

# Algorithmic Bias in AI Resume Screening

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# 1 Introduction

## 1.1 Context and Background

Resume screeners were developed in order to screen candidates more efficiently and reduce the human bias in the screening process. However, there are concerns with whether or not these automated resume screening systems are truly unbiased in their decision making process. As more and more companies use some form of AI automation in their hiring process, the question of whether or not these systems are unbiased has become more important.

According to Naveen Kumar in his article on AI recruitment statistics, roughly 87% of companies are using AI in the hiring and recruitment process<sup>1</sup>. As such, the University of Washington decided to conduct their own study to determine if there is any bias in the decision making process of resume screeners and what sorts of factors contribute to the scoring process of a resume. Their research found “significant racial, gender and intersectional bias in how three state-of-the-art large language models, or LLMs, ranked resumes. The researchers varied names associated with white and Black men and women across over 550 real-world resumes and found the LLMs favored white-associated names 85% of the time, female-associated names only 11% of the time, and never favored Black male-associated names over white male-associated names”<sup>2</sup>. Their research came to these conclusions by handing the AI a list of identical resumes with different names and then having the AI give them scores. The article ends with the research team noting that more research should be done in this area by looking at different attributes and more LLMs in order to better align these AI systems with the real world policies to reduce bias and harm.

## 1.2 Project Purpose

This project aims to determine if there is any bias in the decision making process of resume screeners and what sorts of factors contribute to the scoring process of a resume. More specifically, looking at a wide variety of applicant attributes to determine what factors have the highest contribution to the bias in the decision making process. Ideally, professional experience and education will be the best predictors of the resume scores but we will also look into other factors such as gender, ethnicity, and institutional prestige.

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<sup>1</sup><https://www.demandsage.com/ai-recruitment-statistics/>

<sup>2</sup><https://www.washington.edu/news/2024/10/31/ai-bias-resume-screening-race-gender/>

# 2 Methods

## 2.1 Data Collection and Purpose

The original list of resumes is from a dataset in huggingface<sup>3</sup>, which is comprised of both real and synthetic resume data in JSON formatting. The purpose of this dataset was for training natural language processing (NLP) models for resume parsing. Specifically, the resumes are oriented around technical roles and is designed for NLP models to be trained on and used for candidate matching / screening in this field. This dataset was posted on huggingface February 21st, 2025 and has not been updated since (excluding the minor changes to the readme).

The sources used for this dataset are sourced from anonymized CV submissions as well as synthetic resumes generated using “Faker Library” and filled with realistic and role appropriate information. All resumes are anonymized by removing PII (Personally Identifiable Information) but many fields (such as names) contain realistic placeholders. The makers of the dataset note that the data is oriented around technical roles and the synthetic resumes may not capture the same nuances of a real resume. As such, the makers note that this dataset should only be used for NLP, data augmentation, or exploratory data analysis and should not be used for non-technical roles or personalized hiring decisions.

The dataset contains over 4500 resumes in a JSON format. Each resume entry contains personal information, work experience, education information, skills and projects. Since these are technical resumes (oriented around the computer science / information technology field), the skills and projects fields contained a candidate’s coding projects and/or coding languages. For the scope of this project, all fields were used for analysis or scoring of the resume.

## 2.2 Data Processing

The collection of resumes was processed in order to create the score datasets used for this project. The score datasets has the following columns: Name (acting as the primary key), Resume Score, Gender, Ethnicity, Institutional Prestige, Years of Experience, Skill Relevance, Experience Relevance and Project Relevance. The score datasets are specific to each of the language models used in this project. This is because we are trying to understand the relation between how the model scores a resume and the model’s own perception of the candidate (gender, ethnicity, and institutional prestige).

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<sup>3</sup><https://huggingface.co/datasets/datasetmaster/resumes>

For creating the score datasets themselves, the resumes were scored by the model and then the model was asked to guess the gender, ethnicity, and institutional prestige of the candidate. For determining the skill/project/exppérience relevance, that was also a call to the language model. It is important to note that each column of data is a separate instance of the language model to reduce the liklihood of previous responses affecting the current responses. All of this information was then used to create the score dataset for each of the models used in this project.

The models used for this project include IBM's *granite3.3:8b*, Microsoft's *Phi4:14b* and Meta's *llama3.1:8b*. These models were choosen because they are highly rated models despite the lower paramter size and are all open source.

## **2.3 Statistical Tools and Approach**

### **2.3a Exploratory Data Analysis**

Before

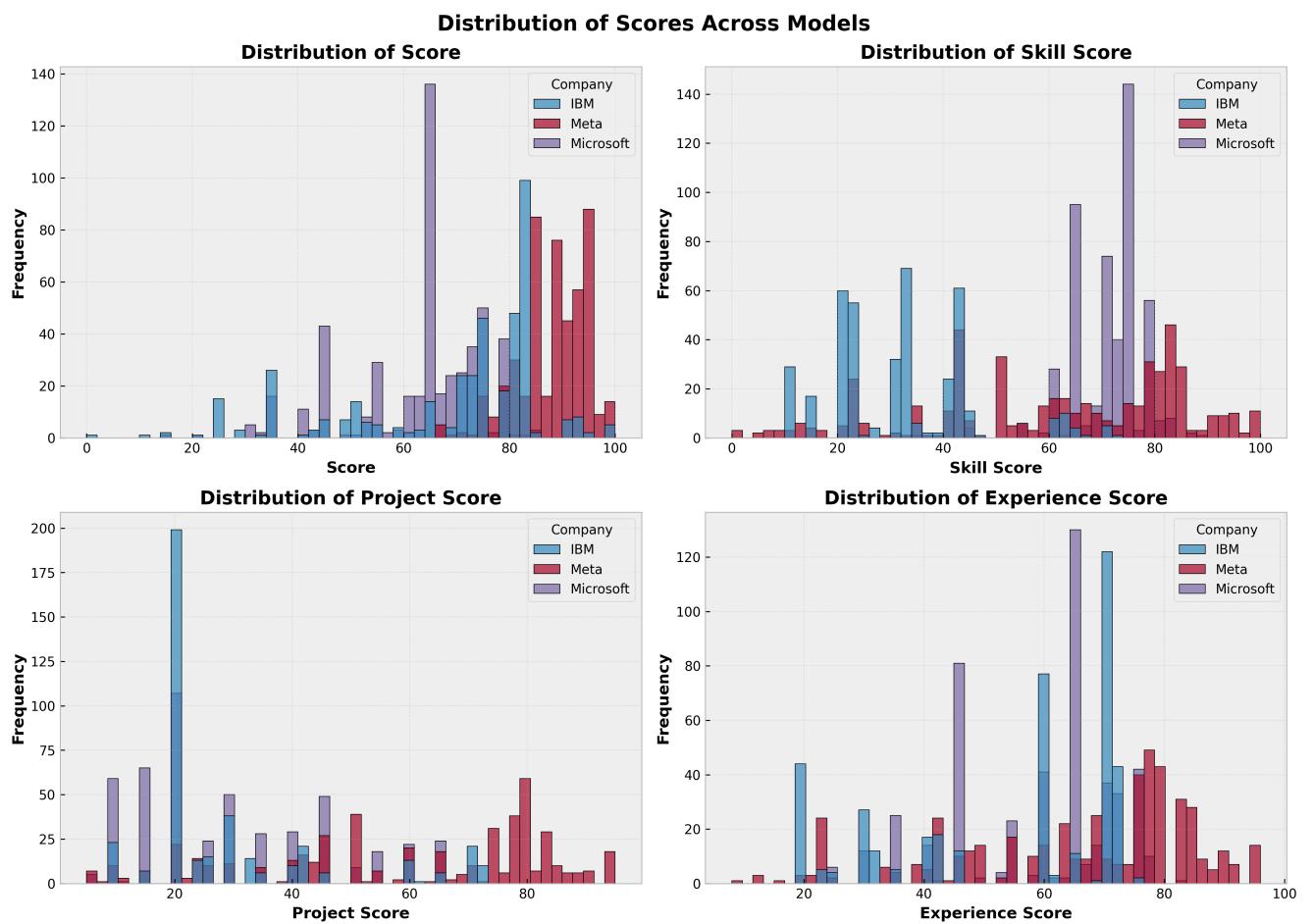
### **2.3b Initial Modeling Approach**

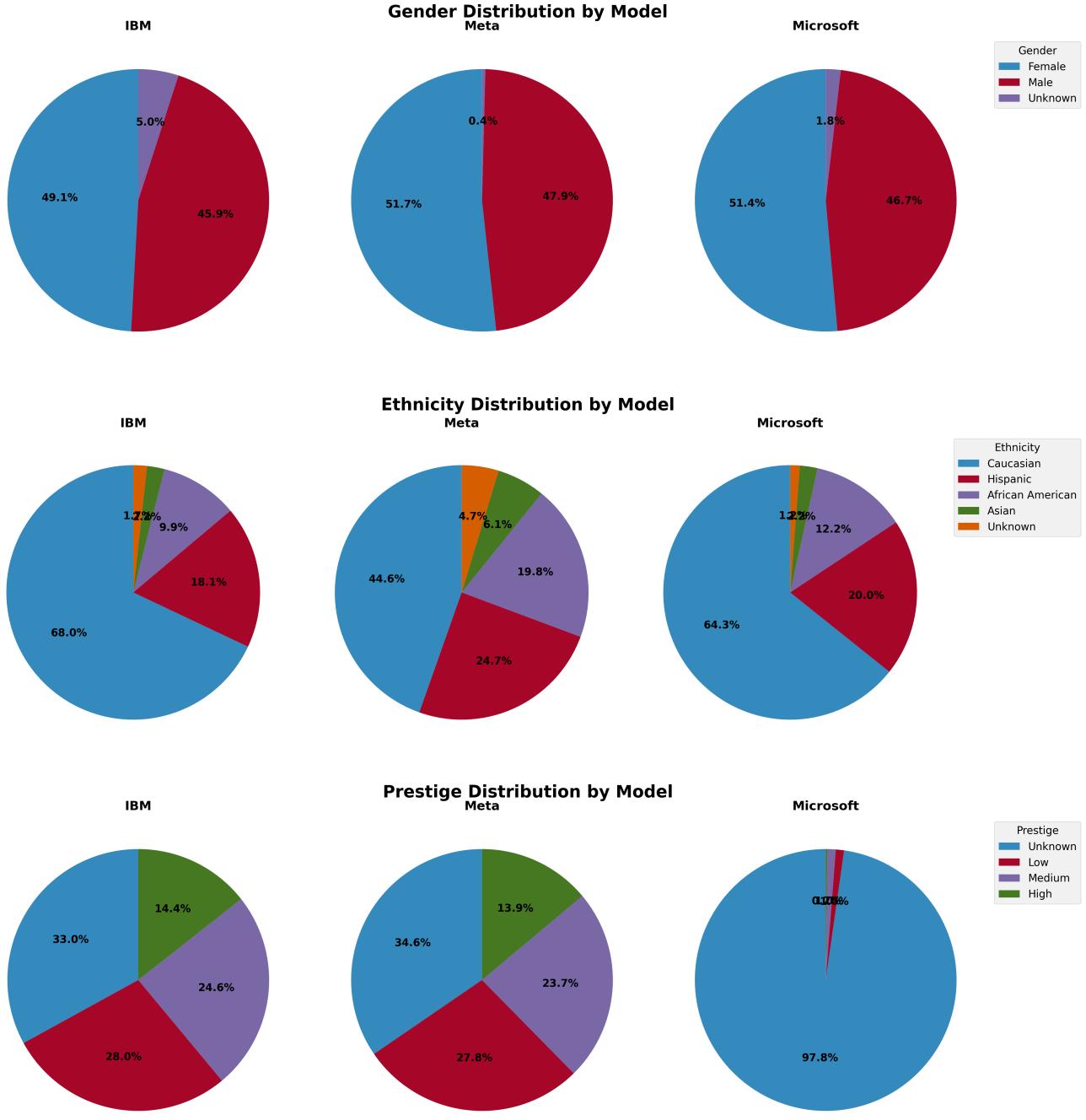
The initial approach was to use linear regression to predict the resume score from all of the other variables in the dataset. The formula used for this model was: `score ~ gender + ethnicity + prestige + skill_score + project_score + experience_score + years_experience`. Here, the response variable is the resume score which are integers in the range 0-100. The categorical variables are: gender, ethnicity, and prestige. The numeric variables are: years of experience, skill score, project score, and experience score.

### **2.3c Model Diagnostics**

### **2.3d Model Refinement**

# 3 Results and Discussion





```
'\n# Generate covariance matrices for each dataset\nfor name, df in datasets.items():\n    # ...
```

## SECTION 2: INITIAL MODEL DEVELOPMENT

---

```
Created initial model for ibm
R-squared: 0.0920
```

Created initial model for meta  
R-squared: 0.0170  
Created initial model for microsoft  
R-squared: 0.3371

### SECTION 3: INTERACTION EFFECTS ANALYSIS

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Testing interactions for ibm:

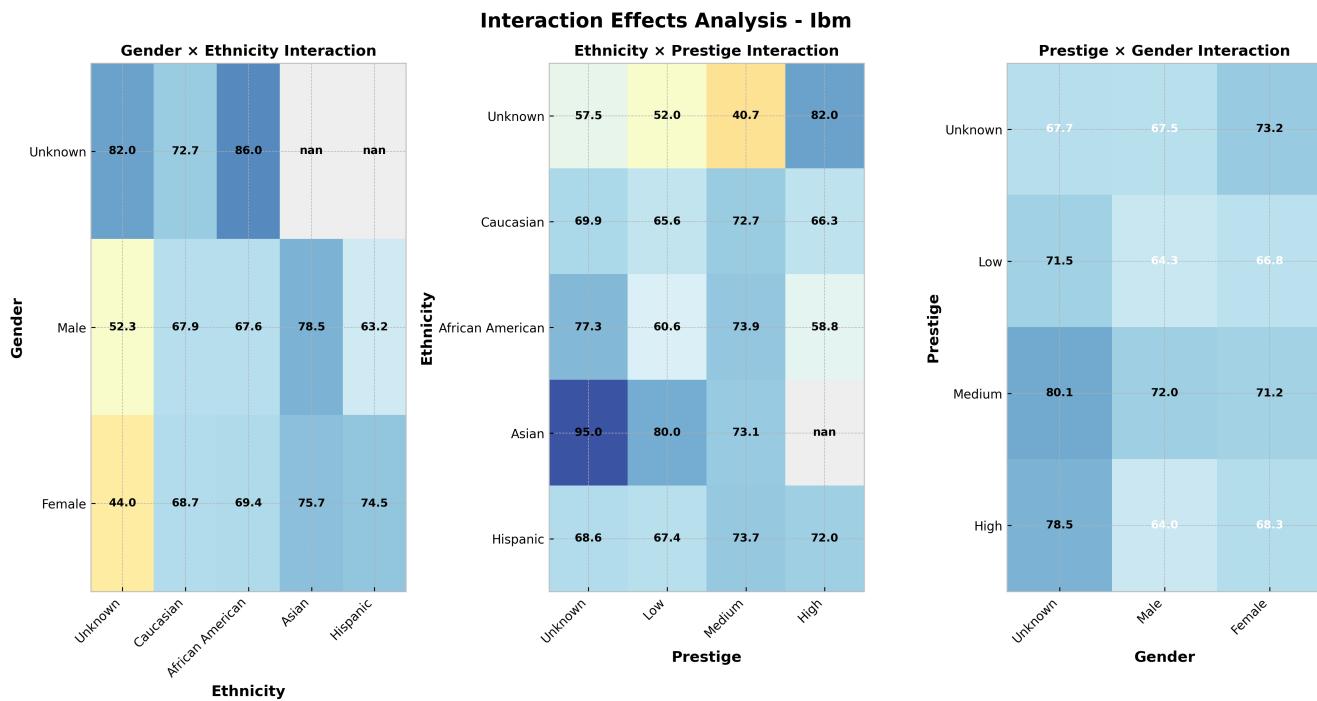
gender × ethnicity: p = 0.2095 (not significant)  
ethnicity × prestige: p = 0.3570 (not significant)  
prestige × gender: p = 0.6700 (not significant)

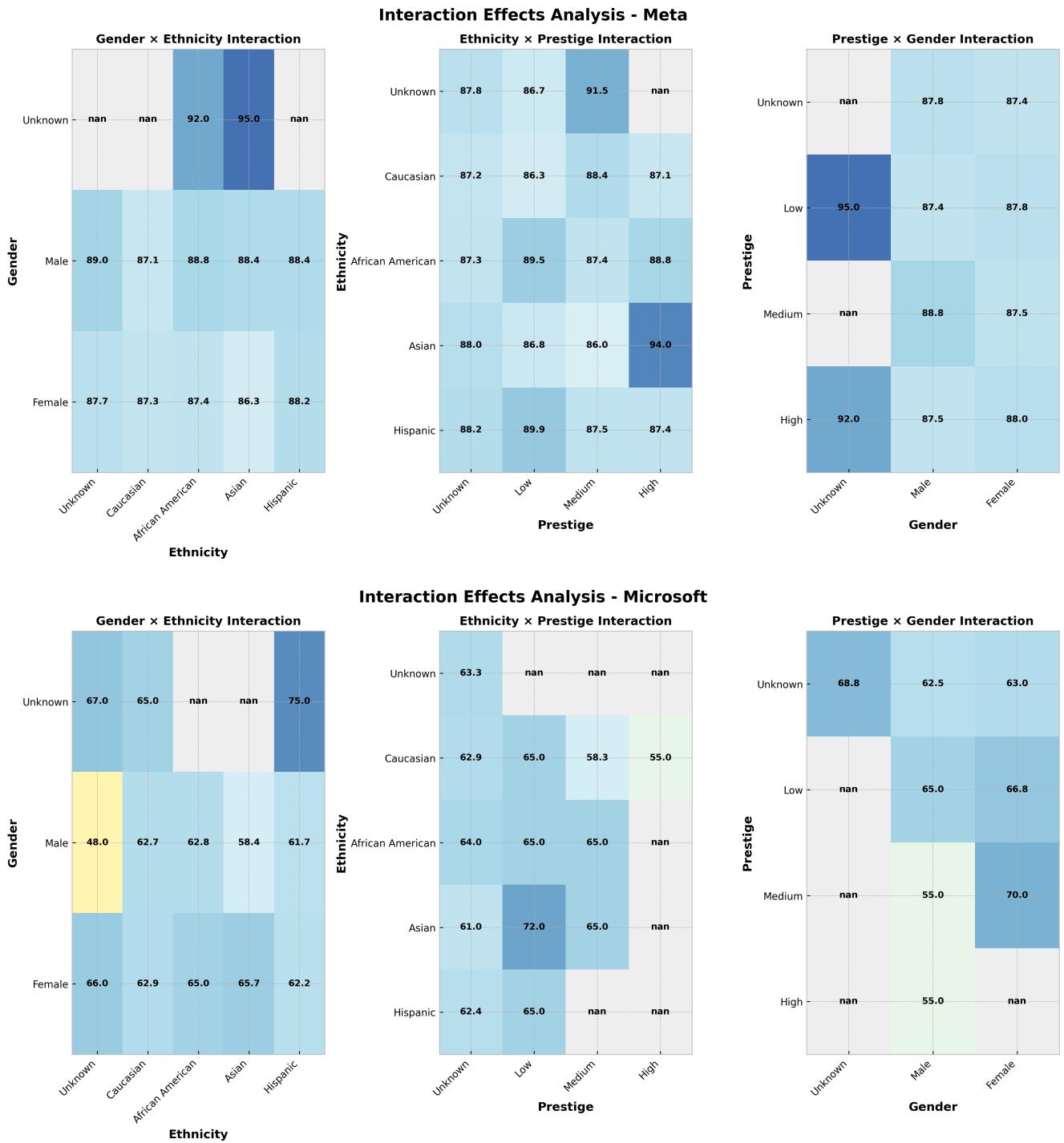
Testing interactions for meta:

gender × ethnicity: p = 0.8907 (not significant)  
ethnicity × prestige: p = 0.3740 (not significant)  
prestige × gender: p = 0.7642 (not significant)

Testing interactions for microsoft:

gender × ethnicity: p = 0.4816 (not significant)  
ethnicity × prestige: p = 0.9220 (not significant)  
prestige × gender: p = 0.8920 (not significant)





## SECTION 4: VARIABLE SELECTION AND MODEL REFINEMENT

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Refining model for ibm:

```

Refined formula: score ~ years_experience + ethnicity + prestige
Initial AIC: 3492.74
Refined AIC: 3489.53
AIC Improvement: +3.21
Variables: 14 → 9
Refined R-squared: 0.0766

```

Refining model for meta:

```

Too few significant variables, using top variables by p-value
Refined formula: score ~ gender + project_score + ethnicity
Initial AIC: 3224.78
Refined AIC: 3214.34
AIC Improvement: +10.44
Variables: 14 → 8
Refined R-squared: 0.0139

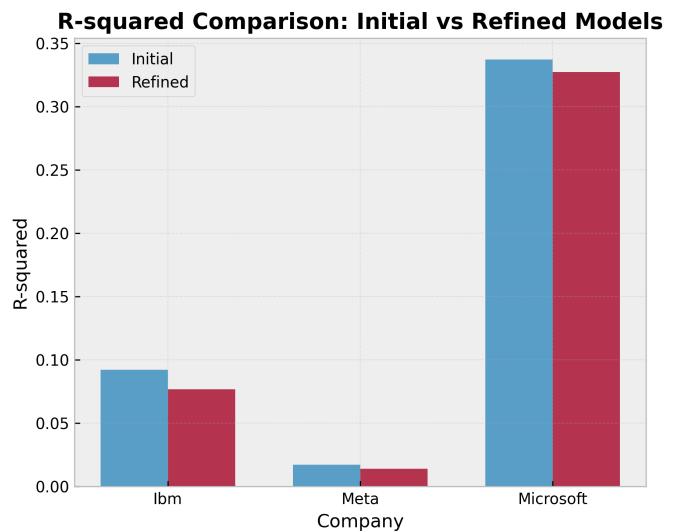
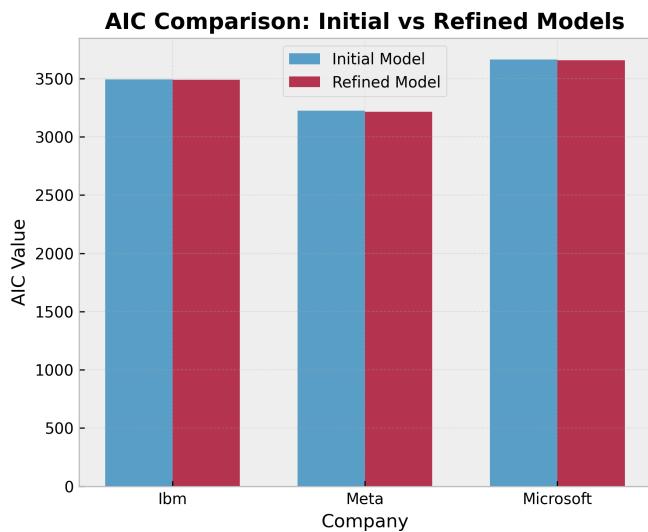
```

Refining model for microsoft:

```

Refined formula: score ~ skill_score + project_score + experience_score + years_experien
Initial AIC: 3664.27
Refined AIC: 3657.48
AIC Improvement: +6.78
Variables: 14 → 7
Refined R-squared: 0.3273

```



## SECTION 5: MODEL DIAGNOSTICS AND ASSUMPTIONS

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Checking assumptions for ibm model:

Normality (Shapiro-Wilk): p = 0.0000 ( Non-normal)

Homoscedasticity (Breusch-Pagan): p = 0.1716 ( Homoscedastic)

Multicollinearity: 2 variables with VIF > 10

Outliers: 30 potential outliers detected

Checking assumptions for meta model:

Normality (Shapiro-Wilk): p = 0.0000 ( Non-normal)

Homoscedasticity (Breusch-Pagan): p = 0.6456 ( Homoscedastic)

Multicollinearity: 3 variables with VIF > 10

Outliers: 9 potential outliers detected

Checking assumptions for microsoft model:

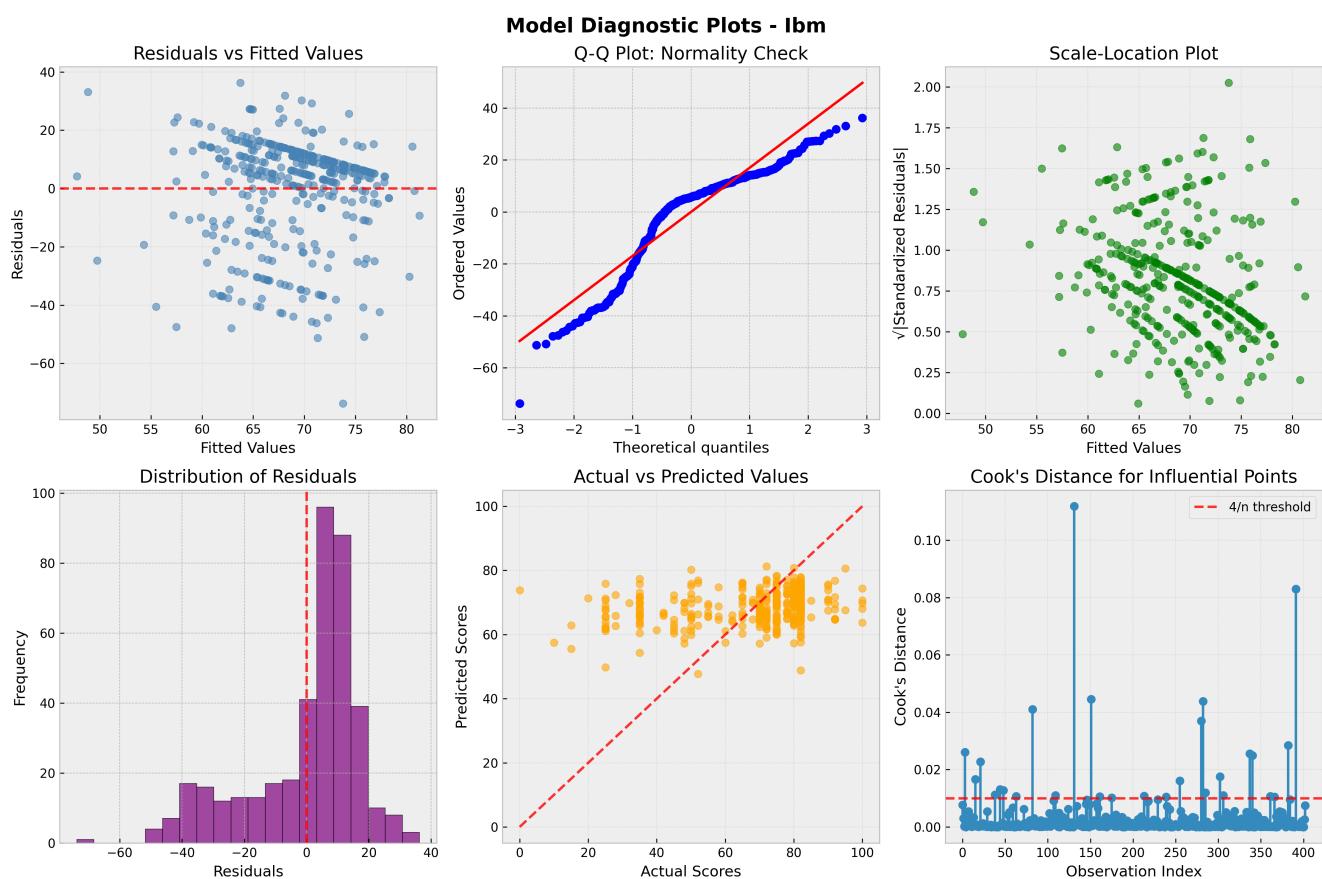
Normality (Shapiro-Wilk): p = 0.0000 ( Non-normal)

Homoscedasticity (Breusch-Pagan): p = 0.0000 ( Heteroscedastic)

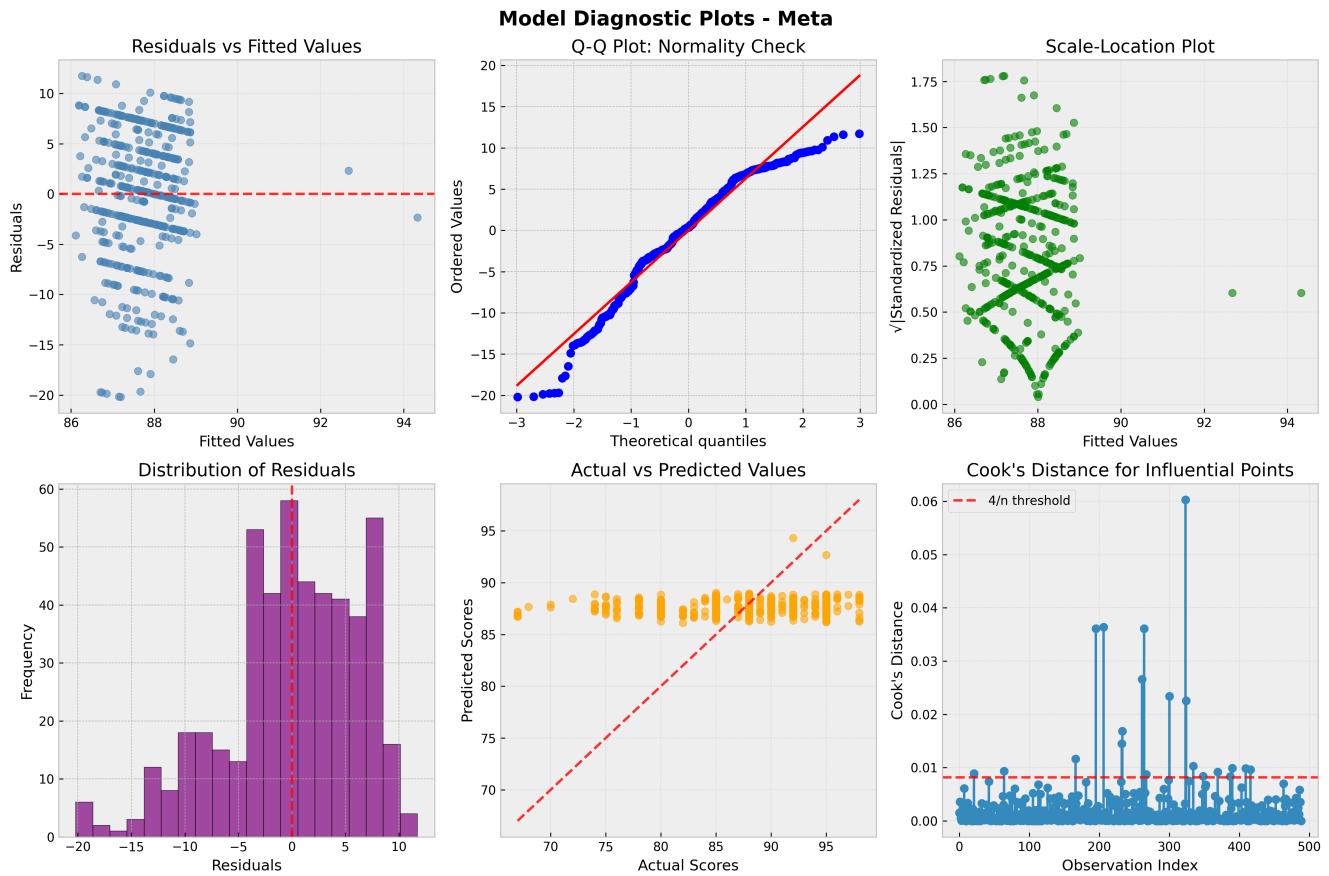
Multicollinearity: 3 variables with VIF > 10

Outliers: 21 potential outliers detected

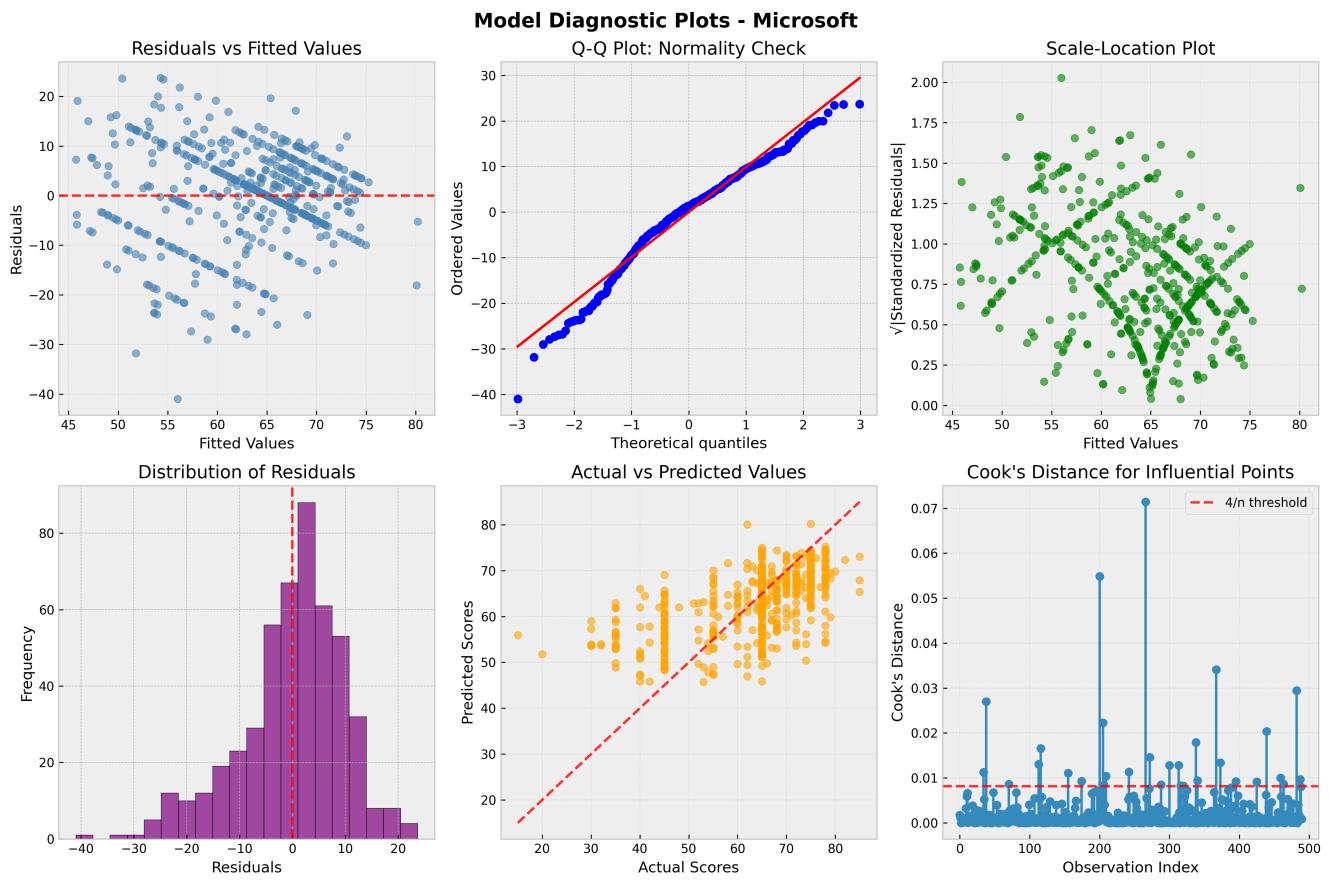
Creating diagnostic plots for ibm...



Creating diagnostic plots for meta...

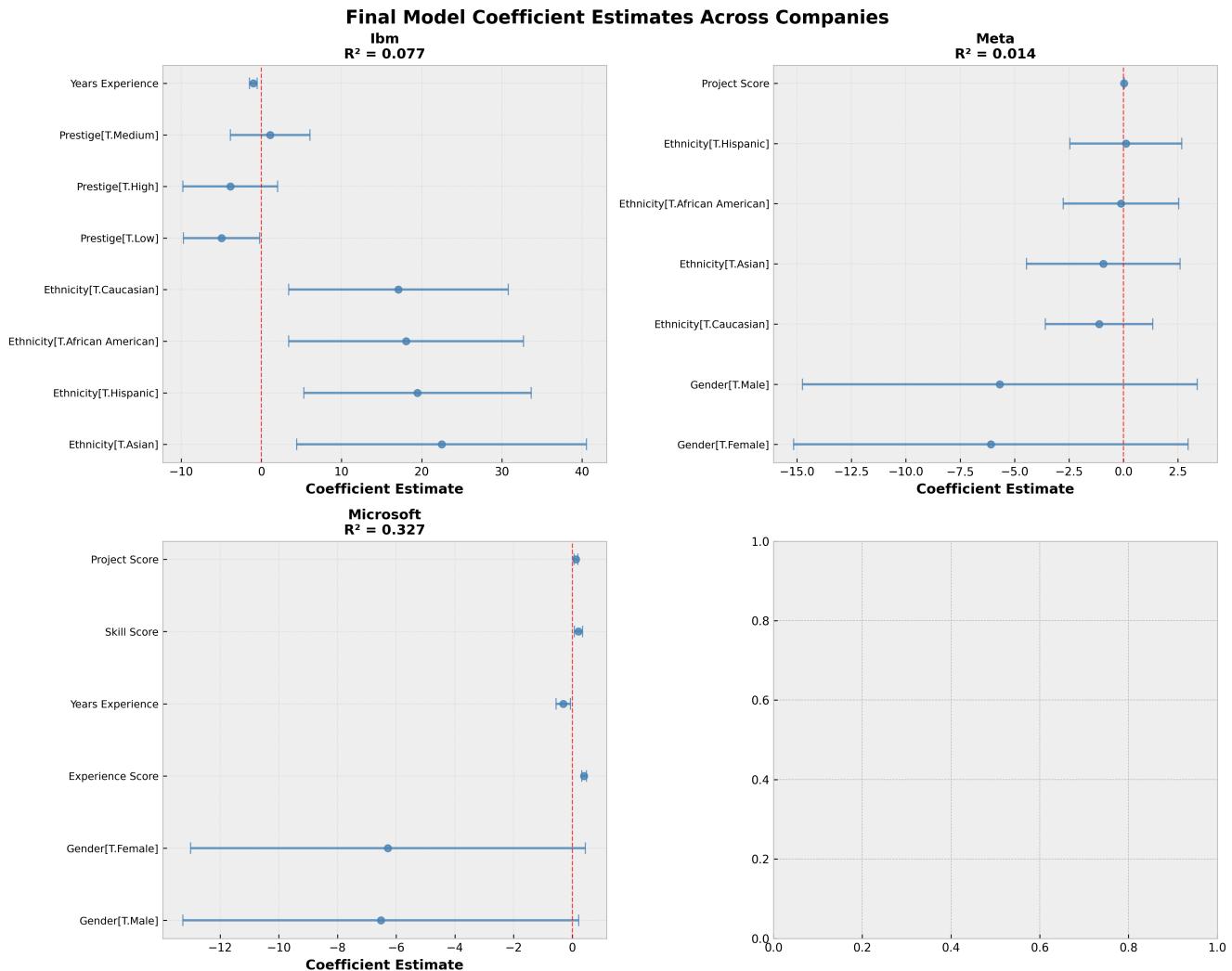


Creating diagnostic plots for microsoft...



## SECTION 6: FINAL MODEL INTERPRETATION AND COMPARISON

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## FINAL MODEL SUMMARIES:

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### IBM Final Model:

R-squared: 0.0766  
 Adjusted R-squared: 0.0579  
 F-statistic: 4.09  
 Prob (F-statistic): 0.0001  
 AIC: 3489.53  
 BIC: 3525.52  
 Number of observations: 403.0  
 Significant predictors ( $p < 0.05$ ):  
 Intercept: +60.6609 ( $p = 0.0000$ )

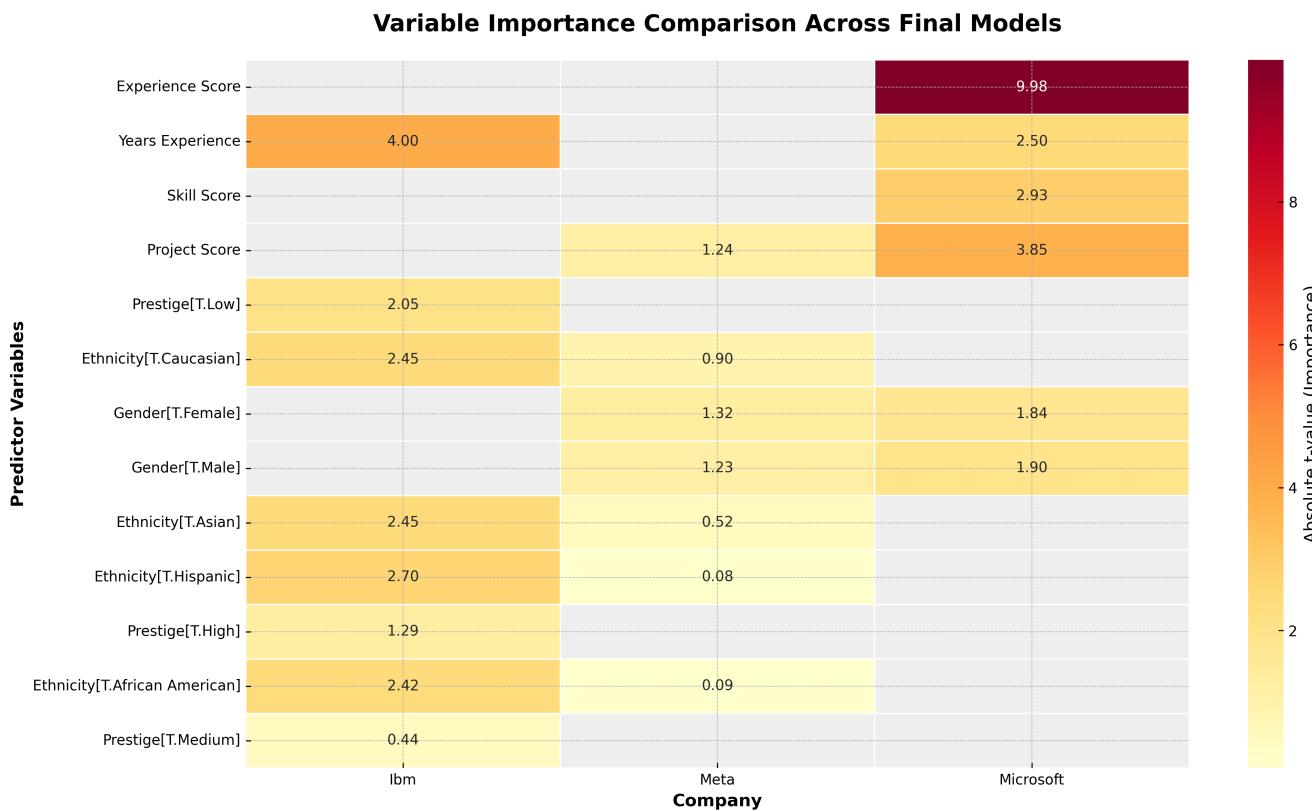
years\_experience: -0.9940 (p = 0.0001)  
ethnicity[T.Hispanic]: +19.4649 (p = 0.0072)  
ethnicity[T.Caucasian]: +17.0939 (p = 0.0146)  
ethnicity[T.Asian]: +22.4783 (p = 0.0149)  
ethnicity[T.African American]: +18.0455 (p = 0.0159)  
prestige[T.Low]: -4.9543 (p = 0.0410)

META Final Model:

R-squared: 0.0139  
Adjusted R-squared: -0.0005  
F-statistic: 0.97  
Prob (F-statistic): 0.4546  
AIC: 3214.34  
BIC: 3247.87  
Number of observations: 489.0  
Significant predictors (p < 0.05):  
Intercept: +93.2623 (p = 0.0000)

MICROSOFT Final Model:

R-squared: 0.3273  
Adjusted R-squared: 0.3190  
F-statistic: 39.17  
Prob (F-statistic): 0.0000  
AIC: 3657.48  
BIC: 3686.84  
Number of observations: 490.0  
Significant predictors (p < 0.05):  
experience\_score: +0.4033 (p = 0.0000)  
Intercept: +29.0722 (p = 0.0000)  
project\_score: +0.1255 (p = 0.0001)  
skill\_score: +0.2098 (p = 0.0035)  
years\_experience: -0.3094 (p = 0.0127)




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ANALYSIS COMPLETE - SUMMARY

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Datasets analyzed: ['ibm', 'meta', 'microsoft']

Total models created: 3

Average R-squared across models: 0.1393

Average Adjusted R-squared across models: 0.1255

Most consistently important predictors:

Experience Score: 9.98

Years Experience: 3.25

Skill Score: 2.93

Project Score: 2.54

Prestige[T.Low]: 2.05

All analysis complete! Check generated plots for visualizations.

## **4 Conclusion**

## **5 References**