dansereau, F., & Dumas, M. Pratfalls and pitfalls in drawing inferences about leader behavior in organizations. In J. Hunt & L. Larson (Eds.), *Leadership: The cutting edge.* Carbondale, Ill.: Southern Illinois University Press, 1977, 68-83.

Dansereau, F., Graen, G., & Haga, W. A vertical dyad linkage approach to leadership within formal organizations. *Organizational Behavior and Human Performance,* 1975, 13, 46-78.

Dretzke, B. J., Levin, J. R., & Serlin, R. C. Testing for regression homogeneity under variance homogeneity. *Psychological Bulletin,* 1982, 91, 376-383.

Firebaugh, G. L. A rule for inferring individual-level relationships from aggregated data. *American Sociological Review,* 1978, 43, 555-572.

Firebaugh, G. L. Assessing group effects: A comparison of two methods. *Sociological Methods and Research,* 1979, 7, 384-395.

Fisher, C. D. On the dubious wisdom of expecting job satisfaction to correlate with performance. *Academy of Management Review,* 1980, 5, 607-612.

Freeman, J. H. The unit of analysis in organizational research. In M. W. Meyer and Associates (Eds.), *Environments and organizations.* San Francisco: Jossey-Bass, 1978, 335-351.

Freeman, J. H. The unit problem in organizational research. In W. M. Evan (Ed.), *Frontiers in organization and management.* New York: Praeger, 1980, 58-68.

Fry, L. W. Technology-structure research: Three critical issues. *Academy of Management Journal,* 1982, 25, 532-552.

Galtung, J. *Theory and methods of social research.* New York: Columbia University Press, 1967.

Graen, G., & Cashman, J. A role-making model of leadership in formal organizations: A developmental approach. In J. Hunt & L. Larson (Eds.), *Leadership frontiers.* Kent, Ohio: Kent State University Press, 1975, 143-166.

Graen, G., Dansereau, F., & Minami, T. Dysfunctional leadership styles. *Organizational Behavior and Human Performance,* 1972, 7, 216-236.

Grimes, A. J., & Klein, S. M. The technological imperative: The relative impact of task unit, modal technology, and hierarchy on structure. *Academy of Management Journal,* 1973, 16, 583-597.

Hackman, J. R., & Oldham, G. R. Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance,* 1976, 16, 250-279.

Hammond, J. L. Two sources of error in ecological correlations. *American Sociological Review,* 1973, 38, 764-777.

Hannan, M. T., Freeman, J. H., & Meyer, J. W. Specification models for organizational effectiveness. *American Sociological Review,* 1976, 41, 136-143.

Hauser, R. M. Context and consex: A cautionary tale. *American Journal of Sociology,* 1970, 75, 645-654.

Hauser, R. M. Contextual analysis revisited. *Sociological Methods and Research,* 1974, 2, 365-375.

Hickson, D. J., Pugh, D. S., & Pheysey, D. C. Operations technology and organization structure: An empirical reappraisal. *Administrative Science Quarterly,* 1969, 14, 378-397.

Hill, G. W. Group versus individual performance: Are N + 1 heads better than one? *Psychological Bulletin,* 1982, 91, 517-539.

Irwin, L., & Lichtman, A. J. Across the great divide: Inferring individual level behavior from aggregate data. *Political Methodology,* 1976, 3, 411-439.

James, L. R. Aggregation bias in estimates of perceptual agreement. *Journal of Applied Psychology,* 1982, 67, 219-229.

James, L. R., & Singh, B. K. An introduction to the logic, assumptions, and basic analytic procedures of two stage least squares. *Psychological Bulletin,* 1978, 85, 1104-1122.

James, L. R., Demaree, R. G., & Hater, J. J. A statistical rationale for relating situational variables and individual differences. *Organizational Behavior and Human Performance,* 1980, 25, 354-364.

James, L. R., Hater, J. J., Gent, M. J., & Bruni, J. R. Psychological climate: Implications from cognitive social learning theory and interactional psychology. *Personnel Psychology,* 1978, 31, 781-813.

Jones, A. P., & James, L. R. Psychological climate: Dimensions and relationships of individual and aggregated work environment perceptions. *Organizational Behavior and Human Performance,* 1979, 23, 201-250.

Katerberg, R., & Hom, P. W. The effects of within-group and between-group variation in leadership. *Journal of Applied Psychology,* 1981, 66, 218-223.

Lawler, E. E., Hall, D. T., & Oldham, G. R. Organizational climate: Relationship to organizational structure, process, and performance. *Organizational Behavior and Human Performance,* 1974, 11, 139-155.

Lincoln, J. R., & Zeitz, G. Organizational properties from aggregate data: Separating individual and structural effects. *American Sociological Review,* 1980, 45, 391-408.

Lincoln, J. R., & Zeitz, G. Levels of causation and levels of data collection in the study of organizational properties. *American Sociological Review,* 1981, 46, 699-702.

Markham, S., Dansereau, F., & Alutto, J. Fundamental problems in leadership research. In E. L. Miller (Ed.), *Proceedings of the 22nd annual conference of the Midwest Academy of Management.* Ann Arbor: Graduate School of Business, University of Michigan, 1979, 404-412.

McCormick, E. J., & Tiffin, J. *Industrial Psychology.* 6th ed. Englewood Cliffs, N. J.: Prentice-Hall, 1974.

Mischel, W. *Personality and assessment.* New York: Wiley, 1968.

Payne, R. L., Fineman, S., & Wall, T. D. Organizational climate and job satisfaction: A conceptual synthesis. *Organizational Behavior and Human Performance,* 1976, 16, 45-62.

Powell, G. N., & Butterfield, D. A. The case for subsystem climates in organizations. *Academy of Management Review,* 1978, 3, 151-157.

Pugh, W. M. Assessment of environmental effects: Method and model. *Organizational Behavior and Human Performance,* 1977, 18, 175-187.

Reimann, B. C. Organization structure and technology in manufacturing: Systems versus workflow level perspectives. *Academy of Management Journal,* 1980, 23, 61-77.

Roberts, K. H., & Burstein, L. (Eds.). *New directions for methodology of social and behavioral science: Issues in aggregation.* San Francisco: Jossey-Bass, 1980.

Roberts, K. H., & Glick, W. The job characteristics approach to task design: A critical review. *Journal of Applied Psychology,* 1981, 66, 193-217.

Roberts, K. H., Hulin, C. L., & Rousseau, D. M. *Developing an interdisciplinary science of organizations.* San Francisco: Jossey-Bass, 1978.

Robinson, W. S. Ecological correlations and the behavior of individuals. *American Sociological Review,* 1950, 15, 351-357.

Rousseau, D. M. Measures of technology as predictors of employee attitude. *Journal of Applied Psychology,* 1978, 63, 213-218.

Schneider, B., & Snyder, R. Some relationships between job satisfaction and organizational climate. *Journal of Applied Psychology,* 1975, 60, 318-328.

Schriesheim, C., House, R., & Kerr, S. Leader initiating structure: A reconciliation of discrepant research results and some empirical tests. *Organizational Behavior and Human Performance,* 1976, 15, 297-321.

Thorndike, E. L. On the fallacy of imputing the correlations found for groups to the individuals or smaller groups composing them. *American Journal of Psychology,* 1939, 52, 122-124.

Van de Ven, A., & Delbecq, A. L. A task contingent model of work unit structure. *Administrative Science Quarterly,* 1974, 19, 183-197.

Vecchio, R. P. A further test of leadership effects due to between-group variation and within-group variation. *Journal of Applied Psychology,* 1982, 67, 200-208.

Webb, N. M. Group process: The key to learning in groups. In K. H. Roberts & L. Burstein (Eds.), *New Directions for methodology of social and behavior research: Issues in aggregation.* San Francisco: Jossey-Bass, 1980, 77-87.

Werts, C. E., & Linn, R. L. Considerations when making inferences within the analysis of covariance model. *Educational and Psychological Measurement,* 1971, 31, 407-416.

Kevin W. Mossholder is Associate Professor of Management and Adjunct Professor of Industrial/Organizational Psychology, Auburn University.

Arthur G. Bedeian is E. L. Lowder Professor of Management, Auburn University.