

Racial and Health Disparities on Academic Outcomes

My Le'25

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Context

The School District of Beloit is diverse with students coming from various racial, ethnic, and socio-economic backgrounds. The data shows an **intersection between student race and health level and academic outcomes.**

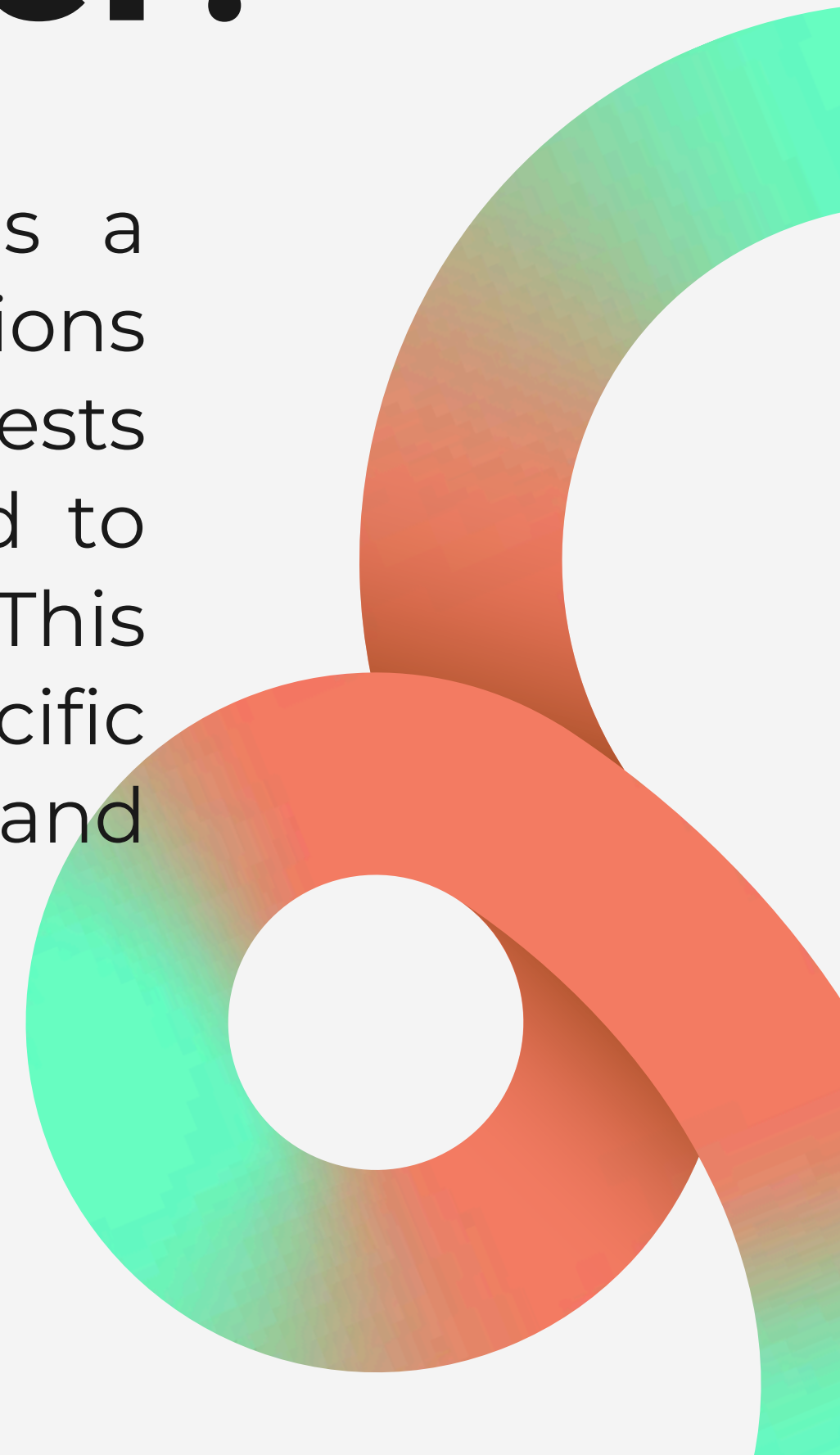
Research Questions

- Are there significant differences in academic performance between students of different racial/ethnic backgrounds?
- Do health disparities, including serious health issues, contribute to these academic differences?

Why does it matter?

The intersection of race and health is a complex issue with significant implications for academic outcomes. *Research suggests that racial disparities in health can lead to disparities in educational attainment. This case study aims to investigate the specific relationship between race, health, and academic performance.

(*): Montez, J. K., & Cheng, K. J. (2022). *Educational disparities in adult health across U.S. states: Larger disparities reflect economic factors*. *Frontiers in public health*, 10, 966434. <https://doi.org/10.3389/fpubh.2022.966434>



Data Cleaning Process

We use Python in Google Colab and Jupyter Notebook for this project:

- Convert A,B,C,D to meaningful values
- Keep scores for Winter 2018-2019 only and removed rest of semesters
- Removed NA values for regression
- One-hot encoding of categorical variables
- Convert regressor features to Float data type

About the dataset

Student Demographics

- Student ID
- Age, Sex, DOB (Date of Birth)
- **Local Race, His/Lat Ethnicity, Multi-Race, Fed Race**
- Special Education and Disability Description
- LEP Designation
- Lunch Code possibly indicating eligibility for free/reduced lunch.
- Rental, Property Value, Rent Price
- Income level
- **Health level**

Academic Information

- Old School, Entity
- Gr (Grade)
- Exam
- **Test scores (e.g., math and reading scores), including RIT scores and percentages for different seasons (Fall, Winter, Spring)**

About the dataset

Student Demographics

- Majority Group
- child_health_level_very_good_compare
- parent_relationship
- bool_child_access_health_care
- bool_child

Academic Information

- WT18_19MathRIT
- WT18_19ReadRIT
- Old School
- Special Education
- Eng_Prof_Full

Overview

Dataset statistics

Number of variables	52
Number of observations	221
Missing cells	1025
Missing cells (%)	8.9%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	89.9 KiB
Average record size in memory	416.6 B

Variable types

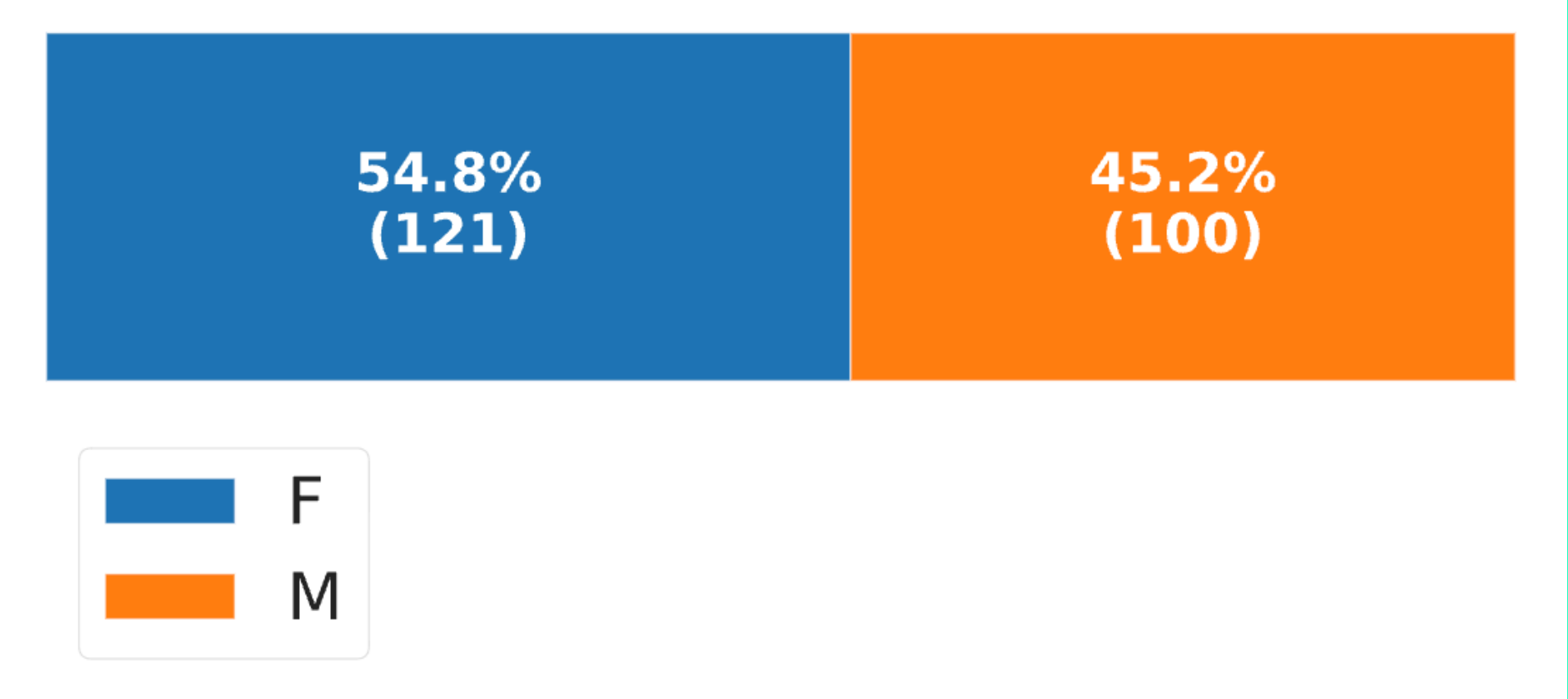
Numeric	5
Categorical	35
Unsupported	7
Boolean	4
Text	1

Students by School

Common Values

Value	Count	Frequency (%)
MCNEEL INTERMEDIATE SCHOOL	67	30.3%
FRUZEN INTERMEDIATE SCHOOL	57	25.8%
CUNNINGHAM INTERMEDIATE SCHOOL	55	24.9%
ALDRICH INTERMEDIATE SCHOOL	42	19.0%

Gender

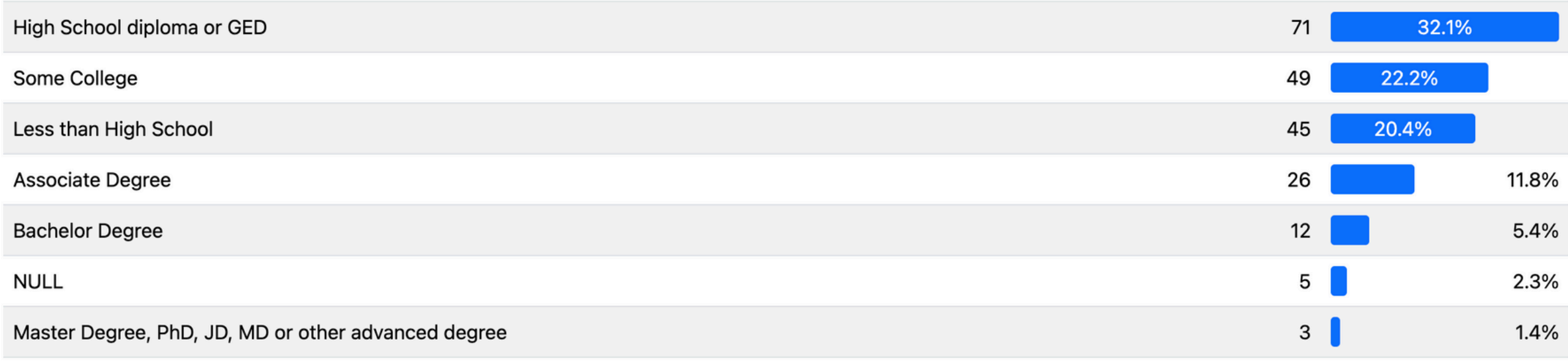


Income level

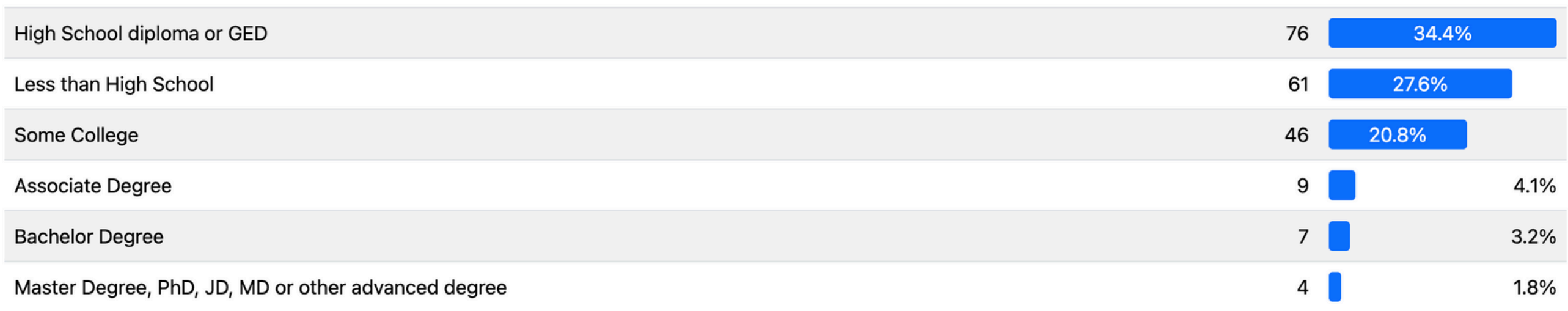
Value	Count	Frequency (%)	
At or less than \$22,459	57	<div><div>25.8%</div></div>	
\$22,460 - \$30,451	42	<div><div>19.0%</div></div>	
At or more than \$110,372	25	<div><div>11.3%</div></div>	
\$38,444 - \$46,435	18	<div><div></div></div>	8.1%
\$62,420 - \$70,411	14	<div><div></div></div>	6.3%
\$46,436 - \$54,427	11	<div><div></div></div>	5.0%
\$54,428 - \$62,419	10	<div><div></div></div>	4.5%
\$78,404 - \$86,395	10	<div><div></div></div>	4.5%
\$70,412 - \$78,403	8	<div><div></div></div>	3.6%

- The distribution is skewed to the left, meaning that a larger proportion of households have lower incomes.
- The highest frequency in income range signals a significant number of households have relatively low incomes.

Mother Education Level



Father Education Level



Distribution of Race

Value	Count	Frequency (%)
White	102	46.2%
American Indian or Alaskan Native	65	29.4%
Black or African American	53	24.0%
Asian	1	0.5%

Hispanic

Value	Count	Frequency (%)
False	137	62.0%
True	84	38.0%

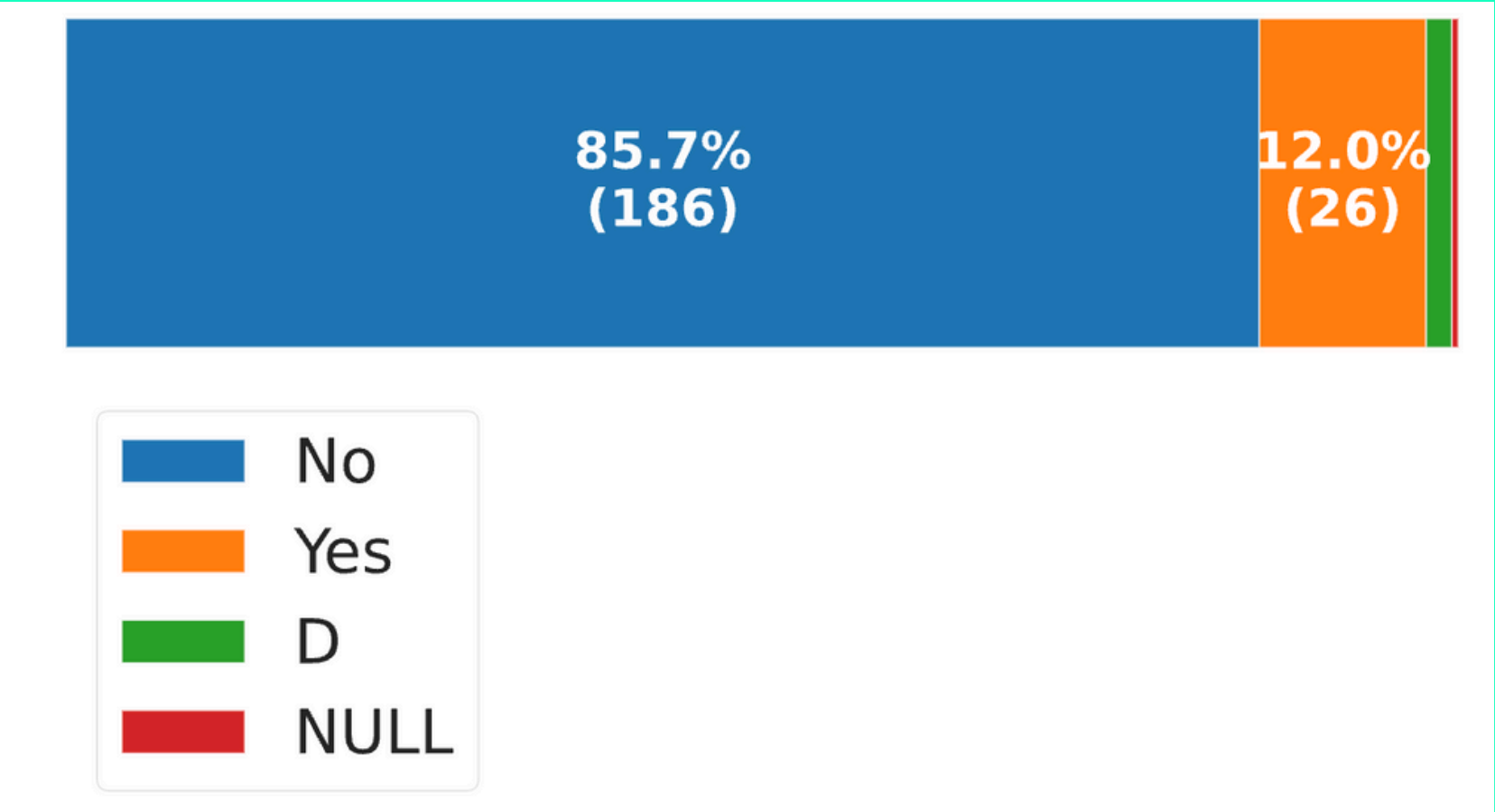
English Proficiency

Value	Count	Frequency (%)
7-Fully English Proficient	156	70.6%
3-Intermediate	28	12.7%
2-Beginning/Production	19	8.6%
4-Advanced Intermediate	8	3.6%
1-Beginning/Preproduction	8	3.6%
5-Advanced	1	0.5%
6-Was LEP/Now Eng Prof	1	0.5%

Health Level

Very Good	135	61.1%
Good	63	28.5%
Average	10	4.5%
NULL	9	4.1%
Very poor	2	0.9%
Poor	2	0.9%

Serious Health Issue



22 students who need Special Education

Disability	
0	183
Speech & Language	19
Other Health Impairment	7
SPECIFIC LEARNING DISABILITY	5
EMOTIONAL BEHAVIORAL DISABILITY	4
Traumatic Brain Injury	1
Significant Development Delay	1

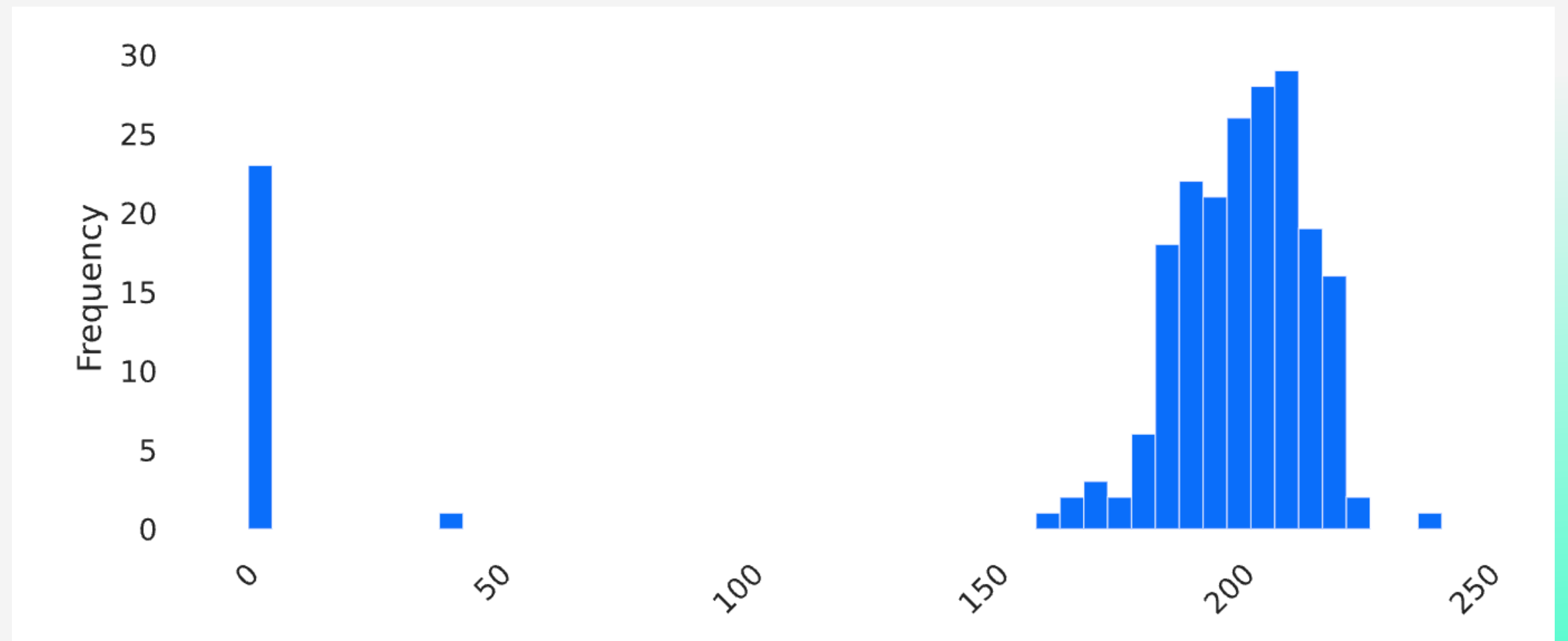
WT18_19

MathRIT

Mean: 180.64545

95-th percentile: 221

Skewness: -2.3648218



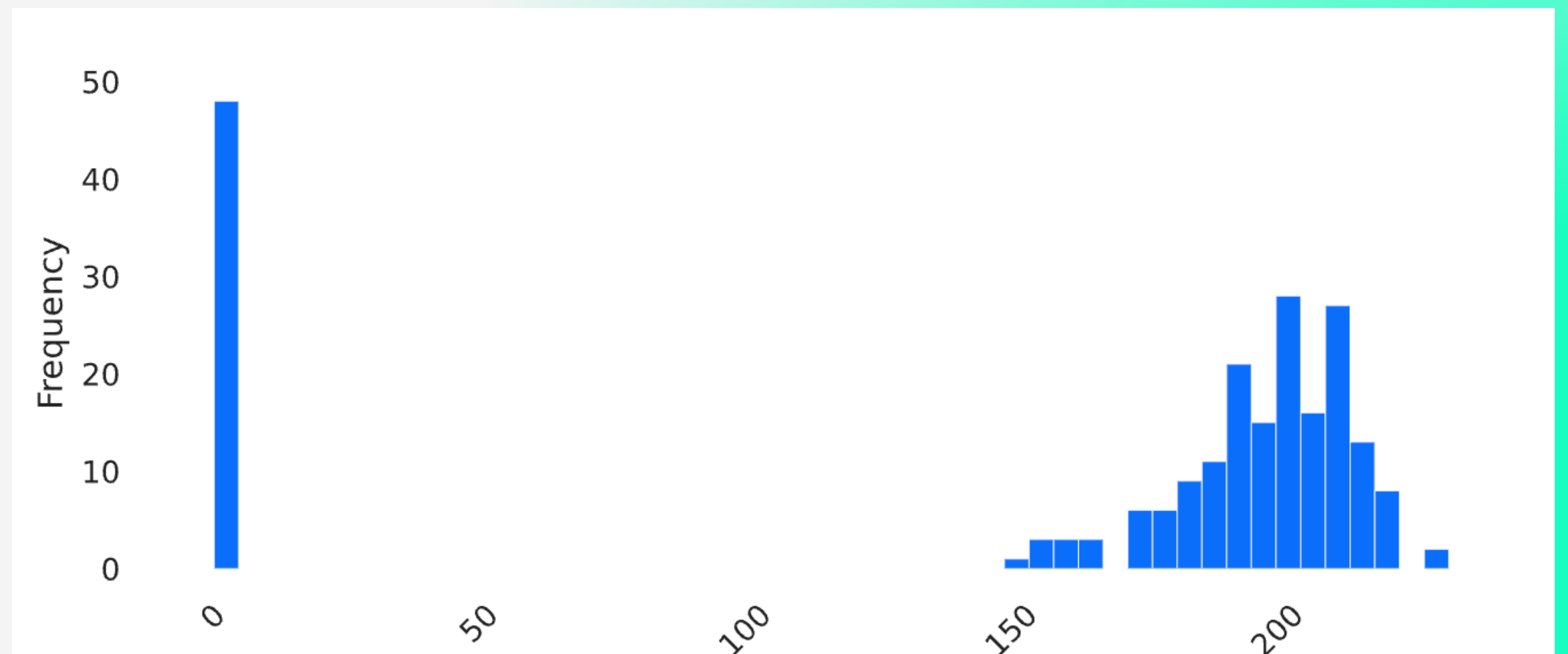
WT18_19

ReadRIT

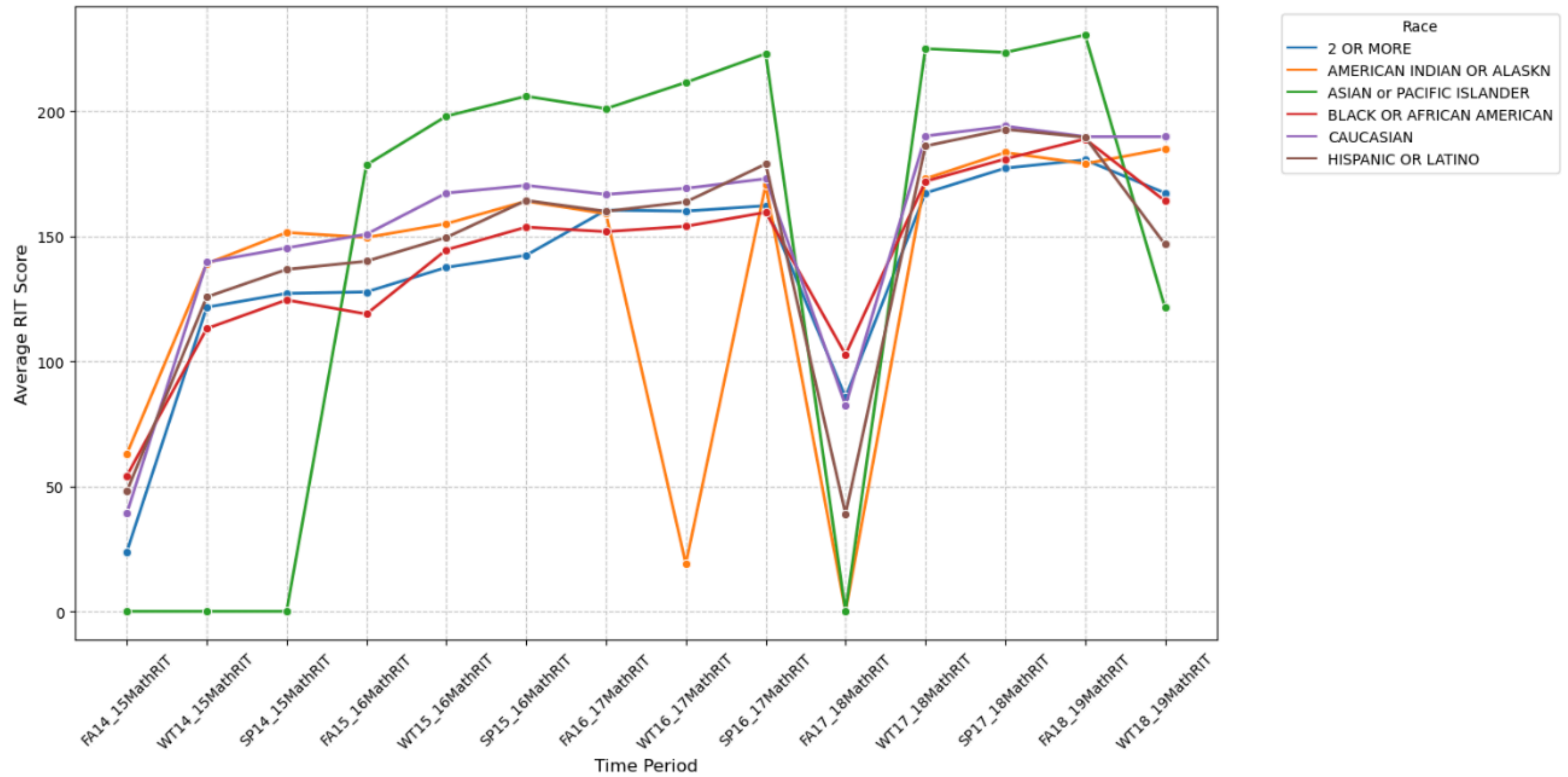
Mean: 155.02727

95-th percentile: 218

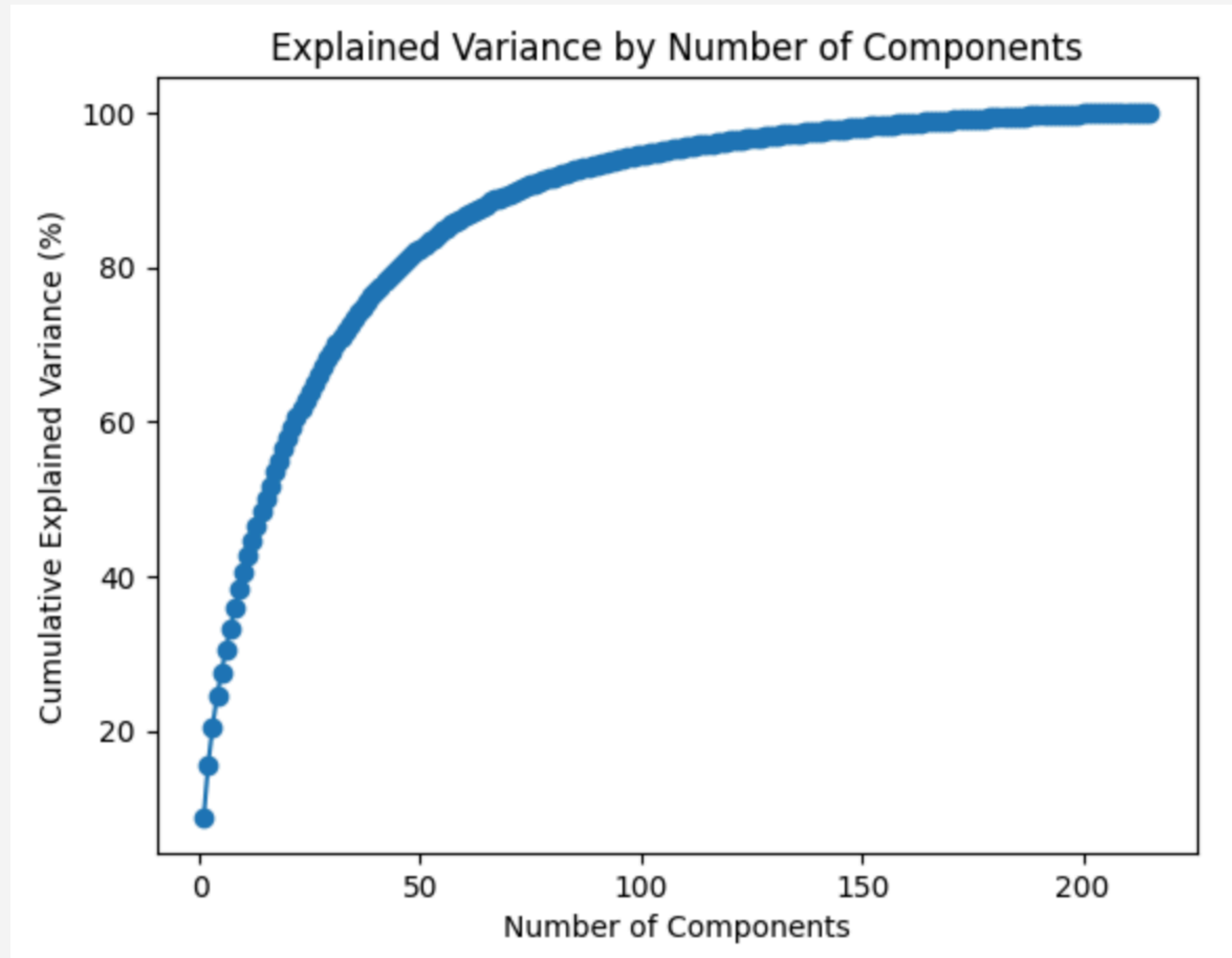
Skewness: -1.279984



Average Test Scores by Race Over Time



Principal Component Analysis (PCA)



Based on Lasso regression

$$\sum_{i=1}^n (y_i - \sum_j x_{ij} \beta_j)^2 + \lambda \sum_{j=1}^p |\beta_j|$$

Regression model:

$$WT1819MathRIT = \alpha + \beta_1 ChildHealthLevelGood + \beta_2 ChildHealthLevelNull + \beta_3 ChildHealthLevelPoor + \beta_4 ChildHealthLevelVeryPoor + \beta_5 FedRaceAsian + \beta_6 FedRaceBlack + \beta_6 FedRaceWhite + \epsilon$$

$$WT1819ReadRIT = \alpha + \beta_1 ChildHealthLevelGood + \beta_2 ChildHealthLevelNull + \beta_3 ChildHealthLevelPoor + \beta_4 ChildHealthLevelVeryPoor + \beta_5 FedRaceAsian + \beta_6 FedRaceBlack + \beta_6 FedRaceWhite + \epsilon$$

We also use Robust Standard Error to correct the heteroskedasticity of the two models

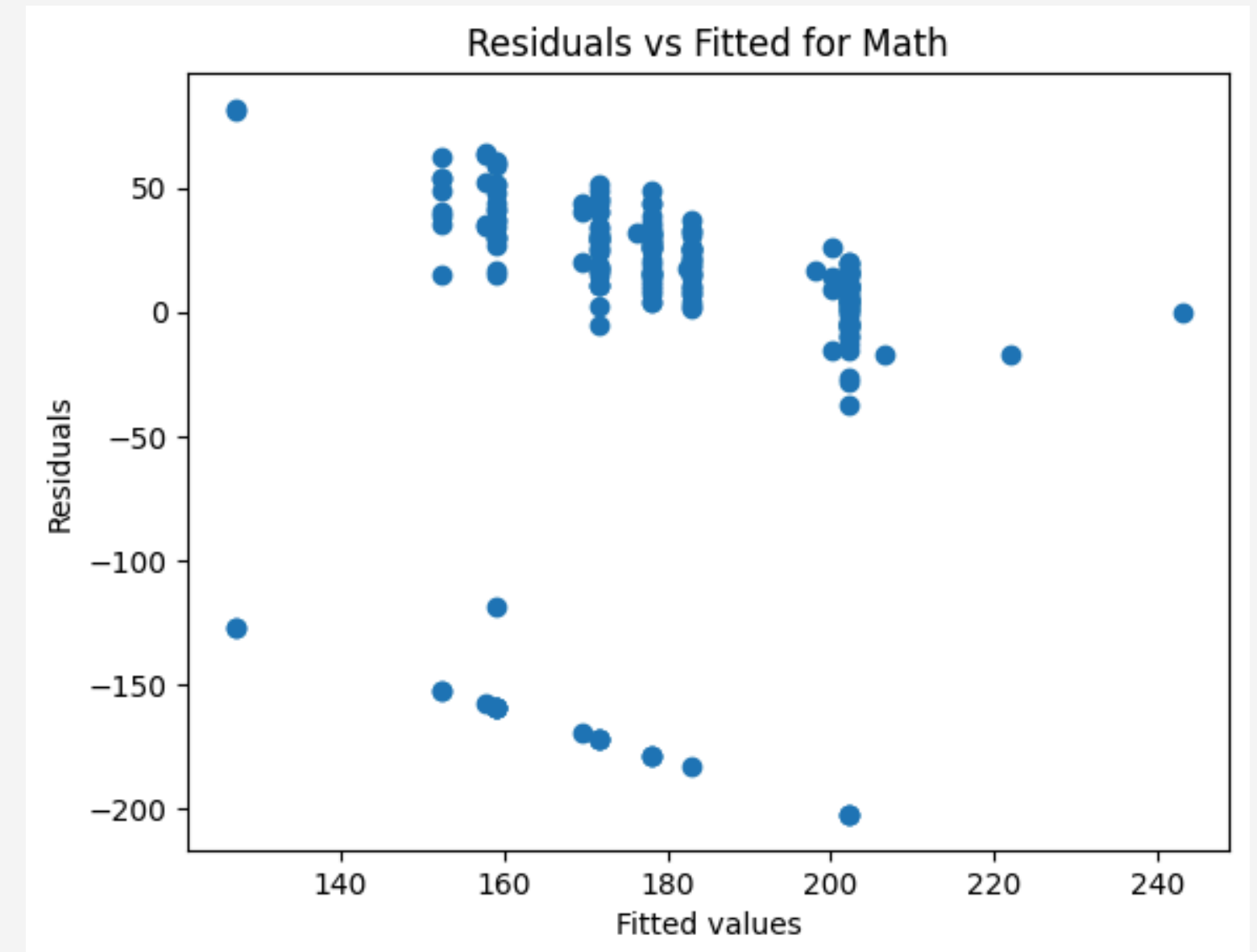
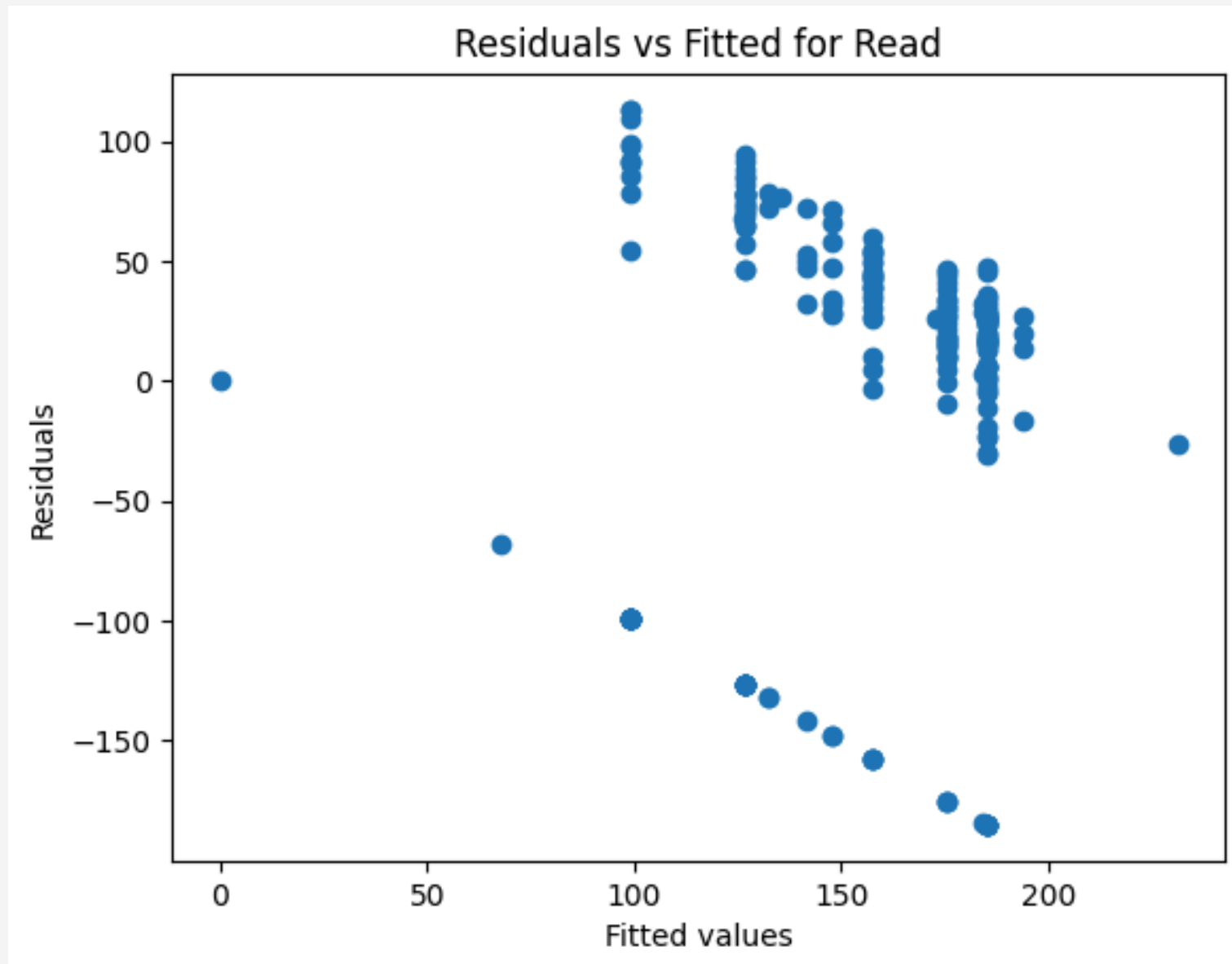
Base group for health level is: Average

Base group for Race is: American Indian or Alaskan Native

Heteroskedasticity



```
White's Test p-value for Read: 0.16791051206480526  
White's Test p-value for Math: 0.3490302204217291  
Breusch-Pagan p-value for Read: 0.9346766142435015  
Breusch-Pagan p-value for Math: 0.23683623813318913
```





OLS Regression Results

```
=====
Dep. Variable:          WT18_19ReadRIT      R-squared:                0.152
Model:                  OLS                 Adj. R-squared:           0.120
Method:                 Least Squares       F-statistic:             4.737
Date:                   Thu, 07 Nov 2024    Prob (F-statistic):      2.32e-05
Time:                   14:52:04            Log-Likelihood:          -1266.2
No. Observations:      220                 AIC:                    2550.
Df Residuals:          211                 BIC:                    2581.
Df Model:               8
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	83.2070	27.387	3.038	0.003	29.220	137.194
child_health_level_Good	15.7061	27.026	0.581	0.562	-37.569	68.981
child_health_level_NULL	52.2136	35.905	1.454	0.147	-18.566	122.993
child_health_level_Poor	89.6142	60.838	1.473	0.142	-30.313	209.542
child_health_level_Very Good	43.4446	25.816	1.683	0.094	-7.447	94.336
child_health_level_Very poor	-15.3858	60.838	-0.253	0.801	-135.313	104.542
Fed_Race_Asian	-126.6516	78.815	-1.607	0.110	-282.017	28.714
Fed_Race_Black or African American	48.9462	14.937	3.277	0.001	19.501	78.391
Fed_Race_White	58.3575	12.555	4.648	0.000	33.609	83.106

```
=====
Omnibus:                32.625      Durbin-Watson:            1.814
Prob(Omnibus):          0.000      Jarque-Bera (JB):         43.761
Skew:                   -1.091     Prob(JB):                 3.14e-10
Kurtosis:                3.097     Cond. No.                  20.0
=====
```



OLS Regression Results

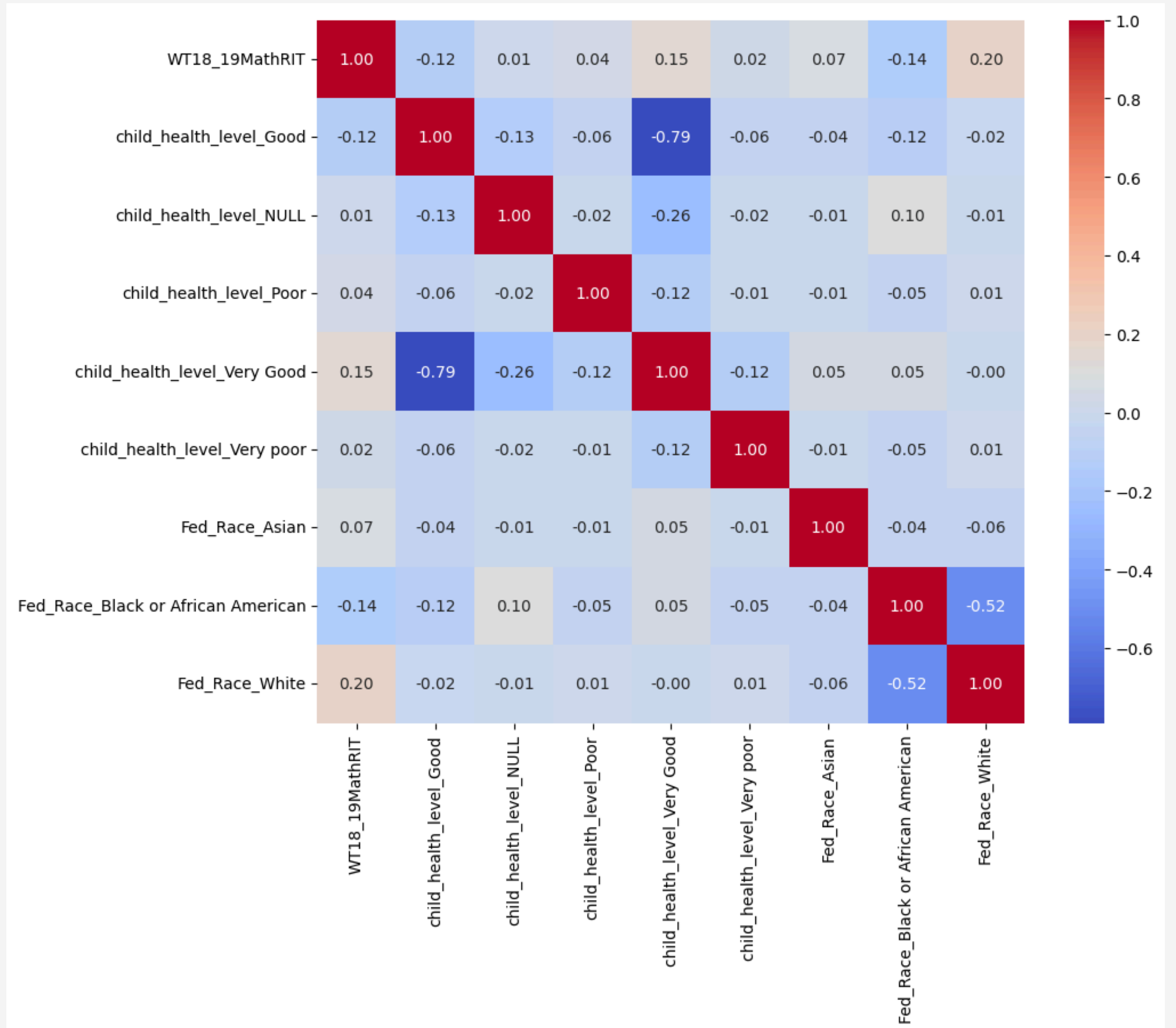


```
=====
Dep. Variable:          WT18_19MathRIT    R-squared:                0.084
Model:                  OLS               Adj. R-squared:           0.049
Method:                 Least Squares     F-statistic:              2.404
Date:                   Thu, 07 Nov 2024  Prob (F-statistic):      0.0167
Time:                   14:53:07          Log-Likelihood:          -1216.9
No. Observations:       220              AIC:                    2452.
Df Residuals:           211              BIC:                    2482.
Df Model:                8
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	133.7487	21.890	6.110	0.000	90.597	176.900
child_health_level_Good	25.1940	21.601	1.166	0.245	-17.388	67.776
child_health_level_NULL	42.4135	28.699	1.478	0.141	-14.160	98.987
child_health_level_Poor	64.2580	48.627	1.321	0.188	-31.599	160.115
child_health_level_Very Good	44.4339	20.635	2.153	0.032	3.757	85.111
child_health_level_Very poor	48.7580	48.627	1.003	0.317	-47.099	144.615
Fed_Race_Asian	64.8174	62.996	1.029	0.305	-59.364	188.999
Fed_Race_Black or African American	-6.6015	11.939	-0.553	0.581	-30.137	16.934
Fed_Race_White	23.9866	10.035	2.390	0.018	4.205	43.768

```
=====
Omnibus:                101.686    Durbin-Watson:              1.577
Prob(Omnibus):           0.000     Jarque-Bera (JB):           282.365
Skew:                    -2.139     Prob(JB):                   4.84e-62
Kurtosis:                 6.535     Cond. No.                   20.0
=====
```


Multi- colinearity



Policy Recommendations

- **Early Intervention Programs**

- Regular Health Checkups: Conduct regular health screenings to identify potential health problems and refer children to appropriate specialists.
- Nutrition Education: Provide education and resources to families on healthy eating habits.
- Physical Activity: Promote physical activity and outdoor play to improve physical health and cognitive development.
- Mental Health Support: Offer mental health screenings and counseling services for young children.

- **Culturally Responsive Pedagogy**

- Train teachers to use culturally responsive teaching methods that address the unique needs of students from diverse backgrounds.
- Provide language support services for students who are using ESL.
- Develop targeted interventions to support students who are struggling academically, such as tutoring and mentoring programs.

Conclusion

Our analysis of the provided dataset has revealed **significant disparities** in academic outcomes based on race and health levels. We have identified key factors that contribute to these disparities including **health levels and races**.

To address these issues, we propose **two key policy recommendations**:

1. **Early Childhood Intervention Programs**: By investing in early childhood education and providing comprehensive health services, we can help close the achievement gap and improve long-term outcomes for disadvantaged students.
2. **Culturally Responsive Teaching**: By implementing culturally responsive teaching practices, we can create more inclusive and equitable learning environments for all students.

Limitations of our analysis

- Missing data points, potential response bias in self-reporting data, and limitations on causal inference due to the observational nature of the data.
- The representation of each category is not uniform
- No control variables were included in the regression model
- The limited time prevents us from looking at the time-series data to provide a more in-depth analysis and recommendations for the problems
- There's a need to look at the combined effect of health and race

Future work

- Improve data collection method for uniform representation across different categories.
- Enhance the understanding of the struggle that each marginalized groups might have with the healthcare system
- Conduct qualitative interviews to have better and more comprehensive data

Thank you!

