<https://www.diverseeducation.com/reports-data/article/15679597/algorithmic-bias-continues-to-impact-minoritized-students>

This article discusses how machine learning imitates typical college algorithms, resulting in them being biased when it comes to Black or Latino students. These algorithms predicted false negatives for 19% of black students and 21% of Latino students. These percentages surrounded the algorithms’ goal of finding whether these students would fail out of college or not. A recent study detected that these models perform better for White and Asian students. This is very problematic since “Institutions use algorithms to predict college success, admissions, allocation for financial aid, inclusion in student success programs, recruitment, and many more tasks.”

“Campus climate, family support, distance from home, and other factors that can affect students’ behavior might be missed in the model. It becomes biased.”

"it is important to consider how models are biased against other historically underserved groups in higher education, like students with disabilities, women in STEM, and students from rural backgrounds.”

Anahideh and Gándara agreed that the workload of administrators and even faculty are greatly eased by algorithms and AI, which can analyze millions of datapoints in milliseconds, saving work, time and resources. It’s a powerful tool and can help make decisions, said Anahideh, “if you have a model that’s fair and accurate enough.”

Omitted variable bias: from leaving some factors out of the equation.

Measurement bias: Some pieces of data could be unnecessary or necessary for some groups.

Direct statistical discrimination

Ethical ramifications: Many people of non-white or Asian backgrounds may not have a chance to be accepted to their rightful college of choice. If a machine learning program were to do this, many lives would be hindered.

**How Biased Data and Algorithms Can Harm Health**

<https://magazine.publichealth.jhu.edu/2022/how-biased-data-and-algorithms-can-harm-health>

The rapid expansion of data in medicine offers both opportunities and risks. Ferryman cautions that automated data, from genetic sequencing to fitness trackers, often appears unbiased because it is machine-collected, but it still reflects human biases. A study on AI’s ability to detect race from chest X-rays—despite race being theoretically unidentifiable from these images—demonstrates how hidden biases can permeate algorithms. This unintentional bias may lead to health disparities, particularly through misdiagnosis among minority groups, underlining the need for continuous auditing and skepticism in AI’s fairness.

Knee pain from osteoarthritis affects 16% of adults worldwide, according to a recent [eClinicalMedicine study](https://www.thelancet.com/journals/eclinm/article/PIIS2589-5370(20)30331-X/fulltext" \o "(opens in a new window)" \t "_blank), but doctors still aren’t good with predicting a person’s pain levels based on X-rays, MRIs, and other imaging data. Researchers trained early algorithms on thousands of X-rays and physician notes. After months of work, the algorithm was able to predict patient-reported pain from X-rays—but only for white patients.

For people of color, AI didn’t perform any better than random chance.

Decisions made by researchers can explain how an equation used to predict kidney function from common laboratory values led to unintentionally racist outcomes. Scientists believed that people of African descent had more muscle mass than those with European ancestry. Since muscle mass is a key variable in estimating kidney function from creatinine levels in the blood, scientists introduced a “race corrector” into the equation.

The problem is that even with the most advanced computing systems, humans are still involved. We decide how health data is collected. We write the code.

Measurement bias: we choose how to view data we collect and make assumptions based on that

Omitted variable bias: things like muscle mass were left out of the equation.

Indirect statistical discrimination

Ethical ramifications: those who were not the target for data may not get the sufficient treatment they need, leading to harsher health problems.