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0.1 Billionaires Statistics Dataset (2023)

Exploring the Global Landscape of Success

Who wouldn't want to be a billionaire? The idea of immense wealth, influence, and the ability to shape the world is a dream shared by many but achieved by very few. Billionaires occupy a unique position in society, wielding power that extends far beyond their bank accounts. From driving technological innovation to influencing global policies, their decisions ripple across industries, politics, and even everyday life. These individuals are more than just wealthy—they are architects of the future.

This project dives into the fascinating lives of billionaires to uncover the patterns and factors that contribute to their success. What common threads run through their stories? How do age, industry, education, and other demographics shape their rise to the top? By answering these questions, we can better understand the mechanisms behind extraordinary wealth and its broader societal impact.

For this analysis, I've selected the Billionaires Statistics Dataset (2023) from Kaggle, a rich collection of data detailing the net worth, industries, and demographics of the world's billionaires. Our goal is to build a predictive model that estimates the net worth (finalWorth) of these individuals based on explanatory variables such as industry, country GDP, education, and more. This exploration not only sheds light on the secrets to immense wealth but also offers insights into global economic and social dynamics.

To deepen our understanding, we will develop and test various predictive models to determine which one best captures the complexity of the data. By comparing the performance of these models, we aim to identify the most effective approach for explaining and predicting billionaire wealth.

Through this analysis, we will address questions such as:

What are the key factors that influence a billionaire's net worth? How does the country of origin or industry type impact wealth accumulation? Are self-made billionaires fundamentally different from those who inherit their wealth? Which modeling techniques provide the best fit for this data? This analysis isn't just about numbers; it's about unraveling the story of power, opportunity, and innovation that underpins the lives of the world's wealthiest individuals while leveraging advanced modeling to bring these insights to life.

Key Features

Rank: The ranking of the billionaire in terms of wealth.

finalWorth: The final net worth of the billionaire in U.S. dollars.

category: The category or industry in which the billionaire's business operates.

personName: The full name of the billionaire.

age: The age of the billionaire.

country: The country in which the billionaire resides.

city: The city in which the billionaire resides.

source: The source of the billionaire's wealth.

industries: The industries associated with the billionaire's business interests.

countryOfCitizenship: The country of citizenship of the billionaire.

organization: The name of the organization or company associated with the billionaire.

selfMade: Indicates whether the billionaire is self-made (True/False). status: "D" represents self-made billionaires (Founders/Entrepreneurs) and "U" indicates inherited or unearned wealth.

gender: The gender of the billionaire.

birthDate: The birthdate of the billionaire.

lastName: The last name of the billionaire.

firstName: The first name of the billionaire.

title: The title or honorific of the billionaire.

date: The date of data collection.

state: The state in which the billionaire resides.

residenceStateRegion: The region or state of residence of the billionaire.

birthYear: The birth year of the billionaire.

birthMonth: The birth month of the billionaire.

birthDay: The birth day of the billionaire.

cpi_country: Consumer Price Index (CPI) for the billionaire's country.

cpi_change_country: CPI change for the billionaire's country.

gdp_country: Gross Domestic Product (GDP) for the billionaire's country.

gross_tertiary_education_enrollment: Enrollment in tertiary education in the billionaire's country.

gross_primary_education_enrollment_country: Enrollment in primary education in the billionaire's country.

life_expectancy_country: Life expectancy in the billionaire's country.

tax_revenue_country_country: Tax revenue in the billionaire's country.

total_tax_rate_country: Total tax rate in the billionaire's country.

population_country: Population of the billionaire's country.

latitude_country: Latitude coordinate of the billionaire's country.

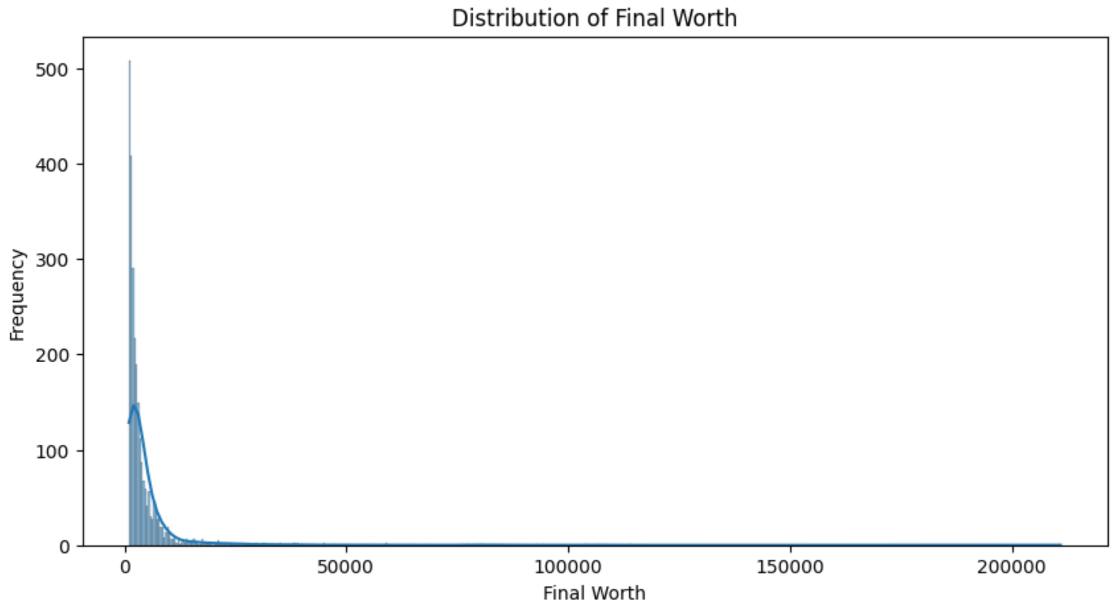
longitude_country: Longitude coordinate of the billionaire's country.

1 Explanatory Data Analysis

1.1 Final Worth Analysis

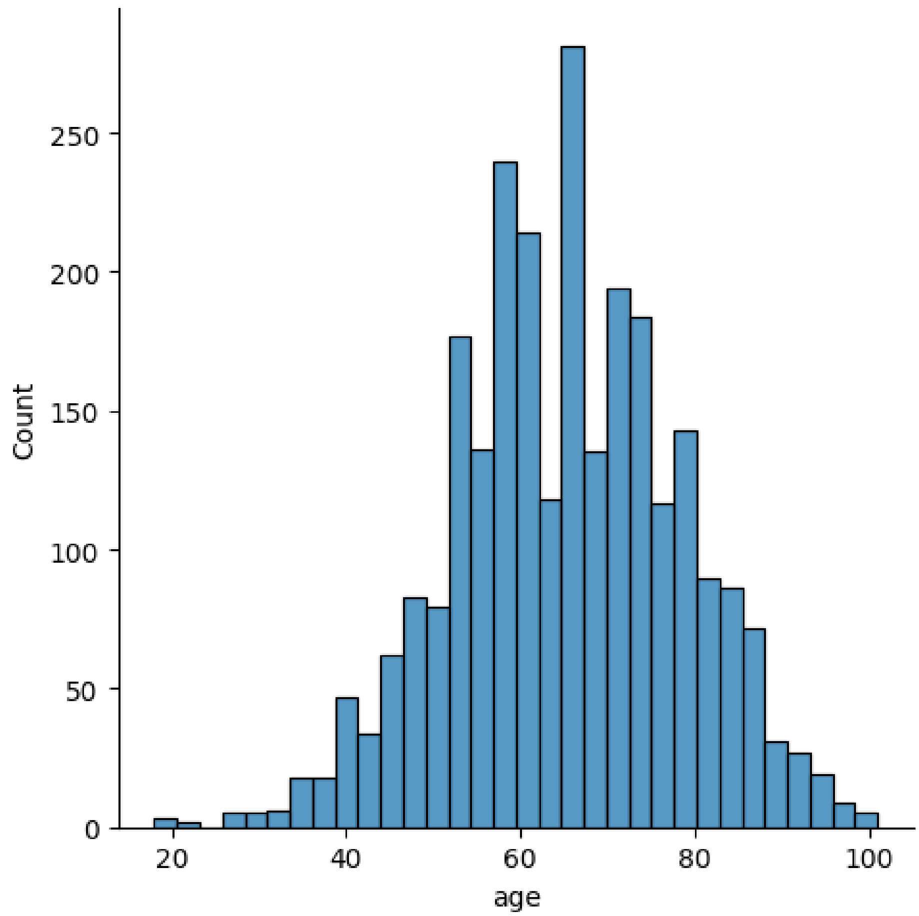
```
count      2640.000000
mean       4623.787879
std        9834.240939
min        1000.000000
25%        1500.000000
50%        2300.000000
75%        4200.000000
max      211000.000000
Name: finalWorth, dtype: float64
```

The data reveals a significant variation in the wealth of billionaires. The average net worth is \$4.62 billion, but the median is \$2.3 billion, indicating that a few extremely wealthy individuals skew the average upward. The highest net worth is \$211 billion, highlighting the considerable wealth disparity. Most billionaires fall within the interquartile range, with net worths between \$1.5 billion and \$4.2 billion, representing the middle 50% of the data. These figures suggest that the distribution is highly uneven, requiring careful handling of extreme values during analysis and prediction.



1.2 Age Analysis

```
<seaborn.axisgrid.FacetGrid at 0x79cf4272ee00>
```




```
age_group
20-30      9
31-40     56
41-50    216
51-60    632
61-70    748
71-80    595
81+      382
Name: count, dtype: int64
```

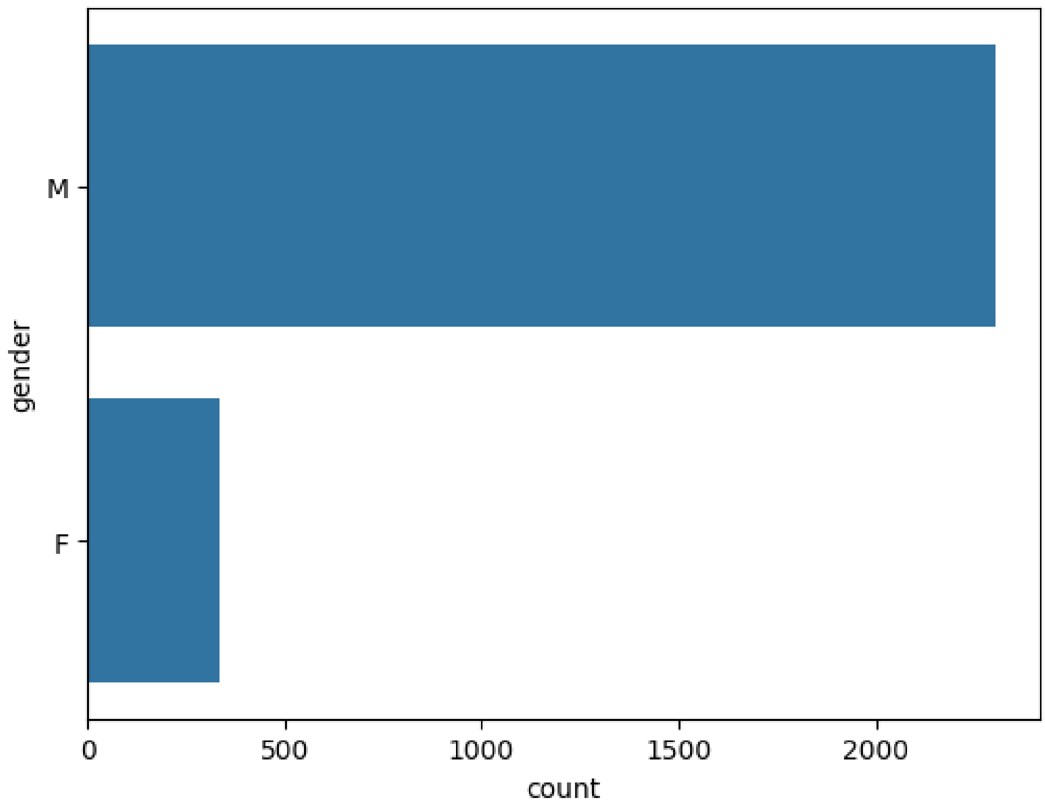
The majority of billionaires fall within the 51-70 age range, with 632 individuals aged 51-60 and 748 aged 61-70, accounting for a significant proportion of the dataset. This suggests that middle-aged to early retirement years are peak periods for accumulating substantial wealth.

Younger billionaires are relatively rare, with only 9 individuals in the 20-30 age range and 56 in the 31-40 range, indicating that becoming a billionaire at a young age is uncommon. On the other hand, the 71-80 group remains substantial with 595 individuals, and 382 billionaires are 81 years or older, showing that a significant number of individuals maintain their billionaire status well into older age.

1.3 Gender alalysis

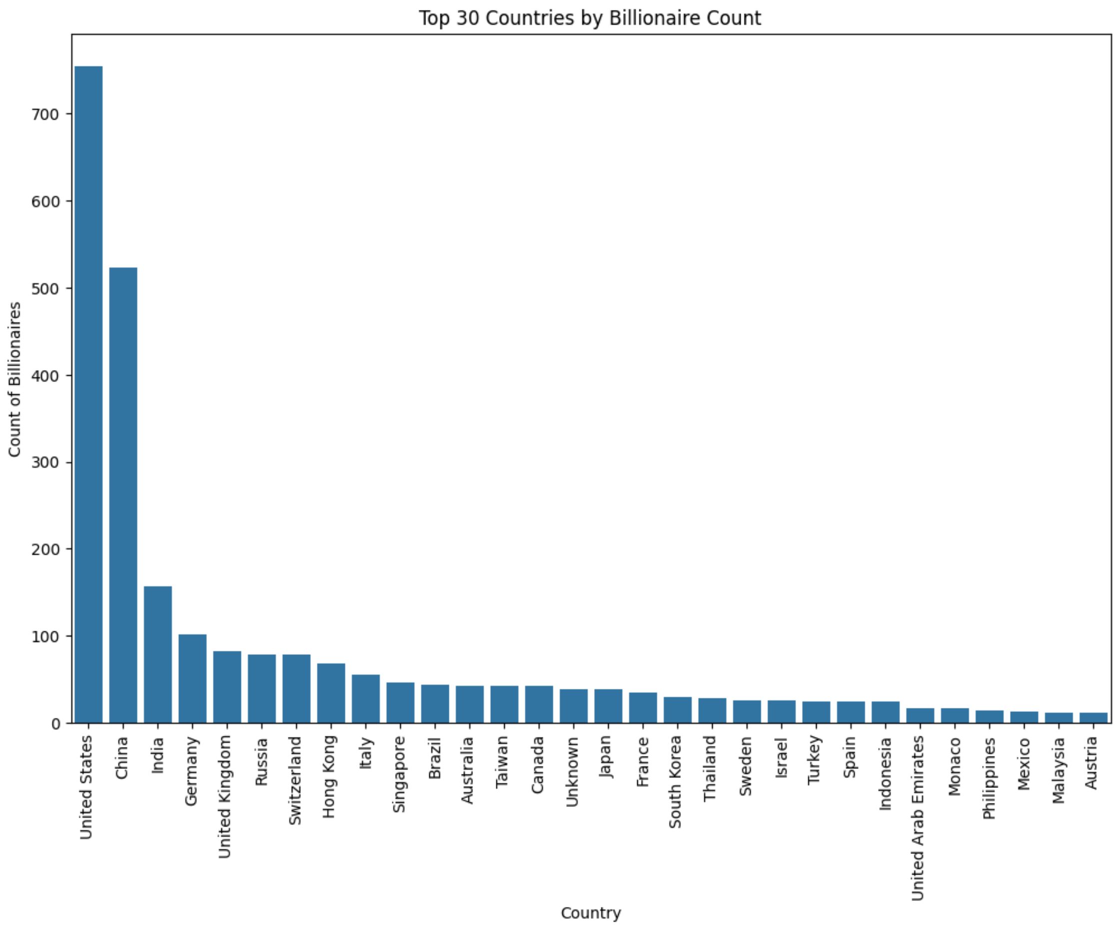
```
gender
M    2303
F     337
Name: count, dtype: int64

<Axes: xlabel='count', ylabel='gender'>
```



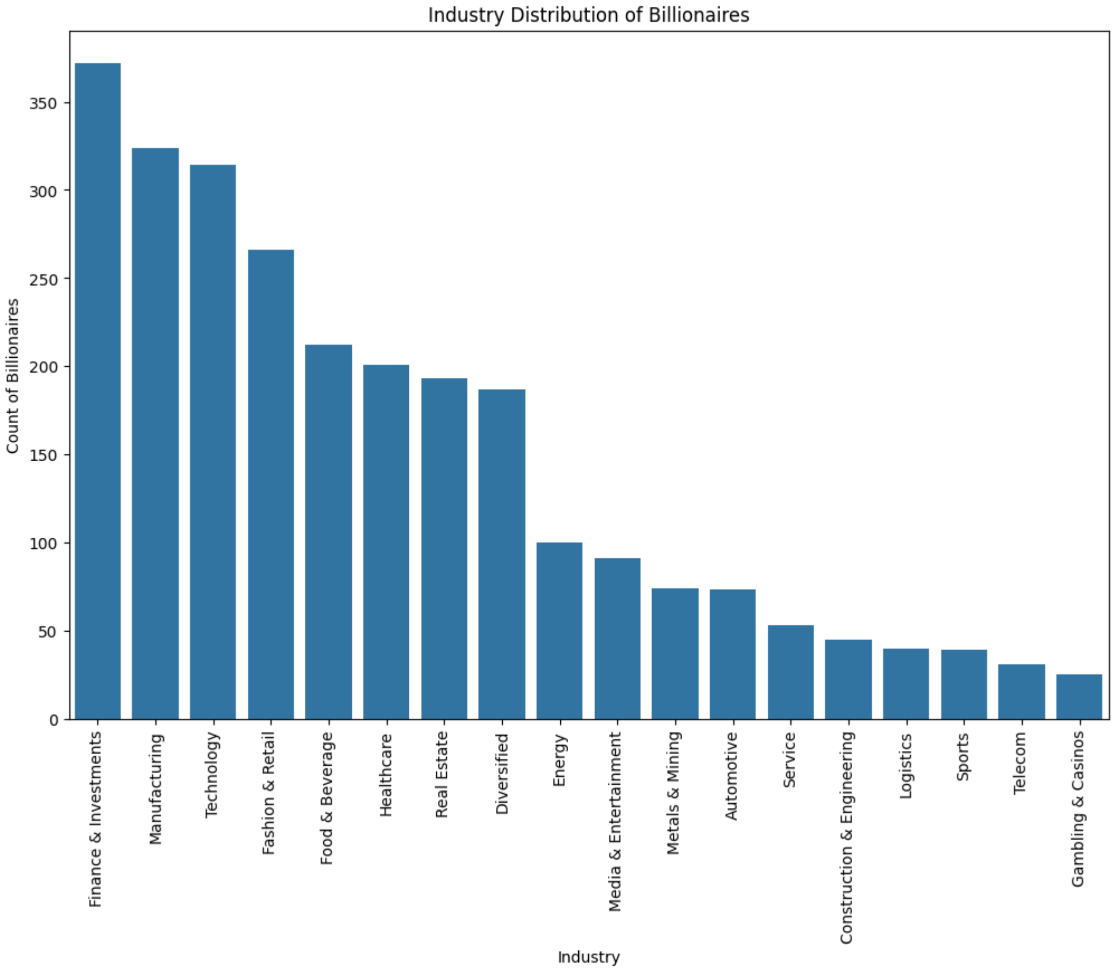
This indicates that men overwhelmingly dominate the billionaire demographic, accounting for approximately 87% of the total, while women represent just 13%. This disparity could be attributed to historical, cultural, and systemic factors that have limited women's access to opportunities for wealth creation, particularly in high-revenue industries and leadership roles.

1.4 Country Analysis



The majority of billionaires originate from the United States, followed by China and India. This concentration emphasizes the global economic dominance of these countries and their ability to create environments conducive to wealth generation. Their strong economies, technological innovation, and entrepreneurial ecosystems contribute significantly to this wealth concentration, showcasing their critical role in shaping global financial landscapes.

1.5 Industry Analysis




```
Number of Billionaires by Industry:
industries
Finance & Investments         372
Manufacturing                 324
Technology                    314
Fashion & Retail              266
Food & Beverage               212
Healthcare                    201
Real Estate                   193
Diversified                   187
Energy                        100
Media & Entertainment          91
Metals & Mining                74
Automotive                     73
Service                        53
Construction & Engineering     45
```

```
Logistics                        40
Sports                           39
Telecom                          31
Gambling & Casinos               25
Name: count, dtype: int64

Average Net Worth per Industry (in USD):
industries
Automotive                     7195.890411
Telecom                        6564.516129
Fashion & Retail               6386.466165
Metals & Mining                6037.837838
Logistics                      5987.500000
Technology                     5980.573248
Diversified                    4840.641711
Gambling & Casinos             4820.000000
Media & Entertainment          4697.802198
Energy                         4535.000000
Food & Beverage                4515.094340
Finance & Investments          4314.784946
Sports                         3448.717949
Real Estate                    3406.217617
Service                        3271.698113
Healthcare                     3200.000000
Manufacturing                  3145.061728
Construction & Engineering     2633.333333
Name: finalWorth, dtype: float64
```

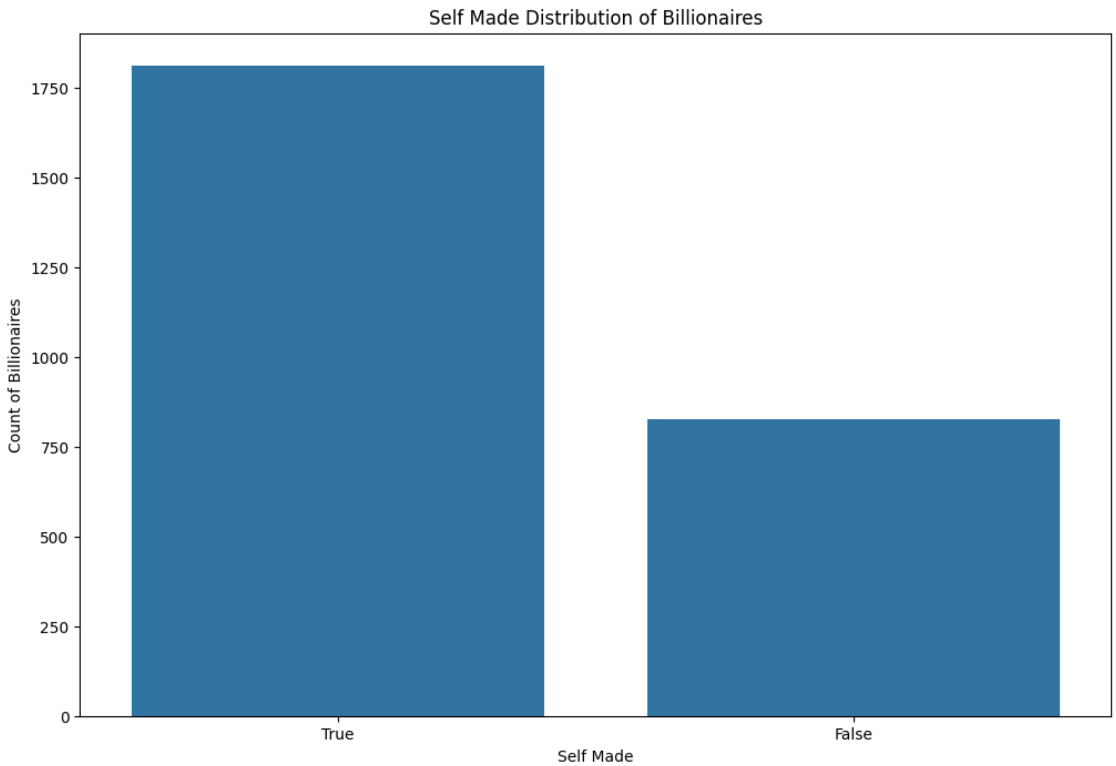
Finance & Investments has the most billionaires (372), followed by Manufacturing (324) and Technology (314), showing that these sectors are big worldwide wealth creators.

In terms of average net worth, Automotive leads with around $7.2 billion, followed by Telecom ($6.6 billion) and Fashion & Retail ($6.4 billion). These industries, while having fewer billionaires than sectors such as finance and manufacturing, have much higher average wealth. This implies that a smaller number of people in these industries have a higher stake.

This implies that a smaller number of people in these industries own a bigger percentage of the wealth, showing a high concentration of wealth among specific businesses or individuals.

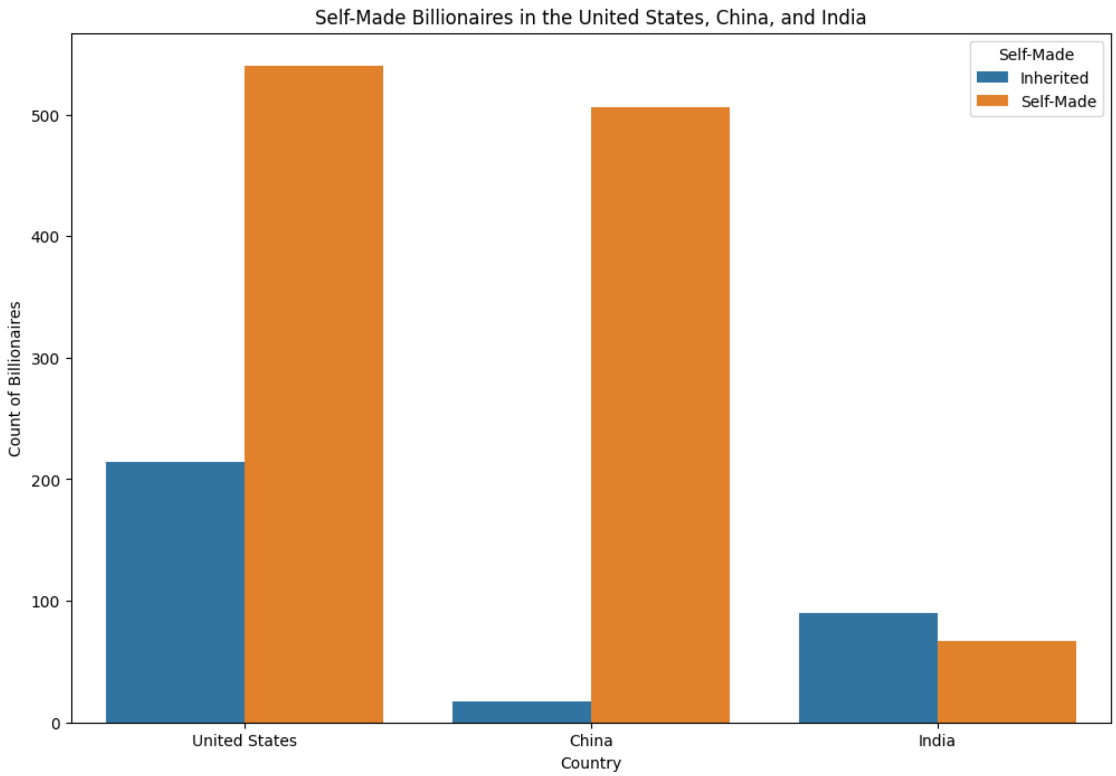
Healthcare ($3.2 billion), Manufacturing ($3.1 billion), and Construction & Engineering ($2.6 billion) have lower average net worths, which could imply that these industries have more billionaires with more evenly distributed wealth, or that their market structures result in less wealth concentration at the top.

1.6 Self Made Analysis



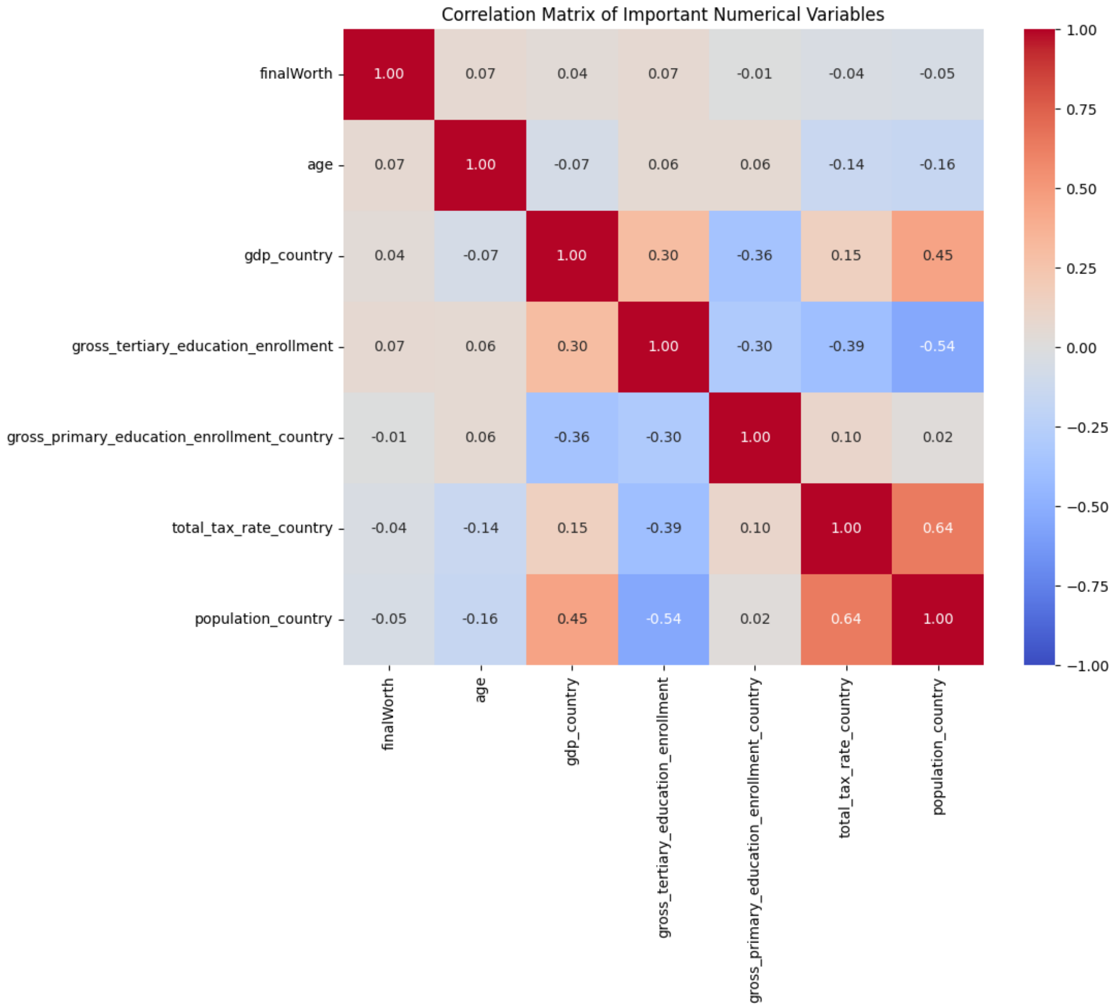
The majority of billionaires are self-made, having accumulated their wealth through their own efforts and ventures. They built their fortunes independently, often starting from humble beginnings and achieving success through innovation, entrepreneurship, and strategic investments.

1.7 Self-Made Billionaires in the United States, China, and India



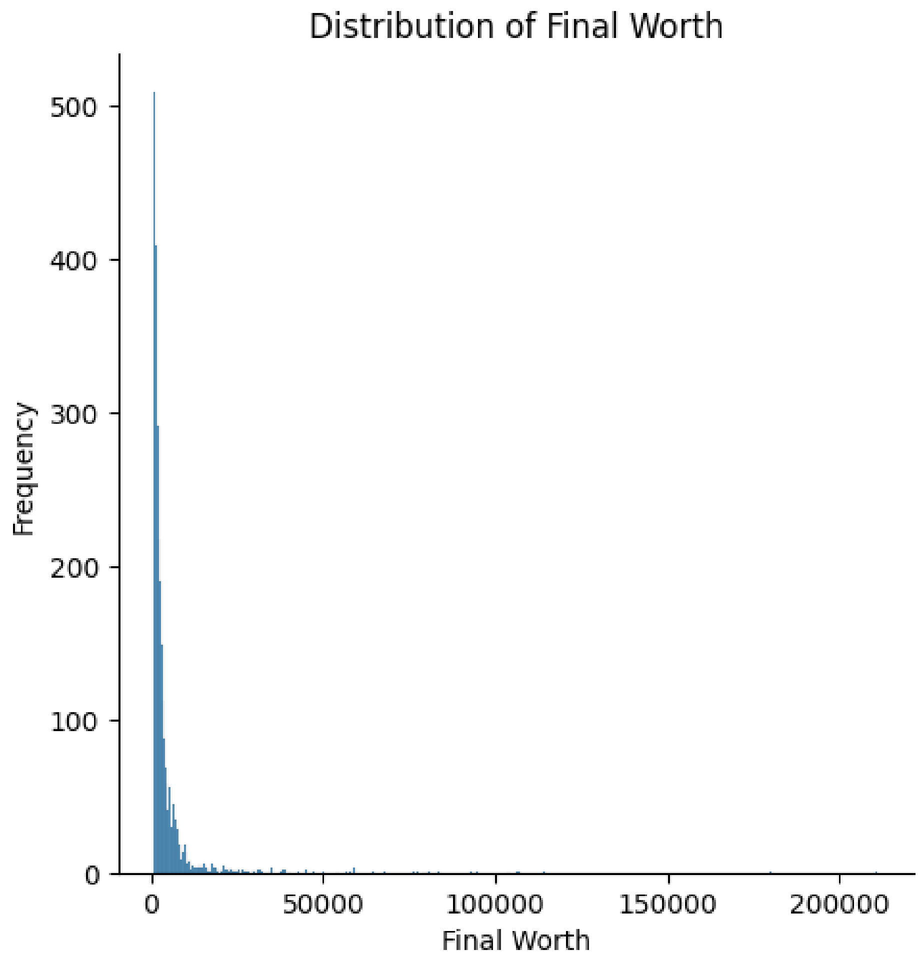
In the United States and China, the majority of billionaires are self-made. However, in India, the majority of billionaires inherit their wealth. In China, the proportion of self-made billionaires is significantly higher compared to inherited wealth, whereas in the United States, there is a notable number of billionaires who inherited their wealth. The contrast is striking, as in China, inherited wealth represents a much smaller portion of the billionaire population.

1.8 Correlation matrix

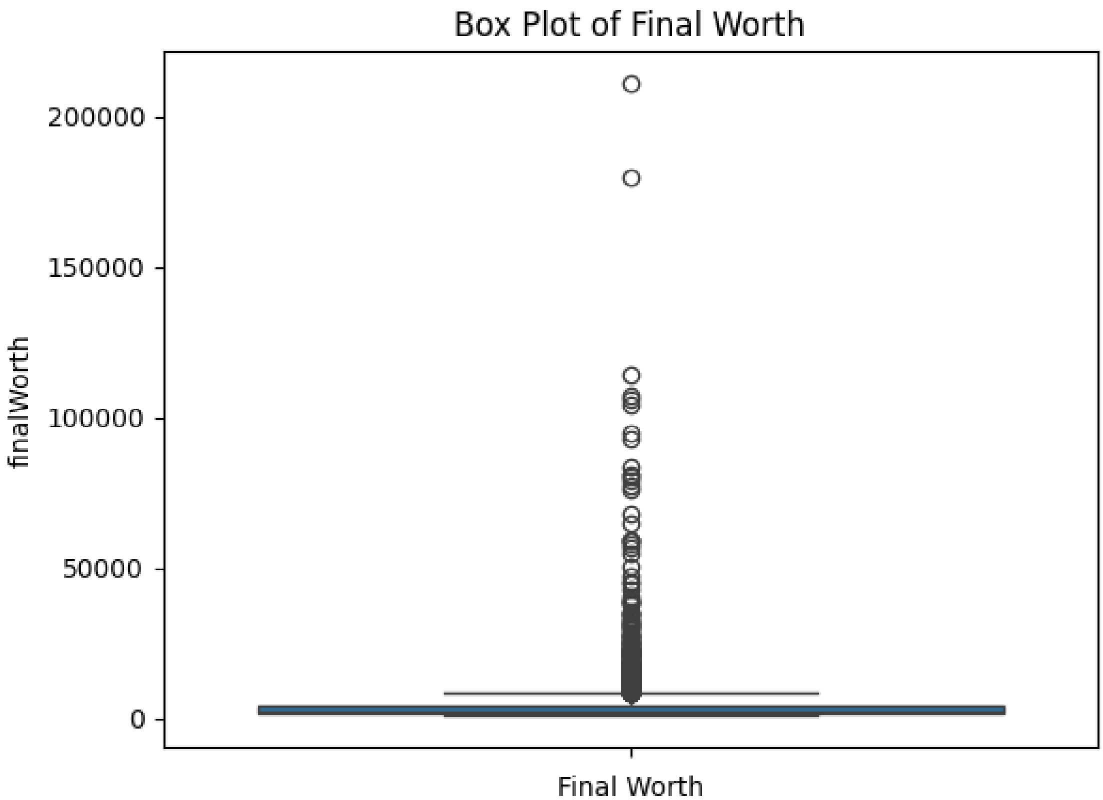


There is no significant correlation between final worth and the other variables based on the linear relationships captured by the correlation analysis. However, this does not mean that there is no connection between the variables; it simply indicates that the relationships may not be linear. In the next section, we will explore non-linear models, which may uncover more complex interactions that linear methods cannot capture.

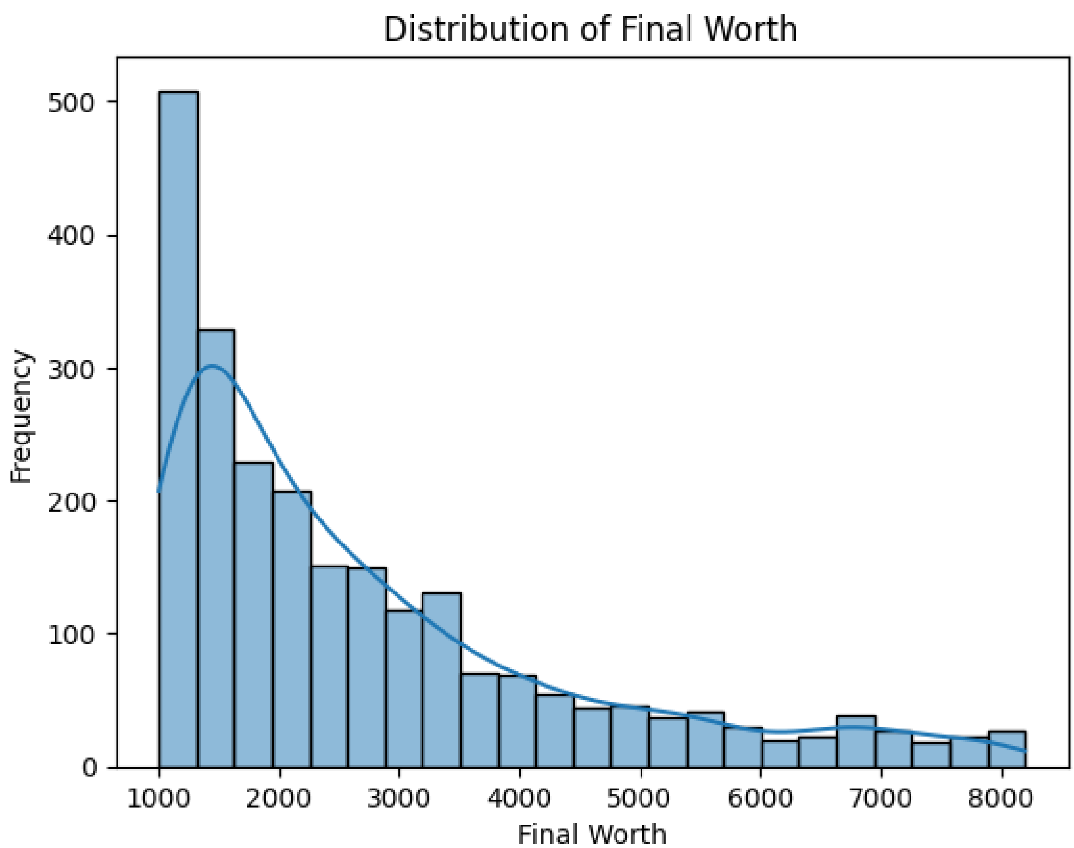
2 Modeling and Interpretation



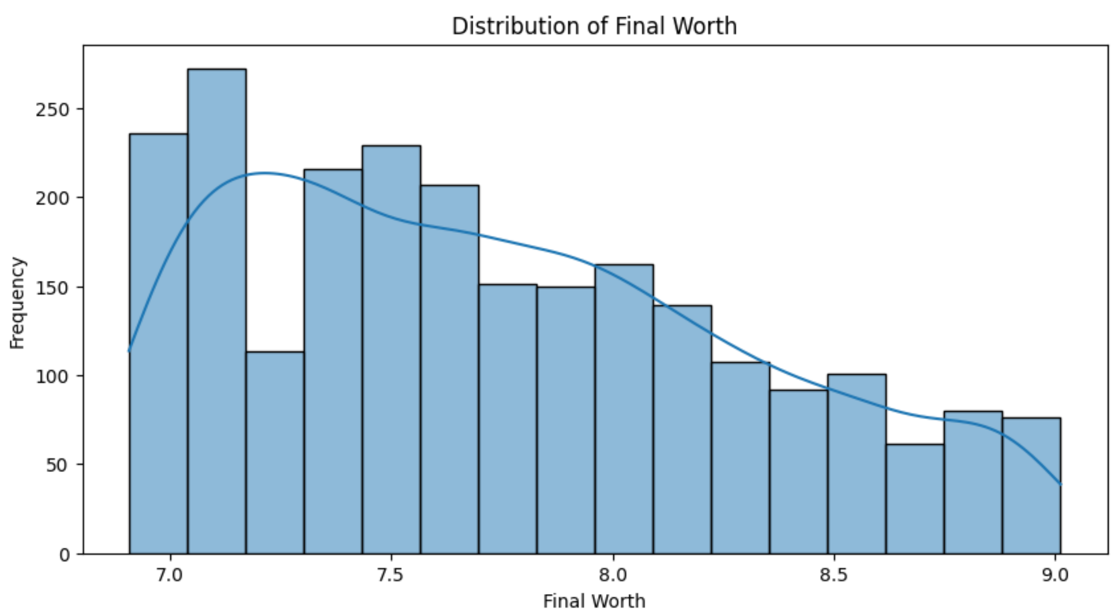
The target variable is highly skewed, which could be problematic for predictive models. As a result, I first examined the boxplot to check for outliers. If any outliers were detected, I proceeded to remove them to improve the model's performance.

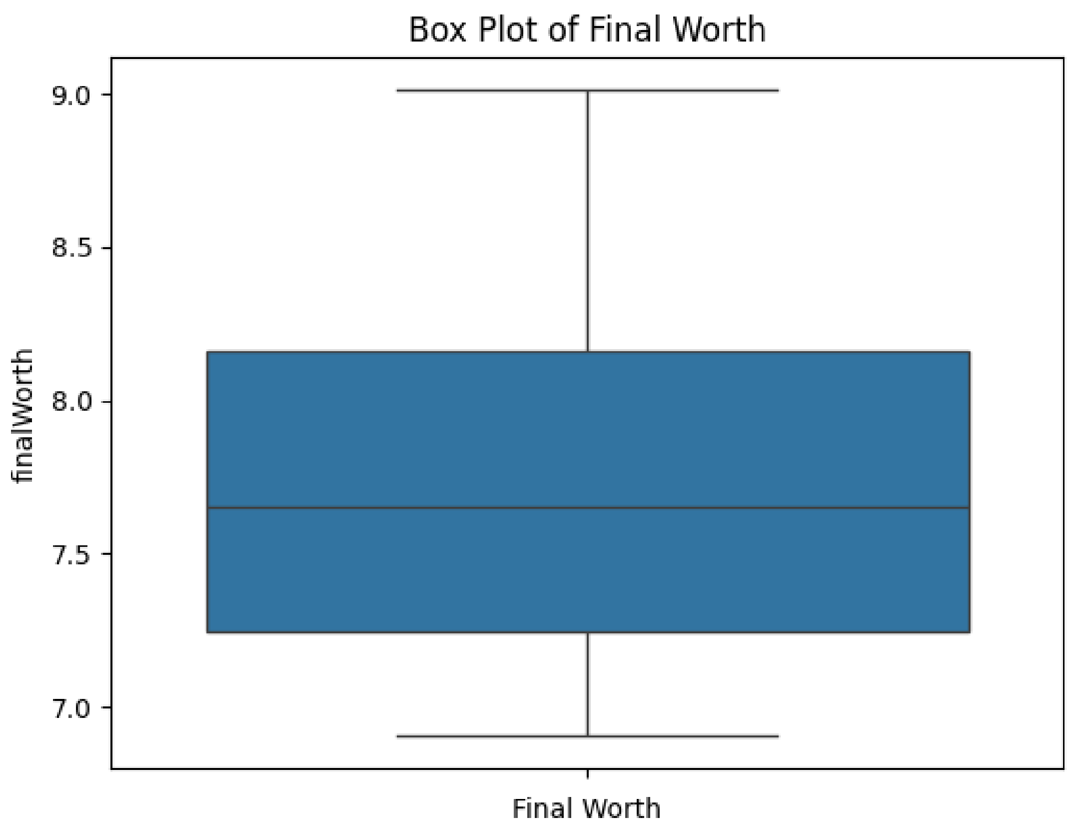



```
count    2392.000000
mean     2729.891304
std      1719.917126
min      1000.000000
25%      1400.000000
50%      2100.000000
75%      3500.000000
max      8200.000000
Name: finalWorth, dtype: float64
```



Then, I applied a logarithmic transformation to the target variable to reduce skewness and improve the model's performance.





2.1 Baseline

```
Baseline Mean Squared Error: 0.3208229296883327
```

2.2 Multiple Regression

```
Pipeline(steps=[('encode',
                 ColumnTransformer(transformers=[('num', StandardScaler(),
                                                  ['age', 'gdp_country',
'gross_tertiary_education_enrollment',
'gross_primary_education_enrollment_country',
                                                   'total_tax_rate_country',
                                                   'population_country']),
                                                 ('cat',
OneHotEncoder(handle_unknown='ignore'),
                                                  ['country', 'industries',
                                                   'selfMade', 'gender'])])),
                ('regressor', LinearRegression())])
```

```
Training MSE: 0.28450735150404
Test MSE: 0.306377843680439

                                     Feature  Coefficient
23                      cat__country_Denmark     1.054455
50                      cat__country_Nigeria     0.927925
20                     cat__country_Colombia     0.914227
12                      cat__country_Belgium    -0.822640
27                      cat__country_Georgia     0.796127
..                                       ...          ...
84           cat__industries_Food & Beverage     0.009382
79  cat__industries_Construction & Engineering   -0.008449
98                             cat__gender_F     0.003673
99                             cat__gender_M    -0.003673
2     num__gross_tertiary_education_enrollment   -0.001635

[100 rows x 2 columns]
```

2.3 K-Nearest Neighbors Regression Model

```
Best Hyperparameters: {'model__n_neighbors': 50}
Training MSE: 0.29610734432526276
Test MSE: 0.3079731604666978
```

2.4 Random Forest

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('encode',
                                        ColumnTransformer(transformers=[('num',
StandardScaler(),
                                                                         ['age',
'gdp_country',
'gross_tertiary_education_enrollment',
'gross_primary_education_enrollment_country',
'total_tax_rate_country',
'population_country']),
                                                                        ('cat',
OneHotEncoder(handle_unknown='ignore'),
['country',
'industries',
'selfMade',
'gender'])])),
                                       ('model', RandomForestRegressor())]),
             param_grid={'model__max_depth': [3, 4, 5],
                         'model__n_estimators': [50, 100, 150]},
             scoring='neg_mean_squared_error')

{'model__max_depth': 4, 'model__n_estimators': 150}
```

```
Training MSE: 0.290871658418162

Test MSE: 0.28952704805141516
```

3 Findings

The linear model does well, with a training MSE of 0.2845 and a test MSE of 0.3064, both of which are lower than the baseline MSE of 0.3208, capturing meaningful patterns.

The K-Nearest Neighbors (KNN) model, with the optimal hyperparameter of 50 neighbors, has a training MSE of 0.2961 and a test MSE of 0.3080, both of which are lower than the baseline MSE of 0.3208. While the KNN model's training MSE is somewhat higher than the linear model's, both models show identical performance in terms of test MSE, implying generalization on unseen data.

The Random Forest model, with a training MSE of 0.2909 and a test MSE of 0.2895, performs similarly to the KNN model in terms of test MSE, with both models falling below the baseline MSE of 0.3208. The Random Forest model exhibits low overfitting, with fairly similar training and test MSE values, indicating that it generalizes effectively without overfitting the data.

When comparing the three models, the linear model has the lowest training MSE, while the KNN and Random Forest models show very similar performance in terms of their test MSE. The Random Forest model, being a more complex model, performs almost as well as the linear model, capturing more complex relationships in the data with minimal overfitting. All three models outperform the baseline, with the linear model slightly ahead in terms of training performance, while the Random Forest and KNN models perform competitively on the test data.

	Importance
age	0.028705
gross_primary_education_enrollment_country	0.021025
total_tax_rate_country	0.018651
country	0.012620
gdp_country	0.012492
industries	0.007034
gross_tertiary_education_enrollment	0.003719
selfMade	0.001631
population_country	0.001587
gender	-0.000126

The feature importance values indicate that Age (0.031516) is the most influential feature in predicting the target variable, followed by Total Tax Rate Country (0.022721) and Gross Primary Education Enrollment Country (0.019119), which also contribute meaningfully to the model.

4 Summary

Model Comparison: The linear model is the best performer in terms of training MSE but slightly lags behind Random Forest and KNN on the test data. Both Random Forest and KNN models offer similar test performance, with Random Forest slightly outperforming KNN.

Best Balance of Complexity and Performance: Random Forest strikes the best balance between complexity and performance, capturing complex relationships while maintaining good generalization without overfitting.

Based on the test MSE and generalization ability, Random Forest emerges as the most well-rounded model for this dataset, though KNN and linear models also perform adequately and may be preferred for simpler, faster implementation in certain contexts. Further hyperparameter tuning and feature engineering could further enhance performance across all models.

5 Next Step/ Improvement

In the next steps, I plan to address several key areas to improve the analysis. First, I aim to update the dataset with the most recent data to reflect current trends, as the existing data is outdated and may not accurately capture the present dynamics. Additionally, I will ensure that all units of measurement are clearly defined and properly documented, as the current dataset lacks clarity on this front. This will enhance the accuracy and transparency of the analysis.

I also intend to expand the dataset by incorporating more relevant features, such as lifestyle-related variables, to deepen the insights. For instance, understanding whether billionaires are first-generation wealth creators, their educational backgrounds, and the industries contributing to their wealth can provide valuable context for the analysis. Exploring these factors will help capture more nuanced relationships within the data.

I plan to use advanced models like XGBoost, SVM, and Neural Networks, along with creating new features, to improve prediction accuracy.

Finally, once the updated data is analyzed, I aim to compare the findings with historical trends to uncover changes in wealth creation patterns, sectoral influences, and other emerging trends. These steps will ensure a comprehensive, accurate, and insightful analysis that better informs decision-making.