Meaning of the Acronym Word in Chess Project

- FIDE-Average International Chess Federation
- GMs-International Grandmaster
- IMs-Life Master"
- FMs-FMs failed / aspiring to become IM
- WGMs-Woman Grandmaster
- WIMs Woman International Master
- WFMs-Woman FIDE Master (WFM)
- CM-Candidate Master
- WCM-woman candidate master

Importing the necessary libraries

In [1]:
```
import seaborn as sns
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

Impporting the Data set into Jupyter

In [2]:
```
CG=pd.read_csv('International_Chess_Stats.csv',index_col=False)
```

Checking the head of the Data set

In [3]:
```
CG.head(7)
```

Out[3]:

	Unnamed: 0	#	Country	Flag	Num Players	Women	% of Women	FIDE Average	GMs	IMs	FMs	WGMs	WIMs	WFMs	Age Avg
0	0	1	Russia	NaN	34497	5734	16.62	1666	236	522	1177	50	101	409	34
1	1	2	India	NaN	32735	3581	10.94	1275	64	114	83	9	41	42	27
2	2	3	Germany	NaN	26577	1751	6.59	1841	94	273	861	18	40	69	49
3	3	4	Spain	NaN	25009	1430	5.72	1429	55	134	365	2	14	37	42
4	4	5	France	NaN	23784	2143	9.01	1580	50	117	234	4	18	21	41
5	5	6	Poland	NaN	10596	1537	14.51	1622	45	105	172	9	30	39	37
6	6	7	Italy	NaN	10256	604	5.89	1621	16	45	161	0	1	13	44

Checking for Missing Value

In [4]:
```
CG.isna().any()
```

Out[4]:
```
Unnamed: 0      False
#               False
Country          True
Flag             True
Num Players     False
Women           False
% of Women      False
FIDE Average    False
GMs             False
IMs             False
FMs             False
WGMs            False
WIMs            False
WFMs            False
Age Avg         False
dtype: bool
```

In [5]:
```
CG.isna().sum()
```

Out[5]:
```
Unnamed: 0        0
#                 0
Country           2
Flag            190
Num Players       0
Women             0
% of Women        0
FIDE Average      0
GMs               0
IMs               0
FMs               0
WGMs              0
WIMs              0
WFMs              0
Age Avg           0
dtype: int64
```

Droping the missing value

In [6]:
```
CG = CG.loc[:, ~CG.columns.str.contains('^Unnamed')]
CG = CG.drop ('Flag', axis=1)
```

In [7]:
```
CG = CG.drop("#", axis='columns')
```

Checking the head after droping the miss vlave

In [8]:
```
CG.head()
```

Out[8]:

	Country	Num Players	Women	% of Women	FIDE Average	GMs	IMs	FMs	WGMs	WIMs	WFMs	Age Avg
0	Russia	34497	5734	16.62	1666	236	522	1177	50	101	409	34
1	India	32735	3581	10.94	1275	64	114	83	9	41	42	27
2	Germany	26577	1751	6.59	1841	94	273	861	18	40	69	49
3	Spain	25009	1430	5.72	1429	55	134	365	2	14	37	42
4	France	23784	2143	9.01	1580	50	117	234	4	18	21	41

Checking if there is still more missing values

In [9]:
```
CG= CG.dropna()
```

In [10]:
```
CG.isna().any()
```

Out[10]:
```
Country         False
Num Players     False
Women           False
% of Women      False
FIDE Average    False
GMs             False
IMs             False
FMs             False
WGMs            False
WIMs            False
WFMs            False
Age Avg         False
dtype: bool
```

Checking the data structure of the data set

In [11]:
```
CG.dtypes
```

Out[11]:

```
Country          object
Num Players       int64
Women             int64
% of Women      float64
FIDE Average      int64
GMs               int64
IMs               int64
FMs               int64
WGMs              int64
WIMs              int64
WFMs              int64
Age Avg           int64
dtype: object
```

General statistics of the data set

In [12]:

```
CG.describe()
```

Out[12]:

	Num Players	Women	% of Women	FIDE Average	GMs	IMs	FMs	WGMs	WIMs	WFMs	Age A
count	188.000000	188.000000	188.000000	188.000000	188.000000	188.000000	188.000000	188.000000	188.000000	188.000000	188.0000
mean	1851.632979	197.750000	11.820638	1634.659574	9.074468	20.462766	42.750000	1.654255	4.351064	9.106383	36.7393
std	4870.425325	561.516593	8.239526	166.601067	23.446031	51.465514	118.988546	4.853207	10.010911	31.322872	8.2676
min	2.000000	0.000000	0.000000	1141.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	21.0000
25%	47.750000	6.000000	5.935000	1544.500000	0.000000	0.000000	2.000000	0.000000	0.000000	0.000000	31.0000
50%	298.500000	33.500000	10.785000	1651.000000	0.000000	3.000000	8.500000	0.000000	0.500000	3.000000	36.0000
75%	1228.750000	181.500000	17.402500	1742.000000	8.250000	22.000000	30.250000	1.000000	4.000000	9.000000	41.2500
max	34497.000000	5734.000000	37.500000	2250.000000	236.000000	522.000000	1177.000000	50.000000	101.000000	409.000000	63.0000

EDA (Exploratory Data Analysis)

Checking the Country again the number of each Country Players

Data Head After Cleaning

In [13]:
```
CG.head()
```

Out[13]:

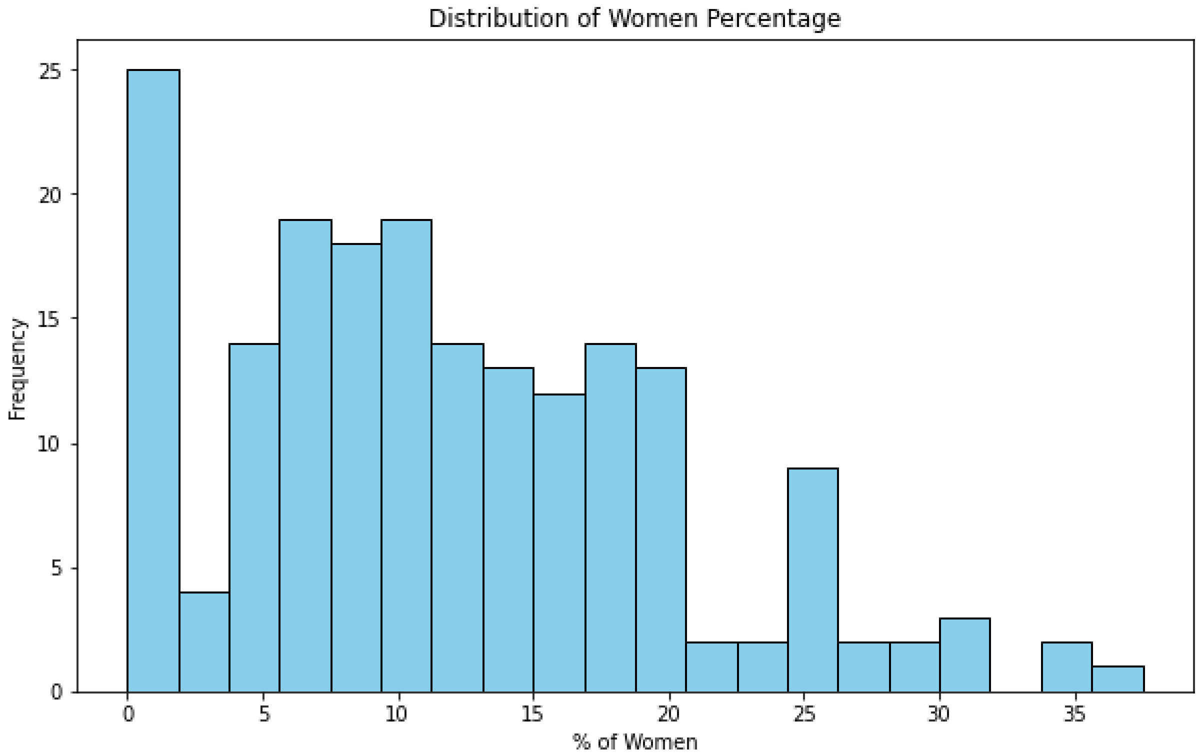
	Country	Num Players	Women	% of Women	FIDE Average	GMs	IMs	FMs	WGMs	WIMs	WFMs	Age Avg
0	Russia	34497	5734	16.62	1666	236	522	1177	50	101	409	34
1	India	32735	3581	10.94	1275	64	114	83	9	41	42	27
2	Germany	26577	1751	6.59	1841	94	273	861	18	40	69	49
3	Spain	25009	1430	5.72	1429	55	134	365	2	14	37	42
4	France	23784	2143	9.01	1580	50	117	234	4	18	21	41

Country havuing the most player

In [14]:
```
# count of the player by country
country_counts = CG['Country']. value_counts()

# Display top countries with the most players
print (country_counts.head())
```

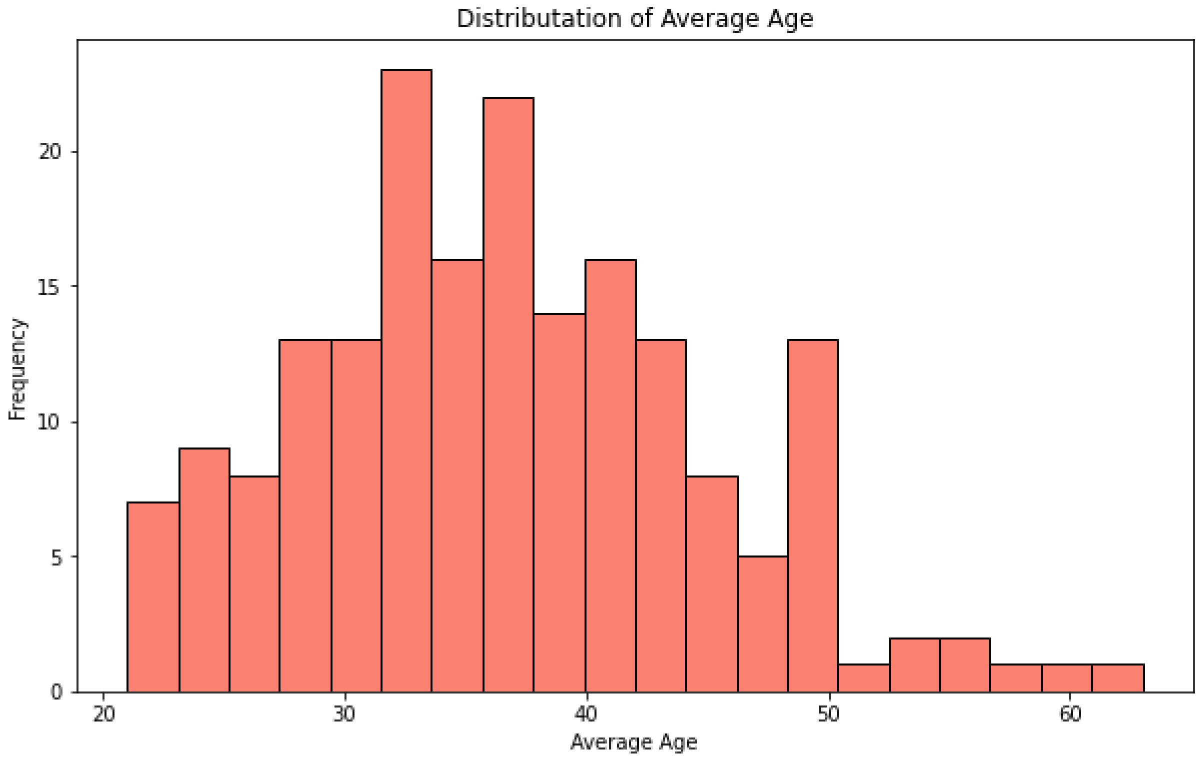
```
Netherlands Antilles    2
Brunei                  2
Russia                  1
Palau                   1
Oman                    1
Name: Country, dtype: int64
```

In [15]:
```
# plotting the distribution of women percentage
plt.figure(figsize=(10,6))
plt.hist(CG['% of Women'], bins=20, color='skyblue', edgecolor='black')
plt.title('Distribution of Women Percentage')
plt.xlabel('% of Women')
plt.ylabel('Frequency')
plt.show()
```

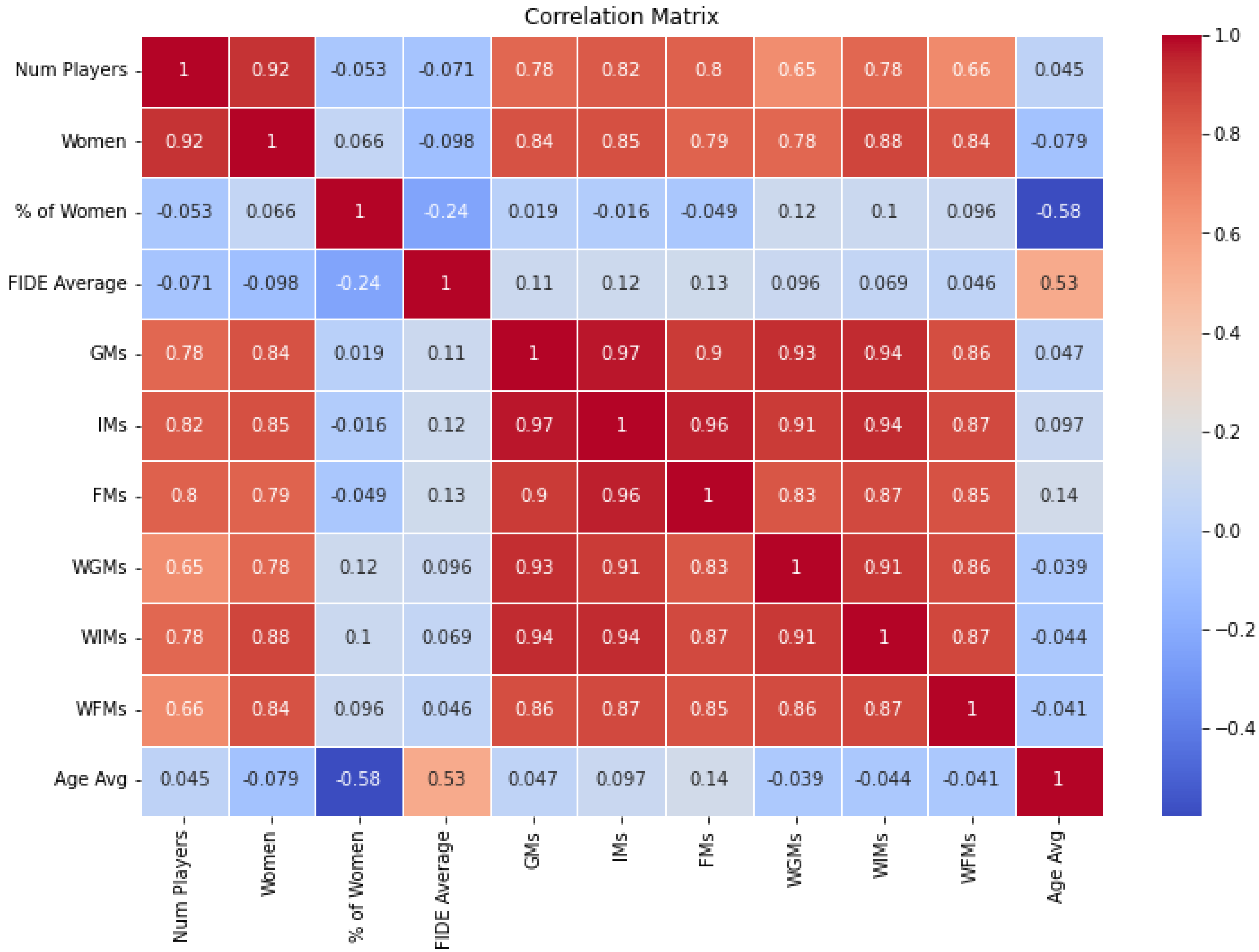



```
In [16]: # Plotting the distribution of avarage age
plt. figure(figsize=(10,6))
plt.hist(CG['Age Avg'], bins=20, color='salmon', edgecolor='black')
plt.title('Distributation of Average Age')
plt.xlabel('Average Age')
plt.ylabel('Frequency')
plt.show
```

```
Out[16]: <function matplotlib.pyplot.show(close=None, block=None)>
```



In [17]:
```
# Correlation matrix

correlation_matrix = CG.corr()

# Heatmap of the correlation matrix
plt.figure(figsize=(12,8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',linewidths=.5)
plt.title('Correlation Matrix')
plt.show()
```



In [18]:

```
# Top countries by average FIDE rating
top_countries_by_rating =CG.groupby ('Country')['FIDE Average']. mean().sort_values(ascending=False)

# Display top countries
print(top_countries_by_rating.head())
```

```
Country
Cambodia       2250.0
South Sudan    1961.0
Kosovo         1923.0
Nigeria        1899.0
Myanmar        1891.0
Name: FIDE Average, dtype: float64
```

In [ ]:

In [19]:
```
# Top countries by number of Grandmasters (GMs)
top_countries_by_gms = CG.groupby('Country')['GMs'].sum().sort_values(ascending=False)

# Display top countries
print(top_countries_by_gms.head())
```

```
Country
Russia           236
United States     95
Germany           94
Ukraine           89
India             64
Name: GMs, dtype: int64
```

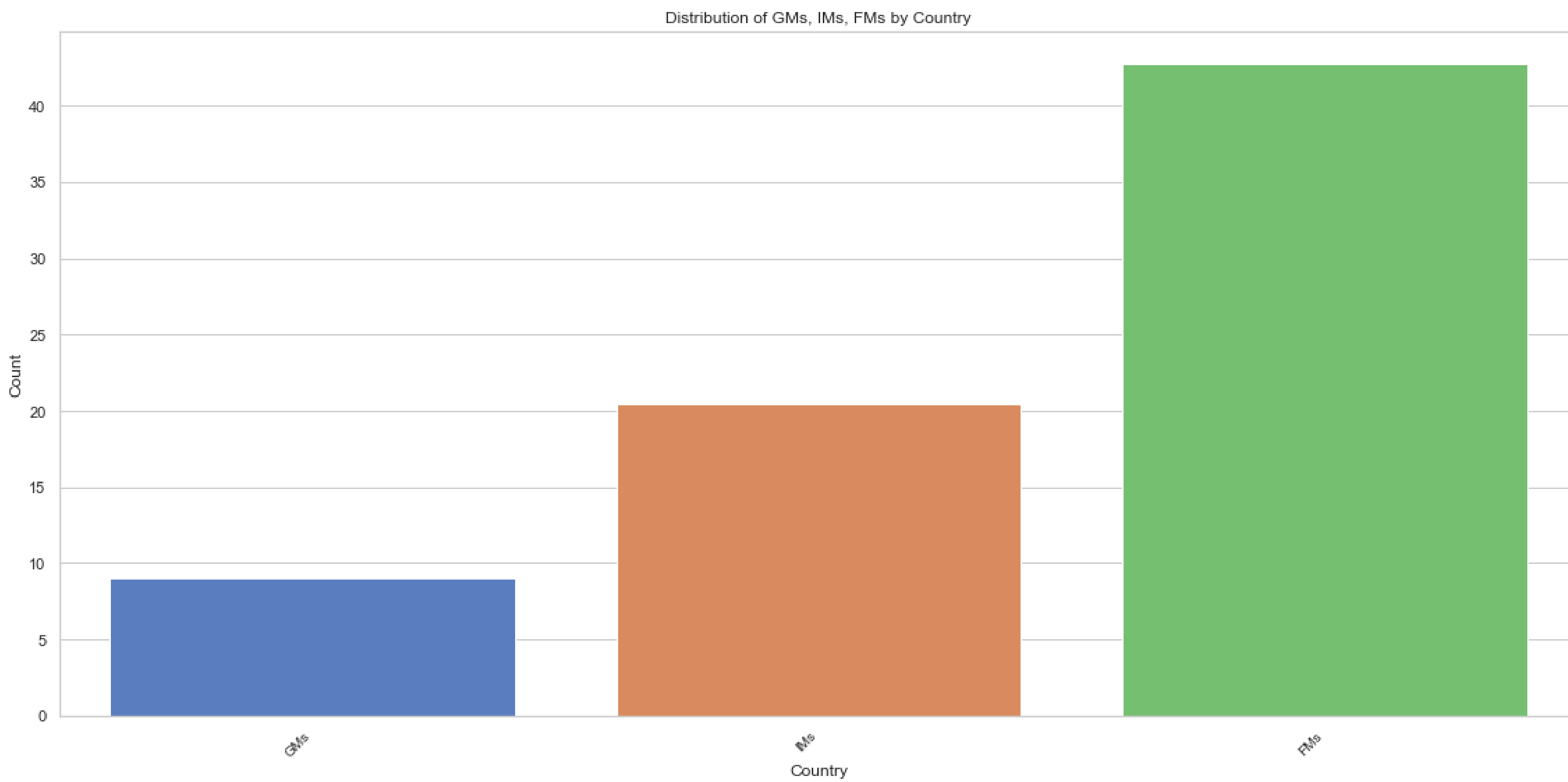
In [20]:
```
# Number of player by country
players_by_country =CG.groupby('Country') ['Num Players'].sum().sort_values(ascending =False)

# display top countries with the most players
print(players_by_country.head())
```

```
Country
Russia     34497
India      32735
Germany    26577
Spain      25009
France     23784
Name: Num Players, dtype: int64
```

In [ ]:

In [21]:
```
# Set Seaborn style
sns.set(style="whitegrid")

# Plotting the distribution of GMs, IMs, FMs
plt.figure(figsize=(16, 8))
```

```
ax = sns.barplot(data=CG[['GMs', 'IMs', 'FMs']], palette="muted", ci=None)

# Customize the plot
ax.set_title('Distribution of GMs, IMs, FMs by Country')
ax.set_xlabel('Country')
ax.set_ylabel('Count')

# Rotate x-axis labels for better readability
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=10)

plt.tight_layout()
plt.show()
```



Machine Learning

Would be Predicting the average FIDE rating this will be base on the bassed on the certain features from the table.

In [22]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

# Features (X) and target variable (y)
X = CG[['Num Players', 'Women', '% of Women', 'GMs', 'IMs', 'FMs', 'WGMs', 'WIMs', 'WFMs', 'Age Avg']]
y = CG['FIDE Average']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the model
model = LinearRegression()

# Fit the model to the training data
model.fit(X_train, y_train)

# Make predictions on the test set
predictions = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, predictions)
print(f'Mean Squared Error: {mse}')
```

```
Mean Squared Error: 26067.279912831626
```

In [ ]:

In [23]:
```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

# Evaluate the model
mse = mean_squared_error(y_test, predictions)
r2 = r2_score(y_test, predictions)
mae = mean_absolute_error(y_test, predictions)

print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
print(f'Mean Absolute Error: {mae}')
```

```
Mean Squared Error: 26067.279912831626
R-squared: 0.12962237949543576
Mean Absolute Error: 117.53287571205537
```

In [26]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV
```

```python
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

# Features (X) and target variable (y)
X = CG[['Num Players', 'Women', '% of Women', 'GMs', 'IMs', 'FMs', 'WGMs', 'WIMs', 'WFMs', 'Age Avg']]
y = CG['FIDE Average']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the Random Forest Regressor
rf_model = RandomForestRegressor()

# Define hyperparameters to tune
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Perform GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error')
grid_search.fit(X_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
print(f'Best Hyperparameters: {best_params}')

# Use the best model from GridSearchCV
best_rf_model = grid_search.best_estimator_

# Make predictions on the test set
rf_predictions = best_rf_model.predict(X_test)

# Evaluate the model
rf_mse = mean_squared_error(y_test, rf_predictions)
rf_r2 = r2_score(y_test, rf_predictions)
rf_mae = mean_absolute_error(y_test, rf_predictions)

print(f'Random Forest Mean Squared Error: {rf_mse}')
print(f'Random Forest R-squared: {rf_r2}')
print(f'Random Forest Mean Absolute Error: {rf_mae}')
```

```
Best Hyperparameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 100}
Random Forest Mean Squared Error: 29633.760335212628
Random Forest R-squared: 0.0105388098253969
Random Forest Mean Absolute Error: 126.54422822207023
```

In [ ]:

In [25]:

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler

# Features (X) and target variable (y)
X = CG[['Num Players', 'Women', '% of Women', 'GMs', 'IMs', 'FMs', 'WGMs', 'WIMs', 'WFMs', 'Age Avg']]
y = CG['FIDE Average']

# Standardize numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Initialize the Random Forest Regressor
rf_model = RandomForestRegressor()

# Define hyperparameters to tune
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Perform GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error')
grid_search.fit(X_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
print(f'Best Hyperparameters: {best_params}')

# Use the best model from GridSearchCV
best_rf_model = grid_search.best_estimator_

# Make predictions on the test set
```

```python
rf_predictions = best_rf_model.predict(X_test)

# Evaluate the model
rf_mse = mean_squared_error(y_test, rf_predictions)
rf_r2 = r2_score(y_test, rf_predictions)
rf_mae = mean_absolute_error(y_test, rf_predictions)

print(f'Random Forest Mean Squared Error: {rf_mse}')
print(f'Random Forest R-squared: {rf_r2}')
print(f'Random Forest Mean Absolute Error: {rf_mae}')
```

```
Best Hyperparameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 200}
Random Forest Mean Squared Error: 29292.202487532235
Random Forest R-squared: 0.021943310322680598
Random Forest Mean Absolute Error: 124.57159016385661
```

In [ ]:

```python

```