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Disentangling Socioeconomic Status and Race in Infant Brain, Birth Weight, and Gestational Age at Birth: A Neural Network Analysis

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ABSTRACT

BACKGROUND: Race is commonly used as a proxy for multiple features including socioeconomic status. It is critical to dissociate these factors, to identify mechanisms that affect infant outcomes, such as birth weight, gestational age, and brain development, and to direct appropriate interventions and shape public policy.

METHODS: Demographic, socioeconomic, and clinical variables were used to model infant outcomes. There were 351 participants included in the analysis for birth weight and gestational age. For the analysis using brain volumes, 280 participants were included after removing participants with missing magnetic resonance imaging scans and those matching our exclusion criteria. We modeled these three different infant outcomes, including infant brain, birth weight, and gestational age, with both linear and nonlinear models.

RESULTS: Nonlinear models were better predictors of infant birth weight than linear models (R^2 = 0.172 vs. R^2 = 0.145, p = .005). In contrast to linear models, nonlinear models ranked income, neighborhood disadvantage, and experiences of discrimination higher in importance than race while modeling birth weight. Race was not an important predictor for either gestational age or structural brain volumes.

CONCLUSIONS: Consistent with the extant social science literature, the findings related to birth weight suggest that race is a linear proxy for nonlinear factors related to structural racism. Methods that can disentangle factors often correlated with race are important for policy in that they may better identify and rank the modifiable factors that influence outcomes.

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Socioeconomic status (SES) is a well-established, robust predictor of child development and health outcomes (1–3). Experiences of deprivation, threat, and trauma, all of which are known to be associated with low SES, play a key role in adversity negatively affecting brain development and health behaviors (4–7). There is also robust evidence of significant health disparities between racial and ethnic groups. Currently, drivers of racial health disparities remain less understood due to the high collinearity between race, SES, experiences of discrimination, and related social stress in many study samples, particularly those in the United States. Distinguishing these effects is a serious, unresolved public health issue for many reasons, including falsely attributing risk factors as being associated with race rather than related to structural racism. Members of minoritized racial groups experience forms of discrimination and related obstacles that bring unique psychosocial stresses, as well as decreased access to necessary services and opportunities. These types of structural and social stressors have deleterious effects on health trajectories (8). Clearly defining race and SES as we intend them to be understood in the context of this study sample is crucial. While race may be understood in several different ways (9,10), in this study, race is a self-assigned categorical variable derived from clinical demographic information that has been binarized given the composition of the study population such that Black was coded as 1 and all others were coded as 0. SES is a combination of social and economic factors such as income, education, and neighborhood information. Despite the complexity of these interrelationships, it is clear from a variety of carefully conducted studies that accounting for SES attenuates the relationships of race to health outcomes (11). However, in previous work using traditional statistical methods, race and low SES have often been found to interact because of the compounding of structural racism with economic disadvantage in the United States, which leads to associations between race and health even after adjustment for SES (12,13). More work is needed to elucidate and identify the factors that account for these residual relationships of race, particularly various forms of discrimination, trauma, and adversity.

Considerable work is being done to understand the effects of experiences of racial discrimination on public health (14,15). Racial discrimination is a risk factor in clinical studies and continues to affect the opportunities that are available to individuals who are discriminated against. Race and SES are intimately intertwined in most communities (16–18), making disentangling their effects difficult. Race is not a biological mechanism for outcomes; higher exposure to social determinants of health results from structural racism. This is a complex and critical issue that affects analyses in a variety of social sciences, hence the several calls to action emphasizing the need to understand the impact of structural racism. The distinction between the social effects of race and experiences of structural racism is a critical one that has yet to be fully interrogated in these fields. Emerging literature suggests that this is not just a public health issue. Several fields such as epidemiology, sociology, and psychology are also encountering this same issue of how to determine drivers of structural racism (19–21).

Machine learning demonstrates superior modeling performance across several domains, including imaging, text analysis, genetics, and medicine (22,23). Linear regression (LR) and other statistical methods such as structural equation modeling (SEM) are often preferred by the medical community for their ease of use and interpretation. LR and SEM work well when underlying relationships are linear. Machine learning, specifically neural networks (NNs), can be interpretable and expose important nonlinear relationships, thereby revealing structures that are otherwise missed and contain critical information. In addition, NNs allow the inclusion of highly correlated variables without loss in performance or robustness. This research aims to investigate the utility of NNs compared with more standard analytic approaches for a typical clinical dataset and their effect on assessment of variable importance. In this analysis, we identified factors suggesting that race may be misinterpreted as a driver of effects in standard analyses when NNs clarify that associated psychosocial and socioeconomic factors drive effects on birth weight, gestational age, and brain volumes independent of race.

Birth weight is one of the first indicators of later health (24–29) and developmental outcomes, and extremes of birth weight, such as small for gestational age (<10th percentile at birth) and large for gestational age (>90th percentile at birth) status, have been identified as sensitive markers of cardiometabolic and neurodevelopmental risk into adulthood (24,25). Critically, data also suggest a relationship between birth weight within the normative spectrum and later childhood cognitive outcomes (26–28) and adult cognitive, educational, and earning achievements (29). For gestational age, the impact is diminished, with marginal impact for increasing weeks beyond the early term period (30–32). Brain volumes at birth are another critical indicator of infant health that have been linked to later cognitive and socioemotional outcomes (33,34). Several studies have provided data suggesting that experiences of structural racism affect the brain and body in adulthood (35–38). Disentangling the social effects of race and social factors associated with race is crucial to inform early intervention. The use of NNs to accomplish these aims could have a high payoff by improving our understanding of the social determinants of infant outcomes.

In the current study, we sought to investigate the differential relationships between SES, race, and other forms of maternal adversity and fetal development during pregnancy in a study of the social determinants of health called “Early Life Adversity and Biological Embedding of Risk for Psychopathology” (eLABE) (39). Previous work from this group using SEM demonstrated the central relationship of social disadvantage, a latent factor including income-to-needs ratio, insurance status, education, area deprivation, and maternal nutrition, to birth weight and brain volumes. While SEM is valuable in its ability to determine relationships between variables, it remains limited by its requirement of linearity. It was unable to dissociate relationships of race and SES to infant outcomes in a previous study (39), likely due to high collinearity between SES and race as is common in many study samples worldwide. Drawing from prior work in social epidemiology and population health, we hypothesized that race often serves as a proxy for complex effects of social and economic disadvantage. Such interrelationships may be nonlinear and often difficult to disentangle using linear statistical methods (40–44). Based on this finding and the central importance of the question, we investigated the utility of NNs in disentangling the relationships of race and social adversity to infant outcomes versus a more standard LR approach.

METHODS AND MATERIALS

The eLABE study is a multiwave, multimethod National Institute of Mental Health–funded investigation designed to study the mechanisms by which prenatal and early-life adversity affect infant neurodevelopment. All study procedures were previously approved by the Washington University in St. Louis Institutional Review Board. Pregnant women who were participants in a large-scale study of preterm birth within the Prematurity Research Center at Washington University in St. Louis with negative drug screens (other than for cannabis) and without known pregnancy complications or known fetal congenital problems were invited to participate. The study recruited 395 women during pregnancy (n = 268 women who were eligible declined participation) and their 399 singleton offspring (n = 4 mothers had 2 singleton births during the recruitment period). Of those originally invited and interested in participation, 26 were deemed ineligible (n = 13 were screened out before consent and n = 13 consented participants were deemed ineligible due to later discovery of substance abuse or congenital anomalies). Women facing social disadvantage were oversampled by increased recruitment from a clinic serving low-income women. The sample was also enriched for preterm infants, with 51 born preterm (<37 weeks' gestation). After removing participants who met exclusion criteria, 351 were included in the analysis for birth weight and gestational age (Figure S1A). For brain volumes, after removing participants missing magnetic resonance imaging (MRI) scans and those meeting our exclusion criteria, 280 were included in the analysis (Figure S1B). Participants with brain injury were excluded from the entire eLABE study.

Data

Data on a variety of variables describing maternal social disadvantage and maternal psychosocial stress were collected and used for analyses throughout this study. Social disadvantage is described by income-to-needs ratio, national Area Deprivation Index or neighborhood disadvantage (45,46), maternal nutrition or diet measured with the Healthy

Table 1. Descriptive Statistics for All Variables Used in the Analyses

Variable	*n*	Mean (SD) or *n* (%)
Maternal Social Disadvantage		
Log_{10} Income/Needs[a]		
First trimester	385	0.24 (0.40)
Second trimester	305	0.28 (0.41)
Third trimester	330	0.26 (0.41)
ADI, Neighborhood Disadvantage	376	69.09 (24.84)
HEI-2016 Total Score	308	58.45 (9.90)
Race	399	
Black		249 (62%)
Not Black		150 (38%)
Health Insurance[b]	399	
Individual/group		200 (50%)
Medicaid		145 (36%)
Medicare		7 (2%)
Uninsured		45 (11%)
VA/military		2 (1%)
Education[c]	355	
Less than high school		26 (7%)
High school graduate		196 (55%)
College graduate		56 (16%)
Postgraduate degree		77 (22%)
Social Disadvantage	399	0.0007 (0.95)
Maternal Psychosocial Stress		
Discrimination Survey[d]	364	1.62 (0.88)
EPDS		
First trimester	396	5.25 (4.88)
Second trimester	331	5.00 (4.94)
Third trimester	332	4.38 (4.70)
PSS		
First trimester	394	13.69 (7.39)
Second trimester	304	13.81 (7.68)
Third trimester	325	13.25 (7.36)
STRAIN, Life Events		
STRAIN-Count	372	6.70 (5.31)
STRAIN-Weighted Severity	372	22.67 (19.91)
Psychosocial Stress	399	0.0002 (0.94)
Clinical		
Self-reported Maternal Tobacco Use	399	
Heavy use (≥6 cigarettes daily)		21 (5.2%)
Some use (<6 cigarettes daily)		29 (7.3%)
None		349 (87.5%)
Maternal Delivery Age, Years	399	29 (5)
Prepregnancy Body Mass Index	307	29.05 (8.34)
Maternal Medical Risk Score	385	1.27 (1.71)
PMA at MRI, Weeks	385	41.2 (1.5)
Cervical Length	358	38.86 (16.44)
Outcomes		
Birth Weight, Grams	399	3134 (599)
Gestational Age, Weeks	399	38.31 (1.99)
Total Cortical Gray Matter	355	119,724 (15,806)
Total Cerebral White Matter	355	183,758 (19,399)
Total Cerebellum	355	28,194 (4337)
Subcortical Gray Matter	355	27,061 (2822)
Left Hippocampus	355	1268 (191)
Right Hippocampus	355	1236 (170)
Left Amygdala	355	904 (97)
Right Amygdala	355	907 (98)
Total Brain Volume	355	257,144 (39,154)
Mean GI	355	1.96 (0.10)
Left Hippocampus, Relative to Total Brain Volume	355	0.0036 (0.00046)
Right Hippocampus, Relative to Total Brain Volume	355	0.0035 (0.0004)
Left Amygdala, Relative to Total Brain Volume	355	0.0025 (0.00016)
Right Amygdala, Relative to Total Brain Volume	355	0.0025 (0.00016)

ADI, Area Deprivation Index; EPDS, Edinburgh Postnatal Depression Scale; GI, gyrification index; HEI, Healthy Eating Index; MRI, magnetic resonance imaging; PMA, postmenstrual age; PSS, Perceived Stress Scale; STRAIN, Stress and Adversity Inventory; VA, Veterans Affairs.

[a]Log transformed because of a skewed distribution of the variable.

[b]Analyzed as Individual/Group vs. all others.

[c]Input as categorical values.

[d]Scored only if perceived as racial, 0 otherwise.

Eating Index (47–50), insurance status, and mother's education. In this analysis, the variable race was added; however, race was not included in the confirmatory analysis. Psychosocial stress is described by self-perceived discrimination if attributed to race (51) and was measured by the Edinburgh Postnatal Depression Scale (52), the Perceived Stress Scale (53), and lifetime stressful and traumatic life events (Stress and Adversity Inventory) (54). A confirmatory factor analysis was used to derive these variables as a two-factor latent construct (39). Data on the following variables were also collected: tobacco use, maternal age at delivery, prepregnancy body mass index, maternal medical risk score (55), postmenstrual age (PMA) at MRI, and cervical length. The outcomes in this analysis were birth weight, gestational age, and several structural brain volumes (Table 1), where each output is continuous. The regions selected for the analyses presented in this paper were key regions of interest in the study of Triplett *et al.* (56), and we used standard analytic techniques based on findings in the extant literature on adverse effects on neurodevelopment. Data collection for all variables, including preprocessing, dyad exclusion data (Table S2), and capturing brain volumetric measures, varied (see Supplemental Methods).

Models

LR is widely used to model data by fitting a linear equation, where $\hat{y} = mX + b$. X is a matrix where every row represents specific patient information. The inputs are linearly combined to output the predictions, $\hat{y}$. LR models output as a linear combination of the inputs; hence, the model will only find linear relationships in the data (Figure 1A). Likewise, LR will not fully control for nonlinear confounding variables. LR can model nonlinear interactions by adding polynomial terms; however, simple LR or SEM models are more commonly used in clinical work. Therefore, LR is our baseline performance model.

NNs make use of nonlinear equations with more parameters. In the simplest form, each layer of a network is computed as $f(X) = \sigma(W^T X + b)$. The data matrix X is linearly transformed by W and b, and each element of the matrix is input to a nonlinear function σ. Multiple layers, each with different sets of parameters, are cascaded to compute the final output. The final architecture used tanh, the hyperbolic tangent function, as the activation function and a single hidden layer (Figure 1B). Several other architectures were tested, but this one exhibited optimal performance (Figure S2). NNs are particularly useful and can perform equivalent to and sometimes exceed a human's ability to analyze data (57). In contrast to LR, NNs use nonlinear functions to model nonlinear relationships. We aimed to test whether NNs were more effective at controlling for nonlinear confounders.

NNs are more complex than LR, requiring more weights to be trained, but also can outperform LR. NNs can model nonlinear relationships between individual inputs and the target output (Figure 1C). Likewise, NNs can model nonlinear interactions between multiple inputs (Figure 1D). NNs can allow for improved correlation performance relative to LR if there are any nonlinear relationships.

Statistical Analyses

We used TensorFlow (58) Adam optimizer to train both models. The TensorFlow error function mirrors ordinary least squares estimation, which is commonly used to train LR. Performance was computed using 10-fold cross-validation. One-tenth of the rows were held out as a validation set, and the remaining observations were used as a training set. Ten models were trained with different holdout sets, such that each observation was in the validation set once. Each model was trained 20 times with a random restart, and the best-performing model was automatically selected, thereby ensuring robust results. In

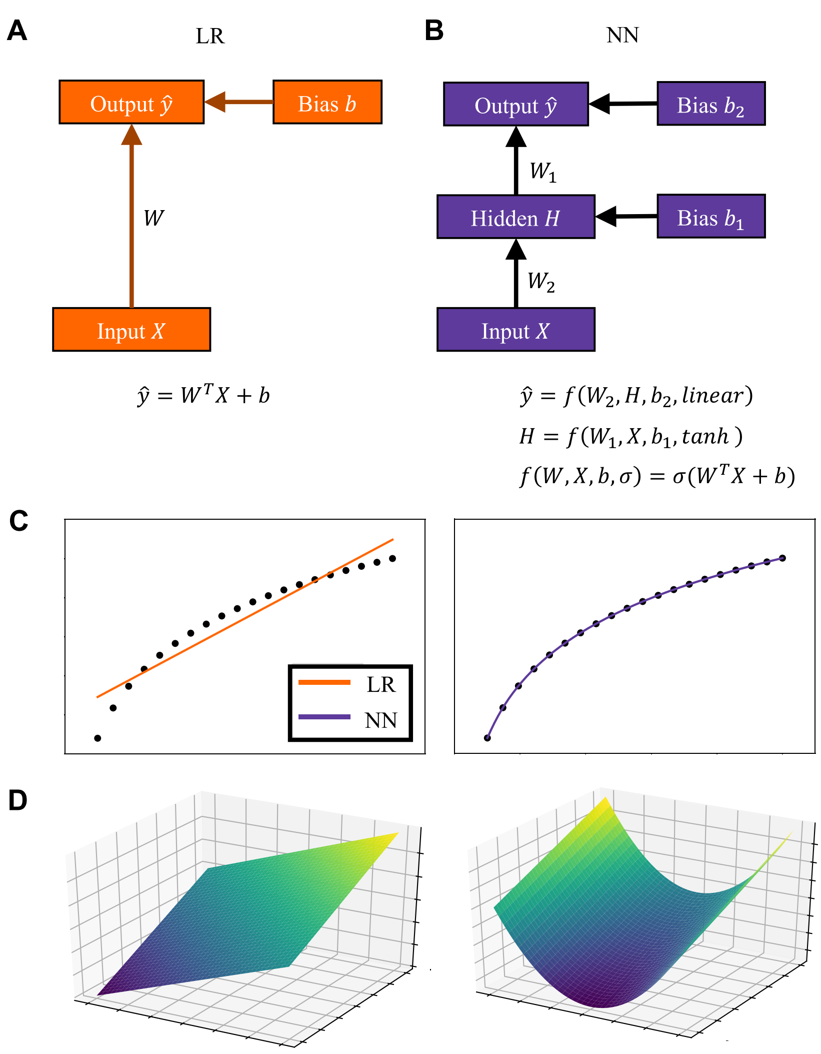

Figure 1. A depiction of the linear and nonlinear models used in this study. Models are depicted in diagrams that show how the modeled infant outcomes were computed from input variables, with vectors depicted as boxes and arrows indicating the flow of information. **(A)** The linear regression (LR) computes the output as a linear transformation of the input vector. **(B)** The neural network (NN) transforms the input vector into a hidden layer of variables, and this layer is transformed into the output. In practice, models operate on normalized data, and therefore, all inputs and outputs are z-normalized. **(C)** The NN can represent nonlinear relationships, such as nonlinear responses, better than LR. **(D)** The NN can better represent nonlinear relationships, such as nonlinear interactions, than LR.

cases where a specific patient datum was missing, simple imputation was applied, and an indicator variable was set to 1 to indicate that the variable was imputed. This input encoding enables models to tune the imputed value to best fit the data.

Models were compared by cross-validated R^2 performance, or amount of variance accounted for. The p values were calculated with a test of correlation differences from dependent samples (59).

We quantified which variables were important for predictive power by holding out variables from the training data. The cross-validated performance on the reduced dataset was computed using the same protocol. A decrease in R^2 quantified the importance of the held-out variables. A large decrease implied that important information was being contributed to performance.

This procedure for measuring variable importance is related to a widely used approach called Shapley additive explanations (60). Shapley additive explanations is used to determine the importance of variables in machine learning algorithms by approximating Shapley values. These values explain how much an input variable affects the output of a model. When using nonlinear models in Shapley additive explanations, the results were not stable, producing different results for each run (Figure S3). In contrast, our approach measured the impact of variables on the global performance, not model output, and yielded stable results across multiple runs.

To quantify nonlinear responses and interactions, we used a clamping test. To measure univariate nonlinearity, we considered a range of fixed values for the test variable. The input matrix transforms by clamping the test variable at a given fixed value, and the average output of a trained model on the clamped dataset is computed. A nonlinear relationship between the average output and the fixed value indicates nonlinearity. We quantified nonlinearity as the root-mean-squared deviation (RMSD) of the best-fit line of these measurements. A line has no nonlinearity, and a larger RMSD indicates more nonlinearity, which was used to rank and quantify the degree of nonlinearity in individual variables.

An analogous, bivariate nonlinearity was computed similarly. Two variables were clamped at a range of values, covering a grid in two-dimensional space. The input matrix transformed to clamp the variables at given values, and the average model output was computed. Again, we quantified nonlinearity as the RMSD of the best-fit plane of these measurements. A flat plane has no nonlinearity, and increased RMSD indicates more nonlinearity between two variables, and we used RMSD to rank pairs of input variables with the most nonlinear response.

RESULTS

For birth weight, the nonlinear model accounted for more variance than the linear model (R^2 = 0.172 vs. R^2 = 0.145, p = .005) (Figure 2). p Values were calculated using a comparison of correlations from dependent samples described in Statistical Analyses (59). The performance of the linear and nonlinear models was comparable for gestational age and structural brain volumes.

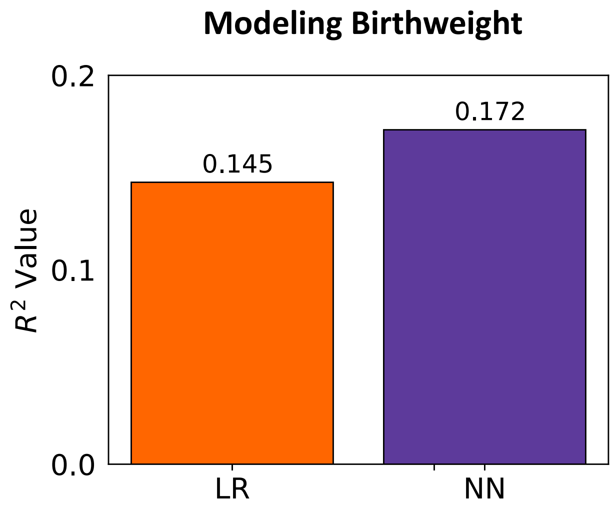

Figure 2. The nonlinear model fits the data better [cross-validated R^2 = 0.172 vs. R^2 = 0.145, p = .005 (59)]. This performance improvement is robust and repeatable across several cross-validation splits and training protocols. This improvement over the linear models—a 2.7% absolute R^2 increase and an 18.6% relative R^2 increase—indicates that there are important nonlinear relationships that the neural network (NN) exploits. LR, linear regression.

Feature Importance

We empirically quantified the contribution of each variable to model performance (Figure 3). The two most important variables for modeling birth weight in both the linear and nonlinear models were maternal medical risk and maternal body mass index. In contrast to the linear model, the nonlinear model was less reliant on the race variable in predicting birth weight (Figure 3A). The linear model ranked race as the next most important variable, followed by household income and neighborhood disadvantage. In contrast, the nonlinear model ranked neighborhood disadvantage, discrimination, and income as more important than race.

A holdout experiment was performed where variables related to SES were removed to determine their importance in relation to race exclusively to quantify importance. Once removed, both models relied more heavily on race; hence, the excluded socioeconomic variables captured information included in race (Figure 3B).

As a negative control, we held out stress, depression, and life events (Figure 3C). We found that income ranked higher than race by the nonlinear model, but the linear model continued to value race over income.

Additional information was derived from each model's single-variable holdout R^2 performance (Figure 3D). The linear model relied more on race, perhaps because it is linearly correlated with the infant outcome and relies on that information for predictive performance. The nonlinear model relied more on income to predict birth weight, perhaps because there is a nonlinear correlation between income and infant outcomes.

Nonlinear Responses and Interactions

The difference in performance and variable importance between NNs and LR seems to be due to several subtle nonlinear

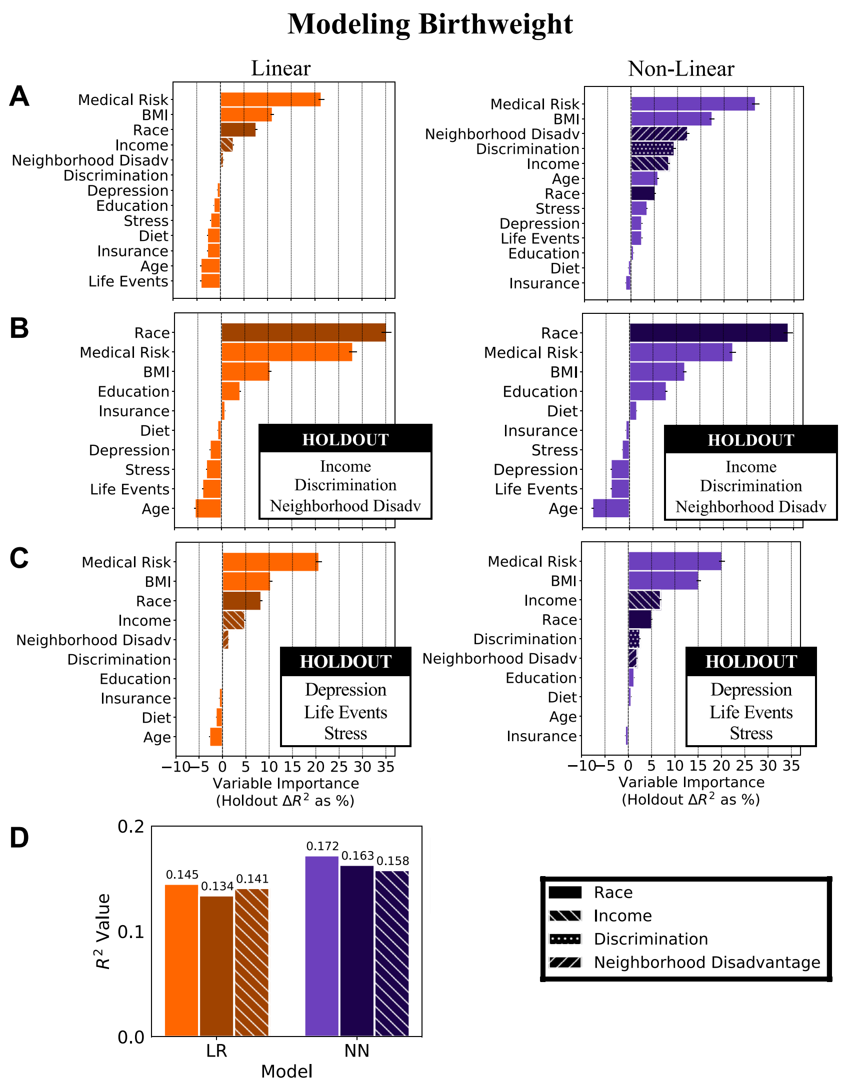

Figure 3. Race is less important in the nonlinear model. Feature importance is robustly quantified by measuring the difference in R^2 performance in models trained with and without the variable in question. **(A)** The nonlinear model makes use of more variables than the linear model. Race is of reduced relative importance (third- vs. seventh-greatest effect) and is of reduced absolute performance (7.58% drop vs. 5.23% drop). Notably, income and discrimination variables are interrelated with race and serve as a control, showing changes in the opposite direction as race in the nonlinear model. **(B)** Both models rely more heavily on race; hence, the excluded variables capture information included in race. The exclusion of these variables is merely a test to quantify importance. **(C)** In a negative control experiment, the impact of race did not decrease when stress, depression, and life events were held out. **(D)** The R^2 performance degrades more with the removal of income (R^2 = 0.172 vs. R^2 = 0.158). BMI, body mass index; disadv, disadvantage; LR, linear regression; NN, neural network.

relationships. To better understand the drivers of the nonlinear model's performance, we first examined the nonlinear relationship of the predictors to the outcome. There were subtle nonlinear relationships between various predictors of birth weight within the model (Figure S4A). The most nonlinear univariate response was to body mass index (RMSD [g] = 17.63) and depression (RMSD [g] = 14.94) (Figure S4B). One notable result is that discrimination was found to be positively associated with birth weight (Figure S7A). However, in a univariate analysis, discrimination was negatively associated with birth weight (R^2 = 0.355) (Figure S7B). This paradoxical result is due to associations between perception of racial discrimination and neighborhood disadvantage (R^2 = 0.059, p = .07) (Figure S7C). The nonlinear model also captured several nonlinear interactions (Figure S5A; Table S1). The largest nonlinear interaction was between depression (RMSD [g] = 32.75) and life events (RMSD [g] = 16.44) (Figure S5B, C). Therefore, the nonlinearities modeled were individually subtle; however, collectively, they dramatically affected the empirical importance of input variables.

Modeling Gestational Age and Structural Brain Volumes

Similar analyses were run with infant gestational age at birth and structural brain volumes. For modeling gestational age, race was not an important variable (Figure 4). Race was in a comparable rank in both linear and nonlinear models (Figure 4A). Income and discrimination were always ranked above race. When we withheld proxy variables, race became more important but not nearly as important as medical risk (Figure 4B). As a negative control, we held out stress, depression, and life events (Figure 4C), and the results were very similar to those with all variables included.

For modeling structural brain volumes, we closely followed the work of Triplett *et al.* (56). We used the same dataset;

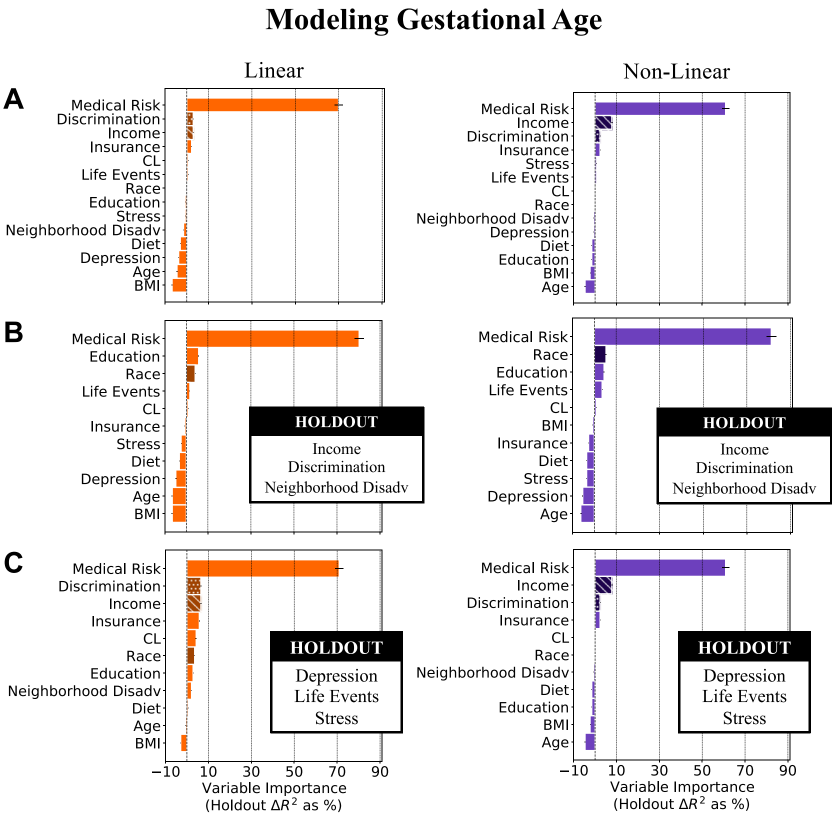

Figure 4. Race is not an important predictor of gestational age. **(A)** We ran similar analyses with gestational age and saw that medical risk was the most important variable. Race is at a comparable rank in the linear and nonlinear models. **(B)** As expected, when proxy variables are removed, race moves up in rank because it is providing the information that has been removed. **(C)** We ran a control in which the survey variables were withheld, and we saw that results are similar to results shown in panel **(A)**. BMI, body mass index; CL, cervical length; disadv, disadvantage.

however, our analysis modeled brain volumes with linear and nonlinear models as opposed to observing correlations. We also included race in our analysis. We empirically quantified the contribution of each variable to model total brain volume (Figure 5). The most important variables for modeling most brain structural volumes were consistently PMA at MRI, infant sex, and birth weight (Figure 5A; Figure S6), which is consistent with the correlation values found in the Triplett *et al.* study. Race had little variable importance when all variables were included for both models. When the variable importance is <5%, we cannot draw any definitive conclusions because this variance could be due to noise; hence, race was not a strong predictor of brain volume outcomes.

When holding out disadvantage, which contains several factors describing structural racism, race did contribute more information, similar to the results we saw from previous analyses, but not nearly as much as PMA at MRI and infant sex (Figure 5B). This further implies that race was not a strong contributor to modeling total brain volume.

As a negative control, psychological stress variables were withheld (Figure 5C). Performance was similar to the analysis including all variables because psychological stress never contributed a lot to performance. Because the psychological stress variable includes racial discrimination, we withheld both disadvantage and psychosocial stress (Figure 5D). Again, most of the variance was contributed by PMA at MRI, infant sex, and birth weight. These are encouraging results indicating that brain volumes are not tightly correlated with race and should be favored over birth weight as an outcome in clinical studies.

DISCUSSION

This research aimed to investigate the utility of NNs compared with standard analytic approaches for a typical clinical dataset and their effect on the assessment of variable importance. We used nonlinear models to better dissociate race from a range of related psychosocial and biological factors known to affect health. While birth weight, which is a key outcome known to be broadly predictive of health trajectories (24–29), was the central outcome, we also included effects on gestational age and brain volumes. We found that nonlinear models accounted for slightly more variance than linear models in our analysis of infant birth weight. However, subtle nonlinear effects can lead to large impacts on variable importance, indicating that the nonlinear models were better at disentangling social determinants of infant health. We found that race was not important for gestational age and structural brain volumes.

These results disentangle the relationships between race, social adversity, and SES to better inform interventions and public policy. Race is highly predictive of many outcomes but is not modifiable by public policy. Methods that can disentangle race from other factors are important for policy in that they may better identify and rank the modifiable factors that influence outcomes. For example, in this study of birth weight,

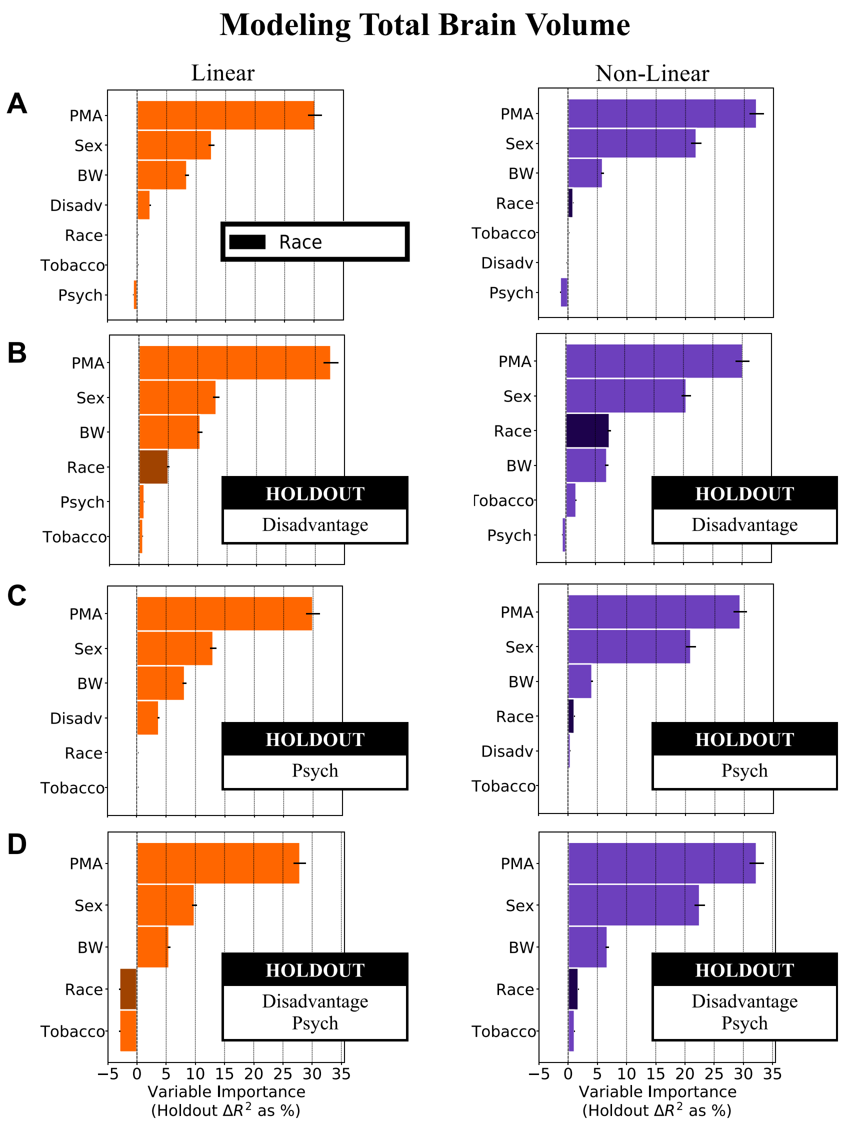

Figure 5. Race is not a strong predictor of total brain volume. **(A)** With the same variables for input as those used by Triplett *et al.* (56), we modeled total brain volume. Postmenstrual age (PMA) at magnetic resonance imaging, infant sex, and birth weight (BW) were the top contributors. **(B)** When we withheld disadvantage, the importance of race became a bit more prominent. **(C)** We withheld psychosocial stress (psych) as our control, and we can see that the results are like the results shown in panel **(A)**. **(D)** Because the psychosocial stress variable includes racial discrimination, we withheld both disadvantage (disadv) and psychosocial stress. These results show that most of the variance is still coming from PMA at magnetic resonance imaging, infant sex, and BW, suggesting that race is not a strong contributor for structural volumes.

income is a more important factor than diet. This is only visible when race is accounted for in a nonlinear model, suggesting that for this outcome, a policy that improves income equity would be more effective than one that selectively improves diet. The importance of income and discrimination have powerful public health implications for the design of prevention programs that should be targeting discrimination and other forms of structural racism and social adversity related to low SES. These data highlight the importance of pregnancy as a key window of time for future preventive health interventions targeting children.

These findings have important implications for understanding elements of the global experience of psychosocial adversity. Furthermore, exploring how these experiences drive risk for poor health outcomes is important. In contrast to prior work about the biological role of race, these findings demonstrate that race is acting as a linear proxy for a variety of nonlinearly correlated adverse experiences, including economic disadvantage and discrimination (40–44). Based on this study, we recommend that future studies report the results from nonlinear models alongside results from linear models, both with and without including race as an independent variable. In many cases, the results will be robust across all approaches, but in others, nonlinear models may explain the data better.

In terms of limitations, the dataset for this study is small compared with many studies that have used NNs; however, the size of the current study sample is relatively large for an infant outcome study. It is important to replicate these findings in additional datasets, such as those being collected for the Environmental Child Health Outcomes (ECHO) study or the upcoming Healthy Brain and Child Development Study (HBCD). This study would benefit from more information capturing access to health care because insurance status is currently the only variable that does this. Because race was binarized into Black and non-Black, it is important to note that other racial groups experience disadvantage and for this study were categorized as non-Black.

A comparison of the linear and nonlinear models is consistent with race acting as a linear proxy for a nonlinear combination of other variables in this dataset. By modeling the nonlinear relationships directly, nonlinear models better disentangled the relationship between race and SES in this study of maternal adversity, birth weight, gestational age, and structural brain development.

Future Work

Similar nonlinear models and feature importance techniques can be used to examine relationships of other infant outcomes. Future studies can explore disentangling groups of variables using causality networks to determine causal relationships between highly correlated variables. Simple imputation was used for missing data in the current study, but future studies should use more complex methods, such as multiple imputation.

Conclusions

In summary, this work begins to disentangle the relationships between race, social adversity, and SES to better inform interventions and public policy. Data describing experiences of adversity and advantage during pregnancy and other factors were used to explore key infant outcomes. Nonlinear models were able to dissociate the relationships of race, likely due to subtle nonlinear responses and interactions. In contrast to linear models, nonlinear models ranked income, neighborhood disadvantage, and experiences of discrimination higher in importance than race. This suggests that race is a proxy for a nonlinear combination of other variables in this high-risk, urban U.S. study sample. Nonlinear components are needed to better model differential impacts on infant outcomes. Race should be used in research to ensure that there is no sampling bias, but findings suggest that race as a variable is not as meaningful as a driver of disadvantage due to systematic racism. As such, these findings significantly extend our understanding of how to disentangle the complex relationships between race and SES in understanding maternal adversity and income outcomes.

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The data will be shared through the National Institute of Mental Health, with standard data sharing policy in effect.

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ARTICLE INFORMATION

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