Why the Gap in Evaluating the Social Constructs and the Value of Medicines?

Jacquelyn McRae¹ · Eberechukwu Onukwughu¹

Accepted: 3 August 2021 / Published online: 30 August 2021
© The Author(s), under exclusive licence to Springer Nature Switzerland AG 2021

Abstract

The compounding effects of occupying two or more social identities, such as being “Black” and “female” have been described in intersectionality theory. Intersectionality, a term coined by legal scholar and activist Kimberlé Crenshaw, is a framework to consider race and other social identities as overlapping, dynamic, and interdependent identities. Since its inception, intersectionality has made significant in-roads to inform the conceptualization and empirical investigations of race, gender, and other social identities in sociology, critical race theory, anthropology, feminist theory, and other disciplines. However, to date, cost effectiveness research has not systematically examined race *intersecting* with other social identities in the valuation of medicines using social theory, such as intersectionality. Consequently, cost effectiveness analysis, which is a method to study the value of medicines in diverse populations, has not been subject to sufficient examination through an intersectionality framework. In the US context, the racial injustices experienced and documented within diverse communities highlight that health outcomes cannot be examined in a vacuum; overlapping social identities such as race and class in relation to context have real effects on health behaviors, measured preferences, and economic costs. Failure to examine the effects of overlapping social identities on heterogeneity in benefits and costs can result in inadequate information for decision makers to evaluate the value of treatments. Without consideration of the overlapping social identities in diverse populations, there is a risk that cost effectiveness analysis results will not accurately reflect the value of treatments in socially disadvantaged populations. In this Current Opinion, we provide an outline for conducting socially conscious cost effectiveness analyses, using intersectionality as one example.

1 The Case for Socially Conscious Cost Effectiveness Research in Value Assessment

Cost effectiveness research simultaneously considers the additional health benefits of a new treatment along with its additional costs in order to quantify the value of the new therapy relative to a comparator treatment. Health equity research has demonstrated a connection between a population’s social experiences as a reflection of a social identity (e.g., racism as a product of race) and their health status [1]. Yet, there has been limited empirical research that has bridged population social experiences as the result of layered social identities with the cost effectiveness of treatments

designed to improve health status. Layered social identities represent the variety of overlapping social characteristics that an individual may occupy. For example, a female individual may be perceived to be of Black race, female gender, and non-disabled. These three social identities are ‘layered’ and jointly impact her lived experiences in, for example, seeking healthcare. As decision makers review the results from cost effectiveness research and the implications for diverse populations, it will be important to consider the effect of compounding social disadvantages on the estimated value of treatments. Without consideration of the overlapping social identities in diverse populations, there is a risk that cost effectiveness analysis (CEA) results will not accurately reflect the value of treatments in socially disadvantaged populations.

Intersectionality offers one approach to incorporating social perspectives into a CEA. Intersectionality was developed by legal scholar and civil rights advocate Kimberlé Crenshaw [2]. Within intersectionality theory, social characteristics, such as race and gender, intersect to define

✉ Jacquelyn McRae
Jacquelyn.mcr@umaryland.edu

¹ Department of Pharmaceutical Health Services Research,
University of Maryland, 220 N. Arch St, 12th Floor,
Baltimore, MD 21201, USA

Key Points for Decision Makers

The compounding effects of occupying two or more social identities, such as being “Black” and “female” have been described in intersectionality theory, which is a framework to consider multiple social identities as overlapping, dynamic, and interdependent.

To date cost effectiveness research has not systematically examined intersecting social identities in the evaluation of medicines using social theory, such as intersectionality.

In this Current Opinion, we provide an outline for conducting socially conscious cost effectiveness analyses, using intersectionality as one example.

overlapping and interdependent pathways through which differences in experiences arise among individuals, e.g., the marginalization of Black women socially through sexism in the Civil Rights Movement and racism in the American Feminist movement [3, 4]. Prior to intersectionality, there was limited literary recognition of the compounding effects of embodying multiple social identities such as Black race and female gender. Although intersectionality has informed contemporary evidence across academic disciplines, intersectionality has not generally informed economic evaluations and our study of heterogeneity in the cost effectiveness of treatments in the USA.

Intersectionality requires researchers to account for the multiple overlapping social systems that define and characterize group experiences and investigate how these dynamic systems inform individuals’ daily choices and outcomes. Multiple systems of oppression, such as racism and classism, ‘sit on top’ of individuals and shape their everyday interactions with the world [5], including health-related decisions. These overlapping systems and individual actions should not be disconnected or studied in isolation. Equity-driven trade-off studies, such as a distributional CEA, evaluate the opportunity costs of deploying a medical treatment based on “equity-relevant” characteristics [6]. Commonly studied equity-relevant characteristics in CEAs include race, socioeconomic status, and geography [7]. Given that characteristics such as race [8] and socioeconomic status are socially mediated variables, their effects must be considered within the context of existing social structures, including discriminatory systems such as racism and classism [5]. As such, measurement and interpretation of overlapping social identities in CEAs is ideally situated within a socially conscious framework, such as intersectionality. Current approaches to examine heterogeneity and equity in CEA do not define or

interpret socially mediated variables within the context of existing social structures.

Over the last two decades, health economists have evaluated the impacts that race/ethnicity and socioeconomic status may have on the estimated cost effectiveness of medicines. Hoch et al. [9] and Willan et al. [10] provided a framework for conducting heterogeneity assessments using regression methods. In their 2004 article, Willan and colleagues examined heterogeneity in the cost effectiveness of psychological interventions for a homeless population in Baltimore by race using clinical trial data. Their work provided an early illustration of the potential for regression-based approaches to identify subgroup differences in the costs and effects of technologies. At the present time, health economic literature has fallen short of routinely incorporating social science frameworks of overlapping systems of oppression into studies of health outcomes, cost, and treatment effectiveness.

We argue that socially conscious CEAs—acknowledging the relationship between an individual’s layered social identities and medication value—are warranted. In the following sections, we illustrate how a regression-based CEA that includes information about the individual’s socially assigned race, social class, geography, and utilization of healthcare services provides an initial opportunity to critically assess heterogeneity in the value of medicines based not only on social categorizations (e.g., race, class) as interdependent subgroups, but also on the overarching social dynamics (e.g., racism, classism) through which the effects are mediated.

2 Heterogeneity in Regression-Based CEAs

We illustrate the implications of an intersectionality perspective for a CEA using statistical regression models, beginning with ordinary least-squares regression models. In a given situation, a more complex model specification will be appropriate, and the main points illustrated here would still apply. In regression-based CEAs, the outcome measure is the incremental net monetary benefit (iNMB). The iNMB is an arithmetic transformation of the incremental cost effectiveness ratio. Equation 1 presents a regression model of the NMB (i.e., y_i), of treatment as a function of the treatment group (x_1), social class (i.e., x_2), and socially assigned race (i.e., x_3), where i represents individuals.

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{1i} \times x_{2i} + \beta_5 x_{1i} \times x_{3i} + \varepsilon_i, \quad (1)$$

x_1 is the treatment (1 = new treatment, 0 = standard of care); x_2 is the social class (1 = high income/college or post-graduate education, 0 = other); x_3 is the socially assigned African American (AA) race (1 = AA, 0 = other); $x_1 \times x_2$ is the interaction between treatment indicator and social class; $x_1 \times$

x_3 is the interaction between treatment indicator and socially assigned AA race.

Excluding the interaction terms, the coefficient on x_1 (i.e., β_1) provides an estimate of the iNMB of the new treatment compared to standard of care. Additional variables in the model control for potential confounding due to social class (x_2) and socially assigned race (x_3) [11]. If the study objective is to investigate heterogeneity in the iNMB, this can be accomplished with interactions between treatment and social class (i.e., $x_1 \times x_2$) or between treatment and socially assigned race (i.e., $x_1 \times x_3$). Statistically significant interaction terms (i.e., β_4 and β_5) demonstrate disparities in the average iNMB according to socially assigned race and social class.

While the finding of statistically significant interaction terms can provide additional information regarding the value of the treatment, additional terms will be needed based on an intersectionality perspective. In order to account for the potential compounding effects of socially assigned AA race and a higher social class, the equation would need to consider the joint effect (i.e., the interaction) of social class and socially assigned race on the iNMB, as shown in Equation 2 below:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{1i} \times x_{2i} + \beta_5 x_{1i} \times x_{3i} + \beta_6 x_{1i} \times x_{2i} \times x_{3i} + \varepsilon_i, \quad (2)$$

x_1 is the treatment (1 = new treatment, 0 = standard of care); x_2 is the social class (1 = high income/college or post-graduate education, 0 = other); x_3 is the socially assigned AA race (1 = AA, 0 = other); $x_1 \times x_2$ is the interaction between treatment indicator and social class; $x_1 \times x_3$ is the interaction between treatment indicator and socially assigned AA race; $x_1 \times x_2 \times x_3$ is the interaction between treatment indicator, socially assigned AA race, and social class.

The coefficient on the three-way interaction (i.e., β_6) considers the additional change to the iNMB associated with the compounded effect of social class and socially assigned race. Using Equation 2, we can now test for a statistically significant variation in the iNMB of treatment among subpopulations belonging to both social categories (i.e., African American AND high income/college or post-graduate education). Absent this three-way interaction term, the additional effects of social class and socially assigned race on iNMB are considered independently of each other (i.e., using separate two-way interaction terms). Consequently, the model is unable to test for the role of interacting relationships that have been discussed within the context of intersectionality. The above example illustrates one implication of intersectionality for model specification. Another implication relates to the interpretation of included measures. The specification of regression models within the context of socially conscious CEAs replaces a focus on ‘risk factors’ with the study of proxies

for social factors. For example, focusing on the inclusion of socially assigned race, one might ask “what are the implications when the included measure (i.e., socially assigned race) does not overlap with other measures of race (e.g., self-reported race)?”. There is published evidence that conclusions regarding health status, health outcomes, and treatment receipt will vary depending on whether socially assigned race or self-reported race is used [11–16]. The implications of using socially assigned race vs self-reported race for value assessments are understudied.

To illustrate how incremental net health benefit might differ across groups, consider a hypothetical study of the cost effectiveness of a prostate cancer treatment among European American and African American men, among whom there are documented disparities in treatment receipt and in the exposure to social stressors. In this case, the iNHB can differ in populations owing to the differing experience of social stressors [17], with potential implications for observed health benefits and costs. For example, African American men are less likely than European American men to receive treatment for prostate cancer [18]. Healthcare costs may be ‘underestimated’ (to a greater degree for low-income African American men [19] and to a lesser degree for insured African American men [19] and appear to be lower than the costs for individuals who do not experience barriers to treatment receipt. In contrast, healthcare costs may be ‘overestimated’ among African American men if disease progression due to a lack of treatment leads to higher utilization of acute care services. When social stressors are conceptualized as getting ‘under the skin’ [20, 21], social stressors may complicate the estimate of treatment effectiveness, resulting in a potential reduced treatment benefit (worsening health inequities if access to treatment is also reduced). An economic evaluation conducted among subgroups that does not account for existing social constructs may result in biased conclusions regarding cost differences, effect differences, and the incremental net monetary benefit estimate.

On its own, the use of multi-way interactions of social categorical variables does not immediately constitute a socially conscious CEA. The effects of identities should be interpreted as the result of differential power dynamics (e.g., classism, racism) that exert the meaning of individual identities [5]. Whether using intersectionality or another framework, the implications of social dynamics for the specification of CEA models and the interpretation of the results should be examined in future studies.

3 Heterogeneity and Multi-Level Modeling

Since the publication of Crenshaw’s manuscript in 1989, other researchers have identified a role for intersectionality in the study of population health [22]. One approach utilizes

intersectionality to motivate a multi-level specification of individuals nested within social identities. Another approach is to utilize the multi-level framework and the focus on social influences to nest individuals within geographic communities that represent distinct social characteristics and then examine the role of cross-level interactions in explaining the value of treatment. To illustrate ideas, we examine one county-level fixed effect (indicator for residence in a rural county), recognizing that there are many other county-level characteristics and geographic units (e.g., Census tract) that can be explored in practice. In Equation 3, we provide a variance components specification, which examines variation in the NMB across defined levels of analysis, e.g., individuals (i) and counties (j):

$$y_{ij} = \beta_0 + \varepsilon_{ij} + v_j. \quad (3)$$

The variance components model can be used to estimate the intraclass correlation coefficient and quantify the variation in the NMB that is attributable to individuals and to counties. In other words, if the outcome is the NMB, then we can estimate the percentage of variation in the NMB that is attributed to individual (i.e., ε_{ij}) and county-level variation (i.e., v_j). This analysis indicates whether further examination of geographic (e.g., county-level) variation in cost effectiveness is warranted:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \beta_3 x_{3j} + \beta_4 x_{1ij} \times x_{2ij} + \beta_5 x_{1ij} \times x_{3j} + \beta_6 x_{1ij} \times x_{2ij} \times x_{3j} + \varepsilon_{ij} + v_j. \quad (4)$$

Using Eq. 4, we can examine variation in the iNMB of a treatment with respect to x_2 , an individual-level measure (e.g., socially assigned race), and x_3 , a county-level fixed effect (e.g., rural county). A statistically significant interaction term, β_6 , indicates that there are disparities in the average iNMB of the new treatment according to the individual's socially assigned race and the rural/urban characteristic of the county in which the individual resides. The multi-level model explicitly considers individuals within the counties in which they reside and thus permits investigation of variation across individuals and across counties. Decision makers can use results from this type of analysis to identify populations with either a high or low value of treatment, while considering who they are and where they live.

Another motivation to study individuals nested within geographic areas is that intersecting racial and environmental inequities may result in differential health outcomes. A socially conscious CEA would account for the intersecting social identities and environmental exposures that impact health, healthcare access, and treatment outcomes. As one example, air pollution can be measured for a defined area and has significant effects on population health. One

particularly harmful air pollutant is particulate matter, a mixture of solid and liquid particles that are found in the air [23, 24]. Short-term and long-term exposure to particulate matter (specifically, particulate matter of 2.5 μm in diameter or less) has been linked to premature mortality and negative cardiovascular health effects [25]. Recent evidence indicates that Black individuals are exposed to a 1.54 times higher proportional burden of particulate matter than the overall US population [26]. Taken together, these findings illustrate how intersecting racial and environmental inequities may result in differential respiratory health outcomes.

More generally, social and structural barriers exert effects that can result in higher or lower observed costs: (1) a lower cost of care can reflect 'underutilization' where the observed utilization is less than the level of care that would have been observed in the absence of social or structural barriers to healthcare [27]; (2) a higher cost of care that results from the use of emergency medical services to replace primary care services could result in 'above-average' costs, not due to an inherent 'above-average' individual need for care but because high-quality primary care services are out of reach because of social or structural barriers. Similarly, (1) decreased neighborhood availability of pharmacies [28] could result in lower effectiveness of medicines and (2) increased participation in community-based health worker programs designed to improve self-management and education of chronic disease [29] could result in higher effectiveness of medicines. Social and structural barriers exert effects that can result in worse individual health status. Social stressors can 'get under the skin' [20, 21] such that observed health is lower than it would have been without the social stressors. Faced with these social stressors prior to the availability of a new treatment, the individual may not be well positioned to fully benefit from the new intervention [30].

These examples illustrate the conceptual challenge to need measurement discussed in Cookson et al., i.e., the divergence between the observed level of need and the ideal counterfactual level that would exist in the absence of social or structural barriers [31]. When considered within the context of these scenarios, the disproportionate care law described by Cookson et al., whereby the availability of healthcare is inversely related to the need in the subgroup, takes on greater significance. The disproportionate care law can extend to situations where the 'need' is not defined solely at the individual level but includes the need for social and structural reforms. The potential health benefits and costs to interventions can then be considered within a package of social and structural barriers, the lifting of which (or variation in which) can have implications for the value of technologies.

Table 1 Five-step approach to conduct socially conscious cost effectiveness analyses

Steps	Intersectionality approach
1	(1a) Engage scholars and individuals with knowledge of social intersectionality theory and to inform empirical analyses (1b) Work alongside underserved communities, those experiencing overlapping sources of oppression, and researchers trained in the social sciences to provide insights on social disadvantages and their impact on the downstream cost and effectiveness of medicines (1c) Supplement quantitative data with data on lived experiences and the social costs of experiencing multiple systems of oppression [37]
2	(2a) Incorporate intersectionality theory into key study elements, including, the study rationale, study objective(s), and analytic methods (2b) Examine and interpret the source of heterogeneity and inefficiencies in distribution as the result of power imbalances rooted in societal privileges [5] (2c) Add “contextual specificity” [38] to quantitative models in order to account for the diversity of social contexts in which healthcare utilization occurs
3	Conduct quantitative cost effectiveness analyses using regression-based methods, as guided by the study design and data Regression-based methods include, but are not limited to, the following: interaction terms, structural equation modeling, hierarchical modeling [39]
4	Report on the uncertainty in results due to limited information about the relevant domains important to measure social constructs or a lack of variables measuring social constructs, which can impact cost and effectiveness estimates
5	Interpret results in context to social power imbalances

4 A Five-Step Approach to Conducting a Socially Conscious CEA

In this section, we describe how to conduct a socially conscious CEA with the use of regression analyses. Specifically, in Table 1, we outline the key steps to conduct a socially conscious CEA rooted in intersectionality.

Step 1 is to build a team of stakeholders with training or lived experiences in the effects of intersectionality on health outcomes and clinical decisions. A similar recommendation has been suggested in the context of reducing algorithmic bias in prediction models that are developed using artificial intelligence techniques [32]. By purposefully incorporating the input from a diverse team with training and/or lived experiences of social oppression, the CEA better reflects the costs, health outcomes, and trade-offs that are relevant to the population of interest. In Step 2, the team incorporates insights from foundational intersectionality literature into the study rationale, objectives, and analytic methods. This step is critical as there has been much progress in social sciences to incorporate intersectionality theory into quantitative methods [33]. However, void of this step, there is a risk of incorrectly attributing results (e.g., lower observed effectiveness or higher costs) to the socially disadvantaged populations, rather than to the social systems that influence these outcomes [34].

At Step 3, the analysts conduct the CEA with due consideration to intersectionality. In the case where individual-level data are available and depending on the study question, regression-based methods described in earlier sections may be appropriate and, if not, the team would utilize more advanced statistical methods. Ideally, and in Step 1, the team would have secured access to a dataset that can be used to estimate a model with multiple interactions. When

individual-level data are not sufficiently powered for multiple interactions, available data may be used to generate study questions and conduct exploratory analyses. In the USA, the increased attention to collect and report health outcomes in relation to race/ethnicity and social determinants of health is a welcome development [35, 36].

At Step 4, the analysts should report on the uncertainty of the results, given the limitations such as the lack of theoretical frameworks on the association(s) between social contexts and outcomes, as well as the lack of sufficient data to test/measure social constructs in relation to health outcomes and costs. For example, there is a theoretical understanding and qualitative data indicating that racism has an intergenerational effect on health behavior and observed healthcare decisions; however, inter-generational data on families are typically lacking from individual-level data. These limitations and their implications for evaluating intersectionality in cost effectiveness studies should be discussed where applicable to the study question. Last, in Step 5, the research team should interpret heterogeneity and the distributional impacts of the CEA in relation to social disadvantages as the result of power imbalances. To be consistent with intersectionality theory, the results should be interpreted in a language that reflects the overlapping social imbalances that reflect either negative or positive impacts on health and health consequences.

5 Key Challenges: Data and Equity Concerns

The investigation of heterogeneity in the value of therapies across subgroups has important implications for how this information will be used for allocation decisions. Depending

on the criteria used to define a particular subgroup, decision makers utilizing subgroup analyses may need to address equity concerns [40]. In some cases, there will be a clear role for the consideration of heterogeneity in value assessments due to a differential clinical burden of illness. For example, given the observed multifactorial disparities of COVID-19 cases, it will be important to examine the value of COVID-19 treatments from a health equity perspective [41]. In chronic diseases, such as diabetes mellitus [42] and asthma [43] with stark epidemiological disparities in the prevalence of disease, utilization management, and access to care, failure to recognize the differential value of treatments in populations affected by compounded disadvantages will lead to a misrepresentation of value in the most marginalized subgroups. For example, low-income individuals with diabetes can struggle to manage the priorities of paying for basic and medical necessities, such as food, housing, transportation, and prescriptions [44]. Evaluations that do not consider potential differences in the effectiveness of medicines because of differences in affordability may lead to biased estimations of value in populations affected by poverty.

We cannot consider the role of intersectionality in cost effectiveness without examining the results that would be used as inputs, namely, the results from trial-based data analyses or comparative effectiveness analyses. Greater capacity to conduct an intersectionality analysis will require more robust data on cost, effectiveness, and social constructs. Analysts in the field of health economics and outcomes research are ideally positioned to advocate for more data on the social determinants that lead to inequities in health outcomes and the social experiences that lead to health decisions because of their reliance on healthcare utilization data.

By drawing attention to the need for more robust data on cost and effectiveness coupled with data on social experiences and social context, analysts can draw attention to the evidence gaps that limit the ability to move CEAs forward towards socially conscious approaches. Opportunities are ripe for analysts to work together with theorists and analysts in the social sciences to bring attention to evidence gaps that hamper the ability to conduct socially conscious CEAs.

Social justice considerations should also be incorporated throughout the research lifecycle. Consistent with the need to conduct health technology assessments with a firm recognition of the social constructs, the COVID-19 pandemic has amplified the need to address and disrupt the power imbalances that lead to inequities in wealth attainment, social welfare, and access to health and healthcare resources. Ideally, social justice considerations will exert an influence early in the process by guiding the design of study protocols (whether it is a clinical trial protocol or protocol for collecting administrative survey data) and the collection of measures (e.g., beyond individual-level data on race/

ethnicity/language/health literacy, collect data on individual experiences of social forces, such as measures of perceived discrimination and individual reports of experience with social and structural barriers).

When weighing efficiency gains as compared to equity gains, there is a concern that an evaluation of social disadvantage in relation to the value of treatments will result in access restrictions among disadvantaged populations. A key premise of this paper is that there are unrealized gains from evaluating social contexts in relation to CEAs. Published work illustrates an approach to weigh and trade off social justice concerns against efficiency using social welfare functions that explicitly incorporate inequality aversion [45, 46]. Future empirical work will be needed to quantify when and how cost, health outcomes, and willingness-to-pay thresholds vary across strata defined by layered social identities. Combining tools of regression-based models (including multi-level models) with innovations in data collection and existing methods of economic evaluation opens up novel avenues for studying the value of medicines.

6 Conclusions

A traditional CEA has not typically considered the role of overlapping social identities in quantifying the value of medicines. While measuring the variation in trade-offs across equity-relevant subgroups, equity-based approaches to CEAs will not be rooted in equity without a clear recognition of social theory and patient experiences. To the extent that health outcomes and healthcare resource utilization are shaped by individuals, their layered social identities, and context, intersectionality provides useful guidance for considering the role of broader social, system, and policy aspects. Cost effectiveness analyses that examine the role of multiple intersecting social categorizations on the valuing of medicines will be needed in order to inform policies designed to optimize the use of medications and improve health outcomes in populations that have been marginalized. Value estimations that lack the effects of overlapping social identities on heterogeneity in benefits and costs can result in inadequate information for decision makers to evaluate the value of treatments.

Declarations

Funding Jacquelyn McRae received an unrestricted grant paid to the University of Maryland, Baltimore from Pharmaceutical Research and Manufacturers of America for the completion of this research.

Conflict of Interest Following completion of this study, Jacquelyn McRae began employment as a Director of Policy and Research at Pharmaceutical Research and Manufacturers of America.

Ethics Approval The study was exempt from institutional review board approval because of a lack of human subject involvement and the use of protected health data.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

Availability of Data and Material Not applicable.

Code Availability Not applicable.

Author Contributions JM co-conceptualized the paper, developed the first draft of the manuscript, and provided significant edits. EO co-conceptualized the paper, provided significant feedback, edited the manuscript, and supervised the paper.

References

- Williams D. Race, racism, and health: an RWJF collection. Robert Wood Johnson Foundation. 2001-2018. 2021. <https://www.rwjf.org/en/library/collections/racism-and-health.html>. Accessed 8 Aug 2021.
- Crenshaw K. Demarginalizing the intersection of race and sex: a black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics [1989]. In: *Feminist legal theory: readings in law and gender*. New York: Taylor and Francis; 2018. pp. 57–80. <https://doi.org/10.4324/9780429500480>.
- Urban DJ. The women of SNCC: struggle, sexism, and the emergence of feminist consciousness, 1960–66. *Int Soc Sci Rev*. 2002;77(3/4):185–90.
- Montoya C. From Seneca to Shelby: intersectionality and women's voting rights. *Oxf Scholarsh Online*. 2020. <https://doi.org/10.1093/oso/9780190265144.003.0005>.
- Crenshaw K. Mapping the margins: intersectionality, identity politics, and violence against women of color. *Stanford Law Rev*. 1991;43(6):1241–99.
- Cookson R, Mirelman AJ, Griffin S. Using cost-effectiveness analysis to address health equity concerns. *Value Health*. 2017;20:206–12. <https://doi.org/10.1016/j.jval.2016.11.027>.
- Avancena ALV, Prosser LA. Examining equity effects of health interventions in cost-effectiveness analysis: a systematic review. *Value Health*. 2021;24(1):136–43. <https://doi.org/10.1016/j.jval.2020.10.010>.
- Morning A. “Everyone knows it’s a social construct”: contemporary science and the nature of race. *Sociol Focus*. 2007;40(4):436–54.
- Hoch JS, Briggs AH, Willan AR. Something old, something new, something borrowed, something blue: a framework for the marriage of health econometrics and cost-effectiveness analysis. *Health Econ*. 2002;11(5):415–30. <https://doi.org/10.1002/hec.678> (PMID: 12112491).
- Willan AR, Briggs AH, Hoch JS. Regression methods for covariate adjustment and subgroup analysis for non-censored cost-effectiveness data. *Health Econ*. 2004;13(5):461–75. <https://doi.org/10.1002/hec.843> (PMID: 15127426).
- Jones CP, Truman BI, Elam-Evans LD, et al. Using “socially assigned race” to probe white advantages in health status. *Ethn Dis*. 2008;18(4):496–504.
- White K, Lawrence JA, Tchangalova B, Huang SJ, Cummings JL. Socially-assigned race and health: a scoping review with global implications for population health equity. *Int J Equity Health*. 2020;19(1):25.
- Green AR, Carney DR, Pallin DJ, Ngo LH, Raymond KL, Iezzoni LI, et al. Implicit bias among physicians and its prediction of thrombolysis decisions for black and white patients. *J Gen Intern Med*. 2007;22(9):1231–8.
- Cobb RJ, Thomas CS, Laster Pirtle WN, Darity WA. Self-identified race, socially assigned skin tone, and adult physiological dysregulation: assessing multiple dimensions of “race” in health disparities research. *SSM Popul Health*. 2016;2:595–602.
- Lawrence JA, White K, Cummings JL, Hardin JW, Torres ME. Socially assigned race and diabetes: findings from the Arizona Behavioral Risk Factor Surveillance System, 2013–2014. *J Racial Ethn Health Dispar*. 2019;6(5):926–34.
- Macintosh T, Desai MM, Lewis TT, Jones BA, Nunez-Smith M. Socially-assigned race, healthcare discrimination and preventive healthcare services. *PLoS ONE*. 2013;8(5):e64522.
- Onukwugha E, Osteen P, Jayasekera J, Mullins CD, Mair CA, Hussain A. Racial disparities in urologist visits among elderly men with prostate cancer: a cohort analysis of patient-related and county of residence-related factors. *Cancer*. 2014;120(21):3385–92. <https://doi.org/10.1002/cncr.28894> (Epub 2014 Jun 24 PMID: 24962590).
- Ziehr DR, Mahal BA, Aizer AA, Hyatt AS, Beard CJ, D’Amico AV, et al. Income inequality and treatment of African American men with high-risk prostate cancer. *Urol Oncol*. 2015;33(1):18. e7–13. <https://doi.org/10.1016/j.urolonc.2014.09.005> (Epub 2014 Oct 11. PMID: 25306287).
- Mahal BA, Ziehr DR, Aizer AA, Hyatt AS, Sammon JD, Schmid M, et al. Getting back to equal: the influence of insurance status on racial disparities in the treatment of African American men with high-risk prostate cancer. *Urol Oncol*. 2014;32(8):1285–91. <https://doi.org/10.1016/j.urolonc.2014.04.014> (Epub 2014 May 17 PMID: 24846344).
- Das A. How does race get “under the skin”? inflammation, weathering, and metabolic problems in late life. *Soc Sci Med*. 2013;77:75–83. <https://doi.org/10.1016/j.socscimed.2012.11.007> (Epub 2012 Nov 14. PMID: 23201190; PMCID: PMC3587959).
- Gehlert S, Sohmer D, Sacks T, Mininger C, McClintock M, Olopade O. Targeting health disparities: a model linking upstream determinants to downstream interventions. *Health Aff (Millwood)*. 2008;27(2):339–49. <https://doi.org/10.1377/hlthaff.27.2.339> (PMID:18332488;PMCID:PMC2494954).
- Green MA, Evans CR, Subramanian SV. Can intersectionality theory enrich population health research? *Soc Sci Med*. 2017;178:214–6. <https://doi.org/10.1016/j.socscimed.2017.02.029>.
- 1990 Clean Air Act Amendment Summary. U.S. Environmental Protection Agency, Updated Jan 2017. Washington, DC; 2021. <https://www.epa.gov/clean-air-act-overview/1990-clean-air-act-amendment-summary>. Accessed 8 Aug 2021.
- Particulate matter (PM) basics. U.S. Environmental Protection Agency, Updated Nov 2018. Washington, DC; 2021. <https://www.epa.gov/pm-pollution/particulate-matter-pm-basics#PM>. Accessed 8 Aug 2021.
- Integrated science assessment (ISA) for particulate matter (final report, 2019). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-19/188, 2019. Updated Jan 2020. 2021. <https://cfpub.epa.gov/ncea/isa/recordisplay.cfm?deid=347534>. Accessed 8 Aug 2021.
- Mikati I, Benson AF, Luben TJ, Sacks JD, Richmond-Bryant J. Disparities in distribution of particulate matter emission sources by race and poverty status. *Am J Public Health*. 2018;108(4):480–5. <https://doi.org/10.2105/AJPH.2017.304297>.

27. Onukwughu E, McRae J, Camelo CW. Cost-related non-utilization of health services and self-perceived reactions to race. *Ethn Dis*. 2020;30(3):399–410. <https://doi.org/10.18865/ed.30.3.399> (PMID: 32742142; PMCID: PMC7360175).
28. Guadamuz JS, Wilder JR, Mouslim MC, Zenk SN, Alexander GC, Qato DM. Fewer pharmacies in black and Hispanic/Latino neighborhoods compared with white or diverse neighborhoods, 2007–15. *Health Aff (Millwood)*. 2021;40(5):802–11. <https://doi.org/10.1377/hlthaff.2020.01699> (PMID: 33939507).
29. Kane EP, Collinsworth AW, Schmidt KL, Brown RM, Snead CA, Barnes SA, et al. Improving diabetes care and outcomes with community health workers. *Fam Pract*. 2016;33(5):523–8. <https://doi.org/10.1093/fampra/cmz055> (Epub 2016 Jul 14 PMID: 27418587).
30. Cookson R, Doran T, Asaria M, Gupta I, Mujica FP. The inverse care law re-examined: a global perspective. *Lancet*. 2021;397(10276):828–38. [https://doi.org/10.1016/S0140-6736\(21\)00243-9](https://doi.org/10.1016/S0140-6736(21)00243-9) (PMID: 33640069).
31. Cookson R, Doran T, Asaria M, Gupta I, Mujica FP. The inverse care law re-examined: a global perspective. *Lancet*. 2021;397(10276):828–38. [https://doi.org/10.1016/S0140-6736\(21\)00243-9](https://doi.org/10.1016/S0140-6736(21)00243-9) (PMID: 33640069).
32. Noseworthy PA, Attia ZI, Brewer LC, Hayes SN, Yao X, Kapa S, et al. Assessing and mitigating bias in medical artificial intelligence: the effects of race and ethnicity on a deep learning model for ECG analysis. *Circ Arrhythm Electrophysiol*. 2020;13(3):e007988. <https://doi.org/10.1161/CIRCEP.119.007988> (Epub 2020 Feb 16. PMID: 32064914; PMCID: PMC7158877).
33. Bauer GR. Incorporating intersectionality theory into population health research methodology: challenges and the potential to advance health equity. *Soc Sci Med*. 2014;110:10–7. <https://doi.org/10.1016/j.socscimed.2014.03.022> (Epub 2014 Mar 25 PMID: 24704889).
34. Samra R, Hankivsky O. Adopting an intersectionality framework to address power and equity in medicine. *Lancet*. 2021;397(10277):857–9. [https://doi.org/10.1016/S0140-6736\(20\)32513-7](https://doi.org/10.1016/S0140-6736(20)32513-7) (Epub 2020 Dec 23 PMID: 33357466).
35. Cassil A. Paradigm Project: using real-world data and artificial intelligence to advance health services research. *AcademyHealth*. 2021. <https://academyhealth.org/publications/2021-06/new-issue-brief-offers-ways-leverage-real-world-data-hsr>. Accessed 8 Aug 2021.
36. CMS.gov. CMS proposes rule to increase price transparency, access to care, safety & health equity. Centers for Medicaid and Medicare. 19 July 2021. 2021. <https://www.cms.gov/newsroom/press-releases/cms-proposes-rule-increase-price-transparency-access-care-safety-health-equity>. Accessed 8 Aug 2021.
37. Fehrenbacher AE, Patel D. Translating the theory of intersectionality into quantitative and mixed methods for empirical gender transformative research on health. *Cult Health Sex*. 2020;22(Suppl. 1):145–60. <https://doi.org/10.1080/13691058.2019.1671494> (Epub 2019 Oct 29. PMID: 31661661; PMCID: PMC7188600).
38. Panch T, Mattie H, Atun R. Artificial intelligence and algorithmic bias: implications for health systems. *J Glob Health*. 2019;9(2):010318. <https://doi.org/10.7189/jogh.09.020318> (PMID: 31788229; PMCID: PMC6875681).
39. Bauer GR, Churchill SM, Mahendran M, Walwyn C, Lizotte D, Villa-Rueda A. Intersectionality in quantitative research: a systematic review of its emergence and applications of theory and methods. *SSM Popul Health*. 2021;14:100798. <https://doi.org/10.1016/j.ssmph.2021.100798>.
40. Sculpher M. Subgroups and heterogeneity in cost-effectiveness analysis. *Pharmacoeconomics*. 2008;26(9):799–806. <https://doi.org/10.2165/00019053-200826090-00009>.
41. Chowkwanyun M, Reed AL. Racial health disparities and Covid-19: caution and context. *N Eng J Med*. 2020;383:201–3. <https://doi.org/10.1056/NEJMp2012910>.
42. Peek ME, Cargill A, Huang ES. Diabetes health disparities. *Med Care Res Rev*. 2007;64(5 Suppl.):101S–S156. <https://doi.org/10.1177/1077558707305409>.
43. Holsey CN, Collins P, Zahran H. Disparities in asthma care, management and education among children with asthma. *Clin Pulm Med*. 2013;20(4):172–7.
44. Pilkington FB, Daiski I, Bryant T, Dina-panaitescu M, Dina-panaitescu S, Raphael D. The experience of living with diabetes for low-income Canadians. *Can J Diabetes*. 2010;34(2):119–26.
45. Asaria M, Griffin S, Cookson R, Whyte S, Tappenden P. Distributional cost-effectiveness analysis of health care programmes: a methodological case study of the UK Bowel Cancer Screening Programme. *Health Econ*. 2015;24(6):742–54. <https://doi.org/10.1002/hec.3058> (Epub 2014 May 2 PMID: 24798212).
46. Robson M, Asaria M, Cookson R, Tsuchiya A, Ali S. Eliciting the level of health inequality aversion in England. *Health Econ*. 2017;26(10):1328–34. <https://doi.org/10.1002/hec.3430> (Epub 2016 Sep 20. PMID: 27649686; PMCID: PMC6120144).