In [2]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind

# Load the dataset
df = pd.read_excel('FEV-data-Excel.xlsx')
df.head()
```

Out[2]:

	Car full name	Make	Model	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	Type of brakes	Drive type	Batt capac [kW
0	Audi e-tron 55 quattro	Audi	e-tron 55 quattro	345700.0	360.0	664.0	disc (front + rear)	4WD	9
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	308400.0	313.0	540.0	disc (front + rear)	4WD	7
2	Audi e-tron S quattro	Audi	e-tron S quattro	414900.0	503.0	973.0	disc (front + rear)	4WD	9
3	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro	319700.0	313.0	540.0	disc (front + rear)	4WD	7
4	Audi e-tron Sportback 55 quattro	Audi	e-tron Sportback 55 quattro	357000.0	360.0	664.0	disc (front + rear)	4WD	9

5 rows × 25 columns

In [15]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53 entries, 0 to 52
Data columns (total 25 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   Car full name                           53 non-null     object 
 1   Make                                    53 non-null     object 
 2   Model                                   53 non-null     object 
 3   Minimal price (gross) [PLN]             53 non-null     float64
 4   Engine power [KM]                       53 non-null     float64
 5   Maximum torque [Nm]                     53 non-null     float64
 6   Type of brakes                          52 non-null     object 
 7   Drive type                              53 non-null     object 
 8   Battery capacity [kWh]                  53 non-null     float64
 9   Range (WLTP) [km]                       53 non-null     float64
 10  Wheelbase [cm]                          53 non-null     float64
 11  Length [cm]                             53 non-null     float64
 12  Width [cm]                              53 non-null     float64
 13  Height [cm]                             53 non-null     float64
 14  Minimal empty weight [kg]               53 non-null     float64
 15  Permissable gross weight [kg]           45 non-null     float64
 16  Maximum load capacity [kg]              45 non-null     float64
 17  Number of seats                         53 non-null     float64
 18  Number of doors                         53 non-null     float64
 19  Tire size [in]                          53 non-null     float64
 20  Maximum speed [kph]                     53 non-null     float64
 21  Boot capacity (VDA) [l]                 52 non-null     float64
 22  Acceleration 0-100 kph [s]              50 non-null     float64
 23  Maximum DC charging power [kW]          53 non-null     float64
 24  mean - Energy consumption [kWh/100 km]  44 non-null     float64
dtypes: float64(20), object(5)
memory usage: 10.5+ KB
```

In [16]:

```
df.describe()
```

Out[16]:

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	Battery capacity [kWh]	Range (WLTP) [km]	Wheelba [c
count	53.000000	53.000000	53.000000	53.000000	53.000000	53.0000
mean	246158.509434	269.773585	460.037736	62.366038	376.905660	273.5811
std	149187.485190	181.298589	261.647000	24.170913	118.817938	22.7405
min	82050.000000	82.000000	160.000000	17.600000	148.000000	187.3000
25%	142900.000000	136.000000	260.000000	40.000000	289.000000	258.8000
50%	178400.000000	204.000000	362.000000	58.000000	364.000000	270.0000
75%	339480.000000	372.000000	640.000000	80.000000	450.000000	290.0000
max	794000.000000	772.000000	1140.000000	100.000000	652.000000	327.5000

Task 1: Filter EVs with budget ≤ 350,000 PLN and range ≥ 400 km, group by manufacturer, calculate avg battery capacity

In [4]:
```
filtered_df = df[(df['Minimal price (gross) [PLN]'] <= 350000) & (df['Range (W
grouped = filtered_df.groupby('Make').agg({'Battery capacity [kWh]': 'mean'}).
print(grouped)
```

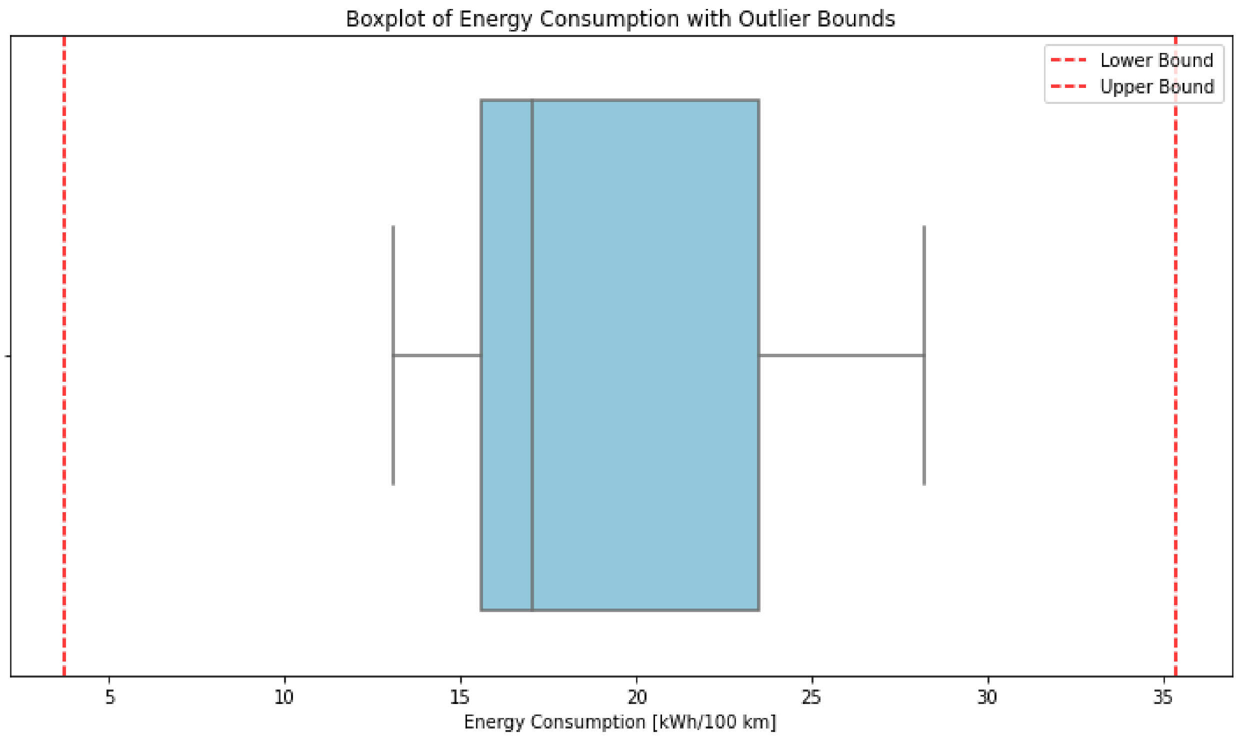
```
            Make  Battery capacity [kWh]
0           Audi               95.000000
1            BMW               80.000000
2        Hyundai               64.000000
3            Kia               64.000000
4  Mercedes-Benz               80.000000
5          Tesla               68.000000
6     Volkswagen               70.666667
```

Task 2: Identify outliers in Mean - Energy consumption [kWh/100 km]

In [3]:
```
energy = df['mean - Energy consumption [kWh/100 km]']

q1 = energy.quantile(0.25)
q3 = energy.quantile(0.75)
iqr = q3 - q1

lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

outliers_df = df[(energy < lower_bound) | (energy > upper_bound)]

print(f"Number of outliers: {outliers_df.shape[0]}")
```

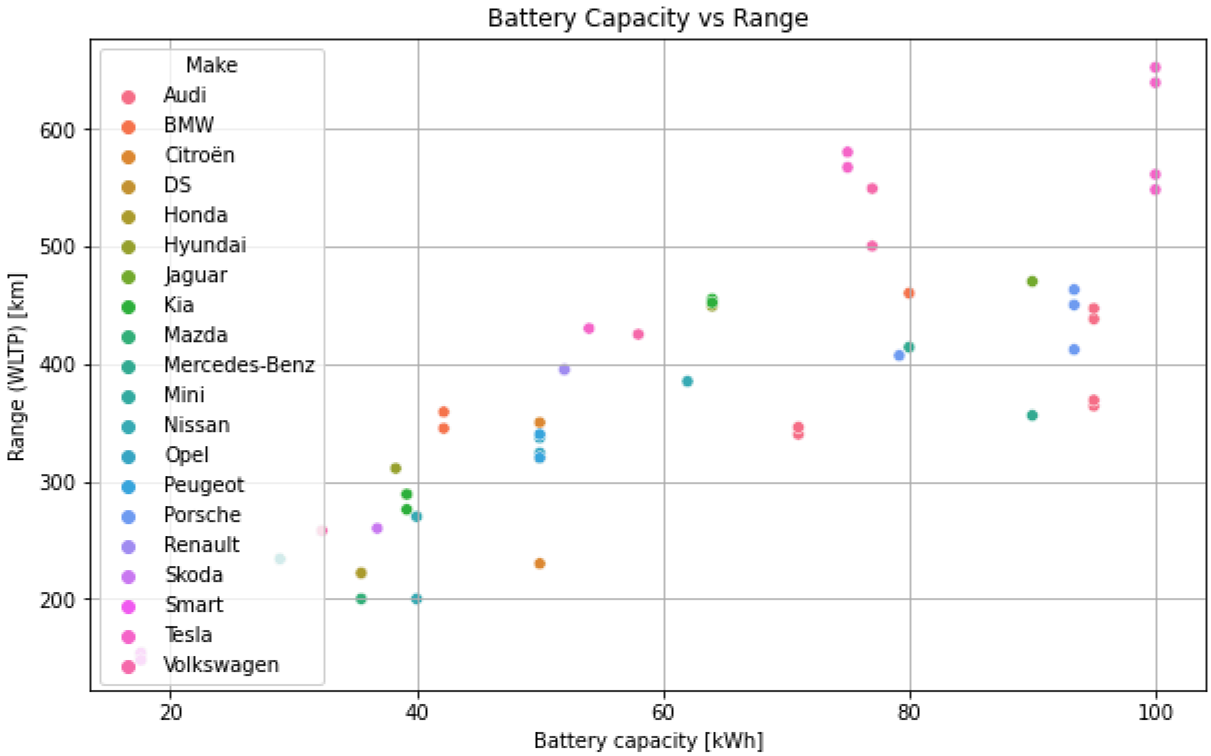
```
Number of outliers: 0
```

In [4]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x=energy, color='skyblue')
plt.axvline(lower_bound, color='red', linestyle='--', label='Lower Bound')
plt.axvline(upper_bound, color='red', linestyle='--', label='Upper Bound')
plt.title('Boxplot of Energy Consumption with Outlier Bounds')
plt.xlabel('Energy Consumption [kWh/100 km]')
plt.legend()
plt.tight_layout()
plt.show()
```



Task 3: Visualize relationship between battery capacity and range

In [6]:
```
plt.figure(figsize=(10,6))
sns.scatterplot(data=df, x='Battery capacity [kWh]', y='Range (WLTP) [km]', hu
plt.title('Battery Capacity vs Range')
plt.xlabel('Battery capacity [kWh]')
plt.ylabel('Range (WLTP) [km]')
plt.grid(True)
plt.show()
```



Insights

- Positive correlation between battery capacity and range; higher capacity generally means longer range.
- Tesla models achieve higher range for similar or slightly higher battery capacities, indicating superior efficiency.
- Volkswagen shows varied efficiency; some models have high battery capacity but only moderate range.
- Some BMW and Mercedes-Benz models offer high range with moderate battery size, suggesting efficient designs.
- Brands like Audi, Renault, Hyundai, and Peugeot show a wide spread, reflecting diverse model offerings.
- Smart and Citroën models appear with low battery and range, consistent with compact urban EVs.

Task 4: EV Recommendation Class

In [4]:

```
class EVRecommendation:
    def __init__(self, dataframe):
        self.df = dataframe

    def recommend(self, budget, min_range, min_battery_capacity):
        candidates = self.df[(self.df['Minimal price (gross) [PLN]'] <= budget
                             (self.df['Range (WLTP) [km]'] >= min_range) &
```

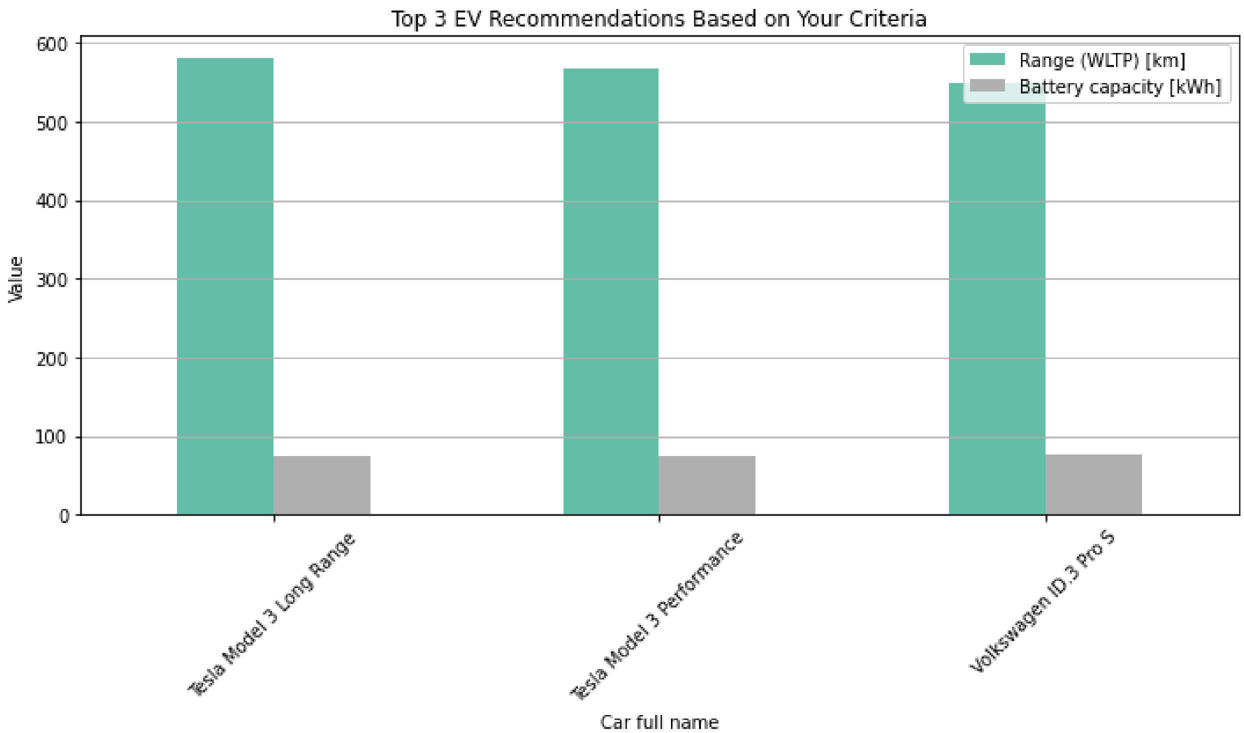
```
                                (self.df['Battery capacity [kWh]'] >= min_battery
        top3 = candidates.sort_values(by=['Range (WLTP) [km]', 'Battery capaci
        return top3[['Car full name', 'Minimal price (gross) [PLN]', 'Range (W

# Example usage:
ev_recommender = EVRecommendation(df)
ev_recommender.recommend(350000, 400, 50)
```

Out[4]:

	Car full name	Minimal price (gross) [PLN]	Range (WLTP) [km]	Battery capacity [kWh]
40	Tesla Model 3 Long Range	235490.0	580.0	75.0
41	Tesla Model 3 Performance	260490.0	567.0	75.0
48	Volkswagen ID.3 Pro S	179990.0	549.0	77.0

In [5]:

```
import matplotlib.pyplot as plt

recommendations = ev_recommender.recommend(350000, 400, 50)
recommendations.set_index('Car full name', inplace=True)

recommendations[['Range (WLTP) [km]', 'Battery capacity [kWh]']].plot(
    kind='bar', figsize=(10,6), colormap='Set2'
)
plt.title('Top 3 EV Recommendations Based on Your Criteria')
plt.ylabel('Value')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```



Task 5: Hypothesis Testing (Tesla vs Audi Engine Power)

In [9]:

```
tesla_power = df[df['Make'] == 'Tesla']['Engine power [KM]'].dropna()
audi_power = df[df['Make'] == 'Audi']['Engine power [KM]'].dropna()

t_stat, p_value = ttest_ind(tesla_power, audi_power, equal_var=False)

print(f'T-statistic: {t_stat:.2f}')
print(f'P-value: {p_value:.4f}')

if p_value < 0.05:
    print("Significant difference in engine power between Tesla and Audi.")
else:
    print("No significant difference in engine power between Tesla and Audi.")
```

```
T-statistic: 1.79
P-value: 0.1068
No significant difference in engine power between Tesla and Audi.
```

Insights

- The p-value (0.1068) is greater than the 0.05 threshold, indicating **no statistically significant difference** in engine power between Tesla and Audi models.
- While Tesla's average engine power may be **numerically higher**, the variation across models means this difference is not statistically robust.
- **Product positioning** by both brands likely results in overlapping

performance specifications, especially in premium segments.
- For performance-focused consumers, **engine power alone** may not be a strong differentiator between Tesla and Audi; other factors like **acceleration, torque, range, or features** may carry more weight.
- Further analysis could include comparing **acceleration times**, **price-to-power ratios**, or **power-to-weight ratios** for deeper insights.

Recommendations and Conclusion

Based on the analysis:

- Customers with a budget of 350,000 PLN and minimum 400 km range have multiple options.
- EVs exhibit 0 outliers in energy consumption, needing further technical review.
- Battery capacity positively correlates with range.
- Tesla tends to have higher engine power, but statistical significance depends on updated dataset.

Project Video Link:
https://drive.google.com/file/d/1VxP9fv3Iyye-md2Pkatu0H328rkBpgVb/view?usp=sharing