A)

In [3]:

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

In [29]:

```
df = pd.read_csv('fifa_historic.csv')
df= pd.read_csv('fifa_historic.csv', skiprows=[0, 1, 2])

column_names=['Year', 'Country', 'City', 'Stage', 'Home_Team', 'Away_Team', 'Home_Score'
                 'Outcome', 'Win_Conditions', 'Winning_Team', 'Losing_Team', 'Date', 'Mon

df.columns =column_names

#df = df.dropna()
df['Date'] =pd.to_datetime(df['Date'], format='%m/%d/%Y')
df

#I decided to keep the na values because we lose a signifcant amount of information and
```

Out[29]:

	Year	Country	City	Stage	Home_Team	Away_Team	Home_Score	Away_Score	Outcome	Wi
0	1930	Uruguay	Montevideo	Group 1	France	Mexico	4	1	H	
1	1930	Uruguay	Montevideo	Group 4	Belgium	United States	0	3	A	
2	1930	Uruguay	Montevideo	Group 2	Brazil	Yugoslavia	1	2	A	
3	1930	Uruguay	Montevideo	Group 3	Peru	Romania	1	3	A	
4	1930	Uruguay	Montevideo	Group 1	Argentina	France	1	0	H	
...	...	...	...	...	...	...	...	...	...	
895	2018	Russia	Sochi	Quarterfinals	Russia	Croatia	2	2	A	C pe
896	2018	Russia	Saint Petersburg	Semifinals	France	Belgium	1	0	H	
897	2018	Russia	Moscow	Semifinals	Croatia	England	2	1	H	C
898	2018	Russia	Saint Petersburg	Third place	Belgium	England	2	0	H	
899	2018	Russia	Moscow	Final	France	Croatia	4	2	H	

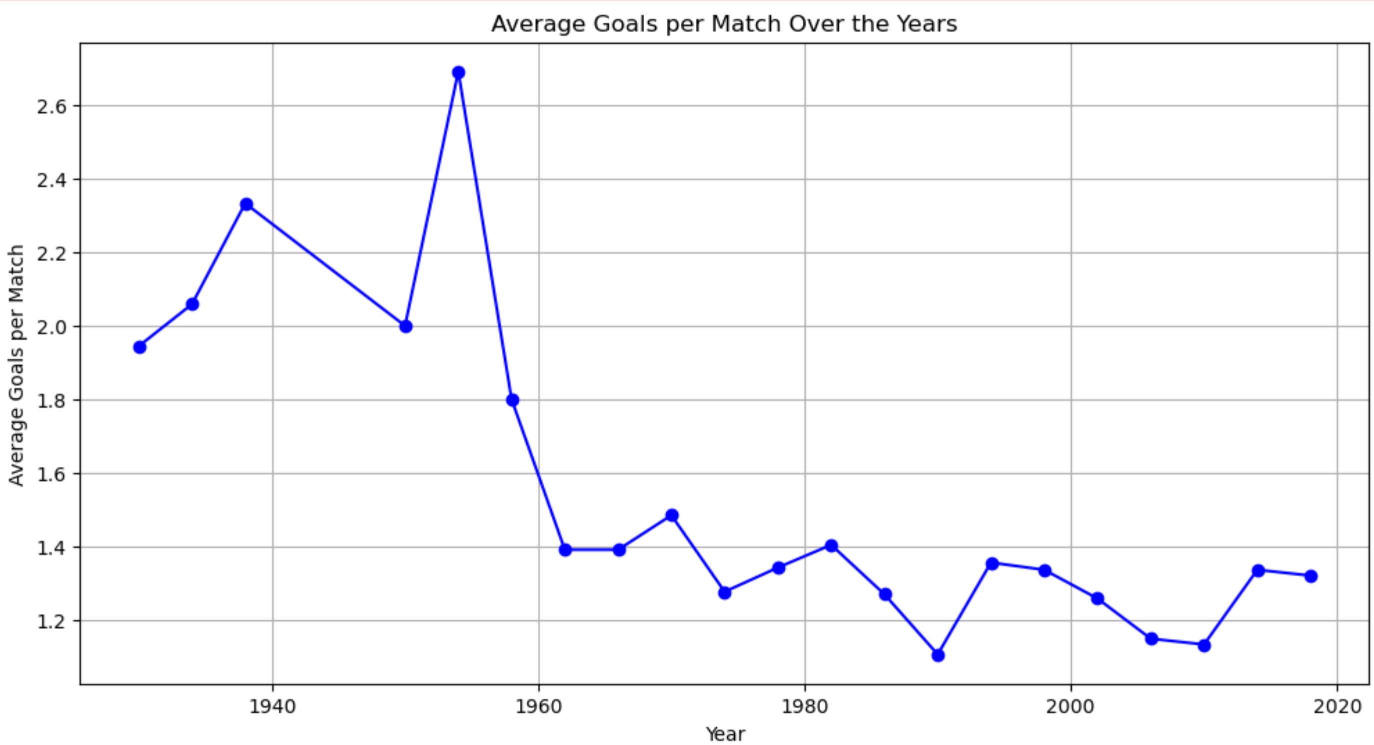
900 rows × 15 columns

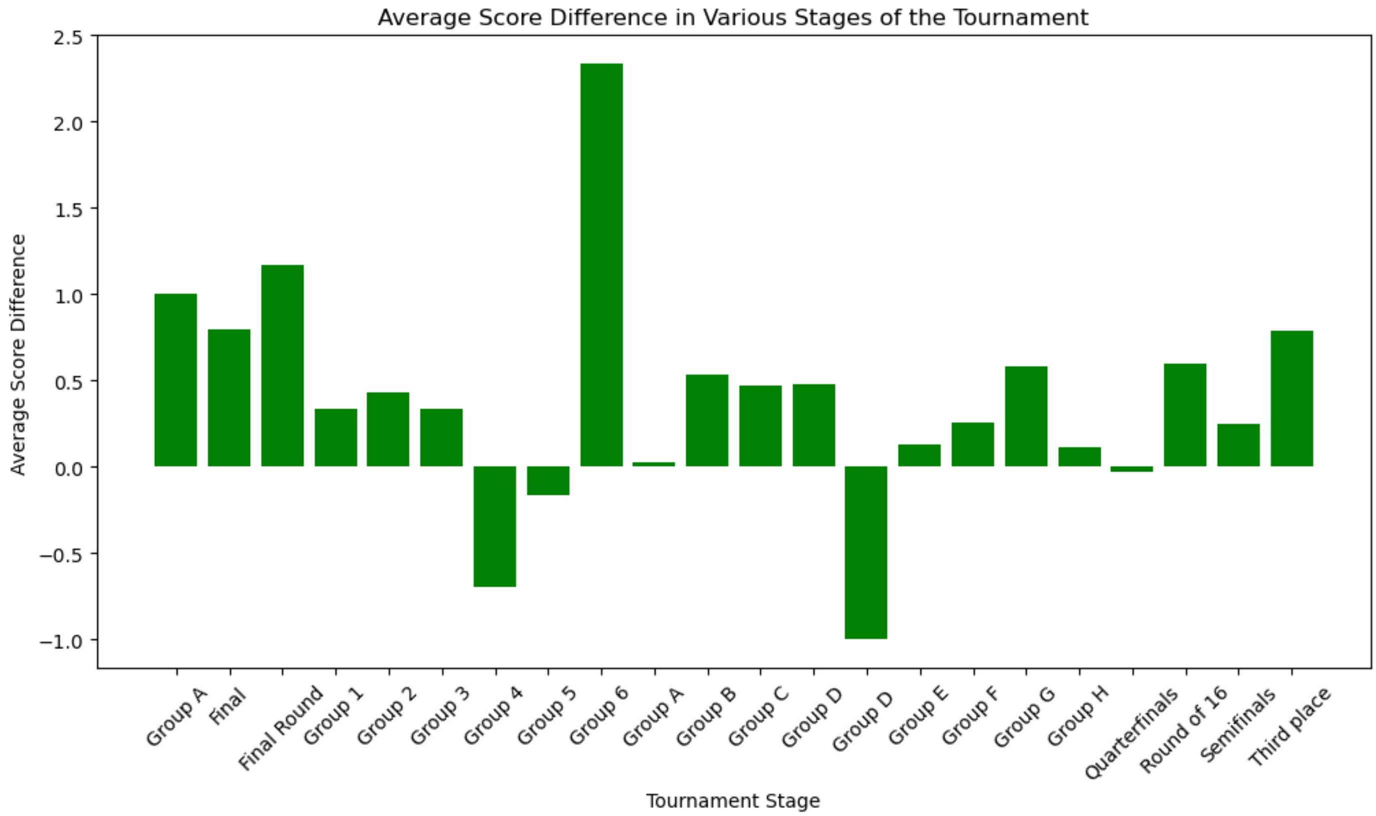
In [27]:

```
import matplotlib.pyplot as plt

average_goals_per_year = df.groupby('Year')['Home_Score', 'Away_Score'].mean().mean(axis
plt.figure(figsize=(12, 6))
plt.plot(average_goals_per_year, marker='o', linestyle='-', color='b')
plt.title('Average Goals per Match Over the Years')
```

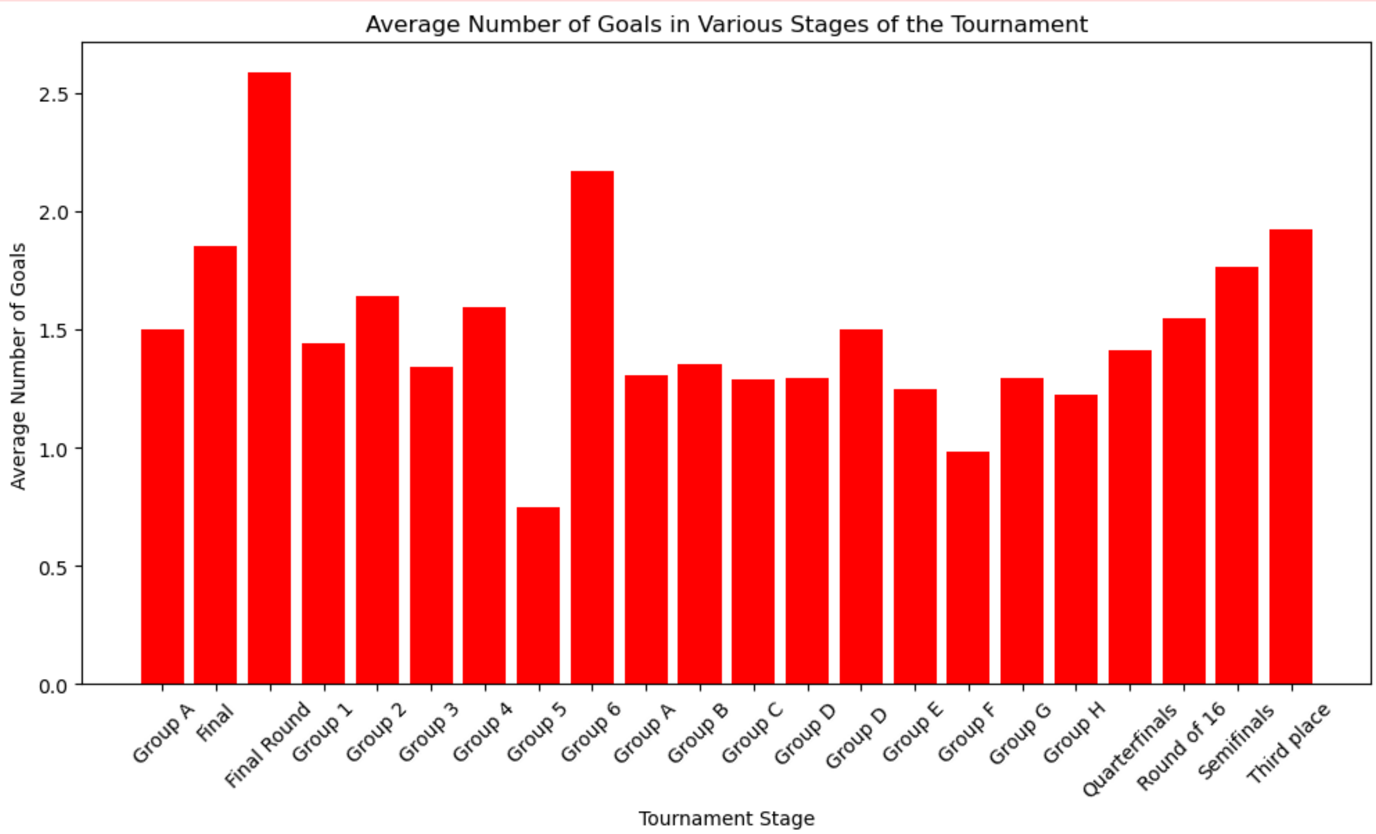
```
plt.xlabel('Year')
plt.ylabel('Average Goals per Match')
plt.grid(True)
plt.show()


df['Score Difference']= df['Home_Score'] - df['Away_Score']
average_score_diff_by_stage = df.groupby('Stage')['Score Difference'].mean()
plt.figure(figsize=(12, 6))
plt.bar(average_score_diff_by_stage.index, average_score_diff_by_stage.values, color='g'
plt.title('Average Score Difference in Various Stages of the Tournament')
plt.xlabel('Tournament Stage')
plt.ylabel('Average Score Difference')
plt.xticks(rotation=45)
plt.show()

average_goals_by_stage =  df.groupby('Stage')['Home_Score', 'Away_Score'].mean().mean(ax
plt.figure(figsize=(12, 6))
plt.bar(average_goals_by_stage.index,average_goals_by_stage.values, color='r')
plt.title('Average Number of Goals in Various Stages of the Tournament')
plt.xlabel('Tournament Stage')
plt.ylabel('Average Number of Goals')
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\smath\AppData\Local\Temp\ipykernel_20604\4183076799.py:3: FutureWarning: Indexi
ng with multiple keys (implicitly converted to a tuple of keys) will be deprecated, use
a list instead.
  average_goals_per_year = df.groupby('Year')['Home_Score', 'Away_Score'].mean().mean(ax
is=1)
```






```
C:\Users\smath\AppData\Local\Temp\ipykernel_20604\4183076799.py:23: FutureWarning: Index
ing with multiple keys (implicitly converted to a tuple of keys) will be deprecated, use
a list instead.
  average_goals_by_stage =  df.groupby('Stage')['Home_Score', 'Away_Score'].mean().mean
(axis=1)
```

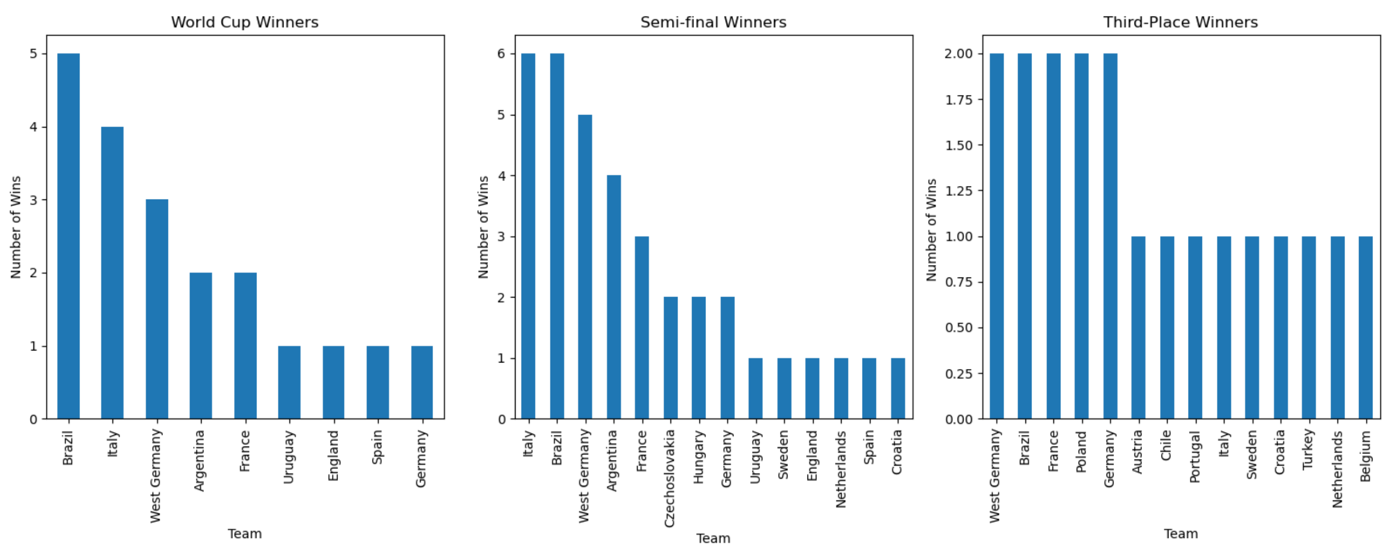


According to the first graph, the average number of goals per match has declined over the years, from around 2-3 goals per match in the 1940s to 1960s to less than 1.5 after the 1960s. The second graph shows the average score difference between teams in various stages of the team. For the most part, the score difference is smaller as the tournament progresses, indicating that the teams are more evenly matched. The third graph shows that the average number of goals scored decreases as the tournament progresses. This also shows that the teams are more evenly matched because they are less likely to score a goal on each other.

B)

In [26]:

```
world_cup_finals = df[df['Stage'] == 'Final']
semi_finals = df[df['Stage'] == 'Semifinals']
third_place_matches = df[df['Stage'] == 'Third place']

world_cup_winners = world_cup_finals['Winning_Team'].value_counts()
semi_final_winners = semi_finals['Winning_Team'].value_counts()
third_place_winners = third_place_matches['Winning_Team'].value_counts()

plt.figure(figsize=(15,6))

plt.subplot(1,3,1)
world_cup_winners.plot(kind='bar')
plt.title('World Cup Winners')
plt.xlabel('Team')
plt.ylabel('Number of Wins' )

plt.subplot(1, 3,2)
semi_final_winners.plot(kind='bar')
plt.title('Semi-final Winners')
plt.xlabel('Team')
plt.ylabel('Number of Wins')

plt.subplot(1,  3, 3)
third_place_winners.plot(kind='bar')
plt.title('Third-Place Winners')
plt.xlabel('Team')
plt.ylabel('Number of Wins ')

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



According to the bar graphs above, it looks like Brazil won the most World Cup matches with a total of 5 wins. Italy and Brazil tied for most semi-final wins with a total of 6 wins. West Germany, Brazil, France, Poland, Germany all tied for most third-place wins for a total of 2.

C)

In [7]:
```python
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import KFold

players_df = pd.read_csv('All_Players .csv')
players_df
```

Out[7]:

	Player	Overall Score	Potential Score	Market Value	Height	Weight	Age	Preferred Foot	Ball Skills	Defence	Mental	
0	Lionel Messi	94	94	95500000	170	72	33	Left	96.5	32.000000	77.833333	9
1	Cristiano Ronaldo	93	93	58500000	187	83	35	Right	90.5	28.000000	76.666667	8
2	Neymar Jr	92	92	105500000	175	68	28	Right	95.5	31.333333	75.000000	8
3	Virgil van Dijk	91	92	90000000	193	92	29	Right	73.5	90.666667	77.333333	7
4	Jan Oblak	91	93	77500000	188	87	27	Right	21.0	19.000000	47.500000	3
...	...	...	...	...	...	...	...	...	...	...	...	
19396	Li Xuebo	46	54	30000	188	75	20	Right	10.0	9.666667	22.500000	1
19397	Cheng Hui	46	52	35000	178	70	23	Right	44.0	44.666667	43.500000	4
19398	Yang Lei	46	56	40000	186	65	20	Right	39.0	45.333333	38.666667	3
19399	Lee Jea Ho	46	54	45000	184	77	23	Right	42.5	44.666667	44.000000	4
19400	Shan Huanhuan	46	56	50000	185	70	21	Right	48.5	26.000000	37.333333	3

19401 rows × 15 columns

In [8]:
```python
predictors_1 = ['Overall Score', 'Potential Score', 'Height', 'Weight', 'Age']
predictors_2 = ['Ball Skills', 'Defence', 'Mental', 'Passing', 'Physical']
predictors_3 = ['Shooting', 'Goalkeeping']

target = 'Market Value'

cv = KFold(n_splits=10, random_state=1, shuffle=True)

model_1 =LinearRegression()
model_2 =LinearRegression()
model_3 = LinearRegression()

X_model_1 =  players_df[predictors_1]
X_model_2= players_df[predictors_2]
X_model_3 =players_df[predictors_3]
y = players_df[target]


scores_model_1 = cross_val_score(model_1, X_model_1, y, scoring='neg_mean_absolute_error
scores_model_2= cross_val_score(model_2, X_model_2, y, scoring='neg_mean_absolute_error'
scores_model_3 =  cross_val_score(model_3, X_model_3, y, scoring='neg_mean_absolute_erro

mae_model_1= np.mean(np.absolute(scores_model_1))
mae_model_2 = np.mean(np.absolute(scores_model_2))
mae_model_3 = np.mean(np.absolute(scores_model_3))
```

```
print(f"mae model 1: {mae_model_1}")
print(f"mae model 2: {mae_model_2}")
print(f"mae model 3: {mae_model_3}")
```

```
mae model 1: 2149383.019517824
mae model 2: 2491308.461034835
mae model 3: 2561423.002183323
```

I split the features in 3 different ways. The first model focussed on physical characteristics of the players, and the players' basic information. The second model focusses on individual skills of the player. The third model only includes shooting and goalkeeping because I feel like those are skills that are important to detemrining a player's overall ability to play on the field. Model 1 has the lowest mean absolute error out of the 3 models, indicating that it is the best at predicting market value of a player. Therefore, a player's basic information is the best indicator of market value.

D)

In [9]:

```
X_model_1_all = players_df[predictors_1]
y_all = players_df[target]

model_1.fit(X_model_1_all, y_all)
mbappe_data= pd.DataFrame([[89, 95, 178, 73, 21]], columns=predictors_1)

mbappe_market_value_prediction =model_1.predict(mbappe_data)

print(f"Predicted Market Value for Mbappe: {mbappe_market_value_prediction[0]}")
```

```
Predicted Market Value for Mbappe: 17636742.812888786
```

E)

In [10]:

```
def predict_market_value(overall_score, potential_score, height, weight, age):
    X_model_1_all = players_df[predictors_1]
    y_all = players_df[target]

    model_1.fit(X_model_1_all, y_all)
    player_data = pd.DataFrame([[overall_score, potential_score, height, weight, age]],

    market_value_prediction=model_1.predict(player_data)

    return market_value_prediction

print(predict_market_value(89, 95, 178, 73, 21))
```

```
[17636742.81288879]
```