Executive Summary

Project Title: Predictive Maintenance for Vehicles Using Machine Learning

Overview:

The objective of this project is to develop a machine learning model that predicts the maintenance needs of vehicles based on various characteristics. By analyzing features such as mileage, vehicle age, maintenance history, and fuel type, this model aims to assist fleet managers and individual vehicle owners in scheduling timely maintenance. The ultimate goal is to enhance vehicle performance and reduce the risk of unexpected breakdowns, thereby improving operational efficiency and safety.

Project Description:

In the automotive industry, maintaining vehicle performance and preventing failures are critical for ensuring safety and reducing operational costs. Predictive maintenance offers significant cost-saving opportunities and allows for better resource allocation. This project leverages historical data related to vehicle characteristics and maintenance history to predict whether a vehicle requires maintenance (1 = Yes, 0 = No). The key focus is to develop a model that can proactively identify when a vehicle is likely to need servicing, helping avoid costly breakdowns and improve operational efficiency.

Dataset Overview:

Dataset Link:
Vehicle Maintenance Data

Data Dictionary:

Feature	Description	Data Type	Example Values
Vehicle_Model	Type of the vehicle (e.g., Car, SUV, Truck)	Categorical	Car, SUV, Truck
Mileage	Total mileage covered by the vehicle	Numeric	15,000, 35,000, 120,000
Maintenance_History	Quality of previous maintenance	Categorical	Good, Average, Poor
Vehicle_Age	Age of the vehicle in years	Numeric	1, 5, 10
Fuel_Type	Type of fuel used by the vehicle (e.g., Gasoline)	Categorical	Gasoline, Diesel
Last_Service_Date	Date of the last service performed	Date	2023-06-15
Engine_Health	Status of engine health	Categorical	Good, Fair, Poor
Tire_Condition	Condition of the tires	Categorical	New, Worn
Weather_Conditions	Conditions during the last trip	Categorical	Sunny, Rainy, Snowy
Driving_Style	Style of driving	Categorical	Aggressive, Moderate
Last_Fuel_Consumption	Fuel consumption during the last trip	Numeric	25, 18.5, 22

Evaluation and Summary of the XGBoost Model

1. Confusion Matrix:

- The confusion matrix shows **no false positives** and **no false negatives**.
  - **2,855** instances where the vehicle **doesn't need maintenance** are correctly classified (True Negatives).
  - **12,145** instances where the vehicle **needs maintenance** are correctly classified (True Positives).
- This indicates a perfect classification by the XGBoost model.

2. ROC Curve and AUC:

- The **ROC curve** shows an **AUC (Area Under the Curve) of 1.00**, representing perfect classification performance.
- The curve reaches the top-left corner, indicating that the model is highly effective at distinguishing between vehicles needing maintenance and those not needing it.

3. Feature Importance Analysis:

- The most important features influencing the model's predictions are:
  1. **Battery_Status**
  2. **Brake_Condition**
  3. **Reported_Issues**
  4. **Maintenance_History**
  5. **Accident_History**
- These features carry the most weight in determining whether a vehicle will require maintenance.
- Other features such as **Fuel Efficiency**, **Odometer Reading**, and **Transmission Type** have much lower importance in comparison.

4. Model Performance Metrics:

- The model achieved perfect scores across all performance metrics:
  - **Accuracy**: 1.00
  - **Precision**: 1.00
  - **Recall**: 1.00
  - **F1 Score**: 1.00
- These results suggest that the model predicts whether a vehicle requires maintenance without making any errors.

Conclusion:

The **XGBoost Classifier** performed exceptionally well, achieving **perfect classification** on the test data. However, such high scores may indicate potential **overfitting**, meaning the model might not generalize as well on unseen data. Despite this, the model's feature importance shows a reasonable distribution of influential factors, with **Battery_Status** and **Brake_Condition** playing key roles in the predictions.

Data Processing and Analysis Steps

1. Distribution Analysis of Maintenance History:

- **Objective**: Analyze the distribution of **Maintenance_History** and its impact on maintenance needs.

- **Actions**: Perform groupby operations to summarize maintenance needs by **Maintenance_History** and visualize the distributions using box plots or count plots.

2. Correlation Analysis:

- **Objective**: Assess how **Mileage** correlates with the likelihood of requiring maintenance.
- **Actions**: Calculate correlation coefficients between **Mileage** and **Need_Maintenance**. Create scatter plots and heatmaps to visualize relationships.

3. Influence of External Factors:

- **Objective**: Investigate how **Weather_Conditions** and **Driving_Style** affect maintenance needs.
- **Actions**: Use statistical tests (e.g., chi-square test) to assess associations between categorical variables and **Need_Maintenance**. Create visualizations to display trends and patterns.

4. Time-Series Analysis of Vehicle Age:

- **Objective**: Determine how **Vehicle Age** influences maintenance requirements over time.
- **Actions**: Aggregate data by vehicle age and calculate the percentage of vehicles needing maintenance. Use line plots to visualize trends over time.

5. Feature Importance Analysis:

- **Objective**: Identify which vehicle features are most predictive of maintenance needs.
- **Actions**: Utilize methods such as **Random Forest** or **XGBoost** to compute feature importances and visualize them using bar charts.

Conclusion

This project aims to utilize machine learning techniques to predict vehicle maintenance needs, offering significant advantages for fleet management and individual vehicle owners. By addressing the outlined data processing and analysis steps, we can derive actionable insights that will aid in the implementation of effective predictive maintenance strategies. The resulting model is expected to be a valuable tool for improving vehicle reliability and efficiency in the automotive industry.

In [1]:
```python
# Import all libraries

import pandas as pd
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
from sklearn.cluster import KMeans
from scipy import stats
from io import StringIO
import time
```

In [2]:
```python
# Import dataset

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

# Confirm dataset loaded
df.head()
```

Out[2]:

	Vehicle_Model	Mileage	Maintenance_History	Reported_Issues	Vehicle_Age	Fuel_Type	Transmission_Type	Engin
0	Truck	58765	Good	0	4	Electric	Automatic	
1	Van	60353	Average	1	7	Electric	Automatic	
2	Bus	68072	Poor	0	2	Electric	Automatic	
3	Bus	60849	Average	4	5	Petrol	Automatic	
4	Bus	45742	Poor	5	1	Petrol	Manual	

Data Preprocessing

In [3]:

```
# Dataset details and summary statistics

print(df.info())

# Categorical Summary Statistics
print(f'Categorical Summary Statistics \ndf.describe(include= object).T\n')

# Numerical Summary Statistics
print(f'Numerical Summary Statistics \ndf.describe(include= np.number).T\n')

# Isolate numerical variables
numeric_df = df.select_dtypes(include=np.number)

# Isolate categorical variables
categorical_df = df.select_dtypes(include=object)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Vehicle_Model        50000 non-null  object 
 1   Mileage              50000 non-null  int64  
 2   Maintenance_History  50000 non-null  object 
 3   Reported_Issues      50000 non-null  int64  
 4   Vehicle_Age          50000 non-null  int64  
 5   Fuel_Type            50000 non-null  object 
 6   Transmission_Type    50000 non-null  object 
 7   Engine_Size          50000 non-null  int64  
 8   Odometer_Reading     50000 non-null  int64  
 9   Last_Service_Date    50000 non-null  object 
 10  Warranty_Expiry_Date 50000 non-null  object 
 11  Owner_Type           50000 non-null  object 
 12  Insurance_Premium    50000 non-null  int64  
 13  Service_History      50000 non-null  int64  
 14  Accident_History     50000 non-null  int64  
 15  Fuel_Efficiency      50000 non-null  float64
 16  Tire_Condition       50000 non-null  object 
 17  Brake_Condition      50000 non-null  object 
 18  Battery_Status       50000 non-null  object 
 19  Need_Maintenance     50000 non-null  int64  
dtypes: float64(1), int64(9), object(10)
memory usage: 7.6+ MB
None
Categorical Summary Statistics 
df.describe(include= object).T

Numerical Summary Statistics 
df.describe(include= np.number).T
```

In [4]:
```python
# Confirm outliers for Numerical variables
def highlight_outliers(s):
    '''
    Highlight values that are outside of 3 standard deviations from the mean.
    '''
    is_outlier = (np.abs(s - s.mean()) > 3 * s.std())
    return ['background-color: red' if v else '' for v in is_outlier]

# Apply function
numeric_df = df.select_dtypes(include=np.number)
styled_df = numeric_df.describe().T.style.apply(highlight_outliers)
styled_df
```

Out[4]:

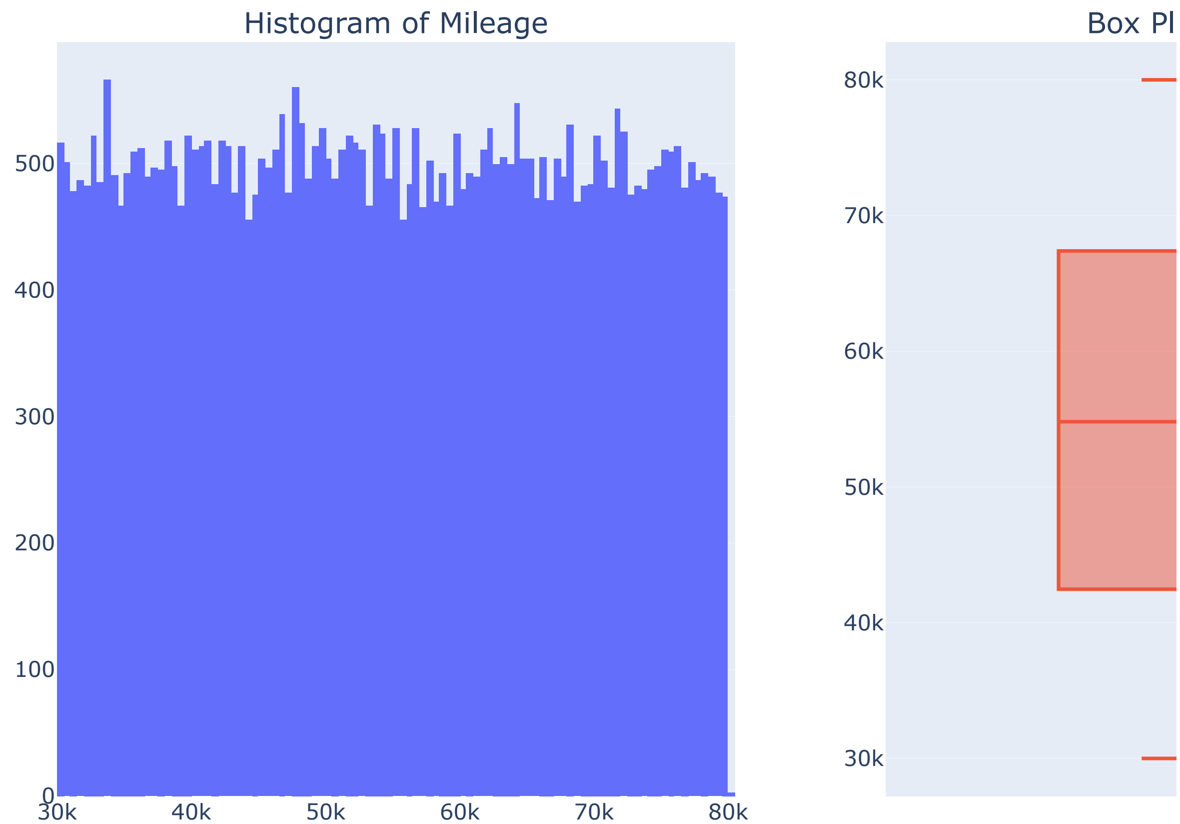
	count	mean	std	min	25%	50%	7
Mileage	50000.000000	54931.232680	14401.912925	30001.000000	42471.500000	54810.000000	67391.500
Reported_Issues	50000.000000	2.497420	1.708781	0.000000	1.000000	2.000000	4.000
Vehicle_Age	50000.000000	5.492260	2.875682	1.000000	3.000000	5.000000	8.000
Engine_Size	50000.000000	1556.292000	627.677218	800.000000	1000.000000	1500.000000	2000.000
Odometer_Reading	50000.000000	75551.187060	43088.105658	1001.000000	38009.000000	75598.500000	112999.500
Insurance_Premium	50000.000000	17465.340700	7223.393401	5000.000000	11189.750000	17477.500000	23692.000
Service_History	50000.000000	5.515560	2.874899	1.000000	3.000000	6.000000	8.000
Accident_History	50000.000000	1.501560	1.119510	0.000000	0.000000	2.000000	3.000
Fuel_Efficiency	50000.000000	14.990323	2.885583	10.000098	12.489037	14.986352	17.474
Need_Maintenance	50000.000000	0.809960	0.392336	0.000000	1.000000	1.000000	1.000

Univariate Analysis

In [5]:
```python
# Distribution of numeric variables

import plotly.subplots as sp
import plotly.graph_objects as go

# isolating numeric variables
numeric_df = df.select_dtypes(include=np.number)

for column in numeric_df.columns:
    # Summary statistics
    print(f"Summary Statistics for {column}:\n{numeric_df[column].describe()}\n")

    # Create subplots
    fig = sp.make_subplots(rows=1, cols=2, subplot_titles=(f"Histogram of {column}", f"Box Plot of

    # Histogram
    fig.add_trace(go.Histogram(x=numeric_df[column]), row=1, col=1)

    # Box plot
    fig.add_trace(go.Box(y=numeric_df[column]), row=1, col=2)

    fig.update_layout(height=600, width=1000, title_text=f"Plots for {column}", showlegend=False)
    fig.show()
```

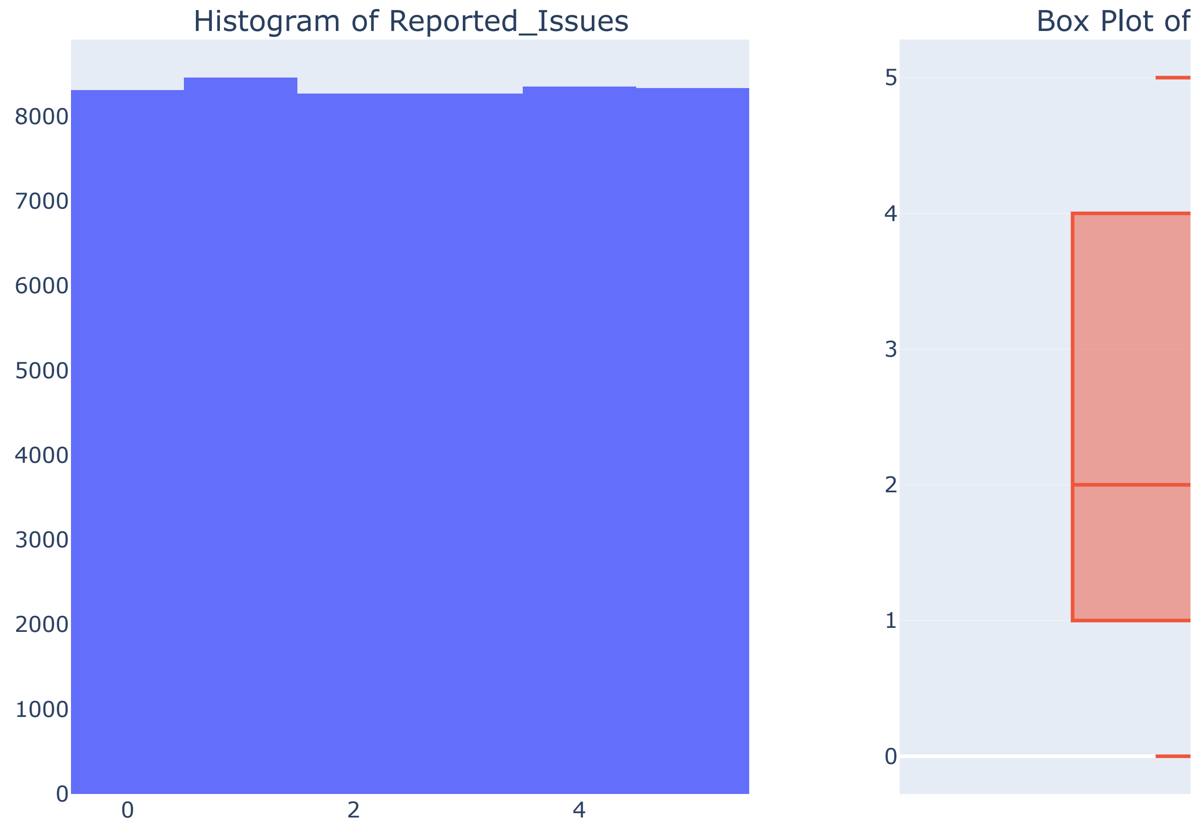
```
Summary Statistics for Mileage:
count    50000.000000
mean     54931.232680
std      14401.912925
min      30001.000000
25%      42471.500000
50%      54810.000000
75%      67391.500000
max      80000.000000
Name: Mileage, dtype: float64
```

Plots for Mileage

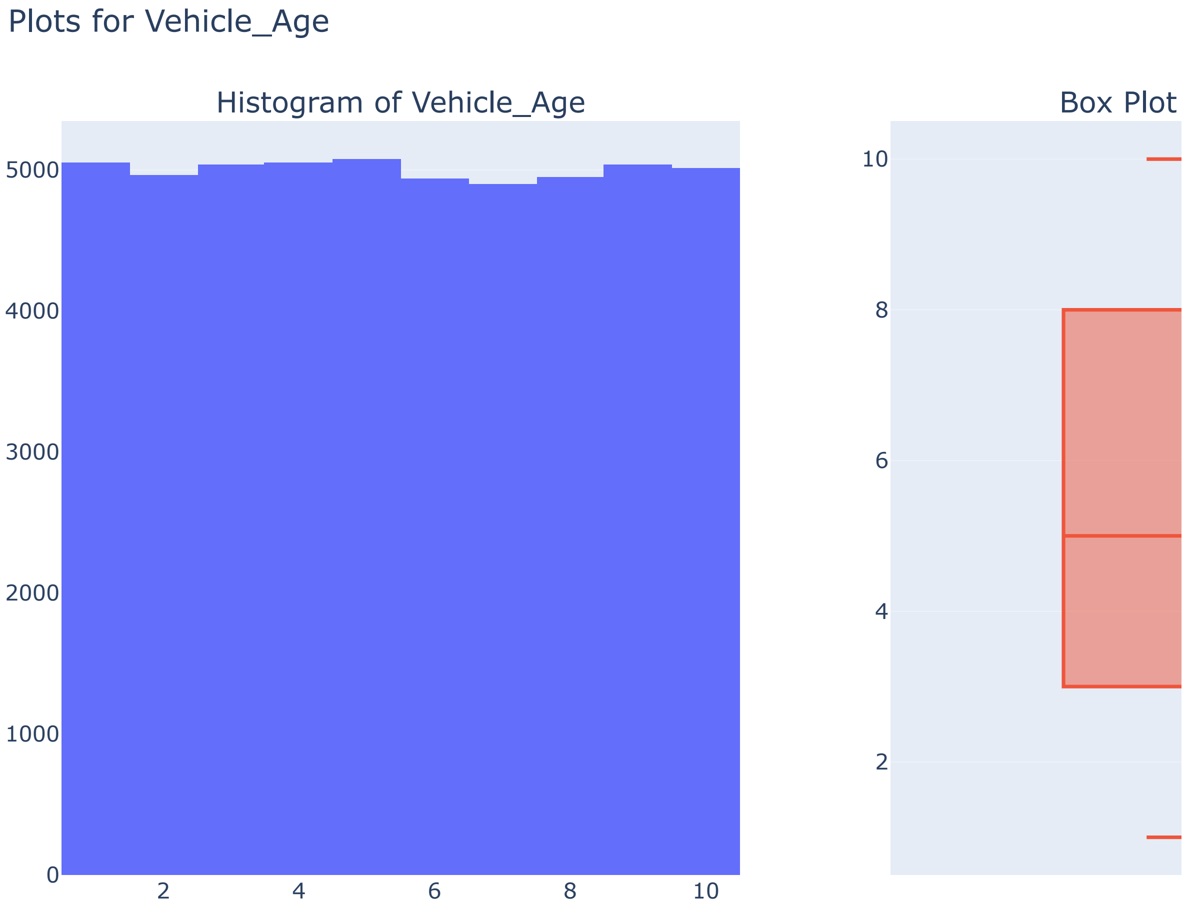



```
Summary Statistics for Reported_Issues:
count    50000.000000
mean         2.497420
std          1.708781
min          0.000000
25%          1.000000
50%          2.000000
75%          4.000000
max          5.000000
Name: Reported_Issues, dtype: float64
```

Plots for Reported_Issues

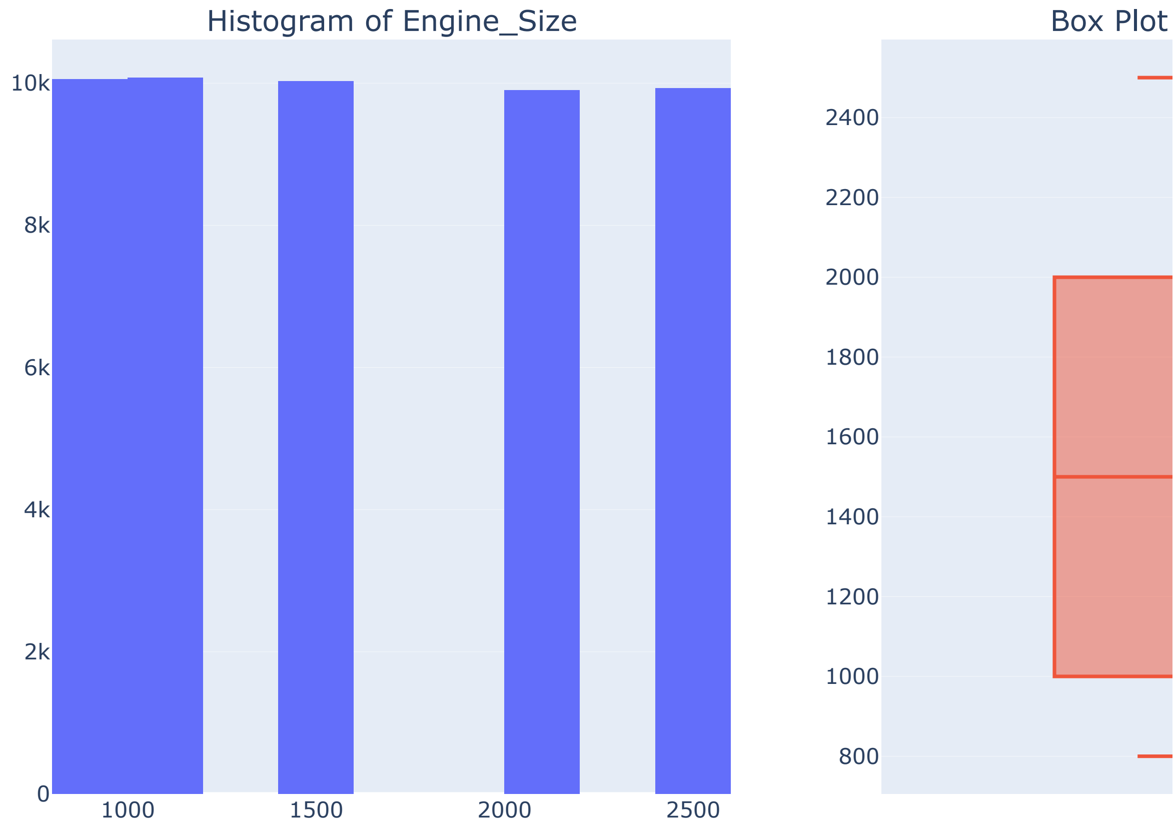



```
Summary Statistics for Vehicle_Age:
count    50000.000000
mean         5.492260
std          2.875682
min          1.000000
25%          3.000000
50%          5.000000
75%          8.000000
max         10.000000
Name: Vehicle_Age, dtype: float64
```



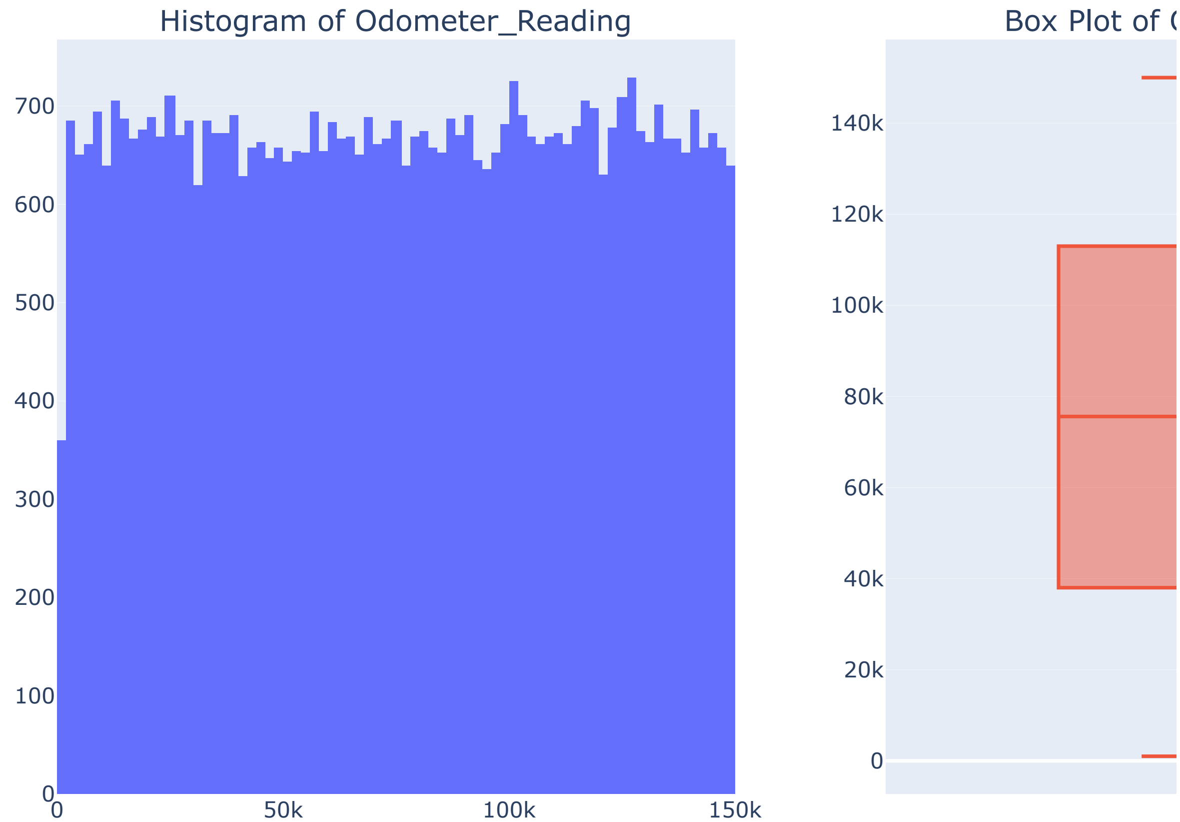

```
Summary Statistics for Engine_Size:
count    50000.000000
mean      1556.292000
std        627.677218
min        800.000000
25%       1000.000000
50%       1500.000000
75%       2000.000000
max       2500.000000
Name: Engine_Size, dtype: float64
```

Plots for Engine_Size

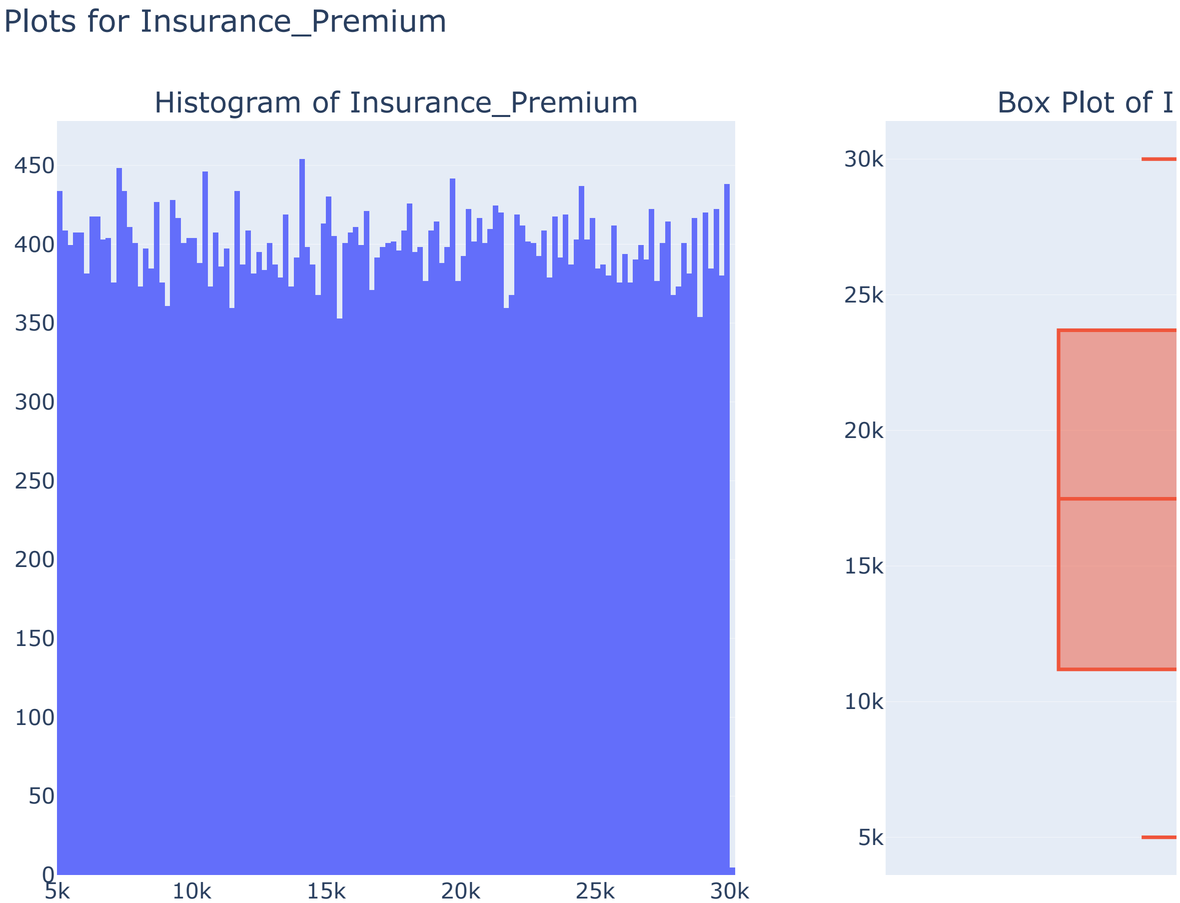



```
Summary Statistics for Odometer_Reading:
count     50000.000000
mean      75551.187060
std       43088.105658
min        1001.000000
25%       38009.000000
50%       75598.500000
75%      112999.500000
max      149999.000000
Name: Odometer_Reading, dtype: float64
```

Plots for Odometer_Reading

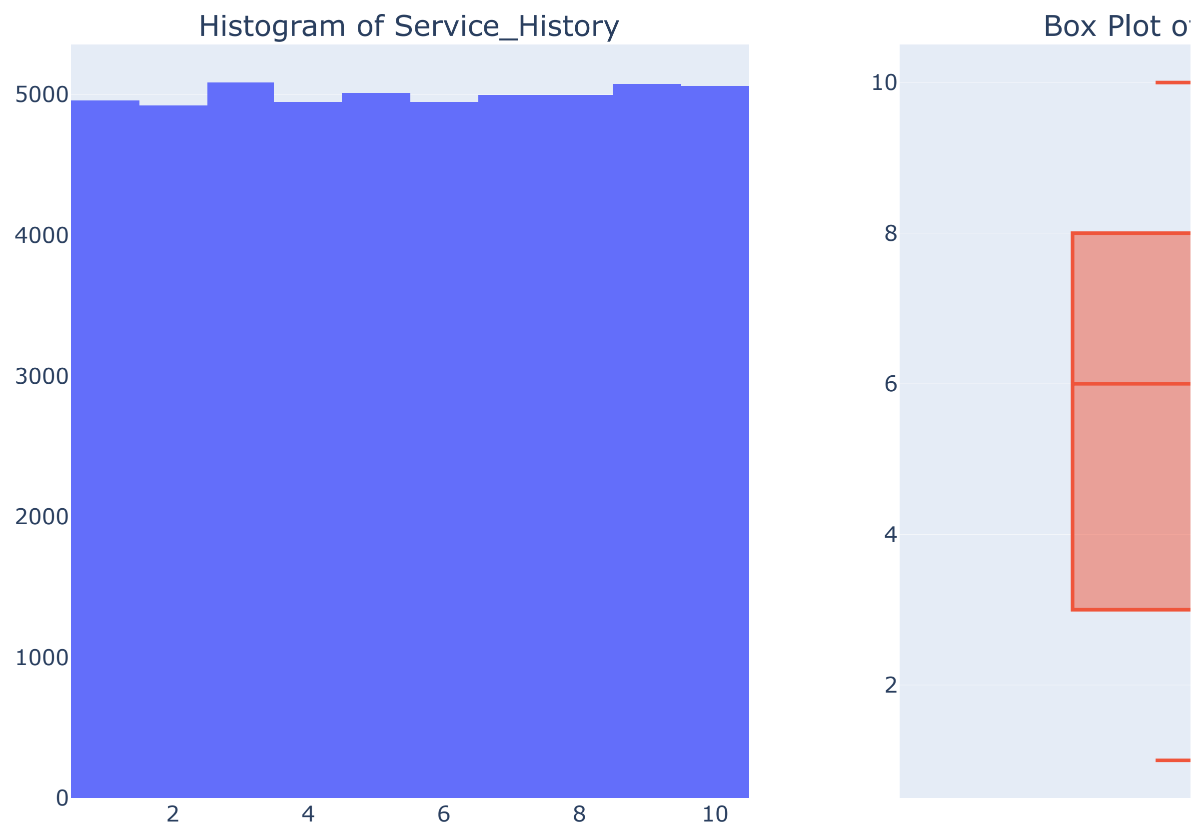



```
Summary Statistics for Insurance_Premium:
count    50000.000000
mean     17465.340700
std       7223.393401
min       5000.000000
25%      11189.750000
50%      17477.500000
75%      23692.000000
max      30000.000000
Name: Insurance_Premium, dtype: float64
```

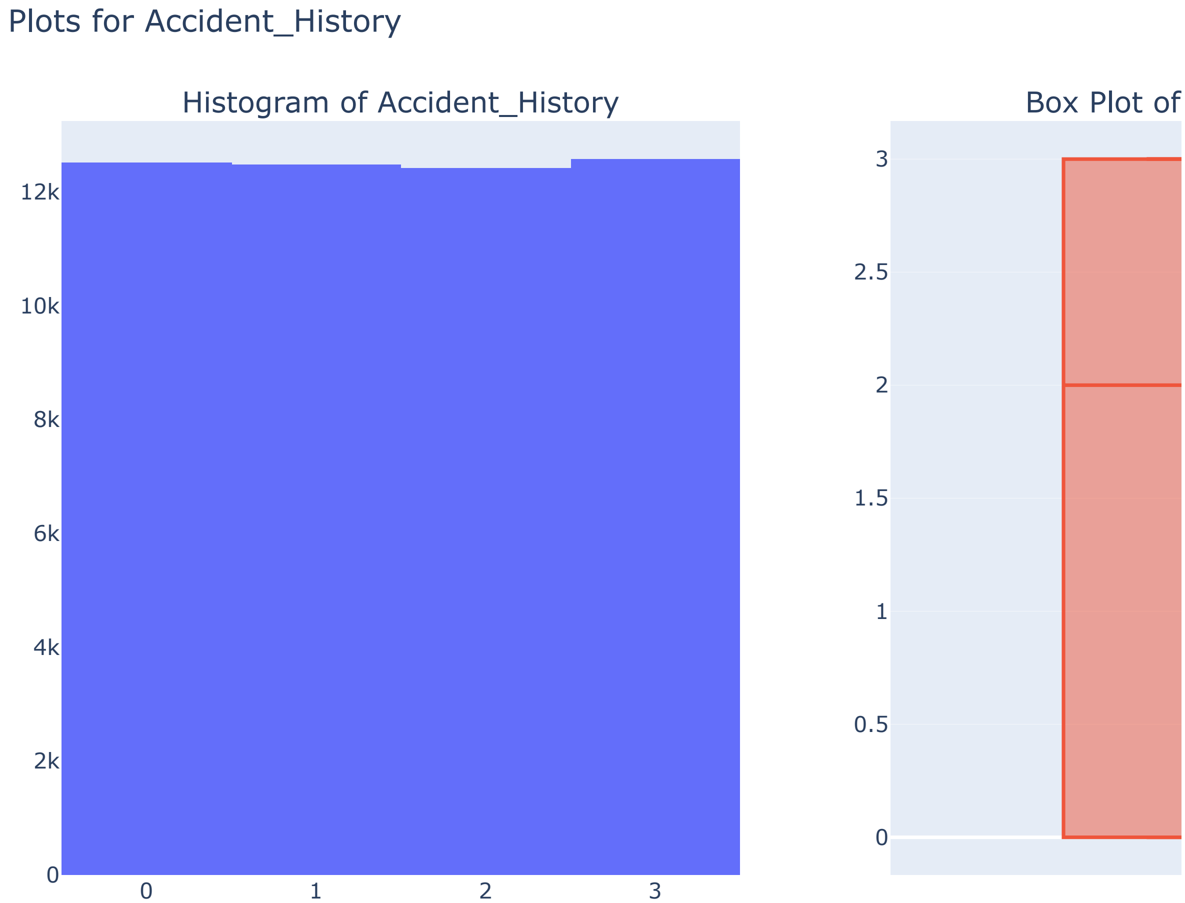



```
Summary Statistics for Service_History:
count    50000.000000
mean         5.515560
std          2.874899
min          1.000000
25%          3.000000
50%          6.000000
75%          8.000000
max         10.000000
Name: Service_History, dtype: float64
```

Plots for Service_History

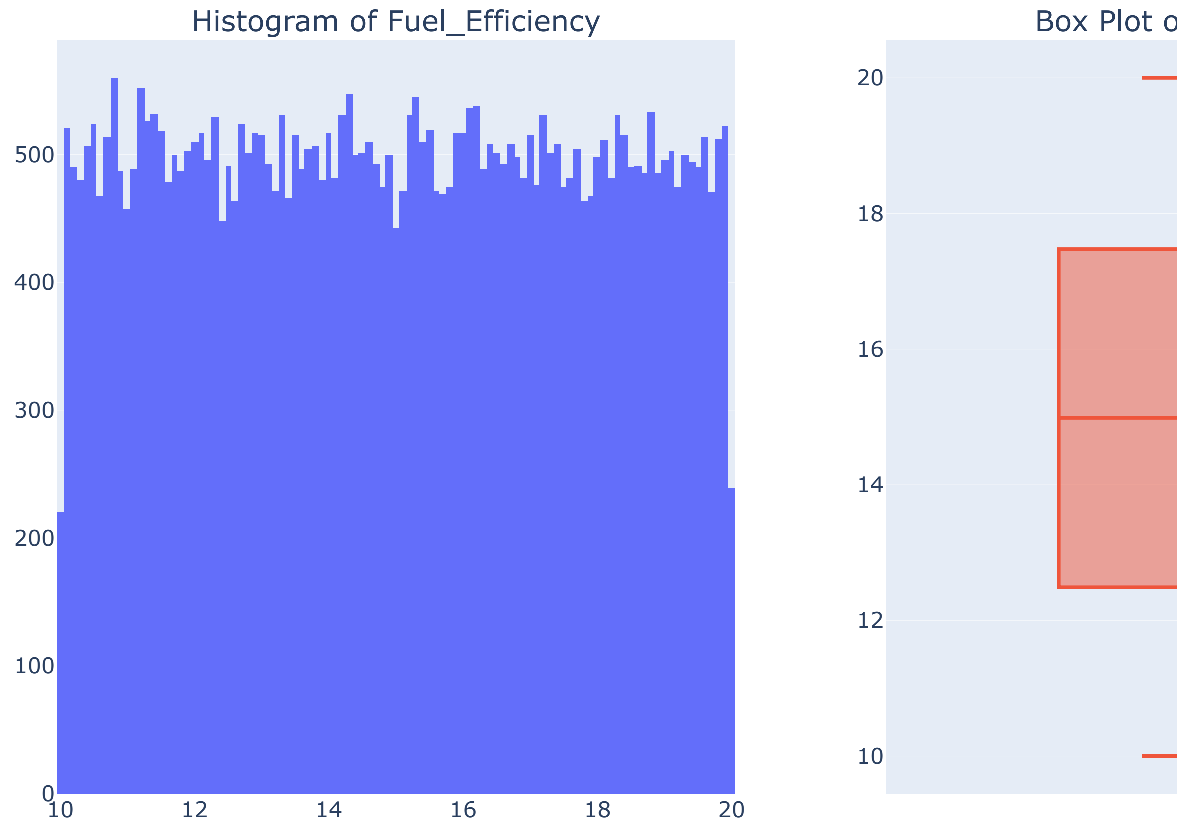



```
Summary Statistics for Accident_History:
count    50000.00000
mean         1.50156
std          1.11951
min          0.00000
25%          0.00000
50%          2.00000
75%          3.00000
max          3.00000
Name: Accident_History, dtype: float64
```

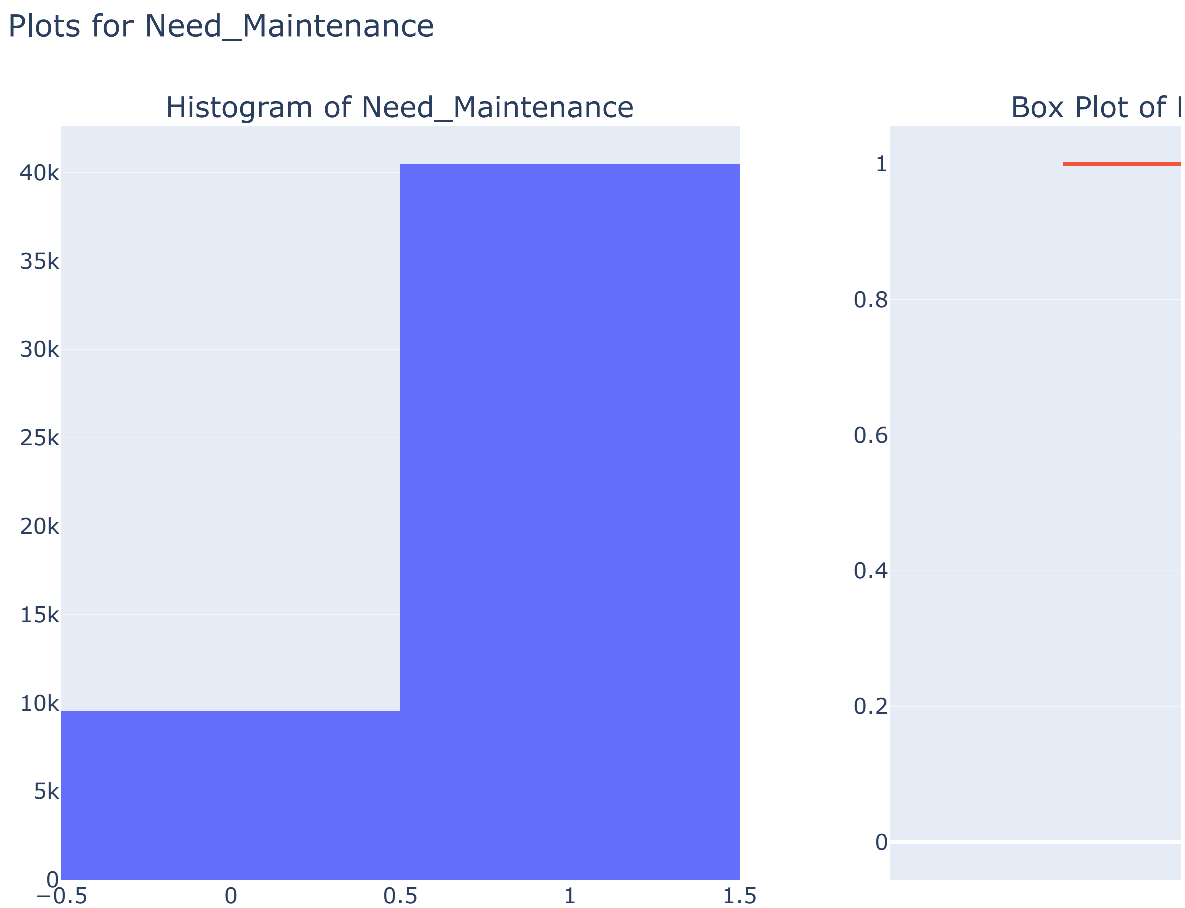



```
Summary Statistics for Fuel_Efficiency:
count    50000.000000
mean        14.990323
std          2.885583
min         10.000098
25%         12.489037
50%         14.986352
75%         17.474676
max         19.999968
Name: Fuel_Efficiency, dtype: float64
```

Plots for Fuel_Efficiency




```
Summary Statistics for Need_Maintenance:
count    50000.000000
mean         0.809960
std          0.392336
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
Name: Need_Maintenance, dtype: float64
```



Summary Insights from Univariate Analysis for Numeric Variables

1. **Mileage & Odometer Reading**:
    - The average mileage is **54,931 km**, with most vehicles ranging from **42,471 km to 67,391 km**.
    - The average odometer reading is **75,551 km**, indicating regular usage and suggesting potential wear and tear.
2. **Vehicle Age**:
    - Vehicles are relatively young, with an average age of **5.5 years**.
    - Most vehicles are less than **8 years old**, which may imply less maintenance required compared to older vehicles.
3. **Reported Issues**:
    - On average, vehicles report approximately **2.5 issues**, with most reporting between **1 and 4 issues**, indicating common maintenance needs.
4. **Engine Size**:

- The average engine size is **1,556 cc**, with a majority falling between **1,000 cc and 2,000 cc**, reflecting a diverse range of vehicle types.

5. **Insurance Premium**:

    - The average insurance premium is around **17,465**, suggesting significant costs associated with vehicle ownership and maintenance.

6. **Service History**:

    - Vehicles have undergone an average of **5.5 services**, with most having between **3 and 8 services**, highlighting a commitment to regular maintenance.

7. **Accident History**:

    - The average number of accidents reported is **1.5**, with most vehicles having no more than **3 accidents**, indicating a relatively safe fleet.

8. **Fuel Efficiency**:

    - The average fuel efficiency stands at **14.99 km/l**, suggesting decent performance, with most vehicles achieving between **12.49 km/l and 17.47 km/l**.

9. **Need for Maintenance**:

    - Approximately **81% of vehicles** are indicated as needing maintenance, underscoring the importance of proactive maintenance practices.

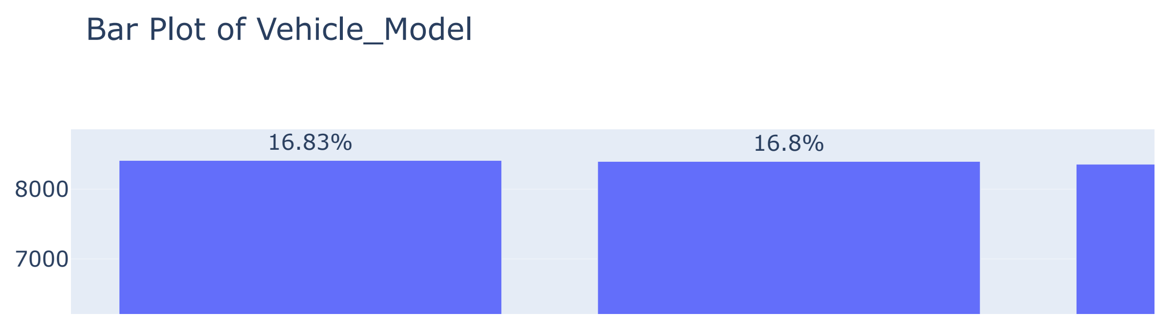
Overall Conclusion:

The dataset suggests that most vehicles are relatively young with moderate mileage and usage. Despite regular maintenance efforts, a significant proportion require attention, particularly concerning reported issues and fuel efficiency. The insights underscore the importance of regular servicing and monitoring to ensure vehicle reliability and safety.

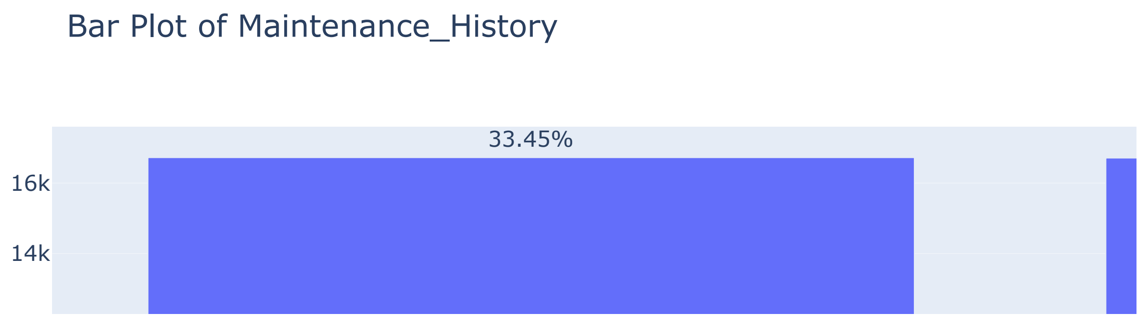
In [6]:

```
# Distribution of Categorical variables
import pandas as pd
import plotly.express as px

# Assuming 'df' is your DataFrame
categorical_df = df.select_dtypes(include=object)

for column in categorical_df.columns:
    # Value counts and percentages
    value_counts = categorical_df[column].value_counts()
    percentages = (value_counts / len(categorical_df) * 100).round(2)
    print(f"Value Counts and Percentages for {column}:\n{value_counts}\n{percentages}\n")

    # Bar plot
    fig = px.bar(
        x=value_counts.index,
        y=value_counts.values,
        title=f"Bar Plot of {column}",
        labels={"x": column, "y": "Count"},
        text=percentages.astype(str) + "%",  # Display percentages on bars
    )
    fig.update_traces(textposition="outside")  # Position percentages outside bars
    fig.show()
```

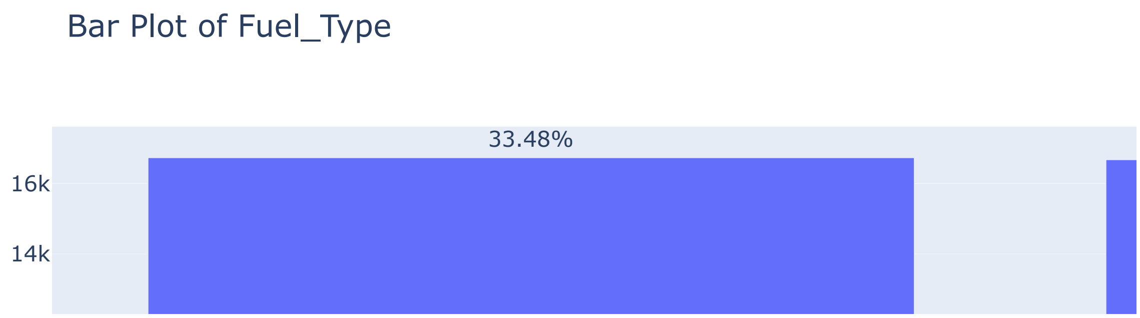
```
Value Counts and Percentages for Vehicle_Model:
Vehicle_Model
Bus           8414
Van           8400
SUV           8360
Truck         8328
Motorcycle    8295
Car           8203
Name: count, dtype: int64
Vehicle_Model
Bus           16.83
Van           16.80
SUV           16.72
Truck         16.66
Motorcycle    16.59
Car           16.41
Name: count, dtype: float64
```



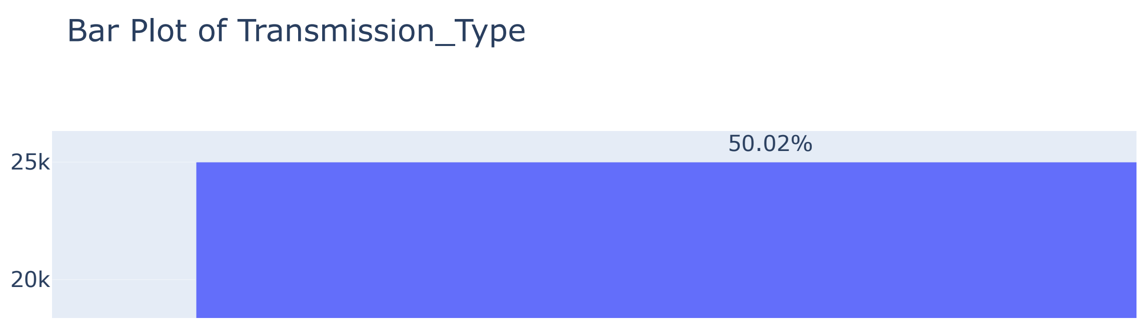

```
Value Counts and Percentages for Maintenance_History:
Maintenance_History
Average    16724
Good       16712
Poor       16564
Name: count, dtype: int64
Maintenance_History
Average    33.45
Good       33.42
Poor       33.13
Name: count, dtype: float64
```



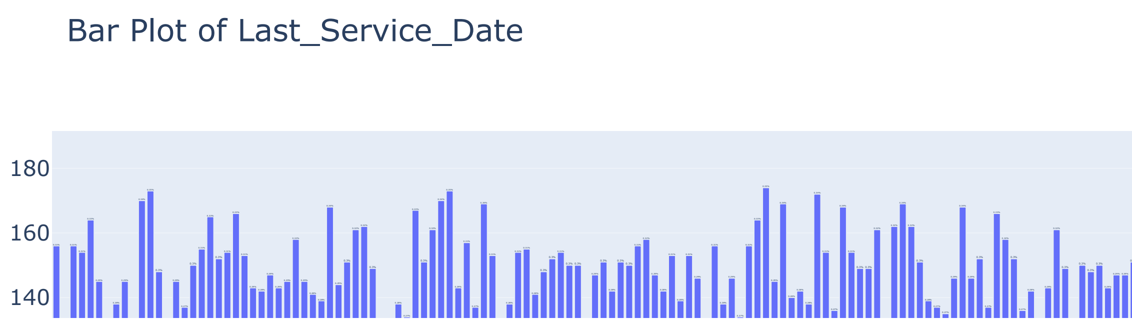

```
Value Counts and Percentages for Fuel_Type:
Fuel_Type
Diesel      16738
Petrol      16680
Electric    16582
Name: count, dtype: int64
Fuel_Type
Diesel      33.48
Petrol      33.36
Electric    33.16
Name: count, dtype: float64
```



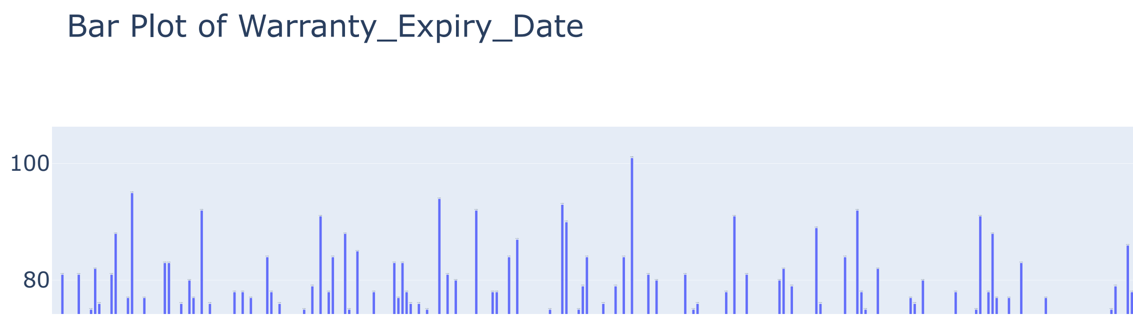

```
Value Counts and Percentages for Transmission_Type:
Transmission_Type
Manual       25009
Automatic    24991
Name: count, dtype: int64
Transmission_Type
Manual       50.02
Automatic    49.98
Name: count, dtype: float64
```




```
Value Counts and Percentages for Last_Service_Date:
Last_Service_Date
2023-11-25    182
2023-08-08    181
2023-11-14    179
2023-10-03    177
2023-12-11    175
             ...
2023-11-09    122
2023-11-08    122
2023-11-16    121
2024-01-21    120
2023-05-07    116
Name: count, Length: 336, dtype: int64
Last_Service_Date
2023-11-25    0.36
2023-08-08    0.36
2023-11-14    0.36
2023-10-03    0.35
2023-12-11    0.35
              ...
2023-11-09    0.24
2023-11-08    0.24
2023-11-16    0.24
2024-01-21    0.24
2023-05-07    0.23
Name: count, Length: 336, dtype: float64
```

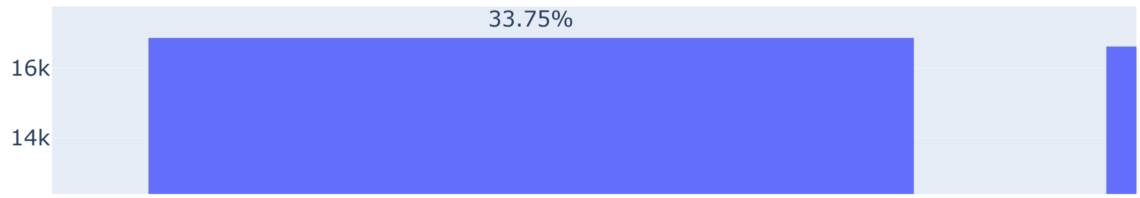



```
Value Counts and Percentages for Warranty_Expiry_Date:
Warranty_Expiry_Date
2024-09-16    101
2025-05-13     99
2025-06-06     98
2024-05-17     95
2024-07-31     94
             ...
2025-07-29     50
2025-02-12     49
2025-10-17     48
2026-01-10     47
2025-11-27     44
Name: count, Length: 701, dtype: int64
Warranty_Expiry_Date
2024-09-16    0.20
2025-05-13    0.20
2025-06-06    0.20
2024-05-17    0.19
2024-07-31    0.19
              ...
2025-07-29    0.10
2025-02-12    0.10
2025-10-17    0.10
2026-01-10    0.09
2025-11-27    0.09
Name: count, Length: 701, dtype: float64
```

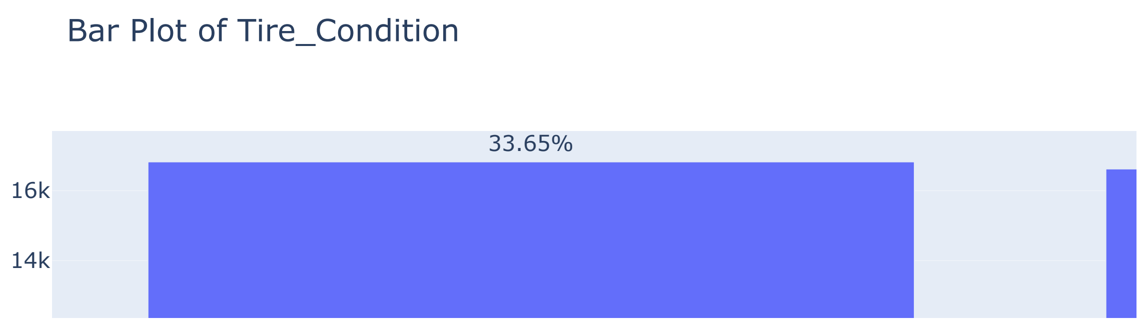



```
Value Counts and Percentages for Owner_Type:
Owner_Type
Second    16875
Third     16630
First     16495
Name: count, dtype: int64
Owner_Type
Second    33.75
Third     33.26
First     32.99
Name: count, dtype: float64
```

Bar Plot of Owner_Type

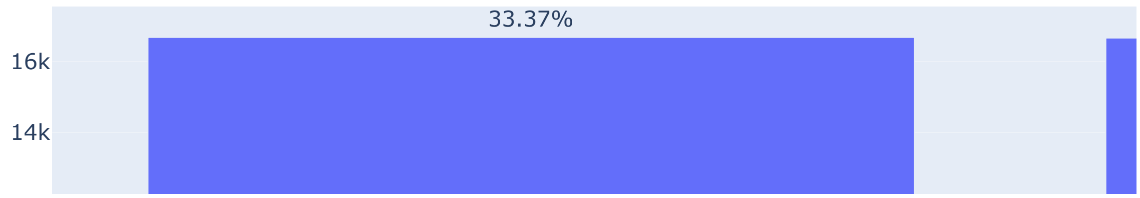



```
Value Counts and Percentages for Tire_Condition:
Tire_Condition
New         16825
Worn Out    16622
Good        16553
Name: count, dtype: int64
Tire_Condition
New         33.65
Worn Out    33.24
Good        33.11
Name: count, dtype: float64
```

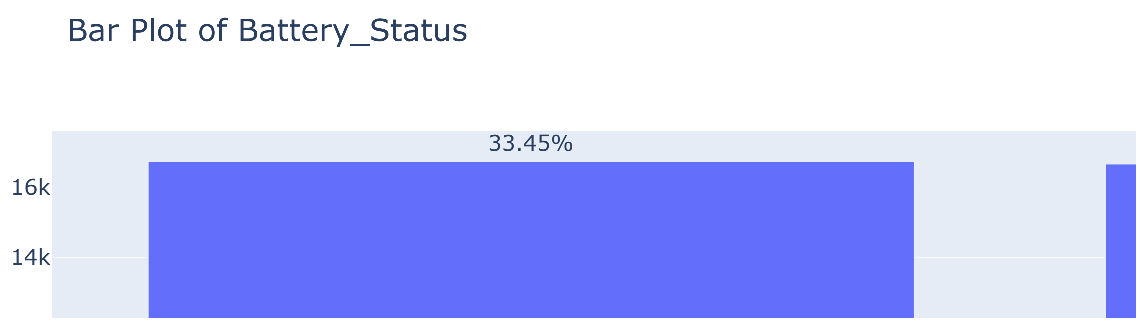



```
Value Counts and Percentages for Brake_Condition:
Brake_Condition
Worn Out    16685
New         16668
Good        16647
Name: count, dtype: int64
Brake_Condition
Worn Out    33.37
New         33.34
Good        33.29
Name: count, dtype: float64
```

Bar Plot of Brake_Condition




```
Value Counts and Percentages for Battery_Status:
Battery_Status
New     16725
Good    16657
Weak    16618
Name: count, dtype: int64
Battery_Status
New     33.45
Good    33.31
Weak    33.24
Name: count, dtype: float64
```



Summary of Vehicle Features

Vehicle Model Distribution

- **Most Common Vehicle Models**:
  - **Bus**: 8,414 (16.83%)
  - **Van**: 8,400 (16.80%)
  - **SUV**: 8,360 (16.72%)
  - **Truck**: 8,328 (16.66%)
  - **Motorcycle**: 8,295 (16.59%)
  - **Car**: 8,203 (16.41%)

All vehicle models are represented fairly evenly in the dataset, with buses being the most common.

Maintenance History

- **Distribution of Maintenance Conditions**:
  - **Average**: 16,724 (33.45%)
  - **Good**: 16,712 (33.42%)
  - **Poor**: 16,564 (33.13%)

The maintenance history shows a balanced distribution, with most vehicles classified as either average or good.

Fuel Type Preferences

- **Fuel Type Count**:
  - **Diesel**: 16,738 (33.48%)
  - **Petrol**: 16,680 (33.36%)
  - **Electric**: 16,582 (33.16%)

Diesel is slightly more prevalent, but petrol and electric vehicles also make up a significant portion.

Transmission Type

- **Transmission Distribution**:
  - **Manual**: 25,009 (50.02%)
  - **Automatic**: 24,991 (49.98%)

There is almost an equal split between manual and automatic transmissions, indicating a diverse range of vehicle preferences.

Last Service Date

- **Recent Service Dates**:
  - The most common recent service dates are:
    - **2023-11-25**: 182 (0.36%)
    - **2023-08-08**: 181 (0.36%)
    - **2023-11-14**: 179 (0.36%)

There are a total of 336 unique service dates, highlighting ongoing vehicle maintenance.

Warranty Expiry Dates

- **Warranty Expiry Distribution**:
  - **2024-09-16**: 101 (0.20%)
  - **2025-05-13**: 99 (0.20%)
  - **2025-06-06**: 98 (0.20%)

A total of 701 unique expiry dates suggests a wide variety of warranty durations across the dataset.

Owner Type Distribution

- **Owner Type Count**:
  - **Second Owner**: 16,875 (33.75%)
  - **Third Owner**: 16,630 (33.26%)
  - **First Owner**: 16,495 (32.99%)

The majority of vehicles are held by second and third owners, indicating a potential for resale market activity.

Tire Condition

- **Tire Condition Overview**:
  - **New**: 16,825 (33.65%)
  - **Worn Out**: 16,622 (33.24%)
  - **Good**: 16,553 (33.11%)

Most tires are either new or worn out, emphasizing the importance of regular tire assessments.

Brake Condition

- **Brake Condition Breakdown**:
  - **Worn Out**: 16,685 (33.37%)
  - **New**: 16,668 (33.34%)
  - **Good**: 16,647 (33.29%)

The brake conditions are quite evenly distributed, with a slight majority classified as worn out.

Battery Status

- **Battery Condition Distribution**:
  - **New**: 16,725 (33.45%)
  - **Good**: 16,657 (33.31%)
  - **Weak**: 16,618 (33.24%)

Most batteries are either new or in good condition, which is favorable for vehicle reliability.

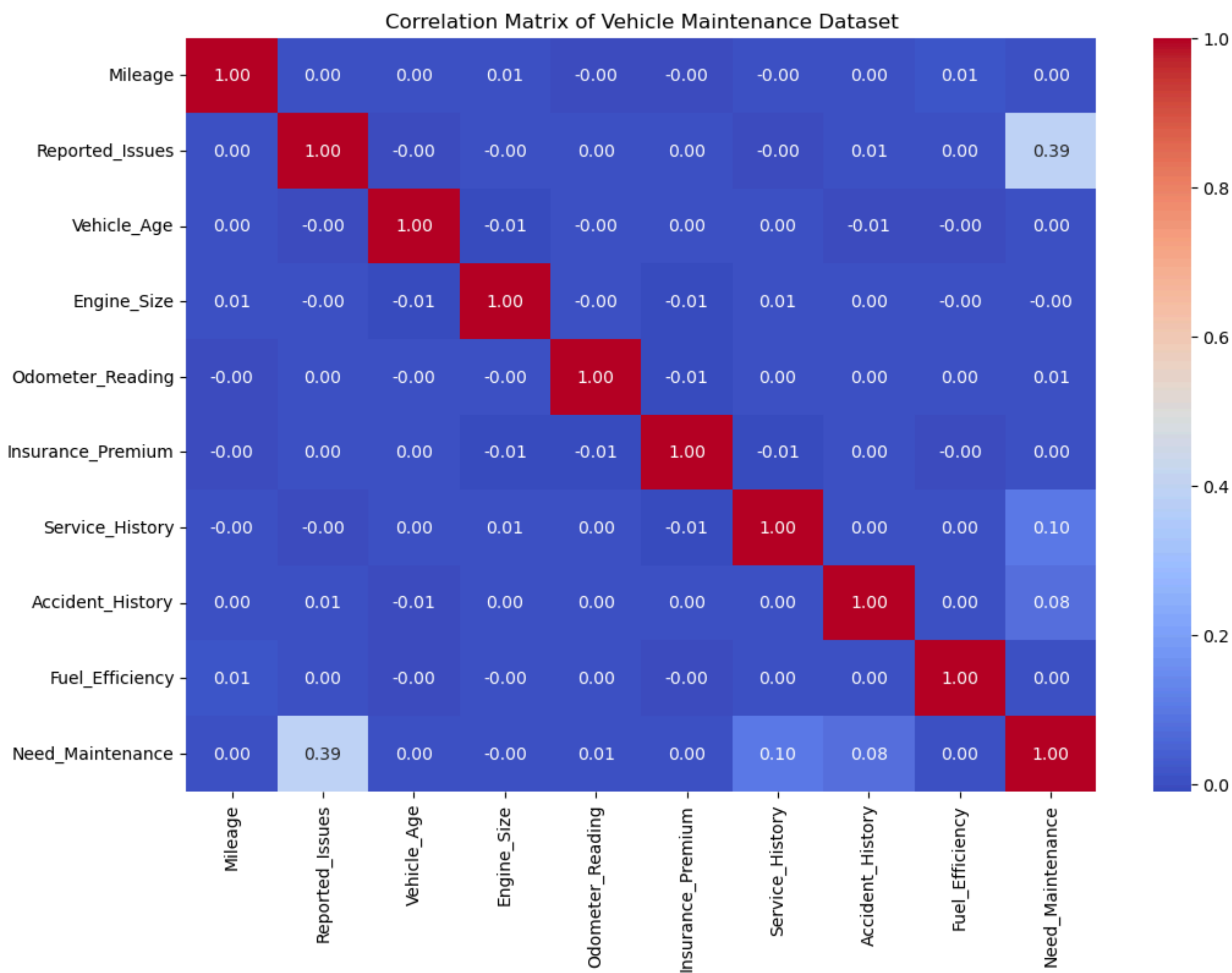
Overall, the data presents a diverse vehicle fleet with a balanced distribution across various features, indicating a well-maintained collection of vehicles. Regular assessments in maintenance history, tire, brake, and battery conditions are crucial for vehicle reliability and safety.

Correlation Analysis

In [7]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objects as go

# Load your DataFrame
df = pd.read_csv('vehicle_maintenance_data.csv')  # Uncomment and load your data

# Calculate correlation matrix, considering only numeric columns
correlation_matrix = df.corr(numeric_only=True)  # Added numeric_only=True

# Create heatmap
plt.figure(figsize=(12, 8))  # Adjust figure size if needed
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix of Vehicle Maintenance Dataset")
plt.show()
```

```python
# Find top 5 and bottom 5 correlated feature pairs
correlation_pairs = correlation_matrix.unstack().reset_index()
correlation_pairs.columns = ['Feature 1', 'Feature 2', 'Correlation']
correlation_pairs = correlation_pairs[correlation_pairs['Feature 1'] != correlation_pairs['Feature
correlation_pairs = correlation_pairs.sort_values(by='Correlation', ascending=False)

# Top 5 correlations
top_5 = correlation_pairs.head(5)
# Bottom 5 correlations
bottom_5 = correlation_pairs.tail(5)

# Combine top and bottom correlations
correlation_summary = pd.concat([top_5, bottom_5])

# Create Plotly table
table = go.Figure(data=[go.Table(
    header=dict(values=list(correlation_summary.columns),
                fill_color='paleturquoise',
                align='left'),
    cells=dict(values=[correlation_summary['Feature 1'], correlation_summary['Feature 2'], correla
               fill_color='lavender',
               align='left'))
])

table.update_layout(title='Top 5 and Bottom 5 Correlations in Vehicle Maintenance Dataset')
table.show()
```



Top 5 and Bottom 5 Correlations in Vehicle Maintenance Dataset

Feature 1	Feature 2
Need_Maintenance	Reported_
Reported_Issues	Need_Mair
Need_Maintenance	Service_Hi
Service_History	Need_Mair

Summary of Correlation Analysis

Strong Positive Correlates

1. **Need_Maintenance ↔ Reported_Issues**: **0.39**
   - This indicates a strong positive relationship, suggesting that a higher number of reported issues is significantly associated with an increased need for maintenance.
2. **Reported_Issues ↔ Need_Maintenance**: **0.39**
   - A reciprocal relationship confirming that the need for maintenance correlates strongly with reported issues.
3. **Need_Maintenance ↔ Service_History**: **0.10**
   - A weaker, yet positive correlation indicating that a greater need for maintenance may be slightly related to the quality or extent of the vehicle's service history.
4. **Need_Maintenance ↔ Accident_History**: **0.08**
   - Suggests a slight positive association between needing maintenance and having a history of accidents.
5. **Insurance_Premium ↔ Service_History**: **0.08**
   - Indicates that vehicles with a more comprehensive service history may have higher insurance premiums.

Strong Negative Correlates

1. **Service_History ↔ Odometer_Reading**: **-0.0094**
   - A very weak negative correlation, indicating that the service history has little relationship with the odometer reading.
2. **Insurance_Premium ↔ Odometer_Reading**: **-0.0094**
   - Shows a negligible negative relationship, suggesting that higher odometer readings do not significantly impact insurance premiums.
3. **Insurance_Premium ↔ Engine_Size**: **-0.0098**
   - A weak negative correlation indicating that larger engine sizes may have a slight influence on lower insurance premiums.
4. **Engine_Size ↔ Insurance_Premium**: **-0.0098**
   - A reciprocal relationship reaffirming the weak association between engine size and insurance premium costs.
5. **Accident_History ↔ Service_History**: **-0.0072**
   - This correlation suggests a minimal negative relationship, indicating that vehicles with poorer service histories may have a slightly higher likelihood of being involved in accidents.

Conclusion

The correlation analysis highlights significant relationships, especially strong positive correlations between the need for maintenance and reported issues. Conversely, many negative correlations are weak, suggesting minimal impact between features like service history and odometer readings. These insights can assist in prioritizing areas for further investigation and decision-making regarding vehicle maintenance strategies.

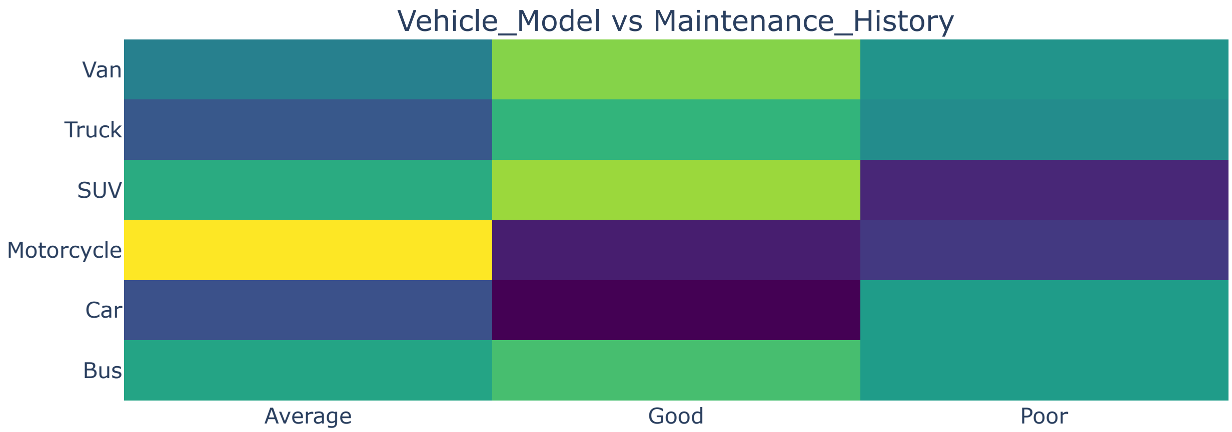
In [9]:

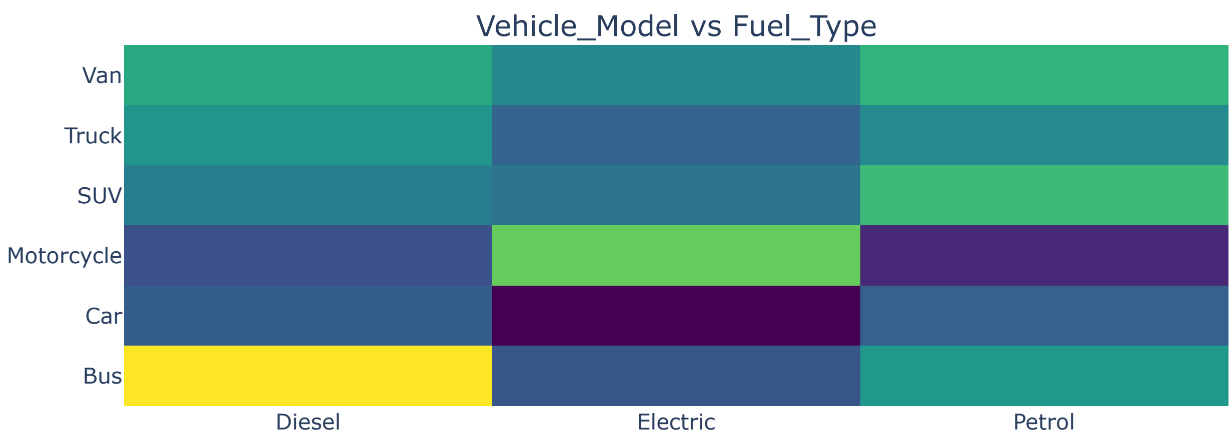
```
!pip install researchpy
import researchpy as rp
import pandas as pd
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from scipy.stats import chi2_contingency

# Isolate the categorical variables
categorical_df = df.select_dtypes(include=['object', 'category'])  # Select only categorical colum

# Create an empty list to store the results of chi-square and Cramer's V calculations
results = []

# Iterate through pairs of categorical variables
for col1 in categorical_df.columns:
    for col2 in categorical_df.columns:
        if col1 != col2:  # Avoid comparing a column with itself
            # Create a cross-tabulation of the two variables
            crosstab = pd.crosstab(df[col1], df[col2])

            # Perform the chi-square test on the crosstab
            chi2, p, dof, expected = chi2_contingency(crosstab)

            # Calculate Cramer's V for association strength
            n = crosstab.sum().sum()  # Total number of observations
            cramer_v = (chi2 / (n * (min(crosstab.shape) - 1))) ** 0.5

            # Append the results to the list
```

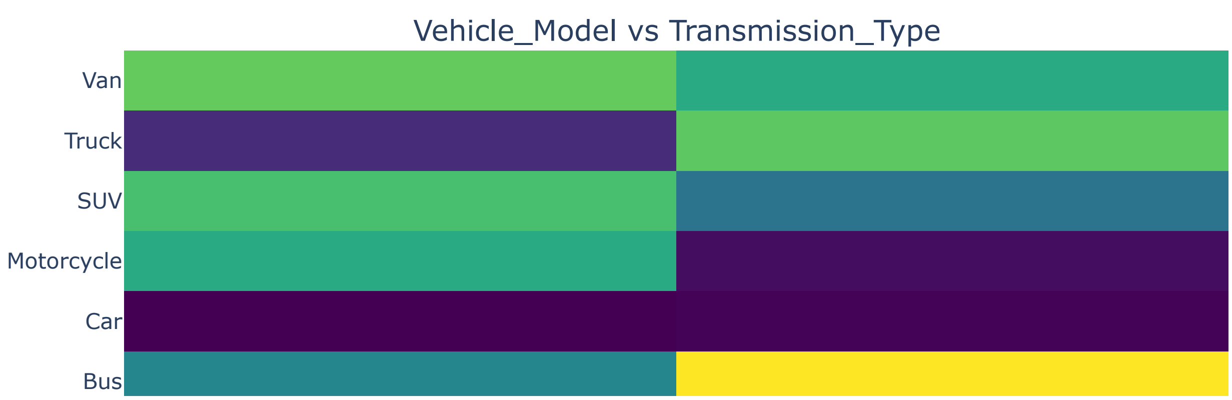
```
            results.append({
                'col1': col1,
                'col2': col2,
                'chi-square': chi2,
                'p-value': p,
                'cramer_v': cramer_v
            })

# Convert the results into a DataFrame for easier manipulation
results_df = pd.DataFrame(results)

# Create subplots for heatmaps and annotations for each pair of categorical variables
fig = make_subplots(
    rows=len(results_df),
    cols=1,
    subplot_titles=[f"{row['col1']} vs {row['col2']}" for _, row in results_df.iterrows()]
)

# Add heatmaps and annotations to each subplot
for i, row in results_df.iterrows():
    # Generate the crosstab for the current pair of variables
    crosstab = pd.crosstab(df[row['col1']], df[row['col2']])

    # Create a heatmap for the crosstab
    heatmap = go.Heatmap(
        z=crosstab.values,
        x=crosstab.columns,
        y=crosstab.index,
        colorscale='Viridis',
        colorbar=dict(title='Count')
    )

    fig.add_trace(heatmap, row=i + 1, col=1)

    # Add annotations for chi-square test results and Cramer's V
    fig.add_annotation(
        text=f"Chi-square: {row['chi-square']:.3f}<br>P-value: {row['p-value']:.3f}<br>Cramer's V:
        xref="paper", yref="paper",
        x=0.05, y=0.95 - i * 0.1,  # Adjust position for each subplot
        showarrow=False
    )

# Update the layout and display the figure
fig.update_layout(
    height=400 * len(results_df),  # Set the height dynamically based on the number of subplots
    width=800,
    title_text="Chi-Square Test Results Between Categorical Variables"
)

# Show the plot
fig.show()
```

```
Collecting researchpy
  Obtaining dependency information for researchpy from https://files.pythonhosted.org/packages/f
2/3a/f89796ede409890a27612c6e27d21bb65763bb7c034cd36d7577abe3edbf/researchpy-0.3.6-py3-none-any.w
hl.metadata
  Downloading researchpy-0.3.6-py3-none-any.whl.metadata (1.2 kB)
Requirement already satisfied: scipy in c:\users\joero\anaconda3\lib\site-packages (from research
py) (1.11.1)
Requirement already satisfied: numpy in c:\users\joero\anaconda3\lib\site-packages (from research
py) (1.24.3)
Requirement already satisfied: pandas in c:\users\joero\anaconda3\lib\site-packages (from researc
hpy) (2.0.3)
Requirement already satisfied: statsmodels in c:\users\joero\anaconda3\lib\site-packages (from re
searchpy) (0.14.0)
Requirement already satisfied: patsy in c:\users\joero\anaconda3\lib\site-packages (from research
py) (0.5.3)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\joero\anaconda3\lib\site-packag
es (from pandas->researchpy) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\joero\anaconda3\lib\site-packages (from p
andas->researchpy) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in c:\users\joero\anaconda3\lib\site-packages (from
pandas->researchpy) (2023.3)
Requirement already satisfied: six in c:\users\joero\anaconda3\lib\site-packages (from patsy->res
earchpy) (1.16.0)
Requirement already satisfied: packaging>=21.3 in c:\users\joero\anaconda3\lib\site-packages (fro
m statsmodels->researchpy) (23.1)
Downloading researchpy-0.3.6-py3-none-any.whl (34 kB)
Installing collected packages: researchpy
Successfully installed researchpy-0.3.6
```

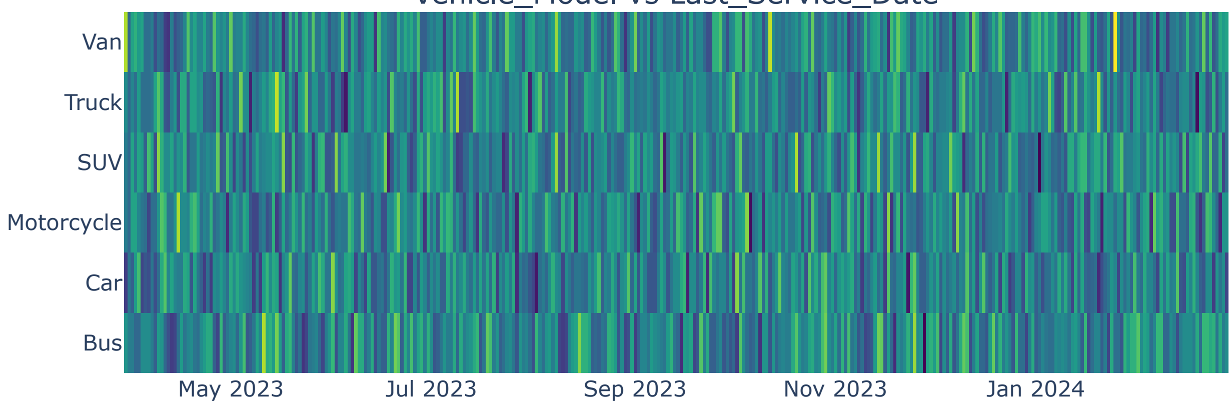
Chi-Square Test Results Between Categorical Variables



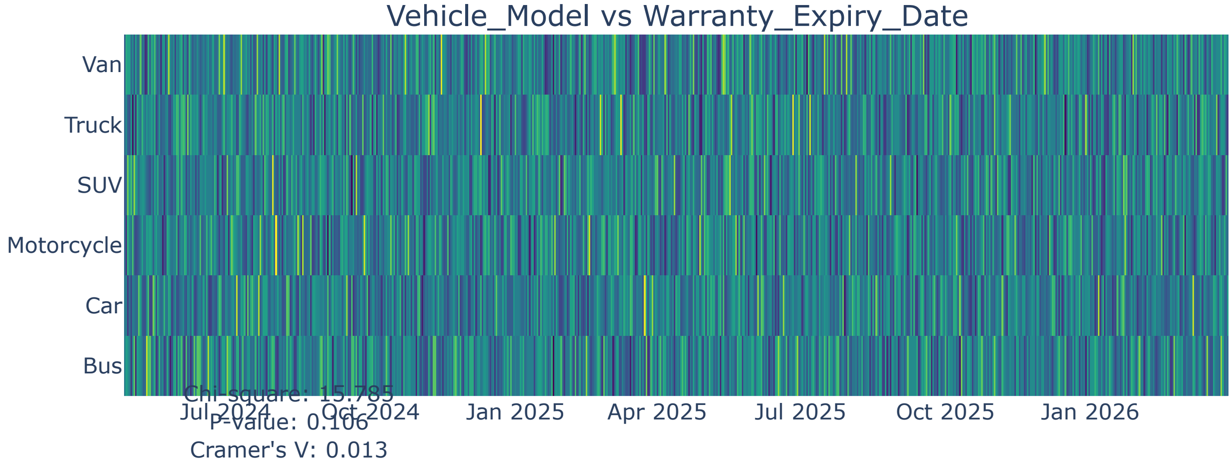




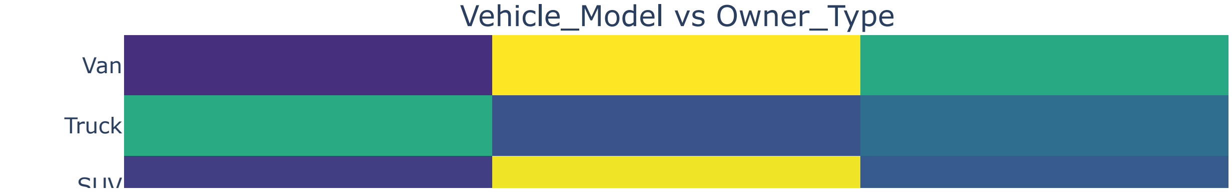
Vehicle_Model vs Last_Service_Date

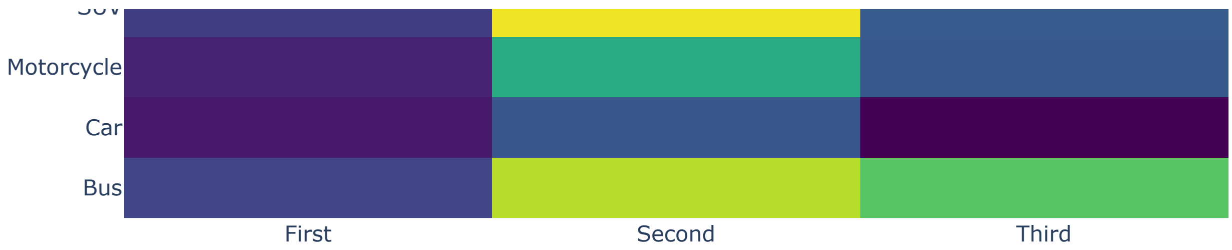


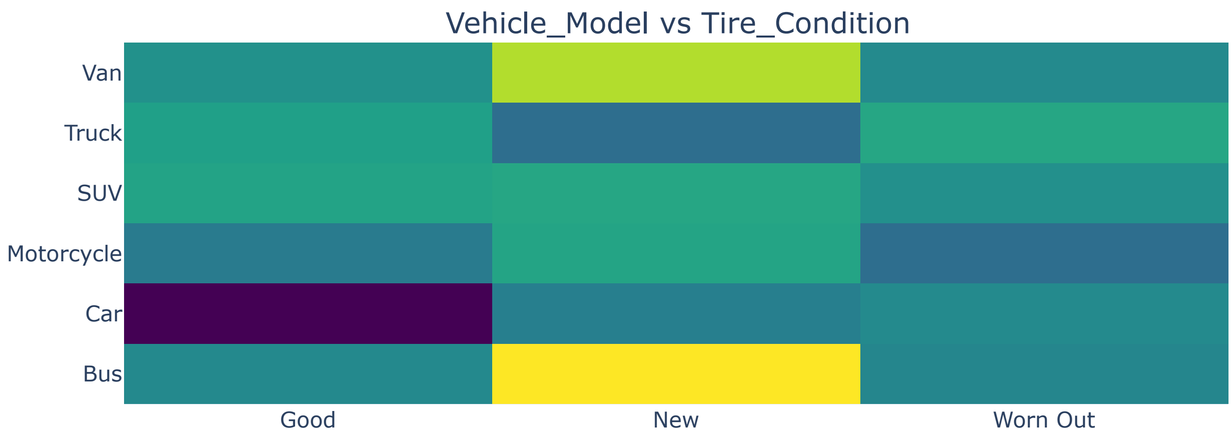
Vehicle_Model vs Warranty_Expiry_Date

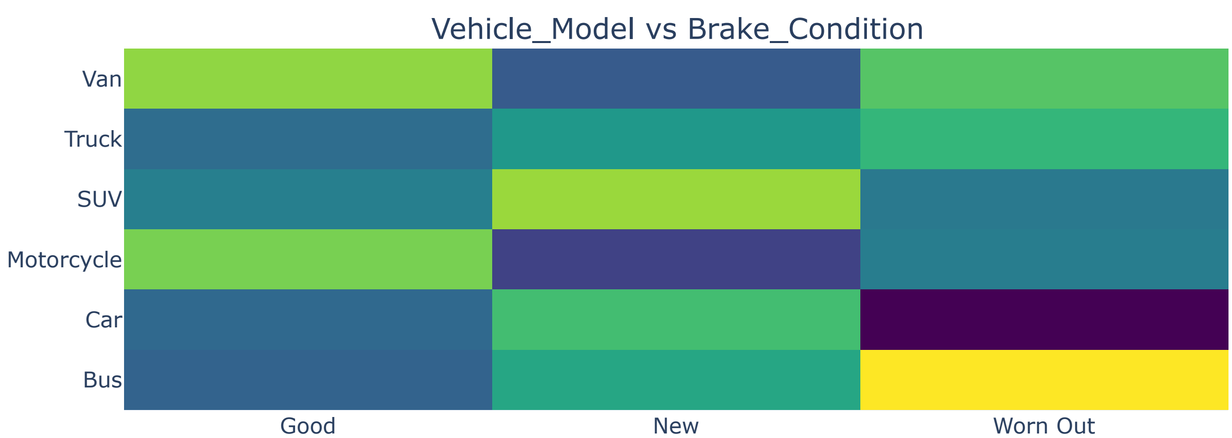


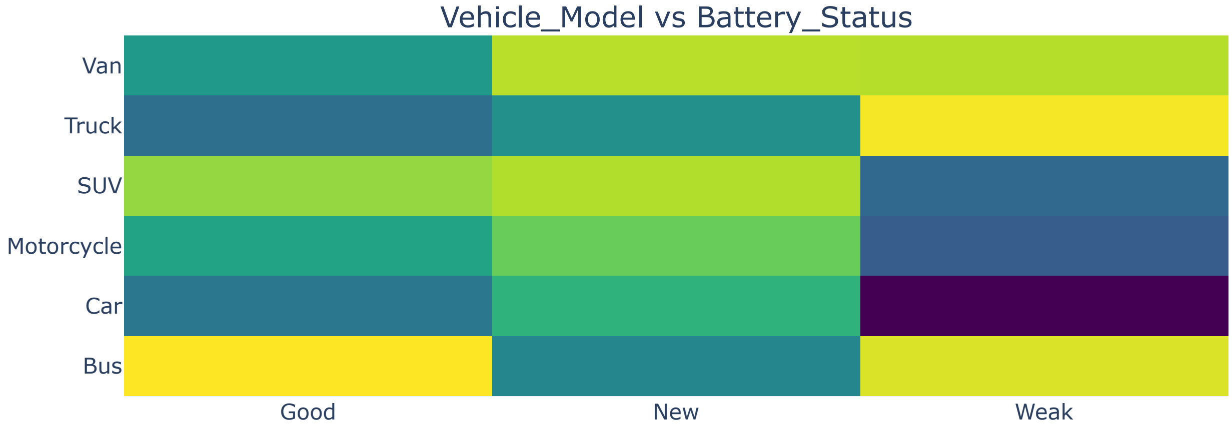
Vehicle_Model vs Owner_Type

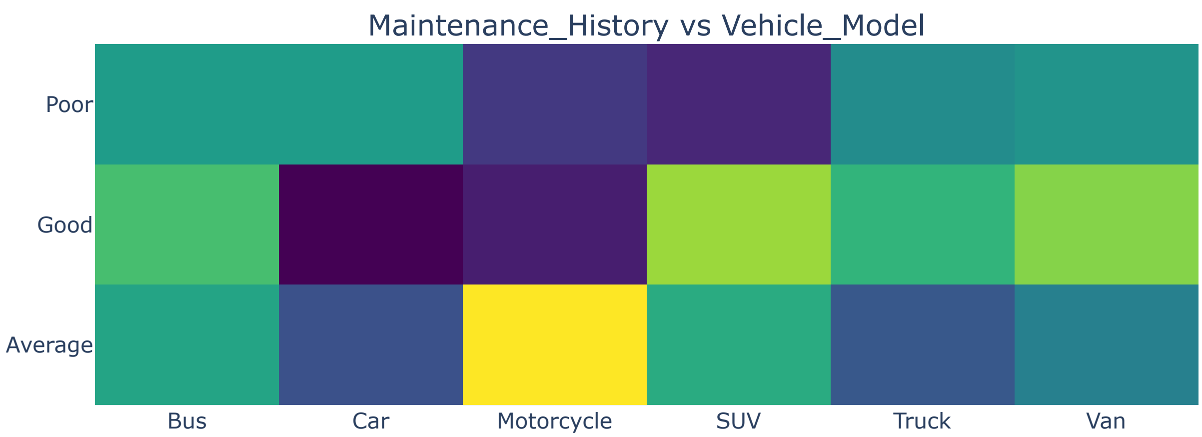


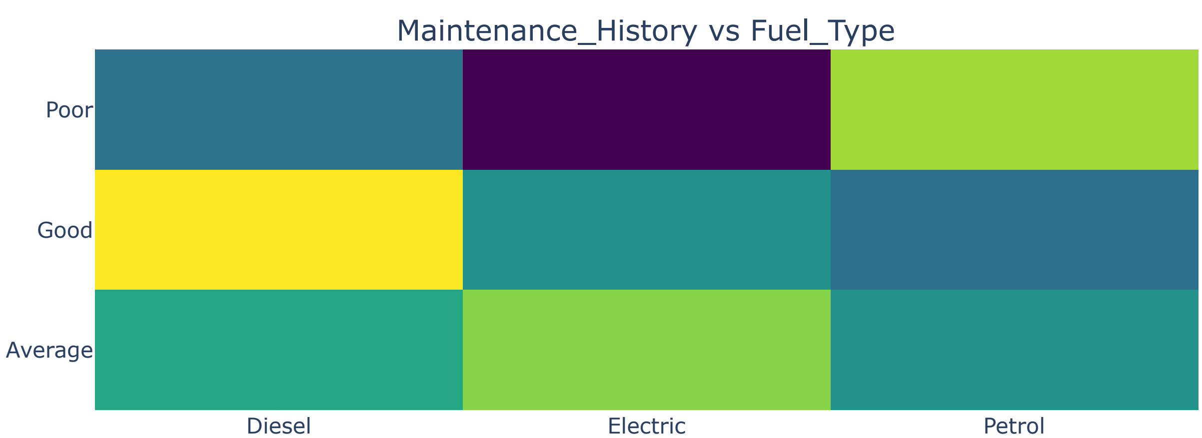

SUV
Motorcycle
Car
Bus
First
Second
Third

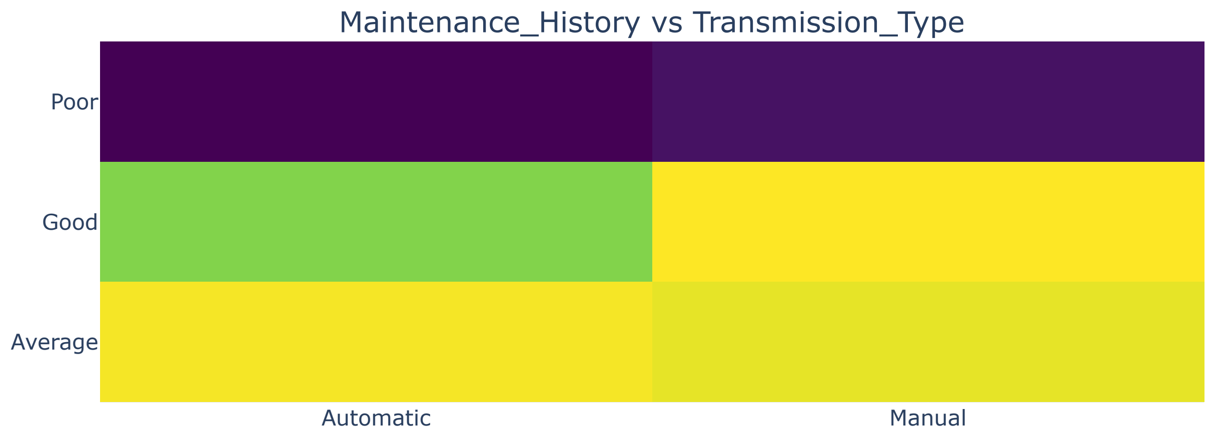

Vehicle_Model vs Tire_Condition
Van
Truck
SUV
Motorcycle
Car
Bus
Good
New
Worn Out

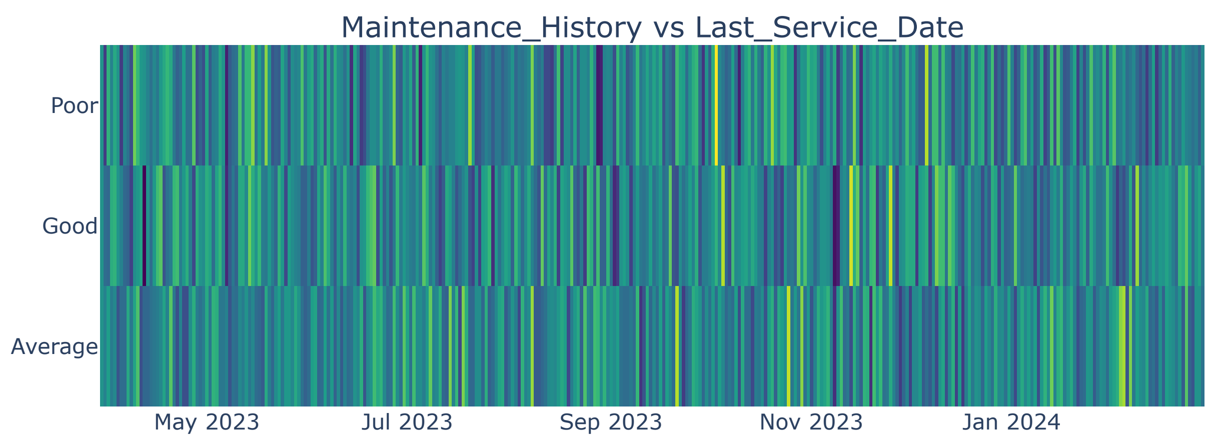

Vehicle_Model vs Brake_Condition
Van
Truck
SUV
Motorcycle
Car
Bus
Good
New
Worn Out

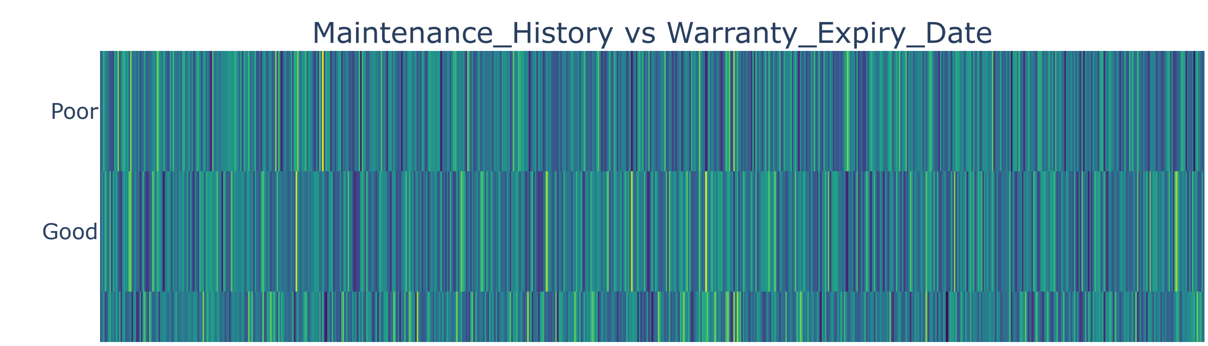

Vehicle_Model vs Battery_Status
Van
Truck
SUV
Motorcycle
Car
Bus
Good
New
Weak

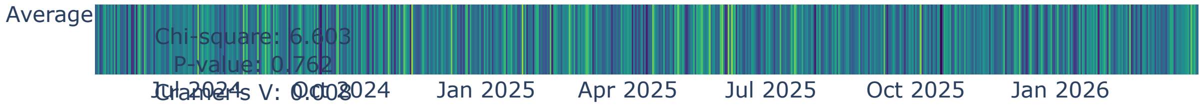

Maintenance_History vs Vehicle_Model
Poor
Good
Average
Bus
Car
Motorcycle
SUV
Truck
Van


Maintenance_History vs Fuel_Type
Poor
Good
Average
Diesel
Electric
Petrol

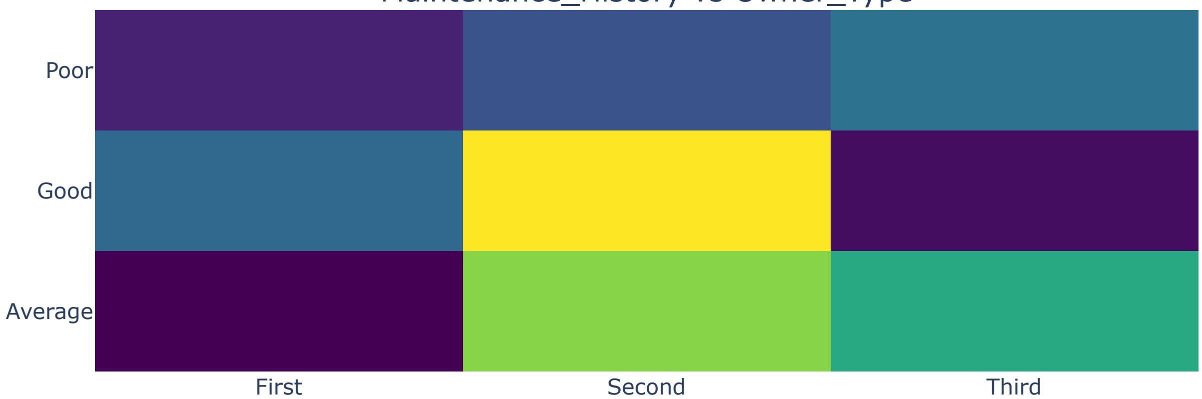

Maintenance_History vs Transmission_Type
Poor
Good
Average
Automatic
Manual


Maintenance_History vs Last_Service_Date
Poor
Good
Average
May 2023
Jul 2023
Sep 2023
Nov 2023
Jan 2024

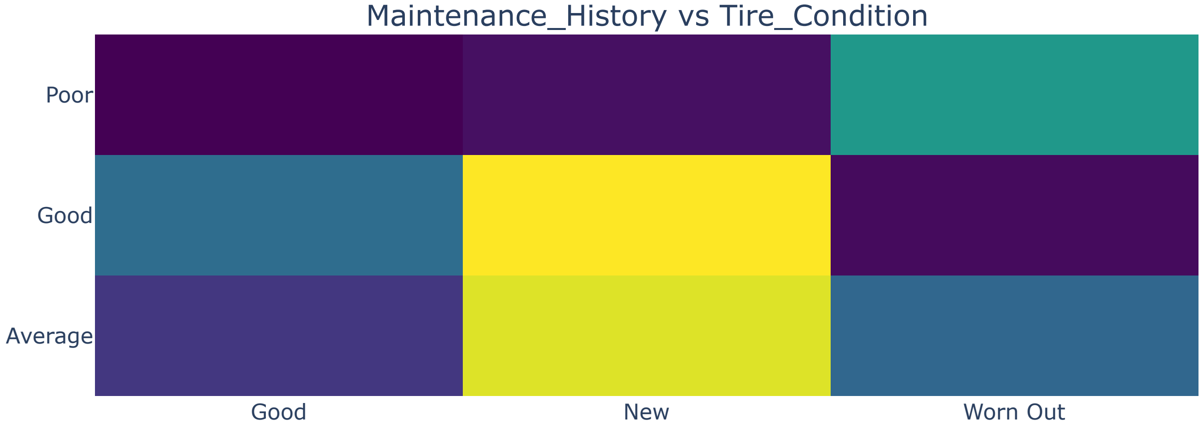

Maintenance_History vs Warranty_Expiry_Date
Poor
Good



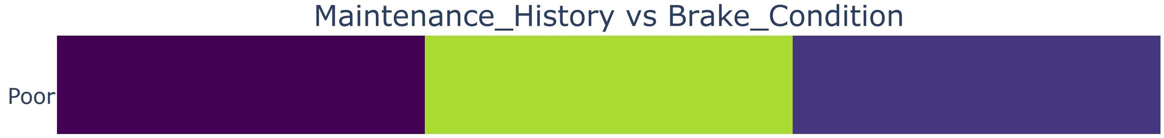
Maintenance_History vs Owner_Type

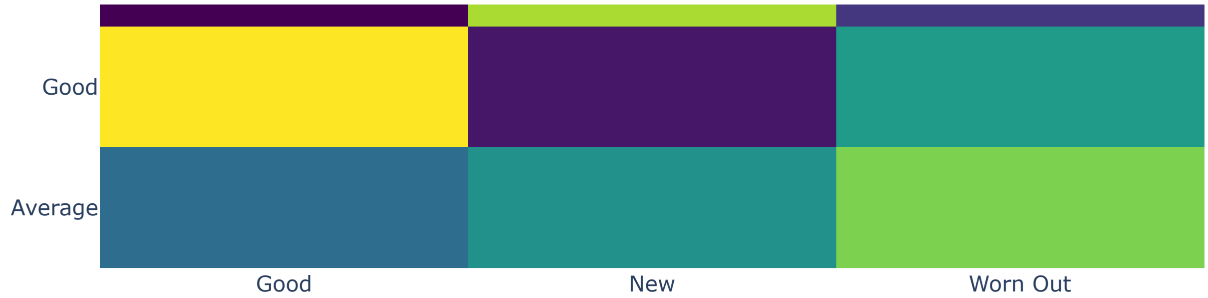


Maintenance_History vs Tire_Condition



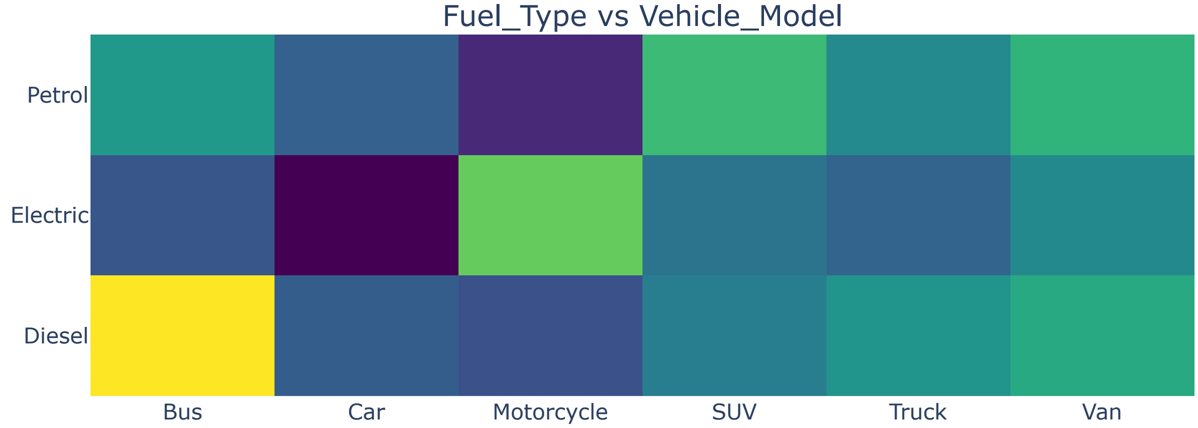
Maintenance_History vs Brake_Condition

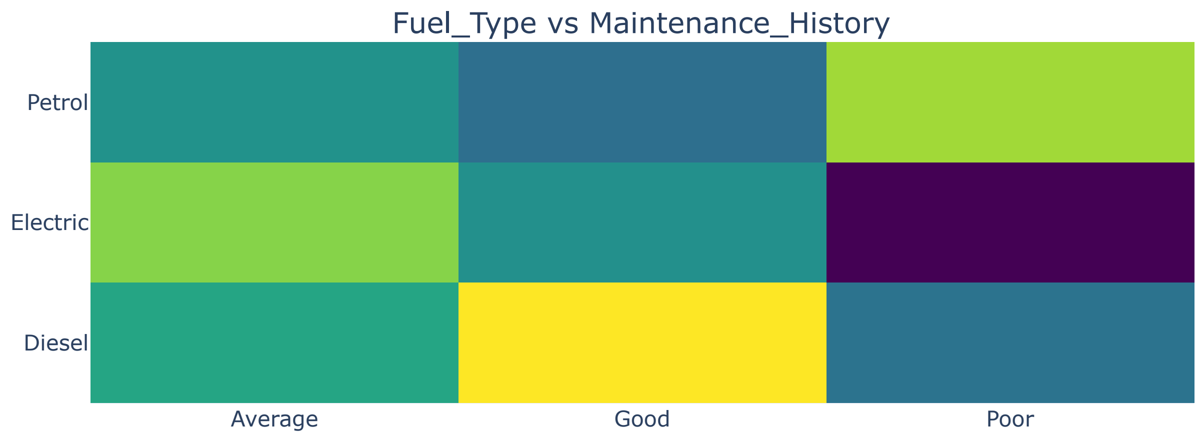


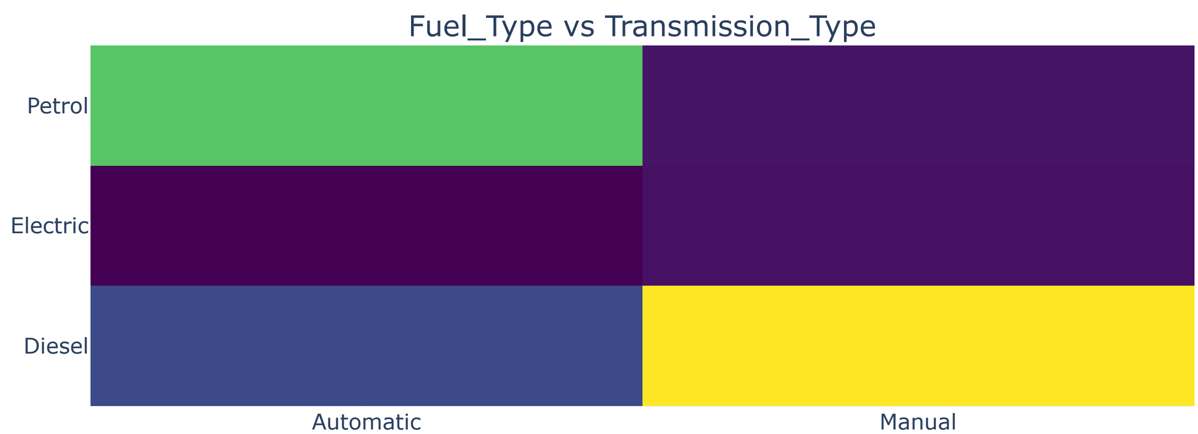


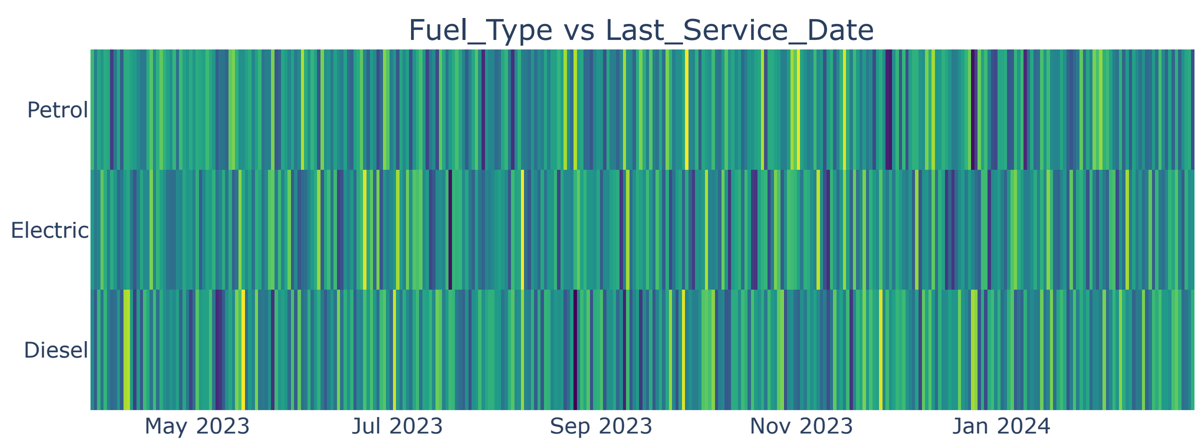
Maintenance_History vs Battery_Status

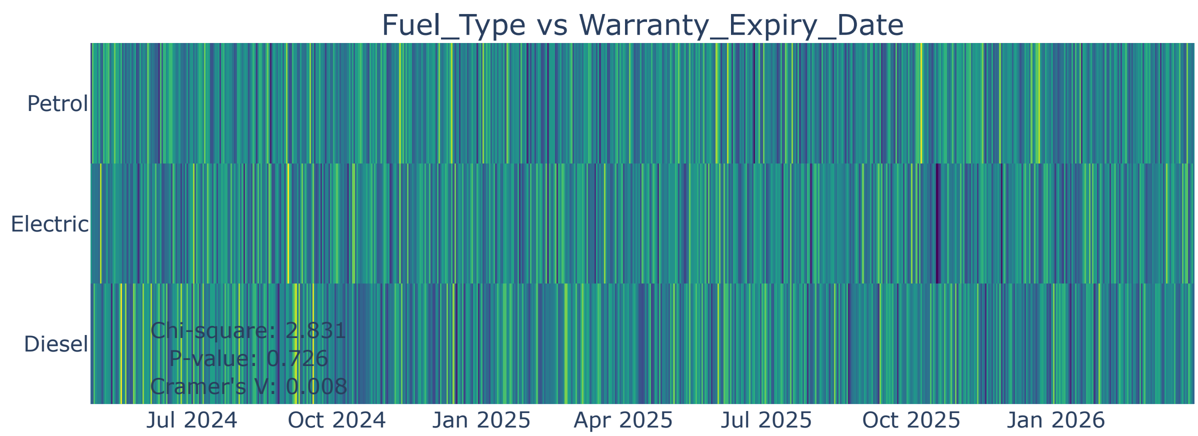
Fuel_Type vs Vehicle_Model



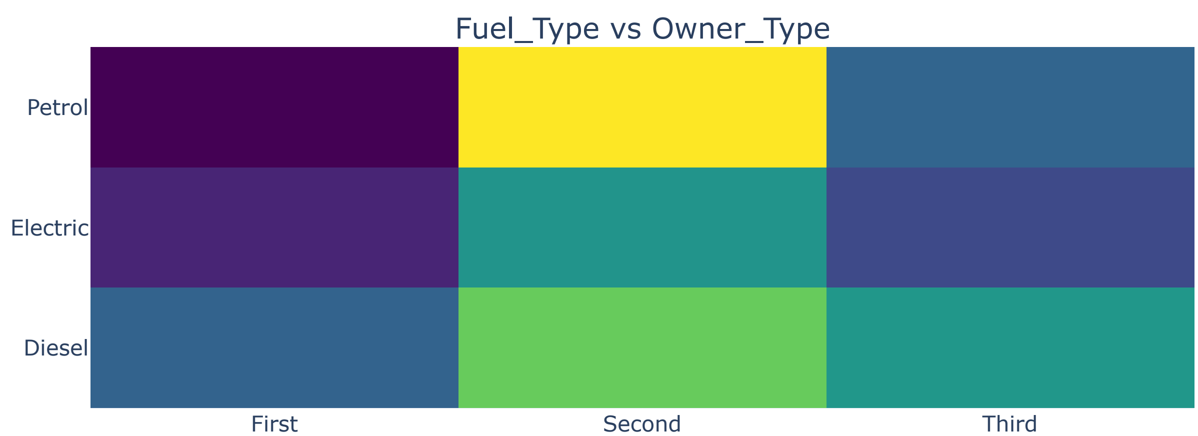

Fuel_Type vs Maintenance_History
Petrol
Electric
Diesel
Average
Good
Poor


Fuel_Type vs Transmission_Type
Petrol
Electric
Diesel
Automatic
Manual

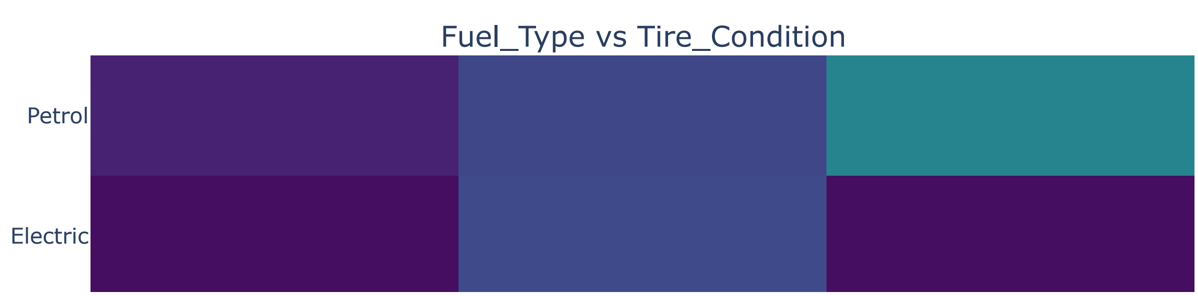

Fuel_Type vs Last_Service_Date
Petrol
Electric
Diesel
May 2023
Jul 2023
Sep 2023
Nov 2023
Jan 2024



Fuel_Type vs Warranty_Expiry_Date
Petrol
Electric
Diesel
Chi-square: 2.831
P-value: 0.726
Cramer's V: 0.008
Jul 2024
Oct 2024
Jan 2025
Apr 2025
Jul 2025
Oct 2025
Jan 2026



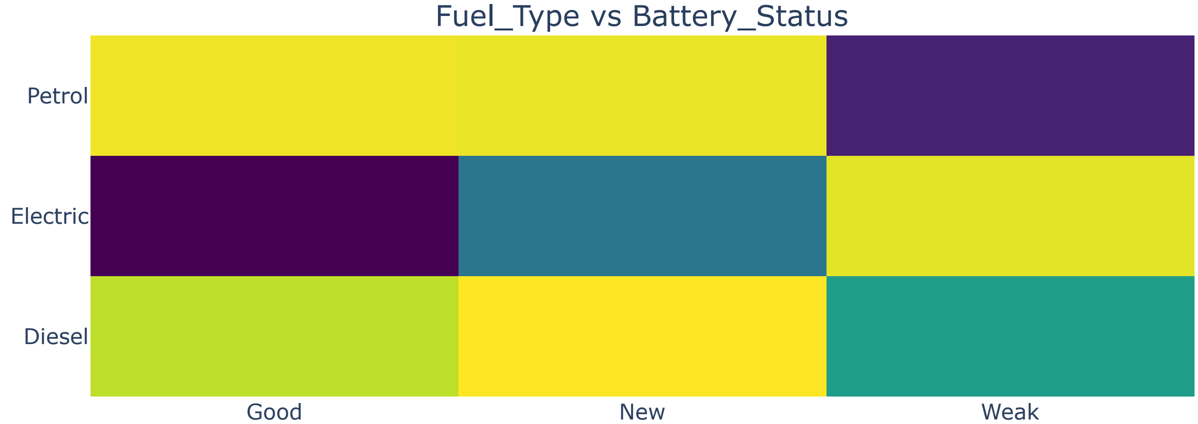
Fuel_Type vs Owner_Type
Petrol
Electric
Diesel
First
Second
Third



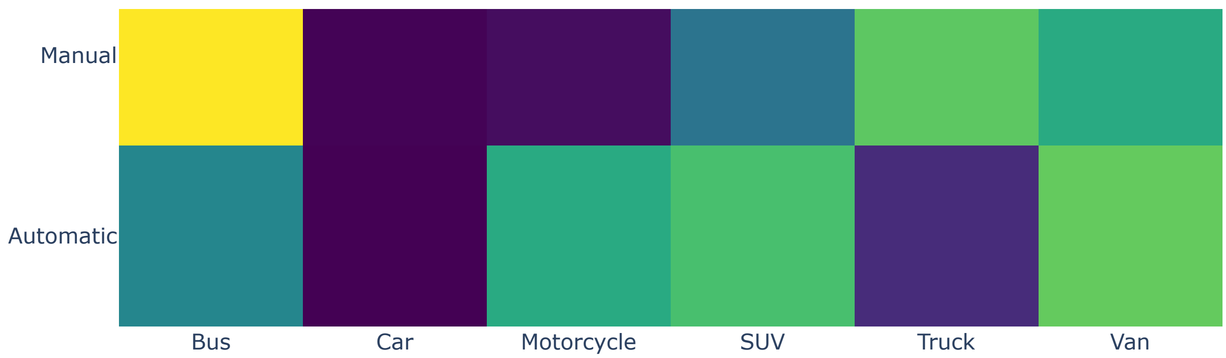
Fuel_Type vs Tire_Condition
Petrol
Electric

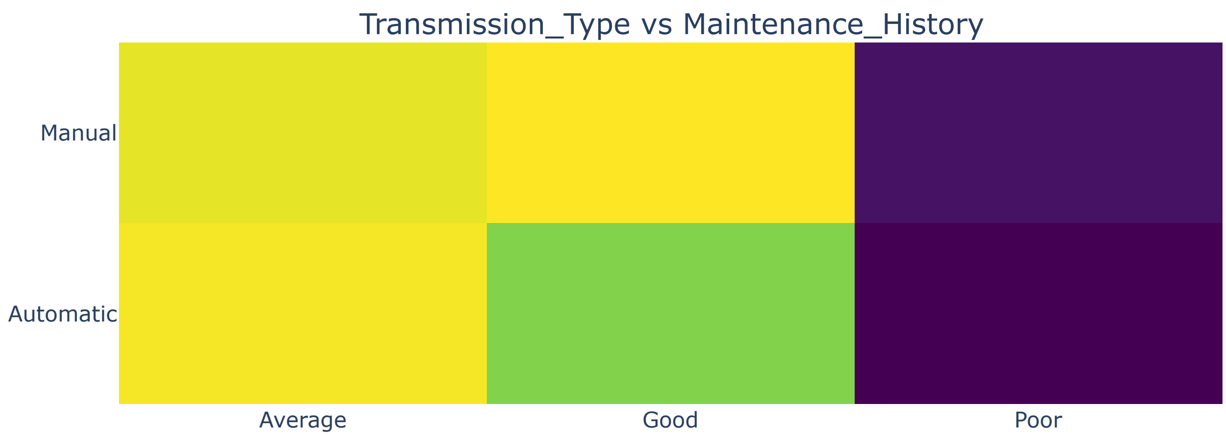
Fuel_Type vs Brake_Condition

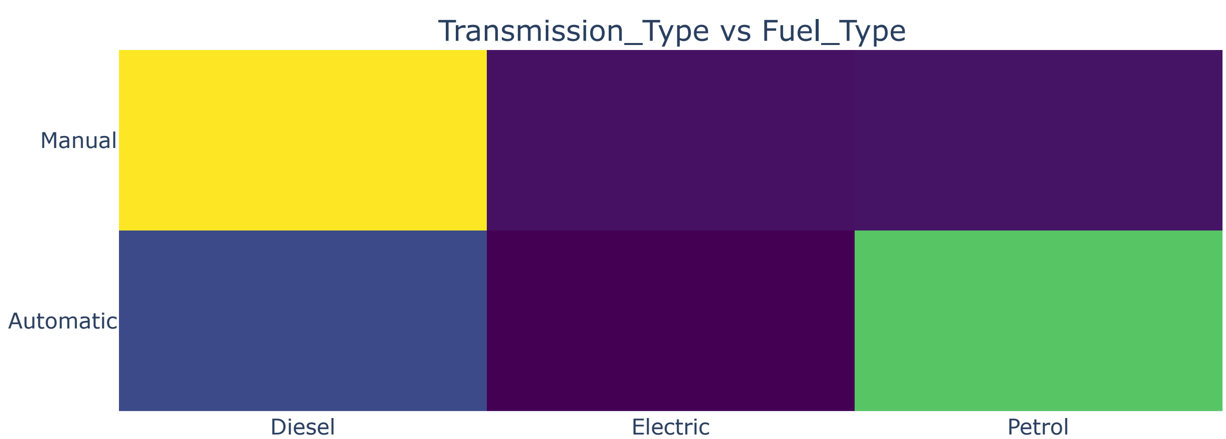
Fuel_Type vs Battery_Status

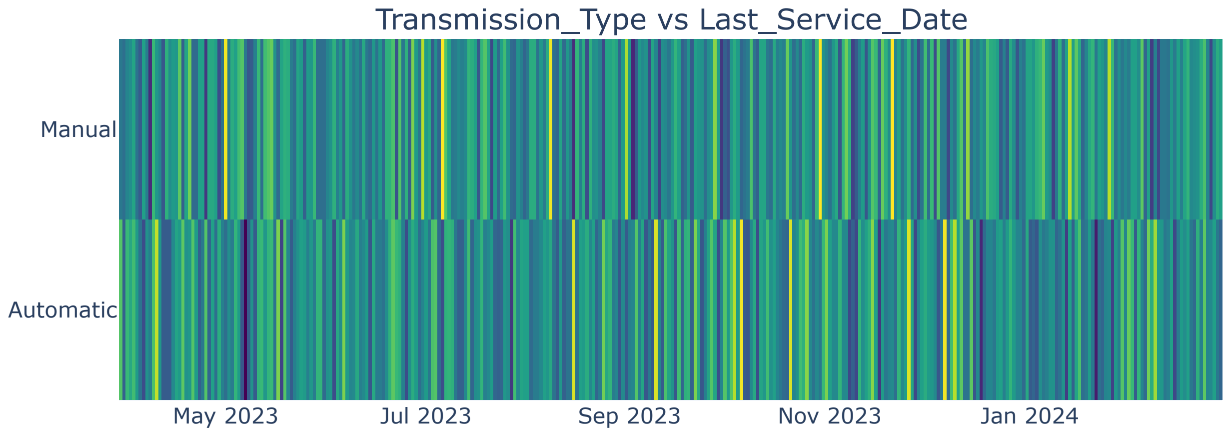


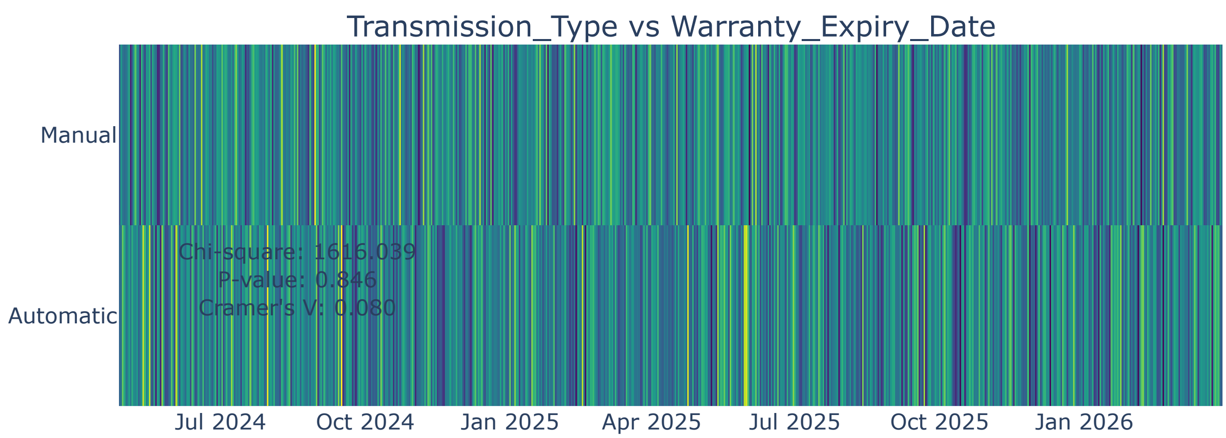
Transmission_Type vs Vehicle_Model

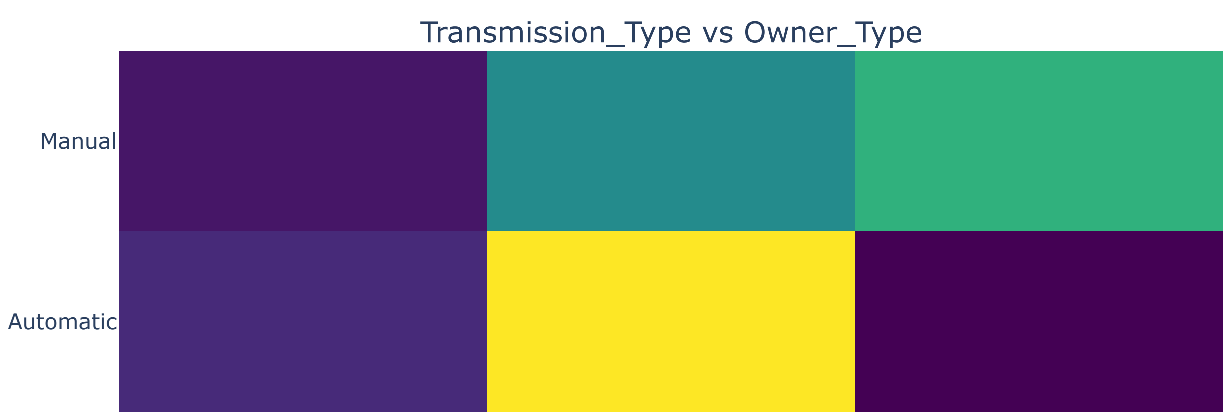

Manual
Automatic
Bus
Car
Motorcycle
SUV
Truck
Van


Transmission_Type vs Maintenance_History
Manual
Automatic
Average
Good
Poor

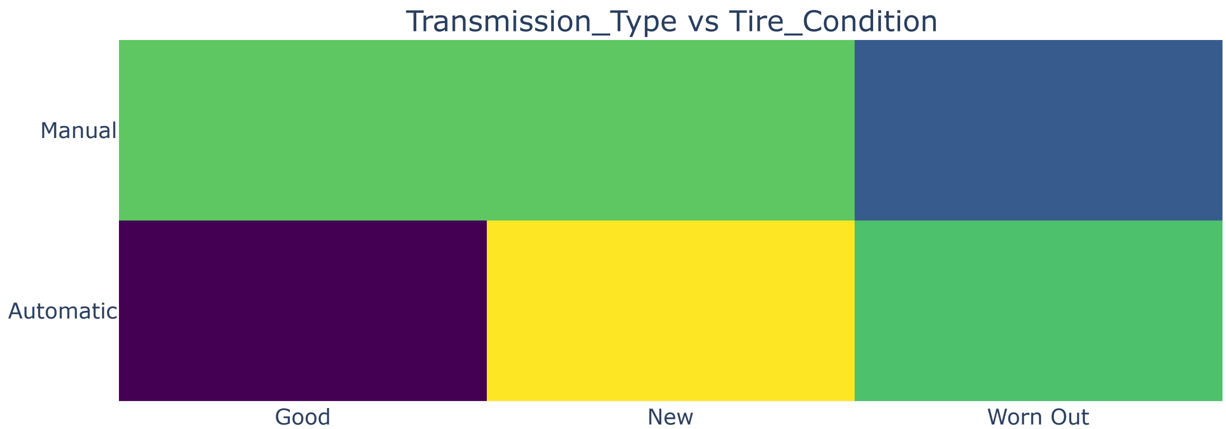

Transmission_Type vs Fuel_Type
Manual
Automatic
Diesel
Electric
Petrol

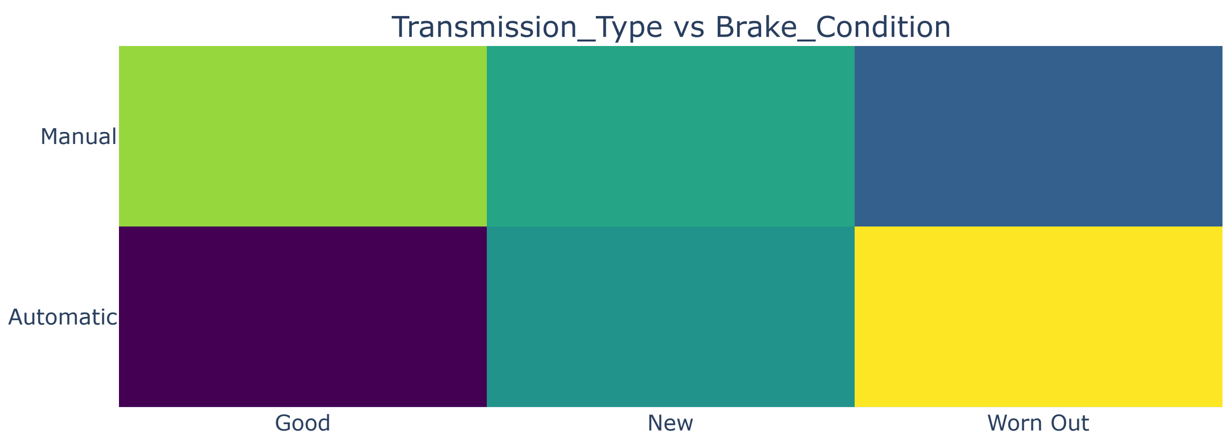

Transmission_Type vs Last_Service_Date
Manual
Automatic
May 2023
Jul 2023
Sep 2023
Nov 2023
Jan 2024

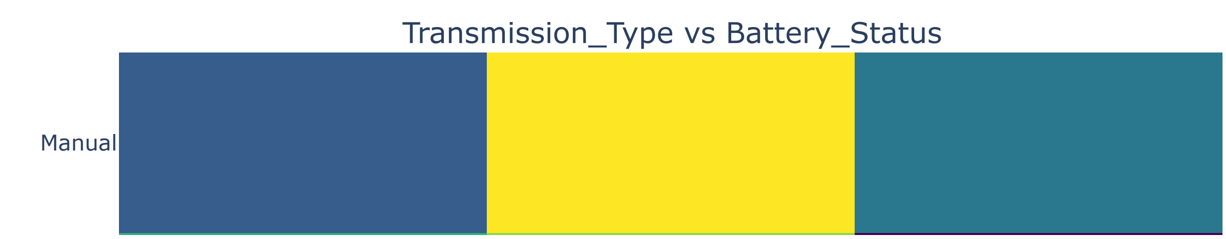

Transmission_Type vs Warranty_Expiry_Date
Manual
Automatic
Chi-square: 1616.039
P-value: 0.846
Cramer's V: 0.080
Jul 2024
Oct 2024
Jan 2025
Apr 2025
Jul 2025
Oct 2025
Jan 2026

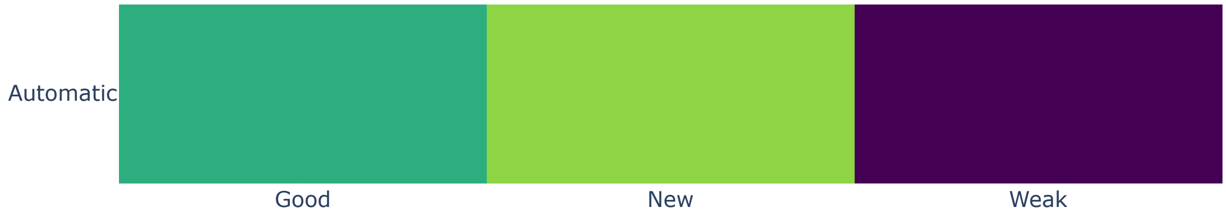

Transmission_Type vs Owner_Type
Manual
Automatic

First Second Third

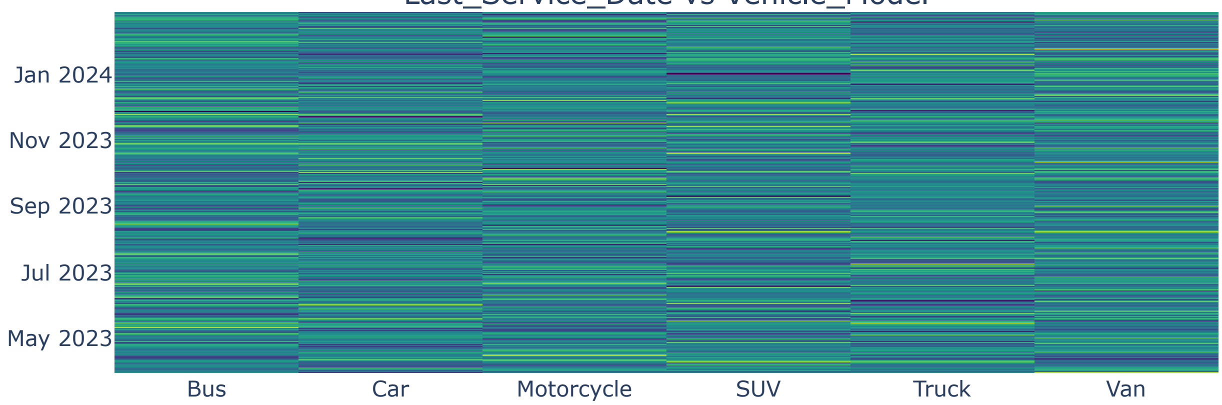




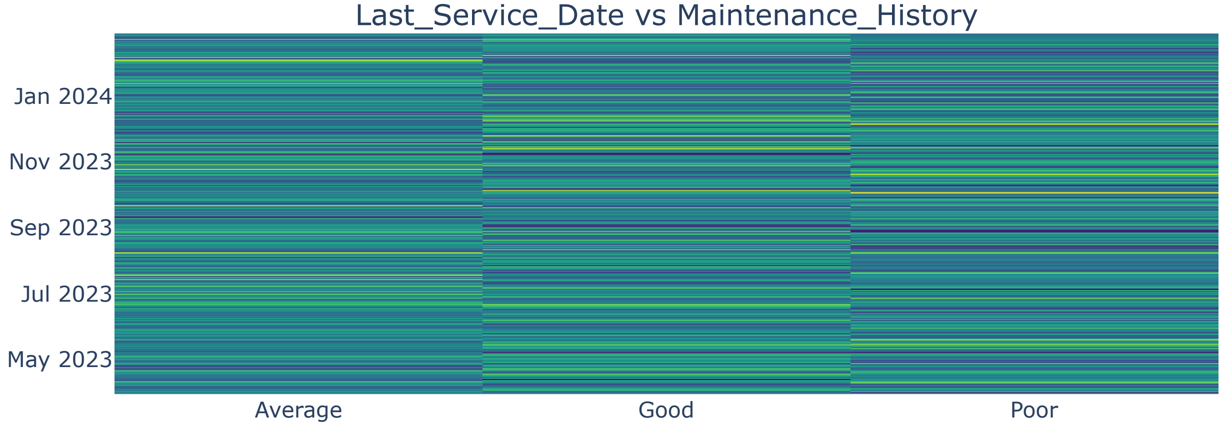




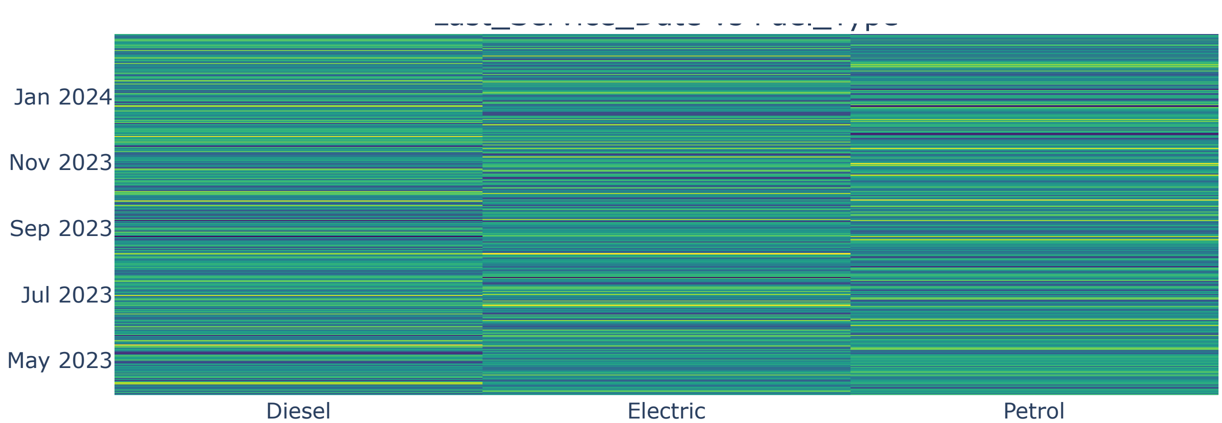
Last_Service_Date vs Vehicle_Model

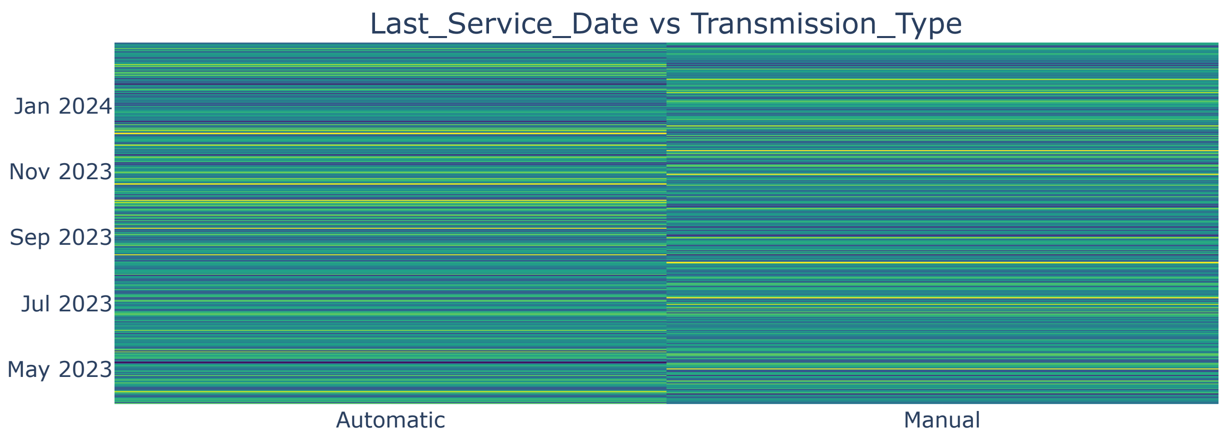


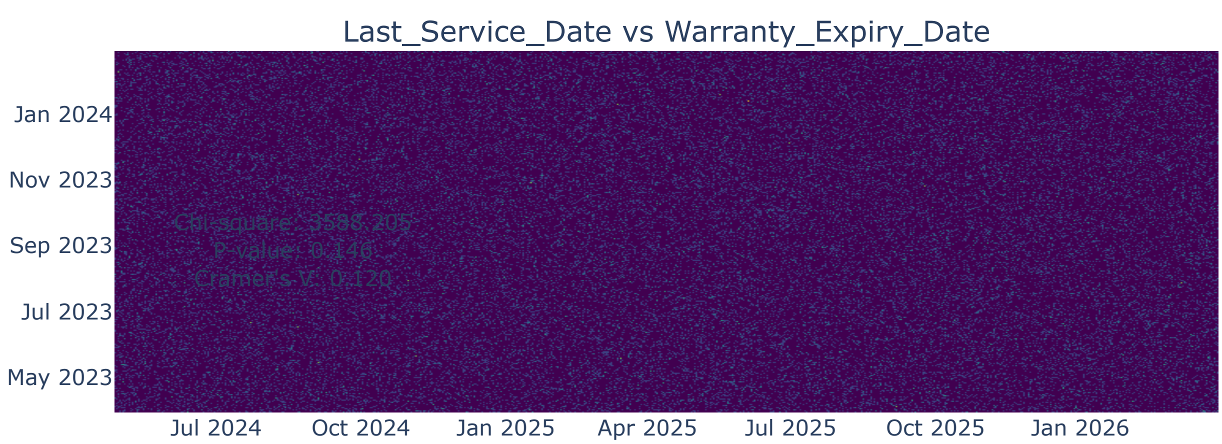
Last_Service_Date vs Maintenance_History

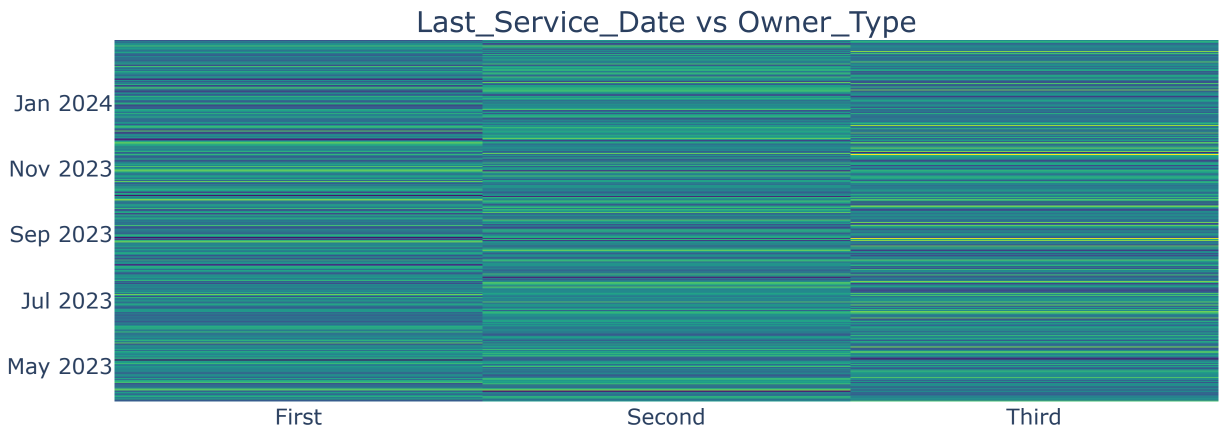


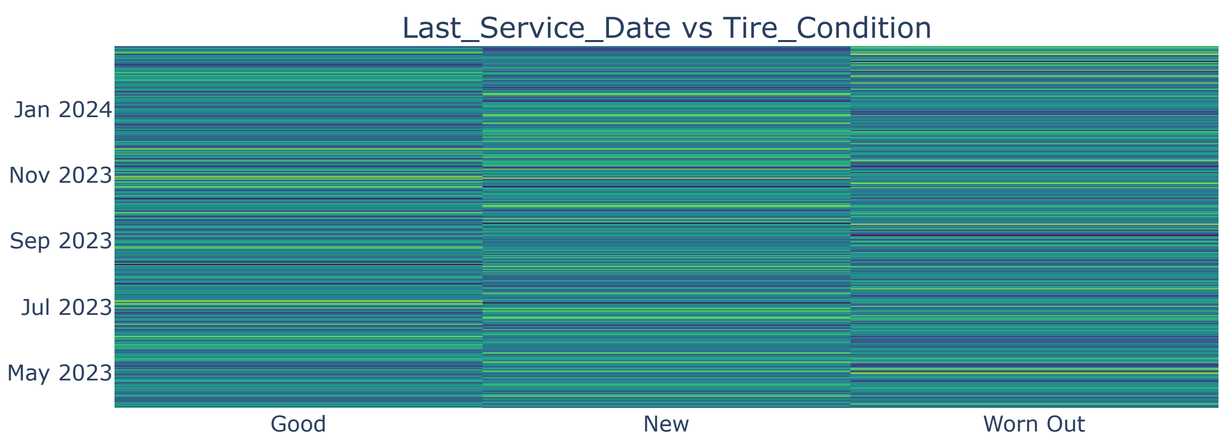
Last_Service_Date vs Fuel_Type

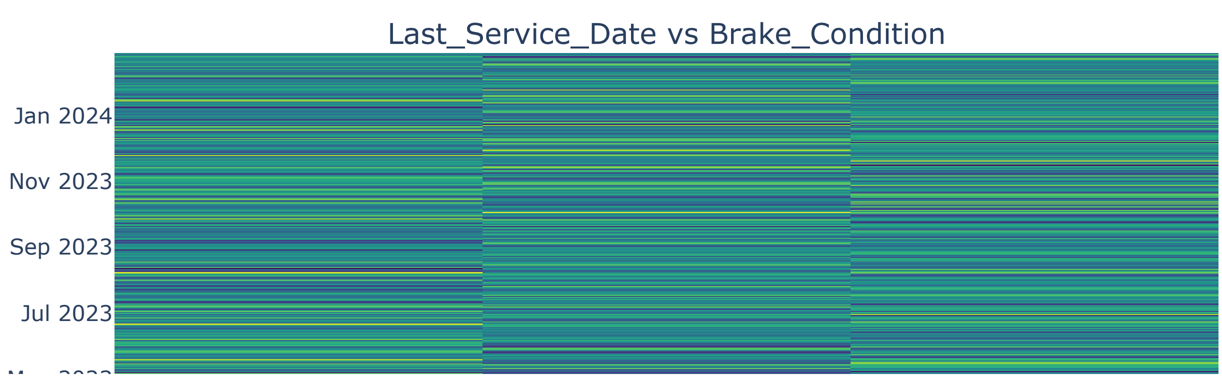

Jan 2024
Nov 2023
Sep 2023
Jul 2023
May 2023
Diesel
Electric
Petrol

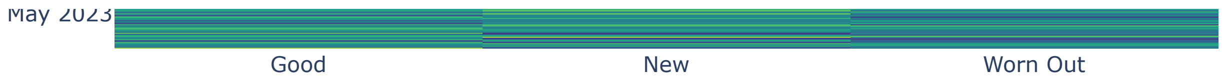

Last_Service_Date vs Transmission_Type
Jan 2024
Nov 2023
Sep 2023
Jul 2023
May 2023
Automatic
Manual


Last_Service_Date vs Warranty_Expiry_Date
Jan 2024
Nov 2023
Sep 2023
Jul 2023
May 2023
Chi-square: 3588.205
P-value: 0.146
Cramer's V: 0.120
Jul 2024
Oct 2024
Jan 2025
Apr 2025
Jul 2025
Oct 2025
Jan 2026

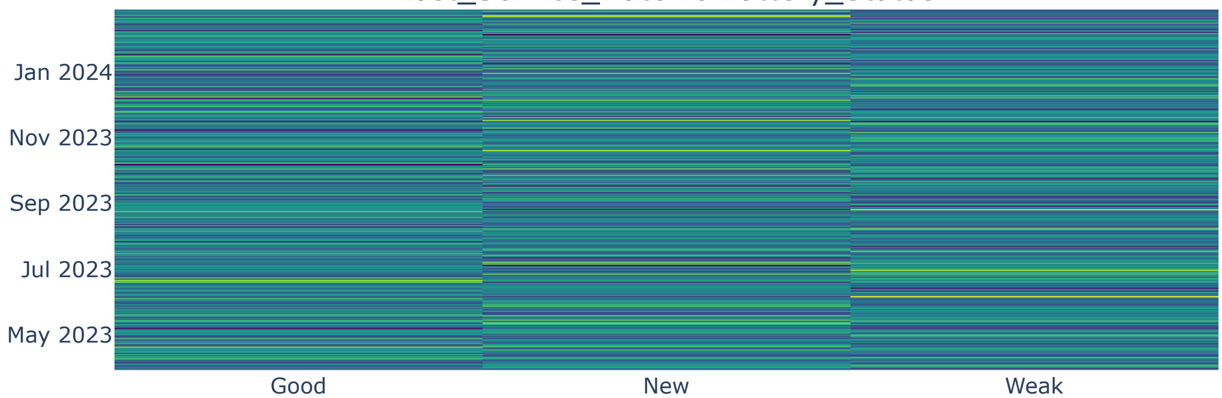

Last_Service_Date vs Owner_Type
Jan 2024
Nov 2023
Sep 2023
Jul 2023
May 2023
First
Second
Third


Last_Service_Date vs Tire_Condition
Jan 2024
Nov 2023
Sep 2023
Jul 2023
May 2023
Good
New
Worn Out

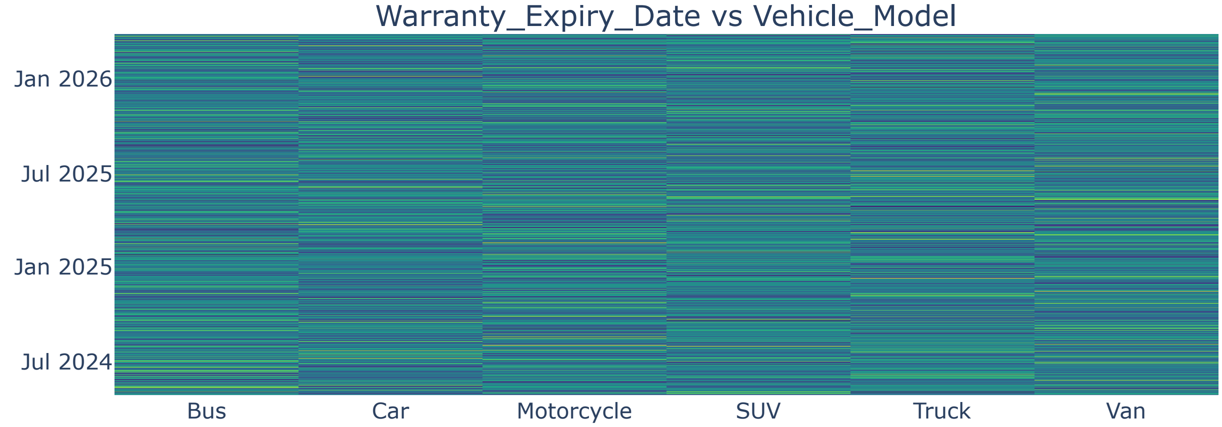

Last_Service_Date vs Brake_Condition
Jan 2024
Nov 2023
Sep 2023
Jul 2023



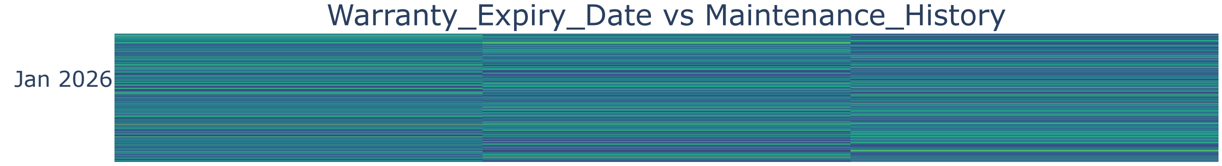
Last_Service_Date vs Battery_Status

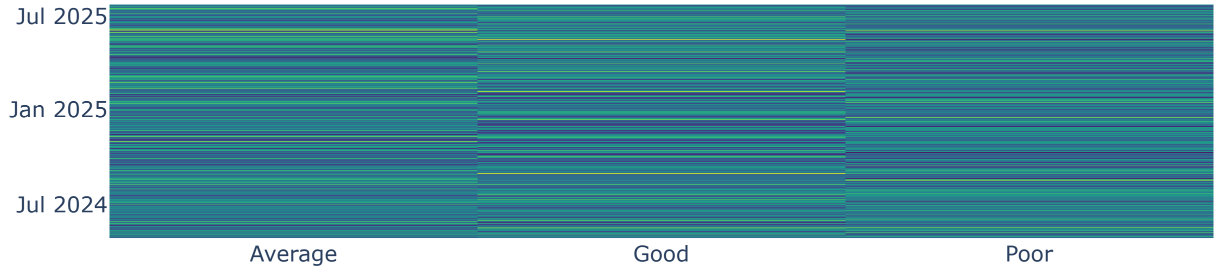


Warranty_Expiry_Date vs Vehicle_Model

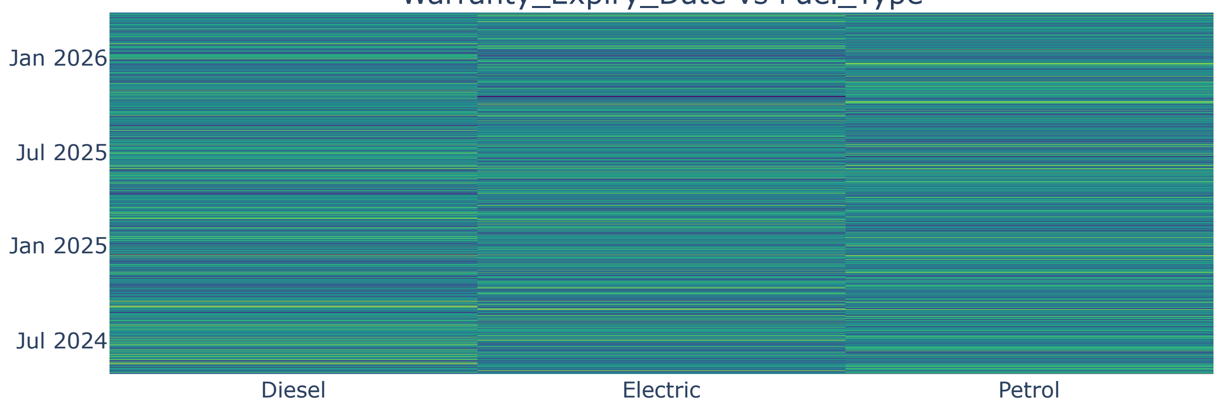


Warranty_Expiry_Date vs Maintenance_History

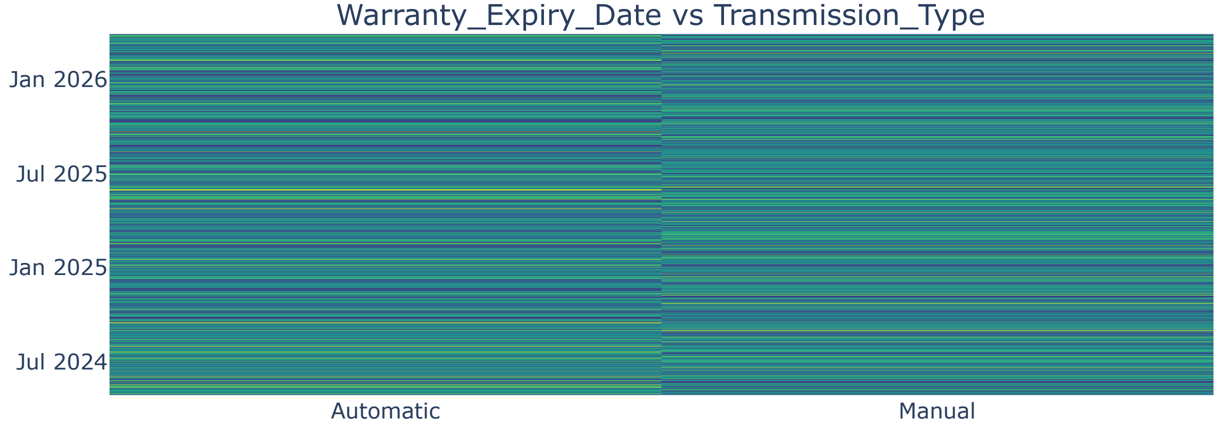


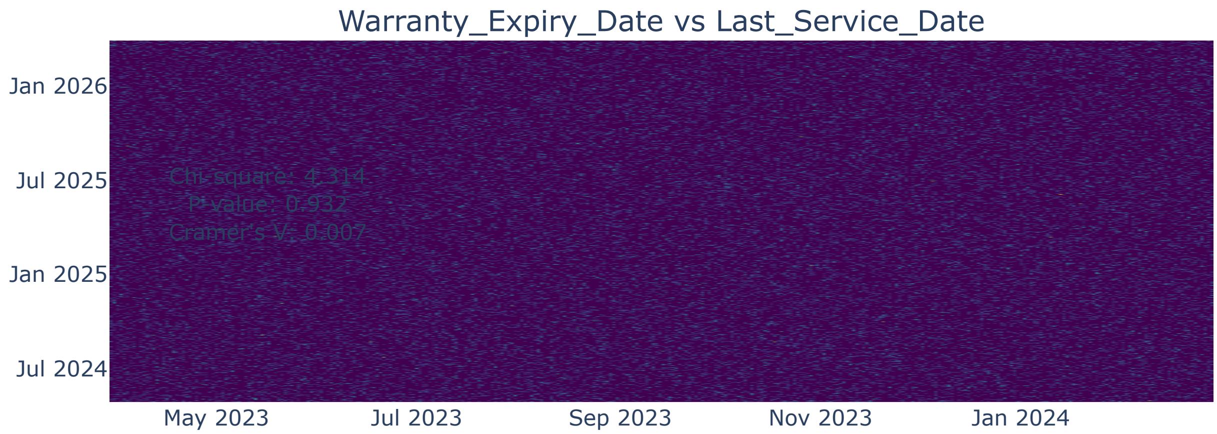


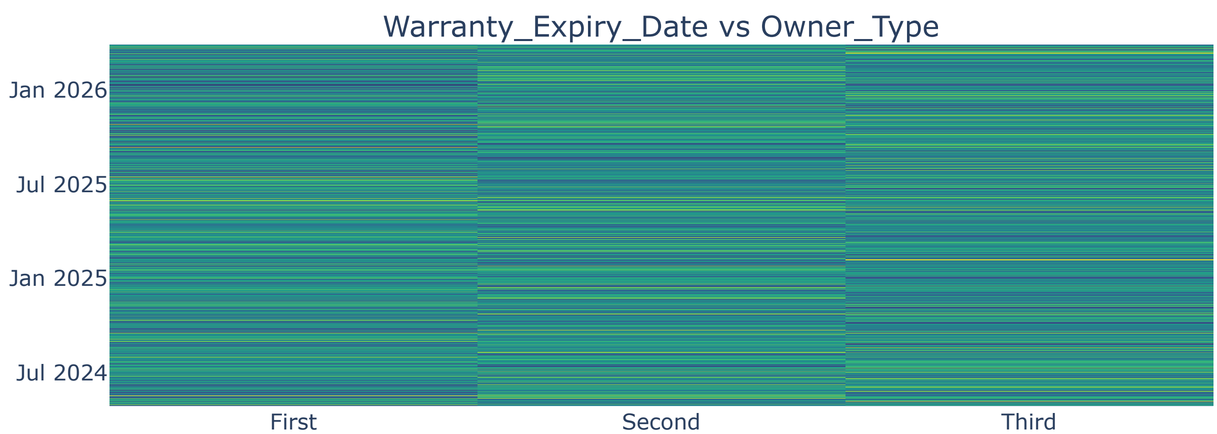
Warranty_Expiry_Date vs Fuel_Type

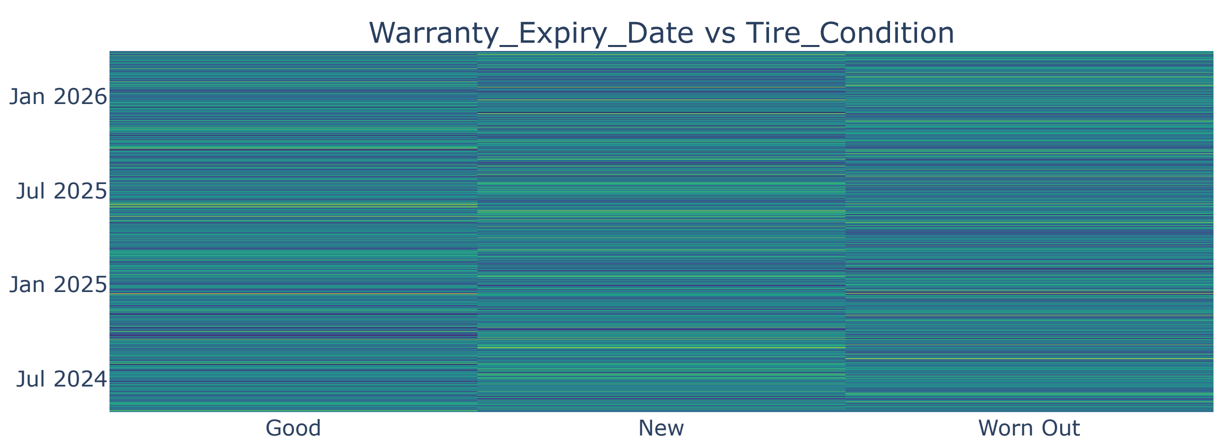


Warranty_Expiry_Date vs Transmission_Type



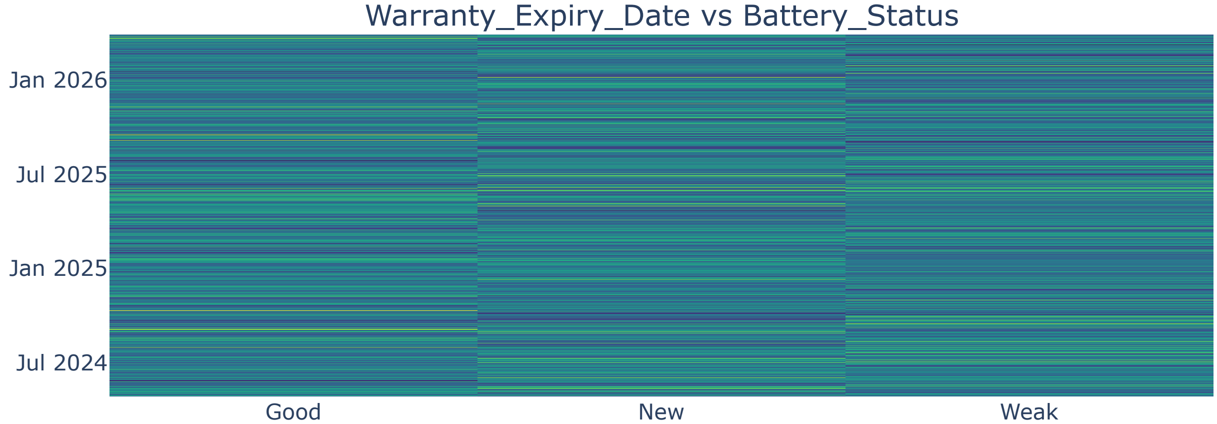

Warranty_Expiry_Date vs Last_Service_Date
Chi-square: 4.314
P-value: 0.932
Cramer's V: 0.007
Jan 2026
Jul 2025
Jan 2025
Jul 2024
May 2023
Jul 2023
Sep 2023
Nov 2023
Jan 2024


Warranty_Expiry_Date vs Owner_Type
Jan 2026
Jul 2025
Jan 2025
Jul 2024
First
Second
Third

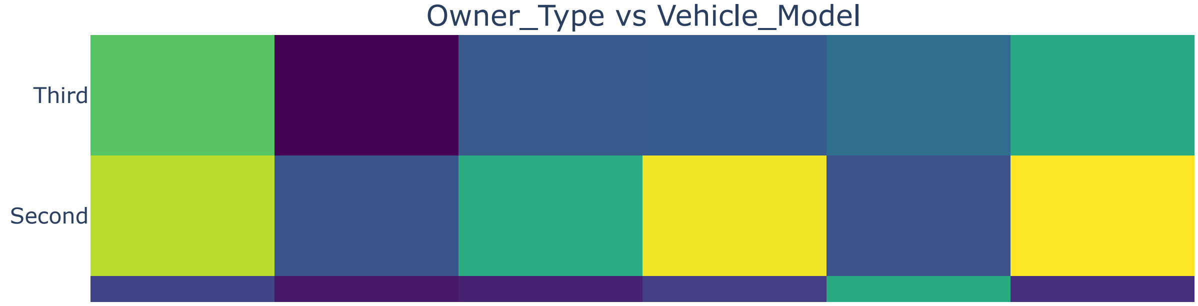

Warranty_Expiry_Date vs Tire_Condition
Jan 2026
Jul 2025
Jan 2025
Jul 2024
Good
New
Worn Out

Warranty_Expiry_Date vs Brake_Condition

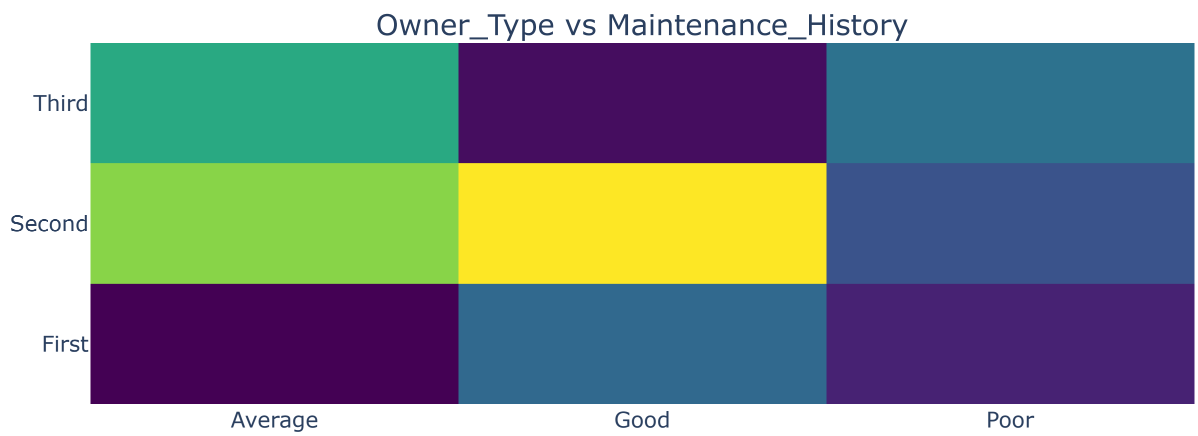
Warranty_Expiry_Date vs Battery_Status

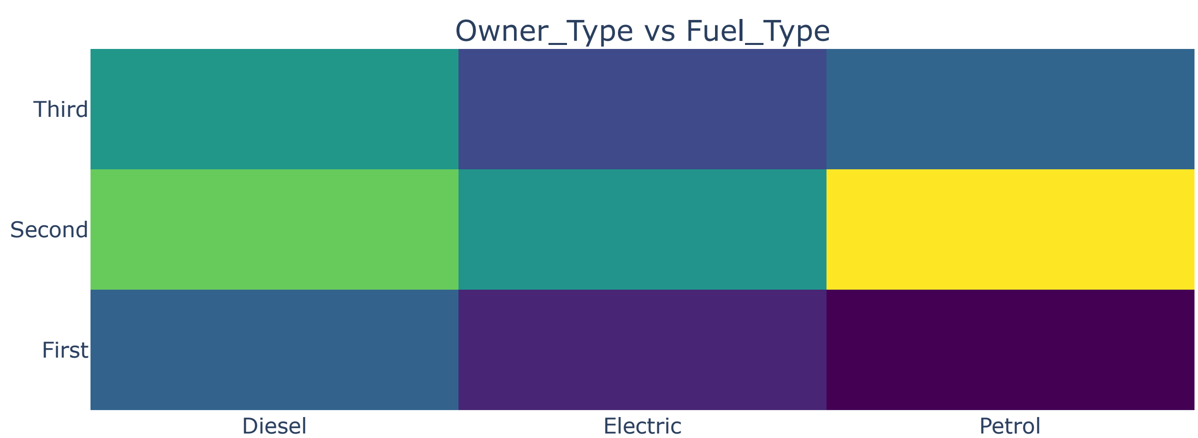


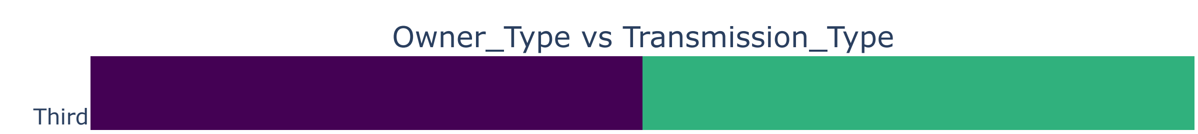
Owner_Type vs Vehicle_Model



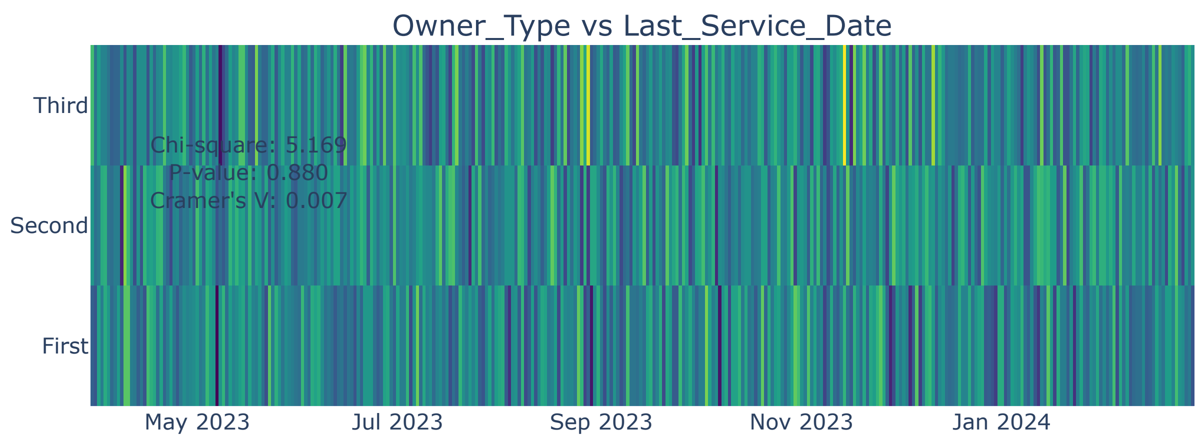

First
Bus
Car
Motorcycle
SUV
Truck
Van

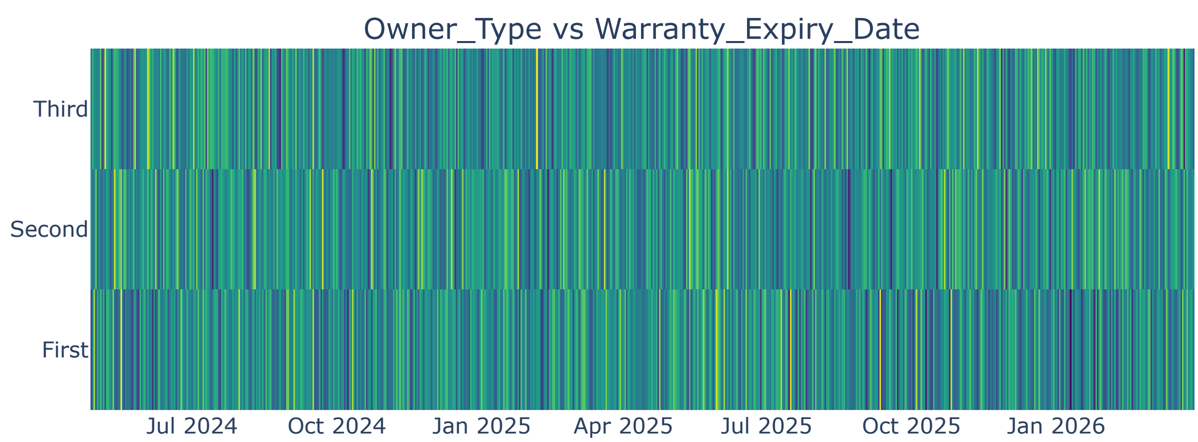

Owner_Type vs Maintenance_History
Third
Second
First
Average
Good
Poor

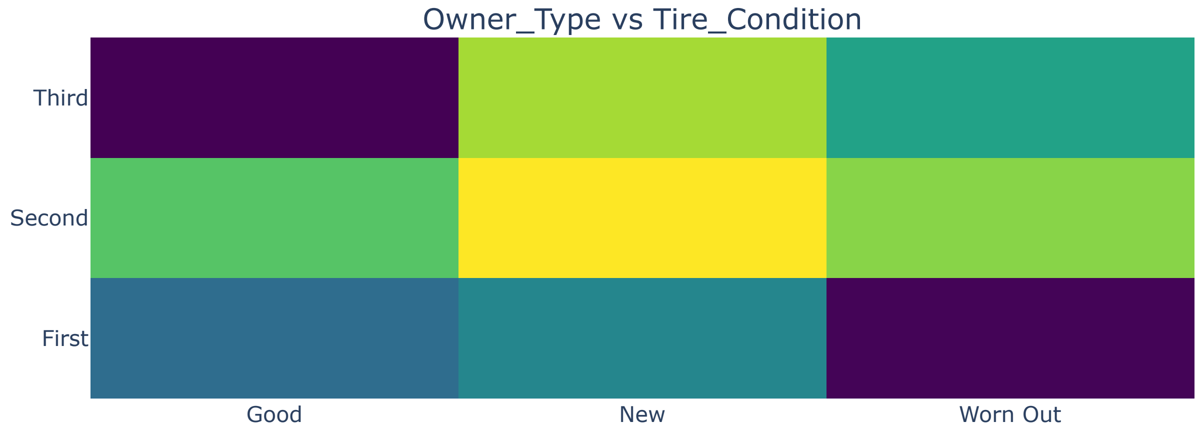

Owner_Type vs Fuel_Type
Third
Second
First
Diesel
Electric
Petrol

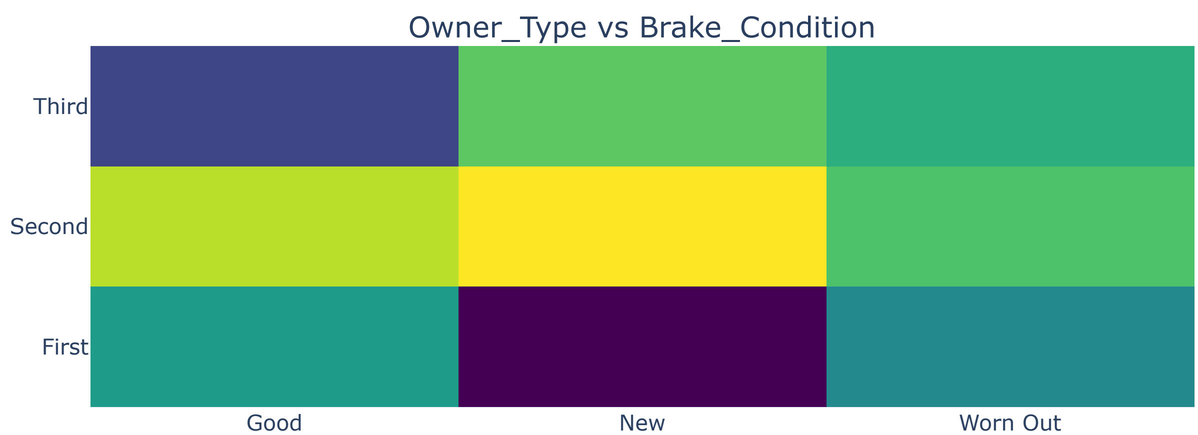

Owner_Type vs Transmission_Type
Third

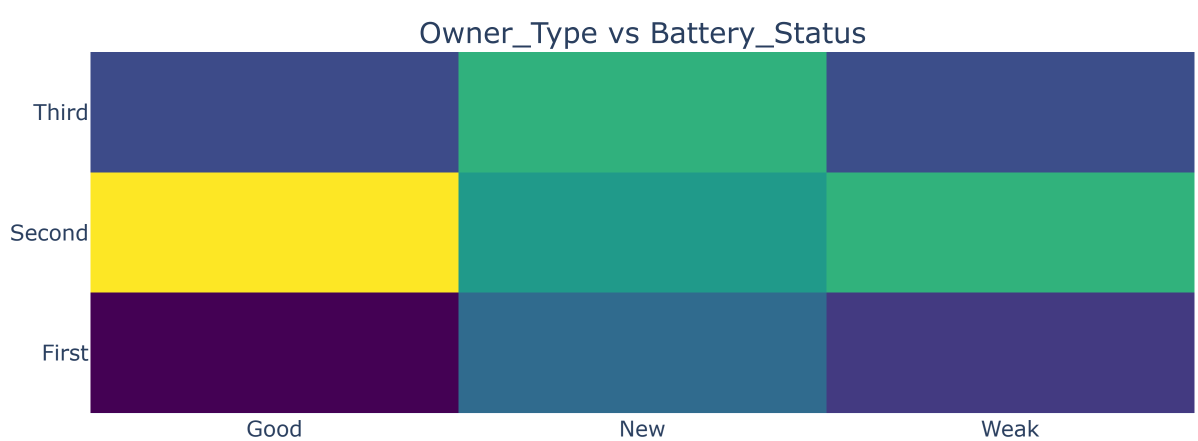

Second
First
Automatic
Manual

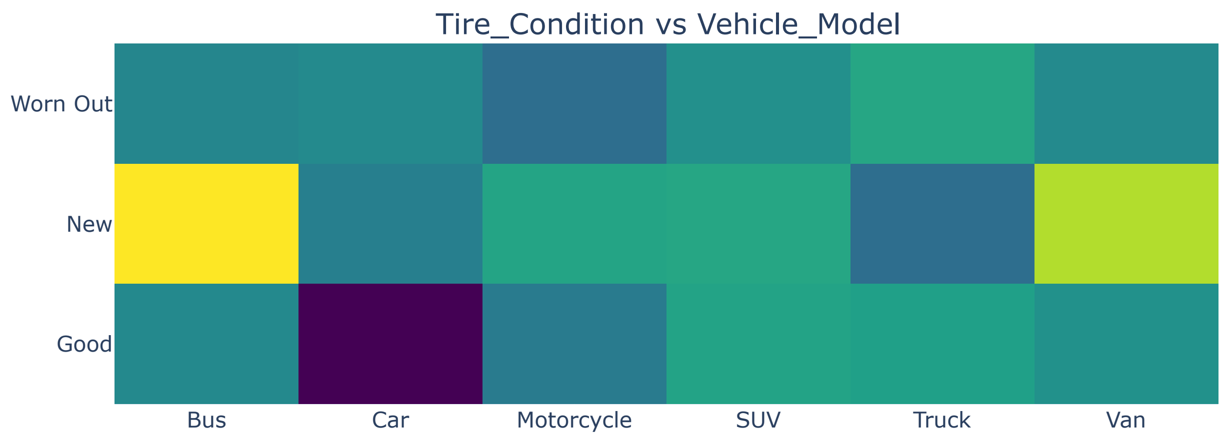

Owner_Type vs Last_Service_Date
Third
Second
First
Chi-square: 5.169
P-value: 0.880
Cramer's V: 0.007
May 2023
Jul 2023
Sep 2023
Nov 2023
Jan 2024

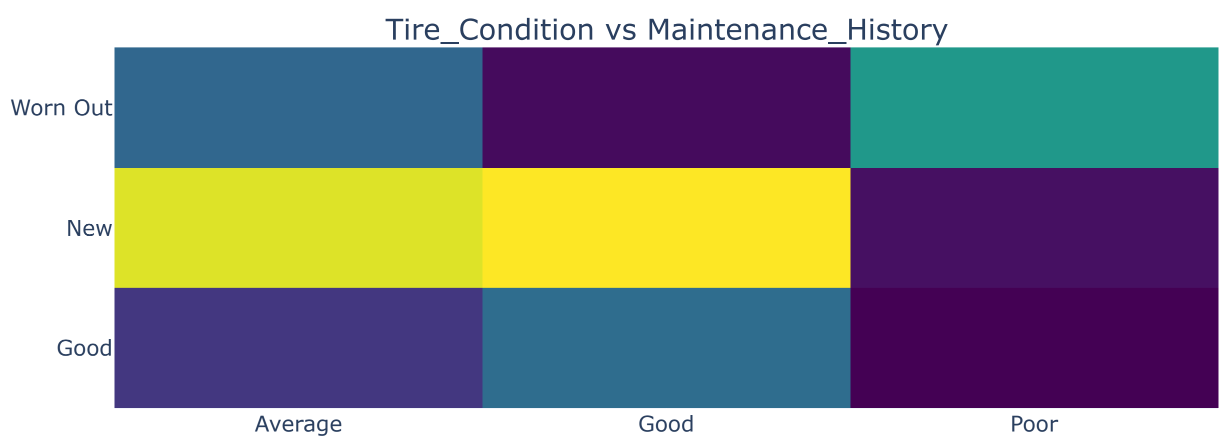

Owner_Type vs Warranty_Expiry_Date
Third
Second
First
Jul 2024
Oct 2024
Jan 2025
Apr 2025
Jul 2025
Oct 2025
Jan 2026

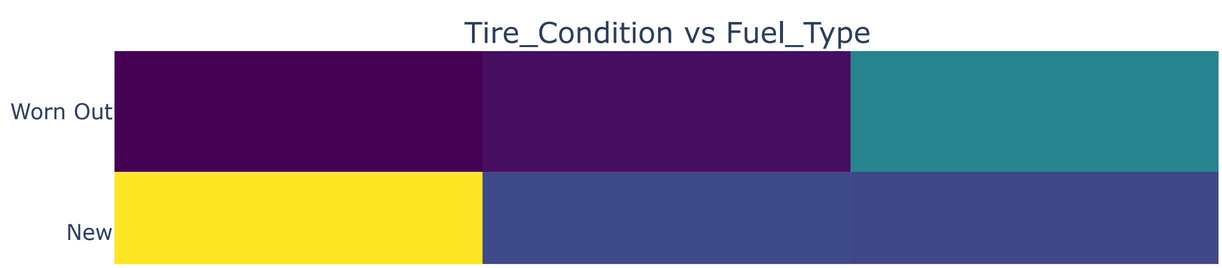

Owner_Type vs Tire_Condition
Third
Second
First
Good
New
Worn Out

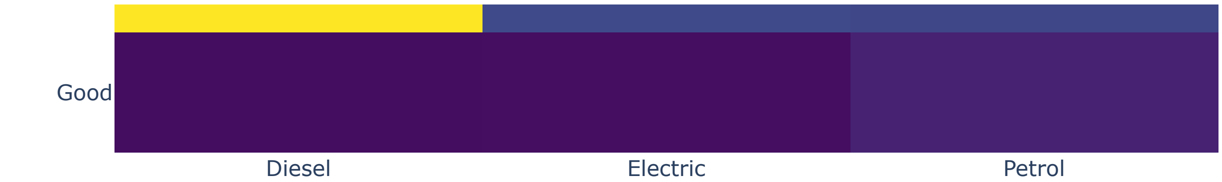

Owner_Type vs Brake_Condition
Third
Second
First
Good
New
Worn Out


Owner_Type vs Battery_Status
Third
Second
First
Good
New
Weak

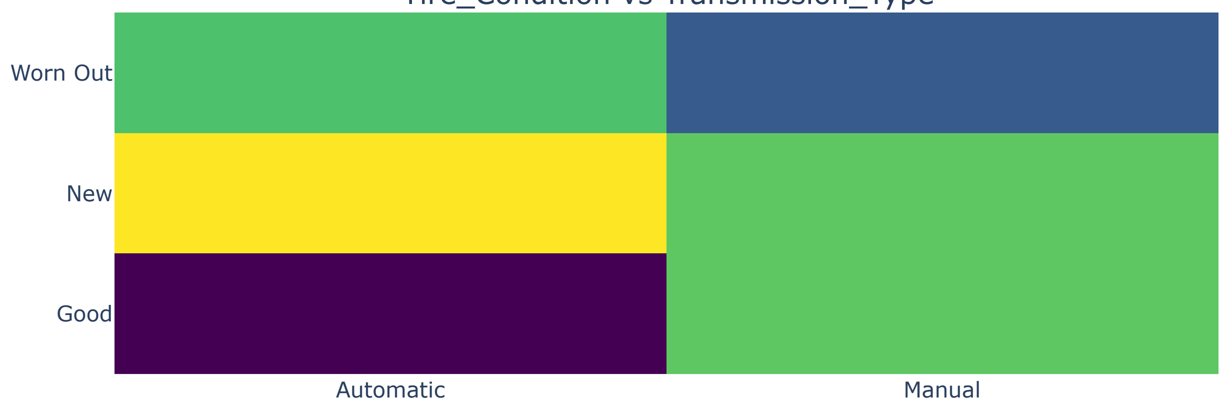

Tire_Condition vs Vehicle_Model
Worn Out
New
Good
Bus
Car
Motorcycle
SUV
Truck
Van


Tire_Condition vs Maintenance_History
Worn Out
New
Good
Average
Good
Poor

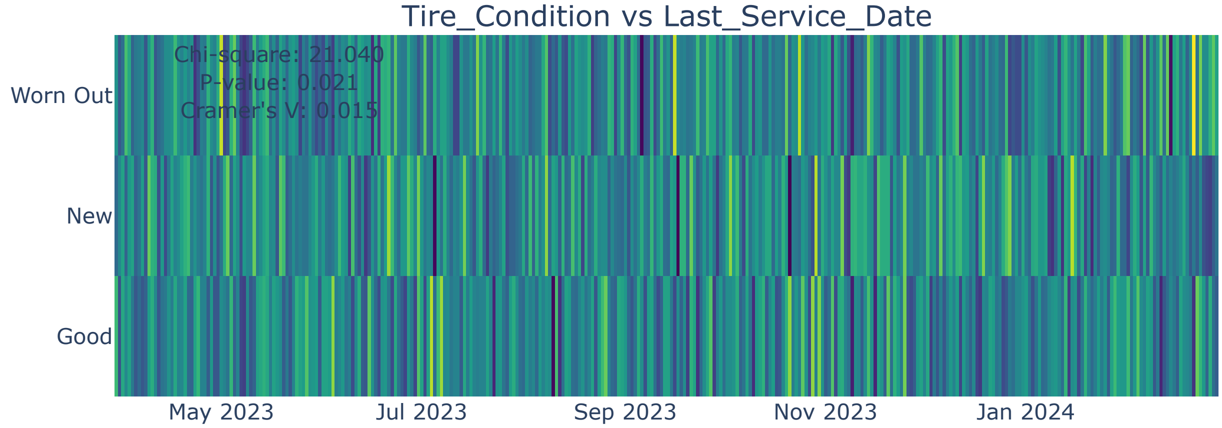

Tire_Condition vs Fuel_Type
Worn Out
New



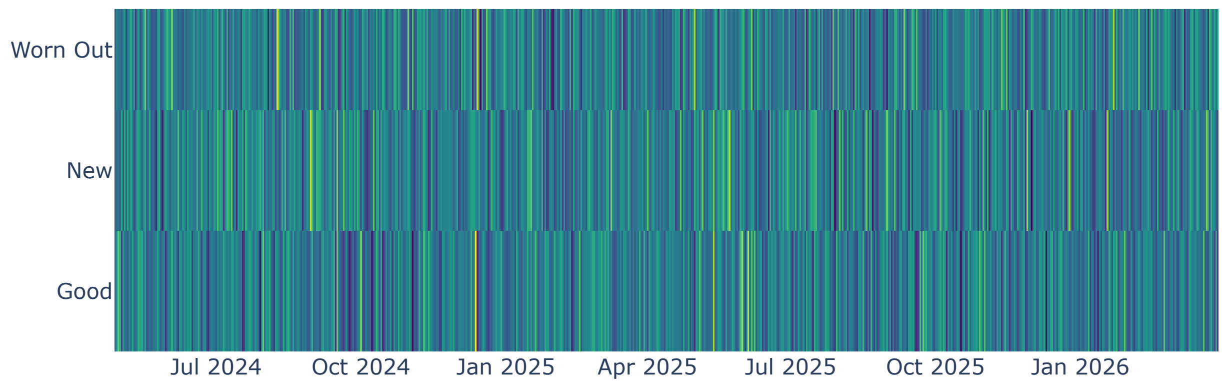
Tire_Condition vs Transmission_Type

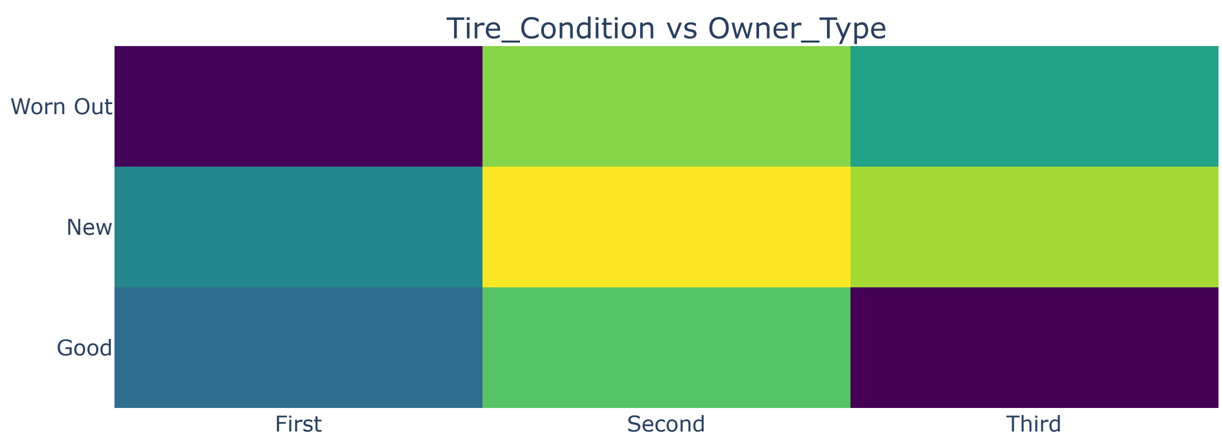


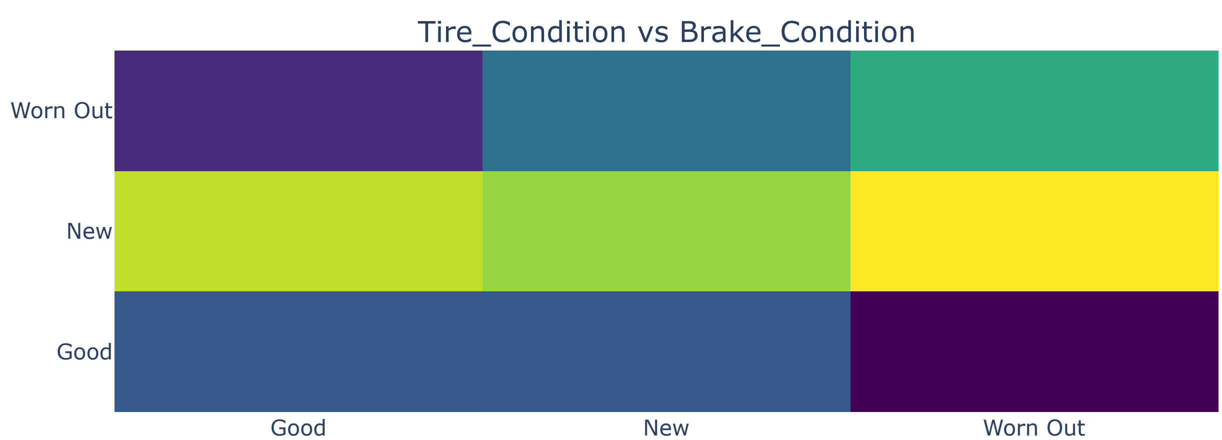
Tire_Condition vs Last_Service_Date

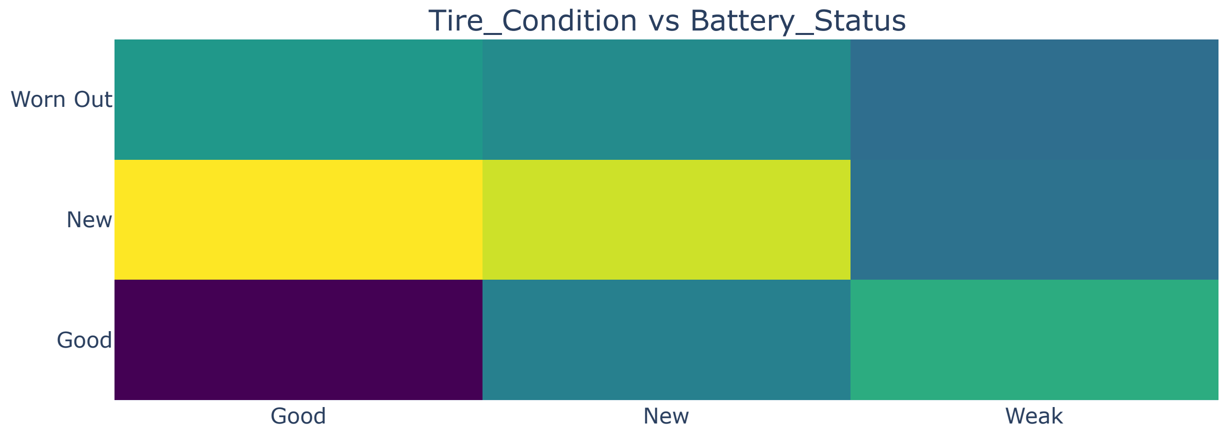


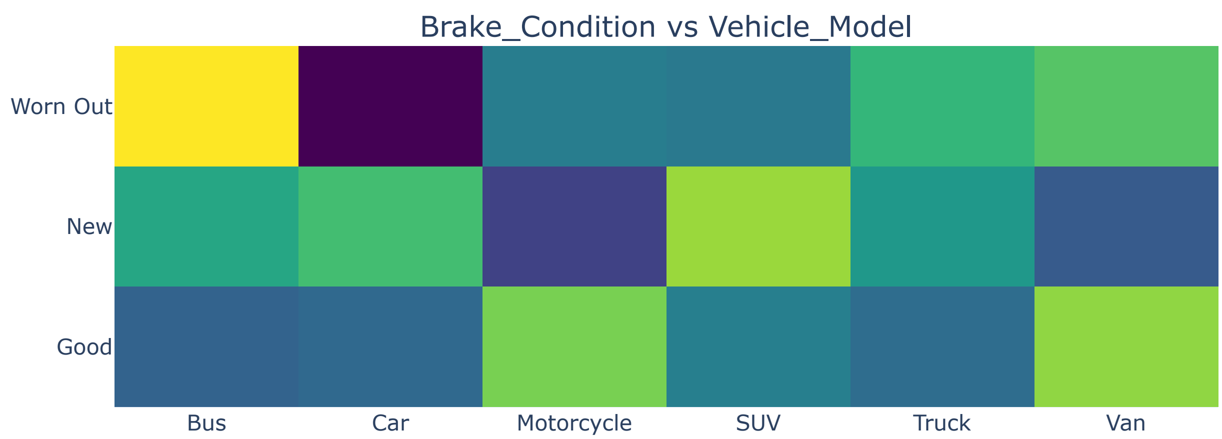
Tire_Condition vs Warranty_Expiry_Date

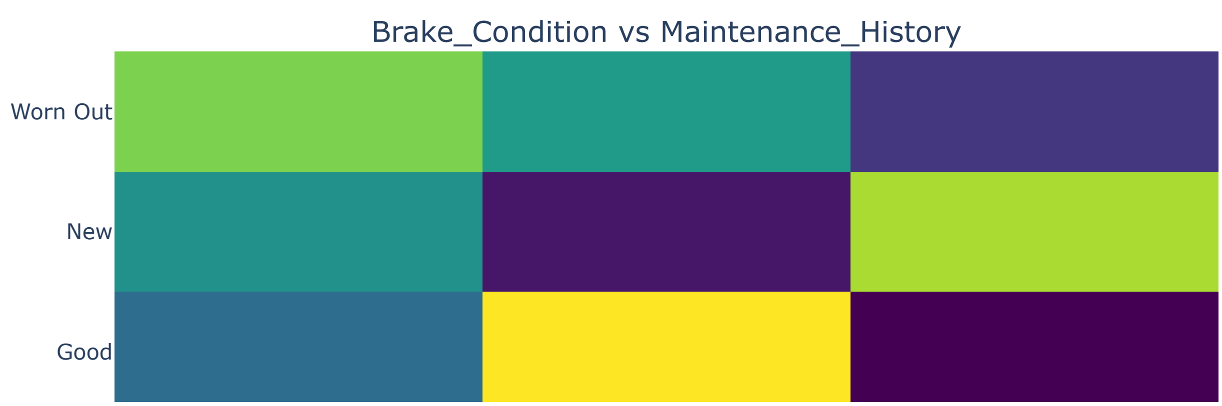

Worn Out
New
Good
Jul 2024
Oct 2024
Jan 2025
Apr 2025
Jul 2025
Oct 2025
Jan 2026


Tire_Condition vs Owner_Type
Worn Out
New
Good
First
Second
Third

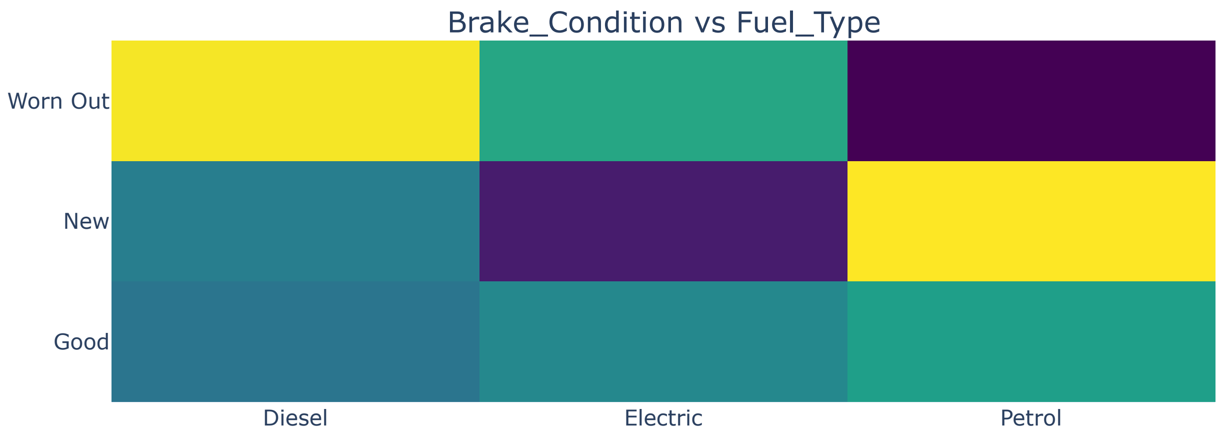

Tire_Condition vs Brake_Condition
Worn Out
New
Good
Good
New
Worn Out

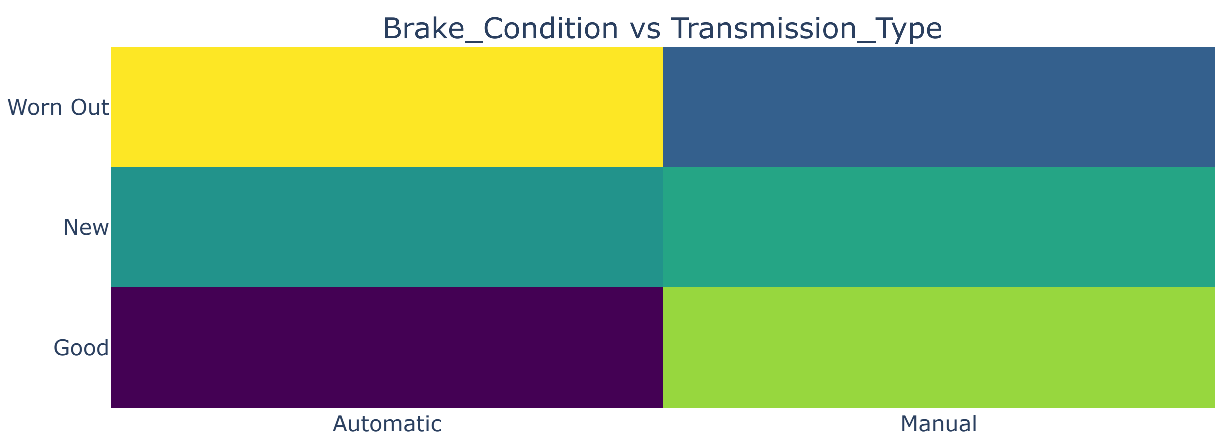

Tire_Condition vs Battery_Status
Worn Out
New
Good
Good
New
Weak

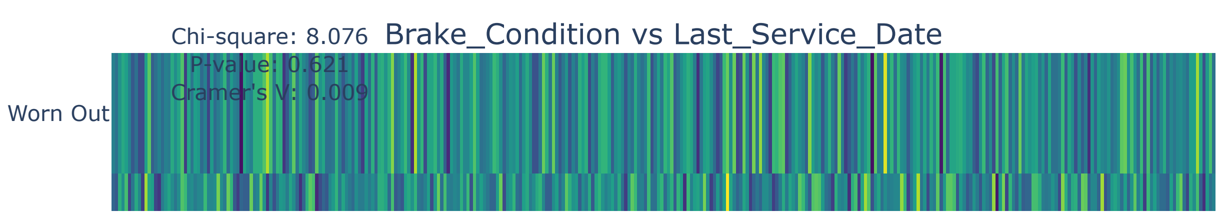

Brake_Condition vs Vehicle_Model
Worn Out
New
Good
Bus
Car
Motorcycle
SUV
Truck
Van

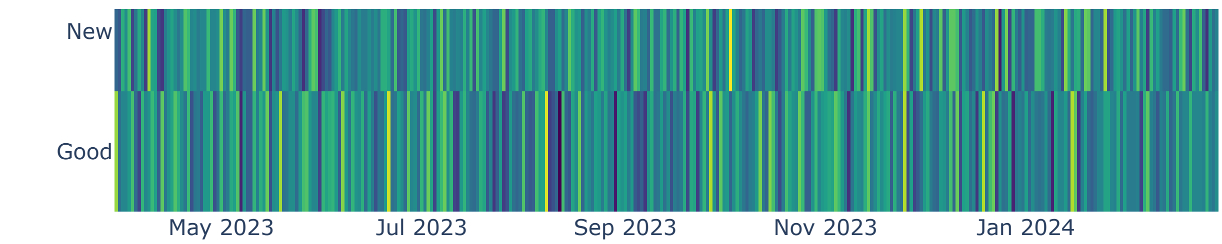

Brake_Condition vs Maintenance_History
Worn Out
New
Good

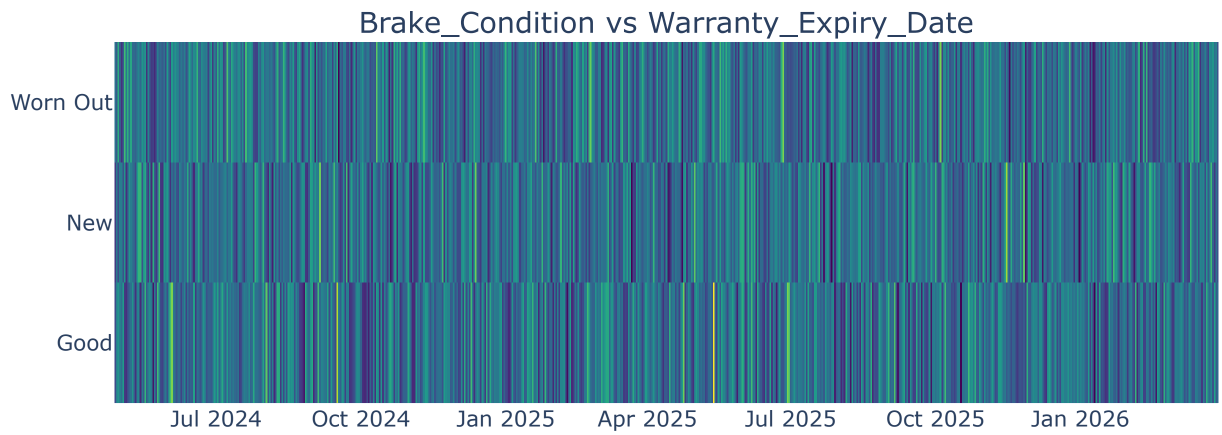

Average
Good
Poor

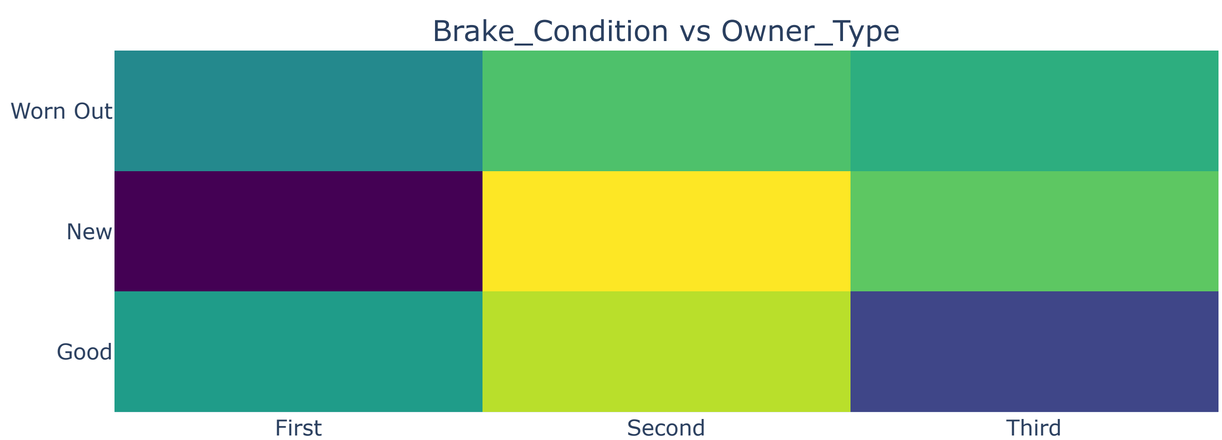

Brake_Condition vs Fuel_Type
Worn Out
New
Good
Diesel
Electric
Petrol

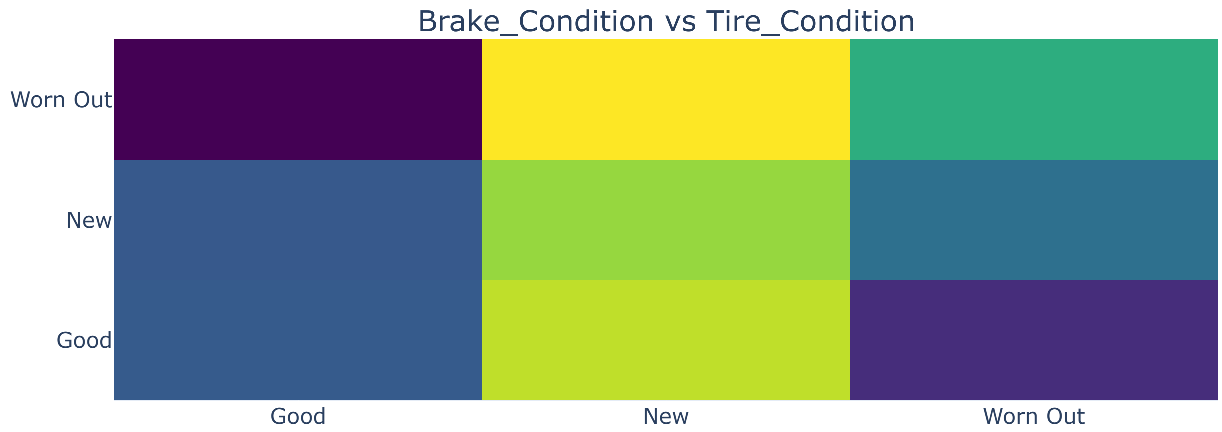

Brake_Condition vs Transmission_Type
Worn Out
New
Good
Automatic
Manual

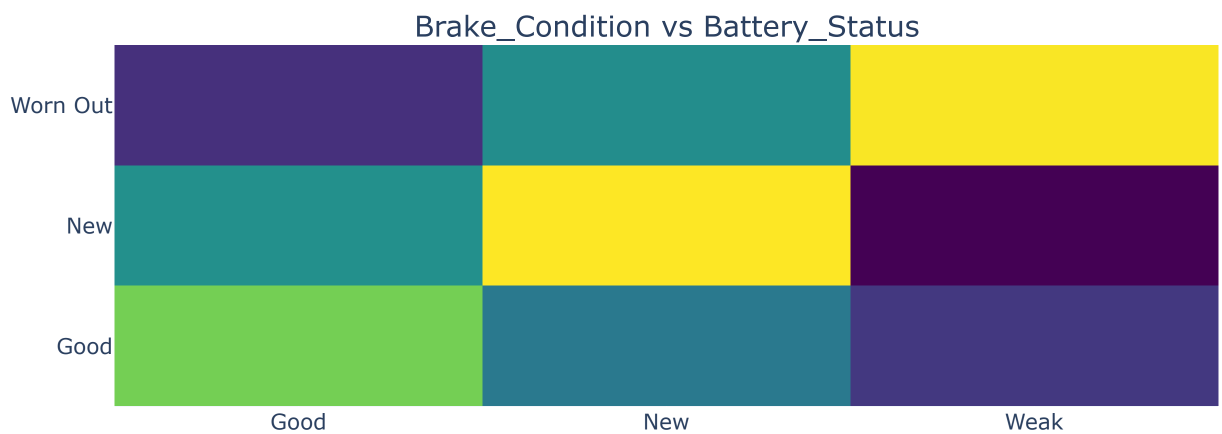

Chi-square: 8.076
P-value: 0.621
Cramer's V: 0.009
Brake_Condition vs Last_Service_Date
Worn Out

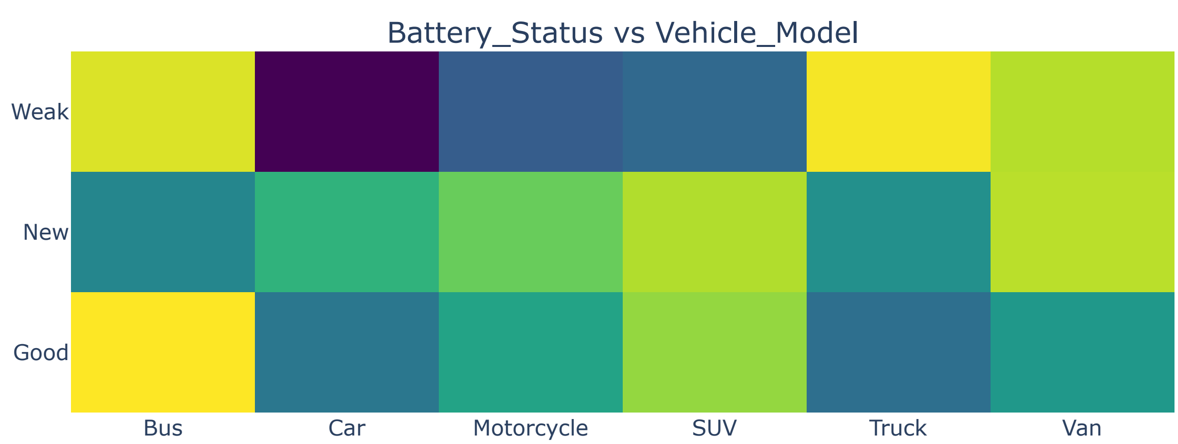

New
Good
May 2023
Jul 2023
Sep 2023
Nov 2023
Jan 2024

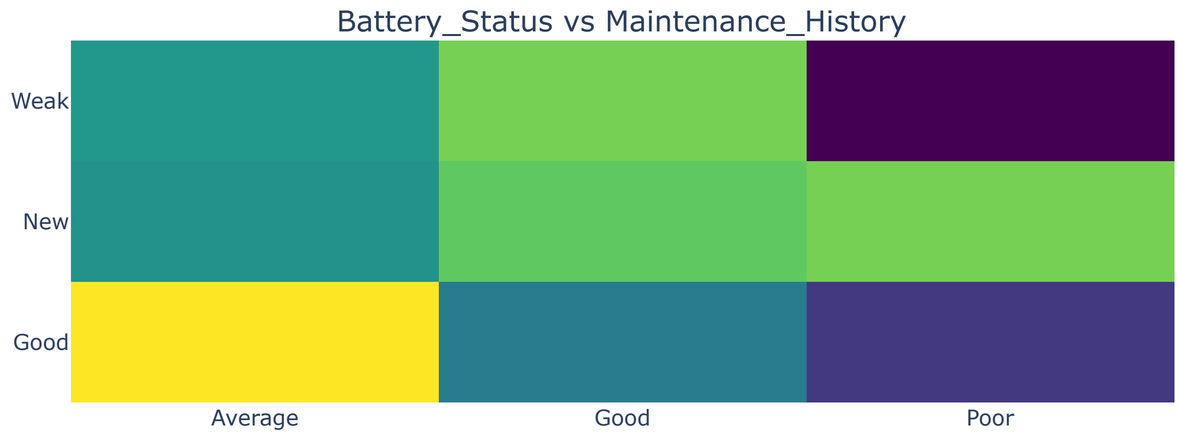

Brake_Condition vs Warranty_Expiry_Date
Worn Out
New
Good
Jul 2024
Oct 2024
Jan 2025
Apr 2025
Jul 2025
Oct 2025
Jan 2026

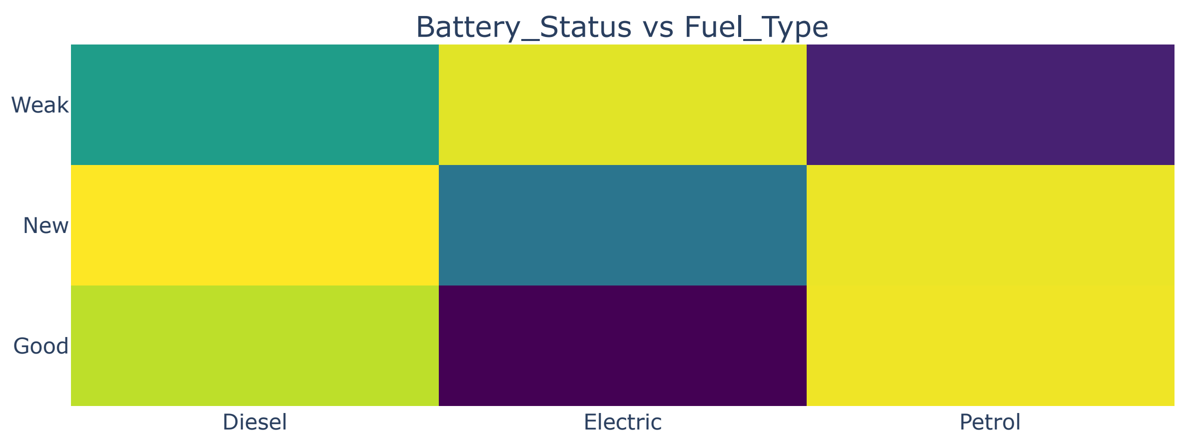

Brake_Condition vs Owner_Type
Worn Out
New
Good
First
Second
Third

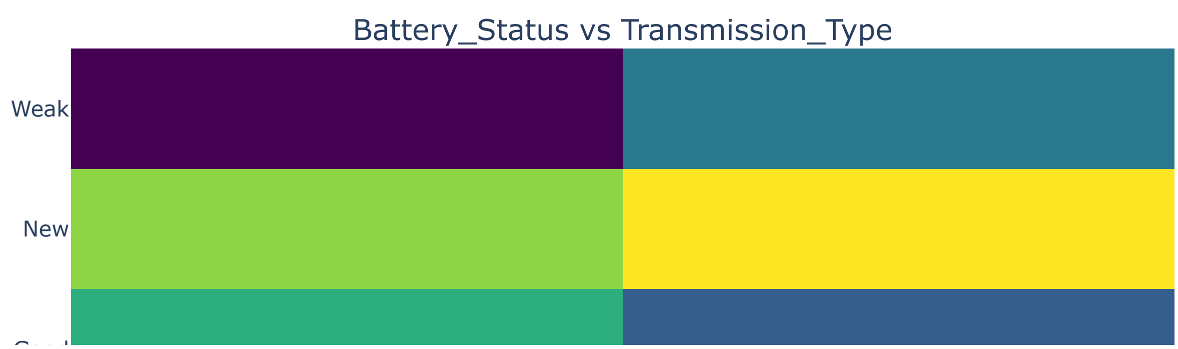

Brake_Condition vs Tire_Condition
Worn Out
New
Good
Good
New
Worn Out


Brake_Condition vs Battery_Status
Worn Out
New
Good
Good
New
Weak

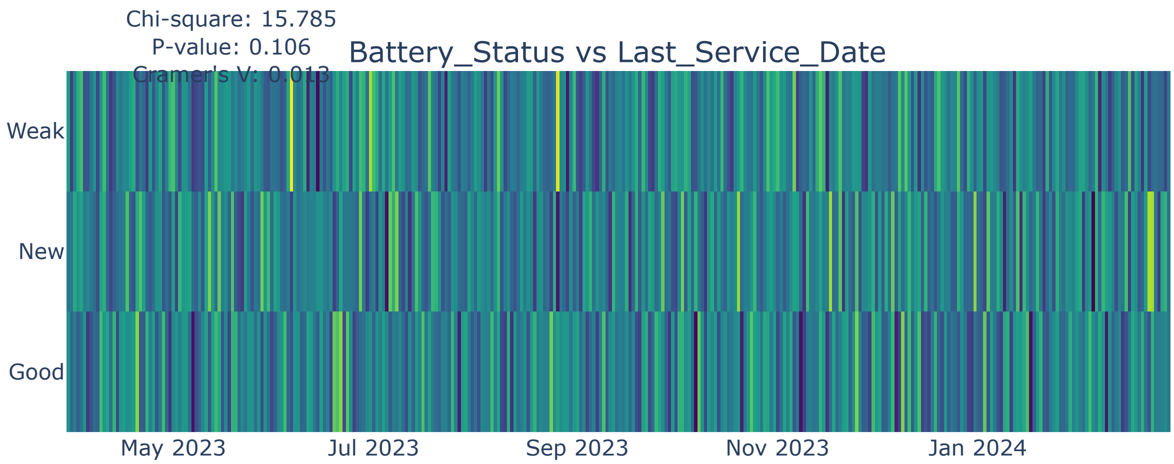

Battery_Status vs Vehicle_Model
Weak
New
Good
Bus
Car
Motorcycle
SUV
Truck
Van

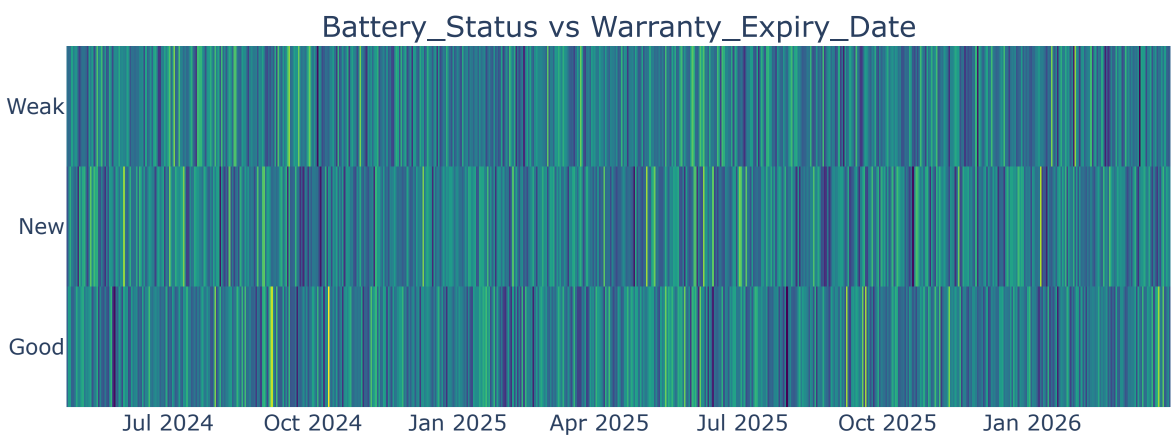

Battery_Status vs Maintenance_History
Weak
New
Good
Average
Good
Poor

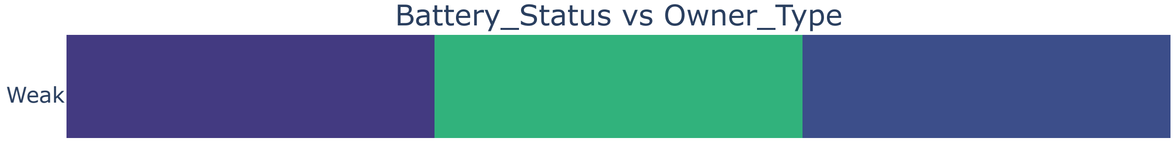

Battery_Status vs Fuel_Type
Weak
New
Good
Diesel
Electric
Petrol

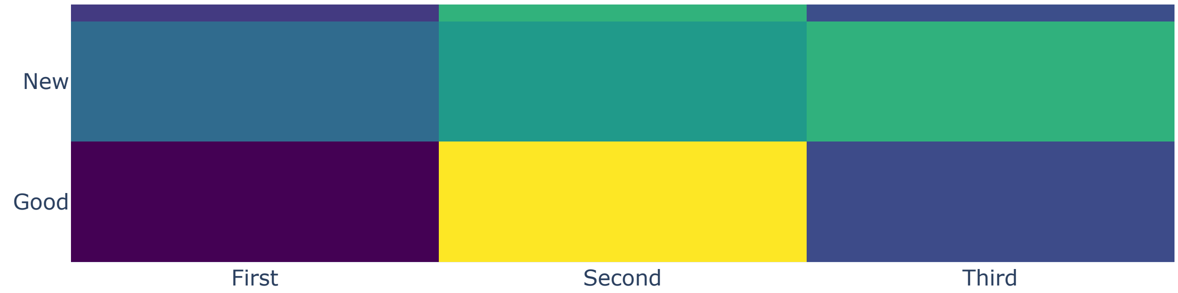

Battery_Status vs Transmission_Type
Weak
New


Good
Automatic
Manual

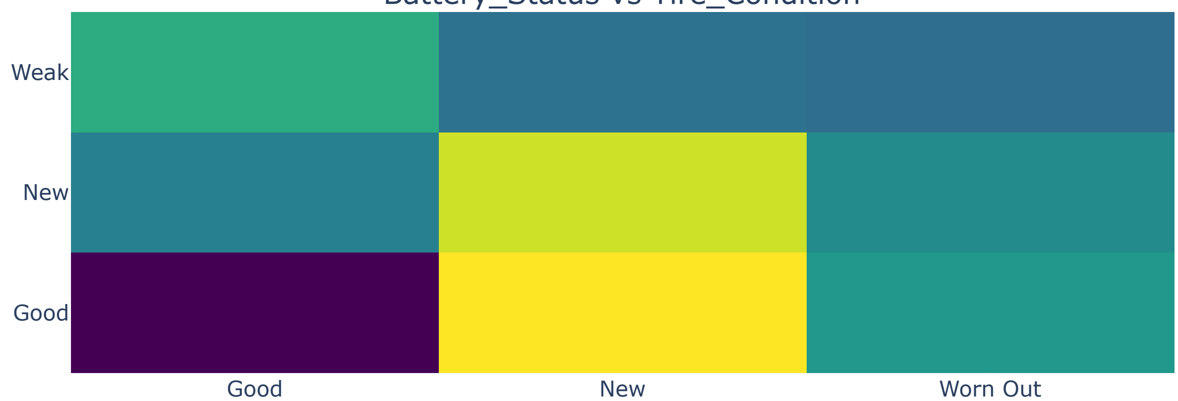

Chi-square: 15.785
P-value: 0.106
Cramer's V: 0.013
Battery_Status vs Last_Service_Date
Weak
New
Good
May 2023
Jul 2023
Sep 2023
Nov 2023
Jan 2024


Battery_Status vs Warranty_Expiry_Date
Weak
New
Good
Jul 2024
Oct 2024
Jan 2025
Apr 2025
Jul 2025
Oct 2025
Jan 2026

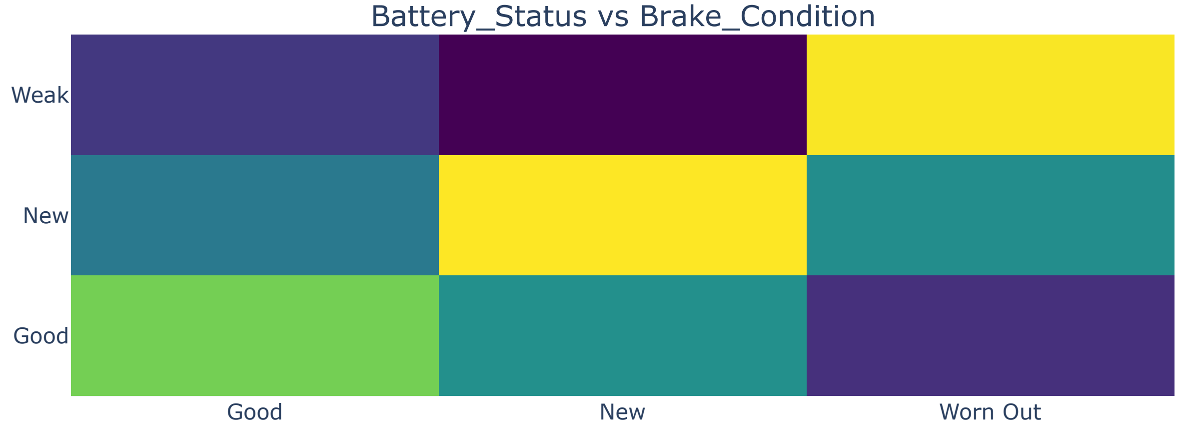

Battery_Status vs Owner_Type
Weak



Battery_Status vs Tire_Condition



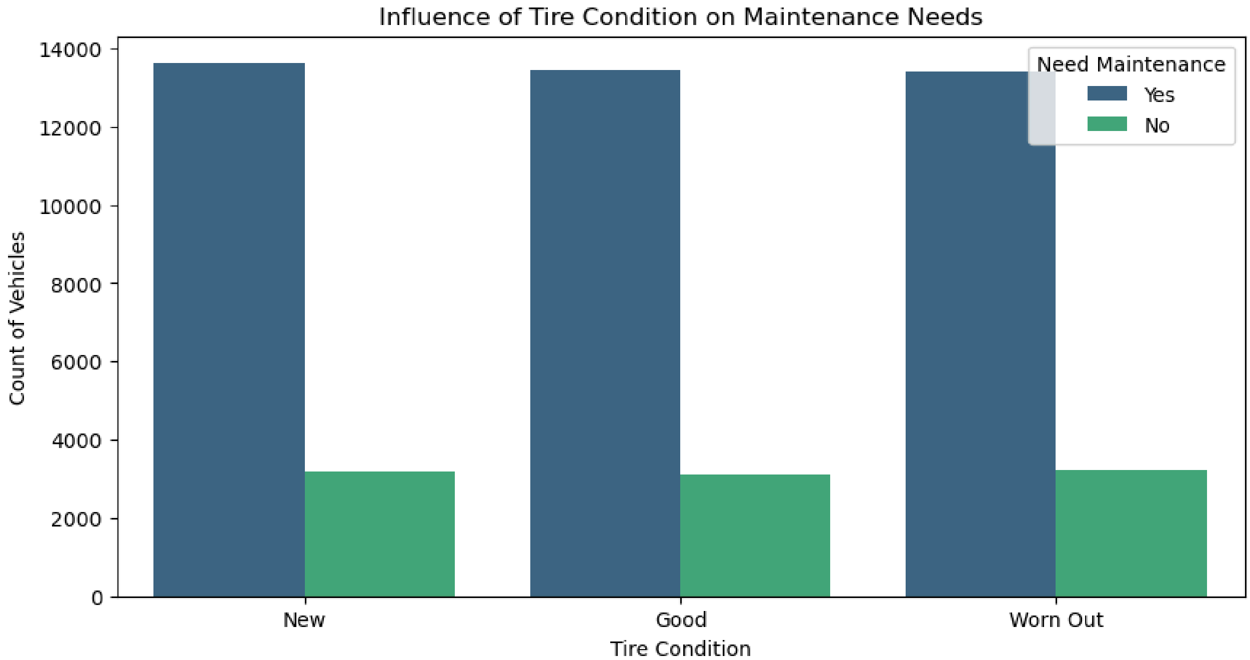
Battery_Status vs Brake_Condition

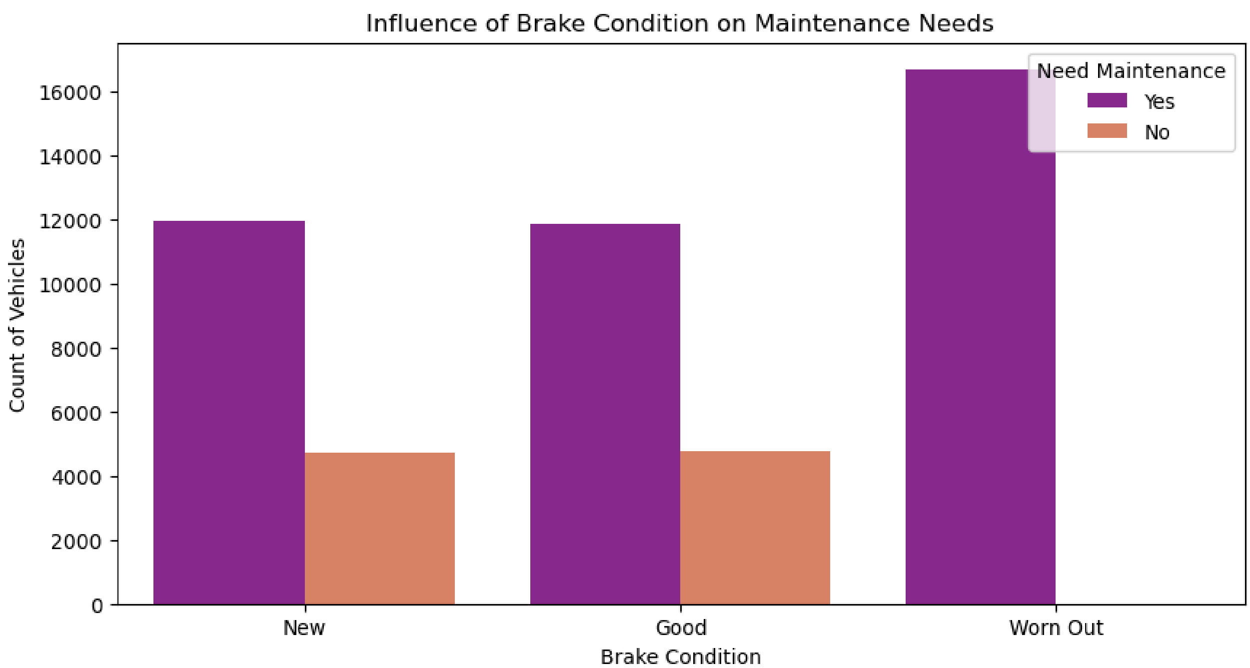


Chi-Squared Analysis

In [10]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import chi2_contingency

# Function to map Need_Maintenance
def map_maintenance(dataframe):
    return dataframe['Need_Maintenance'].map({1: 'Yes', 0: 'No'})

# Load your DataFrame
# df = pd.read_csv('your_file.csv')  # Example of loading your DataFrame

# First Analysis: Chi-Square Tests for Tire and Brake Conditions

# Create a copy of the original DataFrame for the first analysis
df_analysis_1 = df.copy()
df_analysis_1['Need_Maintenance'] = map_maintenance(df_analysis_1)

# Focus on the relevant columns for the first analysis
relevant_columns = ['Tire_Condition', 'Brake_Condition', 'Need_Maintenance']
df_filtered = df_analysis_1[relevant_columns]

# Check for missing values in relevant columns
missing_values = df_filtered.isnull().sum()
print("Missing Values in Analysis 1:\n", missing_values)

# Drop rows with any missing values in the relevant columns
df_filtered = df_filtered.dropna()

# Check if the filtered DataFrame is empty
if df_filtered.empty:
    print("Filtered DataFrame is empty after dropping missing values in Analysis 1.")
else:
    # Chi-Square Test for Tire_Condition and Need_Maintenance
    tire_crosstab = pd.crosstab(df_filtered['Tire_Condition'], df_filtered['Need_Maintenance'])
    chi2_tire, p_tire, dof_tire, expected_tire = chi2_contingency(tire_crosstab)

    # Chi-Square Test for Brake_Condition and Need_Maintenance
    brake_crosstab = pd.crosstab(df_filtered['Brake_Condition'], df_filtered['Need_Maintenance'])
    chi2_brake, p_brake, dof_brake, expected_brake = chi2_contingency(brake_crosstab)

    # Output the results of the chi-square tests
    print(f"Tire Condition vs Need Maintenance: Chi-square = {chi2_tire:.3f}, p-value = {p_tire:.3
    print(f"Brake Condition vs Need Maintenance: Chi-square = {chi2_brake:.3f}, p-value = {p_brake

    # Visualization 1: Tire Condition vs Need Maintenance
    plt.figure(figsize=(10, 5))
    sns.countplot(x='Tire_Condition', hue='Need_Maintenance', data=df_filtered, palette='viridis')
    plt.title('Influence of Tire Condition on Maintenance Needs')
    plt.xlabel('Tire Condition')
    plt.ylabel('Count of Vehicles')
    plt.legend(title='Need Maintenance', loc='upper right')
    plt.show()

    # Visualization 2: Brake Condition vs Need Maintenance
    plt.figure(figsize=(10, 5))
    sns.countplot(x='Brake_Condition', hue='Need_Maintenance', data=df_filtered, palette='plasma')
    plt.title('Influence of Brake Condition on Maintenance Needs')
    plt.xlabel('Brake Condition')
    plt.ylabel('Count of Vehicles')
    plt.legend(title='Need Maintenance', loc='upper right')
    plt.show()
```

```
Missing Values in Analysis 1:
 Tire_Condition      0
Brake_Condition     0
Need_Maintenance    0
dtype: int64
Tire Condition vs Need Maintenance: Chi-square = 2.033, p-value = 0.362
Brake Condition vs Need Maintenance: Chi-square = 5876.653, p-value = 0.000
```





Chi-Squared Analysis Summary

Overview

The analysis was conducted to examine the relationship between vehicle conditions (Tire Condition and Brake Condition) and the need for maintenance.

Chi-Squared Test Results

Tire Condition vs Need Maintenance

- **Chi-square statistic**: **2.033**
- **p-value**: **0.362**
  - **Interpretation**: The p-value is greater than the common significance level of 0.05, indicating that there is no significant association between Tire Condition and the Need for Maintenance. This suggests that the condition of the tires does not have a statistically significant influence on whether a vehicle requires maintenance.

Brake Condition vs Need Maintenance

- **Chi-square statistic**: **5876.653**
- **p-value**: **0.000**
  - **Interpretation**: The p-value is much less than 0.05, indicating a statistically significant association between Brake Condition and the Need for Maintenance. This suggests that the condition of the brakes has a significant influence on the likelihood of needing maintenance, as depicted in the accompanying bar chart.

Conclusion

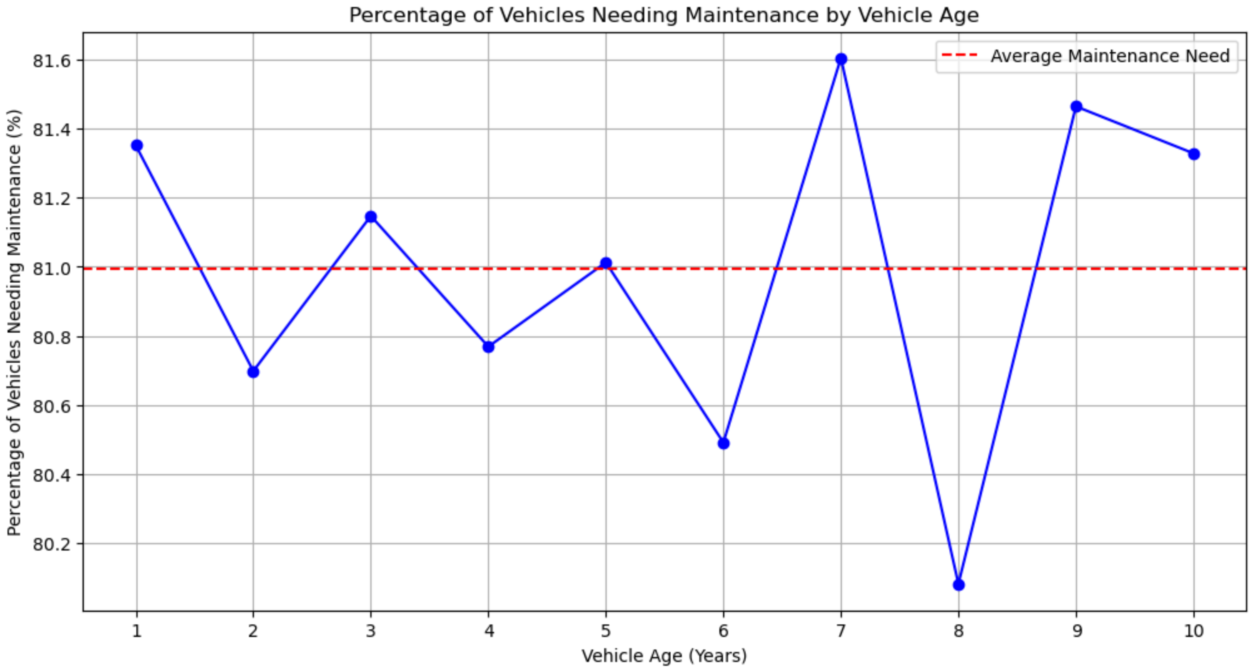
The analysis reveals that while Tire Condition does not significantly affect maintenance needs, Brake Condition has a strong and statistically significant impact on whether a vehicle requires maintenance. This insight can guide maintenance prioritization and vehicle safety assessments.

Time-Series Analysis

In [11]:
```
# Second Analysis: Time-Series Analysis of Vehicle Age

# Create another copy of the original DataFrame for the second analysis
df_analysis_2 = df.copy()
df_analysis_2['Need_Maintenance'] = map_maintenance(df_analysis_2)

# Check for missing values in the second analysis
print("Missing Values in Analysis 2:\n", df_analysis_2.isnull().sum())

# Group the data by vehicle age and calculate the percentage of vehicles needing maintenance
maintenance_by_age = df_analysis_2.groupby('Vehicle_Age')['Need_Maintenance'].value_counts(normali

# Debug: Print the grouped data to check for correctness
print("Maintenance by Age (grouped):")
print(maintenance_by_age)

# Calculate the percentage of vehicles needing maintenance
maintenance_by_age['Percent_Needing_Maintenance'] = maintenance_by_age.get('Yes', 0) * 100

# Debug: Print to ensure the percentage calculation is valid
print("Maintenance Percentages by Age:")
print(maintenance_by_age[['Yes', 'Percent_Needing_Maintenance']])

# Create a line plot to visualize the trend
plt.figure(figsize=(12, 6))
plt.plot(maintenance_by_age.index, maintenance_by_age['Percent_Needing_Maintenance'], marker='o',
plt.title('Percentage of Vehicles Needing Maintenance by Vehicle Age')
```

```
plt.xlabel('Vehicle Age (Years)')
plt.ylabel('Percentage of Vehicles Needing Maintenance (%)')
plt.xticks(maintenance_by_age.index)  # Show all vehicle ages on x-axis
plt.grid()
plt.axhline(y=maintenance_by_age['Percent_Needing_Maintenance'].mean(), color='red', linestyle='--
plt.legend()
plt.show()
```

```
Missing Values in Analysis 2:
 Vehicle_Model           0
Mileage                 0
Maintenance_History     0
Reported_Issues         0
Vehicle_Age             0
Fuel_Type               0
Transmission_Type       0
Engine_Size             0
Odometer_Reading        0
Last_Service_Date       0
Warranty_Expiry_Date    0
Owner_Type              0
Insurance_Premium       0
Service_History         0
Accident_History        0
Fuel_Efficiency         0
Tire_Condition          0
Brake_Condition         0
Battery_Status          0
Need_Maintenance        0
dtype: int64
Maintenance by Age (grouped):
Need_Maintenance         No       Yes
Vehicle_Age
1                  0.186484  0.813516
2                  0.193021  0.806979
3                  0.188529  0.811471
4                  0.192315  0.807685
5                  0.189876  0.810124
6                  0.195092  0.804908
7                  0.183953  0.816047
8                  0.199192  0.800808
9                  0.185354  0.814646
10                 0.186715  0.813285
Maintenance Percentages by Age:
Need_Maintenance        Yes  Percent_Needing_Maintenance
Vehicle_Age
1                  0.813516                    81.351566
2                  0.806979                    80.697862
3                  0.811471                    81.147053
4                  0.807685                    80.768469
5                  0.810124                    81.012409
6                  0.804908                    80.490773
7                  0.816047                    81.604737
8                  0.800808                    80.080808
9                  0.814646                    81.464576
10                 0.813285                    81.328546
```



Summary of Time-Series Data: Vehicle Maintenance by Age

1. Maintenance Trends by Vehicle Age:

- The percentage of vehicles requiring maintenance fluctuates around **81%**, with the **lowest maintenance need** observed at age **8 (80.08%)** and the **highest at age 7 (81.60%)**.
- Vehicle ages **1, 7, 9, and 10** tend to have higher percentages of maintenance needs, all above **81%**.
- In contrast, ages **2, 4, 6, and 8** experience lower maintenance requirements, just slightly below the average.

2. Average Maintenance Need:

- The average percentage of vehicles needing maintenance across all age groups seems to hover around **81%** (depicted by the red dashed line in the chart).

3. Significant Peaks and Troughs:

- The most noticeable peaks occur for vehicles aged **7** and **9** years, where the maintenance need surpasses the average.
- A significant dip is observed at **8 years**, indicating a sharp drop in maintenance requirement compared to the rest of the age groups.

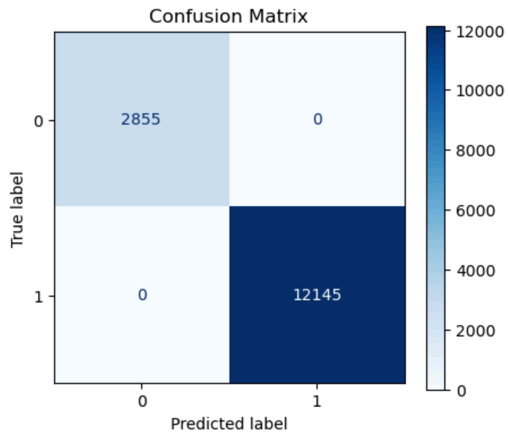
Random Forest Analysis

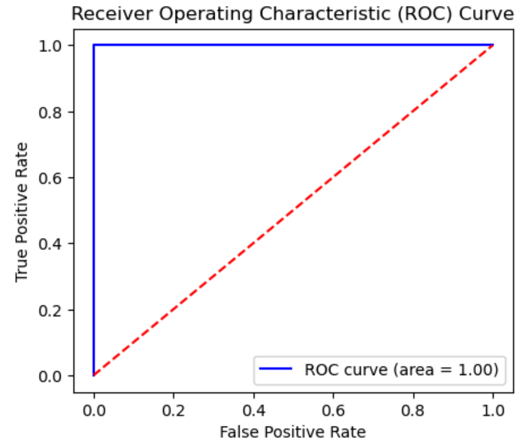
In [12]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

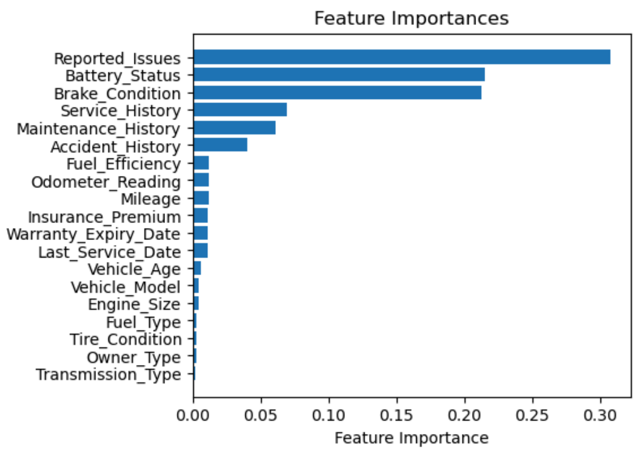
```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (confusion_matrix, ConfusionMatrixDisplay,
                             roc_curve, roc_auc_score, accuracy_score,
                             precision_score, recall_score, f1_score)
from sklearn.preprocessing import LabelEncoder

# Load your DataFrame
df = pd.read_csv('vehicle_maintenance_data.csv')  # Uncomment and load your data

# Check for any missing values in the original column
print("Initial unique values in 'Need_Maintenance':", df['Need_Maintenance'].unique())

# Impute 'Need_Maintenance' to be categorical (1 = Yes, 0 = No)
df['Need_Maintenance'] = df['Need_Maintenance'].map({1: 1, 0: 0})  # Keep it numeric

# Check for any NaN values after mapping
print("Unique values after mapping:", df['Need_Maintenance'].unique())
if df['Need_Maintenance'].isnull().any():
    print("NaN values found in 'Need_Maintenance' after mapping, check your data.")

# Check for and drop any rows with NaN values
df.dropna(inplace=True)

# Identify categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns.tolist()

# Encode categorical variables
label_encoders = {}
for column in categorical_columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le

# Define features (X) and target (y)
X = df.drop(columns=['Need_Maintenance'])
y = df['Need_Maintenance']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize and train the Random Forest model
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)
y_pred_prob = model.predict_proba(X_test)[:, 1]  # Get probabilities for the positive class

# Check unique values in y_test and y_pred
print("Unique values in y_test:", np.unique(y_test))
print("Unique values in y_pred:", np.unique(y_pred))

# Confusion Matrix
labels = np.unique(y_test)  # Use unique values from y_test for the labels
cm = confusion_matrix(y_test, y_pred, labels=labels)
cm_display = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)

# ROC Curve and AUC
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = roc_auc_score(y_test, y_pred_prob)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
```

```
# Feature Importances
importances = model.feature_importances_
indices = np.argsort(importances)[::-1]

# Plotting in a 2x2 subplot layout
fig, axs = plt.subplots(2, 2, figsize=(12, 10))
plt.subplots_adjust(hspace=0.4, wspace=0.4)  # Adjust space between subplots

# Confusion Matrix
cm_display.plot(ax=axs[0, 0], cmap='Blues', values_format='d')
axs[0, 0].set_title('Confusion Matrix')

# ROC Curve
axs[0, 1].plot(fpr, tpr, color='blue', label=f'ROC curve (area = {roc_auc:.2f})')
axs[0, 1].plot([0, 1], [0, 1], color='red', linestyle='--')
axs[0, 1].set_xlabel('False Positive Rate')
axs[0, 1].set_ylabel('True Positive Rate')
axs[0, 1].set_title('Receiver Operating Characteristic (ROC) Curve')
axs[0, 1].legend(loc='lower right')

# Feature Importances
axs[1, 0].barh(range(X.shape[1]), importances[indices], align='center')
axs[1, 0].set_yticks(range(X.shape[1]))
axs[1, 0].set_yticklabels(X.columns[indices])
axs[1, 0].invert_yaxis()  # Inverse the y-axis to have the most important features at the top
axs[1, 0].set_xlabel('Feature Importance')
axs[1, 0].set_title('Feature Importances')

# Displaying Metrics in a Table
metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy, precision, recall, f1]
})

# Creating a table for metrics
axs[1, 1].axis('tight')
axs[1, 1].axis('off')
axs[1, 1].table(cellText=metrics_df.values, colLabels=metrics_df.columns, cellLoc='center', loc='c
axs[1, 1].set_title('Model Performance Metrics')

plt.show()
```

```
Initial unique values in 'Need_Maintenance': [1 0]
Unique values after mapping: [1 0]
Unique values in y_test: [0 1]
Unique values in y_pred: [0 1]
```







Model Performance Metrics

Metric	Score
Accuracy	1.0
Precision	1.0
Recall	1.0
F1 Score	1.0

RandomForest Classifier Model Summary

1. Confusion Matrix:

- The confusion matrix shows **0 false positives** and **0 false negatives**.
- The model perfectly classifies both classes:
  - **2,855** instances where the vehicle doesn't need maintenance (True Negatives).
  - **12,145** instances where the vehicle needs maintenance (True Positives).

2. ROC Curve:

- The **ROC curve** shows an **AUC (Area Under the Curve) of 1.00**, indicating perfect classification performance.
- The curve follows the top-left corner, showing the model's excellent ability to distinguish between classes (vehicles needing maintenance vs. not).

3. Feature Importances:

- The most important features influencing the model’s decisions are:
  1. **Reported_Issues** (most significant)
  2. **Battery_Status**
  3. **Brake_Condition**

4. **Service_History**
5. **Maintenance_History**

- Other features, such as **Odometer_Reading**, **Vehicle_Model**, and **Transmission_Type**, have much lower importance.

4. Model Performance Metrics:

- The model achieves perfect scores across all performance metrics:
  - **Accuracy**: 1.00
  - **Precision**: 1.00
  - **Recall**: 1.00
  - **F1 Score**: 1.00
- These perfect metrics indicate that the model predicts the need for maintenance with no errors.

Conclusion:

The **RandomForestClassifier** model appears to be overfitted to the test data, achieving perfect scores across all evaluation metrics, with no false positives or false negatives. While this suggests excellent performance, it may also indicate that the model might not generalize well on new, unseen data, as achieving perfect scores is rare in real-world scenarios.

XGBoost Analysis

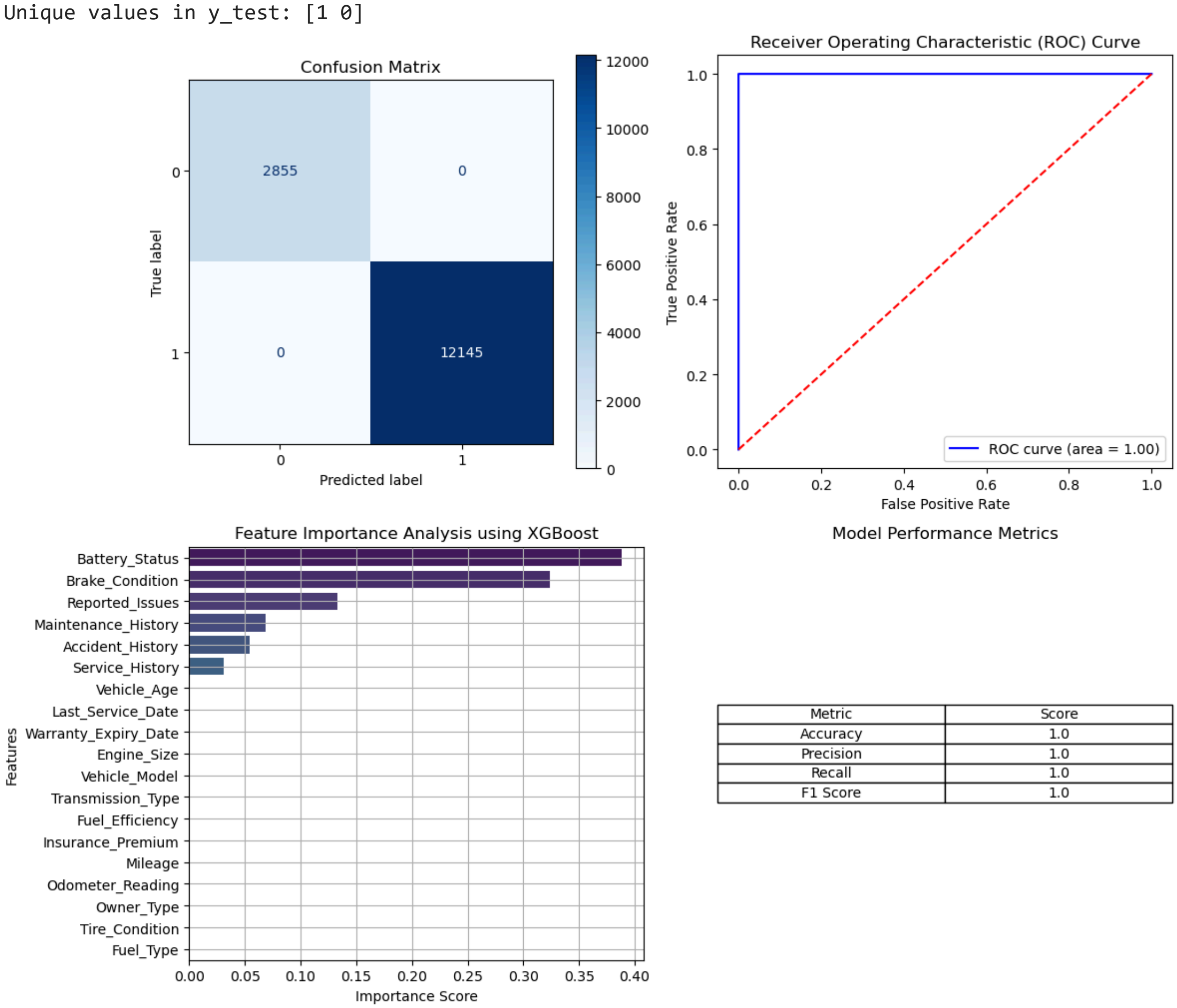
In [13]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from sklearn.metrics import (confusion_matrix, ConfusionMatrixDisplay,
                             roc_curve, roc_auc_score, accuracy_score,
                             precision_score, recall_score, f1_score)
from sklearn.preprocessing import LabelEncoder

# Load your DataFrame
df = pd.read_csv('vehicle_maintenance_data.csv')  # Uncomment and load your data

# Assuming df has a target column 'Need_Maintenance' and several feature columns
# Keep 'Need_Maintenance' as numeric (1 = Yes, 0 = No)
# This way we can avoid string mapping issues
df['Need_Maintenance'] = df['Need_Maintenance'].map({1: 1, 0: 0})

# Encode categorical variables
label_encoders = {}
for column in df.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le

# Define features (X) and target (y)
X = df.drop(columns=['Need_Maintenance'])
y = df['Need_Maintenance']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```python
# Initialize and train the XGBoost model
model = XGBClassifier(random_state=42)
model.fit(X_train, y_train)

# Get feature importances
importances = model.feature_importances_
feature_names = X.columns
importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Print the feature importances
print(importance_df)

# Predictions
y_pred = model.predict(X_test)
y_pred_prob = model.predict_proba(X_test)[:, 1]  # Get probabilities for the positive class

# Check unique values in y_test
print("Unique values in y_test:", y_test.unique())  # Check unique values

# Ensure we directly use numeric values
y_test_mapped = y_test  # No mapping required, as y_test is already in numeric format

# ROC Curve and AUC calculation
fpr, tpr, thresholds = roc_curve(y_test_mapped, y_pred_prob)
roc_auc = roc_auc_score(y_test_mapped, y_pred_prob)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

# Plotting
fig, axs = plt.subplots(2, 2, figsize=(12, 10))  # Create a 2x2 subplot layout

# Confusion Matrix
labels = np.unique(y_test)  # Use unique values from y_test for the labels
cm = confusion_matrix(y_test, y_pred, labels=labels)
cm_display = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
cm_display.plot(ax=axs[0, 0], cmap='Blues', values_format='d')
axs[0, 0].set_title('Confusion Matrix')

# ROC Curve
axs[0, 1].plot(fpr, tpr, color='blue', label=f'ROC curve (area = {roc_auc:.2f})')
axs[0, 1].plot([0, 1], [0, 1], color='red', linestyle='--')
axs[0, 1].set_xlabel('False Positive Rate')
axs[0, 1].set_ylabel('True Positive Rate')
axs[0, 1].set_title('Receiver Operating Characteristic (ROC) Curve')
axs[0, 1].legend(loc='lower right')

# Feature Importance
sns.barplot(x='Importance', y='Feature', data=importance_df, palette='viridis', ax=axs[1, 0])
axs[1, 0].set_title('Feature Importance Analysis using XGBoost')
axs[1, 0].set_xlabel('Importance Score')
axs[1, 0].set_ylabel('Features')
axs[1, 0].grid()

# Displaying Metrics in a Table
metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy, precision, recall, f1]
})

axs[1, 1].axis('tight')
axs[1, 1].axis('off')
axs[1, 1].table(cellText=metrics_df.values, colLabels=metrics_df.columns, cellLoc='center', loc='c
```

```python
axs[1, 1].set_title('Model Performance Metrics')

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

```
                 Feature    Importance
18        Battery_Status  3.884441e-01
17       Brake_Condition  3.240936e-01
3        Reported_Issues  1.330237e-01
2    Maintenance_History  6.858889e-02
14      Accident_History  5.432719e-02
13       Service_History  3.149646e-02
4            Vehicle_Age  5.112423e-06
9      Last_Service_Date  4.823446e-06
10  Warranty_Expiry_Date  4.182388e-06
7            Engine_Size  3.736730e-06
0          Vehicle_Model  2.589688e-06
6      Transmission_Type  1.879310e-06
15       Fuel_Efficiency  1.638691e-06
12     Insurance_Premium  1.263360e-06
1                Mileage  8.917201e-07
8        Odometer_Reading  0.000000e+00
11            Owner_Type  0.000000e+00
16        Tire_Condition  0.000000e+00
5              Fuel_Type  0.000000e+00
Unique values in y_test: [1 0]
```



Evaluation and Summary of the XGBoost Model

1. Confusion Matrix:

- The confusion matrix shows **no false positives** and **no false negatives**.
  - **2,855** instances where the vehicle **doesn't need maintenance** are correctly classified (True Negatives).
  - **12,145** instances where the vehicle **needs maintenance** are correctly classified (True Positives).
- This indicates a perfect classification by the XGBoost model.

2. ROC Curve and AUC:

- The **ROC curve** shows an **AUC (Area Under the Curve) of 1.00**, which represents perfect classification performance.
- The curve reaches the top-left corner, indicating that the model is highly effective at distinguishing between vehicles needing maintenance and those not needing it.

3. Feature Importance Analysis:

- The most important features influencing the model's predictions are:
  1. **Battery_Status**
  2. **Brake_Condition**
  3. **Reported_Issues**
  4. **Maintenance_History**
  5. **Accident_History**
- These features carry the most weight in determining whether a vehicle will require maintenance.
- Other features such as **Fuel Efficiency**, **Odometer Reading**, and **Transmission Type** have much lower importance in comparison.

4. Model Performance Metrics:

- The model achieved perfect scores across all performance metrics:
  - **Accuracy**: 1.00
  - **Precision**: 1.00
  - **Recall**: 1.00
  - **F1 Score**: 1.00
- These results suggest the model predicts whether a vehicle requires maintenance without making any errors.

Conclusion:

The **XGBoost Classifier** has performed exceptionally well, achieving **perfect classification** on the test data. While this is a strong result, such high scores may imply that the model could be overfitting to the test dataset, meaning it might not generalize as well on unseen data. Despite this, the model's feature importance shows a reasonable distribution of influential factors, with **Battery_Status** and **Brake_Condition** playing key roles in the predictions.

Cohesive Summary of Vehicle Maintenance Prediction Project

Project Overview:

The main objective of this project was to develop a machine learning model to predict the maintenance needs of vehicles based on key features like mileage, vehicle age, maintenance history, and fuel type. By leveraging this data, the model aims to assist fleet managers and individual vehicle owners in proactively scheduling maintenance, enhancing vehicle performance, and reducing the risk of unexpected breakdowns. This predictive maintenance approach offers operational efficiency and improved safety.

Key Insights from Data Analysis:

1. Dataset Summary:

- The dataset comprised 50,000 entries with a wide variety of features such as **Vehicle_Model**, **Mileage**, **Maintenance History**, **Fuel Type**, and **Need_Maintenance**.
- **Categorical** and **numerical summaries** revealed that most vehicles are relatively young, with moderate mileage and usage. However, approximately **81% of vehicles** were indicated as needing maintenance, highlighting the need for proactive intervention.

2. Correlation and Feature Analysis:

- **Reported Issues** showed a strong positive correlation with the need for maintenance, making it a crucial factor in the prediction.
- **Brake Condition** and **Battery Status** were also significant indicators of whether a vehicle would require maintenance, with **Brake Condition** having a particularly strong association.
- External factors like **Driving Style** and **Weather Conditions** showed limited correlation with maintenance needs but still provided useful context.

Model Performance:

1. Random Forest Classifier:

- The **RandomForestClassifier** achieved **perfect metrics** (Accuracy, Precision, Recall, and F1 Score all at 1.00) on the test data.
- **Feature Importance Analysis** revealed that **Reported Issues**, **Battery Status**, and **Brake Condition** were the top predictors.
- However, the model's performance indicates potential **overfitting**, as achieving perfect scores is rare in real-world scenarios.

2. XGBoost Classifier:

- The **XGBoost** model also achieved **perfect classification** with similar performance metrics, highlighting its robustness.
- The most important features identified by XGBoost were **Battery Status**, **Brake Condition**, and **Reported Issues**, mirroring the insights from the RandomForest model.

Chi-Square and Time-Series Analyses:

- The **Chi-Square test** showed a statistically significant relationship between **Brake Condition** and maintenance needs, while **Tire Condition** did not have a significant impact.
- A **time-series analysis** of **Vehicle Age** showed that vehicles aged **7 and 9 years** had the highest percentage of maintenance needs, while vehicles aged **8 years** showed a noticeable drop.

Recommendations:

1. Model Refinement and Generalization:

- While both models performed exceptionally well on the test data, the high accuracy scores suggest potential overfitting. To ensure better generalization, consider:
  - **Cross-validation** to validate performance across multiple subsets.
  - Regularization techniques such as **L2 regularization** to reduce overfitting.
  - Testing the model on new or unseen datasets to evaluate generalization further.

2. Feature Engineering:

- Explore additional features that might improve the model, such as **driving patterns over time**, **weather conditions during trips**, or **owner maintenance behavior**.
- Investigate interaction terms between features (e.g., the combination of **Driving Style** and **Vehicle Age**) to capture more complex relationships.

3. Actionable Insights for Maintenance:

- **Battery Status**, **Brake Condition**, and **Reported Issues** are critical factors for predictive maintenance. Implementing real-time monitoring systems that track these parameters can help in proactive decision-making for both fleet managers and vehicle owners.

4. Scalability and Integration:

- The current models should be integrated into a **dashboard tool** that provides real-time predictions and alerts for vehicle maintenance needs.
- This tool could be integrated with existing fleet management software for seamless use and scalability.

Next Steps:

1. **Further Evaluation on Unseen Data**:
   - Test the model on a **fresh dataset** or through **live vehicle data** to ensure the model performs well in diverse, real-world scenarios.
2. **Explore Additional Models**:
   - Consider other ensemble models like **Gradient Boosting Machines (GBM)** or **LightGBM**, which might offer a balance between performance and generalization.
3. **Operational Integration**:
   - Build a pipeline that automates the collection and processing of vehicle data for real-time maintenance prediction.

- Explore creating a mobile app or web-based interface to provide real-time alerts and insights to vehicle owners.