Iowa Initiative for Artificial Intelligence
Final Report

Project title:	Structural Inequity and Intersectional Suicide Deaths in the United States
Principal Investigator:	Jonathan Platt, John Pamplin, Gonzalo Martínez-Alés, Megan Gilster, Carol Coohey, Katherine Keyes
Prepared by (IIAI):	Avinash Mudireddy
Other investigators:	
Date:	13/03/2024

Were specific aims fulfilled:	Yes
Readiness for extramural proposal?	Yes
If yes … Planned submission date	June 2024
Funding agency	NIH
Grant mechanism	R21
If no … Why not? What went wrong?	N/A

<u>Brief summary of accomplished results:</u>

Summary of the results:

The 2022 IIAI-Pilot IPRC project embarked on a pioneering investigation into the intersection of structural inequity and suicide deaths across the United States, utilizing a multifaceted approach that blends intersectional frameworks with advanced machine learning techniques. The core aim of the study was to dissect the intricate web of social determinants impacting suicide rates, with a focus on identifying high-risk groups and elucidating the role of structural social inequities. Methodologically, the project employed a novel AI/ML model, integrating Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) layers to analyze county-level suicide rates against a backdrop of socioeconomic and demographic variables from 2005 to 2020.

The project's findings, derived from testing four key hypotheses, offer insights into the social patterning of suicide. Hypothesis 1 explored the predictive capacity of the model across various demographic intersections, revealing significant disparities in accuracy, with R^2 values ranging from as low as -5.485 to as high as 0.557. Hypothesis 2 refined this analysis to Hispanic and non-Hispanic groups, showing improved model performance and underscoring the nuanced impact of ethnicity on suicide rates. Hypothesis 3 further dissected racial disparities, with the model demonstrating varying levels of predictive success across Asian, Black, and White groups — indicating the profound influence of race on suicide risk factors. Finally, Hypothesis 4 highlighted gender differences in suicide rates, with the model showing a higher predictive accuracy for males compared to females. Collectively, these results underscore the complex interplay between structural inequities and suicide rates, advocating for a nuanced, intersectional approach in suicide prevention efforts.

<u>Research report:</u>

Aims (provided by PI):

Suicide is the leading cause of violent death in the US, accounting for 2.6% of all mortality [1,2]. Suicide deaths have increased to historically high rates in the 21st Century overall, but heterogeneity suggests complex social patterns with greatest increases occurring in historically marginalized groups [3]. Despite congressional calls to address these concerning trends, research focusing on social inequities and suicide is limited. To fill this critical gap, this project will identify emerging high-risk groups and key social inequities as determinants of suicide deaths, utilizing an intersectional framework [4–6] to account for multidimensional social structures, and machine learning (ML) methods to model that complexity with statistical efficiency. To obtain the overall objectives, three *specific aims* will be pursued:

Aim 1. Identify signature elements that characterizes individual-level distribution and group differences in suicide rates. We will utilize a complete census of suicide deaths from the US vital statistics registry. Where data are suppressed due to small sample sizes, we will predict rates, based on contiguous county rates, and county-level variables associated with suicide rates. Based on preliminary data, our *working hypothesis* is that suicide death rates among individuals with greater levels of social disadvantage will have increased relative to those with high levels of social advantage.

Aim 2. Identify signature elements that characterizes county-level distribution of suicide rates from data about county-level social inequities. The predictor will be trained on a set of structural social inequities (input X) and known suicide rates (prediction output Y) from 2005-2020 and its performance tested in a leave-X% manner. We will assemble and link a novel dataset of county-level indicators of structural social inequities (e.g., poverty rates by race/ethnicity, eviction rates) with county-level suicide rates. Our *working hypothesis* is that indicators will be significantly associated with suicide rates and group differences, such that rates among groups with greater social disadvantage will be elevated in areas with greater levels of structural social inequities.

Aim 2b. If the ML-based predictor developed in Aim 2 reaches sufficient predictive performance, rank the indices of social inequities (X) with respect to their ability of achieving the prediction success.

The *expected outcomes* of this project will answer two key questions related to the social patterning of suicide: 1) what social groups are at increasing risk of suicide deaths? 2) how much can suicide rates be explained by structural social inequity? 3) which indicators or types of inequity are the biggest drivers of suicide rates?

The contributions of this project are relevant to IPRC research and directly respond to *two priorities described in the CDC Suicide Prevention Strategic Plan*, 1) to "use new data to better understand, monitor, and prevent suicide…" and 2) to "identify risk and protective factors for suicide prevention in vulnerable populations".

Preliminary data; description of available data to facilitate the proposed research:

The dependent variable in all analyses will be county-level suicide rates, defined as the number of suicide deaths per 100,000 people. Rates will be calculated using death certificates from the US National Vital Statistics System and National Center for Health Statistics, for the periods 2005 to 2020. The dataset will include 3140 counties. Suicide rates ranged from 4.76 suicides per 100,000 people to 64.16 suicides per 100,000 people (median=13.98 per 100,000) in 2005, and from 5.72 to 89.10 per 100,000 (median=17.74 per 100,000) in 2015 [7]. Suicide deaths are classified based on the International Classification of Disease, tenth revision (ICD-10), with the underlying cause of death codes X60-X84, Y87.0, and U03. In addition, four socio-demographic identity variables will be included for each decedent: racial/ethnic identity (American Indian/Alaskan Native, Asian/Pacific Islander, Black, White, Hispanic), sex (man, woman), education (no college degree, college degree or more), and county of residence (based on unique state-county FIPS codes). Residence will be defined as metropolitan vs. nonmetropolitan and county FIPS code for aims 1 and 2, respectively. Underlying causes of death are determined by a coroner, medical examiner, or physician, while socio-demographic identity variables are reported by next of kin. County-level population estimates from the National Center for Health Statistics will be used to calculate mortality rates.

Aim 1 independent variables will include a set of county-level covariates representing risk factors demonstrated previously to be associated with suicide rates, including demographic characteristics (e.g., racial/ethnic distribution, percent of the county that is urban, divorce rates), socioeconomic factors (e.g., median household income, education distribution, unemployment rates), as well as health- and crime-related characteristics (e.g., number of property crimes, prevalence of illicit drug or alcohol abuse/dependence).

Aim 2 independent variables are structural inequities across racial, sex/gender, and class domains. Variables will be defined at the county-level and year (2005—2020). These measures will build on recent research on structural racism [8,9], sexism [10], and classism [11,12] by considering inequity across economic, political, cultural, physical, and cultural domains. In addition, historical indicators will be considered, to examine how they undergird contemporary structural and health inequities [13,14]. Examples of data sources are listed in Table 1, though additional variables will be considered. Sources will include survey, administrative, and other

Table 1. Structural inequity indicators and data sources

Domain	Indicator	Data source
Structural racism		

monitoring/advocacy data. We will seek to obtain raw data from researchers and/or organizations when it is not publicly available.
Covariates will be included to control for confounding and to explore effect modification. At the individual level, confounding variables will include decedent age, certifier type (physician, medical examiner/ coroner, other), and marital status. At the county-level, confounding variables will include continuous life expectancy, percent with health insurance, percent white, percent of the population age 18 and older, and median income. In addition, age (<15, 15-34, 35-64, 65+) and year (2005-2020) will be considered to test for additional heterogeneity in the main model estimates.

Economic	Poverty rate by race/ethnicity	IPUMS CPS
Legal/ judicial	Rate of police encounters by race/ethnicity	Open policing[15]; Washington Post[16]
Structural sexism		
Economic	Ratio (M:F) median usual weekly earnings	Bureau of Labor Statistics
Physical/ reproductive	Ratio of women to abortion providers	Guttmacher Institute
Structural classism		
Residential	Eviction rate	Eviction Lab[17]
Economic	Income inequity (Gini)	IPUMS CPS

<u>Description of needs to obtain/use IIAI services (expertise, computational resources)</u>

During the *<u>Preparation Phase</u>* of the project, the project PI, investigators, and a student research assistant will assemble the structural inequality dataset (US National Vital Statistics dataset is already available). During the *<u>Analytic Phase</u>*, we will utilize the expertise from the IIAI Center to prepare the data for analysis, identify potential data challenges (e.g., imbalanced data), and build/evaluate the ML/MI models. Dr. Platt has already discussed the project with an IIAI affiliate (Nam Le) to answer preliminary questions related to the analytic phase.

Specific Aims for IIAI:

During the different phases of the project, many experiments were conducted to test various hypotheses. Later, in mid-2023, the IIAI affiliate changed from Nam Le to Avinash Mudireddy. In this report, we describe the final few hypotheses that were tested towards the closure of the project.

The data for these hypotheses are described below.

Hypothesis 1: Given that the data is divided into groups of 'race-sex-his' and given a time series of the past 3 years' information on various predictors (X), predict the suicide rate per 100k (Y) for the next year.

Hypothesis 2: Given that the data is divided into groups of 'Hispanic/not Hispanic' and given a time series of the past 3 years' information on various predictors (X), predict the suicide rate per 100k (Y) for the next year.

Hypothesis 3: Given that the data is divided into groups of 'race' and given a time series of the past 3 years' information on various predictors (X), predict the suicide rate per 100k (Y) for the next year.

Hypothesis 4: Given that the data is divided into groups of 'sex' and given a time series of the past 3 years' information on various predictors (X), predict the suicide rate per 100k (Y) for the next year.

Data for Aims:

The study population is described in the Aims section above. The initial dataset contained 770,000 samples across all counties, groups, and years. However, for our analysis, we only considered counties that have at least 20 samples per unique group. Consequently, the total number of group samples for each hypothesis varies between 6,749 and 15,170. For each group, we have continuous time-series data from 2005 to 2020.

predictor variables:
racesexhis = group id variable
fips = county id variable
year = time variable

sex, race, hispanic
SC01.0 : SS11.2

outcome variable:
suiciderate100k

SC01.0 Eviction filing rate: number of filings observed in court-issued data/number of renting households
SC04.0 Gini index: The Gini coefficient ranges from 0, indicating perfect equality (where everyone receives an equal share), to 1, perfect inequality (where only one recipient or group of recipients receives all the income).
SC04.2 Income Inequality, from the county health rankings data
SC05.0 County Unemployment Rate
SC07.0 County poverty rate
SC08.0 Proportion of adults within the county that are uninsured
SC08.2 Percent of individuals 65 or younger within the county that are uninsured
SC09.0 Percent of households receiving public assistance income or food stamps/SNAP in the past 12 months
SC13.1 Ratio of population to primary care providers
SC13.2 Ratio of population to dentists
SC13.3 Ratio of population to mental healthcare providers
SC15.0 Proportion of Children Eligible for Free or Reduced Lunch
SC16.1 Food Environment Index: Indicator of access to healthy foods - 0 is worst, 10 is best
SC16.2 Percentage of population who lack adequate access to food
SR01.0 Percent of population below the poverty line, ratio of B:W
SR09.0 Black/white incarceration ratios
SR15.1 Ratio of B:W High School Graduate or Higher
SR15.2 Ratio of B:W Bachelors Degree or Higher
SR16.0 The index of dissimilarity is a demographic measure of the evenness with which two groups (Black and white residents, in this case) are distributed across the component geographic areas.
The index ranges from 0 (complete integration) to 100 (complete segregation). The index score can be interpreted as the percentage of either Black or white residents that would have to move to different geographic areas in order to produce a distribution that matches that of the larger area.
SS02.0 Ratio of F:M Median earnings in the past 12 months for the civilian, employed population 16 years and older
SS03.0 Ratio of F:M in the workforce, ages 20-64
SS04.0 Percent of population below the poverty line, ratio of W:M
SS05.0 Ratio of F:M holding managerial positions
SS06.1 Ratio of F:M High School Graduate or Higher
SS06.2 Ratio of F:M Bachelors Degree or Higher
State-level Variables
SR03.0 Estimates of Disenfranchised Black Individuals with Felony Convictions
SR07.1 Percentage of the citizen population registered to vote, ratio of B:W
SR07.2 Percentage of the citizen population who voted in the presidential election, ratio of B:W
SR09.2 Black:White incarceration ratios
SS07.0 Percent of women living in a county without an abortion provider
SS09.1 1 = any law preventing domestic violence perpetrators from accessing firearms
0 = no laws preventing domestic violence perpetrators from accessing firearms
SS09.2 Number of laws on the books preventing domestic violence perpetrators from accessing firearms
SS10.0 Percentage of state legislature seats occupied by women
SS11.1 Percentage of the citizen population registered to vote, ratio of F:M
SS11.2 Percentage of the citizen population who voted in the presidential election, ratio of F:M

AI/ML Approach:

This study introduces a time-series regression model that incorporates a Convolutional Neural Network (CNN) layer, Gated Recurrent Unit (GRU) layers within a multi-head attention mechanism, and subsequent dense layers.

The architecture employs a hybrid loss function, combining mean absolute error and logarithmic error, and integrates regularization techniques such as dropout and L1/L2 regularization. The model is optimized using the Adam optimizer with a learning rate of 0.0001. The integrated Conv-GRU structure enhances the model's ability to capture both local patterns and temporal dependencies.

The activation function used within the dense layers is the Rectified Linear Unit (ReLU). ReLU is known for its efficiency in capturing nonlinear relationships in data, making it suitable for this complex task. In the final output layer, a linear activation function is applied for regression, allowing the model to predict the suicide rate.

To enhance the model's generalization capabilities and reduce the risk of overfitting, L1 and L2 regularization with strengths set at 0.01 are applied. This regularization helps the model focus on important features and prevents it from becoming overly complex.

A learning rate of 0. 0001is employed to optimize the model's performance during training. This careful selection of hyperparameters, along with the choice of activation functions and regularization techniques, ensures that the model effectively analyzes patient data and medication records to identify the most nephrotoxic medications.

Experimental methods, validation approach:

The train: test split is 80:20.
Model architecture for all hypotheses is similar with slight variations. Here is the common version:

```
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_3 (InputLayer)           [(None, 3, 15)]      0           []

 conv1d_4 (Conv1D)              (None, 3, 64)        1984        ['input_3[0][0]']

 gru_4 (GRU)                    (None, 3, 128)       74496       ['conv1d_4[0][0]']

 gru_5 (GRU)                    (None, 3, 128)       99072       ['gru_4[0][0]']

 attention_2 (Attention)        (None, 3, 128)       0           ['gru_4[0][0]',
                                                                  'gru_5[0][0]']

 concatenate_2 (Concatenate)    (None, 3, 128)       0           ['attention_2[0][0]']

 conv1d_5 (Conv1D)              (None, 3, 64)        16448       ['concatenate_2[0][0]']

 flatten_2 (Flatten)            (None, 192)          0           ['conv1d_5[0][0]']

 dense_6 (Dense)                (None, 8)            1544        ['flatten_2[0][0]']

 dropout_4 (Dropout)            (None, 8)            0           ['dense_6[0][0]']

 dense_7 (Dense)                (None, 256)          2304        ['dropout_4[0][0]']

 custom_activation_4 (CustomAct  (None, 256)         256         ['dense_7[0][0]']
 ivation)

 dropout_5 (Dropout)            (None, 256)          0           ['custom_activation_4[0][0]']

 dense_8 (Dense)                (None, 1)            257         ['dropout_5[0][0]']

 custom_activation_5 (CustomAct  (None, 1)           1           ['dense_8[0][0]']
 ivation)

==================================================================================================
Total params: 196,362
Trainable params: 196,362
Non-trainable params: 0
__________________________________________________________________________________________________
```

We designed a custom loss function for our model that intelligently combines mean absolute error with logarithmic error, adjusting their influence through a parameter, alpha. This hybrid approach allows for a nuanced assessment of prediction errors, catering to the diverse scales within our data.

The function computes the mean absolute error, which quantifies the average magnitude of errors between the predicted and true values. It adds to this a weighted logarithmic error, calculated as the mean squared difference between the logs of the predicted and true values. This logarithmic component emphasizes relative errors, making it valuable for cases where proportional differences are more critical than absolute differences.

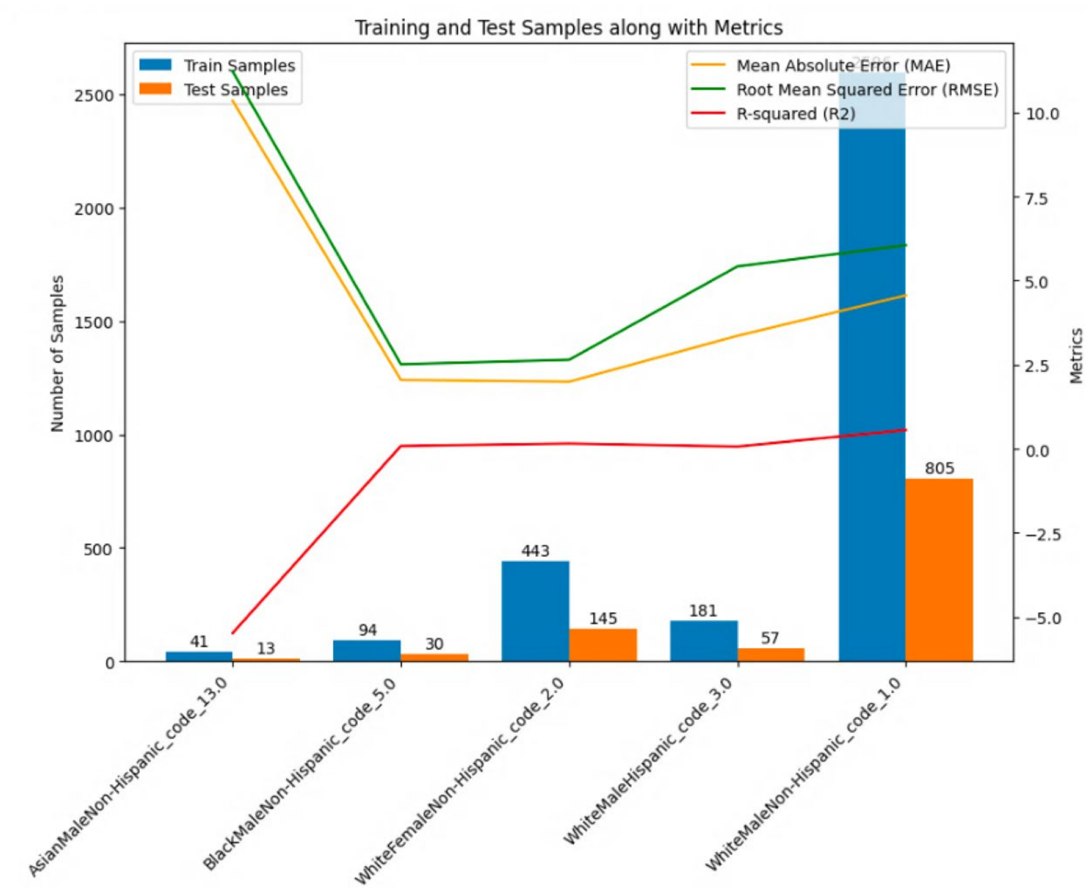
By introducing an alpha parameter, set by default to 0.5, we balance the contribution of mean absolute error and logarithmic error to the total loss. This balance enables the model to not only minimize average prediction errors but also to refine its predictions in a way that respects the relative magnitudes of the target values, enhancing the model's predictive accuracy and robustness across various scales of data.

That is a weighted sum of mean_absolute_error and mean_square_of_log_error

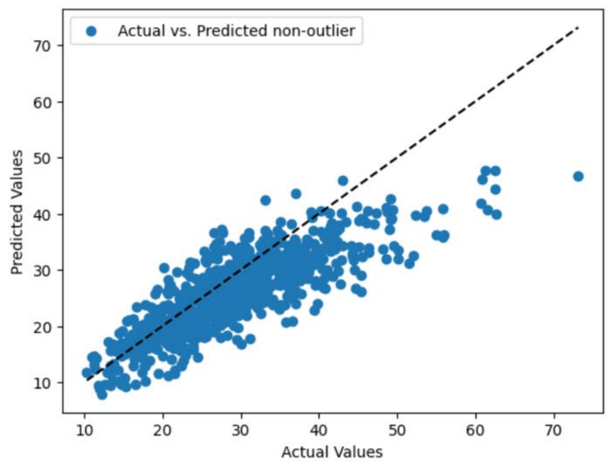
All the models are trained for 200 epochs with 256 as batch size.

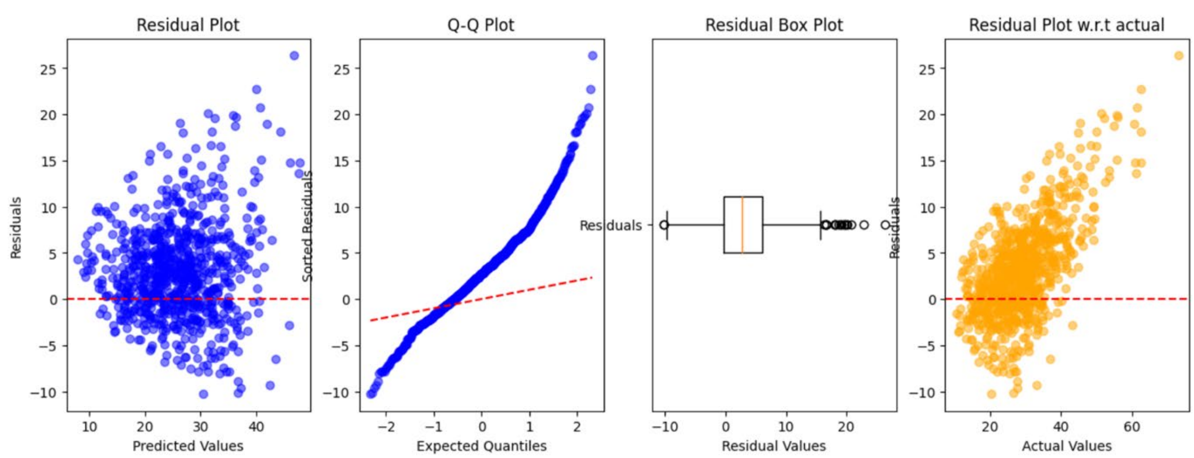
Results:

We measure the following metrics for each of the hypotheses:
Mean Absolute Error (MAE)
The Root Mean Squared Error (RMSE)
The R-squared (R2)
Here are the results
Hypothesis-1:

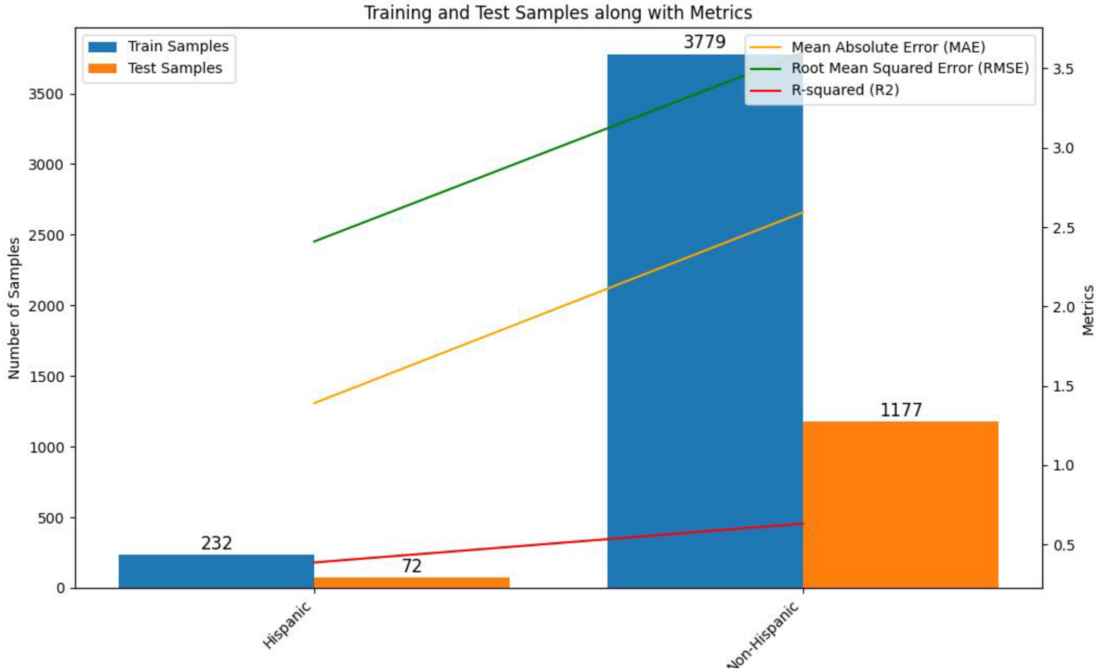


```
[[('Mean Absolute Error (MAE)', 10.35345987122229),
  ('Root Mean Squared Error (RMSE)', 11.227635563554394),
  ('R-squared (R2)', -5.485697555176578)],
 [('Mean Absolute Error (MAE)', 2.0472022050419243),
  ('Root Mean Squared Error (RMSE)', 2.512942132459697),
  ('R-squared (R2)', 0.0827795363727939)],
 [('Mean Absolute Error (MAE)', 1.9933209663805498),
  ('Root Mean Squared Error (RMSE)', 2.6455774115685546),
  ('R-squared (R2)', 0.15532301977259177)],
 [('Mean Absolute Error (MAE)', 3.3599276012467816),
  ('Root Mean Squared Error (RMSE)', 5.42355599834552),
  ('R-squared (R2)', 0.06520927526542075)],
 [('Mean Absolute Error (MAE)', 4.561748946905493),
  ('Root Mean Squared Error (RMSE)', 6.052209277642508),
  ('R-squared (R2)', 0.5576367053721978)]]
```





Hypothesis-2:

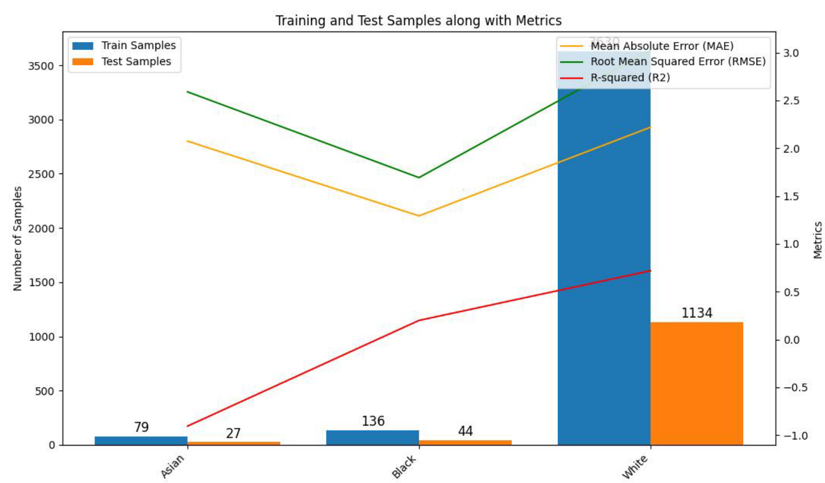


Metrics for Hispanic and Non-Hispanic correspondingly

[[('Mean Absolute Error (MAE)', 1.390891480521214),
('Root Mean Squared Error (RMSE)', 2.4095532681340783),
('R-squared (R2)', 0.38653530606272724)],

[('Mean Absolute Error (MAE)', 2.592809595823251),
('Root Mean Squared Error (RMSE)', 3.5980080560706678),
('R-squared (R2)', 0.6312286366031875)]]

Hypothesis-3:

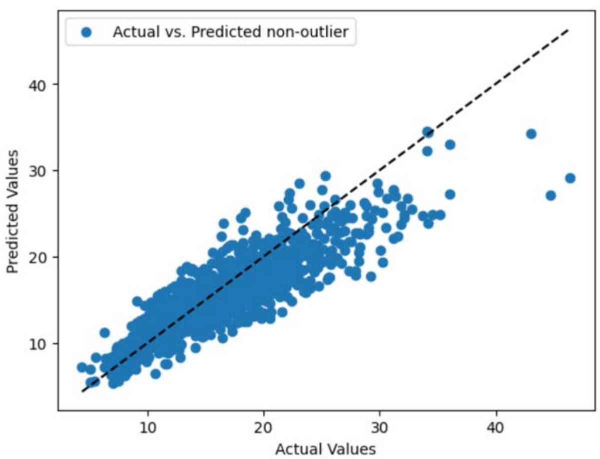


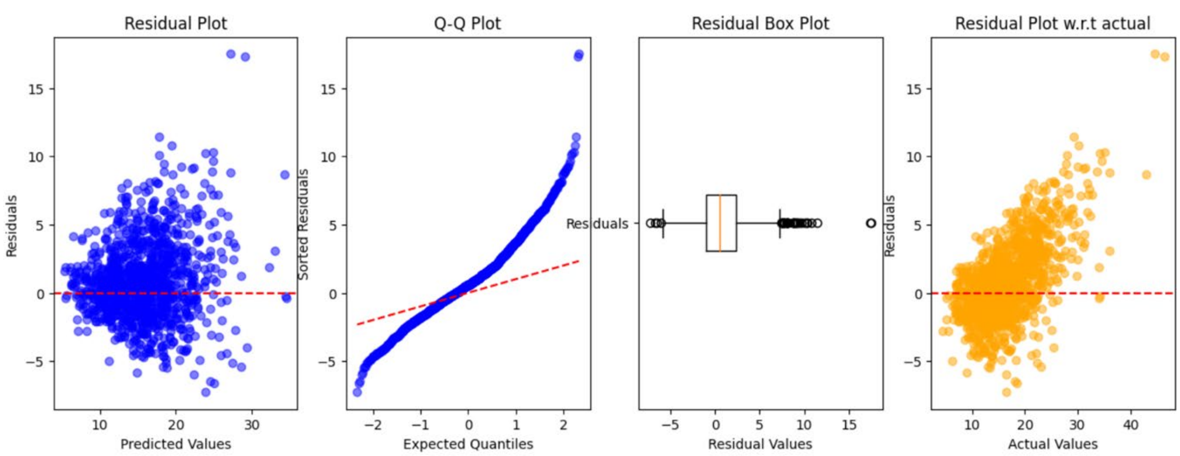
Metrics for Asian, Black and White correspondingly

[[('Mean Absolute Error (MAE)', 2.0745661198573515),
('Root Mean Squared Error (RMSE)', 2.5896594010548424),
('R-squared (R2)', -0.9055504318616945)],

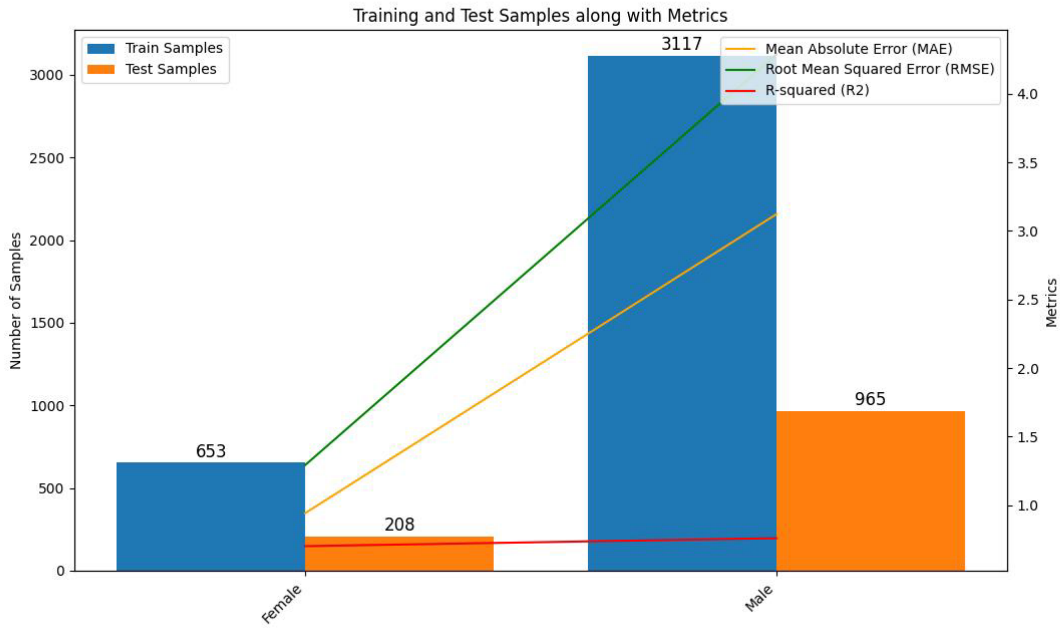
[('Mean Absolute Error (MAE)', 1.2926408304824173),
('Root Mean Squared Error (RMSE)', 1.6928141046672092),
('R-squared (R2)', 0.19976229915674681)],

[('Mean Absolute Error (MAE)', 2.2196510001885796) ,
('Root Mean Squared Error (RMSE)', 3.024715853855328) ,
('R-squared (R2)', 0.7186809950334532)]]





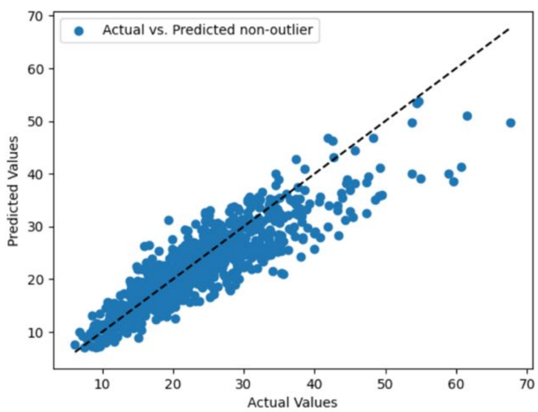
Hypothesis-4:

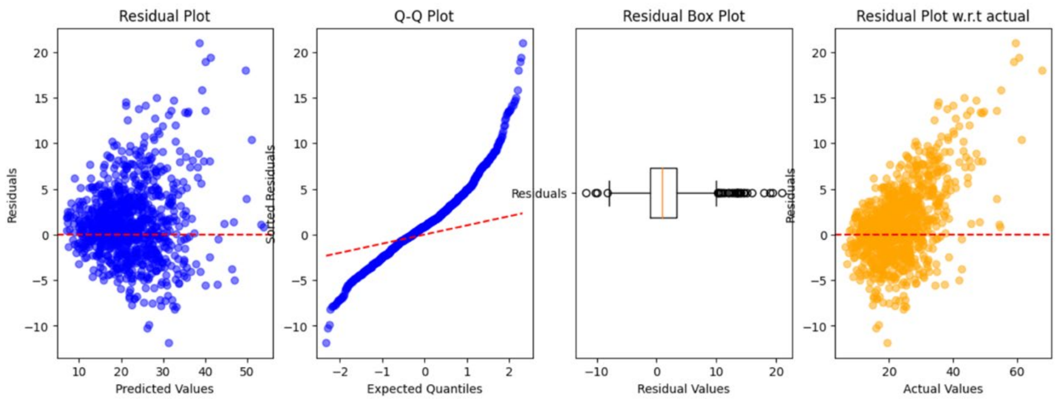


Metrics for Female and Male correspondingly

[[('Mean Absolute Error (MAE)', 0.9419099630807589),
(‘Root Mean Squared Error (RMSE)', 1.2925415974629582),
('R-squared (R2)', 0.701138569546885)],

[('Mean Absolute Error (MAE)', 3.1214826575739667),
(‘Root Mean Squared Error (RMSE)', 4.28721978514925),
('R-squared (R2)', 0.7591363181077259)]]





Ideas/aims for future extramural projects:

Building on the findings and scope of the current project, we are writing an R21 proposal to examine how structural inequities affect rural rates of suicides and drug overdose. This will be done in collaboration with Dr. John Pamplin of Columbia University, a co-investigator on the current project, who will lead a similar project focused on the urban US.

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