📘 Gender Bias in Hiring and Promotions – Final Report

📜 Executive Summary

This report explores potential gender bias in hiring and promotion decisions within an organization, using a synthetic HR dataset. Through a full data science pipeline—including data cleaning, visualization, and predictive modeling—we detect measurable gender-based disparities. Tools used include Python and scikit-learn. Final recommendations provide strategic insights for mitigating structural bias in HR practices.

1️⃣ Problem Framing & Hypothesis

🔍 Problem Statement

Despite formal equity policies, gender disparities persist in corporate promotions and salaries. This study investigates whether gender plays a statistically and practically significant role in promotion and compensation decisions.

🎯 Project Objectives

- Uncover gender-based disparities in promotion and salary
- Measure gender's impact using statistical and ML models
- Provide actionable recommendations for fair HR decision-making

📈 Key Metrics (KPIs)

- Promotion rate by gender
- Salary and performance distribution by gender

📊 Hypotheses

- **H_0 (Null):** Gender has no effect on promotion or salary outcomes
- **H_1 (Alternative):** Gender significantly influences outcomes, independent of performance or experience

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2️⃣ Data Preparation & Bias Simulation

- Dataset contains fields: gender, age, salary, experience, performance_score, position, and promotion status
- Missing values handled, categorical encoding applied
- Simulated gender bias: reduced promotion probability and slightly lower salaries for female employees to reflect real-world inequities

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3️⃣ Descriptive Analysis

📊 Key Statistics by Gender

- **Salary:** Males earn ~10% more on average
- **Promotion Rate:** Male promotion rate is nearly 2x that of females

- **Performance:** No significant gap in performance ratings

📈 **Visual Insights**

- **Bar Charts:** Promotion rate by gender, department
- **Box Plots:** Salary and performance by gender
- **Scatter Plot:** Experience vs promotion by gender

✅ *Insight:* Gender disparities are visible across multiple metrics, despite similar qualifications and performance.

4️⃣ **Diagnostic Analysis**

- Grouped analysis by gender, department, and performance category
- High-performing females less likely to be promoted than males
- Cross-tab and outlier detection highlight systemic discrepancies

✅ *Insight:* Bias appears consistent across roles, experience levels, and departments.

5️⃣ **Predictive Modeling**

🤖 **Model: Random Forest Classifier**

- **Features:** Gender, performance, salary, experience
- **Accuracy:** ~82% (Train/Test split)
- **Evaluation:** Confusion matrix, classification report

✅ *Insight:* Gender was a top predictor in the model, which suggests learned bias.

6️⃣ **Storytelling with Visuals**

📊 **Data-Driven Narratives**

- **Promotion Rate:** Males ~2x more likely to be promoted
- **Salary Gap:** Females underpaid for equal roles

Each visualization is paired with a plain-language interpretation for technical and non-technical audiences.

✅ *Insight:* Visual storytelling clearly communicates disparities, strengthens case for intervention

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7️⃣ **Prescriptive Insights**

💡 **Strategic Recommendations**

1. **Exclude Gender** from any automated decision systems
2. **Implement Blind Reviews** for promotion and performance appraisals

3. **Standardize Evaluation Criteria** across departments
4. **Run Routine Equity Audits** on model and policy outcomes
5. **Train HR & Leadership** on unconscious bias and fairness principles

📌 *These changes ensure fairness, improve retention, and support inclusive culture.*

🚹 Conclusion & Final Thoughts

This analysis confirms that gender bias in promotion is both **quantifiable** and **actionable**. With statistical tests, visual evidence, and predictive modeling, we demonstrated that **gender influences outcomes independently of merit**.

✅ Final Takeaways

- Gender bias exists in promotion decisions in the dataset
- Visual and model-based patterns confirm disparities
- Strategic changes can directly mitigate the bias

Equity is not automatic—it must be measured, reviewed, and intentionally designed.