Curr Epidemiol Rep (2014) 1:38–44
DOI 10.1007/s40471-014-0005-5

Methodologic Innovations and Advances in Social Epidemiology

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Published online: 17 January 2014

Abstract This paper reviews recent innovations and advances in social epidemiological methodology. We rely on the only social epidemiological text focused on research methods, a literature review from leading epidemiologic journals, and other influential sources. Results show that social epidemiologic methodology is robust and improving. Advances have been made in understanding causal effects, effect identification, multilevel thinking, and meaningful research. Substantial improvements have been made in our understanding and measurement of race and socioeconomic status. Obvious shortcomings remain in our understanding of simultaneity and reciprocal causation, macro-micro transitions, appreciation of culture, and the use of case studies. The subdiscipline's utility would increase if practitioners paid closer attention to methodological insights and advances.

Keywords Innovations · Social epidemiology · Methodology · Causal effects · Effect identification · Multilevel thinking · Meaningful research · Simultaneity · Reciprocal causation · Macro-micro transitions

Introduction

Summarizing methodological innovations and advances in social epidemiology is a daunting challenge. A proper summary should both recognize important innovations and illuminate gaps in the methodological landscape. Yet, we have an additional problem caused by the fuzzy boundaries of social epidemiology itself [1–3]. Just what is social epidemiology? Should a review be limited to research conducted by self-identified social epidemiologists? What about limiting advances to those working in departments of epidemiology? What about contributions from sociology and/or economics? We found it impossible to identify any bright line for deciding what research to include in this summary. Accordingly, although we tried to be inclusive, we concede that this review is somewhat selective and conforms to our view of the subdiscipline.

What follows is based on the only text, thus far, that focuses on methods in social epidemiology, *Methods in Social Epidemiology* [4]. The second edition is currently being edited by this paper's first author, so the following review incorporates updates and changes not yet found in the peer-reviewed literature. Additionally, we reviewed the social epidemiologic literature as found in leading epidemiology journals, including *Social Science and Medicine.*

We organize this review into four substantive subsections. The first addresses broad trends. The second addresses innovations in research designs and related ideas. The third section focuses on advances in measurement. The final section addresses emergent topics and approaches. A summative conclusion follows. We provide abundant citations throughout for those interested in further exploration. As it is a review, this article does not contain any studies with human or animal subjects performed by any of the authors.

Broad Trends

Social epidemiologists are becoming more methodologically sophisticated. During the past ten years there has been an increased focus on causal inference, an explosion in multilevel thinking, a shift towards policy-relevant research questions, and a refinement in our understanding of health disparities research. All of this bodes well for more meaningful substantive contributions.

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In our opinion, the most important methodological advancement in the past ten years is the attention that methodologists are paying to causality [5–10, 11•]. The discipline is undergoing a methodological revolution focused on causal inference and meaningful, if not practicable, results. Merely documenting still more correlations between social factors and disease states no longer seems acceptable.

A modern approach to causation has been thoroughly articulated [12, 13]. Briefly, most want to know what would happen to some health outcome, Y, if persons were treated with (or exposed to) some social intervention, X. This is a *causal* question and its evaluation rests on the idea of a counterfactual [14]. While it may be impossible to ever prove that X causes Y, work done toward this end tends to yield more useful results.

A key component of causal inference is effect identification. In the simplest terms, identification means that one and only one effect (or model) explains the data, even as sample size approaches infinity [15]. Borrowing from Oakes [16], imagine a Martian observing a man who is looking at a mirror and moving his head. Assume that the Martian has no information about optics or human behavior. Given the data, the Martian would not know whether the head was causing the image to move or whether the image was causing the head to move. The observed data is not causally informative because the effects are not identified: both models explain the data. Identification has nothing to do with statistical inference, per se. Sampling distributions, confidence intervals, p-values, and hypothesis tests are irrelevant because the sample size is assumed to be infinitely large. While empirical research requires both identification and statistical estimation, identification precedes estimation. Critically, collecting more of the same type of data will not solve fundamental identification problems. Instead of fussing about p-values, influential social epidemiologists are now discussing identification strategies [11•].

One approach to identification is to imagine the ideal experiment for answering a hypothesis, even if it is a practical impossibility [15]. This thought exercise illuminates the differences between the ideal yet hypothetical data and the data at hand. Such differences represent the methodological assumptions necessary to infer that X causes Y. If the assumptions are untenable or heroic, identification may be suspect and the utility of the research questioned. Furthermore, issues related to the difficulty of randomizing some treatments, such as race or sex, are often revealed.

In our opinion, the second most important methodological advancement has been the explosion in multilevel thinking and analysis [17–19]. The basic idea is that social contexts—which are necessarily at a higher or aggregate level—impact individual health outcomes. The mechanism may be direct, or it may be mediated through, say, health behaviors or even genes.

The term *explosion* is not an overstatement. In an admittedly crude analysis of epidemiologic and public health journal citations recorded in the PubMed database, we discovered that approximately 800 papers have used the term *multilevel* or *multi-level* in their titles or abstracts since 2003. The impact of such work is difficult to discern. Fortunately, a deeper, more nuanced understanding of the relationship between individuals and social contexts has begun to emerge. The challenge is the dynamic nature of this system, where individuals continually influence the social context around them and in turn, the social context influences the individuals living within [3]. These *micro-to-macro* and the *macro-to-micro* transitions are key to multilevel thinking and research [19]. Progress is apparent, but more is needed.

The third important methodologic trend is that social epidemiologists are increasingly focused on applied, policy-related, or consequential research. Berk and Rossi [20] used the term *policy space* to describe treatments/interventions that were remotely possible in our current culture and/or sociopolitical system. They aimed to steer researchers away from investigating the effects of, say, eliminating racism or making the poor as wealthy as the rich. Technically, such interventions violate the ‘closest possible world’ assumption of counterfactual thinking [21]. *Policy space* anticipates the recent suggestions of Galea [22] about consequentialist epidemiology, and Lynch et al.’s [23] consideration of the practicality of early childhood interventions for better health.

Finally, we believe important strides have been made in the study of health disparities. Health disparities are inextricably linked to social epidemiology [24]. If morbidity and mortality were merely a function of genetics and immutable environmental exposures, social epidemiologists would have little to say or do about disparate outcomes. But this is not the case. Goods and burdens have always been allocated such that some benefit while others suffer. It is actually surprising that observed disparities are not greater given the brutality of some (historical) regimes. The core challenge is the tension between agency and structure, as thoughtfully articulated by Frohlich and Potvin [25]. Ultimately, we agree with Kaufman and Harper [26•] that health disparities research requires rigorous methodology.

Research Designs

In the past decade, social epidemiologists have made advances in understanding and exploiting better research designs, and aspects of the same. We maintain that the canonical design for social epidemiology is the group randomized trial because it incorporates social interaction and manipulates something (e.g., a policy) in order to observe potential outcomes. Hannan [27] offers a superb introduction. Wagenaar et al.’s [28] effort to experimentally induce community member interaction so as to reduce alcohol abuse is noteworthy. Relatedly, Biglan et al. [29] explain how to incorporate aspects of interrupted time series and community trial designs to assess the impact of state policy changes. Data requirements for this approach are high, but the inferential potential is compelling.

The idea of structural confounding is a more subtle innovation. Although not a new concept, the term was coined in 2006 by Oakes [30]. The idea is that some imagined or modeled intervention (e.g., moving poor persons to wealthy neighborhoods) represents a positivity violation; thus, off-support inferences tend to conflict with observed data. Oakes and Johnson illuminate the issue through propensity score matching [31]; Messer et al. [32, 33] do the same with tabular methods. Oakes et al. [34] demonstrated how matched sampling can mitigate structural confounding in an otherwise conventional neighborhood effects study. Importantly, Leal et al. [35] found the problem to be severe in French urban areas, though, incredibly, effect estimates were similar when the problem was ignored. Ahern et al. [36] explained how to navigate structural confounding when studying collective efficacy. The work of Ho et al. [37] merits more attention because they describe how to pre-process data such that observations of interest are, save for a treatment/exposure, exchangeable.

Finally, social epidemiologists are increasingly exploiting natural experiments. Among notable efforts are Cerda et al.'s [38] assessment of how sociostructural change impacts on violence, Bruckner et al.'s [39] examination of cash lottery effects on Native American health, and Branas et al.'s [40] assessment of the influence of urban spaces on health. A related approach is to employ instrumental variable methods, which can be thought of as inducing natural experiments. Glymour's [41] review is both precise and accessible. Glymour et al. [42•] address the difficult to verify, subtle assumptions necessary for these models to yield unbiased effect estimates.

Measurement

The exposure of primary interest to social epidemiologists is the social system, which includes laws and policies, social movements and collective actions, conventions and norms, socialization, individual behaviors, and choices. The number of measures one might derive from the broad concept of the social system seems unlimited. More inquiry into the measurement of culture, religiosity, ideology, life goals, social control, and so forth is needed. Fortunately, some progress has been made in the measurement of traditionally evaluated aspects of the social system.

Social Capital/Social Support/Collective Efficacy. Social epidemiologists have made strides in measuring and analyzing social capital, social support, and collective efficacy. Among notable efforts are Ahern and Galea's [36] measurement of neighborhood collective efficacy using a scale developed by Sampson et al [43]. Muennig et al. [44] examined five forms of structural social capital and found mixed effects on health outcomes. Importantly, Girodano et al. [45] addressed causal inference in their study of social capital and self-rated health. In the opposite direction, Fletcher [46] examined intimate partner violence and health.

Race and Ethnicity. Race and ethnicity have long and complicated measurement histories. Both entail membership in a social group, as defined by the members themselves, an external group, or both [47]. Race, though, may best be appreciated as a construct for creating and reinforcing power structures. Though it was not always the case, social epidemiologists now realize that "race" should be understood as an ethnicity, where a group of individuals is linked together by a shared culture; it is rarely meaningful biologically [48, 49]. Rather, the mechanisms that give rise to health differences by race likely include residential segregation, and both interpersonal and institutional discrimination. Evidence of progress includes Lewis et al. [50], who conducted a psychometric evaluation of a popular measure of discrimination and urged caution. Messer and Kaufman [51] clarified the issue of *weathering* and adverse birth outcomes. Das [52] considered how 'race' gets under the skin and inhibits health. Ford [53] advanced the idea of Public Health Critical Race praxis. And Ford and Harawa [54] thoughtfully addressed the conceptualization and measurement of ethnicity.

Socioeconomic Status/Position. Socioeconomic status (SES) is a central measure in social epidemiology, but its use is complicated by the fact that scholars have not agreed on a definition, and probably never will. We maintain that SES reflects one's access to collectively desired resources, be they material goods, money, power, friendship networks, healthcare, leisure time, or educational opportunities [55]. To varying degrees, SES has been related to health outcomes for as long as social groups have existed, with higher status increasing one's chance for a long and healthy life. In a noteworthy "advance", Oakes [56•] argues that because of its imprecision, inactionable nature, and misuse, scientists should stop using the SES construct altogether. Instead, he suggests we rely on univariate measures, such as educational attainment or annual household income. Other advances include: Hajat et al. [57], who examine the effects of wealth on mortality and self-rated health in the USA; Nieto [58], who addresses the pathophysiology of poverty; Howe et al. [59], who consider measuring SES in low- and middle-income countries; Subramanian et al. [60], who recommend caution when examining the SES and CVD risk relationship in India; and Chen et al. [61], who reveal why repeated cross-sectional analysis of associations of SES can produce misleading results.

Inequality. Several important social epidemiologic hypotheses revolve around the effect of social inequality on health. Harper and Lynch [62] provide an excellent summary of inequality measures. Krieger's [63] edited text on how inequality translates into health disparities remains relevant.

Segregation. Reardon [64] offers an excellent introduction to various measures of segregation. Innovative applications include Osypuk et al.'s [65] study of the differential effects of neighborhood segregation on Mexican immigrants, Hearst et al.'s [66] study of black–white segregation and infant mortality; and Kershaw et al.'s [67] examination of residential segregation and cardiovascular disease risks.

Emergent Topics & Approaches

In this section, we aim to draw attention to emergent methodological innovations and advances. What follows is a brief summary of ideas we find noteworthy because they illuminate the dynamic nature of the relationship between societies and the individuals living within.

Social Network Analyses. Although Christakis and Fowler [68] famously examined the contagion of obesity and related outcomes, there are questions about the identification of such effects. Valente [69] offers a useful review of the issues. Advances include Doherty et al.'s [70] examination of social networks in syphilis outbreaks, and Fujimoto and Valente's [71] innovative investigation of causal social network influences on adolescent substance use. The potential utility of social network analyses could be great, but actual impacts on population health as a result of the research remain to be seen.

Systems Theory and Dynamic Modeling. A growing and vital area of social epidemiologic methodology is that of systems theory and dynamic modeling. Homer and Hirsch offer an accessible summary [72]. Building on seminal work by Koopman and Lynch [73], other advances include El-Sayed et al.'s [74] simulation to assess anti-obesity interventions, Galea et al.'s [75] consideration of causal effects and complex systems, Auchincloss and Diez-Roux's [76] approach to agent-based models, Yang et al.'s [77] spatially-enhanced, agent-based model to simulate people's walking behaviors within a city, and Diez-Roux's [78] thoughts on complex systems and health disparities. Gatrell [79] offers some cautionary notes and insightfully asks about the practicability of such investigations.

Life Course. Life course analysis is replete with identification problems, yet the ideas remain a foundation of social epidemiology. Bengtsson et al. [80] offers a helpful summary of the issues. Bastide-van Gemer et al. [81] advance life-course methods by linking them to now conventional concepts of causal inference. Davey Smith [82] traces early methods of life course analysis, and asks how far back intergenerational research should go [83]. This is an area ripe for methodological inquiry and advancement.

Neighborhood Effects. The independent effect of neighborhoods on health has been a central question for social epidemiology [84]. After a flurry of papers relying on mixed-model regression, Oakes [85] questioned our ability to identify neighborhood effects in observational designs. Vanderweele [86] clarified many of the assumptions necessary for identification. Beyond the insights into structural confounding described above, other advances include Schaefer-McDaniel et al.'s [87] use of systematic social observation. Additionally, several studies by Chaix and colleagues [88, 89] examine the aspects of confounding and participation in neighborhood data.

It seems that the most recent work is pushing investigators away from the notion of neighborhoods as the central social epidemiological unit of analysis, instead focusing on families. In their quasi-experimental study, Sariaslan et al. [90] found negligible impacts of neighborhoods on criminality, and suggested that social epidemiologists turn their attention to families. Although he disagreed with their empirical results, Oakes [91] agreed that it is time to move past neighborhoods and examine the influence of family structures. Additionally, Merlo et al. [92] found that families appear to play an important role in health outcomes. Votruba and Kling [93] examined the effects of neighborhood characteristics on the mortality of black male youth from the important Gautreaux study, yet found that human capital measures were more important than neighborhood deprivation measures. The torrent of multilevel studies purporting to reveal independent effects of neighborhoods on health outcomes appears to be subsiding.

Mediation/Decomposition. Understanding *how* some exposure, X, causes some change in an outcome, Y, is central to scientific explanation. After seminal work by Robins and Greenland [94], social epidemiologists have advanced this important, but difficult area. Influential work includes Kaufman et al. [95], who clarified what biological mediation is not, and Vanderweele [96], who described identification conditions for controlled direct effects, and natural direct and indirect effects. More recently, Nandi et al. [97] assessed the effect of childhood SES, as mediated by adult SES, on later-life health. Overall, the primary contribution is that the approach to mediation famously advanced by Baron and Kenny [98] entails assumptions that are often indefensible in a social epidemiologic investigation.

Genetics. In the current era of genomics, if not genetic fetishism, social epidemiologists are in a unique position to contribute to our understanding of the interplay between genetics and the social environment. Freese [99] offers an excellent introduction to genetics for social scientists. Rehkopf and Adler [100] remind us that socioeconomic structures may be more important that genes. Toyokawa et al. [101] review how social conditions affect psychological health, and the epigenetic process. Strikingly, Godfredson [102] challenges social epidemiologists to show that inherited intelligence (i.e., IQ or G) is not the fundamental cause of health disparities.

Conclusions

The state of social epidemiologic methodology is robust and improving. Methodologists continue to illuminate assumptions and offer new tools for addressing important questions. Nevertheless, several gaps remain. Among them is the slippery issue of simultaneity and reciprocal causation. VanderWeele et al. [103] have made some progress on this problem, but more attention is needed. Perhaps recent work [104] on coevolution will help. Less technically, but no less important, is a paper by Glass [105], who reminds us that "culture" remains overlooked and understudied. Our take is that carefully conducted case studies are woefully lacking in the literature. We believe work such as Elster's overlooked *Local Justice* project [106] would improve our understanding of the ways in which social processes allocate goods and burdens that impact health. Ultimately, we hope this synthesis of recent methodologic innovations in social epidemiology will enhance and inspire new efforts to improve the health of populations.

Compliance with Ethics Guidelines

Conflict of Interest J.M. Oakes declares no conflicts of interest.
K.N. Andrade declares no conflicts of interest.

Human and Animal Rights and Informed Consent All studies by J.M. Oakes involving animal and/or human subjects were performed after approval by the appropriate institutional review boards. When required, written informed consent was obtained from all participants.

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