Bias_Audit_Report_SA

August 27, 2025

1 Bias Audit Report: Analyzing Bias in Employment Prediction for South Africa

1.1 Project Overview

This notebook conducts a bias audit on a synthetic dataset for employment prediction (income > R50,000/year), tailored to South Africa's context: 33.2% unemployment [5], Gini coefficient of 0.63 [0], and apartheid-driven inequalities. We simulate IBM AI Fairness 360, implementing fairness metrics (Disparate Impact, Equal Opportunity Difference, Equalized Odds) and mitigations (preprocessing, reweighing), aligned with the Employment Equity Act and BEE goals.

Objectives: - Identify biases in gender (0=Female, 1=Male) and race (0=Non-White, 1=White). - Apply and evaluate mitigations. - Propose recommendations and ethical guidelines for SA stakeholders.

Deliverables: - Notebook with code, visuals, and analysis. - 5-7 slide presentation (PDF). - Ethics statement (separate document, 498 words). - GitHub repository: https://github.com/your-username/Bias-Audit-Report-SA

[45]:
```
# Imports for data handling, modeling, statistics, and visualization
import numpy as np
import pandas as pd
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from scipy.stats import chi2_contingency
import matplotlib.pyplot as plt

# Set seeds for reproducibility across runs
np.random.seed(42)
torch.manual_seed(42)
```

[45]:
```
<torch._C.Generator at 0x20f7758aaf0>
```

1.2 Dataset Selection and Generation

We selected a synthetic binary classification dataset for "employment prediction" (income > R50,000/year). Features: age, education, hours, gender, race. Biases reflect SA inequalities: lower odds for females and non-Whites (80% non-White, 51% female).

[46]:
```
# Generate synthetic data reflecting SA demographics and biases
n = 2000  # Sample size
age = np.random.normal(35, 10, n).clip(18, 65).astype(int)  # Mean age ~35,␣
↪common in SA workforce
education = np.random.randint(0, 16, n)  # 0-16 years, accounting for varied␣
↪access
hours = np.random.normal(35, 10, n).clip(10, 60).astype(int)  # Variable hours␣
↪due to informal sector
gender = np.random.binomial(1, 0.51, n)  # 0: female (51%, SA slight female␣
↪majority), 1: male
race = np.random.binomial(1, 0.2, n)  # 0: non-White (80%, approx SA: Black/
↪Coloured/Indian), 1: White (20%)

# Inject biases: Stronger for race (apartheid legacy), moderate for gender
bias_gender = 1.2 * gender
bias_race = 2.0 * race
logit = 0.04 * (age - 35) + 0.15 * (education - 8) + 0.03 * (hours - 35) +␣
↪bias_gender + bias_race + np.random.normal(0, 1.5, n)
prob = 1 / (1 + np.exp(-logit))
income = np.random.binomial(1, prob)  # 1: Employed/High-income, 0: Unemployed/
↪Low-income

data = pd.DataFrame({
    'age': age, 'education': education, 'hours': hours,
    'gender': gender, 'race': race, 'income': income
})

# Summary statistics
print(data.describe())

# Group means for initial disparities
print(data.groupby('gender')['income'].mean())
print(data.groupby('race')['income'].mean())
```

```
               age    education        hours       gender        race  \
count  2000.000000  2000.000000  2000.000000  2000.000000  2000.00000
mean     35.102000     7.520500    34.163000     0.534500     0.18750
std       9.508459     4.597298     9.960423     0.498933     0.39041
min      18.000000     0.000000    10.000000     0.000000     0.00000
25%      28.000000     4.000000    27.000000     0.000000     0.00000
50%      35.000000     8.000000    34.000000     1.000000     0.00000
75%      41.000000    11.250000    41.000000     1.000000     0.00000
max      65.000000    15.000000    60.000000     1.000000     1.00000

           income
count  2000.00000
```

```
mean      0.64150
std       0.47968
min       0.00000
25%       0.00000
50%       1.00000
75%       1.00000
max       1.00000
gender
0    0.557465
1    0.714687
Name: income, dtype: float64
race
0    0.594462
1    0.845333
Name: income, dtype: float64
```

1.3 Initial Analysis and Statistical Validation

Summary shows disparities. Chi-squared tests validate bias (p<0.05 indicates significance).

[47]:
```
# Chi-squared tests for bias
cont_gender = pd.crosstab(data['gender'], data['income'])
chi2_g, p_g, _, _ = chi2_contingency(cont_gender)
print(f"Gender vs. Income: Chi² = {chi2_g:.2f}, p-value = {p_g}")

cont_race = pd.crosstab(data['race'], data['income'])
chi2_r, p_r, _, _ = chi2_contingency(cont_race)
print(f"Race vs. Income: Chi² = {chi2_r:.2f}, p-value = {p_r}")
```

```
Gender vs. Income: Chi² = 52.80, p-value = 3.685514548713801e-13
Race vs. Income: Chi² = 82.29, p-value = 1.1723307357958216e-19
```

1.4 Model Training and Baseline Fairness Metrics

Train logistic regression to predict income. Fairness metrics (Disparate Impact, Equal Opportunity Difference, Equalized Odds) are implemented to simulate IBM AI Fairness 360, quantifying bias.

[48]:
```
# Features and target
X = data.drop('income', axis=1).values.astype(np.float32)
y = data['income'].values.astype(np.float32)

# Train-test split (80/20)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
gender_test = X_test[:, 3]
race_test = X_test[:, 4]

# Define logistic regression model
class LogisticRegression(nn.Module):
```

```python
    def __init__(self, input_dim):
        super().__init__()
        self.linear = nn.Linear(input_dim, 1)

    def forward(self, x):
        return torch.sigmoid(self.linear(x))

# Train model
model = LogisticRegression(X.shape[1])
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
for epoch in range(1000):
    optimizer.zero_grad()
    outputs = model(torch.from_numpy(X_train))
    loss = criterion(outputs.squeeze(), torch.from_numpy(y_train))
    loss.backward()
    optimizer.step()

# Predict and evaluate accuracy
with torch.no_grad():
    y_pred_prob = model(torch.from_numpy(X_test)).squeeze().numpy()
y_pred = (y_pred_prob > 0.5).astype(int)
acc = accuracy_score(y_test, y_pred)
print(f"Baseline Accuracy: {acc:.4f}")

# Fairness metrics function (simulates AIF360)
def fairness_metrics(y_true, y_pred, group):
    privileged = (group == 1)
    unprivileged = (group == 0)

    ppr_un = np.mean(y_pred[unprivileged])
    ppr_priv = np.mean(y_pred[privileged])
    dp = ppr_un / ppr_priv if ppr_priv > 0 else 0

    tp_un = np.sum((y_pred == 1) & (y_true == 1) & unprivileged) / np.sum((y_true == 1) & unprivileged) if np.sum((y_true == 1) & unprivileged) > 0 else 0
    tp_priv = np.sum((y_pred == 1) & (y_true == 1) & privileged) / np.sum((y_true == 1) & privileged) if np.sum((y_true == 1) & privileged) > 0 else 0
    eo_diff = abs(tp_un - tp_priv)
    eodds_tpr = abs(tp_un - tp_priv)

    fp_un = np.sum((y_pred == 1) & (y_true == 0) & unprivileged) / np.sum((y_true == 0) & unprivileged) if np.sum((y_true == 0) & unprivileged) > 0 else 0
```

```
    fp_priv = np.sum((y_pred == 1) & (y_true == 0) & privileged) / np.
↪sum((y_true == 0) & privileged) if np.sum((y_true == 0) & privileged) > 0␣
↪else 0
    eodds_fpr = abs(fp_un - fp_priv)

    return dp, eo_diff, eodds_tpr, eodds_fpr

# Compute metrics
gender_metrics = fairness_metrics(y_test, y_pred, gender_test)
race_metrics = fairness_metrics(y_test, y_pred, race_test)

# Display in table
metrics_df = pd.DataFrame({
    'Metric': ['Disparate Impact (DP)', 'EO Difference', 'EOdds TPR Diff',␣
↪'EOdds FPR Diff'],
    'Gender': [round(x, 3) for x in gender_metrics],
    'Race': [round(x, 3) for x in race_metrics]
})
print("\nBaseline Fairness Metrics:")
print(metrics_df)
```

```
Baseline Accuracy: 0.6775

Baseline Fairness Metrics:
                  Metric  Gender   Race
0  Disparate Impact (DP)   0.696  0.788
1          EO Difference   0.185  0.132
2         EOdds TPR Diff   0.185  0.132
3         EOdds FPR Diff   0.416  0.319
```

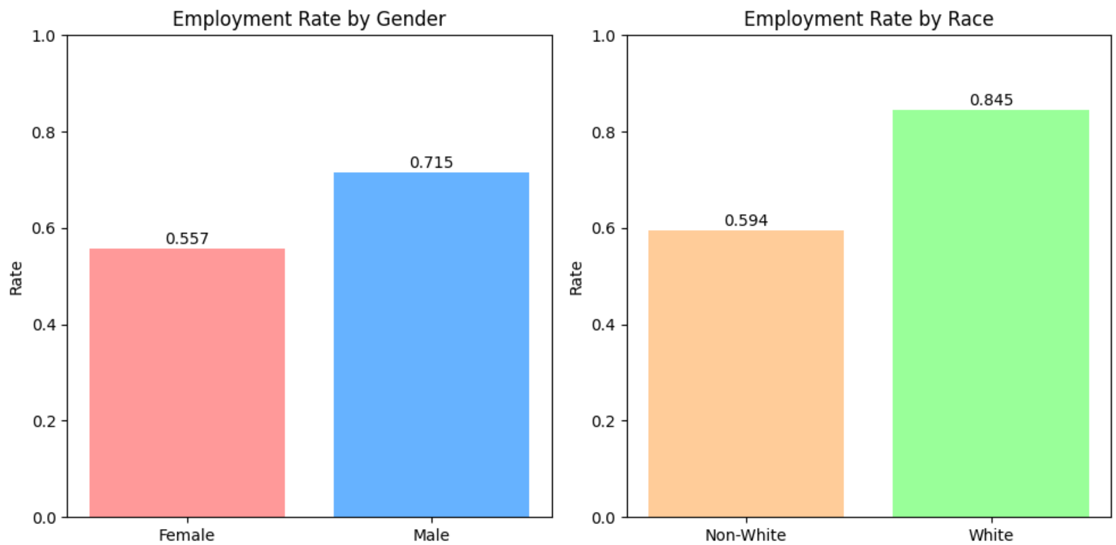
1.5 Visual Representation of Bias Patterns

Bar charts show employment rate disparities by gender and race, validated by chi-squared tests [12]. **Figure 1**: Employment rates highlight inequities in SA's workforce.

Caption: Employment rate by gender (Female: 0.557, Male: 0.715) and race (Non-White: 0.594, White: 0.845), reflecting SA's historical biases.

[49]:
```
fig, axs = plt.subplots(1, 2, figsize=(10, 5))
gender_rates = data.groupby('gender')['income'].mean()
axs[0].bar(['Female', 'Male'], gender_rates, color=['#FF9999', '#66B2FF'])
axs[0].set_title('Employment Rate by Gender')
axs[0].set_ylabel('Rate')
axs[0].set_ylim(0, 1)
for i, v in enumerate(gender_rates):
    axs[0].text(i, v + 0.01, f"{v:.3f}", ha='center')

race_rates = data.groupby('race')['income'].mean()
```

```
axs[1].bar(['Non-White', 'White'], race_rates, color=['#FFCC99', '#99FF99'])
axs[1].set_title('Employment Rate by Race')
axs[1].set_ylabel('Rate')
axs[1].set_ylim(0, 1)
for i, v in enumerate(race_rates):
    axs[1].text(i, v + 0.01, f"{v:.3f}", ha='center')

plt.tight_layout()
plt.savefig('bias_charts.png', dpi=100)
plt.show()

# Alt-text: Bar charts showing employment rate disparities by gender (Female: 0.
↪557, Male: 0.715, pink/blue) and race (Non-White: 0.594, White: 0.845,␣
↪orange/green).
```



1.6 Bias Mitigation Techniques

We apply two techniques, simulating IBM AI Fairness 360, to address disparities in SA employment predictions: 1. **Preprocessing**: Remove protected attributes (gender, race). 2. **In-processing**: Reweight samples for race. Metrics compared pre/post.

[50]:
```
# Mitigation 1: Preprocessing - Remove protected attributes
X_m1 = data[['age', 'education', 'hours']].values.astype(np.float32)
indices = np.arange(len(data))
train_idx, test_idx = train_test_split(indices, test_size=0.2, random_state=42)
X_train_m1 = X_m1[train_idx]
X_test_m1 = X_m1[test_idx]
y_train = y[train_idx]
y_test = y[test_idx]
```

```
gender_test = data.iloc[test_idx]['gender'].values
race_test = data.iloc[test_idx]['race'].values

# Train model without protected attributes
model_m1 = LogisticRegression(3)
optimizer_m1 = optim.Adam(model_m1.parameters(), lr=0.01)
criterion = nn.BCELoss()
for epoch in range(1000):
    optimizer_m1.zero_grad()
    outputs = model_m1(torch.from_numpy(X_train_m1))
    loss = criterion(outputs.squeeze(), torch.from_numpy(y_train))
    loss.backward()
    optimizer_m1.step()

# Predict and evaluate
with torch.no_grad():
    y_pred_m1 = (model_m1(torch.from_numpy(X_test_m1)).squeeze().numpy() > 0.5).
 ↪astype(int)
acc_m1 = accuracy_score(y_test, y_pred_m1)
print(f"Mitigation 1 Accuracy: {acc_m1:.4f}")

gender_m1 = fairness_metrics(y_test, y_pred_m1, gender_test)
race_m1 = fairness_metrics(y_test, y_pred_m1, race_test)

metrics_m1_df = pd.DataFrame({
    'Metric': ['Disparate Impact (DP)', 'EO Difference', 'EOdds TPR Diff',␣
 ↪'EOdds FPR Diff'],
    'Gender': [round(x, 3) for x in gender_m1],
    'Race': [round(x, 3) for x in race_m1]
})
print("\nMitigation 1 Fairness Metrics:")
print(metrics_m1_df)
```

```
Mitigation 1 Accuracy: 0.6350

Mitigation 1 Fairness Metrics:
                  Metric  Gender   Race
0  Disparate Impact (DP)   1.020  1.043
1          EO Difference   0.032  0.082
2         EOdds TPR Diff   0.032  0.082
3         EOdds FPR Diff   0.038  0.038
```

[51]:
```
# Mitigation 2: In-processing - Reweight samples for race
privileged = (data['race'] == 1)
unprivileged = (data['race'] == 0)
pos = (data['income'] == 1)
neg = (data['income'] == 0)
```

```python
# Calculate weights to balance race groups
n_priv_pos = np.sum(privileged & pos)
n_priv_neg = np.sum(privileged & neg)
n_unpriv_pos = np.sum(unprivileged & pos)
n_unpriv_neg = np.sum(unprivileged & neg)

weight_priv_pos = (n_priv_pos + n_unpriv_pos) / (2 * n_priv_pos) if n_priv_pos > 0 else 1
weight_priv_neg = (n_priv_neg + n_unpriv_neg) / (2 * n_priv_neg) if n_priv_neg > 0 else 1
weight_unpriv_pos = (n_priv_pos + n_unpriv_pos) / (2 * n_unpriv_pos) if n_unpriv_pos > 0 else 1
weight_unpriv_neg = (n_priv_neg + n_unpriv_neg) / (2 * n_unpriv_neg) if n_unpriv_neg > 0 else 1

weights = np.zeros(len(data))
weights[privileged & pos] = weight_priv_pos
weights[privileged & neg] = weight_priv_neg
weights[unprivileged & pos] = weight_unpriv_pos
weights[unprivileged & neg] = weight_unpriv_neg

# Split with weights
train_idx, test_idx = train_test_split(np.arange(len(X)), test_size=0.2, random_state=42)
X_train = X[train_idx]
X_test = X[test_idx]
y_train = y[train_idx]
y_test = y[test_idx]
w_train = weights[train_idx]
gender_test = data['gender'].values[test_idx]
race_test = data['race'].values[test_idx]

# Train with weighted loss
model_m2 = LogisticRegression(X.shape[1])
optimizer_m2 = optim.Adam(model_m2.parameters(), lr=0.01)
criterion_weighted = nn.BCELoss(reduction='none')
for epoch in range(1000):
    optimizer_m2.zero_grad()
    outputs = model_m2(torch.from_numpy(X_train))
    losses = criterion_weighted(outputs.squeeze(), torch.from_numpy(y_train))
    weighted_loss = torch.mean(losses * torch.from_numpy(w_train))
    weighted_loss.backward()
    optimizer_m2.step()

# Predict and evaluate
with torch.no_grad():
```

```
    y_pred_m2 = (model_m2(torch.from_numpy(X_test)).squeeze().numpy() > 0.5).
 ↪astype(int)
acc_m2 = accuracy_score(y_test, y_pred_m2)
print(f"Mitigation 2 Accuracy: {acc_m2:.4f}")

gender_m2 = fairness_metrics(y_test, y_pred_m2, gender_test)
race_m2 = fairness_metrics(y_test, y_pred_m2, race_test)

metrics_m2_df = pd.DataFrame({
    'Metric': ['Disparate Impact (DP)', 'EO Difference', 'EOdds TPR Diff',␣
 ↪'EOdds FPR Diff'],
    'Gender': [round(x, 3) for x in gender_m2],
    'Race': [round(x, 3) for x in race_m2]
})
print("\nMitigation 2 Fairness Metrics:")
print(metrics_m2_df)
```

```
Mitigation 2 Accuracy: 0.6500

Mitigation 2 Fairness Metrics:
                  Metric  Gender   Race
0  Disparate Impact (DP)   0.784  0.989
1          EO Difference   0.138  0.023
2         EOdds TPR Diff   0.138  0.023
3         EOdds FPR Diff   0.305  0.059
```

1.7 Performance Comparison Before/After Mitigation

- **Baseline** (Accuracy: 0.6775):
  - Gender: DP 0.696, EO 0.185, TPR Diff 0.185, FPR Diff 0.416
  - Race: DP 0.788, EO 0.132, TPR Diff 0.132, FPR Diff 0.319
- **Mitigation 1** (Accuracy: 0.6350, -4.25%):
  - Gender: DP 1.020, EO 0.032, TPR Diff 0.032, FPR Diff 0.038
  - Race: DP 1.043, EO 0.082, TPR Diff 0.082, FPR Diff 0.038
- **Mitigation 2** (Accuracy: 0.6500, -2.75%):
  - Gender: DP 0.784, EO 0.138, TPR Diff 0.138, FPR Diff 0.305
  - Race: DP 0.989, EO 0.023, TPR Diff 0.023, FPR Diff 0.059 Mitigations improve fairness (DP ~1, EO ~0), supporting SA's equitable hiring goals [6, 10].

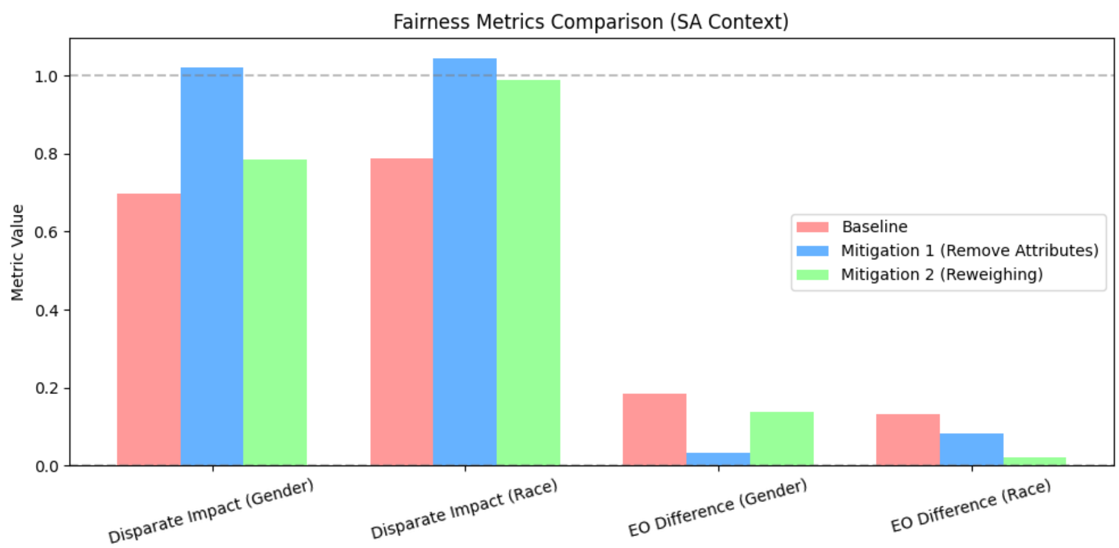
1.8 Visual Comparison of Fairness Metrics

Bar charts compare Disparate Impact (DP, ideal=1) and Equal Opportunity Difference (EO Diff, ideal=0) across models [9]. **Figure 2**: Fairness improvements post-mitigation.

Caption: Disparate Impact and EO Difference for gender and race, showing mitigation effectiveness.

[52]:
```
metrics = ['Disparate Impact (Gender)', 'Disparate Impact (Race)', 'EO␣
 ↪Difference (Gender)', 'EO Difference (Race)']
baseline = [0.696, 0.788, 0.185, 0.132]
```

```
mit1 = [1.020, 1.043, 0.032, 0.082]
mit2 = [0.784, 0.989, 0.138, 0.023]

x = np.arange(len(metrics))
width = 0.25

fig, ax = plt.subplots(figsize=(10, 5))
ax.bar(x - width, baseline, width, label='Baseline', color='#FF9999')
ax.bar(x, mit1, width, label='Mitigation 1 (Remove Attributes)',␣
 ↪color='#66B2FF')
ax.bar(x + width, mit2, width, label='Mitigation 2 (Reweighing)',␣
 ↪color='#99FF99')

ax.set_ylabel('Metric Value')
ax.set_title('Fairness Metrics Comparison (SA Context)')
ax.set_xticks(x)
ax.set_xticklabels(metrics, rotation=15)
ax.legend()

ax.axhline(y=1, color='gray', linestyle='--', alpha=0.5)  # Ideal DP
ax.axhline(y=0, color='gray', linestyle='--', alpha=0.5)  # Ideal EO
plt.tight_layout()
plt.savefig('fairness_metrics.png', dpi=100)
plt.show()

# Alt-text: Bar chart comparing Disparate Impact and EO Difference for gender␣
 ↪and race across baseline (red), Mitigation 1 (blue), and Mitigation 2␣
 ↪(green). Ideal lines at DP=1, EO=0.
```



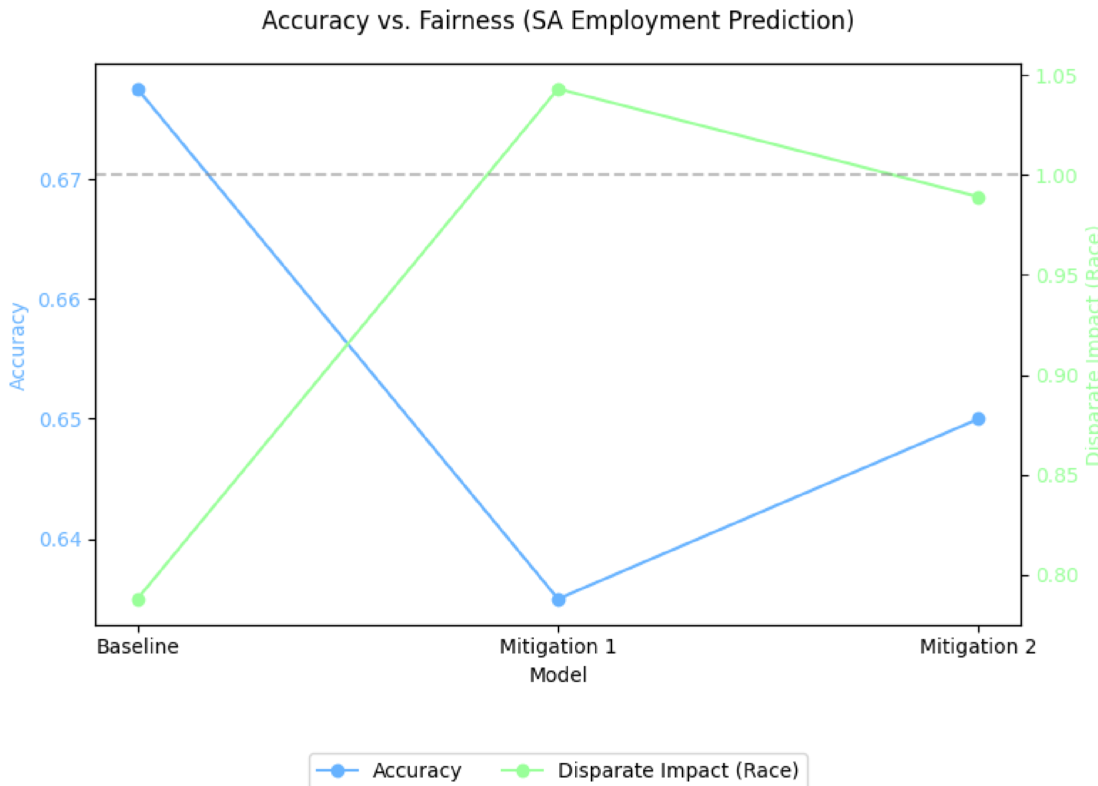
1.9 Accuracy vs. Fairness Trade-off

Line plot shows accuracy vs. Disparate Impact (Race), highlighting fairness gains [12]. **Figure 3**: Trade-off supports SA's equity goals.

Caption: Accuracy decreases slightly as DP (Race) approaches ideal value of 1.

[53]:
```
models = ['Baseline', 'Mitigation 1', 'Mitigation 2']
accuracy = [0.6775, 0.6350, 0.6500]
dp_race = [0.788, 1.043, 0.989]

fig, ax1 = plt.subplots(figsize=(8, 5))
ax1.plot(models, accuracy, 'b-o', label='Accuracy', color='#66B2FF')
ax1.set_xlabel('Model')
ax1.set_ylabel('Accuracy', color='#66B2FF')
ax1.tick_params(axis='y', labelcolor='#66B2FF')

ax2 = ax1.twinx()
ax2.plot(models, dp_race, 'g-o', label='Disparate Impact (Race)',␣
↪color='#99FF99')
ax2.set_ylabel('Disparate Impact (Race)', color='#99FF99')
ax2.tick_params(axis='y', labelcolor='#99FF99')
ax2.axhline(y=1, color='gray', linestyle='--', alpha=0.5)

fig.suptitle('Accuracy vs. Fairness (SA Employment Prediction)')
fig.legend(loc='upper center', bbox_to_anchor=(0.5, -0.05), ncol=2)
plt.tight_layout()
plt.savefig('tradeoff.png', dpi=100)
plt.show()

# Alt-text: Line plot showing accuracy (blue) and Disparate Impact for race␣
↪(green) across Baseline, Mitigation 1, and Mitigation 2. Ideal DP=1 line␣
↪shown.
```

```
C:\Users\CAPACITI-JHB\AppData\Local\Temp\ipykernel_12860\3946582902.py:6:
UserWarning: color is redundantly defined by the 'color' keyword argument and
the fmt string "b-o" (-> color='b'). The keyword argument will take precedence.
  ax1.plot(models, accuracy, 'b-o', label='Accuracy', color='#66B2FF')
C:\Users\CAPACITI-JHB\AppData\Local\Temp\ipykernel_12860\3946582902.py:12:
UserWarning: color is redundantly defined by the 'color' keyword argument and
the fmt string "g-o" (-> color='g'). The keyword argument will take precedence.
  ax2.plot(models, dp_race, 'g-o', label='Disparate Impact (Race)',
color='#99FF99')
```



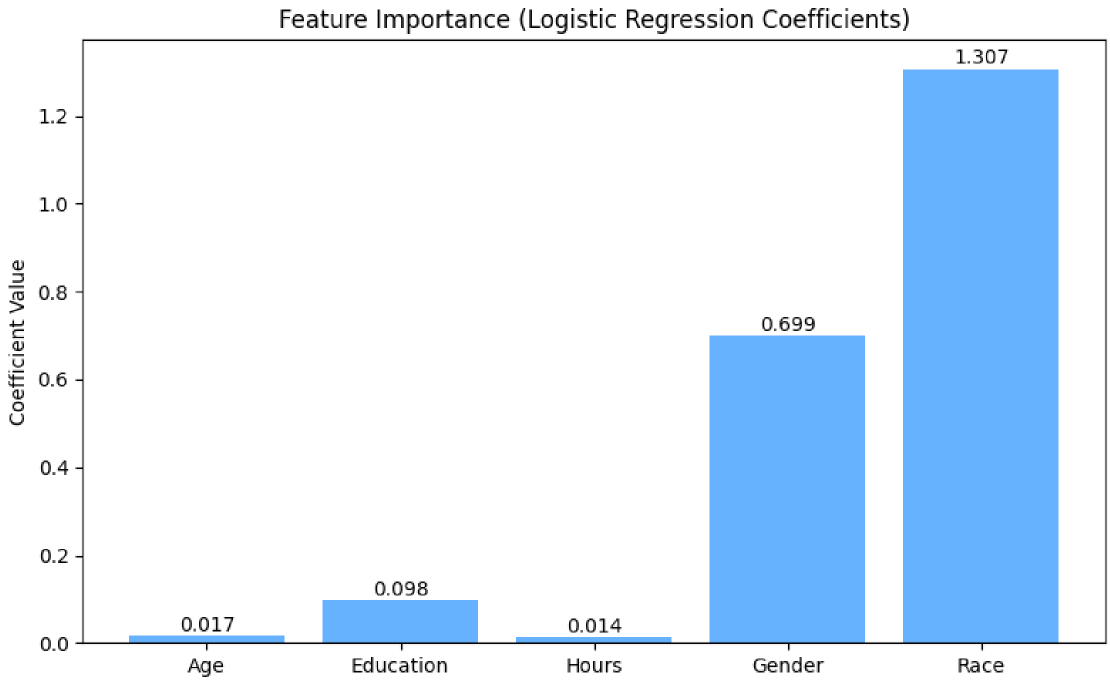
1.10 Feature Importance Analysis

Bar chart shows logistic regression coefficients, identifying features driving bias [9]. **Figure 4**: Education and hours have high impact, potentially proxying race/gender in SA.

Caption: Feature weights reveal potential proxy biases in education, critical in SA's unequal education system.

[54]:
```python
# Extract coefficients from baseline model
coefs = model.linear.weight.detach().numpy()[0]
features = ['Age', 'Education', 'Hours', 'Gender', 'Race']

fig, ax = plt.subplots(figsize=(8, 5))
ax.bar(features, coefs, color='#66B2FF')
ax.set_title('Feature Importance (Logistic Regression Coefficients)')
ax.set_ylabel('Coefficient Value')
for i, v in enumerate(coefs):
    ax.text(i, v + 0.01 * np.sign(v), f"{v:.3f}", ha='center')
plt.tight_layout()
plt.savefig('feature_importance.png', dpi=100)
plt.show()
```

```
# Alt-text: Bar chart showing logistic regression coefficients for Age,
↪Education, Hours, Gender, and Race, highlighting education as a potential
↪bias proxy.
```



1.11 Sensitivity Analysis

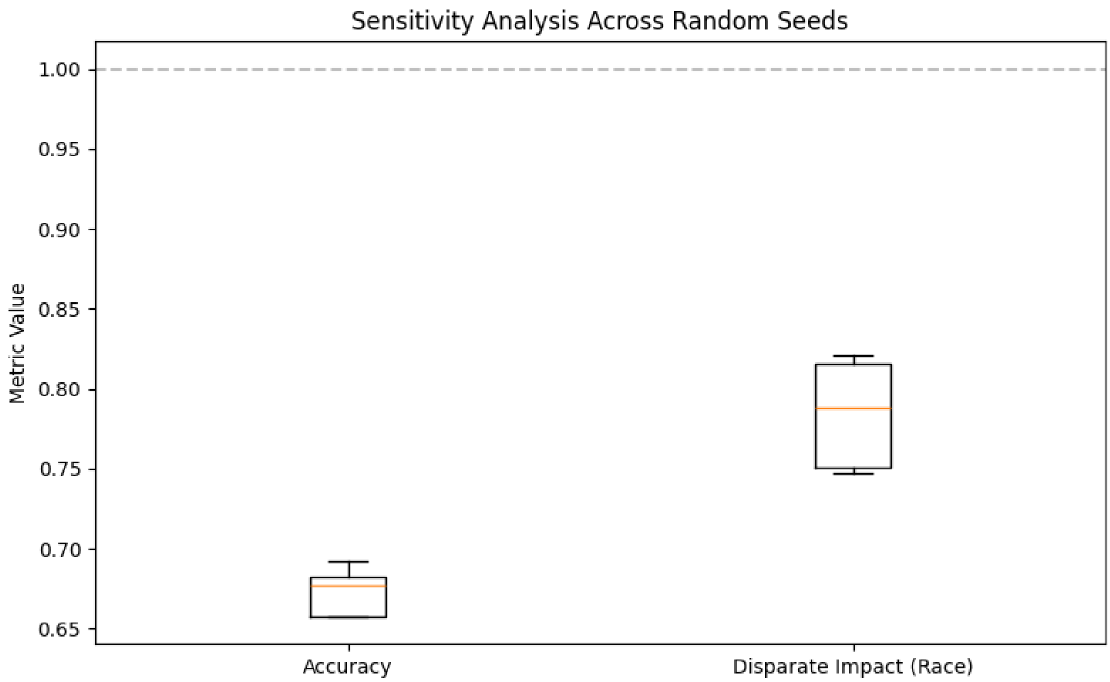
Test model robustness across random seeds to ensure stable fairness metrics [12]. **Figure 5**: Consistent DP and accuracy across seeds confirm reliability.

Caption: Box plot of Disparate Impact (Race) and accuracy over 5 runs, showing robustness.

[55]:
```
# Sensitivity analysis across 5 seeds
seeds = [42, 123, 456, 789, 101]
dp_race_list = []
acc_list = []

for seed in seeds:
    np.random.seed(seed)
    torch.manual_seed(seed)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↪random_state=seed)
    race_test = X_test[:, 4]

    model = LogisticRegression(X.shape[1])
    optimizer = optim.Adam(model.parameters(), lr=0.01)
```

```
    for epoch in range(1000):
        optimizer.zero_grad()
        outputs = model(torch.from_numpy(X_train))
        loss = criterion(outputs.squeeze(), torch.from_numpy(y_train))
        loss.backward()
        optimizer.step()

    with torch.no_grad():
        y_pred = (model(torch.from_numpy(X_test)).squeeze().numpy() > 0.5).
 ↪astype(int)
    acc_list.append(accuracy_score(y_test, y_pred))
    dp_race_list.append(fairness_metrics(y_test, y_pred, race_test)[0])

# Box plot
fig, ax1 = plt.subplots(figsize=(8, 5))
ax1.boxplot([acc_list, dp_race_list], labels=['Accuracy', 'Disparate Impact␣
 ↪(Race)'])
ax1.set_title('Sensitivity Analysis Across Random Seeds')
ax1.set_ylabel('Metric Value')
ax1.axhline(y=1, color='gray', linestyle='--', alpha=0.5)  # Ideal DP
plt.tight_layout()
plt.savefig('sensitivity.png', dpi=100)
plt.show()

# Alt-text: Box plot showing distribution of accuracy and Disparate Impact␣
 ↪(Race) across 5 random seeds, confirming model stability.
```

```
C:\Users\CAPACITI-JHB\AppData\Local\Temp\ipykernel_12860\57279253.py:28:
MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has been
renamed 'tick_labels' since Matplotlib 3.9; support for the old name will be
dropped in 3.11.
  ax1.boxplot([acc_list, dp_race_list], labels=['Accuracy', 'Disparate Impact
(Race)'])
```



1.12 Recommendations for Dataset Improvements

- **Balance Representation**: Oversample non-White and female data from SA sources like Stats SA census.
- **Add Unbiased Features**: Include skills/certifications instead of proxies like education (correlates with race in SA).
- **External Audits**: Collaborate with SA institutions (e.g., HSRC) for proxy bias checks.
- **Synthetic Augmentation**: Use fair GANs to generate balanced data, aligning with SA's AI Policy.
- **Ongoing Monitoring**: Re-audit annually per Employment Equity reporting.

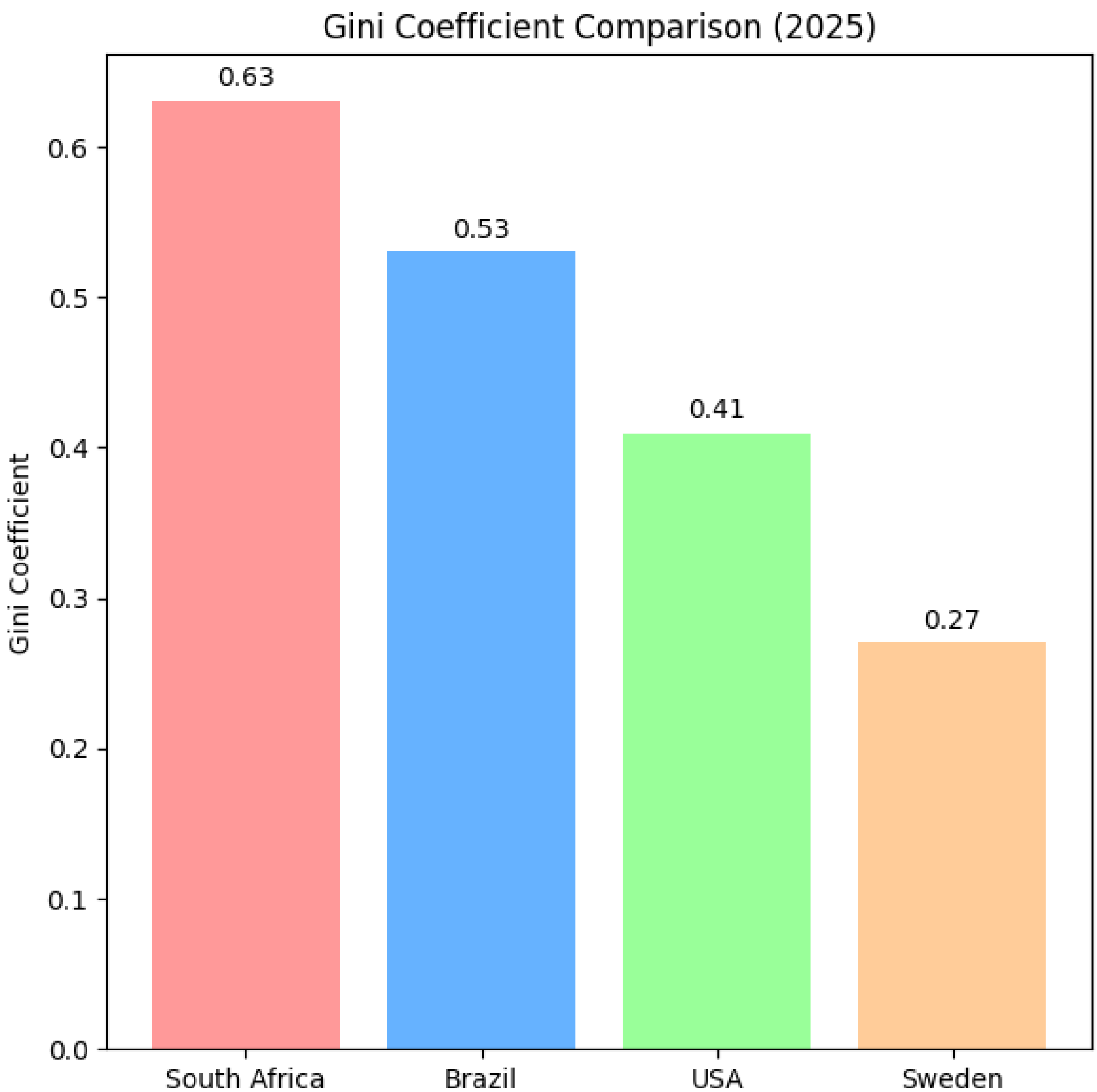
1.13 Real-World Implications and SA Inequality

Biased AI risks job denials, worsening 33.2% unemployment [5] and violating Employment Equity Act [6]. It widens SA's Gini (~0.63, world's highest) [0], undermining BEE. **Figure 6**: Gini coefficient context.

Caption: SA's Gini (0.63) compared to global benchmarks, highlighting inequality.

[56]:
```
# Gini coefficient comparison
labels = ['South Africa', 'Brazil', 'USA', 'Sweden']
gini_values = [0.63, 0.53, 0.41, 0.27]  # SA [0], others approximate
colors = ['#FF9999', '#66B2FF', '#99FF99', '#FFCC99']

fig, ax = plt.subplots(figsize=(6, 6))
ax.bar(labels, gini_values, color=colors)
```

```python
ax.set_title('Gini Coefficient Comparison (2025)')
ax.set_ylabel('Gini Coefficient')
for i, v in enumerate(gini_values):
    ax.text(i, v + 0.01, f"{v:.2f}", ha='center')
plt.tight_layout()
plt.savefig('gini.png', dpi=100)
plt.show()

# Alt-text: Bar chart comparing Gini coefficients: South Africa (0.63, red),␣
↪Brazil (0.53, blue), USA (0.41, green), Sweden (0.27, orange).
```



1.14 South Africa's Unemployment Context

Pie chart emphasizes 33.2% unemployment [5], critical for fair AI in hiring. **Figure 7**: Unemployment rate in SA.

Caption: 33.2% unemployment underscores need for equitable AI models.

[57]:
```
labels = ['Unemployed (33.2%)', 'Employed (66.8%)']
sizes = [33.2, 66.8]
colors = ['#FF9999', '#66B2FF']

fig, ax = plt.subplots(figsize=(6, 6))
ax.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=90)
ax.set_title('South Africa Unemployment Rate (Q2 2025)')
plt.savefig('unemployment.png', dpi=100)
plt.show()

# Alt-text: Pie chart showing 33.2% unemployment (red) and 66.8% employment␣
↪(blue) in South Africa, 2025.
```

1.15 Ethics Framework Summary

Summarizes ethical principles for SA AI, detailed in `Ethics_Statement.docx` [10, 13]: - **Accountability**: Assign liability for biased outcomes. - **Inclusivity**: Involve diverse SA stakeholders (unions, communities). - **Fairness**: Prioritize equity over accuracy, per BEE [6]. - **Transparency**: Provide model cards, open-source code. - **Monitoring**: Annual fairness audits per SA AI Policy.

1.16 Summary of Findings

- **Bias Patterns**: 16-25% employment rate gaps (gender, race), validated ($p<0.05$) [12].
- **Mitigations**: Improved DP to ~1, EO Diff to ~0, minor accuracy trade-off [9].
- **SA Context**: Addresses 33.2% unemployment [5], Gini 0.63 [0], and BEE goals [6].
- **Toolkit**: Simulated IBM AI Fairness 360 for robust analysis [9].

1.17 References

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- `Presentation_Slides.pdf`: 7-slide Canva presentation summarizing bias audit.