Importing all the necessary liraries that are useful for our analysis

[141]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import shapiro,levene, ttest_ind, mannwhitneyu
```

Importing the EV dataset into python

[143]:
```
df = pd.read_excel('FEV-data-Excel.xlsx')
```

[144]:
```
df.describe() # statistical analysis
```

[144]:
```
       Minimal price (gross) [PLN]  Engine power [KM]  Maximum torque [Nm]  \
count                    53.000000          53.000000            53.000000
mean                 246158.509434         269.773585           460.037736
std                  149187.485190         181.298589           261.647000
min                   82050.000000          82.000000           160.000000
25%                  142900.000000         136.000000           260.000000
50%                  178400.000000         204.000000           362.000000
75%                  339480.000000         372.000000           640.000000
max                  794000.000000         772.000000          1140.000000

       Battery capacity [kWh]  Range (WLTP) [km]  Wheelbase [cm]  Length [cm]  \
count               53.000000          53.000000       53.000000    53.000000
mean                62.366038         376.905660      273.581132   442.509434
std                 24.170913         118.817938       22.740518    48.863280
min                 17.600000         148.000000      187.300000   269.500000
25%                 40.000000         289.000000      258.800000   411.800000
50%                 58.000000         364.000000      270.000000   447.000000
75%                 80.000000         450.000000      290.000000   490.100000
max                100.000000         652.000000      327.500000   514.000000

       Width [cm]  Height [cm]  Minimal empty weight [kg]  \
count   53.000000    53.000000                  53.000000
mean   186.241509   155.422642                1868.452830
std     14.280641    11.275358                 470.880867
min    164.500000   137.800000                1035.000000
25%    178.800000   148.100000                1530.000000
```

```
50%    180.900000  155.600000               1685.000000
75%    193.500000  161.500000               2370.000000
max    255.800000  191.000000               2710.000000

       Permissable gross weight [kg]  Maximum load capacity [kg]  \
count                      45.000000                   45.000000
mean                     2288.844444                  520.466667
std                       557.796026                  140.682848
min                      1310.000000                  290.000000
25%                      1916.000000                  440.000000
50%                      2119.000000                  486.000000
75%                      2870.000000                  575.000000
max                      3500.000000                 1056.000000

       Number of seats  Number of doors  Tire size [in]  Maximum speed [kph]  \
count        53.000000        53.000000       53.000000            53.000000
mean          4.905660         4.849057       17.679245           178.169811
std           0.838133         0.455573        1.868500            43.056196
min           2.000000         3.000000       14.000000           123.000000
25%           5.000000         5.000000       16.000000           150.000000
50%           5.000000         5.000000       17.000000           160.000000
75%           5.000000         5.000000       19.000000           200.000000
max           8.000000         5.000000       21.000000           261.000000

       Boot capacity (VDA) [l]  Acceleration 0-100 kph [s]  \
count                52.000000                    50.00000
mean                445.096154                     7.36000
std                 180.178480                     2.78663
min                 171.000000                     2.50000
25%                 315.000000                     4.87500
50%                 425.000000                     7.70000
75%                 558.000000                     9.37500
max                 870.000000                    13.10000

       Maximum DC charging power [kW]  mean - Energy consumption [kWh/100 km]
count                       53.000000                               44.000000
mean                       113.509434                               18.994318
std                         57.166970                                4.418253
min                         22.000000                               13.100000
25%                        100.000000                               15.600000
50%                        100.000000                               17.050000
75%                        150.000000                               23.500000
max                        270.000000                               28.200000
```

[145]:
```
df.shape
```

[145]:
```
(53, 25)
```

[146]:
```
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     int64
 4   Engine power [KM]                        53 non-null     int64
 5   Maximum torque [Nm]                      53 non-null     int64
 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     int64
 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     int64
 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     int64
 18  Number of doors                          53 non-null     int64
 19  Tire size [in]                           53 non-null     int64
 20  Maximum speed [kph]                      53 non-null     int64
 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     int64
 24  mean - Energy consumption [kWh/100 km]   44 non-null     float64
dtypes: float64(10), int64(10), object(5)
memory usage: 10.5+ KB
```

Analysis:

- There are missing values in dataset.

[148]:
```
df.isnull().sum()
```

[148]:
```
Car full name                   0
Make                            0
Model                           0
Minimal price (gross) [PLN]     0
Engine power [KM]               0
Maximum torque [Nm]             0
Type of brakes                  1
```

```
Drive type                                 0
Battery capacity [kWh]                     0
Range (WLTP) [km]                          0
Wheelbase [cm]                             0
Length [cm]                                0
Width [cm]                                 0
Height [cm]                                0
Minimal empty weight [kg]                  0
Permissable gross weight [kg]              8
Maximum load capacity [kg]                 8
Number of seats                            0
Number of doors                            0
Tire size [in]                             0
Maximum speed [kph]                        0
Boot capacity (VDA) [l]                    1
Acceleration 0-100 kph [s]                 3
Maximum DC charging power [kW]             0
mean - Energy consumption [kWh/100 km]     9
dtype: int64
```

Analysis:

- Columns like 'Type of brakes', 'Permissable gross weight [kg]', 'Maximum load capacity [kg]', 'Boot capacity (VDA) [l]', 'Acceleration 0-100 kph [s]', 'mean - Energy consumption [kWh/100 km]' has missing values.

[150]:
```python
(df.isnull().sum()/len(df.index))*100
```

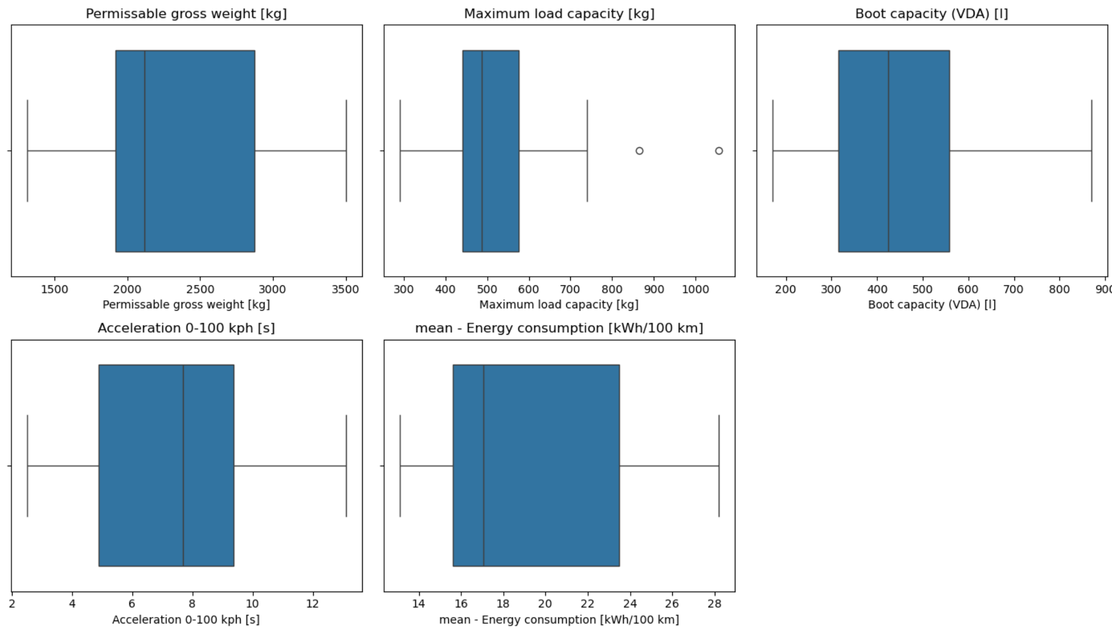
[150]:
```
Car full name                              0.000000
Make                                       0.000000
Model                                      0.000000
Minimal price (gross) [PLN]                0.000000
Engine power [KM]                          0.000000
Maximum torque [Nm]                        0.000000
Type of brakes                             1.886792
Drive type                                 0.000000
Battery capacity [kWh]                     0.000000
Range (WLTP) [km]                          0.000000
Wheelbase [cm]                             0.000000
Length [cm]                                0.000000
Width [cm]                                 0.000000
Height [cm]                                0.000000
Minimal empty weight [kg]                  0.000000
Permissable gross weight [kg]             15.094340
Maximum load capacity [kg]                15.094340
Number of seats                            0.000000
Number of doors                            0.000000
```

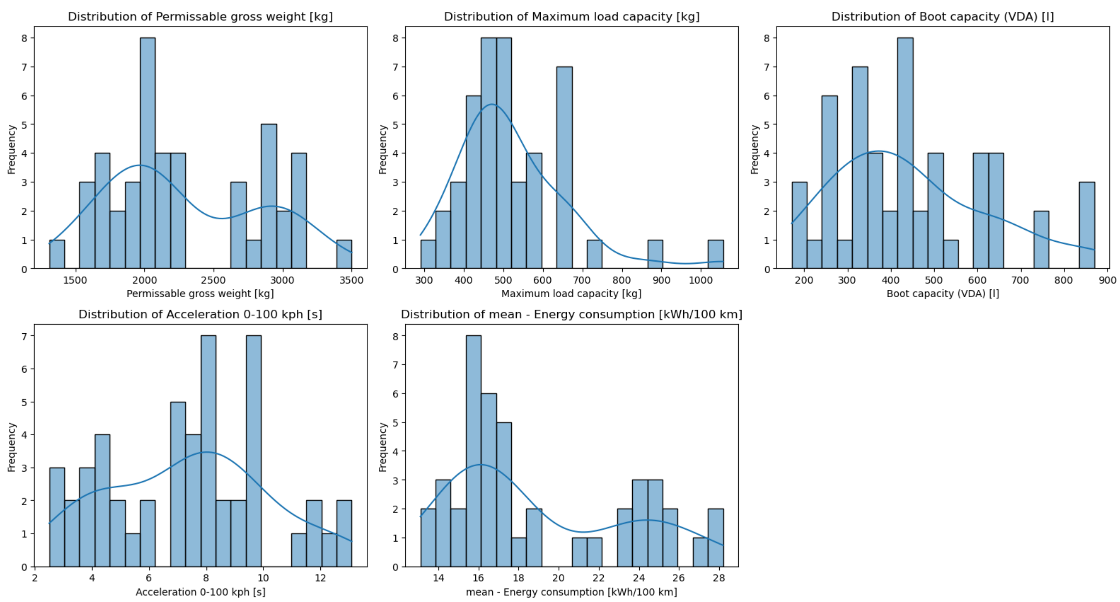
```
Tire size [in]                                 0.000000
Maximum speed [kph]                            0.000000
Boot capacity (VDA) [l]                        1.886792
Acceleration 0-100 kph [s]                     5.660377
Maximum DC charging power [kW]                 0.000000
mean - Energy consumption [kWh/100 km]        16.981132
dtype: float64
```

Analysis: There are more number of missing values in 3 columns i.e 'Permissable gross weight [kg]', 'Maximum load capacity [kg]', 'mean - Energy consumption [kWh/100 km]'

Distribution Analysis: To understand the shape of data and choose the correct imputation strategy, I plotted histograms and boxplots for all numerical columns.

[153]:
```
numeric_cols = [
    'Permissable gross weight [kg]',
    'Maximum load capacity [kg]',
    'Boot capacity (VDA) [l]',
    'Acceleration 0-100 kph [s]',
    'mean - Energy consumption [kWh/100 km]'
]

plt.figure(figsize=(14, 8))

for i, col in enumerate(numeric_cols, 1):
    plt.subplot(2, 3, i)
    sns.boxplot(x=df[col])
    plt.title(col)

plt.tight_layout()
plt.show()

plt.figure(figsize=(16, 25))

for i, col in enumerate(numeric_cols, 1):
    plt.subplot(6, 3, i)  # adjust rows/cols based on number of columns
    sns.histplot(df[col], kde=True, bins=20)
    plt.title(f"Distribution of {col}")
    plt.xlabel(col)
    plt.ylabel("Frequency")

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





Analysis:

- All five numerical columns with missing values show mild-to-moderate skewness.
- Maximum load capacity has strong outliers, visible in the boxplot.
- Acceleration and energy consumption columns are right-skewed, typical for EVs.
- Because of these characteristics, median imputation is the most appropriate choice for handling missing values.

- for categorical column like types of brake, mode imputation is better option.

[155]:
```python
numeric_cols = [
    'Permissable gross weight [kg]',
    'Maximum load capacity [kg]',
    'Boot capacity (VDA) [l]',
    'Acceleration 0-100 kph [s]',
    'mean - Energy consumption [kWh/100 km]'
]
df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].median())

df['Type of brakes'] = df['Type of brakes'].fillna(df['Type of brakes'].
  ↪mode()[0])
```

[156]:
```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     int64
 4   Engine power [KM]                       53 non-null     int64
 5   Maximum torque [Nm]                     53 non-null     int64
 6   Type of brakes                          53 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     int64
 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     int64
 15  Permissable gross weight [kg]           53 non-null     float64
 16  Maximum load capacity [kg]              53 non-null     float64
 17  Number of seats                         53 non-null     int64
 18  Number of doors                         53 non-null     int64
 19  Tire size [in]                          53 non-null     int64
 20  Maximum speed [kph]                     53 non-null     int64
 21  Boot capacity (VDA) [l]                 53 non-null     float64
 22  Acceleration 0-100 kph [s]              53 non-null     float64
 23  Maximum DC charging power [kW]          53 non-null     int64
 24  mean - Energy consumption [kWh/100 km]  53 non-null     float64
dtypes: float64(10), int64(10), object(5)
memory usage: 10.5+ KB
```

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

- a) Your task is to filter out EVs that meet these criteria.
- b) Group them by the manufacturer (Make).
- c) Calculate the average battery capacity for each manufacturer.

[158]:
```
cust_choice = df[(df['Minimal price (gross) [PLN]'] <= 350000) & (df['Range␣
↪(WLTP) [km]'] >= 400 )]
cust_choice
```

[158]:
```
                       Car full name           Make  \
0            Audi e-tron 55 quattro           Audi
8                            BMW iX3            BMW
15        Hyundai Kona electric 64kWh        Hyundai
18                 Kia e-Niro 64kWh            Kia
20                 Kia e-Soul 64kWh            Kia
22                Mercedes-Benz EQC  Mercedes-Benz
39  Tesla Model 3 Standard Range Plus          Tesla
40           Tesla Model 3 Long Range          Tesla
41          Tesla Model 3 Performance          Tesla
47    Volkswagen ID.3 Pro Performance     Volkswagen
48              Volkswagen ID.3 Pro S     Volkswagen
49              Volkswagen ID.4 1st     Volkswagen

                        Model  Minimal price (gross) [PLN]  \
0            e-tron 55 quattro                       345700
8                          iX3                       282900
15          Kona electric 64kWh                      178400
18                e-Niro 64kWh                       167990
20                e-Soul 64kWh                       160990
22                         EQC                       334700
39  Model 3 Standard Range Plus                      195490
40          Model 3 Long Range                       235490
41         Model 3 Performance                       260490
47         ID.3 Pro Performance                      155890
48                  ID.3 Pro S                       179990
49                    ID.4 1st                       202390

    Engine power [KM]  Maximum torque [Nm]         Type of brakes  \
0                 360                  664      disc (front + rear)
8                 286                  400      disc (front + rear)
15                204                  395      disc (front + rear)
18                204                  395      disc (front + rear)
20                204                  395      disc (front + rear)
22                408                  760      disc (front + rear)
39                285                  450      disc (front + rear)
```

40	372	510	disc (front + rear)
41	480	639	disc (front + rear)
47	204	310	disc (front) + drum (rear)
48	204	310	disc (front) + drum (rear)
49	204	310	disc (front) + drum (rear)

	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	…	\
0	4WD	95.0	438	…	
8	2WD (rear)	80.0	460	…	
15	2WD (front)	64.0	449	…	
18	2WD (front)	64.0	455	…	
20	2WD (front)	64.0	452	…	
22	4WD	80.0	414	…	
39	2WD (rear)	54.0	430	…	
40	4WD	75.0	580	…	
41	4WD	75.0	567	…	
47	2WD (rear)	58.0	425	…	
48	2WD (rear)	77.0	549	…	
49	2WD (rear)	77.0	500	…	

	Permissable gross weight [kg]	Maximum load capacity [kg]	\
0	3130.0	640.0	
8	2725.0	540.0	
15	2170.0	485.0	
18	2230.0	493.0	
20	1682.0	498.0	
22	2940.0	445.0	
39	2119.0	486.0	
40	2119.0	486.0	
41	2119.0	486.0	
47	2270.0	540.0	
48	2280.0	412.0	
49	2660.0	661.0	

	Number of seats	Number of doors	Tire size [in]	Maximum speed [kph]	\
0	5	5	19	200	
8	5	5	19	180	
15	5	5	17	167	
18	5	5	17	167	
20	5	5	17	167	
22	5	5	19	180	
39	5	5	18	225	
40	5	5	18	233	
41	5	5	20	261	
47	5	5	18	160	
48	5	5	19	160	
49	5	5	20	160	

```
    Boot capacity (VDA) [l]  Acceleration 0-100 kph [s]  \
0                     660.0                        5.7
8                     510.0                        6.8
15                    332.0                        7.6
18                    451.0                        7.8
20                    315.0                        7.9
22                    500.0                        5.1
39                    425.0                        5.6
40                    425.0                        4.4
41                    425.0                        3.3
47                    385.0                        7.3
48                    385.0                        7.9
49                    543.0                        8.5

    Maximum DC charging power [kW]  mean - Energy consumption [kWh/100 km]
0                              150                                   24.45
8                              150                                   18.80
15                             100                                   15.40
18                             100                                   15.90
20                             100                                   15.70
22                             110                                   21.85
39                             150                                   17.05
40                             150                                   17.05
41                             150                                   17.05
47                             100                                   15.40
48                             125                                   15.90
49                             125                                   18.00

[12 rows x 25 columns]
```

Analysis:

- There are only 12 cars whose range is >= 400 km and price is <= 350000 PLN.

- These include brands like Audi,BMW,Hyundai,Kia,Mercedes-Benz,Tesla,Volkswagen.This means that there is very high competition in mid-range EV segment.

- Tesla and Volkswagen stand out for delivering high range at competitive prices.
- Most of the brands offer higher range between 430-580 km making it suitable for highways as well as cities.

[160]:
```
grouped = cust_choice.groupby('Make')
```

[161]:
```
grouped['Battery capacity [kWh]'].mean()
```

[161]:
```
Make
Audi             95.000000
BMW              80.000000
Hyundai          64.000000
Kia              64.000000
Mercedes-Benz    80.000000
Tesla            68.000000
Volkswagen       70.666667
Name: Battery capacity [kWh], dtype: float64
```

Analysis:

- Premium brands like Audi, BMW, Mercedes-Benz has more battery capacity although their range is less.
- Tesla and Volkswagen offer higher range although their battery capacity is less.

Task 2: You suspect some EVs have unusually high or low energy consumption. Find the outliers in the mean - Energy consumption [kWh/100 km] column.

[164]:
```python
Q1 = df['mean - Energy consumption [kWh/100 km]'].quantile(0.25)
Q3 = df['mean - Energy consumption [kWh/100 km]'].quantile(0.75)
IQR = Q3 - Q1
LB = Q1 - 1.5*IQR
UB = Q3 + 1.5*IQR
outliers = df[(df['mean - Energy consumption [kWh/100 km]'] < LB) | (df['mean -␣
↪Energy consumption [kWh/100 km]'] > UB)]
outliers
```

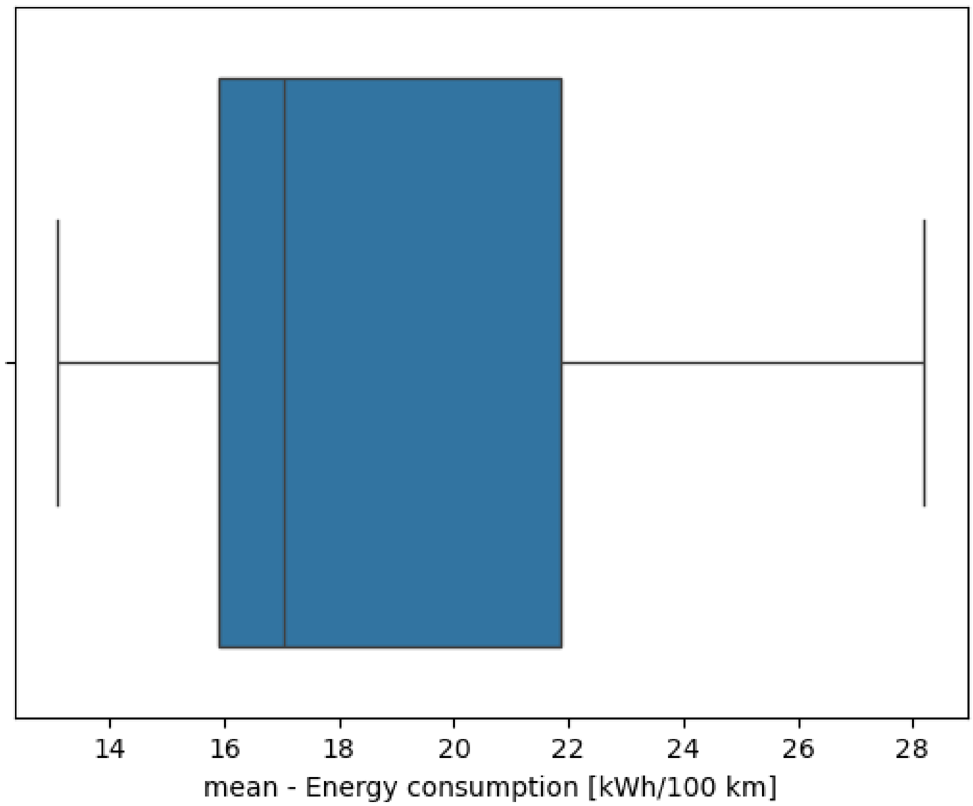
[164]:
```
Empty DataFrame
Columns: [Car full name, Make, Model, Minimal price (gross) [PLN], Engine power
[KM], Maximum torque [Nm], Type of brakes, Drive type, Battery capacity [kWh],
Range (WLTP) [km], Wheelbase [cm], Length [cm], Width [cm], Height [cm], Minimal
empty weight [kg], Permissable gross weight [kg], Maximum load capacity [kg],
Number of seats, Number of doors, Tire size [in], Maximum speed [kph], Boot
capacity (VDA) [l], Acceleration 0-100 kph [s], Maximum DC charging power [kW],
mean - Energy consumption [kWh/100 km]]
Index: []

[0 rows x 25 columns]
```

[165]:
```python
df['mean - Energy consumption [kWh/100 km]'].describe()
```

[165]:
```
count    53.000000
mean     18.664151
std       4.084791
min      13.100000
25%      15.900000
```

```
50%      17.050000
75%      21.850000
max      28.200000
Name: mean - Energy consumption [kWh/100 km], dtype: float64
```

[166]:
```python
sns.boxplot(x=df['mean - Energy consumption [kWh/100 km]'])
plt.show()
```



Analysis:

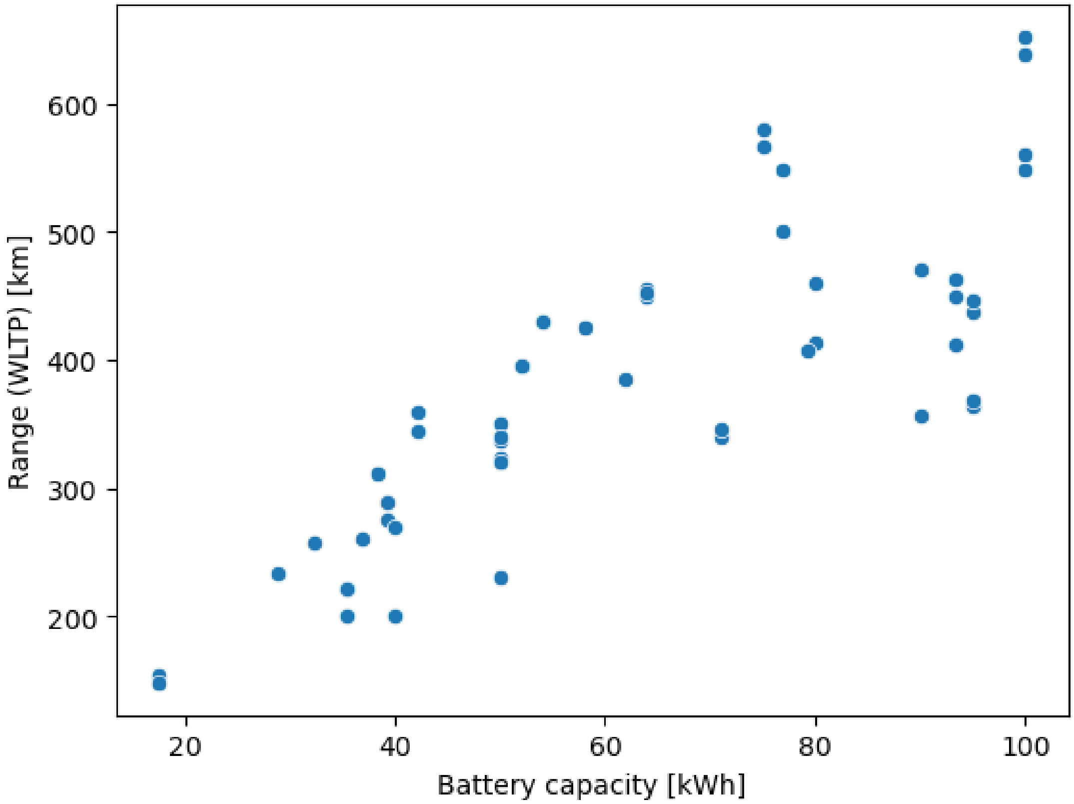
- Using the IQR method, no outliers were detected in the mean energy consumption (kWh/100 km) column.
- This indicates that the EV energy consumption values are consistent across models and fall within the expected range for electric vehicles (typically 14–25 kWh/100 km).
- The data appears clean, with no unusually high or low energy usage values.

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

a) Create a suitable plot to visualize.

b) Highlight any insights.)

[169]:
```python
sns.scatterplot(x=df['Battery capacity [kWh]'], y=df['Range (WLTP) [km]'])
plt.show()
```



Analysis: The scatter plot is used to show relationship between 2 variables. It shows a clear positive correlation between battery capacity and driving range. EVs with larger batteries consistently achieve higher ranges. However, cars with similar battery capacities show range variations, indicating that efficiency, vehicle design, and aerodynamics also play important roles. No significant outliers are present, and the trend supports that battery capacity is a strong predictor of range in electric vehicles.

Task 4: Build an EV recommendation class. The class should allow users to input their budget, desired range, and battery capacity. The class should then return the top three EV matching their criteria.

[172]:
```python
import pandas as pd

class EVRecommender:
    """
    Simple recommender for EVs based on:
    - budget (max price in PLN)
    - desired range (min WLTP range in km)
```

```python
    - desired battery capacity (min kWh)
    """

    def __init__(self, df: pd.DataFrame):
        # store a copy so original df is not modified
        self.df = df.copy()

    def recommend(self, budget: float, min_range: float, min_battery: float,␣
↪top_n: int = 3):
        """
        Returns top_n EVs that:
        - cost <= budget
        - have range >= min_range
        - have battery capacity >= min_battery

        EVs are sorted by:
        1) higher range first
        2) lower price (tie-breaker)
        """
        mask = (
            (self.df['Minimal price (gross) [PLN]'] <= budget) &
            (self.df['Range (WLTP) [km]'] >= min_range) &
            (self.df['Battery capacity [kWh]'] >= min_battery)
        )

        filtered = self.df[mask].copy()

        if filtered.empty:
            print("No EVs match the given criteria.")
            return filtered  # empty DataFrame

        # sort: highest range first, then lowest price
        filtered = filtered.sort_values(
            by=['Range (WLTP) [km]', 'Minimal price (gross) [PLN]'],
            ascending=[False, True]
        )

        cols_to_show = [
            'Car full name',
            'Make',
            'Model',
            'Minimal price (gross) [PLN]',
            'Battery capacity [kWh]',
            'Range (WLTP) [km]'
        ]

        return filtered[cols_to_show].head(top_n)
```

[173]:
```
recommender = EVRecommender(df)

top_cars = recommender.recommend(
    budget=300000,
    min_range=400,
    min_battery=60
)

top_cars
```

[173]:
```
                  Car full name        Make                 Model  \
40   Tesla Model 3 Long Range       Tesla   Model 3 Long Range
41  Tesla Model 3 Performance       Tesla  Model 3 Performance
48       Volkswagen ID.3 Pro S  Volkswagen           ID.3 Pro S

    Minimal price (gross) [PLN]  Battery capacity [kWh]  Range (WLTP) [km]
40                       235490                    75.0                580
41                       260490                    75.0                567
48                       179990                    77.0                549
```

Analysis:

- I have created EVRecommender class which will recommend user top 3 EV's based on price, battery capacity and range which user wants.First priority is given to range and second priority is given to price, so it will return EV's based on these things.

Task 5: Inferential Statistics – Hypothesis Testing Test whether there is a significant difference in the average Engine power [KM] of vehicles manufactured by two leading manufacturers i.e. Tesla and Audi. What insights can you draw from the test results? Recommendations and Conclusion: Provide actionable insights based on your analysis. (Conduct a two sample t-test using ttest_ind from scipy.stats module)

- Null Hypothesis: Average Engine Power of Tesla = Average Engine Power of Audi
- Alternate Hypothesis: Average Engine Power of Tesla != Average Engine Power of Audi
- significance level = 5%

[177]:
```
sam1 = df[df['Make'] == 'Audi']     # filtered out Audi data
sam1_avg = sam1['Engine power [KM]'].mean()  # average engine power of Audi
sam2 = df[df['Make'] == 'Tesla']    # filtered out Tesla data
sam2_avg = sam2['Engine power [KM]'].mean()  # average engine power of Tesla

# checking whether both samples are normal or not using Shakiro Wilk test
stat_audi, p_audi = shapiro(sam1['Engine power [KM]'])
stat_tesla, p_tesla = shapiro(sam2['Engine power [KM]'])
print("p-value of audi for normality check:",p_audi)
print("p-value of tesla for normality check:",p_tesla)

# Normality assumption fails, so we will perform Mann Whitney U Rank test
```

```
u_stat, p_value = mannwhitneyu(sam1['Engine power [KM]'], sam2['Engine power␣
↪[KM]'], alternative='two-sided')
print("p-value for mann whitney u rank test:",p_value) # p=13% > 5% so we fail␣
↪to reject null hypothesis.

# But in task it is mentioned to perform ttest_ind test although normality␣
↪assumption failed, therefore i am performing ttest_ind test
# first we will perform Lavene's test to pero
stat , p_val = levene(sam1['Engine power [KM]'], sam2['Engine power [KM]'])
print("p-value for variance equality check:",p_val) # p=0.21 > 0.05 which means␣
↪that variance are equal

# performing ttest_ind test
stat, p_val = ttest_ind(sam1['Engine power [KM]'], sam2['Engine power [KM]'],␣
↪equal_var=True)
print("p-value for ttest_ind:",p_val) # p=0.11 > 0.05 so we fail to reject null␣
↪hypothesis
```

```
p-value of audi for normality check: 0.04407741501927376
p-value of tesla for normality check: 0.3819012939929962
p-value for mann whitney u rank test: 0.13093895003234252
p-value for variance equality check: 0.21961763884678553
p-value for ttest_ind: 0.11672692675082785
```

Analysis:

- Conclusion: Both the t-test (as required) and the Mann–Whitney U test show that there is no statistically significant difference in the average Engine Power between Tesla and Audi vehicles in this dataset. p-values from both methods are greater than 0.05, meaning we fail to reject the null hypothesis.
- Tesla and Audi offer comparable engine power in their EV segments.
- Audi's vehicles may appear slightly more varied (due to non-normal distribution), but average performance remains similar.
- Customers choosing between Tesla and Audi should focus on:
  range
  price
  charging speed
  features
  rather than engine power.

[ ]:

Recommendations:
- Improve efficiency rather than just battery capacity.
- Adjust pricing for low-value score models.
- Focus more on mid-range EV models.