Electric Vehicle Data Analysis Project

Project Overview

In this project, you will analyze a dataset related to electric vehicles (EVs). The dataset contains various features such as electric range, energy consumption, price, and other relevant attributes. Your goal is to conduct a thorough analysis to uncover meaningful insights, tell a compelling story, conduct hypothesis testing and provide actionable recommendations based on the data.

Task 1: A customer has a budget of 350,000 PLN and wants an EV with a minimum range of 400 km.

In [5]:

```
# (a) filter out EVs that meet these criteria.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
# Load the dataset
df=pd.read_excel('FEV-data-Excel.xlsx')
# Filter EVs based on the given budget and range
filtered_df = df[(df['Minimal price (gross) [PLN]'] <= 350000) & (df['Range (WLT
# Display the filtered dataframe
filtered_df.head()
```

Out[5]:

	Car full name	Make	Model	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	Type of brakes	Drive type	Battery capacity [kWh]
0	Audi e-tron 55 quattro	Audi	e-tron 55 quattro	345700	360	664	disc (front + rear)	4WD	95.0
8	BMW iX3	BMW	iX3	282900	286	400	disc (front + rear)	2WD (rear)	80.0
15	Hyundai Kona electric 64kWh	Hyundai	Kona electric 64kWh	178400	204	395	disc (front + rear)	2WD (front)	64.0
18	Kia e-Niro 64kWh	Kia	e-Niro 64kWh	167990	204	395	disc (front + rear)	2WD (front)	64.0
20	Kia e-Soul 64kWh	Kia	e-Soul 64kWh	160990	204	395	disc (front + rear)	2WD (front)	64.0

5 rows × 25 columns

In [7]:
```
# (b) Group them by the manufacturer (make)
grouped_by_make =filtered_df.groupby('Make').size().reset_index(name="Number of
# groupby() function is used to group the filtered EVs by the manufacturer (Make
# size() function is used to count the number of rows
# reset_index() function is used to convert this Series into a DataFrame and pro
grouped_by_make
```

Out[7]:

	Make	Number of Cars
0	Audi	1
1	BMW	1
2	Hyundai	1
3	Kia	2
4	Mercedes-Benz	1
5	Tesla	3
6	Volkswagen	3

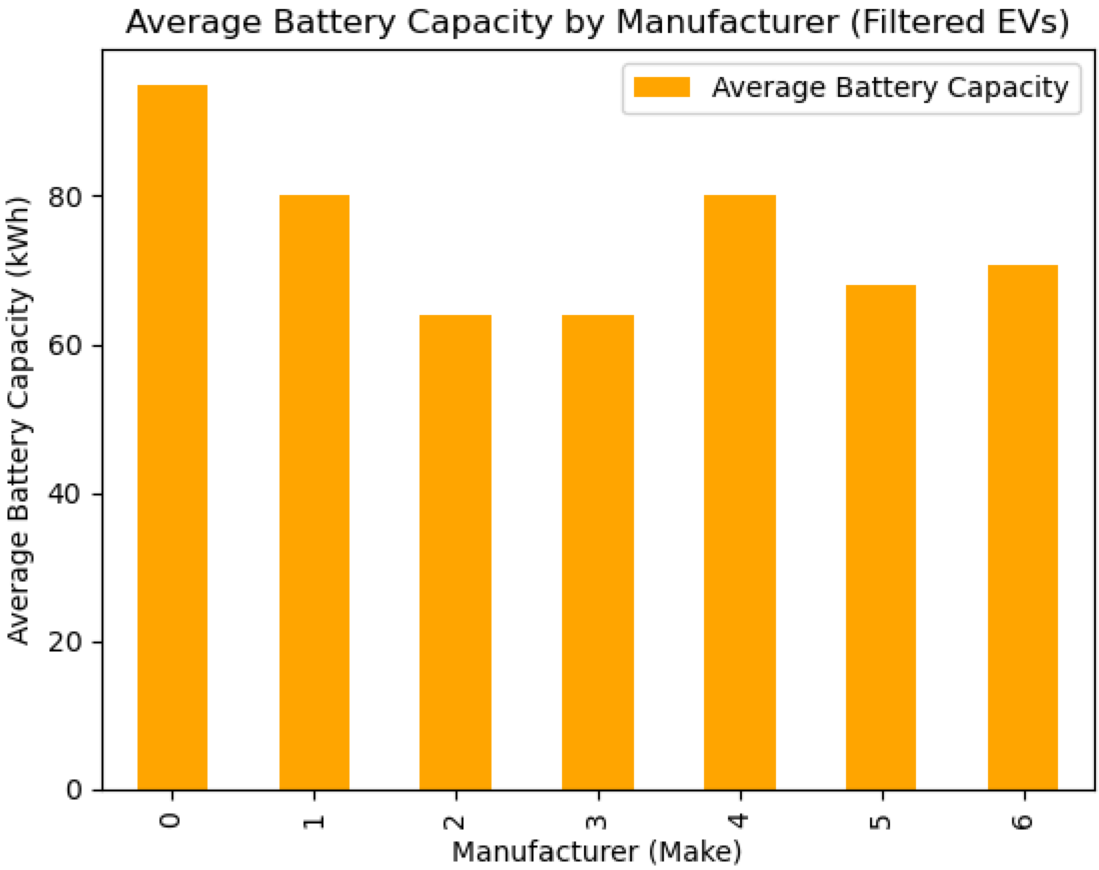
In [9]:
```
# (c) Calculate the average battery capacity for each manufacturer
# Group by manufacturer (make) and calculate the average battery capacity using
average_battery_capacity = filtered_df.groupby('Make')['Battery capacity [kWh]']
average_battery_capacity
```

Out[9]:

	Make	Average Battery Capacity
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

In [11]:
```
# Plot the results
plt.figure(figsize=(12, 6))
average_battery_capacity.plot(kind='bar', color='orange')
plt.title("Average Battery Capacity by Manufacturer (Filtered EVs)")
plt.xlabel("Manufacturer (Make)")
plt.ylabel("Average Battery Capacity (kWh)")
plt.show()
```

```
<Figure size 1200x600 with 0 Axes>
```

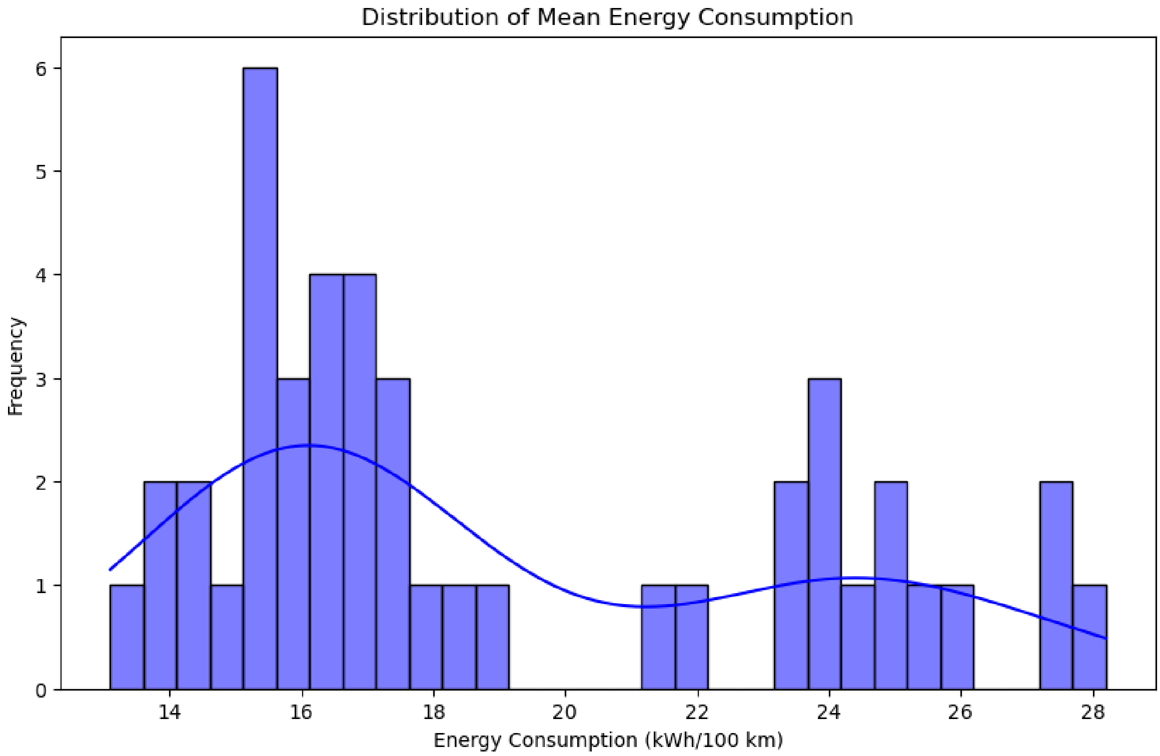


Task 2: You suspect some EVs have unusually high or low energy consumption

In [13]:
```
# Descriptive statistics for energy consumption
print(df['mean - Energy consumption [kWh/100 km]'].describe())

# Plot the distribution
plt.figure(figsize=(10, 6))
# plotting a histogram with a KDE (Kernel Density Estimate) overlay
sns.histplot(df['mean - Energy consumption [kWh/100 km]'], kde=True, bins=30, cc
plt.title("Distribution of Mean Energy Consumption")
plt.xlabel("Energy Consumption (kWh/100 km)")
plt.ylabel("Frequency")
plt.show()
```

```
count    44.000000
mean     18.994318
std       4.418253
min      13.100000
25%      15.600000
50%      17.050000
75%      23.500000
max      28.200000
Name: mean - Energy consumption [kWh/100 km], dtype: float64
```



In [15]:

```
# Find the outliers in the mean- Energy consumption [kWh/100 km] column
Q1 = df['mean - Energy consumption [kWh/100 km]'].quantile(0.25)  # First quarti
Q3 = df['mean - Energy consumption [kWh/100 km]'].quantile(0.75)  # Third quarti
# IQR (Interquartile Range) is a standard method for detecting outliers based on
IQR = Q3 - Q1  # Interquartile Range

# Define lower and upper bound for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter the outliers
outliers = df[(df['mean - Energy consumption [kWh/100 km]'] < lower_bound) |
              (df['mean - Energy consumption [kWh/100 km]'] > upper_bound)]

# Display outliers
outliers
```

Out[15]:

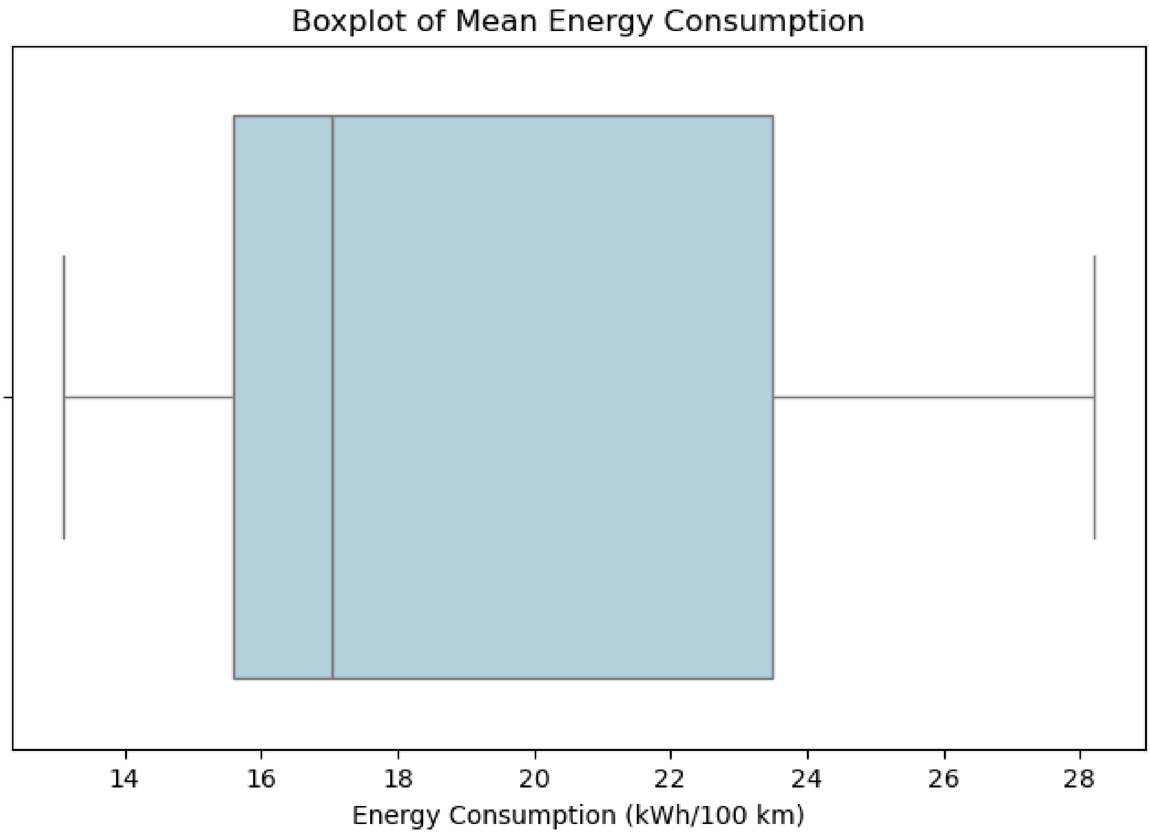
Car full name	Make	Model	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	Type of brakes	Drive type	Battery capacity [kWh]	Range (WLTP) [km]

0 rows × 25 columns

In [17]:

```
# A boxplot helps in quickly identifying outliers
# Set plot size
plt.figure(figsize=(8,5))
# Create a boxplot
sns.boxplot(x=df['mean - Energy consumption [kWh/100 km]'], color='lightblue')
# Add title
plt.title('Boxplot of Mean Energy Consumption')
plt.xlabel('Energy Consumption (kWh/100 km)')
```

```
# Show plot
plt.show()
# Any points outside the whiskers in the boxplot indicate outliers.
```



In [19]:
```
# To differentiate mild and extreme outliers, we can define extreme outliers as
# Define extreme outliers (3 * IQR rule)
extreme_lower_bound = Q1 - 3 * IQR
extreme_upper_bound = Q3 + 3 * IQR

# Filter extreme outliers
extreme_outliers = df[(df['mean - Energy consumption [kWh/100 km]'] < extreme_lo
                      (df['mean - Energy consumption [kWh/100 km]'] > extreme_up

# Display extreme outliers
extreme_outliers
```

Out[19]:

Car full name	Make	Model	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	Type of brakes	Drive type	Battery capacity [kWh]	Range (WLTP) [km]

0 rows × 25 columns

Task 3: Your manager wants to know if there's a strong relationship between battery capacity and range.

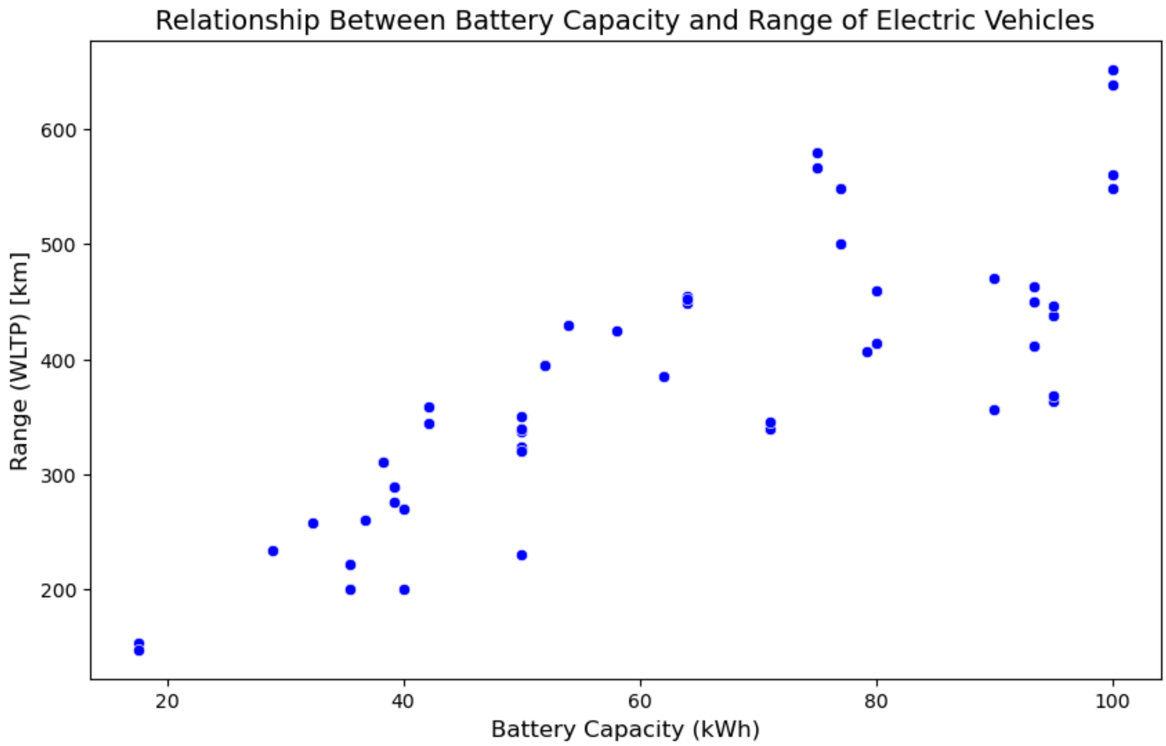
In [21]:
```
# Create a suitable plot to visualize
plt.figure(figsize = (10,6))

# Create scatter plot
```

```
sns.scatterplot(x=df['Battery capacity [kWh]'], y=df['Range (WLTP) [km]'], color

# Add titles and labels
plt.title("Relationship Between Battery Capacity and Range of Electric Vehicles"
plt.xlabel("Battery Capacity (kWh)", fontsize=12)
plt.ylabel("Range (WLTP) [km]", fontsize=12)

# Show plot
plt.show()
```



In [23]:
```
# Calculate the correlation coefficient
correlation = df['Battery capacity [kWh]'].corr(df['Range (WLTP) [km]'])
print(f"Correlation between Battery Capacity and Range: {correlation}")

# Highlighting insights
print("\n### Highlighting Insights ###")

print("\n1. Strong Positive Correlation")
print("- A high correlation exists between battery capacity and driving range.")
print("- Larger battery capacities generally provide longer driving distances.")
print("- Consumers looking for long-range EVs should focus on high-capacity batt

print("\n2. Outliers: When High Battery Capacity Doesn’t Mean Higher Range")
print("- Some EVs with high battery capacity do not have the expected range.")
print("- Possible reasons:")
print("  (a) Inefficient battery technology (not fully utilizing capacity).")
print("  (b) Heavy vehicle weight (reduces efficiency and increases energy consu
print("  (c) Design inefficiencies (power-draining features or poor aerodynamics
print("- Identifying these outliers helps consumers avoid inefficient EV models.

print("\n3. Small Battery EVs: Cost-Effective but Limited Range")
print("- EVs with smaller battery capacities (≤40 kWh) typically offer 150-350 k
print("- Best suited for city commutes and short trips due to affordability and

print("\n4. The Trade-Off Between Cost and Range")
print("- Larger battery EVs are more expensive but offer a greater range.")
print("- Consumers must balance cost vs. range based on their daily driving need
```

```
print("- City drivers may prefer smaller, more affordable EVs.")

print("\n5. Future Trends & Technological Improvements")
print("- Most EVs follow the trend: higher battery capacity = longer range.")
print("- Battery technology is evolving to provide greater range at lower costs.
print("- Future EVs will be more practical and affordable for long-distance trav

print("\n6. Key Consumer Takeaway")
print("- Consumers should assess their driving habits before choosing an EV.")
print("- For long road trips → Choose an EV with a high-capacity battery.")
print("- For city driving → A smaller, cost-effective battery may be sufficient.
```

```
Correlation between Battery Capacity and Range: 0.8104385771936846

### Highlighting Insights ###

1. Strong Positive Correlation
- A high correlation exists between battery capacity and driving range.
- Larger battery capacities generally provide longer driving distances.
- Consumers looking for long-range EVs should focus on high-capacity battery mode
ls.

2. Outliers: When High Battery Capacity Doesn't Mean Higher Range
- Some EVs with high battery capacity do not have the expected range.
- Possible reasons:
  (a) Inefficient battery technology (not fully utilizing capacity).
  (b) Heavy vehicle weight (reduces efficiency and increases energy consumption).
  (c) Design inefficiencies (power-draining features or poor aerodynamics).
- Identifying these outliers helps consumers avoid inefficient EV models.

3. Small Battery EVs: Cost-Effective but Limited Range
- EVs with smaller battery capacities (≤40 kWh) typically offer 150–350 km range.
- Best suited for city commutes and short trips due to affordability and efficien
cy.

4. The Trade-Off Between Cost and Range
- Larger battery EVs are more expensive but offer a greater range.
- Consumers must balance cost vs. range based on their daily driving needs.
- City drivers may prefer smaller, more affordable EVs.

5. Future Trends & Technological Improvements
- Most EVs follow the trend: higher battery capacity = longer range.
- Battery technology is evolving to provide greater range at lower costs.
- Future EVs will be more practical and affordable for long-distance travel.

6. Key Consumer Takeaway
- Consumers should assess their driving habits before choosing an EV.
- For long road trips → Choose an EV with a high-capacity battery.
- For city driving → A smaller, cost-effective battery may be sufficient.
```

Task 4: Build an EV recommendation class

In [25]:
```
# The class should allow users to input their budget, desired range, and battery
class EVRecommendation:
    def __init__(self,df):
        self.df=df
    def recommend_evs(self):
        # Takes user input for budget, desired range, and battery capacity.
        # Filters and returns the top 3 EVs matching the criteria.
        try:
```

```
            # Taking user inputs
            budget = float(input("Enter your budget in PLN: "))
            min_range = float(input("Enter the minimum required range (km): "))
            min_battery_capacity = float(input("Enter the minimum battery capaci
             # Filtering EVs based on user criteria
            filtered_evs = self.df[
            (self.df['Minimal price (gross) [PLN]'] <= budget) &
            (self.df['Range (WLTP) [km]'] >= min_range) &
            (self.df['Battery capacity [kWh]'] >= min_battery_capacity)
            ]
            # Sort by range (descending) and select top 3
            top_evs = filtered_evs.sort_values(by='Range (WLTP) [km]', ascending
            if top_evs.empty:
                print("No EVs match your criteria. Try adjusting your filters.")
                return None
            display(top_evs[['Car full name', 'Make', 'Model', 'Range (WLTP) [km
                             'Minimal price (gross) [PLN]']])
        except ValueError:
            print("Invalid input! Please enter numerical values for budget, rang

# Create an instance of EVRecommendation
ev_recommender = EVRecommendation(df)

# Call the method to take user input and recommend EVs
ev_recommender.recommend_evs()
```

	Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
40	Tesla Model 3 Long Range	Tesla	Model 3 Long Range	580	75.0	235490
41	Tesla Model 3 Performance	Tesla	Model 3 Performance	567	75.0	260490
48	Volkswagen ID.3 Pro S	Volkswagen	ID.3 Pro S	549	77.0	179990

Task 5: Inferential Statistics– Hypothesis Testing

In [27]:

```
# Test whether there is a significant difference in the average Engine power [KM
# Filter Tesla and Audi EVs
tesla_power = df[df['Make'] == 'Tesla']['Engine power [KM]']
audi_power = df[df['Make'] == 'Audi']['Engine power [KM]']

# Calculate Average Engine Power
tesla_avg_power = tesla_power.mean()
audi_avg_power = audi_power.mean()
print(f"Average Engine Power of Tesla: {tesla_avg_power:.2f} KM")
print(f"Average Engine Power of Audi: {audi_avg_power:.2f} KM")

# Perform t-test
t_stat, p_value = stats.ttest_ind(tesla_power, audi_power, equal_var=False)
# using equal_var=False makes the test more accurate for real-world data.
print(f"\nHypothesis Testing Results:")
print(f"T-Statistic: {t_stat:.4f}")
print(f"P-Value: {p_value:.4f}")
```

```
# Interpret Results
alpha = 0.05  # Significance level

if p_value < alpha:
    conclusion = "There is a significant difference in the average engine power
else:
    conclusion = "There is no statistically significant difference in the averag

# Actionable Insights & Recommendations
insights = """
(1) Power Is Not a Key Differentiator:
   - Since Tesla and Audi have similar average engine power, consumers should fo

(2) Additional Performance Metrics Should Be Considered:
   - Instead of just engine power, analyzing acceleration (0-100 km/h), torque,

(3) Tesla vs. Audi: Differentiation in Other Aspects:
   - Tesla is known for longer range and better charging infrastructure, while A

(4) Further Analysis for Specific Models:
   - A brand-wide comparison may overlook performance differences between specif
"""

# Final Recommendations
recommendations = """
For manufacturers:
   - They should highlight and market other performance aspects (battery efficie

For customers:
   - Buyers should consider factors beyond engine power, such as range, pricing,
"""

# Displaying results
print("### Conclusion ###")
print(conclusion)

print("\n### Actionable Insights & Recommendations ###")
print(insights)

print("\n### Final Recommendations ###")
print(recommendations)
```

```
Average Engine Power of Tesla: 533.00 KM
Average Engine Power of Audi: 392.00 KM

Hypothesis Testing Results:
T-Statistic: 1.7940
P-Value: 0.1068
### Conclusion ###
There is no statistically significant difference in the average engine power betw
een Tesla and Audi.

### Actionable Insights & Recommendations ###

(1) Power Is Not a Key Differentiator:
   - Since Tesla and Audi have similar average engine power, consumers should foc
us on other factors like battery efficiency, charging speed, driving range, and p
ricing.

(2) Additional Performance Metrics Should Be Considered:
   - Instead of just engine power, analyzing acceleration (0-100 km/h), torque, o
r power-to-weight ratio might give better insights into actual driving performanc
e.

(3) Tesla vs. Audi: Differentiation in Other Aspects:
   - Tesla is known for longer range and better charging infrastructure, while Au
di may offer superior build quality and luxury interiors. These factors could be
more influential than just engine power when choosing between brands.

(4) Further Analysis for Specific Models:
   - A brand-wide comparison may overlook performance differences between specifi
c models (e.g., Tesla Model S Plaid vs. Audi e-tron GT). Future analysis should b
e model-specific to provide more accurate insights.


### Final Recommendations ###

For manufacturers:
   - They should highlight and market other performance aspects (battery efficien
cy, charging speed) rather than focusing on engine power alone.

For customers:
   - Buyers should consider factors beyond engine power, such as range, pricing,
charging time, and interior features, to make a well-informed decision.
```

Task 6: Project Video Explanation Link

https://drive.google.com/file/d/14RJ75LKMjCXiF068-5V4bb7WLdskDEC5/view?usp=sharing

In [ ]: