Data Science Intern - Assignment

The Dataset contains information and numbers of over 20000 Chess games played on Lichess.com. Understand the data and approach for the following:

1. Provide insights on the data such as:

- General trends of ‘White’ players with respect to ‘Black’ players
- Any trend of winners with respect to turns and match time?
- Go to openings with respect to rank and color. Provide additional relevant insights that portray information regarding the overall player population on Lichess. Go for quality insights over quantity insights.

2. Using the opening moves, opening styles, color, and other features, Is it possible to predict

In [1]:
```python
#importing required libraries.

import pandas as pd
import numpy  as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```python
#importing the data set and shape of dataset.
data=pd.read_csv('games.csv', encoding='ascii')
data.shape
```

Out[2]: (20058, 16)

In [3]:
```python
#dataset
data.head()
```

3	kWKvrqYL	True	1.504110e+12	1.504110e+12	61	mate	white	20+
4	9tXo1AUZ	True	1.504030e+12	1.504030e+12	95	mate	white	30+

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20058 entries, 0 to 20057
Data columns (total 16 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   id              20058 non-null  object 
 1   rated           20058 non-null  bool   
 2   created_at      20058 non-null  float64
 3   last_move_at    20058 non-null  float64
 4   turns           20058 non-null  int64  
 5   victory_status  20058 non-null  object 
 6   winner          20058 non-null  object 
 7   increment_code  20058 non-null  object 
 8   white_id        20058 non-null  object 
 9   white_rating    20058 non-null  int64  
 10  black_id        20058 non-null  object 
 11  black_rating    20058 non-null  int64  
 12  moves           20058 non-null  object 
 13  opening_eco     20058 non-null  object 
 14  opening_name    20058 non-null  object 
```

In [5]:
```
#Describing the dataset and its numerical parameter
data.describe()
```

Out[5]:

	created_at	last_move_at	turns	white_rating	black_rating	opening_ply
count	2.005800e+04	2.005800e+04	20058.000000	20058.000000	20058.000000	20058.000000
mean	1.483617e+12	1.483618e+12	60.465999	1596.631868	1588.831987	4.816981
std	2.850151e+10	2.850140e+10	33.570585	291.253376	291.036126	2.797152
min	1.376772e+12	1.376772e+12	1.000000	784.000000	789.000000	1.000000
25%	1.477548e+12	1.477548e+12	37.000000	1398.000000	1391.000000	3.000000
50%	1.496010e+12	1.496010e+12	55.000000	1567.000000	1562.000000	4.000000
75%	1.503170e+12	1.503170e+12	79.000000	1793.000000	1784.000000	6.000000
max	1.504493e+12	1.504494e+12	349.000000	2700.000000	2723.000000	28.000000

In [6]:
```
null_counts = data.isnull().sum()
null_percentages = data.isnull().sum() / len(data) * 100
data_types = data.dtypes

null_summary = pd.concat([null_counts, null_percentages, data_types],
null_summary.columns = ['Null Count', 'Null Percentage', 'Data Type']

print(null_summary)
```

```
                Null Count  Null Percentage Data Type
id                       0              0.0    object
rated                    0              0.0      bool
created_at               0              0.0   float64
last_move_at             0              0.0   float64
turns                    0              0.0     int64
victory_status           0              0.0    object
winner                   0              0.0    object
increment_code           0              0.0    object
white_id                 0              0.0    object
white_rating             0              0.0     int64
black_id                 0              0.0    object
black_rating             0              0.0     int64
moves                    0              0.0    object
opening_eco              0              0.0    object
opening_name             0              0.0    object
opening_ply              0              0.0     int64
```

No Null Value is present

In [7]:
```
data['victory_status'] = data['victory_status'].astype('category')
data['winner'] = data['winner'].astype('category')
data['opening_name'] = data['opening_name'].astype('category')
data['opening_ply'] = data['opening_ply'].astype('int')
data['rated'] = data['rated'].astype('int')
```

Changing decimal value to date time format

In [8]:
```
def convert_to_datetime(column):
    # Convert scientific notation values to decimal values
    decimal_values = column.apply(lambda x: float(x))

    # Convert decimal values to strings and then to datetime objects
    datetime_column = pd.to_datetime(decimal_values.astype(int).astype

    return datetime_column
```

In [9]:
```
import pandas as pd

def convert_milliseconds_to_datetime(column):
    # Convert milliseconds to seconds and then to datetime objects
    datetime_column = pd.to_datetime(column.astype(int) // 1000, unit=

    return datetime_column

# Convert 'last_move_at' column to datetime objects
data['created_at'] = convert_milliseconds_to_datetime(data['created_at
data['last_move_at'] = convert_milliseconds_to_datetime(data['last_mov
```

In [10]:
```
data.head()
```

3	kWKvrqYL	1	2017-08-30 16:20:00	2017-08-30 16:20:00	61	mate	white	20+0	(
4	9tXo1AUZ	1	2017-08-29 18:06:40	2017-08-29 18:06:40	95	mate	white	30+3	

In [11]:
```
# Managing Datetime and extracting month, day, and hour data
for i in ['created_at', 'last_move_at']:
    data[i] = pd.to_datetime(data[i])
    data['{}_month'.format(i)] = data[i].dt.month
    data['{}_day_name'.format(i)] = data[i].dt.day_name()
    data['{}_hour'.format(i)] = data[i].dt.hour
```

Univatriate and Bivariate analysis

In [12]:
```
value_counts_dict = {}

for column in data.columns:
    value_counts_dict[column] = data[column].value_counts().nunique()


for column, value_counts in value_counts_dict.items():
    print(f"Value counts for column '{column}':")
    print(value_counts)
    print("-----------------------------------------------------------------
```

```
22
-----------------------------------------------------------------
Value counts for column 'created_at_month':
12
-----------------------------------------------------------------
Value counts for column 'created_at_day_name':
7
-----------------------------------------------------------------
Value counts for column 'created_at_hour':
24
-----------------------------------------------------------------
Value counts for column 'last_move_at_month':
12
-----------------------------------------------------------------
Value counts for column 'last_move_at_day_name':
7
-----------------------------------------------------------------
Value counts for column 'last_move_at_hour':
24
-----------------------------------------------------------------
```

In [13]:
```
white_win_rate = (data[data['winner'] == 'white'].shape[0] / data.shap
black_win_rate = (data[data['winner'] == 'black'].shape[0] / data.shap

white_average_rating = data['white_rating'].mean()
black_average_rating = data['black_rating'].mean()

victory_status_counts = data.groupby(['victory_status', 'winner']).siz
```

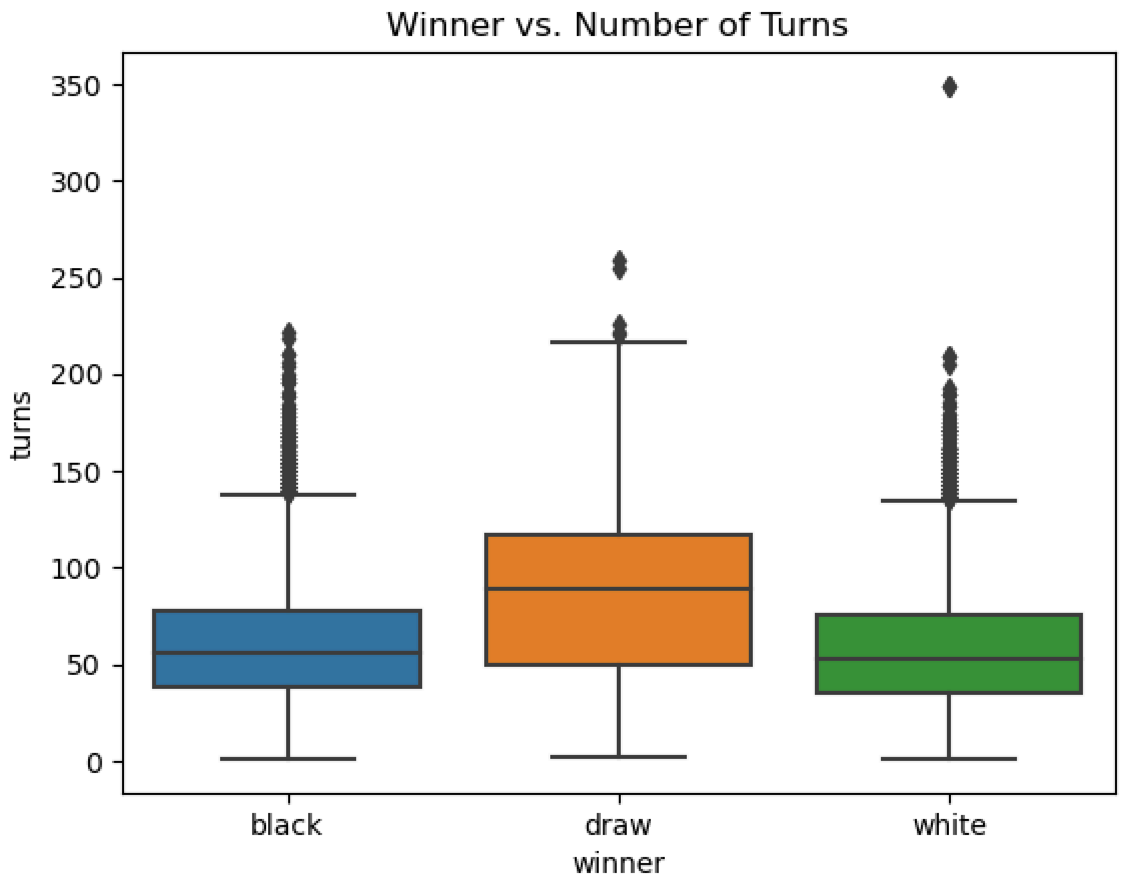
In [14]:
```
data['id'].unique()
```

Out[14]:
```
array(['TZJHLljE', 'l1NXvwaE', 'mIICvQHh', ..., 'yrAas0Kj', 'b0v4tRy
F',
       'N8G2JHGG'], dtype=object)
```

In [15]:
```
data['victory_status'].unique()
```

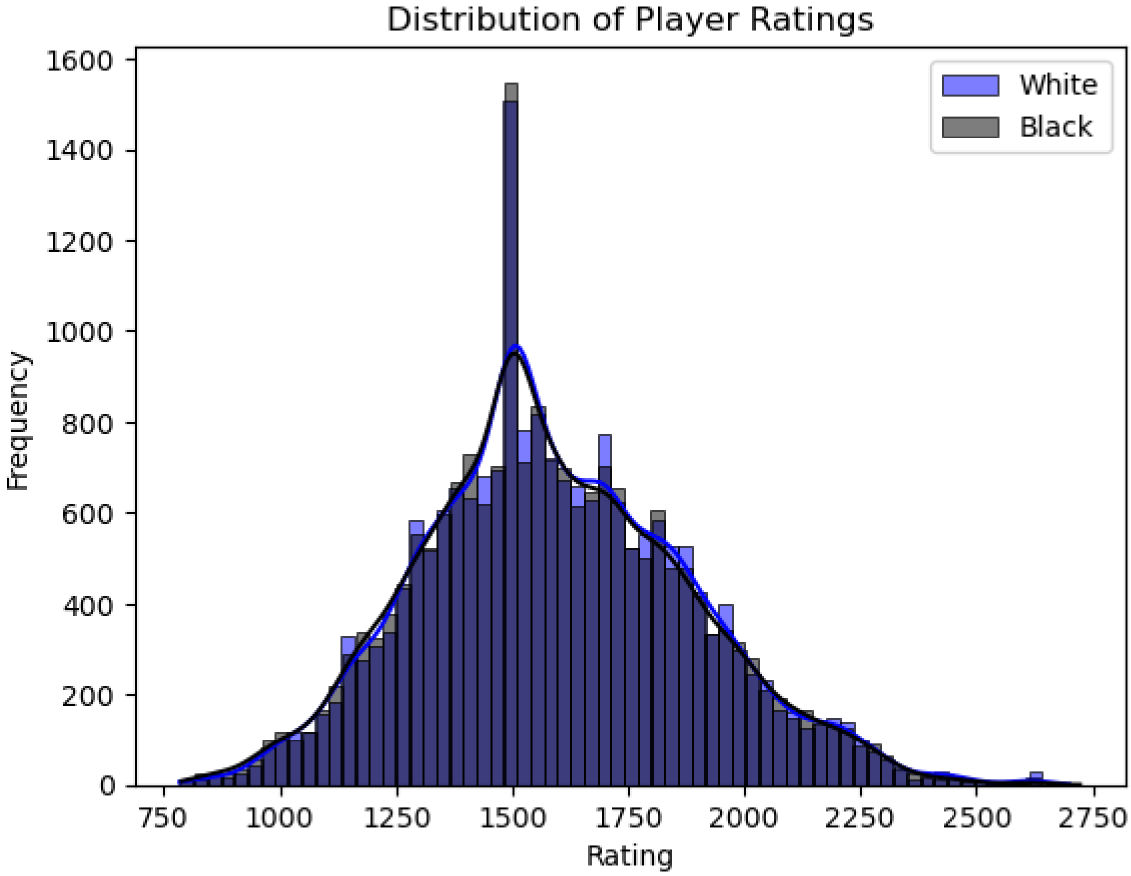
Out[15]:
```
['outoftime', 'resign', 'mate', 'draw']
Categories (4, object): ['draw', 'mate', 'outoftime', 'resign']
```

In [16]:
```
sns.boxplot(x='winner', y='turns', data=data)
plt.title("Winner vs. Number of Turns")
plt.show()
```

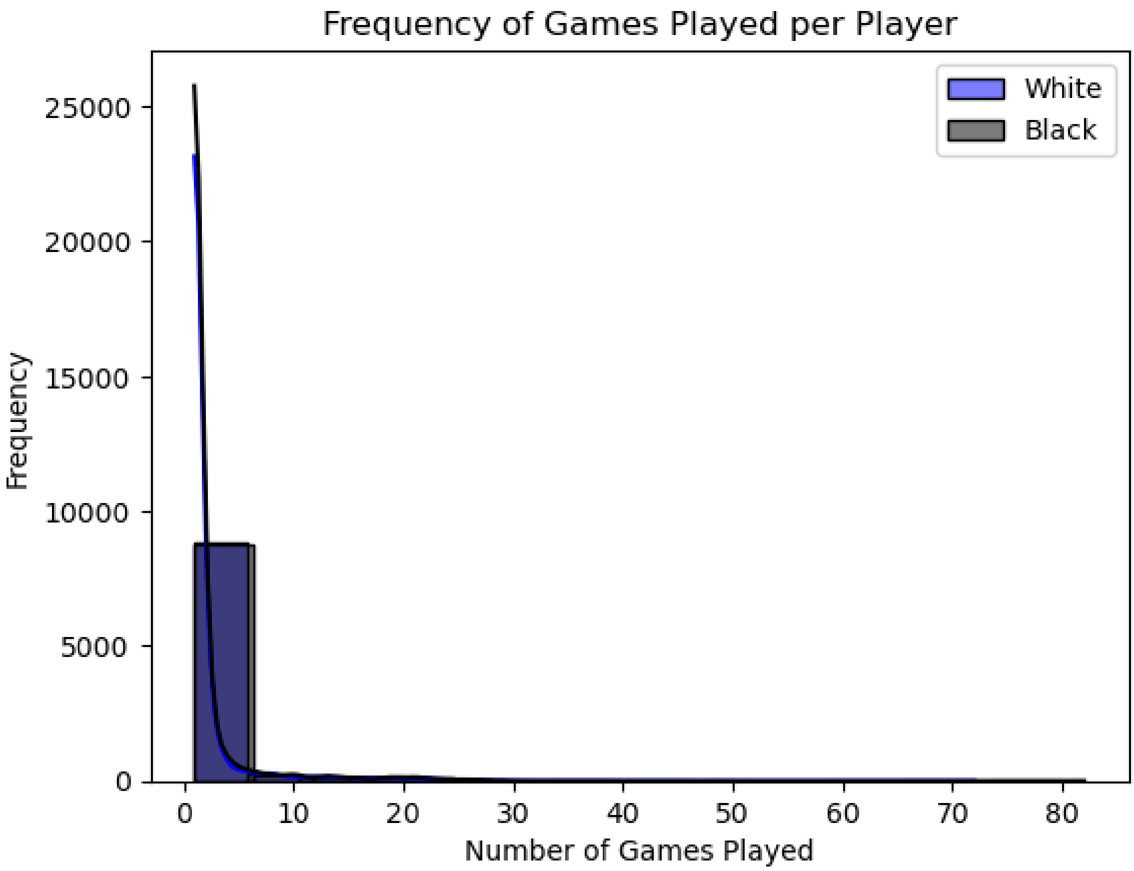


In [17]:
```
top_openings_by_rank = data.groupby(['white_rating', 'opening_name']).
top_openings_by_color = data.groupby(['winner', 'opening_name']).size(

sns.histplot(data['white_rating'], kde=True, color='blue', label='Whit
sns.histplot(data['black_rating'], kde=True, color='black', label='Bla
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.title('Distribution of Player Ratings')
plt.legend()
plt.show()
```



In [18]:
```
sns.histplot(data['white_id'].value_counts(), kde=True, color='blue',
sns.histplot(data['black_id'].value_counts(), kde=True, color='black',
plt.xlabel('Number of Games Played')
plt.ylabel('Frequency')
plt.title('Frequency of Games Played per Player')
plt.legend()
plt.show()
```

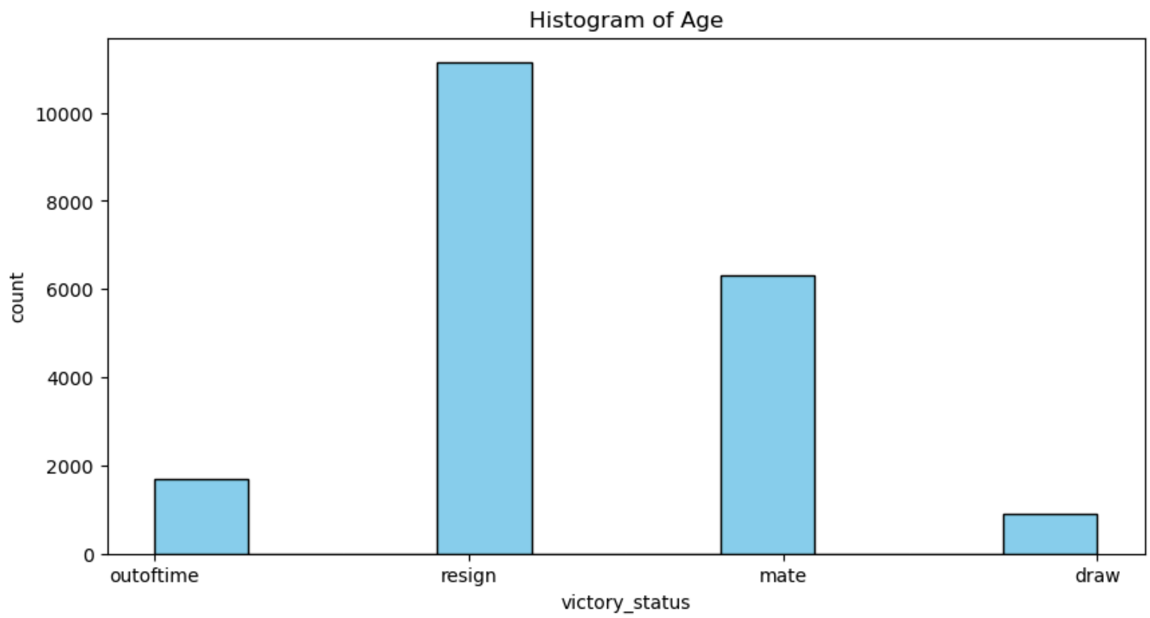


In [19]:

```
plt.figure(figsize=(10,5))
plt.hist(data['victory_status'],bins=10,color='skyblue', edgecolor='bl
plt.xlabel('victory_status')
plt.ylabel('count')
plt.title('Histogram of Age')
plt.show
```

Out[19]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [20]:

```
data['winner'].unique()
```

Out[20]:

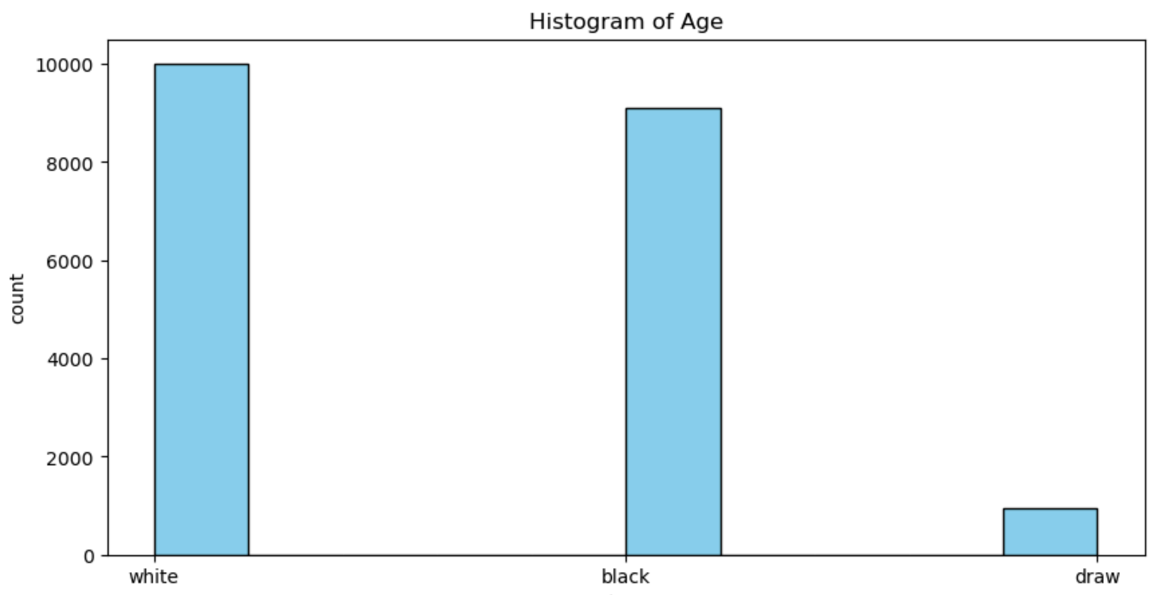
```
['white', 'black', 'draw']
Categories (3, object): ['black', 'draw', 'white']
```

In [21]:

```
plt.figure(figsize=(10,5))
plt.hist(data['winner'],bins=10,color='skyblue', edgecolor='black')
plt.xlabel('winner')
plt.ylabel('count')
plt.title('Histogram of Age')
plt.show
```

Out[21]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```

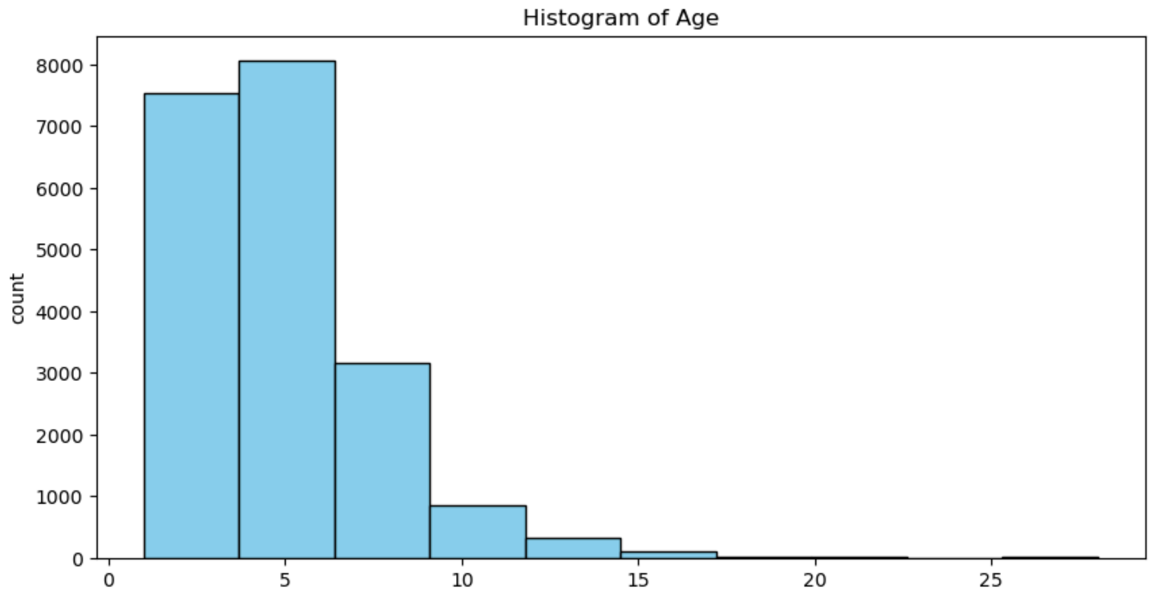


In [22]:
```
data['opening_ply'].unique()
```

Out[22]:
```
array([ 5,  4,  3, 10,  6,  1,  9,  2,  8,  7, 17, 11, 12, 13, 18, 1
9, 15,
       16, 14, 28, 20, 22, 24])
```

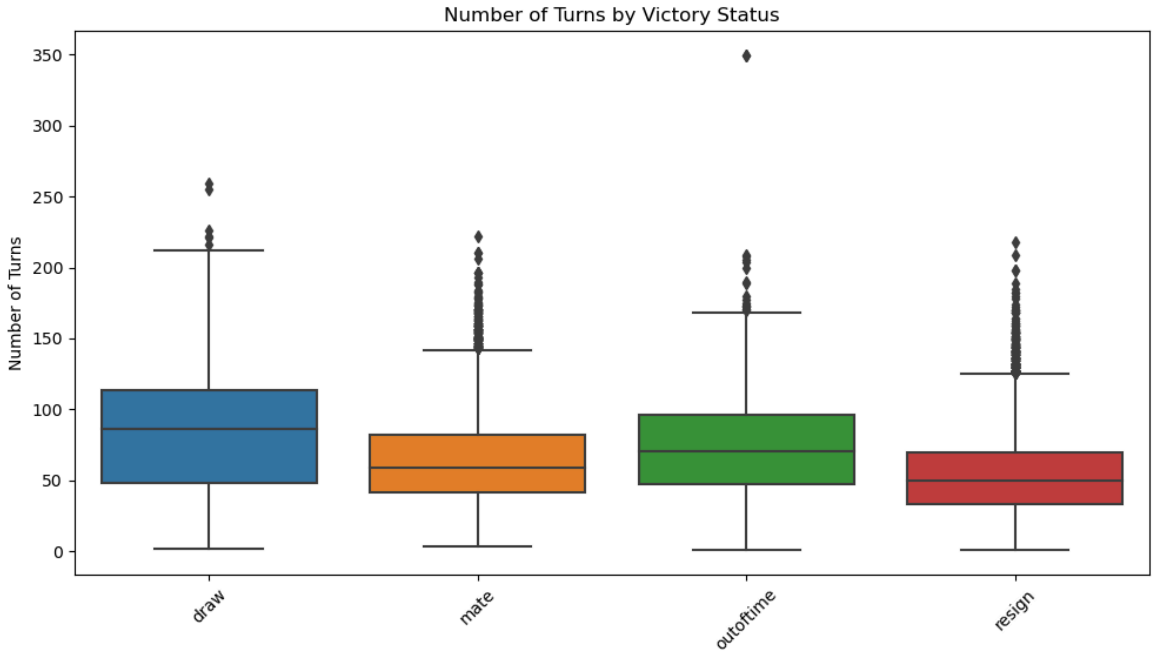
In [23]:
```
plt.figure(figsize=(10,5))
plt.hist(data['opening_ply'],bins=10,color='skyblue', edgecolor='black
plt.xlabel('opening_ply')
plt.ylabel('count')
plt.title('Histogram of Age')
plt.show
```

Out[23]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Cheaking the outliers

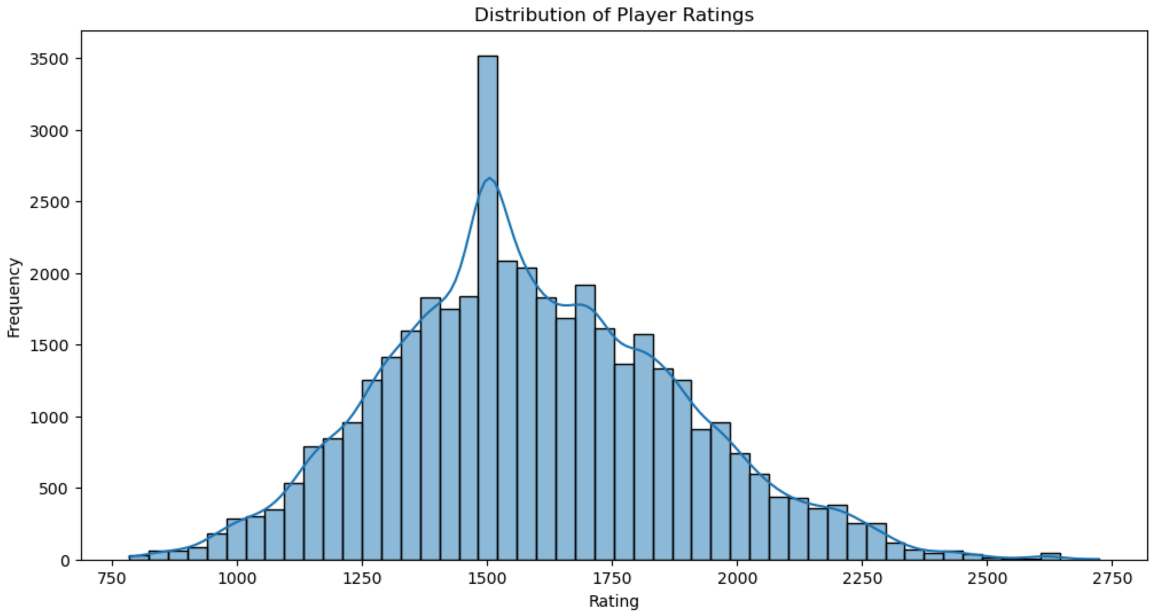
In [24]:
```
plt.figure(figsize=(10, 6), facecolor='white')
sns.boxplot(x='victory_status', y='turns', data=data)
plt.title('Number of Turns by Victory Status')
plt.xlabel('Victory Status')
plt.ylabel('Number of Turns')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



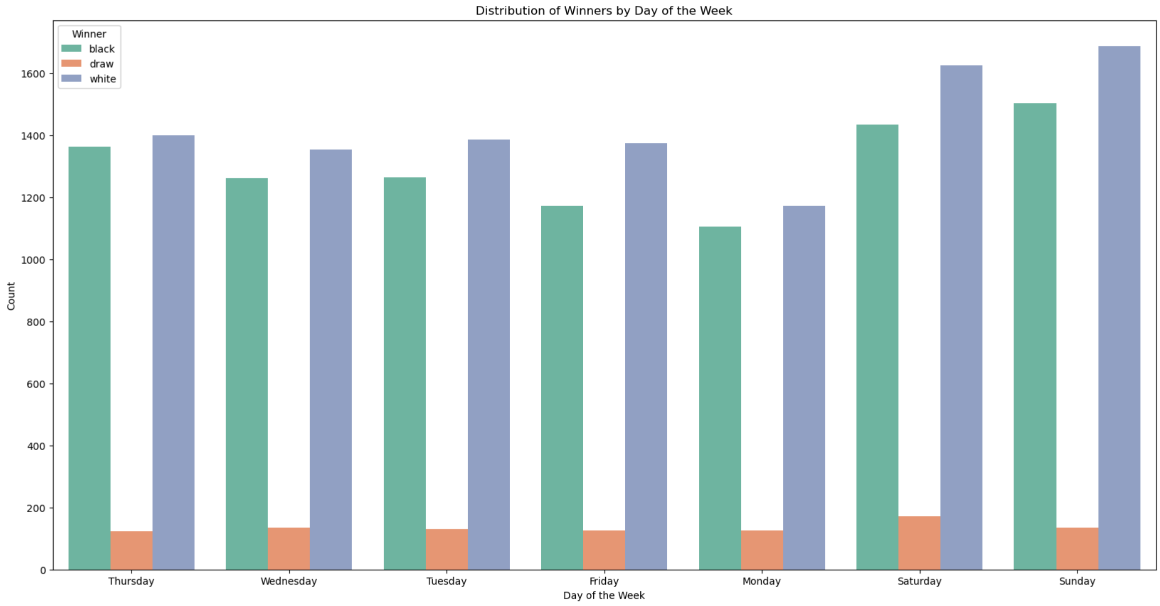
In [25]:
```
#distribution of ratings for the players in the dataset
plt.figure(figsize=(12, 6), facecolor='white')

# Combine both white and black player ratings into a single series
ratings = pd.concat([data['white_rating'], data['black_rating']])

sns.histplot(ratings, bins=50, kde=True)
plt.title('Distribution of Player Ratings')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()
```

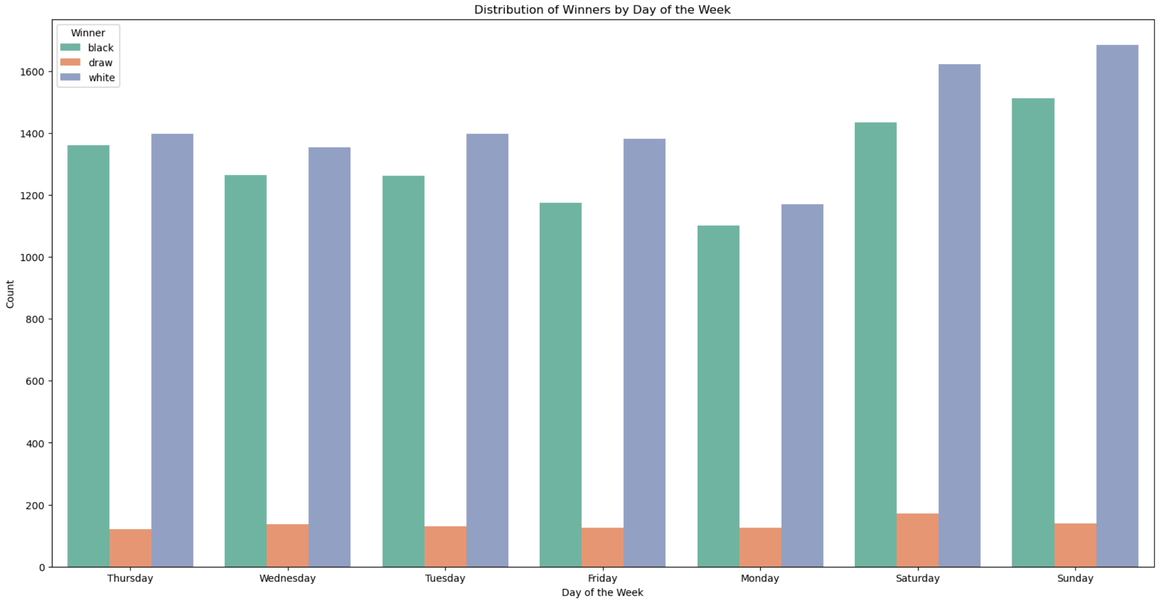


In [26]:
```
plt.figure(figsize=(20, 10))
sns.countplot(x="created_at_day_name", hue="winner", data=data, palett
plt.xlabel('Day of the Week')
plt.ylabel('Count')
plt.title('Distribution of Winners by Day of the Week')
plt.legend(title='Winner')
plt.show()
```



In [27]:
```
plt.figure(figsize=(20, 10))
sns.countplot(x="last_move_at_day_name", hue="winner", data=data, pale
plt.xlabel('Day of the Week')
plt.ylabel('Count')
plt.title('Distribution of Winners by Day of the Week')
plt.legend(title='Winner')
```

Out[27]: <matplotlib.legend.Legend at 0x14e655d90>



In [28]:
```
#comparing the distribution of white player ratings to black player ra
plt.figure(figsize=(12, 8), facecolor='white')

# Create separate data for white and black player ratings
white_ratings = data['white_rating']
black_ratings = data['black_rating']

# Plotting both distributions on the same plot for comparison
sns.kdeplot(white_ratings, label='White Player Ratings', shade=True)
sns.kdeplot(black_ratings, label='Black Player Ratings', shade=True)
plt.title('Comparison of White and Black Player Ratings')
plt.xlabel('Rating')
plt.ylabel('Density')
plt.legend()
plt.show()
```

```
/var/folders/_z/n55vt86j6xx6nvj6w_wlt5_00000gn/T/ipykernel_1349/3908
624449.py:9: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your cod
e.

  sns.kdeplot(white_ratings, label='White Player Ratings', shade=Tru
e)
/var/folders/_z/n55vt86j6xx6nvj6w_wlt5_00000gn/T/ipykernel_1349/3908
624449.py:10: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your cod
e.

  sns.kdeplot(black_ratings, label='Black Player Ratings', shade=Tru
e)
```

Comparison of White and Black Player Ratings

In [29]:
```
# Calculating mean, median, and mode for 'white_rating'
white_mean = data['white_rating'].mean()
white_median = data['white_rating'].median()
white_mode = data['white_rating'].mode()[0]

# Calculating mean, median, and mode for 'black_rating'
black_mean = data['black_rating'].mean()
black_median = data['black_rating'].median()
black_mode = data['black_rating'].mode()[0]

# Print the results
print("White Rating:")
print(f"Mean: {white_mean}")
print(f"Median: {white_median}")
print(f"Mode: {white_mode}")
print("\nBlack Rating:")
print(f"Mean: {black_mean}")
print(f"Median: {black_median}")
print(f"Mode: {black_mode}")
```

```
White Rating:
Mean: 1596.6318675840064
Median: 1567.0
Mode: 1500

Black Rating:
Mean: 1588.8319872370128
Median: 1562.0
Mode: 1500
```

In [30]:
```
#Cheaking the column with numeric Data type
numerical = data.select_dtypes(include=['int64','float64','Int64'])[:]
numerical.dtypes
```

Out[30]:
```
rated           int64
turns           int64
white_rating    int64
black_rating    int64
opening_ply     int64
dtype: object
```

In [31]:
```
Numerical_column=['rated','created_at','last_move_at','turns','white_r
```

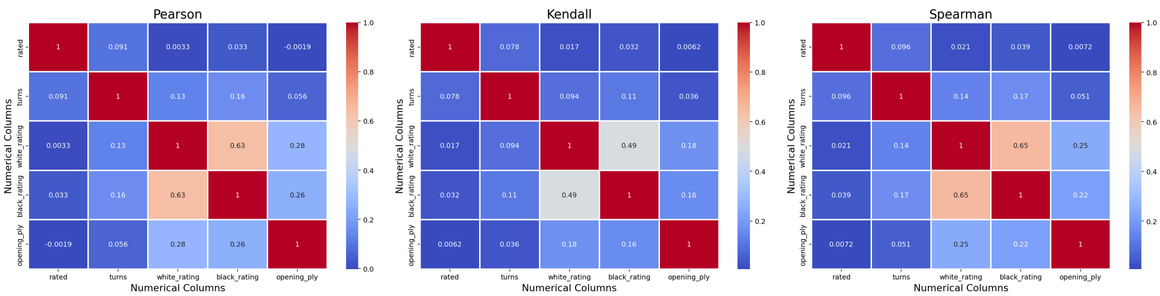
In [32]:
```
correlation_matrix = data[Numerical_column].corr()
correlation_matrix
```

Out[32]:

	rated	created_at	last_move_at	turns	white_rating	black_rating	openin
rated	1.000000	-0.001171	-0.001176	0.090698	0.003284	0.032655	-0.00
created_at	-0.001171	1.000000	1.000000	0.083185	0.116170	0.133316	0.10
last_move_at	-0.001176	1.000000	1.000000	0.083196	0.116172	0.133318	0.10
turns	0.090698	0.083185	0.083196	1.000000	0.129753	0.160467	0.05
white_rating	0.003284	0.116170	0.116172	0.129753	1.000000	0.634171	0.27
black_rating	0.032655	0.133316	0.133318	0.160467	0.634171	1.000000	0.25
opening_ply	-0.001906	0.100201	0.100203	0.055999	0.277379	0.255396	1.00

In [33]:
```
plt.figure(figsize=(24, 6), dpi=140)
methods = ['Pearson', 'Kendall', 'Spearman']
for j, method in enumerate(['pearson', 'kendall', 'spearman']):
    plt.subplot(1, 3, j+1)
    correlation = numerical.dropna().corr(method=method)
    sns.heatmap(correlation, annot=True, cmap='coolwarm', linewidths=2
    plt.title(method.capitalize(), fontsize=18)
    plt.xlabel('Numerical Columns', fontsize=14)
    plt.ylabel('Numerical Columns', fontsize=14)

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



Applying label encoding and onehot label encoding

In [34]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20058 entries, 0 to 20057
Data columns (total 22 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     20058 non-null  object
 1   rated                  20058 non-null  int64
 2   created_at             20058 non-null  datetime64[ns]
 3   last_move_at           20058 non-null  datetime64[ns]
 4   turns                  20058 non-null  int64
 5   victory_status         20058 non-null  category
 6   winner                 20058 non-null  category
 7   increment_code         20058 non-null  object
 8   white_id               20058 non-null  object
 9   white_rating           20058 non-null  int64
 10  black_id               20058 non-null  object
 11  black_rating           20058 non-null  int64
 12  moves                  20058 non-null  object
 13  opening_eco            20058 non-null  object
 14  opening_name           20058 non-null  category
 15  opening_ply            20058 non-null  int64
 16  created_at_month       20058 non-null  int32
 17  created_at_day_name    20058 non-null  object
 18  created_at_hour        20058 non-null  int32
 19  last_move_at_month     20058 non-null  int32
 20  last_move_at_day_name  20058 non-null  object
 21  last_move_at_hour      20058 non-null  int32
dtypes: category(3), datetime64[ns](2), int32(4), int64(5), object
(8)
memory usage: 2.7+ MB
```

In [35]:
```
data.drop('id', axis=1, inplace=True)
data.drop('last_move_at', axis=1, inplace=True)
data.drop('created_at', axis=1, inplace=True)
data.drop('white_id', axis=1, inplace=True)
data.drop('black_id', axis=1, inplace=True)
data.drop('opening_name', axis=1, inplace=True)
data.drop('moves', axis=1, inplace=True)
```

In [36]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
```

In [37]:
```
data['last_move_at_day_name'] = data['last_move_at_day_name'].map({'Su
data['created_at_day_name'] = data['created_at_day_name'].map({'Sunday
data['victory_status'] = data['victory_status'].map({'resign': 0,'mate
data['winner'] = data['winner'].map({'white': 0,'black': 1,'draw':2})
```

In [38]:
```
data['last_move_at_day_name'] = data['last_move_at_day_name'].astype('
data['created_at_day_name'] = data['created_at_day_name'].astype('int'
data['victory_status'] = data['victory_status'].astype('int')
data['winner'] = data['winner'].astype('int')
```

In [39]:
```
data.head()
```

Out[39]:

	rated	turns	victory_status	winner	increment_code	white_rating	black_rating	opening_ec
0	0	13	2	0	15+2	1500	1191	D1
1	1	16	0	1	5+10	1322	1261	B0
2	1	61	1	0	5+10	1496	1500	C2
3	1	61	1	0	20+0	1439	1454	D0
4	1	95	1	0	30+3	1523	1469	C4

In [40]:
```
data.info()
```

```
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   rated                  20058 non-null  int64
 1   turns                  20058 non-null  int64
 2   victory_status         20058 non-null  int64
 3   winner                 20058 non-null  int64
 4   increment_code         20058 non-null  object
 5   white_rating           20058 non-null  int64
 6   black_rating           20058 non-null  int64
 7   opening_eco            20058 non-null  object
 8   opening_ply            20058 non-null  int64
 9   created_at_month       20058 non-null  int32
 10  created_at_day_name    20058 non-null  int64
 11  created_at_hour        20058 non-null  int32
 12  last_move_at_month     20058 non-null  int32
 13  last_move_at_day_name  20058 non-null  int64
 14  last_move_at_hour      20058 non-null  int32
dtypes: int32(4), int64(9), object(2)
memory usage: 2.0+ MB
```

In [41]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
```

In [42]:
```
encoder= OneHotEncoder()
```

In [43]:
```
data_object = data.select_dtypes(include=['object'])
```

In [44]:
```
encoded_data = encoder.fit_transform(data_object)
```

In [45]:
```
encoded_data_dense = encoded_data.toarray()
```

In [46]:
```
category_names = encoder.get_feature_names_out(input_features=data_obj
```

In [47]:
```
encoded_df = pd.DataFrame(encoded_data_dense, columns=category_names)
```

In [48]:
```
data = data.drop(columns=data_object.columns)
```

In [49]:
```
data = pd.concat([data, encoded_df], axis=1)
```

In [50]:
```
data.head()
```

Out[50]:

er	white_rating	black_rating	opening_ply	created_at_month	created_at_day_name	created_at_I
0	1500	1191	5	8	4	
1	1322	1261	4	8	3	
0	1496	1500	3	8	3	
0	1439	1454	3	8	3	
0	1523	1469	5	8	2	

Splitting the Dataset

In [51]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [52]:
```
#Importing Required libraries to train the model
from sklearn.ensemble import RandomForestRegressor
```

In [53]:
```
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import cross_val_score
```

In [54]:
```
x=data.drop(["winner"],axis=1)
y=data["winner"]
```

In [55]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,randc
```

In [56]:
```
print('x_train =',x_train.shape)
print('y_train =',y_train.shape)
print('x_test =',x_test.shape)
print('y_test =',y_test.shape)
```

```
x_train = (16046, 777)
y_train = (16046,)
x_test = (4012, 777)
y_test = (4012,)
```

In [57]:
```
sc=StandardScaler()
sc.fit(x_train)

x_train=sc.transform(x_train)
x_test=sc.transform(x_test)
```

In [58]:
```
def evaluate_random_forest(x_train, y_train, x_test, y_test):
    model = RandomForestRegressor()

    # Model Training
    model.fit(x_train, y_train)

    # Cross-validation
    cv_scores = cross_val_score(model, x_train, y_train, cv=5, scoring
    cv_mean_score = np.mean(cv_scores)

    # Model Prediction
    y_pred = model.predict(x_test)

    # Evaluation
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    results = {
        'Cross-Validation Mean R2 Score': cv_mean_score,
        'Mean Squared Error (MSE)': mse,
        'R-squared (R2) Score': r2
    }

    return results

results = evaluate_random_forest(x_train, y_train, x_test, y_test)

# Print results for Random Forest model
print("Random Forest Model:")
print(f"Cross-Validation Mean R2 Score: {results['Cross-Validation Mea
print(f"Mean Squared Error (MSE): {results['Mean Squared Error (MSE)']
print(f"R-squared (R2) Score: {results['R-squared (R2) Score']}")
```

```
Random Forest Model:
Cross-Validation Mean R2 Score: 0.4137088892864396
Mean Squared Error (MSE): 0.1970756480558325
R-squared (R2) Score: 0.4201986707638228
```

In [59]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [60]:
```
def evaluate_decision_tree(x_train, y_train, x_test, y_test):
    model = DecisionTreeRegressor()

    # Model Training
    model.fit(x_train, y_train)

    # Cross-validation
    cv_scores = cross_val_score(model, x_train, y_train, cv=5, scoring
    cv_mean_score = np.mean(cv_scores)

    # Model Prediction
    y_pred = model.predict(x_test)

    # Evaluation
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    results = {
        'Cross-Validation Mean R2 Score': cv_mean_score,
        'Mean Squared Error (MSE)': mse,
        'R-squared (R2) Score': r2
    }

    return results

results = evaluate_decision_tree(x_train, y_train, x_test, y_test)

# Print results for Decision Tree model
print("Decision Tree Model:")
print(f"Cross-Validation Mean R2 Score: {results['Cross-Validation Mea
print(f"Mean Squared Error (MSE): {results['Mean Squared Error (MSE)']
print(f"R-squared (R2) Score: {results['R-squared (R2) Score']}")
```

```
Decision Tree Model:
Cross-Validation Mean R2 Score: -0.06756436833963404
Mean Squared Error (MSE): 0.3601694915254237
R-squared (R2) Score: -0.05962736642934763
```

In [ ]: