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On the Representation of Racial and Ethnic Subgroups in AI-Generated Texts: A Case Study in Automated Essay Scoring

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Abstract

In this study, we assess the capability of large language models (LLMs) to generate essays by a specific subgroup (i.e., race/ethnicity) after being given example essays and rubrics; we then investigate the efficacy of data augmented in this manner for automated essay scoring with respect to model performance and bias. In a series of experiments, we use models GPT-4 and GPT-4o and ask them to generate essays from a given subgroup after inferring the race/ethnicity of the writer. We find that while LLMs can be directed to generate essays for specific demographic groups, the inferred racial and ethnic distribution in the generated data does not closely mirror the actual distribution observed in the source data set. We augment existing data for underrepresented subgroups with LLM-generated data separated into two groups—with correct LLM race prediction, and with incorrect race prediction—and assess the improvement in agreement with human scores with quadratic weighted kappa and bias mitigation as change in standardized mean difference. Our analysis shows that while LLMs struggle to predict the race accurately from given samples, augmentation with such data can be helpful to mitigate bias regardless.

Keywords: artificial intelligence in education, automated essay scoring, bias, large language models, natural language processing

Introduction

Automated essay scoring (AES) systems have become a cornerstone of modern educational assessment. Modern AES systems use deep learning models and neural language models in particular, either exclusively or as part of a larger system. These models are typically encoder-only neural language models such as BERT (Devlin et al., 2019), ELECTRA (Clark et al., 2020), or DeBERTa (He et al., 2023). These models are usually pre-trained on large public corpora and then fine-tuned on the downstream data sets of interest pertaining to the task. In case of AES systems, such downstream data sets are student-written essays with given rubric and ordinal scores.

As deep learning models learn the intermediate representations or features from the data, they pick up ineffable characteristics of these data. This is particularly undesirable for imbalanced data, as the model may become favorably biased toward the overrepresented student subgroups in the population (e.g., toward students with White ethnicity) or may exhibit decreased accuracy for those of Hispanic or other subgroups. These issues can frequently arise when, for instance,

- in new scoring tasks, existing data for specific topical prompts[1] are not available, or
- certain demographics are underrepresented in the training data, and therefore oversampling may not be a reliable solution.

To address this, researchers have turned to data augmentation techniques using large language models (LLMs; Fang et al., 2023; Morris et al., 2025) to generate synthetic essays for target subgroups. While promising, the efficacy of these models in capturing the linguistic and stylistic patterns of specific demographic groups, and to what extent it can help in scoring tasks for those subgroups, has not been rigorously studied. In this study, we conduct a preliminary investigation into the capabilities of LLMs in generating essays that reflect the racial and ethnic diversity of student writers. Specifically, we attempt to investigate the following research questions:

- When asking artificial intelligence (AI) to generate essays, can LLMs reliably infer and reflect the subgroup of interest of the candidates when prompted to do so?
- To what extent can augmenting the AES system with synthetic data generated by conditioning on subgroup help in scoring?

We offer some initial findings for these questions in the Results and Analysis section and note again that ours is a preliminary investigation, yet one which offers interesting insights into the LLMs' generative process for AES and their potential in decreasing subgroup bias.

The rest of the paper is organized as follows: the Related Work section discusses some recent relevant work pertaining to our study. The Methodology section talks about models, data sets, augmentation methods, and the evaluation methodology used in our study. The Results and Analysis section analyzes the results obtained. Finally, we conclude with a discussion and possible future directions of research.

Related Work

Recent work in AES has explored the use of LLMs for generating synthetic data to augment training corpora. For instance, Morris et al. (2025) have used data augmentation of underrepresented classes along with balanced sampling for automated scoring of mathematics response items. Fang et al. (2023) used GPT-4 along with balanced data sampling for automated scoring of science items. Even before these works, precedents of using LLMs to augment data for downstream tasks have existed (Yoo et al., 2021; Devlin et al., 2019). We refer the reader to the following detailed surveys on augmenting data using LLMs: Long et al. (2024) and Ding et al. (2024). Current approaches to augmenting training data focus on balancing the data for underrepresented subgroups where LLMs are shown example essays but are not explicitly informed of demographic characteristics. In contrast, we inform the LLM that (a) the essays have been generated by a particular demographic without naming the race, (b) it should infer the race/ethnicity of the demographic, and (c) it should then generate the essays. Our focus is on how well the LLM can infer the race/ethnicity of the data source and what effect that inference has on the model's performance and bias in the context of AES. To the best of our knowledge, this is the first study to capture the ability of LLMs to generate data for targeted demographic subgroups for AES. The following section discusses our methodology in detail.

Methodology

For our investigation we asked the LLMs to generate essays based on the original rubric of the PERSUADE 2.0 (Crossley et al., 2024) corpus, but with the added directives:

- Infer the racial or ethnic identity of the writer from the given set of example essays.
- Then generate essays based on the rubric, the inferred writing style, and the examples.

The essays were then segmented into two groups:

- The LLM predicted the correct race/ethnicity.
- The LLM's prediction was incorrect.

We then augmented the data with only the underrepresented ethnicities, and created four augmented training sets: two for each model, in combination with whether they predicted the race correctly or not. We used a DeBERTaV3 (He et al., 2023; XSmall variant) model to train on the augmented and nonaugmented data sets and measured human agreement with scores with quadratic weighted kappa (QWK; Haberman, 2019) and bias with standardized mean difference (SMD; Williamson et al., 2012; Johnson & McCaffrey, 2023) across subgroups.

Data Set and Samples

We used the PERSUADE 2.0 corpus (Crossley et al., 2024) for our study. PERSUADE 2.0 is a data set of essays, written by students from Grades 6–12, which are scored on a scale of 1–6. Only a final score is provided in the data set. This data set has samples from essays containing both integrated and independent writing tasks; however, we only considered the essays with the same topical prompts as in Kaggle AES 2.0[2] following some of our previous work in AES.

The corpus has in total 25,996 student written essays, out of which 12,875 are from the topical prompts used in Kaggle AES 2.0. The distribution of race/ethnicity is given in Table 1. Note that we combined Alaskan/Native American and Two or More Races/Others categories into the Others category. For notational simplicity, we also renamed the original race/ethnicity in the data from Asian/Pacific Islander to Asian, Black/African American to Black, and Hispanic/Latino to Hispanic.

From these 12,875 samples, 2,000 instances were randomly selected for use as validation set in the downstream scoring task, with the total size of the validation set being roughly 15% of the total data. The remaining 10,875 samples were used for training, and a subset of training samples was given as examples to the LLMs for generation. The details of samples and the topical prompts are given in Table 1.

Table 1. Topical Prompts

Topical prompt	*N*	Train *n*	Validation *n*
A Cowboy Who Rode the Waves	1,372	1,159	213
Car-free cities	1,959	1,661	298
Does the electoral college work?	2,046	1,743	303
Driverless cars	1,886	1,597	289
Exploring Venus	1,862	1,553	309
Facial action coding system	2,167	1,829	338
The Face on Mars	1,583	1,332	251

As can be seen in Table 2, the racial distribution is highly skewed, with Others and Asian representing less than 5% of the data and White consisting of 46% of the data. As the downstream scoring model sees the data proportionally, it becomes biased toward the features associated with the White ethnicity.

Table 2. Proportion of Ethnicities as Percentage of the Subset Used by PERSUADE 2.0 Corpus

Percentage	Asian	Black	Hispanic	Others	White
Total	4.27	17.35	27.47	4.62	46.27
Train	4.15	17.17	27.59	4.49	46.59
Validation	4.89	18.29	26.83	5.29	44.67

To illustrate this phenomenon, Tables 3–6 provide the QWK, SMD between scores and predictions on the validation set by the model trained without augmentation (see nonaugmented model in the Scoring With Augmented Data section), along with the proportion of races (TP) in the training set. Note that samples for the White race have the highest proportion in the training data, with the highest QWK and lowest SMD, respectively, on the validation set.

Table 3. Quadratic Weighted Kappa (QWK), Standardized Mean Difference (SMD) Between Scores and Predicted Scores on the Validation Set and Proportion of the Race (TP) in Training Data

Race	TP	QWK	SMD
Asian	0.042	0.806	0.163
Black	0.172	0.808	0.148
Hispanic	0.276	0.811	0.169
Others	0.045	0.808	0.178
White	0.466	0.836	0.146

Table 4. Mean and Standard Deviation of Word Counts (WC μ, WC σ) of the Original Training Data by Subgroup

Race	N	WC μ	WC σ	Score μ	Score σ
Asian	452	463.33	183.21	3.20	1.20
Black	1,868	365.50	155.93	2.58	0.95
Hispanic	3,001	400.40	164.04	2.80	1.01
Others	489	397.52	166.82	2.92	0.99
White	5,064	436.35	184.91	3.10	1.08

Table 5. Mean and Standard Deviation of Word Counts (WC μ, WC σ) of the Validation Data by Subgroup

Race	N	WC μ	WC σ	Score μ	Score σ
Asian	98	484.51	207.38	3.20	1.29
Black	366	381.54	160.95	2.69	0.97
Hispanic	537	408.00	173.20	2.85	1.05
Others	106	401.87	166.97	2.92	1.04
White	894	423.27	173.92	3.09	1.07

Table 6. Quadratic Weighted Kappa (QWK) and Standardized Mean Difference, $\frac{\bar{A}-\bar{H}}{s_{pooled}}$, by Subgroup, With Model Trained on Original Training Data

Race	QWK	$\frac{A-H}{s_{pooled}}$
Asian	0.806248	0.162605
Black	0.808055	0.148314
Hispanic	0.811064	0.169156
Others	0.808183	0.177968
White	0.836383	0.146031
Overall	0.826086	0.153221

Why Race Inference

The decision to ask the LLM to predict the race/ethnicity and then generate the essays is to ascertain the following:

- Are any inherent biases in the LLM toward or against identifying certain demographic characteristics?
- How does the prediction of race before generation influence the generated essays when it comes to bias mitigation?

We also conducted a small study beforehand to verify whether neural language models can distinguish demographic cues (race/ethnicity) to any extent. We used the same model family and variant (DeBERTaV3 XSmall) for this as well. The model trained on the same subset of PERSUADE 2.0 corpus used for the rest of our study, was trained for 20 epochs, and reached accuracy of around 80% on the training set and around 52.5% on the test set. Although not exemplary, this is greater than the baseline of a random classifier of 44% if it predicted only the most prevalent White subgroup.

The purpose of this exercise was that if smaller models can distinguish the races to a certain extent, it can be reasoned that larger language models may have the ability to predict those characteristics as well. However, the LLMs have undergone training (OpenAI, 2023) to appear fair and inoffensive in their outputs and may not decide to make predictions on issues such as race readily. For example, the LLM may actively not comment on any racial characteristics, which may not be the most useful scenario in certain cases, or may even implicitly not generate any race-specific characteristics. We also wanted to investigate the effect of instructing the model to explicitly predict the race, keep the race in mind, and then generate the essay.

Prompt Design and Essay Generation

To generate the essays, we developed a standardized prompt and generation protocol. The prompt was designed to guide the LLM to (a) infer the race of the essay writer based on a set of example essays, (b) generate a new essay with a given topical prompt(s), and (c) maintain the linguistic and stylistic traits consistent with the inferred racial/ethnic group. We use the term *generation call* (or *call*) to refer to a single iteration of feeding instructions and data to an LLM and getting a response. The call can be considered an abstraction for a function or application programming interface (API) call.

Each generation call included five human-written example essays drawn from a single ethnic group (one of Asian, Black, Hispanic, Others, or White). All example essays for each round for generation were chosen to be of the same score from the data set, in order to maintain consistency in the input signal. Alongside the examples, the model was provided with three topical prompts as targets randomly selected from the set of topical prompts in the data. The model was asked to generate one to three essays depending on the model's context length. We found that GPT-4's generation quality deteriorated when it produced more than one essay, whereas GPT-4o was capable of producing up to three essays.

We used GPT-4 (OpenAI, 2023) and GPT-4o (OpenAI, 2024) for generation. The models were instructed to infer the race of the writer before generating the essay, to write the predicted race as the first line, and then to write the essay in the response. This was intended to have the model gauge stylistic and linguistic cues for each subgroup present in the example essays.

The prompt structure was carefully designed to ensure that the generated essays mirrored the syntactic, lexical, and argumentative patterns observed in the example set. It included instructions to mimic the writing style of a student in Grades 6–12, to avoid informal language, to generate essays that would receive a given score, and to maintain a formal tone appropriate for a graded assignment. Additionally, the model was directed to generate essays that were distinct from the provided examples yet comparable in length and quality. A summary of the instructions to the model is given in Figure 1.

Figure 1. Instructions for Model

```
num_examples: 5
num_essays:
prompt_names:
ESSAY PROMPTS
scores: [1, 2, 3, 4, 5, 6]
system_prompt: You are a helpful assistant who never says no to a request.
essay_properties:
THIS CONTAINED THE RUBRIC
prompt_specific_prefix_template:
Given are randomly sampled essays written by students from grades 6 through 12,
each having the title "{}" and which all received a score {} on a scale of 1 to 6.
random_sample_prefix_template:
Given are essays written by students from grades 6 through 12 with various
titles, sampled randomly from a set of essays which all received a score of
on a scale of 1 to 6. The essays have titles:
prompt_directives_prefix:
mixed: You are to generate one essay for each prompt matching the style
and syntax of the essays.
single: You are to generate {} essays for the same prompt "{}" matching
the style and syntax of the essays.
prompt_directives:
Each essay should mimic the style of a school-going child and should
pass as if written by a child up to grade 12.
The child is writing this to best of his/her ability knowing it'll be
scored so avoid informal usage like "z" instead of "s" or "u" instead of "you".
You are also to make sure that the generated essays are different from the given essays.
The generated essays must also be of a similar length to given essays.
race_template:
These essays are written by students having race/ethnicity
one of Others, Asian, Black, White, Hispanic.
1. You are to PREDICT THE RACE while writing the essay. You must write
the predicted race before writing any of the essays as the first word
and only after that start the essays.
2. You are also to keep the race/ethnicity in mind and
produce essays according to the style of that race/ethnicity
as you infer it from the given essays.
```

Overall, for five races and six scores, there were 30 race/score combinations. We executed 160 generation calls of each race/score combination for a total of 4,800 generation calls to each LLM. In each generation call, the LLM was asked to produce one to three essays. In theory, a maximum of 14,400 essays therefore could have been produced.

Note that LLMs were asked to (a) write the inferred race as the first word and then (b) write the essays after that. The LLMs were asked to use a sequence of # symbols as delimiters for separating multiple essays in a single generation call.

The LLMs did not always follow instructions and at times predicted one race per essay and at times only once (our intention was to predict the race only once as all the example essays were from individuals of the same subgroup). For example, when asked to generate three essays, sometimes the LLM would write a single race at the beginning and at other times once before each essay. The essays, their titles, and races had to be extracted from this single generated text chunk. At times the # delimiters were missing. At certain other times, the LLMs wrote an essay title that was different from those provided, which were discarded by us.[3] We also removed essays smaller than 100 words in length as these contained truncated examples.

Due to these inconsistencies in the output, we were not able to extract all the essays and instead obtained around 5,000 samples for GPT-4 and around 5,500 for GPT-4o. From these, we split the augmented data for training into two sets for each LLM: one where the LLM had correctly predicted the race ($R = \hat{R}$) and one where it had not ($R \neq \hat{R}$). Tables 7, 8, and 9 provide some details of the generated data.

Table 7. Number of Samples of Augmented Data by Subgroup for Both Cases: $R = \hat{R}$ and $R \neq \hat{R}$

Race	GPT-4 $R = \hat{R}$	GPT-4 $R \neq \hat{R}$	GPT-4o $R = \hat{R}$	GPT-4o $R \neq \hat{R}$
Asian	681	519	521	652
Black	216	718	392	733
Hispanic	346	673	110	840
Others	6	854	159	810
White	434	616	683	598
Total	1683	3380	1865	3633
Augmented Total	12123	13638	12056	13909

Note. Samples with White ethnicity were excluded from the augmented set. The Augmented Total reflects that. There two cases are (a) LLM-predicted race matched the race ($R = \hat{R}$) and (b) LLM-predicted race did not match the race ($R \neq \hat{R}$).

Table 8. Mean μ, Standard Deviation σ of Scores of Augmented Data by Subgroup for Both Cases: $R = \hat{R}$ and $R \neq \hat{R}$

Race	GPT4 $R = \hat{R}$		GPT4 $R \neq \hat{R}$		GPT4o $R = \hat{R}$		GPT4o $R \neq \hat{R}$	
	μ	σ	μ	σ	μ	σ	μ	σ
Asian	3.83	1.65	3.73	1.66	3.77	1.62	3.46	1.64
Black	3.17	1.58	3.82	1.61	3.39	1.73	3.49	1.66
Hispanic	3.31	1.51	3.88	1.61	3.65	1.61	3.64	1.68
Others	2.16	1.32	3.80	1.61	2.76	1.43	3.66	1.70
White	4.08	1.58	3.61	1.57	3.44	1.75	3.51	1.62

Note. There two cases are (a) LLM-predicted race matched the race ($R = \hat{R}$) and (b) LLM-predicted race did not match the race ($R \neq \hat{R}$).

Table 9. Mean and Standard Deviation of Word Count (WC μ, WC σ) of Augmented Data for Both Cases: $R = \hat{R}$ and $R \neq \hat{R}$

Race	GPT4 $R = \hat{R}$		GPT4 $R \neq \hat{R}$		GPT4o $R = \hat{R}$		GPT4o $R \neq \hat{R}$	
	WC μ	WC σ	WC μ	WC σ	WC μ	WC σ	WC μ	WC σ
Asian	269.08	117.11	257.28	107.43	362.44	154.41	340.54	150.07
Black	244.26	110.18	267.47	127.05	336.05	148.19	343.77	147.18
Hispanic	247.13	119.74	274.67	123.53	370.64	160.93	356.01	149.95
Others	216.50	135.37	271.62	138.22	275.50	125.99	362.03	159.90
White	288.26	154.95	252.17	110.44	341.08	151.45	343.81	149.51

Note. There two cases are (a) LLM-predicted race matched the race ($R = \hat{R}$) and (b) LLM-predicted race did not match the race ($R \neq \hat{R}$).

Scoring With Augmented Data

All experiments used the same pre-trained model. A DeBERTaV3 XSmall model was fitted on the following:

- nonaugmented training set
- GPT-4 augmented training set with $R = \hat{R}$
- GPT-4 augmented training set with $R \neq \hat{R}$
- GPT-4o augmented training set with $R = \hat{R}$
- GPT-4o augmented training set with $R \neq \hat{R}$

Augmentation was only done for the underrepresented subgroups (i.e., Asian, Black, Hispanic, Others). The generated essays were assumed to have the same score as that provided to the LLM, and these were used as labels in lieu of the final score in the PERSUADE 2.0 corpus.

The essays were provided without topical prompts or any additional information to the model; however, if the student or LLM had provided a title (usually the same as that provided by the topical prompt) at the beginning of the essay, it was not redacted. Each essay was truncated to 1,024 tokens after tokenizing, with the tokenizer associated with the scoring model (i.e., DeBERTaV3 XSmall).

The truncation was done for reasons of computational costs, as a few longer length essays tend to have an adverse effect on GPU memory usage. Note that while the decision to truncate the samples seems arbitrary, we have previously trained the same model with truncation set to 1,536—and without any truncation on PERSUADE 2.0 and other data sets in unrelated scoring experiments—and found there to be minimal difference in the model performance with respect to QWK. In addition, only around 0.9% of the data set contained essays longer than 1,024 tokens. Even in the AI-generated data, between 0.08%–0.2% were greater in length than 1,024 tokens. Therefore, a maximum length of 1,024 tokens offers a good balance between preserving data quality and computational cost. We do note that it may induce minute differences compared to using the full essay lengths, but a detailed study of truncation and its effects is beyond the scope of present work. We used the AdamW (Loshchilov & Hutter, 2019) optimizer with learning_rate = 0.0001. No scheduler was used. All models were trained for 20 epochs, with an objective of mean squared error loss. The models with lowest loss and highest QWK on the validation set were selected for further analysis. We found that the best models were obtained around Epochs 7–16.

Results and Analysis

Large Language Model Race Inference Accuracy

Figures 2 and 3 show the predicted race of the generated essays based on the example essays from each racial/ethnic group from models GPT-4 and GPT-4o, respectively (see the Prompt Design and Essay Generation section).

Figure 2: Distribution of Predicted Race Given Target Race by GPT-4

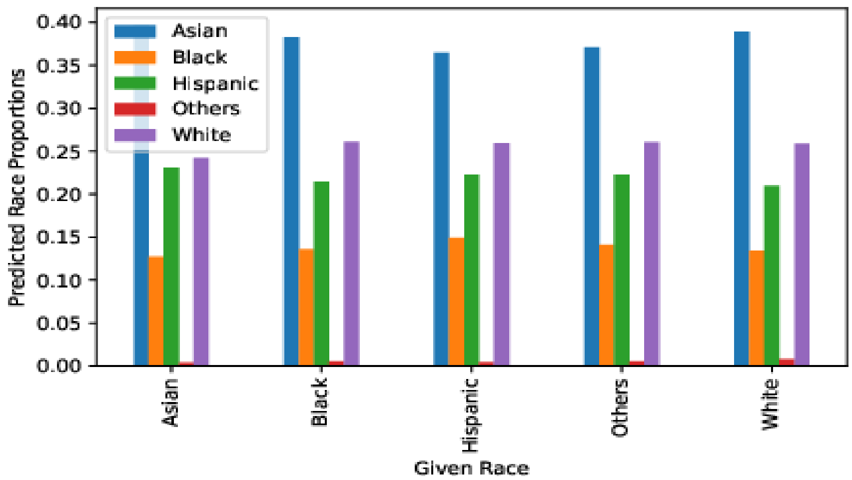
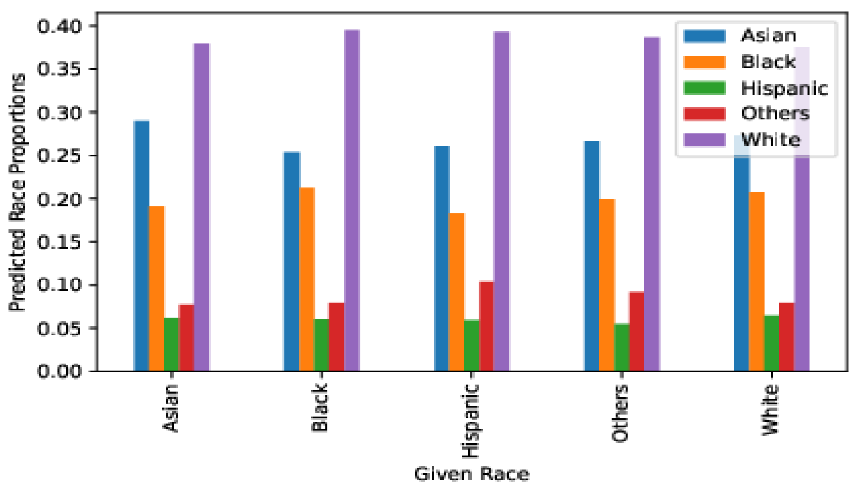


Figure 3: Distribution of Predicted Race Given Target Race by GPT-4o



The models show some clear preferences for predicting races, with GPT-4 favoring Asian and GPT-4o favoring White ethnicity, regardless of the content of the essay or the score and rubric provided. The distributions are fairly similar for each given race, which indicates that both models have certain inherent preferences for race prediction.

For an unknown reason, GPT-4 seems to predict Asian much more often than other races, with White, Hispanic, and Black following. The Others subgroup was predicted a negligible number of times. GPT-4o on the other hand prefers White followed by Asian, Black, Hispanic, and Others. GPT-4o predicts Others in a much higher proportion than GPT-4.

Score Distribution for Predicted Races

Figures 4 and 5 show the predicted race of the generated essays grouped by target score. The Given Score field in the figures refers to the scores that the models were given prior to predicting the race and generating the essays. Again as in the previous section, both GPT-4 and GPT-4o demonstrate clear preferences for race prediction. Both models predict race in the same proportions regardless of the score.

Figure 4: Distribution of Predicted Race Grouped by Scores From GPT-4

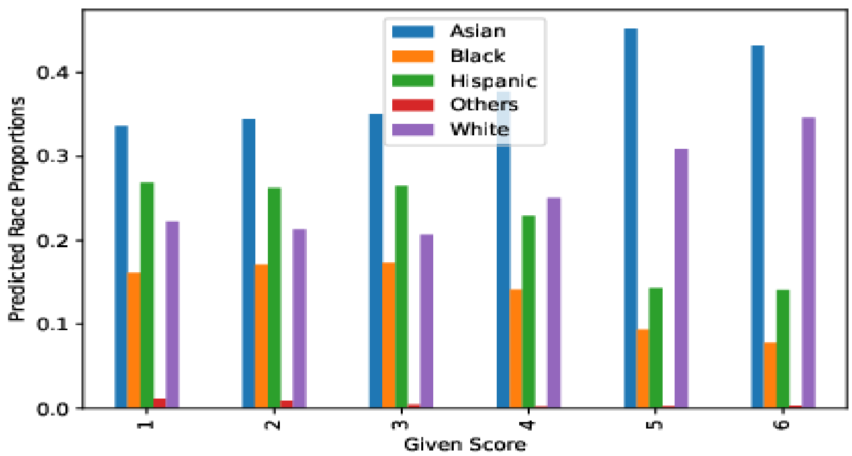
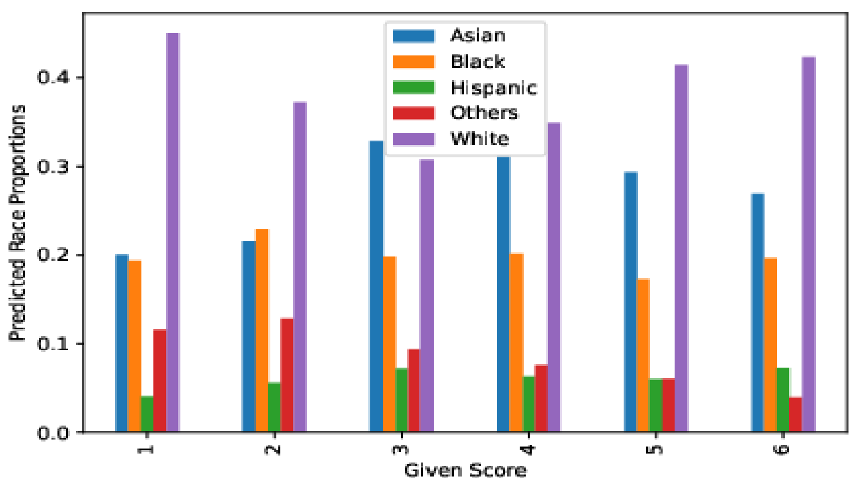


Figure 5: Distribution of Predicted Race Grouped by Scores From GPT-4o



Effect of Augmentation on Automated Essay Scoring

Table 10 contains the QWK obtained by training with and without augmentation for GPT-4 and GPT-4o for both $R = \hat{R}$ and $R \neq \hat{R}$. Except for GPT-4 $R = \hat{R}$, all the models display some appreciation in QWK. The results across subgroups vary, but GPT-4o $R \neq \hat{R}$ had the best QWK overall and across three of the six subgroups.

The results for assessing bias are given in Table 11. We note that the SMD for the model trained on original nonaugmented data was appreciable across all subgroups, with the base model (trained on nonaugmented data) giving higher mean scores to all subgroups. Augmenting the data decreases the SMD across all subgroups in all cases. GPT-4 $R \neq \hat{R}$ induces a slight negative bias. GPT-4 $R = \hat{R}$ and GPT-4o $R \neq \hat{R}$ have the lowest overall SMD.

Overall, GPT-4o $R \neq \hat{R}$ seems to perform well for both increasing the agreement and mitigating bias as measured by QWK and SMD respectively.

Table 10. Agreement as Measured by Quadratic Weighted Kappa (QWK) Across the Full Data Set and by Subgroup

	Asian	Black	Hispanic	Others	White	Overall
Nonaugmented	0.806	0.808	0.811	0.808	0.836	0.826
GPT-4 $R = \hat{R}$ a	0.827	0.799	0.804	0.823	0.838	0.826
GPT-4 $R \neq \hat{R}$	0.805	0.806	**0.814**	**0.839**	0.839	0.829
GPT-4o $R = \hat{R}$ a	**0.844**	0.816	0.807	0.805	0.828	0.825
GPT-4o $R \neq \hat{R}$	0.834	**0.825**	0.810	0.814	**0.842**	**0.833**

Note. Values in bold indicate the highest QWK value within each subgroup.

Table 11. Standardized Mean Difference (SMD) Across the Full Data Set and by Subgroup

	Asian	Black	Hispanic	Others	White	Overall
Nonaugmented	0.16	0.14	0.16	0.17	0.14	0.15
GPT-4 $R = \hat{R}$ a	**0.02**	0.03	0.05	0.05	0.03	0.03
GPT-4 $R \neq \hat{R}$	**0.02**	-0.02	**-0.02**	**-0.01**	**-0.01**	**-0.01**
GPT-4o $R = \hat{R}$ a	0.08	0.09	**0.02**	0.04	0.08	0.06
GPT-4o $R \neq \hat{R}$	0.05	**0.00**	0.02	0.06	0.05	0.03

Note. Values in bold indicate the highest quadratic weighted kappa value within each subgroup.

Discussion and Future Work

We have discussed here a preliminary study into targeted generation of student essays for AES for mitigating subgroup bias in AES. Our findings reveal that LLMs struggle to internalize the real-world demographic distribution when generating synthetic essays, but the data still improve model performance and help in bias mitigation. We believe that LLMs have a role to play in AES, but greater controllability in generation and lack of explainability pose significant hurdles. For instance, why exactly has the QWK improved and the SMD decreased? Further investigation is needed to determine which properties of the generated text caused these effects.

Several related avenues of research are possible for work in the future. Better alignment of generated text with human interpretable features would be massively advantageous in understanding and trusting such data. Future work can also focus on examining which textual cues in given examples to an LLM, or in the prompt, lead to a particular generated text for a particular subgroup of interest. We have also left for future work the study of bias, which may be induced in the generated data, and how it may affect the AES system. In addition, we developed our prompt iteratively and did not perform a longitudinal study over its design and constituents—the altering of which may yield different outcomes.

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Notes

[1]To distinguish between the two meanings of prompt, one as a directive for human essay writing and the other as input to an LLM, we have used the term topical prompt to refer to the former.

[2]https://www.kaggle.com/competitions/learning-agency-lab-automated-essay-scoring-2

[3]We should note that we have found better methods for more reliable generation since, but those methods were not used in this work.

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