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

df = pd.read_csv('bmw.csv')

df.shape
```

```
(10781, 9)
```

```python
df.head(10)
```

```
       model  year  price transmission  mileage fuelType  tax   mpg  \
0   5 Series  2014  11200    Automatic    67068   Diesel  125  57.6
1   6 Series  2018  27000    Automatic    14827   Petrol  145  42.8
2   5 Series  2016  16000    Automatic    62794   Diesel  160  51.4
3   1 Series  2017  12750    Automatic    26676   Diesel  145  72.4
4   7 Series  2014  14500    Automatic    39554   Diesel  160  50.4
5   5 Series  2016  14900    Automatic    35309   Diesel  125  60.1
6   5 Series  2017  16000    Automatic    38538   Diesel  125  60.1
7   2 Series  2018  16250       Manual    10401   Petrol  145  52.3
8   4 Series  2017  14250       Manual    42668   Diesel   30  62.8
9   5 Series  2016  14250    Automatic    36099   Diesel   20  68.9

   engineSize
0         2.0
1         2.0
2         3.0
3         1.5
4         3.0
5         2.0
6         2.0
7         1.5
8         2.0
9         2.0
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10781 entries, 0 to 10780
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   model         10781 non-null  object
 1   year          10781 non-null  int64
 2   price         10781 non-null  int64
 3   transmission  10781 non-null  object
 4   mileage       10781 non-null  int64
 5   fuelType      10781 non-null  object
 6   tax           10781 non-null  int64
```

```
 7   mpg           10781 non-null  float64
 8   engineSize    10781 non-null  float64
dtypes: float64(2), int64(4), object(3)
memory usage: 758.2+ KB
```

```python
pd.isnull(df)
```

```
       model   year  price  transmission  mileage  fuelType    tax  
mpg  \
0      False  False  False         False    False     False  False  
False   
1      False  False  False         False    False     False  False  
False   
2      False  False  False         False    False     False  False  
False   
3      False  False  False         False    False     False  False  
False   
4      False  False  False         False    False     False  False  
False   
...      ...    ...    ...           ...      ...       ...    ...  
...   
10776  False  False  False         False    False     False  False  
False   
10777  False  False  False         False    False     False  False  
False   
10778  False  False  False         False    False     False  False  
False   
10779  False  False  False         False    False     False  False  
False   
10780  False  False  False         False    False     False  False  
False   

       engineSize  
0           False  
1           False  
2           False  
3           False  
4           False  
...           ...  
10776       False  
10777       False  
10778       False  
10779       False  
10780       False  

[10781 rows x 9 columns]
```

```python
# check full null Values
pd.isnull(df).sum()
```

```
model           0
year            0
price           0
transmission    0
mileage         0
fuelType        0
tax             0
mpg             0
engineSize      0
dtype: int64
```

```
df.dropna(inplace=True)

print("\nStatistical Summary:")
print(df.describe())
```

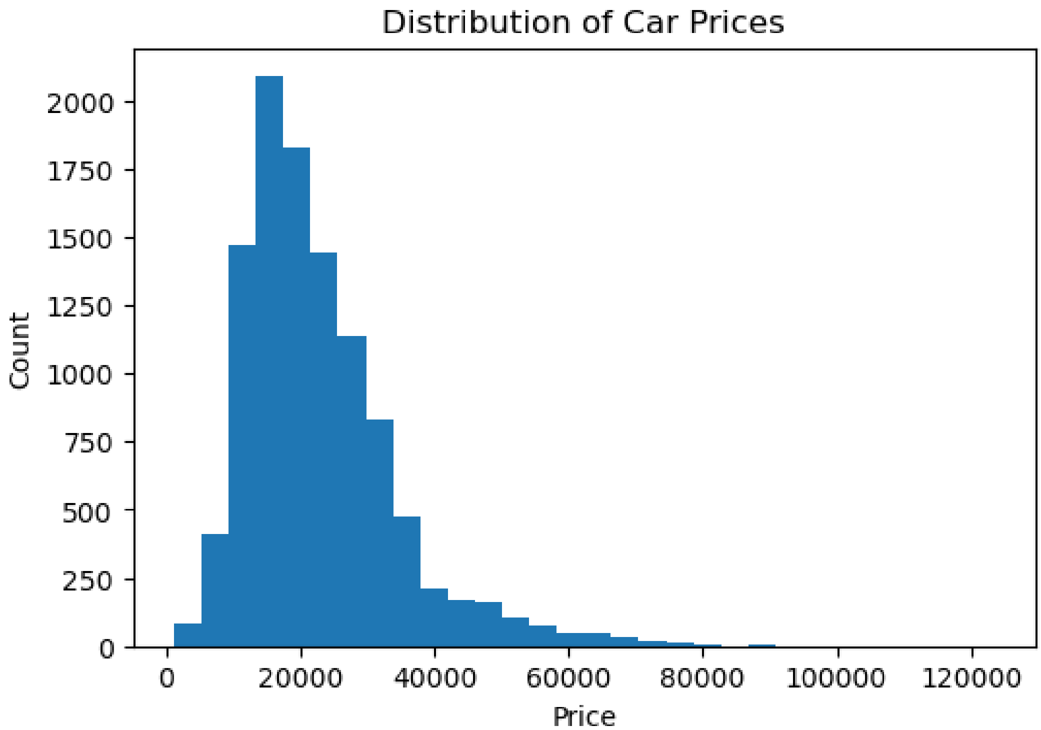
```
Statistical Summary:
               year          price        mileage            tax
mpg  \
count  10781.000000   10781.000000   10781.000000   10781.000000
10781.000000
mean    2017.078935   22733.408867   25496.986550     131.702068
56.399035
std        2.349038   11415.528189   25143.192559      61.510755
31.336958
min     1996.000000    1200.000000       1.000000       0.000000
5.500000
25%     2016.000000   14950.000000    5529.000000     135.000000
45.600000
50%     2017.000000   20462.000000   18347.000000     145.000000
53.300000
75%     2019.000000   27940.000000   38206.000000     145.000000
62.800000
max     2020.000000  123456.000000  214000.000000     580.000000
470.800000

         engineSize
count  10781.000000
mean       2.167767
std        0.552054
min        0.000000
25%        2.000000
50%        2.000000
75%        2.000000
max        6.600000
```

```
# Data Cleaning
df = df.drop_duplicates()
```

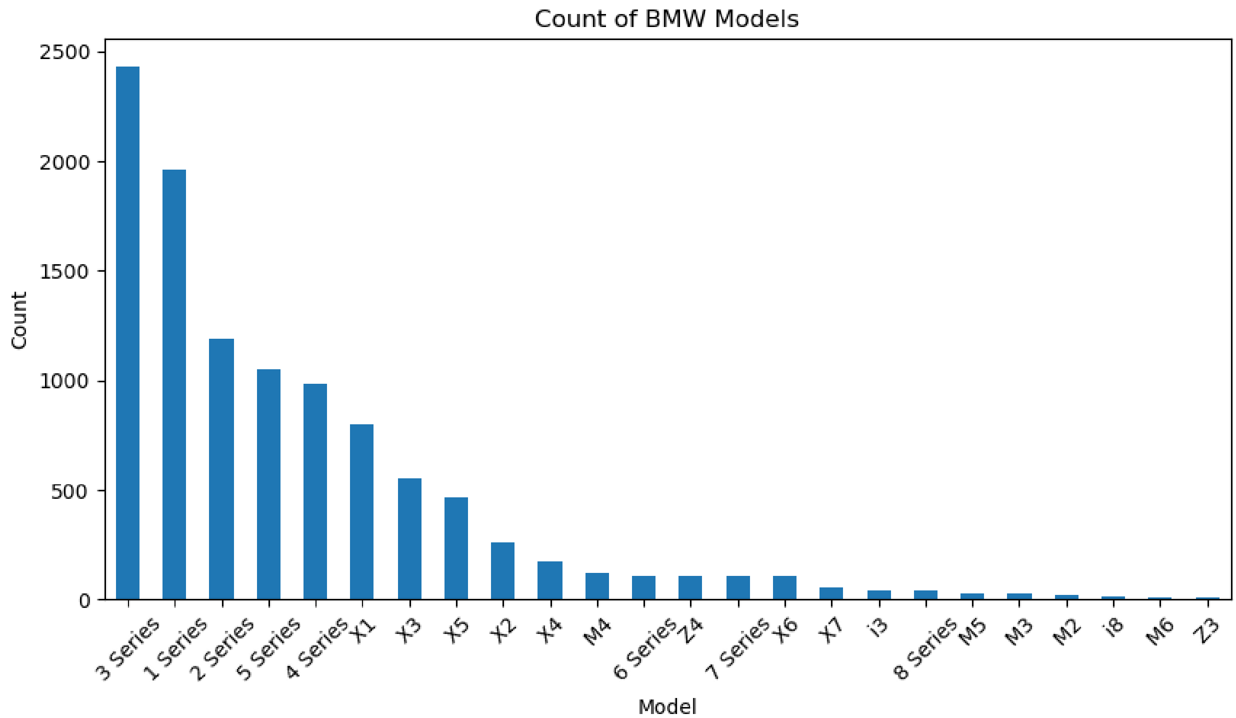
```python
# Handle missing values
df = df.ffill()   # forward fill (new recommended syntax)

print("\ncleaned Dataset Info:")
print(df.info())
```

```
cleaned Dataset Info:
<class 'pandas.core.frame.DataFrame'>
Index: 10664 entries, 0 to 10780
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   model         10664 non-null  object
 1   year          10664 non-null  int64
 2   price         10664 non-null  int64
 3   transmission  10664 non-null  object
 4   mileage       10664 non-null  int64
 5   fuelType      10664 non-null  object
 6   tax           10664 non-null  int64
 7   mpg           10664 non-null  float64
 8   engineSize    10664 non-null  float64
dtypes: float64(2), int64(4), object(3)
memory usage: 833.1+ KB
None
```

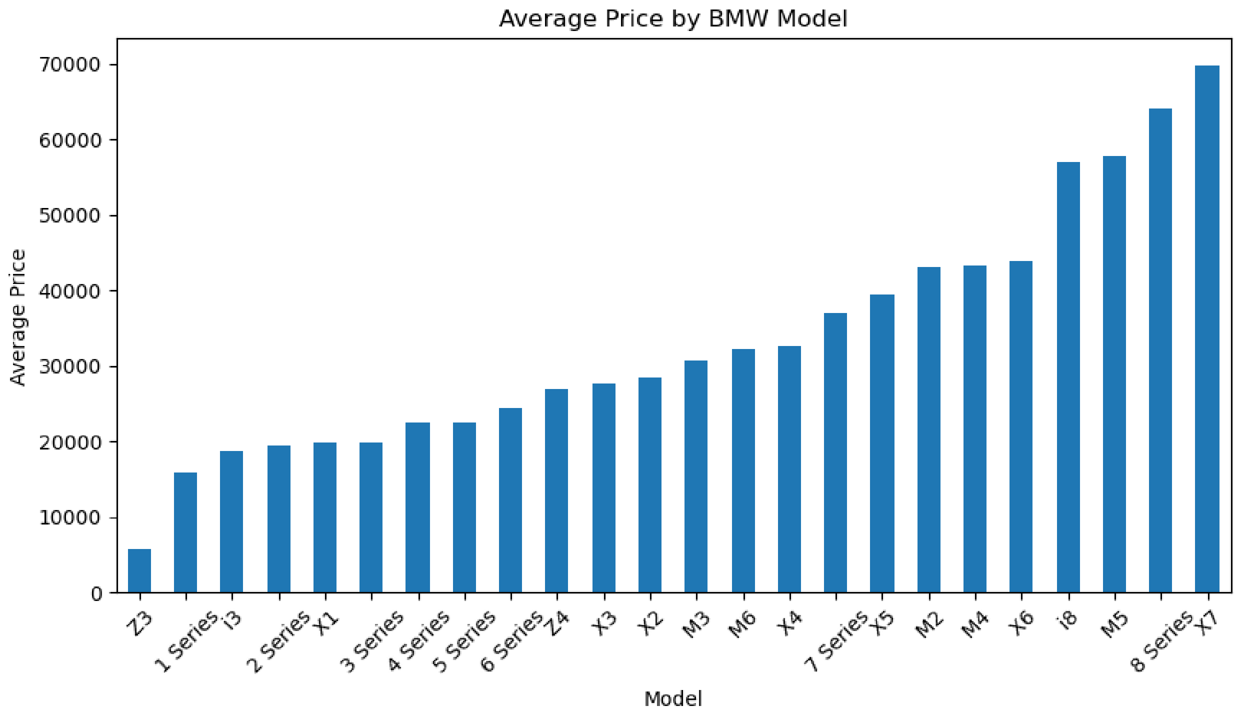
```python
if 'price' in df.columns:
    plt.figure(figsize=(6,4))
    plt.hist(df['price'], bins=30)
    plt.title("Distribution of Car Prices")
    plt.xlabel("Price")
    plt.ylabel("Count")
    plt.show()
```



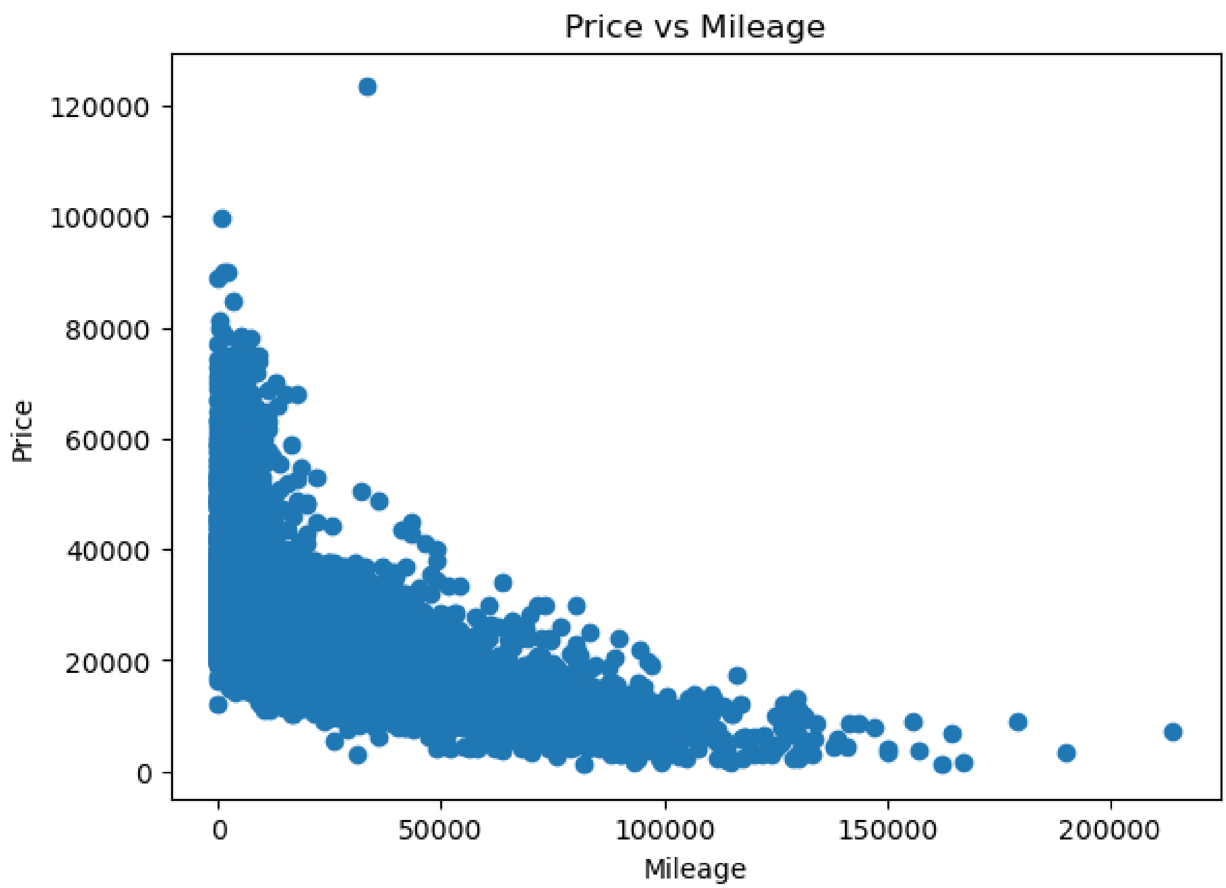

```
if 'model' in df.columns:
    plt.figure(figsize=(10,5))
    df['model'].value_counts().plot(kind='bar')
    plt.title("Count of BMW Models")
    plt.xlabel("Model")
    plt.ylabel("Count")
    plt.xticks(rotation=45)
    plt.show()
```



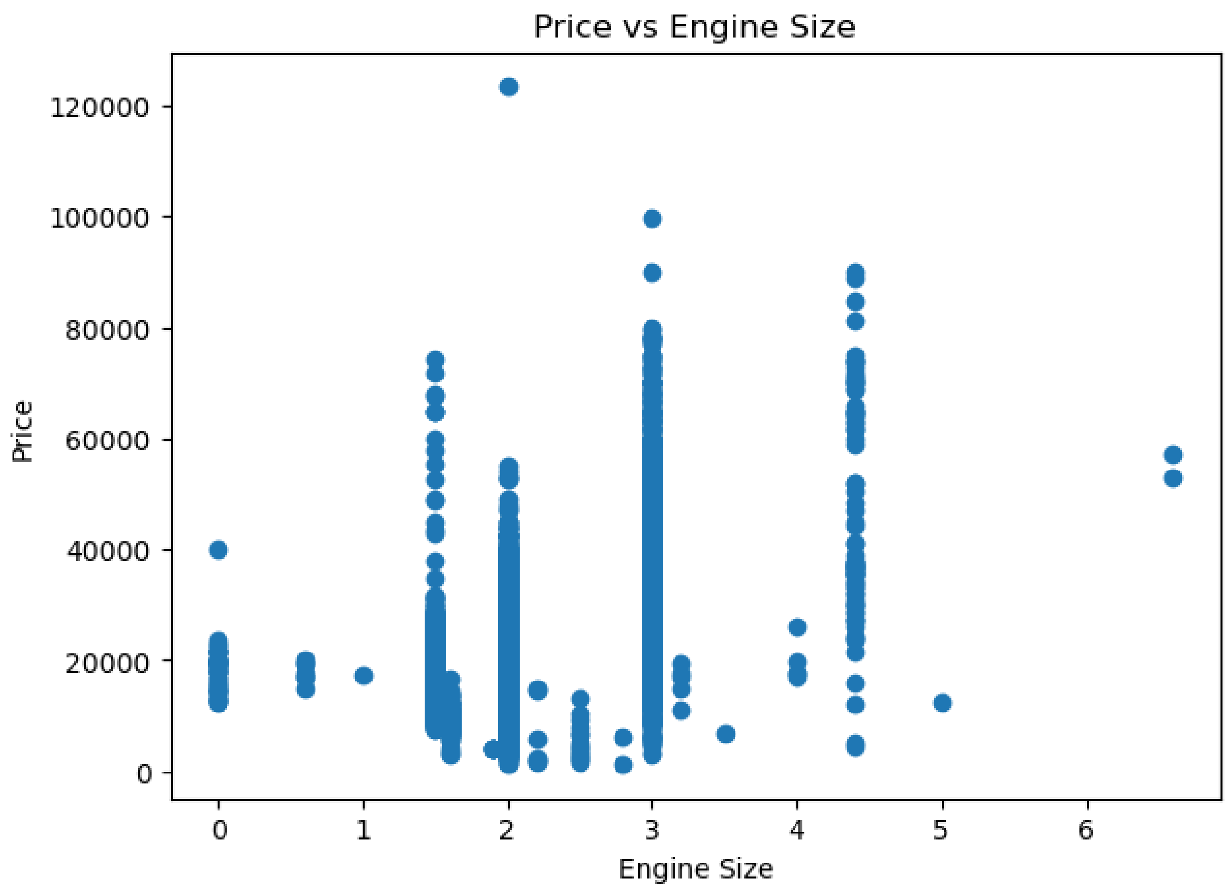

```
if 'price' in df.columns and 'model' in df.columns:
    plt.figure(figsize=(10,5))
    df.groupby('model')['price'].mean().sort_values().plot(kind='bar')
    plt.title("Average Price by BMW Model")
    plt.xlabel("Model")
    plt.ylabel("Average Price")
    plt.xticks(rotation=45)
    plt.show()
```



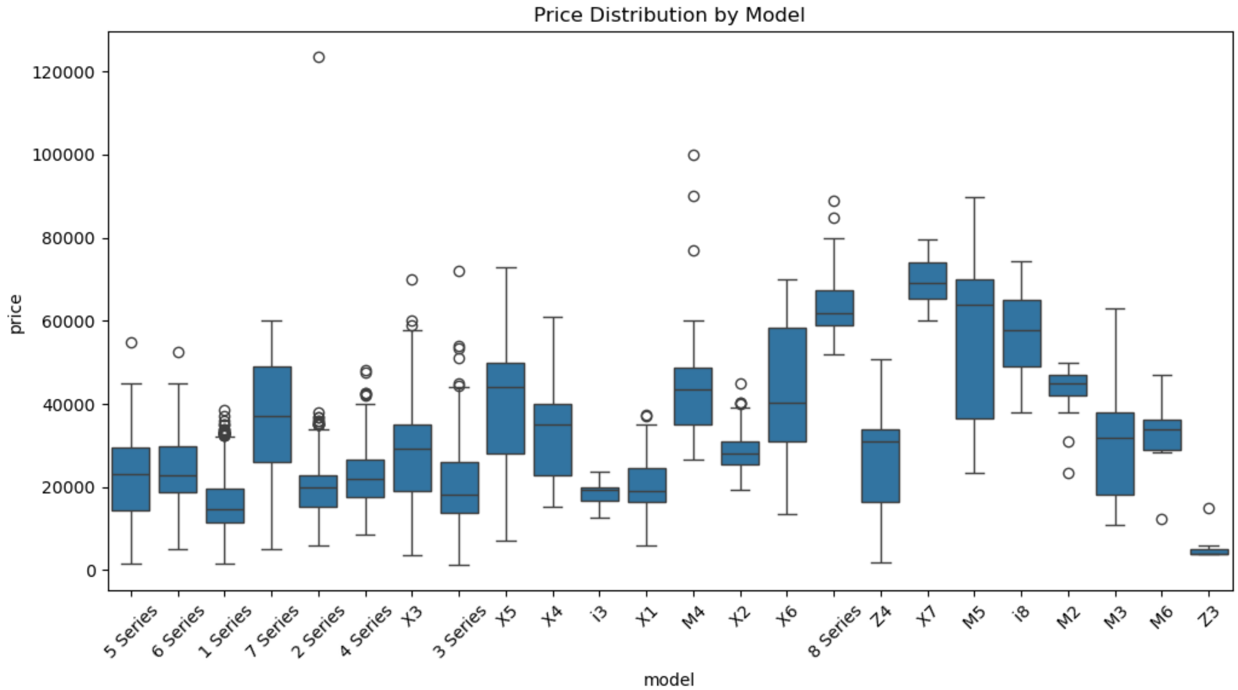

```python
if 'mileage' in df.columns and 'price' in df.columns:
    plt.figure(figsize=(7,5))
    plt.scatter(df['mileage'], df['price'])
    plt.title("Price vs Mileage")
    plt.xlabel("Mileage")
    plt.ylabel("Price")
    plt.show()
```



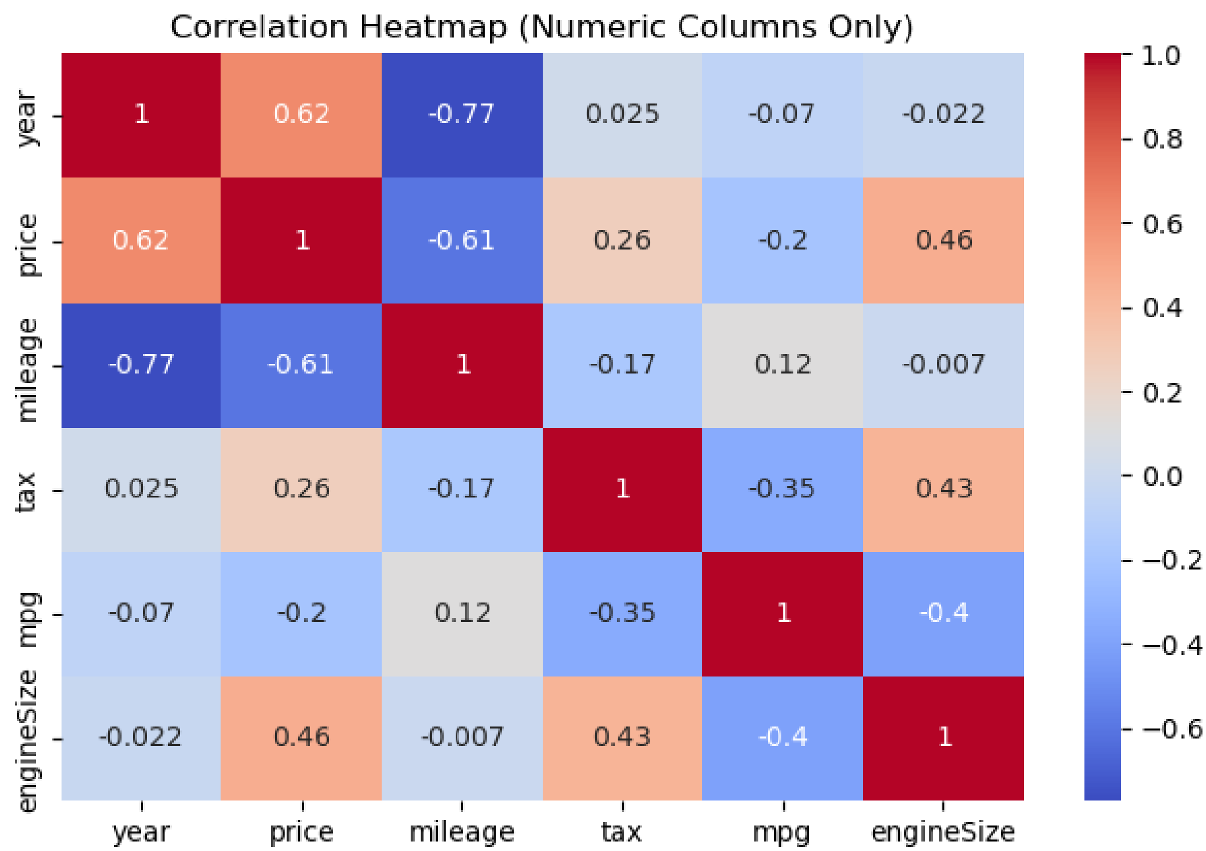

```
if 'engineSize' in df.columns and 'price' in df.columns:
    plt.figure(figsize=(7,5))
    plt.scatter(df['engineSize'], df['price'])
    plt.title("Price vs Engine Size")
    plt.xlabel("Engine Size")
    plt.ylabel("Price")
    plt.show()
```



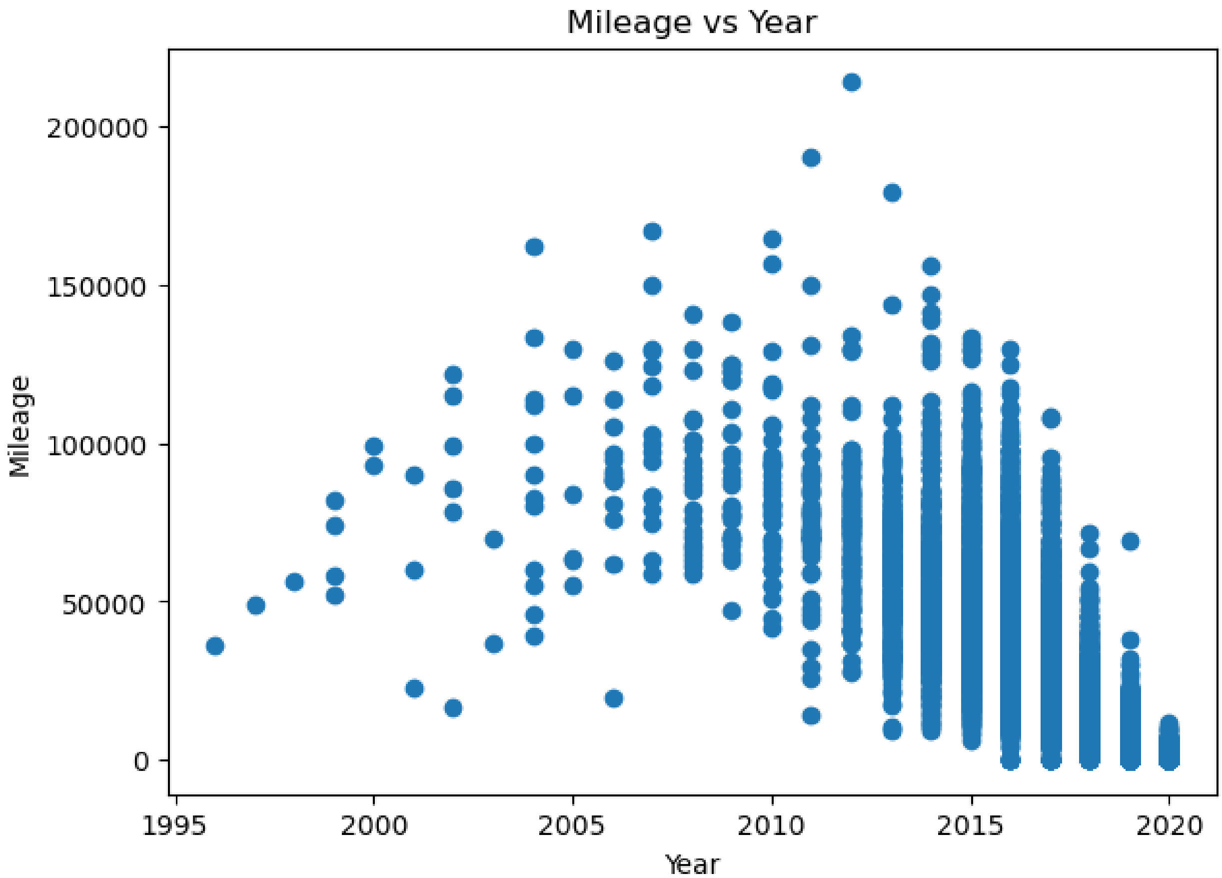

```
import seaborn as sns

if 'price' in df.columns and 'model' in df.columns:
    plt.figure(figsize=(12,6))
    sns.boxplot(x='model', y='price', data=df)
    plt.title("Price Distribution by Model")
    plt.xticks(rotation=45)
    plt.show()
```



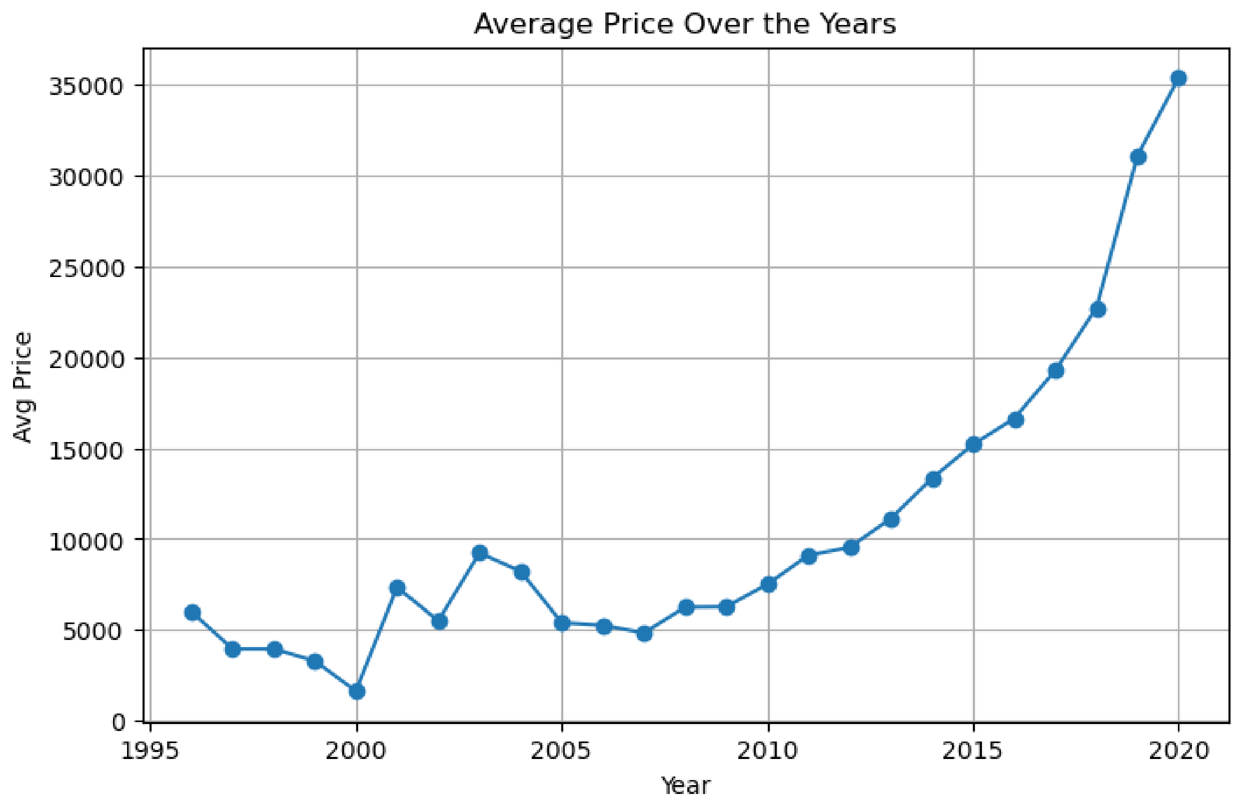

```
import seaborn as sns
import matplotlib.pyplot as plt

# Select only the numeric columns
numeric_df = df.select_dtypes(include=['int64', 'float64'])

# Compute correlation
corr_matrix = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(8,5))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap (Numeric Columns Only)")
plt.show()
```



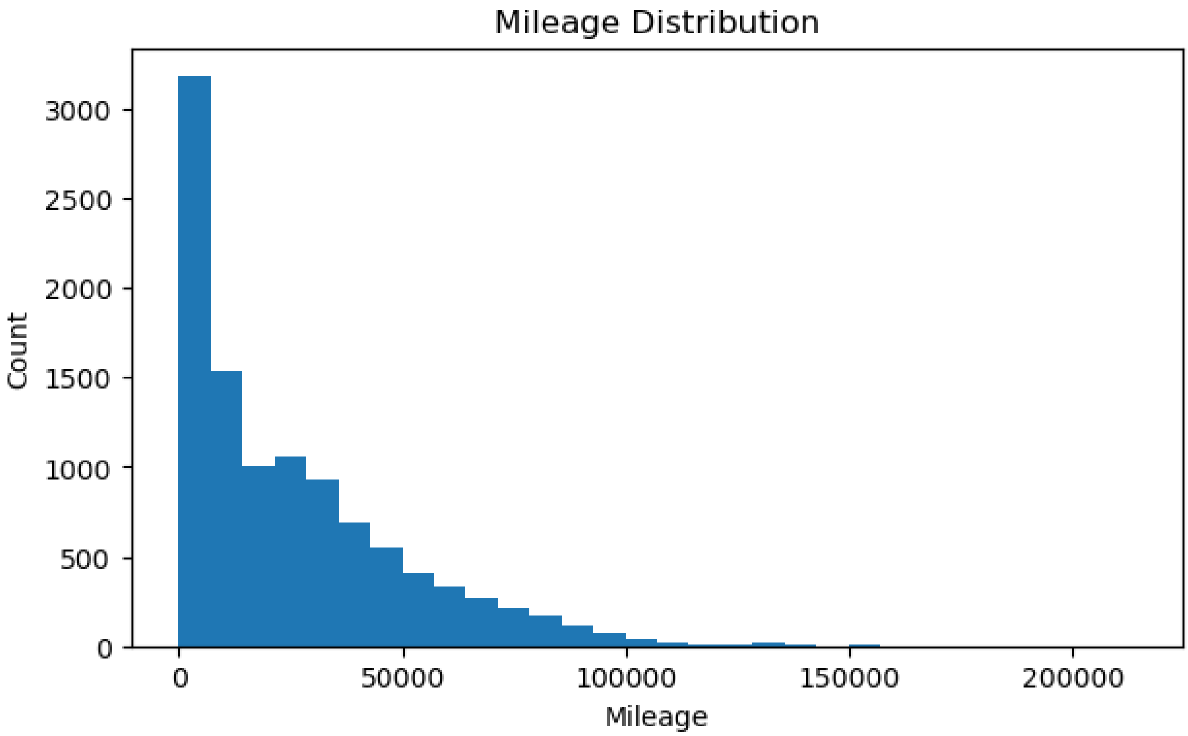

```
if 'year' in df.columns and 'mileage' in df.columns:
    plt.figure(figsize=(7,5))
    plt.scatter(df['year'], df['mileage'])
    plt.title("Mileage vs Year")
    plt.xlabel("Year")
    plt.ylabel("Mileage")
    plt.show()
```



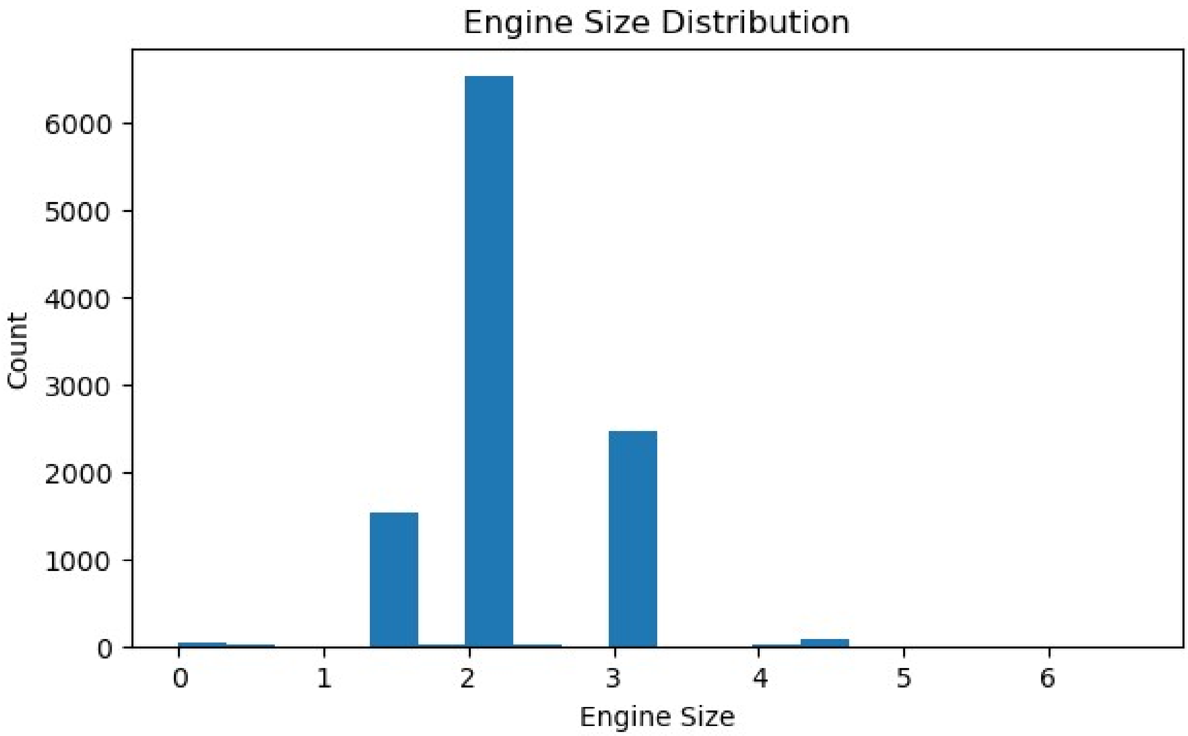

```
if 'year' in df.columns and 'price' in df.columns:
    plt.figure(figsize=(8,5))
    df.groupby('year')['price'].mean().plot(kind='line', marker='o')
    plt.title("Average Price Over the Years")
    plt.xlabel("Year")
    plt.ylabel("Avg Price")
    plt.grid()
    plt.show()
```




```python
if 'mileage' in df.columns:
    plt.figure(figsize=(7,4))
    plt.hist(df['mileage'], bins=30)
    plt.title("Mileage Distribution")
    plt.xlabel("Mileage")
    plt.ylabel("Count")
    plt.show()
```




```
if 'engineSize' in df.columns:
    plt.figure(figsize=(7,4))
    plt.hist(df['engineSize'], bins=20)
    plt.title("Engine Size Distribution")
    plt.xlabel("Engine Size")
    plt.ylabel("Count")
    plt.show()
```




```
# Key insights Summary
def insight(text):
    print("-", text)

print("\n*KEY INSIGHTS:")
insight("Newer cars tend to have higher prices (positive
correlation).")
insight("Higher mileage cars usually have lower market value.")
insight("Strong correlation found between car year, mileage, and
price.")
insight("Price distribution is skewed depending on luxury model
variants.")
```

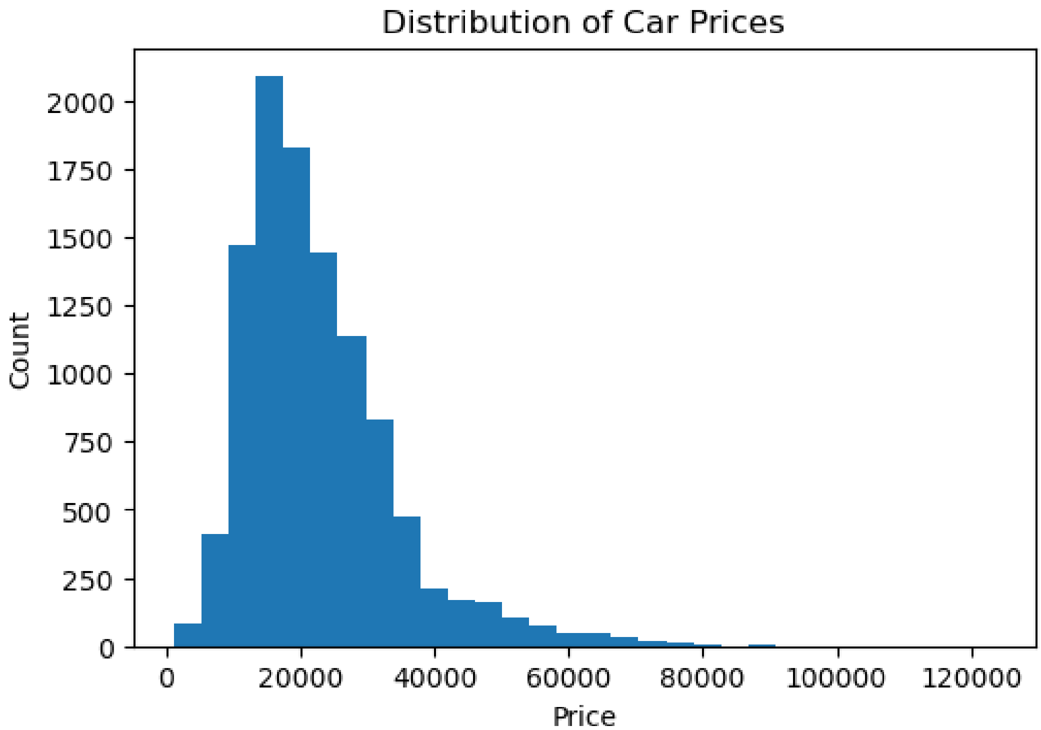
```
*KEY INSIGHTS:
- Newer cars tend to have higher prices (positive correlation).
- Higher mileage cars usually have lower market value.
- Strong correlation found between car year, mileage, and price.
- Price distribution is skewed depending on luxury model variants.
```

```
df.to_csv("cleaned_bmw_dataset.csv", index=False)
print("\nCleaned dataset saved as: cleaned_bmw_dataset.csv")
```

```
Cleaned dataset saved as: cleaned_bmw_dataset.csv
```

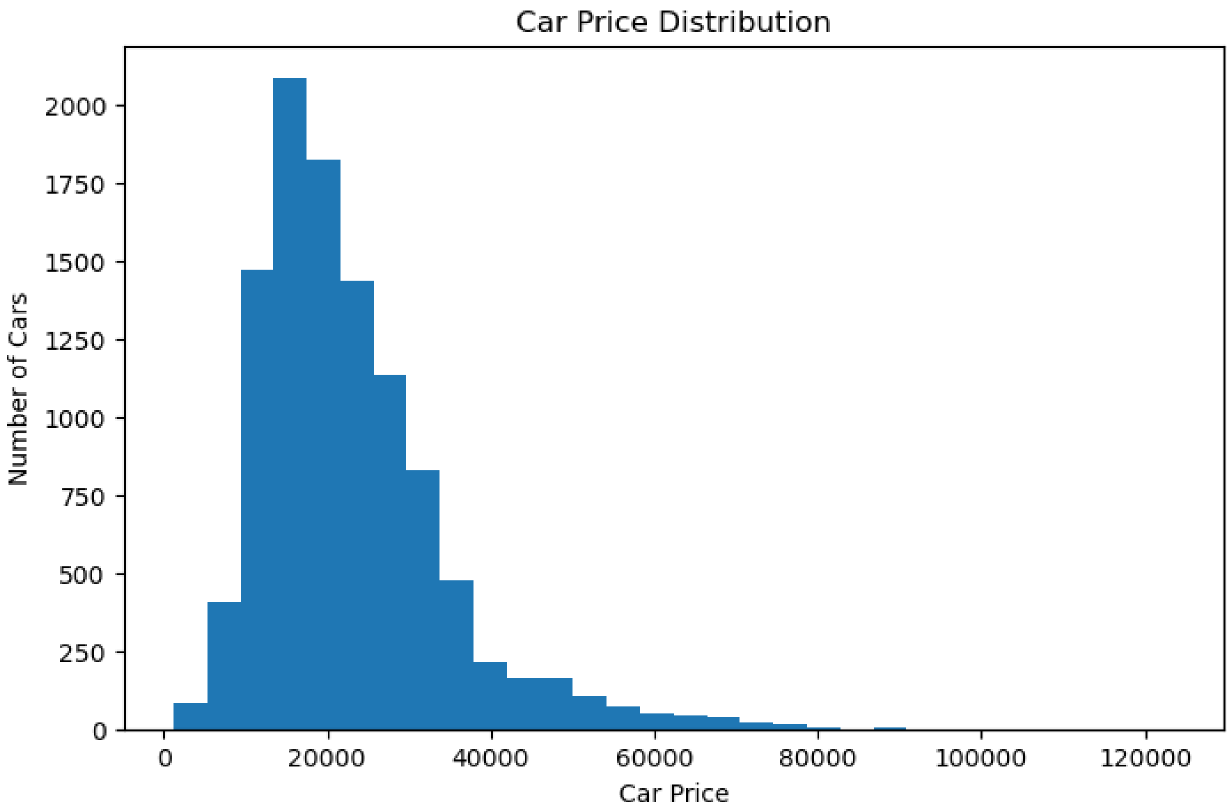
```
import matplotlib.pyplot as plt
```

```python
# Check if 'price' column exists to avoid runtime errors
if 'price' in df.columns:

    # Create figure for better readability
    plt.figure(figsize=(6,4))

    # Plot histogram to understand price distribution
    plt.hist(df['price'], bins=30)

    # Add chart title and axis labels
    plt.title("Distribution of Car Prices")
    plt.xlabel("Price")
    plt.ylabel("Count")

    # Display the plot
    plt.show()

    """
    INSIGHTS:
    1. This histogram shows how car prices are distributed across the
dataset.
    2. A higher bar height indicates more cars within that price
range.
    3. If most bars are concentrated on the lower price side, the data
is right-skewed,
       meaning budget cars dominate the market.
    4. Very high price values appearing at the extreme right indicate
outliers,
       which can negatively impact linear regression.
    5. This analysis helps decide whether price transformation or
outlier handling
       is required before building a regression model.
    """
else:
    print("Column 'price' not found in dataset")
```



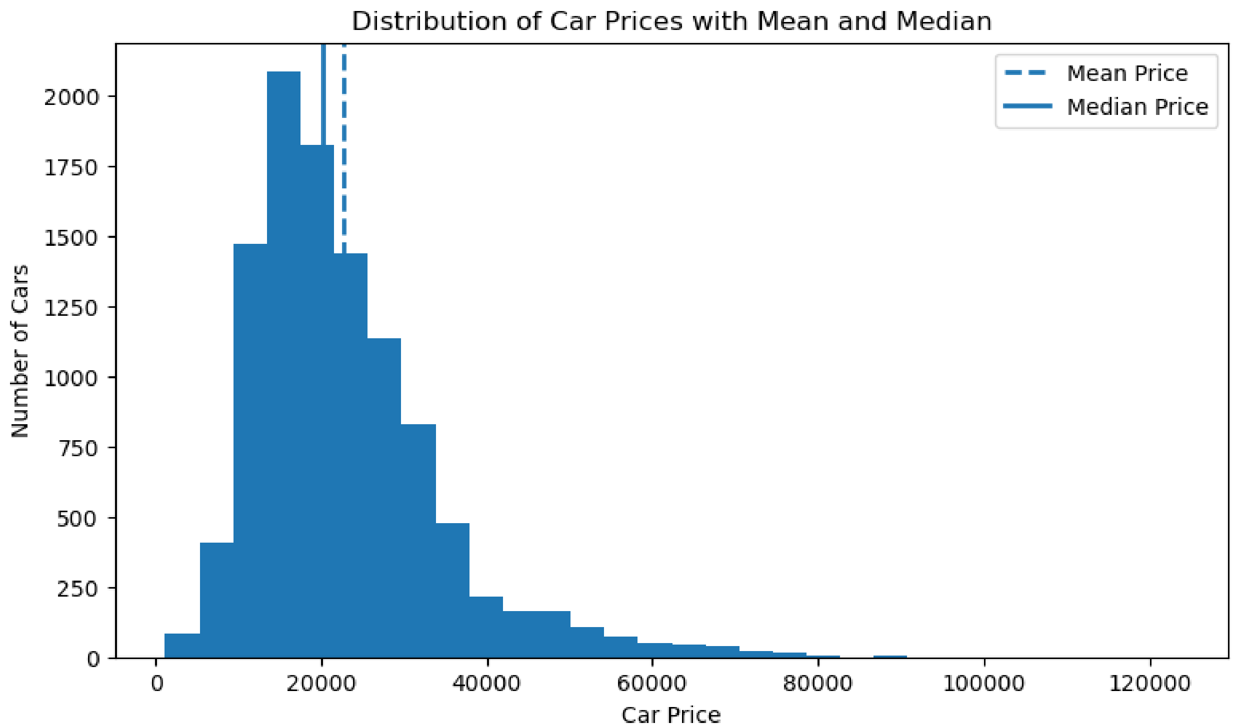

```
import matplotlib.pyplot as plt

# Check column existence for safe execution
if 'price' in df.columns:

    # Create a larger and clearer chart
    plt.figure(figsize=(8,5))

    # Plot price distribution
    plt.hist(df['price'], bins=30)

    # Titles and labels
    plt.title("Car Price Distribution")
    plt.xlabel("Car Price")
    plt.ylabel("Number of Cars")

    # Show chart
    plt.show()

    # Clean insights for project explanation
    """
    INSIGHTS:
    • The chart shows how car prices are distributed across the
dataset.
    • Most cars fall within the lower to mid price range, indicating a
right-skewed distribution.
    • A small number of cars appear at very high prices, suggesting
```

```
the presence of outliers.
    • Such skewness and outliers can influence linear regression
results.
    • This analysis helps decide whether price transformation or
outlier treatment is needed
      before building a predictive model.
    """
else:
    print("The column 'price' is not available in the dataset.")
```




```
import matplotlib.pyplot as plt
import numpy as np

# Check column existence
if 'price' in df.columns:

    # Calculate statistics
    mean_price = df['price'].mean()
    median_price = df['price'].median()

    # Create larger, clearer figure
    plt.figure(figsize=(9,5))

    # Plot histogram
```

```
    plt.hist(df['price'], bins=30)

    # Mean and Median lines
    plt.axvline(mean_price, linestyle='--', linewidth=2, label='Mean
Price')
    plt.axvline(median_price, linestyle='-', linewidth=2,
label='Median Price')

    # Titles and labels
    plt.title("Distribution of Car Prices with Mean and Median")
    plt.xlabel("Car Price")
    plt.ylabel("Number of Cars")

    # Legend
    plt.legend()

    # Show plot
    plt.show()

    """
    GRAPH INSIGHTS:
    1. The histogram displays how car prices are distributed across
the dataset.
    2. Taller bars represent price ranges with a higher number of
cars.
    3. The concentration of bars on the lower price side indicates
that most cars
       are budget to mid-range.
    4. The long tail on the right side shows the presence of high-
priced cars,
       confirming a right-skewed distribution.
    5. The mean price lies to the right of the median, which further
confirms
       positive skewness caused by expensive outliers.
    6. These outliers can impact linear regression, making
preprocessing steps
       such as transformation or capping important.
    """
else:
    print("Column 'price' not found in the dataset.")
```



Distribution of Car Prices with Mean and Median
Mean Price
Median Price
Number of Cars
Car Price
0
250
500
750
1000
1250
1500
1750
2000
20000
40000
60000
80000
100000
120000