1. Libraries

In [73]:
```
!pip install stargazer
!pip install statsmodels
!pip install imgkit

from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import accuracy_score, classification_report, confus
from sklearn.metrics import accuracy_score, classification_report, roc_au
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from stargazer.stargazer import Stargazer
from IPython.display import HTML
import imgkit
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import statsmodels.api as sm
```

```
Requirement already satisfied: stargazer in /usr/local/lib/python3.11/site
-packages (0.0.7)

[notice] A new release of pip is available: 23.3.1 -> 25.2
[notice] To update, run: python3.11 -m pip install --upgrade pip
Requirement already satisfied: statsmodels in /usr/local/lib/python3.11/si
te-packages (0.14.4)
Requirement already satisfied: numpy<3,>=1.22.3 in /usr/local/lib/python3.
11/site-packages (from statsmodels) (1.26.1)
Requirement already satisfied: scipy!=1.9.2,>=1.8 in /usr/local/lib/python
3.11/site-packages (from statsmodels) (1.15.1)
Requirement already satisfied: pandas!=2.1.0,>=1.4 in /usr/local/lib/pytho
n3.11/site-packages (from statsmodels) (2.1.2)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/s
ite-packages (from statsmodels) (1.0.1)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.1
1/site-packages (from statsmodels) (23.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/py
thon3.11/site-packages (from pandas!=2.1.0,>=1.4->statsmodels) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/s
ite-packages (from pandas!=2.1.0,>=1.4->statsmodels) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.1
1/site-packages (from pandas!=2.1.0,>=1.4->statsmodels) (2023.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/site-
packages (from python-dateutil>=2.8.2->pandas!=2.1.0,>=1.4->statsmodels)
(1.16.0)

[notice] A new release of pip is available: 23.3.1 -> 25.2
[notice] To update, run: python3.11 -m pip install --upgrade pip
Requirement already satisfied: imgkit in /usr/local/lib/python3.11/site-pa
ckages (1.2.3)
Requirement already satisfied: six in /usr/local/lib/python3.11/site-packa
ges (from imgkit) (1.16.0)

[notice] A new release of pip is available: 23.3.1 -> 25.2
[notice] To update, run: python3.11 -m pip install --upgrade pip
```

2. Loading Tennis Data

In [3]:
```
# Load dataset
# ATP Match Data & WTA Match Data
# ATP Player Data & WTA Player Data
atp_match = pd.read_csv("Output/ATP_match_final_file.csv")
atp_player = pd.read_csv("atp_player_final.csv")
wta_match = pd.read_csv("Output/WTA_match_final_file.csv")
wta_player = pd.read_csv("wta_player_final.csv")

# Display first few rows
print(atp_match.head())
print(atp_player.head())
print(wta_match.head())
print(wta_player.head())
```

```
        match_id tourney_id tourney_name  tourney_date  match_num  draw_si
ze  \
0  2023-0301-271  2023-0301     Auckland      20230109        271         
32
1  2023-0301-271  2023-0301     Auckland      20230109        271         
32
2  2023-0301-272  2023-0301     Auckland      20230109        272         
32
3  2023-0301-272  2023-0301     Auckland      20230109        272         
32
4  2023-0301-273  2023-0301     Auckland      20230109        273         
32

  tourney_level  best_of round  minutes  ...  1stWon 2ndWon  SvGms  bpSave
d  \
0            A        3   R32     88.0  ...    29.0   16.0   11.0      1.
0   
1            A        3   R32     88.0  ...    30.0    9.0   10.0      6.
0   
2            A        3   R32    157.0  ...    49.0   20.0   17.0      5.
0   
3            A        3   R32    157.0  ...    43.0   17.0   17.0      7.
0   
4            A        3   R32    109.0  ...    35.0   12.0   11.0      2.
0   

   bpFaced  1stWon_pct  WIN  surface_Clay  surface_Grass  surface_Hard
0      1.0    0.828571    1             0              0             1
1      8.0    0.769231    0             0              0             1
2     10.0    0.569767    1             0              0             1
3     14.0    0.623188    0             0              0             1
4      4.0    0.686275    1             0              0             1

[5 rows x 32 columns]
   player_id name_first      name_last hand         dob  ioc  height  \
0     100644  Alexander         Zverev    R  19970420.0  GER   198.0   
1     104792       Gael        Monfils    R  19860901.0  FRA   193.0   
2     104925      Novak       Djokovic    R  19870522.0  SRB   188.0   
3     104926      Fabio        Fognini    R  19870524.0  ITA   178.0   
4     105138    Roberto  Bautista Agut    R  19880414.0  ESP   183.0   

  wikidata_id  rank  
0   Q13990552     2  
1     Q186429    55  
2       Q5812     6  
3     Q251980    83  
4     Q966542    46  
        match_id tourney_id tourney_name  tourney_date  match_num  draw_si
ze  \
0  2023-1003-271  2023-1003         Doha      20230213        271         
32
1  2023-1003-271  2023-1003         Doha      20230213        271         
32
2  2023-1003-272  2023-1003         Doha      20230213        272         
32
3  2023-1003-272  2023-1003         Doha      20230213        272         
32
4  2023-1003-273  2023-1003         Doha      20230213        273         
32
```

```
  tourney_level  best_of round  minutes  ...  1stWon 2ndWon  SvGms  bpSave
d  \
0             P        3   R32     77.0  ...    24.0   15.0   10.0      2.
0
1             P        3   R32     77.0  ...    29.0    9.0   10.0      1.
0
2             P        3   R32    123.0  ...    41.0   12.0   11.0      7.
0
3             P        3   R32    123.0  ...    24.0   11.0   10.0      2.
0
4             P        3   R32    101.0  ...    32.0    8.0   10.0      4.
0

   bpFaced  1stWon_pct  WIN  surface_Clay  surface_Grass  surface_Hard
0      3.0    0.827586    1             0              0             1
1      5.0    0.617021    0             0              0             1
2     10.0    0.585714    1             0              0             1
3      6.0    0.685714    0             0              0             1
4      8.0    0.592593    1             0              0             1

[5 rows x 32 columns]
   player_id name_first       name_last hand         dob  ioc  height  \
0     201458   Victoria        Azarenka    R  19890731.0  BLR   180.0
1     201499  Anastasia  Pavlyuchenkova    R  19910703.0  RUS   177.0
2     201514     Sorana         Cirstea    R  19900407.0  ROU   176.0
3     201518     Yanina       Wickmayer    R  19891020.0  BEL   182.0
4     201520      Petra         Kvitova    L  19900308.0  CZE   183.0

  wikidata_id  rank  points  tours
0      Q10118    23    1916     21
1     Q487182    60    1045     17
2     Q230242    26    1800     23
3     Q228983    67     949     21
4      Q30812    17    2715     17
```

In [15]:

```
# Basic exploration
print(atp_match.info())
print(wta_match.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5424 entries, 0 to 5423
Data columns (total 33 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   match_id       5424 non-null   object
 1   tourney_id     5424 non-null   object
 2   tourney_name   5424 non-null   object
 3   tourney_date   5424 non-null   int64
 4   match_num      5424 non-null   int64
 5   draw_size      5424 non-null   int64
 6   tourney_level  5424 non-null   object
 7   best_of        5424 non-null   int64
 8   round          5424 non-null   object
 9   minutes        5424 non-null   float64
 10  player_id      5424 non-null   int64
 11  player_name    5424 non-null   object
 12  seed           5424 non-null   float64
 13  rank           5424 non-null   float64
 14  rank_points    5424 non-null   float64
 15  age            5424 non-null   float64
 16  height         5424 non-null   float64
 17  hand           5424 non-null   int64
 18  ace            5424 non-null   float64
 19  df             5424 non-null   float64
 20  svpt           5424 non-null   float64
 21  1stIn          5424 non-null   float64
 22  1stWon         5424 non-null   float64
 23  2ndWon         5424 non-null   float64
 24  SvGms          5424 non-null   float64
 25  bpSaved        5424 non-null   float64
 26  bpFaced        5424 non-null   float64
 27  1stWon_pct     5424 non-null   float64
 28  WIN            5424 non-null   int64
 29  surface_Clay   5424 non-null   int64
 30  surface_Grass  5424 non-null   int64
 31  surface_Hard   5424 non-null   int64
 32  const          5424 non-null   int64
dtypes: float64(16), int64(11), object(6)
memory usage: 1.4+ MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4800 entries, 0 to 4799
Data columns (total 33 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   match_id       4800 non-null   object
 1   tourney_id     4800 non-null   object
 2   tourney_name   4800 non-null   object
 3   tourney_date   4800 non-null   int64
 4   match_num      4800 non-null   int64
 5   draw_size      4800 non-null   int64
 6   tourney_level  4800 non-null   object
 7   best_of        4800 non-null   int64
 8   round          4800 non-null   object
 9   minutes        4800 non-null   float64
 10  player_id      4800 non-null   int64
 11  player_name    4800 non-null   object
 12  seed           4800 non-null   float64
 13  rank           4800 non-null   float64
```

```
 14  rank_points    4800 non-null   float64
 15  age            4800 non-null   float64
 16  height         4800 non-null   float64
 17  hand           4800 non-null   int64
 18  ace            4800 non-null   float64
 19  df             4800 non-null   float64
 20  svpt           4800 non-null   float64
 21  1stIn          4800 non-null   float64
 22  1stWon         4800 non-null   float64
 23  2ndWon         4800 non-null   float64
 24  SvGms          4800 non-null   float64
 25  bpSaved        4800 non-null   float64
 26  bpFaced        4800 non-null   float64
 27  1stWon_pct     4800 non-null   float64
 28  WIN            4800 non-null   int64
 29  surface_Clay   4800 non-null   int64
 30  surface_Grass  4800 non-null   int64
 31  surface_Hard   4800 non-null   int64
 32  const          4800 non-null   int64
dtypes: float64(16), int64(11), object(6)
memory usage: 1.2+ MB
None
```

3. Stargazer

In [16]:

```python
# Add constant column for dummy regression
atp_match['const'] = 1
wta_match['const'] = 1

# Use any numeric column for dummy regression
atp_y = atp_match.select_dtypes('number').iloc[:, 0]
wta_y = wta_match.select_dtypes('number').iloc[:, 0]

# Dummy OLS models
atp_model = sm.OLS(atp_y, atp_match[['const']]).fit()
wta_model = sm.OLS(wta_y, wta_match[['const']]).fit()

# Stargazer summary
stargazer = Stargazer([atp_model, wta_model])
stargazer.title("ATP and WTA Match Data Overview")

with open("stargazer_summary.tex", "w", encoding="utf-8") as f:
    f.write(stargazer.render_latex())
```

In [17]:

```python
atp_y = atp_match["WIN"].astype(float)
wta_y = wta_match["WIN"].astype(float)

# Independent variables
X_vars = ["rank", "1stWon", "ace"]

atp_X = sm.add_constant(atp_match[X_vars])
wta_X = sm.add_constant(wta_match[X_vars])

# Fit OLS models (formatting only)
atp_model = sm.OLS(atp_y, atp_X, missing="drop").fit()
wta_model = sm.OLS(wta_y, wta_X, missing="drop").fit()

# Stargazer summary
```

```
stargazer = Stargazer([atp_model, wta_model])
stargazer.title("ATP and WTA match data overview - WIN as dependent varia
html = stargazer.render_html()

# Display in Jupyter + save to Overleaf
HTML(html)
with open("stargazer_summary_iv.tex", "w", encoding="utf-8") as f:
    f.write(stargazer.render_latex())
```

In [18]:
```
def dataset_summary(df, name="Dataset"):
    print(f"--- {name} ---")
    summary = pd.DataFrame({
        "Column": df.columns,
        "Data Type": df.dtypes.values,
        "Missing Values": df.isnull().sum().values,
        "Unique Values": df.nunique().values
    })
    display(summary)

# Run for both match datasets
dataset_summary(atp_match, "ATP Match Data")
dataset_summary(wta_match, "WTA Match Data")


print("Number of variables in ATP Match dataset:", atp_match.shape[1])
print("Number of variables in WTA Match dataset:", wta_match.shape[1])
```

```
--- ATP Match Data ---
```

	Column	Data Type	Missing Values	Unique Values
0	match_id	object	0	2712
1	tourney_id	object	0	118
2	tourney_name	object	0	118
3	tourney_date	int64	0	50
4	match_num	int64	0	200
5	draw_size	int64	0	7
6	tourney_level	object	0	5
7	best_of	int64	0	2
8	round	object	0	8
9	minutes	float64	0	244
10	player_id	int64	0	323
11	player_name	object	0	323
12	seed	float64	0	33
13	rank	float64	0	357
14	rank_points	float64	0	1246
15	age	float64	0	216
16	height	float64	0	17
17	hand	int64	0	2
18	ace	float64	0	42
19	df	float64	0	23
20	svpt	float64	0	189
21	1stIn	float64	0	128
22	1stWon	float64	0	100
23	2ndWon	float64	0	49
24	SvGms	float64	0	32
25	bpSaved	float64	0	24
26	bpFaced	float64	0	28
27	1stWon_pct	float64	0	920
28	WIN	int64	0	2
29	surface_Clay	int64	0	2
30	surface_Grass	int64	0	2
31	surface_Hard	int64	0	2
32	const	int64	0	1

```
--- WTA Match Data ---
```

	Column	Data Type	Missing Values	Unique Values
0	match_id	object	0	2400
1	tourney_id	object	0	80
2	tourney_name	object	0	80
3	tourney_date	int64	0	44
4	match_num	int64	0	204
5	draw_size	int64	0	10
6	tourney_level	object	0	6
7	best_of	int64	0	1
8	round	object	0	8
9	minutes	float64	0	182
10	player_id	int64	0	314
11	player_name	object	0	314
12	seed	float64	0	34
13	rank	float64	0	564
14	rank_points	float64	0	1325
15	age	float64	0	218
16	height	float64	0	29
17	hand	int64	0	2
18	ace	float64	0	23
19	df	float64	0	23
20	svpt	float64	0	135
21	1stIn	float64	0	103
22	1stWon	float64	0	68
23	2ndWon	float64	0	38
24	SvGms	float64	0	21
25	bpSaved	float64	0	23
26	bpFaced	float64	0	29
27	1stWon_pct	float64	0	776
28	WIN	int64	0	2
29	surface_Clay	int64	0	2
30	surface_Grass	int64	0	2
31	surface_Hard	int64	0	2
32	const	int64	0	1

```
Number of variables in ATP Match dataset: 33
Number of variables in WTA Match dataset: 33
```

4. Data Preprocessing WTA and ATP Match Data

In [19]:
```
# Check missing values
print(atp_match.isnull().sum())
print(atp_player.isnull().sum())

print(wta_match.isnull().sum())
print(wta_player.isnull().sum())
```

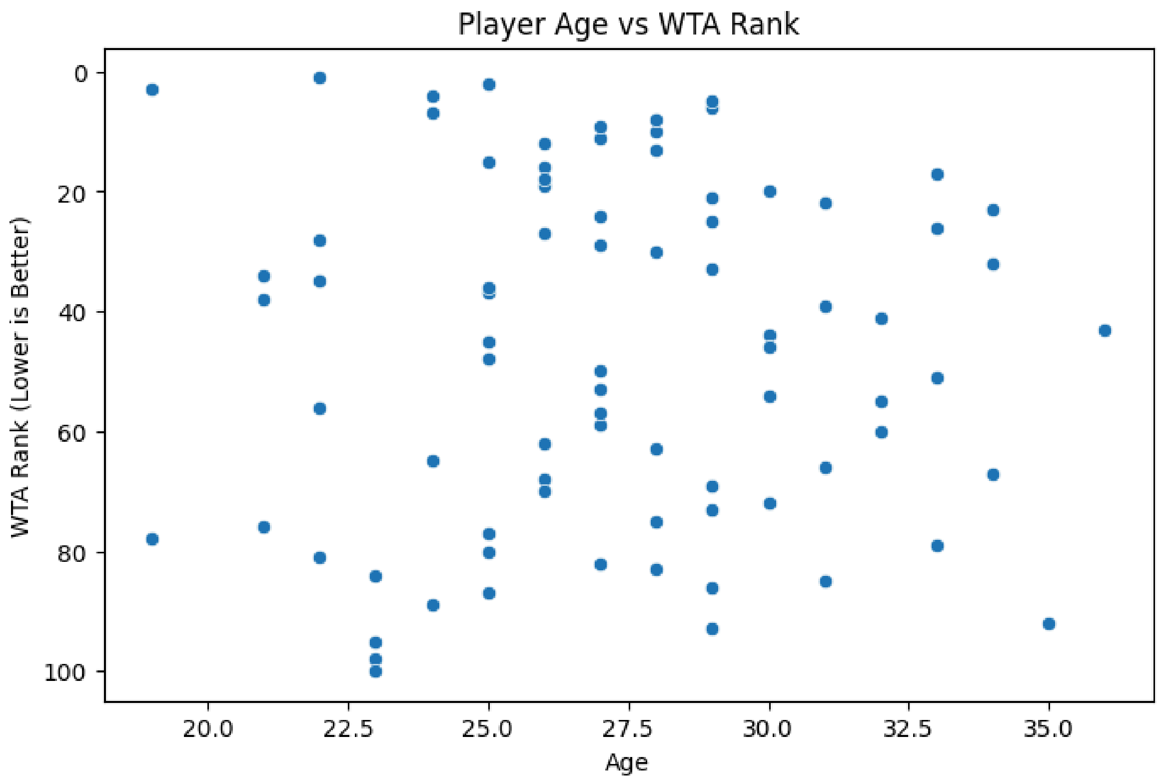
```
match_id         0
tourney_id       0
tourney_name     0
tourney_date     0
match_num        0
draw_size        0
tourney_level    0
best_of          0
round            0
minutes          0
player_id        0
player_name      0
seed             0
rank             0
rank_points      0
age              0
height           0
hand             0
ace              0
df               0
svpt             0
1stIn            0
1stWon           0
2ndWon           0
SvGms            0
bpSaved          0
bpFaced          0
1stWon_pct       0
WIN              0
surface_Clay     0
surface_Grass    0
surface_Hard     0
const            0
dtype: int64
player_id       0
name_first      0
name_last       0
hand            0
dob             0
ioc             0
height         15
wikidata_id    13
rank            0
dtype: int64
match_id         0
tourney_id       0
tourney_name     0
tourney_date     0
match_num        0
draw_size        0
tourney_level    0
best_of          0
round            0
minutes          0
player_id        0
player_name      0
seed             0
rank             0
rank_points      0
age              0
```

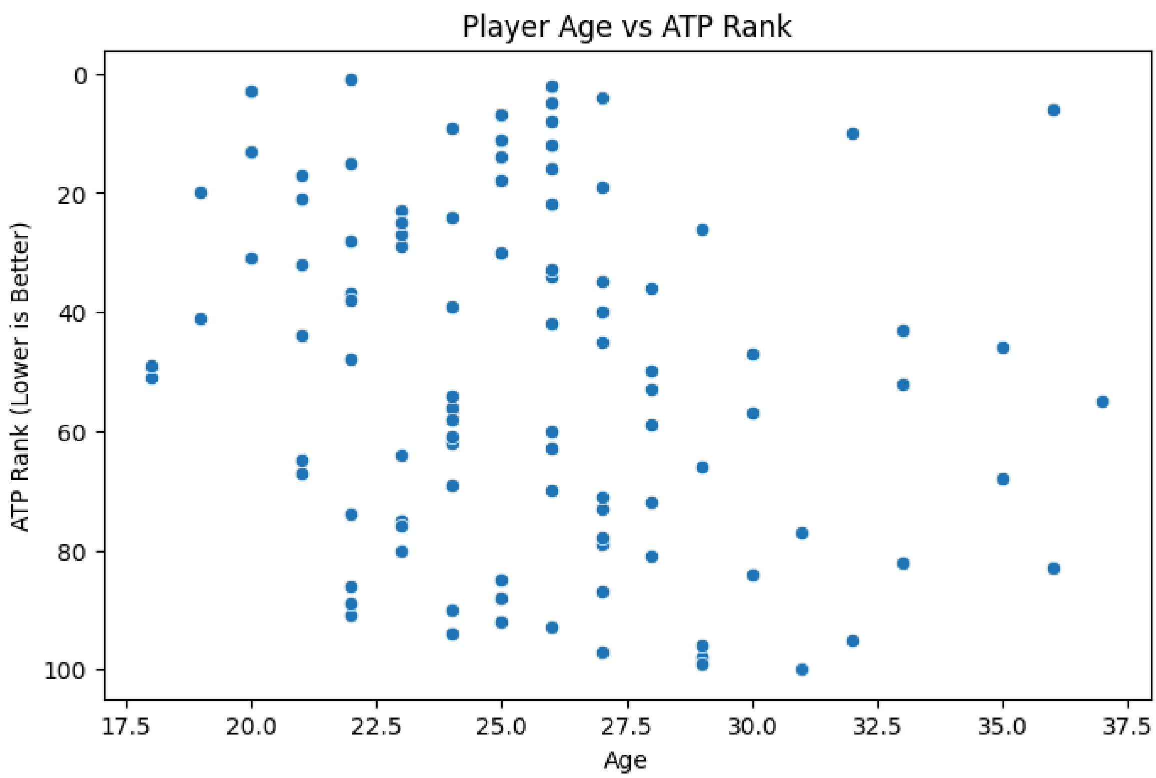
```
height           0
hand             0
ace              0
df               0
svpt             0
1stIn            0
1stWon           0
2ndWon           0
SvGms            0
bpSaved          0
bpFaced          0
1stWon_pct       0
WIN              0
surface_Clay     0
surface_Grass    0
surface_Hard     0
const            0
dtype: int64
player_id       0
name_first      0
name_last       0
hand            0
dob             0
ioc             0
height         19
wikidata_id     3
rank            0
points          0
tours           0
dtype: int64
```

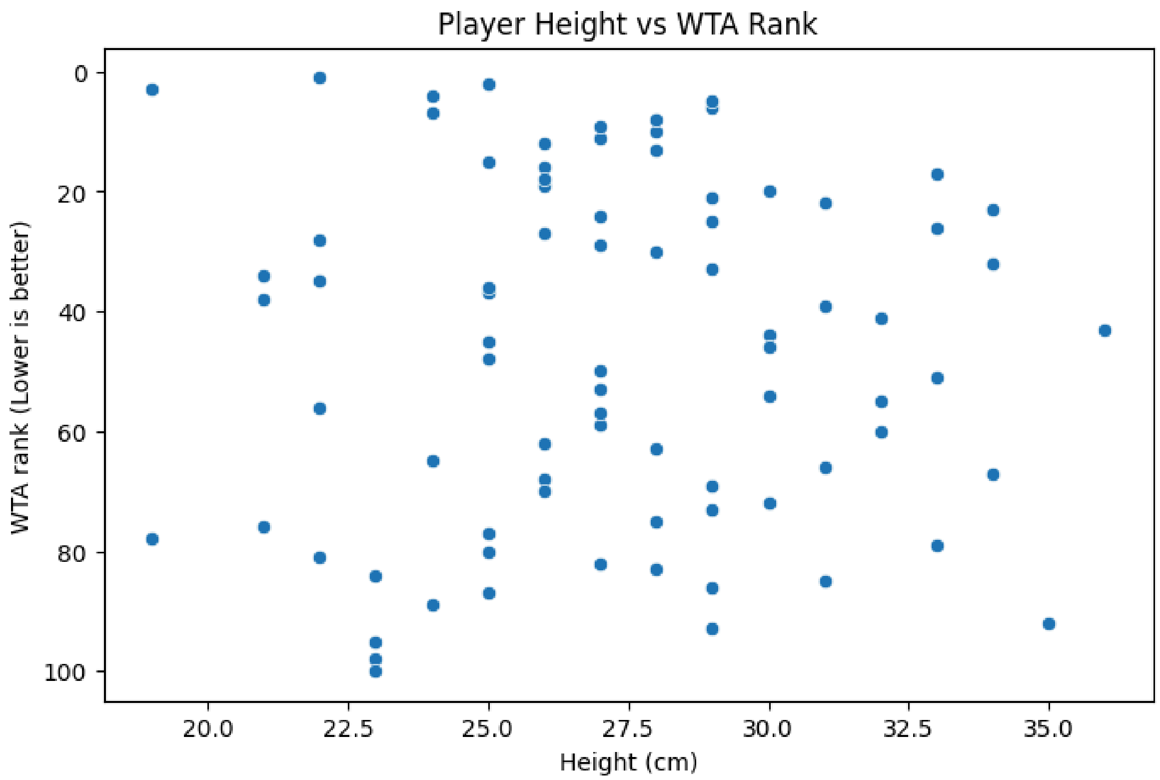
WTA

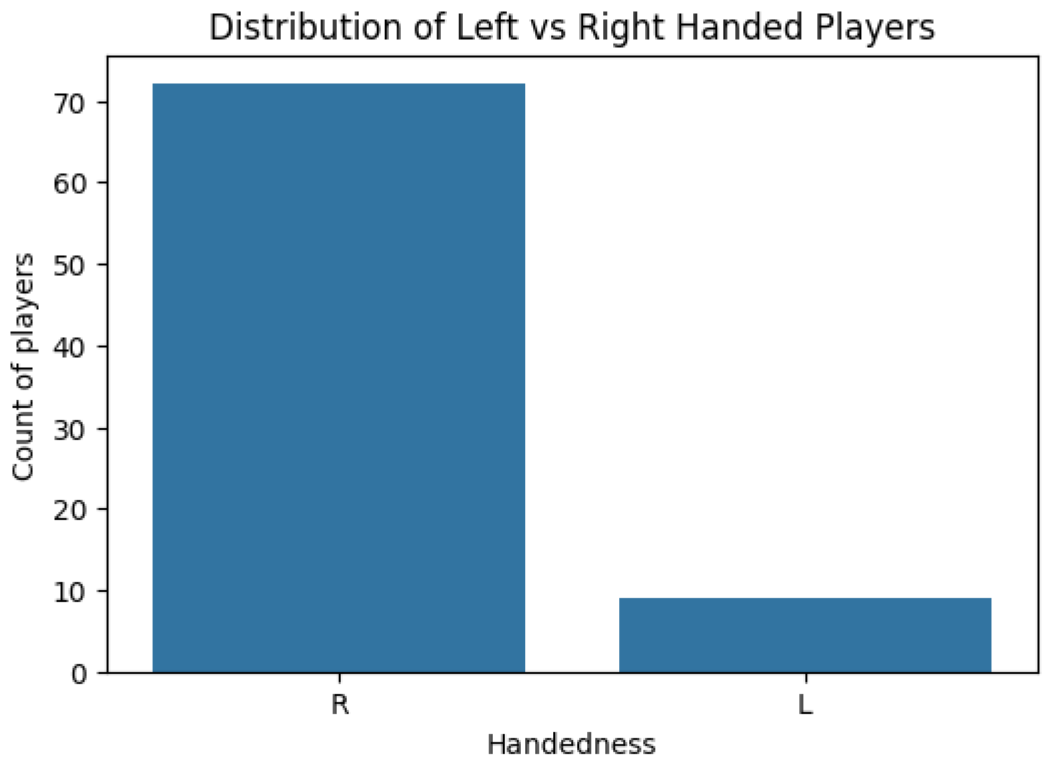
In [22]:
```python
# Convert date of birth (dob) to age
# Extract year and compute age
wta_player["age"] = 2023 - (wta_player["dob"] // 10000)
atp_player["age"] = 2023 - (atp_player["dob"] // 10000)

# Drop NaN values in height for better visualisation
wta_player.dropna(subset=["height"], inplace=True)

# Plot: Age vs Rank
plt.figure(figsize=(8,5))
sns.scatterplot(x=wta_player["age"], y=wta_player["rank"])
plt.xlabel("Age")
plt.ylabel("WTA Rank (Lower is Better)")
plt.title("Player Age vs WTA Rank")
plt.gca().invert_yaxis()  # Higher rank is better
plt.savefig("AgeVsRank_WTA.png", dpi=300)
plt.show()
plt.close()

# ATP Plot: Age vs Rank
plt.figure(figsize=(8,5))
sns.scatterplot(x=atp_player["age"], y=atp_player["rank"])
plt.xlabel("Age")
plt.ylabel("ATP Rank (Lower is Better)")
plt.title("Player Age vs ATP Rank")
```

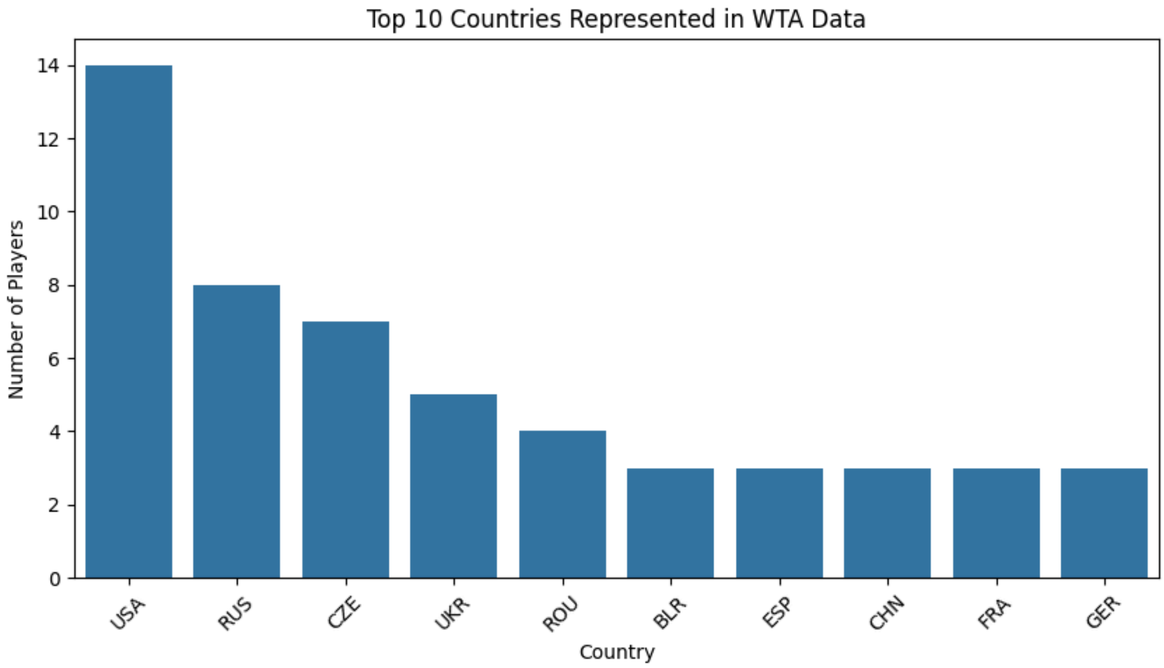
```
plt.gca().invert_yaxis()  # Higher rank is better
plt.savefig("AgeVsRank_ATP.png", dpi=300)
plt.show()
plt.close()

# Plot: Height vs Rank
plt.figure(figsize=(8,5))
sns.scatterplot(x=wta_player["age"], y=wta_player["rank"])
plt.xlabel("Height (cm)")
plt.ylabel("WTA rank (Lower is better)")
plt.title("Player Height vs WTA Rank")
plt.gca().invert_yaxis()
plt.savefig("HeightVsRank_WTA.png", dpi=300)
plt.show()
plt.close()

# Plot: Handedness Distribution
plt.figure(figsize=(6,4))
sns.countplot(x=wta_player["hand"])
plt.xlabel("Handedness")
plt.ylabel("Count of players")
plt.title("Distribution of Left vs Right Handed Players")
plt.savefig("Handedness_Wta.png", dpi=300)
plt.show()
plt.close()

# Plot: Top 10 Countries with Most Players
plt.figure(figsize=(10,5))
top_countries = wta_player["ioc"].value_counts().head(10)
sns.barplot(x=top_countries.index, y=top_countries.values)
plt.xlabel("Country")
plt.ylabel("Number of Players")
plt.title("Top 10 Countries Represented in WTA Data")
plt.xticks(rotation=45)
plt.savefig("Countrie_WTA.png", dpi=300)
plt.show()
plt.close()
```


Player Age vs WTA Rank
WTA Rank (Lower is Better)
0
20
40
60
80
100
20.0
22.5
25.0
27.5
30.0
32.5
35.0
Age


Player Age vs ATP Rank
ATP Rank (Lower is Better)
0
20
40
60
80
100
17.5
20.0
22.5
25.0
27.5
30.0
32.5
35.0
37.5
Age


Player Height vs WTA Rank
WTA rank (Lower is better)
0
20
40
60
80
100
20.0
22.5
25.0
27.5
30.0
32.5
35.0
Height (cm)

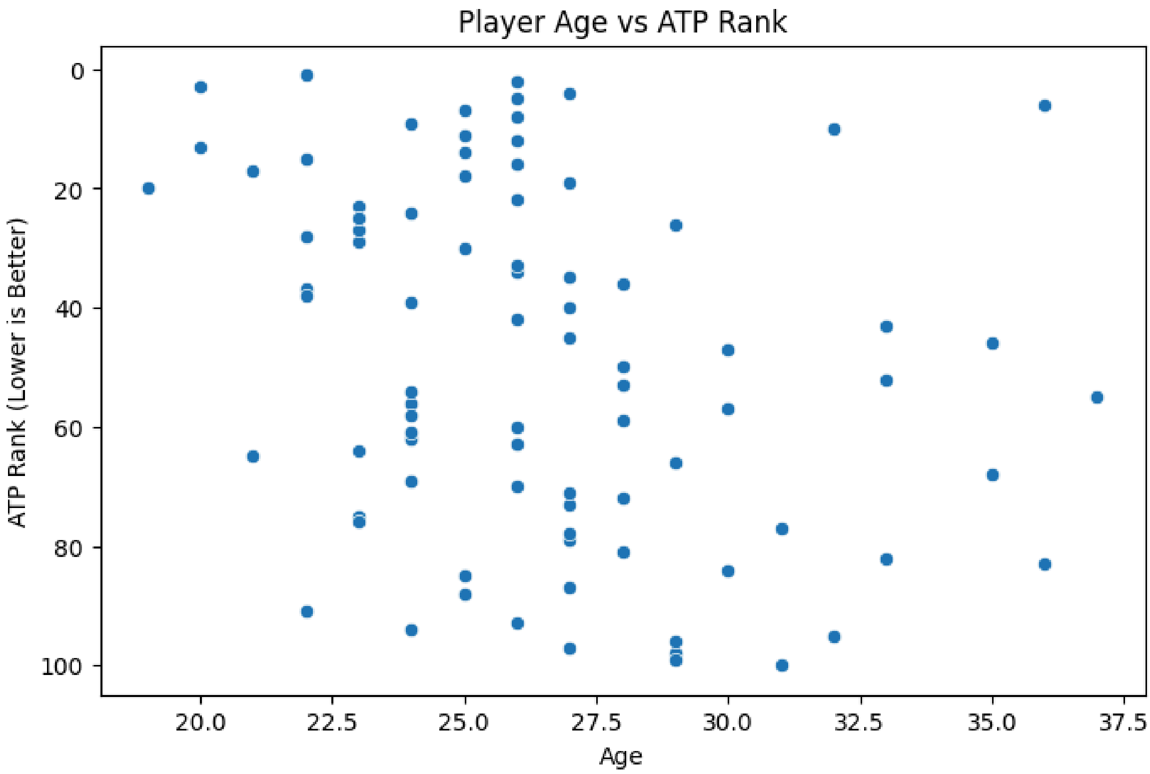

Distribution of Left vs Right Handed Players
Count of players
0
10
20
30
40
50
60
70
R
L
Handedness

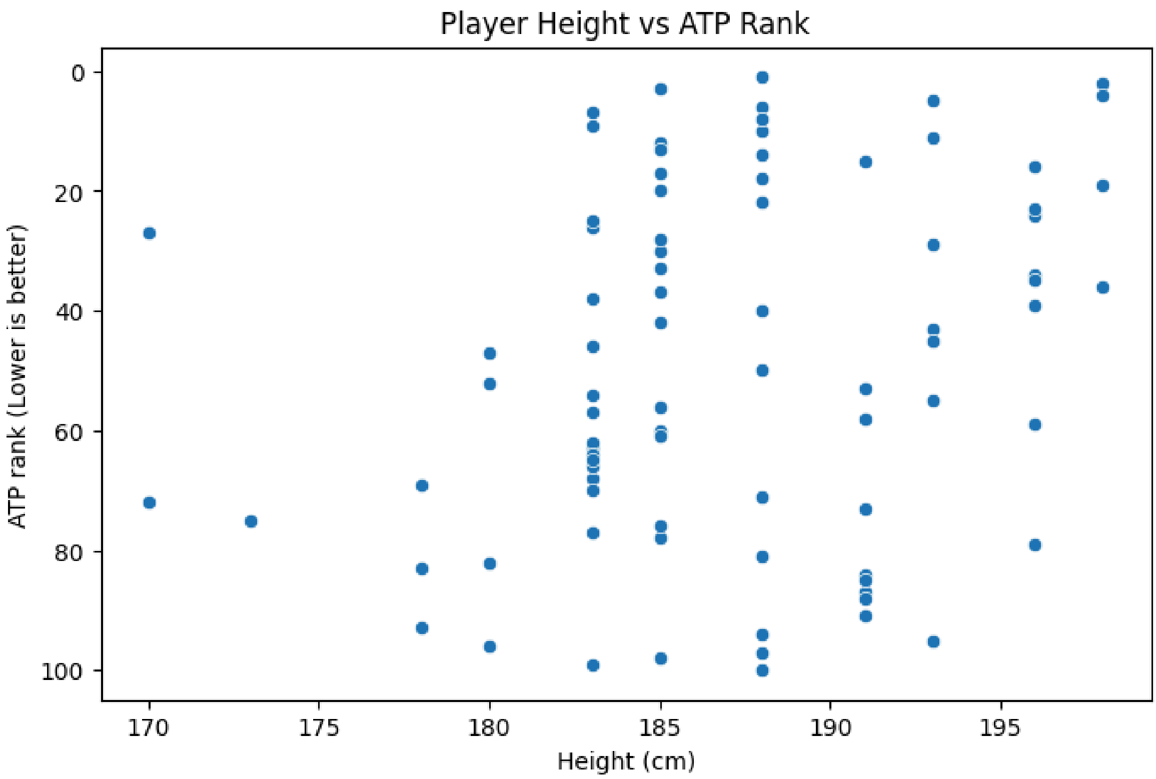


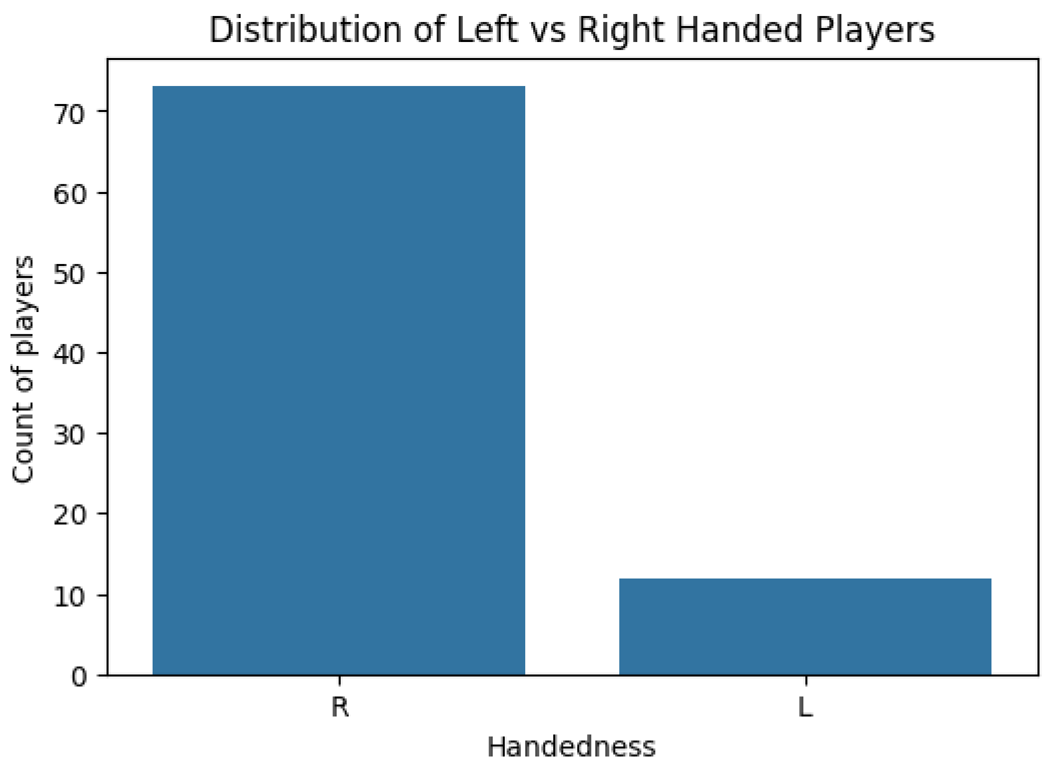
In [23]:

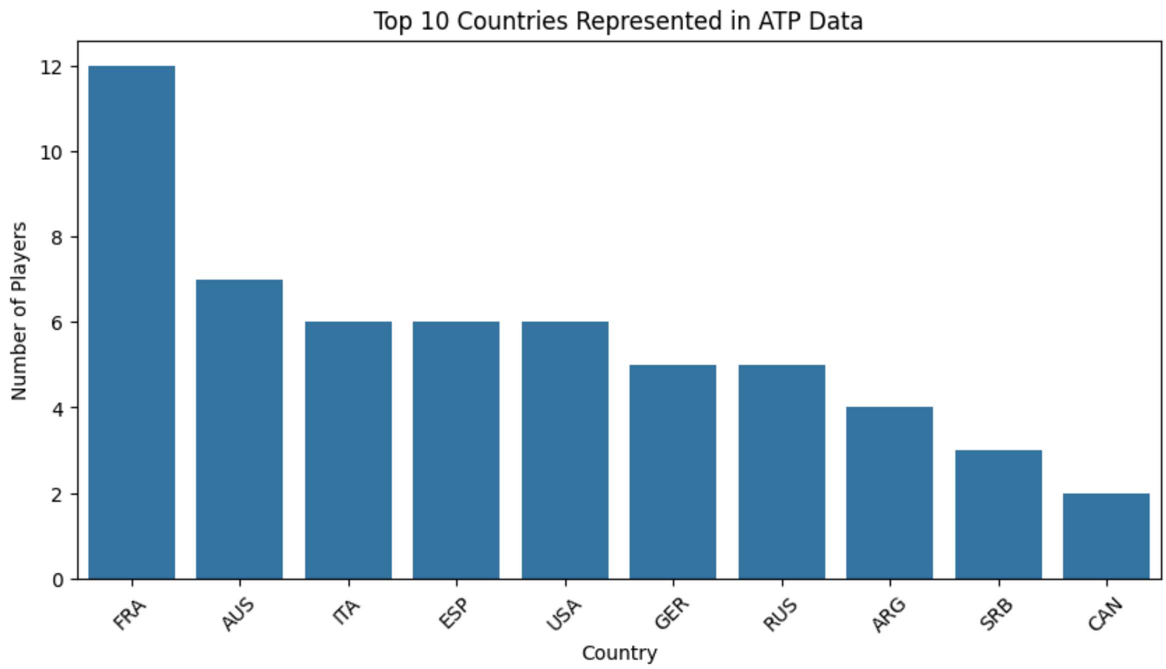
```
# Convert DOB to Age
atp_player["age"] = 2023 - (atp_player["dob"] // 10000)  # Extract year a

# Drop NaN values in height for better visualization
atp_player.dropna(subset=["height"], inplace=True)

# Plot: Age vs Rank
plt.figure(figsize=(8,5))
sns.scatterplot(x=atp_player["age"], y=atp_player["rank"])
plt.xlabel("Age")
plt.ylabel("ATP Rank (Lower is Better)")
plt.title("Player Age vs ATP Rank")
plt.gca().invert_yaxis()  # Higher rank is better
plt.savefig("AgeVsRank_Atp.png", dpi=300)
plt.show()
plt.close()

# Plot: Height vs Rank
plt.figure(figsize=(8,5))
sns.scatterplot(x=atp_player["height"], y=atp_player["rank"])
plt.xlabel("Height (cm)")
plt.ylabel("ATP rank (Lower is better)")
plt.title("Player Height vs ATP Rank")
plt.gca().invert_yaxis()
plt.savefig("HeightVsRank_Atp.png", dpi=300)
plt.show()
plt.close()

# Plot: Handedness Distribution
plt.figure(figsize=(6,4))
sns.countplot(x=atp_player["hand"])
plt.xlabel("Handedness")
plt.ylabel("Count of players")
plt.title("Distribution of Left vs Right Handed Players")
plt.savefig("Handedness_Atp", dpi=300)
plt.show()
plt.close()

# Plot: Top 10 Countries with Most Players
```

```
plt.figure(figsize=(10,5))
top_countries = atp_player["ioc"].value_counts().head(10)
sns.barplot(x=top_countries.index, y=top_countries.values)
plt.xlabel("Country")
plt.ylabel("Number of Players")
plt.title("Top 10 Countries Represented in ATP Data")
plt.xticks(rotation=45)
plt.savefig("Countrie_Atp.png", dpi=300)
plt.show()
plt.close()
```

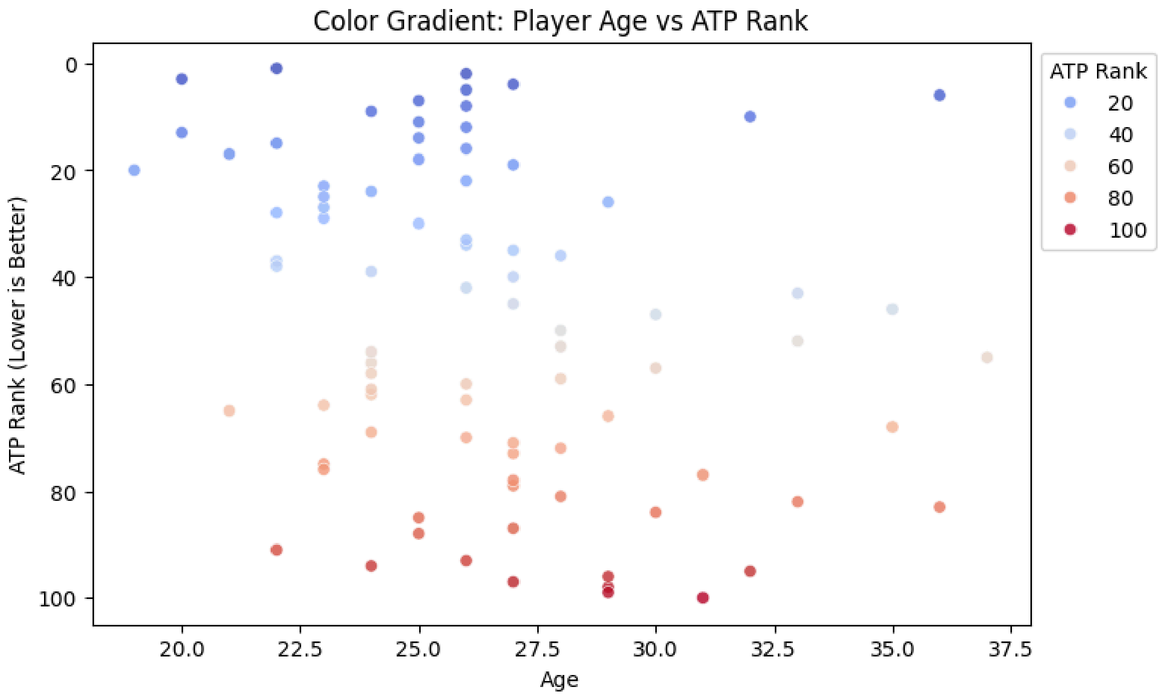




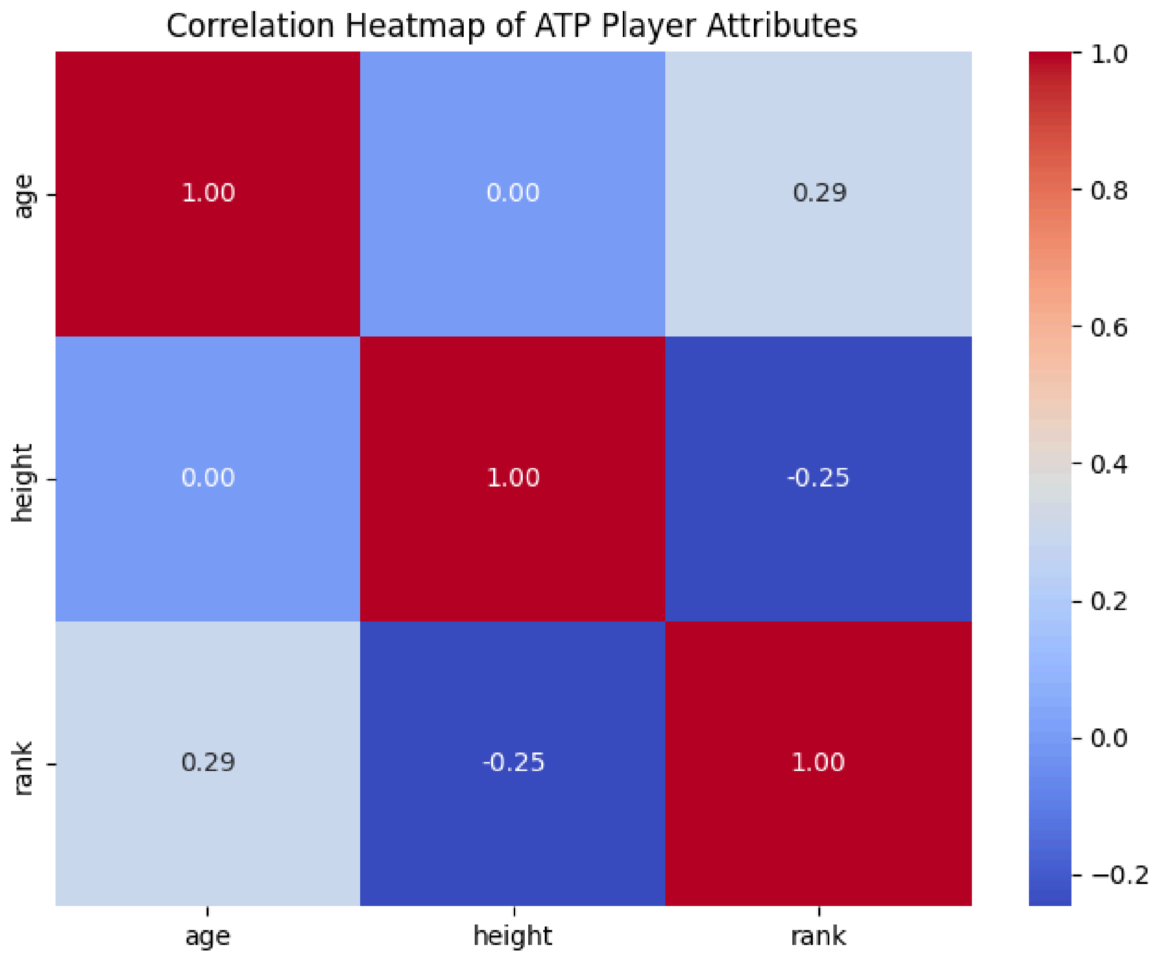




In [24]:
```
# Scatterplot with color mapping
plt.figure(figsize=(8,5))
sns.scatterplot(x=atp_player["age"], y=atp_player["rank"], hue=atp_player
plt.xlabel("Age")
plt.ylabel("ATP Rank (Lower is Better)")
plt.title("Color Gradient: Player Age vs ATP Rank")
plt.gca().invert_yaxis()
plt.legend(title="ATP Rank", bbox_to_anchor=(1,1))
plt.show()
```

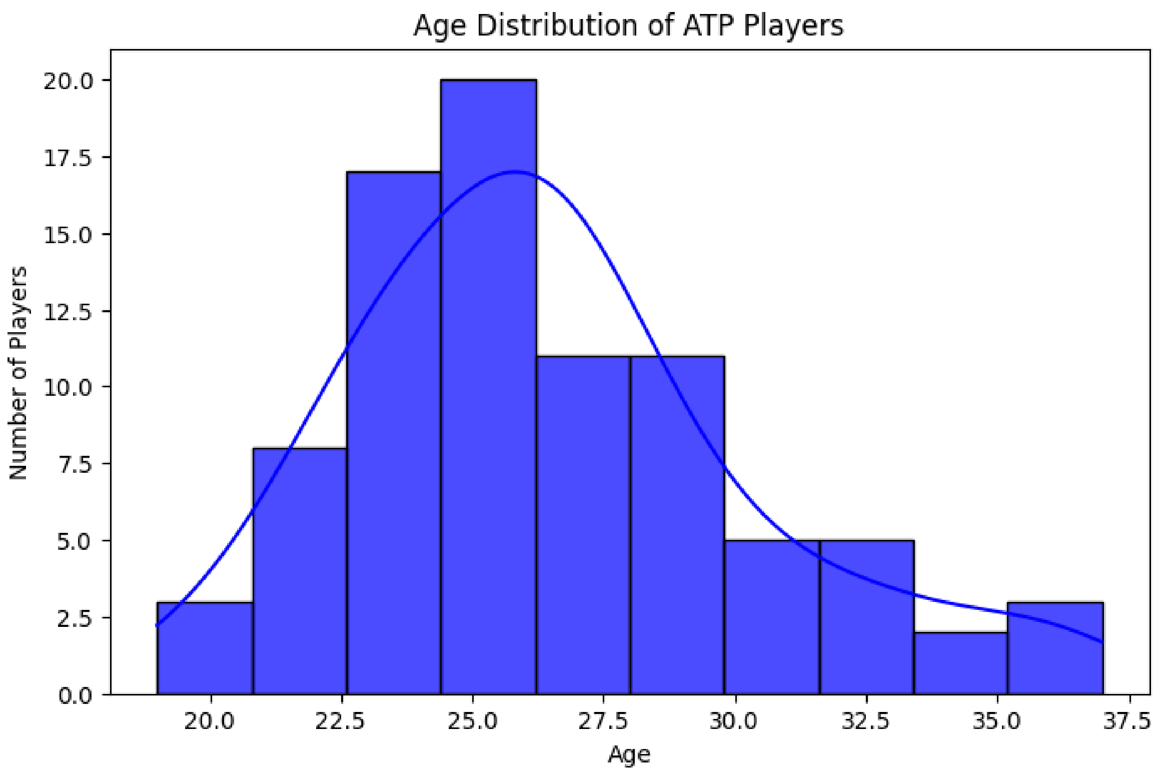


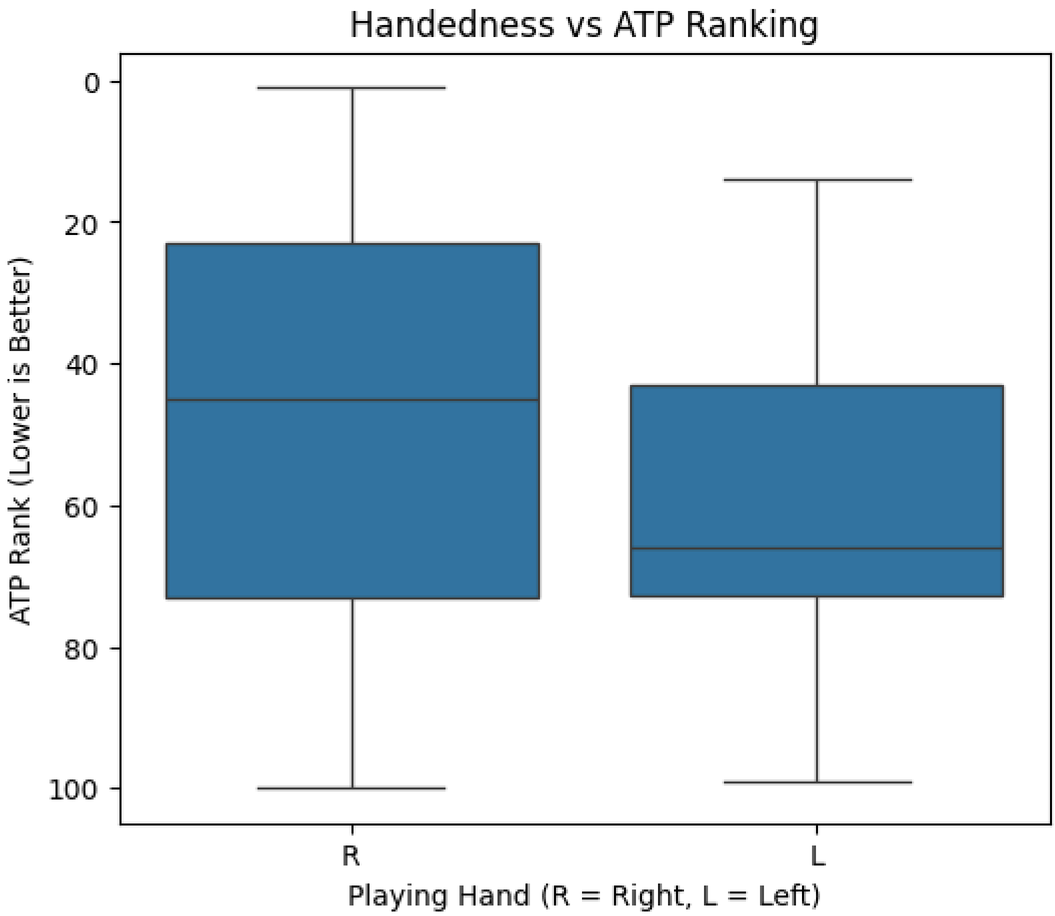
In [26]:
```
# Correlation Heatmap
plt.figure(figsize=(8,6))
sns.heatmap(atp_player[["age", "height", "rank"]].corr(), annot=True, cma
plt.title("Correlation Heatmap of ATP Player Attributes")
plt.savefig("CorrelationHeatmapAtpAttributes.png", dpi=300)
plt.show()
plt.close()
```



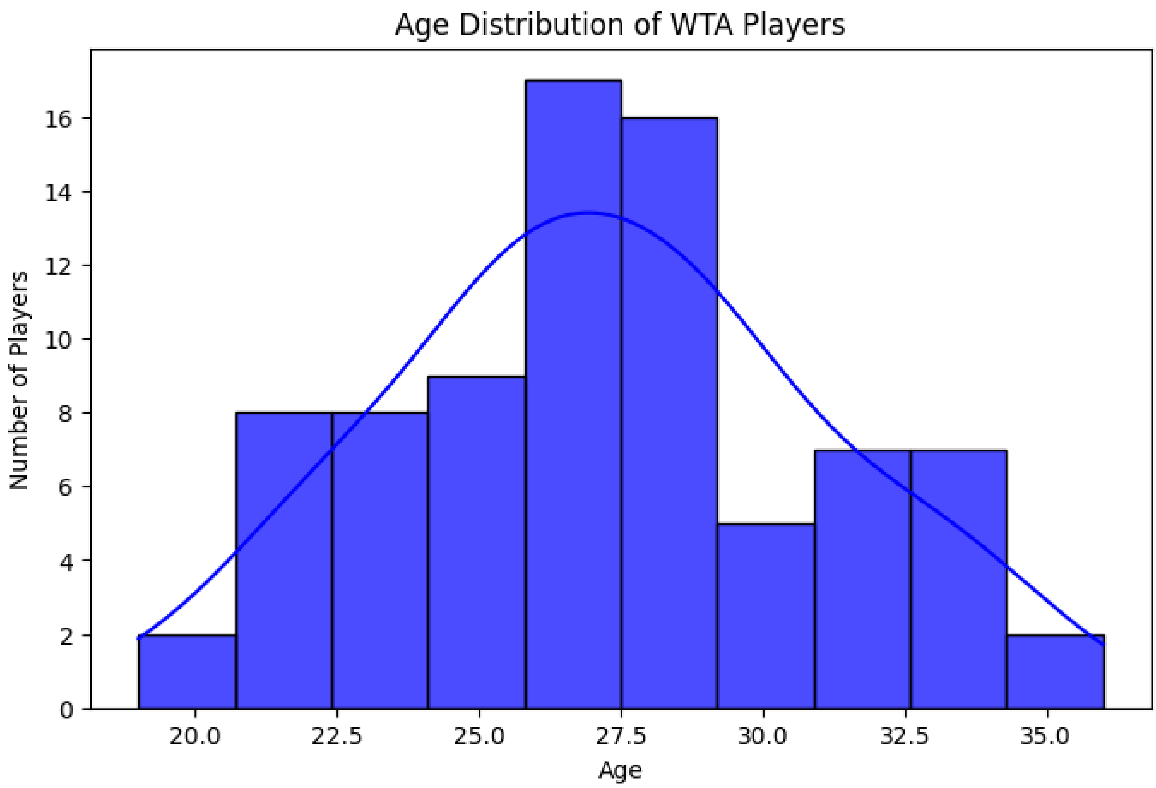
Age has a weak positive correlation with ranking, meaning older players are slightly more likely to be ranked lower (worse). Height has a weak negative correlation with ranking, meaning taller players may have a slight advantage. No connection between age and height.

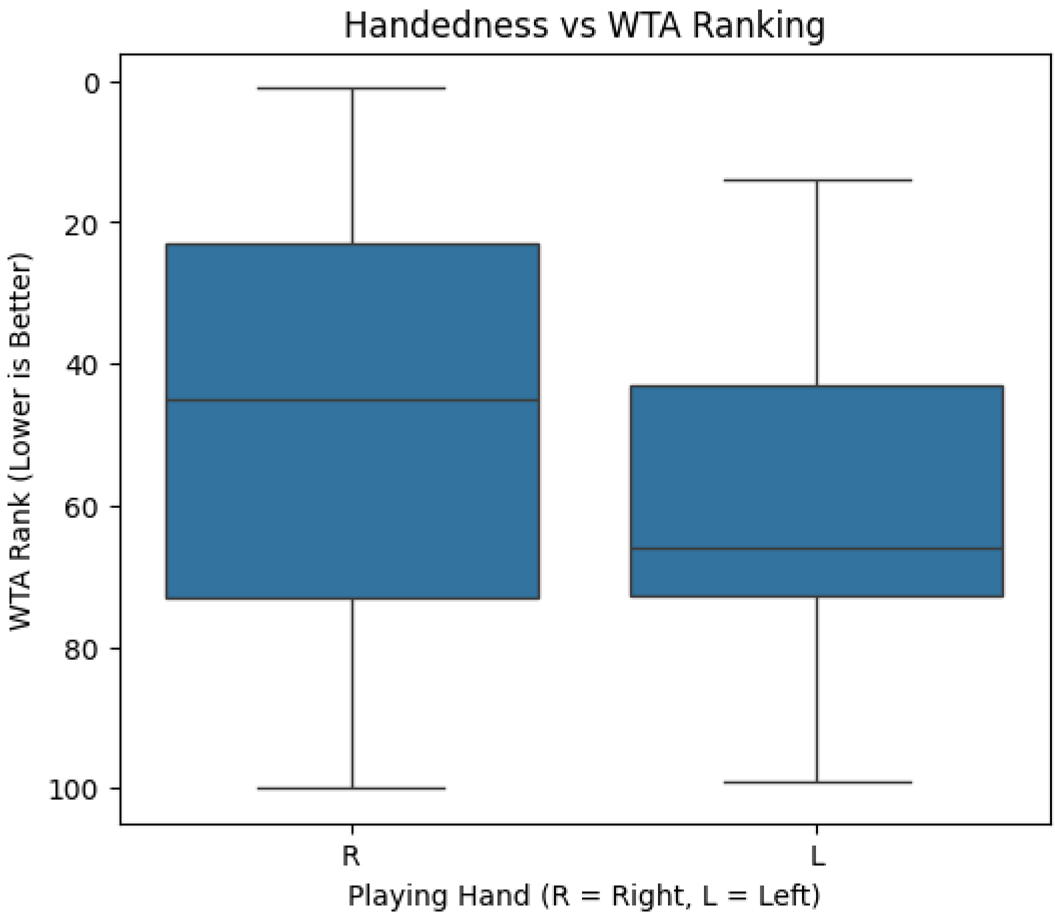
In [27]:
```
# Age
# Age Distribution
plt.figure(figsize=(8,5))
sns.histplot(atp_player["age"], bins=10, kde=True, color="blue", alpha=0.
plt.xlabel("Age")
plt.ylabel("Number of Players")
plt.title("Age Distribution of ATP Players")
plt.savefig("AgeDistributionAtp.png", dpi=300)
plt.show()
plt.close()

# Boxplot: Left-Handed vs Right-Handed Players' Success
plt.figure(figsize=(6,5))
sns.boxplot(x=atp_player["hand"], y=atp_player["rank"])
plt.xlabel("Playing Hand (R = Right, L = Left)")
plt.ylabel("ATP Rank (Lower is Better)")
plt.title("Handedness vs ATP Ranking")
plt.gca().invert_yaxis()
plt.savefig("HandPlayerATP", dpi=300)
plt.show()
plt.close()
```





In [28]:
```
# WTA
# Age
# Age Distribution
plt.figure(figsize=(8,5))
sns.histplot(wta_player["age"], bins=10, kde=True, color="blue", alpha=0.
plt.xlabel("Age")
plt.ylabel("Number of Players")
plt.title("Age Distribution of WTA Players")
plt.savefig("AgeDistributionWTA.png", dpi=300)
plt.show()
plt.close()

# Boxplot: Left-Handed vs Right-Handed Players' Success
plt.figure(figsize=(6,5))
sns.boxplot(x=atp_player["hand"], y=atp_player["rank"])
plt.xlabel("Playing Hand (R = Right, L = Left)")
plt.ylabel("WTA Rank (Lower is Better)")
plt.title("Handedness vs WTA Ranking")
plt.gca().invert_yaxis()
plt.savefig("HandPlayerWTA", dpi=300)
plt.show()
plt.close()
```





Atp Match Data analyse

In [29]:
```
atp_match.head()
```

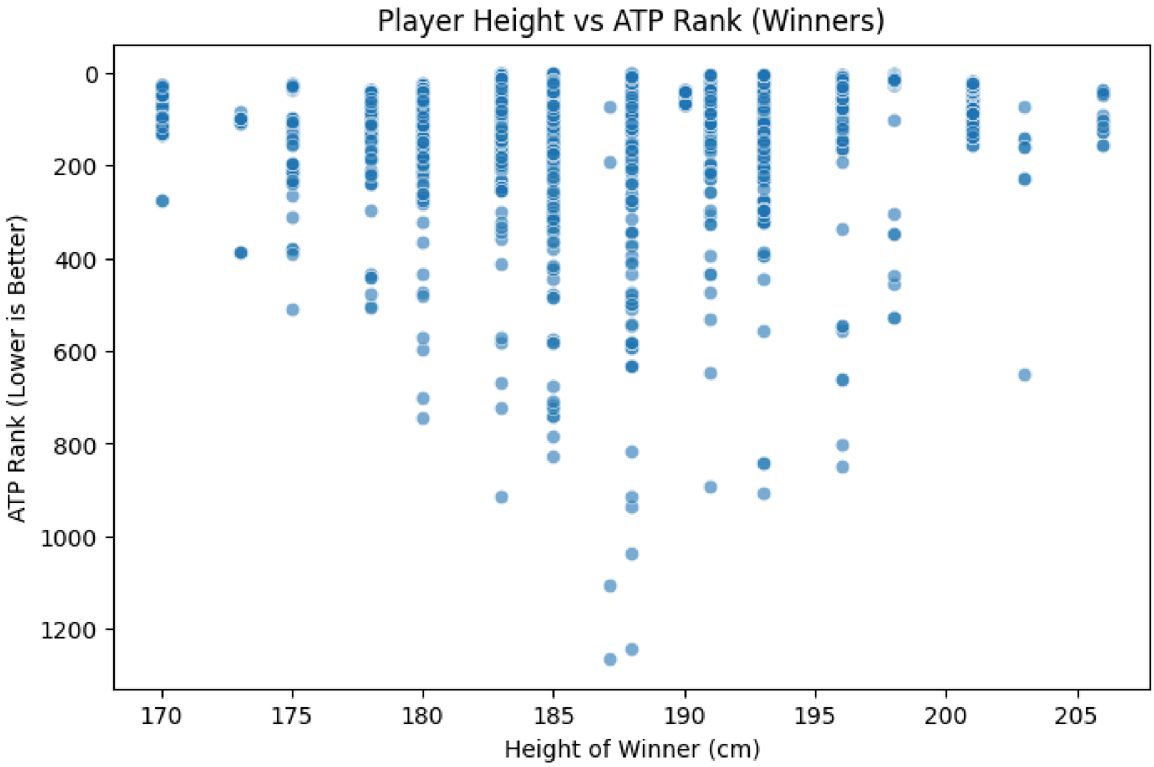
Out[29]:

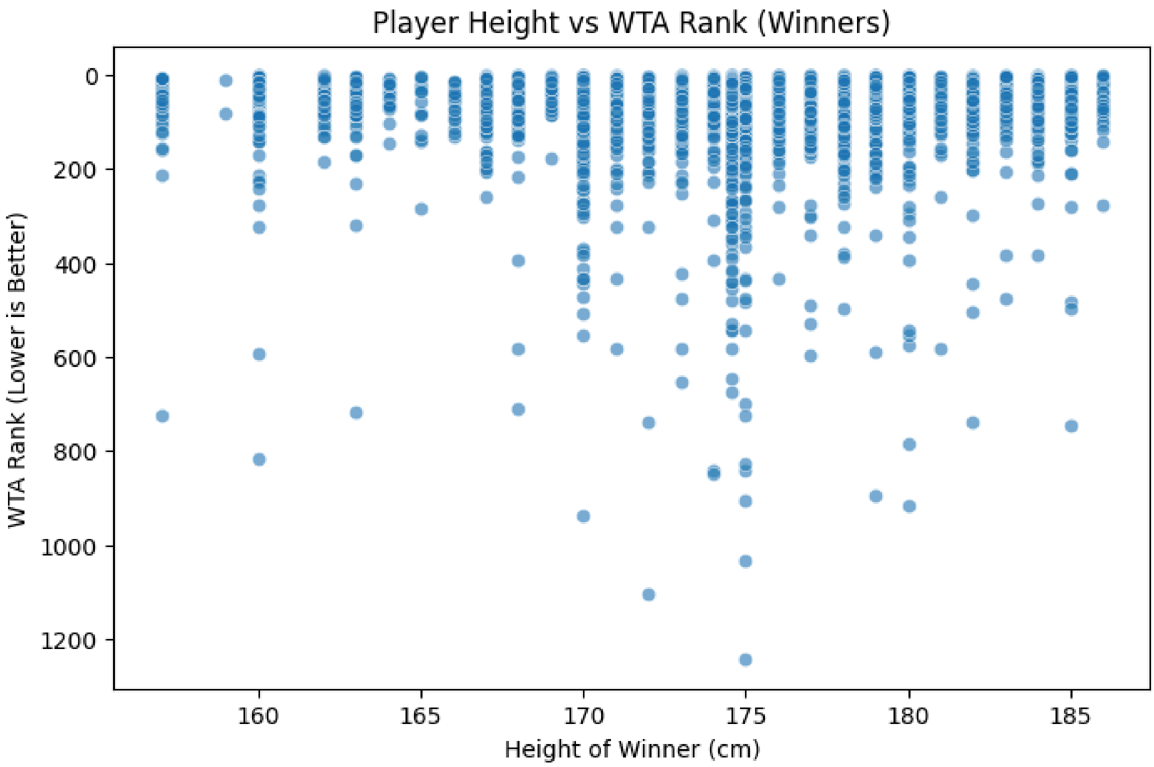
	match_id	tourney_id	tourney_name	tourney_date	match_num	draw_size	tou
0	2023-0301-271	2023-0301	Auckland	20230109	271	32	
1	2023-0301-271	2023-0301	Auckland	20230109	271	32	
2	2023-0301-272	2023-0301	Auckland	20230109	272	32	
3	2023-0301-272	2023-0301	Auckland	20230109	272	32	
4	2023-0301-273	2023-0301	Auckland	20230109	273	32	

5 rows × 33 columns

In [31]:

```
# ATP
# Height vs. ATP Ranking (Winner's Perspective)
plt.figure(figsize=(8,5))
sns.scatterplot(x=atp_match["height"], y=atp_match["rank"], alpha=0.6)
plt.xlabel("Height of Winner (cm)")
plt.ylabel("ATP Rank (Lower is Better)")
plt.title("Player Height vs ATP Rank (Winners)")
plt.gca().invert_yaxis()
plt.savefig("PlayerHeightAtpRank.png", dpi=300)
plt.show()
plt.close()

#WTA
plt.figure(figsize=(8,5))
sns.scatterplot(x=wta_match["height"], y=atp_match["rank"], alpha=0.6)
plt.xlabel("Height of Winner (cm)")
plt.ylabel("WTA Rank (Lower is Better)")
plt.title("Player Height vs WTA Rank (Winners)")
plt.gca().invert_yaxis()
plt.savefig("PlayerHeightWTARank.png", dpi=300)
plt.show()
plt.close()
```





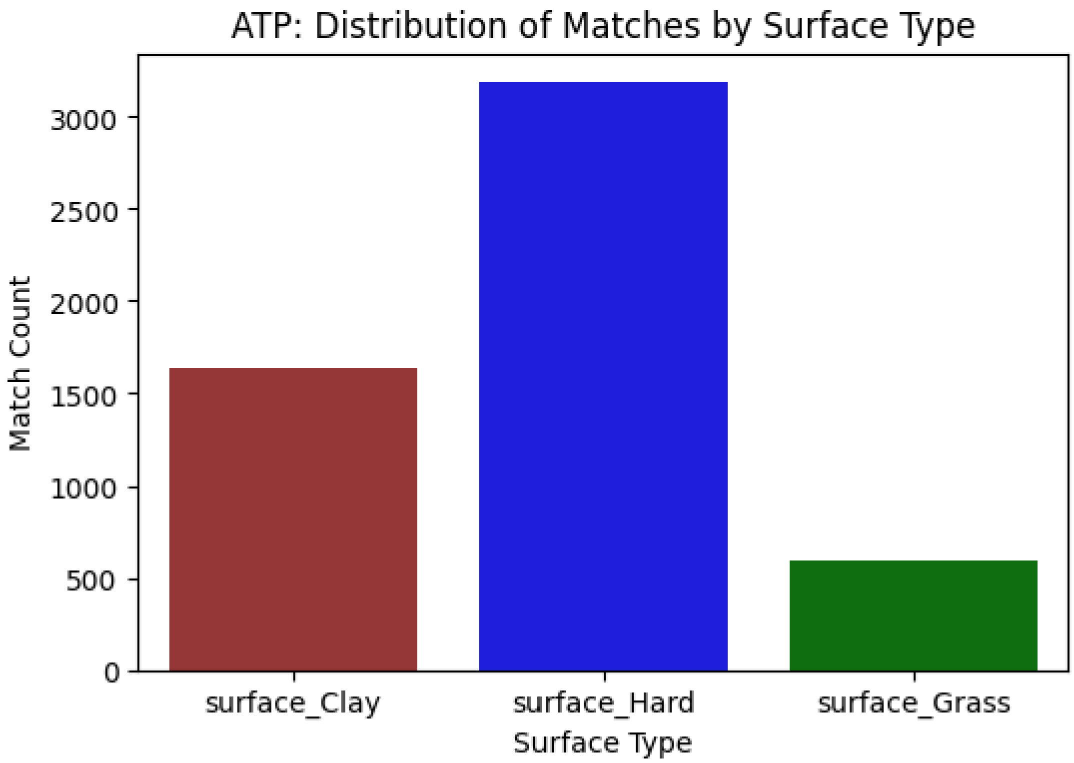
In [ ]:

In [62]:

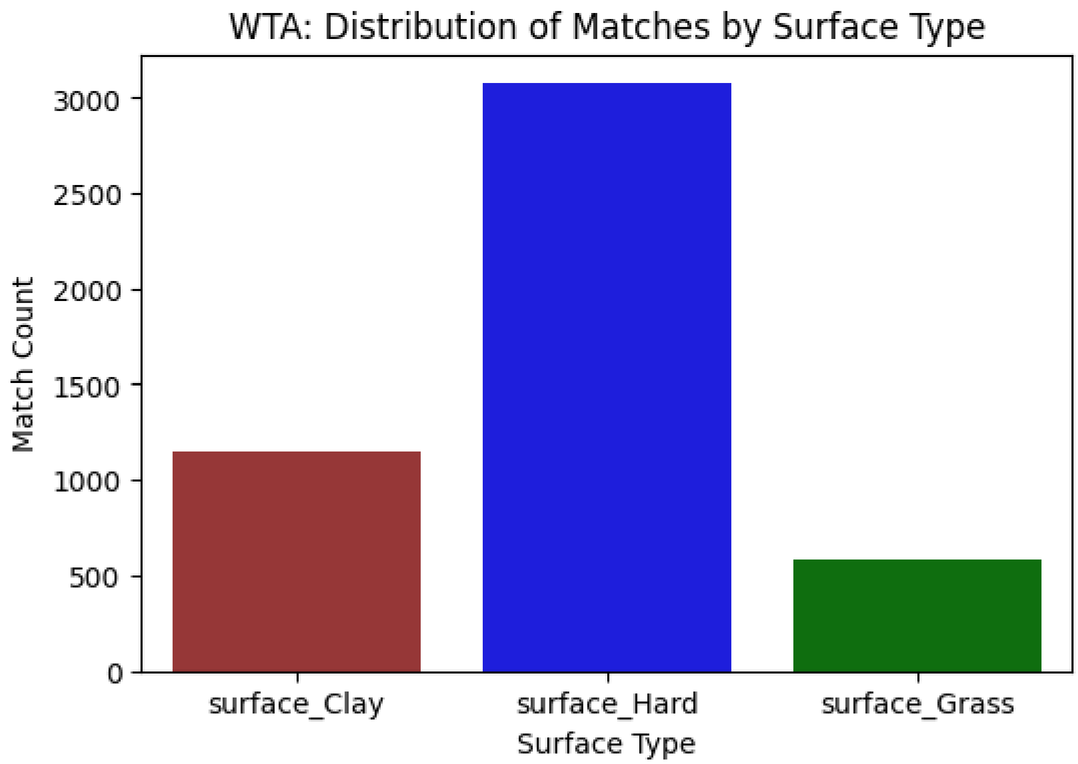
```
# ATP
# Sum up number of matches played on each surface
surface_counts = atp_match[['surface_Clay', 'surface_Hard', 'surface_Gras
surface_df = surface_counts.reset_index()
surface_df.columns = ["Surface Type", "Match Count"]

# Plot surface distribution
plt.figure(figsize=(6,4))
sns.barplot(x="Surface Type", y="Match Count", data=surface_df, palette=[
```

```python
plt.xlabel("Surface Type")
plt.ylabel("Match Count")
plt.title("ATP: Distribution of Matches by Surface Type")
plt.savefig("MatchDistributionSurfaceATP.png", dpi=300)
plt.show()
plt.close()

# WTA
surface_counts = wta_match[['surface_Clay', 'surface_Hard', 'surface_Gras
surface_df = surface_counts.reset_index()
surface_df.columns = ["Surface Type", "Match Count"]

# Plot surface distribution
plt.figure(figsize=(6,4))
sns.barplot(x="Surface Type", y="Match Count", data=surface_df, palette=[
plt.xlabel("Surface Type")
plt.ylabel("Match Count")
plt.title("WTA: Distribution of Matches by Surface Type")
plt.savefig("MatchDistributionSurfaceWTA.png", dpi=300)
plt.show()
plt.close()
```

```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_59742/221625335
2.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.barplot(x="Surface Type", y="Match Count", data=surface_df, palette=
['brown', 'blue', 'green'])
```

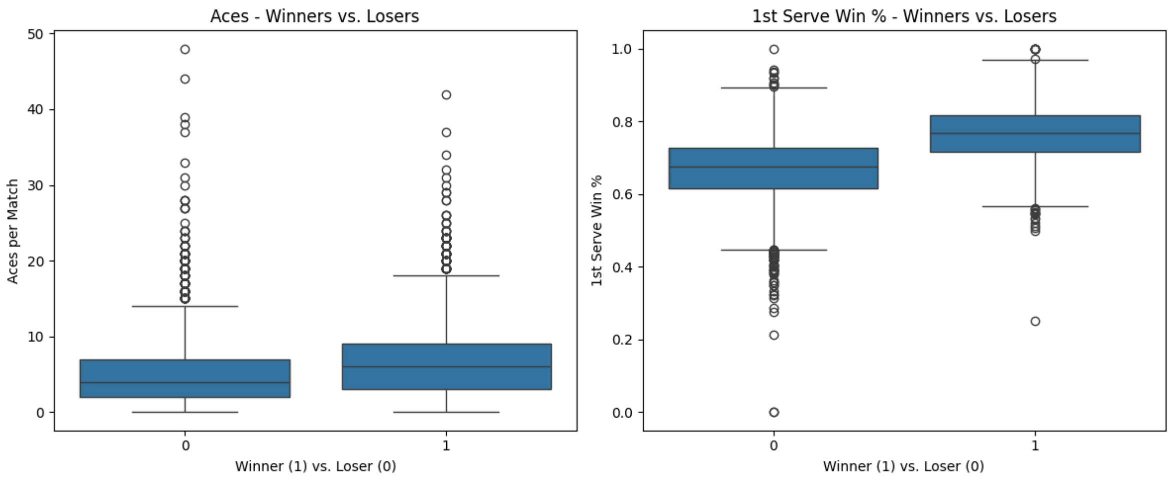


```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_59742/221625335
2.py:24: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.barplot(x="Surface Type", y="Match Count", data=surface_df, palette=
['brown', 'blue', 'green'])
```

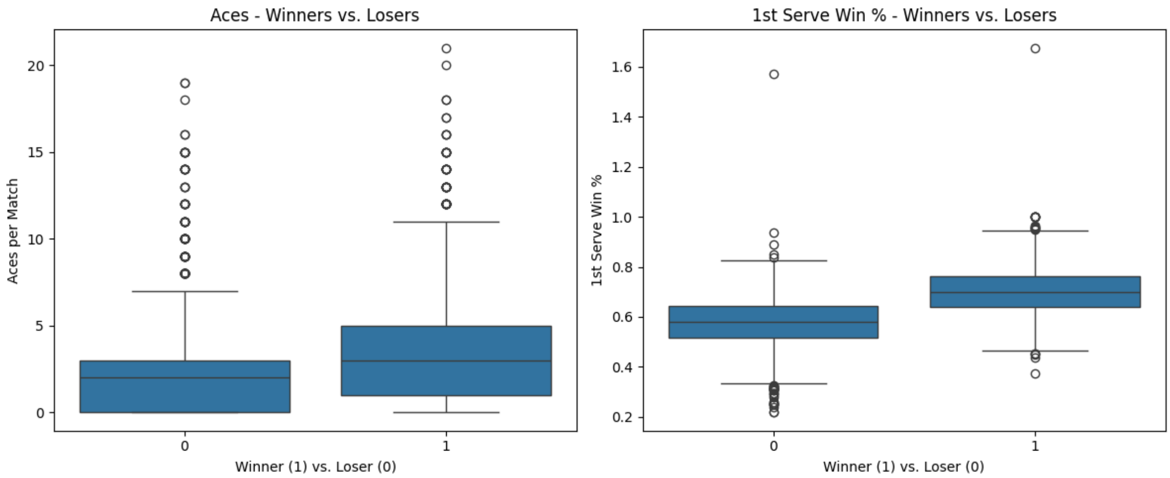


In [32]:

```
# Winners vs. Losers – Aces & Serve Performance
fig, axes = plt.subplots(1, 2, figsize=(12,5))

# Aces per Match (Winners vs. Losers)
sns.boxplot(data=atp_match, x="WIN", y="ace", ax=axes[0])
axes[0].set_title("Aces – Winners vs. Losers")
axes[0].set_xlabel("Winner (1) vs. Loser (0)")
axes[0].set_ylabel("Aces per Match")

# 1st Serve Win % (Winners vs. Losers)
sns.boxplot(data=atp_match, x="WIN", y="1stWon_pct", ax=axes[1])
axes[1].set_title("1st Serve Win % – Winners vs. Losers")
axes[1].set_xlabel("Winner (1) vs. Loser (0)")
axes[1].set_ylabel("1st Serve Win %")

plt.tight_layout()
plt.savefig("WinnersVsLosers_Aces_ServePerformance.png", dpi=250)
plt.show()
plt.close()
```

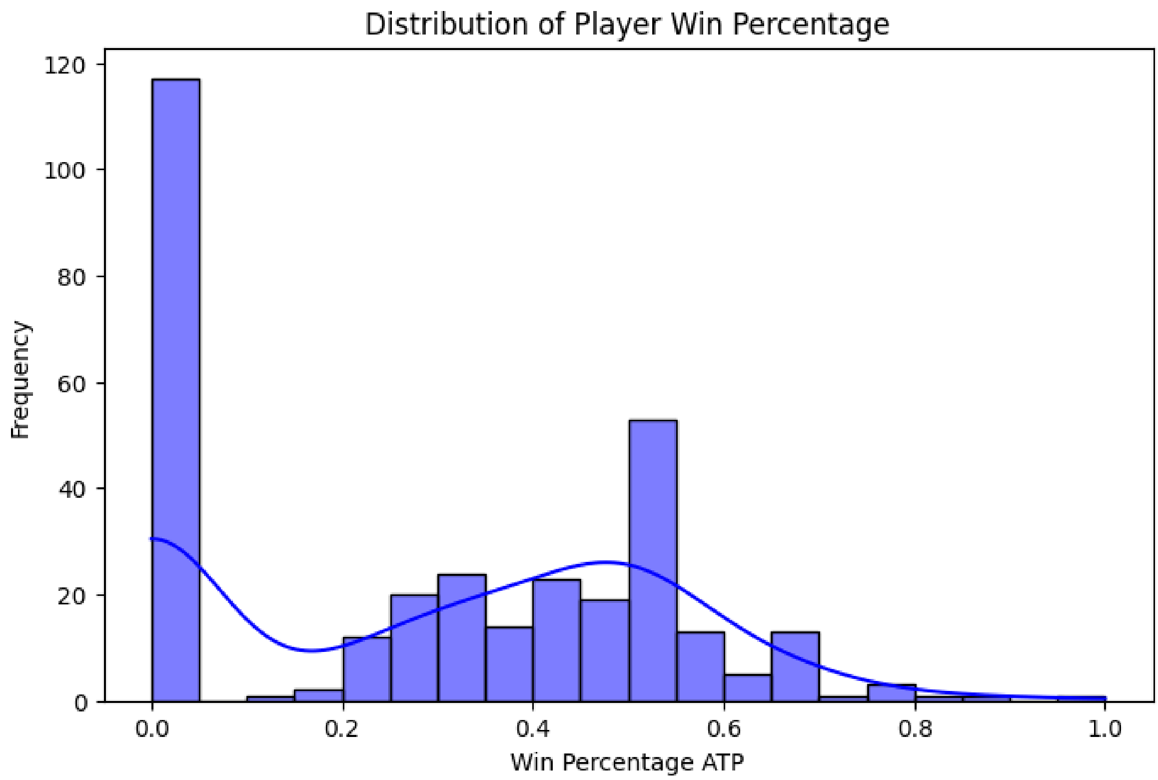


In [33]:
```
# Winners vs. Losers - Aces & Serve Performance
fig, axes = plt.subplots(1, 2, figsize=(12,5))

# Aces per Match (Winners vs. Losers)
sns.boxplot(data=wta_match, x="WIN", y="ace", ax=axes[0])
axes[0].set_title("Aces - Winners vs. Losers")
axes[0].set_xlabel("Winner (1) vs. Loser (0)")
axes[0].set_ylabel("Aces per Match")

# 1st Serve Win % (Winners vs. Losers)
sns.boxplot(data=wta_match, x="WIN", y="1stWon_pct", ax=axes[1])
axes[1].set_title("1st Serve Win % - Winners vs. Losers")
axes[1].set_xlabel("Winner (1) vs. Loser (0)")
axes[1].set_ylabel("1st Serve Win %")

plt.tight_layout()
plt.savefig("WinnersVsLosers_Aces_ServePerformance_WTA.png", dpi=250)
plt.show()
plt.close()
```



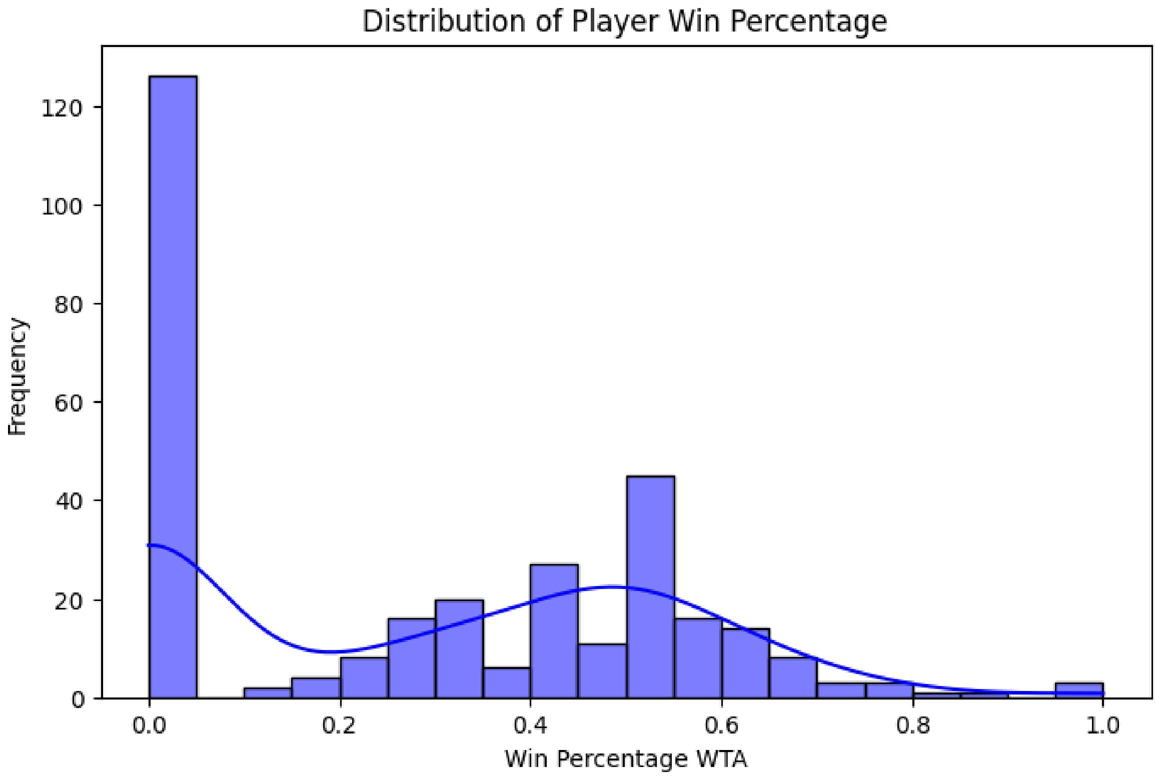
In [70]:
```
# Distribution of win percentage
# Checks if the dataset is balanced or if most players have a similar win

# Calculate win percentage per player
player_stats = atp_match.groupby("player_name").agg(
    matches_played=pd.NamedAgg(column="WIN", aggfunc="count"),
    matches_won=pd.NamedAgg(column="WIN", aggfunc="sum")
)
player_stats["win_percentage"] = player_stats["matches_won"] / player_sta
```

```
# Plot: Distribution of win percentage
plt.figure(figsize=(8,5))
sns.histplot(player_stats["win_percentage"], bins=20, kde=True, color="bl
plt.xlabel("Win Percentage ATP")
plt.ylabel("Frequency")
plt.title("Distribution of Player Win Percentage")
plt.savefig("Player_Win_Percentage_Distribution.png", dpi=250)  # Correct
plt.show()
plt.close()


# left-skewed, most players have low win rates
# Analyse the distribution of player win percentages across the season
# Most players have very low win rates due to the competitive structure o
# where only one player wins per match and top players dominate match vic
# The distribution is left-skewed, highlighting that success is concentra
# This insight supports using win percentage as a strong predictor in pla
```



In [34]:
```
# Distribution of win percentage
# Checks if the dataset is balanced or if most players have a similar win

# Calculate win percentage per player for WTA
player_stats = wta_match.groupby("player_name").agg(
    matches_played=pd.NamedAgg(column="WIN", aggfunc="count"),
    matches_won=pd.NamedAgg(column="WIN", aggfunc="sum")
)
player_stats["win_percentage"] = player_stats["matches_won"] / player_sta

# Plot: Distribution of win percentage
plt.figure(figsize=(8,5))
sns.histplot(player_stats["win_percentage"], bins=20, kde=True, color="bl
plt.xlabel("Win Percentage WTA")
plt.ylabel("Frequency")
plt.title("Distribution of Player Win Percentage")
plt.savefig("Player_Win_Percentage_DistributionWTA.png", dpi=250)  # Corr
```

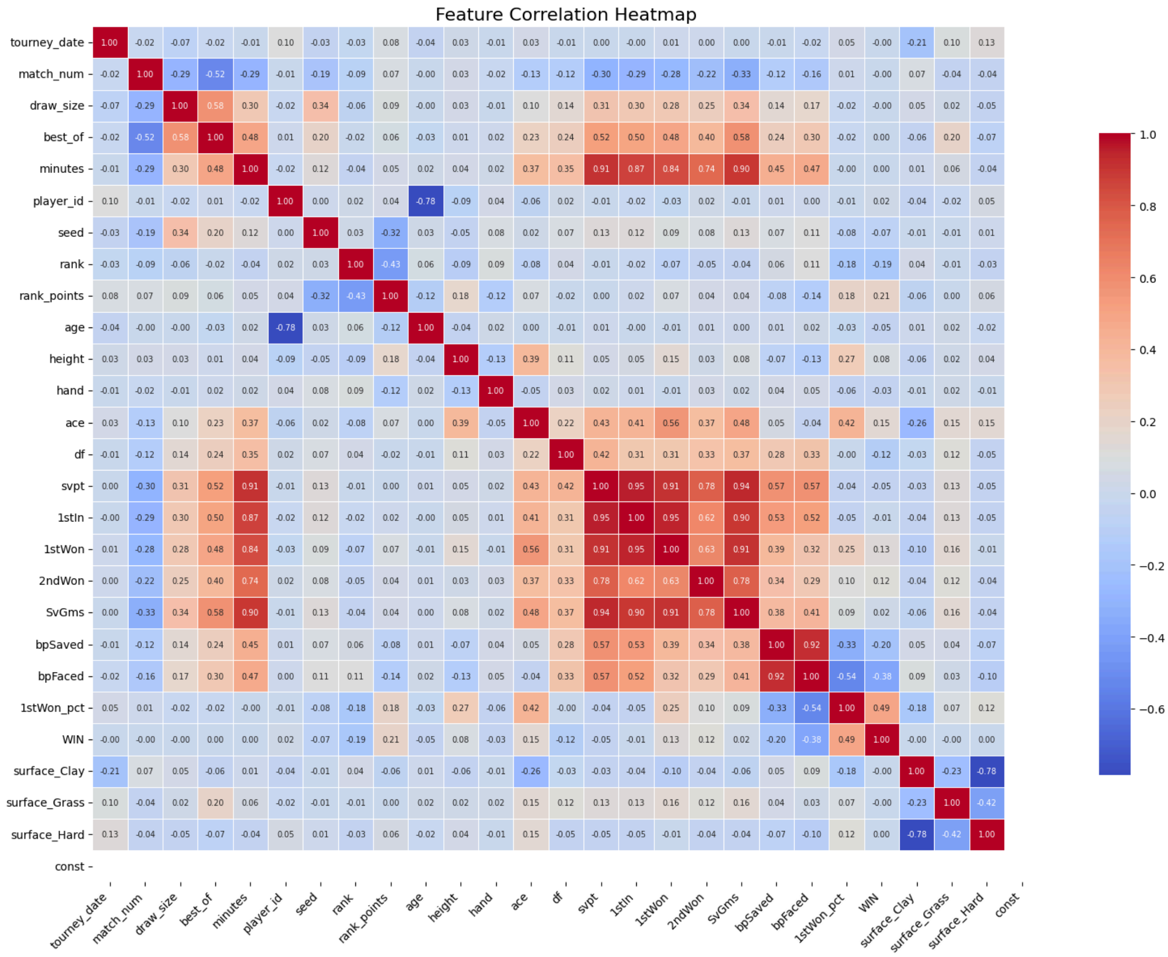
```
plt.show()
plt.close()
```



In [35]:

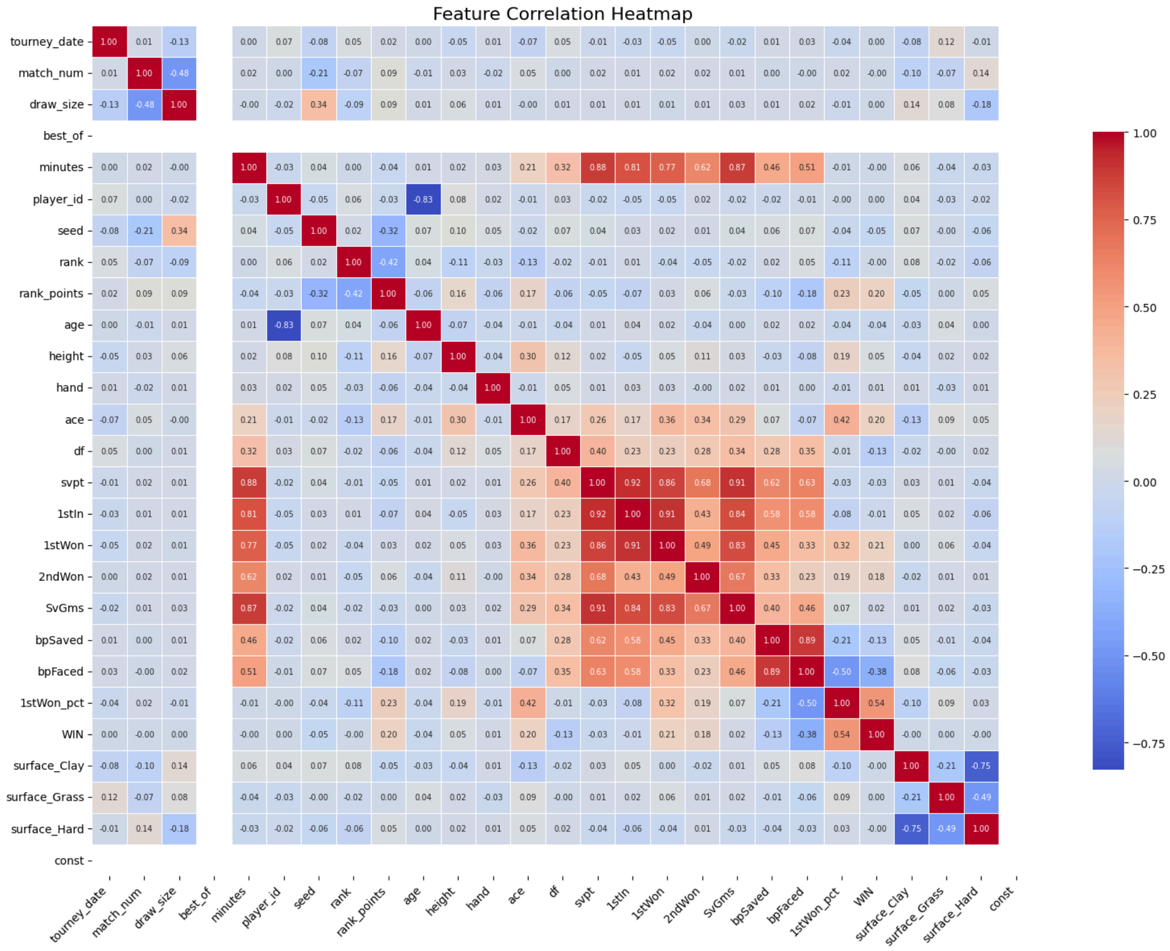
```
# Calculate correlation matrix
corr_matrix = atp_match.corr(numeric_only=True)

# Create full heatmap
plt.figure(figsize=(16,12))
sns.heatmap(
    corr_matrix,
    annot=True,                  # show numbers
    cmap="coolwarm",             # color scheme
    fmt=".2f",                   # 2 decimal places
    linewidths=0.5,              # grid lines
    annot_kws={"size": 7},       # smaller font size
    cbar_kws={"shrink": 0.75}    # shrink color bar
)

# Make axis labels readable
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)

# Title and layout
plt.title("Feature Correlation Heatmap", fontsize=16)
plt.tight_layout()

# Save and display
plt.savefig("CorrelationHeatmapATP_FullMatrix.png", dpi=300)
plt.show()
plt.close()



# Values near +1 mean a strong positive correlation (e.g., rank_points vs
# Values near -1 mean a strong negative correlation (e.g., rank vs. WIN,
# If WIN has high correlations with ranking, serve stats, or height, thes
```

```
# Correlation Analysis – Key Insights:
# heatmap helps identify features that are strongly associated with match
# Positive correlations with WIN include:
# – rank_points: Higher-ranked players (more points) tend to win more mat
# – 1stWon, 1stWon_pct: Winning on the first serve is crucial for success
# – SvGms (service games won): Strong servers have a higher chance of win
# Negative correlations with WIN:
# – rank: Lower numeric rank (better player) is associated with more wins
# – bpFaced: Players who face fewer break points tend to win more matches
# Features with high correlation to each other (e.g., 1stIn, Svpt, SvGms)
# For predictive modeling, focus on features with strong correlation to W
```



In [38]:
```
# Calculate correlation matrix
corr_matrix = wta_match.corr(numeric_only=True)

# since the "best_of" is always the numeric number 3, it is going to be e
wta_clean = wta_match.loc[:, wta_match.nunique() > 1]


# Create full heatmap
plt.figure(figsize=(16,12))
sns.heatmap(
    corr_matrix,
    annot=True,                 # show numbers
    cmap="coolwarm",            # color scheme
    fmt=".2f",                  # 2 decimal places
    linewidths=0.5,             # grid lines
    annot_kws={"size": 7},      # smaller font size
    cbar_kws={"shrink": 0.75}   # shrink color bar
)
```

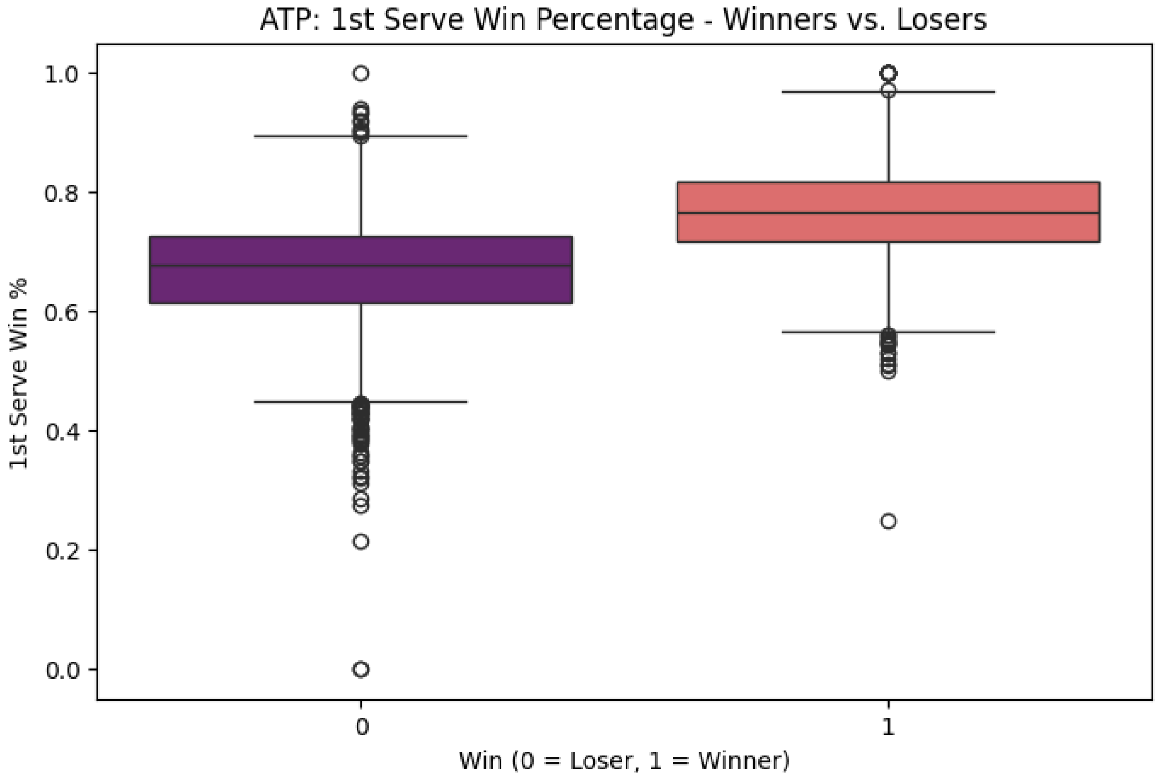
```
# Make axis labels readable
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)

plt.title("Feature Correlation Heatmap", fontsize=16)
plt.tight_layout()

plt.savefig("CorrelationHeatmapWTA_FullMatrix.png", dpi=300)
plt.show()
plt.close()

# In WTA matches, success (WIN) is most positively correlated with:
# - 1st serve win percentage (1stWon_pct)
# - Ranking points (rank_points)
# - Service games won (SvGms)
# - Break points saved (bpSaved)
# A high number of break points faced (bpFaced) negatively correlates wit
# Serve-related features are highly correlated with each other, so only a
```



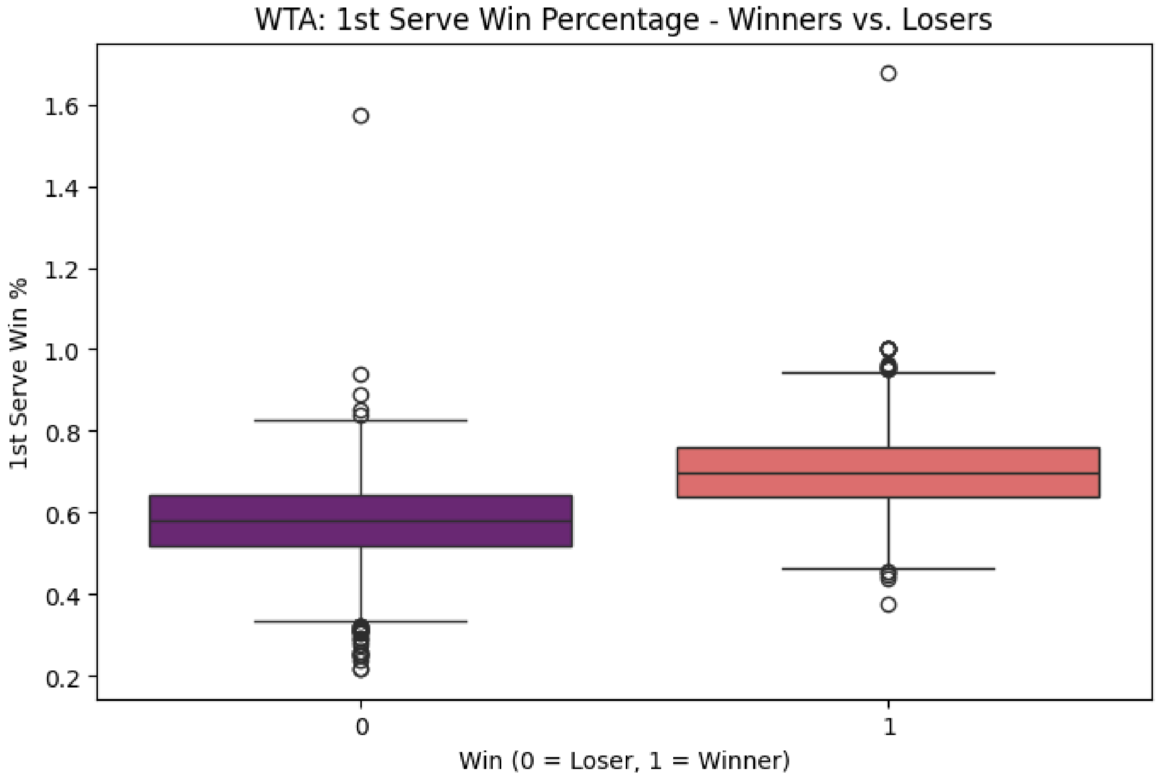
In [39]:
```
# ATP
# Serve Performance vs. Win Rate
plt.figure(figsize=(8,5))
sns.boxplot(data=atp_match, x="WIN", y="1stWon_pct", palette="magma")
plt.xlabel("Win (0 = Loser, 1 = Winner)")
plt.ylabel("1st Serve Win %")
plt.title("ATP: 1st Serve Win Percentage - Winners vs. Losers")
plt.savefig("1stserveWinPercentageATP.png", dpi=300)
plt.show()

#Boxplots compare winners and losers based on first-serve win percentage.
```

```
#If winners have higher median values than losers, it suggests that first
#Overlapping distributions indicate that this feature alone may not be en

# WTA
# Serve Performance vs. Win Rate
plt.figure(figsize=(8,5))
sns.boxplot(data=wta_match, x="WIN", y="1stWon_pct", palette="magma")
plt.xlabel("Win (0 = Loser, 1 = Winner)")
plt.ylabel("1st Serve Win %")
plt.title("WTA: 1st Serve Win Percentage - Winners vs. Losers")
plt.savefig("1stserveWinPercentageWTA.png", dpi=300)
plt.show()
```

```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_28320/213867309
5.py:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(data=atp_match, x="WIN", y="1stWon_pct", palette="magma")
```

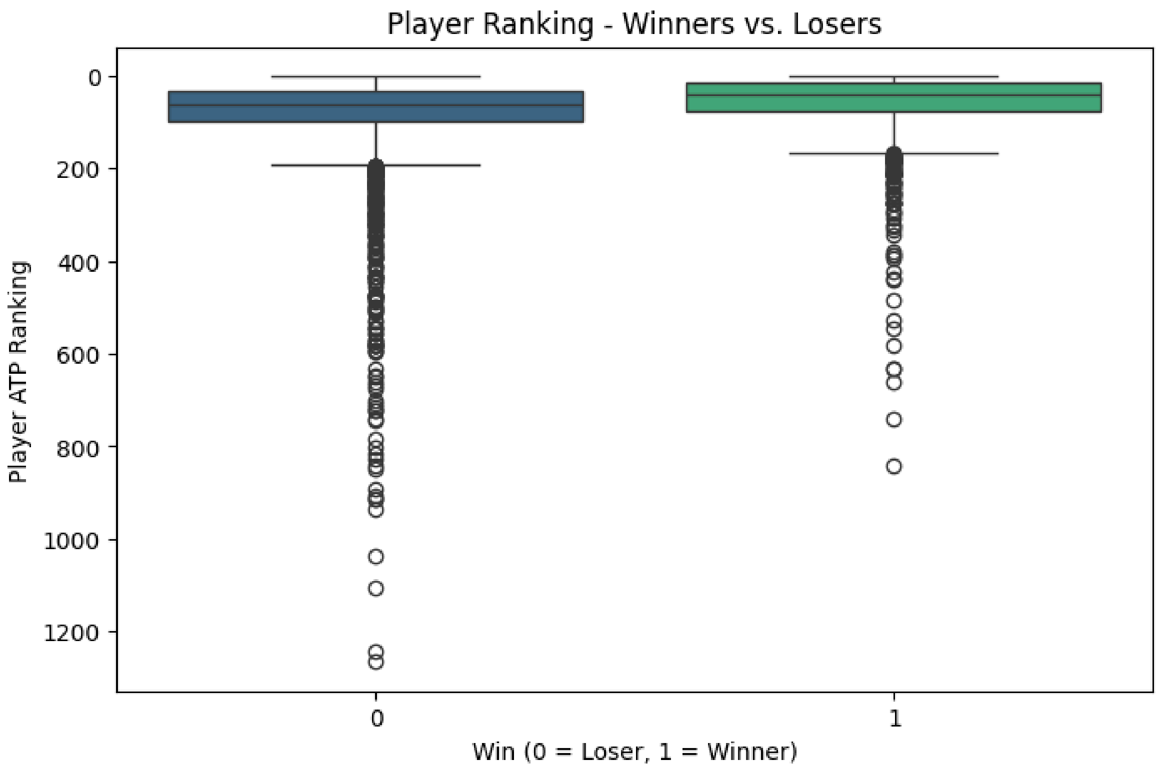



```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_28320/213867309
5.py:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(data=wta_match, x="WIN", y="1stWon_pct", palette="magma")
```

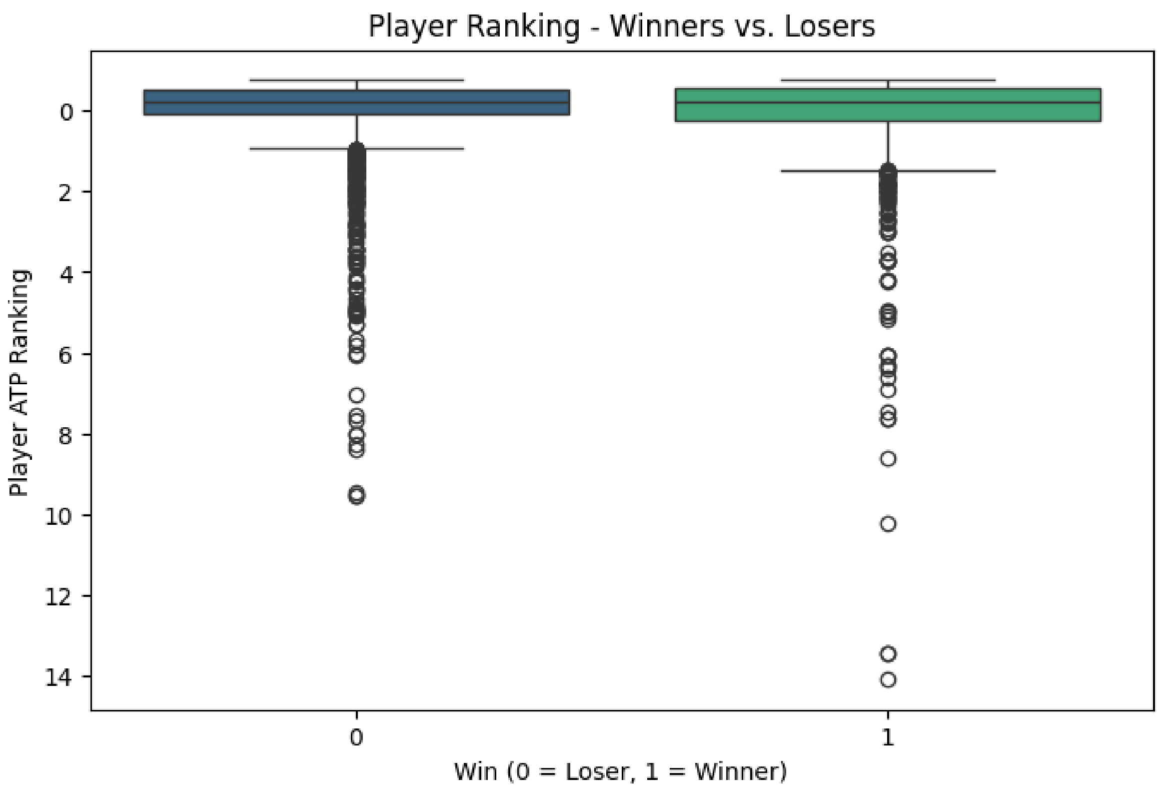


In [40]:
```
# ATP
# Ranking vs. Win Rate
plt.figure(figsize=(8,5))
sns.boxplot(data=atp_match, x="WIN", y="rank", palette="viridis")
plt.xlabel("Win (0 = Loser, 1 = Winner)")
plt.ylabel("Player ATP Ranking")
plt.title("Player Ranking – Winners vs. Losers")
plt.gca().invert_yaxis()  # Lower rank = better player
plt.savefig("RankingWinRateATP", dpi=300)
plt.show()

#Lower-ranked players (closer to rank to 1) should have higher win rates
#If the median rank for winners is significantly lower than for losers, r
#If there’s a lot of overlap, ranking alone may not be the best predictor

# WTA
plt.figure(figsize=(8,5))
sns.boxplot(data=wta_match, x="WIN", y="rank", palette="viridis")
plt.xlabel("Win (0 = Loser, 1 = Winner)")
plt.ylabel("Player ATP Ranking")
plt.title("Player Ranking – Winners vs. Losers")
plt.gca().invert_yaxis()  # Lower rank = better player
plt.savefig("RankingWinRateWTA", dpi=300)
plt.show()
```

```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_28320/128303580
4.py:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(data=atp_match, x="WIN", y="rank", palette="viridis")
```

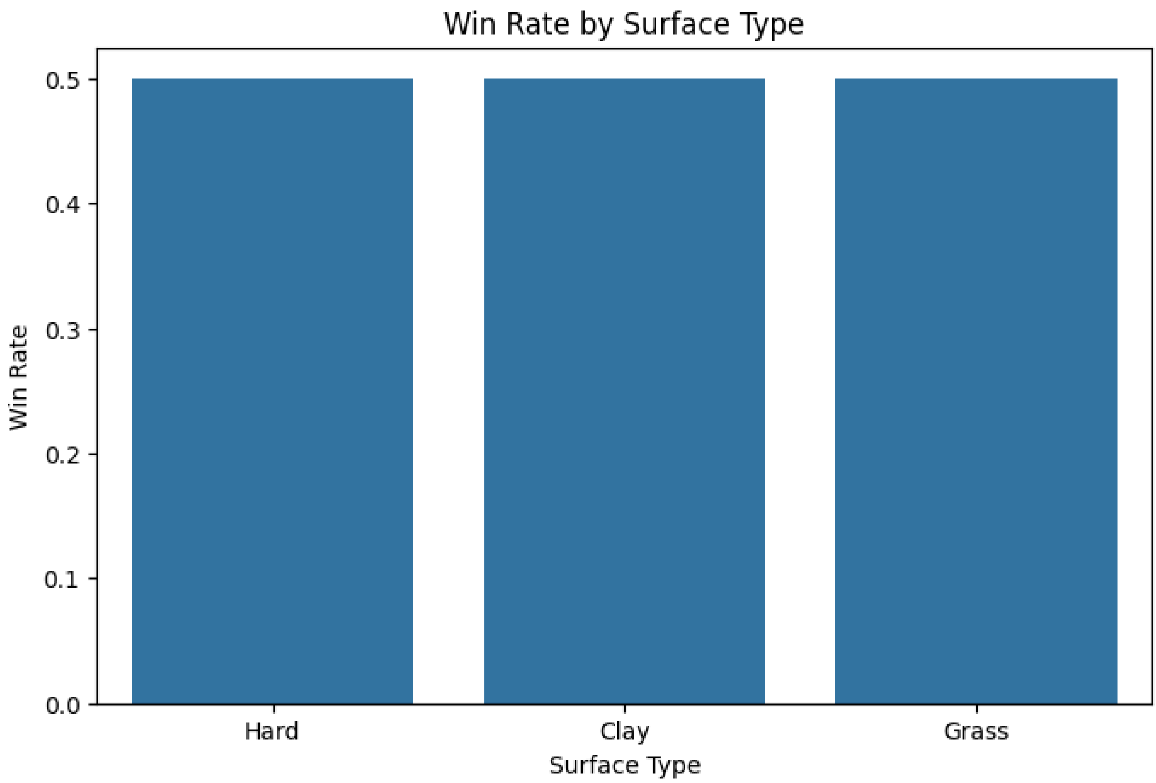


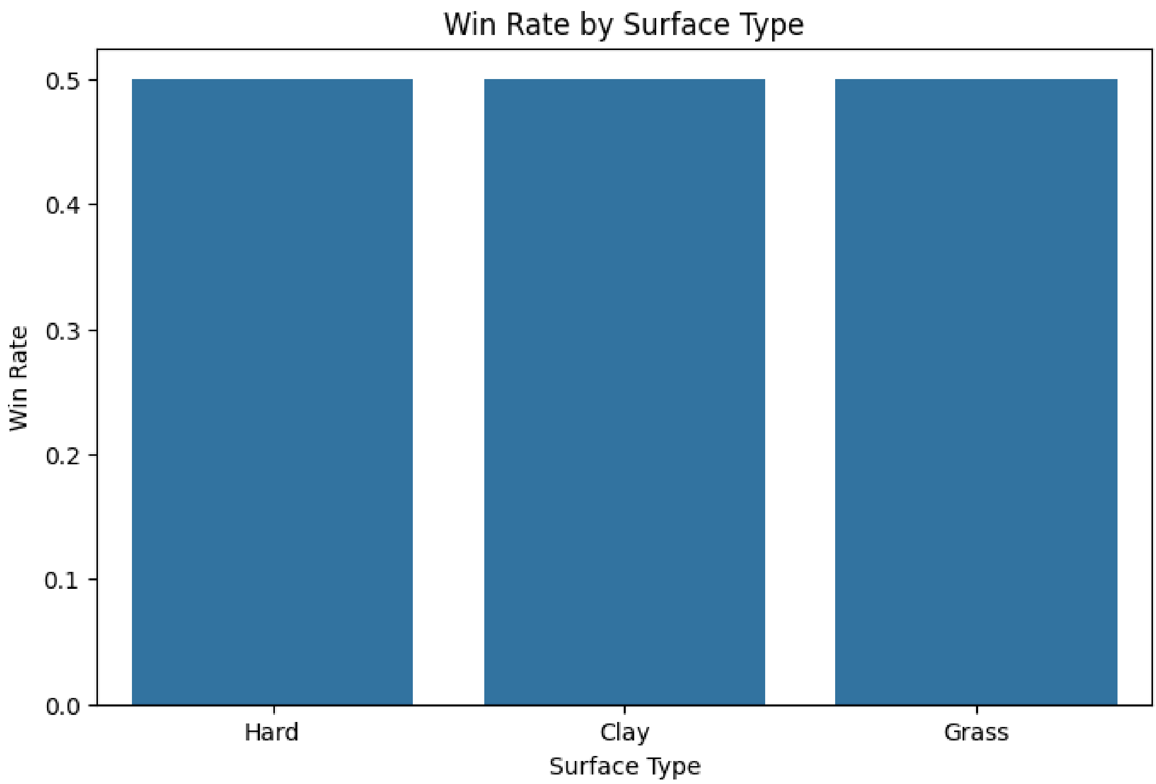

```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_28320/128303580
4.py:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(data=wta_match, x="WIN", y="rank", palette="viridis")
```



In [41]:
```
# ATP
# Surface Type vs. Win Rate
plt.figure(figsize=(8,5))
sns.barplot(x=["Hard", "Clay", "Grass"],
```

```
            y=[atp_match[atp_match["surface_Hard"] == 1]["WIN"].mean(),
               atp_match[atp_match["surface_Clay"] == 1]["WIN"].mean(),
               atp_match[atp_match["surface_Grass"] == 1]["WIN"].mean()])
plt.xlabel("Surface Type")
plt.ylabel("Win Rate")
plt.title("Win Rate by Surface Type")
plt.savefig("SurfaceWInRateATP.png", dpi=300)
plt.show()

#WTA
plt.figure(figsize=(8,5))
sns.barplot(x=["Hard", "Clay", "Grass"],
            y=[wta_match[wta_match["surface_Hard"] == 1]["WIN"].mean(),
               wta_match[wta_match["surface_Clay"] == 1]["WIN"].mean(),
               wta_match[wta_match["surface_Grass"] == 1]["WIN"].mean()])
plt.xlabel("Surface Type")
plt.ylabel("Win Rate")
plt.title("Win Rate by Surface Type")
plt.savefig("SurfaceWInRateWTA.png", dpi=300)
plt.show()

# win rates are similar across surfaces -> surface type has less impact o
```





Applying Logisitc regression

1. Select features (X) and target (y)
2. Train-Test Split (80% training, 20% testing)
3. Scale features for better model performance
4. Train logistic regression model
5. Evaluate the model (Accuracy, Precision, Recall, Confusion Matrix)
6. Analyse feature importance to identify success factors

In [42]:
```
# libraries
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confus
```

In [44]:
```
# Define features (X) and target variable (y)
features = [
    "rank", "rank_points", "age", "height", "ace", "df", "svpt","1stWon",
    "surface_Clay", "surface_Grass", "surface_Hard"]


X = atp_match[features]  # Independent variables (player attributes)
y = atp_match['WIN']  # Target variable (1 = winner, 0 = loser)

# Split data into training & test Sets (80% Train, 20% Test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

# Standardise features for better model performance
scaler = StandardScaler()
```

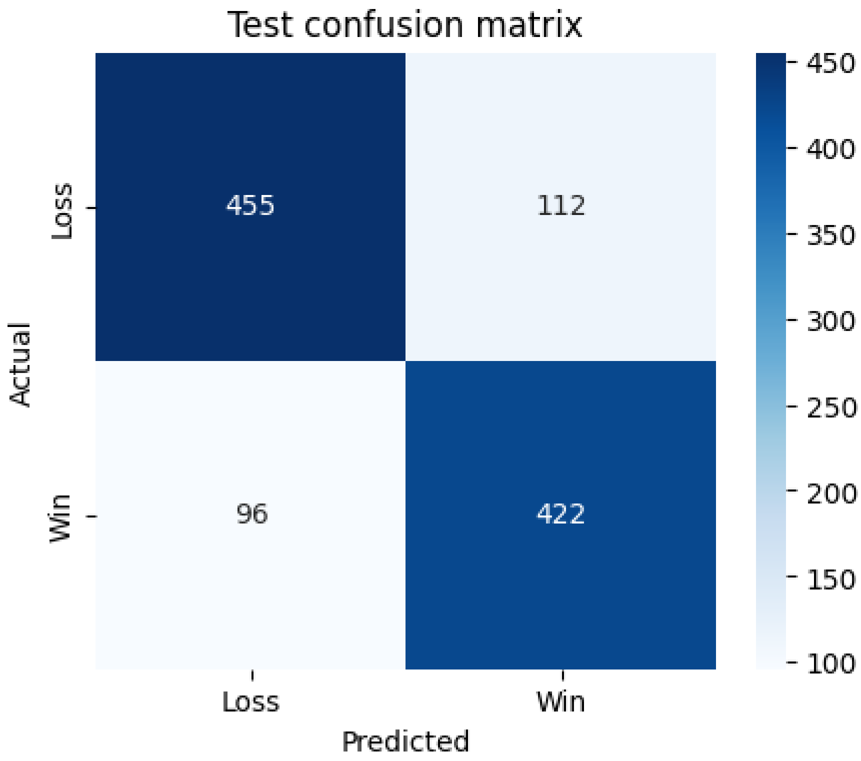
```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [45]:
```
# Train the logisitc regression model

model = LogisticRegression(max_iter=500)
model.fit(X_train_scaled, y_train)

# Make Predictions
y_pred = model.predict(X_test_scaled)
```

In [46]:
```
# Evaluate model performance
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

# Display results
print("Model Trained Successfully!")
print(f" Accuracy: {accuracy:.4f}")
print("\nConfusion Matrix:\n", conf_matrix)
print("\nClassification Report:\n", classification_rep)
```

```
Model Trained Successfully!
 Accuracy: 0.8083

Confusion Matrix:
 [[455 112]
 [ 96 422]]

Classification Report:
               precision    recall  f1-score   support

           0       0.83      0.80      0.81       567
           1       0.79      0.81      0.80       518

    accuracy                           0.81      1085
   macro avg       0.81      0.81      0.81      1085
weighted avg       0.81      0.81      0.81      1085
```

In [47]:
```
# Confusion matrix
test_conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(test_conf_matrix, annot=True, fmt="d", cmap="Blues", xticklab
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Test confusion matrix")
plt.savefig("confusion_matrix.png", dpi=300)
plt.show()
plt.close()
```



Confusion Matrix: 112 losses misclassified as wins 97 wins misclassified as losses

Classification Report: Precision (0.82 for losses, 0.79 for wins): How often the model is correct when predicting a win or loss. Recall (0.80 for losses, 0.81 for wins): How well the model finds all true wins/losses. Balanced Performance: F1-scores around 0.80 show consistency.

In [48]:
```
# Identify key success fyctors
# Feature importance analysis
feature_importance = pd.DataFrame({'Feature': features, 'Importance': np.
feature_importance = feature_importance.sort_values(by='Importance', asce

# Display top success factors
print("\n Top Success Factors:\n", feature_importance)
```

```
 Top Success Factors:
           Feature  Importance
8           1stIn    3.550591
6            svpt    2.819069
12        bpFaced    2.355099
11        bpSaved    1.847993
13    1stWon_pct    1.399597
7          1stWon    1.391168
9          2ndWon    1.184774
14   surface_Clay    0.231480
0            rank    0.207563
1     rank_points    0.205815
4             ace    0.152153
3          height    0.149515
10          SvGms    0.143484
15  surface_Grass    0.106050
5              df    0.058598
16   surface_Hard    0.035034
2             age    0.009934
```

First Serve In % (1stIn) has the highest impact on winning. Total Service Points Played (svpt) is also strongly influential. Break Points Faced (bpFaced) and Saved (bpSaved) are key indicators of match success. First Serve Win Percentage (1stWon_pct) also plays a significant role.

In [49]:

```
# Store feature importance for each surface
surface_importance_results = {}

# Define relevant features (exclude surface columns to avoid leakage)
features = [
    "rank", "rank_points", "age", "height", "ace", "df", "svpt",
    "1stWon", "1stIn", "2ndWon", "SvGms", "bpSaved", "bpFaced", "1stWon_p
]

# Loop through each surface type
for surface in ["surface_Hard", "surface_Clay", "surface_Grass"]:
    # Select matches played on the given surface
    atp_surface = atp_match[atp_match[surface] == 1]

    # Define features and target
    X_surface = atp_surface[features]
    y_surface = atp_surface["WIN"]

    # Split Data (80% Train, 20% Test)
    X_train_s, X_test_s, y_train_s, y_test_s = train_test_split(X_surface

    # Scale Features (Fit on Train, Transform on Train & Test)
    scaler = StandardScaler()
    X_train_s_scaled = scaler.fit_transform(X_train_s)
    X_test_s_scaled = scaler.transform(X_test_s)

    # Train Random Forest Model
    rf_surface = RandomForestClassifier(n_estimators=100, random_state=42
    rf_surface.fit(X_train_s_scaled, y_train_s)

    # Extract feature importance
    feature_imp_s = pd.DataFrame({"Feature": features, "Importance": rf_s
    feature_imp_s = feature_imp_s.sort_values(by="Importance", ascending=

    # Store results
    surface_importance_results[surface] = feature_imp_s

    # Print Top 5 Features for Each Surface
    print(f"\nSuccess Factors for {surface}:")
    print(feature_imp_s.head(5))
```

```
Success Factors for surface_Hard:
        Feature  Importance
13   1stWon_pct    0.193559
12      bpFaced    0.128319
1   rank_points    0.074054
0          rank    0.071048
9        2ndWon    0.068571

Success Factors for surface_Clay:
        Feature  Importance
13   1stWon_pct    0.184481
12      bpFaced    0.130977
7        1stWon    0.081835
1   rank_points    0.072596
0          rank    0.066990

Success Factors for surface_Grass:
        Feature  Importance
13   1stWon_pct    0.193298
12      bpFaced    0.151070
1   rank_points    0.066434
7        1stWon    0.063292
4           ace    0.062950
```

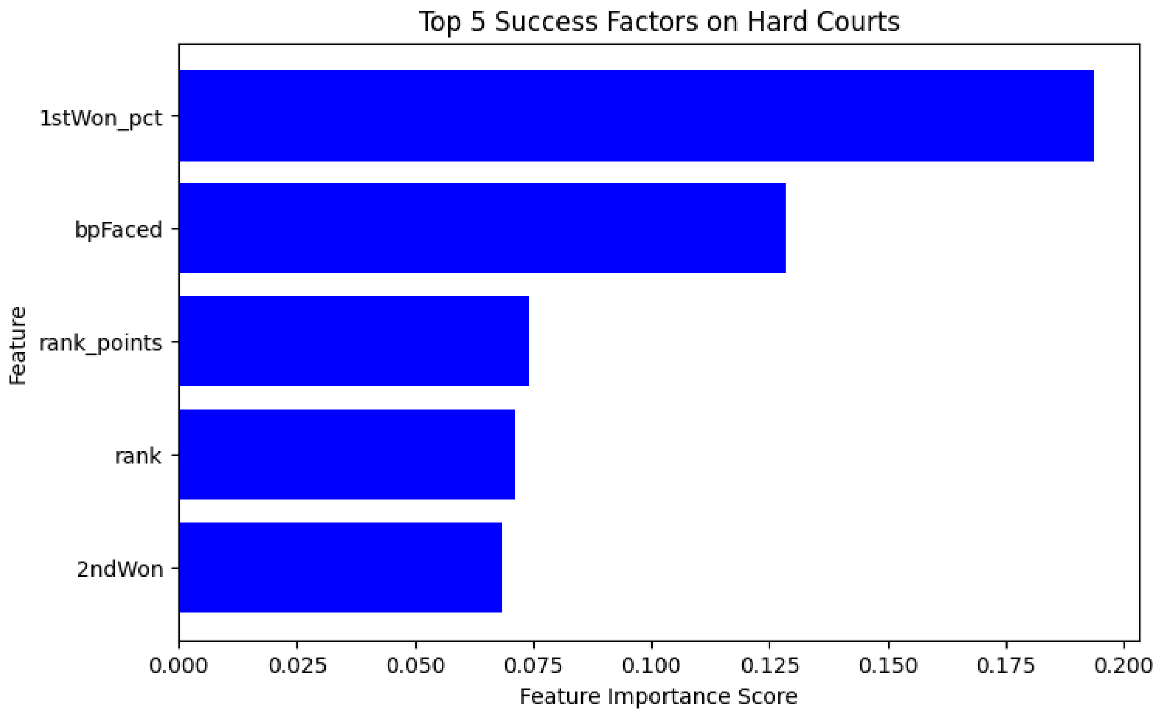
In [ ]:

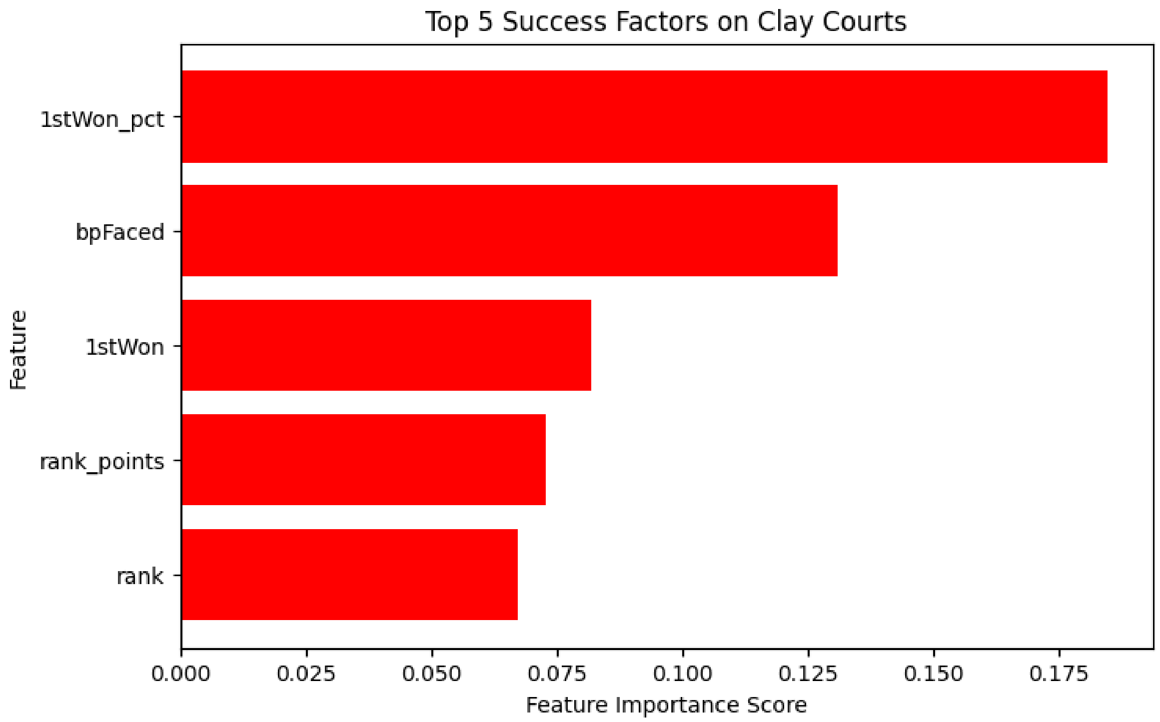
Interpretation of results

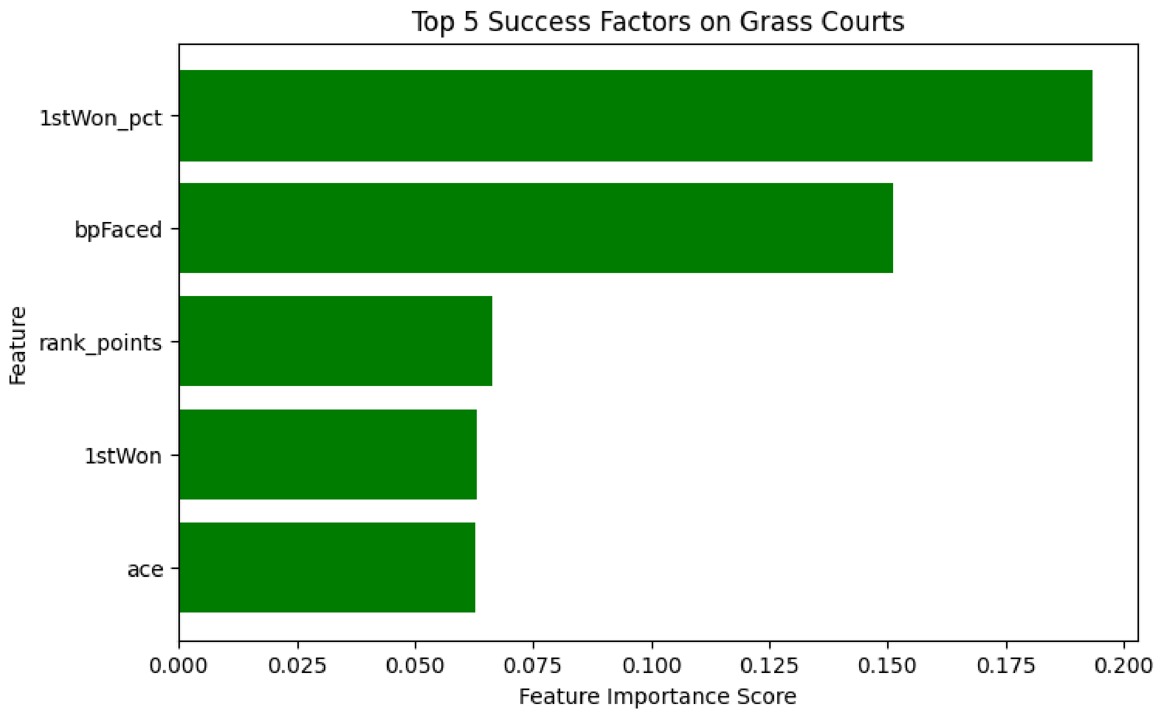
If 1st serve win % is critical on Hard but not on Clay, adjust training strategies. If height matters more on Grass than Clay, adjust player selection & coaching. This directly answers your research question about player success differences.

Cluster 0 = Strong Servers (High 1st Serve %, Low bpFaced) Cluster 1 = Defensive Baseliners (Higher 2nd serve win rate, lower serve dominance) Cluster 2 = Aggressive Players (Low rank, High rank points) --> This helps coaches and sponsors understand player strengths.

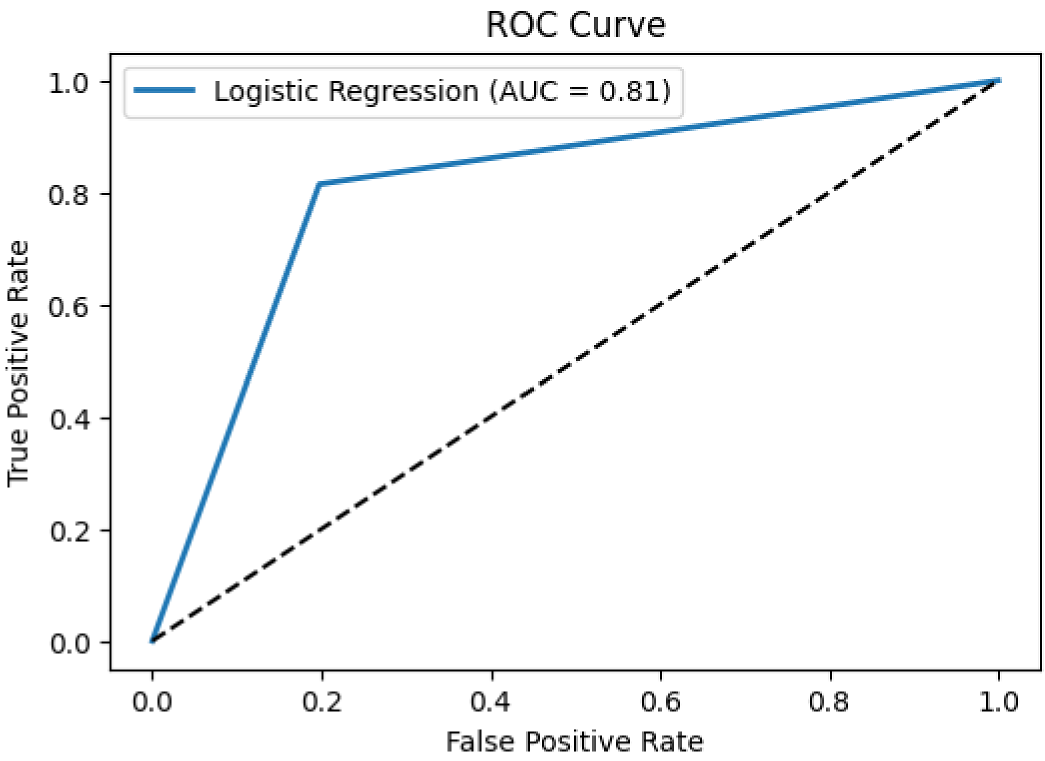
In [50]:
```
surface_colors = {
    "surface_Hard": "blue",
    "surface_Clay": "red",
    "surface_Grass": "green"
}

# Plot Feature Importance for Each Surface
for surface, df in surface_importance_results.items():
    plt.figure(figsize=(8, 5))
    plt.barh(df["Feature"][:5], df["Importance"][:5], color=surface_color
    plt.xlabel("Feature Importance Score")
    plt.ylabel("Feature")
    plt.title(f"Top 5 Success Factors on {surface.replace('surface_', '')
    plt.gca().invert_yaxis()  # Invert y-axis for better readability
    plt.savefig("SuccessFactorsSurfaceATP", dpi=300)
    plt.show()
    plt.close()
```


Top 5 Success Factors on Hard Courts
1stWon_pct
bpFaced
rank_points
rank
2ndWon
Feature
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
Feature Importance Score


Top 5 Success Factors on Clay Courts
1stWon_pct
bpFaced
1stWon
rank_points
rank
Feature
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
Feature Importance Score



In [51]:
```
from sklearn.metrics import roc_auc_score, roc_curve

# Compute AUC-ROC
roc_auc = roc_auc_score(y_test, y_pred)
fpr, tpr, _ = roc_curve(y_test, y_pred)

# Plot ROC Curve
plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, label=f'Logistic Regression (AUC = {roc_auc:.2f})', li
plt.plot([0, 1], [0, 1], 'k--')  # Random guess line
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.savefig("roc_curve_atp_math.png", dpi=300)
plt.show()
plt.close()
```



Logistic Regression Results & Interpretation Lgistic regression model is performing well

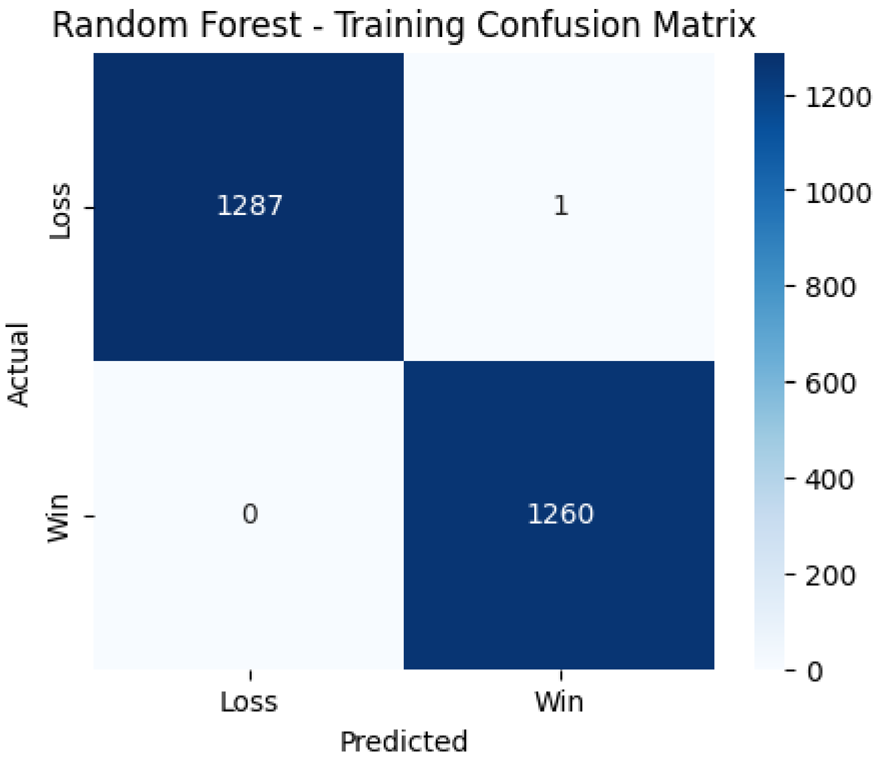
Model Performance Accuracy: approx. 74.7% -> Decent predictive power. AUC-ROC Score: approx. 0.84 --> The model has good discrimination ability. Classification Report: Precision and recall values are balanced both around 75% The model is correctly predicting 74.7% of match outcomes. The AUC-ROC curve shows a solid predictive ability.

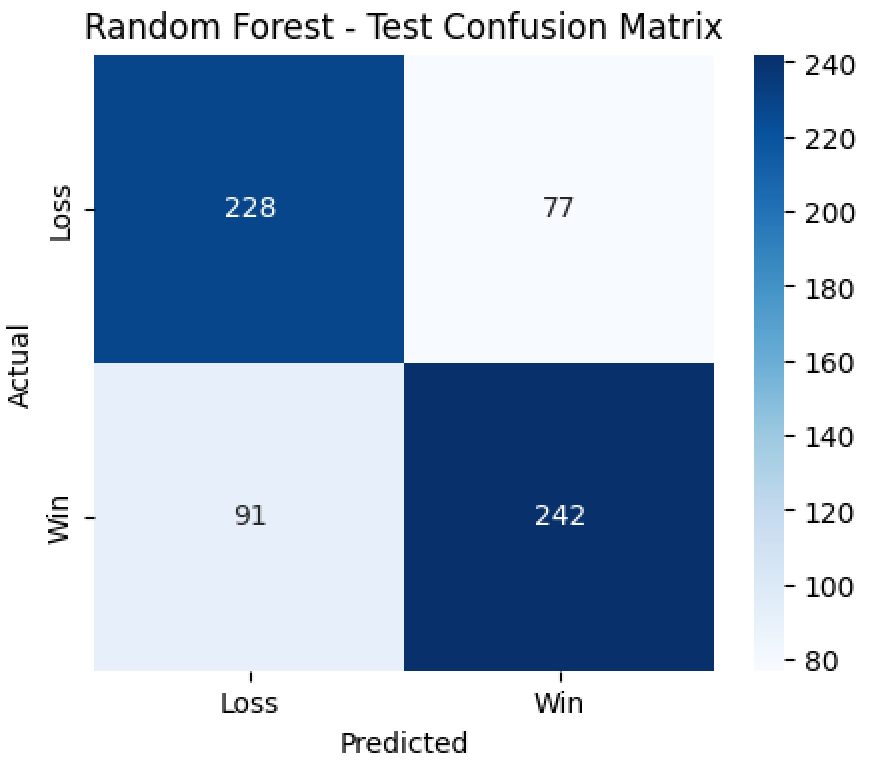
Model improvements by Random Forest

In [52]:

```
# Define feature set (excluding surface indicators -> prevent leakage)
features_rf = [
    "rank", "rank_points", "age", "height", "ace", "df", "svpt",
    "1stWon", "1stIn", "2ndWon", "SvGms", "bpSaved", "bpFaced", "1stWon_p
]

# Select a surface for analysis (Hard)
surface_rf = "surface_Hard"
atp_surface_rf = atp_match[atp_match[surface_rf] == 1]

# Define features and target for Random Forest
X_rf = atp_surface_rf[features_rf]
y_rf = atp_surface_rf["WIN"]

# Split data (80% Train, 20% Test)
X_train_rf, X_test_rf, y_train_rf, y_test_rf = train_test_split(X_rf, y_r

# Scale features
scaler_rf = StandardScaler()
X_train_rf_scaled = scaler_rf.fit_transform(X_train_rf)
X_test_rf_scaled = scaler_rf.transform(X_test_rf)
```

```python
# Train Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_rf_scaled, y_train_rf)

# Generate training confusion matrix for Random Forest
y_train_pred_rf = rf_model.predict(X_train_rf_scaled)
train_conf_matrix_rf = confusion_matrix(y_train_rf, y_train_pred_rf)

# Plot training confusion matrix for Random Forest
plt.figure(figsize=(5, 4))
sns.heatmap(train_conf_matrix_rf, annot=True, fmt="d", cmap="Blues", xtic
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Random Forest - Training Confusion Matrix")
plt.savefig("train_confusion_matrix_rf.png", dpi=300)
plt.show()
plt.close()

# Generate test confusion matrix for Random Forest
y_test_pred_rf = rf_model.predict(X_test_rf_scaled)
test_conf_matrix_rf = confusion_matrix(y_test_rf, y_test_pred_rf)

# Plot test confusion matrix for Random Forest
plt.figure(figsize=(5, 4))
sns.heatmap(test_conf_matrix_rf, annot=True, fmt="d", cmap="Blues", xtick
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Random Forest - Test Confusion Matrix")
plt.savefig("test_confusion_matrix_rf.png", dpi=300)
plt.show()
plt.close()

# Print accuracy for training and test sets for Random Forest
train_accuracy_rf = accuracy_score(y_train_rf, y_train_pred_rf)
test_accuracy_rf = accuracy_score(y_test_rf, y_test_pred_rf)

print(f"Random Forest - Training Accuracy: {train_accuracy_rf:.2%}")
print(f"Random Forest - Test Accuracy: {test_accuracy_rf:.2%}")
```






```
Random Forest - Training Accuracy: 99.96%
Random Forest - Test Accuracy: 73.67%
```

Overfitting! Training Accuracy: 99.96% The training confusion matrix shows almost perfect classification: 1287 true negatives (correctly predicted losses) 1260 true positives (correctly predicted wins) Only 1 false positive, 0 false negatives

The model has learned the training data almost too well, suggesting overfitting. This means the model might not generalize well when applied to new, unseen matches.

--> The gap between training accuracy (99.96%) and test accuracy (73.67%) is large → The model is overfitting to training data.

In [53]:
```
# Import necessary libraries
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score

# Define parameter grid for tuning
param_grid = {
    "n_estimators": [50, 100],
    "max_depth": [10, 20],
    "min_samples_split": [2, 5],
    "min_samples_leaf": [1, 2],
    "bootstrap": [True]
}

# Initialize Random Forest model
rf_model_tuned = RandomForestClassifier(random_state=42)

# Perform grid search with 3-Fold cross-validation
grid_search = GridSearchCV(estimator=rf_model_tuned, param_grid=param_gri
                           cv=3, n_jobs=-1, verbose=2, scoring="accuracy"

# Fit grid search on the training set
grid_search.fit(X_train_rf_scaled, y_train_rf)

# Get the best model from grid search
best_rf_model = grid_search.best_estimator_

# Predict on the test set with the optimized model
y_test_pred_best_rf = best_rf_model.predict(X_test_rf_scaled)

# Compute accuracy of the optimized model
test_accuracy_best_rf = accuracy_score(y_test_rf, y_test_pred_best_rf)

# Display best parameters and new test accuracy
best_rf_params = grid_search.best_params_
print(f"\nBest Parameters for Random Forest: {best_rf_params}")
print(f"Tuned Random Forest Test Accuracy: {test_accuracy_best_rf:.2%}")
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits

Best Parameters for Random Forest: {'bootstrap': True, 'max_depth': 20, 'm
in_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 50}
Tuned Random Forest Test Accuracy: 74.61%
```

In [54]:
```
from sklearn.linear_model import LogisticRegression

# Train Logistic Regression Model
log_reg_model = LogisticRegression(max_iter=500, random_state=42)
log_reg_model.fit(X_train_rf_scaled, y_train_rf)

# Predict on the test set using Logistic Regression
y_test_pred_logreg = log_reg_model.predict(X_test_rf_scaled)

# Compute Accuracy for Logistic Regression
test_accuracy_logreg = accuracy_score(y_test_rf, y_test_pred_logreg)

# Compare Results
print(f"\nLogistic Regression Test Accuracy: {test_accuracy_logreg:.2%}")
print(f"Tuned Random Forest Test Accuracy: {test_accuracy_best_rf:.2%}")
```

```
Logistic Regression Test Accuracy: 79.00%
Tuned Random Forest Test Accuracy: 74.61%
```

In [ ]:

Feature Importance Analysis

In [55]:

```
# Extract feature importance from the tuned Random Forest model

feature_importance_rf = pd.DataFrame(
    {"Feature": features_rf, "Importance": best_rf_model.feature_importan
).sort_values(by="Importance", ascending=False)

# Optional: Print top 10 for inspection
print(feature_importance_rf.head(10))

# Plot and save PNG
plt.figure(figsize=(8, 5))
plt.barh(feature_importance_rf["Feature"][:10], feature_importance_rf["Im
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.title("Feature Importance – Random Forest Model (ATP)")
plt.gca().invert_yaxis()

# Save to file
plt.tight_layout()
plt.savefig("feature_importance_rf_atp.png", dpi=300)
plt.close()
```

```
         Feature  Importance
13    1stWon_pct    0.221446
12      bpFaced     0.145185
0          rank     0.069864
1    rank_points    0.069536
9        2ndWon     0.068488
7        1stWon     0.065603
2           age     0.057390
6          svpt     0.055490
11      bpSaved     0.050864
8         1stIn     0.046580
```

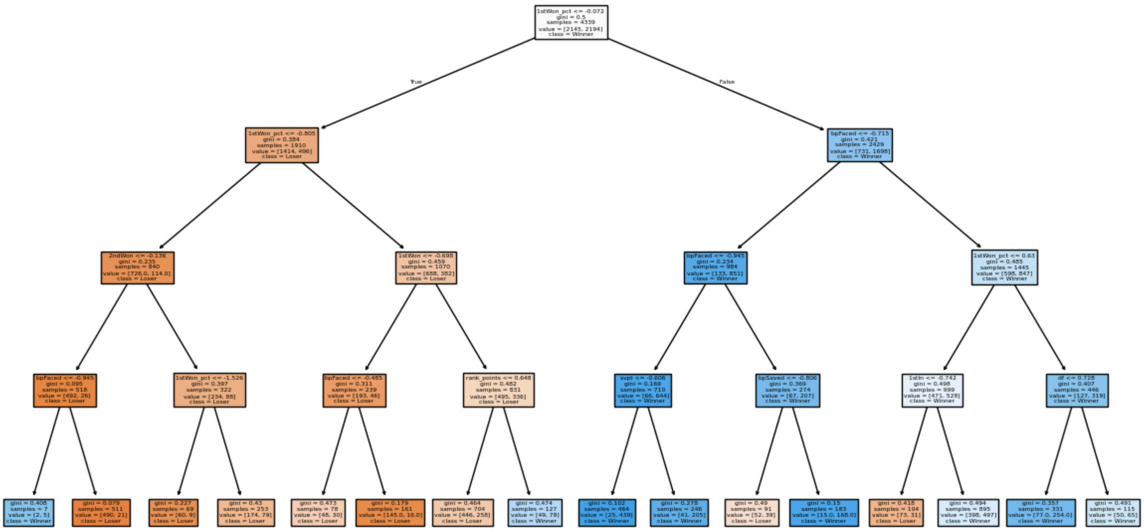
In [ ]:

In [5]:

```
# Decision Tree and Random FOrests
```

In [56]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree

# Train Decision Tree (Depth 4)
dt_model = DecisionTreeClassifier(max_depth=4, random_state=42)
dt_model.fit(X_train_scaled, y_train)
plt.figure(figsize=(15, 8))
tree.plot_tree(dt_model, feature_names=features, class_names=["Loser", "W
plt.savefig("decision_tree_atpmatch.png", dpi=300)
plt.show()
plt.close()
```



In [ ]:

WTA Dataset

In [57]:

```
file_path = "Output/WTA_match_final_file.csv"
wta_df = pd.read_csv(file_path)

print(f"Dataset Shape: {wta_df.shape}")

# Check for missing values
missing_values = wta_df.isnull().sum()
print("Missing Values Per Column:")
print(missing_values[missing_values > 0])

# Display column data types
print("Column Data Types:")
print(wta_df.dtypes)

# Display first few rows
print("Data Preview:")
print(wta_df.head())
```

```
Dataset Shape: (4800, 32)
Missing Values Per Column:
Series([], dtype: int64)
Column Data Types:
match_id          object
tourney_id        object
tourney_name      object
tourney_date       int64
match_num          int64
draw_size          int64
tourney_level     object
best_of            int64
round             object
minutes          float64
player_id          int64
player_name       object
seed             float64
rank             float64
rank_points      float64
age              float64
height           float64
hand               int64
ace              float64
df               float64
svpt             float64
1stIn            float64
1stWon           float64
2ndWon           float64
SvGms            float64
bpSaved          float64
bpFaced          float64
1stWon_pct       float64
WIN                int64
surface_Clay       int64
surface_Grass      int64
surface_Hard       int64
dtype: object
Data Preview:
        match_id tourney_id tourney_name  tourney_date  match_num  draw_si
ze  \
0  2023-1003-271  2023-1003         Doha      20230213        271
32
1  2023-1003-271  2023-1003         Doha      20230213        271
32
2  2023-1003-272  2023-1003         Doha      20230213        272
32
3  2023-1003-272  2023-1003         Doha      20230213        272
32
4  2023-1003-273  2023-1003         Doha      20230213        273
32

  tourney_level  best_of round  minutes  ...  1stWon 2ndWon  SvGms  bpSave
d  \
0             P        3   R32     77.0  ...    24.0   15.0   10.0      2.
0
1             P        3   R32     77.0  ...    29.0    9.0   10.0      1.
0
2             P        3   R32    123.0  ...    41.0   12.0   11.0      7.
0
3             P        3   R32    123.0  ...    24.0   11.0   10.0      2.
```

```
0
4            P        3   R32    101.0  ...    32.0    8.0   10.0      4.
0

   bpFaced  1stWon_pct  WIN  surface_Clay  surface_Grass  surface_Hard
0      3.0    0.827586    1             0              0             1
1      5.0    0.617021    0             0              0             1
2     10.0    0.585714    1             0              0             1
3      6.0    0.685714    0             0              0             1
4      8.0    0.592593    1             0              0             1

[5 rows x 32 columns]
```

In [58]:

```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder

#Handle missing values (fill numeric NaNs with column mean)
numeric_cols = wta_df.select_dtypes(include=['float64', 'int64']).columns
wta_df[numeric_cols] = wta_df[numeric_cols].fillna(wta_df[numeric_cols].m

# Encode categorical variables convert to numerical values
categorical_cols = ['round', 'tourney_level']
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    wta_df[col] = le.fit_transform(wta_df[col])
    label_encoders[col] = le

# Define features (X) and target variable (y)
X = wta_df.drop(columns=['WIN', 'player_name', 'match_id', 'tourney_id',
y = wta_df['WIN']

# Split dataset into training & test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

# Scale numerical features (optional, useful for some models)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Preprocessing complete
print("Data preprocessing complete. Now model training")
```

```
Data preprocessing complete. Now model training
```

In [59]:

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree

# Train Decision Tree WTA
dt_model = DecisionTreeClassifier(max_depth=4, random_state=42)
dt_model.fit(X_train_scaled, y_train)
plt.figure(figsize=(15, 8))
tree.plot_tree(dt_model, feature_names=features, class_names=["Loser", "W
plt.savefig("decision_tree_WTAmatch.png", dpi=300)
plt.show()
plt.close()
```

```
---------------------------------------------------------------------------
-
ValueError                                Traceback (most recent call las
t)
Cell In[59], line 7
      5 # Train Decision Tree WTA
      6 dt_model = DecisionTreeClassifier(max_depth=4, random_state=42)
----> 7 dt_model.fit(X_train_scaled, y_train)
      8 plt.figure(figsize=(15, 8))
      9 tree.plot_tree(dt_model, feature_names=features, class_names=["Los
er", "Winner"], filled=True)

File /usr/local/lib/python3.11/site-packages/sklearn/base.py:1389, in _fit
_context.<locals>.decorator.<locals>.wrapper(estimator, *args, **kwargs)
   1382     estimator._validate_params()
   1384 with config_context(
   1385     skip_parameter_validation=(
   1386         prefer_skip_nested_validation or global_skip_validation
   1387     )
   1388 ):
-> 1389     return fit_method(estimator, *args, **kwargs)

File /usr/local/lib/python3.11/site-packages/sklearn/tree/_classes.py:102
4, in DecisionTreeClassifier.fit(self, X, y, sample_weight, check_input)
    993 @_fit_context(prefer_skip_nested_validation=True)
    994 def fit(self, X, y, sample_weight=None, check_input=True):
    995     """Build a decision tree classifier from the training set (X,
y).
    996
    997     Parameters
   (...)
   1021         Fitted estimator.
   1022     """
-> 1024     super()._fit(
   1025         X,
   1026         y,
   1027         sample_weight=sample_weight,
   1028         check_input=check_input,
   1029     )
   1030     return self

File /usr/local/lib/python3.11/site-packages/sklearn/tree/_classes.py:355,
in BaseDecisionTree._fit(self, X, y, sample_weight, check_input, missing_v
alues_in_feature_mask)
    352 max_leaf_nodes = -1 if self.max_leaf_nodes is None else self.max_l
eaf_nodes
    354 if len(y) != n_samples:
--> 355     raise ValueError(
    356         "Number of labels=%d does not match number of samples=%d"
    357         % (len(y), n_samples)
    358     )
    360 if sample_weight is not None:
    361     sample_weight = _check_sample_weight(sample_weight, X, DOUBLE)

ValueError: Number of labels=3840 does not match number of samples=4339
```

```
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=50; total time=   0.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=50; total time=   0.5s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=50; total time=   0.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=50; total time=   0.3s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=50; total time=   0.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=100; total time=   1.3s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=100; total time=   1.2s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=50; total time=   0.7s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=50; total time=   0.6s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=50; total time=   1.3s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=100; total time=   1.4s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=100; total time=   1.0s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=50; total time=   0.7s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=100; total time=   0.9s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=50; total time=   0.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=100; total time=   0.7s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=100; total time=   1.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=100; total time=   1.2s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=50; total time=   0.7s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=100; total time=   1.9s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=100; total time=   1.4s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=100; total time=   1.1s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=100; total time=   1.1s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=50; total time=   0.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=100; total time=   0.8s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=100; total time=   0.7s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=100; total time=   1.3s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=50; total time=   0.7s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=50; total time=   0.6s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=100; total time=   1.4s
```

```
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=50; total time=   1.3s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=50; total time=   0.6s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=50; total time=   0.7s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=100; total time=   1.0s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=100; total time=   1.0s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=50; total time=   0.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=100; total time=   0.8s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=100; total time=   0.7s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=50; total time=   0.4s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=50; total time=   1.0s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=50; total time=   0.6s
[CV] END bootstrap=True, max_depth=10, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=100; total time=   1.1s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=2, n_estimators=100; total time=   2.0s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=1, min_samples_spl
it=5, n_estimators=100; total time=   1.4s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=2, n_estimators=50; total time=   0.6s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=50; total time=   0.5s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=50; total time=   0.7s
[CV] END bootstrap=True, max_depth=20, min_samples_leaf=2, min_samples_spl
it=5, n_estimators=100; total time=   0.7s
```

In [63]:

```python
# 1) Split first
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# 2) Drop NaNs CONSISTENTLY on X_train and align y_train by index
train_mask = X_train.notna().all(axis=1)  # or a subset of columns you ex
X_train = X_train.loc[train_mask]
y_train = y_train.loc[train_mask]

# 3) Scale AFTER alignment
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

# 4) Fit model
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier(max_depth=4, random_state=42)
dt_model.fit(X_train_scaled, y_train)
print("Decision tree model fitted.")
```

```
Decision tree model fitted.
```

In [ ]:

In [64]:
```
# Define features (X) and target variable (y)
X = wta_df.drop(columns=['WIN', 'player_name', 'match_id', 'tourney_id',
y = wta_df['WIN']

#  Split dataset into training & test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

# Scale numerical features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train models
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier()
}

results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1] if hasattr(model, "predic

    accuracy = accuracy_score(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)
    auc_roc = roc_auc_score(y_test, y_proba) if y_proba is not None else

    results[name] = {
        "Accuracy": accuracy,
        "Classification Report": class_report,
        "AUC-ROC": auc_roc
    }

    print(f"\n{name} Performance:")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"AUC-ROC: {auc_roc}")
    print(class_report)

print("Model training & evaluation complete")
```

```
Logistic Regression Performance:
Accuracy: 0.8115
AUC-ROC: 0.8934114583333334
              precision    recall  f1-score   support

           0       0.82      0.79      0.81       480
           1       0.80      0.83      0.82       480

    accuracy                           0.81       960
   macro avg       0.81      0.81      0.81       960
weighted avg       0.81      0.81      0.81       960


Decision Tree Performance:
Accuracy: 0.8635
AUC-ROC: 0.8635416666666667
              precision    recall  f1-score   support

           0       0.86      0.87      0.86       480
           1       0.87      0.86      0.86       480

    accuracy                           0.86       960
   macro avg       0.86      0.86      0.86       960
weighted avg       0.86      0.86      0.86       960


Random Forest Performance:
Accuracy: 0.8698
AUC-ROC: 0.9338888888888889
              precision    recall  f1-score   support

           0       0.87      0.88      0.87       480
           1       0.87      0.86      0.87       480

    accuracy                           0.87       960
   macro avg       0.87      0.87      0.87       960
weighted avg       0.87      0.87      0.87       960

Model training & evaluation complete
```

In [65]:

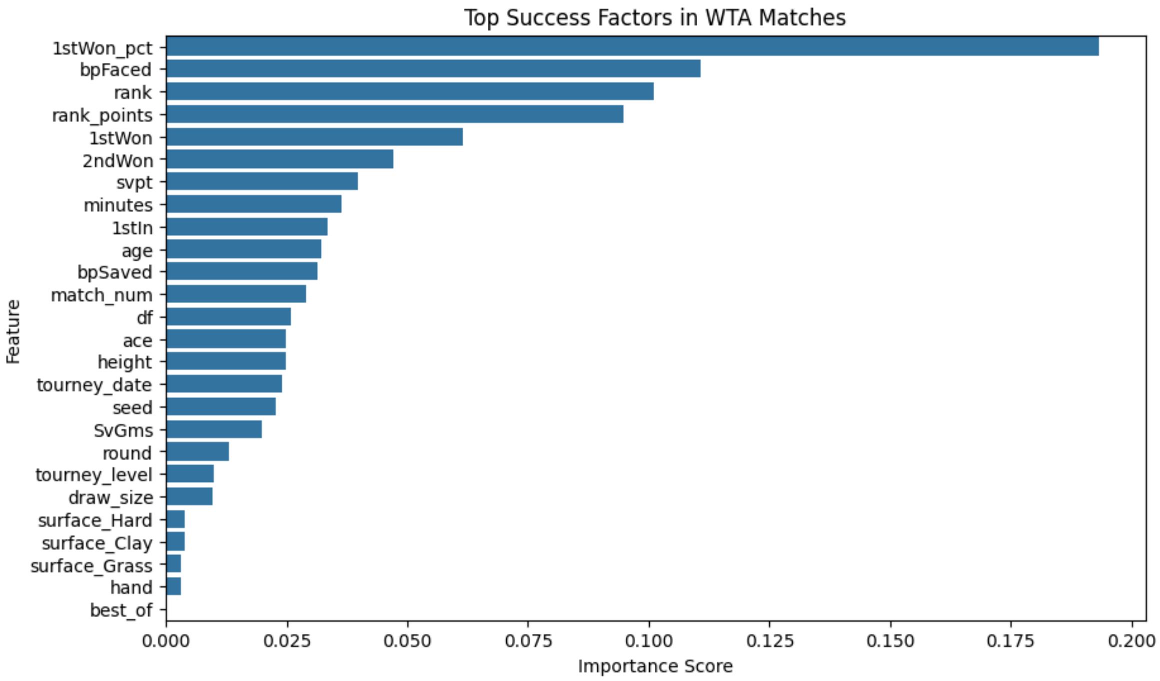
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, roc_au
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay


# Load the dataset
file_path = "Output/WTA_match_final_file.csv"
wta_df = pd.read_csv(file_path)

# Get dataset shape
print(f"Dataset Shape: {wta_df.shape}")

# Check for missing values
```

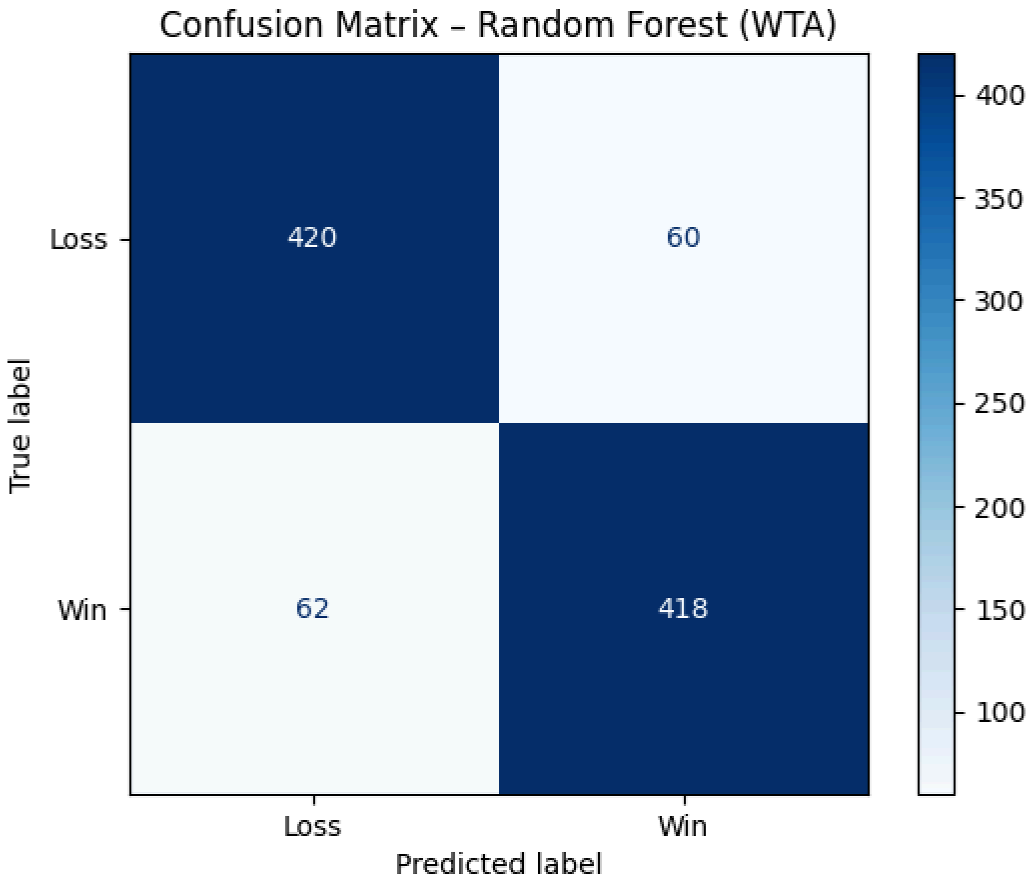
```
missing_values = wta_df.isnull().sum()
print("Missing Values Per Column:")
print(missing_values[missing_values > 0])

# Display column data types
print("Column Data Types:")
print(wta_df.dtypes)

# Handle missing values (fill numeric NaNs with column mean)
numeric_cols = wta_df.select_dtypes(include=['float64', 'int64']).columns
wta_df[numeric_cols] = wta_df[numeric_cols].fillna(wta_df[numeric_cols].m

# Encode categorical variables (convert to numerical values)
categorical_cols = ['round', 'tourney_level']
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    wta_df[col] = le.fit_transform(wta_df[col])
    label_encoders[col] = le

# Define features (X) and target variable (y)
X = wta_df.drop(columns=['WIN', 'player_name', 'match_id', 'tourney_id',
y = wta_df['WIN']

# Split dataset into training & test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

# Scale numerical features (optional, useful for some models)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train models
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier()
}

results = {}
feature_importance = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1] if hasattr(model, "predic

    accuracy = accuracy_score(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)
    auc_roc = roc_auc_score(y_test, y_proba) if y_proba is not None else

    results[name] = {
        "Accuracy": accuracy,
        "Classification Report": class_report,
        "AUC-ROC": auc_roc
    }

    print(f"\n{name} Performance:")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"AUC-ROC: {auc_roc}")
    print(class_report)
```

```
    # Extract feature importance
    if name == "Logistic Regression":
        importance = model.coef_[0]
    else:
        importance = model.feature_importances_

    feature_importance[name] = pd.Series(importance, index=X.columns).sor

# Compare feature importance across models
importance_df = pd.DataFrame({
    "Logistic Regression": feature_importance["Logistic Regression"],
    "Decision Tree": feature_importance["Decision Tree"],
    "Random Forest": feature_importance["Random Forest"]
})

# Identify top 10 success factors
top_features = importance_df.mean(axis=1).sort_values(ascending=False).he
print("\n Top 10 Success Factors:")
print(top_features)


# Plot feature importance for the best model -> Random Forest
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance["Random Forest"].values, y=feature_impor
plt.title("Top Success Factors in WTA Matches")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.savefig("FeatureImportanceWTA.png", dpi=300)
plt.show()
plt.close()



# Predict again using Random Forest
y_pred_rf = models["Random Forest"].predict(X_test)

# Create and plot confusion matrix
cm = confusion_matrix(y_test, y_pred_rf)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Loss'
disp.plot(cmap='Blues')
plt.title('Confusion Matrix – Random Forest (WTA)')
plt.savefig('confusion_matrix_randomForest_wta.png', bbox_inches='tight')
plt.show()
```

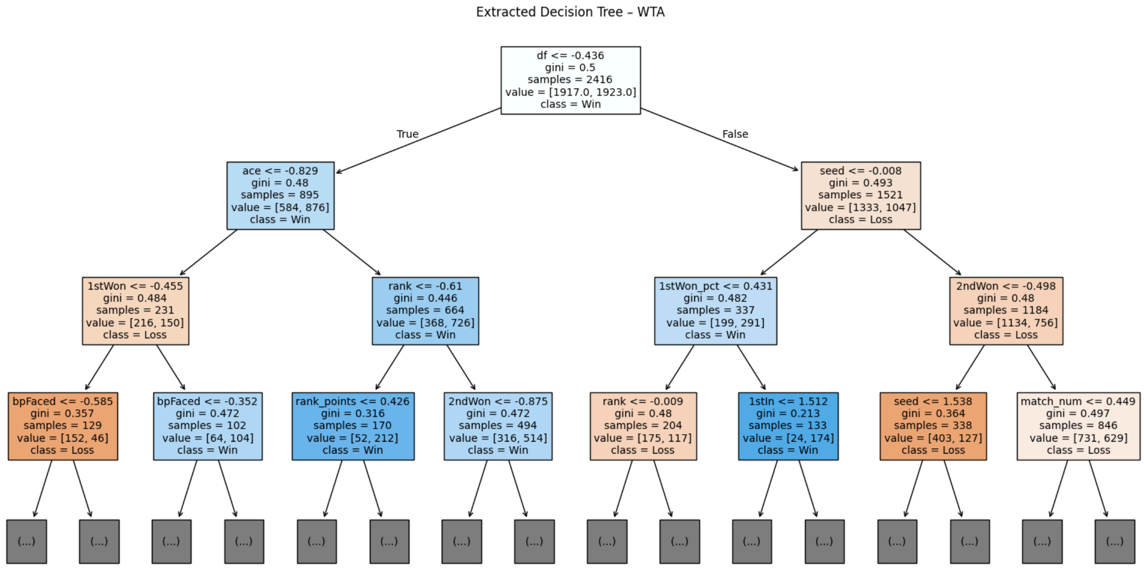
```
Dataset Shape: (4800, 32)
Missing Values Per Column:
Series([], dtype: int64)
Column Data Types:
match_id          object
tourney_id        object
tourney_name      object
tourney_date       int64
match_num          int64
draw_size          int64
tourney_level     object
best_of            int64
round             object
minutes          float64
player_id          int64
player_name       object
seed             float64
rank             float64
rank_points      float64
age              float64
height           float64
hand               int64
ace              float64
df               float64
svpt             float64
1stIn            float64
1stWon           float64
2ndWon           float64
SvGms            float64
bpSaved          float64
bpFaced          float64
1stWon_pct       float64
WIN                int64
surface_Clay       int64
surface_Grass      int64
surface_Hard       int64
dtype: object

Logistic Regression Performance:
Accuracy: 0.8115
AUC-ROC: 0.8934114583333334
              precision    recall  f1-score   support

           0       0.82      0.79      0.81       480
           1       0.80      0.83      0.82       480

    accuracy                           0.81       960
   macro avg       0.81      0.81      0.81       960
weighted avg       0.81      0.81      0.81       960


Decision Tree Performance:
Accuracy: 0.8552
AUC-ROC: 0.8552083333333333
              precision    recall  f1-score   support

           0       0.85      0.87      0.86       480
           1       0.87      0.84      0.85       480

    accuracy                           0.86       960
```

```
   macro avg       0.86      0.86      0.86       960
weighted avg       0.86      0.86      0.86       960


Random Forest Performance:
Accuracy: 0.8729
AUC-ROC: 0.9379622395833334
              precision    recall  f1-score   support

           0       0.87      0.88      0.87       480
           1       0.87      0.87      0.87       480

    accuracy                           0.87       960
   macro avg       0.87      0.87      0.87       960
weighted avg       0.87      0.87      0.87       960


 Top 10 Success Factors:
1stIn           1.088885
1stWon_pct      0.739029
bpSaved         0.510322
2ndWon          0.410821
rank_points     0.260949
rank            0.210755
minutes         0.077117
tourney_date    0.048429
surface_Clay    0.044435
df              0.042897
dtype: float64
```



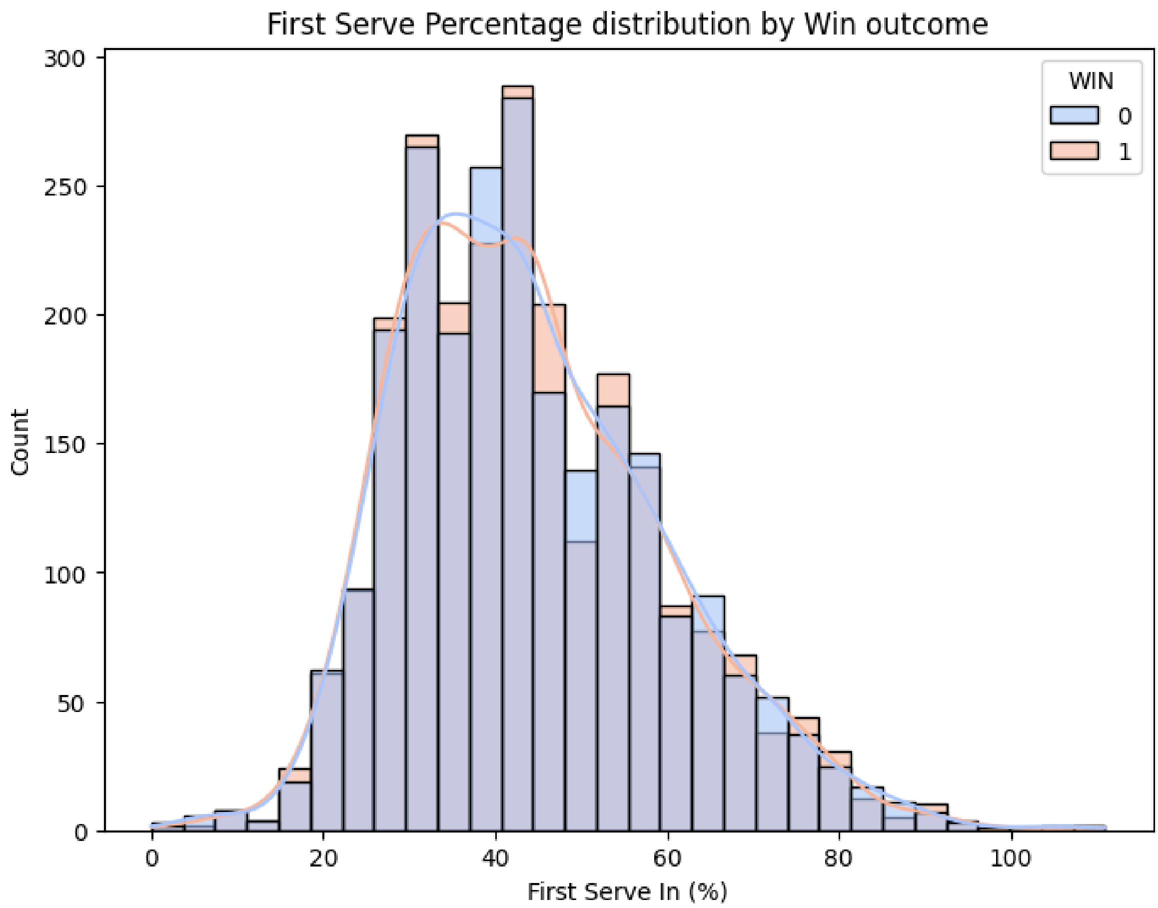


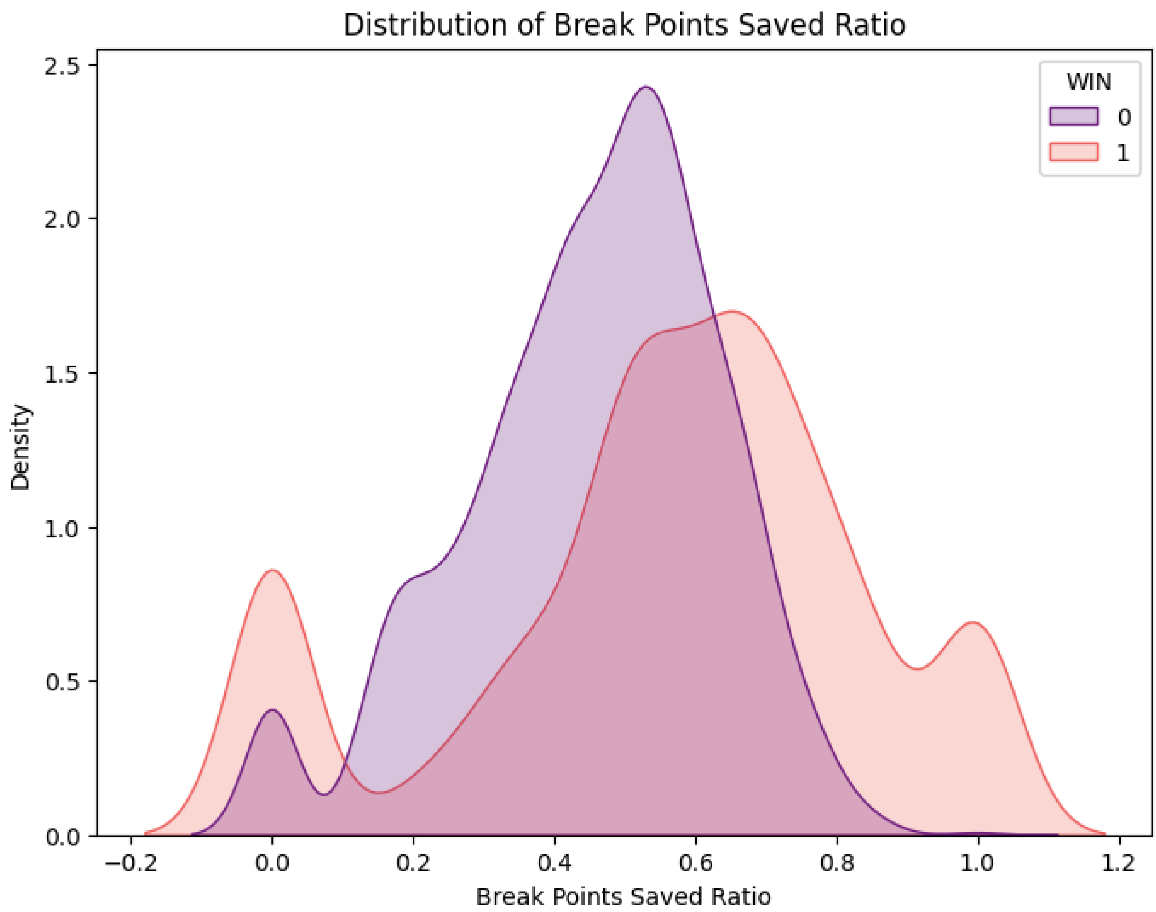
In [66]:
```
from sklearn.tree import plot_tree

# Extract one decision tree from the Random Forest
estimator = models["Random Forest"].estimators_[0]

plt.figure(figsize=(20, 10))
plot_tree(
    estimator,
    feature_names=X.columns,
    class_names=["Loss", "Win"],
    filled=True,
    max_depth=3,  # Limit tree depth for clarity
    fontsize=10
)
plt.title("Extracted Decision Tree – WTA")
plt.savefig("tree_wta.png", bbox_inches='tight')
plt.show()
```



In [68]:

```
# Histogram: First Serve percentage vs. Win rate
plt.figure(figsize=(8, 6))
sns.histplot(data=wta_df, x='1stIn', hue='WIN', kde=True, bins=30, palett
plt.title("First Serve Percentage distribution by Win outcome")
plt.xlabel("First Serve In (%)")
plt.ylabel("Count")
plt.savefig("1stInWTAWin.png", dpi=300)
plt.show()
plt.close()

# Break Points saved ratio distribution
wta_df['bpSavedRatio'] = wta_df['bpSaved'] / (wta_df['bpFaced'] + 1e-6)
plt.figure(figsize=(8, 6))
sns.kdeplot(data=wta_df, x='bpSavedRatio', hue='WIN', fill=True, common_n
plt.title("Distribution of Break Points Saved Ratio")
plt.xlabel("Break Points Saved Ratio")
plt.ylabel("Density")
plt.savefig("BreakPointsWta.png", dpi=300)
plt.show()
plt.close()
```





Comparison of ATP and WTA Dataset

- Extracting the top 10 success factors for ATP and WTA using the Random Forest model.
- Creating a side-by-side bar chart to compare the feature importance rankings.
- Interpreting the key differences between ATP and WTA success factors.

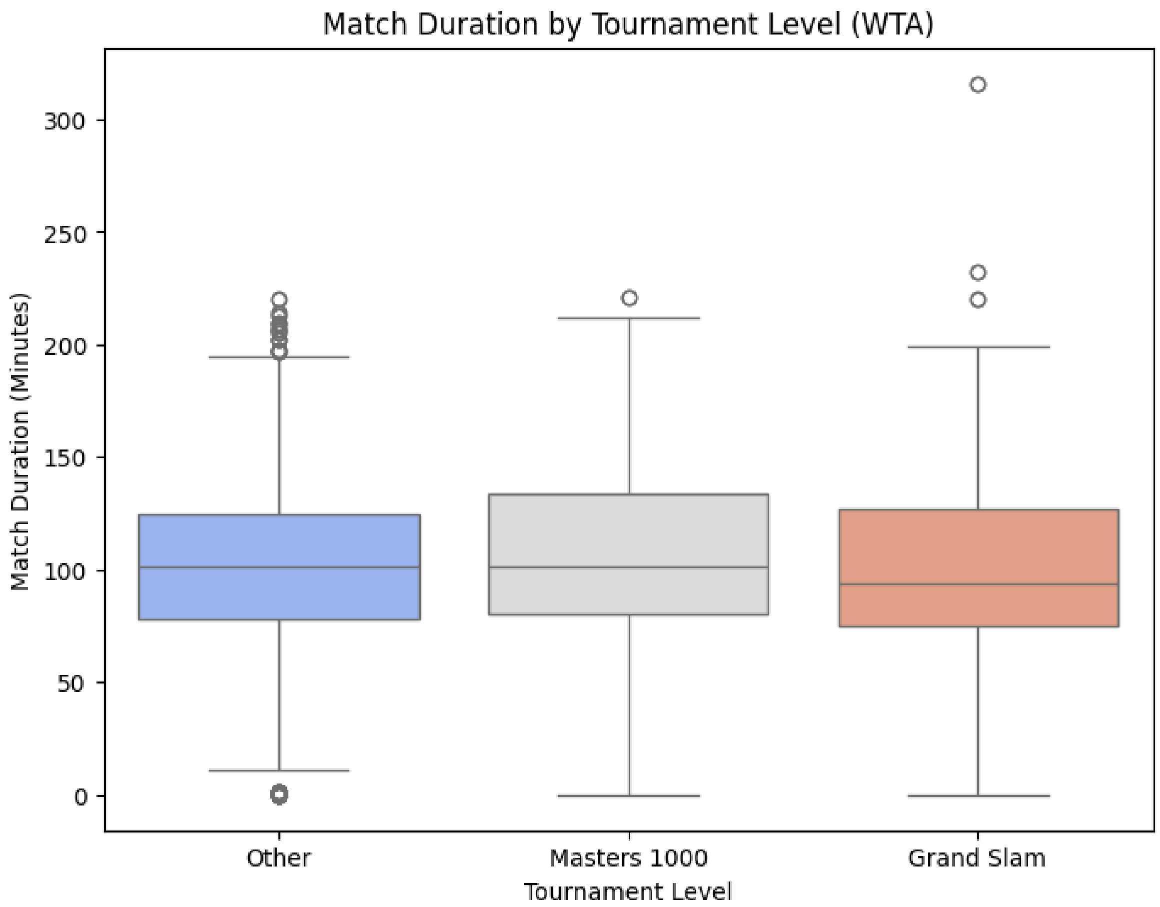
General Comparison before applying any machine learning algorithm

In [43]:
```
#WTA dataset
wta_file_path = "Output/WTA_match_final_file.csv"
wta_match_1 = pd.read_csv(wta_file_path)

# ATP dataset
atp_file_path = "Output/ATP_match_final_file.csv"
atp_match_1 = pd.read_csv(atp_file_path)

# Handle missing values (fill numeric NaNs with column mean)
numeric_cols_wta = wta_match_1.select_dtypes(include=['float64', 'int64']
wta_match_1[numeric_cols_wta] = wta_match_1[numeric_cols_wta].fillna(wta_

numeric_cols_atp = atp_match_1.select_dtypes(include=['float64', 'int64']
atp_match_1[numeric_cols_atp] = atp_match_1[numeric_cols_atp].fillna(atp_

# Print unique values for debugging
print("Unique WTA tourney levels:", wta_match_1["tourney_level"].unique()
print("Unique ATP tourney levels:", atp_match_1["tourney_level"].unique()

# Adjust tournament level categories
wta_tourney_mapping = {"G": "Grand Slam", "PM": "Masters 1000", "WTA 500"
atp_tourney_mapping = {"G": "Grand Slam", "M": "Masters 1000", "A": "Othe

wta_match_1["tourney_category"] = wta_match_1["tourney_level"].map(wta_to
atp_match_1["tourney_category"] = atp_match_1["tourney_level"].map(atp_to

# Handle NaN values in tourney_category
wta_match_1["tourney_category"].fillna("Other", inplace=True)
atp_match_1["tourney_category"].fillna("Other", inplace=True)

# Tournament Category Comparison
plt.figure(figsize=(8, 6))
sns.boxplot(x=wta_match_1['tourney_category'], y=wta_match_1['minutes'],
plt.title("Match Duration by Tournament Level (WTA)")
plt.xlabel("Tournament Level")
plt.ylabel("Match Duration (Minutes)")
plt.savefig("WTA_TourneyLevel_vs_MatchTime.png", dpi=300)
plt.show()

plt.figure(figsize=(8, 6))
sns.boxplot(x=atp_match_1['tourney_category'], y=atp_match_1['minutes'],
plt.title("Match Duration by Tournament Level (ATP)")
plt.xlabel("Tournament Level")
plt.ylabel("Match Duration (Minutes)")
plt.savefig("ATP_TourneyLevel_vs_MatchTime.png", dpi=300)
plt.show()

# Overall Match Duration Comparison (Using Bar Plot)
avg_match_duration = {
    "WTA": wta_match_1["minutes"].mean(),
```

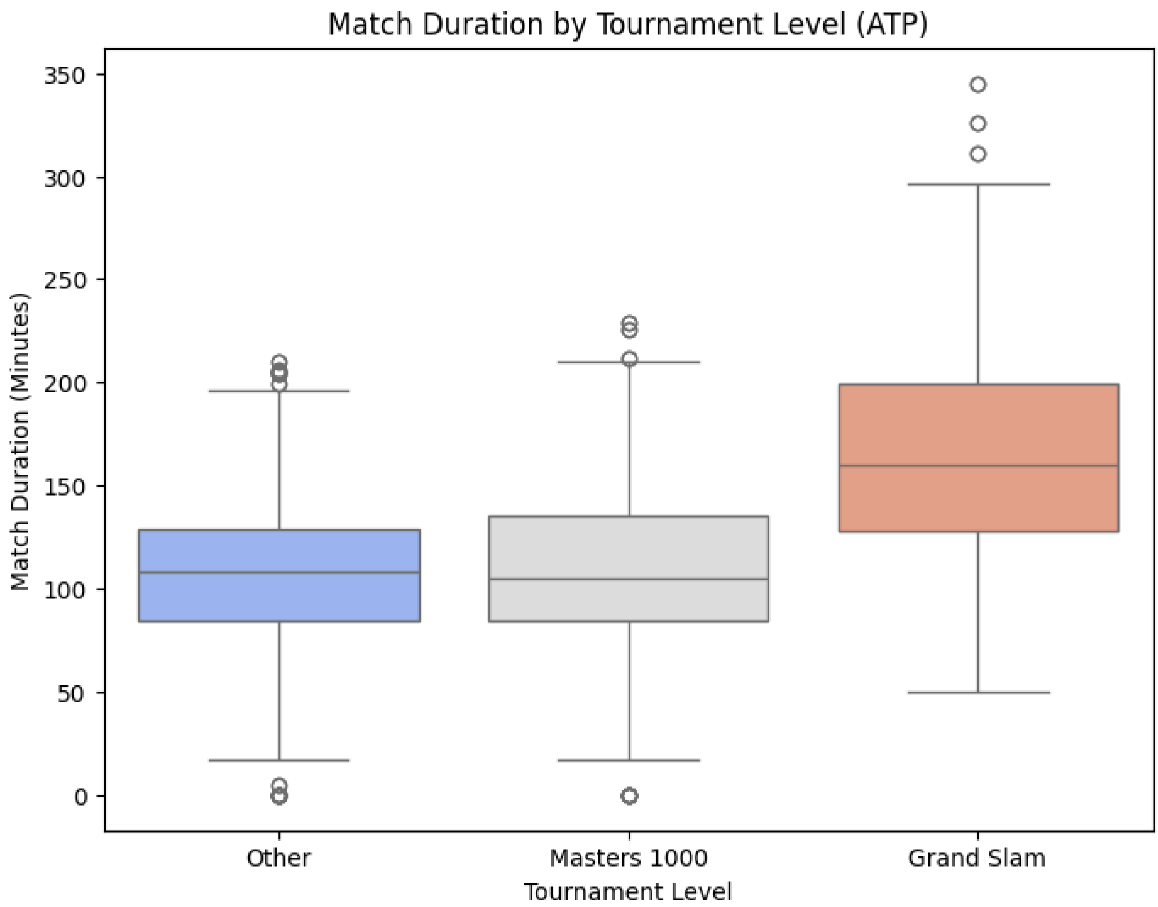
```
    "ATP": atp_match_1["minutes"].mean()
}

plt.figure(figsize=(8, 6))
sns.barplot(x=list(avg_match_duration.keys()), y=list(avg_match_duration.
plt.title("Average Match Duration Comparison: ATP vs. WTA")
plt.ylabel("Average Match Duration (Minutes)")
plt.xlabel("Tour")
plt.savefig("ATP_WTA_MatchTime_Comparison.png", dpi=300)
plt.show()
```

```
Unique WTA tourney levels: ['P' 'I' 'PM' 'F' 'G' 'D']
Unique ATP tourney levels: ['A' 'M' 'G' 'F' 'D']
```

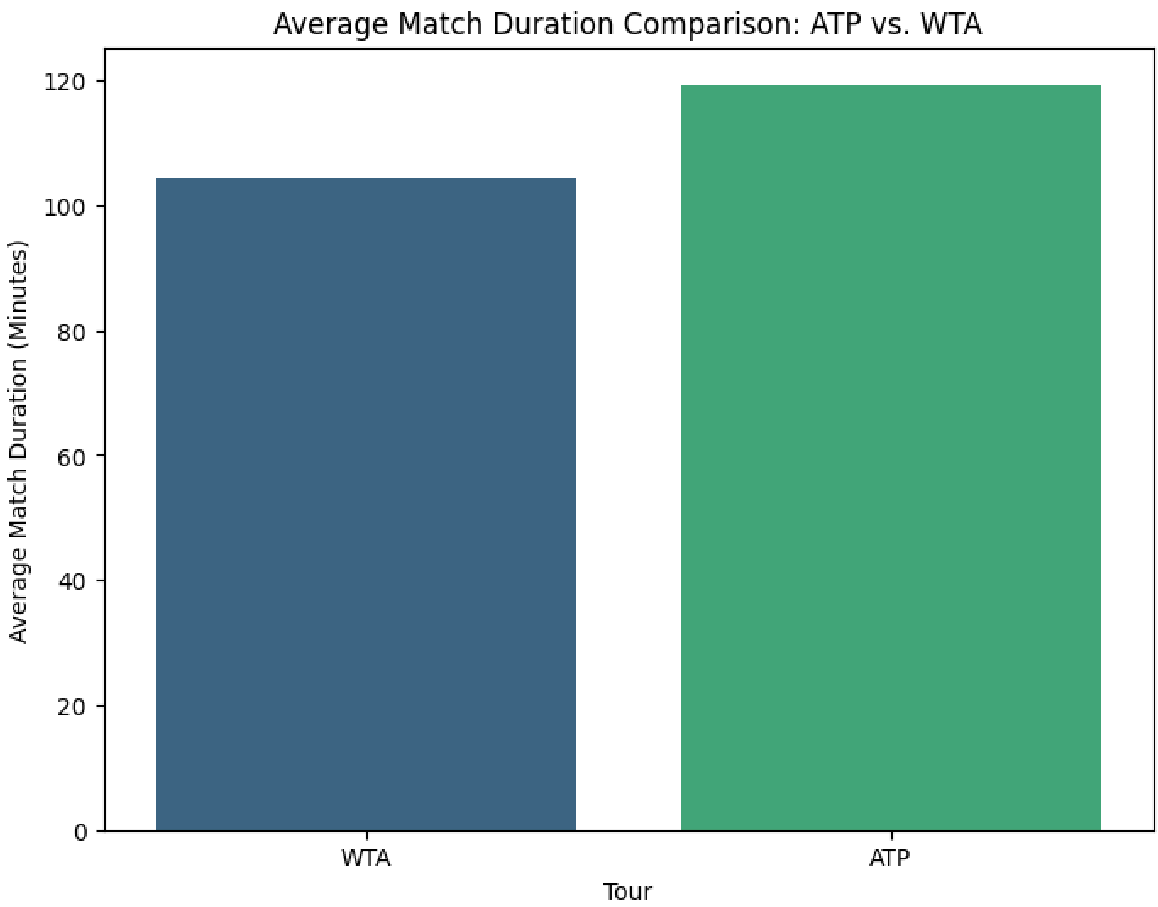
```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_3063/409663207
5.py:33: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(x=wta_match_1['tourney_category'], y=wta_match_1['minutes'],
palette="coolwarm")
```




```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_3063/409663207
5.py:41: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(x=atp_match_1['tourney_category'], y=atp_match_1['minutes'],
palette="coolwarm")
```




```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_3063/409663207
5.py:55: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.barplot(x=list(avg_match_duration.keys()), y=list(avg_match_duratio
n.values()), palette="viridis")
```



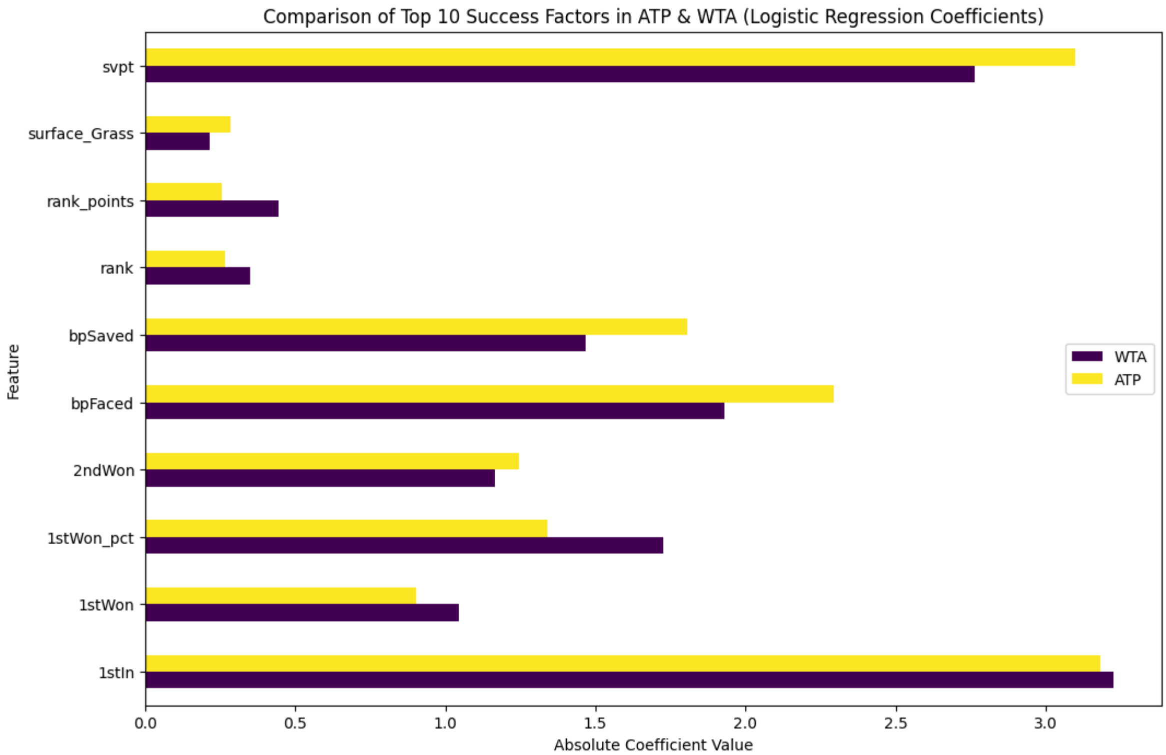
In [ ]:

In [69]:

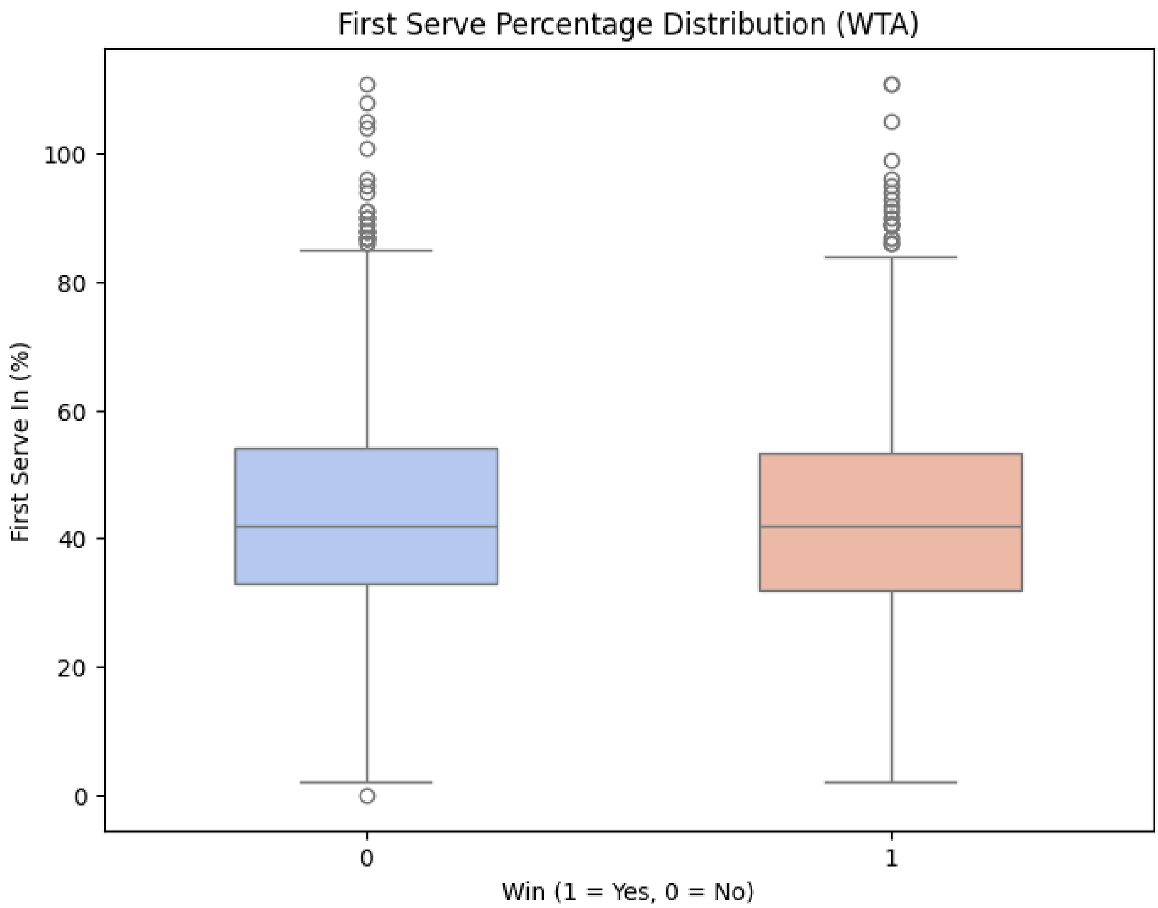
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Load the WTA dataset
wta_file_path = "Output/WTA_match_final_file.csv"
wta_df = pd.read_csv(wta_file_path)

# Load the ATP dataset
atp_file_path = "Output/ATP_match_final_file.csv"
atp_df = pd.read_csv(atp_file_path)

# Handle missing values (fill numeric NaNs with column mean)
numeric_cols_wta = wta_df.select_dtypes(include=['float64', 'int64']).col
wta_df[numeric_cols_wta] = wta_df[numeric_cols_wta].fillna(wta_df[numeric

numeric_cols_atp = atp_df.select_dtypes(include=['float64', 'int64']).col
atp_df[numeric_cols_atp] = atp_df[numeric_cols_atp].fillna(atp_df[numeric

# Encode categorical variables (convert to numerical values)
categorical_cols = ['round', 'tourney_level']
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    wta_df[col] = le.fit_transform(wta_df[col])
    atp_df[col] = le.fit_transform(atp_df[col])
```

```
    label_encoders[col] = le

# Define features (X) and target variable (y)
X_wta = wta_df.drop(columns=['WIN', 'player_name', 'match_id', 'tourney_i
y_wta = wta_df['WIN']

X_atp = atp_df.drop(columns=['WIN', 'player_name', 'match_id', 'tourney_i
y_atp = atp_df['WIN']

# Split dataset into training & test sets
X_train_wta, X_test_wta, y_train_wta, y_test_wta = train_test_split(X_wta
X_train_atp, X_test_atp, y_train_atp, y_test_atp = train_test_split(X_atp

# Scale numerical features
scaler = StandardScaler()
X_train_wta = scaler.fit_transform(X_train_wta)
X_test_wta = scaler.transform(X_test_wta)
X_train_atp = scaler.fit_transform(X_train_atp)
X_test_atp = scaler.transform(X_test_atp)

# Train Logistic Regression models
lr_model_wta = LogisticRegression(max_iter=1000)
lr_model_wta.fit(X_train_wta, y_train_wta)

lr_model_atp = LogisticRegression(max_iter=1000)
lr_model_atp.fit(X_train_atp, y_train_atp)

# Extract feature importance from Logistic Regression
feature_importance_wta = pd.Series(abs(lr_model_wta.coef_[0]), index=X_wt
top_features_wta = feature_importance_wta.head(10)

feature_importance_atp = pd.Series(abs(lr_model_atp.coef_[0]), index=X_at
top_features_atp = feature_importance_atp.head(10)

# Compare ATP & WTA Feature Importance
comparison_df = pd.DataFrame({'WTA': top_features_wta, 'ATP': top_feature
comparison_df.plot(kind='barh', figsize=(12, 8), colormap="viridis")
plt.title("Comparison of Top 10 Success Factors in ATP & WTA (Logistic Re
plt.xlabel("Absolute Coefficient Value")
plt.ylabel("Feature")
plt.legend(["WTA", "ATP"])
plt.savefig("ATP_WTA_Comparison_LogReg.png", dpi=300)
plt.show()
plt.close()

# Serve Performance Comparison
plt.figure(figsize=(8, 6))
sns.boxplot(data=wta_df, x='WIN', y='1stIn', palette="coolwarm", width=0.
plt.title("First Serve Percentage Distribution (WTA)")
plt.xlabel("Win (1 = Yes, 0 = No)")
plt.ylabel("First Serve In (%)")
plt.savefig("ServeWTA.png", dpi=300)
plt.show()

plt.figure(figsize=(8, 6))
sns.boxplot(data=atp_df, x='WIN', y='1stIn', palette="coolwarm", width=0.
plt.title("First Serve Percentage Distribution (ATP)")
plt.xlabel("Win (1 = Yes, 0 = No)")
plt.ylabel("First Serve In (%)")
plt.savefig("ServeATP.png", dpi=300)
```

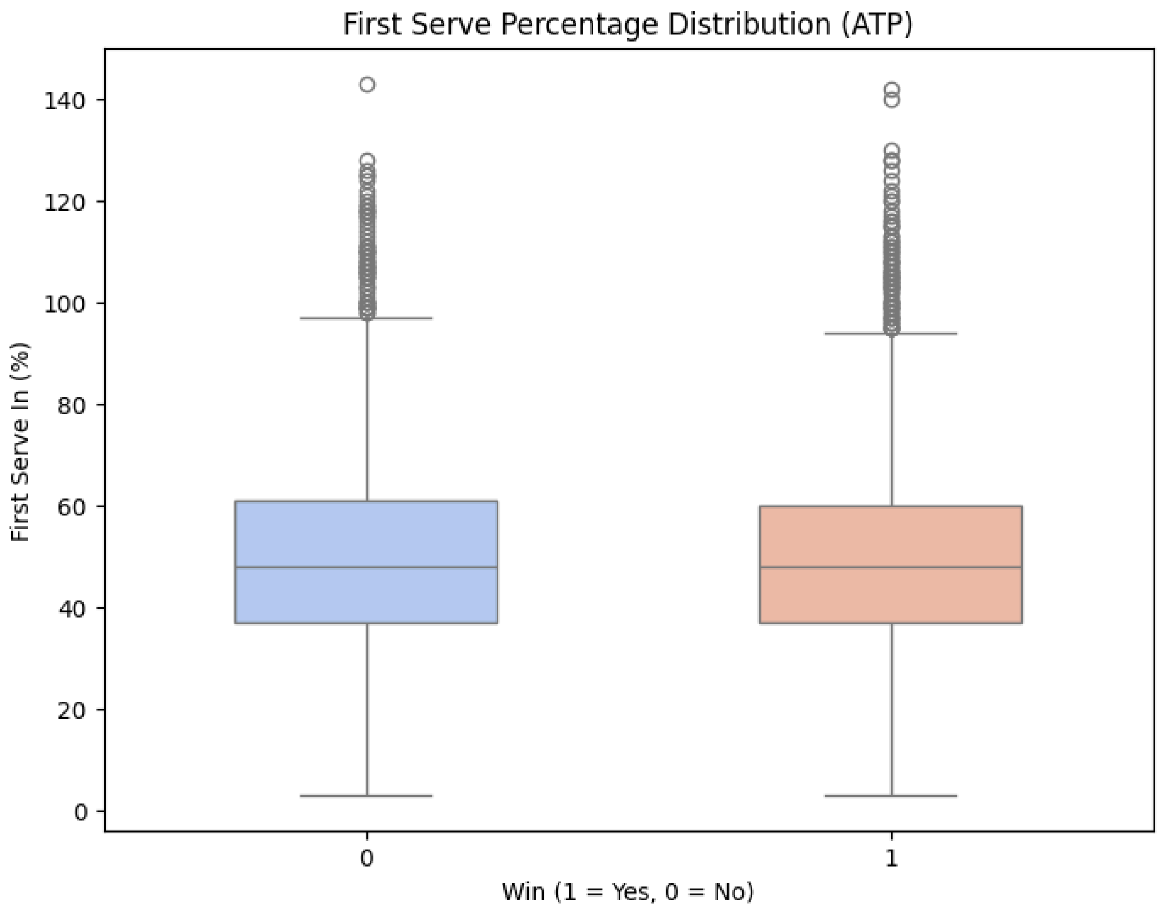
```
plt.show()

# Break Point Resilience Comparison
plt.figure(figsize=(8, 6))
sns.kdeplot(data=wta_df, x=wta_df['bpSaved'] / (wta_df['bpFaced'] + 1e-6)
plt.title("Break Points Saved Ratio (WTA)")
plt.xlabel("Break Points Saved Ratio")
plt.ylabel("Density")
plt.savefig("BreakPointsWTA.png", dpi=300)
plt.show()

plt.figure(figsize=(8, 6))
sns.kdeplot(data=atp_df, x=atp_df['bpSaved'] / (atp_df['bpFaced'] + 1e-6)
plt.title("Break Points Saved Ratio (ATP)")
plt.xlabel("Break Points Saved Ratio")
plt.ylabel("Density")
plt.savefig("BreakPointsATP.png", dpi=300)
plt.show()

print("ATP vs. WTA success factor comparison with additional analyses com
```

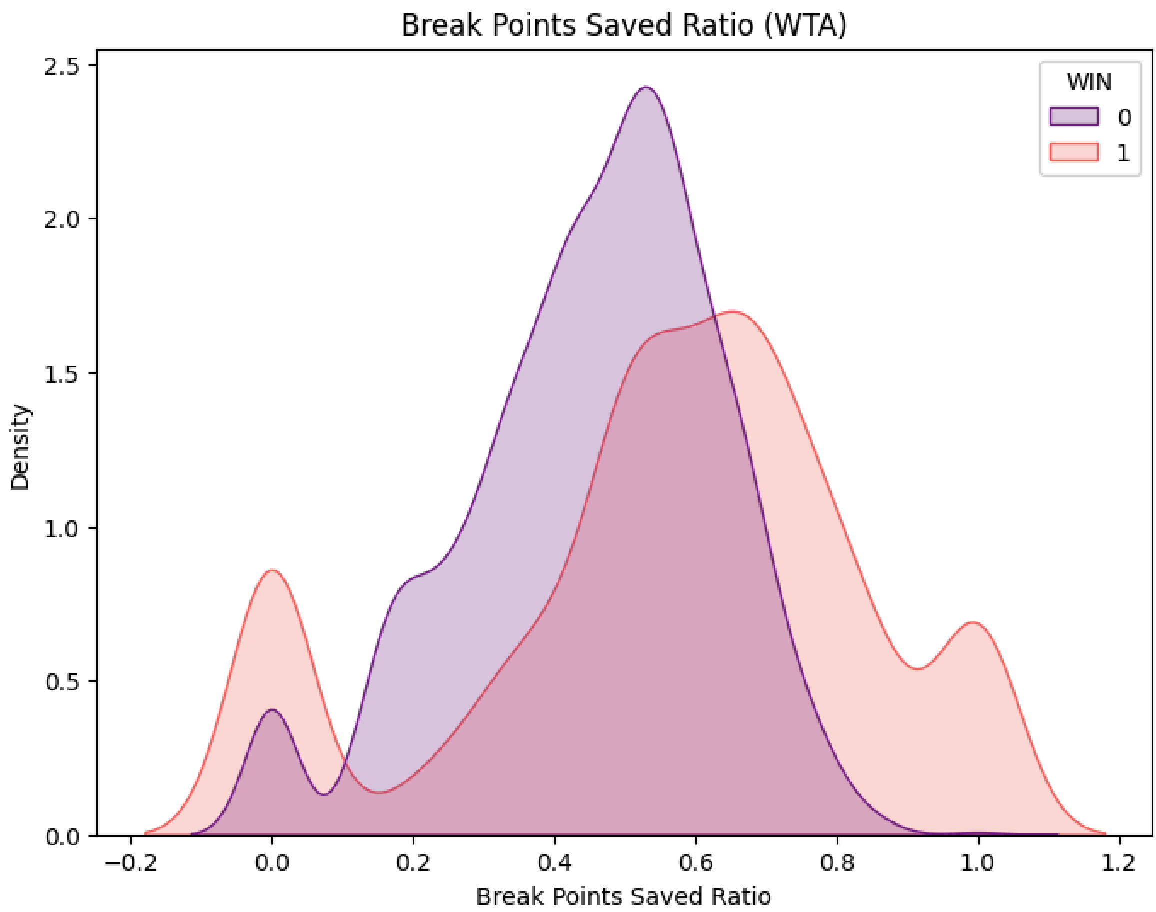


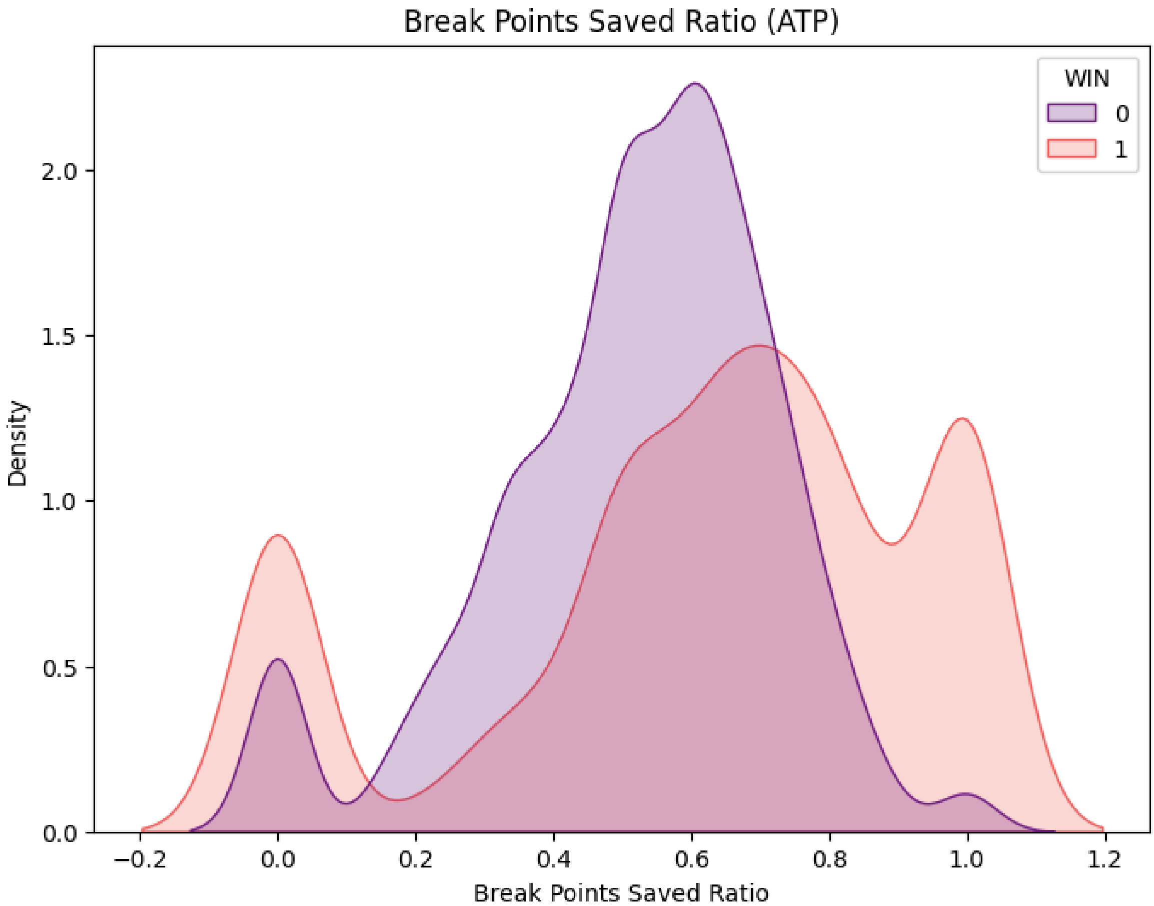

```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_28320/226903917
3.py:77: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(data=wta_df, x='WIN', y='1stIn', palette="coolwarm", width=
0.5)
```




```
/var/folders/tf/bv57pwsn06q3k6xg7rc9yfvm0000gn/T/ipykernel_28320/226903917
3.py:85: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for
the same effect.

  sns.boxplot(data=atp_df, x='WIN', y='1stIn', palette="coolwarm", width=
0.5)
```


First Serve Percentage Distribution (ATP)
First Serve In (%)
0
20
40
60
80
100
120
140
0
1
Win (1 = Yes, 0 = No)


Break Points Saved Ratio (WTA)
Density
0.0
0.5
1.0
1.5
2.0
2.5
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Break Points Saved Ratio
WIN
0
1




```
ATP vs. WTA success factor comparison with additional analyses completed!
```

In [ ]:

In [ ]:

In [ ]: