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# Adding interactions to models of intersectional health inequalities: Comparing multilevel and conventional methods

Clare R. Evans

*Department of Sociology, 1291 University of Oregon, Eugene, OR, 97403, USA*

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ABSTRACT

Examining health inequalities intersectionally is gaining in popularity and recent quantitative innovations, such as the development of intersectional multilevel methods, have enabled researchers to expand the number of dimensions of inequality evaluated while avoiding many of the theoretical and methodological limitations of the conventional fixed effects approach. Yet there remains substantial uncertainty about the effects of integrating numerous additional interactions into models: will doing so *reveal* statistically significant interactions that were previously hidden or *explain* away interactions seen when fewer dimensions were considered? Furthermore, how does the multilevel approach compare empirically to the conventional approach across a range of conditions? These questions are essential to informing our understanding of population-level health inequalities. I address these gaps using data from the National Longitudinal Study of Adolescent to Adult Health by evaluating conventional and multilevel intersectional models across a range of interaction conditions (ranging from six points of interaction to more than ninety, interacting gender, race/ethnicity/immigration status, parent education, family income, and sexual identification), different model types (linear and logistic), and seven diverse dependent variables commonly examined by health researchers: body mass index, depression, general self-rated health, binge drinking, cigarette use, marijuana use, and other illegal drug use. Findings suggest that adding categories to intersectional analyses will tend to reveal new points of interaction. Stratum-level results from the multilevel approach are robust to cross-classification by school context. Conventional and multilevel approaches differ substantially when tested empirically. I conclude with a detailed consideration of the origin of these differences and provide recommendations for future scholarship of intersectional health inequalities.

## 1. Introduction

Intersectionality is a framework for analysis that originates in black feminist scholarship (Collins, 1990; Crenshaw, 1989) and directs our attention to the interlocking systems of privilege and oppression that shape social experiences. While intersectionality was originally formulated in terms of identities and the social processes affecting them, it has been broadened to include dimensions of resources, capital, power and status such as income and education. Intersections between axes of identity and social process, such as female *and* black, are not intersections in the sense that two roads cross each other and continue on unaffected in their original directions (Choo and Ferree, 2010; Ken, 2008). Rather, the points of intersection describe social positions that may entail unique advantages or disadvantages with potential relevance to a range of outcomes, including human health. Adoption of intercategorical intersectional analyses (McCall, 2005) into population health research has been widely called for and is increasingly popular (Bauer, 2014; Bowleg, 2012; Schulz and Mullings, 2006), partially because intersectional frameworks pair well with domain-specific theories such as fundamental causes of illness (Link and Phelan, 1995) and ecosocial theory (Krieger, 1994, 2011). Fueled by intersectional theory and expanded recognition of the many social processes/identities shaping health inequalities, scholars are encouraged to move beyond the traditional focus on gender and race/ethnicity to consider how factors such as immigration status, education, income, and sexual identification interact. Yet there remains substantial uncertainty about whether integrating more dimensions of identity and process is expected to result in finding *fewer* or *more* statistically significant interactions. Answering this question is central to informing both our understanding of the social patterning of health inequalities and our expectations for future research using an intersectional approach.

Failing to consider important factors such as sexual identification may obscure unique sets of social experiences that affect health outcomes. Therefore, adding more dimensions to the analysis might reasonably be expected to *reveal* statistically significant interactions, aiding public health practitioners in identifying particularly burdened

*E-mail address:* cevans@uoregon.edu.

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populations. On the other hand, inclusion of more interacting categories in an analysis may *reduce* the number of statistically significant interactions because between-stratum differences might be explained by inclusion of these previously omitted factors. For instance, in a classic analysis of gender by race/ethnicity interactions, some of the differences between intersectional social strata might be explained by different average levels of income across strata. Perhaps as we continue to expand our analyses into additional categories and dimensions of identity/social process (e.g., income, education, sexual identification) we will find a *reduction* in the between-stratum differences that remain to be explained? Taken to its logical extreme, successfully incorporating numerous dimensions of inequality into an intersectional analysis might paradoxically result in finding no statistically significant interactions, which might be (mis)interpreted as a refutation of intersectionality. Intersectional studies in the population health literature have thus far been inconsistent in their consideration of various axes of inequality, the number of points of intersection considered, and the health outcomes of interest. Therefore, there have been no systematic evaluations across a range of outcomes to see what happens as more intersections are added. Additionally, the answer to this empirical question may also vary depending on the modeling approach used.

Until recently it was difficult to satisfactorily evaluate the effects of adding numerous categories of identity and social process to intersectional models because of limitations of the conventional approach (Bauer, 2014; Bowleg, 2012; Evans et al., 2018; Veenstra, 2013). A recent innovation, the use of multilevel models to conduct intersectional analyses, has been proposed (Evans, 2015; Evans et al., 2018; Green et al., 2017; Jones et al., 2016; Merlo, 2018). Multilevel models are typically used to account for the "nesting" of respondents within physical contexts such as neighborhoods, making possible an examination of heterogeneity within and between contexts (i.e., Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) (Merlo, 2003)). Intersectional MAIHDA involves modeling respondents as nested within intersectional social strata. This approach offers many advantages, both practical/methodological and theoretical, over conventional intersectional models (Evans et al., 2018), and for this reason they have been hailed as "the new gold standard for investigating health disparities in (social) epidemiology" (Merlo, 2018).

While considerable excitement has been generated by this approach and new studies applying and further developing the method are becoming available (Axelsson Fisk et al., 2018; Evans and Erickson, 2019; Wemrell et al., 2017), the finer points of its application are still being discovered and discussed. In particular, no systematic empirical comparisons have yet been done between conventional and MAIHDA intersectional models across a range of conditions. In sharp contrast to a range of studies using the conventional approach that find evidence of interactions (e.g., Patil et al., 2017; Schulz and Mullings, 2006; Veenstra, 2013), early findings from these studies using MAIHDA suggest that few intersectional strata show evidence of statistically significant interaction effects. For instance, Evans and Erickson (2019) find no evidence of statistically significant interactions in intersectional MAIHDA models of depression, whereas in their recent review Patil et al. (2017) identify many studies which conclude that there is evidence of intersectional effects for depression. Are MAIHDA models in fact less likely than their conventional counterparts to find statistically significant interactions, and if so, what might explain these differences? If MAIHDA continues to be rapidly adopted, then it is essential to understand more fully the relationship between the two modeling approaches.

The purpose of this study is therefore twofold: (1) to determine whether adding more categories of social identity/process to intersectional analyses *reveals* new interaction effects or *explains* them away, and (2) to compare the conventional and multilevel approaches empirically across a range of conditions.

### *1.1. MAIHDA versus conventional fixed effect models of intersectionality – a brief overview*

Modeling intercategorical intersectionality using the conventional fixed effects approach involves fitting a regression model inclusive of additive "main" effects plus all possible permutations of interaction terms in order to provide a unique estimate of the dependent variable for each combination of identity, status, or resources/capital. Identities and other factors measured at the individual-level are framed as proxies for sets of social experience within interlocking power structures and systems of marginalization—not necessarily as individual-level determinants of the outcome. Intersectional approaches "are by definition alert to the need for analysis of interactions" (Choo and Ferree, 2010). Accordingly, considerable attention is directed to the parameter estimates for the interactions rather than to the main effects or the main effects-plus-interactions (what Weldon (2008) calls the "intersection-plus" model in which main effects also remain important to the analysis). Conventionally, finding statistically significant interaction parameters is interpreted as evidence for an "intersectional effect."

MAIHDA models of intersectionality are two-level hierarchical regression models nesting respondents (level 1) within their intersectional social strata (level 2). Sufficient social strata are included in the analysis to represent each unique combination of the categories of social determinants being evaluated, and again these are theorized as proxies for social experience.

The practical and theoretical advantages of the MAIHDA approach have been discussed elsewhere (Evans et al., 2018; Merlo, 2018), so I summarize them only briefly. Methodologically, MAIHDA intersectional models: (1) are easily scalable for inclusion of additional dimensions and categories of social identity; (2) are more parsimonious; (3) automatically adjust estimates for social strata based on the number of respondents at those intersections, down-weighting extreme estimates based on too few respondents and therefore providing more reliable (if conservative) estimates; and (4) provide results that are easier to interpret and summarize. On a theoretical level, MAIHDA models: (1) provide a remedy against the "tyranny of the averages" (Merlo, 2014; Merlo and Wagner, 2012) by explicitly encouraging simultaneous consideration of between-stratum variation, within-stratum heterogeneity, and discriminatory accuracy—thus acknowledging the existence of meaningful inequalities between strata while also recognizing the inability of such "group" labels to distinguish between those who will become sick and those who will not; and (2) treat intersections of identity and process as more akin to contexts than separate axes, thus removing somewhat the temptation to revert to single-axis thinking and bringing intersectional methods closer into alignment with intersectional theorizing (Bauer, 2014; Collins, 1990; Crenshaw, 1989; Choo and Ferree, 2010; Nash, 2008; Patil et al., 2017; Weldon, 2008). MAIHDA models do have the modest disadvantage that they require Bayesian estimation (though frequentist approaches often yield reasonable approximations) (Evans et al., 2018).

### *1.2. Addressing gaps*

In this study I address these two critical gaps in the literature on health inequalities and intersectional methods by evaluating conventional and MAIHDA intersectional models across a range of conditions and seven diverse dependent variables commonly examined by health researchers: body mass index (BMI), depression (measured using CESD scores), general self-rated health, binge drinking, cigarette use, marijuana use, and other illegal drug use. See Table 1 for a summary of these variables. These outcomes were selected to represent a variety of variable types (physical health, mental health, health risk behaviors) and model types (linear, logistic). Using data from the National Longitudinal Study of Adolescent to Adult Health (Add Health) the sample of respondents was divided up differently across a range of numbers of strata—ranging from the simplest case of six strata (defined by

**Table 1**
Summary of dependent variables.

| | BMI | CESD | Fair or Poor Health | Binge | Cigarette | Marijuana | Drugs |
|---|---|---|---|---|---|---|---|
| Dependent variable is a measure of: | Biomarker Physical Health | Mental Health | General Physical Health | Health Risk Behavior | Health Risk Behavior | Health Risk Behavior | Health Risk Behavior |
| Description: | Body Mass Index (weight in kg/height in meters-squared). | Center for Epidemiologic Studies-Depression scale. | Dichotomized Self-Rated General Health (1 = fair/poor, 0 = good/very good/excellent). | Self-report ever binge drunk (5 + alcoholic drinks in a row) in the past 12 months. | Self-report ever used cigarettes in the past 30 days. | Self-report ever used marijuana in the past 30 days. | Self-report ever used illegal drugs other than marijuana, such as: cocaine, heroin, LSD, PCP, ecstasy, mushrooms, etc. |
| Model Type: | Linear | Linear | Logistic | Logistic | Logistic | Logistic | Logistic |
| Evidence of Interaction in Conventional Fixed Model of Gender × Race/Ethnicity in this Sample? | Yes | Yes | No | No | Yes | Yes | Yes |

interactions of dichotomous gender and race/ethnicity (black, white, Latinx)) to more than ninety strata (interacting gender, race/ethnicity/immigration status, parent education, low income status, and sexual identification). For each dependent variable and number of strata, conventional and MAIHDA models were fit and compared.

## 2. Methods

### 2.1. Data

Add Health is a longitudinal cohort survey of a nationally representative sample of U.S. adolescents who were in grades 7–12 during the first wave of interviews (1994–95). The primary sampling frame was derived from the Quality Education Database and was used to select a stratified sample of 80 high schools and 52 middle schools. Respondents were selected through a combination of stratified random sampling and over-sampling of minorities in order to ensure representation. Of the 20,745 respondents surveyed in wave 1, 15,694 respondents were surveyed in wave 4 (collected in 2008). For this empirical demonstration, the majority of variables come from wave 1. However, two necessary measures—immigration status and sexual identification—were collected in wave 4. Therefore, the analyzed sample was limited to those respondents who completed both waves 1 and 4 interviews. I also include data collected from the wave 1 parent/guardian survey. Further details of Add Health's design and response rates are well documented (http://www.cpc.unc.edu/projects/addhealth).

I dropped respondents whose primary racial/ethnic identification was other than the three categories included in this analysis (Hispanic or Latinx all races, Black or African American non-Hispanic, or White non-Hispanic), reducing the sample size to 14,298. Deletions were also made based on missing gender ($N = 2$), race/ethnicity ($N = 11$), parent education ($N = 147$), low income status in wave 1 ($N = 33$), and sexual identification ($N = 64$), resulting in $N = 14{,}041$ respondents. The final analyzed sample varied by dependent variable. Table 2 provides descriptive statistics for the sample.

### 2.2. Dependent variables

*Body Mass Index (BMI)* in wave 1 was calculated by dividing respondents' measured weight in kilograms by their height in meters squared. All models of BMI were linear.

*Depression* was measured in wave 1 using a modified (19-item) version of the 20-item Center for Epidemiologic Studies Depression (CESD) scale (Radloff, 1977). The CESD scale is composed of a series of items coded on a four-point scale indicating the frequency of symptoms occurring in the past week with 0 = never or rarely, 1 = sometimes, 2 = a lot of the time, 3 = most of the time or all of the time. After reverse coding relevant items each respondent's average item score was calculated and then multiplied by 20 in order to ensure comparability in point values with other studies. Possible final scores range from 0 to 60. Higher point values indicate greater likelihood to be experiencing clinical depression, though the scale is not diagnostic. Following convention for handling missing data on the CESD scale (Bono et al., 2007), participants who responded to most scale items (> 80%) were not dropped from the analysis. All models of CESD were linear.

*Fair or Poor Health* in wave 1 was constructed by dichotomizing responses to a 5-point Likert scale of general self-rated health: 1 = fair or poor health and 0 = good/very good/excellent health. All models of fair/poor health were logistic.

*Binge drinking* was measured through self-report of ever having binged alcohol (5 + drinks in a row) during the previous 12 months (1 = yes,0 = no) in wave 1. All models of binge drinking were logistic.

*Cigarette use* was measured through self-report of ever smoking cigarettes during the previous 30 days (1 = yes,0 = no) in wave 1. All models of cigarette use were logistic.

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**Table 2**
Descriptive statistics of sample.

| DEPENDENT VARIABLES | | | | | | | |
|---|---|---|---|---|---|---|---|
| | *N* | *N* missing | Median | Mean | SD | Min | Max |
| TOTAL | 14,041 | | | | | | |
| BMI | 13,694 | 347 | 21.65 | 22.66 | 4.50 | 11.26 | 63.56 |
| CESD | 14,022 | 19 | 10.53 | 11.74 | 7.92 | 0.00 | 58.95 |
| | *N* | *N* missing | *N* "Yes" | % "Yes" | | | |
| Fair/Poor Health | 14,035 | 6 | 981 | 6.99 | | | |
| Binge | 13,884 | 157 | 3686 | 26.25 | | | |
| Cigarette | 13,867 | 174 | 3636 | 25.90 | | | |
| Marijuana | 13,809 | 232 | 1937 | 13.80 | | | |
| Drugs | 13,904 | 137 | 1213 | 8.64 | | | |
| SOCIAL STRATA DIMENSIONS | | | | | | | |
| | *N* | % | | | | | |
| Gender | | | | | | | |
| Male | 6532 | 46.52 | | | | | |
| Female | 7509 | 53.48 | | | | | |
| Race/Ethnicity/Immigration | | | | | | | |
| Immigrant Latinx | 480 | 3.42 | | | | | |
| Non-immigrant Latinx | 1962 | 13.97 | | | | | |
| Black | 3416 | 24.33 | | | | | |
| White | 8183 | 58.28 | | | | | |
| Parent Education | | | | | | | |
| High School or Less | 5343 | 38.05 | | | | | |
| Some College | 4105 | 29.24 | | | | | |
| College Degree Plus | 4593 | 32.71 | | | | | |
| Low Income | | | | | | | |
| No | 5768 | 41.08 | | | | | |
| Yes | 8273 | 58.92 | | | | | |
| Exclusively Straight | | | | | | | |
| No | 1963 | 13.98 | | | | | |
| Yes | 12,078 | 86.02 | | | | | |

*Marijuana use* was measured through self-report of ever using marijuana during the previous 30 days (1 = yes,0 = no) in wave 1. All models of marijuana use were logistic.

*Drug use* was measured through self-report of any illicit drug use (other than marijuana) in their life time (1 = yes,0 = no) in wave 1. Such drugs included cocaine, heroin, LSD, PCP, ecstasy, and mushrooms. All models of drug use were logistic.

### 2.3. Social strata dimensions

*Gender* was self-reported by respondents. By modern standards this survey item is not ideal both because it conflates sex and gender and because it allows for only two response categories. Because they were the options provided to respondents I continue to use the labels "male" and "female." For the purposes of strata ID coding, male = 1 and female = 2.

*Race/Ethnicity* identities included in this analysis are: Hispanic or Latinx, all races; black or African American; and white (hereafter Latinx, black, and white). Where respondents indicated identification with more than one race/ethnicity a Census Bureau algorithm was used to code for a single identity.

*Immigrant status* was measured in both waves 1 and 4, however the wave 1 survey item ("Were you born a U.S. citizen?") was not asked of all respondents. In wave 4 the question was asked of all respondents, so I use data from this wave to code for immigrant status. Importantly there is only sufficient data to assess immigrant status for Latinx respondents. The Latinx identity was therefore interacted with immigrant status, for a composite race/ethnicity/immigrant dimension of identity with 4 categories: Latinx immigrant, Latinx non-immigrant, black, and white.

*Low income* in wave 1 was coded dichotomously (1 = yes/low income, 0 = no/not low income). Low income status was determined based on parent/guardian responses to multiple survey items. Parents reported their family's total income before taxes in 1994. This value was compared to the Federal Poverty Level (FPL) in 1994 for a family of the size and number of dependents reported by the parent. Families reporting income at or below 200% of the FPL were coded as "low income" while families reporting income above this threshold were coded as "not low income." Parents were also asked a series of questions about receipt of public assistance in the previous month from various sources: Supplemental Security Income, Aid to Families with Dependent Children, Food Stamps, Unemployment or Worker Compensations, Housing Subsidy or Public Housing. Qualifying for these sources of assistance required prior demonstration of financial need (though the exact criteria varied by program and across the country). Those reporting receipt of one or more types of assistance were therefore also coded as "low income."

*Parent Education* was obtained from the parent/guardian survey in wave 1. Parents indicated both their own and their spouse/partners education level. Where data was missing I used reports of parental education from the adolescent respondent. Parent education was coded as: 1 = completed high school or less, 2 = some college or additional education, 3 = completed college degree or more. An alternate version of the parent education variable was constructed for some analyses: *low parent education* was coded dichotomously (1 = yes/high school degree or less, 0 = no/some college or more).

*Straight sexual identification* was measured in wave 4 using the survey item: "*Please choose the description that best fits how you think about yourself*." Options included: 100% heterosexual (straight), mostly heterosexual (straight) but somewhat attracted to people of your own sex, bisexual (attracted to men and women equally), mostly homosexual (gay) but somewhat attracted to people of the opposite sex, 100% homosexual (gay), not sexually attracted to either males or females, and don't know. Responses were dichotomized into as exclusively straight (100% heterosexual) versus all other sexual identification options; "don't know" was coded as missing. This aspect of social identity was measured in wave 4 (versus wave 1 for all dependent variables), which is not ideal because sexual identification may change throughout adolescence. However, because it was not measured until subsequent waves, I use this measure as a proxy for sexual identification in adolescence.

*Social strata IDs* were constructed in order to hierarchically nest respondents in intersectional social strata in different versions of MAIHDA analyses. For example, in versions of the MAIHDA model where there were 6 possible social strata, intersecting gender (male/female) by race/ethnicity (black/white/Latinx), a two-digit ID code (corresponding to the two axes of categorization) was created in order to uniquely identify every combination of gender and race/ethnicity. For simplicity, this was referred to as the strata6 ID code. Similar ID codes were created for other versions of the model when additional categories were included:

Strata12: three-digit ID code reflecting the 12 possible combinations of gender (male/female), race/ethnicity (black/white/Latinx), and low parent education (yes/no).

Strata18: three-digit ID code reflecting the 18 possible combinations of gender (male/female), race/ethnicity (black/white/Latinx), and parent education (high/middle/low).

Strata36: four-digit ID code reflecting the 36 possible combinations of gender (male/female), race/ethnicity (black/white/Latinx), parent education (high/middle/low), and low income status.

Strata48: four-digit ID code reflecting the 48 possible combinations of gender (male/female), race/ethnicity/immigrant status (black/white/Latinx-immigrant/Latinx-non-immigrant), parent education (high/middle/low), and low income (yes/no).

Strata96: five-digit ID code reflecting the 96 possible combinations of gender (male/female), race/ethnicity/immigrant status (black/white/Latinx-immigrant/Latinx-non-immigrant), parent education (high/middle/low), low income (yes/no), and straight sexual identification (yes/no). After deletions based on missing values for dependent variables the actual number of strata represented in the "96" level of analysis was lower: 92 strata had respondents in the MAIHDA analyses for BMI and fair/poor health, whereas the other outcomes had 91 strata.

## 3. Analysis

### 3.1. Conventional fixed effects models of intersectionality

For each version of the model (in the matrix of possible dependent variables and number of social strata) I fit a fixed effect version of the model. This entailed using the same variables as those used to construct strata IDs for the MAIHDA analyses. Models were two-level random intercepts models nesting respondents in schools. All fixed parameters were individual-level variables and all necessary interactions were included to fully specify the model for all possible social strata. Models were fit using Stata 14.1.

### 3.2. Intersectional MAIHDA models

All MAIHDA models are two-level hierarchical regression models nesting respondents (level 1) within their intersectional social strata (level 2). Sufficient social strata are included in the analysis to represent each unique combination of the dimensions and categories of social determinants being evaluated. A general linear version of the model takes the form:

$$y_{ij} = \beta\gamma_j + \mu_{0j} + e_{0ij} \tag{1}$$

Level 2:

$$\mu_{0j} \sim N(0, \sigma_{u0}^2)$$

Level 1:

$$e_{0ij} \sim N(0, \sigma_{e0}^2)$$

where $y_{ij}$ is the value of the outcome for individual *i* in social stratum *j*, $\gamma_j$ is a vector of fixed effects (e.g., the intercept and possibly additive main effects) and $\beta$ is a vector of associated parameter values. $\mu_{0j}$ is the difference between the value for stratum *j* estimated based on the fixed parameters and the total estimated value for stratum *j*. $e_{0ij}$ represents the individual-level residual. Stratum-level residuals ($\mu_{0j}$) are normally distributed with mean 0 and variance $\sigma_{u0}^2$ while individual-level residuals ($e_{0ij}$) are normally distributed with mean 0 and variance $\sigma_{e0}^2$. Two versions of each model were fit: version A was a null model which included no additive main effects, and version B was a main effects model which included all additive main effects but no interaction parameters. In version B of the models, assuming no omitted variable biases exist, the stratum-level residual represents how different the stratum's expected value actually is from what we might expect for it based only on additive effects. In this sense, the residual in the main effects model is a "total interaction effect" for that stratum.

In order to obtain stratum-level residual estimates from logistic models, which unlike their linear counterparts are fit on the multiplicative scale, I followed procedures innovated by Axelsson Fisk et al. (2018). Briefly, the residuals are obtained by first calculating the total predicted probability for each stratum based on both additive and interaction (residual) effects, then calculating the predicted probability for each stratum based solely on additive effects, and then by calculating the differences (i.e., the residual) between the two predicted probabilities. Also outlined by Axelsson Fisk et al. is a procedure for obtaining 95% credible intervals (CI) for all estimates (including residuals and total predicted probabilities). Using their code as an example for obtaining CI in the logistic case, I extrapolated this to the linear case in order to determine the statistical significance of each stratum's residual ($\mu_{0j}$) in both linear and logistic models.

For each linear model the Variance Partition Coefficient (VPC) was calculated as follows:

$$VPC = \frac{Between\ Stratum\ Variance}{Total\ Variance} \times 100\% = \frac{\sigma_{u0}^2}{\sigma_{u0}^2 + \sigma_{e0}^2} \times 100\% \tag{2}$$

The VPC is the percent of the total variation in the dependent variable that is attributable to the between–stratum level after adjustment for any included covariates (such as additive effects in model versions B). As others have articulated (e.g., Axelsson Fisk et al., 2018), the VPC is a measure of discriminatory accuracy (DA), or the ability of the model to correctly discriminate between people with or without the outcome of interest. In the case of logistic models, the VPC was calculated using a latent response approach as described by Goldstein et al. (2002) in which the individual-level variance ($\sigma_{e0}^2$) is set to $\pi^2/3 = 3.29$.

The Proportional Change in Variance (PCV) was also calculated, which indicates the percent of the total between-stratum variance from the null model that is explained after adjustment for additive main effects. The between stratum-variance parameter ($\sigma_{u0}^2$) from the A (null) and B (main effects) versions of the models were used to calculate the PCV:

$$PCV = \frac{\sigma_{u0,Model\ A}^2 - \sigma_{u0,Model\ B}^2}{\sigma_{u0,Model\ A}^2} \times 100\% \tag{3}$$

To date no examples of intersectional MAIHDA models have been published that demonstrate how to adjust for artifacts of residual clustering due to sample design (e.g., school-based cluster sampling). Clustering by school is a concern in Add Health and since the fixed effects models control for school-based clustering, technically the most comparable version of the MAIHDA models would also adjust for school-based clustering. However, intersectional MAIHDA is still a fairly novel approach and therefore I present the established model version as the primary set of analyses in this study. In order to evaluate the robustness of these results and to ensure comparability, however, I fit a supplemental set of models that cross-classify intersectional strata by school. The results from these cross-classified multilevel models (CCMM), and the code used to obtain them, are provided in the online Supplement in order to demonstrate how addressing this issue can be accomplished.

All MAIHDA models were run in MLwiN 3.02 (Rasbash et al., 2017) called from Stata 14.1 using the *runmlwin* command (Leckie and Charlton, 2013). Estimations were performed using Bayesian Markov Chain Monte Carlo (MCMC) estimation procedures (Browne, 2017) with diffuse priors. Quasilikelihood methods were used to provide the MCMC procedure with initialization values. For all models a burn-in of 5000 iterations and total length of 50,000 iterations (with thinning every 50 iterations) was used. All code used to fit MAIHDA models is provided in the online Supplement.

## 4. Results

The most recognizable results, typical of conventional intersectional analyses, are the gender by race/ethnicity analyses presented in Table 3. As is clear from this, almost all of the outcomes (excepting fair/poor health and binge drinking) exhibit some evidence of statistically significant interactions ($p \leq 0.05$) when gender and race/ethnicity are interacted. Results such as these fuel the wide-spread interest in the effects of intersectional experiences on health outcomes/behaviors.

Table 4 presents the full matrix of comparisons. In this table, values

**Table 3**
Summary of results from conventional fixed intersectional models of gender × race/ethnicity.

| | BMI | | | CESD | | | Fair or Poor Health | | | Binge | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Parameter | Est | SD | p | Est | SD | p | OR | SD | p | OR | SD | p |
| Female | −0.664 | 0.099 | 0.000 | 1.799 | 0.172 | 0.000 | 1.495 | 0.143 | 0.000 | 0.729 | 0.036 | 0.000 |
| Latinx | 0.987 | 0.170 | 0.000 | 1.284 | 0.293 | 0.000 | 1.739 | 0.250 | 0.000 | 1.037 | 0.091 | 0.683 |
| Black | 0.273 | 0.152 | 0.074 | 0.953 | 0.263 | 0.000 | 1.162 | 0.167 | 0.296 | 0.390 | 0.036 | 0.000 |
| Female × Latinx | −0.167 | 0.206 | 0.418 | 1.252 | 0.357 | 0.000 | 0.784 | 0.137 | 0.164 | 1.043 | 0.110 | 0.689 |
| Female × Black | 1.344 | 0.183 | 0.000 | 0.427 | 0.318 | 0.178 | 1.264 | 0.212 | 0.162 | 1.016 | 0.116 | 0.887 |
| Intercept | 22.385 | 0.105 | 0.000 | 9.920 | 0.172 | 0.000 | 0.048 | 0.004 | 0.000 | 0.392 | 0.028 | 0.000 |

| | Cigarette | | | Marijuana | | | Drugs | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | OR | SD | p | OR | SD | p | OR | SD | p |
| Female | 1.166 | 0.057 | 0.002 | 0.837 | 0.054 | 0.006 | 1.063 | 0.077 | 0.404 |
| Latinx | 0.845 | 0.078 | 0.070 | 0.969 | 0.107 | 0.776 | 0.973 | 0.123 | 0.829 |
| Black | 0.394 | 0.037 | 0.000 | 1.019 | 0.103 | 0.852 | 0.263 | 0.047 | 0.000 |
| Female × Latinx | 0.772 | 0.087 | 0.021 | 0.994 | 0.135 | 0.963 | 0.773 | 0.120 | 0.096 |
| Female × Black | 0.688 | 0.080 | 0.001 | 0.697 | 0.089 | 0.005 | 0.549 | 0.139 | 0.018 |
| Intercept | 0.365 | 0.022 | 0.000 | 0.143 | 0.011 | 0.000 | 0.095 | 0.007 | 0.000 |

*Notes:* Models are two-level multilevel models of respondents (level 1) nested in schools (level 2). All parameters are fixed effects.

represent the number of interaction parameters found to be statistically significant in each model. Interaction parameters in fixed models (e.g., "female" by "straight") were considered statistically significant at $p \leq 0.05$, whereas in MAIHDA models statistical significance refers to stratum-level residuals for which the 95% credible interval did not overlap zero. It is important to note that in fixed models the maximum possible number of "interaction parameters" is smaller than in MAIHDA models because in fixed models interaction parameters are those that describe only some points of intersection (e.g., those with multiple marginalized categorizations) whereas stratum-level residuals are estimated for all strata in MAIHDA models.

Focusing first on the conventional fixed models we see that for all outcomes at least some versions of the model revealed statistically significant interactions. In particular, this was true when more dimensions or categories were included. For fair/poor health and binge drinking, for instance, interactions were not found to be statistically significant when fewer categories were included but both exhibited evidence of interactions when more were included. For all other outcomes the results were more consistent: interactions were significant in models with few or many interactions. While it is inadvisable to take too seriously the "threshold" of $p = 0.05$, these results do suggest that generally speaking adding dimensions/categories to intersectional analyses in conventional models will tend to *reveal* interactions rather than to explain them away. In cases where fixed models seemed to oscillate between having and not having statistically significant interaction parameters as more categories were added, this was almost

**Table 4**
Number of statistically significant interaction effects detected in conventional fixed models versus MAIHDA models.

| | BMI | | CESD | | Fair/Poor Health | | Binge | | Cigarette | | Marijuana | | Drugs | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| # Strata | Fixed | MAIHDA | Fixed | MAIHDA | Fixed | MAIHDA | Fixed | MAIHDA | Fixed | MAIHDA | Fixed | MAIHDA | Fixed | MAIHDA |
| 6 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 1 | 0 | 1 | 0 |
| 12 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18 | 5 | 1 | 3 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| 36 | 2 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 0 | 0 | 1 | 0 |
| 48 | 2 | 3 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | 1 | 0 | 1 | 0 |
| 91 + [a] | 4 | 6 | 1 | 0 | 6 | 0 | 2 | 0 | 2 | 3 | 1 | 0 | 5 | 0 |

Notes.
Fixed Models: Value indicates the number of interaction parameters found to be statistically significant ($p \leq 0.05$). Where values are zero, most fixed models did have interaction parameters that were marginally statistically significant at $p \leq 0.10$. The exception to this is binge drinking, where models with fewer strata did not have interactions with marginal significance.
MAIHDA Models: Value indicates the number of stratum-level residuals found to be statistically significant (95% credible interval not overlapping 0) after adjustment for additive main effects.
Comparison of Fixed and MAIHDA: In fixed models the maximum possible number of "interaction parameters" is smaller than in MAIHDA models. This is because in fixed models interaction parameters are those that describe points of intersection with multiple marginalized social positions (e.g., female and black) whereas stratum-level residuals ("residual interactions") are estimated for all strata in MAIHDA models.
[a] Of 96 possible strata intersections, four were not populated with respondents for any dependent variable. BMI and Fair/Poor Health models had 92 strata with respondents in MAIHDA models, all other MAIHDA models had 91 strata. In this level often additional strata were dropped in fixed versions of the models due to estimation issues.
6 strata: gender (male/female) by race/ethnicity (black/white/Latinx).12 strata: gender (male/female) by race/ethnicity (black/white/Latinx) by low parent education (yes/no).
18 strata: gender (male/female) by race/ethnicity (black/white/Latinx) by parent education (high/middle/low).
36 strata: gender (male/female) by race/ethnicity (black/white/Latinx) by parent education (high/middle/low) by income (high/low).
48 strata: gender (male/female) by race/ethnicity/immigrant (black/white/Latinx-immigrant/Latinx-non-immigrant) by parent education (high/middle/low) by income (high/low).
91 + strata: gender (male/female) by race/ethnicity/immigrant (black/white/Latinx-immigrant/Latinx-non-immigrant) by parent education (high/middle/low) by income (high/low) by straight sexual identification (yes/no).

always because some parameters estimates had p-values close to the 0.05 level and small changes in model structure resulted in them counting or not counting as "significant."

Importantly, when many points of intersection were evaluated (e.g., 91 + strata) a number of practical issues arose when attempting to get the fixed models to converge, particularly for logistic models. In many cases entire strata (and all respondents in those strata) were dropped from the analysis by Stata because all respondents in a particular stratum happened to have identical responses (e.g., 100% reported no cigarette use). This was more likely to occur in strata with small sample sizes, but occasionally occurred in larger strata ($N > 30$) as well. In practice, therefore, the sample size was smaller, fewer parameters were estimated, and estimates were not obtained for some strata. A number of techniques were used to ensure the models converged, such as extending the maximum number of iterations beyond the default. These issues were entirely expected based on the known limitations of fixed effects models (Evans et al., 2018).

Turning our attention to the MAIHDA models, this empirical exercise confirms an emerging trend of findings in the literature: intersectional MAIHDA models seem less likely to find statistically significant stratum-level residuals (after adjustment for additive effects) than their conventional counterparts are to find statistically significant interaction parameters. However, this exercise also reveals that adding more categories to the analysis does not seem to predictably reduce the frequency of detecting significant residuals in MAIHDA. In other words, when the sample is divided up along fewer axes of inequality (as in the case with 6 strata) the MAIHDA model is not finding significant residuals that then disappear when more categories are included. In fact, the opposite seems to be true. As in the case of the conventional fixed models, considering more interacting categories such as immigration status or sexual identification reveals interactions that were not apparent previously (such as for BMI and cigarette use). This pattern is not consistent across dependent variables, but these results are intriguing and hopefully will stimulate future research.

Table 5 provides the VPC in "A" (null) and "B" (main effects) versions of the MAIHDA models, as well as the PCV between models A and B. These estimates reveal a number of interesting findings. First, for all seven dependent variables we see substantial between-stratum variability in predicted values and predicted probabilities, as reflected in the VPCs from the model As. In particular, strata substantially differ from each other with respect to propensity to engage in binge drinking, cigarette smoking, and other illicit drug use. Still-meaningful differences between strata exist for the other dependent variables (BMI, CESD, fair/poor health, and marijuana use) but the effects are not as large. Second, within a given dependent variable the VPC does not predictably increase or decrease monotonically as interactions are added. Fourth, the extent to which the additive main effects explain the between-stratum differences varies by dependent variable and number of strata. Generally speaking, the PCV is fairly large, indicating that for most outcomes the vast majority of the VPC in model A is explained by the additive main effects. This is true for BMI but substantially less so than for the other outcomes. It is also interesting to note that it is possible to obtain negative PCV values (as in the case of BMI with six strata) when the VPC increases upon addition of additive effects.

As a robustness check on these results I re-fit all MAIHDA models as cross-classified models nesting respondents (level 1) within both social strata (level 2) and schools (level 2). These results are provided in Supplemental Table 1. Similar magnitude VPCs at the stratum-level were obtained using CCMM as the hierarchical approach, though modest attenuation was observed, particularly for the "risk behaviors" binge drinking and use of cigarettes, marijuana and other illicit drugs. Both the hierarchical and CCMM versions of the models found the same strata to have residuals that were statistical significant, except in a few cases where the CCMM's modest attenuation resulted in some strata no longer having statistically significant residual effects. This indicates that both models found similar estimates by stratum but that adjustment for school may slightly reduce the chances of observing a significant interaction effect at a given intersection. The results presented above are therefore largely robust to adjustment for school-level clustering.

**Table 5**
Variance partition coefficients (%) and percent change in variance (%) between null (A) and main effects (B) models.

| # Strata | Value | BMI | CESD | Fair/Poor Health | Binge | Cigarette | Marijuana | Drugs |
|---|---|---|---|---|---|---|---|---|
| 6 | VPC model A | 3.37 | 6.83 | 3.84 | 11.88 | 12.40 | 2.15 | 23.66 |
| | VPC model B | 4.65 | 1.45 | 1.52 | 0.40 | 1.00 | 1.19 | 3.51 |
| | **PCV** | **−37.93** | **78.77** | **60.36** | **96.62** | **91.92** | **44.87** | **85.17** |
| 12 | VPC model A | 2.74 | 6.08 | 4.00 | 9.22 | 10.20 | 1.40 | 19.43 |
| | VPC model B | 1.71 | 0.21 | 0.66 | 0.17 | 0.89 | 0.28 | 0.64 |
| | **PCV** | **37.51** | **96.58** | **83.58** | **98.19** | **91.29** | **79.98** | **96.72** |
| 18 | VPC model A | 2.97 | 5.49 | 4.80 | 8.14 | 9.71 | 1.42 | 19.90 |
| | VPC model B | 1.60 | 0.22 | 0.74 | 0.11 | 1.01 | 0.32 | 0.63 |
| | **PCV** | **46.29** | **96.01** | **84.58** | **98.59** | **89.61** | **77.53** | **96.85** |
| 36 | VPC model A | 2.84 | 4.55 | 4.55 | 7.05 | 9.72 | 1.18 | 19.40 |
| | VPC model B | 1.12 | 0.17 | 0.43 | 0.10 | 0.69 | 0.20 | 0.56 |
| | **PCV** | **60.44** | **96.16** | **90.56** | **98.52** | **92.92** | **83.36** | **97.09** |
| 48 | VPC model A | 2.94 | 4.66 | 4.33 | 7.73 | 10.88 | 3.08 | 19.59 |
| | VPC model B | 1.18 | 0.16 | 0.35 | 0.14 | 0.47 | 0.14 | 0.37 |
| | **PCV** | **59.90** | **96.51** | **92.02** | **98.15** | **95.70** | **95.49** | **98.09** |
| 91 +[a] | VPC model A | 3.83 | 6.85 | 4.41 | 7.51 | 11.48 | 4.01 | 21.67 |
| | VPC model B | 1.37 | 0.19 | 0.25 | 0.45 | 1.29 | 0.42 | 1.07 |
| | **PCV** | **64.23** | **97.20** | **94.34** | **94.06** | **88.76** | **89.52** | **95.08** |

Notes: VPC and PCV are provided in the form of percentages.
6 strata: gender (male/female) by race/ethnicity (black/white/Latinx).
12 strata: gender (male/female) by race/ethnicity (black/white/Latinx) by low parent education (yes/no).
18 strata: gender (male/female) by race/ethnicity (black/white/Latinx) by parent education (high/middle/low).
36 strata: gender (male/female) by race/ethnicity (black/white/Latinx) by parent education (high/middle/low) by income (high/low).
48 strata: gender (male/female) by race/ethnicity/immigrant (black/white/Latinx-immigrant/Latinx-non-immigrant) by parent education (high/middle/low) by income (high/low).
91 + strata: gender (male/female) by race/ethnicity/immigrant (black/white/Latinx-immigrant/Latinx-non-immigrant) by parent education (high/middle/low) by income (high/low) by straight sexual identification (yes/no).
[a] BMI and Fair/Poor Health MAIHDA models had 92 strata and all other MAIHDA models had 91 strata.

## 5. Discussion

Intersectional approaches for examining health inequalities are now rapidly being adopted and widely encouraged (Axelsson Fisk et al., 2018; Bauer, 2014; Bowleg, 2012; Evans and Erickson, 2019; Evans et al., 2018; Merlo, 2018; Patil et al., 2017; Schulz and Mullings, 2006; Veenstra, 2013; Wemrell et al., 2017) yet much is unknown about what researchers can expect when incorporating more interacting categories of social determinants into their analyses. Furthermore, recent innovations in quantitative approaches to intersectionality such as intersectional MAIHDA are insufficiently understood in relation to more conventional approaches. This study set out to examine two critical questions in the literature on health inequalities and intersectional methods by evaluating conventional and MAIHDA intersectional models across a range of conditions and seven diverse dependent variables commonly examined by health researchers. The first question is whether adding dimensions to an intersectional analysis will *explain* away between-stratum interactions that existed when fewer dimensions were considered or will *reveal* new interactions specific to more narrowly-defined social strata. These results suggest that interactions can be found with relatively few points of intersection and with many, though there is evidence of a slight tendency to reveal new points of interaction as more dimensions are considered. For example, in the case of fair/poor health and binge drinking the conventional approach found no evidence of statistically significant interaction effects when few dimensions were considered (e.g., gender by race/ethnicity) but as new dimensions were added to the analyses (e.g., parent education, immigration status, low income status, sexual identification) interactions were uncovered. Intersectional MAIHDA results suggested something similar, with no stratum-level residuals found to be statistically significant when fewer strata were analyzed for BMI and cigarette use, but statistically significant residuals revealed at higher-dimensions of interaction.

It is important to consider that as more points of intersection are added to the analyses, issues of multiple testing may emerge, producing patterns such as those revealed in these empirical examples. In other words, it is possible that by continually parsing a sample into narrower and narrower strata we increase the chances of identifying at least some strata with statistically significant interactions. While the narrative of uncovering previously hidden interactions fits well with intersectional scholarship arguing that it is important to consider numerous dimensions of interaction, issues of multiple testing ought to be taken seriously by researchers employing high-dimension intersectional analyses.

The second question addressed by this study is the extent to which conventional and MAIHDA approaches differ from each other. The limited number of studies published to date that use the intersectional MAIHDA approach have tended to find relatively few statistically significant stratum-level residuals (Axelsson Fisk et al., 2018; Evans et al., 2018; Evans and Erickson, 2019; Wemrell et al., 2017), in sharp contrast to a wider literature using the conventional fixed effect approach in which statistically significant interactions are frequently reported. These empirical results confirm this trend: intersectional MAIHDA models appear substantially less likely to find evidence of statistically significant interactions than their conventional counterparts. The proportional change in variance between null and main effects models tends to be substantial (circa 70–95% in all models, except for BMI where the VPC was lower). This indicates that in MAIHDA the majority of between-stratum differences in predicted values tend to be explained by additive main effects. These results were robust to inclusion of schools as a cross-classified context. In CCMM versions of the MAIHDA model, the stratum-level VPCs were often modestly attenuated by inclusion of schools. This attenuation is similar to what has been observed in other studies using CCMM and has been referred to as *omitted context bias* (Dunn et al., 2015; Evans et al., 2016; Meyers and Beretvas, 2006), or the tendency to modestly over-estimate the VPC for a level 2 context when other relevant contexts are not included in the analysis. Therefore, the finding that intersectional MAIHDA models are less likely to find statistically significant interactions than fixed effect versions of the model is exacerbated by cross-classification by school.

This study does have some limitations, particularly related to issues with the data set itself. For instance, the measure of gender in Add Health presented respondents with only two options and somewhat conflated gender with biological sex, the measure of immigrant status was not asked of all respondents in wave 1 (necessitating the use of a wave 4 version of the item instead), and sexual identification was not asked at all in wave 1 (necessitating the use of a wave 4 version of the measure as a proxy for earlier identification). These issues with measurement may have resulted in respondent misclassification. Additionally, the coding of “low income” is fairly simple and overlooks many of the complex facets of socioeconomic status. Furthermore, due to sample limitations it was not possible to distinguish between immigrant and non-immigrant respondents who identified as black/African American or white. Finally, Add Health wave 1 was collected in 1994–1995, meaning that the results of this study may be specific to this cohort and may not be representative of younger cohorts. Despite these limitations, Add Health remains one of the largest and most comprehensive, nationally representative surveys of adolescents, their social and economic circumstances, and their health behaviors and outcomes. For this reason, Add Health was an ideal data set in which to explore systematically the intersectional patterning of a range of health inequalities and to compare the results of conventional and MAIHDA approaches. Understanding why conventional and MAIHDA intersectional approaches yield different results is essential. I turn now to a brief consideration of the possible explanations for these differences.

### 5.1. *What might explain differences between the MAIHDA and Conventional approaches?*

#### 5.1.1. *Estimation-related explanations*

There are many possible explanations for differences between MAIHDA and conventional models that could explain the former being less likely to find statistically significant “interaction effects.” First is a category of explanations I group together under the label of “estimation-related explanations.” These include: (1) differences in estimation procedures (Bayesian vs. frequentist); (2) software automatically dropping respondents when fitting conventional models due to convergence issues; and (3) adjustment for contexts such as schools in conventional but not MAIHDA models. This class of explanations may generate minor differences but is unlikely to be the root cause of major substantive differences between the approaches. For instance, dropping respondents in the conventional approach is more likely to result interactions not being statistically significant rather than the other way around, and as previously mentioned fitting MAIHDA models using frequentist estimation typically results in similar effect estimates to Bayesian estimation. Furthermore, the CCMM analyses in this study revealed that the MAIHDA results were robust to inclusion of schools in the analysis.

#### 5.1.2. *Adjustment of MAIHDA estimates based on sample size*

A second possibility is the automatic down-weighting of estimates for social strata with few respondents in the MAIHDA approach. This explanation carries some water, because MAIHDA models will be more likely to provide conservative estimates for strata with small sample sizes. For instance, when estimating the total predicted value of a continuous dependent variable for each social stratum the conventional fixed approach is analogous to calculating the mean separately for each stratum. It seems clear, therefore, why the fixed approach is not ideal for these purposes—the predicted means will be highly sensitive to errors resulting from small samples. Wide swings in estimates are to be expected, and the “interaction effects” must make up the difference between the total expected value for the stratum and the value predicted by the additive effects. Using MAIHDA, such a stratum's estimated residual would be modest to insignificant in magnitude, and therefore unlikely to be found to be statistically significant. Still, careful researchers using the conventional approach are likely to take into account sample size when reporting findings and the interaction parameters themselves—though potentially large in magnitude—are less likely to be found to be statistically significant when based on few estimates. So this explanation may be worth considering but it is unlikely to account for major substantive differences between the approaches.

#### *5.1.3. Adding many categories results in fewer strata with significant residuals*

A third possible explanation is that MAIHDA models can more readily handle inclusion of many interacting categories, and therefore this might explain away some of the between-stratum differences. This was one possible explanation for why the few studies published thus far using MAIHDA have found little evidence of interactions. The empirical results of this study now address this possibility: adding categories to the intersectional analysis does not appear to predictably reduce the likelihood of finding statistically significant interactions. If anything, these results suggest that the opposite may be true in both conventional and MAIHDA models.

#### *5.1.4. Making fundamentally different comparisons*

A fourth explanation for why MAIHDA models seem to find less evidence of interactions than their conventional counterparts is the fact that the two approaches are making fundamentally different comparisons when estimating "interaction effects" because they differ also in what is meant by "additive main effects." In any regression model where only additive effects are included these "main effects" have a fundamentally different interpretation than in a model inclusive of interaction parameters. For instance, consider the case of six intersectional strata where we include additive parameters for female, Latinx and black; here the parameter for "black" represents the average difference between black and white respondents, inclusive of all genders. In a model inclusive of interaction parameters, as in Table 3, the parameter for "black" represents something else entirely—the average difference between black males and white males. This difference in interpretation helps to explain some of the differences in conclusions between the two modeling approaches.

The example of black women is illustrative. MAIHDA models include only additive main effects while conventional intersectional models include additive effects and interaction parameters. Therefore, the "total interaction effect" from the MAIHDA model (i.e., the stratum-level residual for black women) is not equivalent to the "interaction effect" for female *and* black in the conventional model. The stratum-residual in MAIHDA must only explain how this stratum deviates from average values that already include black women when estimating the effects of "black" and "female." The interaction parameter from the conventional models is dependent on the magnitude and directionality of other parameters describing expected values for other strata. This model setup, by its very nature, reduces the expected magnitude of stratum-level residuals in MAIHDA and may explain why we see fewer strata with residuals statistically different from zero.

More generally, in MAIHDA the "effect of being black" includes black populations of all genders, class levels, sexual identities, and so on. A stratum's residual effect (after adjusting for additive effects) will be significant only if that stratum distinguishes itself by having a predicted value that significantly breaks with the overall pattern—either by having a particularly *exaggerated* effect in the same direction as expected or by running *counter* to the general pattern expected (e.g., a low socioeconomic status minority stratum that experiences better health outcomes than minorities and low SES populations overall).

Depending on the particular interests of the researchers involved, between-stratum comparisons made using the conventional or MAIHDA approaches to intersectionality may be more relevant. I argue here only that care should be taken to consider that these two approaches are assessing something fundamentally different when describing "additive main effects" and therefore when estimating the significance of "interaction" (or residual) effects. *Needless to say the tendency for the conventional approach to find statistically significant interaction parameters should in no way be used as justification for favoring the conventional approach.*

#### *5.1.5. Issues to consider when applying MAIHDA intersectional models*

As this study has illustrated, there are many differences between MAIHDA and conventional intersectional models—most importantly that they evaluate "interaction effects" in fundamentally different ways—and these differences can help to explain why the MAIHDA approach will be predisposed to finding fewer social strata with statistically significant residuals after adjustment for additive effects. Researchers choosing to use the MAIHDA approach may be less likely to detect "significant interaction effects" but this does not mean that an equivalent model fit using the conventional approach would result in no evidence of interactions between axes of identity and social process. In fact, as the empirical analysis here demonstrated, the conventional fixed approach found evidence of interactions across a wide variety of dependent variables when many dimensions of identity were interacted and the MAIHDA approach often did not. What is meant by "evidence of intersectionality" is therefore definitional—what do we consider to be an "additive effect" or an "interaction effect"? From this exercise and the wider literature, it seems apparent that interactions do exist across diverse health outcomes and these are worthy of exploration. Regardless of the method used, it is essential that scholars continue to identify such social strata through intersectional analysis. Strata exhibiting evidence of interaction effects with respect to health outcomes may be experiencing particularly perverse sets of social disadvantage and marginalization that place their health at risk, or they may be utilizing privileges or exhibiting forms of resilience worthy of investigation. Even if scholars using both approaches tend to find little evidence of interaction effects, by whatever definition, the project of searching for interactions is central to the mission of health inequalities research.

It is therefore clear that intersectional analysis should continue to be used—but what about MAIHDA models in particular? Conventional intersectional models have been widely used to make substantial contributions to our present knowledge, and depending on the particular goals of the scholars these remain a solid choice for analysis. As mentioned previously, MAIHDA is an excellent alternative for numerous reasons—both practical/methodological and theoretical. It is worth reiterating that in the empirical exercise presented here, the conventional models struggled with inclusion of many interacting dimensions of social determinants due to the expected practical limitations of this approach. Though it may be tempting for researchers who are eager to present non-null results to favor the conventional approach (perhaps understandably due to well-documented publication biases against null results), this alone should not be used to justify this choice of model. The MAIHDA approach does an excellent job of identifying strata whose expected values of the outcome differ substantially from what is expected, either by having particularly intense effects in the expected direction or by breaking with general patterns all together.

#### *5.1.6. Recommendations for future research*

Based on these observations, I now outline a few recommendations for future intersectional scholarship on health inequalities. First, it is important for researchers and readers alike to take care when discussing "additive effects" and "interaction effects" to specify which modeling approach was used—conventional or MAIHDA intersectional. As illustrated, these terms have substantially different meanings in the two contexts.

Second, as Geoffrey Rose famously noted (1992), a small shift in a population's distribution (and thus a modest change in the mean value) can result in substantial excess cases of illness. In intersectional work we might apply this insight as follows: a small difference between the total expected value for a social stratum and what is predicted for it based on additive effects alone can still represent a meaningful excess burden (or benefit) associated with that intersectional social position. Rather than thinking of strata residuals exclusively in terms of their statistical significance, it behooves us to consider their actual magnitude and direction as well. For instance, we might examine the extent to which strata experience an unexplained residual effect of a given magnitude or larger, where the magnitude used for comparison purposes is a known and meaningful value such as the overall inequality between those of the highest versus lowest income level (Evans et al., 2018). Additionally, I echo other scholars who have called for "intersection-plus" approaches (Weldon, 2008) that allow for consideration of total effects (inclusive of additive and interaction/residual components) intersectionally. While a focus on interaction parameters and residuals is perhaps inherent to the project of quantitative intersectional analysis, there are advantages to not losing sight of the magnitude and direction of the inequalities themselves.

Third, it is important to differentiate the intersectionality of *experiences* from the *effects* these unique, intersectional experiences have on outcomes for social strata (Evans and Erickson, 2019). From its beginnings in black feminist scholarship, intersectionality has primarily been formulated as describing the social experiences unique to individuals at particular positions in interlocking systems of oppression and privilege, such as the unique forms of discrimination experienced by black women (Collins, 1990; Crenshaw, 1989). While intersectionality of experiences may well result in statistically significant interaction *effects* for health outcomes there is no guarantee that this will be the case, and furthermore, failure to find such statistical effects does not invalidate the premise of intersectionality that different intersectional identities are experienced or performed differently. For instance, the forms of discrimination and structural barriers faced by low income immigrant Latinas in the U.S. varies by documentation status—indicating that documentation status likely interacts with gender, race/ethnicity and income in terms of the social meaning and experiences associated with these intersectional identities/processes. Yet there is no obvious reason to assume that this will necessarily result in statistically significant interaction effects for health risk behaviors such as propensity to use tobacco products. Angie Hancock notes that since its original formulation, leading intersectional scholars have argued that intersectionality ought to be considered as more akin to an analytic framework than a hypothesis that is testable (Hancock, 2013). In some sense the application of intersectionality in population health research will necessarily entail hypothesis testing, yet it is also important for us to recognize that use of an intersectional analytic framework is fundamentally a claim about how we theorize the nature of social identities and experiences in historical, social, political and economic context—namely, that social processes are interlocking and inseparable, capable of generating unique social positions in society.

Fourth, future researchers should consider incorporating contextual-effects such as schools, neighborhoods, and workplaces into their quantitative intersectional analyses. In particular, this will be important when using data collected through cluster-based sampling, such as in Add Health. As revealed in the robustness checks using CCMM in this study, inclusion of schools in the analysis often modestly attenuated stratum-level estimates of the VPC. While the need for explicit consideration of environments in quantitative intersectional analyses has been recognized (Bauer, 2014), few examples exist in the literature demonstrating a means of doing so. The implications of doing so are also, at present, under-theorized and should be explored more in future research. I provide my code used in the CCMM analyses in the hopes of encouraging and enabling other scholars to explore this issue further.

## 6. Conclusion

Intersectional scholarship has the potential to transform our understanding of health inequalities and should continue to be used widely. I have argued that researchers and readers should not be alarmed at failing to find statistically significant stratum-level residuals after adjustment for main effects when the MAIHDA approach is used, and importantly that such findings do not invalidate the intersectional framework. By using this method, we remain true to the mission of intersectional health inequalities scholarship which is to rigorously explore the unique social positions created by interlocking systems of privilege and oppression and the potential implications this has for human health. MAIHDA is a promising avenue for intersectional scholarship with many advantages, both methodological and theoretical, over the conventional approach and it should continue to be employed to study health inequalities.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2018.11.036.

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