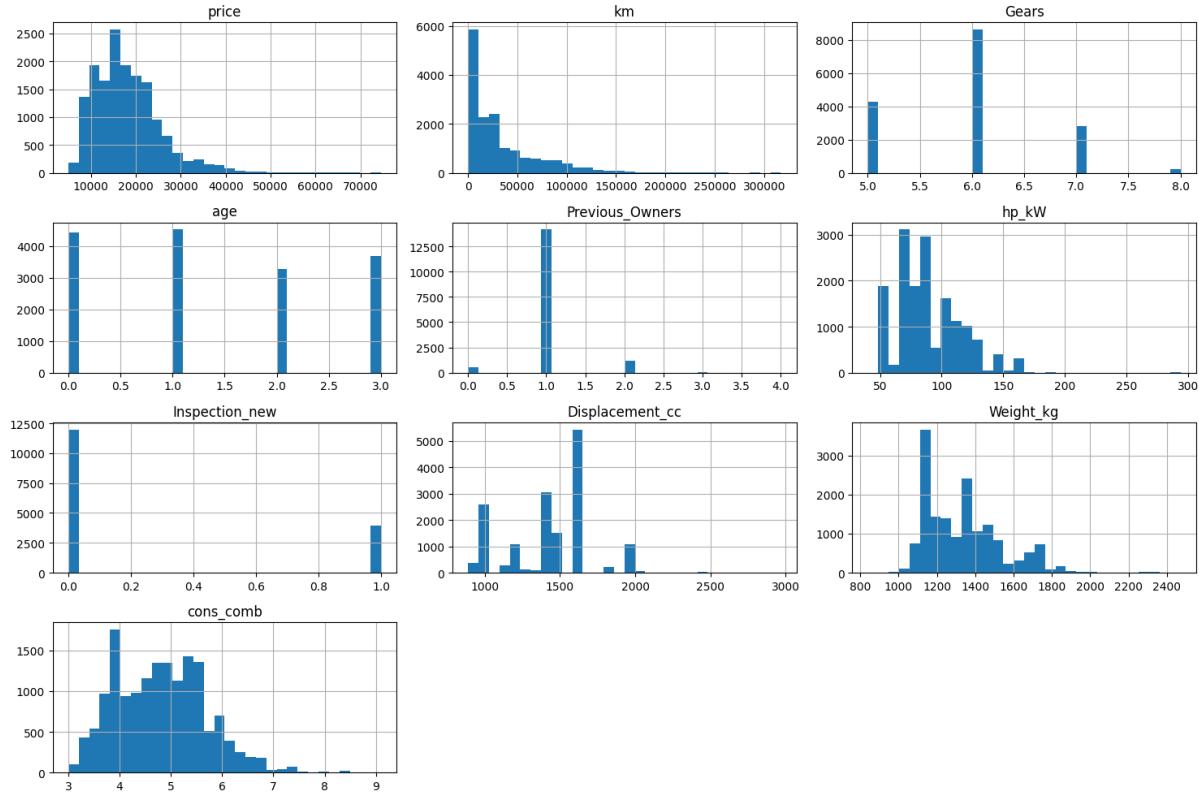


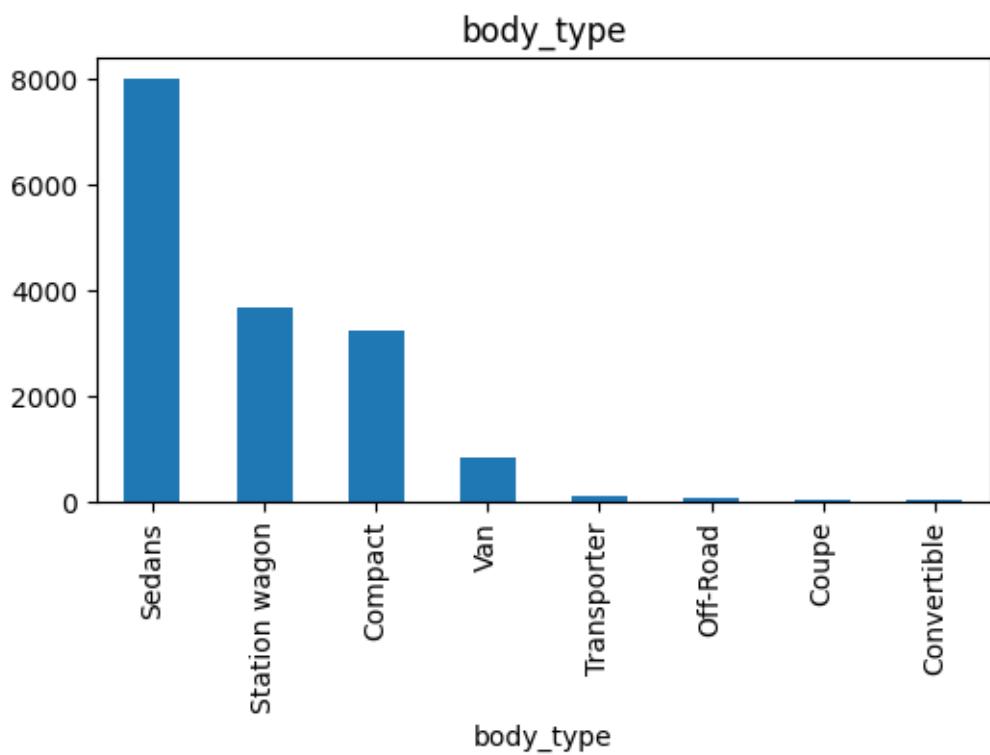
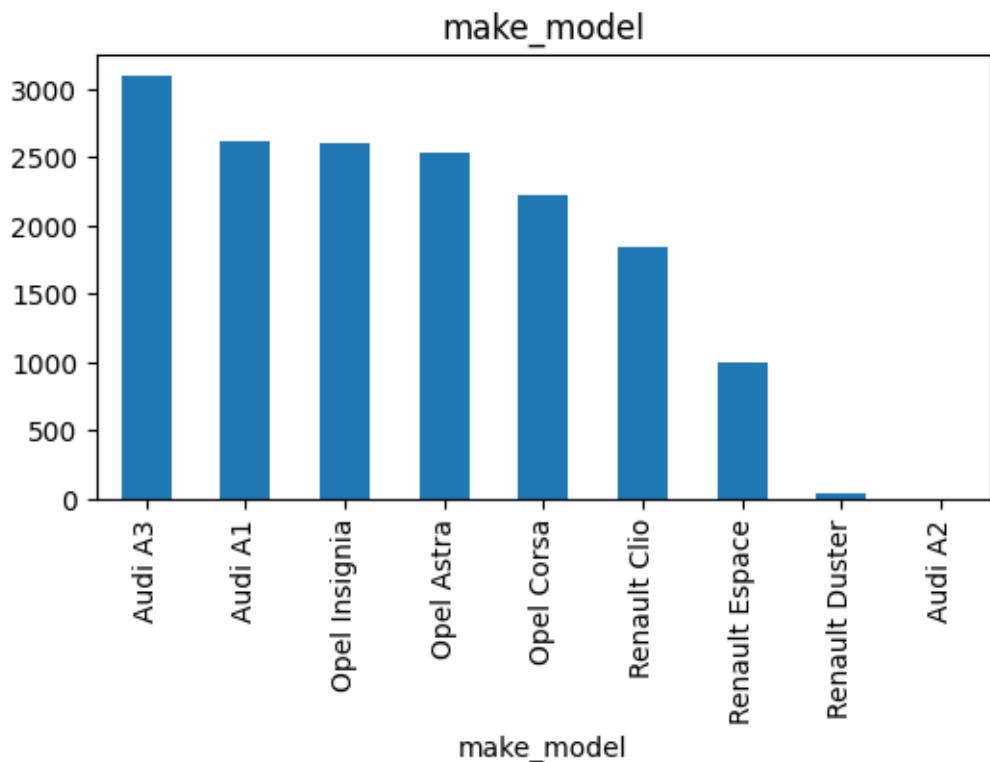
## EDMLDS - C4 - Regularisation Assignment

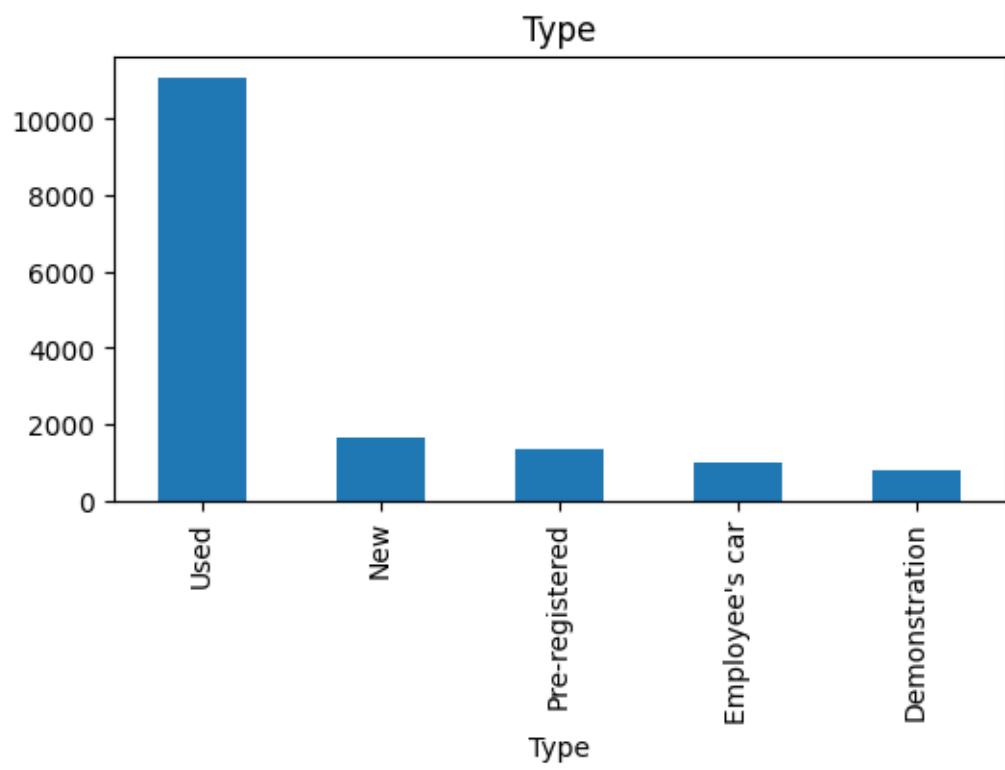
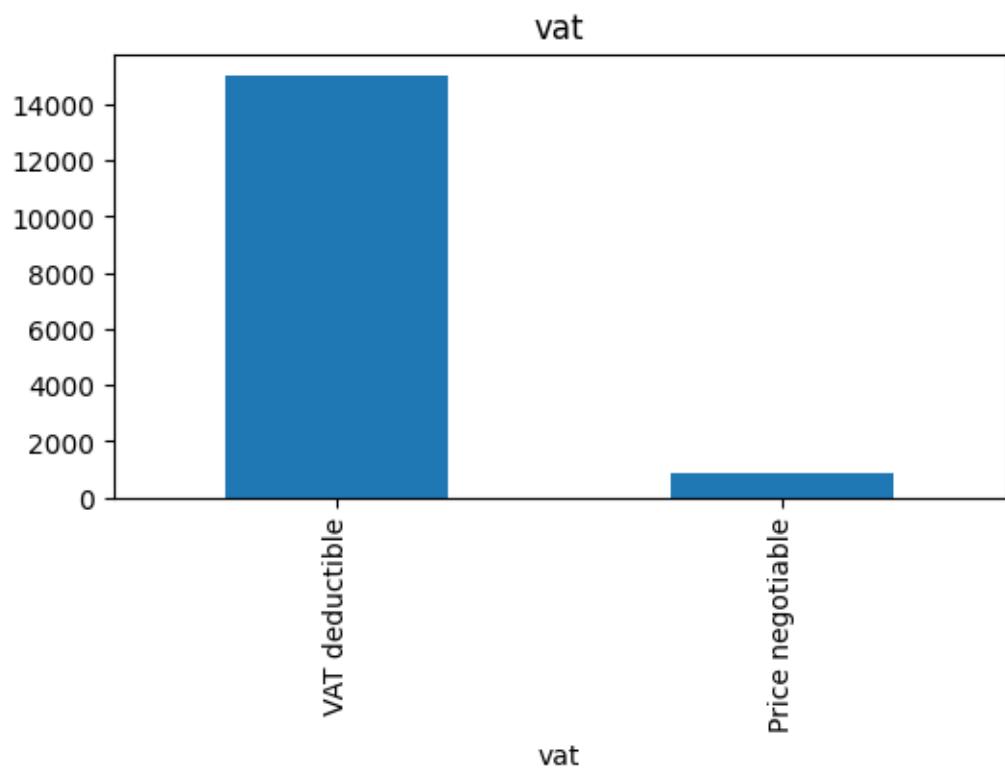
Rishabh Uniyal

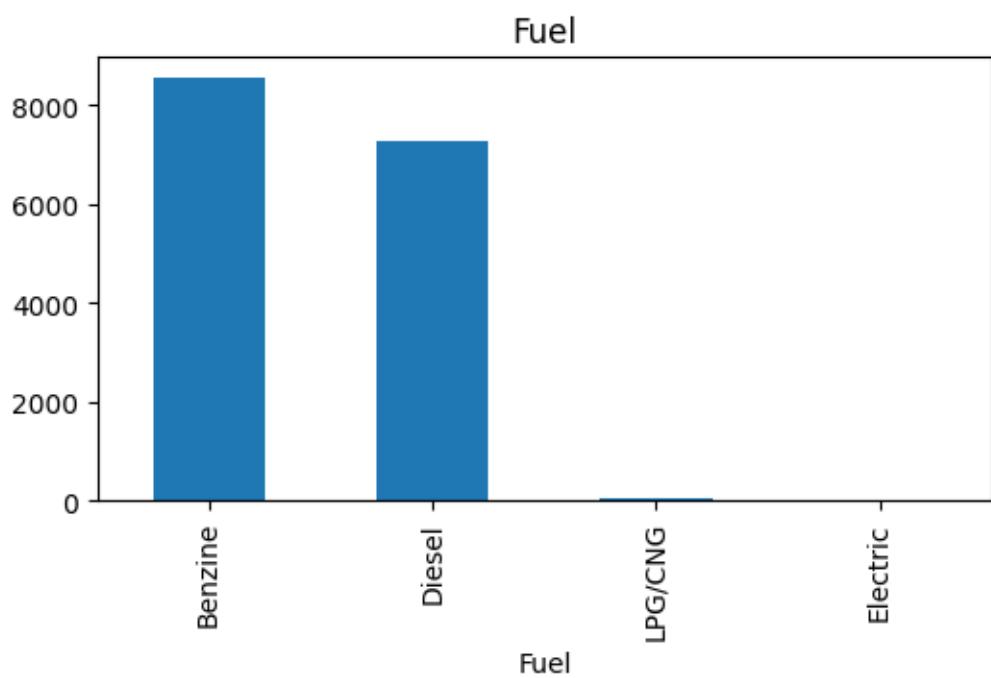
Identify numerical predictors and plot their frequency distributions.

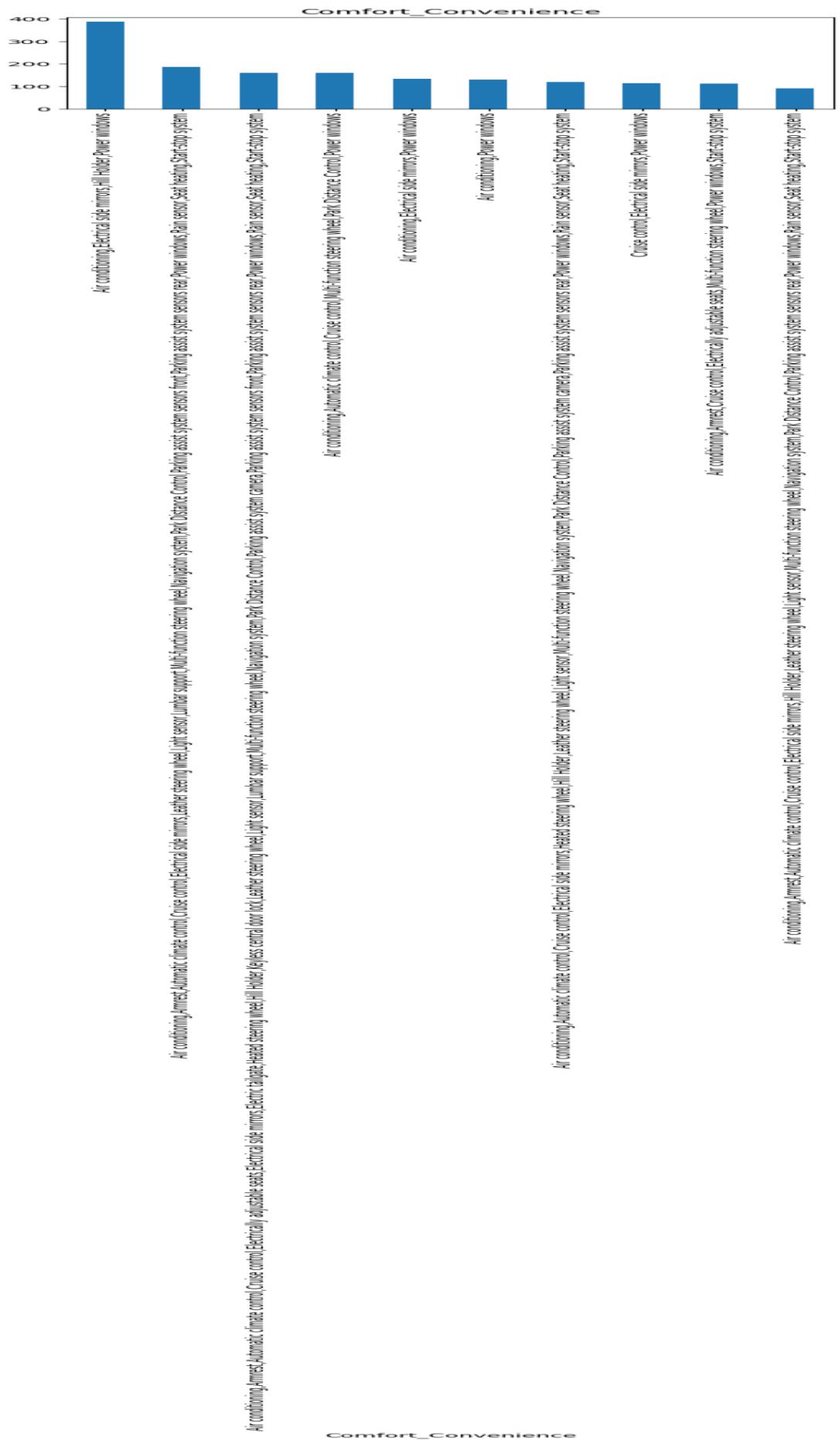


Identify categorical predictors and plot their frequency distributions.

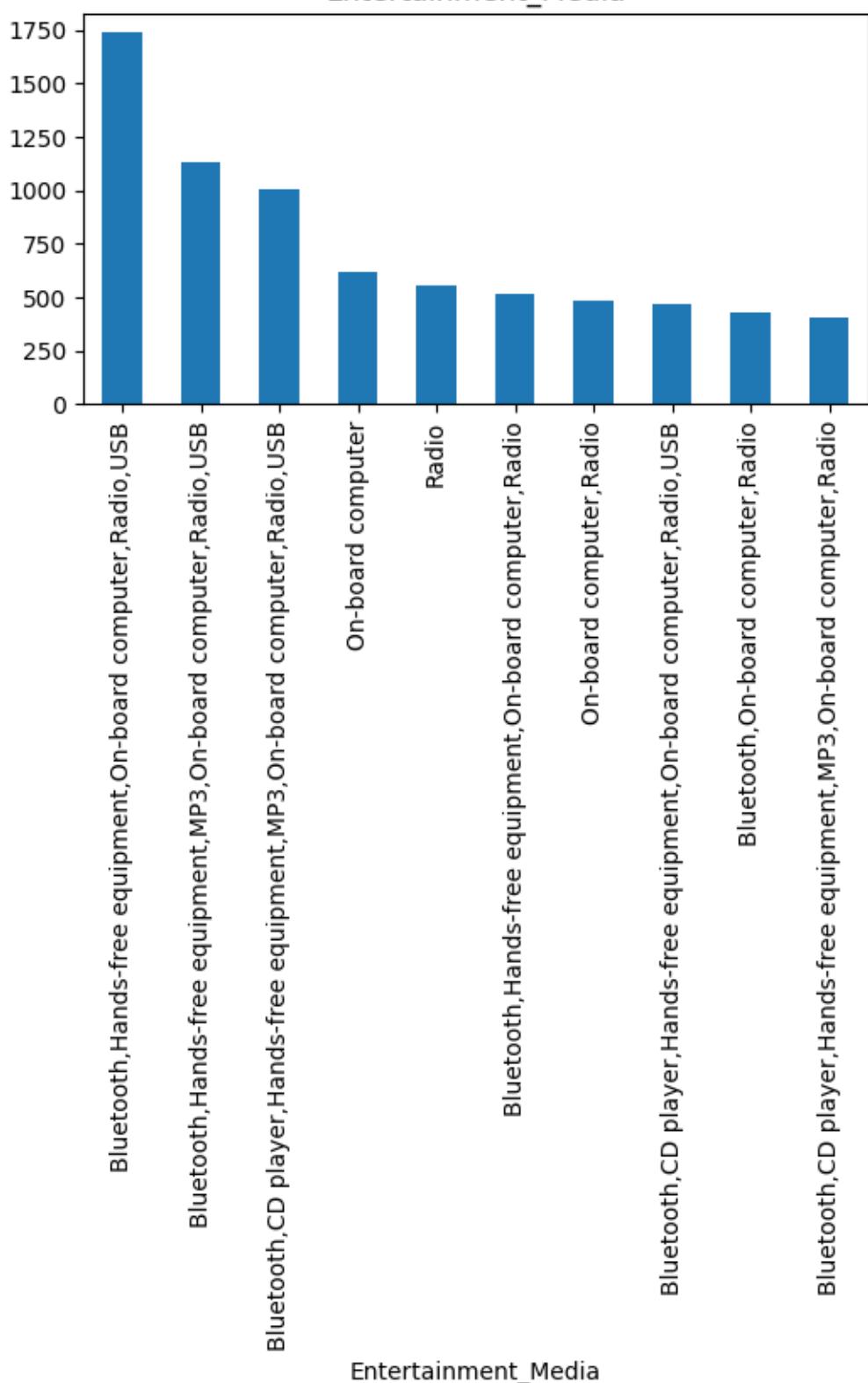




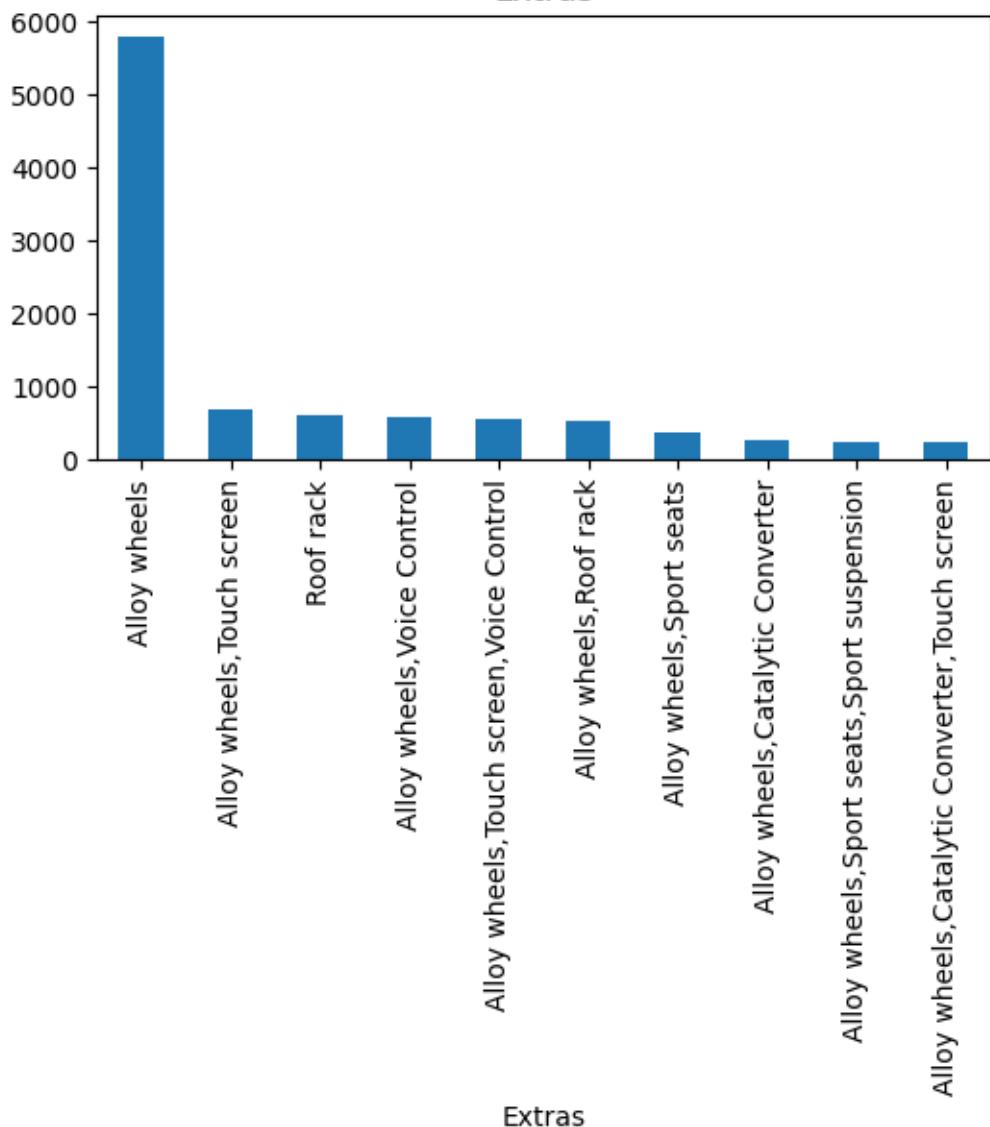




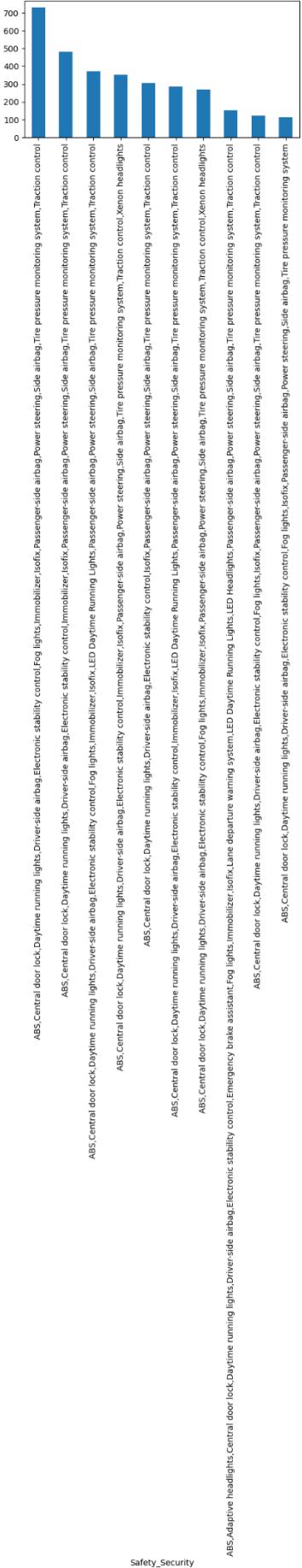
Entertainment\_Media

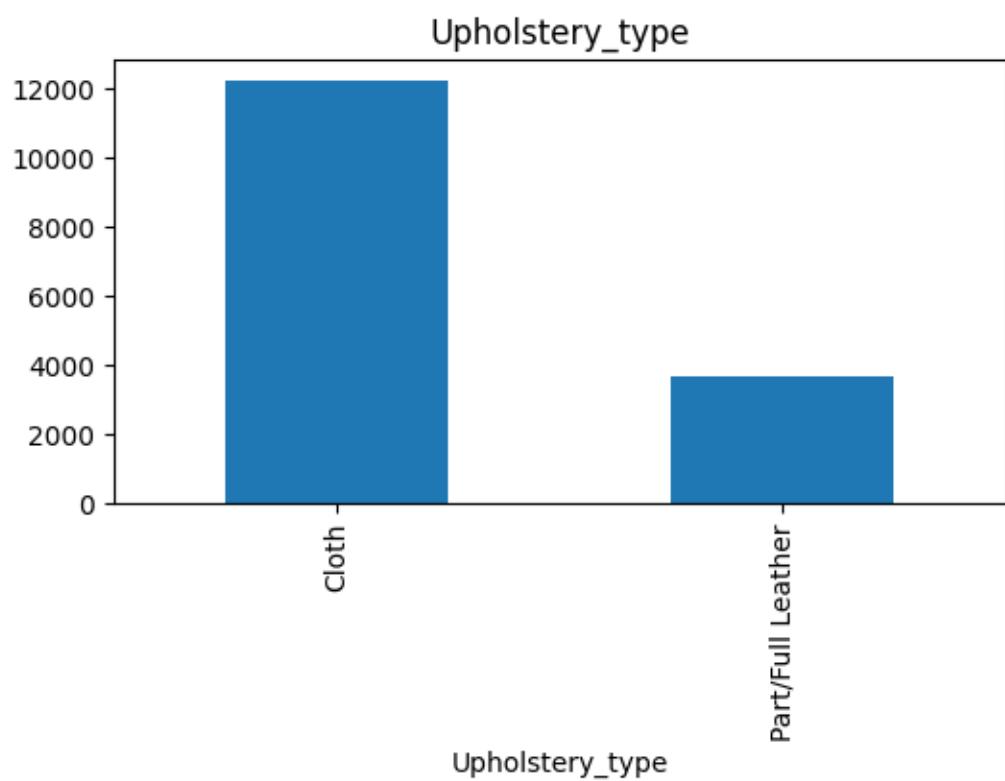
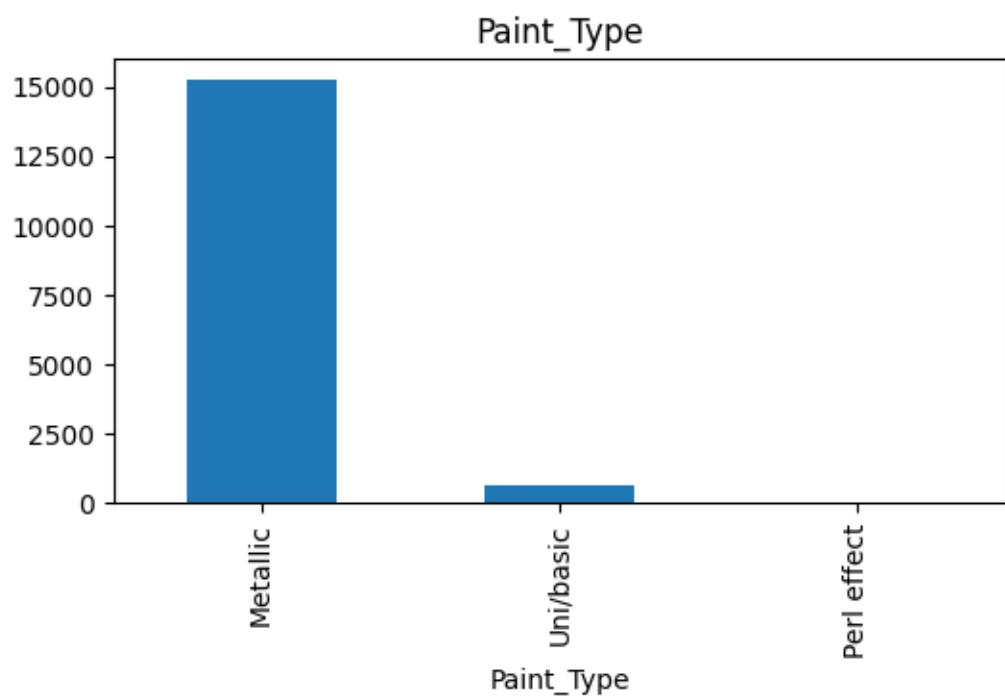


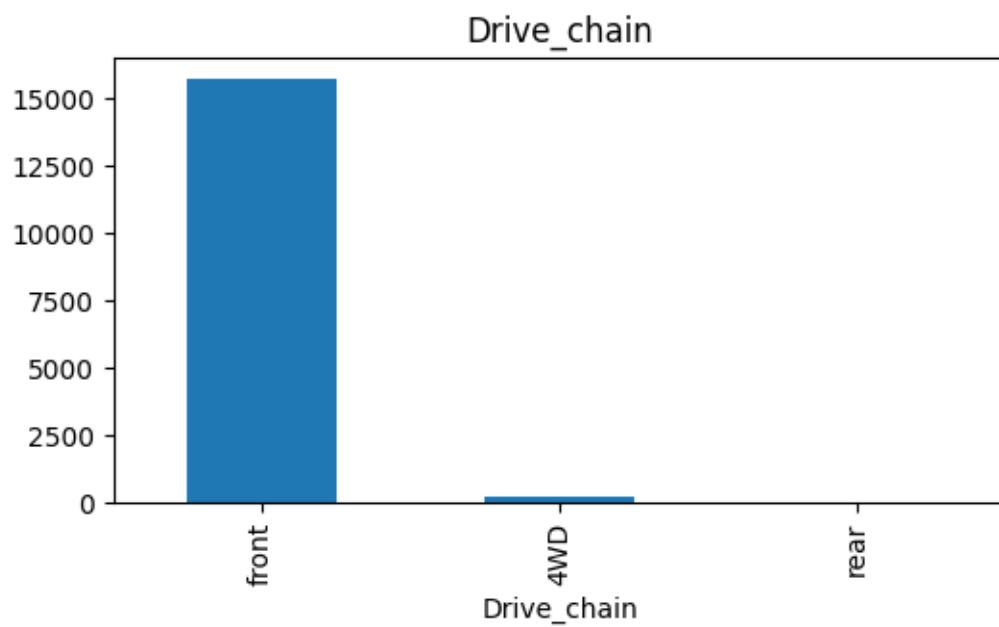
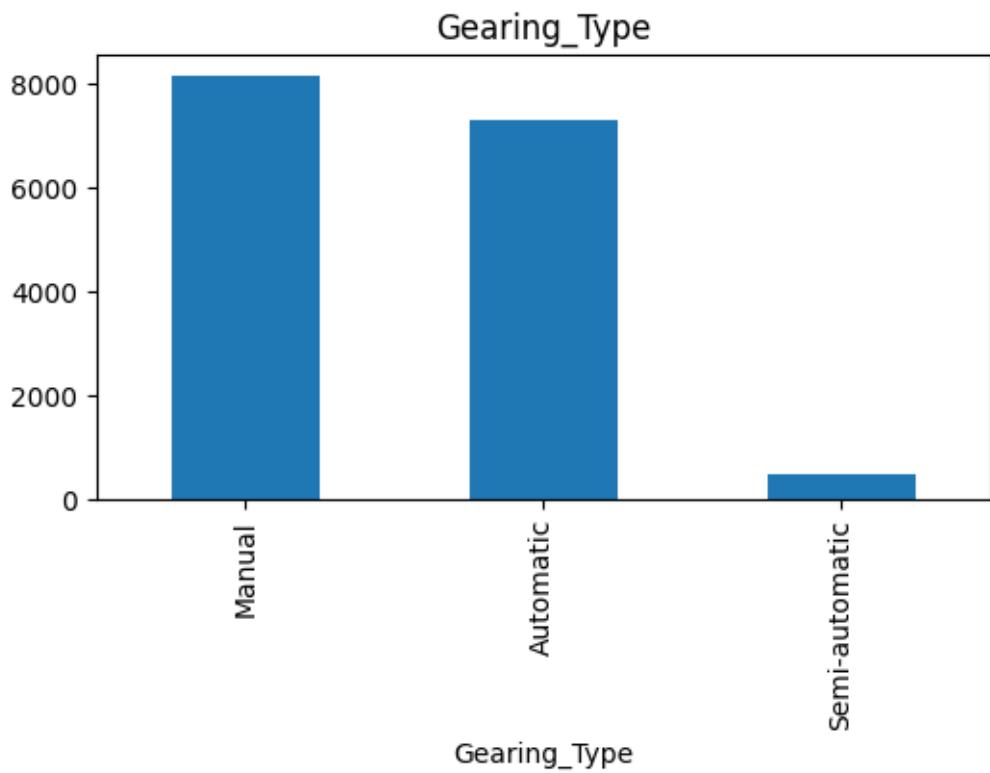
### Extras



Safety\_Security

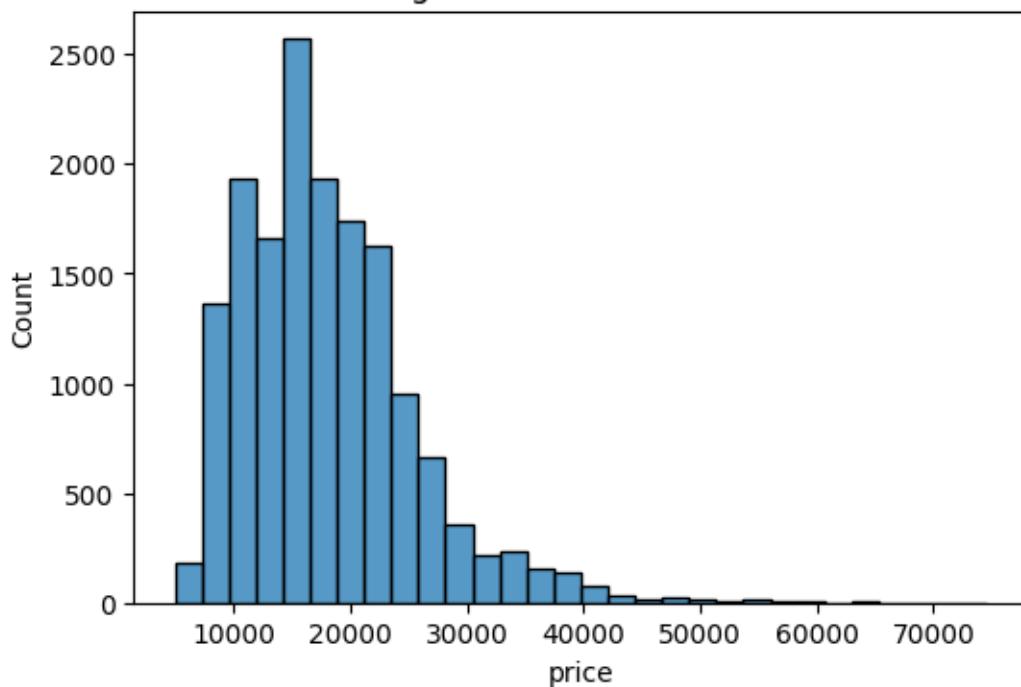




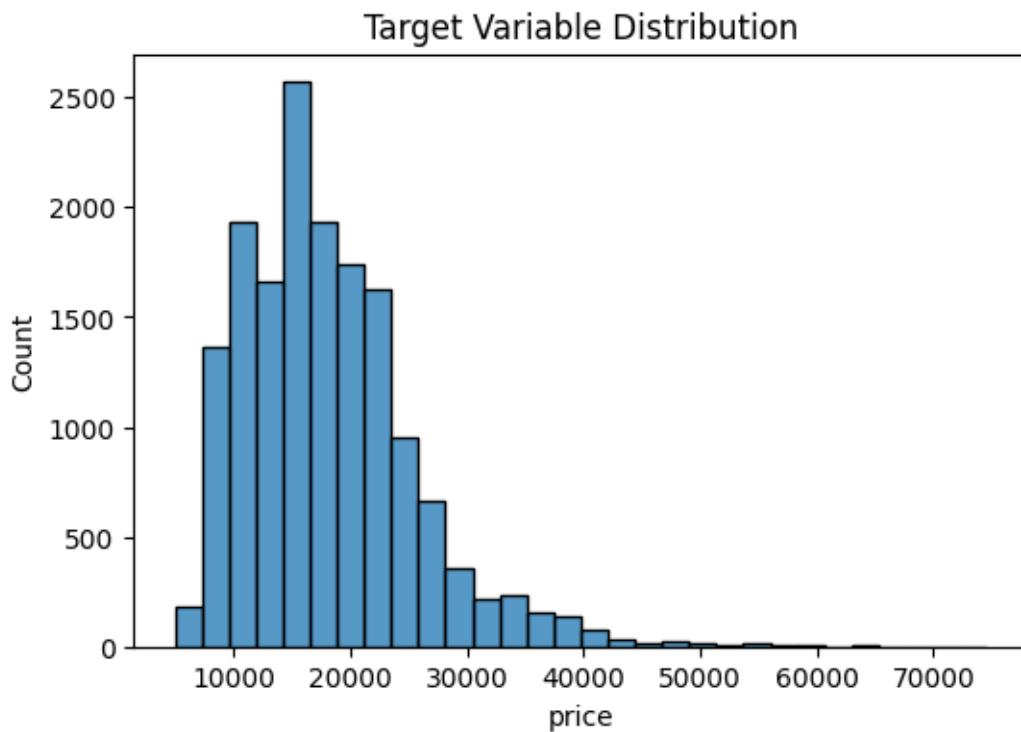


Identify target variable and plot the frequency distributions

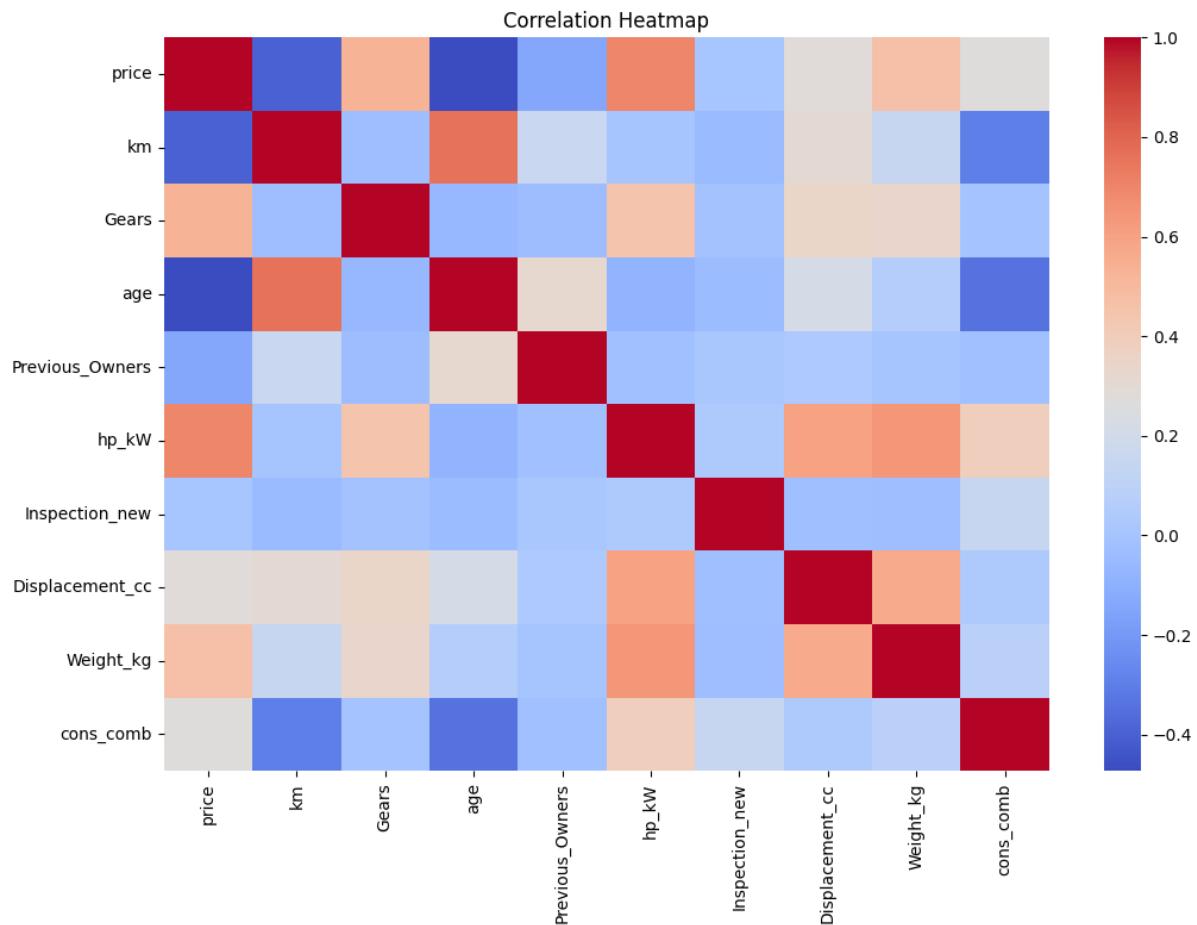
### Target Variable Distribution



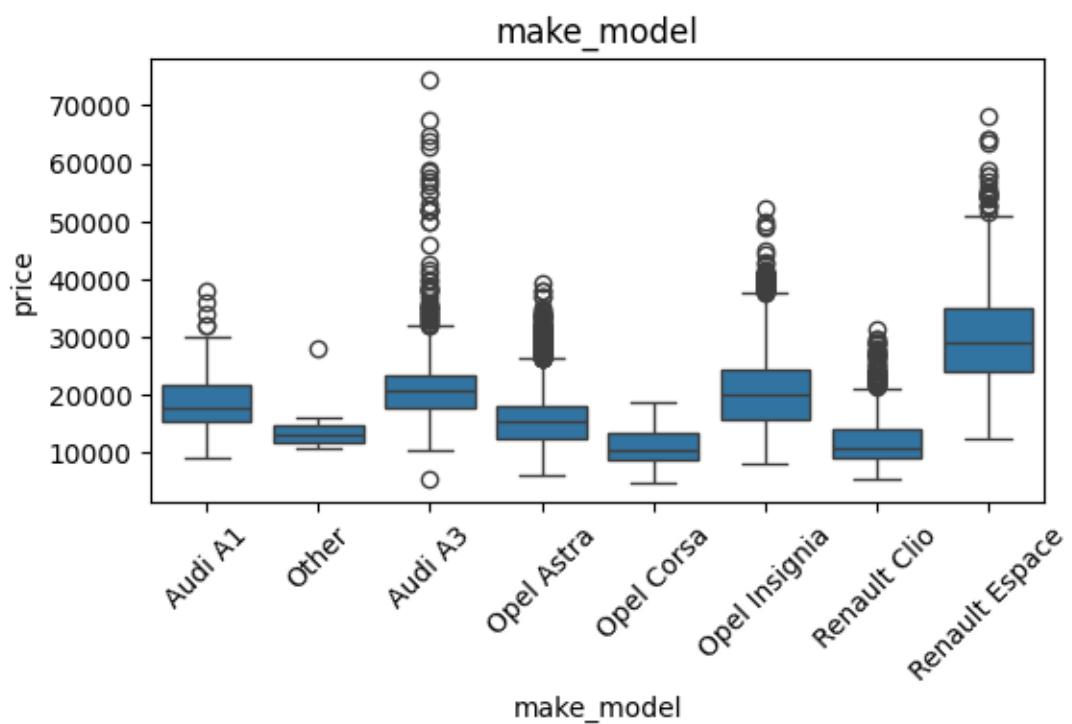
Transform the target feature

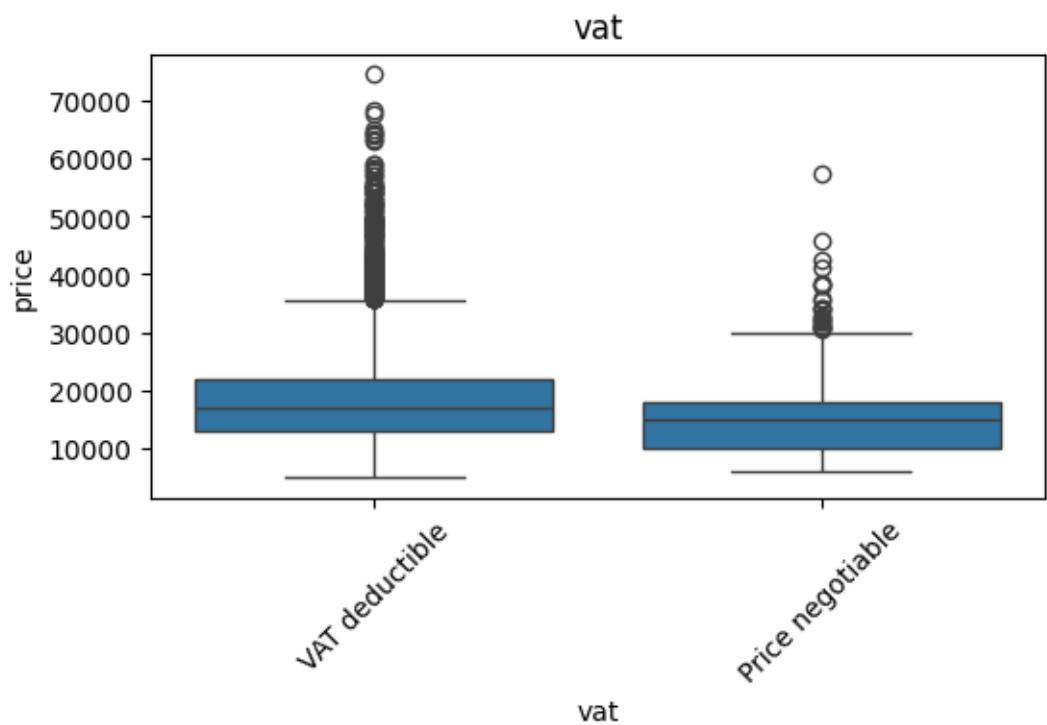
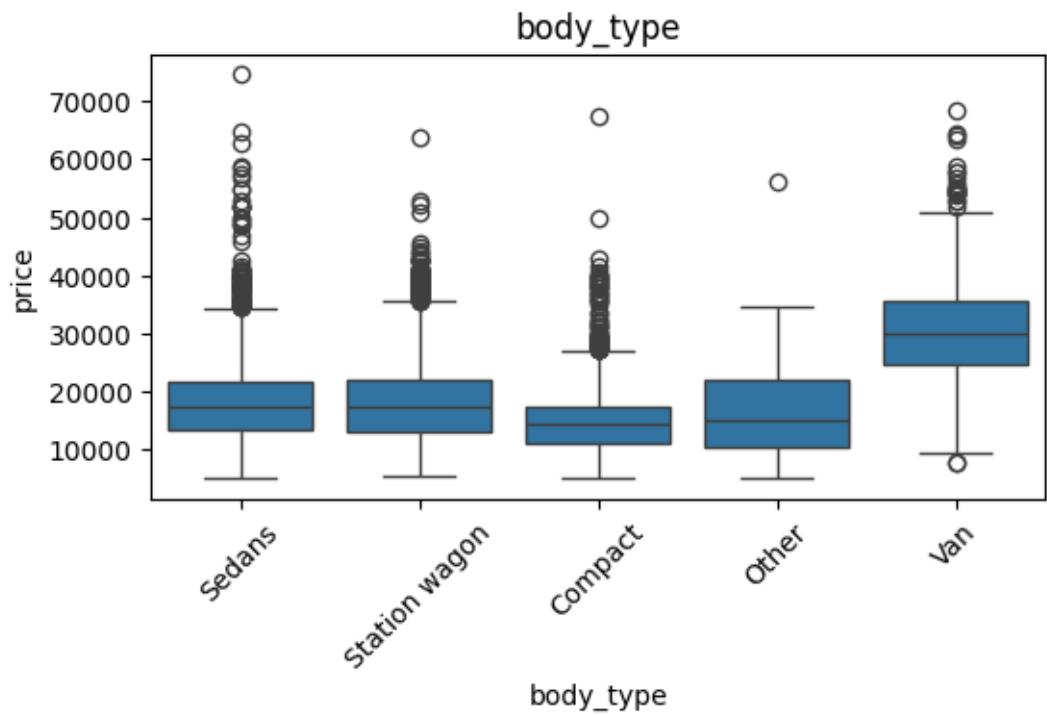


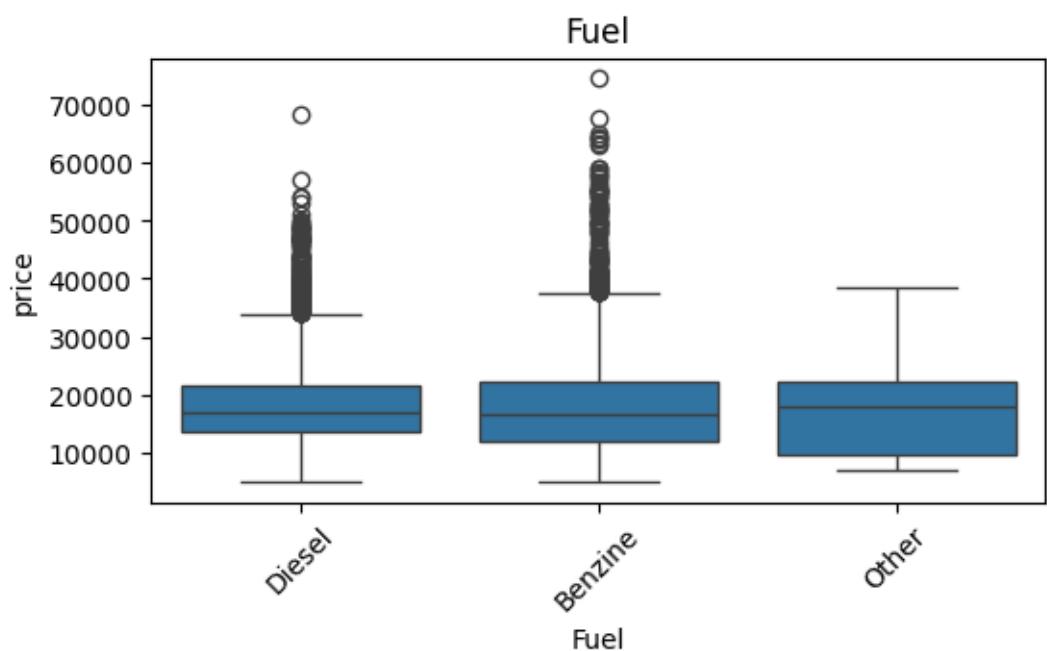
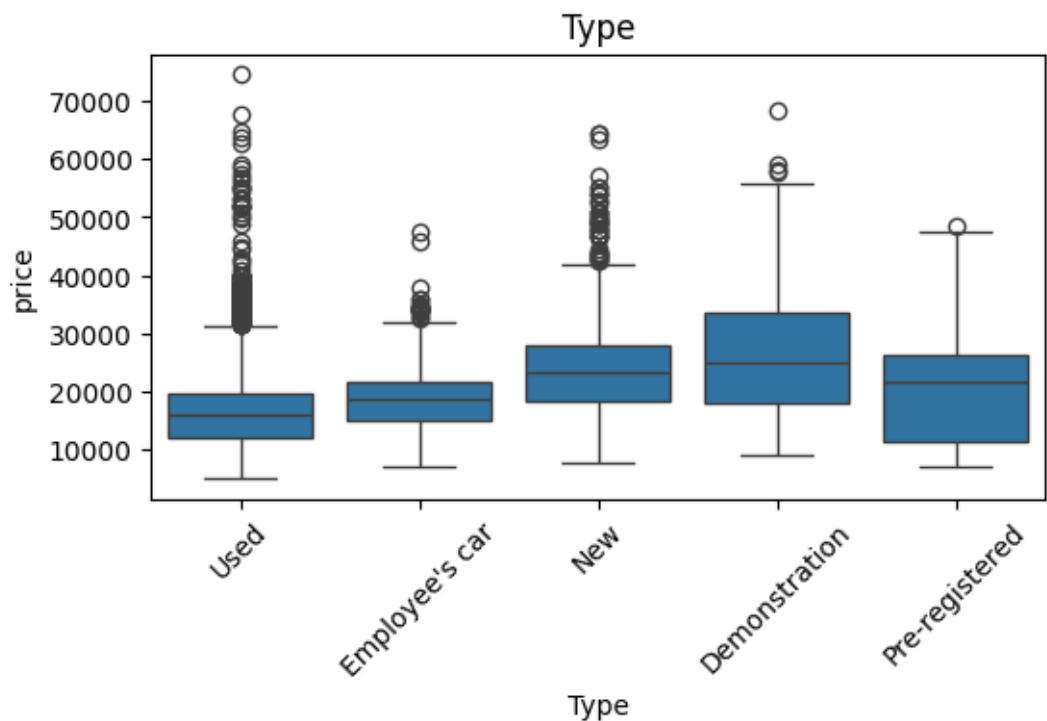
Plot the correlation map between features and target variable.

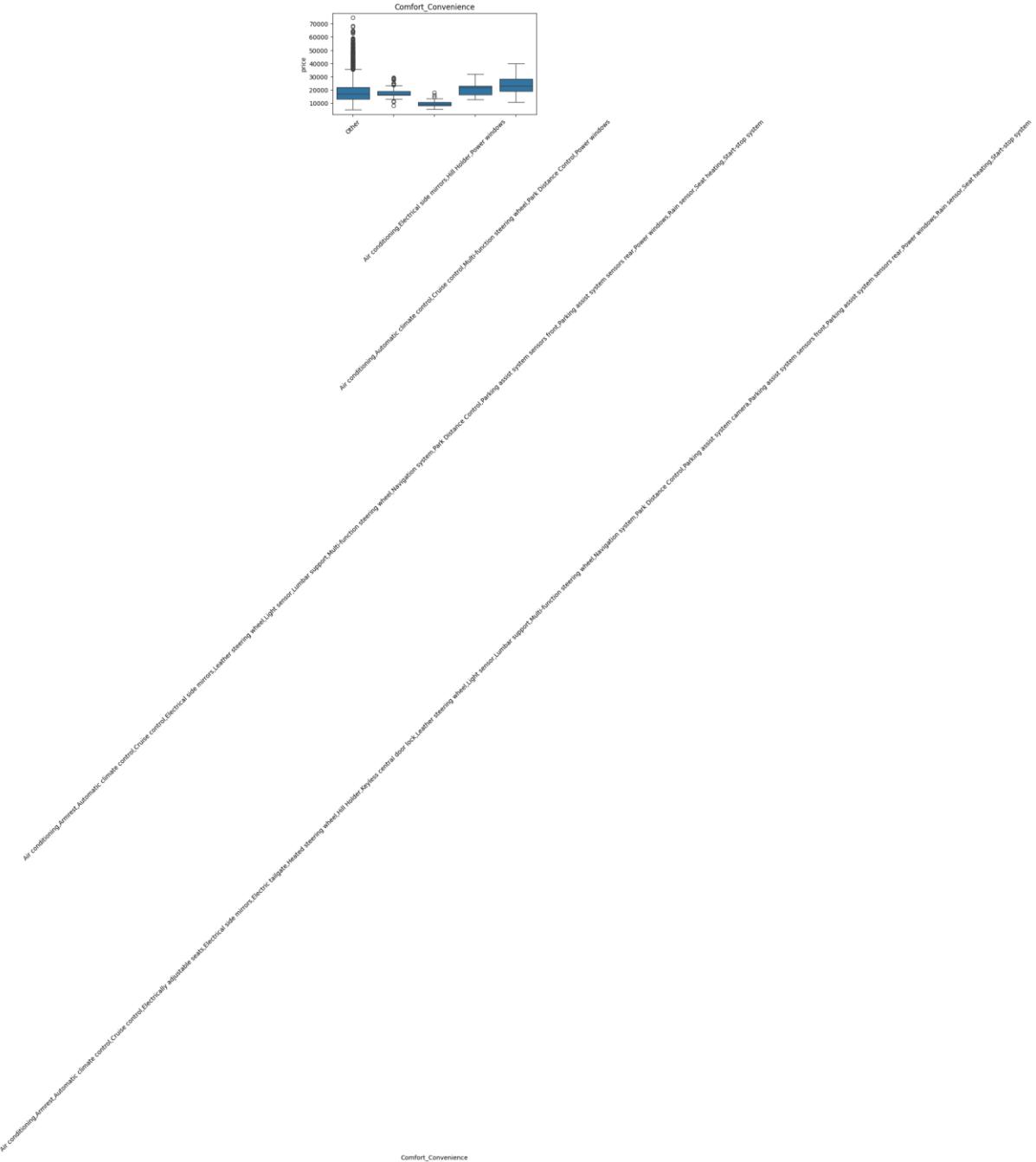


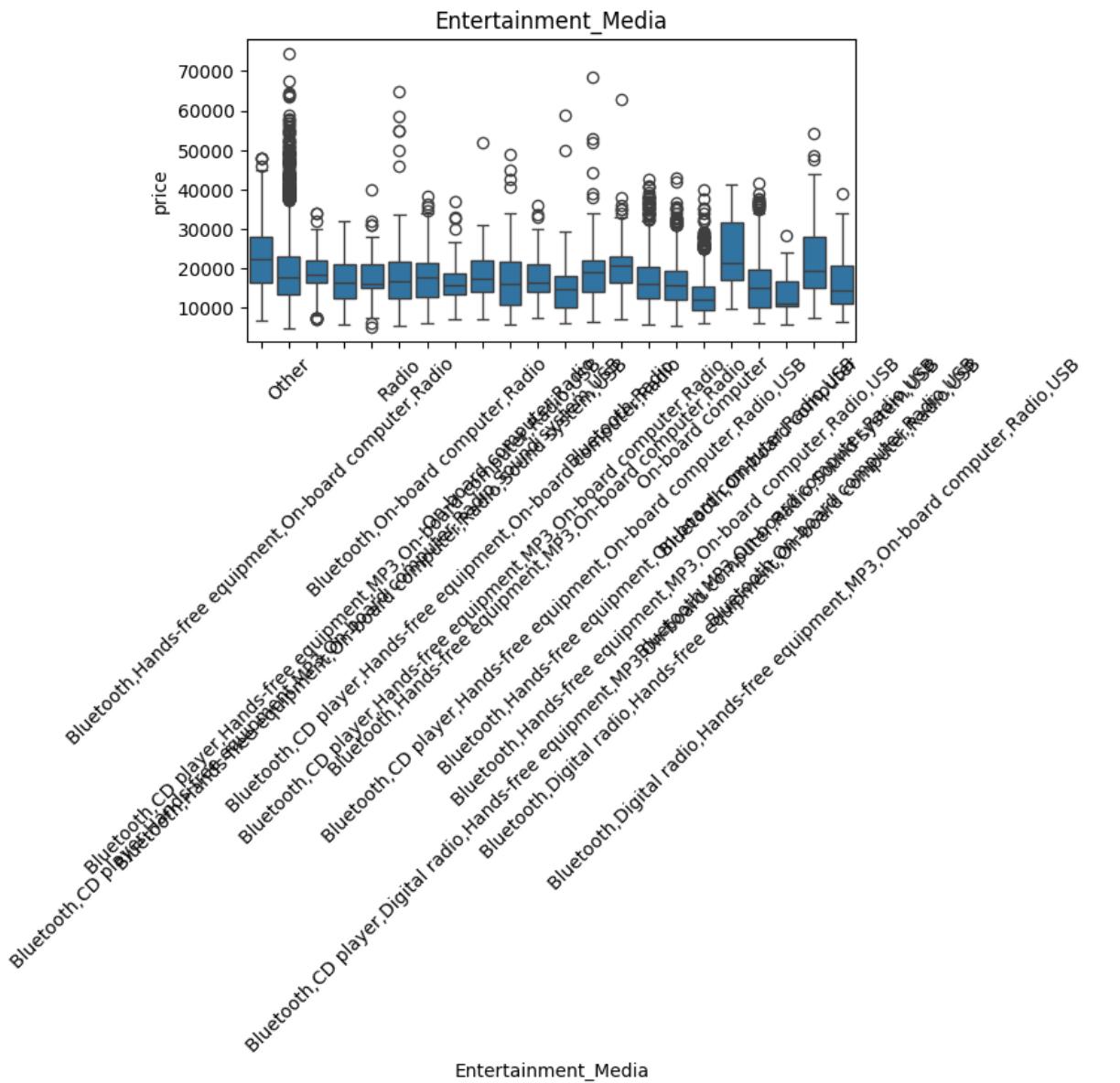
Analyse correlation between categorical features and target variable.

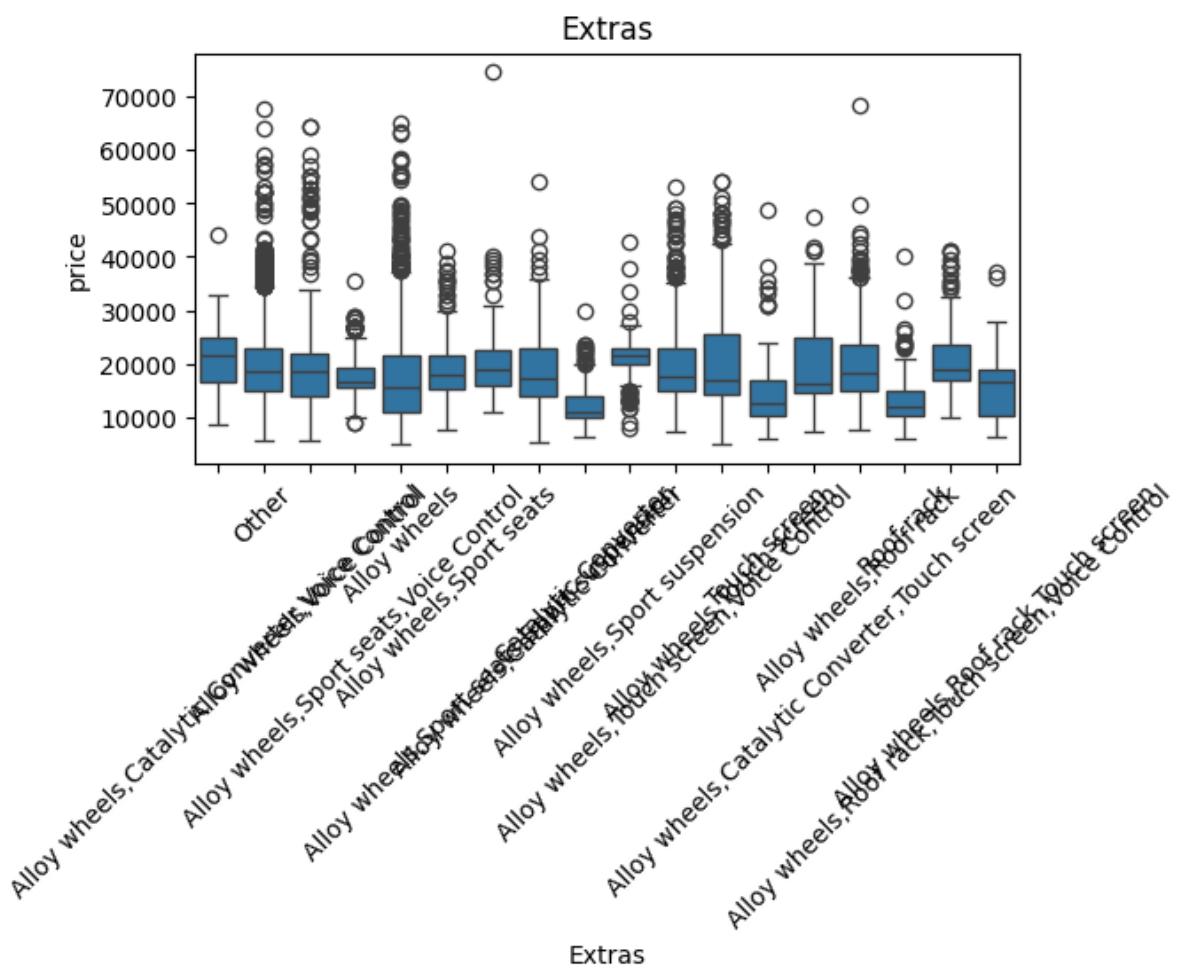


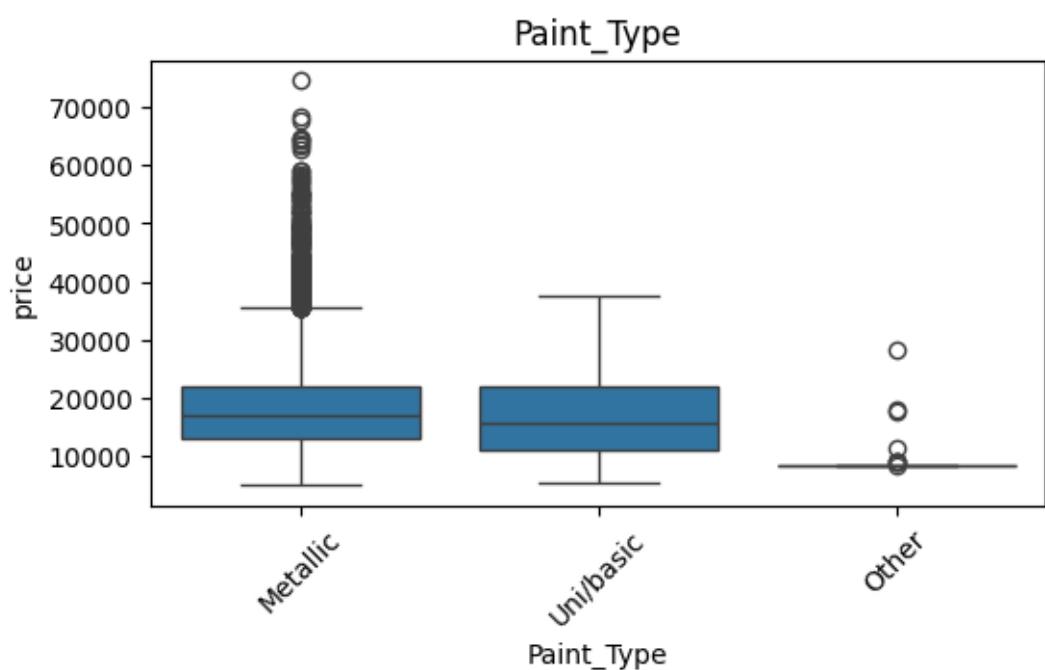
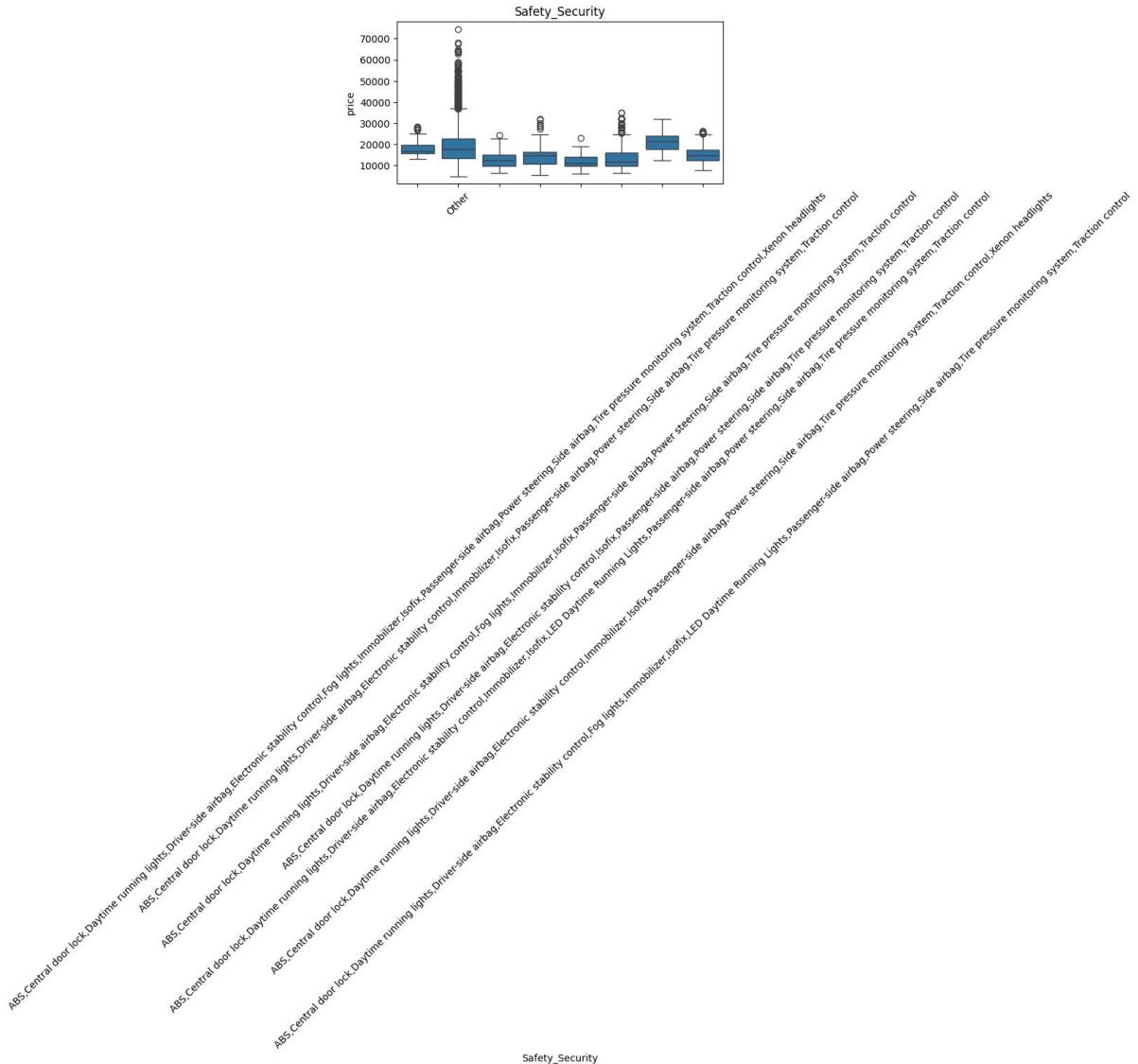


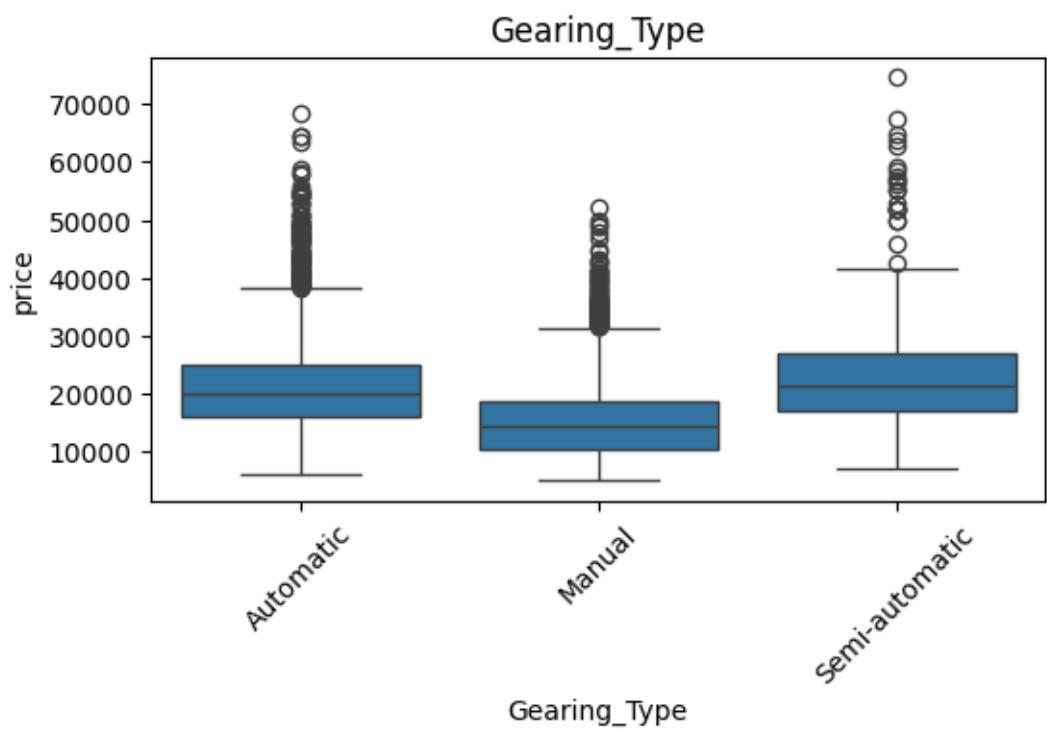
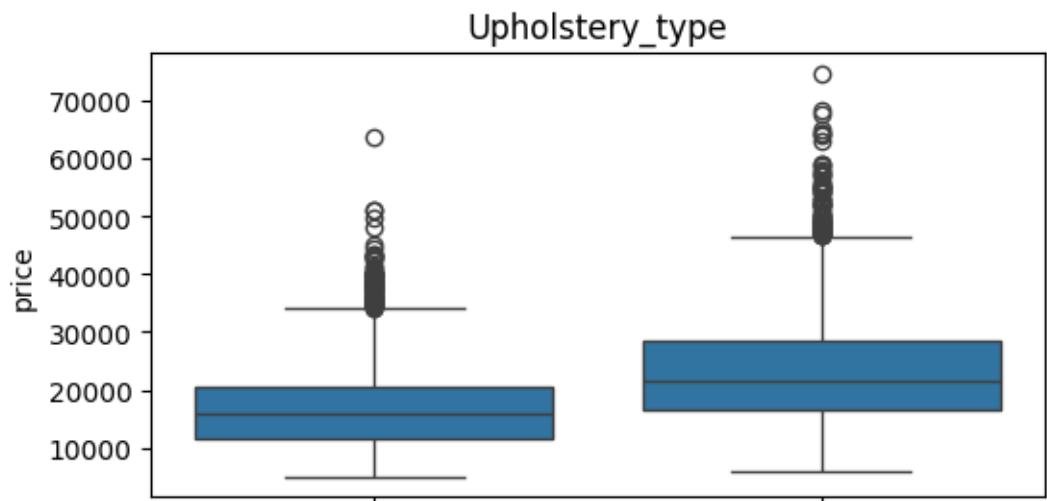


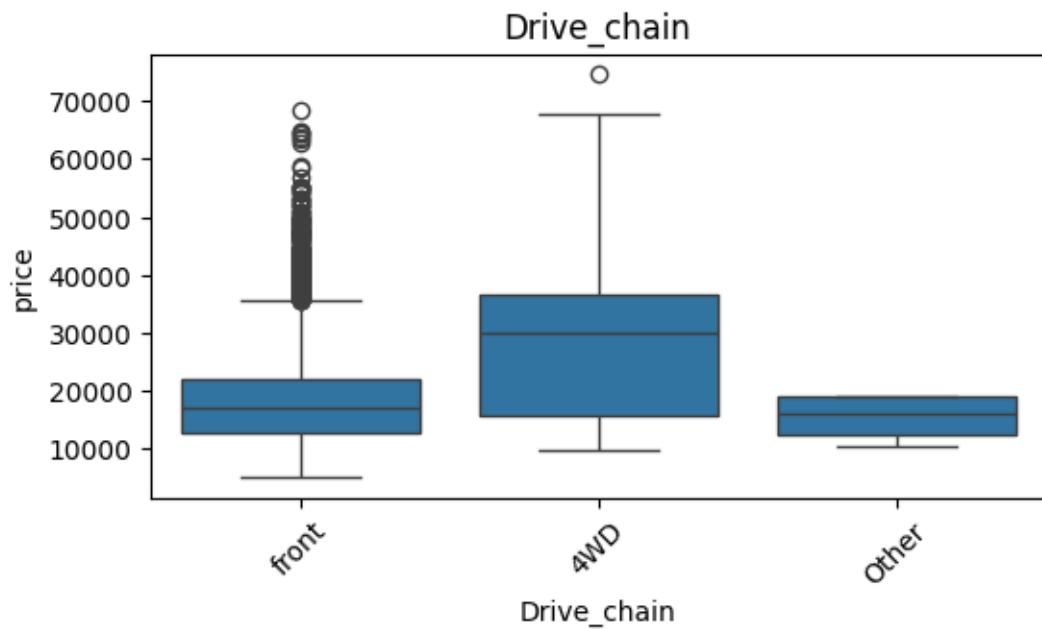






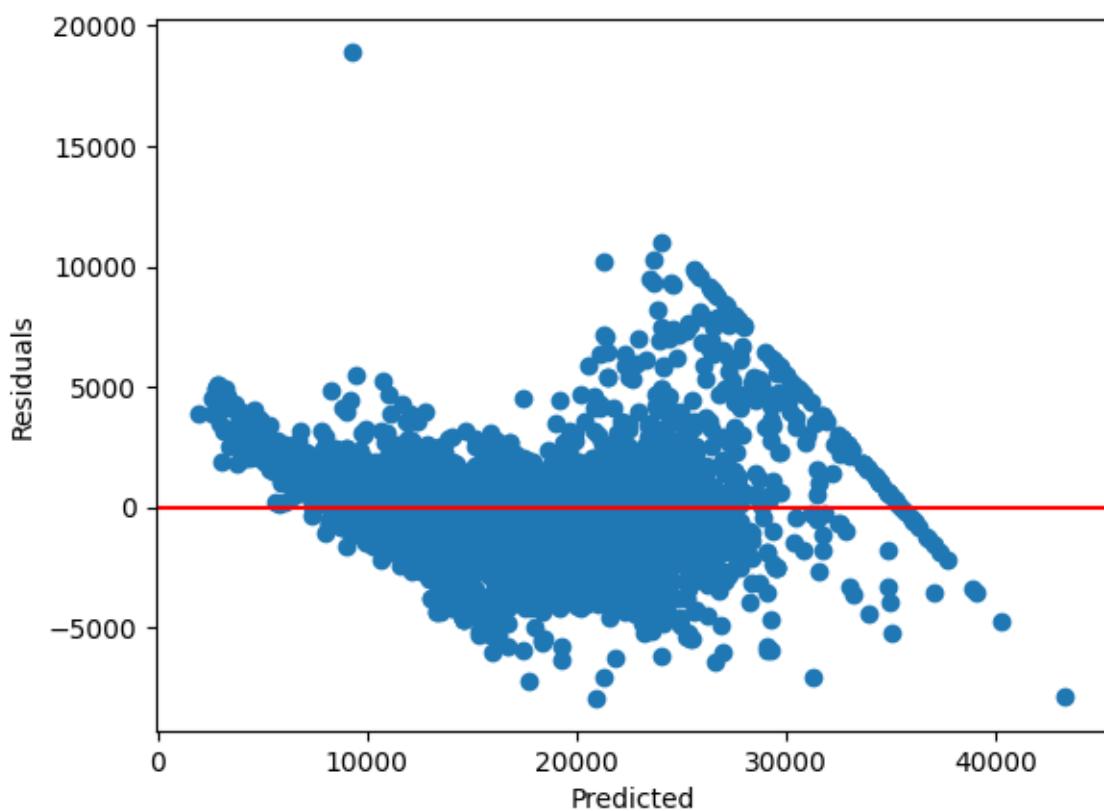




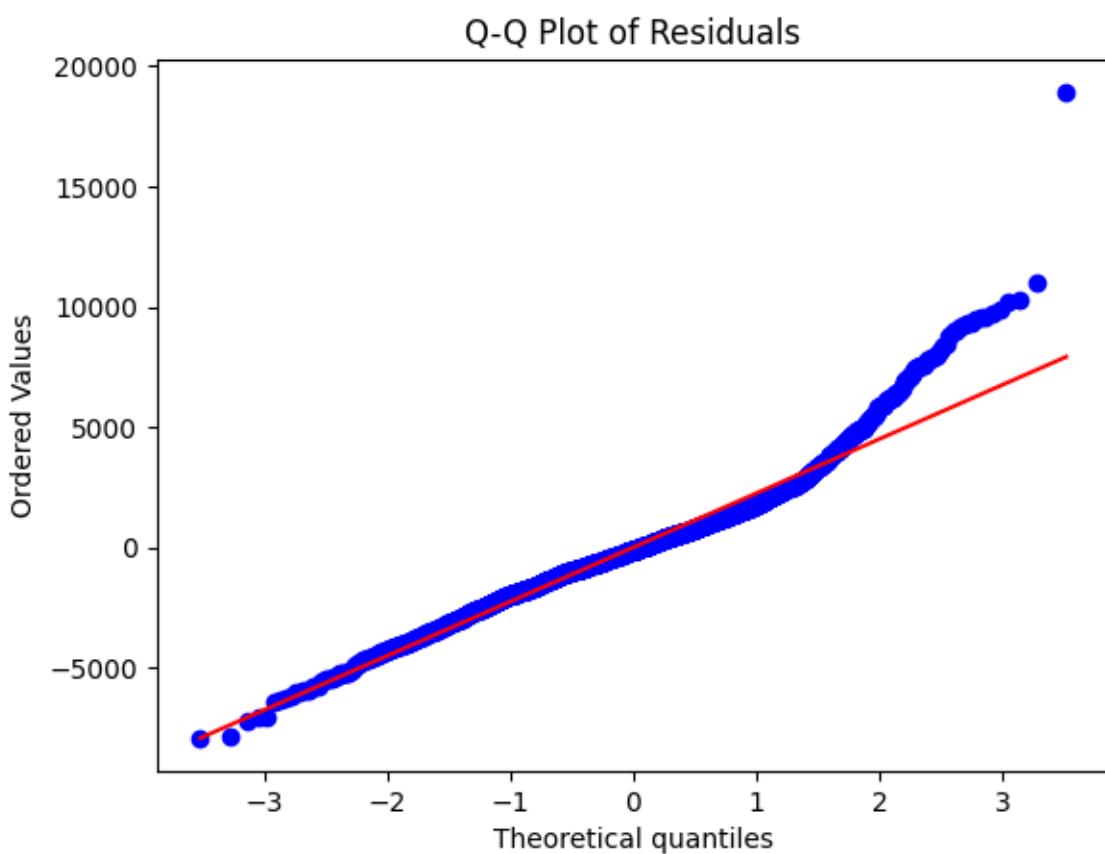
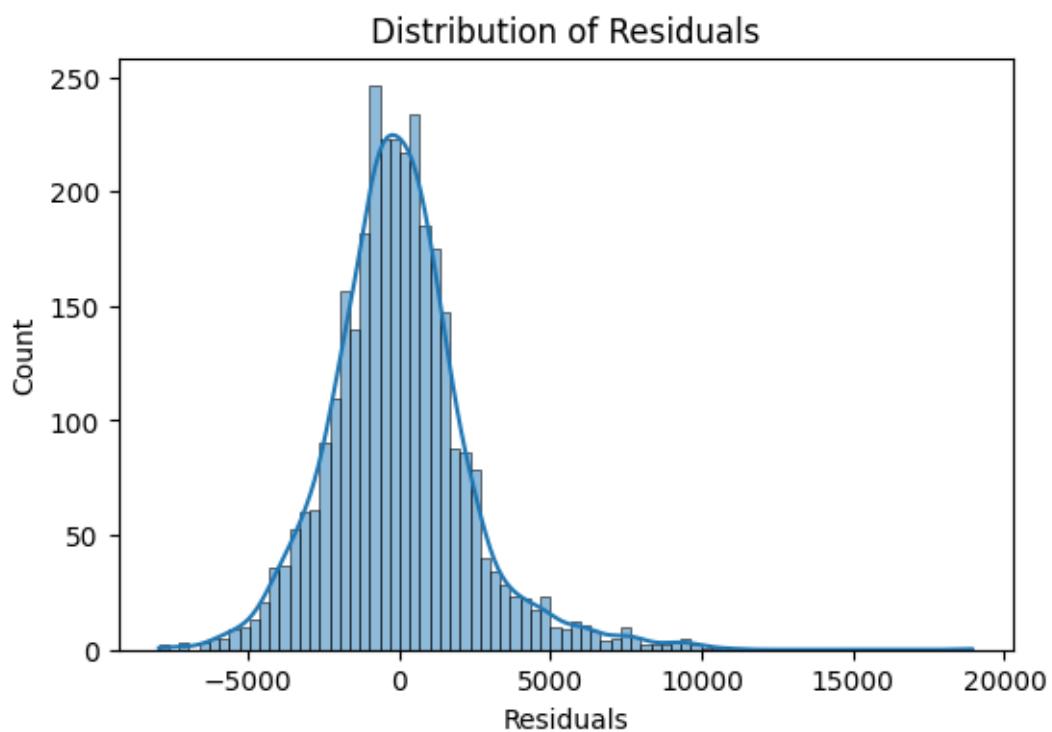


### Linear Regression Models

Analyse residuals and check other assumptions of linear regression.



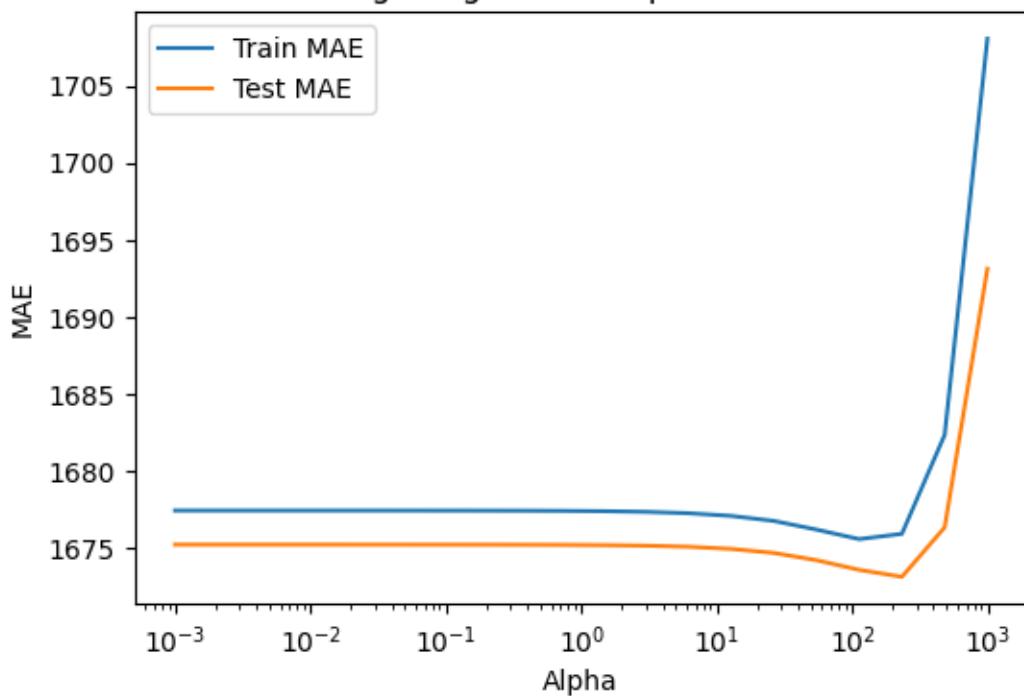
normality in residual distribution



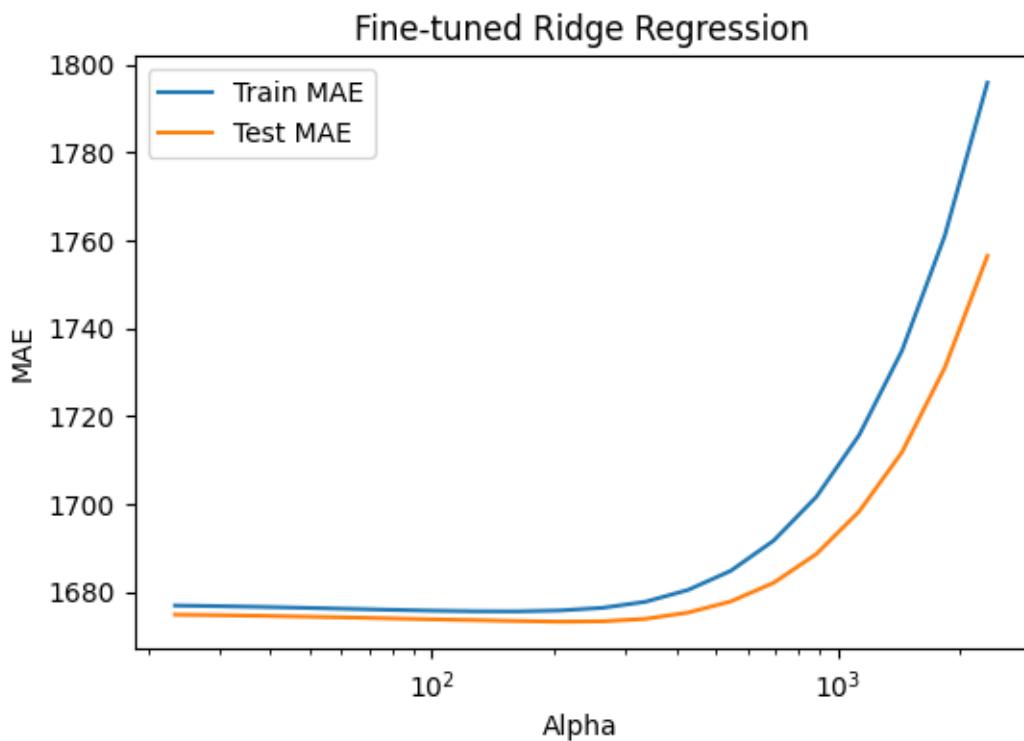
Apply Ridge Regularisation and find the best value of alpha from the list

Plot train and test scores against alpha

Ridge Regression: Alpha vs Error



Plot the error-alpha graph again and find the actual optimal value for alpha.

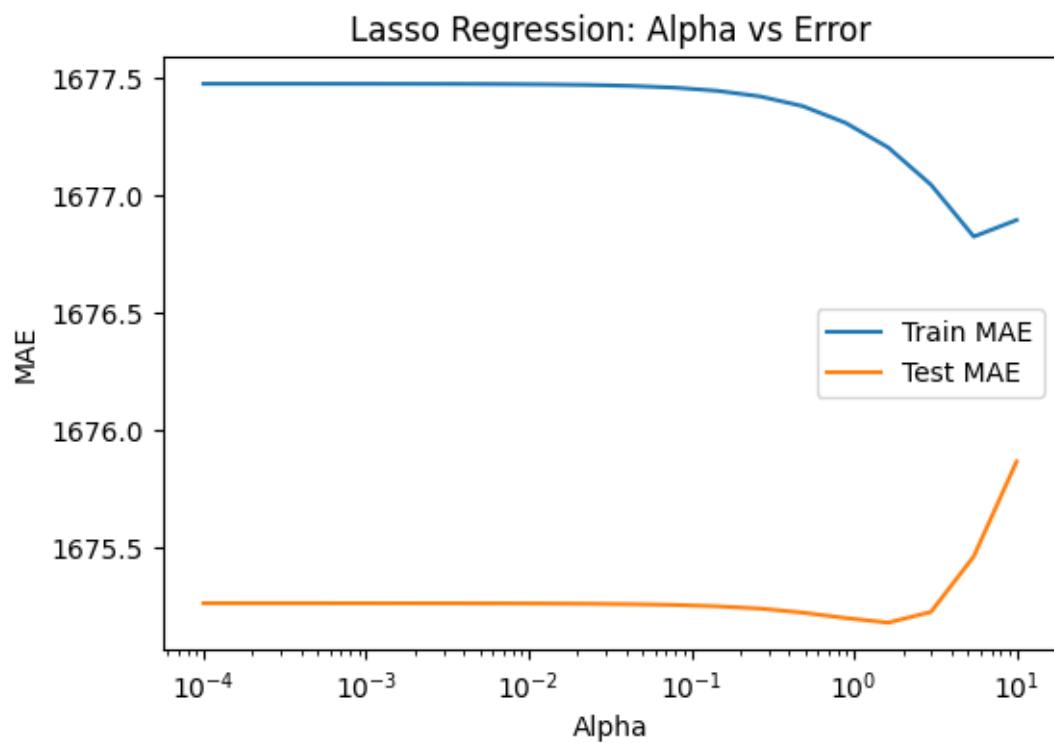


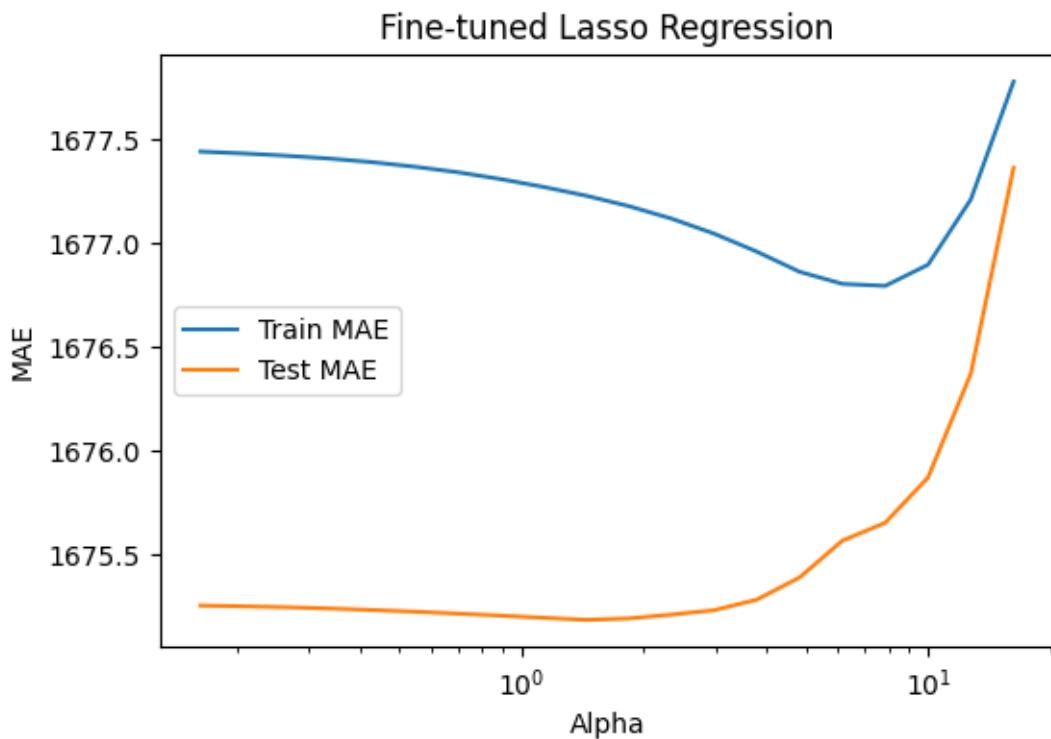
Ridge(alpha=np.float64(206.9138081114788))

	0
hp_kw	2042.446649

	<b>0</b>
<b>age</b>	-1907.786564
<b>make_model_Opel Corsa</b>	-1895.323680
<b>make_model_Renault Clio</b>	-1713.646690
<b>km</b>	-1290.357447
<b>make_model_Opel Astra</b>	-1228.392091
<b>Type_Used</b>	-1189.136552
<b>Gearing_Type_Manual</b>	-905.134462
<b>make_model_Renault Espace</b>	891.978514
<b>Type_Employee's car</b>	-690.264104

### Lasso Regression Implementation





```
Lasso(alpha=np.float64(1.438449888287662), max_iter=5000)
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**

**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

Lasso

[?Documentation for Lasso](#)[iFitted](#)

```
Lasso(alpha=np.float64(1.438449888287662), max_iter=5000)
```

	<b>0</b>
<b>hp_kw</b>	2126.655867
<b>age</b>	-1955.670793
<b>make_model_Opel Corsa</b>	-1951.300206
<b>make_model_Renault Clio</b>	-1789.776225
<b>make_model_Opel Astra</b>	-1299.732279
<b>Type_Used</b>	-1299.472968
<b>km</b>	-1284.116944
<b>Gearing_Type_Manual</b>	-930.379001

	<b>0</b>
<b>make_model_Renault Espace</b>	904.889208
<b>Type_Employee's car</b>	-763.572395

**dtype:** float64

### Regularisation Comparison & Analysis

Compare metrics for each model

	<b>Model</b>	<b>R2</b>	<b>MAE</b>
<b>0</b>	Linear	0.886127	1675.265187
<b>1</b>	Ridge	0.886029	1673.195330
<b>2</b>	Lasso	0.886146	1675.181613

Compare the coefficients for the three models.

	<b>Linear</b>	<b>Ridge</b>	<b>Lasso</b>
<b>hp_kW</b>	2138.384463	2042.446649	2126.655867
<b>age</b>	1956.363814	1907.786564	1955.670793
<b>make_model_Opel Corsa</b>	1946.802631	1895.323680	1951.300206
<b>make_model_Renault Clio</b>	1793.202014	1713.646690	1789.776225
<b>make_model_Opel Astra</b>	1304.113830	1228.392091	1299.732279
<b>Type_Used</b>	1316.331277	1189.136552	1299.472968
<b>km</b>	1285.918999	1290.357447	1284.116944
<b>Gearing_Type_Manual</b>	930.690630	905.134462	930.379001
<b>make_model_Renault Espace</b>	904.776010	891.978514	904.889208
<b>Type_Employee's car</b>	774.466049	690.264104	763.572395

### Conclusion & Key Takeaways

This analysis aimed to build a reliable pricing model for used cars while understanding how different vehicle characteristics influence market value. The baseline linear regression model already performed strongly, explaining nearly 89% of the variation in prices. This indicates that

the dataset was rich and informative, and that many pricing drivers follow a largely linear relationship.

Regularisation helped refine the model rather than dramatically improve performance. Ridge regression stabilised coefficient estimates by reducing the impact of multicollinearity, making the model more robust and dependable for real-world use. Lasso regression offered an additional benefit by automatically removing less important features, resulting in a simpler and more interpretable model without sacrificing accuracy. The similar performance across all three models suggests that overfitting was minimal and the data size was sufficient for this task.

From a business perspective, vehicle age, mileage, engine power, and safety and comfort features consistently emerged as the most influential price drivers. This aligns well with buyer expectations and real-world pricing behaviour. Overall, linear models with regularisation are well-suited for used car price prediction. However, to capture more complex market dynamics, future work could explore non-linear models such as tree-based or ensemble methods.