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A Half Century of Longitudinal Methods in Social Gerontology: Evidence of Change in the *Journal*

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Objectives. With a focus on the use of longitudinal data, this study reviews trends in the quantitative analysis of social science data on aging during the past half century.

Methods. A content analysis was performed on 227 articles from 12 volumes that were systematically sampled from the *Journal of Gerontology: Social Sciences* to examine change in the type of data and quantitative methods used (1946–2000).

Results. Cross-sectional analysis remains the single most frequent type of study, but the publication of analyses based on longitudinal panel data increased appreciably over the five decades studied. There was little increase in the use of repeated cross-sectional analysis.

Discussion. Despite the widespread use of cross-sectional analysis, interest in data with more than one occasion of measurement has grown among social scientists who are reviewing for and publishing in the *Journal*. Given the longitudinal data now available, social science research on aging should give more explicit attention to three issues: attrition, change in repeated measures of independent variables, and models to account for many waves of data.

MOST scientific fields of inquiry make use of some form of data that capture processes over time. Chemists measure the lifetimes of compounds. Physicians take repeated measurements of physiologic data. Economists track financial trends over time. Whether on the scale of nanoseconds or centuries, repeated measurements over a span of time enable researchers to describe and, it is hoped, understand the processes and mechanisms of change. Within social gerontology, it is considered axiomatic to prefer repeated measurements of outcome variables. Indeed, it has been argued that the analysis of longitudinal data is "one of the most productive approaches to the study of aging and human development" (Alwin & Campbell, 2001, p. 22).

The purpose of this paper is to systematically examine the use of longitudinal data in social gerontology during the past five decades. A brief review of the key factors likely to increase the use of longitudinal analysis is presented, and a content analysis of the *Journal of Gerontology: Social Sciences* is used to document change in methods used.

Increase in Longitudinal Analyses in Social Gerontology?

Research using cross-sectional data has made—and will continue to make—a number of contributions to the field of social gerontology. For example, cross-sectional studies have generated important findings by examining unique or rare populations ranging from older mothers of chronically disabled children (Pruchno, Patrick, & Burant, 1996) to elders in rural all-Black towns (McAuley, 1998). Moreover, cross-sectional data that allow for comparisons across cultures or nations provide social scientists an opportunity to understand the universality of a relationship or phenomenon (Su & Ferraro, 1997; Venkatraman, 1995). In these cases, and many others, the analysis of cross-sectional data has provided invaluable contributions to the literature.

The challenge emerges, however, when research questions focus on the process of aging or changes over the life course (e.g., adaptation to life events). It has long been recognized that a common fallacy in gerontological research is that age differences are synonymous with age changes. Researchers using data collected at only one point in time are faced with the burden of separating the unique effects of age, period, and cohort (Glenn, 1977). Aging is a process; thus, research on aging or age-related changes must confront temporal issues related to biography, history, and cohort flow (Riley, 1987). As Campbell and Alwin (1996, p. 33) explained, "even the most simple (and, we would argue, flawed) cross-sectional comparison of age groups implies a developmental, or aging, perspective." As a result of the skepticism about interpretations of "age effects" in cross-sectional analyses, longitudinal data are often regarded as more useful for aging research.

The value of longitudinal data has been advanced repeatedly in the discussion section of articles using cross-sectional data and in chapters on research design in gerontology handbooks (e.g., Alwin & Campbell, 2001) and textbooks (e.g., Morgan & Kunkel, 2001). Longitudinal data are not the panacea for gerontology, but most scholars conclude that they offer greater potential for advancing the science of aging. Unlike with cross-sectional data, there is the potential to distinguish age differences from age changes with data from multiple points in time.

Beyond exhortations to use data collected at multiple points in time, the convergence of several forces in recent decades has made longitudinal data analysis more feasible. First, the paradigm for social science research on aging has shifted somewhat in recent decades from one focused on the study of *older people* to the *process of aging*. Interest in age

stratification (Riley, Johnson, & Foner, 1972), dialectical operations in adulthood (Riegel, 1973), the life course (Elder, 1974), and life-span development (Baltes, Reese, & Lipsitt, 1980) spurred greater interest in aging as a *lifelong* process. Moreover, empirical studies that tracked people over decades offered unique insight into the life course (Giele & Elder, 1998). For example, the Terman Study of Gifted Children, the Berkeley Guidance Study, and the Oakland and Berkeley Growth Studies followed children born in the 1920s for decades. These and other long-term studies helped shift social gerontology away from cohort-centric studies of older people to more life course analysis and comparisons of age groups. Evidence of this paradigmatic shift may also be noted in the name change for the American Sociological Association's section dedicated to the study of aging. It was long known as Sociology of Aging, but in 1997 it was changed to Sociology of Aging and the Life Course (the second time it was proposed).

Second, federal funding of prospective longitudinal studies, especially by the U.S. Department of Labor and National Institute on Aging, resulted in a greater *supply* of data for studying the aging process. The National Longitudinal Surveys and the Panel Study of Income Dynamics were launched in the 1960s to monitor work and economic behavior over the life course (Giele & Elder, 1998). Although the National Institute on Aging supported several major longitudinal studies in the 1980s, most were focused on tracking older adults over time (e.g., Longitudinal Study on Aging, National Long-Term Care Survey, and Established Populations for the Epidemiologic Study of the Elderly); exceptions included Americans' Changing Lives and the National Health and Nutrition Examination Survey I: Epidemiologic Followup Study. In the 1990s, the Health and Retirement Study reflected this interest in the long-term study of the aging process, albeit with the transition to retirement serving as the fulcrum of sample selection. Despite differences in the ages of adults studied, the message is clear: longitudinal data and analyses are key to advancing the field.

Third, public data archives made the supply of longitudinal data more *available* to potential investigators. The development of the Inter-university Consortium for Political and Social Research (ICPSR), established in 1962, meant that both longitudinal panel data and repeated cross-sectional data were available to a wide array of scientists (Rockwell & Abeles, 1998). The National Archive of Computerized Data on Aging, a division of ICPSR, enhanced scores of data sets by providing syntax to conveniently define files and made the data available to researchers at institutions that were not members of ICPSR.

Fourth, the revolution in statistical computing in recent decades helped spawn a new generation of *analytic resources* for longitudinal data. The 1960s witnessed the publication of Schaie's (1965) sequential design methodology, spurring discussions of ways to handle the age–period–cohort confound (Glenn, 1977; Mason, Winsborough, Mason, & Poole, 1973). The discussion engaged methodologists interested in change, as evidenced in key publications in the 1970s regarding longitudinal methods. Besides cohort analytic methods (Glenn, 1977), this decade included the publication of seminal works on event history methods (Cox, 1972) and the use of structural equation modeling for longitudinal data (Jöreskog & Sörbom, 1977). The application of these methods proliferated in the 1980s, aided by less technical works that helped clarify their power and utility (e.g., Allison, 1984; Campbell & Mutran, 1982). Seminal works on multiple imputation for missing data (Dempster, Laird, & Rubin, 1977) and selection bias modeling (Heckman, 1979) were published in the 1970s, but the application of these methods to adjust for attrition in panel studies is much more recent. Both growth curve modeling and hierarchical linear models were introduced in the social sciences in the 1980s (Bryk & Raudenbush, 1987; McArdle & Epstein, 1987). Recent applications of these methods in social gerontology are encouraging, but it may be too early to gauge their long-term impact.

With powerful techniques of analysis, readily available longitudinal data, and a growing interest in aging across the life course, one may anticipate a major shift in social gerontology toward longitudinal analyses. The purpose of the present research is to systematically examine such an assertion. To begin, we ask, how common has longitudinal analysis become? Are a majority of published studies now longitudinal? It seems reasonable to anticipate the growing use of longitudinal data in the 1980s and 1990s, but limited use of methods to handle attrition until very recently. In addition, whether an increase occurs for the analysis of both panel and repeated cross-sectional data is more difficult to predict. The analysis of repeated cross-sections avoids the attrition problem, but have social scientists increased their use of this type of data?

Methods

Content analysis was performed on articles from a systematic sample of volumes from the *Journal of Gerontology: Social Sciences* to examine change in the use of longitudinal data from 1946 to 2000. The *Journal of Gerontology: Social Sciences*, hereafter referred to as the *Journal,* was selected because it is widely regarded as the premiere publication for original research in social gerontology. The *Journal of Gerontology*, from which the *Journal* was spawned, is the oldest journal dedicated to the scientific study of aging. The *Journal* has played a pivotal role in shaping the field, both from the submissions it attracts and the expectations of its reviewers. Thus, one may anticipate that methodological advances, especially innovations in longitudinal analysis, would be more likely to appear in the *Journal* and then diffuse to other journals. In addition, there have been many calls for longitudinal analyses over the years in articles, editorials, and selected essays in the *Journal.*

In a series of essays marking the 50th anniversary of the *Journal*, key gerontologists remarked on the progress of the first half-century of research on aging and the future directions for the field. Related to the present investigation, Schulz (1995) heralded the growth in the number of longitudinal data sets as a positive step in the study of aging. Cutler (1995, p. S64) further argued that "many of the fundamental issues with which we are most concerned involve social, social-psychological, and other dimensions of *change* associated with aging. For these topics, there is no substitute for studies that follow the same individuals over time or for data sets that can be arrayed so as to follow cohorts." In addition, Kasl (1995) noted that the vast improvements in technology and statistical analysis have facilitated the sophisticated use of longitudinal data in social gerontology. Although these authors agreed that research using longitudinal data can be beneficial to advancing the field of

aging and that it is reasonable to expect greater use of data from multiple points in time, we are unaware of any systematic study of this *Journal* (or any other) to document change in the use of such data. Our aim is to use the flagship journal of social gerontology to examine how quantitative methods of analyses have changed since 1946, thereby tracking the use of longitudinal methods over the past 55 years.

There were 55 volumes of the *Journal of Gerontology* published between 1946 and 2000. In addition to the inaugural one, volumes from every fifth year were systematically sampled for this research (i.e., 1946, 1950, 1955, . . . , 1995, 2000), resulting in nearly 22% of all volumes published. Content analysis was performed on articles from the 12 volumes to examine change in the use of longitudinal data from 1946 to 2000. A total of 227 social science articles were selected for this analysis (all social science articles in each volume were examined).

Systematic sampling of journal articles is common when a content analysis of documents collected over a long period of time is conducted. For example, Jones, LaVeist, and Lillie-Blanton (1991) used a 10-year interval to study a 70-year period. A 5-year interval was selected for the present research to better detect change over the 55-year period. An analysis of the population of articles would, of course, have merit, but the 5-year interval is a reasonable approach to capture change. Moreover, methodological innovations take time to permeate the research community, so sampling every fifth year should be sufficient to capture the "standard setting" function of the *Journal* with regard to longitudinal methods.

Numerous changes in the organization of the *Journal* have transpired—including a name change in 1988—but this research examines only those articles classified as social science. Although the *Journal* has had some type of sectional organization since 1972, this also has changed repeatedly. The social sciences section title emerged in 1985; thus, all articles in this section since 1985 were considered for the given years. Prior to that time, all social science articles were selected after they were read by K. Ferraro. Articles classified as psychological sciences were excluded from the analysis because the focus here is on nonexperimental approaches to longitudinal analysis. Many psychological experiments involve longitudinal data (pretests and posttests), but the diffusion of longitudinal methods is likely quite different for experimental and nonexperimental approaches. Assuredly, there are nonexperimental psychological approaches in the *Journal of Gerontology: Psychological Sciences*, but the scope of the project is clearer by focusing on social science research (i.e., articles prior to 1985 on psychological topics such cognition, perception, and dementia were excluded, but works examining social psychological topics such as social support or exchange were included). The classification of social science articles was based on topic, method, and, if necessary, author affiliation.

Of the 227 total articles, 15 (6.6%) were excluded from subsequent analysis because they were classified as theoretical or qualitative. For each of the remaining 212 quantitative articles, the type of analysis was coded into one of three categories: first, cross-sectional (includes studies that pool data across time and ignore year-to-year variation); second, longitudinal panel; and third, repeated cross-sectional (RC-S) or cohort analysis (Glenn, 1977). A few articles used both cross-sectional and cohort analyses on more than one data set, and these were classified as RC-S. The analytic procedures used were coded regardless of the data structure. It is important to recognize that there are longitudinal data and longitudinal methods. This distinction can be clearly discerned by a few studies that reported cross-sectional analysis on longitudinal panel data. In an attempt to keep the distinction clear, we use the term *analysis* rather than *design* to differentiate between those that used multiple waves and those that used a single wave of longitudinal data.

Each article was read by at least two raters. Each rater was trained on the coding procedures and given one volume to analyze. Before proceeding to additional volumes, raters discussed responses to the first volume with the senior author in order to clarify coding procedures. Even after the training period, raters were encouraged to bring difficult cases to the senior author for resolution. Kappa values for interrater reliability, calculated after case resolution, exceeded .83 for each volume (Landis & Koch, 1977). Some additional characteristics of the articles were coded and are described later in more detail.

Results

As noted earlier, the *Journal* experienced many changes over the 55 years, including the number of articles published per volume. To launch our analysis of change in methods, it should be noted first that the number of social science articles increased appreciably over time. For each volume through 1965, fewer than 10 social science articles were published. Beginning in 1990, more than 30 social science articles were published in each volume examined.

Not surprisingly, there was a clear increase in the proportion of articles using data collected at multiple points in time, but some caution is necessary when differences in the earliest volumes are examined because of the infrequency of social science articles during the first 20 years. Figure 1 shows the distribution of studies by type of analysis over the 55 years of publication. There were some sharp fluctuations over time in the use of longitudinal panel data, but the overall trend was for an increase of such articles; the proportion increased as well. In contrast, repeated cross-sectional analysis did not increase appreciably over time. The number of data sets available for repeated cross-sectional analysis grew substantially, but there is no increase in this type of analysis during the past four decades.

Approximately 62% of all articles examined were cross-sectional analyses only. Whereas at least 60% of all articles in each volume of the *Journal* before 1975 were cross-sectional, this was not the case in most of the volumes examined since then (beginning in 1975, four volumes had less than 60% cross-sectional analyses). Indeed, in 1990, the percentage declined to less than 50. Articles using some type of longitudinal data have held steady at approximately 40–45% in the past decade. Although articles using data collected at multiple time points became more common, cross-sectional analyses remained the single most common type of article published.

Several additional variables were coded for each study, including the number of waves of data collection and type of sample. Not only did longitudinal data become more widely used over time, but the number of waves of data collection also increased over time (the correlation between number of waves and date published was .283). A 6-wave study appeared in 1955,

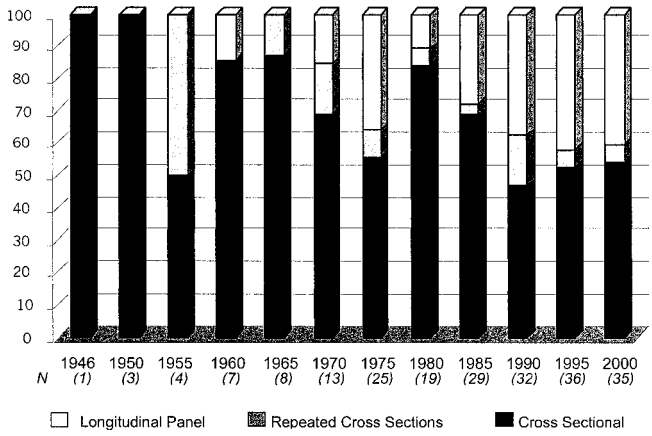

Figure 1. Type of analysis in the *Journal of Gerontology: Social Sciences* (1946–2000).

but it was another 25 years before another study was published with 6 or more waves. The number of waves increased sharply in the longitudinal articles appearing in the *Journal* by the mid-1990s. Studies ranged from 1 to 11 waves in 1995 and 2000.

In addition to more observation points, the geographic variability increased in studies over time. With their growing accessibility through data archives, national samples surpassed all other types of samples in 1995. When national samples are combined with multiple-state samples, single-location samples have been the minority since 1980. Social scientists prize external validity, and the availability of nationally representative samples has attracted considerable use. As might be expected, the type of analysis varied by type of sample. National samples were reported for approximately 83% of the cohort analyses, 35% of the cross-sectional analyses, and 24% of the longitudinal panel analyses. Nearly half of the longitudinal panel studies were based on local samples. (A logistic regression analysis for the use of national data revealed significant independent effects for three variables: National data were more likely to be used in more recent studies and in cohort and cross-sectional studies than for longitudinal panel studies.)

One of the basic issues facing scientists analyzing longitudinal panel data, especially over longer time periods, is attrition (i.e., nonresponse, loss to follow-up, and mortality). Although many of the longitudinal panel studies examined attrition patterns and tempered their conclusions in light of them, only 9 of the 63 longitudinal panel studies made some type of formal adjustment for attrition. This may seem less than exemplary, but all 9 of those studies were published in 1995 or 2000. Thus, there is evidence of a substantial shift toward the use of such procedures by scholars using longitudinal panel data.

To examine the validity of this premise more closely, we reviewed all articles for the 1995–2000 period. Given that the first occurrence of an adjustment for attrition was in 1995, a finer grained analysis may help to identify if this truly signals a change since the methods first appeared in the sampled years. Thus, beyond the 227 articles systematically sampled from 1946 to 2000, all 132 articles were examined in the period 1996–1999, yielding a 6-year population of articles.

The review of those articles reveals that adjusting parameter estimates to account for attrition has, indeed, become more common. For each year between 1995 and 2000, at least 20% of the articles using repeated measures undertook some type of adjustment for attrition. Interestingly, a wide variety of methods were used to adjust parameter estimates for attrition, ranging from weighting to multiple imputation. Of the remaining articles, about half mentioned attrition or performed supplementary analyses to show how selection bias may have influenced the findings. In short, the majority of articles published in recent years address attrition in one way or another—a sign that longitudinal analysis alone is not sufficient. The emerging standard in social gerontology expects authors and reviewers to be aware of the potential problems caused by nonrandom attrition and to temper conclusions in light of selection bias.

Discussion

Longitudinal data are often heralded for improving the science of aging, and there has been a growing use of longitudinal data in recent decades as uncovered in a content analysis of the *Journal*. Cross-sectional analysis was the most frequently used approach in 15 out of the 16 volumes of the *Journal* examined, but the trend toward an increase in the use of longitudinal data is manifest in recent years. Although one volume—1996—had more longitudinal than cross-sectional analyses, the pattern of at least 40–45% of the articles reporting some type of longitudinal analysis has been fairly steady for the past decade. Accompanying the growth in the use of longitudinal data, both the number of measurement points and the length of observation increased. We have witnessed reports of findings from more long-term panel studies of aging, and we believe that these studies provide unique scientific contributions.

A closer look at the growing prevalence of longitudinal analysis reveals that it was primarily due to the analysis of panel data. By contrast, repeated cross-sectional analyses did not increase appreciably over time. There has been a steady stream of cohort analyses published in the *Journal*, but given the supply and availability of repeated cross sections, cohort analyses hold untapped potential for advancing our understanding of aging, social change, and cohort flow (Campbell, 1994). Examples of studies published in the *Journal* that have clarified the role of these forces include findings on growth in noncitizen Supplemental Security Income caseloads (Van Hook & Bean, 1999), interstate migration of elders (Golant, 1990), retirement preparation (Ferraro, 1990), disability (Schoeni, Freedman, & Wallace, 2001), and verbal ability (Alwin & McCammon, 2001). Most social scientists are familiar with census data and the General Social Survey being used as repeated cross sections, but many other surveys merit attention. Examples include the Health Interview Survey, the National Home and Hospice Surveys, the National Hospital Discharge Survey, the National Medical Expenditure Survey, and the Survey of Consumer Finances.

It needs to be recognized that an analysis of repeated cross sections permits assessment of change. It is not change within an individual's life, as is customarily seen in panel studies, but change within a set of people defined by date of birth or some other event. It should also be recalled that aging represents a link between history and biography (Riley, 1987). Much can be gleaned from the analysis of repeated cross sections to identify how the changes observed in cohorts may be dependent

on social or historical circumstances. Another advantage of repeated cross-sectional analysis is that sample attrition is not a concern.

Although the use of cohort analysis remained relatively constant over the five decades, longitudinal panel analysis became more popular among social scientists during this time. One reason for its attraction is that, unlike a cohort analysis, a longitudinal panel analysis permits assessment of intra-individual change. As a result, it is widely viewed as helpful for examining mediating effects and the causal processes associated with aging.

Unlike the analysis of repeated cross sections, longitudinal panel designs face the possibility of attrition and nonrandom selection effects (Diggle & Kenward, 1994; Elias & Robbins, 1991; Little, 1995; McArdle & Hamagami, 1992). Panel studies of older adults are particularly sensitive to the effects of selective mortality, institutionalization, and cognitive decline. Failing to account for nonrandom attrition and other mechanisms of selection may produce estimates on a relatively privileged sample in terms of health, socioeconomic status, or cognitive ability.

A content analysis of the *Journal* revealed that the first explicit application of methods to adjust for attrition occurred in the past decade. Concerns about the role of attrition on findings from panel studies were articulated decades ago (e.g., Riegel, Riegel, & Meyer, 1967), but the development of methods for systematically handling attrition has been fairly recent. However, there is evidence on the pages of the *Journal* that social gerontologists are aware of the problem of nonrandom selection bias and are taking steps to account for it in panel studies. Because of the high likelihood of nonrandom attrition in samples with older adults, social gerontologists are not only beginning to apply these methods but are also helping to develop them.

Awareness of the problem has grown with demonstrations of differences in parameter estimates with and without adjusting for nonrandom attrition (Lillard & Panis, 1998). A variety of techniques are available to account for attrition such as Heckman two-stage estimators (Heckman, 1979; Stolzenberg & Relles, 1997), multiple imputation (Little & Schenker, 1995; Schafer, 2001), full-information maximum likelihood methods (Arbuckle, 1996), and multigroup estimation with structural equation models (Allison, 1987; Bollen, 1989; McArdle, 1994; McArdle, Hamagami, Elias, & Robbins, 1991). The greater use of longitudinal panel data is one sign of the maturation of social gerontology as a field of inquiry, but increased attention to possible bias introduced by attrition in panel studies is another one that should logically follow. Nonrandom attrition may not be consequential to parameter estimates, but scientists studying the aging process should study attrition in panel studies and test whether nonrandom attrition matters.

The content analysis of the *Journal* suggests other important features of change in the conduct of longitudinal analyses. Perhaps what is most important is that, as longitudinal analyses increased, so did the number of waves of data collection. There are two major implications of this trend. First, three or more waves of data permit the use of a whole other set of analytic procedures than are commonly used with two-wave panel studies. Time series methods such as autoregression (Dufour & Torres, 2000) and Markov state analysis (Allison, 1996) are powerful estimation procedures for assessing serial change over time. Latent growth curves are another class of models to assess change over multiple waves, but they measure both intra-individual and the interindividual trajectories over time (Willett & Sayer, 1994). There are two major approaches for estimating growth curves: hierarchical linear models (Bryk & Raudenbush, 1987) and structural equation models (Curran & Bollen, 2001). Each approach, and the software for using it, has its advantages and disadvantages. (For example, unequal interval lengths across three or more waves of data are conveniently handled in hierarchical linear models, but structural equation models are better for dealing with measurement error.) Nevertheless, both make efficient use of information and can account for attrition. Studies using growth curve or Markov models have provided fresh insights into the dynamics of health or social relationships in adulthood and helped to crystallize the value of the life course perspective.

With an increasing number of waves of data, there are also new opportunities to incorporate information from repeated measures of the independent variable(s). If possible, it is useful to update the information on the respondent to that which is most proximate to the outcome of interest as well as take advantage of the observed change in the independent variables. With three or more waves of data, it is possible to lag the change in presumed independent variables so as to be sensitive to temporal ordering and causal mechanisms.

A growing number of studies permit incorporation of continuous time variables such as a daily indication of whether a heart transplant occurred, date of institutionalization, or hourly measurements of blood pressure. Statistical models have been developed that conveniently incorporate covariates that can change over time, deepening our understanding of the influence of these factors as we age. Other studies have repeated measures at discrete time points such as depression, self-rated health, and employment status updated at each wave of data collection. For example, models that use only baseline data to predict subsequent outcomes implicitly assume that individuals do not change over time. Not all samples have repeated measures, either continuous or discrete, for such modeling. However, for those that do, inclusion of these types of variables allows researchers to calculate how risk varies over time based on the changing covariates (Allison, 1995; Fisher & Lin, 1999). The application of these types of models is growing in social gerontology (Ferraro & Kelley-Moore, 2001; Hayward, Friedman, & Chen, 1998).

Finally, as longitudinal analyses become both more common and complex, it is important to remember that longitudinal data have to be thought of in terms of the research question. Cross-sectional data may be not only sufficient but also more appropriate for some research questions. Even if longitudinal data are preferred, the length of time between waves is a critical criterion when the utility of the data is judged. Subtle changes can be captured when observations are repeated every week, month, or even year. Studies with longer intervals—5 or 10 years—provide a different lens for assessing change. The effect size of relationships may vary over time, so it is important that observation windows are appropriate for the research question (Gollob & Reichardt, 1987).

Some samples, such as the Established Populations for the Epidemiologic Study of the Elderly (EPESE), have seven

annual observation points taken in consecutive years (Cornoni-Huntley et al., 1993). This provides an in-depth examination of a relatively short time period for older adults. In contrast, the Stanford–Terman study was initiated in 1922 and subjects were followed to 1986—a total of 12 waves of data, with interval length ranging from 5 to 10 years (Elder & Pavalko, 1993). Gerontology has gained much from studies of varying interval length; we need both lenses to advance the field.

The present study systematically examined change in longitudinal analyses in the *Journal*. The findings show growth in longitudinal panel analysis, stable but meager use of repeated cross sections for studying cohort change, and recent implementation of methods to account for attrition. Although these findings help us to understand change in the *Journal*, one limitation of the present study is that conclusions about this one journal may not accurately portray changes in social gerontology more generally. The *Journal* is regarded as the flagship for social gerontology, but other journals dedicated to the study of aging have proliferated in the past three decades, and important innovations in longitudinal methods may have appeared in those journals. Moreover, the flagship journals of the home disciplines (e.g., economics and sociology) may be where many of the innovations are introduced prior to application here.

Although limited to one serial, this review of quantitative research in the *Journal* shows important changes in social gerontology. Social scientists should continue to value cross-sectional research that contributes to our understanding of age differences. At the same time, the growing use of longitudinal data has the potential to reshape our understanding of the aging process. Findings from longitudinal data published in the *Journal* have challenged and helped redefine what we know about many topics in gerontology. Given recent trends in the supply and availability of longitudinal data and statistical resources to analyze them, we anticipate more longitudinal analyses in the field. At the same time, there are important challenges in analyzing longitudinal data, especially as the number of waves and periods of observation increase. These challenges are to be welcomed as a sign of success for the field and a call to make the best use of available data. With the challenges for analyzing longitudinal data comes the potential to better understand the mechanisms and processes of aging.

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