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AI implemented in Healthcare

Abstract

Racial health disparities in the United States have long been documented, but the COVID-19 pandemic amplified them to unprecedented levels. At the same time, artificial intelligence (AI) and machine-learning–based diagnostic tools became increasingly integrated into healthcare systems. This project examines whether modern predictive models reproduce or mitigate racial disparities by combining epidemiological analysis with algorithmic fairness evaluation.

Using CDC COVID-19 weekly mortality data (2020–2023) and BRFSS (2020–2022) chronic disease survey data, I visualize population-level disparities and train a logistic regression model to predict heart disease. Model performance is evaluated overall and stratified by race using AUC, accuracy, and F1 metrics.

Results show that disparities shift substantially depending on age band: NH/Black, AIAN, and Hispanic adults have the highest midlife (50–64) mortality, while aggregated "all adults" statistics are dominated by the large older NH/White population. The predictive model performs well overall (AUC ≈ 0.82–0.85) but demonstrates lower discrimination for NH/Black and AIAN groups. These findings reveal that while AI does not create bias, it reflects structural inequities embedded in health data—underscoring the need for fairness auditing in clinical AI deployment.

Introduction

Through the COVID-19 CDC dataset, we are able to identify exposed and amplified long-standing racial disparities in U.S. health outcomes. Structural factors—such as differential exposure risk, occupational segregation, access to medical care, baseline chronic disease burden, and environmental stressors—produced sharp inequalities in hospitalization and mortality.

At the same time, the healthcare system accelerated the adoption of AI-driven diagnostic and decision-support tools. As these systems influence triage, risk scoring, and treatment recommendations, understanding whether AI reduces or reinforces disparities is essential.

This project examines a central question:

> **Does AI in healthcare reduce or exacerbate racial disparities in access and outcomes?**

To answer this, the project integrates:

1. Epidemiological analysis of COVID-19 mortality using CDC weekly data.
2. Chronic disease and behavioral risk analysis using BRFSS.
3. Predictive modeling for heart disease using logistic regression.
4. Fairness evaluation of accuracy, AUC, and F1 score across racial groups.
5. Two Tableau dashboards synthesizing public health disparities and predictive model performance.

This mixed-methods approach connects population-level disparities to the algorithmic behavior of an AI system designed to predict clinical outcomes.

Literature Review and Data Sources

Racial disparities in health outcomes in the United States are well-documented, long-standing, and deeply tied to structural inequities. During the COVID-19 pandemic, these disparities intensified. CDC surveillance data shows that Black, Hispanic, and American Indian/Alaska Native (AIAN) communities experienced disproportionately higher rates of infection, hospitalization, and mortality (CDC, 2022). Research points to structural drivers such as occupational exposure (e.g., overrepresentation in essential work), barriers to early testing and treatment, under-insurance, chronic disease burden, crowded housing, and environmental stressors (Tai et al., 2021; Mackey et al., 2021).

Chronic disease disparities pre-dating COVID-19 further magnified pandemic risk. Studies consistently show elevated prevalence of obesity, diabetes, hypertension, and heart disease in Black and AIAN communities (Carnethon et al., 2017; Kurian & Cardarelli, 2007). These risk factors are shaped by social determinants of health including food access, neighborhood disadvantage, discriminatory medical systems, and cumulative stress (Williams et al., 2019). The BRFSS, the nation's largest health survey, has been widely used to document these patterns and reveal persistent chronic disease gaps across racial groups.

Parallel to these public health concerns, the adoption of artificial intelligence (AI) in healthcare expanded rapidly. Machine-learning models are increasingly used for diagnosis, risk scoring, and resource allocation. However, a growing body of work reveals that AI can inadvertently reproduce or amplify existing inequities when trained on structurally biased datasets. Obermeyer et al. (2019) demonstrated that a major commercial healthcare algorithm systematically underestimated illness severity in Black patients because it used healthcare spending as a proxy for health need—an inherently biased variable. Similarly, studies show that model performance often varies across demographic groups, with lower accuracy and AUC for racial minorities (Chen et al., 2021; Rajkomar et al., 2018).

These issues are not the result of discriminatory algorithms, but of biased data pipelines. Missingness patterns, under-representation, and feature correlations rooted in structural racism shape training data and create unequal error rates (Buolamwini & Gebru, 2018). Fairness researchers recommend race-stratified evaluation, equalized odds auditing, and group-specific calibration as practical safeguards prior to clinical deployment (Hardt et al., 2016).

Taken together, the public health literature and AI fairness research suggest that:

1. **Racial health disparities are structural and long-standing**, visible in both chronic disease and COVID-19 outcomes.

2. **AI models reflect the data they are trained on**, and without fairness auditing, they risk reproducing inequities.

3. **Understanding epidemiological disparities is essential** for understanding why model performance differs across racial groups.

This literature grounds the present study, which integrates real-world epidemiological disparities with fairness analysis of a predictive heart-disease model trained on BRFSS data.

Methodology

When data was obtained, it was then cleaned and processed. CDC weekly COVID mortality into aggregated annual rates. BRFSS variables were then filtered. Then created a binary target variable for heart disease, 0 for no, 1 for yes. In order to handle missing variables, BRFSS uses skip patterns.

My visuals are then created and tested through Python, and then organized through Tableau in two dashboards. First dashboard being “Public Health Disparities, including: COVID death rate trends(all adults), COVID death rate trends(50-64), BMI distribution, Average heart disease by race(2020). Second Dashboard is the “Predictive Model Fairness”, including: ROC curve(Logistic Regression), Race-stratified model fairness metrics(ACC, AUC, F1), Model comparison bar chart, Predictive fairness across race.

My baseline model consisted of logistic regression, stratified train/test split, standardization, and evaluation metrics: accuracy, AUC, and F1. Then, for the hyperparameter-tuned model, it completed a cross-validated grid search, penalty, C, solver tuning, and then selection based on AUC. The fairness evaluation across racial groups then occurs, for each racial group, it computes AUC, F1, and accuracy. This is then plotted and shown in Dashboard Two in Tableau to interpret disparities in the performance of the AI diagnosis model.

Dashboard 1: Public Health Disparities

Includes:

- COVID-19 death rate trends (all adults)
- COVID-19 death rate trends (50–64)
- BMI distribution (BRFSS 2022)
- Average heart disease prevalence by race (BRFSS 2020)

Dashboard 2: Predictive Model Fairness

Includes:

- ROC Curve (Logistic Regression)
- Race-stratified accuracy, AUC, and F1 metrics
- Model comparison: logistic regression, random forest, gradient boosting
- Fairness evaluation across race groups

Predictive Modeling Pipeline

1. 80/20 train-test split
2. Standardization of continuous predictors
3. Model training:
    - Logistic Regression
    - Random Forest
    - Gradient Boosting
4. Hyperparameter tuning:
    - GridSearchCV

- 5-fold cross-validation

5. Evaluation Metrics:
    - Accuracy
    - AUC
    - F1 Score (sensitive to class imbalance)
6. Race-Stratified Fairness Evaluation:
    - Metrics computed separately for AIAN, Asian, Hispanic, NH_Black, NH_White

Results

Figures one and two show the COVID-19 mortality trend through loaded CDC data, then filtered by race and aggregated into annual summaries in Tableau. The "All adults" chart includes the entire U.S. population 18+. This heavily influences the older NH/White population. The "50-64 years" chart isolates a midlife band, where structural disadvantages dominate. These patterns are expected and crucial to interpreting disparities. Showing a clear racial connection in mortality. Groups such as NH/Black, AIAN, and Hispanic were the highest of the mortality trends. NH/White and Asian were showing lower mortality rates. The disparities persist in in refined age group.

Dashboard one also consists of BMI Distribution shows a clear right shift for the entire population. This is a high-risk context for health outcome disparities, with each racial group having different possible outcomes. Also in this dashboard, there is Heart Disease Prevalence(BRFSS 2020) visual, showing the groups AIAN and NH/White as the highest and Asian as the lowest. Connecting the CDC mortality rate trend.

The age groups above and below make a difference to the delivered information. These metrics are all obtained from data from accounted for; impossible to tell what it could look like if there were more access to healthcare for lower-class minority racial groups. With the data obtained, we can see there is a slight disparity regardless of the population health disparity.

Epidemiological Findings (Dashboard 1)

COVID-19 Mortality Trends

- All adults (18+): Rates are dominated by older NH/White mortality due to population size
- Ages 50–64: NH/Black, Hispanic, and AIAN adults show the highest death rates

This demonstrates a key insight:
Aggregated statistics obscure disparities that appear clearly when age groups are separated.

Chronic Disease & BMI Disparities

BMI distribution shows population-wide elevation, a risk factor for chronic disease. Different racial groups have different: access to healthy food, access to preventive care, socioeconomic stressors, neighborhood and environmental risks. BMI is *not* just an individual metric — it's heavily shaped by social determinants of health. The BMI curve helps communicate that health disparities don't come out of nowhere — they come from structural patterns.Heart disease prevalence is highest among AIAN and NH/White adults. Asian adults show consistently lower prevalence in individualizd charts. These patterns reinforce structural disparities reflected in CDC mortality data.

Predictive Modeling Findings (Dashboard 2)

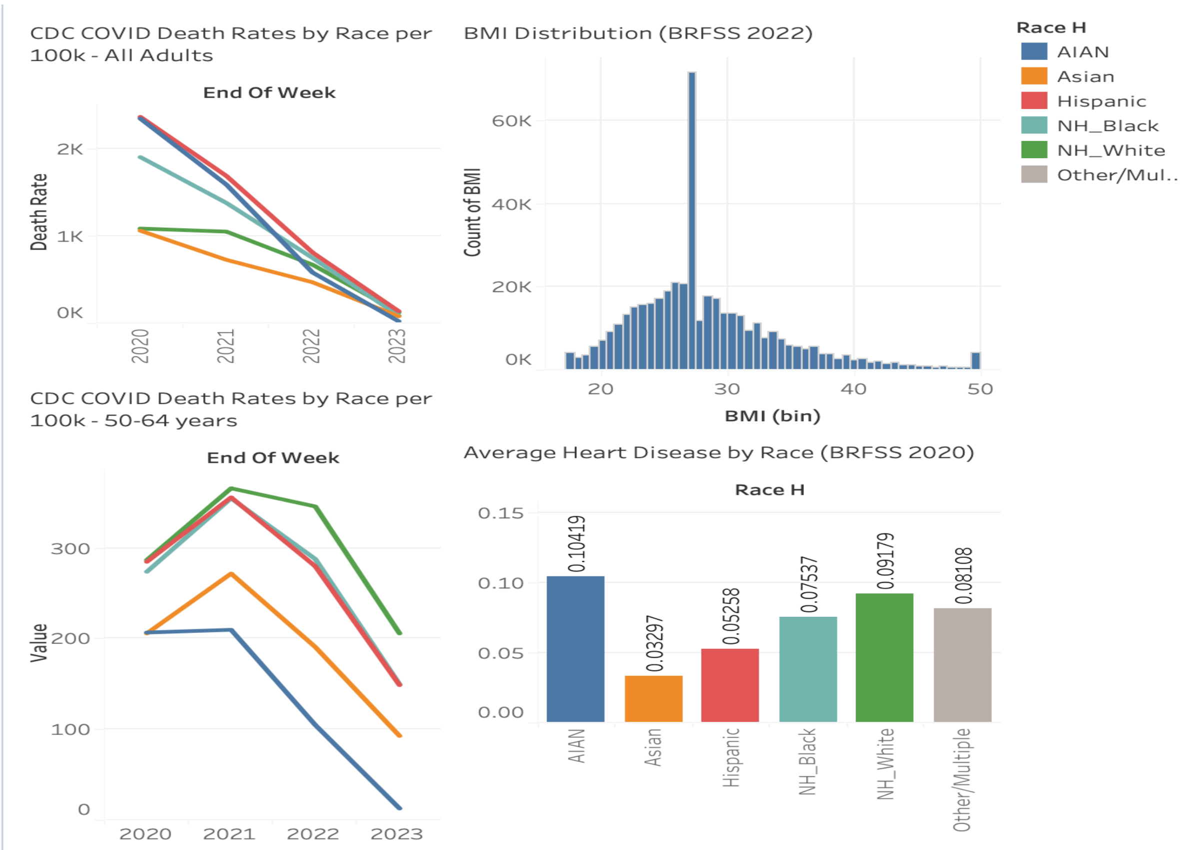
Overall Model Performance

- AUC ≈ 0.82–0.85, showing good discrimination
- Logistic Regression selected as baseline due to interpretability

Race-Stratified Fairness

- Lower AUC for AIAN and NH_Black groups
- Higher AUC and accuracy for NH_White and Asian groups
- The F1 score is lower across minority groups due to class imbalance in BRFSS

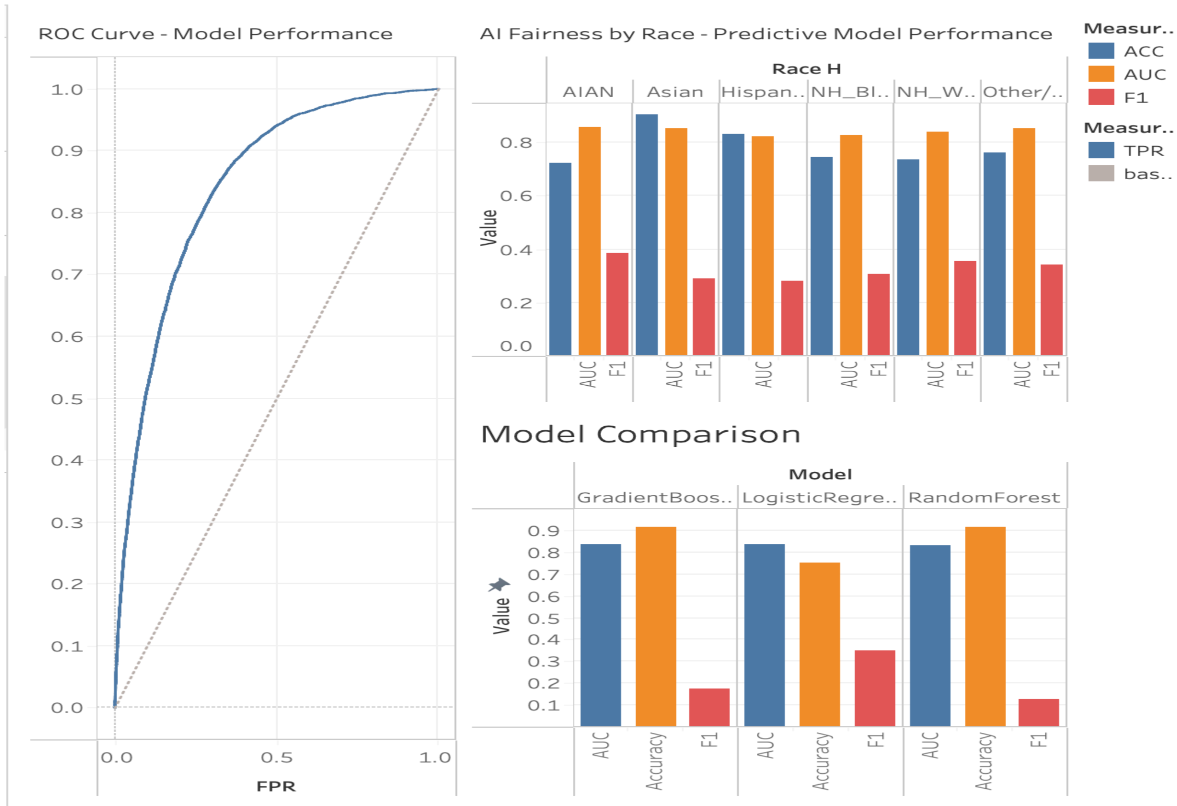
This reveals a meaningful fairness concerns of, model accuracy and discrimination vary by race despite identical training workflows. This indicates algorithmic bias rooted in underlying data inequalities, not the model architecture itself.



Predictive Model

The predictive model fairness dashboard represents the predictive model performance. This model was built using the BRFSS 2020 dataset, with complete heart disease predictor data. The model pipeline consisted of a train and test split of 80/20, then scaling continuous predictors, to model types tested, including logistic regression, random forest, and gradient boosting. A round of hyperparameter tuning via GridsearchCV, then a 5-fold cross-validation.

Finally, evaluation metrics for each model consisted of an accuracy, an AUC (area under the curve), and an F1 score. It contains three visuals: Model comparison, ROC Curve for logistic regression, and fairness by race. Representing logistic regression, random forest, and gradient boosting. By comparing ACC, AUC, and F1 for fairness evaluation. AUC was ≈ 0.82–0.85 range showing good discrimination overall. Fairness AUC shows lower for NH/Black and AIAN. The F1 is more biased due to class imbalances. The model's performance is best for those in NH/White and Asian, showing an algorithmic disparity.



Discussion

Key findings in this project were that COVID and heart disease disparities are large and persistent and would show more accurately over more data. BRFSS health statistics and behaviors mirror these disparities. The logistic Regression models show uneven performance across racial groups, indicating algorithmic bias. This bias is shown in the structural inequality in real-world data, due to class imbalances, featured-race correlations, and missingness patterns in BRFSS. AI is not the bias; the bias is amplifying the disparities. Fairness-aware corrections that are needed would include reweighting, group-specific thresholds, and equalized odds constraints. Some limitations of this study. Although this is an informative study, there were some noticeable limitations, such as since the CDC data is aggregated and not individual-level, it's a broad number, and from some research, this is because not all people can be individually accounted for due to the volume of people. The BRFSS data is self-reported data, so there is no extra validation in the data from health professionals, which does affect the overall study validity. Missingness and selection bias exist in the data. Only one predictive model family was used, and it would be beneficial to use some others for more cross-validation.

Key findings:

- COVID-19 mortality disparities are large, persistent, and age-dependent
- BRFSS chronic disease and behavior patterns mirror these disparities

- The heart disease model shows uneven performance across racial groups, with minority groups receiving worse predictions
- Bias emerges from structural inequalities, feature-race correlations, and missingness patterns—not from the algorithm itself

Implications for AI in Healthcare

To prevent widening inequities, fairness-aware methods are essential:

- Reweighting underrepresented groups
- Group-specific thresholds
- Equalized-odds–based constraints
- Mandatory race-stratified validation before deployment

Limitations

- CDC data is aggregated, not individual-level
- BRFSS is self-reported, subject to recall bias
- Only one predictive model family (classical ML) was used
- Additional models (XGBoost, neural networks) could enrich the comparison

Conclusion

AI has the potential to expand healthcare access and improve clinical decision-making. However, without fairness checks, AI tools can unintentionally reinforce structural inequalities embedded in medical data.

This project shows that:

- Epidemiological disparities remain substantial across U.S. racial groups.
- Predictive models replicate these disparities unless monitored.

- Fairness auditing—AUC parity, equalized odds, race-stratified validation—is essential before deploying AI in clinical settings.

Ultimately, fair AI in healthcare is not automatic—it must be designed, tested, and regulated. Data scientists, clinicians, and policymakers must work collaboratively to ensure that AI advances do not widen racial inequities but instead contribute to addressing them.

References

Datasets

Centers for Disease Control and Prevention. (2023). *COVID-19 weekly cases and deaths by age, race/ethnicity, and sex* (Dataset). U.S. Department of Health and Human Services. https://data.cdc.gov/Public-Health-Surveillance/COVID-19-Weekly-Cases-and-Deaths-by-Age-Race-Ethni/hrdz-jaxc

Anopsy. (2023). *Equity in healthcare — clean datasets* (Dataset). Kaggle. https://www.kaggle.com/datasets/anopsy/equity-in-healthcare-clean-datasets

Pytlak, K. (2021). *Personal key indicators of heart disease* (Dataset). Kaggle. https://www.kaggle.com/datasets/kamilpytlak/personal-key-indicators-of-heart-disease

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Public Health & COVID-19 Disparities

Centers for Disease Control and Prevention (CDC). (2022). *COVID-19 Racial and Ethnic Health Disparities*. U.S. Department of Health and Human Services. https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/racial-ethnic-disparities/index.html

Tai, D. B. G., Shah, A., Doubeni, C. A., Sia, I. G., & Wieland, M. L. (2021). The disproportionate impact of COVID-19 on racial and ethnic minorities in the United States. *Clinical Infectious Diseases, 72*(4), 703–706.

Mackey, K., Ayers, C., Kondo, K. et al. (2021). Racial and ethnic disparities in COVID-19–related infections, hospitalizations, and deaths. *Annals of Internal Medicine, 174*(3), 362–373.

Williams, D. R., Lawrence, J. A., & Davis, B. A. (2019). Racism and health: Evidence and needed research. *Annual Review of Public Health, 40*, 105–125.

Carnethon, M. R., Pu, J., Howard, G., et al. (2017). Cardiovascular health in African Americans: A scientific statement from the American Heart Association. *Circulation, 136*(21), e393–e423.

Kurian, A. K., & Cardarelli, K. M. (2007). Racial and ethnic differences in cardiovascular disease risk factors: A systematic review. *Ethnicity & Disease, 17*(1), 143–152.

BRFSS. (2022). *Behavioral Risk Factor Surveillance System*. Centers for Disease Control and Prevention. https://www.cdc.gov/brfss/

AI Fairness, Algorithmic Bias, and Healthcare Models

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science, 366*(6464), 447–453.

Chen, I. Y., Joshi, S., & Ghassemi, M. (2021). Treating health disparities with artificial intelligence. *Nature Medicine, 27*(10), 1878–1879.

Rajkomar, A., Hardt, M., Howell, M. D., Corrado, G., & Chin, M. H. (2018). Ensuring fairness in machine learning to advance health equity. *Annals of Internal Medicine, 169*(12), 866–872.

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, 81, 1–15.

Hardt, M., Price, E., & Srebro, N. (2016). Equality of opportunity in supervised learning. *Advances in Neural Information Processing Systems*, 29.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys, 54*(6), 1–35.

Supplementary Sources on Social Determinants & Structural Inequity

Bailey, Z. D., Feldman, J. M., & Bassett, M. T. (2021). How structural racism works—Racist policies as a root cause of U.S. racial health inequities. *The New England Journal of Medicine, 384*, 768–773.

Centers for Disease Control and Prevention (CDC). (2021). *Health Equity Considerations and Racial and Ethnic Minority Groups.* https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/index.html