# Editorial

## Multilevel Analysis in Health Services Research

This issue of *The Open Health Services and Policy Journal* features articles stemming from contextual and multilevel analyses of health services utilization [1, 2]. Multilevel analysis techniques are widely utilized in observational and randomized studies of health care systems, patients, and providers, and in epidemiologic and behavioral research [3-21]. In addition, varying approaches to multilevel analysis have been applied in health services research. Although most studies have been well done, sometimes the methods have been applied incorrectly. The utility of these techniques stems in part from the fact that individual health behaviors are influenced by the social and situational context in which they occur. Multilevel analysis enables researchers to analyze data using statistical approaches that are more compatible with socioecological frameworks for understanding determinants of health and wellness in populations [4]. For example, in exploring factors associated with healthy behaviors such as utilization of cancer screening tests, investigators can examine both individual-level factors such as age, race, ethnicity, income, and health insurance status and contextual factors such as the socioeconomic characteristics of the neighborhoods in which the study participants live [3, 5-9]. In epidemiologic and health services research, effects of group-level characteristics (for example, characteristics of neighborhoods, providers, or health care systems) have been observed across a wide range of health outcomes, independent of factors associated with individual patients or community residents [10]. Outcomes examined in multilevel analyses in health services research have varied remarkably and include breast and cervical cancer screening among U.S. women [1, 5-9, 11], referral of patients with colon cancer to a medical oncologist [12], mortality among patients undergoing coronary artery bypass graft surgery [13, 14], enrollment of patients in cardiac rehabilitation [15], chronic obstructive pulmonary disease care [16], mental health care quality indicators [17, 18], health outcomes among women veterans who had been sexually traumatized [19], number of physical therapy treatment sessions in patients with low back pain [20], and the accessibility, continuity, and coordination of primary health care [21], to cite a few examples.

### ADVANTAGES OF MULTILEVEL ANALYSIS

Multilevel analytic techniques have several potential advantages for health services research. These techniques are a robust approach for studying contextual effects within a quantitative framework [4]. Advantages of multilevel statistical techniques include their flexibility and generality and the ability to test for interactions between individual-level and contextual factors [6, 9, 22]. Economic studies of health care costs and incremental net benefits are amenable to multilevel analysis [23-26]. In addition to economic research, multilevel techniques have been applied to several study designs of interest to health services researchers including repeated measures analysis and longitudinal models [4, 27, 28], survival analysis [29], and cluster-designed randomized trials and observational studies of patients and providers [30-33]. Although no analytic technique can fully compensate for study designs that are not thoughtfully planned and executed, statistical methods that more accurately reflect the structure of the data are most likely to offer useful information [34].

Many randomized or observational studies of important health topics have involved clustered data with a hierarchical structure. Examples include studies of health care systems or providers and the patients they care for and preventive trials involving randomization by school, worksite, or geographic location. In clustered data, individual observations are correlated or dependent. If this source of variation within specific levels and dependency of observations is ignored in the analysis, the resulting model can be underspecified, leading to underestimated standard errors and inflated levels of statistical significance [30]. As noted by Bingenheimer and Raudenbush [28], researchers have known for several decades that individual-level analyses of data from cluster-randomized trials (for example, those in which participants are randomized by community, school, classroom, worksite, clinic, or health care provider) produce excessive Type I errors. Fortunately, multilevel statistical techniques such as hierarchical linear modeling and generalized linear mixed models are available that can handle measurements made at different levels of a hierarchical structure (for example, at the level of persons residing in a sample of communities or neighborhoods *vs* at the community or neighborhood level) [27, 28, 30, 34].

In situations where the outcome variable is binary, ordinal, continuous, or even multivariate, multilevel analytic techniques are available for studies with a longitudinal design [34]. Thus, an advantage of multilevel analytic techniques is that they offer some potential advantages over general linear models for repeated measures data [34]. As noted by O'Connell and McCoach [34], multilevel analytic techniques are well-suited for analyzing data from longitudinal studies where there are missing observations or unbalanced data. For example, hierarchical linear models can clarify temporal trends even when observations are missing for some persons across the waves of data collection. In addition, such techniques can accommodate situations in which the time of data collection varies across persons. In hierarchical linear models, time can be treated as a fixed or random effect [34].

### POTENTIAL CONCERNS IN MULTILEVEL ANALYSIS

Multilevel analyses do have certain shortcomings. One concern is that many multilevel analyses of health services research topics have been cross-sectional in nature rather than analyses of longitudinal data [35]. Cross-sectional studies may have limited ability to decipher temporal relationships between some individual- or group-level variables and the outcome of interest. In some studies, for example, questions may be asked about whether persons residing in a sample of communities or neighborhoods moved there before or

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after the time point at which the outcome occurred. Since patients may switch doctors or insurance plans over time, and health insurance status may change from one time period to another, similar questions may arise in cross-sectional studies of patients, providers, and health care systems.

Like in most areas of research, there is also a need to consider the adequacy of the available sample sizes or statistical power. In multilevel analysis, a sufficient number of sampled units or observations must be available at each level (for example, a sample of physicians or nurse practitioners and patients seen by each provider) in order to have sufficient statistical power [30]. Not all multilevel analyses of health services research topics have had adequate sample sizes. In order to have adequate power for group-level analysis, for a fixed overall n, it is better to facilitate more groups by allocating fewer observations/individuals per group than it is to define fewer groups with more observations per group.

A further concern is that published studies have been inconsistent in controlling for individual-level variables. There has often been a lack of consensus about whether individual-level variables should be conceptualized as confounders, mediators, or modifiers of the effect of the associations between group-level variables and the outcome of interest [35]. In order to address such concerns, investigators should consider developing a conceptual framework or model that clarifies the pathways by which various individual- and group-level variables, alone or in combination, are associated with the outcome of interest [9].

An additional concern is that the group-level unit of analysis has not always been adequately defined. In some population studies, for example, the group-level variable has variously been referred to as neighborhood, small area, local area, and place [35]. In such studies, there is a need to consider whether the spatial contours of the group-level unit of analysis has intrinsic meaning in relation to health, in terms of being consistent with how the residents define and experience their residential area [35]. For example, a contextual analysis of health care access in Sweden used health care district as a group-level variable [36].

A further issue is that a distinction should be drawn between conventional logistic regression models that include both individual-level and group-based or area-based contextual variables and more refined techniques such as hierarchical linear models [34]. Multilevel analyses of individual- and group-level variables associated with breast and cervical cancer screening, for example, have variously employed logistic regression techniques [3, 6-9] and hierarchical logistic regression [37].

## POTENTIAL FUTURE DIRECTIONS FOR MULTILEVEL ANALYSES IN HEALTH SERVICES RESEARCH

One possible future direction for multilevel analyses in health services research is the use of Bayesian procedures to fit a range of models [27]. Bayesian estimation procedures, which take into account prior information, are less well known to many researchers trained in frequentist statistical traditions. However, they may be particularly useful in studies with sparse data. The use of Bayesian methods of regression modeling has been discussed by Greenland [38] and by Browne and Draper [39]. Not all statisticians favor a Bayesian approach to hierarchical modeling.

Several software packages are now available for fitting multilevel models including SAS, STATA, S-plus, HLM5, and MLwiN [27, 34]. However, currently available software programs to conduct hierarchical logistic regression cannot specify appropriate variance estimates for data from complex, multistage surveys. The modification of software programs for hierarchical logistic regression to enable them to fully take into account complex multistage sampling would be a useful enhancement of existing software programs for hierarchical logistic regression.

With increased use of multivariate modeling techniques and hierarchical logistic regression by health services researchers and epidemiologists, there is a continuing need to address problems associated with model misspecification resulting from omitted or mismeasured individual- and group-level variables. Likely improvements in future studies may include longitudinal study designs and greater attention to statistical power. In addition, there is a need to better understand health care in contexts beyond neighborhoods and counties, for example, through spatial analyses of the effects of place on health care utilization [35, 40].

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