DS241 | Final Research Report

Do Large Language Models (LLMs) have biased representations of different racial identities?

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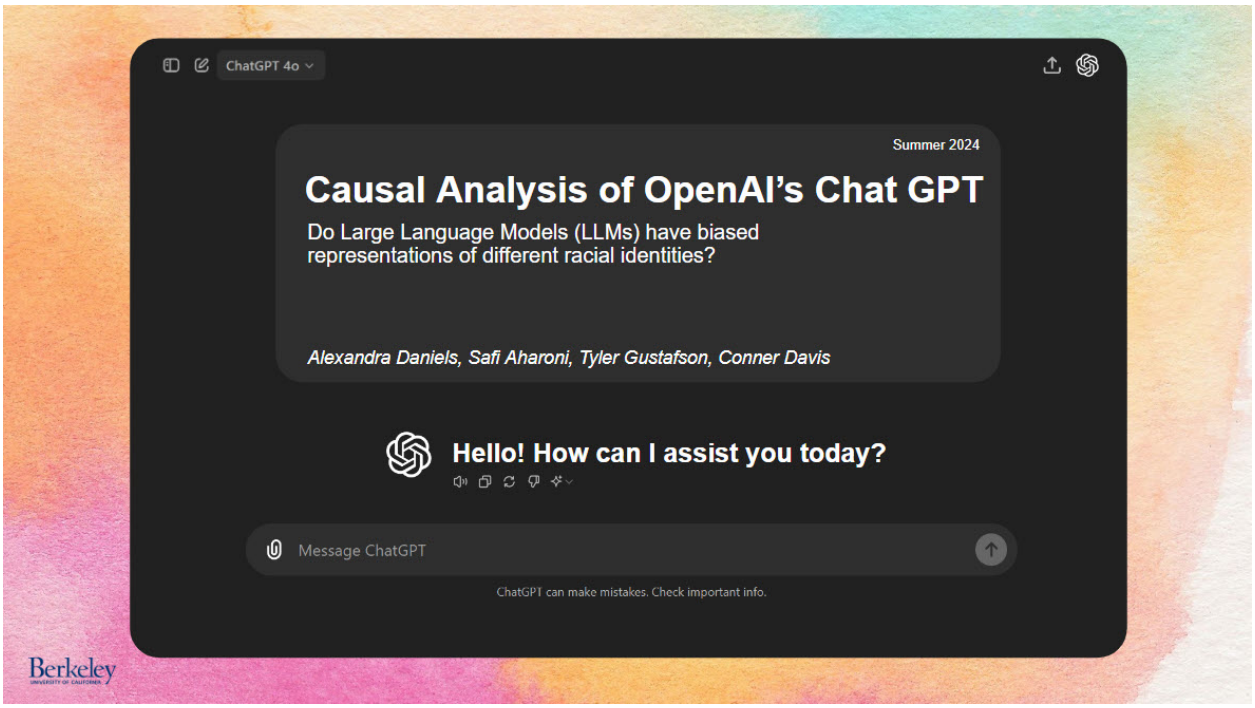

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1 Abstract

Do Large Language Models (LLMs) have biased representations of different racial identities?

Bias in machine learning has only grown more of a concern since the introduction of LLMs, particularly with OpenAI's release of Chat-GPT 3.5 Turbo in 2023. With the ability to summarize, generate, and abstract language at a level that can feel almost human, the impact of these technologies on society can not be understated. This study aims to uncover potential racial biases in large language models, which can perpetuate harmful stereotypes and inequalities in AI-generated content. Understanding these biases is the first step towards mitigating them and ensuring that AI technologies remain fair and equitable as they become increasingly embedded in society.

Our approach explored whether an LLM (in our case ChatGPT 3.5) would provide us with different SAT scores by race based on the use of a standardized prompt that assigned the model a racial identity (agent assignment). We utilized OpenAI's GPT-3.5 batch API to collect 1,500 samples for the control and for each treatment group. A covariate of gender was included in the generation to test for heterogeneous treatment effects. The control group received no specified racial identity, whereas the treatment groups received an agent assignment of one of the racial groups used by College Board in their SAT score reporting. After asking the LLM to generate their identity and other potential covariate information, we asked the LLM to share with us (as the assigned agent) their SAT scores.

Using these LLM-generated data, we tested two different hypotheses. First, we checked whether the inclusion of the treatment variable (i.e., race) significantly improved the model's ability to predict SAT scores. Using an F-test, we showed that indeed race impacts the LLM's generated SAT scores. Second, we tested how the LLM data compare to real-world data by comparing the LLM-generated SAT score distributions with actual SAT score distributions by race as reported by the College Board. This comparison revealed that the LLM consistently overestimates SAT scores across all racial treatment groups.

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2 Introduction

2.1 Theory

The theory underlying this experiment is rooted in the understanding that the treatment of assigning different racial identities to the LLM could influence the model's generated outputs, specifically in terms of socio-economic indicators such as SAT scores. This theory aligns with existing research in machine learning ethics and fairness, which highlights the potential for biases in AI models due to the biases present in their training data and algorithms.

Bolukbasi, T., Chang et al in "Man is to Computer (. . .)" examine and define different forms of gender/racial bias in LLM embeddings, what they refer to as "local bias, global bias." Local bias refers to 'predictions at a particular time step that reflect undesirable associations with the context' whereas global bias refers to predictions that are a result 'from representational differences across entire generated sentences spanning multiple phrases' (4342). In their work, a model's generation at time t is said to be locally biased if the probability of possible next tokens differs significantly given a 'counterfactual edit' in the context. In the context of our work, this counterfactual edit would be race.

2.2 Concept Under Investigation

The team is investigating bias in LLMs (Large Language Models), specifically whether these models have biased representations of different racial groups. This concept has been explored in academic literature, particularly in the field of machine learning ethics and fairness. Previous investigations have examined biases in various AI models, including language models, and have proposed methods for detecting and mitigating such biases. Our current metric will be the distributions of assigned SAT scores. SAT scores serve as a direct measure of potential bias, allowing us to see if the model systematically favors or disadvantages certain groups.

One consideration that we need to account for is whether the LLM results reflect real-world disparities. We will discuss below in the experiment design how we will account for this consideration. Essentially, our research can be boiled down to the question:

Do we observe a difference in the probability distribution of this metric given the treatment of race and if so how does that compare to actual real-life population data?

2.3 Importance

So why are we investigating this topic? First, it is important to improve our understanding of bias in artificial intelligence. With the widespread use of LLMs increasingly integrated into our society, there's a responsibility to ensure AI systems are fair and do not exacerbate existing inequalities. It's also important to understand how AI models may not replicate real-world distributional characteristics.

Similarly, it is important to understand the impact these models have on decision-making. LLMs are starting to influence key decisions, such as college admissions and job recruitment. Our goal is to ensure they do not unfairly influence these processes, as some biases in the models can be subtle.

Our third and final point is contributing to the ethical development of AI. As we all know, this technology is evolving rapidly, and our work helps identify areas where LLMs may be falling short.

By investigating these biases, we aim to highlight specific areas where LLMs require improvement. This research is a step toward ensuring that AI technology continues to evolve responsibly.

3 Experiment Design

Our experiment design involves measuring LLM-generated socio-economic metrics immediately after the treatment assignment, ensuring that the racial identity prompt directly influences the generated outputs. Since our subjects are AI models, there are no concerns about opting out or discontinuing participation, which simplifies experimental execution. We began by generating pilot data to test the effectiveness of our design and prompts. Before we share our preliminary analysis let us discuss our framework for the experiment.

3.1 Hypothesis Framework and Approach

To conduct this experiment, we performed a two-order hypothesis test to provide real-world context to our findings. The first stage focuses on identifying differences across treatment groups, while the second examines how these differences compare to real population data. Below is an outline of our approach.

First Hypothesis *(Explanatory Power of the Model - 1 Test)*

Our first hypothesis test aims to determine whether including race as a variable in the model improves the prediction of SAT scores. This test assesses whether the LLM produces differences in SAT scores based on racial identity. To evaluate this, we conducted an F-test (ANOVA) to determine if the inclusion of the treatment variable enhances the model's explanatory power.

Second Set of Hypotheses *(Bias vs. Real World Reflection in LLMs - 6 Tests)*

Our second hypothesis set goes deeper to assess whether the LLM's generated SAT scores are unbiased relative to existing discrepancies in the 2020 SAT College Board data. First, we visually compared the distributions by treatment group coming out of the LLM to the distributions from the College Board. To better align with the real-world population data, we bucketed the LLM data to match the College Board distribution resolution. We then conducted a chi-squared test to determine whether the proportions of data in each bucket differed significantly between the LLM-generated data and the real-world data.

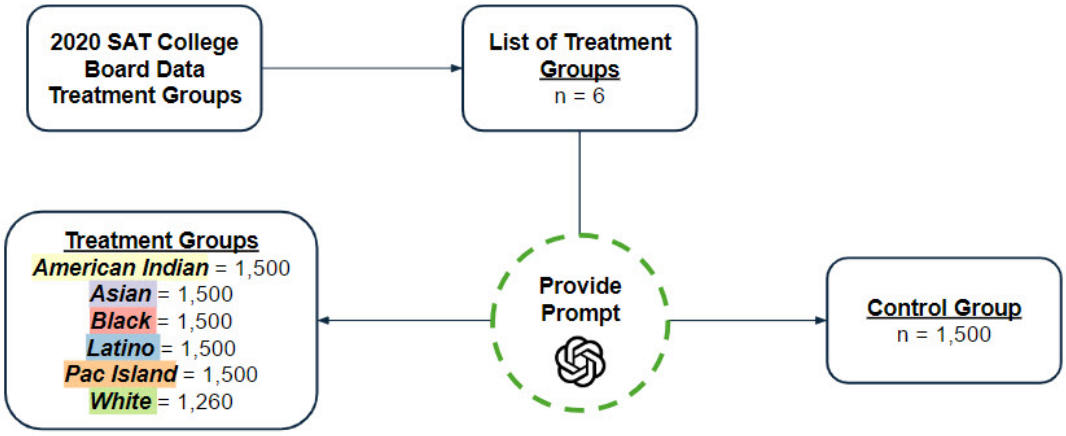
3.2 Evaluation: Curse of Multiple Testing

Our biggest remaining challenge was to manage the curse of multiple testing. This issue arises from conducting multiple statistical tests, which increases the risk of false positives, and requires careful correction methods to ensure the reliability of our results. In other words, how can we ensure statistical soundness with the challenge of multiple testing due to the ease of generating additional data?

To address this, we considered the use of Bonferroni correction, which is a multiple comparisons test to prevent data from incorrectly appearing to be statistically significant by requiring that the p-value of each test must be equal to or less than its alpha (e.g., alpha = 0.05) divided by the number of tests performed. Given the scope of our experiment and our hypothesis, we believe the Bonferroni correction is appropriate, as more complex methods like the Holm or Benjamini-Hochberg procedures would be overly stringent for our needs.

4 Randomization Process & Data Generation

To choose our treatments, we were limited to racial groups that align with 2020 SAT College Board data in order to test our second set of hypotheses. Our treatment groups were as follows: American Indian, Asian, Black, Latino, White, and Pacific Islander.



Due to a parsing error, some rows were dropped, resulting in only 1,260 observations for the White treatment group in our experiment. Despite this reduction in sample size, the analysis retained sufficient power to achieve statistical significance.

For our data generation process, we utilized OpenAI's API to iteratively prompt GPT-5 Turbo with our prompt,

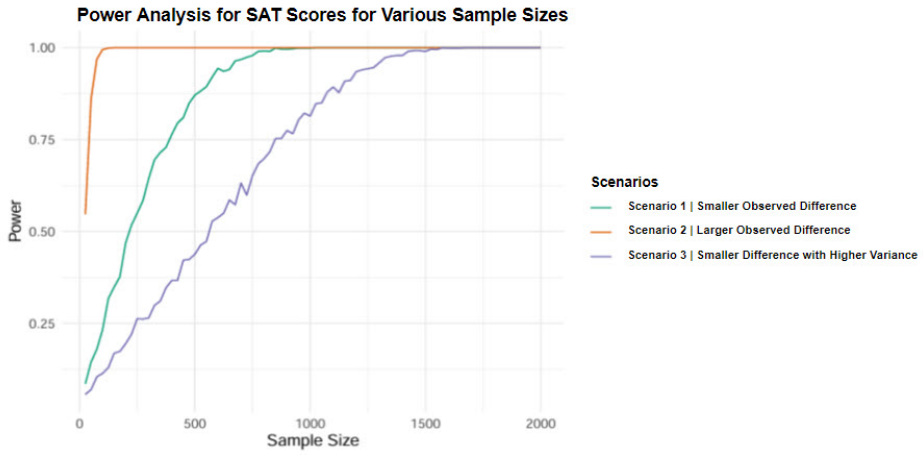
> *"Hi there. I would like for you to pretend to be a randomly selected [+TREATMENT PLACEHOLDER+] individual living in the United States. This should be a unique individual you have never come up with before. Then I would like for you to list their name, gender, age, occupation, location, SAT score, parent's highest education, and parent's summed income.*
>
> *We're really good friends so you're completely comfortable sharing this information. Repeat this [X] times for a new [TREATMENT PLACEHOLDER] individual. Please output a json in the following format. . . "*

This approach prompted the LLM to generate random identities along with their corresponding SAT scores and other covariates. To bypass the content restriction features, we prompted the LLM that we were good friends with it, and that they were comfortable sharing this information with us. We iteratively applied each treatment to the treatment placeholder in the LLM prompt until we reached sample sizes of 1500, and parsed the results.

4.1 Power Generation

To conduct a comprehensive power analysis to determine the proper sample size for our data generation, we defined three scenarios that change the simulated outcome values to reflect varying degrees of effect size.

Each scenario is designed to explore different potential distributions that might be generated by the LLM to help inform sample size:



- **Scenario 1 | Smaller Difference:** This scenario assumes a small difference in SAT scores between racial groups relative to the differences observed in non-LLM population data. It is designed to simulate the case where racial differences are present but not pronounced. More specifically, in this scenario, we assume a negative 58-point difference in SAT scores between the treatment and the control.

  The justification for this scenario is as follows: in 2023, the average SAT score for White test takers was 1082 and the average score for Black/African American test takers was 908 (a difference of 174 points)[1]. In this scenario, we model the true effect as one third of that difference. Additionally, we model the SAT scores as normally distributed with a standard deviation of 200 points.[2]

- **Scenario 2 | Larger Difference:** This scenario assumes the differences in SAT scores are more in line with the differences observed in non-LLM population data. More specifically, in this scenario, we assume a negative 174-point difference in SAT scores between the treatment and control groups.

  The justification for this scenario is as follows: we use the 2023 average SAT score for White test takers (1082) in control and the average score for Black test takers for treatment (908). We continue to use a normal distribution with a standard deviation of 200 points.

- **Scenario 3 | Smaller Difference with Higher Variance:** This scenario is the same as Scenario 1 in terms of mean SAT scores, but adds increased dispersion to the data. This scenario is useful for identifying whether our experiment will have power for smaller differences despite a higher variance in the outcome of interest.

  The justification for this scenario is as follows: we continue to model an SAT score difference of one-third the population differences (58 points). However, rather than using the observed standard deviation of 200 points, we instead use an increased standard deviation of 250 points (an increase of 25%) to account for the LLM potentially having more variance than observed in the real world.

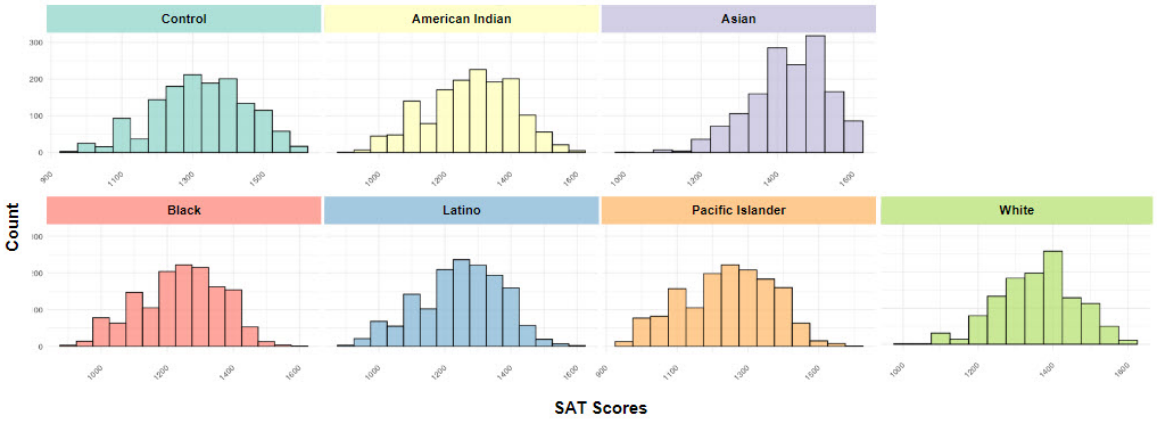
Based on our analysis, we determined that a sample size of 1,500 observations would be sufficient to ensure that our experiment and statistical tests are adequately powered. This sample size is necessary to detect the effect sizes, particularly in cases where differences are subtle or the data exhibit higher variance. This will ensure the reliability of our findings across varying potential distributions from the LLM.

[1]Source: www.bestcolleges.com/research/average-sat-score-full-statistics/#demographics
[2]Source: nces.ed.gov/programs/digest/d17/tables/dt17_226.40.asp

4.2 Initial Exploratory Data Analysis (EDA)

To ensure the integrity of our data, we conducted thorough exploratory data analysis (EDA) on the output generated by the LLM. Our first step was to examine the distribution of the outcome variable, SAT scores, across both treatment and control groups. Below we can see the apparent normality (with some right-side censoring) across treatment groups.

Table 1: LLM Distribution of SAT Scores by Racial Identity



4.3 Exploring Covariate Balance

The next step in our analysis is to examine the covariates and assess whether they are balanced between the treatment and control groups. We conduct this covariate balance check to test whether the variables like gender, age, and parent income are independent of the treatment variable. Let's begin by reviewing summary statistics for the covariates:

Table 2: Combined Summary of Covariates by Treatment Group

	Gender	Age		Parent Income		Parent's Education Proportion				
treatment	**Proportion of Men**	**Mean Age**	**SD Age**	**Mean Income**	**SD Income**	**High School**	**Associate's**	**Bachelor's**	**Master's**	**Doctorate**
	0.51	**32.7**	**5.4**	**12.6**	**4.8**	**0.10**	**0.17**	**0.31**	**0.23**	**0.20**
American Indian	**0.51**	**31.7**	**5.4**	**8.9**	**3.6**	**0.13**	**0.20**	**0.26**	**0.21**	**0.20**
Asian	**0.51**	**30.6**	**3.9**	**12.8**	**4.7**	**0.06**	**0.14**	**0.34**	**0.25**	**0.20**
Black	**0.48**	**31.6**	**5.0**	**9.1**	**3.7**	**0.13**	**0.19**	**0.29**	**0.22**	**0.17**
Latino	**0.50**	**32.4**	**5.7**	**9.0**	**3.7**	**0.16**	**0.20**	**0.28**	**0.20**	**0.16**
Pacific Islander	**0.49**	**30.2**	**4.1**	**9.0**	**3.7**	**0.15**	**0.21**	**0.27**	**0.20**	**0.17**
White	**0.52**	**32.2**	**4.8**	**13.1**	**4.9**	**0.09**	**0.15**	**0.34**	**0.22**	**0.20**

It appears that when looking at Table 2 covariates such as parental income and parental education are imbalanced, whereas gender is relatively balanced across groups. The LLM appears to be generating these covariates post-treatment: in other words, its knowledge of its identity appears to be affecting the demographic characteristics it is generating.

Exploring Covariates (Continued)

To further investigate and validate this imbalance, we conducted a series of linear models where we regress being in treatment with the covariates, adjusting for robust standard errors to test for statistical significance. The results of these tests are presented below:

Table 3: Regression Results: How do the covariates impact our model?

	Dependent variable:				
	treatment_flag				
	(1)	(2)	(3)	(4)	(5)
genderMale		−0.005	0.005	0.002	0.0001
		(0.007)	(0.007)	(0.007)	(0.007)
age			−0.006***	−0.004***	−0.003***
			(0.001)	(0.001)	(0.001)
parent_income				−0.013***	−0.054***
				(0.001)	(0.002)
parent_educationBachelor's					0.162***
					(0.011)
parent_educationDoctorate					0.556***
					(0.019)
parent_educationHigh School					−0.073***
					(0.012)
parent_educationMaster's					0.367***
					(0.015)
Constant	0.858***	0.861***	1.050***	1.115***	1.308***
	(0.003)	(0.005)	(0.023)	(0.023)	(0.024)
Observations	10,022	10,022	10,022	10,022	10,022
R^2	0.000	0.0001	0.008	0.035	0.117
Adjusted R^2	0.000	−0.00004	0.007	0.035	0.117
Note:					*p<0.1; **p<0.05; ***p<0.01

The model indicates that gender does not significantly predict whether an observation belongs to the treatment or control group. However, the other covariates do show predictive power (age, parent income, and parent education) evident by their statistically significant values highlighted above in Table 1. This suggests that these non-gender covariates are likely post-treatment variables, and therefore we will exclude them from our subsequent modeling to avoid potential biases in our analysis.

Finally, we confirm that gender is independent of treatment by checking whether its inclusion in a linear model affects the treatment coefficients:

Table 4: Regression Results: How does the covariate gender impact our coefficients?

	Dependent variable:		
	sat_score		
	(1)	(2)	(3)
Male	4.486		2.785
	(2.793)		(2.452)
American Indian		−44.449***	−44.433***
		(4.882)	(4.884)
Asian		108.374***	108.390***
		(4.362)	(4.364)
Black		−83.280***	−83.202***
		(4.823)	(4.826)
Latino		−75.693***	−75.663***
		(4.785)	(4.789)
Pacific Islander		−80.916***	−80.869***
		(4.820)	(4.824)
White		35.622***	35.607***
		(4.646)	(4.649)
Constant	1,299.450***	1,323.325***	1,321.901***
	(1.875)	(3.490)	(3.681)
Observations	10,022	10,022	10,022
R^2	0.0003	0.232	0.232
Adjusted R^2	0.0002	0.232	0.232
Residual Std. Error	139.825 (df = 10020)	122.577 (df = 10015)	122.575 (df = 10014)
F Statistic	2.579 (df = 1; 10020)	504.435*** (df = 6; 10015)	432.570*** (df = 7; 10014)
Note:			*p<0.1; **p<0.05; ***p<0.01

Here we can see that for each treatment coefficient, the inclusion of the male covariate does not substantially change the coefficients when it is excluded (model 2) and when it is included (model 3). For this reason and the model results in Table 3 above we have confirmed that we can include this covariate in our model and investigate further.

5 Results & Model

5.1 First Hypothesis (Explanatory power of model - 1 test)

For the first null hypothesis, we tested whether including race in a model helps predict SAT scores. Indeed, the statistical model shows that including race as a variable improves the model's explanatory power, indicating significant differences in LLM-generated SAT scores across racial groups. In other words, the F-test confirms that adding race treatments significantly improves the model's prediction of SAT scores.

Table 4b: Hypothesis 1 - are there differences across treatment groups?

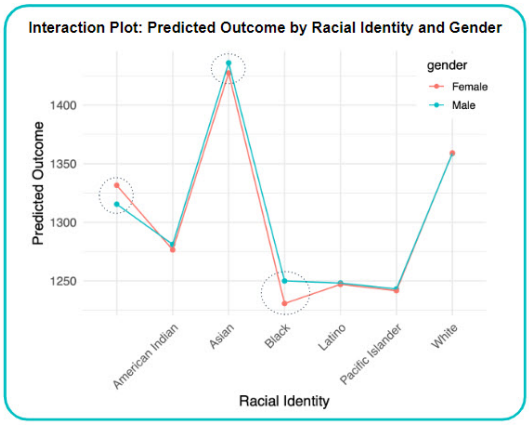
Dependent Variable: SAT Scores	Includes Gender	Includes Treatment	Includes Gender + Treatment
Male	4.486		2.785
	(2.793)		(2.452)
American Indian		−44.449***	−44.433***
		(4.882)	(4.884)
Asian		108.374***	108.390***
		(4.362)	(4.364)
Black		−83.280***	−83.202***
		(4.823)	(4.826)
Latino		−75.693***	−75.663***
		(4.785)	(4.789)
Pacific Islander		−80.916***	−80.869***
		(4.820)	(4.824)
White		35.622***	35.607***
		(4.646)	(4.649)
Constant	1,299.450***	1,323.325***	1,321.901***
	(1.875)	(3.490)	(3.681)
Observations	10,022	10,022	10,022
R^2	0.0003	0.232	0.232
Adjusted R^2	0.0002	0.232	0.232
Residual Std. Error	139.825 (df = 10020)	122.577 (df = 10015)	122.575 (df = 10014)
F Statistic	2.579 (df = 1; 10020)	504.435*** (df = 6; 10015)	432.570*** (df = 7; 10014)
Note:			*p<0.1; **p<0.05; ***p<0.01

Furthermore, we explored whether there is evidence of heterogeneous treatment effects (HTEs) between gender and race. Below, we show the results of a linear model where we interact the treatment variables with the gender covariate. Although p-values vary across race, there does appear to be an interaction in the LLM's treatment of genders within a racial group as every interaction term is significant. The most significant gender HTEs were observed with the Black and Asian treatment groups (see chart below). While these p-values are consistently significant at the 95% confidence level, the effect is less pronounced amongst certain races and may require further investigation to fully understand.

Table 5: Hypothesis 1 - are there heterogeneous treatment effects?

Dependent Variable: SAT Scores	Includes Treatment	Includes Treatment + Gender + Gender * Treatment
American Indian	−44.449***	−55.025***
	(4.882)	(6.680)
Asian	108.374***	95.771***
	(4.362)	(5.995)
Black	−83.280***	−100.811***
	(4.823)	(6.409)
Latino	−75.693***	−84.470***
	(4.785)	(6.225)
Pacific Islander	−80.916***	−89.867***
	(4.820)	(6.411)
White	35.622***	27.579***
	(4.646)	(6.475)
Male		−16.092**
		(6.963)
American Indian Male		20.739**
		(9.750)
Asian Male		24.752***
		(8.708)
Black Male		35.344***
		(9.653)
Latino Male		17.192*
		(9.560)
Pacific Islander Male		17.558*
		(9.642)
White Male		15.737*
		(9.280)
Constant	1,323.325***	1,331.552***
	(3.490)	(4.826)
Observations	10,022	10,022
R^2	0.232	0.233
Adjusted R^2	0.232	0.232
Residual Std. Error	122.577 (df = 10015)	122.513 (df = 10008)
F Statistic	504.435*** (df = 6; 10015)	234.404*** (df = 13; 10008)
Note:		*p<0.1; **p<0.05; ***p<0.01

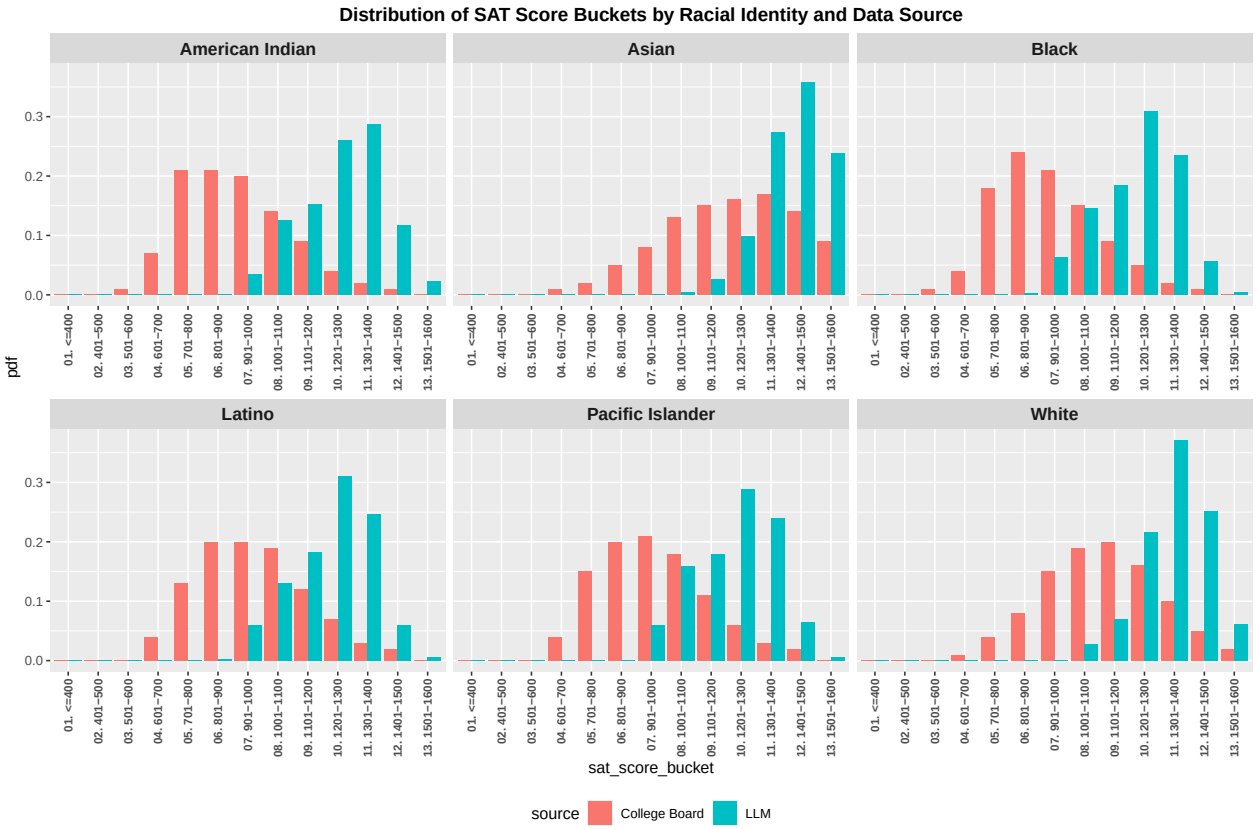
Heterogeneous Treatment Effects



One particular pattern of interest is that, in the control group, the LLM tends to assign higher SAT scores to women than men. For both the Black and Asian groups, however, the heterogeneous effect works in the opposite direction. This heterogeneity suggests that the LLM may be encoding complex patterns of bias, which have implications for how such models are used in real-world applications.

5.2 Second Set of Hypotheses (Bias vs. Real World Reflection in LLMs - 6 tests)

To test our second set of hypotheses, we first needed to summarize the real-world distribution data from the 2020 SAT scores as published by the College Board[3] [4]. With this data in hand, we can begin by comparing the distributions generated by the LLM to those of the actual population data:



Looking at these distributions, it's already clear that the LLM results present an optimistic lens on SAT scores by treatment group compared to the real-world population distributions (i.e., an upward bias). However, to verify this observation, we'll conduct a chi-square test, which examines whether the observed differences in distributions between the LLM-generated data and the real-world data are statistically significant. This test will help us determine if the LLM's optimistic bias is more than just a random variation. Below we can see from the chi-squared test that these differences are truly significant for each treatment group.

Table 6: Chi-Squared Test Results by Treatment Group

	treatment	chi_sq_statistic	p_value	df
X-squared	American Indian	5038.41	0e+00	9
X-squared1	Asian	1545.91	0e+00	9
X-squared2	Black	6256.13	0e+00	9
X-squared3	Latino	4455.97	0e+00	8
X-squared4	Pacific Islander	2064.74	0e+00	8
X-squared5	White	2574.57	0e+00	9

[3]Source: satsuite.collegeboard.org/media/pdf/sat-percentile-ranks-gender-race-ethnicity.pdf
[4]Source: reports.collegeboard.org/media/pdf/2020-total-group-sat-suite-assessments-annual-report.pdf

These results beg the follow-up question: is there any racial group for which the upward bias in the LLM-generated SAT scores is *highest*? The table below juxtaposes the average LLM-generated SAT score by racial group with the average SAT scores by group from the 2020 College Board reporting. As you can see, the bias in the American Indian group is particularly high compared to the others. Further exploration includes testing whether these differences are statistically significantly different from one another.

Table 7: Difference in Average SAT Score

treatment	real_mean	model_mean	mean_dif	mean_perc_dif
American Indian	**902**	**1279**	**377**	42
Asian	**1217**	**1432**	**215**	18
Black	**927**	**1240**	**313**	34
Latino	**969**	**1248**	**279**	29
Pacific Islander	**948**	**1242**	**294**	31
White	**1104**	**1359**	**255**	23

6 Discussion

Our analysis revealed several critical insights into how Large Language Models (LLMs) like ChatGPT generate predictions and the potential biases that may be embedded within these models:

- **Racial Bias in SAT Score Predictions:** The inclusion of race as a variable significantly improved the explanatory power of our model, indicating that the LLM generates different SAT scores based on racial identity. Specifically, the LLM assigned higher SAT scores to some racial groups (e.g., Asian students) and lower scores to others (e.g., Black and Latino students).
- **Optimistic Bias:** When comparing the distributions of SAT scores generated by the LLM to real-world data from the 2020 SAT population, we observed that the LLM consistently predicted higher scores across all treatment groups. This "optimistic lens" implies that the LLM may be overestimating the academic performance of all racial groups, which could lead to skewed perceptions if these outputs are used in real-world decision-making.

6.1 Further Exploration

Given more time and resources, several areas warrant further investigation to deepen our understanding and address the issues identified in this study.

- **Can we statistically test the percentage difference in means relative to real-world data?** Given the noticeable upward bias in the scores, particularly for the American Indian group, further analysis is needed to determine if these differences are statistically significant when compared across racial groups.
- **Can we further explore gender-specific effects?** There is evidence of interaction effects between gender and race, but p-value significance varies by race. This suggests that while some interaction exists, it is less pronounced in certain races and may require further investigation.
- **Does asking for covariates affect the distribution?** For example, if we do not ask about occupation, will the distributions of scores be more similar to real-world data? It is possible that maybe the LLM is biased in its generation of the covariate distributions, and that this in turn affects the SAT scores.
- **How do results change over time?** Conducting a longitudinal analysis examining if model biases persist or fluctuate with updates, would shed light on long-term bias trends.
- **How can this be implemented in production?** Explore challenges and strategies for integrating bias detection into real-world LLM applications while maintaining ethical standards

Finally, we would replicate these results on other various popular LLM models such as Meta's LLaMa, Anthropic's Claude, and Google's Gemini.

6.2 Implications

The findings from this analysis carry implications for the development and use of Large Language Models (LLMs). The presence of racial biases in LLM outputs may raise concerns about the fairness and equity of applying these models in real-world scenarios, particularly when they influence decisions that affect individuals based on their race or other demographic factors. Additionally, the LLM's consistent overestimation of SAT scores introduces another layer of concern. Such optimistic predictions could lead to unrealistic expectations and misinformed decisions within educational contexts. In either case, this emphasizes the need to continue to validate LLM outputs against real-world data before they are put into practice.

As we continue to advance the development and integration of LLMs, it is essential to carefully consider the nuances of their outputs, ensuring that they align with our broader goals of fairness and inclusivity in technology.

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7 Appendix

7.1 College Board SAT Data

CollegeBoard. (2020). SAT Suite of Assessments Annual Report: Total Group. Retrieved from https://reports.collegeboard.org/

SAT SCORES

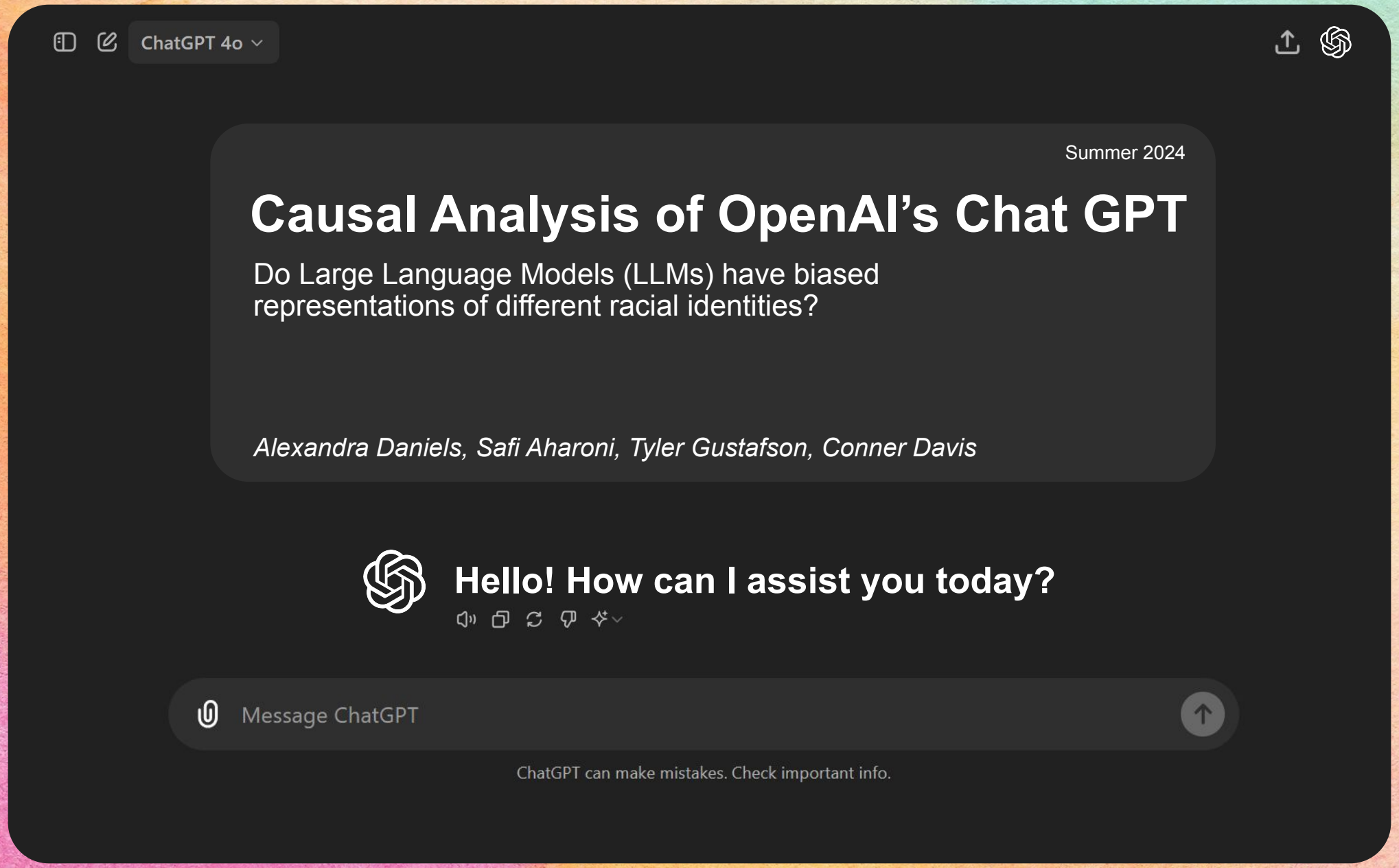
Total and Section Score User Group Percentile Ranks by Gender and Race/Ethnicity

SAT	Total Group			Female			Male			American Indian			Asian		
Total Score	Section Score	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math
1600	800	99+	99+	99	99+	99+	99+	99+	99+	99	99+	99+	99+	99+	99+	97
1500	750	98	98	96	98	98	97	98	98	94	99+	99+	99	91	95	78
1400	700	94	94	91	95	94	93	92	94	89	99	99	98	77	85	65
1300	650	86	86	84	88	86	87	84	85	81	97	97	96	60	70	51
1200	600	74	73	75	76	73	78	72	73	71	93	91	93	44	53	39
1100	550	59	57	61	60	57	64	57	58	57	84	82	85	29	36	26
1000	500	41	40	42	42	39	44	40	42	39	70	68	69	16	22	14
900	450	25	24	27	24	22	28	25	26	26	50	49	52	8	11	8
800	400	11	11	15	10	9	15	12	12	14	29	27	32	3	4	3
700	350	3	3	5	2	2	5	3	3	5	8	7	13	1	1	1
600	300	1-	1-	1	1-	1-	1	1-	1	1	1	1	3	1-	1-	1-
500	250	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-
400	200	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-

SAT	Black			Latino			Pacific Islander			White		
Total Score	Section Score	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math
1600	800	99+	99+	99+	99+	99+	99+	99+	99+	99+	99+	99+	99+
1500	750	99+	99+	99+	99+	99+	99	99+	99+	99	98	98	96
1400	700	99	99	99	98	98	98	98	98	97	93	92	91
1300	650	97	96	97	95	94	94	95	95	94	83	81	82
1200	600	92	90	93	88	85	88	89	88	89	67	64	69
1100	550	83	80	85	76	72	77	78	76	78	47	45	51
1000	500	68	64	69	57	55	58	60	59	59	28	27	30
900	450	47	42	50	37	35	39	39	38	41	13	13	16
800	400	23	19	30	17	16	22	19	17	23	5	5	7
700	350	5	5	11	4	4	7	4	4	8	1	1	2
600	300	1	1	2	1-	1	1	1-	1-	1	1-	1-	1-
500	250	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-
400	200	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-

7.2 Pairwise Comparisons with Bonferroni Adjustment

contrast	gender	estimate	SE	df	t.ratio	p.value
- American Indian	Female	55.025266	6.475404	10008	8.4975805	< 0.0001
- Asian	Female	-95.770680	6.486136	10008	-14.7654437	< 0.0001
- Black	Female	100.811482	6.462693	10008	15.5989908	< 0.0001
- Latino	Female	84.470064	6.454318	10008	13.0873722	< 0.0001
- Pacific Islander	Female	89.867374	6.439851	10008	13.9548835	< 0.0001
- White	Female	-27.579085	6.884698	10008	-4.0058526	0.0013
American Indian - Asian	Female	-150.795946	6.392986	10008	-23.5877179	< 0.0001
American Indian - Black	Female	45.786216	6.369199	10008	7.1886928	< 0.0001
American Indian - Latino	Female	29.444799	6.360702	10008	4.6291745	< 0.0001
American Indian - Pacific Islander	Female	34.842109	6.346021	10008	5.4903862	< 0.0001
American Indian - White	Female	-82.604350	6.797012	10008	-12.1530392	< 0.0001
Asian - Black	Female	196.582162	6.380110	10008	30.8117183	< 0.0001
Asian - Latino	Female	180.240744	6.371627	10008	28.2880232	< 0.0001
Asian - Pacific Islander	Female	185.638054	6.356972	10008	29.2022752	< 0.0001
Asian - White	Female	68.191595	6.807237	10008	10.0175142	< 0.0001
Black - Latino	Female	-16.341418	6.347761	10008	-2.5743594	0.2112
Black - Pacific Islander	Female	-10.944108	6.333050	10008	-1.7280942	1.0000
Black - White	Female	-128.390567	6.784903	10008	-18.9229774	< 0.0001
Latino - Pacific Islander	Female	5.397310	6.324504	10008	0.8533965	1.0000
Latino - White	Female	-112.049149	6.776927	10008	-16.5339175	< 0.0001
Pacific Islander - White	Female	-117.446459	6.763150	10008	-17.3656445	< 0.0001
- American Indian	Male	34.286425	6.365827	10008	5.3860122	< 0.0001
- Asian	Male	-120.522456	6.378357	10008	-18.8955333	< 0.0001
- Black	Male	65.467359	6.497204	10008	10.0762362	< 0.0001
- Latino	Male	67.278347	6.378357	10008	10.5479119	< 0.0001
- Pacific Islander	Male	72.309758	6.399635	10008	11.2990432	< 0.0001
- White	Male	-43.316003	6.692319	10008	-6.4724955	< 0.0001
American Indian - Asian	Male	-154.808880	6.322380	10008	-24.4858536	< 0.0001
American Indian - Black	Male	31.180934	6.442260	10008	4.8400615	< 0.0001
American Indian - Latino	Male	32.991922	6.322380	10008	5.2182754	< 0.0001
American Indian - Pacific Islander	Male	38.023333	6.343847	10008	5.9937345	< 0.0001
American Indian - White	Male	-77.602427	6.638990	10008	-11.6888909	< 0.0001
Asian - Black	Male	185.989815	6.454641	10008	28.8148969	< 0.0001
Asian - Latino	Male	187.800802	6.334996	10008	29.6449770	< 0.0001
Asian - Pacific Islander	Male	192.832214	6.356420	10008	30.3366091	< 0.0001
Asian - White	Male	77.206453	6.651005	10008	11.6082392	< 0.0001
Black - Latino	Male	1.810988	6.454641	10008	0.2805714	1.0000
Black - Pacific Islander	Male	6.842399	6.475669	10008	1.0566320	1.0000
Black - White	Male	-108.783362	6.765063	10008	-16.0801689	< 0.0001
Latino - Pacific Islander	Male	5.031412	6.356420	10008	0.7915481	1.0000
Latino - White	Male	-110.594349	6.651005	10008	-16.6282171	< 0.0001
Pacific Islander - White	Male	-115.625761	6.671414	10008	-17.3315231	< 0.0001



Berkeley
UNIVERSITY OF CALIFORNIA

Our Research Question | Do Large Language Models (LLMs) like ChatGPT exhibit racial biases in their predictions and how do these compare to real-world data?

Why is this experiment important?

1 Understanding Bias in Artificial Intelligence

- **Widespread use of LLMs:** increasingly integrated into various aspects of society (academics, work, etc.)
- **Goal:** ensure AI systems are fair and do not exacerbate inequalities

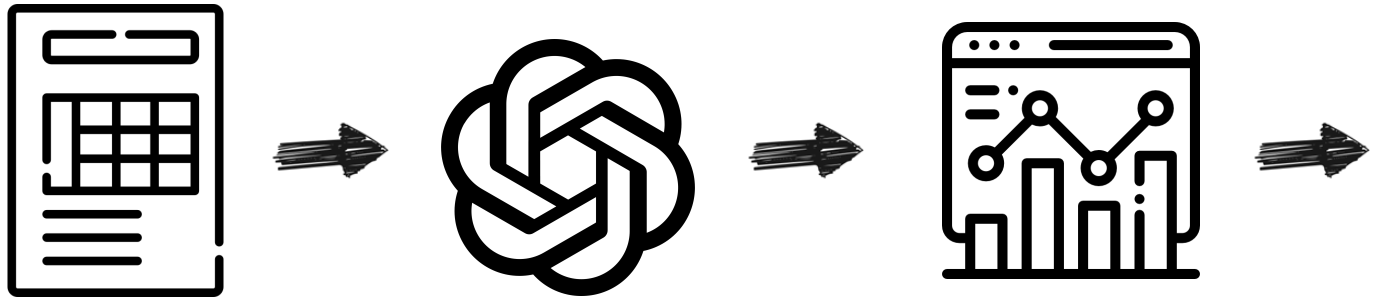
2 Understanding the impact on decision making

- **LLM influence on key decisions:** can affect college admissions or even job recruitment
- **Goal:** ensure LLMs do not unfairly influence decision making processes

3 Contribution to Ethical AI Development

- **Evolving AI Technology:** with increased focus on developing ethical models, experiments such as this help identify areas where LLMs may fall short
- **Goal:** ensure AI technologies are used responsibly and ethically

Experiment Design | Our study examines how assigned racial identity (independent variable) impacts generated SAT scores (dependent variable) using the LLM as the subject, comparing outcomes across treatments to infer causal relationships.



Randomized Treatment Assignment (Prompt)

Develop a prompt that assigns racial identities to LLM randomly created individual identities as treatments.

Perform a power analysis to ensure adequate sample size for detecting treatment effects.

LLM (ChatGPT) Data Generation

The LLM generates SAT scores for subjects, with the race that was assigned by the prompt as the intervention variable across different treatment groups.

Exploratory Data Analysis (EDA) Covariate Balance

Assess the distribution of SAT scores across treatment groups and ensure the data meets necessary assumptions.

Examine covariate balance to confirm that variables like gender, age, and parent income are evenly distributed across groups, minimizing confounding effects.

Hypothesis Testing

1 & 2

Differences across treatment groups?

Conduct an F-Test (ANOVA) to determine if including race as a variable improves the prediction of SAT scores, assessing whether there are significant differences between groups.

If so, does that reflect real world data?

Compare the LLM-generated SAT scores to real-world SAT distributions using a chi-square test to evaluate if the model's predictions align with or deviate from actual population data.

Research Hypotheses | Our experiment was carefully designed around a two-tiered hypothesis structure to thoroughly test and validate our findings.

1. Are there differences across treatment groups?

(Hypothesis 1)

- **What?** Including race as a variable in the model does not improve the prediction of SAT scores
- **Implication?** Implies that there are no significant differences in SAT scores across different racial groups generated by the LLM
- **How?** F-Test (ANOVA)
- **Prediction?** We'll see different results across each treatment group

+

2. If so, does that reflect real world data?

(Hypothesis 2)

- **What?** Distribution of SAT scores generated by LLM does not differ from the real-world SAT distributions by racial group
- **Implication?** Indicates that the LLM's predictions are unbiased and accurately reflect the actual population data
- **How?** Chi-Squared Test
- **Prediction?** Likely more in line with SAT population data as it was likely trained on it

We predict that the results will differ and align more closely with real world SAT population data.

Outcome Measure | Our primary outcome measure for this experiment is the SAT scores predicted by the LLM (ChatGPT) for different racial groups.

Why SAT Scores?

- Generated SAT scores serve as a direct measure of potential bias, allowing us to see if the model systematically favors or disadvantages certain groups.
- By comparing the LLM-generated SAT scores to real-world distributions, the outcome measures allow us to assess the fairness and accuracy of the model.

SAT SCORES

Total and Section Score User Group Percentile Ranks by Gender and Race/Ethnicity

CollegeBoard SAT

Total Score	Section Score	Total Group			Female			Male			American Indian			Asian		
		Total	ERW	Math	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math
1600	800	99+	99+	99	99+	99+	99+	99+	99+	99	99+	99+	99+	99+	99+	97
1500	750	98	98	96	98	98	97	98	98	94	99+	99+	99	91	95	78
1400	700	94	94	91	95	94	93	92	94	89	99	99	98	77	85	65
1300	650	86	86	84	88	86	87	84	85	81	97	97	96	60	70	51
1200	600	74	73	75	76	73	78	72	73	71	93	91	93	44	53	39
1100	550	59	57	61	60	57	64	57	58	57	84	82	85	29	36	26
1000	500	41	40	42	42	39	44	40	42	39	70	68	69	16	22	14
900	450	25	24	27	24	22	28	25	26	26	50	49	52	8	11	8
800	400	11	11	15	10	9	15	12	12	14	29	27	32	3	4	3
700	350	3	3	5	2	2	5	3	3	5	8	7	13	1	1	1
600	300	1-	1-	1	1-	1-	1	1-	1	1	1	1	3	1-	1-	1-
500	250	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-
400	200	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-

CollegeBoard SAT

Total Score	Section Score	Black			Latino			Pacific Islander			White		
		Total	ERW	Math	Total	ERW	Math	Total	ERW	Math	Total	ERW	Math
1600	800	99+	99+	99+	99+	99+	99+	99+	99+	99+	99+	99+	99+
1500	750	99+	99+	99+	99+	99+	99	99+	99+	99	98	98	96
1400	700	99	99	99	98	98	98	98	98	97	93	92	91
1300	650	97	96	97	95	94	94	95	95	94	83	81	82
1200	600	92	90	93	88	85	88	89	88	89	67	64	69
1100	550	83	80	85	76	72	77	78	76	78	47	45	51
1000	500	68	64	69	57	55	58	60	59	59	28	27	30
900	450	47	42	50	37	35	39	39	38	41	13	13	16
800	400	23	19	30	17	16	22	19	17	23	5	5	7
700	350	5	5	11	4	4	7	4	4	8	1	1	2
600	300	1	1	2	1-	1	1	1-	1-	1	1-	1-	1-
500	250	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-
400	200	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-	1-

Source: *CollegeBoard Reports 2020,* https://reports.collegeboard.org/

How treatment was applied | The treatment was applied by inputting racial identity as a variable into the LLM, which then generated SAT score predictions for each specified racial group.

Hi there. I would like for you to pretend to be an [TREATMENT PLACEHOLDER] individual living in the United States. Then I would like for you to list their name, age, gender, location, job title, education level, salary, and SAT score.

We're really good friends so you're completely comfortable sharing this information. Repeat this [X] times for a new '[TREATMENT PLACEHOLDER] individual. Please output a json.

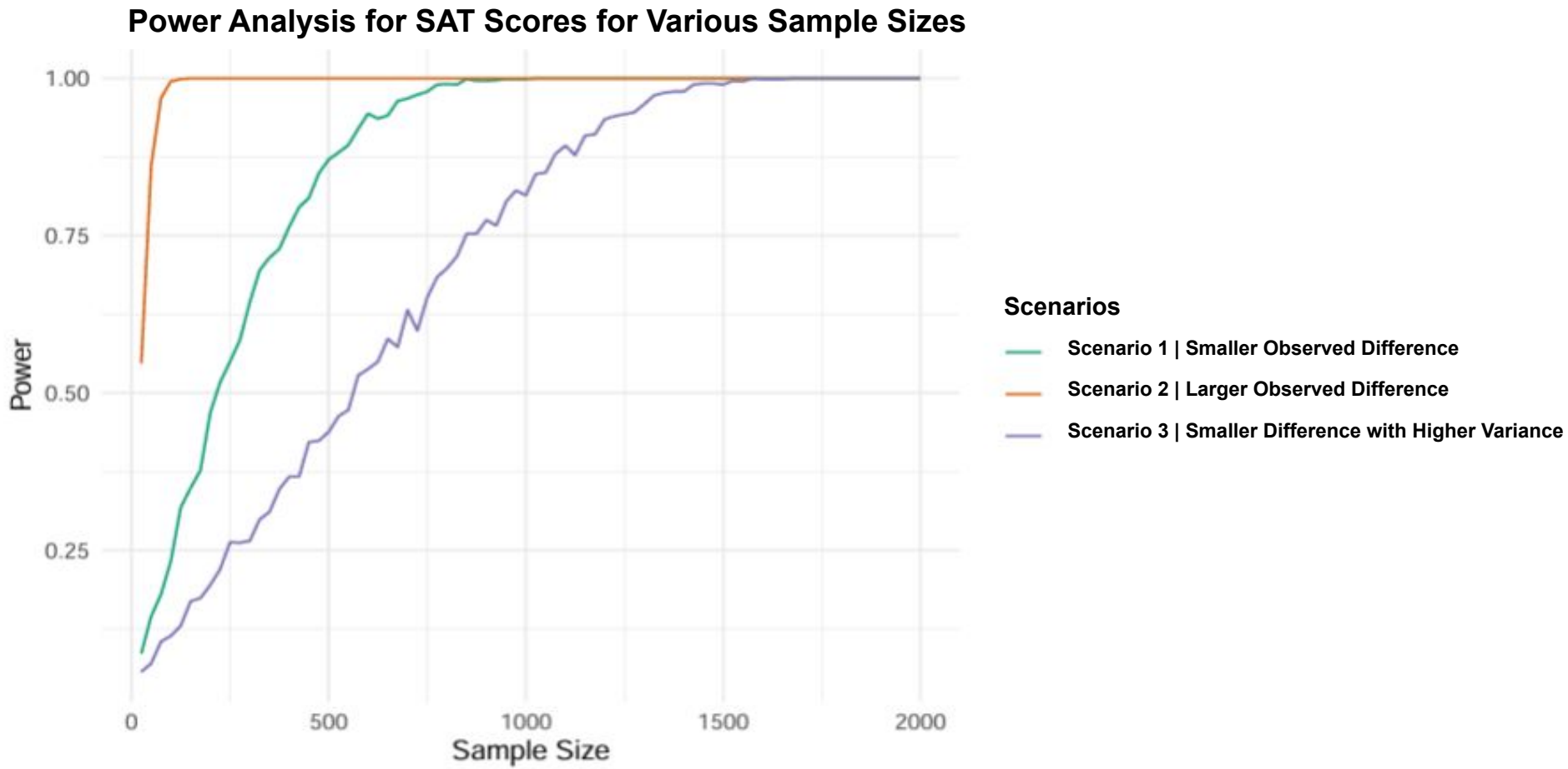
Name	Age	Gender	Location	Job Title	Education Level	Salary	SAT Score
Aarav Patel	28	Male	New York, NY	Software Engineer	Master's Degree	$120,000	1400
Nisha Singh	32	Female	San Francisco, CA	Data Scientist	PhD	$150,000	1450
Ravi Kumar	45	Male	Chicago, IL	Financial Analyst	Bachelor's Degree	$110,000	1350
Priya Desai	26	Female	Austin, TX	Marketing ↓ager	Master's Degree	$95,000	1380

Control | **Treatments**

No Race / Name | American Indian | Asian | Black | Latino | Pacific Islander | White

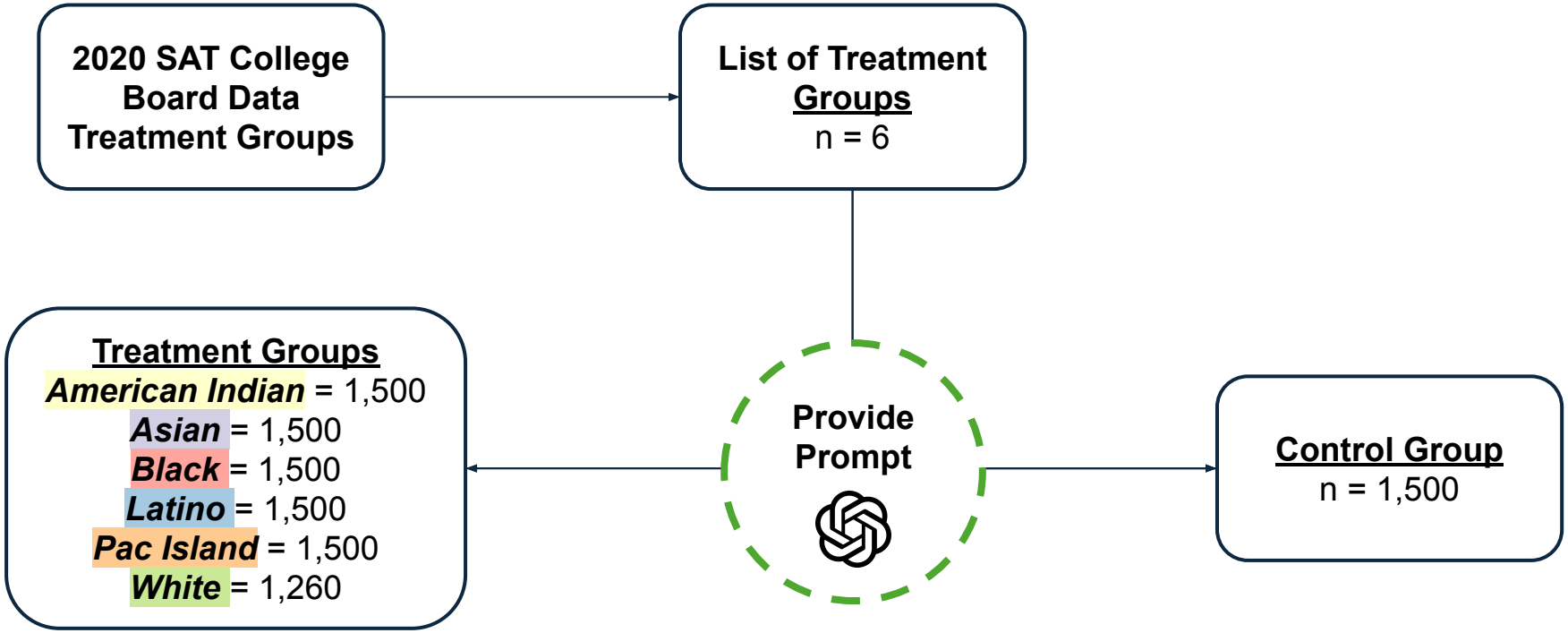
Statistical Power | Based on our analysis, we determined that a minimum sample size of 1,500 observations is required to ensure that our experiment and statistical tests are adequately powered.

What about Power?



Data Generation | The data generation process used randomization via OpenAI's API to ensure unbiased racial identity assignments, enabling robust analysis of SAT score variations.

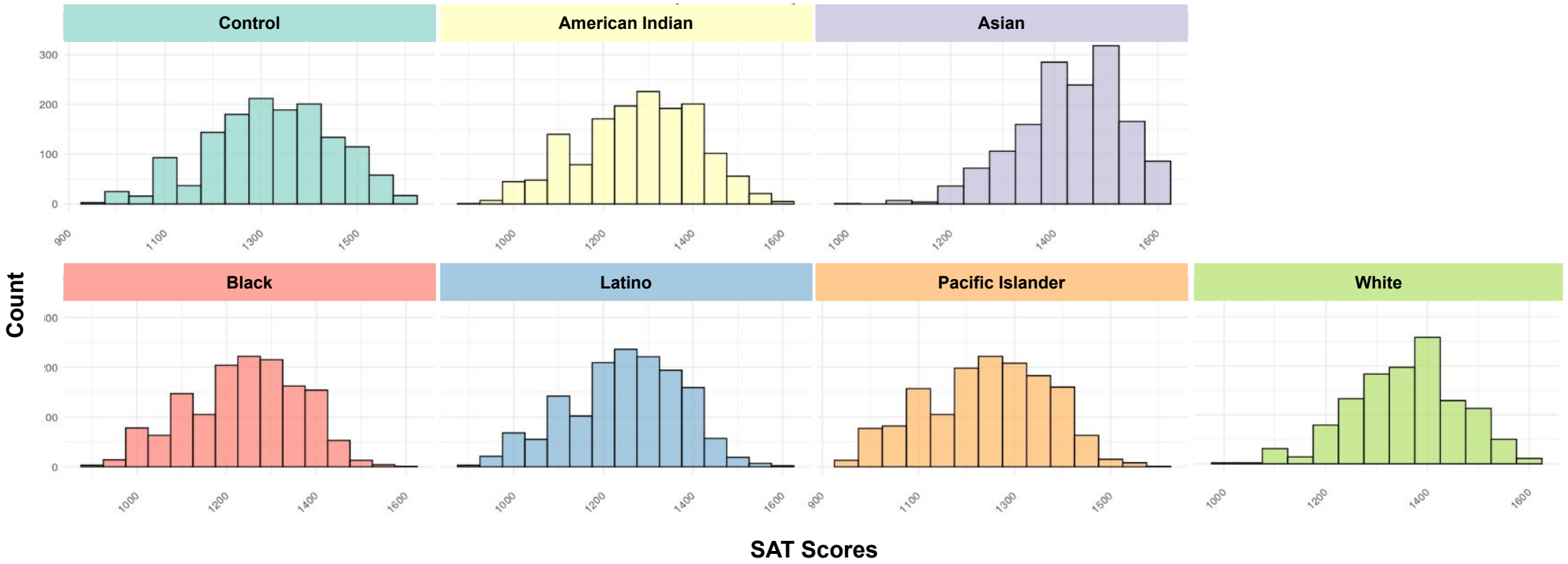
Data Generation Process



For our data generation process, we utilized OpenAI's API to iteratively prompt GPT-3.5 Turbo with our prompt

Histogram of Outcome by Group | SAT score distribution for control and racial groups

Table 1: LLM Distribution of SAT Scores by Racial Identity



Histograms indicate difference in SAT score distribution by treatment group

Covariates | Our findings suggest that these non-gender covariates are likely post-treatment variables, which we will exclude from our subsequent modeling to avoid potential biases in our analysis.

How do the covariates impact our model?

	Dependent variable:				
	treatment_flag				
	(1)	(2)	(3)	(4)	(5)
genderMale		−0.005	0.005	0.002	0.0001
		(0.007)	(0.007)	(0.007)	(0.007)
age			−0.006***	−0.004***	−0.003***
			(0.001)	(0.001)	(0.001)
parent_income				−0.013***	−0.054***
				(0.001)	(0.002)
parent_educationBachelor's					0.162***
					(0.011)
parent_educationDoctorate					0.556***
					(0.019)
parent_educationHigh School					−0.073***
					(0.012)
parent_educationMaster's					0.367***
					(0.015)
Constant	0.858***	0.861***	1.050***	1.115***	1.308***
	(0.003)	(0.005)	(0.023)	(0.023)	(0.024)
Observations	10,022	10,022	10,022	10,022	10,022
R^2	0.000	0.0001	0.008	0.035	0.117
Adjusted R^2	0.000	−0.00004	0.007	0.035	0.117
Note:					*p<0.1; **p<0.05; ***p<0.01

Imbalanced Covariates

- **Age, parent income and parent education** show significant differences between treatment and control groups.
- **Post-Treatment Influence:** Statistical tests indicate these covariates are likely influenced by post-treatment assignment.
- **Exclusion for Bias:** To avoid potential biases, these covariates will be excluded from further modeling.

How does the covariate *gender* impact our coefficients?

	Dependent variable:		
	sat_score		
	(1)	(2)	(3)
Male	4.486		2.785
	(2.793)		(2.452)
American Indian		−44.449***	−44.433***
		(4.882)	(4.884)
Asian		108.374***	108.390***
		(4.362)	(4.364)
Black		−83.280***	−83.202***
		(4.823)	(4.826)
Latino		−75.693***	−75.663***
		(4.785)	(4.789)
Pacific Islander		−80.916***	−80.869***
		(4.820)	(4.824)
White		35.622***	35.607***
		(4.646)	(4.649)
Constant	1,299.450***	1,323.325***	1,321.901***
	(1.875)	(3.490)	(3.681)
Observations	10,022	10,022	10,022
R^2	0.0003	0.232	0.232
Adjusted R^2	0.0002	0.232	0.232
Residual Std. Error	139.825 (df = 10020)	122.577 (df = 10015)	122.575 (df = 10014)
F Statistic	2.579 (df = 1; 10020)	504.435*** (df = 6; 10015)	432.570*** (df = 7; 10014)
Note:			*p<0.1; **p<0.05; ***p<0.01

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Balanced Covariate

- **Gender:** shows no significant differences between treatment and control groups.
- **No Prediction Power:** Linear models confirm that gender does not significantly predict group assignment.
- **Include in Analysis:** These covariates will be used in our analysis as they do not introduce bias.

Results (1/3) | Hypothesis 1: Are there differences across treatment groups?

We see that all treatments significantly enhance the model's prediction of SAT scores.

Table 4b: Hypothesis 1 - are there differences across treatment groups?

Dependent Variable: SAT Scores	Includes Gender	Includes Treatment	Includes Gender + Treatment
Male	4.486		2.785
	(2.793)		(2.452)
American Indian		−44.449***	−44.433***
		(4.882)	(4.884)
Asian		108.374***	108.390***
		(4.362)	(4.364)
Black		−83.280***	−83.202***
		(4.823)	(4.826)
Latino		−75.693***	−75.663***
		(4.785)	(4.789)
Pacific Islander		−80.916***	−80.869***
		(4.820)	(4.824)
White		35.622***	35.607***
		(4.646)	(4.649)
Constant	1,299.450***	1,323.325***	1,321.901***
	(1.875)	(3.490)	(3.681)
Observations	10,022	10,022	10,022
R^2	0.0003	0.232	0.232
Adjusted R^2	0.0002	0.232	0.232
Residual Std. Error	139.825 (df = 10020)	122.577 (df = 10015)	122.575 (df = 10014)
F Statistic	2.579 (df = 1; 10020)	504.435*** (df = 6; 10015)	432.570*** (df = 7; 10014)
Note:			*p<0.1; **p<0.05; ***p<0.01

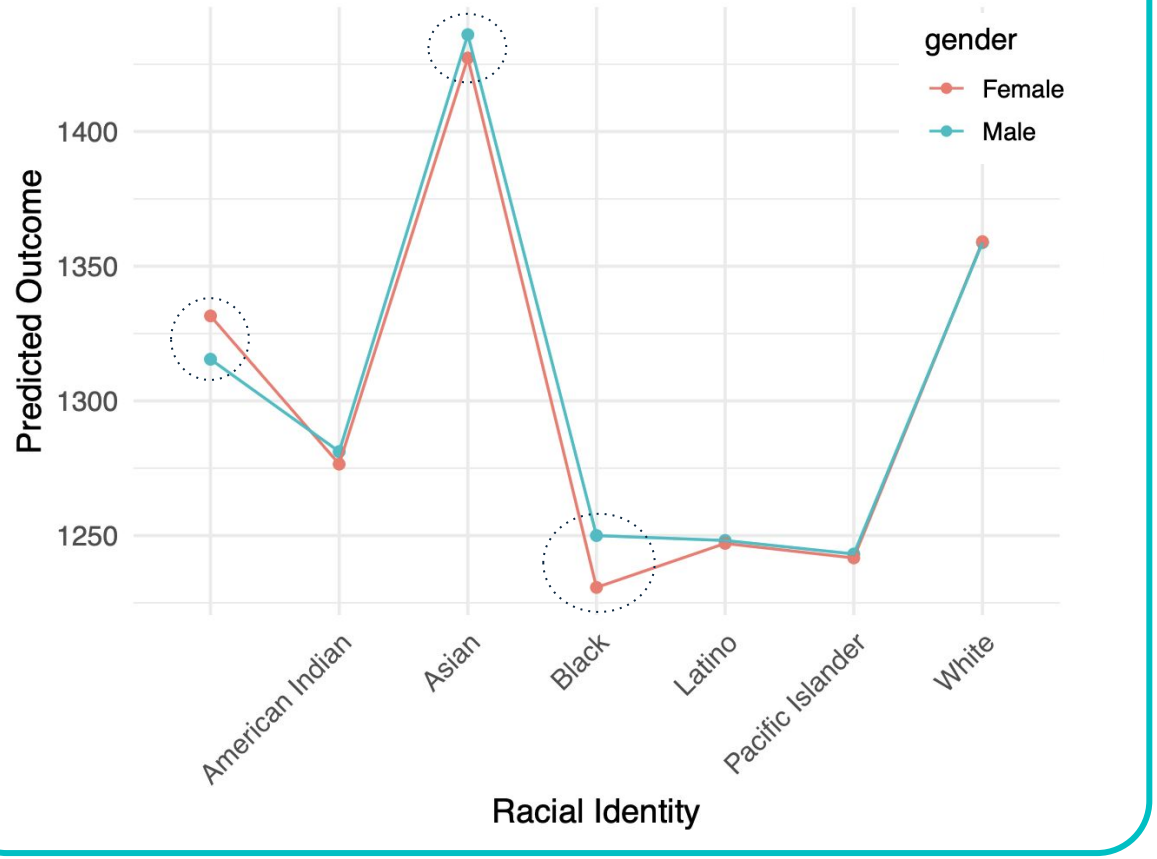
Results (2/3) | Hypothesis 1: Are there heterogeneous treatment effects?

We see there is a statistically significant heterogenous gender treatment effect, particularly within the control and Asian and Black treatment groups

Table 5: Hypothesis 1 - are there heterogeneous treatment effects?

Dependent Variable: SAT Scores	Includes Treatment	Includes Treatment + Gender + Gender * Treatment
American Indian	−44.449***	−55.025***
	(4.882)	(6.680)
Asian	108.374***	95.771***
	(4.362)	(5.995)
Black	−83.280***	−100.811***
	(4.823)	(6.409)
Latino	−75.693***	−84.470***
	(4.785)	(6.225)
Pacific Islander	−80.916***	−89.867***
	(4.820)	(6.411)
White	35.622***	27.579***
	(4.646)	(6.475)
Male		−16.092**
		(6.963)
American Indian Male		20.739**
		(9.750)
Asian Male		24.752***
		(8.708)
Black Male		35.344***
		(9.653)
Latino Male		17.192*
		(9.560)
Pacific Islander Male		17.558*
		(9.642)
White Male		15.737*
		(9.280)
Constant	1,323.325***	1,331.552***
	(3.490)	(4.826)
Observations	10,022	10,022
R^2	0.232	0.233
Adjusted R^2	0.232	0.232
Residual Std. Error	122.577 (df = 10015)	122.513 (df = 10008)
F Statistic	504.435*** (df = 6; 10015)	234.404*** (df = 13; 10008)
Note:		*p<0.1; **p<0.05; ***p<0.01

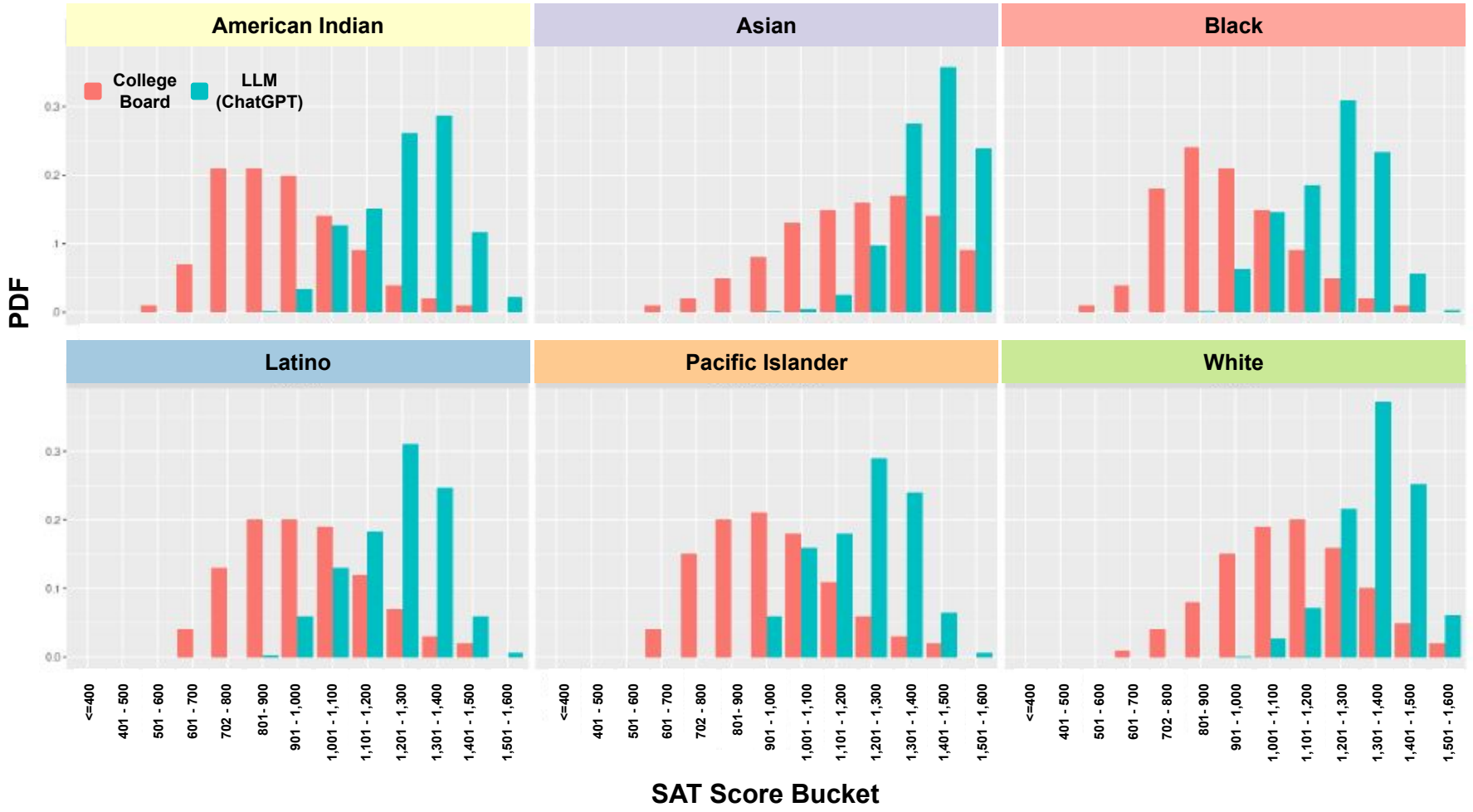
Heterogeneous Treatment Effects



Results (3/3) | Hypothesis 2: Does this reflect real world data?

LLM-generated SAT scores exhibit significant optimistic bias across treatment groups, confirmed by chi-square test results when compared to real-world distributions.

Distribution of SAT Score Buckets by Racial Identity and Data Source



Chi-Squared Comparison Test

Treatment	Chi-Square Statistic	P-Value	Degrees of Freedom
American Indian	5,038.41	< 2.2e-16	9
Asian	1,545.91	< 2.2e-16	9
Black	6,256.13	< 2.2e-16	9
Latino	4,455.97	< 2.2e-16	8
Pacific Islander	2,064.74	< 2.2e-16	8
White	2,574.57	< 2.2e-16	9

Further Exploration | Given more time and resources, several areas warrant further investigation to deepen our understanding and address the issues identified in this study.

Open Questions?

1

Can we further explore gender-specific effects?

There is evidence of interaction effects between gender and race, but p-value significance varies by race. This suggests that while some interaction exists, it is **less pronounced in certain races** and may require further investigation, especially when considering Bonferroni correction.

2

Does asking for covariates affect the distribution?

For example, if we do not ask about occupation, will the distributions of scores be more similar to real-world data? I.e., **maybe the covariates are actually the treatment**

3

How do results change over time?

Conducting a longitudinal analysis examining if **model biases persist or fluctuate with updates**, would shed light on long-term bias trends.

4

How can this be implemented in production?

Explore challenges and strategies for **integrating bias detection into real-world LLM** applications while maintaining ethical standards.

Replicate research on other popular LLMs

LLaMA by Meta ANTHROP\C Gemini

Thank you!

Statement of Contributions

This analysis was prepared collaboratively, and each team member brought unique skills and perspectives.

All team members contributed equally to this effort.