Title

An investigation of quantitative methods for assessing intersectionality in health research: A systematic review

Authors

Guan, Alice
Thomas, Marilyn
Vittinghoff, Eric
et al.

Publication Date

2021-12-01

DOI

10.1016/j.ssmph.2021.100977

Peer reviewed

SSM - Population Health 16 (2021) 100977

Contents lists available at ScienceDirect

SSM - Population Health

journal homepage: www.elsevier.com/locate/ssmph

An investigation of quantitative methods for assessing intersectionality in health research: A systematic review

Alice Guan [a], Marilyn Thomas [a,b], Eric Vittinghoff [a], Lisa Bowleg [c], Christina Mangurian [a,b,d], Paul Wesson [a,*]

[a] Department of Epidemiology and Biostatistics, University of California, San Francisco, San Francisco, CA, USA
[b] Department of Psychiatry and Behavioral Sciences, University of California, San Francisco, San Francisco, CA, USA
[c] Department of Psychological and Brain Sciences, The George Washington University, Washington, DC, USA
[d] Center for Vulnerable Populations, University of California, San Francisco, San Francisco, CA, USA

ARTICLE INFO

Keywords:
Epidemiology
Intersectionality
Statistics
Research methods
Systematic review

ABSTRACT

Intersectionality is a theoretical framework that investigates how interlocking systems of power and oppression at the societal level influence the lived experiences of historically and socially marginalized groups. Currently, there are no consistent or widely adopted quantitative methods to investigate research questions informed by intersectionality theory. The objective of this systematic review is to describe the current landscape of quantitative methods used to assess intersectionality and to provide recommendations on analytic best practices for future research. We searched PubMed, EMBASE, and the Web of Science in December 2019 to identify studies using analytic quantitative intersectionality approaches published up to December 2019 (PROSPERO CRD42020162686). To be included in the study, articles had to: (1) be empirical research, (2) use a quantitative statistical method, (3) be published in English, and (4) incorporate intersectionality. Our initial search yielded 1889 articles. After screening by title/abstract, methods, and full text review, our final analytic sample included 153 papers. Eight unique classes of quantitative methods were identified, with the majority of studies employing regression with an interaction term. We additionally identified several methods which appear to be at odds with the key tenets of intersectionality. As quantitative intersectionality continues to expand, careful attention is needed to avoid the dilution of the core tenets. Specifically, emphasis on social power is needed as methods continue to be adopted and developed. Additionally, clear explanation of the selection of statistical approaches is needed and, when using regression with interaction terms, researchers should opt for use of the additive scale. Finally, use of methods that are potentially at odds with the tenets of intersectionality should be avoided.

1. Introduction

1.1. Definition and evolution of intersectionality

Intersectionality is a critical theoretical framework for understanding how interlocking systems of power manifest to uniquely and differentially shape the lived experiences of intersectional social positions (Crenshaw, 1989, 1991). These experiences are embedded within, and reflective of, multiple, intersecting, and mutually constitutive systems of social, economic, and political power. Intersectionality has roots in Black feminist activism, tracing back to Sojourner Truth's 1851 speech at the Women's Rights Convention, where she described her lived experience at the nexus of gender, class, and race inequality (Alexander-Floyd, 2012). Amidst the movements of the 20th century, Angela Davis and Audre Lorde continued to build upon the foundation laid by Truth, vocalizing their opposition to the exclusion of Black women from the feminist agenda. In 1989, Kimberlé Crenshaw coined the term "intersectionality," expanding on earlier scholarship and illustrating the shortcomings of the feminist movement and anti-racist politics in understanding the interaction of gender and race in shaping oppressive experiences (Crenshaw, 1989, 1991). As intersectionality traveled across disciplines (Berger, 2017; Choo & Ferree, 2010; Cole,

* Corresponding author. Department of Epidemiology and Biostatistics. University of California, San Francisco, 550 16th Street, 3rd Floor, San Francisco, CA, 94158, USA.
E-mail addresses: Alice.Guan@ucsf.edu (A. Guan), Marilyn.Thomas@ucsf.edu (M. Thomas), Eric.Vittinghoff@ucsf.edu (E. Vittinghoff), lbowleg@gwu.edu (L. Bowleg), Christina.Mangurian@ucsf.edu (C. Mangurian), Paul.Wesson@ucsf.edu (P. Wesson).

https://doi.org/10.1016/j.ssmph.2021.100977
Received 30 June 2021; Received in revised form 16 November 2021; Accepted 19 November 2021
Available online 20 November 2021

2009; Few-Demo, 2014), different aspects of this theoretical framework have been emphasized (Cole, 2009; Collins, 2015b; McCall, 2005). However, two fundamental tenets have remained at the backbone of the intersectionality framework: (1) intersectionality seeks to understand the unique experiences at the nexus of multiple social positions of power, and (2) the goal of intersectionality is fundamentality political, and the goal of applying intersectionality principles to research must be to advance social justice.

Central to intersectionality work is the recognition of structural inequities through Black scholarship that articulates the intersecting oppressions experienced by Black women. Scholars have criticized that the appropriation of intersectionality across disciplines erases such attempts of Black scholarship to transform the social hierarchies responsible for inequality (Rice et al., 2019). When intersectionality is distanced from its roots in Black feminist activism, scholars have warned of its becoming a shorthand for "multiple identities" (Carbado et al., 2013; Demos & Segal, 2009; Grzanka, 2014; Grzanka & Miles, 2016) or a hollow theoretical buzzword (Choo & Ferree, 2010; Davis, 2008). Intersectionality scholars have described the depoliticization of intersectionality as an erasure of its original function of praxis for social change (Bilge, 2013; Bowleg, 2021). Bilge furthermore articulates that the adoption of the language of intersectionality devoid of interrogation of interpersonal, social, and political power transforms its fundamental function into a "diversity tool [used] by dominant groups to attain … institutional goals" (Bilge, 2013, p. 407). To prevent the depoliticization of intersectionality as it travels through mainstream scholarship, it is therefore necessary to faithfully translate the social justice focus of this theoretical framework (Bowleg, 2021).

Several concepts have emerged to describe joint or intersectional effects: Simultaneity suggests that all social positions exist together, and that axes of inequality should not be ranked (i.e., giving more importance or value to one axis over another). Intersectional multiplicativity suggests that axes of inequality (example: sexism and racism) interact to create unique social positions which cannot be explained as a sum of their parts (Bowleg, 2008; Collins, 1998; Hankivsky & Christoffersen, 2008). Multiple jeopardy (also referred to as double or triple jeopardy, depending on the number of axes investigated), describes the extra disadvantages or oppressions experienced by individuals with multiple marginalized social positions (King, 1988). Finally, intersectional invisibility hypothesizes that social oppression experienced by easily recognized "prototypical" members of marginal groups differ from less visible "marginal" members (Biernat & Sesko, 2013; Purdie-Vaughns & Eibach, 2008). In other words, intersectional invisibility acknowledges the context specific nature of oppression.

1.2. Intersectionality in the quantitative sciences

Although intersectionality was not originally intended to be a guide for empirical methodology (Syed, 2010), its relevance to public health is clear (Agénor, 2020; Bauer, 2014; Bowleg, 2012; Bowleg & Bauer, 2016), and it has evolved to become a critical analytic tool to inform scholarship, research, and practice. Schulman et al.'s (1999) examination of gender and racial bias in referrals for cardiac catheterization provides one of the most compelling cases for the necessity of an intersectional approach (Schulman et al., 1999). This study concluded that female (Black and White) patients were less likely to be referred than male patients, and that all Black patients (male and female) were less likely to be referred than white patients. However, this conclusion is incorrect because of the inaccurate interpretations of main effects in the presence of an interaction between race and gender (L. M. Schwartz et al., 1999). Re-analyzing the data, accounting for the interaction of race and gender, Black women were the only group to be significantly less likely to be referred for catheterization (78.8% compared to 90.6% for the other groups). This study emphasizes the importance of an intersectional approach when analyzing data to appropriately identify and compare risk between subgroups.

In a seminal article on the importance of incorporating intersectionality into public health, Bowleg describes the methodological challenges for intersectionality research (Bowleg, 2012). For quantitative researchers specifically, Bowleg describes an absence of guidelines for capturing the complexity of interlocking social positions with current standards of measurement (Bowleg, 2012). Furthermore, there is currently no clear guidance regarding the appropriateness of different quantitative methods for studying intersectionality (Nash, 2016). For example, some have argued for examining interactions on the multiplicative scale (i.e., ratio measures), using logistic, Poisson, Cox and other models with log or logit links, to understand intersectional effects (Dubrow, 2008). Other prominent intersectionality researchers have suggested that interaction on the additive scale (i.e., difference measures) is most relevant for public health research (Bauer, 2014), considering their direct relevance to quantifying excess cases (Szklo & Nieto, 2014). Additionally, little is known about how different methods compare, or which methods are most appropriate for the study setting, the research question, and the confines of the data.

To better understand the different analytic methods that have been used, we conducted a systematic review of analytic approaches that were applied to study intersectionality within quantitative studies. This systematic review is distinct from, and builds upon, recent reviews of quantitative intersectionality (Bauer et al., 2021; Phillips et al., 2020) by expanding upon specific statistical methods that have been applied to study intersectionality. Bauer et al. established an important foundation with their review by describing the landscape of research and critiquing the incorporation of theory into supposed quantitative intersectionality studies (Bauer et al., 2021). As recommended by Bauer et al. (2021), we focus our review on providing an expanded and detailed description of the application of methods, the link between methods and the core tenets of intersectionality, and the analytical constraints and considerations for each method.

2. Methods

2.1. Design and search strategy

The protocol for this systematic review was submitted to PROSPERO (CRD42020162686) in December 2019 and was registered in April 2020 in accordance with PRISMA guidelines (Moher et al., 2009). We implemented a search in PubMed, Web of Science, and EMBASE for records published up to December 2019 using the following terms: [("intersectional*" or "additive interaction" or "additive scale") and ("quantitative" or "evaluating" or "assessing" or "estimating")]. To capture a broader range of intersectionality studies, we did not specify specific health outcomes. The search yielded a total of 1889 studies (Fig. 1). After identification and removal of duplicates, 1394 records were uploaded into Covidence software for assessment of eligibility (Covidence Systematic Review Software, n.d.).

2.2. Screening and assessment of eligibility

Articles were included in this review if they fulfilled the following criteria: (1) were empirical research (i.e., reviews, reports, and commentaries were excluded), (2) utilized a quantitative statistical method (i.e., genetic studies, scale validations or development of new scales, and qualitative studies were excluded), (3) were published in English, and (4) used intersectionality as an a priori theoretical framework.

The inclusion process consisted of several stages and were conducted by three independent reviewers. In the first stage, 1394 unduplicated studies were screened based on title, abstract, and key words. We excluded 1132 papers which either did not use a quantitative method or were not empirical studies (n = 262). In the second stage, we conducted a screening of the methods section and excluded studies which were not informed by intersectionality. Specifically, studies at this stage were excluded if one of the exposures investigated was not reflective of a

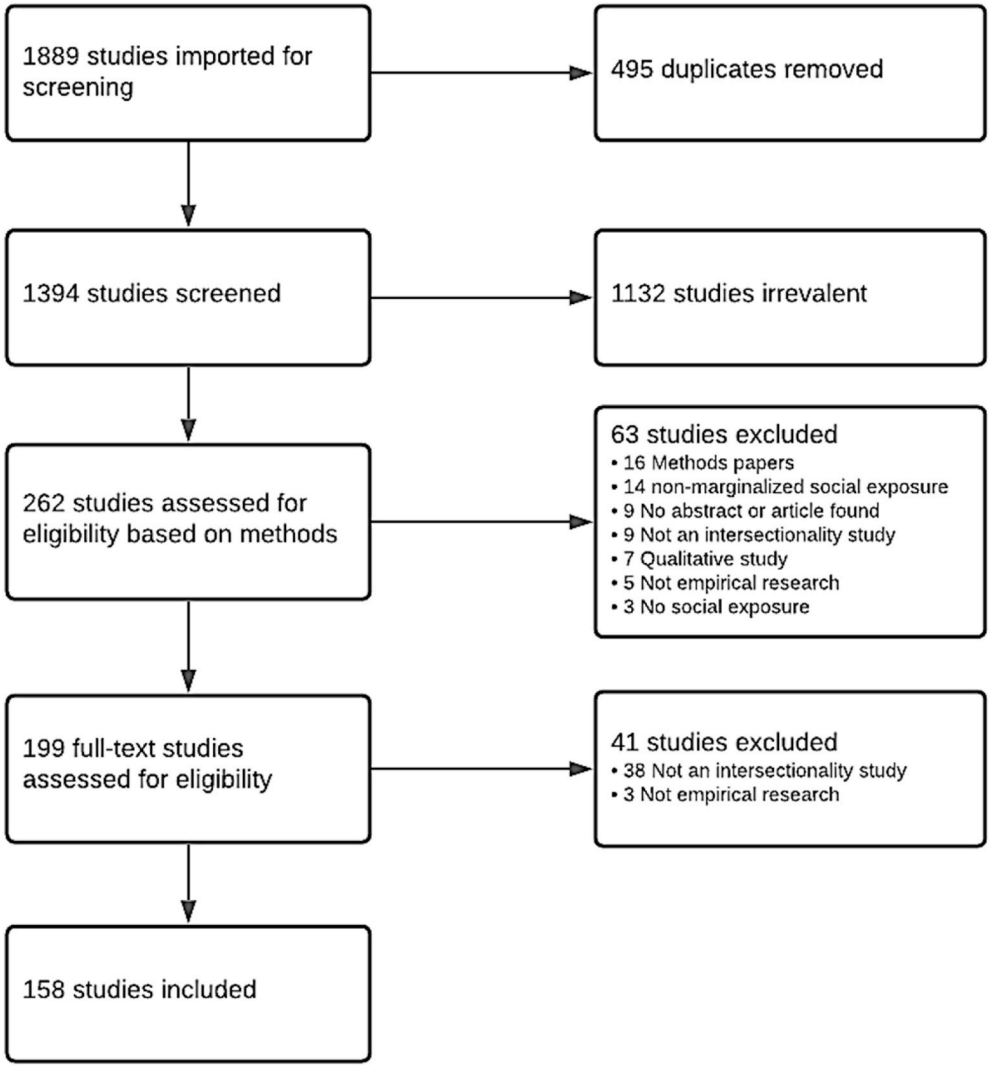

Fig. 1. Study flow diagram for systematic review process.

broader social system of power. A frequent example included studies of interactive effects of gender with a genetic factor. While we can conceptualize gender as existing on a social hierarchy (i.e., that social and economic resources are disproportionately distributed on the basis of gender), genetic factors do not. As such, these studies did not fundamentally examine multiple social axes. This left 199 eligible records for full-text evaluation. In the final stage of screening, full text of articles was reviewed, and conflicts were discussed within the record screening team and resolved by full consensus. At this stage, we excluded three additional studies which were not empirical research and 41 studies which provided no context or justification of intersectionality in the introduction or discussion section. Our final analytic sample included 158 studies. Fig. 1 depicts a flow diagram of the screening process.

2.3. Assessment of quality

We did not rate or assess studies for quality because the field of analytic quantitative intersectionality is evolving, and standard recommendations have not been established.

3. Results

3.1. Study characteristics

Key features of the studies included are summarized in Table 1. Most studies took place in North America (79.1%), followed by Europe (15.2%). The majority of studies were observational and based on cross-sectional data (76.0%), followed by longitudinal/cohort data (16.5%) and repeated cross-sectional data (5.1%). Nearly 2 out of 3 studies (63.9%) used probability-based sampling approaches.

A majority (89.1%) of the studies described intersectional positions in terms of simultaneity or intersectional multiplicativity. A smaller number of studies described their intersectional hypotheses using the language of double/multiple jeopardy (9.0%) or intersectional invisibility (1.9%). Fewer than half of the studies in this review mentioned the concept of social power or inequality (42.4%) (Table 1).

The most common intersectional positions assessed were race/ethnicity and gender (24.7%) followed by race/ethnicity, gender, and class (8.9%) and race/ethnicity and sexual minority status (7.6%). Of note, there was substantial heterogeneity in the way in which exposure variables were measured across studies. For instance, experiences of social oppression due to race/ethnicity were represented by variables for self-reported race/ethnicity, perceived racial discrimination, and visible racial minority status, to give a few examples. Though we describe these

Table 1
Characteristics of the included studies (N = 158).

	N (%)
Region of study	
North America[a]	126 (79.1)
Europe	25 (15.2)
Asia	7 (4.4)
Africa	1 (0.6)
Study design	
Cross-sectional	120 (76.0)
Longitudinal/Cohort	26 (16.5)
Repeated cross-sectional	8 (5.1)
Randomized trial	2 (1.3)
Case study	1 (0.6)
Sampling methodology	
Probability based sample	101 (63.9)
Non-probability-based sample	57 (36.1)
Exposure assessed (Categories below are not mutually exclusive)[b, c]	
Race/ethnicity	119 (75.3)
Gender/Sex	101 (63.9)
Class (education, employment status, SES, poverty, income), caste, or occupational factors	52 (32.9)
Sexual minority status	45 (28.5)
Immigration factors (nativity, language, nationality, immigration status)	22 (13.9)
Age	14 (8.9)
Health related variables (visible or invisible conditions (i.e., HIV or mental illness), access to care, markers of stress, medication use)	10 (6.3)
Neighborhood and contextual factors (segregation, racial composition, rurality, wealth of neighborhood, neighborhood resources, state legislator demographics)	9 (5.7)
Other (military status, social support or alienation, parental status, Body Mass Index, political party)	9 (5.7)
Religion or religiosity	6 (3.8)
Disability	4 (2.5)
Skin color	4 (2.5)
Marital status	3 (1.9)
Stigma	1 (0.6)
Type of outcome assessed	
Behavioral and mental health	59 (37.3)
Socioeconomic outcome (education, employment, income, etc.)	37 (23.4)
Physical health	23 (14.6)
Experiences of discrimination	18 (11.4)
Other (e.g., judicial outcomes, gender ideology, support for the Iraq war, perspectives on science or religion, eligible voters, indicators of social distance, geographic access to types of food stores)	12 (7.6)
Multiple outcomes evaluated (combination of outcomes above)	9 (5.7)
How was intersectionality described?	
Intersectional Multiplicativity/Simultaneity	136 (89.10)
Double jeopardy	14 (9.0)
Intersectional invisibility	3 (1.9)
Was the concept of social or structural power mentioned?	
No	91 (57.6)
Yes	67 (42.4)
Quantitative Intersectionality Methods (Categories below are not mutually exclusive)[b]	
Regression with interaction terms (e.g., linear and other models with identity link, multiplicative and other models with logit or log links, ANOVA-based methods, chi-square, t-tests)	101 (63.9)
Additive scale	39 (50.7)
Additive and multiplicative scale (outcome dependent)	7 (9.1)
Multiplicative scale	31 (40.3)
Models using stratification	20 (12.7)
Approaches using categorized intersectional positions (e.g., crude construction, latent class analysis, profile analysis, sum of marginalized identities)	16 (10.1)
Methods to estimate mediation of intersectional effects (path analysis/structural equation modeling, causal mediation decomposition)	7 (4.4)
Prediction models (e.g., Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy [MAIHDA], Area Under the Receiver Operating Curve [AUROC], Classification and Regression Trees [CART], and Exhaustive Chi-square Automatic Interaction Detection [CHAID])	6 (3.8)
Decomposition of inequality measures (e.g., general entropy class of measures, mutual information index, Oaxaca-Blinder decomposition)	3 (1.9)
Surrogate measures of additive interaction [e.g., RERI, AP, SI, RJE]	3 (1.9)
Block/set regression	2 (1.3)

[a] 10 studies used samples exclusively in Canada, 113 used samples exclusively in the United States, 2 used samples across the US-Canadian border, and 1 study used a sample consisting of participants from Canada, the United States, and the United Kingdom.

[b] Because multiple topics or methods are evaluated in most studies, column totals will not equal 100%.

[c] There was substantial heterogeneity in the way in which exposure variables were assessed across studies. For instance, race/ethnicity was measured using self-identified race and/or ethnicity, perceived racial discrimination, and visible ethnic minority status (just to provide a few examples). The same was true for many of the exposure factors listed here.

identity-based factors in Table 1, we note that in intersectionality research, any measured exposures should be used and interpreted as proxies for social and historical systems of power and oppression. Behavioral and mental health conditions were the most assessed outcomes across studies (36.6%), which included diagnosed mental health illnesses and symptoms, substance use disorders, attitudes, and life satisfaction. Socioeconomic outcomes were the second most assessed across studies (22.9%), followed by physical health outcomes including all diagnosable diseases (14.6%) (Table 1).

3.2. Quantitative analytic approaches

We identified 28 unique analytic quantitative methods from 153 studies, which we organized into 8 categories, listed and described below in order of frequency: 1) Regression with interaction terms, 2) Models using stratification, 3) Approaches using categorized intersectional positions, 4) Methods to estimate mediation of intersectional effects, 5) Prediction models, 6) Decomposition of inequality measures, 7) Surrogate measures of additive interaction, and 8) Block/set regression (Table 2). The most frequently used method was regression with an interaction term (48.7%), followed by basic descriptive statistics (15.2%) and stratified regression analysis (12.0%). Below, we provide an overview of each category of methods, a description of what is being quantified, and an example of a study that employed the method. To facilitate understanding of how each class of methods was used in the literature, we have selected illustrative examples based on representativeness and simplicity. We acknowledge that the statistical language of "effects" obscures the reality that the focus should be about interlocking inequity, discrimination, oppression, and stigma; which are all premised on whichever social positions are marginalized. For the purpose of accurately describing each study below, we have opted to summarize methods and interpretation of results in the language used by the authors of the original studies. In instances in which effects are described based on identity-based factors, we have included editorial comments to indicate how language could be modified to be reflective of effects of social oppression. Further details on each method, including practical and theoretical constraints are provided in Table 2. Our choice to present the data in this table are to provide insight into potential methods that could accommodate estimation of meaningful descriptive measures and reduce bias (e.g., controlling for covariates), as well as potential sample size constraints.

3.2.1. Regression with interaction terms (63.9% of studies)

Description: Regression methods evaluate whether joint effects of two or more social positions are greater than their individual components. In statistical terms, interactions are present when the combined effect of two variables on an outcome differs from the sum or product of the individual effects. In analyses using linear regression and other models with an identity link, including ANOVA, MANOVA, and ANCOVA, an interaction between two exposures on the additive scale implies that their joint effect differs from the *sum* of each effect on its own, as captured by the so-called main effects. In contrast, interaction on the multiplicative scale, estimated using logistic, Cox, Poisson and other models with logit or log links, implies that the joint effect of two or

Table 2
Description of quantitative methods for intersectionality inquiry.

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
Regression with interaction terms							
Linear and other models with identity link; multiplicative and other models with logit or log links (Barden et al., 2016; Berg, 2010; Cummings & Jackson, 2008; Harnois, 2015; Sen et al., 2009; Szmer et al., 2015; Velez et al., 2018; S.-L. L.; Williams et al., 2018)	This approach involves including an interaction term in a regression model. Both statistical scales (additive and multiplicative) were used by papers in this review. Some studies additionally used post-estimation to predict the marginal probabilities of the outcome for each intersectional position. Example equation: Y = B0 + B1*gender + B2*race + B3*gender*race + e Where Race: white/non-white Gender: male/female Y denotes the outcome variable of interest. B0 denotes the model intercept, e.g., the average outcome among white males. B1 denotes the effect of being female on the outcome among white individuals. B2 denotes the effect of being non-white among males. B3 denotes the additional effect of being non-white among females (or vice versa, the additional effect of being female among non-white individuals).	111–3,484,185	2–6	Yes	When an interaction term is introduced into a regression model, the interpretation of main effects must be in reference to a specific value of the other factor in the interaction. See example in description for more detail. Multiplicative scale: statistically significant interaction implies departure from statistical multiplicativity (i.e., the effect estimate for the interaction term is greater than the product of the main effects). Additive scale: statistically significant interaction implies departure from statistical additivity (i.e., the effect estimate for the interaction term is greater than the sum of the main effects) and can be used to further estimate the number of excess cases that are caused or presented because of the exposure(s).	Including an interaction term in a regression model is easy to implement. This method can provide a straightforward summary of effects across multiple exposure categories.	- Caution is needed to select the appropriate scale if investigators are evaluating intersectional hypotheses – assessing interaction on the additive scale is a more appropriate test for statistical multiplicativity. Additionally, additive scale interaction is more desirable from a public health perspective. - A relatively large sample size is needed in order to evaluate interaction using standard regression methods; - No significant interaction does not necessarily imply lack of intersectional effect - Statistical power is diminished with each dimension of interaction that is added - If causal inference is the goal of the study, confounders of both interaction factors must be adjusted for to yield valid causal estimates. However, even if causal inference is not the goal, appropriate covariate adjustment is needed to yield meaningful associational quantities. - When significant main effects (intersectional additive models) are used to inform the formation of intersectional multiplicative models, it's possible that interaction effects will be "missed" – i.e., in the presence of qualitative interaction. - Evaluation of interaction terms must be done a priori rather than

(*continued on next page*)

Table 2 (*continued*)

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
							using a data driven approach.
Distributions by subgroups (Covarrubias, 2011; Covarrubias & Lara, 2014; Covarrubias & Liou, 2014; Goldstein et al., 2016)	The distribution of outcomes is presented based on categories defined by two or more intersectional positions.	13,773[a]	3–4	–	These exploratory analyses could provide insight into potential patterns in outcome variables between subgroups defined by intersectional categories.	These exploratory analyses are easy to implement and do not require any statistical assumptions to implement.	Distributions of the outcome by subgroups in the sample could be more reflective of who is represented in the sample.
ANOVA based methods (Fasoli et al., 2018; Friedman & Leaper, 2010; Greaves et al., 2017; Lefevor et al., 2018; Manzi et al., 2019; Moorman & Harrison, 2016; Quandt, 2019; Wilson et al., 2017)	ANOVA methods evaluate whether distributions of a continuous outcome differ between two or more groups. ANCOVA and MANCOVA allow for control of covariates. Factorial ANOVA allows for inclusion of interactions.	83–64,271	2–6	Yes, for ANCOVA and MANCOVA	ANOVA methods can be used to evaluate whether the distribution of a continuous outcome across intersectional subgroups differs significantly.	This method is robust even with small sample sizes.	If there are more than three groups of interest, one-way ANOVA only informs us that at least one pair of means is different but does not identify this comparison.
Chi-square (Bouris & Hill, 2017; Landstedt & Gådin, 2012; McGovern, 2017)	The chi-squared test evaluates whether two categorical variables are related to each other in the same population	163–1663	2	No	Chi-square analysis to evaluate an intersectionality hypothesis involves creation of a categorical variable combining 2 (or more) factors and evaluating whether this variable is predictive of a categorical outcome of interest.	Chi-square is robust to data distribution and can be useful when parametric assumptions of other tests cannot be fulfilled.	The validity of the chi-squared test is dependent on sample size, and may be unreliable for small sample sizes
T-tests (Budge et al., 2016; Gupta, 2019; Woodhams et al., 2015)	The *t*-test evaluates whether the distribution of a continuous outcome variable differs between two groups.	442–1,114,308	2–4	No	Statistically significant results for these tests suggest that the distribution of outcome differs between subgroups (i.e., intersectional positions).	This method is robust even with small sample sizes.	The distribution of data must be approximately normal to test the *t*-test hypothesis.
Categorization							
Investigator-constructed intersectional variables (Bostwick et al., 2019; Cage et al., 2018; Chua et al., 2016; DuPont-Reyes et al., 2019; Hsieh & Ruther, 2016; Peck et al., 2014; Warner & Brown, 2011)	This approach involves the creation of a single "intersectional" variable containing all possible combinations of the social axes of interest as unique levels of the variable.	429-62,302	2–3	Yes, when combined with other analytic approaches (e.g., regression analysis) that allow for the control of confounders	This method serves as a preliminary step to setting up the data for an intersectional analysis (e.g., including the constructed intersectional variable in a regression model).	Once created, the intersectional variable can be employed across a variety of statistical methods (e.g., bivariate t-tests, regression, etc.)	- Depending on the number of categories, this method would require a large sample size. - Results may be less meaningful depending on the group specified to serve as the reference, which could be subjective. - If one social position being combined is measured poorly, this method could amplify measurement bias
Data reduction methods (latent class analysis, profile analysis) (Aguirre et al.,	This approach uses a data reduction method to create an "intersectional" variable, such as latent class analysis, principal components analysis, or	152-68,464	2–4	Yes, when combined with other analytic approaches (e.g.,	This method classifies individuals into "profiles" or "classes" that are defined using the individual	- Data reduction methods could be particularly useful for hypothesis generation - When a large array of	- Naming of categories/classes resulting from data reduction methods may be subjective. Though classes are

(*continued on next page*)

Table 2 (*continued*)

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
2016; Goodwin et al., 2018; Juan et al., 2016; Price et al., 2019; Taggart et al., 2019; Tomlinson et al., 2019; Whaley & Dubose, 2018)	profile analysis. In essence, all social factors of interest (i.e., gender, race, housing, etc.) will be reduced to a single variable, and labeled according to which factors contributed most to the categories created.			regression analysis) that allow for the control of confounders	components – e.g., race, gender, sexual minority status. Subsequent class membership could be considered an "intersectional position". The resulting classes can then be used in subsequent statistical techniques (e.g., including a categorical variable representing all classes into a regression model.).	variables is of interest and it is not possible to include all in a regression model due to lack of statistical power/precision, data reduction strategies could be used to identify and group individuals in meaningful ways.	often defined based on the variables that contributed most, there is still an element of subjectivity. - Group membership is based on probabilities (i.e., if LCA yields 5 classes, participant is assigned to the class that they have the highest probability of belonging). - Entirely data driven methods are agnostic to social hierarchies or processes that shape intersectional experiences. - There is a potential for systematic bias in sample recruitment and selection - These methods do not provide a clear reference group or appropriate comparison group.
Sum of marginalized identities (Lavaysse et al., 2018; Remedios & Snyder, 2018)	This approach collapses multiple social positions into a continuous variable by adding the number of marginalized identities an individual has (larger numbers imply a greater number of marginalized identities).	497–602	4–6	Yes, when combined with other analytic approaches (e.g., regression analysis) that allow for the control of confounders	When added to a regression model, the interpretation of this term in a regression model could be a test for whether adding more marginalized identities (i.e., having 5 versus 4 marginalized identities) increases the risk of an outcome.	This method could potentially be used for testing specific hypotheses related to multiple jeopardy.	- The summary variable equally weights all social positions, which could be an inaccurate reflection of an individual's lived experiences. - The summary variable is created without acknowledgement of the ways in which each of the factors used to create it are connected to one another (a concept central to intersectionality analyses).
Structural analyses and mediation approaches							
Path analysis, structural equation modeling (Y. Kim & Calzada, 2019; Lewis et al., 2017; Toosi et al., 2019; Velez et al., 2018; Watson et al., 2016; M. G. Williams & Lewis, 2019)	This approach assesses the influence of a moderating variable on a hypothesized mediated relationship between a primary exposure and outcome of interest, i.e., a test of whether the indirect effect of a mediation analysis is modified by different levels of another variable. If the mediation analysis (first step) confirms an indirect pathway, then the moderation hypothesis (second step) is tested.	231–750	2–3	Yes	Statistically significant coefficient for the interaction term in the moderation model provides evidence for moderated mediation. If evaluating an intersectional variable as the primary exposure, both the mediation and moderation hypothesis could provide potential explanations regarding the mechanisms linking	- Explicitly defines a proposed relationship between variables. - Can provide evidence for significant factors which could be the target of intervention. - Could be particularly useful to evaluate discrimination hypotheses (e.g., exposure as race, mediator as racial discrimination)	If testing a mediation hypothesis in which both the exposure and mediator are a social factor (e.g., the effect of gender on wage earning mediated through education), decomposition into indirect and direct effects (the mediation hypothesis) is not intuitively aligned with intersectionality theory (i.e., decomposition into effect of variable 1 mediated through variable 2 rather than the combined or

(*continued on next page*)

Table 2 (*continued*)

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
					an intersectional position to an outcome of interest.		additional effect of having both factors).
Three-way causal mediation decomposition (Bauer & Scheim, 2019b)	In contrast to the traditional Baron-Kenny mediation decomposition, three-way decomposition evolved from the causal inference literature and (1) allows for the assessment of exposure-mediator interaction and (2) defines direct and indirect effects within the counterfactual framework. There are four structural assumptions for causal mediation decomposition which need to be fulfilled in order to make valid causal inferences: (i) no mediator-exposure confounders, (ii) no mediator-outcome confounders, (iii) no exposure-outcome confounders, and (iv) no causal intermediates – i.e., confounders of the mediator-outcome relationship which occur downstream of the exposure.	2542[a]	2	Yes	- In the intersectionality context, the exposure of interest is a social factor (e.g., gender) and the mediator of interest is a discrimination factor (e.g., sexism). Estimates from this approach allow investigators to make conclusions about potential effects of interventions which equalize the mediator for all intersections to that of the most advantaged intersection. - One of the quantities that can be computed using this approach is the pure direct effect (PDE). This can be interpreted as the residual causal intersectional effect on the outcome that would persist if the mediator were set to the level it would take for the reference group. Additionally, a statistically significant pure indirect effect (PIE) would suggest that the mediator plays a causally mediating role.	- Provides potential evidence for factors which could be targeted for intervention to address disparities - If assumptions are satisfied, provides a rigorous approach to assess causality - This method could be a powerful tool for informing clear interventions, which is critical for intersectionality scholarship.	- Causal models require clear temporality, which will not always be clear in cross-sectional data. - Causal interpretation is dependent on confounding control and its sufficiency must always be considered. Additionally, the assumption that no mediator-outcome confounders (measured or un-measured) are affected by the exposure must be fulfilled to make causal inferences. - This approach is computationally rigorous, and the interpretation can be complex and difficult for non-scientific audiences to understand, potentially limiting widespread utility and adoption.
Decomposition of inequality measures (see structural analysis and mediation approaches under "Three-way causal mediation decomposition")							
Decomposition of the general entropy class of measures (Chakraborty & Mukhopadhyay, 2017)	Broadly speaking, the general entropy class of measures are a tool to measure inequality in populations. General entropy measures vary between zero (representing perfect equality) and infinity (representing perfect inequality).	46,655[a]	2	Yes	Decomposing the general entropy measure of inequality allows one to examine the salience of the social factors (e.g., race, class, etc.) as grouping parameters. One can also explore whether adding additional grouping parameters will influence the between group components. This could potentially allow for exploration of potential social	Does not allow for test of statistical significance for decomposed quantities.	- Decomposition of the general entropy class of measure is difficult to interpret.

(*continued on next page*)

Table 2 (*continued*)

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
					factors that may explain an observed inequality.		
Decomposition of the mutual information index (Guinea-Martin et al., 2015)	Like the general entropy class of measures, the mutual information index is a measure of inequality in a population. In relation to evaluating intersectionality, the first step is to develop the mutual information index, using data from the population (e.g., data on race and gender). The second step is to estimate the proportion of the index which is attributed exclusively to either factor (e.g., proportion attributed to either race or to gender). Finally, the last step is to compare the sum of the proportions attributed to either factor to a proportion attributed to the joint inequality.	22,200,000[a]	2	Yes	By comparing the sum of the proportions that are attributed to each individual factor exclusively to a proportion of the inequality that is attributed to the factors jointly, one can effectively test an interaction hypothesis. This can be a direct assessment of the multiple jeopardy hypothesis.	The mutual information index has strong group decomposition properties.	- The mutual information index does not completely separate groups unless they are completely mutually exclusive and have identical demographic characteristics. - The M index is sensitive to changes in the shares of each subgroup in the population and in the overall outcome mix.
Oaxaca-Blinder decomposition (Y.-M. Kim, 2017)	Oaxaca-Blinder decomposition is a method used to explain differences in an inequality variable by decomposing the component that is due to an "explained" and "unexplained" component. The "explained" part is the proportion of the gap in outcome that could be explained by observable characteristics, and the "unexplained" part.	4224[a]	2	Yes	Though the interpretation of the unexplained component is controversial, in its historical introduction, this component was thought to represent either discrimination or systemic processes which were inherent to the inequality. In the intersectionality scholarship, this could potentially represent a structural or political force that enacts inequality beyond what can be explained by the variables included in the decomposition.	Oaxaca-Blinder decomposition is simple to implement and only requires effect estimates from regression models and summary data for any independent variables used.	When variables in the Oaxaca-Blinder decomposition are discrete, the decomposition effects are sensitive to reference category choice.
Prediction							
Multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) (Evans & Erickson, 2019; Evans C.R. et al., 2019)	The first step of the MAIHDA approach involves creating a "social strata" variable that corresponds to every social position of interest. Example, if interested in gender (male/female) and race (White, Black, Latino), the MAIHDA analysis would create a social strata variable with six unique categories. The multilevel MAIHDA model nests individuals (level 1) within their social strata (level 2). There are several MAIHDA models with corresponding interpretations. In a null model, the total variation	15,388–32,788	3–4	Yes	The variance partition coefficient (VPC), calculated following each MAIHDA model, is interpreted as the percent of the total variation in the outcome that is attributable to the between-strata level after adjustment for any variables (including main effects and covariates). The VPC is a measure of discriminatory accuracy, i.e., the ability of the model	- Hierarchical models typically function best when more level 2 units are included in the analysis. Therefore, in contrast to fixed effects models, it is better in MAIHDA models to include more dimensions of social position/process and/or more categories within each dimension. - MAIHDA models are more scalable and parsimonious. - Automatically adjusts estimates based on	- Estimates using a MAIHDA approach are inherently more conservative in cases where a stratum has few respondents. - Using mixed models forces the explicit and appropriate modeling of the random effects (level 2), which could potentially leave more room for error. - This method assumes that stratum specific residuals are normally

(*continued on next page*)

Table 2 (*continued*)

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
	between social strata is represented by the between-stratum variance parameter. In a MAIHDA model adjusting for main effects, the stratum specific residual can be interpreted as the remaining total "interaction effect" that remains unexplained by the main effects.				to correctly discriminate between people with/without the outcome of interest. The proportional change in variance (PCV), calculated following each MAIHDA model, indicates the total between stratum variance from the null model that is explained after adjustment for additive main effects and covariates. Differences between the total predicted effect and the predicted effect based only on the additive main effects allows for the examination of intersectionality for all strata of the dimensions of interest.	the observed sample size, providing more conservative and reliable estimates for strata with small N. - Simulation analyses suggest that MAIHDA models provide more reliable estimates and are less likely to erroneously detect interactions of statistical significance due to chance alone than their conventional single-level counterparts.	distributed, which is less likely for highly marginalized groups
Area under the receiver operating curve (AUROC) (Wemrell et al., 2017)	This approach involves developing models of increasing complexity and using the AUROC to compare the discriminatory ability of each model. The regression models to be compared (using AUROC) could include one variable, followed by a model adjusting for all other social factors of interest, and finally a model including an "intersectional variable".	3,600,000[a]	4	Yes	- Comparison of the AUROC between the separate models provides a measure of the increased ability to discriminate between outcome/no outcome. - This method could provide evidence that adding additional aspects of social position could lead to stronger prediction of outcome. This could imply that social identities themselves should be evaluated in combination with others.	This method could capture accurate risk exposure between groups indicative of power relationships	Not necessarily a limitation, but this method should be used in prediction settings rather than seen as a way of quantifying intersectional effects.
Classification and regression trees (CART) (Cairney et al., 2014; Greene et al., 2019)	Broadly speaking, CART is a method that includes two different types of decision trees: classification trees (for categorical outcomes) and regression trees (for continuous outcomes). Ultimately, the goal of CART analysis is to develop a classification structure which seeks to best predict an outcome variable. These classification structures are developed based on recursive procedures, which split the tree based on values of variables that best differentiate	691-1213	4–5	Yes	Sensitivity, specificity, positive predictive value, and negative predictive value of the CART model are interpretable as the model's predictive accuracy. Good accuracy in individual terminal nodes allows for the identification of specific subgroups of the sample that are more/less likely to have the outcome. The final CART model reveals how	- No assumptions about variable distributions or relationships. - Capable of identifying complex and unsuspected interactions. - Can identify complex interactions in studies that are unable to use linear models for interactions. - Nonparametric - Method facilitates hypothesis generation	- One concern about CART is that this method is obligated to select specific cut-points, so doesn't work well with continuous predictors – making replication of results difficult. - Classifications can be determined by covariates that do not reflect social categories of marginalization or hierarchies of power

(*continued on next page*)

Table 2 (*continued*)

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
	observations on the outcome of interest.				individual predictor variables intersect to predict an outcome, which maps directly onto intersectionality theory		
Exhaustive chi-square automatic interaction detection (CHAID) (Shaw et al., 2012)	This approach investigates possible interactions across a large number of categorical data. Classification trees are used to test predictor variables one at a time and detect the strongest associations between predictors and outcomes. The goal is to identify the classification which best differentiates the outcome variable. This approach divides the sample into subgroups characterized by different combinations of the predictor variables and assigns an index score to each group, representing the proportion of outcomes observed in that group.	211,736[a]	4	No	Using this method, a wide variety of data are distilled into groups that are more or less predictive of the outcome of interest. One can evaluate the compositions of groups (i.e., which combinations of factors) that are more or less predictive of the outcome as a means of evaluating how combinations of factors influence the ability to predict outcome risk.	- Each of the subgroups represents a combination of different predictor variables and intrinsically acknowledges the interconnectedness of different social positions - Exhaustive CHAID does not require distributional assumptions of traditional analyses; - Could identify intersections that were not previously theorized; could be useful for hypothesis generation - Decision tree method could be used to rank variables and identify social categories that are "most" important for explaining the outcome.	- Predictors in CHAID models must be measured on either the nominal or ordinal scale
Regression stratified by subgroups							
Regression stratified by subgroups (Parent et al., 2018; Rodriguez-Seijas et al., 2019; Rosenfield, 2012; Sen & Iyer, 2012; Veenstra & Patterson, 2016)	This approach has been used in studies in which more than two intersectional positions were of interest. Rather than including a three-way interaction term, which is difficult to interpret, this method assesses the association between a 2-way interaction term between two axes of interest by strata of a third axis of social position. Effectively, this is an evaluation of effect modification. Formal assessment of differences between strata can be evaluated using the Chow test.	237-1,065,110	2–5	Yes	The Chow test compares whether a stratified model explains more variance than a pooled model. Statistically significant results for the Chow test suggest that the interaction effect differs significantly between strata of a third variable of interest. In relation to intersectionality, this method provides evidence of differences in outcomes at intersectional subgroups.	This approach provides similar information as including a three-way interaction term in a regression model. However, interpretation may be easier as parameter estimates are interpreted within levels of the stratifying variable.	This approach would require a large enough sample for each stratum in order to detect intersections.
Geographically weighted regression (Jang & Kim, 2018)	Geographically weighted regression is an extension of ordinary least squares regression that allows for the association between predictor and outcome variables to differ based on location. In other words, it allows for the modeling of predictors and outcomes at the local level. This method implements a regression model for each location in a dataset,	1164[a]	2	Yes	When implementing this method for intersectionality research, one could examine whether the association between intersectional social categories and an outcome of interest differs based on setting. This could potentially facilitate the identification of particularly vulnerable	For outcomes that are particularly localized (e.g., anti-bullying policies implemented at the school district level, access to food or health care), geographically weighted regression could complement traditional OLS techniques by allowing for potential special nuances.	This method is sensitive to the choice of bandwidth (i.e., distance band for each "neighborhood" defined).

(*continued on next page*)

Table 2 (*continued*)

Method	Description	Sample size (range)	Number of social positions observed	Adjustment for confounders possible?	Connection to intersectionality	Strengths	Limitations
	specifying bandwidths around each location.				neighborhoods which could be targets for intervention.		
Surrogate measures of additive interaction. The below are measure of additive interaction that are calculated using effect estimates from a multiplicative model. Equations below are for risk ratios. Similar measures exist for odds ratios, which have been described elsewhere (VanderWeele & Knol, 2014).							
Relative Excess Risk due to Interaction, RERI (Jackson et al., 2016; Kanchi et al., 2018; Tejera et al., 2019)	The relative excess risk of interaction (RERI) represents a ratio between the excess intersectional disparity and the mean outcome in the non-marginalized group. $RERI_{RR} = RR_{11} - RR_{01} - RR_{10} + 1$	1527–10,386	2	Yes	• In the absence of interaction, RERI = 0. RERI>0 provides evidence of positive additive interaction, and RERI<0 provides evidence for negative additive interaction.	Statistically significant additive interaction maps directly onto the concept of intersectional multiplicativity.	Surrogate measures provide a way to directly translate multiplicative measures of interaction into additive measures. Requires additional post-estimation following multiplicative regression analysis, potential for error in coding. In order for interaction effects to have a causal interpretation, must adjust for confounders of both interaction factors. Significant surrogate measures of additive interaction can only provide direction and presence of interactive effect, but not magnitude.
Attributable Proportion, AP (Jackson et al., 2016; Kanchi et al., 2018; Tejera et al., 2019)	The attributable proportion (AP) is the proportion of the mean outcome in a doubly marginalized group that is explained by the excess intersectional disparity. $AP = \frac{RR11 - RR10 - RR01}{RR11}$	1527–10,386	2	Yes	• In the absence of interaction, AP = 1. AP is interpreted as the proportion of disease that is due to the interaction among people who are doubly exposed.		
Synergy Index, SI (Jackson et al., 2016; Kanchi et al., 2018; Tejera et al., 2019)	The synergy index (SI) is a ratio of the observed joint disparity that would have been expected if there was no excess intersectionality disparity. $SI = \frac{RR11 - 1}{(RR10 - 1) + (RR01 - 1)}$	1527–10,386	2	Yes	• SI is interpreted as the excess risk of double exposure in the presence of interaction relative to the risk from exposure with no interaction. In the absence of interaction, SI = 1		
Ratio of Observed and Expected Joint Effects, RJE (Jackson et al., 2016; Kanchi et al., 2018; Tejera et al., 2019)	The ratio of observed versus expected joint effects on the relative scale (RJE) compares the observed mean outcome in the multiply marginalized group versus the expected mean if one axis alone could explain the mean outcome $RJE = \frac{observed\ RR11}{Exoected\ RR11}$ Expected RR11 = RR10 + RR01 -1 RJE = 1/(1-AP)	1527–10,386	2	Yes	- RJE>1 implies positive additive interaction, RJE<1 implies negative additive interaction.		
Block/set regression							
Block/set regression (Reisen C.A. et al., 2013; Ro & Loya, 2015)	Block/set regression is a hierarchical modeling approach which adds sets of characteristics to a model one at a time and evaluates the variance in the outcome explained.	301-5017	2	Yes	The variance in the outcome after adding a new set of characteristics is compared to a model without that set of characteristics.	If there are complicated constructs of social position comprised of highly correlated factors (such as sexual minority status, which typically comprises three domains: attraction, behavior, and identity), this approach may be useful for model building.	Adding characteristics as sets of variables does not allow for the evaluation of potential relationships that exist between variables across sets, thus not allowing for the evaluation of mutual constitutions of intersectional positions that may be important for a given outcome of interest.

[a] Sample size is from a single study.

more exposures differs from the *product* of their main effects. We note that additive-scale interactions, which may have the more substantive interpretation, can be estimated from multiplicative models using regression standardization (VanderWeele & Knol, 2014).

Methods: This method involves including an **interaction term** in multivariable regression models. Of the studies that used this method, 51.3% were on the additive scale. The remaining studies reported results on the multiplicative scale (39.5%) or, for studies with both binary and continuous outcomes, results were reported on both scales (9.2%). In some cases, post-estimation methods were used to present the predicted probabilities of the outcome at the intersections of interest.

Intersectional question: Is the expectation of the outcome (e.g., risk, odds, prevalence) at each intersectional position different from what would be expected if there was no interaction between the social positions?

Strengths and limitations: This class of method is relatively easy to implement and yields easily interpretable effect parameters. Though the validity of regression with interactions and chi-square analysis are dependent on sample size, other methods in this class are relatively robust to small sample sizes. However, when using regression with interaction terms, caution is needed to select the appropriate scale when evaluating intersectional hypotheses.

Example: One study investigated the risk of self-reported hypertension at the intersections of race, gender, class, and sexuality using a nationally representative sample of Canadian adults, (Veenstra, 2013). Starting with a logistic model including main effects only, the authors added two-, three-, and four-way interactions between the four variables of interest. Lower-level interactions were added to the model sequentially, and only examined when the higher-level interactions were not statistically significant. Graphical checks showed that the main effects model was poorly calibrated for several subgroups, underestimating the prevalence of hypertension among higher SES Black men and higher SES South Asian women. The authors concluded that the intersectional model with interaction terms fit their data better than the main effects model, in particular showing that gender interacted with the other factors they examined.

3.2.2. Models using stratification (12.7% of studies)

Description: Stratification methods facilitate ease of interpretation by avoiding or reducing the number and degree of interaction terms (i.e., when more than two intersectional positions are of interest). This method typically involves specifying models for the effects of one or two intersectional positions, stratified by an additional axis.

Methods: Stratification commonly estimates traditional **effect modification** – when main effects differ within strata (e.g., assessments of SES stratified by gender). This method has been employed in several studies using a **two-way interaction term** in regression models **stratified by a third axis** of social position (e.g., assessments of the joint effects of race/ethnicity and SES, stratified by gender). The Chow test for heterogeneity between two regression models can be used to evaluate whether the interactions in separate stratified models are statistically different. Other studies estimated the effects of a primary exposure of interest on an outcome within strata of intersectional subgroups, which allows for the assessment of effect modification by intersectional position (e.g., associations of same sex union status with health outcomes stratified by both race and gender (Liu et al., 2017)). One study implemented a geographically weighted regression, which allows for assessment of heterogeneity by locality in both the main effects of each social position and intersections between them (Jang & Kim, 2018).

Intersectional question: Does the intersectional effect of one or two social positions differ across strata of another social position?

Strengths and limitations: When more than two social positions are of interest, implementing stratified regression (as opposed to regression with interaction terms) are more easily interpreted. However, large sample sizes may be required to represent each strata. To fully express intersectional meaning and to communicate simultaneity from estimates using this method, the interpretation of effects must be communicated in the context of the levels of the stratified variable (Jackson et al., 2016).

Example: One study investigated whether the intersecting effects of race and sexual minority status on mental health and substance use differed by gender using data from a cohort of racially/ethnically diverse college students in Georgia (Vu et al., 2019). The authors used two models, each with an interaction term for race and sexual minority status, stratified by gender. They found that the adverse intersectional effects of racial and sexual minority status discrimination on depressive symptoms, alcohol use, tobacco use, and marijuana use were stronger among women than among men and called for future studies to jointly assess social positions.

3.2.3. Approaches using categorized intersectional position (10.1% of studies)

Description: Distinct intersectional positions are coded as unique levels of a single nominal categorical or continuous exposure variable (examples below).

Methods: The most common methods used complete **categorical cross-classifications** to define intersectional positions. For example, the Schulman study (Schulman et al., 1999) defined unique intersectional positions using a four-level categorical variable contrasting Black women, Black men, White women, and White men. Of note, this model is equivalent to the more conventional intersectional model including indicators for race, gender, and their interaction – and can easily be used to estimate the same three parameters; this holds more generally for analyses considering two or more intersectional positions, provided all higher order interactions are included in the model. Another approach used the ***number* of social positions** defined to be stigmatized based on context, including race, marital status, gender, sexual minority status, military status, age, religion, and nationality (Lavaysse et al., 2018). Notably, this approach assumes that the effects of all social positions are similar. Finally, **data-reduction** methods such as latent class and profile analysis, which group individuals on shared characteristics, were used to construct subgroups (Landale et al., 2017; Whaley & Dubose, 2018).

Intersectional question: Compared to the reference group (often though not required to be those with the most privilege), do other subgroups defined by the intersectional position experience worse outcomes?

Strengths and limitations: Any intersectional variables that are created can be easily used in a variety of statistical methods. Additionally, there are multiple ways to conceptualize and create variables that are representative of intersectional positions. However, if variables being used to construct intersectional variables are mismeasured, this method could potentially amplify misclassification bias. Additionally, caution is needed to select the appropriate reference group.

Example: One study examined the intersection between racial/ethnic and sexual minority status on depression and victimization using data from a community-based longitudinal study of racially diverse sexual minority women (Bostwick et al., 2019). The authors used a six-category "intersection" variable defined by sexual minority status (lesbian, bisexual) and race/ethnicity (White, Black, Latina) in a mixed effects logistic regression, with White lesbians as the reference category. They found that, compared with White lesbians, Black bisexual and lesbian women had lower odds of depression despite reporting higher levels of victimization, and that Latina bisexual and lesbians did not differ from White lesbians on depression. Overall, they concluded that some sexual minority women of color may have social and cultural factors that are protective against depression and call for the deliberate oversampling of Black and Latino bisexual and lesbian women to further investigate factors associated with depression.

3.2.4. Methods to estimate mediation of intersectional effects (4.4% of studies)

Description: Mediation methods explain the differences in average outcomes across intersectional positions, which are often non-

modifiable, by investigating the roles of potentially modifiable mediators (e.g., discrimination).

Methods: **Simple mediation analyses** use the methods of Baron and Kenny to decompose the total effect of an intersectional position into an indirect effect via the proposed mediator and the direct effect, usually assuming that the mediator has the same effect across intersectional positions (Baron & Kenny, 1986). More recently developed methods accommodate **exposure-mediator interaction**, including decomposition methods described in detail in the example below as well as in decomposition of inequality measures (described below in section 3.2.6), thus allowing the effect of the mediator to differ across intersectional positions (VanderWeele & Knol, 2014). **Structural equation modeling**, used to define unobserved or *latent* constructs within the observed data, has also been used for mediation analysis.

Intersectional question: To what extent do potentially modifiable mediators explain intersectional inequalities?

Strengths and limitations: This class of methods provides a clearly proposed relationship between variables, which could potentially be more useful for the development of interventions and policies. However, rigid structural assumptions are required in order to yield unbiased estimates. For example, structural assumptions for the causal mediation decomposition approach (VanderWeele, 2016) requires no unmeasured/unadjusted confounding in the (1) exposure-mediator relationship, (2) mediator-outcome relationship, (3) the exposure outcome relationship, and (4) no mediator-outcome confounders (measured or unmeasured) which occur downstream of the exposure. While the fourth assumption is already very unlikely to hold in most settings, the causal criteria for consistency makes this assumption even more difficult (Rehkopf et al., 2016), as socially constitutive processes are inherently complex and heterogeneous, and naturally take on different meanings in different contexts. In other words, the causal link between the exposure and the "causal intermediate" could exist for only some (but not all) versions of the exposure. Jackson further expanded upon confounding assumptions and interpretations for mediation analysis (Jackson, 2017). As an additional point, in the context of mediation analysis, recent scholarship has commented on the inappropriateness of adjusting for covariates which could potentially explain disparities of interest and help illuminate potential points of intervention (Jackson, 2020). Inappropriate adjustment for confounders in mediation analyses could open backdoor pathways, creating spurious associations between exposures and the outcome. Separately, inappropriate confounder adjustment can result in the estimation of conditional disparities rather than marginal disparities; that is, disparities among intersectional groups with the same value(s) of the confounder(s) (Jackson, 2017; Jackson & VanderWeele, 2019). Therefore, for researchers interested in identifying specific targets for intervention using this suite of methods, covariate control in this context should complement the goals of the investigative inquiry.

Example: One study evaluated the extent to which differences in psychological distress across intersectional positions defined by race/ethnicity and sexual/gender minority (SGM) status could be explained by daily experiences of discrimination (Bauer & Scheim, 2019b). . In VanderWeele's original work on causal mediation decomposition, the quantities of decomposition represent the effects of comparing counterfactual outcomes after manipulating the values of both the exposure and the mediator (VanderWeele, 2016). In this present study and analysis, the authors decomposed the total effects of intersectional positions into three components: (1) the pure direct effect (PDE; the expected difference in the outcome between intersectional positions that would be expected if, possibly counter to fact, the comparison position experienced the same level of discrimination as the reference position), (2) the pure indirect effect (PIE; the expected between-position difference in the outcome due to the reference-position effect of the between-position difference in level of discrimination), and (3) the mediated interaction effect (the between-position difference in *level* of discrimination due to the between-position difference in the *effect* of discrimination). These three component effects were compared across 11 intersectional positions defined by race and sexual minority status. The authors found that, had the experiences of discrimination for each of the intersectional positions been reduced to the levels experienced by White non-SGMs, inequalities in psychological distress would have persisted for some groups (Indigenous and Middle Eastern SGMs), but would have been reduced for others (Black non-SGMs). They additionally found that the effect via the mediated pathway of discrimination was statistically significant for all groups except Asian and Latin American non-SGMs. Overall, the authors concluded that using causal mediation as an analytic quantitative intersectionality approach is promising for the development of direct and implementable intervention targets.

3.2.5. *Prediction methods (3.8% of studies)*

Description: Prediction-based approaches describe the predictive ability (i.e., discriminatory accuracy) of modeling choices. These methods are most appropriate for hypothesis generation and can provide preliminary evidence of specific subgroups or intersections that could be investigated in future studies. In comparison to categorization methods, prediction methods use data-driven approaches to identify intersectional positions that best explain the outcome and predict differences in the prevalence of the outcome.

Methods: Methods included multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA, which nests individual respondents into social strata representing all possible intersectional effects and interprets model residuals as additional intersectional effects), estimating the area under the receiver operating curve (AUROC, explained further in the example below), classification and regression tree (CART, which uses a decision tree approach to determine factors most predictive of the outcome variable) and exhaustive chi-square automatic interaction detection (CHAID, which sequentially tests predictor variables to detect factors that explain most of the variation in the outcome). These methods provide a measure of discriminatory accuracy (i.e., the ability to predict the presence or absence of an outcome) (Page et al., 1995, pp. 7–8).

Intersectional question: Does including interactions between social positions improve a model's discriminatory accuracy? Which social positions are most predictive of an outcome, and what are the ideal classifications to differentiate an outcome variable? What interactions between which variables best predict an outcome of interest?

Strengths and limitations: Multilevel modeling could allow for the investigation of multiple dimensions of structural and social oppression. Additionally, this class of methods could be easily implemented even with small sample sizes. However, the adjusted mean in predicted models is most precise for the largest group, which is oftentimes the lowest risk group and is used as the reference by default. Importantly, the comparison group can be changed (e.g., instead contrasting other groups with the highest risk group), and the discussion of the results can focus on contrasts with the most marginalized group as the reference. Estimates from these contrasts may be less precise if the group chosen as the reference also has a small sample size.

Example (AUROC): One study used the AUROC to examine whether incorporating intersectional positions would increase the researchers' ability to predict ischemic heart disease in the population of middle-aged adults living in Sweden (Wemrell et al., 2017). Two models were compared to each other, each stratified by gender. The first model was additive in age and other social factor variables, whereas the second model included age and a constructed intersectional variable combining recent immigrant status, disposable household income, marital or civil status, and prescription medication usage. Although the authors found substantial differences in risk between the intersectional groups, the intersectional model achieved only slight increases in the AUROC (+0.002 for both genders). The researchers concluded that in this population intersectionality defined in terms of the available covariates was of limited use in predicting ischemic heart disease. However, they argued for discriminatory ability as a relevant measure of the

importance of intersectional position in predicting health risk.

3.2.6. Decomposition of inequality measures (1.9% of studies)

Description: Adopted from economics, these methods decompose a measure of inequality into within and between subgroup components. Subgroups are defined by intersectional positions. Between-subgroup inequality is assessed before and after intersectional positions are explicitly considered.

Methods: Methods included the **Oaxaca-Blinder** decomposition (decomposing outcome differences into the parts due to within- and between-group effects) (Blinder, 1973; Oaxaca, 1973), decomposition of the **mutual information index** (a multigroup index comparing the sum of the proportion attributed to each social factor to a joint inequality), and decomposition of the **general entropy** class of measures (redundancy in data that estimates outcome inequality between groups).

Intersectional question: What proportion of the total observed inequality can be attributed exclusively to each individual social position, and what proportion can be attributed to the intersectional position?

Strengths and limitations: This class of methods may be useful if an inequality metric (i.e., measures which summarize inequalities in outcomes. An example of one such metric is the Gini coefficient of income inequality, which quantifies the extent to which the distribution of wealth in an economy deviates from an equal distribution) is readily accessible to researchers. However, there is heterogeneity in the strength of the decomposition properties of each measure. Finally, the application of decomposition methods to intersectionality inquiries is growing, accompanied by robust debate surrounding the appropriateness of certain decomposition methods in investigating intersectionality (Jackson, 2017; Jackson et al., 2016; S.; Schwartz, 2017).

Example: One study decomposed inequality in nutritional status among children in India by caste and economic class (Chakraborty & Mukhopadhyay, 2017). Although their focus was methodologic, this approach could be used to assess the increase in the total inequality explained by caste and class when their intersections are considered. In their decomposition of total inequality, the authors found that the proportion of intersectional inequality exceeded between-class- and between-caste inequality in the urban setting but had lower between-class inequality in the rural setting.

3.2.7. Surrogate measures of additive interaction (1.9% of studies)

Description: For studies of intersectional positions, surrogate measures provide proxies for the additive interaction (AI) effect from ratio effect estimates. These methods can be applied to case-control data where the baseline risk is unknown or to summary data in which only relative risks are provided.

Methods: The **relative excess risk due to interaction** (**RERI**) equals AI as a multiple of the (unknown) baseline risk. The **synergy index** (**S**) is defined as the excess risk among the doubly marginalized, relative to the reference group, as a multiple of the sum of the excess risks in the two singly marginalized groups. Both RERI and S have the same sign as AI but are otherwise uninformative about its magnitude. The **attributable proportion** (**AP**) is equal to the AI as a multiple of the absolute risk in the doubly marginalized group, and interpretable as the proportion of the absolute risk in that group due to AI. Finally, the **ratio of joint effects** (**RJE**) is defined as the absolute risk in the doubly marginalized group as a proportion of the risk that would be expected in the absence of interaction (Gebrekristos & Howe, 2015).

Intersectional question: Is there statistical evidence for additive interaction? If so, what is the direction of the additive interaction (synergistic/positive or antagonistic/negative)? What proportion of the risk in the doubly marginalized group can be explained by the interaction between social identities?

Strengths and limitations: Measures of additive interaction have direct relevance to public health and clinical practice, as they may be interpreted as excess cases caused or prevented by the exposure(s). Measures of statistical interaction on the additive scale are therefore considered to better align with the tenet of intersectional multiplicativity, compared to statistical interaction on the multiplicative scale. When multiplicative models are implemented, surrogate measures require additional computation. Additionally, if logistic regression models are employed (yielding odds ratios) and the outcomes evaluated are common, computations of surrogate measures may be overestimated.

Example: One study investigated the intersecting associations of gender and race with cardiovascular disease risk factors by deriving measures of AI from logistic models in a representative sample of adults in New York (Kanchi et al., 2018). Specifically, they show that while women overall had lower prevalence of CVD risk factors than men, this advantage was restricted largely to non-Latino White women, and that non-Latino Black women experienced a higher burden of CVD risk factors compared to other gender and racial/ethnic groups. The authors used RERI to show that the adverse effect of being Black *and* a woman was more adverse than expected based on the individual effects of these factors considered singly. Of note, although statistical results are interpreted through identity-based framing (e.g., Black women), the authors acknowledge and contextualize the driving patterns of these inequities as environmental (i.e., cumulative exposure to racism).

3.2.8. Block/set regression (1.3% of studies)

Description: Block/set methods use a form of forward selection in which blocks or sets of variables determined a priori (e.g., demographic set, socioeconomic set, etc.), usually based on a causal model, are sequentially added.

Methods: Block/set regression allows investigators to assess the **joint contribution of each newly added set** to the current model at each step. Hypothesis tests (e.g., Wald test) can be used to evaluate the best fit between two regression models.

Intersectional question: Does the addition of the intersections between previously entered sets, each defined by a set of pre-determined factors, explain additional variance in the outcome of interest?

Strengths and limitations: This method could be potentially helpful if highly correlated constructs of social position are being investigated. However, intersectional effects must be explicitly coded within each block/set.

Example: One study used this approach to investigate whether demographic characteristics (age, education, income, and region of birth), gender nonconformity (a single continuous scale), and discrimination (by race and by sexual minority status) were associated with depression and gay collective identity in a sample of HIV-positive, Latino gay men (Reisen et al., 2013). Both Wald and likelihood ratio tests confirmed that each set provides additional explanatory power, and they concluded that both forms of discrimination were associated with depression. Although the authors focus on the main effects of axes of social identity, and did not directly examine the explanatory power of intersections between them as additional blocks, the block/set regression approach could easily be extended for this purpose, and was implicitly used in the Veenstra study (Veenstra, 2013) discussed in the Regression with Interaction Term section (section 3.2.1).

4. Discussion

In this systematic review, we identified 28 unique quantitative analytic methods which applied intersectionality as a theoretical framework. Below, we present several broad themes that emerged from our findings, specifically: (1) a loss of attention to social power as intersectionality has continued to travel across scholarly disciplines, (2) quantitative methods that appear to be at odds with the fundamental tenets of intersectionality, and (3) the most common and reasonable statistical approaches and their limitations.

Consistent with recent reviews, we found that meaningful theoretical elements of intersectionality, such as the conceptualization of social

power, are lost in the translation to quantitative approaches (Bauer et al., 2021; Phillips et al., 2020). This oversight is partially manifested in the exposure definition across studies – specifically, most of the studies in this review focused on social identity factors, rather than intersecting social structures and power relations, which can lead to attention being shifted away from structural factors in favor of individual-level interventions (Lofters & O'Campo, 2012). This limitation in the analytical intersectionality literature is perhaps reflective of the individualistic focus of the disciplines and methods that are central in health research. Alas, if the intention of intersectionality work is to advance social justice and equity, it is critical for researchers to focus on modifiable social processes (e.g., racism and other interlocking types of oppression such as sexism, classism, heterosexism, etc.) and not just demographic intersectional positions (Yudell et al., 2020). Researchers must be able to move beyond proxies and learn how to conceptualize and assess systems of power and oppression in order to examine the actual structures and power relations that are central to intersectionality (Krieger, 2020). As an example of a promising approach, Bauer et al. recently piloted the adoption of VanderWeele's causal mediation decomposition to examine the social process of discrimination, through which demographic intersectional positions operate (Bauer & Scheim, 2019a). Relatedly, and perhaps because of the choice and limitations of exposure variables that quantify social position as demographic factors, most of the studies in this review made inferences based on identity alone. While these studies do provide evidence for social inequality, inferences made based on identity place the onus of change on individuals within the hierarchy, rather than on the hierarchy itself.

Because intersectionality did not originate as an empirically testable framework, there is no singular quantitative method that provides a perfect match to the complexities of this theory. However, statistical analyses are not all equally agnostic to theory, as many methods encode assumptions about how social processes and systems influence and inform health. Thus, it is important to acknowledge that every method will have its own challenges, and investigators should be aware of these in their future works. Below, we describe potential issues investigators should consider when applying quantitative methods to the study of intersectionality. First, while models broadly classified as decomposition methods (including mediation analyses) are valuable in parsing out causal effects, thereby identifying modifiable targets for intervention (e.g., discrimination) to reduce inequities, readers should exercise caution when implementing decomposition methods that seek to parse out inequities attributable to axes of marginalization (e.g., decomposing an inequality into effects attributed solely to sexism, or solely to racism, and a component which is explained by the sum of both combined). The tenets of intersectionality theory specifically claim that social inequality results from mutually reinforcing, and fundamentally connected systems of power. The value of implementing analytic intersectionality is to acknowledge and investigate interlocking and joint effects, not separate them (S. Schwartz, 2017). This interconnectedness is analogous to not being able to extract the sugar from the flour after you've blended the ingredients for a cake (Bowleg, 2013). The core tenets of intersectionality suggest that you cannot separate an individual's social position into individual components (Bowleg, 2012, 2013). While in this paper we describe all decomposition methods together, we must emphasize that decomposition methods encompass a broad suite of methods, and we specifically call attention to those which seek to separate mutually constitutive effects into distinct elements. Thus, if decomposition methods are used for intersectionality, investigators should be particularly cautious not to interpret effect parameters attributed to individual components (for methods which quantify these values).

As another example, the approach of summarizing the number of marginalized or stigmatized social positions held by an individual views oppression as simply additive (Bowleg, 2008), and ignores the intractably interconnected nature of oppression. This approach also ignores the unique interactive effects of specific interesting axes of social power and oppression (intersectional multiplicativity). For example, two people could score a 3 on a continuous variable reflecting many social positions, but their scores may reflect very different intersectional axes (e.g., one score could be based on the intersection of racism, classism, and sexism while the other could be based on the intersection of heterosexism, classism, and immigration status). Additionally, when using block/set regression, investigators must explicitly code for the examination of joint effects in order to uncover the intersectional positions that could be relevant for intervention.

With respect to analytic approaches, regression with interaction terms (including additive and multiplicative models, as well as ANOVA-based methods, chi-square, and t-tests) was the most common analytic approach observed in this review. Few studies, however, articulated their rationale for mathematical scale beyond potential constraints of the outcome variables (i.e., binary outcomes are often modeled on the multiplicative scale). Although some scholars have suggested the use of multiplicative interaction terms to assess intersectional effects (Dubrow, 2008), leading intersectionality scholars have asserted that the assessment of additive scale interaction is the most relevant for health related intersectionality research (Bauer, 2014). In her paper describing the incorporation of intersectionality into population health research, Bauer describes the additive-scale interaction as more representative of Hancock's intersectional multiplicativity. Intersectional multiplicativity, which is conceptually linked to the tenets of power, relationality, and complexity, suggests that any individual's social location is not equivalent to the *sum* of all their social identities (Hancock, 2007a, 2019). This concept is more analogous to the test of additive interaction, and as such, measures of additive interaction are more fundamentally aligned with the description of intersectional multiplicativity. Additionally, it is widely acknowledged in the field of public health and medicine that additive measures are more informative for clinical decision making and public health interventions, as they directly translate to excess cases that are caused or prevented by the exposure (Szklo & Nieto, 2014). Therefore, for studies that use regression with interaction terms to evaluate intersectional hypotheses, authors should interpret their findings on the additive scale. As noted in our review, even if investigators are constrained to multiplicative models, additive interaction may still be estimated using surrogate measures (RERI, S, AP, RJE) or post-estimation predicted probabilities of the outcome for each intersectional position.

Several limitations must be considered when interpreting the results from our review. Due to our inclusion criteria, only studies that mentioned or described intersectionality were included in this analysis. As a result, we may have missed studies that attempted to answer research questions which, in spirit, were aligned with the understanding of the health outcomes at the interplay between multiple systems of oppression but did not explicitly mention intersectionality. Additionally, in Collins' work on the definitional dilemmas of intersectionality, she describes the disconnection between intersectionality as a scholarly practice from its use within social justice projects, which has widened since its adoption into the academy (Collins, 2015a). However, the practical application of intersectionality has been described to be the most important stage of its adoption into health research (Bowleg, 2021), and quantitative intersectionality which fails to emphasize processes or policies for intervention simply perpetuates inequity (Bauer, 2014). Although we made an earnest attempt to define and capture the element of praxis in this review, we were ultimately unable to quantify the "translatability" of study findings into meaningful health interventions. Future studies and reviews on intersectionality should further evaluate and describe the extent to which the disconnection between intersectionality in the academy and within social justice projects exists. Finally, it is imperative to acknowledge the dynamic nature of power and privilege through social space and time (Collins, 1991). However, considering the nascency of analytic quantitative intersectionality methods, we were unable to extract this information in the review.

In conclusion, our study provides insight into the range of

quantitative analytic methods that have been adopted to investigate intersectionality, comparing and contrasting their strengths and limitations. It is important to note that intersectionality as a theoretical framework was not developed to be empirically tested or operationalized (Syed, 2010), thus numerous methodological challenges and debates remain regarding guidelines and approaches to conduct this research (Bowleg, 2012; Else-Quest & Hyde, 2016a, 2016b). While the earliest applications of intersectionality utilized qualitative methods, scholars have adopted intersectionality across disciplines and many statistical methods have been employed in an earnest attempt to contribute to the translation of intersectionality into the quantitative sphere (Bauer, 2014; Hancock, 2007b; McCall, 2005). As analytic quantitative intersectionality scholarship continues to evolve, researchers must be aware of the utility and limitations of statistical approaches that we describe in this piece. Specifically, the choice of any particular statistical method does not inherently incorporate intersectionality into a study. Rather, intersectionality requires and emphasizes the role of power and structural oppression in reinforcing social inequity (Cho et al., 2013). Furthermore, while methods described in this review can provide evidence of quantitative differences, theory and mixed methods are required to derive qualitative meanings and experiences of intersectional oppression (Jackson, 2017). Thus, scholarship purporting to use intersectionality must be interpreted through the context of social and structural power, as statistical approaches themselves do not reflect this necessary component of the framework. To better represent the tenets of intersectionality, it is up to the investigator to: (1) justify their exploration of the intersectional positions they choose to investigate, acknowledging the potential limitations of existing measures, (2) clearly explain the selection of a statistical approach and, when using regression with interaction terms, opt for the interpretation of additive effects, (3) contextualize results from statistical analyses within broader systems of power and oppression, and (4) identify clear and implementable solutions which could be used to advance social and health equity.

Funding sources

This work was supported by the National Institutes of Health (NIMH R01MH112420; NIA T32AG049663; NIAID K01 AI145572). This research was also supported by a grant from the National Institutes of Health, University of California, San Francisco, Center for AIDS Prevention Studies, #P30MH062246.

Declaration of competing interest

The authors have no conflicts of interest to declare.

References

Agénor, M. (2020). Future directions for incorporating intersectionality into quantitative population health research. *American Journal of Public Health, 110*(6), 803–806. https://doi.org/10.2105/AJPH.2020.305610

Aguirre, C. G., Bello, M. S., Andrabi, N., Pang, R. D., Hendricks, P. S., Bluthenthal, R. N., & Leventhal, A. M. (2016). Gender, ethnicity, and their intersectionality in the prediction of smoking outcome expectancies in regular cigarette smokers. *Behavior Modification, 40*(1–2), 281–302. https://doi.org/10.1177/0145445515608146. PsycINFO.

Alexander-Floyd, N. G. (2012). Disappearing Acts: Reclaiming intersectionality in the social sciences in a post-black feminist era. *Feminist Formations, 24*(1), 1–25. https://doi.org/10.1353/ff.2012.0003

Barden, E. P., Barry, R. A., Khalifian, C. E., & Bates, J. M. (2016). Sociocultural influences on positive affect: Social support adequacy from one's spouse and the intersections of race and SES. *Journal of Social and Clinical Psychology, 35*(6), 455–470. https://doi.org/10.1521/jscp.2016.35.6.455. PsycINFO.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. https://doi.org/10.1037//0022-3514.51.6.1173

Bauer, G. R. (2014). Incorporating intersectionality theory into population health research methodology: Challenges and the potential to advance health equity. *Social Science & Medicine (1982), 110*, 10–17. https://doi.org/10.1016/j.socscimed.2014.03.022

Bauer, G. R., Churchill, S. M., Mahendran, M., Walwyn, C., Lizotte, D., & Villa-Rueda, A. A. (2021). Intersectionality in quantitative research: A systematic review of its emergence and applications of theory and methods. *SSM - Population Health, 14*, 100798. https://doi.org/10.1016/j.ssmph.2021.100798

Bauer, G. R., & Scheim, A. I. (2019a). Advancing quantitative intersectionality research methods: Intracategorical and intercategorical approaches to shared and differential constructs. *Social Science & Medicine, 226*, 260–262. https://doi.org/10.1016/j.socscimed.2019.03.018. PsycINFO.

Bauer, G. R., & Scheim, A. I. (2019b). Methods for analytic intercategorical intersectionality in quantitative research: Discrimination as a mediator of health inequalities. *Social Science & Medicine, 226*, 236–245. https://doi.org/10.1016/j.socscimed.2018.12.015. PsycINFO.

Berg, J. A. (2010). Race, class, gender, and social space: Using an intersectional approach to study immigration attitudes. *The Sociological Quarterly, 51*(2), 278–302. https://doi.org/10.1111/j.1533-8525.2010.01172.x. PsycINFO.

Berger, M. T. (2017). Does intersectional training Endure? Examining trends in a global database of women's and gender studies graduates (1995-2010). *Atlantis-Critical Studies in Gender Culture & Social Justice, 38*(1), 28–40.

Biernat, M., & Sesko, A. K. (2013). Evaluating the contributions of members of mixed-sex work teams: Race and gender matter. *Journal of Experimental Social Psychology, 49*(3), 471–476. https://doi.org/10.1016/j.jesp.2013.01.008

Bilge, S. (2013). Intersectionality undone: Saving intersectionality from feminist intersectionality studies. *Du Bois Review: Social Science Research on Race, 10*(2), 405–424. https://doi.org/10.1017/S1742058X13000283

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources, 8*(4), 436. https://doi.org/10.2307/144855

Bostwick, W. B., Hughes, T. L., Steffen, A., Veldhuis, C. B., & Wilsnack, S. C. (2019). Depression and victimization in a community sample of bisexual and lesbian women: An intersectional approach. *Archives of Sexual Behavior, 48*(1), 131–141. https://doi.org/10.1007/s10508-018-1247-y. PsycINFO.

Bouris, A., & Hill, B. J. (2017). Exploring the mother–adolescent relationship as a promotive resource for sexual and gender minority youth. *Journal of Social Issues, 73*(3), 618–636. https://doi.org/10.1111/josi.12234. PsycINFO.

Bowleg, L. (2008). When Black + lesbian + woman ≠ Black lesbian woman: The methodological challenges of qualitative and quantitative intersectionality research. *Sex Roles: Journal of Research, 59*(5–6), 312–325. https://doi.org/10.1007/s11199-008-9400-z. PsycINFO.

Bowleg, L. (2012). The problem with the phrase women and minorities: Intersectionality—an important theoretical framework for public health. *American Journal of Public Health, 102*(7), 1267–1273. https://doi.org/10.2105/AJPH.2012.300750

Bowleg, L. (2013). "Once you've blended the cake, you Can't take the parts back to the main ingredients": Black gay and bisexual men's descriptions and experiences of intersectionality. *Sex Roles, 68*(11–12), 754–767. https://doi.org/10.1007/s11199-012-0152-4

Bowleg, L. (2021). Evolving intersectionality within public health: From analysis to action. *American Journal of Public Health, 111*(1), 88–90. https://doi.org/10.2105/AJPH.2020.306031

Bowleg, L., & Bauer, G. (2016). Invited reflection: Quantifying intersectionality. *Psychology of Women Quarterly, 40*(3), 337–341. https://doi.org/10.1177/0361684316654282

Budge, S. L., Thai, J. L., Tebbe, E. A., & Howard, K. A. S. (2016). The intersection of race, sexual orientation, socioeconomic status, trans identity, and mental health outcomes. *The Counseling Psychologist, 44*(7), 1025–1049. https://doi.org/10.1177/0011000015609046. PsycINFO.

Cage, J., Corley, N. A., & Harris, L. A. (2018). The educational attainment of maltreated youth involved with the child welfare system: Exploring the intersection of race and gender. *Children and Youth Services Review, 88*, 550–557. https://doi.org/10.1016/j.childyouth.2018.04.006. PsycINFO.

Cairney, J., Veldhuizen, S., Vigod, S., Streiner, D. L., Wade, T. J., & Kurdyak, P. (2014). Exploring the social determinants of mental health service use using intersectionality theory and CART analysis. *Journal of Epidemiology & Community Health, 68*(2), 145–150. https://doi.org/10.1136/jech-2013-203120. PsycINFO.

Carbado, D. W., Crenshaw, K. W., Mays, V. M., & Tomlinson, B. (2013). Intersectionality: Mapping the movements of a theory. *Du Bois Review: Social Science Research on Race, 10*(2), 303–312. https://doi.org/10.1017/S1742058X13000349

Chakraborty, A., & Mukhopadhyay, S. (2017). Decomposing nutritional inequality by caste and class: A quantitative approach to Reckon intersectionality. *Economics Bulletin, 37*(2), 1339–+.

Cho, S., Crenshaw, K. W., & McCall, L. (2013). Toward a field of intersectionality studies: Theory, applications, and praxis. *Signs: Journal of Women in Culture and Society, 38*(4), 785–810. https://doi.org/10.1086/669608

Choo, H. Y., & Ferree, M. M. (2010). Practicing intersectionality in sociological research: A critical analysis of inclusions, interactions, and Institutions in the study of inequalities. *Sociological Theory, 28*(2), 129–149. https://doi.org/10.1111/j.1467-9558.2010.01370.x

Chua, V., Mathews, M., & Loh, Y. C. (2016). Social capital in Singapore: Gender differences, ethnic hierarchies, and their intersection. *Social Networks, 47*, 138–150. https://doi.org/10.1016/j.socnet.2016.06.004. PsycINFO.

Cole, E. R. (2009). Intersectionality and research in psychology. *American Psychologist, 64*(3), 170–180. https://doi.org/10.1037/a0014564

Collins, P. H. (1991). *Black feminist thought: Knowledge, Consciousness, and the politics of empowerment (Reprint)*. Routledge.

Collins, P. H. (1998). It's all in the family: Intersections of gender, race, and nation. *Hypatia, 13*(3), 62–82. https://doi.org/10.1111/j.1527-2001.1998.tb01370.x
Collins, P. H. (2015a). Intersectionality's definitional dilemmas. *Annual Review of Sociology, 41*(1), 1–20. https://doi.org/10.1146/annurev-soc-073014-112142
Collins, P. H. (2015b). Black feminist thought: Knowledge, consciousness and the politics of Empowerment. *Ethnic and Racial Studies, 38*(13). https://doi.org/10.1080/01419870.2015.1058515, 2314–2314.
Covarrubias, A. (2011). Quantitative intersectionality: A critical race analysis of the Chicana/o educational pipeline. *Journal of Latinos and Education, 10*(2), 86–105. https://doi.org/10.1080/15348431.2011.556519. PsycINFO.
Covarrubias, A., & Lara, A. (2014). The undocumented (im)migrant educational pipeline: The influence of citizenship status on educational attainment for people of Mexican origin. *Urban Education, 49*(1), 75–110. https://doi.org/10.1177/0042085912470468. PsycINFO.
Covarrubias, A., & Liou, D. D. (2014). Asian American education and income attainment in the era of post-racial America. *Teachers College Record, 116*(6), 1–20 (PsycINFO).
Covidence systematic review software. Veritas Health Innovation (n.d.) www.covidence.org.
Crenshaw, K. (1989). *Demarginalizing the intersection of race and sex: A black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics* (pp. 139–168).
Crenshaw, K. (1991). *Mapping the Margins: Intersectionality, Identity, and Violence Against Women of Color, 43* pp. 1241–1300), 6.
Cummings, J. L., & Jackson, P. B. (2008). Race, gender, and SES disparities in self-assessed health, 1974-2004. *Research on Aging, 30*(2), 137–168. https://doi.org/10.1177/0164027507311835. PsycINFO.
Davis, K. (2008). Intersectionality as buzzword: A sociology of science perspective on what makes a feminist theory successful. *Feminist Theory, 9*(1), 67–85. https://doi.org/10.1177/1464700108086364
Demos, V. P., & Segal, M. T. (Eds.). (2009). *Perceiving gender locally, globally, and intersectionally* (1st ed.). Emerald Jai.
Dubrow, J. K. (2008). How can we Account for intersectionality in quantitative analysis of survey data? Empirical illustration for central and Eastern Europe. *Ask: Research and Methods, 17*(1), 85–100.
DuPont-Reyes, M. J., Villatoro, A. P., Phelan, J. C., Painter, K., & Link, B. G. (2019). Adolescent views of mental illness stigma: An intersectional lens. *American Journal of Optics and Photonics*. https://doi.org/10.1037/ort0000425
Else-Quest, N. M., & Hyde, J. S. (2016a). Intersectionality in quantitative psychological research: I. Theoretical and epistemological issues. *Psychology of Women Quarterly, 40*(2), 155–170. https://doi.org/10.1177/0361684316629797. PsycINFO.
Else-Quest, N. M., & Hyde, J. S. (2016b). Intersectionality in quantitative psychological research: II. Methods and techniques. *Psychology of Women Quarterly, 40*(3), 319–336. https://doi.org/10.1177/0361684316647953. PsycINFO.
Evans, C. R., & Erickson, N. (2019). Intersectionality and depression in adolescence and early adulthood: A MAIHDA analysis of the national longitudinal study of adolescent to adult health. *Social Science & Medicine (1982), 220*, 1–11. https://doi.org/10.1016/j.socscimed.2018.10.019
Evans, C. R., Leckie, G., & Merlo, J. (2019). *Multilevel versus single-level regression for the analysis of multilevel information: The case of quantitative intersectional analysis. Social Science and Medicine, (Evans C.R., cevans@uoregon.edu). Eugene, OR, United States.* Embase: Department of Sociology, 1291 University of Oregon. https://doi.org/10.1016/j.socscimed.2019.112499
Fasoli, F., Cadinu, M., Carnaghi, A., Galdi, S., Guizzo, F., & Tassara, L. (2018). How do you self-categorize? Gender and sexual orientation self-categorization in homosexual/heterosexual men and women. *Personality and Individual Differences, 123*, 135–139. https://doi.org/10.1016/j.paid.2017.11.011. PsycINFO.
Few-Demo, A. L. (2014). Intersectionality as the "new" critical approach in feminist family studies: Evolving racial/ethnic feminisms and critical race theories: Evolving feminisms. *Journal of Family Theory & Review, 6*(2), 169–183. https://doi.org/10.1111/jftr.12039
Friedman, C., & Leaper, C. (2010). Sexual-minority college women's experiences with discrimination: Relations with identity and collective action. *Psychology of Women Quarterly, 34*(2), 152–164. https://doi.org/10.1111/j.1471-6402.2010.01558.x. PsycINFO.
Gebrekristos, H. T., & Howe, C. J. (2015). Ratio of observed and expected joint effects. *Epidemiology, 26*(1), e3–e4. https://doi.org/10.1097/EDE.0000000000000200
Goldstein, N. D., Burstyn, I., LeVasseur, M. T., & Welles, S. L. (2016). Drug use among men by sexual behaviour, race and ethnicity: Prevalence estimates from a nationally representative US sample. *International Journal of Drug Policy, 36*, 148–150. https://doi.org/10.1016/j.drugpo.2016.01.008. PsycINFO.
Goodwin, L., Gazard, B., Aschan, L., MacCrimmon, S., Hotopf, M., & Hatch, S. L. (2018). Taking an intersectional approach to define latent classes of socioeconomic status, ethnicity and migration status for psychiatric epidemiological research. *Epidemiology and Psychiatric Sciences, 27*(6), 589–600. https://doi.org/10.1017/S2045796017000142. PsycINFO.
Greaves, L. M., Barlow, F. K., Huang, Y., Stronge, S., & Sibley, C. G. (2017). Personality across sexual identity and gender in a national probability sample in New Zealand. *Sex Roles: Journal of Research, 77*(9–10), 653–662. https://doi.org/10.1007/s11199-017-0752-0. PsycINFO.
Greene, M. Z., Hughes, T. L., Hanlon, A., Huang, L., Sommers, M. S., & Meghani, S. H. (2019). Predicting cervical cancer screening among sexual minority women using Classification and Regression Tree analysis. *Preventive Medicine Reports, 13*, 153–159. https://doi.org/10.1016/j.pmedr.2018.11.007
Grzanka, P. R. (Ed.). (2014). *Intersectionality: A foundations and frontiers reader* (1st ed.). Westview Press, a member of the Perseus Books Group.
Grzanka, P. R., & Miles, J. R. (2016). The problem with the phrase "intersecting identities": LGBT affirmative therapy, intersectionality, and neoliberalism. *Sexuality Research and Social Policy: A Journal of the NSRC, 13*(4), 371–389. https://doi.org/10.1007/s13178-016-0240-2. PsycINFO.
Guinea-Martin, D., Mora, R., & Ruiz-Castillo, J. (2015). The joint effect of ethnicity and gender on occupational segregation. An approach based on the Mutual Information Index. *Social Science Research, 49*, 167–178. https://doi.org/10.1016/j.ssresearch.2014.08.007. PsycINFO.
Gupta, N. (2019). Intersectionality of gender and caste in academic performance quantitative study of an elite Indian engineering institute. *Gender, Technology and Development, 23*(2), 165–186. https://doi.org/10.1080/09718524.2019.1636568
Hancock, A.-M. (2007a). When multiplication doesn't equal quick addition: Examining intersectionality as a research Paradigm. *Perspectives on Politics, 5*. https://doi.org/10.1017/S1537592707070065, 01.
Hancock, A.-M. (2007b). Intersectionality as a normative and empirical Paradigm. *Politics and Gender, 3*. https://doi.org/10.1017/S1743923X07000062, 02.
Hancock, A.-M. (2019). Empirical intersectionality: A tale of two approaches. In O. Hankivsky, & J. S. Jordan-Zachery (Eds.), *The Palgrave Handbook of intersectionality in public policy* (pp. 95–132). Springer International Publishing. https://doi.org/10.1007/978-3-319-98473-5_5.
Hankivsky, O., & Christoffersen, A. (2008). Intersectionality and the determinants of health: A Canadian perspective. *Critical Public Health, 18*(3), 271–283. https://doi.org/10.1080/09581590802294296
Harnois, C. E. (2015). Jeopardy, consciousness, and multiple discrimination: Intersecting inequalities in contemporary Western Europe. *Sociological Forum, 30*(4), 971–994. https://doi.org/10.1111/socf.12204. PsycINFO.
Hsieh, N., & Ruther, M. (2016). Sexual minority health and health risk factors: Intersection effects of gender, race, and sexual identity. *American Journal of Preventive Medicine, 50*(6), 746–755. https://doi.org/10.1016/j.amepre.2015.11.016. PsycINFO.
Jackson, J. W. (2017). Explaining intersectionality through description, counterfactual thinking, and mediation analysis. *Social Psychiatry and Psychiatric Epidemiology: The International Journal for Research in Social and Genetic Epidemiology and Mental Health Services, 52*(7), 785–793. https://doi.org/10.1007/s00127-017-1390-0. PsycINFO.
Jackson, J. W. (2020). *Meaningful causal decompositions in health equity research: Definition, identification, and estimation through a weighting framework*. ArXiv: 1909.10060 [Econ, Stat] http://arxiv.org/abs/1909.10060.
Jackson, J. W., & VanderWeele, T. J. (2019). Intersectional decomposition analysis with differential exposure, effects, and construct. *Social Science & Medicine, 226*, 254–259. https://doi.org/10.1016/j.socscimed.2019.01.033
Jackson, J. W., Williams, D. R., & VanderWeele, T. J. (2016). Disparities at the intersection of marginalized groups. *Social Psychiatry and Psychiatric Epidemiology, 51*(10), 1349–1359. https://doi.org/10.1007/s00127-016-1276-6
Jang, S., & Kim, J. (2018). Remedying food policy invisibility with spatial intersectionality: A case study in the detroit metropolitan area. *Journal of Public Policy and Marketing, 37*(1), 167–187. https://doi.org/10.1509/jppm.16.194. PsycINFO.
Juan, M. J. D., Syed, M., & Azmitia, M. (2016). Intersectionality of race/ethnicity and gender among women of color and White women. *Identity: An International Journal of Theory and Research, 16*(4), 225–238. https://doi.org/10.1080/15283488.2016.1229606. PsycINFO.
Kanchi, R., Perlman, S. E., Chernov, C., Wu, W., Tabaei, B. P., Trinh-Shevrin, C., Islam, N., Seixas, A., Rodriguez-Lopez, J., & Thorpe, L. E. (2018). Gender and race disparities in cardiovascular disease risk factors among New York city adults: New York city health and nutrition examination survey (NYC HANES). *Journal of Urban Health : Bulletin of the New York Academy of Medicine, 95*(6), 801–812. https://doi.org/10.1007/s11524-018-0287-x
Kim, Y.-M. (2017). Rethinking double jeopardy: Differences in the gender disadvantage between organizational insiders and outsiders in Korea. *Sociological Perspectives, 60*(6), 1082–1096. https://doi.org/10.1177/0731121417726978. PsycINFO.
Kim, Y., & Calzada, E. J. (2019). Skin color and academic achievement in young, Latino children: Impacts across gender and ethnic group. *Cultural Diversity and Ethnic Minority Psychology, 25*(2), 220–231. https://doi.org/10.1037/cdp0000230. PsycINFO.
King, D. K. (1988). Multiple jeopardy, multiple consciousness: The context of a black feminist Ideology. *Signs: Journal of Women in Culture and Society, 14*(1), 42–72. https://doi.org/10.1086/494491
Krieger, N. (2020). Measures of racism, sexism, heterosexism, and gender binarism for health equity research: From structural Injustice to Embodied harm—an Ecosocial analysis. *Annual Review of Public Health, 41*(1), 37–62. https://doi.org/10.1146/annurev-publhealth-040119-094017
Landale, N. S., Oropesa, R. S., & Noah, A. J. (2017). Experiencing discrimination in Los Angeles: Latinos at the intersection of legal status and socioeconomic status. *Social Science Research, 67*, 34–48. https://doi.org/10.1016/j.ssresearch.2017.05.003. PsycINFO.
Landstedt, E., & Gådin, K. G. (2012). Seventeen and stressed—do gender and class matter? *Health Sociology Review, 21*(1), 82–98. https://doi.org/10.5172/hesr.2012.21.1.82. PsycINFO.
Lavaysse, L. M., Probst, T. M., & Arena, D. F. J. (2018). Is more Always merrier? Intersectionality as an Antecedent of job Insecurity. *International Journal of Environmental Research and Public Health, 15*(11). https://doi.org/10.3390/ijerph15112559
Lefevor, G. T., Park, S. Y., & Pedersen, T. R. (2018). Psychological distress among sexual and religious minorities: An examination of power and privilege. *Journal of Gay & Lesbian Mental Health, 22*(2), 90–104. https://doi.org/10.1080/19359705.2017.1418696. PsycINFO.

Lewis, J. A., Williams, M. G., Peppers, E. J., & Gadson, C. A. (2017). Applying intersectionality to explore the relations between gendered racism and health among Black women. *Journal of Counseling Psychology, 64*(5), 475–486. https://doi.org/10.1037/cou0000231. PsycINFO.

Liu, H., Reczek, C., Mindes, S. C. H., & Shen, S. (2017). The health disparities of same-sex cohabitors at the intersection of race-ethnicity and gender. *Sociological Perspectives, 60*(3), 620–639. https://doi.org/10.1177/0731121416663685. PsycINFO.

Lofters, A., & O'Campo, P. (2012). Differences that matter. In P. O'Campo, & J. R. Dunn (Eds.), *Rethinking social Epidemiology* (pp. 93–109). Springer Netherlands. https://doi.org/10.1007/978-94-007-2138-8_5.

Manzi, C., Paderi, F., Benet-Martínez, V., & Coen, S. (2019). Age-based stereotype threat and negative outcomes in the workplace: Exploring the role of identity integration. *European Journal of Social Psychology, 49*(4), 705–716. https://doi.org/10.1002/ejsp.2533. PsycINFO.

McCall, L. (2005). The complexity of intersectionality. *Signs: Journal of Women in Culture and Society, 30*(3), 1771–1800. https://doi.org/10.1086/426800

McGovern, J. (2017). The boundaries of Latino sport leadership: How skin tone, ethnicity, and nationality construct baseball's color line. *Sociological Inquiry, 87*(1), 49–74. https://doi.org/10.1111/soin.12152. PsycINFO.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group.. (2009). Preferred reporting Items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine, 6*(7), Article e1000097. https://doi.org/10.1371/journal.pmed.1000097

Moorman, J. D., & Harrison, K. (2016). Gender, race, and risk: Intersectional risk management in the sale of sex online. *The Journal of Sex Research, 53*(7), 816–824. https://doi.org/10.1080/00224499.2015.1065950. PsycINFO.

Nash, J. C. (2016). Feminist originalism: Intersectionality and the politics of reading. *Feminist Theory, 17*(1), 3–20. https://doi.org/10.1177/1464700115620864. PsycINFO.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review, 14*(3), 693. https://doi.org/10.2307/2525981

Page, R. M., Cole, G. E., & Timmreck, T. C. (1995). *Basic Epidemiologic methods and Biostatistics: A practical Guidebook*.

Parent, M. C., Hammer, J. H., Bradstreet, T. C., Schwartz, E. N., & Jobe, T. (2018). Men's mental health help-seeking behaviors: An intersectional analysis. *American Journal of Men's Health, 12*(1), 64–73. https://doi.org/10.1177/1557988315625776. PsycINFO.

Peck, J. H., Leiber, M. J., & Brubaker, S. J. (2014). Gender, race, and juvenile court outcomes: An examination of status offenders. *Youth Violence and Juvenile Justice, 12*(3), 250–267. https://doi.org/10.1177/1541204013489713. PsycINFO.

Phillips, S. P., A, V., S, Y., R, R., S, I., E, Z., & S, F. (2020). Systematic review of methods used to study the intersecting impact of sex and social locations on health outcomes. *SSM - Population Health, 12*, 100705. https://doi.org/10.1016/j.ssmph.2020.100705

Price, M., Polk, W., Hill, N. E., Liang, B., & Perella, J. (2019). The intersectionality of identity-based victimization in adolescence:A person-centered examination of mental health and academic achievement in a U. S. high school. *Journal of Adolescence, 76*, 185–196. https://doi.org/10.1016/j.adolescence.2019.09.002. PsycINFO.

Purdie-Vaughns, V., & Eibach, R. P. (2008). Intersectional invisibility: The distinctive advantages and disadvantages of multiple subordinate-group identities. *Sex Roles, 59*(5–6), 377–391. https://doi.org/10.1007/s11199-008-9424-4

Quandt, A. (2019). Variability in perceptions of household livelihood resilience and drought at the intersection of gender and ethnicity. *Climatic Change, 152*(1), 1–15. https://doi.org/10.1007/s10584-018-2343-7

Rehkopf, D. H., Glymour, M. M., & Osypuk, T. L. (2016). The consistency assumption for causal inference in social epidemiology: When a Rose is not a Rose. *Current Epidemiology Reports, 3*(1), 63–71. https://doi.org/10.1007/s40471-016-0069-5

Reisen, C. A., Brooks, K. D., Zea, M. C., Poppen, P. J., & Bianchi, F. T. (2013). Can additive measures add to an intersectional understanding? Experiences of gay and ethnic discrimination among HIV-positive Latino gay men. *Cultural Diversity and Ethnic Minority Psychology, 19*(2), 208–217. https://doi.org/10.1037/a0031906

Reisen, C. A., Brooks, K. D., Zea, M. C., Poppen, P. J., & Bianchi, F. T. (2013). Can additive measures add to an intersectional understanding? Experiences of gay and ethnic discrimination among HIV-positive Latino gay men. *Cultural Diversity and Ethnic Minority Psychology, 19*(2), 208–217. https://doi.org/10.1037/a0031906. Embase.

Remedios, J. D., & Snyder, S. H. (2018). Intersectional oppression: Multiple stigmatized identities and perceptions of invisibility, discrimination, and stereotyping. *Journal of Social Issues, 74*(2), 265–281. https://doi.org/10.1111/josi.12268. PsycINFO.

Rice, C., Harrison, E., & Friedman, M. (2019). Doing justice to intersectionality in research. *Cultural Studies ↔ Critical Methodologies, 19*(6), 409–420. https://doi.org/10.1177/1532708619829779

Rodriguez-Seijas, C., Eaton, N. R., & Pachankis, J. E. (2019). Prevalence of psychiatric disorders at the intersection of race and sexual orientation: Results from the national Epidemiologic survey of alcohol and related conditions-III. *Journal of Consulting and Clinical Psychology, 87*(4), 321–331. https://doi.org/10.1037/ccp0000377. PsycINFO.

Ro, H. K., & Loya, K. I. (2015). The effect of gender and race intersectionality on student learning outcomes in engineering. *The Review of Higher Education: Journal of the Association for the Study of Higher Education, 38*(3), 359–396. https://doi.org/10.1353/rhe.2015.0014. PsycINFO.

Rosenfield, S. (2012). Triple jeopardy? Mental health at the intersection of gender, race, and class. *Social Science & Medicine, 74*(11), 1791–1801. https://doi.org/10.1016/j.socscimed.2011.11.010. PsycINFO.

Schulman, K. A., Berlin, J. A., Harless, W., Kerner, J. F., Sistrunk, S., Gersh, B. J., Dubé, R., Taleghani, C. K., Burke, J. E., Williams, S., Eisenberg, J. M., Ayers, W., & Escarce, J. J. (1999). The effect of race and sex on Physicians' recommendations for cardiac catheterization. *New England Journal of Medicine, 340*(8), 618–626. https://doi.org/10.1056/NEJM199902253400806

Schwartz, S. (2017). Commentary: On the application of potential outcomes-based methods to questions in social psychiatry and psychiatric epidemiology. *Social Psychiatry and Psychiatric Epidemiology, 52*(2), 139–142. https://doi.org/10.1007/s00127-016-1334-0

Schwartz, L. M., Woloshin, S., & Welch, H. G. (1999). Misunderstandings about the effects of race and sex on Physicians' referrals for cardiac catheterization. *New England Journal of Medicine, 341*(4), 279–283. https://doi.org/10.1056/NEJM199907223410411

Sen, G., & Iyer, A. (2012). Who gains, who loses and how: Leveraging gender and class intersections to secure health entitlements. *Social Science & Medicine, 74*(11), 1802–1811. https://doi.org/10.1016/j.socscimed.2011.05.035. PsycINFO.

Sen, G., Iyer, A., & Mukherjee, C. (2009). A methodology to analyse the intersections of social inequalities in health. *Journal of Human Development and Capabilities, 10*(3), 397–415. https://doi.org/10.1080/19452820903048894

Shaw, L. R., Chan, F., & McMahon, B. T. (2012). Intersectionality and disability harassment: The interactive effects of disability, race, age, and gender. *Rehabilitation Counseling Bulletin, 55*(2), 82–91. https://doi.org/10.1177/0034355211431167. PsycINFO.

Syed, M. (2010). Disciplinarity and methodology in intersectionality theory and research. *American Psychologist, 65*(1), 61–62. https://doi.org/10.1037/a0017495

Szklo, M., & Nieto, F. J. (2014). *Epidemiology: Beyond the basics* (3rd ed.). Jones & Bartlett Learning.

Szmer, J., Christensen, R. K., & Kaheny, E. B. (2015). Gender, race, and dissensus on state supreme courts. *Social Science Quarterly, 96*(2), 553–575. https://doi.org/10.1111/ssqu.12133. PsycINFO.

Taggart, T., Powell, W., Gottfredson, N., Ennett, S., Eng, E., & Chatters, L. M. (2019). A person-centered approach to the study of black adolescent religiosity, racial identity, and sexual initiation. *Journal of Research on Adolescence, 29*(2), 402–413. https://doi.org/10.1111/jora.12445. PsycINFO.

Tejera, C. H., Horner-Johnson, W., & Andresen, E. M. (2019). Application of an intersectional framework to understanding the association of disability and sexual orientation with suicidal ideation among Oregon Teens. *Disability and Health Journal, 12*(4), 557–563. https://doi.org/10.1016/j.dhjo.2019.05.006. PsycINFO.

Tomlinson, J., Valizade, D., Muzio, D., Charlwood, A., & Aulakh, S. (2019). Privileges and penalties in the legal profession: An intersectional analysis of career progression. *British Journal of Sociology, 70*(3), 1043–1066. https://doi.org/10.1111/1468-4446.12375

Toosi, N. R., Mor, S., Semnani-Azad, Z., Phillips, K. W., & Amanatullah, E. T. (2019). Who can lean in? The intersecting role of race and gender in negotiations. *Psychology of Women Quarterly, 43*(1), 7–21. https://doi.org/10.1177/0361684318800492. PsycINFO.

VanderWeele, T. J. (2016). Mediation analysis: A Practitioner's guide. *Annual Review of Public Health, 37*(1), 17–32. https://doi.org/10.1146/annurev-publhealth-032315-021402

VanderWeele, T. J., & Knol, M. J. (2014). A tutorial on interaction. *Epidemiologic Methods, 3*(1). https://doi.org/10.1515/em-2013-0005

Veenstra, G. (2013). Race, gender, class, sexuality (RGCS) and hypertension. *Social Science & Medicine, 89*, 16–24. https://doi.org/10.1016/j.socscimed.2013.04.014. PsycINFO.

Veenstra, G., & Patterson, A. C. (2016). South Asian-White health inequalities in Canada: Intersections with gender and immigrant status. *Ethnicity and Health, 21*(6), 639–648. https://doi.org/10.1080/13557858.2016.1179725. PsycINFO.

Velez, B. L., Cox, R., Jr., Polihronakis, C. J., & Moradi, B. (2018). Discrimination, work outcomes, and mental health among women of color: The protective role of womanist attitudes. *Journal of Counseling Psychology, 65*(2), 178–193. https://doi.org/10.1037/cou0000274. PsycINFO.

Vu, M., Li, J., Haardorfer, R., Windle, M., & Berg, C. J. (2019). Mental health and substance use among women and men at the intersections of identities and experiences of discrimination: Insights from the intersectionality framework. *BMC Public Health, 19*(1), 108. https://doi.org/10.1186/s12889-019-6430-0

Warner, D. F., & Brown, T. H. (2011). Understanding how race/ethnicity and gender define age-trajectories of disability: An intersectionality approach. *Social Science & Medicine, 72*(8), 1236–1248. https://doi.org/10.1016/j.socscimed.2011.02.034. PsycINFO.

Watson, L. B., DeBlaere, C., Langrehr, K. J., Zelaya, D. G., & Flores, M. J. (2016). The influence of multiple oppressions on women of color's experiences with insidious trauma. *Journal of Counseling Psychology, 63*(6), 656–667. https://doi.org/10.1037/cou0000165. PsycINFO.

Wemrell, M., Mulinari, S., & Merlo, J. (2017). Intersectionality and risk for ischemic heart disease in Sweden: Categorical and anti-categorical approaches. *Social Science & Medicine, 177*, 213–222. https://doi.org/10.1016/j.socscimed.2017.01.050, 1982.

Whaley, A. L., & Dubose, J. (2018). Intersectionality of ethnicity/race and gender in the phenomenology of African American college students' presenting problems: A profile analysis using nonmetric multidimensional scaling. *International Journal for the Advancement of Counselling, 40*(3), 279–297. https://doi.org/10.1007/s10447-018-9326-2. PsycINFO.

Williams, S.-L. L., Cabrera-Nguyen, E. P., & Johnson, S. D. (2018). Examining the impact of race/ethnicity and gender intersectionality on preferences of social distance from individuals with mental health conditions. *Journal of Human Behavior in the Social Environment, 28*(3), 370–380. https://doi.org/10.1080/10911359.2018.1433572. PsycINFO.

Williams, M. G., & Lewis, J. A. (2019). Gendered racial microaggressions and depressive symptoms among black women: A moderated mediation model. *Psychology of Women*

Quarterly, 43(3), 368–380. https://doi.org/10.1177/0361684319832511. PsycINFO.

Wilson, J. P., Remedios, J. D., & Rule, N. O. (2017). Interactive effects of obvious and ambiguous social categories on perceptions of leadership: When double-minority status may be beneficial. *Personality and Social Psychology Bulletin, 43*(6), 888–900. https://doi.org/10.1177/0146167217702373. PsycINFO.

Woodhams, C., Lupton, B., & Cowling, M. (2015). The presence of ethnic minority and disabled men in feminised work: Intersectionality, vertical segregation and the glass escalator. *Sex Roles: Journal of Research, 72*(7–8), 277–293. https://doi.org/10.1007/s11199-014-0427-z. PsycINFO.

Yudell, M., Roberts, D., DeSalle, R., Tishkoff, S., & 70 signatories. (2020). NIH must confront the use of race in science. *Science, 369*(6509), 1313–1314. https://doi.org/10.1126/science.abd4842