Fair and Ethical Admissions: Mitigating Bias with Data-Driven Solutions

A Case of iLink University

Team- “**Data Ninjas”**
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Problem Overview

Challenge

- Biases in historical admissions data
- Preferences for legacy admissions
- Disparities related to demographic factors like gender and cultural identity

Impact

- Perpetuates unfairness
- Leads to an underrepresentation of certain demographic groups
- Undermines diversity within the M.S. in Analytics program

Goal

- Develop a data-driven, ethical admissions process
- Mitigate bias and promote fairness
- Ensure evaluation of all applicants based on their true potential

Data Discovery (EDA)

Dataset Overview

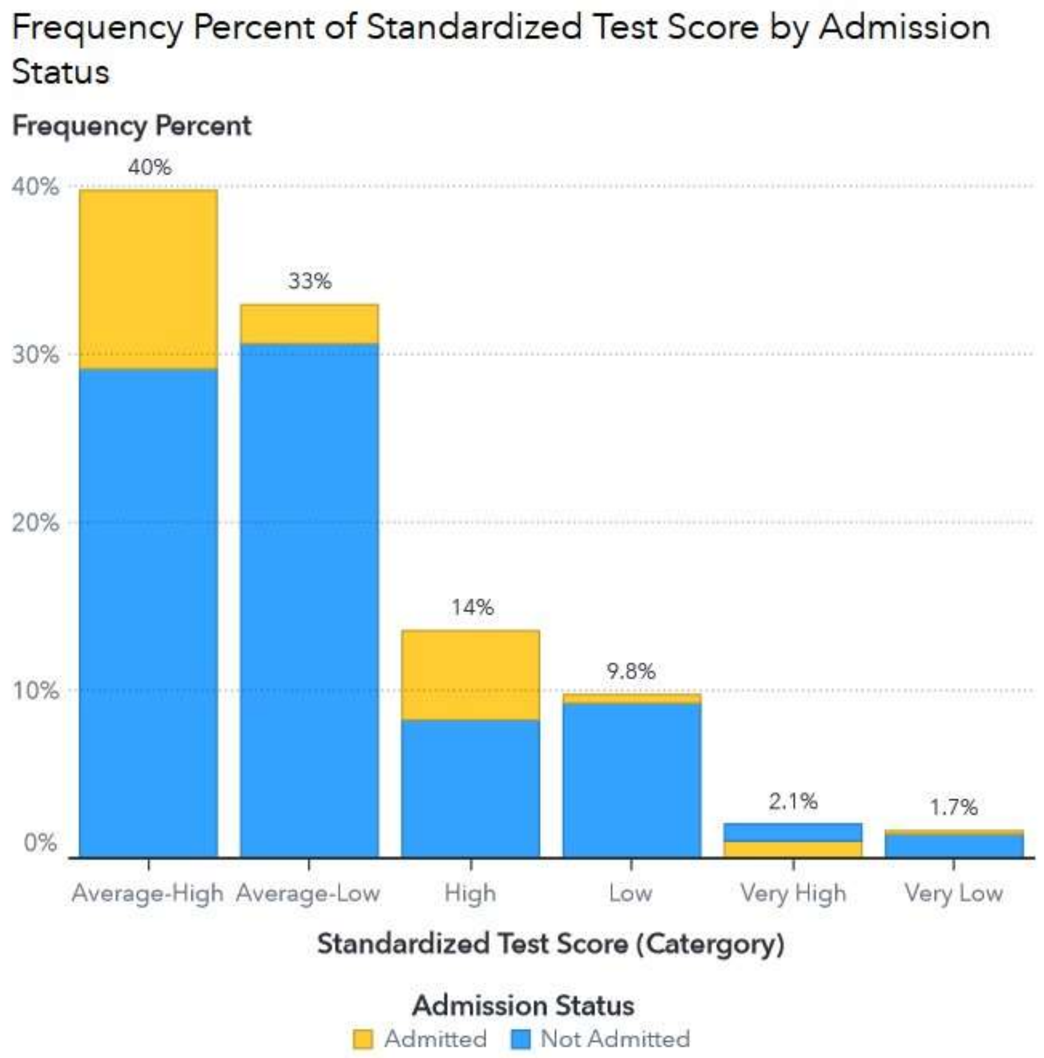
- **Dataset Size**: 1,000 applicants
- **Target Variable**: Admitted (Yes = 1, No = 0)
- **Admission Breakdown**: 80% not admitted, 20% admitted

Feature Engineering Applied to

- **Test Scores:** Categorized into 'Low,' 'Average,' 'High'
- **Work Experience, Recommendations**

Key Findings

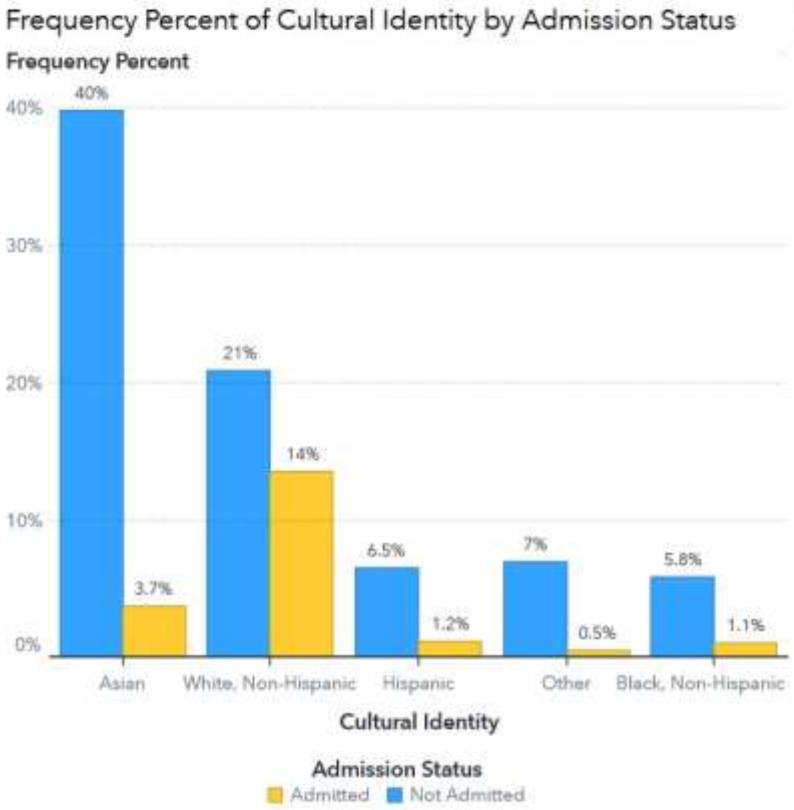
- **High Test Scores:** 52% admission rate
- **Weak Recommendations:** Only 2.5% admission rate

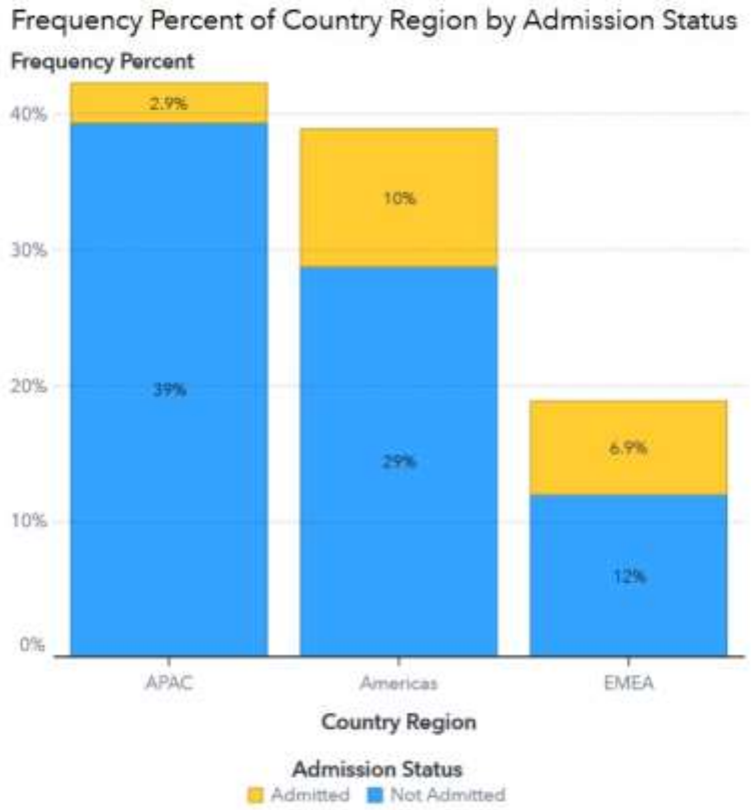


Data Discovery (EDA)

Bias Indications:

- **Cultural Bias**: White, Non-Hispanic admitted at 14%, Asians at 3.7%.
- **Regional Bias**: Americas 10%, APAC 2.9%, EMEA 6.9%.
- **Underrepresentation**: Black and Hispanic rates lower than White, Non-Hispanic.

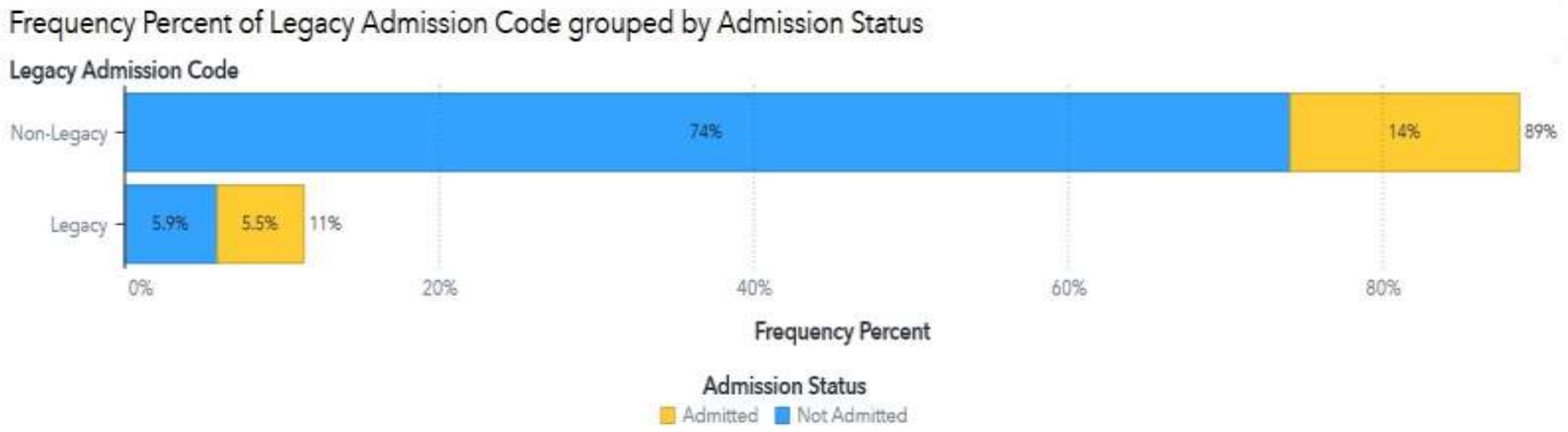


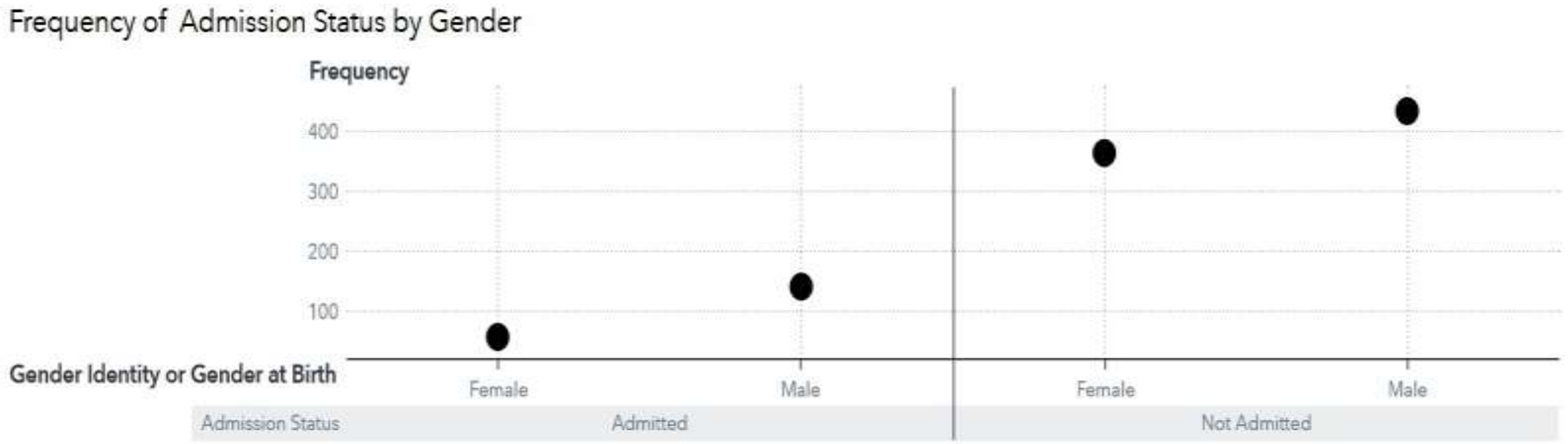


Data Discovery (EDA)

Bias Indications:

- **Legacy Bias:** Legacy admitted at 48%, non-legacy at 16%.
- **Gender Bias:** Males admitted more often than females.
- **Rejection Rates:** Non-legacy 74%, legacy 52%.

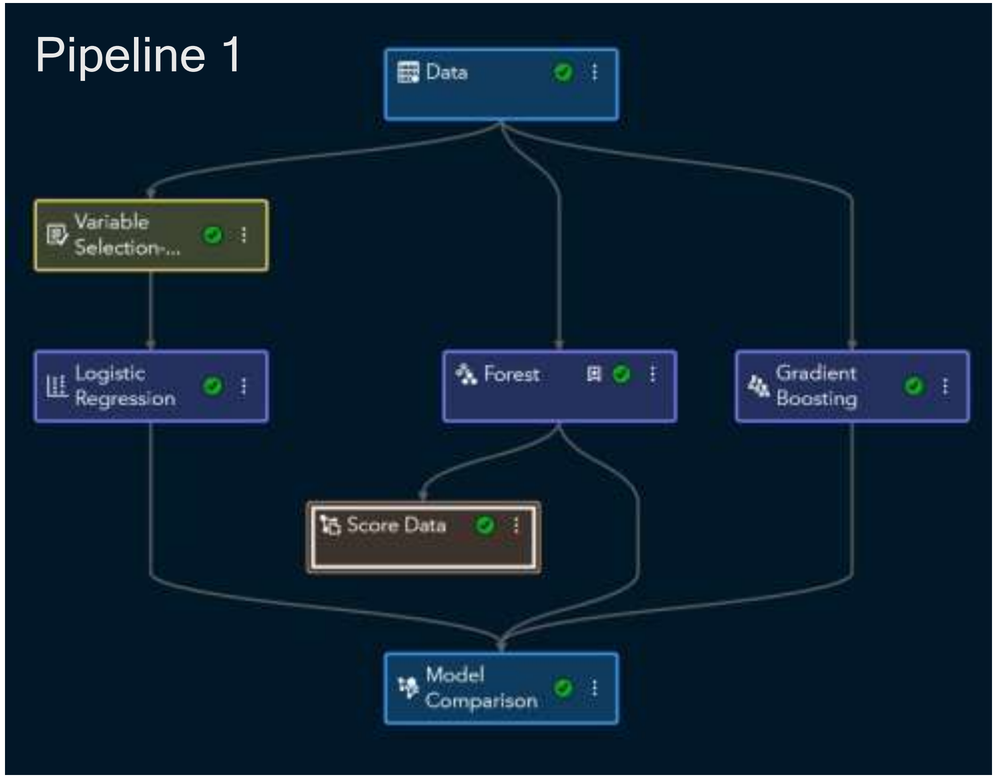


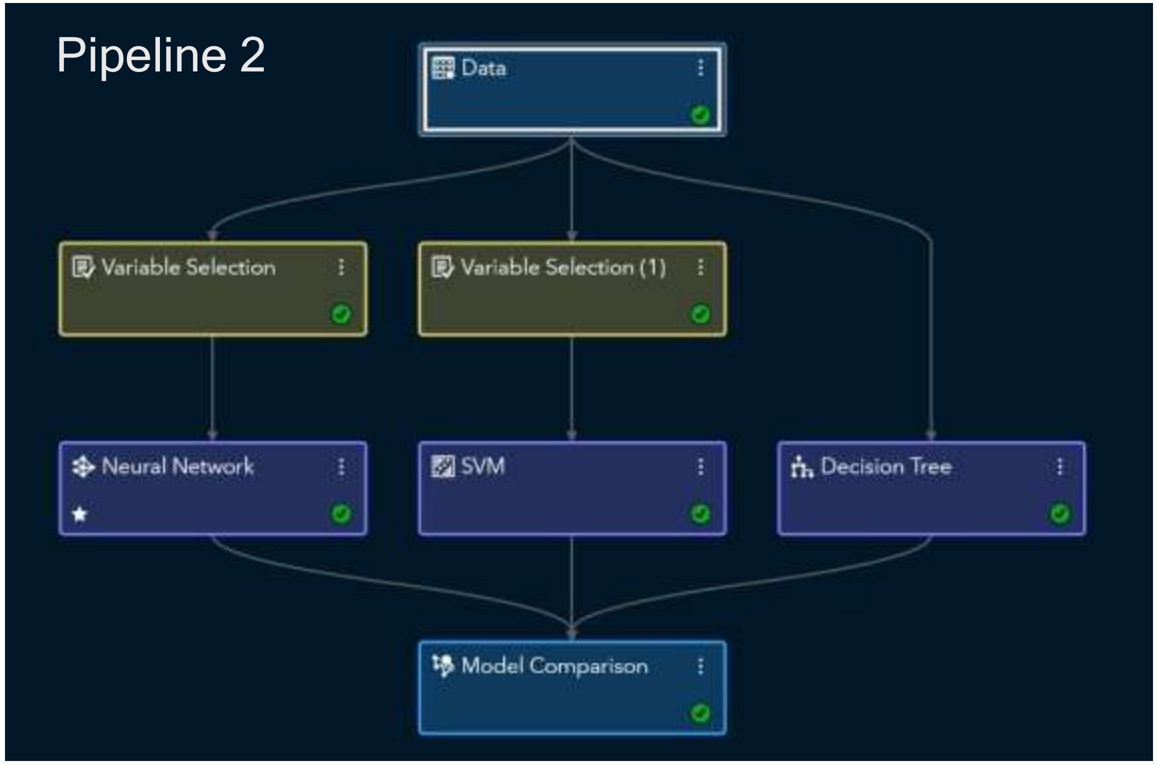


Initial Model Building

Model Strategies and Pipeline Design

- **Pipeline 1**: Logistic Regression, Forest, Gradient Boosting.
- **Pipeline 2**: SVM (RBF kernel), Neural Networks, Decision Trees.
- **Variable Selection**: Applied to Logistic Regression, SVM, and Neural Networks to optimize performance.
- **Exclusion** of Mission Statement: Omitted due to subjectivity and missing data.





The Champion Model

Forest Model: Outperformed others with high accuracy, KS, and AUC.

Class Imbalance: 20% admitted; adjusted by sorting predictions by probability to meet the target of 40 students.

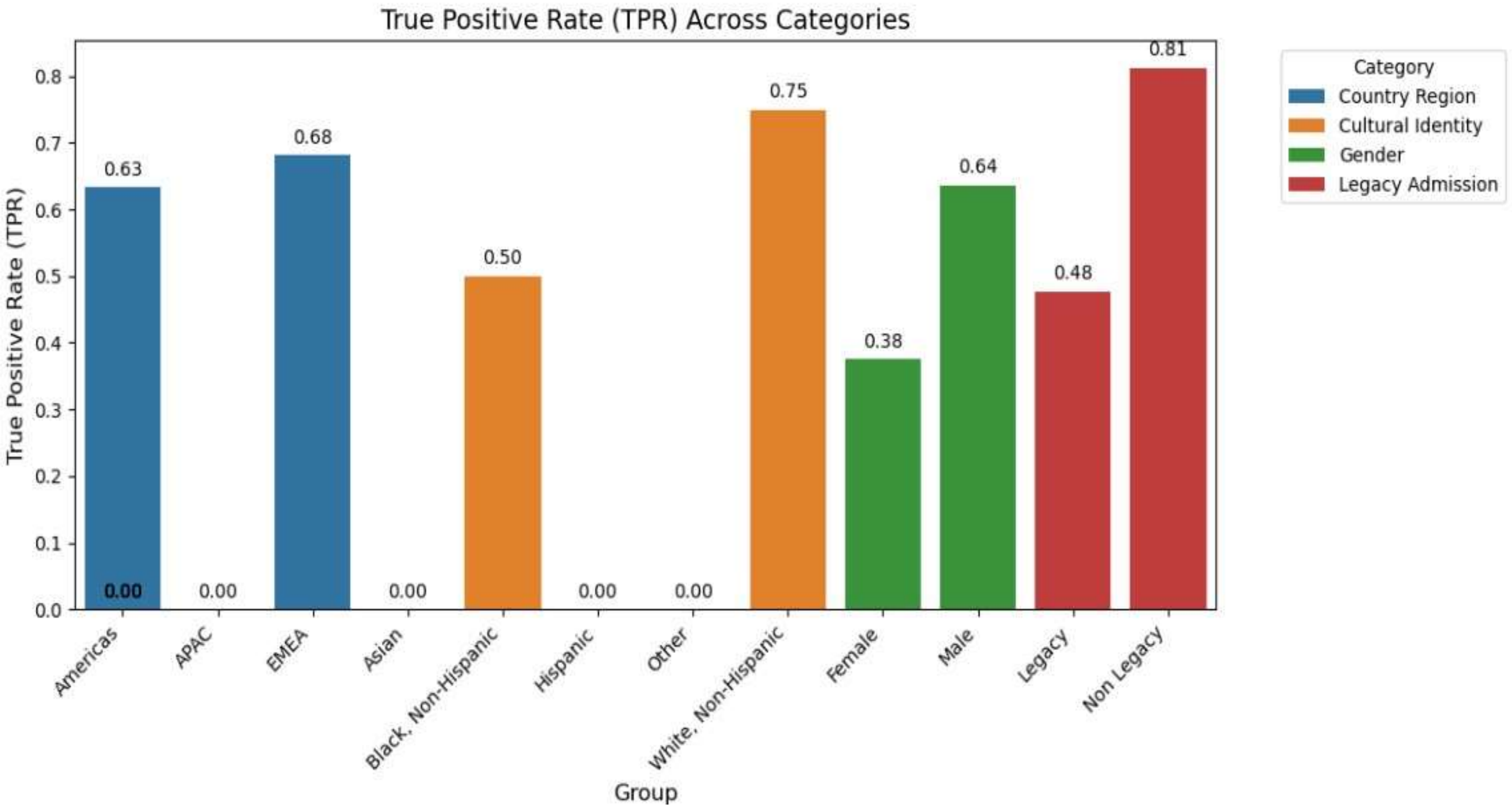
Bias Indicators: Disparities detected in cultural identity, gender, and legacy status, prompting bias assessment.

Model Comparison

Model	Accuracy	KS	Lift	AUC	F1 Score
Forest	0.88	0.65	5	0.9045	0.6538
Neural Network	0.8867	0.6125	3.6667	0.8724	0.6792
Logistic Regression	0.873	0.6375	3.3333	0.887	0.6667
Decision Tree	0.8367	0.55	2.2222	0.8039	0.6016
SVM	0.8167	0.5917	3	0.8721	0.1791
Gradient Boosting	0.8	0.5833	3.9189	0.842	0

BIAS Assessment: Identifying Inequities

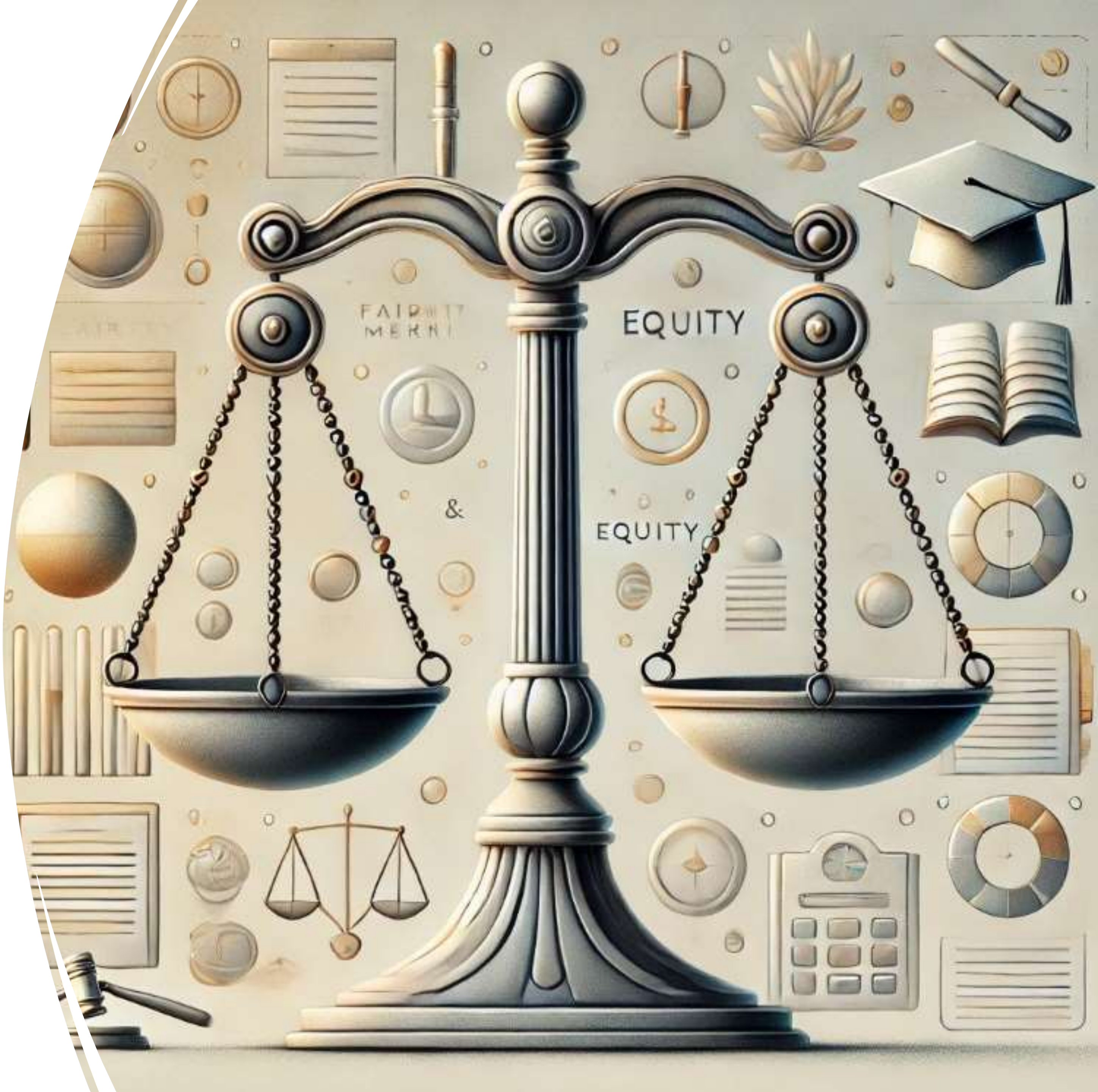
- **Performance Bias**: Significant disparities in TPR across groups (e.g., 75% for White, 0% for Asian).
- **Prediction Bias**: Model more likely to favor specific groups (e.g., White over Asian, male over female).
- **Next Steps**: Address biases to ensure fairer outcomes.

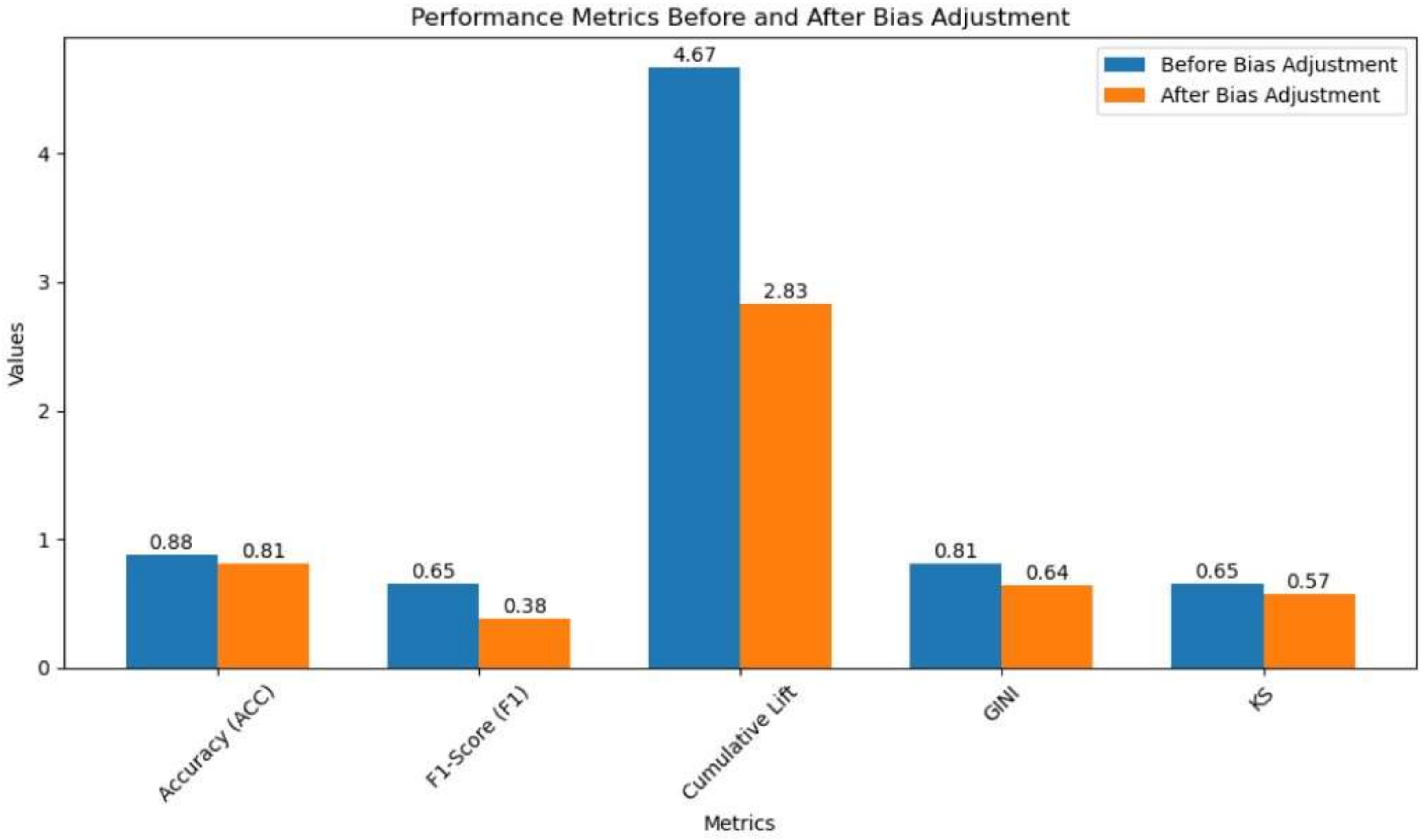


Rebuilding The Model

Rebuilding the Model for Fairness

- To ensure fairness, we removed key biased variables: Gender, Cultural Identity, Country/Region, and Legacy Admission.
- This action aimed to eliminate skewed predictions and provide an equitable admissions process across all groups.
- The rebuilt model focused solely on merit-driven variables, reducing the risk of biased decision-making.





The Trade Offs: Performance Vs. Fairness

Compromised Performance

- Accuracy dropped by 6.7%, indicating it's slightly less precise in predicting admissions.
- F1 Score decreased by 27.6%, showing a reduced ability to balance precision and recall, meaning the model struggles more to predict true admissions and avoid false positives.
- Cumulative Lift also declined, indicating the model is now less effective at identifying top candidates compared to random guessing

The Trade Offs: Performance Vs. Fairness

Improved Fairness

Metric	Before Bias Adjustment	After Bias Adjustment	Comments
True Positive Rate (TPR)	Max difference: **0.75** (Cultural Identity: White vs Asian)	Max difference: **0.5** (Cultural Identity: Black vs Other)	**Improved parity** across groups, indicating better balance in positive admissions predictions.
False Positive Rate (FPR)	Max difference: **0.16** (Cultural Identity: White vs Asian)	Max difference: **0.11** (Cultural Identity: Other vs Black)	**Reduced disparity** in incorrect positive predictions, which indicates fewer false admissions across groups.
Accuracy	Max difference: **0.14** (Cultural Identity)	Max difference: **0.24** (Cultural Identity)	Slight **increase in accuracy disparity**; however, the fairness trade-off often leads to such variations.
Area Under ROC (AUC)	Max difference: **0.21** (Legacy Admission)	Max difference: **0.07** (Legacy Admission)	AUC parity significantly **improved**, indicating better balanced performance post-adjustment.
Kolmogorov-Smirnov (KS)	Max difference: **0.78** (Gender: Male vs Female)	Max difference: **0.59** (Gender: Male vs Female)	**Reduced KS disparity,** indicating improved model fairness in distinguishing admitted vs. non-admitted students across genders.
Predicted Probability	Max difference: **0.304** (Cultural Identity: White vs Asian)	Max difference: **0.084** (Cultural Identity: White vs Black)	**Significantly reduced prediction bias**, showing a much more equitable model in terms of admissions predictions.

Admissions: Before vs. After Bias Adjustment

<u>**Shifts in Diversity and Representation**</u>

- **Cultural Identity**

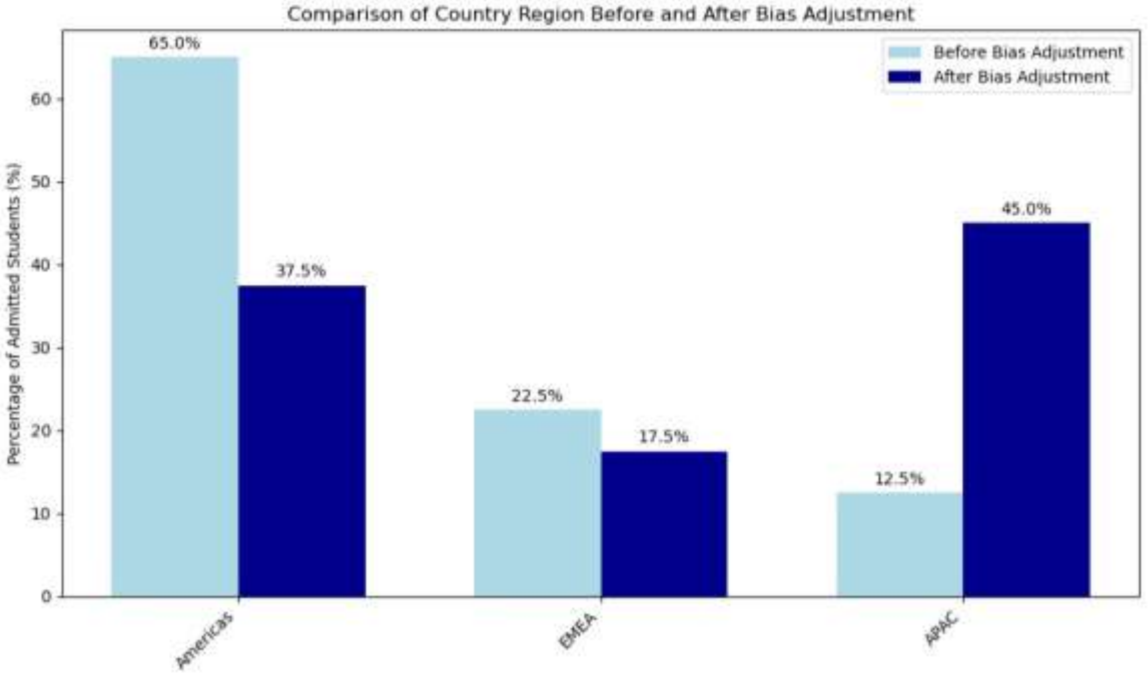
✓ More equitable admissions process that actively recognizes and includes underrepresented groups post adjustment.

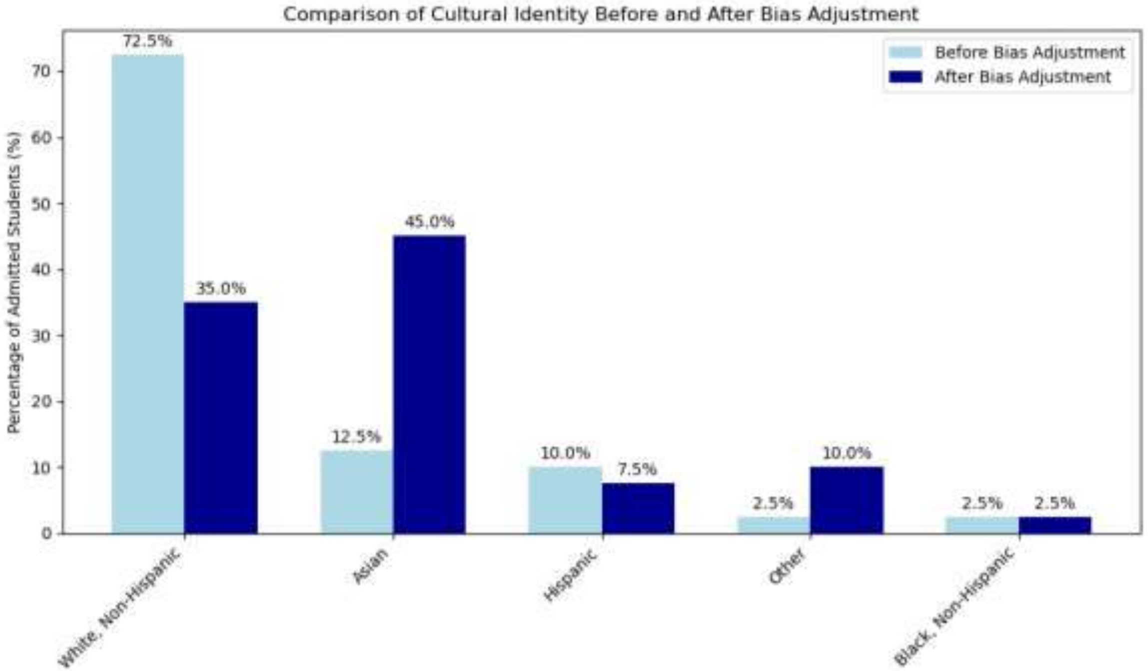
✓ Representation of Asian applicants increased significantly from **12.5% to 45%**, while White applicants decreased from **72.5% to 35%**.

- **Country Region**

✓ Commitment to global diversity, ensuring that students from various regions contribute to a richer academic environment.

✓ Admissions from the Americas dropped from **65% to 37.5%,** while representation from the APAC region rose from **12.5% to 45%**.





Admissions: Before vs. After Bias Adjustment

Shifts in Diversity and Representation

- **Legacy Admission**

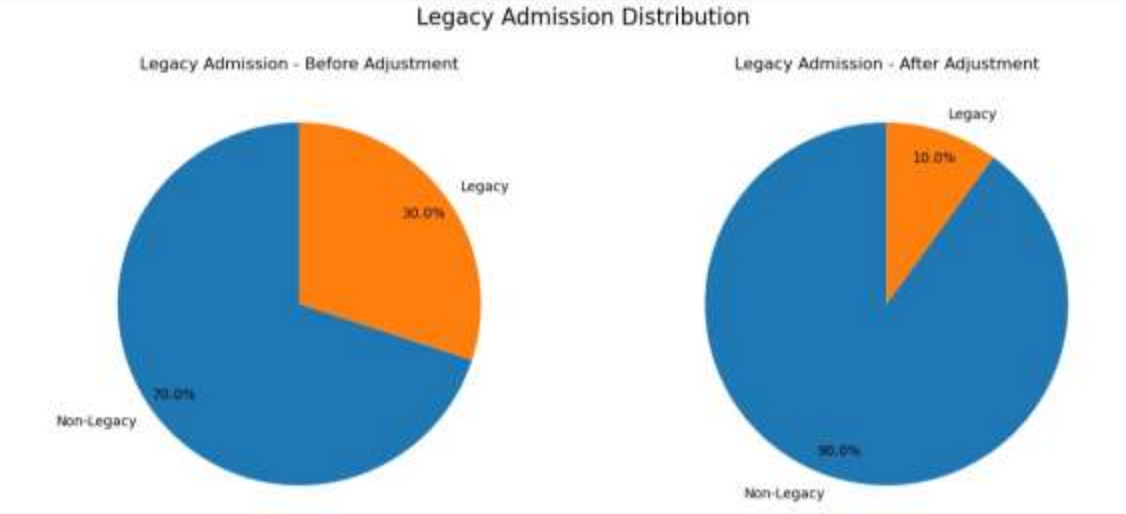
✓ move towards a merit-based admissions process, prioritizing qualifications over legacy status, which enhances fairness and inclusivity.

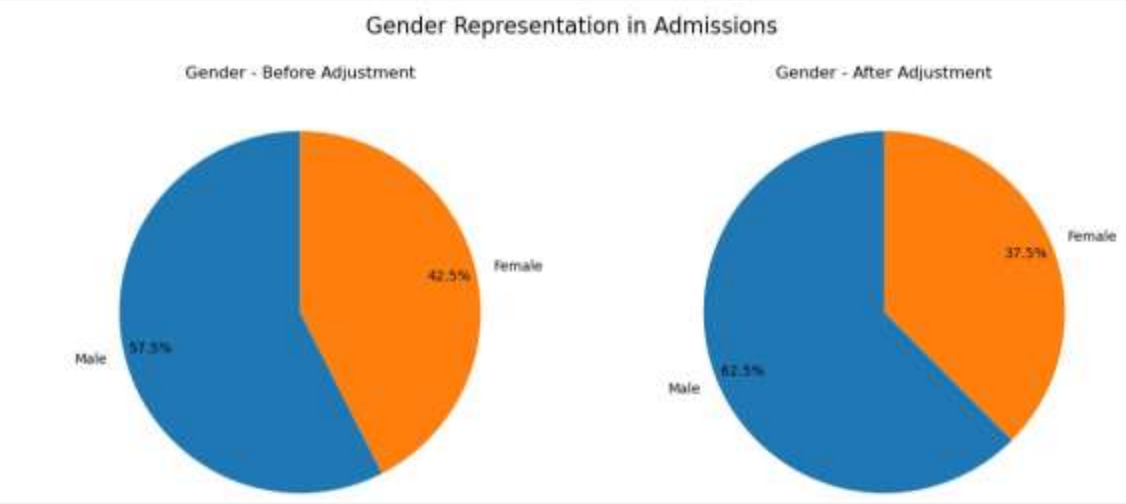
✓ Percentage of legacy students admitted dropped from 30% to 10%, while non-legacy admissions increased from 70% to 90%.

- **Gender**

✓ Male admissions rose from 57.5% to 62.5%, while female admissions decreased from 42.5% to 37.5%.

✓ The reduction in female admissions highlights a cost of fairness that the university must address through policies aimed at ensuring gender equality and representation.





Merit-Based Admissions: Reinforcing Bias Adjustment

- **<u>Stronger Academic Performance:</u>**

Increased average standardized test scores post-adjustment, emphasizing high-achieving candidates.

- **<u>Relevant Work Experience:</u>**

Rise in mean years of work experience, favoring candidates with practical skills.

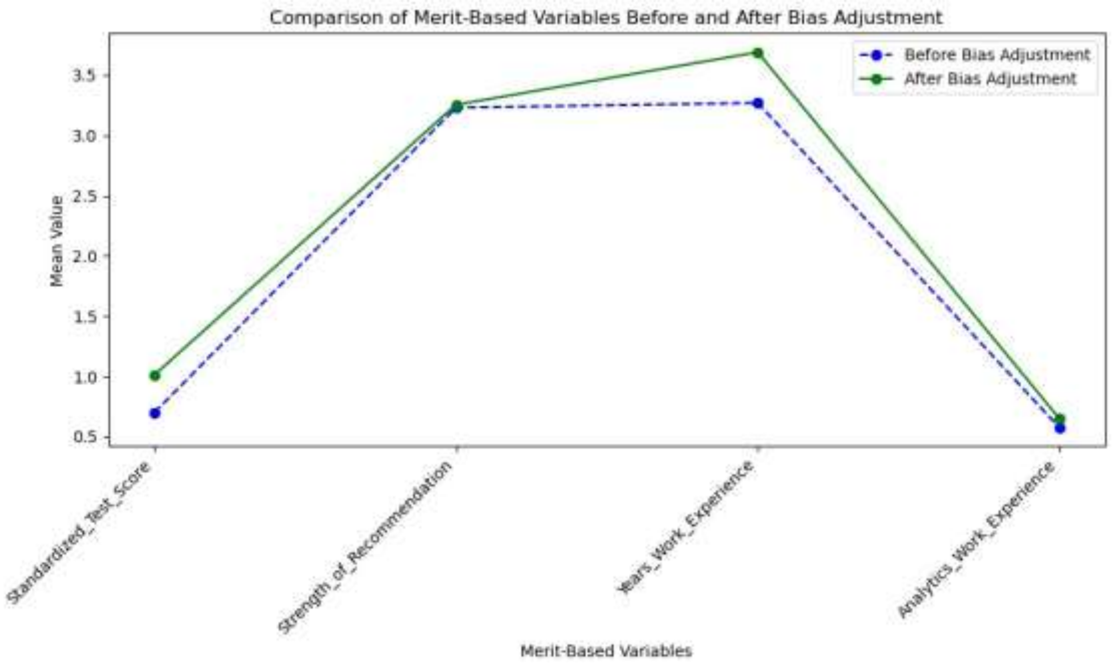
- **<u>Additional Considerations:</u>**

Strength of Recommendation: Consistent importance of peer and mentor support.

Analytics Work Experience: Increased focus on candidates with specialized skills.

- **<u>Diverse Perspectives:</u>**

Prioritizing merit fosters a well-rounded student body, enriching the academic environment.



Bringing Fairness to Admissions: A Balanced Approach

Mission

- Removing bias for fair, merit-based admissions

Key Wins

- Increased representation for underrepresented groups
- Reduced legacy admissions
- Balanced academic standards with fairness

The Human Touch

- SOPs and Mission Statements matter!

Call to Action

- Combining data and human judgment for a better future
- Standardized assessments or situational judgment tests for soft skills and cultural competency
- Project-based for practical evidence of skills and experience beyond personal narratives
- Gather behavioral data from how applicants interact with application platforms

THANK YOU FOR YOUR TIME!

TEAM DATA NINJAS