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Introduction to Quantitative Methods

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In recent years, there has been some debate in the field of community-based research regarding the use of quantitative methods. On the one hand, more action-oriented proponents in the field argue in favor of constructivist or relativistic paradigms to promote greater engagement with the contextual and community-based influences that impact our areas of study (Lincoln & Guba, 2000). From this perspective, there is concern about the potential limitations, or even the potential harms to those who are disenfranchised, of more objective experimental paradigms (e.g., positivism and postpositivisism). On the other hand, proponents of these quantitative methods argue that as a scientific discipline seeking to expand the influence of our field's perspective on the way social and community research is conducted, we should embrace the strengths of methods based on these paradigms to facilitate rigorous hypothesis testing, produce research that is both internally valid and externally generalizable, and assess cause-and-effect relationships between constructs (Johnson & Onwuegbuzie, 2004).

For many, this inherent tension suggests a need for the more pragmatic approach of methodological pluralism, or mixed methods research (Barker & Pistrang, 2005, 2012; Tebes, 2005). Barker, Pistrang, and Elliott (2002) defined methodological pluralism as a recognition that all research methods have relative advantages and disadvantages and that researchers should draw upon a variety of methods and use those most appropriate to the specific questions being studied. At its core, a mixed methods approach represents a call for the incorporation or integration of quantitative and qualitative methods in the same research study (Greene, Caracelli, & Graham, 1989; Langhout, 2003; Yin, 2006). Despite potential incompatabilities among these methods (Howe, 1988; Johnson & Onwuegbuzie, 2004), community-based research appears to be evidencing a growing affinity toward a mixed methods approach. A pragmatic justification for this approach is well grounded in both methodological and epistemological concerns (Kloos, 2005; Morgan, 2007; Tebes, 2005). This perspective recognizes that both quantitative and qualitative approaches have inherent strengths and weaknesses. Thus, researchers should draw from an array of methods and approaches, taking advantage of the strengths associated with each to better understand social phenomena. Furthermore, a pragmatitic perspective maintains that the research question should drive the methods to be used, with researchers selecting the most appropriate tool or method to answer the particular research question under investigation (Onwuegbuzie & Leech, 2005).

Although a mixed methods approach does expand the field's ability to incorporate greater contextual understanding of influences on the subject matter that we study, it is equally important (and not incompatible with a mixed methods approach) that the quantitative methods used by community-based researchers provide a strong framework for investigating complex and contextualized phenomena in their own right. To maintain pace with the field's complex theories of the "interplay between people and contexts" (Shinn & Rapkin, 2000, p. 185), community researchers should use data-analytic methods that best represent the relationship of ecological and contextual domains to the phenomena being investigated. This means that community researchers need to adopt measurement approaches that do a better job of capturing contextual information, such as social network analysis (SNA) or geographic information systems (GIS) methods (Luke, 2005), or "ecometric" approaches (Raudenbush & Sampson, 1999, p. 3) to the assessment of ecological contexts. Community researchers also must make greater use of data-analytic methods that incorporate contextual (i.e., setting-level) and cross-level (i.e., interactions between setting-level and individual-level) effects (Raudenbush & Bryk, 2002), as well as more complex processes (e.g., indirect or mediating effects, moderation effects) cross-sectionally, longitudinally, and across contextual settings (Bollen & Curran, 2006; Duncan, Duncan, & Strycker, 2006; Kline, 2006; Preacher, Zyphur, & Zhang, 2010; Raykov & Marcoulides, 2006; Tanaka, 2000). Finally, analytic methods should be dynamic and adaptable to the challenges of complex research designs and data structures. However, previous examinations of the state of the field's statistical methods (e.g., Luke, 2005) revealed that community researchers continue to rely on more traditional data-analytic methods (e.g., analysis of variance [ANOVA], regression, and correlation), rather than methods permitting greater complexity (e.g., structural equation modeling [SEM], cluster analysis, and SNA) or contextualization (e.g., multilevel modeling [MLM] and GIS analysis).

In the remainder of this chapter I frame the issue of what considerations should drive a researcher's selection of quantitative methods when conducting community-based research, including the nature of the research question. This overview is intended to set up the subsequent chapters of this section of the volume, which provide a more in-depth view of many of these advanced methods. In addition, I present an update of Luke's (2005) review of the state of statistical analyses in community-based research to assess the current use of methods that are able to incorporate greater complexity and contextualization relative to more traditional statistical methods. Luke's original review revealed that traditional analytic methods still predominated the field of community-based research. Luke argued that community researchers should embrace contemporary analytic methods (e.g., MLM, cluster analysis, GIS, and SNA) more consistent with the values and perspectives of the field with regard to the incorporation of contextual and community-based effects. This updated review will demonstrate the degree to which community researchers have heeded Luke's call to incorporate such methods within the field and where further efforts are necessary to expand their use.

FRAMING THE CHOICE OF QUANTITATIVE METHODS FOR COMMUNITY-BASED RESEARCH

In selecting the appropriate type of quantitative statistical methods to be used in a given study, there are a number of factors that need to be considered. Ideally, these considerations are made prior to the collection and analysis phases of a study (e.g., during the study conceptualization and design phases), but there are instances when the determination of data-analytic methods to be used occurs after data have already been collected (e.g., in the case of secondary analysis of existing data). A primary factor that should drive selection is the nature of the specific research questions to be answered. A secondary set of concerns relates to the nature of the data that have been collected to answer the research question (e.g., number and type of dependent and independent variables, inclusion of covariates, and whether the data are cross-sectional or longitudinal; Tabachnick & Fidell, 2013). For community-based research, an added set of concerns to be factored into the data-analytic planning process are the means by which contextual factors are measured and how their relationship to other study constructs is to be assessed. A frequent focus of community-based research is the understanding of people in context and the variability of behaviors or other phenomena across social contexts (Barker & Pistrang, 2005). Many community-based studies involve data collected at multiple levels to capture both individual and contextual processes. However, many traditional statistical procedures assume independence among our data elements. Thus, for community researchers, selection of appropriate data-analytic methods should also be informed by the contextual levels at which the researcher has designed the study and collected data.

As indicated, the nature of the research question is a primary factor in determining the type of data-analytic method to be used. In addition to questions of a primarily descriptive nature (e.g., the characteristics of a particular group or phenomenon), Tabachnick and Fidell (2013) identified five primary types of research questions requiring quantitative statistical methods that support hypothesis testing (i.e., inferential statistics). These include questions about (a) the degree of relationship among two or more variables, (b) the significance of group differences on a set of measures, (c) predictors of group membership, (d) measurement and structure of constructs, and (e) the time course of events.

The following sections briefly summarize the core aims of each of these types of research questions, indicating traditional statistical methods that are relevant to each and highlighting examples of more sophisticated methods that facilitate the incorporation of more complex or contextualized analyses relevant to community-based research. A number of these methods are described in greater detail in the chapters that follow. The specific types of analyses are meant primarily as a guide, as the lines between these different analytic methods are not necessarily fixed. Most can be considered variations of the generalized linear model, permitting skilled analysts and researchers to select from a wide array of data-analytic methods to answer the questions most appropriately (Onwuegbuzie & Leech, 2006; Tabachnick & Fidell, 2013). Muthén (2002) further extended the overlap among these methods through a general latent variable modeling framework implemented in the Mplus statistical software that facilitates even greater flexiblity to incorporate multilevel data, latent variable measurement models, and process-oriented structural models to address complex mediating and moderating relationships among variables within the context of an array of different types of variables (e.g., continuous, discrete, or count variables).

Degree of Relationship Questions

Degree of relationship questions focus on the extent to which two or more factors covary in a consistent manner; they are among the most common staticstical questions in psychological research. Traditional statistical methods include simple correlation (e.g., bivariate *r*) or standard regression techniques in the case of multiple continuous independent variables (IVs) or covariates and a single dependent variable (DV). For community-based research, these types of questions become more complex with the inclusion of setting-level data to contextualize effects. Delany-Brumsey, Mays, and Cochran (2014), for example, examined the extent to which neighborhood social capital (a contextual factor) serves as a protective buffer for family-related risks on child-level outcomes. Such a study asks not only about the direct effect of a contextual influence on an individual-level outcome but also about the extent to which that contextual influence interacts with a micro-level factor (e.g., family risk effects on child-level outcomes may vary by the level of social capital within a given neighborhood) to influence that outcome.

Traditional methods for assessing such a question (e.g., regression-based models) assume a single-level data structure in which data are collected only at the individual level, or any contextual information is disaggregated so that it is linked to individual participants (Duncan, Jones, & Moon, 1998). In addition, these methods assume independence among participants (i.e., that participants are not clustered within higher order structures such as neighborhoods). When these assumptions are violated, the resulting anslyses may produce elevated Type I error rates and biased parameter estimates (Peugh, 2010; Raudenbush & Bryk, 2002). Finally, disaggregation of group-level information to the individual level (e.g., treating contextual information about community settings as person-level data) also has the effect of treating all effects as fixed across contextual settings, a limitation that reduces the functionality of assessing for contextual effects in the first place (Duncan et al.,1998; Luke, 2005). Thus, for studies investigating the degree of relationship among variables it is critical that community-based researchers move away from traditional regression-based approaches to more appropriate multilevel models (Duncan & Raudenbush, 2001; Raudenbush & Bryk, 2002) that more accurately reflect the association among contextual factors and outcomes.

Significance of Group Differences Questions

Significance of group differences questions focus on the degree to which indicators of interest vary across meaningful groups (e.g., across experimental or quasi-experimental groups or across groups based on other criteria, such as status, context, or group affiliation). A number of traditional statistical methods are available for addressing such questions, including the *t* test, one-way ANOVA, and factorial ANOVA for continuous DVs with one or more discrete IVs; analysis of covariance

(ANCOVA) for the inclusion of covariates; and multivariate analysis of variance (MANOVA) or multivariate analysis of covariance (MANCOVA) when multiple DVs are included. For categorical indicators, contingency table methods (e.g., chi-square) can be used to detect group differences in distribution.

As with traditional regression-based models, ANOVA-based models also assume a single-level data structure that can lead to biased parameter estimates or increased rates of Type I error if the study design does not match the analytic approach. Hoffman and Rovine (2007) provided a thorough overview of specification procedures for multilevel models to test group differences in place of more traditional ANOVA models.

Cluster randomized trials (CRT; see Chapter 17) are one example of a community-based research design that poses a problem for traditional analytic methods when investigating group differences, as randomization occurs at the setting level rather than at the individual level. This design introduces a nested data structure in which individuals are grouped into settings, with treatment condition linked to the setting level and potential covarites available at both the individual and setting levels—the typical data structure of a multilevel model. In a recent example of a CRT, Hagelskamp, Brackett, Rivers, and Salovey (2013) randomly assigned 62 schools to a universal social-emotional learning intervention, with quality of classroom-level interactions as a primary outcome of interest. Given this data structure (i.e., classrooms clustered in schools, randomization at the school level), MLM was used to analyze intervention effects, providing less biased parameter estimates of these effects and also allowing for school-level variation in classroom-level effects associated with the intervention.

Prediction of Group Membership Questions

Prediction of group membership questions are similar in some respects to the more general question of the degree of relationship among constructs, except that the outcome of interest is typically discrete or categorical in nature. Rather than assessing the degree to which changes in a given construct result in changes in a continuous outcome variable, the focus is on the degree to which a given set of independent variables increases or decreases the likelihood of being classified into a particular group (a categorical dependent variable) among a range of possible group classifications. Simple examples of these types of outcomes might include identification of predictors of being a smoker, graduating from high school, or joining a self-help group, although more complex group-level outcomes are possible in which there are multiple competing group outcomes (e.g., being a nonsubstance user, engaging in social use, or engaging in problematic levels of use). The traditional statistical approach would typically involve logistic regression (for a binary outcome) or multinomial regression (for nominal outcomes with more than two categories), in the case of a single dependent variable, or discriminant function analysis for multivariate outcomes. As with standard regression methods, extensions of MLM permit the incorporation of higher level contextual effects into these types of research questions (Merlo et al., 2006). Gregory and Huang (2013), for example, were interested in understanding the unique predictive influences of student, parent, and math and English teacher expectations in the 10th grade on postsecondary status 4 years later. Using an extension of multilevel modeling that permits cross-classification of students in multiple settings (e.g., classrooms), the researchers demonstrated the unique effects of expectations at the teacher, family, and student levels, as well as interactions between teacher expectations and child and family-level factors (e.g., socioeconomic factors) on the likelihood of continuing to postsecondary education.

Another set of statistical methods that are beginning to be used more frequently by community-based researchers to investigate predictors of group membership is mixture modeling (e.g., latent class analysis [LCA] or latent transition analysis [LTA]; Lanza, Flaherty, & Collins, 2003). The goal of these methods are similar to that of cluster analysis, in that the aim is to identify homogeneous groups within a heterogeneous population based on similar patterns of response to a given set of indicators or on similar characteristics. These methods provide a way of recognizing the variability within a given sample and identifying subgroups that may have unique needs or characteristics. Once distinct groups are identified, researchers often try to identify those factors that predict likelihood of being in the particular groups that have been identified or understanding how group membership may influence subsequent outcomes differentially across groups. Fowler et al. (2013), for example, used multilevel LCA to estimate the prevalence of inadequate housing based on multiple indicators for families involved with child protective services. Through their analyses, they differentiated two groups, a normative group that did not show risk of housing instability and a smaller group of households (16%) that were more likely to exhibit risks for housing instability. Analyses identified a number of family and service-related factors that were associated with greater likelihood of membership in the housing risk group and showed that families in this risk group were nearly four times more likely to require housing-related services at 12-month follow-up.

Measurement and Structure Questions

Measurement and structure questions focus on the underlying latent structure of a set of variables. These types of questions are at the heart of how researchers operationalize a construct and demonstrate the validity of measurement strategies. These types of traditional measurement-related analyses typically involve either exploratory or confirmatory factor analytic methods (Floyd & Widaman, 1995; Preacher & MacCallum, 2003). Raudenbush and Sampson (1999, p. 3) argued that contextual measurement and structure questions need to evolve beyond traditional methods, or the result is a "serious mismatch . . . in studies that aim to integrate individual and ecological assessments." To correct for this limitation, they proposed an ecometric corollary to psychometric approaches that combines MLM with aspects of item response theory, generalizability theory, and factor analysis. Their example provides a framework for developing measures of ecological context, using both survey and observational methods, that capture within- and between-setting variation more accurately than traditional methods do. Barile, Darnell, Erickson, and Weaver (2012) engaged in a similar type of contextual measurement analysis, using multilevel confirmatory factor analysis (MCFA) to assess collaborative functioning among members of nearly 160 community-based collaboratives. MCFA, like the approach of Raudenbush and Sampson, addresses the clustering inherent in community-level measurement strategies with multiple informants but does so from a latent variable modeling perspective that permits identification of the underlying factor structure to facilitate examination of structural relationships after accounting for measurement error.

Measurement-related models often also examine more complex structural relationships (e.g., indirect or mediating relationships) among latent constructs, representing a combination of both structural and regression-based models to assess association. SEM is a widely used method for analyzing such questions that has been used with increasing frequency by community researchers (Luke, 2005). A more recent development that mirrors the use of MCFA described earlier is multilevel SEM (MSEM; see Chapter 16). MSEM capitalizes on the strengths of the SEM approach over traditional regression models, as well as those of more general MLM approaches that disentangle within- and between-person variance. An added advantage of the MSEM approach over general MLM methods is the ability to specify and test cross-level mediation effects to explicate the mechanisms by which contextual effects influence individual-level outcomes (Preacher, Zhang, & Zyphur, 2011; Preacher et al., 2010).

Time Course of Events Questions

Time course of events questions, the final analytic question type in the continuum presented by Tabachnick and Fidell (2013), focus on one of two aspects of longitudinal measurement, either (a) the amount of time to a given event or outcome or (b) the rate or trajectory of change in a dependent variable over time. Time to event analyses are traditionally analyzed using survival analysis, a type of statistical method that allows the user to assess both the likelihood of event occurrence over time (e.g., time to relapse in a treatment study or time to employment in a jobs program evaluation), as well as factors that influence the timing of event occurrence (Allison, 1995; Connell, 2012). With the adoption of a more general latent variable modeling framework (Muthén, 2002) described earlier, there have been significant advances in survival analytic methods to incorporate contextual effects through multilevel survival analytic models (Asparouhov, Masyn, & Muthén, 2006).

To assess changes in a dependent variable over time, traditional methods include repeated measures ANOVA as well as time-series analysis, an approach that has not been used frequently in community research (see Chapter 18). Due to restrictions in repeated measures ANOVA assumptions, repeated measures approaches also have been conceptualized from a multilevel framework, with time treated as a Level-1 variable that is nested within the individual, now treated as the Level-2 model (Hoffman & Rovine, 2007; Singer & Willett, 2003) or from a latent variable framework (Bollen & Curran, 2006; Duncan et al., 2006). Both approaches have some advantages and disadvantages, and each can accommodate additional contextual influences through higher order multilevel settings. Chapter 14 provides an overview of latent growth modeling methods as applied to community-based research from this latter perspective.

Alternative methods of examining longitudinal trajectories in outcomes over time are based on mixture modeling approaches described previously. LTA (Lanza et al., 2003) is a longitudinal extension of the LCA model that examines transitions of individuals between classes over time. In contrast, latent growth mixture modeling and its variants, such as latent class growth analysis (LCGA), identify subgroups within a heterogeneous population that follow more consistent trajectories of change over time. Lowe, Galea, Uddin, and Koenen (2014), for example, used LCGA to examine predictors of divergent trajectories of posttraumatic stress among urban residents, revealing four unique posttraumatic stress trajectories (low, high, increasing, and decreasing) and particular contextual risks associated with detrimental trajectories.

THE CURRENT STATE OF ANALYTIC METHODS IN COMMUNITY-BASED RESEARCH

With the recent advances in statistical methodology that incorporate more complex, contextualized data-analytic approaches to address community-based research questions, how is the field of community psychology moving to embrace these methods? It has been more than 10 years since Luke (2005) conducted a review of quantitative methods used in empirical papers within the *American Journal of Community Psychology (AJCP)*, the flagship journal of the Society for Community Research and Action (SCRA), for two 3-year periods (1981–1983 and 2001–2003) representing a 20-year period of research in the field of community science. This review provided a means of observing changes in the data-analytic practices of community-based researchers to move beyond traditional analytic frameworks (e.g., ANOVA, regression) toward more contemporary methods better suited to the particular research questions and types of data encountered by community researchers. A total of 215 empirical papers—126 from the early 1980s and 89 from the early 2000s—were examined.

Luke's analysis revealed a continuing reliance on traditional data-analytic methods into the early 2000s, including ANOVA (37% of manuscripts), regression (37% of manuscripts), psychometric analysis (45% of manuscripts), and categorical analysis (e.g., chi-square analysis, 26% of manuscripts), as well as a heavy reliance on descriptive analyses (75% of manuscripts) and correlational methods (35% of manuscripts). In addition, Luke's analysis revealed relatively infrequent use of more advanced analytic methods (e.g., SEM, 11% of manuscripts) or techniques that were specifically developed to incorporate contextually focused analyses, such as SNA, MLM, cluster analysis, or GIS. Each of these methods was used in fewer than 4% of manuscripts published in either the early 1980s or early 2000s. To encourage greater use within the field, Luke provided a brief overview of these latter methods (i.e., SNA, MLM, cluster analysis, and GIS), demonstrating their particular applicability to community-focused research.

To examine the degree to which the field of community research has advanced in its use of more sophisticated analytic methods to incorporate context in the past decade, I conducted a similar review of *AJCP* manuscripts from 2012 through 2014. Unlike Luke (2005), I focused this review on original research articles, including those in special issues, that included some level of quantitative or qualitative analysis. A total of 218 manuscripts were indicated as "Original Articles" by *AJCP* for this period, but 45 manuscripts were excluded that presented no data analyses (e.g., conceptual or review manuscripts). This resulted in a final sample of 173 manuscripts that were coded for the present chapter.

To code the primary data-analytic methods used in *AJCP* during the 3-year period, the abstract, methods, and results sections of each manuscript were reviewed to identify the primary analytic method (or methods) used to answer the primary research questions posed by the study. Most studies also included some level of descriptive or correlational analyses, but for purposes of this current review such methods were recorded only if they were used as a primary analytic method (as opposed to standard reporting of descriptive sample characteristics). After an intial round of coding, some categories were collapsed based on a common underlying focus to the analytic approach. For example, ANOVA, ANCOVA, MANOVA, and *t*-test analyses were combined because all have a common analytic purpose (e.g., to evaluate the significance of group differences), differing primarily on factors such as the number and type of DVs, IVs, and whether they accommodate additional covariates. MLM and other methods that were used to address hierarchical or nested data structures (e.g., generalized estimating equations [GEE]; generalized linear mixed models [GLMM]) were combined based on the primary emphasis of addressing a multilevel data structure. Similarly, multiple regression and logistic regression were combined (regression), as were exploratory and confirmatory factor analytic methods (factor analysis), and cluster analysis and various mixture modeling approaches (cluster/mixture). Finally, in addition to studies that included multiple distinct data-analytic methods, some types of analyses resulted in the application of multiple codes for a single analytic method. For example, although some repeated measures analyses were conducted using latent growth methods, there were also papers that used MLM to examine growth trajectories. For these papers both MLM and latent growth were coded. Similarly, some manuscripts involved latent growth mixture modeling and were coded for both mixture and latent growth modeling.

Figure 13.1 shows the frequency with which various analytic methods were used by papers published in AJCP during the period examined. The majority of manuscripts (59.5%) involved use of a single analytic approach to address the primary research question or questions. Approximately 29% used two different analytic methods, and 12% used three or four different analytic methods for primary analyses.

This review revealed some significant shifts in the data-analytic methods being used by the field in just the past decade. The most striking finding was a dramatic increase in the use of more sophisticated methods to incorporate contextual influences into research or to model more complex structural relationships among constructs. In particular, MLM and related methods (e.g., GLMM) have seen tremendous growth in their use among community researchers, with nearly a quarter (23.1%) of papers using these methods, compared to only about 5% in the early 2000s. This represents a nearly fivefold increase in the rate of use of these methods in the past 10-year period. Similarly, the use of SEM has continued to grow among community researchers in the past decade. As recently as the early 2000s, only about 11% of *AJCP* manuscripts used SEM, compared to 16% in the most recent 3-year period. In addition, latent growth modeling (which extends SEM to analyze repeated measures data) was used by an additional 6% of research papers, suggesting that the use of SEM-based methods has doubled in the past decade.

Another data-analytic method that showed a significant increase in use over the past decade is cluster analytic and mixture modeling analyses (e.g., LCA, LTA, and growth mixture modeling). Only 3% of papers used these methods in the early 2000s, while the current rates have tripled to more than 9%. Furthermore, there has been a shift to greater use of mixture modeling approaches compared to more traditional cluster analytic methods during that same period.

These increases in multilevel and SEM-based methods are mirrored by a corresponding decrease in the frequency of use of more traditional analytic methods, such as ANOVA-based group-level comparisons or of regression-based models (including both multiple regression and logistic regression methods). In the past 30 years, the use of ANOVA and related methods has declined from approximately 66% in the 1980s to 37% in the 2000s to 22% in the most recent 3-year period. Regression-based models, which had been fairly stable from the 1980s to the 2000s, declined fairly steeply, from nearly 48% to 20% in the most recent period.

These two parallel sets of changes in frequency of MLM and SEM, on the one hand, and ANOVA and regression modeling on the other, speak to an important shift in the ways in which community-based research studies are being analyzed and reported. As indicated, traditional ANOVA and regression-based models are appropriate for single levels of analysis but are not able to adequately incorporate contextual effects (as is done with MLM) or test more complex relationships among variables (as is done with SEM). These changes suggest that community-based research (as represented by *AJCP* publications in

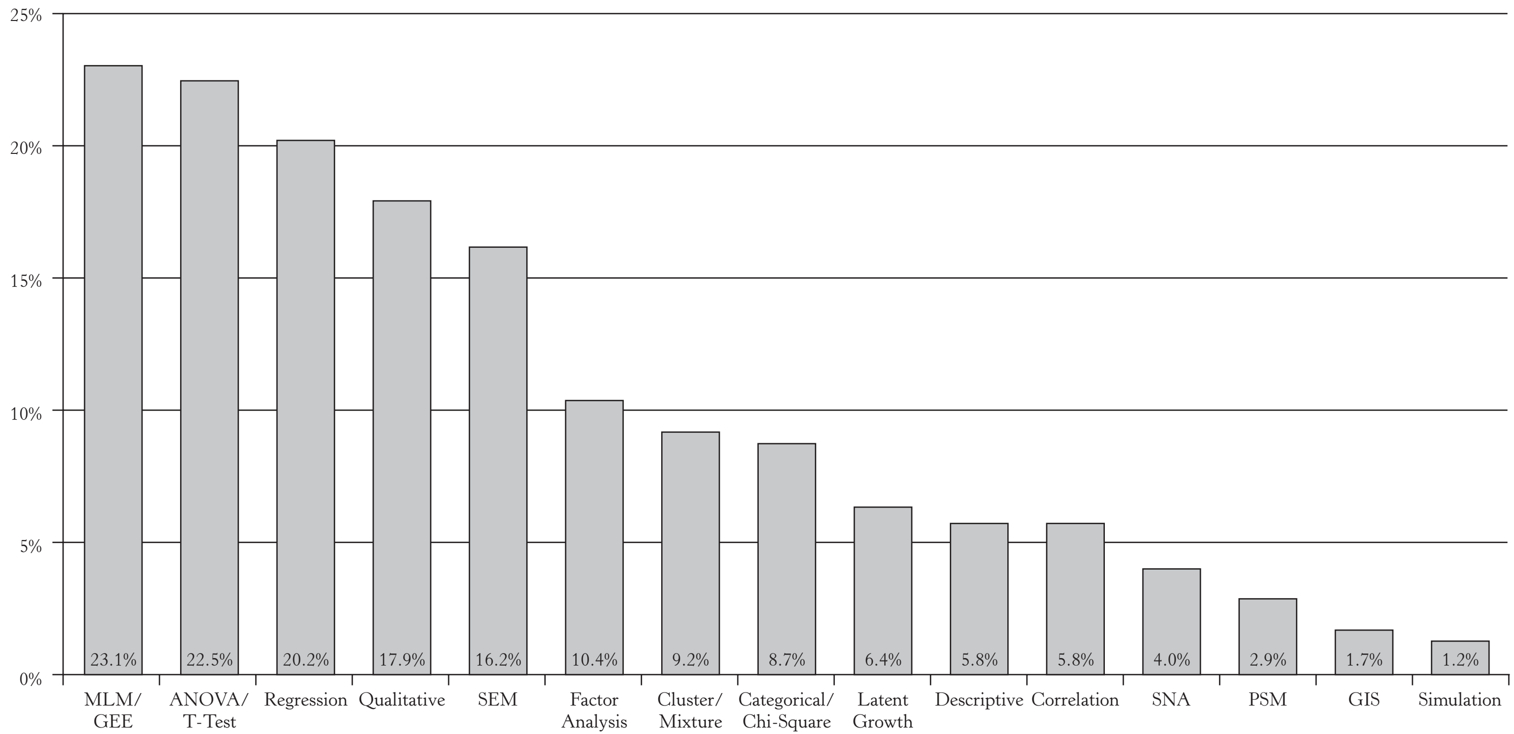

FIGURE 13.1: Primary analytic methods used in the *American Journal of Community Psychology*, 2012 through 2014 ($N = 173$ original papers reporting data analysis).

the field of community psychology for this review) is adopting statistical methods that are much more consistent with the questions that are being asked by researchers and the designs that are being used within the field.

In addition to these notable changes toward the greater integration of complex modeling, this review also revealed that some techniques remain underutilized despite their relevance to the types of research questions and data used by community researchers. In 2005, Luke highlighted four analytic approaches that were largely absent from the field in the early 2000s: MLM, cluster analysis, SNA, and GIS. As already indicated, the use of both MLM and cluster-related methods has increased significantly since the review conducted 10 years ago. However, the use of SNA and GIS continues to remain quite low (4.0% and 1.7%, respectively). Both SNA and GIS are reflected in chapters in this volume (SNA: see Chapters 21 and 22; GIS: see Chapter 10). Two additional methods, propensity score methods (PSM; Caliendo & Kopeinig, 2008; Rubin, 2001) and simulation-based methods such as agent-based modeling (ABM; Macy & Willer, 2002), were both utilized at relatively low rates as well (e.g., 2.9% and 1.2%, respectively). Luke and Stamatakis (2012) presented a useful overview of ABM in public health contexts that has significant implications for its use in community research, and Neal and Lawlor (see Chapter 20) provide a rich overview of their applications in a broader community context. PSM also has significant relevance to community researchers, providing a valuable means for removing selection bias and assessing group differences or causal effects in the context of quasi-experimental studies in which random assignment is not practical or possible. Given that many community researchers and evaluators frequently utilize these types of quasi-experimental conditions, PSM offers a valuable means of more rigorous testing of effects than do traditional comparative approaches.

Finally, although this chapter is primarily focused on the use of quantitative methods, the review of papers in *AJCP* also highlighted some interesting findings with respect to qualitative and mixed methods analyses. Luke's (2005) review revealed that the rates of qualitative analyses in *AJCP* increased from 4% in the early 1980s to 17% in the early 2000s. The rate of qualitative analyses appears to have remained steady at 18% in the most recent period. Of the 31 papers that included qualitative analyses, approximately one third also included quantitative analyses (i.e., had mixed methods analyses). Most frequently, the quantitative components included regression analyses (46%), ANOVA or *t* tests (36%), or categorical analyses (e.g., chi-square analyses; 27%) to assess group differences in the variables of interest. More sophisticated methods (e.g., SNA, MLM, GIS, or PSM) were used in conjunction with qualitative analyses for only one to two of the mixed methods papers reviewed.

CONCLUSION

Over the past 50 years, there has been a consistent call for advancement in the use of appropriate statistical methods to capture the complexity of community-based research questions. Such questions push the boundaries of traditional analytic methods, as they typically incorporate broader contextual influences on individual-level outcomes, examine complex processes as they unfold across person and context over time, or focus primarily on changes at the contextual level. These types of questions are critical to our central aim of understanding the complex relationships between person and context (Shinn & Rapkin, 2000). Unfortunately, our methods of statistical analysis have served as a potential limiting factor in realizing the full potential of community science to understand these phenomena, relying on traditional methods to test our hypotheses of these complex processes (Luke, 2005).

It does appear, however, that the field is beginning to make a significant shift in the use of more advanced statistical and data-analytic methods to appropriately model the complexity of our research questions and designs. In just a 10-year period, the level of methodological sophistication in our published research has made a seismic shift, particularly with respect to the use of MLM approaches as well as latent variable methods to capture complex processes (e.g., indirect effects), longitudinal effects, and population-level variation in phenomena of interest. This development is a critical stage in advancing community-based research, providing a strong foundation to test how theories and constructs operate within and across settings.

REFERENCES

Allison, P. D. (1995). *Survival analysis using the SAS System: A practical guide*. Cary, NC: SAS Institute.

Asparouhov, T., Masyn, K., & Muthén, B. (2006, August). *Continuous time survival in latent variable models*. Paper presented at the meeting of the American Statistical Association Section on Biometrics, Seattle, WA.

Barile, J. P., Darnell, A. J., Erickson, S. W., & Weaver, S. R. (2012). Multilevel measurement of dimensions of collaborative functioning in a network of collaboratives that promote child and family well-being. *American Journal of Community Psychology, 49*, 270–282.

Barker, C., & Pistrang, N. (2005). Quality criteria under methodological pluralism: Implications for conducting and evaluating research. *American Journal of Community Psychology, 35*, 201–212.

Barker, C., & Pistrang, N. (2012). Methodological pluralism: Implications for consumers and producers of research. In L. A. Jason & D. Glenwick (Eds.), *Methodological approaches to community-based research* (pp. 33–50.). Washington, DC: American Psychological Association.

Barker, C., Pistrang, N., & Elliott, R. (2002). *Research methods in clinical psychology*. Chichester, England: Wiley.

Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: A structural equation perspective*. Hoboken, NJ: Wiley.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*, 31–72.

Connell, C. M. (2012). Survival analysis in prevention and intervention programs. In L. A. Jason & D. S. Glenwick (Eds.), *Innovative methodological approaches to community-based research: Theory and application* (pp. 147–164). Washington, DC: American Psychological Association.

Delany-Brumsey, A., Mays, V. M., & Cochran, S. D. (2014). Does neighborhood social capital buffer the effects of maternal depression on adolescent behavior problems? *American Journal of Community Psychology, 53*, 275–285.

Duncan, C., Jones, K., & Moon, G. (1998). Context, composition and heterogeneity: Using multilevel models in health research. *Social Science and Medicine, 46*, 97–117.

Duncan, G. J., & Raudenbush, S. W. (2001). Neighborhoods and adolescent development: How can we determine the links? In A. Booth & A. C. Crouter (Eds.), *Does it take a village? Community effects on children, adolescents, and families* (pp. 105–136). Mahwah, NJ: Erlbaum.

Duncan, T. E., Duncan, S. C., & Strycker, L. A. (2006). *An introduction to latent variable growth curve modeling: Concepts, issues, and applications* (2nd ed.). Mahwah, NJ: Erlbaum.

Floyd, F. J., & Widaman, K. F. (1995). Factor analysis in the development and refinement of clinical assessment instruments. *Psychological Assessment, 7*, 286–299.

Fowler, P. J., Henry, D. B., Schoeny, M., Landsverk, J., Chavira, D., & Taylor, J. J. (2013). Inadequate housing among families under investigation for child abuse and neglect: Prevalence from a national probability sample. *American Journal of Community Psychology, 52*, 106–114.

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis, 11*, 255–274.

Gregory, A., & Huang, F. (2013). It takes a village: The effects of 10th grade college-going expectations of students, parents, and teachers four years later. *American Journal of Community Psychology, 52*, 41–55.

Hagelskamp, C., Brackett, M. A., Rivers, S. E., & Salovey, P. (2013). Improving classroom quality with the ruler approach to social and emotional learning: Proximal and distal outcomes. *American Journal of Community Psychology, 51*, 530–543.

Hoffman, L., & Rovine, M. J. (2007). Multilevel models for the experimental psychologist: Foundations and illustrative examples. *Behavior Research Methods, 39*, 101–117.

Howe, K. R. (1988). Against the quantitative-qualitative incompatibility thesis, or dogmas die hard. *Educational Researcher, 17*, 10–16.

Johnson, R. B., & Onwuegbuzie, A. J. (2004). Mixed methods research: A research paradigm whose time has come. *Educational Researcher, 33*, 14–26.

Kline, R. B. (2006). *Structural equation modeling*. New York, NY: Guilford Press.

Kloos, B. (2005). Community science: Creating an alternative place to stand? *American Journal of Community Psychology, 35*, 259–267.

Langhout, R. D. (2003). Reconceptualizing quantitative and qualitative methods: A case study dealing with place as an exemplar. *American Journal of Community Psychology, 32*, 229–244.

Lanza, S. T., Flaherty, B. P., & Collins, L. M. (2003). Latent class and latent transition analysis. In J. A. Schinka & W. F. Velicer (Eds.), *Handbook of psychology, Vol. 2. Research methods in psychology* (pp. 663–685). Hoboken, NJ: Wiley.

Lincoln, Y., & Guba, E. (2000). Paradigmatic controversies, contradictions and emerging confluences. In N. K. Denzin & Y. Lincoln (Eds.), *Handbook of qualitative research* (pp. 163–188). Thousand Oaks, CA: Sage.

Lowe, S. R., Galea, S., Uddin, M., & Koenen, K. C. (2014). Trajectories of posttraumatic stress among urban residents. *American Journal of Community Psychology, 53*, 159–172.

Luke, D. A. (2005). Getting the big picture in community science: Methods that capture context. *American Journal of Community Psychology, 35*, 185–200.

Luke, D. A., & Stamatakis, K. A. (2012). Systems science methods in public health: Dynamics, networks, and agents. *Annual Review of Public Health, 33*, 357–376.

Macy, M. W., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology, 28*, 143–166.

Merlo, J., Chaix, B., Ohlsson, H., Beckman, A., Johnell, K., Hjerpe, P., . . . Larsen, K. (2006). A brief conceptual tutorial of multilevel analysis in social epidemiology: Using measures of clustering in multilevel logistic regression to investigate contextual phenomena. *Journal of Epidemiology and Community Health, 60*, 290–297.

Morgan, D. L. (2007). Paradigms lost and pragmatism regained methodological implications of combining qualitative and quantitative methods. *Journal of Mixed Methods Research, 1*, 48–76.

Muthén, B. O. (2002). Beyond SEM: General latent variable modeling. *Behaviormetrika, 29*, 81–117.

Onwuegbuzie, A. J., & Leech, N. L. (2005). On becoming a pragmatic researcher: The importance of combining quantitative and qualitative research methodologies. *International Journal of Social Research Methodology, 8*, 375–387.

Onwuegbuzie, A. J., & Leech, N. L. (2006). Linking research questions to mixed methods data analysis procedures. *Qualitative Report, 11*, 474–498.

Peugh, J. L. (2010). A practical guide to multilevel modeling. *Journal of School Psychology, 48*, 85–112.

Preacher, K. J., & MacCallum, R. C. (2003). Repairing Tom Swift's electric factor analysis machine. *Understanding Statistics, 2*, 13–43.

Preacher, K. J., Zhang, Z., & Zyphur, M. J. (2011). Alternative methods for assessing mediation in multilevel data: The advantages of multilevel SEM. *Structural Equation Modeling, 18*, 161–182.

Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychological Methods, 15*, 209.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Raudenbush, S. W., & Sampson, R. J. (1999). Ecometrics: Toward a science of assessing ecological settings, with application to the systematic social observation of neighborhoods. *Sociological Methodology, 29*, 1–41.

Raykov, T., & Marcoulides, G. A. (2006). *A first course in structural equation modeling*. Mahwah, NJ: Erlbaum.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: Application to the tobacco litigation. *Health Services and Outcomes Research Methodology, 2*, 169–188.

Shinn, M., & Rapkin, B. D. (2000). Cross-level research without cross-ups in community psychology. In J. Rappaport & E. Seidman (Eds.), *Handbook of community psychology* (pp. 669–695). New York, NY: Springer.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. New York, NY: Oxford University Press.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Boston, MA: Pearson.

Tanaka, J. (2000). Statistical models for change. In J. Rappaport & E. Seidman (Eds.) *Handbook of community psychology* (pp. 697–723). New York, NY: Springer.

Tebes, J. K. (2005). Community science, philosophy of science, and the practice of research. *American Journal of Community Psychology, 35*, 213–230.

Yin, R. K. (2006). Mixed methods research: Are the methods genuinely integrated or merely parallel? *Research in the Schools, 13*, 41–47.