```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import statsmodels.api as sm
from scipy.stats import f_oneway, ttest_ind, chi2_contingency
from mpl_toolkits.mplot3d import Axes3D

cars_df = pd.read_csv('/content/drive/MyDrive/5502/car_data_set.csv')
```

```python
cars_df.shape
```

```
(11914, 16)
```

```python
cars_df.head(5)
```

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size	Vehicle Style	highway MPG	c
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	2.0	Factory Tuner,Luxury,High-Performance	Compact	Coupe	26	
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Convertible	28	
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,High-Performance	Compact	Coupe	28	
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Coupe	28	
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury	Compact	Convertible	28	

```python
print(cars_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11914 entries, 0 to 11913
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Make               11914 non-null  object
 1   Model              11914 non-null  object
 2   Year               11914 non-null  int64
 3   Engine Fuel Type   11911 non-null  object
 4   Engine HP          11845 non-null  float64
 5   Engine Cylinders   11884 non-null  float64
 6   Transmission Type  11914 non-null  object
 7   Driven_Wheels      11914 non-null  object
 8   Number of Doors    11908 non-null  float64
 9   Market Category    8172 non-null   object
 10  Vehicle Size       11914 non-null  object
 11  Vehicle Style      11914 non-null  object
 12  highway MPG        11914 non-null  int64
 13  city mpg           11914 non-null  int64
 14  Popularity         11914 non-null  int64
 15  MSRP               11914 non-null  int64
dtypes: float64(3), int64(5), object(8)
memory usage: 1.5+ MB
None
```

```python
print(cars_df.dtypes)
```

```
Make                  object
Model                 object
Year                   int64
Engine Fuel Type      object
Engine HP            float64
Engine Cylinders     float64
```

```
Transmission Type     object
Driven_Wheels         object
Number of Doors      float64
Market Category       object
Vehicle Size          object
Vehicle Style         object
highway MPG            int64
city mpg               int64
Popularity             int64
MSRP                   int64
dtype: object
```

```
cars_df.describe()
```

	Year	Engine HP	Engine Cylinders	Number of Doors	highway MPG	city mpg	Popularity	MSRP
count	11914.000000	11845.00000	11884.000000	11908.000000	11914.000000	11914.000000	11914.000000	1.191400e+04
mean	2010.384338	249.38607	5.628829	3.436093	26.637485	19.733255	1554.911197	4.059474e+04
std	7.579740	109.19187	1.780559	0.881315	8.863001	8.987798	1441.855347	6.010910e+04
min	1990.000000	55.00000	0.000000	2.000000	12.000000	7.000000	2.000000	2.000000e+03
25%	2007.000000	170.00000	4.000000	2.000000	22.000000	16.000000	549.000000	2.100000e+04
50%	2015.000000	227.00000	6.000000	4.000000	26.000000	18.000000	1385.000000	2.999500e+04
75%	2016.000000	300.00000	6.000000	4.000000	30.000000	22.000000	2009.000000	4.223125e+04
max	2017.000000	1001.00000	16.000000	4.000000	354.000000	137.000000	5657.000000	2.065902e+06

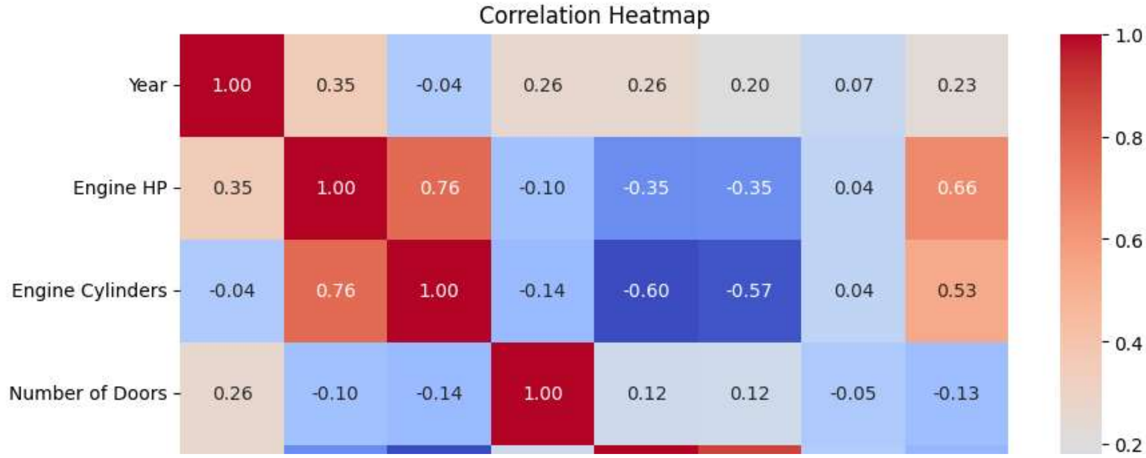
```
def check_missing_values(df):
    null_values = df.isnull().sum()
    print("Null Values:")
    print(null_values)

    nan_values = df.isna().sum()
    print("\nNaN Values:")
    print(nan_values)

    empty_values = (df == '').sum()
    print("\nEmpty Values:")
    print(empty_values)


def preprocess_data(df, numeric_columns, categorical_columns):
    for col in numeric_columns:
        col_mean = df[col].mean()
        df[col].fillna(col_mean, inplace=True)

    for col in categorical_columns:
        df[col].fillna(df[col].mode()[0], inplace=True)

    return df


check_missing_values(cars_df)

numeric_cols = ['Engine HP', 'Engine Cylinders', 'Number of Doors', 'highway MPG', 'city mpg', 'Popularity', 'MSRP']
categorical_cols = ['Engine Fuel Type', 'Market Category']

cars_df = preprocess_data(cars_df, numeric_cols, categorical_cols)

check_missing_values(cars_df)
```

```
Vehicle Size         0
Vehicle Style        0
highway MPG          0
city mpg             0
Popularity           0
MSRP                 0
dtype: int64

NaN Values:
Make                 0
Model                0
Year                 0
Engine Fuel Type     0
Engine HP            0
Engine Cylinders     0
Transmission Type    0
Driven_Wheels        0
Number of Doors      0
Market Category      0
Vehicle Size         0
Vehicle Style        0
highway MPG          0
city mpg             0
Popularity           0
MSRP                 0
dtype: int64

Empty Values:
Make                 0
Model                0
Year                 0
Engine Fuel Type     0
Engine HP            0
Engine Cylinders     0
Transmission Type    0
Driven_Wheels        0
Number of Doors      0
Market Category      0
Vehicle Size         0
Vehicle Style        0
highway MPG          0
city mpg             0
Popularity           0
MSRP                 0
dtype: int64
```

CORRELATION HEATMAP

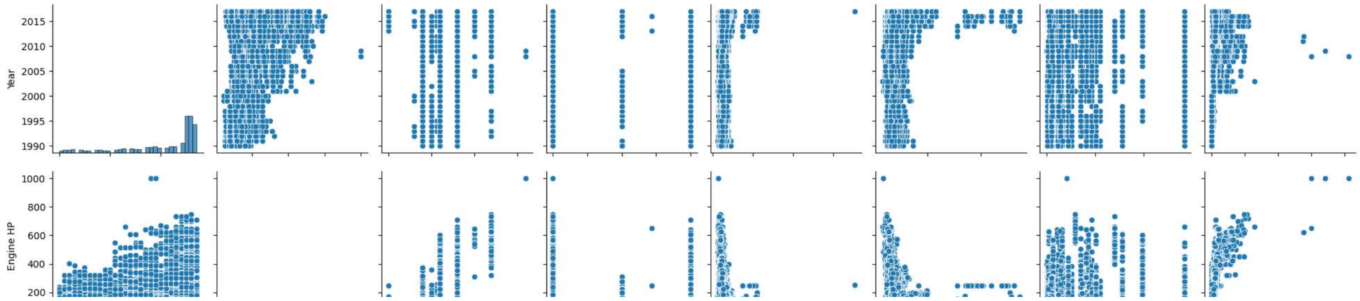
```
plt.figure(figsize=(10, 8))
sns.heatmap(cars_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```

```
<ipython-input-8-17d755946109>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version,
  sns.heatmap(cars_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
```



Numerical vs Numerical

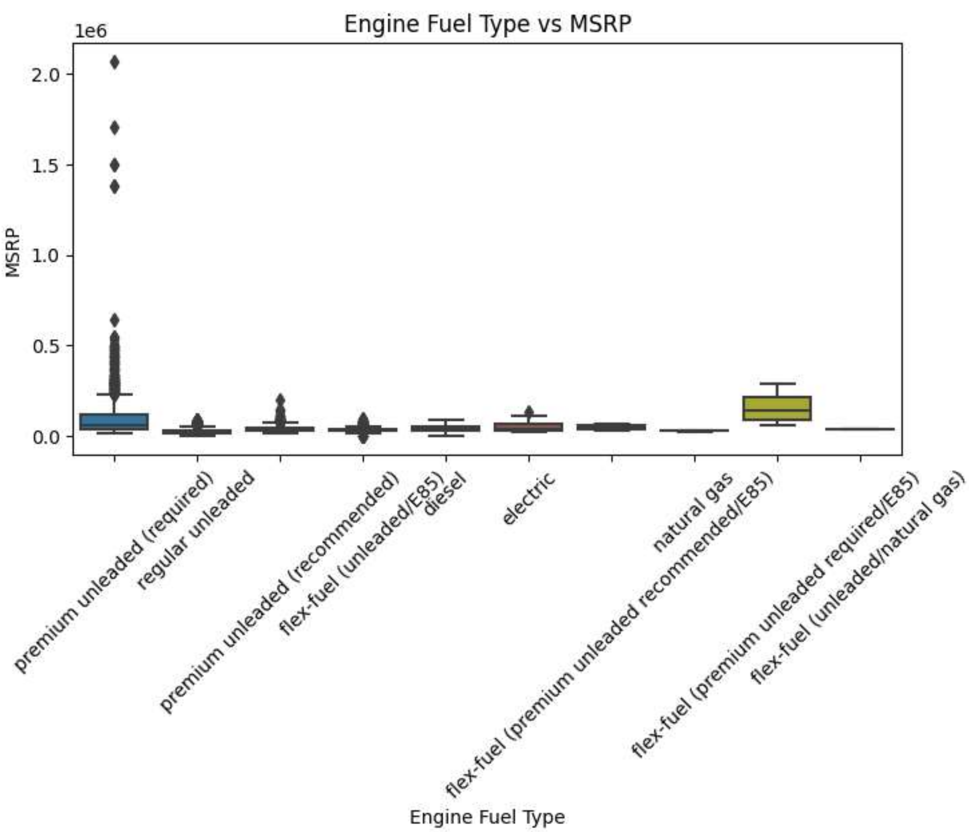
```
sns.pairplot(cars_df)
plt.show()
```



Numerical vs Categorical:

Boxplot: Engine Fuel Type vs MSRP

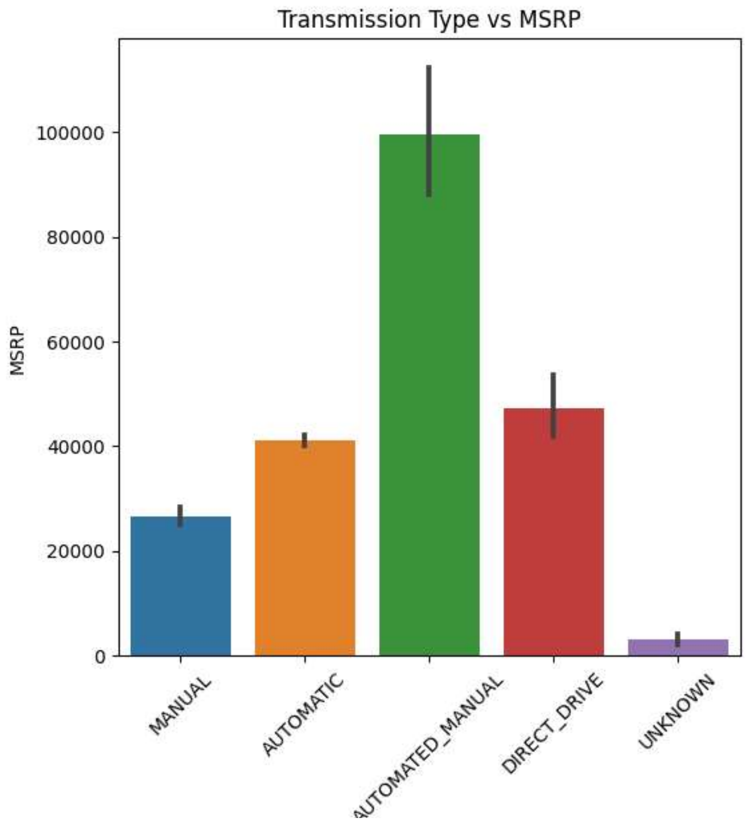
```
plt.figure(figsize=(8, 4))
sns.boxplot(x='Engine Fuel Type', y='MSRP', data=cars_df)
plt.title('Engine Fuel Type vs MSRP')
plt.xticks(rotation=45)
plt.show()
```



Numerical vs Categorical:

Barplot: Transmission Type vs MSRP

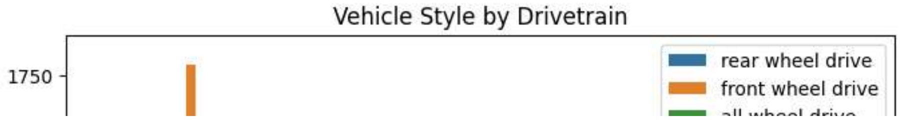
```
plt.figure(figsize=(6, 6))
sns.barplot(x='Transmission Type', y='MSRP', data=cars_df)
plt.title('Transmission Type vs MSRP')
plt.xticks(rotation=45)
plt.show()
```



Categorical vs Categorical:

Countplot: Vehicle Style by Drivetrain

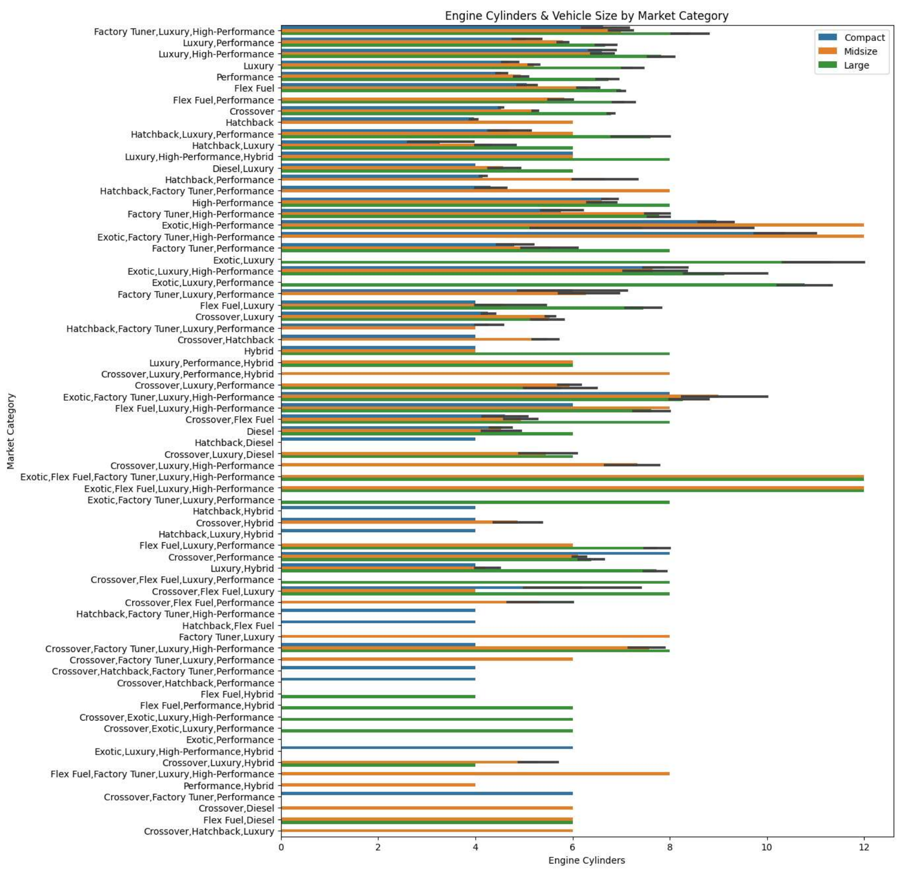
```
plt.figure(figsize=(8, 6))
sns.countplot(x='Vehicle Style', hue='Driven_Wheels', data=cars_df)
plt.title('Vehicle Style by Drivetrain')
plt.legend(loc='upper right')
plt.xticks(rotation=45)
plt.show()
```



Numerical and Categorical vs Categorical:

Barplot: Engine Cylinders & Vehicle Size by Market Category

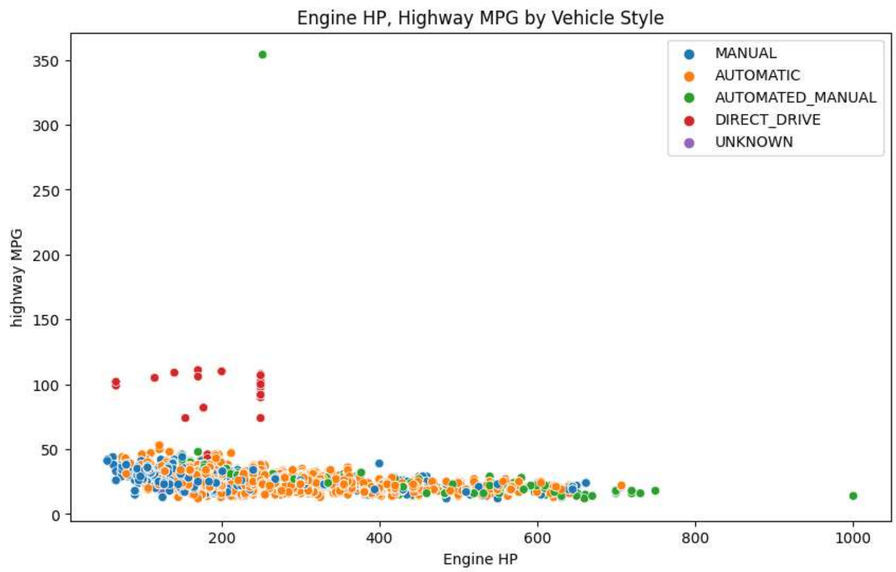
```
plt.figure(figsize=(12, 16))
sns.barplot(x='Engine Cylinders', y='Market Category', hue='Vehicle Size', data=cars_df)
plt.title('Engine Cylinders & Vehicle Size by Market Category')
plt.legend(loc='upper right')
plt.show()
```



Two Numerical vs One Categorical:

Scatterplot: Engine HP, Highway MPG by Vehicle Style

```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Engine HP', y='highway MPG', hue='Transmission Type', data=cars_df)
plt.title('Engine HP, Highway MPG by Vehicle Style')
plt.legend(loc='upper right')
plt.show()
```



Three Numerical Variables:

3D Scatterplot: Engine HP, Highway MPG, City MPG

```
Q1 = cars_df.quantile(0.25)
Q3 = cars_df.quantile(0.75)
IQR = Q3 - Q1

outliers = ((cars_df < (Q1 - 1.5 * IQR)) | (cars_df > (Q3 + 1.5 * IQR))).sum()
print("Potential Outliers (using IQR method):")
print(outliers)
```

```
Potential Outliers (using IQR method):
Driven_Wheels          0
Engine Cylinders     357
Engine Fuel Type       0
Engine HP            509
MSRP                 996
Make                   0
Market Category        0
Model                  0
Number of Doors        0
Popularity           881
Transmission Type      0
Vehicle Size           0
Vehicle Style          0
Year                 661
city mpg             316
highway MPG          192
dtype: int64
<ipython-input-15-73b63a5a9663>:1: FutureWarning: The default value of numeric_only in DataFrame.quantile is deprecated. In a future ver
```

```
  Q1 = cars_df.quantile(0.25)
<ipython-input-15-73b63a5a9663>:2: FutureWarning: The default value of numeric_only in DataFrame.quantile is deprecated. In a future ver
  Q3 = cars_df.quantile(0.75)
<ipython-input-15-73b63a5a9663>:5: FutureWarning: Automatic reindexing on DataFrame vs Series comparisons is deprecated and will raise V
  outliers = ((cars_df < (Q1 - 1.5 * IQR)) | (cars_df > (Q3 + 1.5 * IQR))).sum()
```

T-TEST

```
premium_unleaded = cars_df[cars_df['Engine Fuel Type'] == 'premium unleaded (required)']
regular_unleaded = cars_df[cars_df['Engine Fuel Type'] == 'regular unleaded']

t_stat, p_value = stats.ttest_ind(premium_unleaded['MSRP'], regular_unleaded['MSRP'])
print(f"T-test results - t-statistic: {t_stat}, p-value: {p_value}")

alpha = 0.05  #significance level

if p_value < alpha:
    print("Reject null hypothesis: There is a significant difference in MSRP based on engine type.")
else:
    print("Fail to reject null hypothesis: No significant difference in MSRP based on engine type.")
```

```
T-test results - t-statistic: 53.05815695600708, p-value: 0.0
Reject null hypothesis: There is a significant difference in MSRP based on engine type.
```

Correlation Analysis

```
correlation_matrix = cars_df[['Engine HP', 'MSRP']].corr(method='pearson')
print("Correlation between Engine HP and MSRP:")
print(correlation_matrix)
```

```
Correlation between Engine HP and MSRP:
           Engine HP      MSRP
Engine HP   1.000000  0.661644
MSRP        0.661644  1.000000
```

ANOVA TEST

```
grouped_data = cars_df.groupby('Vehicle Style')['MSRP'].apply(list)
f_statistic, p_value = f_oneway(*grouped_data)
print("\nANOVA Test - MSRP variation among Vehicle Styles:")
print(f"F-Statistic: {f_statistic}, p-value: {p_value}")
```

```
ANOVA Test - MSRP variation among Vehicle Styles:
F-Statistic: 92.55549649004786, p-value: 5.613983147064976e-271
```

T - TEST

```
engine_fuel_types = cars_df['Engine Fuel Type'].unique()

for fuel_type in engine_fuel_types:
    subset = cars_df[cars_df['Engine Fuel Type'] == fuel_type]['MSRP']
    t_stat, p_value = ttest_ind(subset, cars_df['MSRP'])
    print(f"\nT-test for {fuel_type} Engine Fuel Type and MSRP:")
    print(f"T-statistic: {t_stat}, p-value: {p_value}")
```

```
T-test for premium unleaded (required) Engine Fuel Type and MSRP:
T-statistic: 34.910868116537976, p-value: 4.7306254324863656e-256
```

```
T-test for regular unleaded Engine Fuel Type and MSRP:
T-statistic: -24.345905204481735, p-value: 5.905242990090284e-129

T-test for premium unleaded (recommended) Engine Fuel Type and MSRP:
T-statistic: 0.14094797183948202, p-value: 0.8879131574803788

T-test for flex-fuel (unleaded/E85) Engine Fuel Type and MSRP:
T-statistic: -2.1588670958355616, p-value: 0.030878987504420384

T-test for diesel Engine Fuel Type and MSRP:
T-statistic: 0.039873987036859695, p-value: 0.9681942496423356

T-test for electric Engine Fuel Type and MSRP:
T-statistic: 0.9926277529140373, p-value: 0.3209114461704788

T-test for flex-fuel (premium unleaded recommended/E85) Engine Fuel Type and MSRP:
T-statistic: 0.6825686452754542, p-value: 0.4948926966706487

T-test for natural gas Engine Fuel Type and MSRP:
T-statistic: -0.2947803041303683, p-value: 0.7681668493734748

T-test for flex-fuel (premium unleaded required/E85) Engine Fuel Type and MSRP:
T-statistic: 14.483807998706142, p-value: 3.838640790513522e-47

T-test for flex-fuel (unleaded/natural gas) Engine Fuel Type and MSRP:
T-statistic: -0.05707185895069415, p-value: 0.9544889099295308
```

Chi-square Test:

```
cross_tab = pd.crosstab(cars_df['Vehicle Style'], cars_df['Market Category'])
chi2, p, dof, expected = chi2_contingency(cross_tab)
print("\nChi-square Test - Association between Vehicle Style and Market Category:")
print(f"Chi-square value: {chi2}, p-value: {p}")
```

```
Chi-square Test - Association between Vehicle Style and Market Category:
Chi-square value: 27100.05046976974, p-value: 0.0
```

```
X = cars_df['Engine HP']  # Independent variable
y = cars_df['MSRP']  # Dependent variable

X = sm.add_constant(X)  # Add a constant term for intercept
model = sm.OLS(y, X).fit()  # Fit the model
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   MSRP   R-squared:                       0.438
Model:                            OLS   Adj. R-squared:                  0.438
Method:                 Least Squares   F-statistic:                     9275.
Date:                Thu, 16 Nov 2023   Prob (F-statistic):               0.00
Time:                        23:54:11   Log-Likelihood:            -1.4458e+05
No. Observations:               11914   AIC:                         2.892e+05
Df Residuals:                   11912   BIC:                         2.892e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       -5.05e+04   1032.111    -48.932      0.000   -5.25e+04   -4.85e+04
Engine HP    365.2884      3.793     96.308      0.000     357.854     372.723
==============================================================================
Omnibus:                    23521.060   Durbin-Watson:                   0.713
Prob(Omnibus):                  0.000   Jarque-Bera (JB):        105879175.386
Skew:                          15.628   Prob(JB):                         0.00
Kurtosis:                     463.771   Cond. No.                         680.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```