These Supplemental Digital Contents are provided by the authors of the following paper, to provide additional detail for interested readers:

**Mahendran M, Lizotte D, Bauer GR. Describing intersectional health outcomes: An evaluation of data analysis methods.** *Epidemiology***.**

# Supplemental Digital Content



## <span id="page-1-0"></span>eAppendix 1: Additional simulation processes

### <span id="page-1-1"></span>1a. Comparing Bayesian and Frequentist MAIHDA models

100 simulations were conducted for each of the three scenarios. Sample sizes of 10,000 were used for each model. The Bayesian multilevel models were calculated using the R brms package. Bayesian (B) multilevel models were performed each with 1000 burn ins, 2000 total. Frequentist (F) multilevel models were created with package lme4, using R version 3.5.3. Presented below are 0.025 and 0.975 percentiles of estimates from the 100 simulations).

**Scenario 1:**  $y = x1 + x2 + x3 + x4 + x5 + x1*x2$ 

$$
P(x1=1) = 50\%
$$
;  $P(x2=1) = 50\%$ ;  $P(x3=1) = 50\%$ ;  $P(x4=1) = 50\%$ ;  $P(x5=1) = 50\%$ ;







## **Scenario 2:**  $y = x1 + x2 + x3 + x4 + x5 + x1*x2$

 $P(x1=1) = 70\%$ ;  $P(x2=1) = 70\%$ ;  $P(x3=1) = 50\%$ ;  $P(x4=1) = 50\%$ ;  $P(x5=1) = 50\%$ ;

eTable 2. 0.025 and 0.975 percentiles of Scenario 2 from 100 simulations



### **Scenario 3:**  $y = x1 + x2 + x3 + x4 + x5 - 2(x1*x2)$

 $P(x1=1) = 20\%$ ;  $P(x2=1) = 20\%$ ;  $P(x3=1) = 50\%$ ;  $P(x4=1) = 50\%$ ;  $P(x5=1) = 50\%$ ;

eTable 3. 0.025 and 0.975 percentiles of Scenario 3 from 100 simulations



#### <span id="page-4-0"></span>1b. Description of power calculation for beta coefficients

Minimum effect size was determined by a power analysis using a main effects regression at sample size 25000. The minimum effect size was when variables X1 to X5 were detected as significant 80% of the time at  $p<0.05$ . 100 iterations were used to determine 80% power.

The input variables for the power calculation were X1 to X6, where all variables were either binary or categorical, based on the predictor combination shown in Table 1 of the main text. Two changes were made to the categorical inputs model that differed from what is shown in Table1, that were justified based on the aim to remain relevant to intersectionality research. Firstly, the models for the power calculations were created and evaluated with main effects only, even though the models in the actual simulations include interaction terms. Presumably if an effect size is significant for an "additive effects" model (additive effects by the intersectionality definition, meaning no interaction), then it is still an important enough size for the detection of interaction terms. Secondly, the input variables did not have the same distribution as in the actual simulation models. In the power calculation models, variables X1 to X3, and X5 and X6 were split in equally sized categories. Only X4 was not equally distributed, due to the mediation relationship between X3 and X4. The justification is that in ideal circumstances, calculating outcomes for each intersectional group would not be affected by intersection size, especially when those experiencing marginalization may belong to groups with smaller cell sizes.

The sampling of positive and negative beta coefficients was centred around 1 and -1. Based on the power calculation the minimum effect size was 0.06/ Positive coefficients were selected from a truncated normal distribution with a minimum of  $0.06$  and a maximum of  $(2 0.06 = 1.94$ ). The negative coefficients were selected from a truncated normal distribution with a minimum of  $(-2 + 0.06 = -1.94)$  and a maximum of  $-0.06$ .

# <span id="page-5-0"></span>eAppendix 2: Method-specific NHANES results

<span id="page-5-1"></span>2a. Variable selection results (single decision trees)



eFigure 1. NHANES variable selection example CART model

The CTree image below can be zoomed in to view the individual splitting patterns.



eFigure 2. NHANES variable selection example CTree model

### <span id="page-7-0"></span>2b. Cross-classification results

#### eTable 4. Cross-classification results





## <span id="page-9-0"></span>2c. Main effects regression (non-intersectional method) results

Note that results presented here are for individual coefficient estimates, but outcome estimates for each intersection, as presented in the main text, were calculated using the "predict" function in R.

	<b>Estimate</b>	<b>SE</b>	<b>P-value</b>		
Intercept	117.23	0.51	< 0.001		
Gender (ref = Male)					
Female	$-2.44$	0.36	< 0.001		
Race/ethnicity $(ref = White)$					
<b>Black</b>	5.84	0.49	< 0.001		
Hispanic	0.31	0.48	0.508		
Asian	$-0.18$	0.59	0.757		
Other	1.86	0.91	0.04		
Education ( $ref = High school$ or less)					
College	$-2.11$	0.37	< 0.001		
Age (ref = 20 to 39)					
40-59	9.49	0.45	< 0.001		
60 plus	19.27	0.44	< 0.001		

eTable 5. Main effects regression results

## <span id="page-10-0"></span>2d. Regression (saturated) results

Note that results presented here are for individual coefficient estimates, but outcome estimates for each intersection, as presented in the main text, were calculated using the "predict" function in R.

![](_page_10_Picture_253.jpeg)

![](_page_10_Picture_254.jpeg)

![](_page_11_Picture_349.jpeg)

#### <span id="page-12-0"></span>2e. MAIHDA results

The MAIHDA model used to create the final intersection predictions is what is referenced in eTable 6 as the "Full model". The "Null model" is a model fitted with only random effects, and no fixed effects. The null model was only used to calculate estimates of discriminatory accuracy, the variance partition coefficient (VPC), and the proportional change in variance (PCV). The formulas for calculating VPC and PCV are as follows, where  $\sigma_{u(0)}^2$  is between-stratum variance of the "null model",  $\sigma_{u(0)}^2$  is within-stratum variance of the "null model", and  $\sigma_{u(1)}^2$  is from the "full model":

$$
VPC = \frac{\sigma_{u(0)}^2}{\sigma_{u(0)}^2 + \sigma_{e(0)}^2} \times 100\% \qquad PCV = \frac{\sigma_{u(0)}^2 - \sigma_{u(1)}^2}{\sigma_{u(0)}^2} \times 100\%
$$

Note that results presented here are for coefficient estimates, but outcome estimates for each intersection, as presented in the main text, were calculated using the "predict" function in R.

![](_page_12_Picture_271.jpeg)

#### eTable 7. MAIHDA results

### <span id="page-13-0"></span>2f. CART results

Outcome estimates for each intersection, as presented in the main text, were calculated for the model shown in eFigure3, using the "predict" function in R.

![](_page_13_Figure_2.jpeg)

eFigure 3. CART model

![](_page_14_Figure_0.jpeg)

eFigure 4. CART model using continuous age variable

### <span id="page-15-0"></span>2g. CTree results

The CTree images below can be zoomed in to view the individual splitting patterns. For ease of interpretation, composition of the final subgroups created by the CTree model in Supplementary eFigure 5 has been summarized in table form. Outcome estimates for each intersection, as presented in the main text, were calculated for the model shown in eFigure5, using the "predict" function in R.

![](_page_15_Figure_2.jpeg)

eFigure 5. CTree model

![](_page_16_Figure_0.jpeg)

eFigure 6. CTree model using continuous age variable

Age	Gender	Race	Education	Mean SBP
				(mm Hg)
20-39	male	white, Black, Hispanic,		121.183
		other		
20-39	male	Asian	HS or less	120.889
20-39	male	Asian	some college or	116.093
			more	
20-39	female	white, Hispanic		111.125
20-39	female	Asian		108.716
20-39	female	Black, other		115.578
40-59		white, Hispanic, Asian,	HS or less	125.288
		other		
40-59	male	white, Hispanic, Asian,	some college or	124.468
		other	more	
40-59	female	white, Hispanic, Asian,	some college or	121.293
		other	more	
40-59		<b>Black</b>	HS or less	134.646
40-59		<b>Black</b>	some college or	130.059
			more	
$60+$		<b>Black</b>		139.850
$60+$		white, Hispanic, Asian,	some college or	133.012
		other	more	
$60+$	male	white, Hispanic, Asian,	HS or less	134.132
		other		
$60+$	female	white, Hispanic, Asian,	HS or less	137.679
		other		

eTable 8. CTree model subgroup results

# <span id="page-18-0"></span>eAppendix 3: Additional methods citations

For readers unfamiliar with the novel methods included in this study (CART, CTree, random forest, and MAIHDA), we provide a starter list of example applications and methods papers. Papers are labelled as follows:

- **<sup>a</sup>** Methods citation
- **<sup>b</sup>** Other methods papers
- **<sup>c</sup>** Example analysis

### **MAIHDA:**

- Evans CR, Williams DR, Onnela JP, Subramanian SV. A multilevel approach to modeling health inequalities at the intersection of multiple social identities. *Soc Sci Med* 2018:203:64-73. a
- Lizotte DJ, Mahendran M, Churchill SM, Bauer GR. Math versus meaning in MAIHDA: a commentary on multilevel statistical models for quantitative intersectionality. *Soc Sci Med* 2020;245:112500. <sup>b</sup>
- Bell A, Holman D, Jones K. Using shrinkage in multilevel models to understand intersectionality. *Methodology* 2019;15(2):88-96. <sup>b</sup>
- Evans CR, Erickson N. Intersectionality and depression in adolescence and early adulthood: a MAIHDA analysis of the national longitudinal study of adolescent to adult health, 1995–2008. *Soc Sci Med*. 2019 1;220:1-1. <sup>c</sup>
- Persmark A, Wemrell M, Zettermark S, Leckie G, Subramanian SV, Merlo J. Precision public health: Mapping socioeconomic disparities in opioid dispensations at Swedish pharmacies by Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA). *PloS one*. 2019 27;14(8):e0220322.

### **CART:**

- Breiman L, Friedman J, Olshen R, Stone C. Classification and regression trees. New York: Chapman and Hall/CRC, 1984.<sup>a</sup>
- Villanti AC, Gaalema DE, Tidey JW, Kurti AN, Sigmon SC, Higgins ST. Co-occurring vulnerabilities and menthol use in US Young adult cigarette smokers: findings from wave 1 of the PATH Study, 2013–2014. *Prev. Med.* 2018;117:43-51. <sup>c</sup>
- Cairney J, Veldhuizen S, Vigod S, Streiner DL, Wade TJ, Kurdyak P. Exploring the social determinants of mental health service use using intersectionality theory and CART analysis. *J Epidemiol Community Health.* 2014;68(2):145-50. <sup>c</sup>

#### **CTree:**

- Hothorn T, Hornik K, Zeileis A. Unbiased recursive partitioning: a conditional inference framework. *J Comput Graph Stat* 2006;15(3):651-74. <sup>a</sup>
- Venkatasubramaniam A, Wolfson J, Mitchell N, Barnes T, JaKa M, French S. Decision trees in epidemiological research. *Emerg. Themes Epidemiol.* 2017 Dec 1;14(1):11. <sup>b, c</sup>

#### **Random Forest:**

- Breiman L. Random forests. *Machine learning*. 2001;45(1):5-32. **<sup>a</sup>**
- Altmann A, Toloşi L, Sander O, Lengauer T. Permutation importance: a corrected feature importance measure. *Bioinformatics* 2010;26(10):1340-7. **<sup>b</sup>**
- Nayak S, Hubbard A, Sidney S, Syme SL. A recursive partitioning approach to investigating correlates of self-rated health: The CARDIA Study. *SSM-population health*. 2018 1;4:178-88.