Analyzing Gender, Racial, & Ethnic Disparities & Predicting Priority Scores of NIDA Grant Portfolio

Office of Research Training, Diversity, and Disparities (ORTDD)
National Institute on Drug Abuse (NIDA)

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NIH

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NIDA Office of Research Training, Diversity, and Disparities (ORTDD) Mission

The **Office of Research Training, Diversity, and Disparities** (ORTDD) is committed to developing a cutting-edge, diverse research workforce to address urgent public health substance use and addiction problems.

ORTDD funds **training, career development,** and **research grants** to support substance use and addiction research scientists throughout the career pipeline, with a focus on the development of **underrepresented researchers.**

Project Goals: Using 2010 – 2020 NIDA grant portfolio data,

- Analyze disparities in NIDA grant applications and awards
- Identify factors that predict whether a NIDA grant application is likely to be funded
- Derive insights to eliminate disparities and increase racial and ethnic equity in substance use and addiction science

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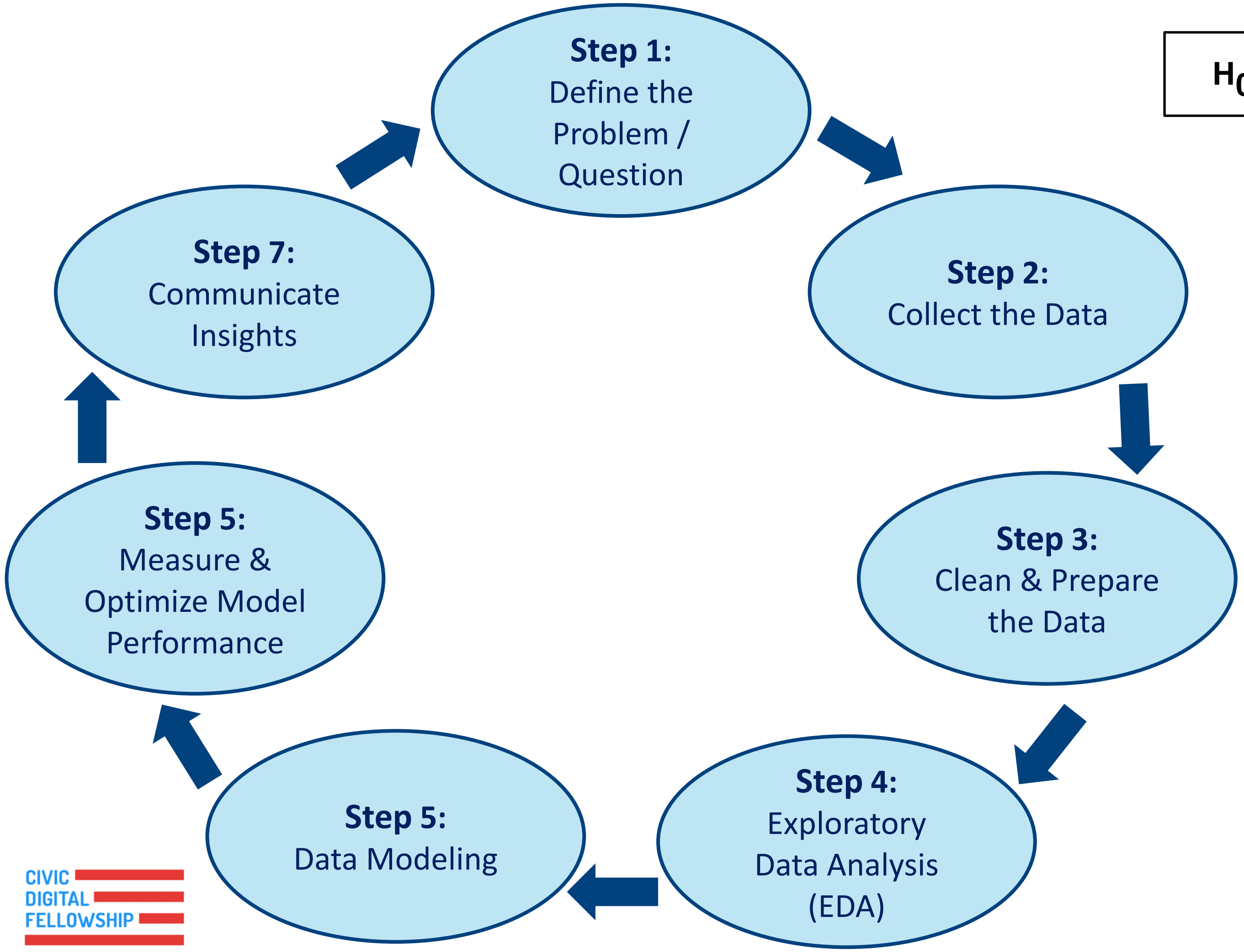
The Data Science Life Cycle



H_0: No disparities exist in NIDA grant applications or awards.

Research Questions

1. Do **disparities** exist in the NIDA grant application and/or award pools?
2. What factors **predict** whether a NIDA grant application is likely to be funded (i.e., receive a **Priority Score < 30**)?
3. What can we do to **eliminate disparities**?

Where is **outreach** most needed?
Among prospective applicants at **institutions** or stakeholders in **review**?

Methods

Data: Anonymized data on all NIDA grant applications

- FY 2010 – FY 2020
- 35,035 rows x 34 columns
- NIH Office of Extramural Research
- 1 row = 1 grant application
- New and competing awards, all NIH grant mechanisms
- Type 1 and 2

Variables: Fiscal Year, Activity Code, Priority Score, Organization Name, Age, Gender, Race, Ethnicity, Early-Stage Investigator (ESI)…

Engineered Features (Y/N): Priority Score < 30, Minority-Serving Institution (MSI), Top 50 NIH-Funded Institution…

Data were **cleaned, visualized,** and **analyzed** using

- Python (Jupyter Notebook via Anaconda)
  - Pandas, NumPy, SciPy, Scikit-Learn, Statsmodels, Matplotlib, Seaborn, Plotly

Statistical Analyses

- Data quality assurance
- Data visualization
- Hypothesis testing
- Feature importance

Machine Learning Models

- Logistic Regression *(baseline)*
- Random Forest *(baseline)*
- XGBoost

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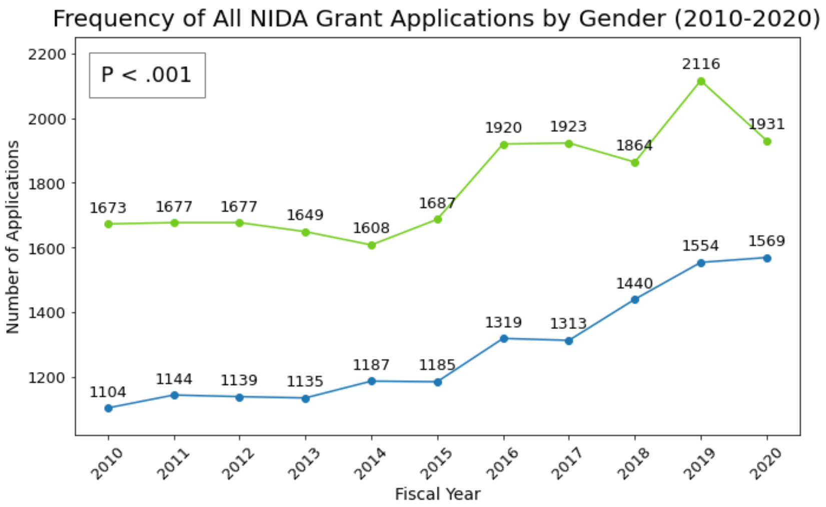
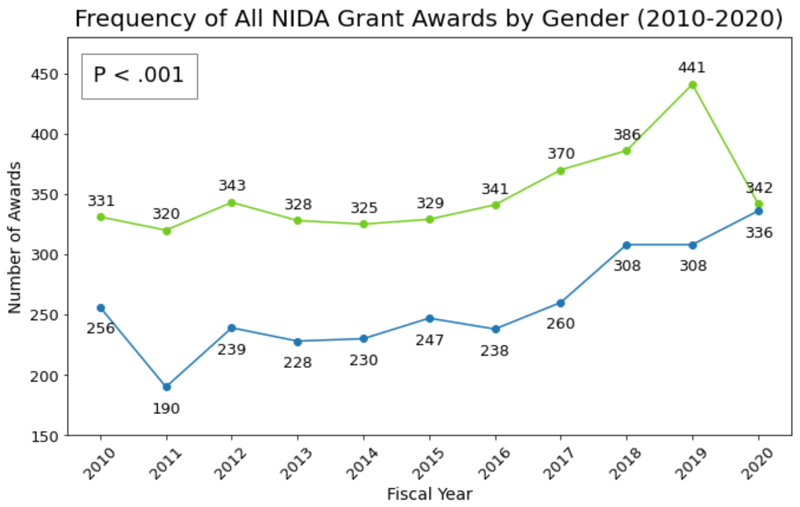
Gender Disparities in Applications & Awards Are Decreasing

New & Competing Applications/Awards, All Grant Mechanisms

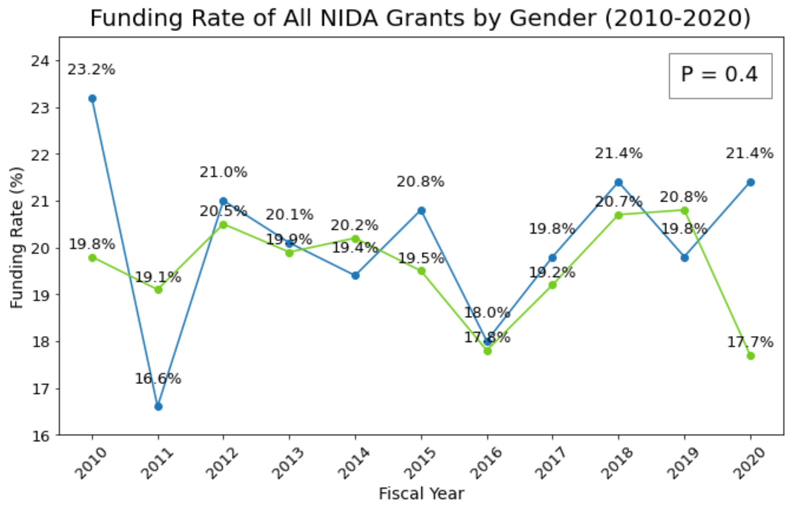
Applications



Awards



Funding Rate



Applications/Awards with ‘Unknown’ or ‘Withheld’ data for ‘Gender’ not shown.

Funding Rate

$$= \left(\frac{\text{X Awards}}{\text{X Applications}}\right) \text{x } 100\%$$

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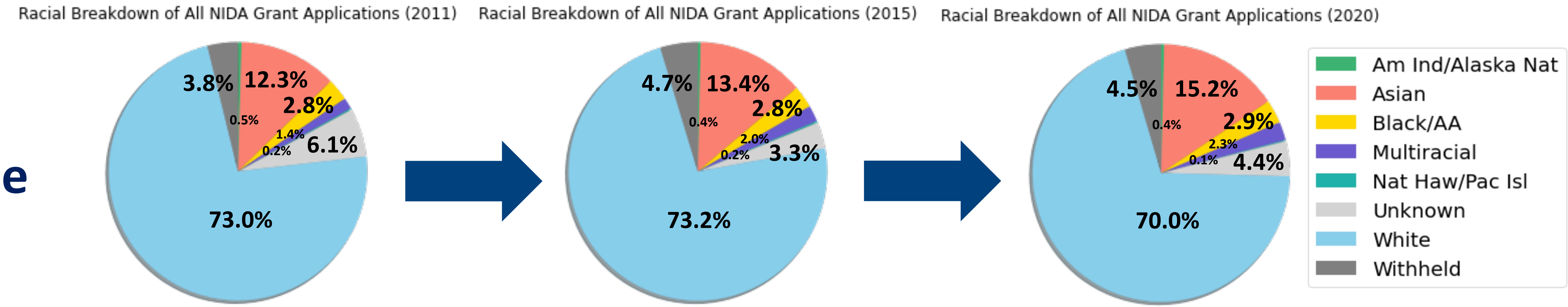
Over the Past Decade, Little Increase in Racial & Ethnic Diversity

New & Competing Applications, All Grant Mechanisms

FY 2011 | FY 2015 | FY 2020

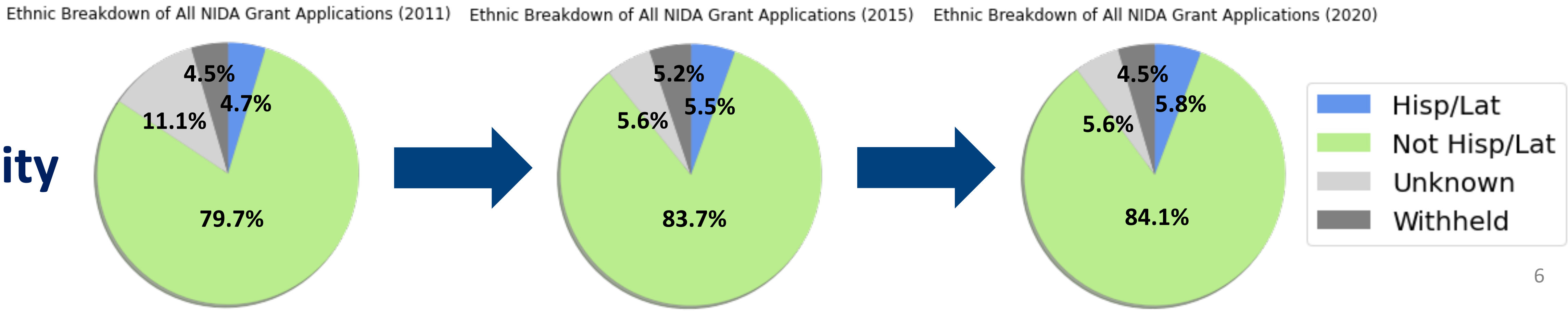
P < .001 (%)

Race



P < .001 (%)

Ethnicity



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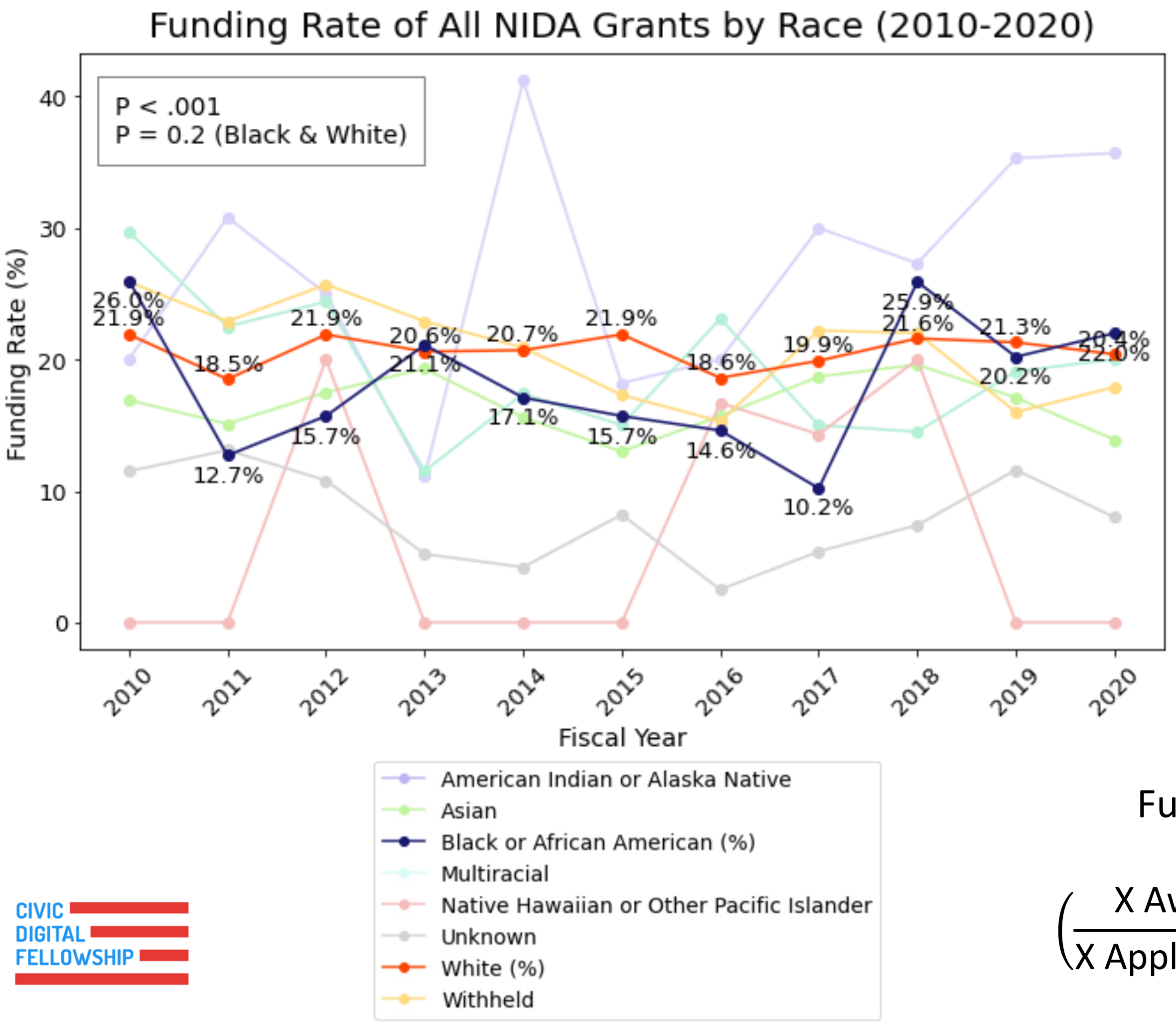
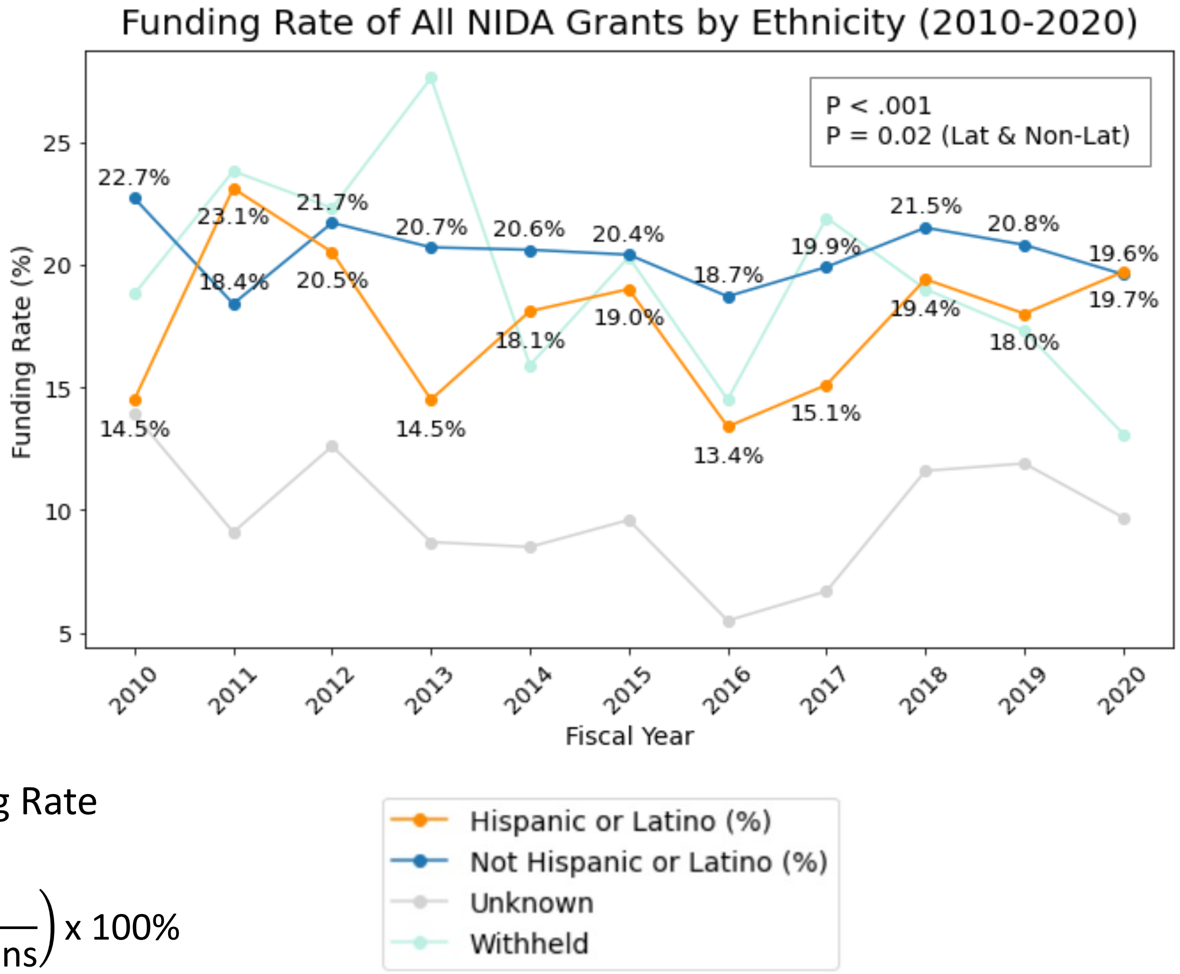
Racial & Ethnic Disparities in Funding Rates Are Decreasing

New & Competing Applications, All Grant Mechanisms

Race



Ethnicity



Funding Rate

$$= \left(\frac{\text{X Awards}}{\text{X Applications}}\right) \text{x } 100\%$$

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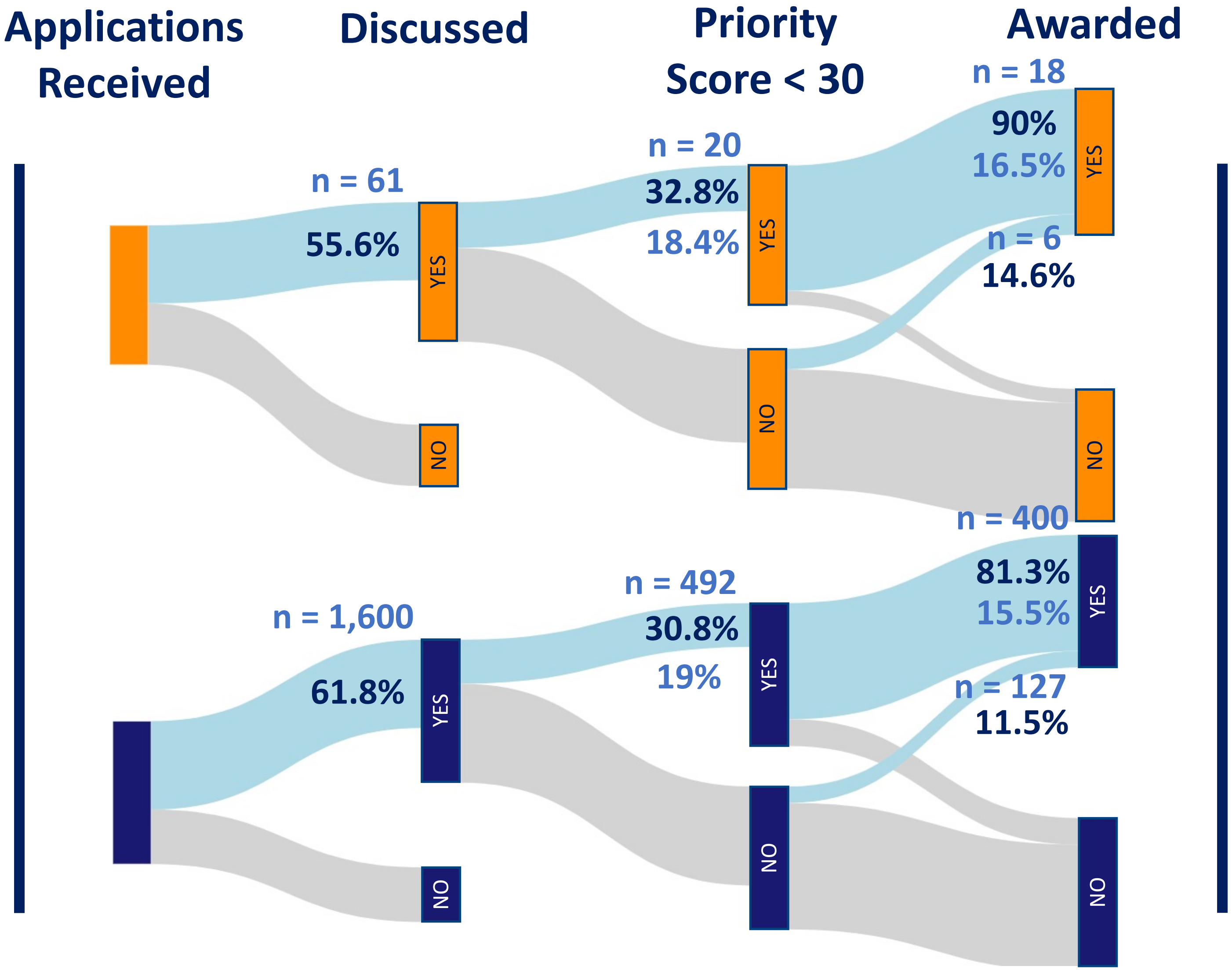
NIDA Grant Review Outcomes by Race (FY 2020)

New & Competing Applications, All Grant Mechanisms

Total n Applications
% of X Race Applications

Applications from Black Applicants
N = 109
2.9%

Applications from White Applicants
N = 2,588
70%



Awards to Black Applicants
N = 24
Funding Rate = 22%

Awards to White Applicants
N = 527
Funding Rate = 20.4%

Predictive Modeling Problem Definition

Objective: Using FY 2010 – FY 2020 NIDA Research Project Grant (RPG) application data, predict whether a NIDA RPG application is likely to be funded, or receive a **Priority Score < 30**.

Target Variable: Whether a NIDA grant application receives a Priority Score < 30

Binary Classification Rule

- 1 = Priority Score < 30
- 0 = Priority Score ≥ 30 / Not Discussed

Features:

- Fiscal Year
- Gender
- Race
- Ethnicity
- Early-Stage Investigator (ESI)
- Minority-Serving Institution (MSI)
- Top 50 NIH-Funded Institution
- A1
- Application Type Code
- Activity Code (RPGs Only)

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Building & Optimizing Machine Learning Models

Machine Learning Models

1. Logistic Regression *(baseline)*
2. Random Forest *(baseline)*
3. XGBoost

Preprocessing Data

- Clean and normalize data
- Feature engineering
- One-hot encoding
- Balance classes
- Split data into train (80%) and test (20%) sets

Building & Optimizing Models

- Tune hyperparameters
- Fit classifier on train set
- Make predictions on test set
- Measure and optimize model performance
- Analyze feature importance

Logistic Regression & Random Forest

Baseline Machine Learning Models

1 = Priority Score < 30

0 = Priority Score ≥ 30 / ND

Logistic Regression

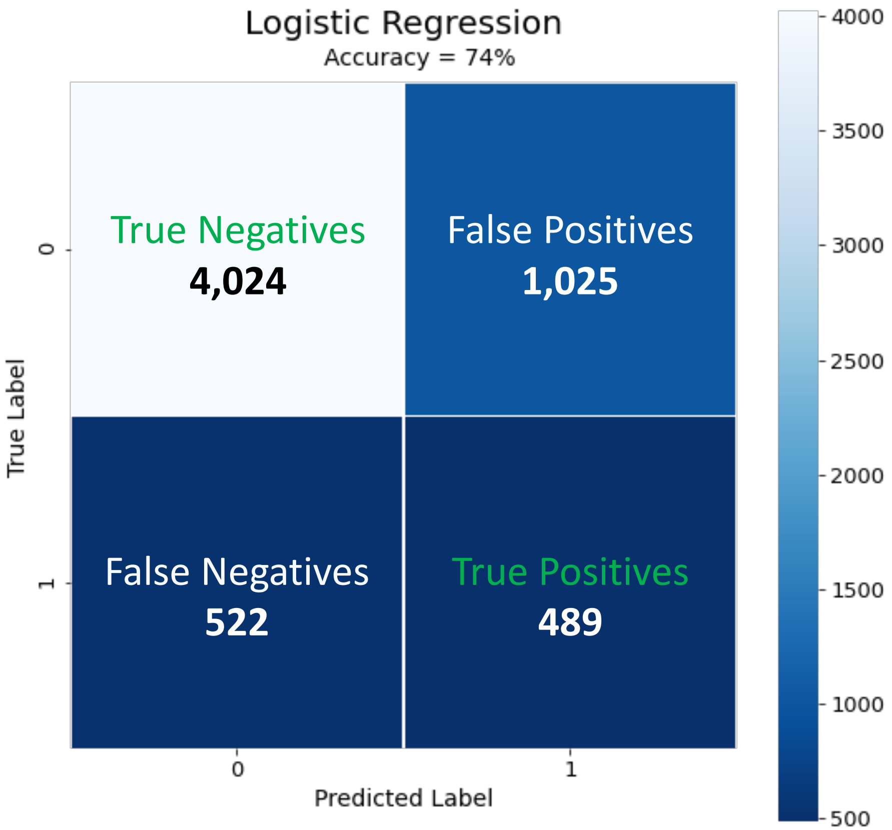
Accuracy = 74%

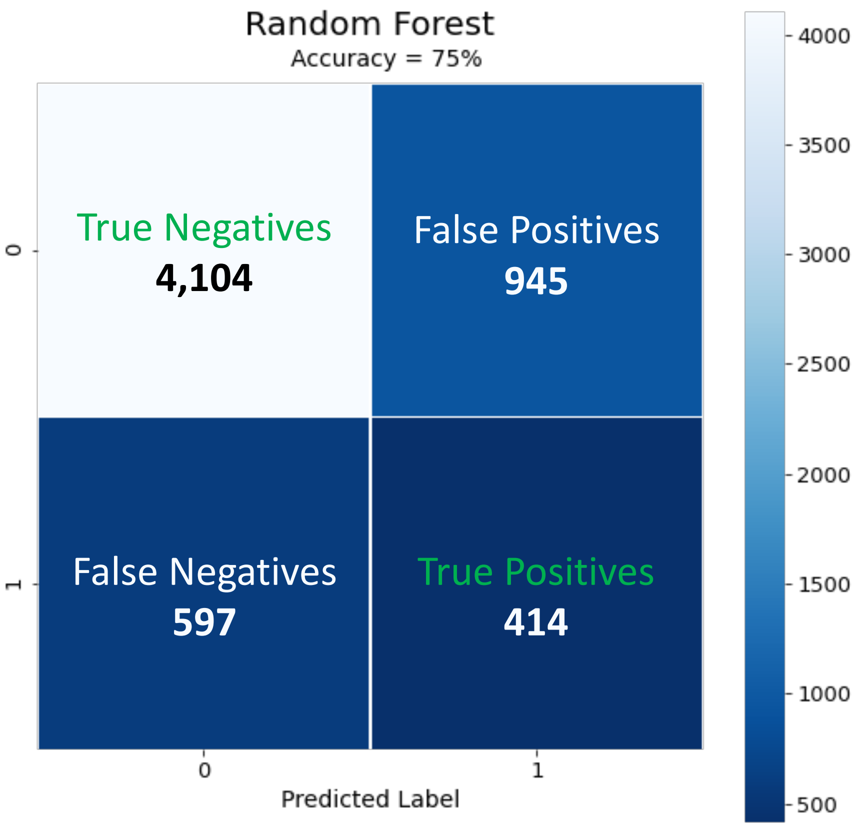
Precision = 79%

Recall = 74%

F-1 Score = 76%

Logistic Regression *predicts the probability that a sample belongs to a certain class using the sigmoid function.*





Random Forest

Accuracy = 75%

Precision = 78%

Recall = 75%

F-1 Score = 76%

Random Forest *builds many decision trees using random subsets of features and outputs the classification predicted by most trees.*

$$\text{Precision} = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN} \qquad \text{F-1 Score} = 2 \times \frac{\text{Precision x Recall}}{\text{Precision + Recall}}$$

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XGBoost

Optimized Machine Learning Model

1 = Priority Score < 30

0 = Priority Score ≥ 30 / ND

Accuracy

78%

Precision

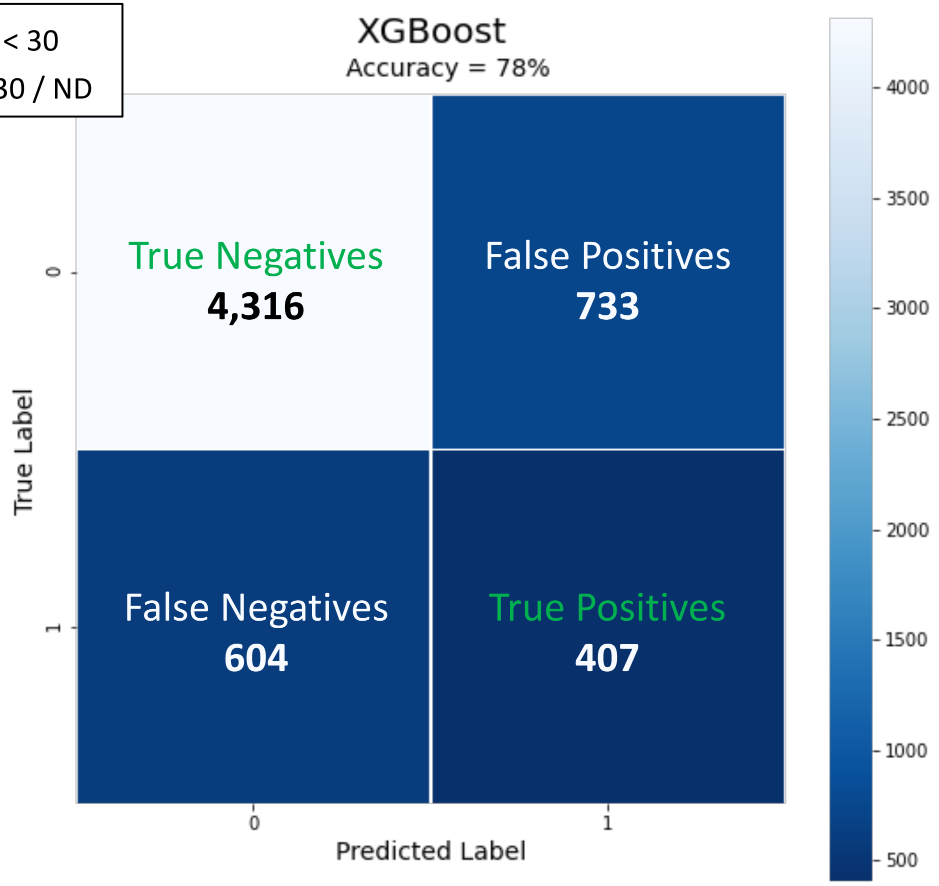
79%

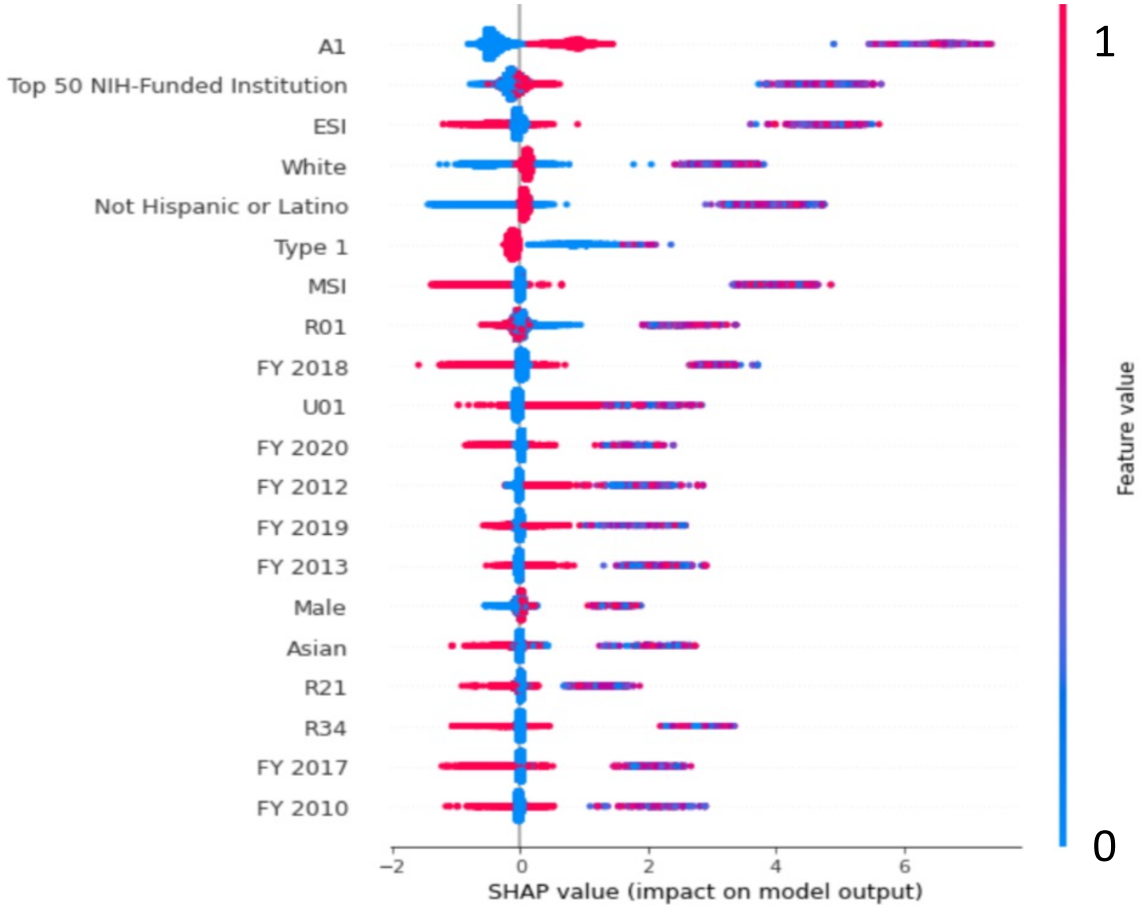
Recall

78%

F-1 Score

78%





XGBoost (Extreme Gradient Boosting) *uses gradient boosted decisions trees to achieve high speed and performance.*

The ***SHAP (Shapley Additive exPlanations)*** *value explains how much each feature contributes –* ***positively*** *or* ***negatively*** *– to the model's predictions.*

Conclusions

1. **Gender disparities** in NIDA grant awards are **almost eliminated**, with increasing applications from women and gender equity in funding rates playing a crucial role.

2. Over 11 years, **little increase in racial and ethnic diversity** in NIDA grant applications and awards.

3. **No significant disparities in funding rates** between Black and White applicants and disparities in funding rates between Latinx and non-Latinx applicants are decreasing.

4. There are proportionally more **Early-Stage Investigators (ESIs)** and no significant disparities in ESI funding rates among Black and Latinx applicants compared to White and non-Latinx applicants, respectively.

5. **Resubmission, institution, ESI, race, ethnicity, activity code,** and **gender** strongly **influence** whether a NIDA RPG application receives a **Priority Score less than 30**.

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What Can We Do?

1. Implement racial and ethnic equity **initiatives to increase applications** from underrepresented researchers, especially Black and Latinx researchers.

2. Increase **outreach** about NIDA funding opportunities and ORTDD programs to **Minority-Serving Institutions (MSIs), especially HBCUs.**

3. **Measure and disseminate ORTDD program impact** to increase applications and representation of BIPOC in substance use and addiction science.

4. **Further analyze** the causes of low applications and awards among underrepresented researchers, including potential biases and barriers within review and institutions.

Project Challenges, Achievements & Next Steps

Challenges

- Anonymized data vs. unique identifiers
- Class imbalance (80% / 20%)
- Duplicates
- Low N values

Achievements

- Presented to the Director of NIDA
- Preparing to publish my project's findings
- Invited to continue interning with ORTDD part-time

Next Steps

- Odds ratio analysis
- NLP on abstracts to identify textual predictors of Priority Score < 30
- Track resubmission rates
- Analyze causes of low applications from underrepresented researchers

Thank You!

Questions?

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