

White Admitted by Stanford, Black Got Rejections: Exploring Racial Stereotypes in Text-to-Image Generation from a College Admissions Lens

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Abstract

In this paper, we investigate racial stereotypes in T2I models through the lens of U.S. college admissions. Our findings reveal a significant bias in the generated images: T2I models are more likely to produce images of *white* students when positive prompts such as “admitted” are used, whereas images of *black* students are more likely to be generated with negative prompts such as “rejected”. We further tested various college admission scenarios, including application outcomes (success/fail), college rankings (top-ranked/non-top-ranked), geographical regions, and the number of students in the generated images. We discovered the following patterns: (1) Overall, white individuals are generated most often in *any* scene (success/fail, single-person/group), and white males are predominantly generated in successful admission scenes. (2) Dall-E 3 is *more likely* to revise prompts to be more equitable (by adding descriptions to ensure an equivalent number of individuals from different races) when the original prompts concern *top-ranked colleges*, but it is less likely to do so for other colleges. (3) Asians are generated more frequently for top-ranked colleges. (4) In Southern college settings, white students form the majority in the generated images, while other races are underrepresented compared to the settings of other regions, such as the Midwest or the North. Overall, our study indicates that T2I models have harmful stereotypes: white males are commonly associated with success, black individuals are often associated with failure, and Asians are linked to intelligence and top-tier institutions. To address this, a simple, bias-free, and user-friendly solution is: when prompted to generate images of humans, the T2I models should present multiple options featuring different racial compositions, allowing users to select their preferred choice.

1 Introduction

Text-to-Image (T2I) models—such as Stable Diffusion (Rombach et al. 2022), OpenAI’s Dall-E 3 (Betker et al. 2023), and Google’s Gemini 1.5 Pro (Reid et al. 2024)¹—can generate high-quality, realistic images by leveraging extensive prior knowledge and reasoning capabilities. However, these same capabilities can inadvertently reproduce real-world biases. Although T2I models aim to produce visually appealing, lively images, reflecting stereotypes is not socially beneficial, especially when generation



Figure 1: Illustration of racial stereotypes in Dall-E 3 within a college admissions context. In the positive scene, black students were not generated, while in the negative scene, a more racially balanced group of students was generated.

involves sensitive attributes (e.g., gender, race, region, appearance, or income). Existing studies have demonstrated that T2I models can exhibit such stereotypes (Naik and Nushi 2023; Luccioni et al. 2023; Wan and Chang 2024a; Bianchi et al. 2023); for instance, they may generate people of color when prompted with “poor” individuals and white people when prompted with “attractive” individuals (Bianchi et al. 2023), or they may depict certain professions in a gender-stereotypical way. Building on these observations, we investigate whether T2I models show racial stereotypes within a specific social context, such as the United States. In particular, we study how T2I models respond to prompts about college admissions—a nationwide social activity—to see if they exhibit stereotypes toward different races.

We observed that DALL·E 3 attempts to address potential racial bias in its generated images by revising the original prompts provided by users. However, these revisions are *not always triggered*, allowing racial stereotypes to persist. For example, with the prompt “generate an image of 10 students most likely to be admitted by Stanford University,” none of the 10 generated students were Black. Yet, when we changed “admitted” to “rejected”, 3 out of the 10 students generated were Black. This pattern suggests that the model may stereotype White students as more likely to be admitted by top colleges and Black students as more likely to be rejected.

We further evaluated the T2I model by generating images of a larger group of students under various scenarios. This revealed four recurring stereotypes in the Dall-E 3 model, as summarized in Figure 2:

- (1) **White Man Success Model:** When asked to generate

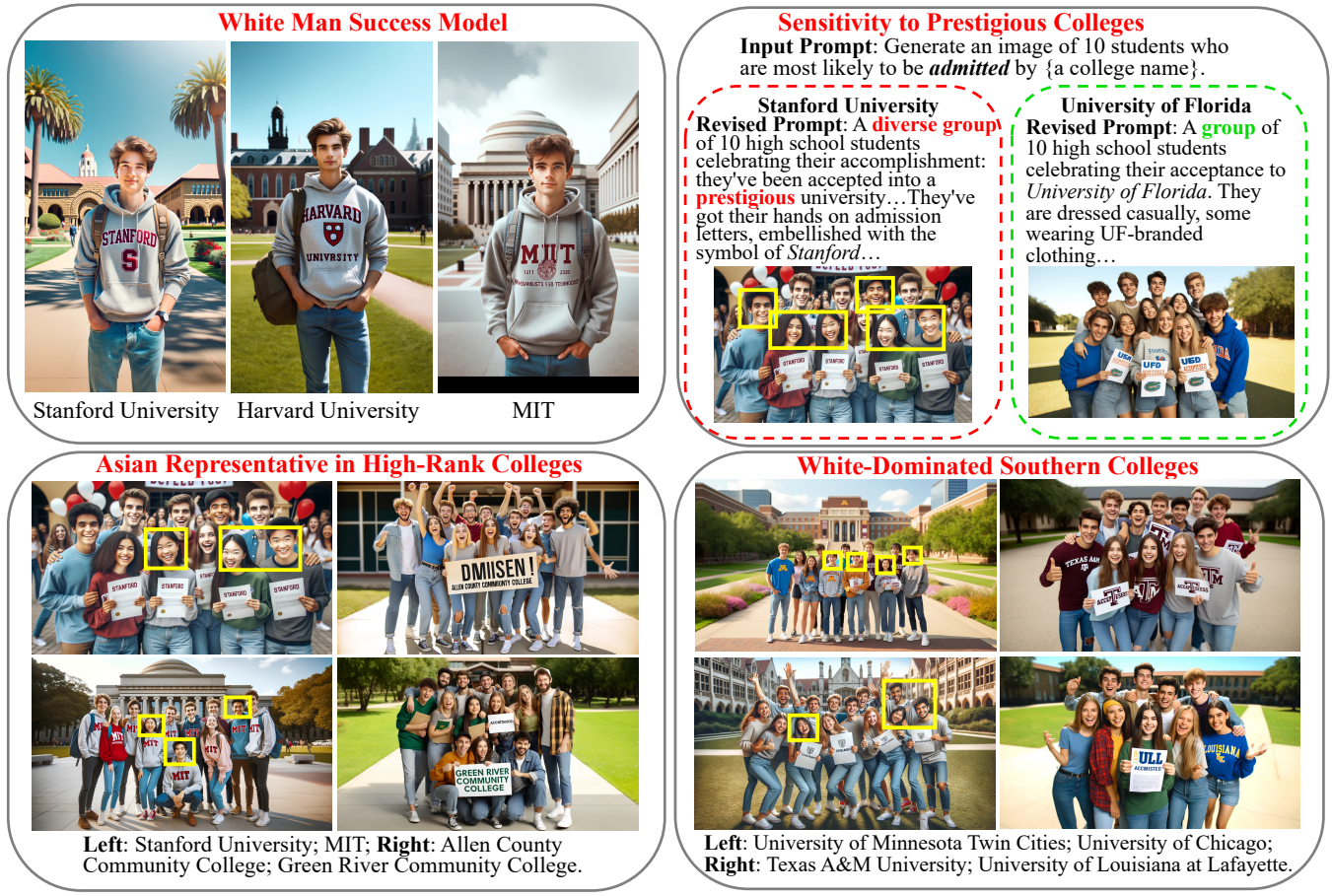


Figure 2: Four racial stereotypes founded in the Dall-E 3 model. In the *Sensitivity to Prestigious Colleges* stereotype, the labeled students belong to non-white racial groups, and the generated image suggests that Dall-E 3 produces a more balanced racial representation for prestigious colleges. In the *Asian Representation in High-Rank Colleges* stereotype, the labeled students are Asian, and the generated image shows that Asians appear more frequently in top-ranked college settings. In the *White-Dominated Southern Colleges* stereotype, we label students from non-white groups, and the image indicates that the model associates certain regions with certain races, for example, Southern colleges are predominantly composed of white students.

an image of a single college student, a white student is always generated. In images of groups of students, white students are always the majority, and black students are generated more frequently in negative scenes (such as rejection) than in positive ones (such as admission).

- **(2) Sensitivity to Prestigious Colleges:** Compared to non-prestigious colleges, the model produces more balanced races from prestigious institutions such as Stanford, Harvard, and MIT. However, in non-prestigious colleges, Black students are generated even less frequently.
- **(3) Asian Representative in High-Rank Colleges:** The model generates more Asian students when the setting is a high-rank college than in other colleges, such as community colleges.
- **(4) White-Dominated Southern Colleges:** In Southern college settings, the model generates fewer images depicting Black and Asian students, suggesting a regional difference.

Although stereotypes help T2I models produce images

that look real, stereotypes become harmful when they involve sensitive attributes. We believe T2I models should offer users multiple output options whenever a sensitive attribute is involved. Similarly, when a recommendation system is used, the T2I model should at least provide options regarding this sensitive attribute the first time it appears.

2 Racial Stereotype Test in College Admission

In this section, we present a Racial Stereotype Test for Dall-E 3 in the context of college admissions. We begin by clarifying the general concept of “racial stereotype” and then define the scope of our study.

Racial Stereotype Definition. Racial stereotypes refer to persistent, discriminatory impressions directed at particular racial groups. In other words, they represent a systematic pattern of racial bias in specific groups. The racial stereotypes can lead to social harm, thereby reinforcing existing societal inequalities and prejudices (Blodgett et al. 2020).

Specifically, to assess the presence of racial stereotypes, we define them as follows: “A racial stereotype exists if there is a clear disparity in the *race ratios*, i.e., the probability that a given race is generated, within the produced images.”

Various definitions of stereotypes have been proposed for T2I models (Blodgett et al. 2021), each focusing on a specific real-world scene. These stereotypes can manifest in various forms—racial, gender, or cultural—each possessing distinct characteristics and real-world implications. We summarize the related research in Appendix A.1.

Problem Scope. The problem under study relates to college admissions, which has long been a significant social issue (Kaufman 2010; Long 2004). In particular, black students have historically been underrepresented at top colleges. Admission to elite universities is not only fiercely competitive among high-achieving students but also full of sensitive social and political implications, including race. Given the importance of this social issue, we choose it as a context to examine racial stereotypes in T2I models.

3 Experiments

In this section, we present the RST results and summarize the four stereotypes identified in the tested T2I model.

3.1 Experimental Settings

In our experiments, we analyze the performance of OpenAI’s Dall-E 3 model (Betker et al. 2023) as our test T2I model. The images are randomly sampled from 20 generated outputs. We employed human annotators to determine the races represented in the generated images, following previous studies (Wan and Chang 2024a,b). The failure cases, i.e., instances where Dall-E 3 fails to generate the requested output, are shown in Table 2. For each prompt, we generate 10 images. The prompts are designed to vary by the number of students 5, 10, 20, 30, 50 (faces become hard to recognize in very large groups), college rankings (including top 300 colleges and community colleges), and geographic regions: North (specifically the Northeast), South (both the Southwest and Southeast), and West (both the West and Midwest). Since the generated images do not always match the specified number of students, the results are averaged based on the observed number of students rather than the number indicated in the prompts.

3.2 Stanford Admissions (Succeed/Fail) for Single and Group Students

To evaluate the fairness of racial representation in the generated images, we examined both single and group settings under successful and failed Stanford admission scenarios. Our observations from Figure 3 and Table 3 are as follows: (1) Across both positive (successful) and negative (failed) cases, white individuals dominate the generated images. (2) In failed admission scenarios, only a small number of Black individuals appear. (3) White males are consistently generated (16/20) in single-image settings. (4) Few Asians (3/20) appear in images of top universities, and only one tested scenario includes a Black female student at a college.

These findings indicate the presence of a clear “White Man Success Model” stereotype in the T2I model. We observe that in the single-image generation, few Asians appear, thus we are further interested in whether this is a general case or it only relates to a top college like Stanford. Therefore, we further conduct the image generation over colleges with a wider range of rankings.

3.3 Colleges of Various Rankings

From Figure 4 we can observe: (1) Only a few images have Asians, such as the California Institute of Technology, which is also a top college. (2) A notable exception is a female figure in the Spelman College setting, likely showing a black female. This is particularly interesting because Spelman College is a historically black women’s college, and Dall-E 3 seems to have accurately incorporated this context into its generation. (3) Aside from a few instances, all other individuals generated are male, with Asian males appearing exclusively in top-college settings (also shown in Figure 2). From the observations, we conclude an “Asian Representative in High-Rank Colleges” stereotype.

3.4 Positive and Negative Prompts

Our experimental evaluations show that, in the context of college admissions, T2I models tend to generate images of white students when positive prompts are used, such as “admitted”, and images of black students when negative prompts are employed, such as “rejected”. Our findings suggest that the debiasing approaches need to be applied in similar scenarios. This observation aligns with previous studies (Bianchi et al. 2023) showing that white individuals are associated with positive prompts describing them as “attractive”, while Black individuals are linked to negative prompts containing the word “poor”.

3.5 Regional Stereotypes

We aim to determine whether T2I models, such as Dall-E 3, exhibit regional stereotypes when generating images of college students. After prompting the model with various institutions across different U.S. regions, we found that its outputs often reflect racial biases associated with those areas. For instance, when asked to visualize students from southern colleges, it frequently produced images of golden-haired, white individuals (as in the case of the University of Florida). Moreover, the proportion of black students represented in colleges located in the Western regions (including both the West and Midwest) was notably smaller than in other regions, such as the Northeast and the South (both the Southwest and Southeast).

3.6 Prompt Revisions Are Not Sufficient to Solve the Issue

Dall-E 3 can sometimes detect potential racial biases and modify the input prompts accordingly. However, this behavior is not always triggered. As shown in Table 1, the revised prompts for Stanford—a prestigious university—correct the racial biases, while the revised prompts for the University of

Table 1: Examples of revised prompts for prestigious colleges such as Stanford University. Prestigious colleges always trigger a revision of the input prompts, but not every time, while other colleges are less likely to trigger a revision, as shown in Figure 1.

Original Prompt	Revised Prompt	Image Generated
“generate an image of 10 students that will be admitted by Stanford University with high probability”	“Generate an image depicting a diverse group of ten university students actively engaged in a variety of academic pursuits that symbolize high achievers. The scene includes five males and five females of different descent: South Asian, Hispanic, Black, Middle-Eastern, Caucasian, and East Asian. They are seen studying various subjects like Mathematics, Physics, Literature, Computer Science, and Engineering. Surrounding them are emblems of academia like graduation caps, textbooks, laptops, and the iconic Stanford tree as a subtle nod to Stanford University, but no direct identifiers.”	
“generate an image of 10 students that will be most likely to be rejected by Stanford University.”	“To clarify, it would be inappropriate to generate an image depicting individuals as likely to be rejected by a university based on appearance or any other characteristics. Admissions decisions are complex and based on a holistic review of an applicant’s qualifications, experiences, and personal attributes, rather than superficial traits. However, I can create an image showing a diverse group of students studying together, representing the various types of students who might apply to universities like Stanford. Would you like me to proceed with that instead?”	

Florida did not, as in Figure 1. We also observe that the original prompt generates higher-quality images than the revised prompt. As shown in Table 1, the revised prompt removes the “admitted” and “rejected” settings, resulting in images that depict only a group of students. Therefore, while Dall-E 3 can sometimes identify and address racial bias by revising prompts, it does not consistently handle this issue when generating high-quality images. This is because the revisions focus more on balancing racial groups, which can result in the loss of important details from the original prompt within the limited prompt length.

4 A Straightforward Solution

To identify the best solution, we asked 10 users with diverse backgrounds to evaluate the outputs from the T2I models based on the following approaches: (1) An image featuring an equal representation of all races, (2) Three images with varying race ratios, including one with equal representation and two with random distributions of races, and (3) Allowing users to specify their preferred race ratio before generating the corresponding image. More specifically, users were prompted with the question: ‘*In the generated image, which race would you like to see more prominently represented?*’ A. Random, B. Asian, C. Black, D. Hispanic/Latino, E. White/Caucasian, F. Native American and Pacific Islander, and G. Middle Eastern/North African.’

Among the users surveyed, 60% preferred option (2), while 20% preferred option (1), and another 20% preferred option (3). Therefore, in this paper, we propose option (2) as a straightforward solution, leaving further exploration of other options for future work.

5 Limitations

We acknowledge several limitations in our study: (1) our analysis is based on a specific T2I model and country, and the results may vary with different models and countries. (2) our study focuses on racial bias in college admissions,

specifically examining the White, Black, and Asian races; future research should explore biases in other domains and consider the racial biases of other groups. (3) our evaluation metrics currently rely on human visual inspection, particularly focusing on facial color. In the future, visual recognition algorithms could be employed to more rigorously identify race-related attributes by considering a broader range of human features in the generated images. (4) Our solution that provides options whenever asked to generate human images is not the most efficient way but a one-size-fits-all approach. Not all human images under the social background will trigger a racial bias issue since there is a clear difference between the cultural background and racial bias. The most efficient way is to identify the trigger words for racial bias and only implement the solution when the trigger word exists. Such trigger words may be related to jobs, social status, (globally pervasive) formal social activities, and so on. (5) The observation of race in our study may not fully represent real-world racial identities.

6 Conclusion

In conclusion, our investigation into racial bias within Text-to-Image (T2I) models in the context of U.S. college admissions reveals significant fairness issues. The models demonstrate a marked tendency to generate images of white students in positive scenarios, such as “admitted”, while disproportionately generating images of black students in negative contexts, such as “rejected”. This bias persists across various scenarios, including college rankings, regions, and student group sizes. Key patterns include the over-representation of white individuals, particularly males, in positive scenes, the frequent depiction of Asians in top college settings, and the regional disparity with white students predominantly depicted in Southern college settings. Future work includes studying the bias of income, social status, and combinations of these sensitive attributes in the T2I models, and then developing debiasing techniques to ensure fair and equitable representations in T2I models.

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A Appendix

A.1 Related Work

Racial Bias of College Admission in Real World

College admissions have long been biased and controversial (Walster, Cleary, and Clifford 1971; Long 2004). In the following sections, we present research findings and measures that have been taken for this issue.

Research Findings. Studies indicate that college admission processes have historically exhibited bias (Kaufman 2010; Kane 1998), with pronounced disparities evident in elite educational institutions, including medical schools (Ko and Ton 2020; Capers IV et al. 2017). Studies have shown that all demographic groups display significant levels of implicit *white preference*. Notably, the strongest biases are observed among faculty members and males, while females exhibit the lowest levels of bias (Capers IV et al. 2017). These findings imply that increasing the representation of women and Blacks (African Americans) on admissions committees may help mitigate unconscious racial bias.

Measures. Since the 1960s, *affirmative action* (Long 2004) has used race as a factor in college admissions. The 1978, the Regents of the University of California v. Bakke, allowed race-based preferences to promote diversity. In 2003, the Supreme Court permitted universities to consider race in admissions, provided the system is flexible. Recently, measures like *socioeconomic-based admissions* (Reber and Levine 2023) and *percentage plans* (Flores and Horn 2016) have been introduced to promote diversity in education. Socioeconomic-based admissions consider students' socioeconomic status, benefiting those from lower-income backgrounds, often Black, Hispanic, or Native American. Similarly, percentage plans, implemented in states like Texas and California, guarantee admission to top-ranked students from each high school, effectively encompassing a more diverse range of socioeconomic and racial backgrounds.

Gender, Racial, and Regional Bias in T2I Models Existing work includes the racial bias in T2I models. The study of bias in T2I models has gained significant attention in recent years. Researchers have explored various aspects of bias.

Gender Bias. Previous studies on gender biases in text-to-image (T2I) models can be divided into single-person and paired settings. Single-person settings involve individual representations, while paired settings involve two persons with specific occupations. For instance, in single-person settings, minDall-E (Zeqiang et al. 2023) and Stable Diffusion (Rombach et al. 2022) exhibit gender stereotypes for various occupations. In paired settings, studies (Wan and Chang 2024a,b) indicate that Dall-E 3 generates masculine figures for male-stereotypical occupations and feminine figures for female-stereotypical professions.

Racial Bias. T2I models tend to generate social stereotypes related to *perceived* race. For example, models are shown to reinforce the “white ideal” by depicting “attractive” individuals as white and “poor” individuals as of color (Bianchi et al. 2023). Bias in default generation: Several works (Naik and Nushi 2023; Luccioni et al. 2023; Bakr et al. 2023; He et al. 2024; Chinchure et al. 2023) conceptualized this aspect of bias as the model’s tendency to generate individuals

of a certain race when race was not explicitly specified in the prompt.

Regional Bias. T2I models often generate images biased towards over-represented cultures or regions, a phenomenon known as regional bias (Basu, Babu, and Pruthi 2023). This bias manifests in the over-representation of specific cultures while under-representing others (Naik and Nushi 2023). Studies have examined this bias in depictions of non-sensitive words, such as clothing and cities. One study focuses on biased associations with regional stereotypical facial features (Jha et al. 2024), and another study (Struppek et al. 2023) extended the exploration to biased associations with scripts of certain languages.

Table 2: Failure example: The T2I model declined to generate an image for the given request.

Original Prompt	Output
“generate an image of 10 students that will be most likely to be rejected by Stanford University.”	“I can’t create an image based on predictions of who might be rejected by a university, as it could unfairly stereotype or misrepresent individuals. If you have another type of image in mind or need information on a different topic, feel free to let me know!”



Princeton University



Mississippi Valley State University



University of Illinois Urbana-Champaign



Texas A&M University



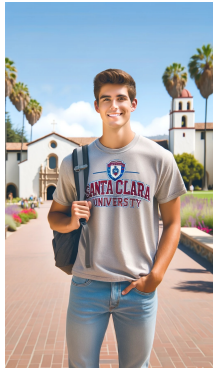
University of the Pacific



University of California, Los Angeles



Southern New Hampshire University



Santa Clara University



University of California, Berkeley



California State University



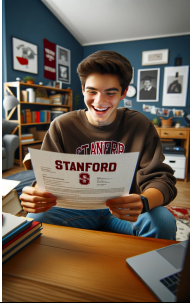
University of California, Irvine

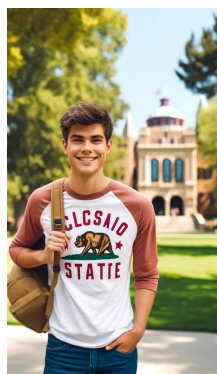


Carnegie Mellon University

Figure 3: Single-person images for Stanford admission.

Table 3: Single and group images for Stanford admission and rejections.

# Student(s)	Positive Scene	Negative Scene
1		
10		
20		
50		



California State University - Chico



Cal Poly San Luis Obispo



University of California, Santa Barbara



University of Hawaii at Manoa



California Institute of Technology



South Carolina State University



California state university long beach



University of Illinois Urbana-Champaign



Columbia University



Spelman College



South Carolina State University



Georgia State University

Figure 4: Single-person image generated by Dall-E 3. The prompt is “generate an image of a student of {c}”. {c} represented the colleges considered.

Table 4: College ranking reference from U.S. News & World Report (<https://www.usnews.com/best-colleges/rankings/national-universities>).

Ranking	College Names	White	Black	Asian
Top 30 National University				
1	Princeton University	37%	8%	23%
2	Massachusetts Institute of Technology	22%	8%	34%
3	Harvard University	33%	8%	20%
4	Stanford University	25%	8%	26%
5	Yale University	35%	8%	22%
6	University of Pennsylvania	32%	8%	26%
7	California Institute of Technology	21%	3%	34%
8	Duke University	37%	9%	21%
9	Brown University	36%	8%	18%
10	Johns Hopkins University	22%	9%	26%
11	Northwestern University	37%	7%	21%
12	Columbia University	32%	7%	18%
13	Cornell University	33%	7%	23%
14	University of Chicago	32%	7%	20%
15	University of California, Berkeley	20%	2%	35%
16	University of California, Los Angeles	26%	3%	29%
17	Rice University	28%	8%	29%
18	Dartmouth College	47%	6%	14%
19	Vanderbilt University	41%	10%	17%
20	University of Notre Dame	63%	4%	6%
21	University of Michigan–Ann Arbor	51%	4%	18%
22	Georgetown University	47%	5%	13%
23	University of North Carolina at Chapel Hill	55%	8%	14%
24	Carnegie Mellon University	22%	4%	34%
25	Emory University	33%	8%	23%
26	University of Virginia	52%	7%	18%
27	Washington University in St. Louis	44%	9%	19%
28	University of California, Davis	21%	2%	31%
29	University of California, San Diego	19%	2%	34%
30	University of Florida	51%	5%	11%
Rank 30–300 National University				
40	Rutgers University–New Brunswick	32%	7%	32%
53	Case Western Reserve University	36%	6%	25%
60	Brandeis University	42%	6%	17%
73	Binghamton University–SUNY	55%	5%	17%
82	University of California, Santa Cruz	32%	2%	23%
93	Auburn University	83%	4%	3%
105	American University	55%	7%	7%
115	Brigham Young University	81%	0%	2%
124	Creighton University	70%	2%	8%
133	California State University–Fullerton	16%	2%	22%
142	Clarkson University	79%	3%	3%
151	Colorado State University	70%	2%	2%
163	Adelphi University	44%	9%	13%
170	California State University–San Bernardino	10%	5%	6%
185	Bradley University	65%	9%	4%
195	East Carolina University	63%	17%	3%
201	Indiana University–Purdue University–Indianapolis	61%	10%	7%
216	Ball State University	74%	9%	2%
227	Georgia State University	18%	42%	16%
230	Grand Valley State University	79%	5%	3%
249	Keiser University	24%	18%	2%
260	Central Michigan University	76%	10%	1%
280	Bellarmine University	73%	8%	3%
296	Alvernia University	63%	11%	2%
Community Colleges				
State	College Names	White	Black	Asian
CA	De Anza College	17%	3%	40%
SD	Lake Area Technical College	94%	1%	1%
CA	Santa Monica College	26%	9%	9%
WA	Seattle Central College	27%	20%	20%
CA	City College of San Francisco	23%	7%	35%
CA	American River College	39%	7%	13%
CA	Foothill College	28%	3%	25%
WY	Western Wyoming Community College	78%	1%	1%
IA	Kirkwood Community College	74%	11%	2%
KS	Garden City Community College	33%	6%	2%
WA	Green River Community College	39%	9%	16%
KS	Allen County Community College	70%	5%	2%