Methodological Approaches to Understanding Causes of Health Disparities

Understanding health disparity causes is an important first step toward developing policies or interventions to eliminate disparities, but their nature makes identifying and addressing their causes challenging.

Potential causal factors are often correlated, making it difficult to distinguish their effects. These factors may exist at different organizational levels (e.g., individual, family, neighborhood), each of which needs to be appropriately conceptualized and measured. The processes that generate health disparities may include complex relationships with feedback loops and dynamic properties that traditional statistical models represent poorly.

Because of this complexity, identifying disparities' causes and remedies requires integrating findings from multiple methodologies. We highlight analytic methods and designs, multilevel approaches, complex systems modeling techniques, and qualitative methods that should be more broadly employed and adapted to advance health disparities research and identify approaches to mitigate them. (*Am J Public Health*. 2019;109:S28–S33. doi:10.2105/AJPH.2018.304843)

Neal Jeffries, PhD, Alan M. Zaslavsky, PhD, Ana V. Diez Roux, MD, PhD, John W. Creswell, PhD, Richard C. Palmer, DrPH, Steven E. Gregorich, PhD, James D. Reschovsky, PhD, Barry I. Graubard, PhD, Kelvin Choi, PhD, Ruth M. Pfeiffer, PhD, Xinzhi Zhang, MD, PhD, and Nancy Breen, PhD

Understanding health disparity causes is critical to developing policies to eliminate them. However, identifying these causes is challenging for several reasons: Causal factors are frequently correlated or interact with each other and may form long causal chains that hinder the effort to distinguish causal effects from noncausal associations. Causal mechanisms may operate at different levels, which include social structures, behaviors, and genes, each of which entail different approaches to conceptualization and measurement. Causal processes leading to disparities may involve feedback loops and dependencies that result in dynamic relations and emergent properties that are not easily reducible to independent effects. Key to understanding complex causes is selecting appropriate methodologies and using complementary approaches.

These challenges engender recommendations that researchers further develop and expand the use of (1) study design and analytical methods that maximize the ability to draw causal inferences from observational data, (2) modeling techniques that account for the multilevel nature of health disparity causes, (3) complex systems and simulation methods for modeling dynamic relations, and (4) qualitative and mixed methods that allow a better understanding of relationships that cannot be achieved using quantitative methods alone. We highlight methods supporting these recommendations.

STUDY DESIGN AND ANALYTICAL APPROACHES

Causal effects may be defined as the difference between potential outcomes that would arise from different treatments.[1] But for a particular participant at a particular time, only the outcome associated with the "assigned" treatment can be observed; the outcome associated with the treatment that was not provided is counterfactual. Research study design and analysis are largely concerned with finding ways to compare observed outcomes and appropriate counterfactuals to make inferences regarding a causal effect.

Conceptual models are critical to social science research, and in recent decades formal graphical tools have been adopted to guide analyses and interpretation from a causal inference perspective. In particular, directed acyclic graphs[2] are used to explicate the hypothesized causal relationships, determine what causes are identifiable considering the information available (and under what conditions), and identify unintended consequences of some analytical approaches (e.g., increasing rather than decreasing bias as a result of statistical adjustment). By forcing investigators to be explicit and share their underlying assumptions, these approaches also can enhance the understanding of conflicting results and facilitate discussion of plausible causal pathways. Ideally, this process provides researchers a clearer understanding of relevant relationships and suggests analytical approaches to identify the causal effects of interest. In our discussion of analytic and study design approaches, directed acyclic graphs can be used to focus on the assumptions and requirements for causal inference.[3]

ABOUT THE AUTHORS

Neal Jeffries is with the National Heart, Lung, and Blood Institute, National Institutes of Health (NIH), Bethesda, MD. Alan M. Zaslavsky is with the Department of Health Care Policy, Harvard Medical School, Boston, MA. Ana V. Diez Roux is with the Dornsife School of Public Health, Drexel University, Philadelphia, PA. John W. Creswell is with the Department of Family Medicine, University of Michigan, Ann Arbor. Richard C. Palmer, Kelvin Choi, Xinzhi Zhang, and Nancy Breen are with the National Institute on Minority Health and Health Disparities, NIH, Bethesda. Steven E. Gregorich is with the Department of Medicine, University of California, San Francisco. James D. Reschovsky is with Mathematica Policy Research, Washington, DC. Barry I. Graubard and Ruth M. Pfeiffer are with the National Cancer Institute, NIH, Bethesda. Richard C. Palmer and Nancy Breen are also Guest Editors for this supplement issue.

Correspondence should be sent to Neal Jeffries, PhD, National Heart, Lung, and Blood Institute, National Institutes of Health, Room 9194, MSC 7913, 6701 Rockledge Drive, Bethesda, MD 20892 (e-mail: nealjeff@nhlbi.nih.gov). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints" link.

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Experiments and Observational Studies

When practical, randomized experiments provide an ideal setting for evaluating a causal effect. When "treatments" (or exposure to the hypothesized causal factor) are applied under the control of a random process, the researcher can have the most confidence that the treatment is independent of other factors that might affect outcomes and bias the estimates of treatment effects.

Experimental randomization provides powerful evidence for the internal validity of a study, specifically, the causal interpretation of differences in outcomes within the study sample. Experimental research on health disparities faces 2 major challenges: it may be logistically or ethically infeasible to "randomize" causal factors of interest (e.g., exposure to racism, neighborhood attributes like walkability), and there is uncertainty about the generalizability of effects seen in the experiment to other populations and situations. Issues of generalizability become especially salient when interactions between factors are important, as may often be the case for determinants of population health, and therefore the broader context (or constellation of other cooccurring factors) of the trial may influence its results. Also, generalization may be further limited[4] because randomization excludes individuals' self-selection to treatment options that might work better for them than a randomly assigned treatment. Primarily for these feasibility and generalizability reasons, observational studies have become the mainstay of much research on health disparity causes.

In observational studies, the researcher does not control the treatment or exposure. Without randomization, the exposure of interest (e.g., income) may be correlated with other variables (e.g., education) that contribute to a disparity. This confounding is the key challenge in using observational studies to identify health disparity causes. The intercorrelated and interrelated nature of many factors of interest makes identifying the causal pathway an especially vexing problem in this field. The following section highlights some of the analytical and design approaches used to improve the utility of observational studies in drawing causal inferences in minority health and heath disparities.

Addressing Confounding of Observational Data

Regression analysis. Regression analysis is a primary tool for analyzing observational studies; therefore, correct application and interpretation of regression techniques are critical to health disparities research. Regression-based methods are applied to observational data to create "comparability" (i.e., adjust for potential confounding covariates) across treated and untreated groups to improve causal inference regarding the disparity (defined as the treatment's or exposure's effect on health). The validity of estimates of health disparities attributable to membership in a disadvantaged group, as in any causal inference drawn from regression modeling, depends on the assumption of a correctly specified model in which all the important covariates and confounders are included as independent variables in the correct functional form. Determining these assumptions' viability may be especially problematic, considering the many potentially relevant factors and the complex relationships among each that are common in health disparity settings.

The Peters-Belson[5,6] and related Oaxaca-Blinder[7,8] methods are regression extensions that are well suited for assessing health disparities by modeling counterfactuals.[9] The Peters-Belson method first regresses a health outcome on individual-level covariates using data from the majority group and then uses the coefficients from the fitted model to estimate the expected values of the outcome for minority group individuals as if they were members of the majority group. These counterfactuals applied to group differences in the observed health disparity are decomposed into a part that is explained by the covariates and a remaining part that is not explained by the covariates.[10]

For example, Rao et al.[11] used logistic regression to apply the Peters-Belson method to assess Black–White disparities in screening for colorectal cancer. First, they used a logistic regression model with only the White race sample to estimate coefficients for the covariates (e.g., income, having insurance coverage, having a usual source of medical care) associated with the rate of colorectal cancer screening and the difference between Whites and Blacks. Then, they used these regression coefficients for Whites to predict rates of colorectal screening for Blacks. The difference between the observed mean (i.e., proportion screened) for Whites and the mean of the predicted values for Blacks is the part that is explained by the covariates in the model. The remainder is the unexplained disparity. Because the Peters-Belson method only fits the regression to the majority group, it is useful when the minority group sample is small.

This partitioning technique also can be used to estimate the potential reduction in a disparity if an intervention is implemented to modify the covariates between the groups. The Oaxaca-Blinder method is similar to the Peters-Belson method but can be used to further decompose the unexplained disparity.

Matching. Matching can be used as an alternative or adjunct to regression to improve comparability between treated and untreated groups by pairing treated cases with untreated cases manifesting similar covariate values. When applied correctly, matching avoids 3 possible pitfalls of simple regression adjustment: extrapolation of regression predictions beyond the range of observed data, manipulation of regression models to obtain a desired outcome, and bias arising from a misspecified regression model. Matching may be difficult when there are many variables under consideration.

Propensity score. An aid to this process is the propensity score, defined as the probability that an observation will be in the treated or exposed group because of its covariates. If a suitable propensity score model can be identified, the resulting estimated scores can be used in several ways to help bolster a causal inference about a health disparity.[12] These include stratifying on propensity score values during analyses, weighting each group's data inversely to its propensity score, and matching control- and treatment-group individuals by propensity scores. Importantly, these methods can promise balance only on observed covariates; the causal claims arising from these methods depend on the assumptions that there are no unmeasured confounders and that the propensity model correctly specifies the functional relationship between covariates and propensity score. These assumptions may be problematic for health disparities research, considering the complex range of social and biological contributors.

Instrumental variable analysis. Instrumental variable analysis provides an alternative approach to controlling for confounding. An instrumental variable affects the probability of receiving a particular treatment or exposure but has no plausible direct effect on the outcome.[13] For example, studies of cancer survivors find differences by income in quality of life. Yet, these associations cannot be interpreted as demonstrating causal effects of income on quality of life, because quality of life also affects income. A suitable instrumental variable would exclude this possibility of reverse causation.

Short and Mallonee[14] constructed an instrumental variable for income information on home ownership, sources of unearned income, marital status at diagnosis, and spousal characteristics. Because the instrument represented resources acquired or measured before the onset of cancer, reverse causality could be excluded as an alternative explanation for these effects. The assumption that the instrumental variable for income has no causal effect on or association with the quality of life outcome, except through its effect on income, is the "exclusion condition" in this example. The exclusion condition is essential to instrumental variable analysis, but it cannot be proven empirically. Instead it must be founded on previous theory about the possible causal mechanisms at work (in this case the exclusion condition might be questioned if one believes marital status at diagnosis has a direct effect on later quality of life that is independent of income).

When a satisfactory instrument can be identified, the analysis has the benefit of controlling for both measured and unmeasured confounders. Because unmeasured confounders are common in health disparities research, instrumental variable analysis can be important for health disparities analysis. However, finding a suitable instrument that plausibly meets the exclusion condition is challenging, especially if one is limited to the variables available from secondary use of an existing data set.

Natural experiments. Natural experiments can be useful in assessing the impacts of policies relevant to health disparities. In natural experiments or quasiexperiments, the treatment is not randomized[15] but instead is determined by some actor or force in ways that approximate randomization in that it is plausibly unrelated to potentially confounding factors. Examples include differential geographic availability of health services or phase-in of a policy such as a new educational approach or health insurance through Medicaid expansion. The researcher identifies a situation in which a treatment is applied and selects an analysis method to extract information relevant to assessing the causal effects. In the interrupted time series design, the change occurs at a particular time, such as enactment of a new law (e.g., banning housing discrimination, reducing the thresholds for Medicaid coverage). The pre- and postchange outcome trends are compared, possibly in comparison with simultaneous effects on another group unaffected by the change. In the regression discontinuity design,[15] we defined exposure as falling on 1 side of a threshold of some characteristic. For example, areas become eligible for a program when the percentage in poverty exceeds a program cutoff. In both designs, including control groups can be used to strengthen causal inference.

Behrman,[16] for example, used a discontinuity design to evaluate whether a change in national education policies to increase primary school opportunities for women would lead to reduced HIV transmission. Natural experiments, like randomized studies, are subject to concerns regarding generalizability to broader settings, as the environment allowing comparisons of similar groups might reflect unusual circumstances that are not widely available but may influence the measured outcome. For instance, a cigarette tax passing with voter support may reflect a populace favoring reduced cigarette consumption.

Marginal structural models. Major challenges in studying health disparities are the presence of time-varying confounders and the possibility of variables being simultaneously confounders and mediators. For example, neighborhood of residence may affect income (through access to jobs) and income may in turn affect residential location, and both income and neighborhood may affect cardiovascular risk. Income is therefore both a confounder and a mediator for neighborhood health effects. Marginal structural models[17] have been developed to address biased results from standard regression techniques for handling confounding with this type of complication, improving on some older methods. This modeling approach uses inverse proportional weighting to create pseudopopulations in which an exposure's effect is not confounded with the covariates used for adjustment. This approach allows causal inference that reduces bias arising from time-varying confounders. Such confounders are common in health disparities research that collects longitudinal data reflecting complex relationships among variables.

Fixed-effects models. Causal inference from observational data in health disparities may be greatly enhanced when at least some individual-level confounders can be held constant. This is possible in some longitudinal settings with data collected from individuals over time. Although the use in economics is longstanding, only recently have econometric fixed-effects models been adopted in public health and epidemiology. In fixed-effects models,[18] an indicator variable for each individual (or group if that is the unit of analysis) stands in for all time-invariant characteristics, observed or not, thus estimating the effects of a time-varying individual-level treatment while conditioning on all time-invariant person-level characteristics.

Different specifications of fixed-effects models are adapted to analyses of various data-collection designs as well as various assumptions about the structure of the intervention's time-varying effect. For example, a difference-in-differences analysis can be used to estimate the effect of a single intervention applied at a single time point. More general versions incorporating pre- and post-intervention trends are commonly applied to analyzing data collected under an interrupted time series design, whereas change versus change models identify changes in trend at multiple time points corresponding to introduction of several interventions.

Fixed-effects models do have limitations: they may be subject to confounding by unmeasured time-varying covariates, are not well suited to the investigation of causal processes with long-term lags, and may be inefficient if little within-person variation is observed. Mujahid et al. examined fixed-effects models in a health disparities context to assess whether between-person differences in cardiovascular outcomes (e.g., racial differences) persist after controlling for higher-level differences (e.g., neighborhood factors).[19]

The selection of techniques is not comprehensive but instead emphasizes some of the more common and useful approaches to mitigating confounding. In a broad review of US health disparities, Adler and Rehkopf[20] highlighted a similar set of methodological approaches to reduce confounding. We, instead, focus on methods to address specific challenges in disparities research and include more recently developed approaches.

Confounding may be the most acknowledged problem for observational studies, but a separate, related problem concerns appropriate analysis for causes that can arise from multiple levels of analysis. Analyses that neglect this multilevel aspect can also lead to biased estimates and incorrect inferences.

MULTILEVEL NATURE OF HEALTH DISPARITY CAUSES

Considering the complexity of health disparities etiology, factors driving health outcomes may arise from different levels. For example, when modeling cancer mortality, differences by socioeconomic status may be related to the patient's genetic background, health history, residential and work environment, and state-based health care policies. Multiple levels may need to be incorporated into modeling. The multilevel nature of potential health disparities causes might occasion significant analytic complexities.

Factors may affect individuals in the same way, for example, individuals in a common neighborhood may share environmental exposures, health care providers, and state policies. This sharing introduces correlation between individual outcomes that must be accommodated in statistical modeling. Hierarchical, or multilevel, models have been developed to account for correlation in such situations.[21,22]

Furthermore, failure to incorporate a relevant level in the analysis can lead to incorrect inferences. For example, 2 related questions could be posed: across hospitals, does higher average patient income result in lower readmission rates and, within hospitals, do patients with higher incomes (relative to other patients in the same hospital) have lower readmission rates? To address these questions, consider a sample of hospitals and their patients' income and readmission information. A model that decomposes the effect of income into between- and within-hospital effects would include 2 income variables: a hospital-level variable describing average patient income and a patient-level variable describing the difference between the patient's income and the hospital's mean value. In a multilevel model, the effect of hospital-level mean income on 30-day readmission represents a between-hospital income effect addressing the first question.

The effect of patient-level income deviation scores represents a within-hospital effect, reflecting how patients' income affected their probability of 30-day readmission relative to their same hospital counterparts with average incomes. When the corresponding between- and within-hospital effects are not equivalent, a simpler model that regressed the outcome onto the observed patient-level income variable would be misspecified; the estimated income effect would represent a weighted average of the between- and within-hospital effects of patient income and would obfuscate the potentially complex relationships between patient income and the modeled outcome.[23]

A related feature of multilevel models important to health disparities research is their ability to separate the factor effects at different levels and to model interactions across levels. For example, the effect of patient income on measures of diabetes control might be different in clinics that have nurse educators who follow up with patients than in those that do not. The moderating effect of clinic staffing on income disparity is represented by a cross-level interaction in the multilevel model (in this case, between the clinic and individual patient level). Such effects may elucidate the mechanisms of the income effect or suggest interventions, possibly operating at several levels, to reduce disparity.

The multilevel nature of health disparity relationships needs to be characterized by more complex structures among factors. In Subramanian et al.,[24] a multilevel model reexamination of 1930 census data shows that the interpretation of the relationship between an individual's race and literacy is improved by accounting for state-level policy characteristics and their cross-level interaction with individual characteristics. The richness of these models may lead to better understanding but will also require more complicated analyses. Hierarchical modeling is a common analytic approach to building multilevel models, but other methods can also incorporate this type of complexity. Complex systems and simulation-based analyses can capture these relationships and model feedback loops and other complexities in relationships among health disparities factors.

COMPLEX SYSTEMS AND SIMULATION MODELING

Complex systems approaches can be used to provide insight into how a system functions, identify points for intervention, explore specific hypotheses about causation, and identify plausible impacts and unintended consequences of an intervention under varying conditions. These methods are especially useful in situations involving factors at different levels, feedback, and dependencies, all of which characterize health disparity questions.[25] The complex systems perspective is general and encompasses several analytic approaches, including agent-based modeling, system dynamics simulation, network analysis, and microsimulation. The choice of analytic approaches depends on the research question.[26]

Agent-based models allow the modeling of interactions and the responses to a set of conditions, considering the rules used to define the agent's behaviors (these can be either probabilistic or deterministic[27]) and can assess these interactions' effects. For example, Orr et al.[28] used agent-based modeling to forecast the effect of improving the quality of neighborhood schools on reducing racial disparities in obesity-related dietary behaviors. System dynamics simulations are particularly well suited for understanding population-level processes and flows. The Prevention Impacts Simulation Model, a system dynamics model, was used to examine the potential influence of different types of interventions for reducing cardiovascular risks.[29]

Network analysis investigates how social ties between individuals, groups, or organizations contribute to health disparities. Buchthal and Maddock[30] employed network analysis to identify the gap in communication and collaboration patterns of organizations that provide nutrition education to a low-income, ethnically diverse population in Hawaii.

These models have great potential to improve the assessment and identification of effective interventions to reduce health disparities. As computational capabilities grow, system approaches may lead to more sophisticated modeling reflecting realistic complexities, and simulation methods will illuminate the relationships among important factors to address health disparities.[25,31] For all models, however, underlying assumptions need to be carefully assessed to ensure interpretable and meaningful results. Using evidence and data to formulate the dynamic models, set parameter values, and validate model functioning is also crucial. Comparing models is thus an important aspect of systems analysis, as is done comprehensively in the Cancer Intervention and Surveillance Modeling Network.[32]

INCORPORATING QUALITATIVE APPROACHES

The quantitative methods discussed are best employed in the context of an existing conceptual model with hypothesized relationships between outcomes and possible causal factors. Qualitative research can be used to identify plausible causal factors and processes that are relevant to health disparities, generate and refine conceptual models and hypotheses, and explain the relationships among factors documented in quantitative studies. These analyses may be especially valuable for uncovering important factors when applied to populations for which little previous research exists. Qualitative approaches to identifying health disparity causes can serve as stand-alone analyses or can augment, guide, or enhance quantitative methods. Building a holistic picture using the descriptions study participants provide to understand complex social, economic, or organizational phenomenon is the common element that resonates in all qualitative research.[33]

Qualitative research is primarily inductive and depends on the purposeful selection of participants. This perspective distinguishes qualitative from quantitative research.[34,35] Ideally, qualitative research provides a realistic interpretation of the world from the participants' perspectives. However, these interpretations need to be validated (e.g., member checking, intercoder agreement checks[36]). Qualitative research findings focus on specific situations and contexts and, consequently, have limited generalizability. Using qualitative approaches in health disparities research remains limited and only recently has been integrated with quantitative work.

Quantitative and qualitative methods, once seen as diametrically opposed, have emerged as essential complementary tools in community-based participatory research and other types of health disparities research.[37,38] Mixed methods research integrates quantitative and qualitative methods to corroborate results, generate causal hypotheses, elaborate on findings, or augment intervention trials or program evaluations.[39] Mixed methods may use qualitative and quantitative methods simultaneously or sequentially. In sequential designs, a component produces data or theory that informs the next component.[34,40]

Stewart et al.[41] presented 2 exemplar mixed model studies illustrating the use of qualitative methods. The first examined social exclusion and social isolation in low-income populations sequentially. The authors used qualitative interviews in the first phase to guide item development for second phase survey questions. The second study examined family caregivers' support of seniors with chronic conditions. Qualitative interview data were collected during and after the intervention to explore processes, such as the participants' perceived impacts and satisfaction with the intervention. The richness of data obtained from a mixed methods approach allows findings to be corroborated and expanded. Corroboration is important for health disparities studies, especially studies of hard-to-reach populations because of the limited background literature

RECOMMENDATIONS FOR IMPROVING HEALTH DISPARITIES RESEARCH

Recommendation 1: Strengthen and promote analytic methods that maximize the ability to draw causal inferences from observational studies and enable a better understanding of health disparity causes.

Recommendation 2: Incorporate and further develop models that reflect the multilevel nature of health disparity causes to provide richer and more accurate characterizations of plausible causal pathways.

Recommendation 3: Expand the use of complex systems and simulation modeling to increase the ability to model intricate relationships between health disparities and health determinants and to assess health disparities interventions.

Recommendation 4: Incorporate the further use of qualitative and mixed methods analysis so participant perspectives can illuminate plausible causal mechanisms and provide better understanding of the impacts of policies and interventions.

on these populations. More approaches to integrate quantitative methods with qualitative approaches to identify causes and validated findings are needed.

CONCLUSIONS

Research of health disparities causes is subject to several sources of complexity. Disparities may arise from multiple causes that are susceptible to cofounding that masks true effects. These causes may arise from different levels, thereby requiring more complex analytic methods. Causal pathways may exhibit feedback loops and interdependencies that are poorly assessed using simple, standard modeling approaches. The box on page S32 provides recommendations to address these challenges.

Linking research on causes to policy action (and vice versa) is critical to making etiologic research policy relevant and improving etiologic research so more effective policies and interventions can be identified. To do so, it is vital to improve available methods and the training of future generations of diverse researchers in multiple methodologic approaches. AJPH

CONTRIBUTORS

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