Electronic Vehicle in India – Market Segmentation

Reeva Mishra

Electric Vehicles (EVs) are vehicles that operate using an electric motor instead of a traditional internal combustion engine. They are powered by batteries, which can be recharged using electricity from the grid. EVs are considered more environmentally friendly than traditional vehicles because they produce zero emissions at the tailpipe, reduce dependency on fossil fuels, and have the potential to lower overall greenhouse gas emissions when paired with renewable energy sources.

Types of EVs

1. Battery Electric Vehicles (BEVs): Fully electric vehicles that rely solely on electricity for power. Examples include the Tesla Model S and Nissan Leaf.

2. Plug-in Hybrid Electric Vehicles (PHEVs): Vehicles that combine an electric motor with a traditional internal combustion engine. They can run on electric power for a certain range before switching to gasoline. Examples include the Toyota Prius Prime.

3. Hybrid Electric Vehicles (HEVs): These vehicles have both an electric motor and a gasoline engine, but cannot be plugged in to charge. The electric motor assists the engine, leading to improved fuel efficiency. Examples include the Toyota Prius.

Electric Vehicle Market in India

India is rapidly evolving as a significant player in the global electric vehicle market, driven by the government's push for clean mobility, increasing environmental concerns, and rising fuel prices.

Market Growth

- Government Initiatives: The Indian government has introduced several policies and incentives to boost EV adoption, including the Faster Adoption and

Manufacturing of Hybrid and Electric Vehicles (FAME) scheme, which offers subsidies to manufacturers and buyers of EVs.

- Increasing Awareness: With growing awareness about climate change and environmental sustainability, there is a shift towards electric mobility among Indian consumers.

- Infrastructure Development: The Indian government is working on expanding EV infrastructure, including setting up charging stations across major cities and highways.

Challenges

- High Initial Costs: The upfront cost of EVs is still higher than traditional vehicles, mainly due to the expensive battery technology.

- Charging Infrastructure: Although expanding, the availability of charging stations remains limited, particularly in rural areas.

- Range Anxiety: Consumers are concerned about the driving range of EVs and the availability of charging facilities on longer trips.

Key Players

- Tata Motors: One of the leading manufacturers of EVs in India with models like the Tata Nexon EV.

- Mahindra Electric: A pioneer in the Indian EV market, offering models like the eVerito.

- Ola Electric: Entered the EV space with its electric scooters and is planning to expand into electric cars.

- Ather Energy: Known for its electric scooters, Ather has become a significant player in the two-wheeler segment.

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

```
df = pd.read_csv('/content/data (1).csv')
```

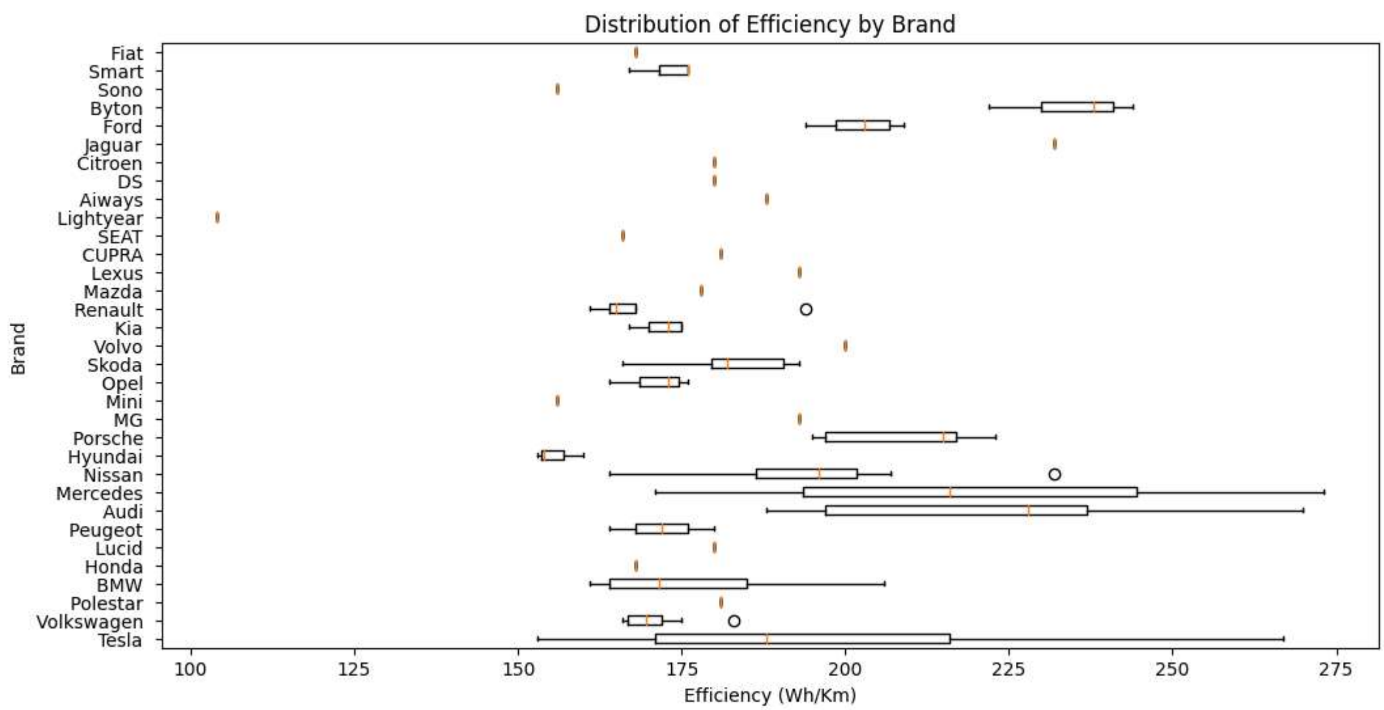
```
df.head()
```

	Unnamed: 0	Brand	Model	AccelSec	TopSpeed_KmH	Range_Km	Efficiency_WhKm	FastCharge_KmH	RapidCharge	PowerTrain	PlugType	Boc
0	0	Tesla	Model 3 Long Range Dual Motor	4.6	233	450	161	940	Yes	AWD	Type 2 CCS	
1	1	Volkswagen	ID.3 Pure	10.0	160	270	167	250	No	RWD	Type 2 CCS	Ha
2	2	Polestar	2	4.7	210	400	181	620	Yes	AWD	Type 2 CCS	
3	3	BMW	iX3	6.8	180	360	206	560	Yes	RWD	Type 2 CCS	

Next steps: Generate code with df | View recommended plots | New interactive sheet

Distribution of Efficiency by Brand

Show code



This box plot visually represents the distribution of energy efficiency (measured in Wh/Km) for different car brands.

Key Insights:

- **Brand Comparison:** You can easily compare the median efficiency (represented by the line inside the box) across different brands.
- **Efficiency Spread:** The length of the boxes indicates the interquartile range (IQR), which shows how spread out the efficiency values are within each brand.

- **Outliers:** The dots beyond the "whiskers" of the boxes represent outlier vehicles that have unusually high or low efficiency compared to others within their brand.

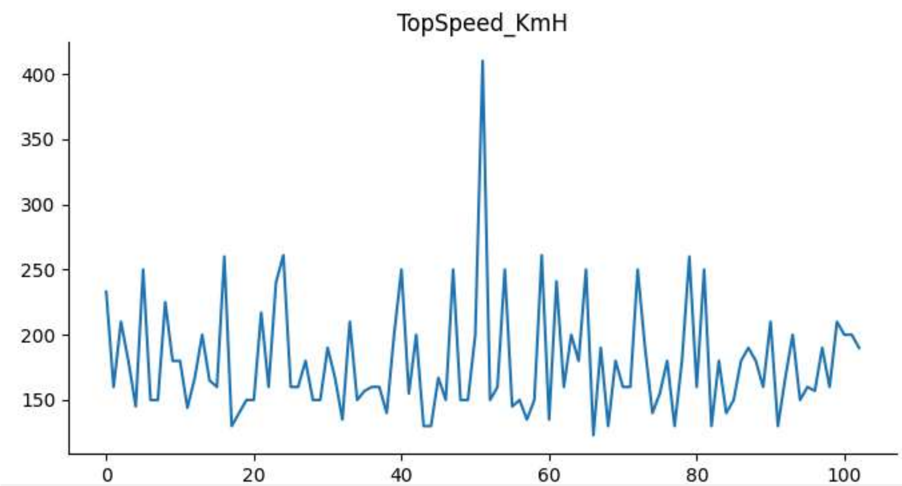
Possible Interpretations:

- Brands with shorter boxes and higher median lines generally indicate more efficient vehicles.
- Brands with longer boxes might suggest a wider variety of models with varying efficiency levels.
- Outliers could be investigated further to understand the reasons behind their exceptional efficiency (or lack thereof).

Overall, this plot provides a quick visual summary of how energy efficiency varies across different car brands.

TopSpeed_KmH

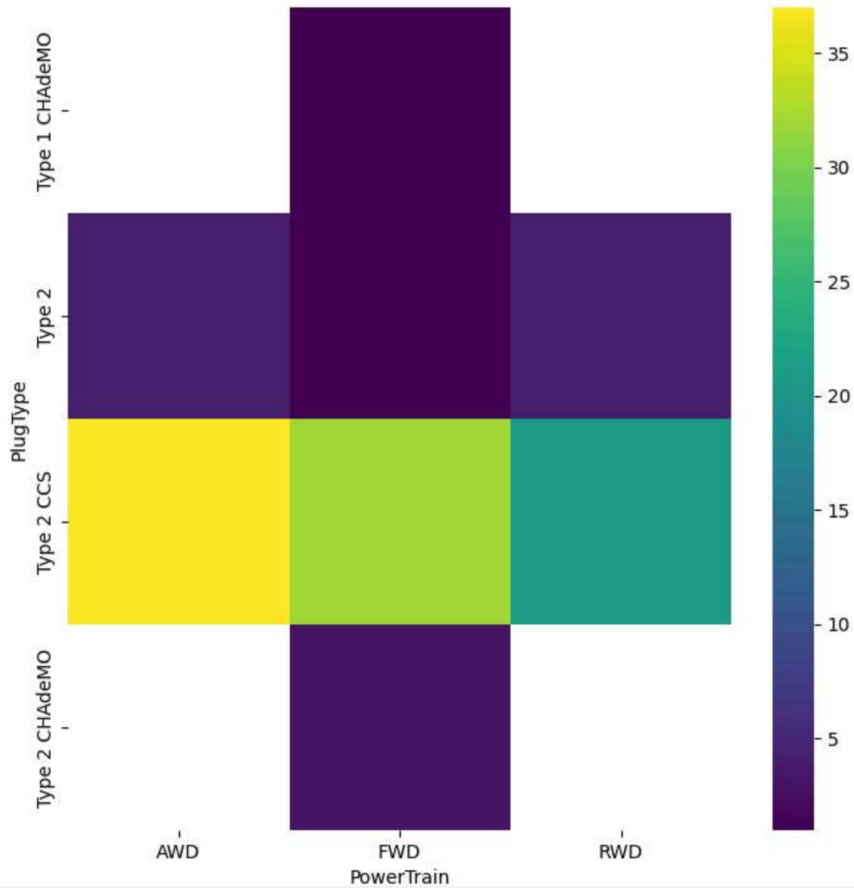
Show code



The plot shows the trend of 'TopSpeed_KmH' over an unspecified index. It appears to be a time series plot where the x-axis represents time and the y-axis represents the TopSpeed_KmH values. The plot gives a visual representation of how the TopSpeed_KmH changes over time, showing any increases, decreases, or fluctuations in the values. The absence of top and right spines makes the plot look cleaner and focuses attention on the data itself.

PowerTrain vs PlugType

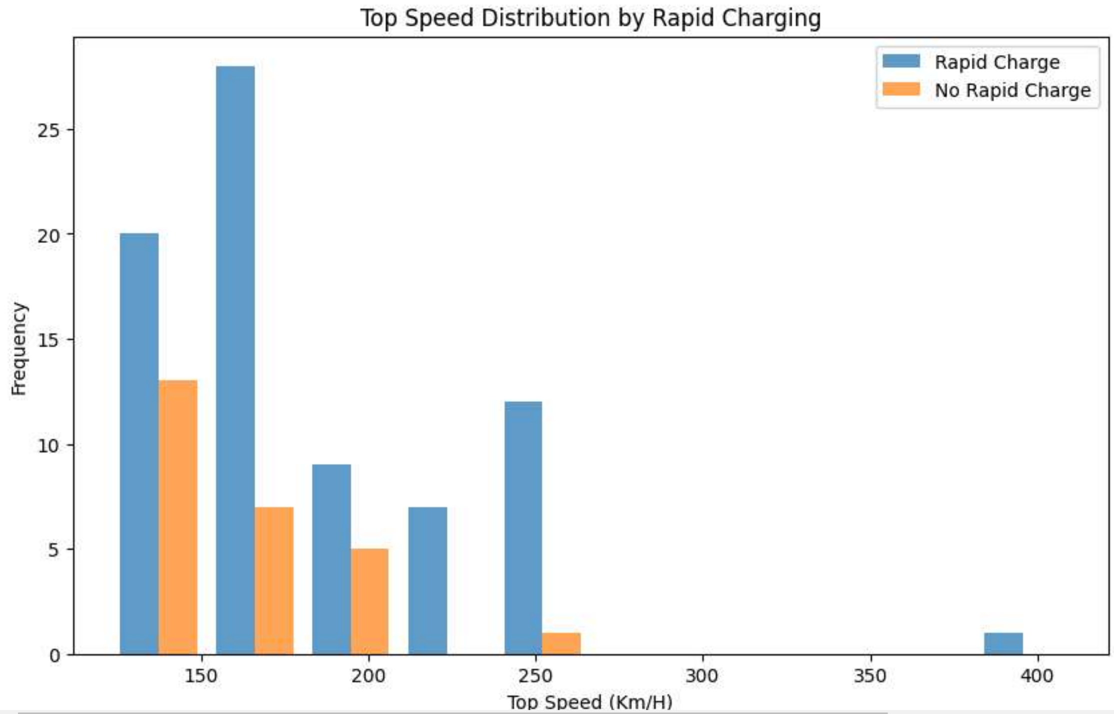
Show code



The heatmap visualizes the relationship between 'PowerTrain' and 'PlugType' in the dataset. Each cell in the heatmap represents the count of occurrences for a specific combination of 'PowerTrain' and 'PlugType'. The color intensity indicates the frequency of that combination, with darker colors representing higher counts. This visualization helps in understanding the distribution of 'PlugType' across different 'PowerTrain' categories.

Top Speed Distribution by Rapid Charging

Show code



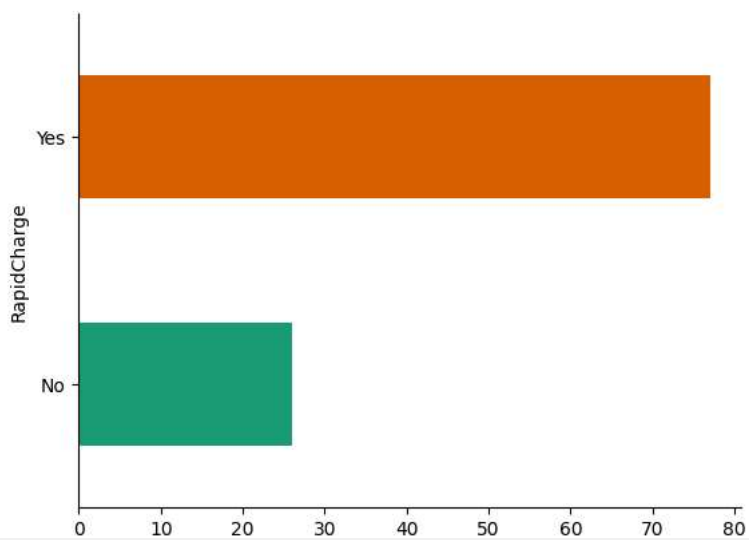
The histogram visualizes the distribution of top speeds for electric vehicles, categorized by whether they support rapid charging or not.

Observations:

- Vehicles with rapid charging capability tend to have a slightly higher average top speed compared to those without.
- Both distributions show a right skew, indicating a higher concentration of vehicles with lower top speeds.
- There is some overlap in the top speed ranges between the two categories, suggesting that rapid charging is not the sole determinant of top speed.

RapidCharge

Show code



Interpretation:

The bar chart visually represents how many cars in the dataset support rapid charging and how many do not. The length of each bar corresponds to the count of cars in each category. This allows for a quick understanding of the prevalence of rapid charging support among the cars in the dataset.

Further Analysis:

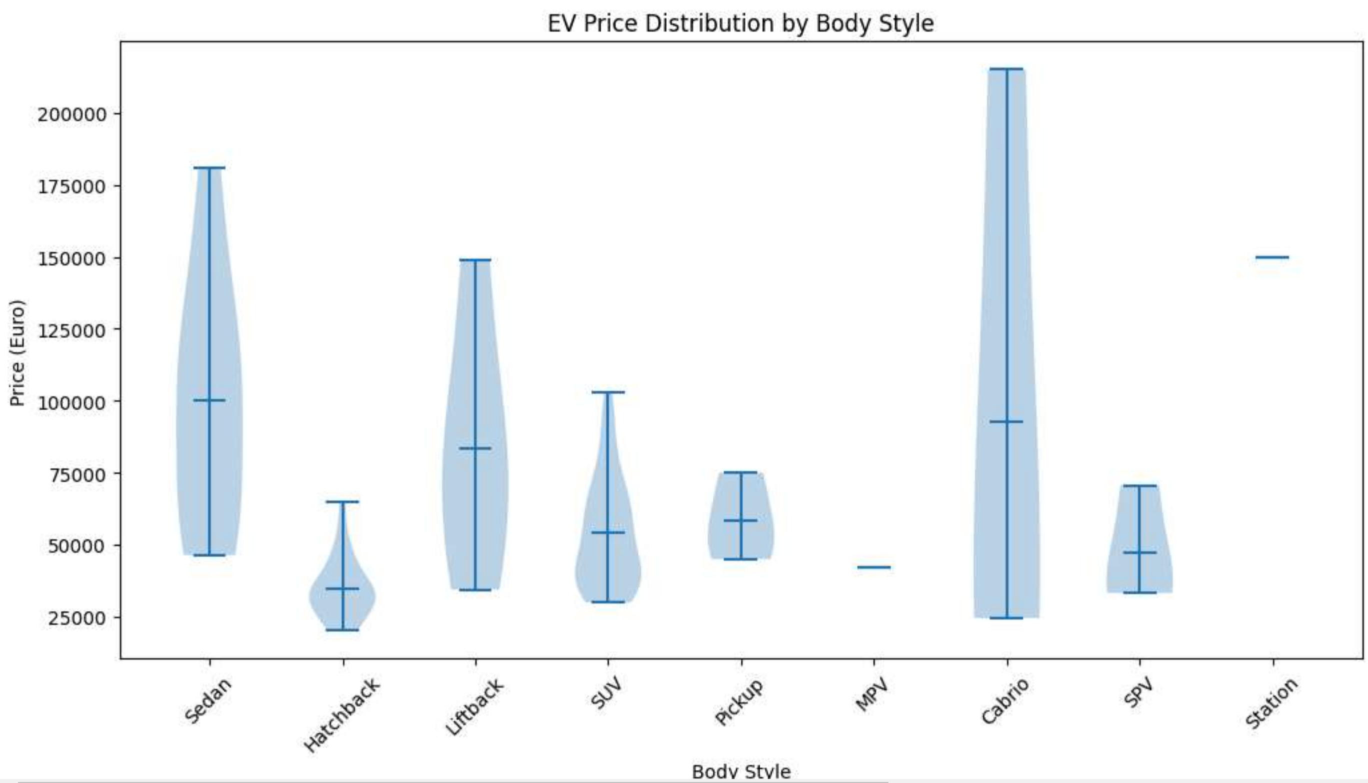
This visualization can be a starting point for further analysis, such as:

- Comparing the distribution of rapid charging support across different car brands or models.
- Investigating the relationship between rapid charging support and other features, such as price or range.
- Exploring trends in rapid charging adoption over time.

Double-click (or enter) to edit

EV Price Distribution by Body Style

Show code



The violin plot shows the distribution of EV prices for different body styles. The wider sections of the violin represent a higher density of EVs at that price point, while the thinner sections indicate a lower density. The white dot within each violin represents the median price for that body style. For example, SUVs tend to have a wider price range and a higher median price compared to hatchbacks.

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Select relevant features for segmentation
features = ['PriceEuro', 'Range_Km', 'Efficiency_WhKm', 'TopSpeed_KmH', 'FastCharge_KmH']
X = df[features]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Determine the optimal number of clusters using the Elbow method
inertia = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

plt.plot(range(1, 11), inertia, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.show()

# Based on the Elbow method, choose the optimal number of clusters (e.g., 3)
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
df['Segment'] = kmeans.fit_predict(X_scaled)

# Visualize the segments
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Range_Km', y='PriceEuro', hue='Segment', data=df, palette='viridis', s=100)
plt.title('Market Segmentation of EVs')
plt.xlabel('Range (Km)')
plt.ylabel('Price (Euro)')
plt.show()

# Analyze the characteristics of each segment
segment_means = df.groupby('Segment')[features].mean()
print(segment_means)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarning: The default value of `n_init` will change fro
  super()._check_params_vs_input(X, default_n_init=10)
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  super()._check_params_vs_input(X, default_n_init=10)
```
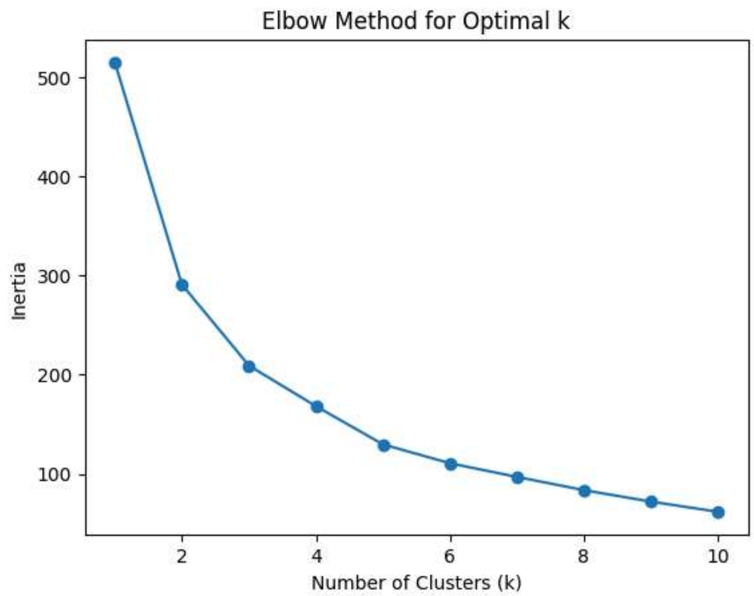
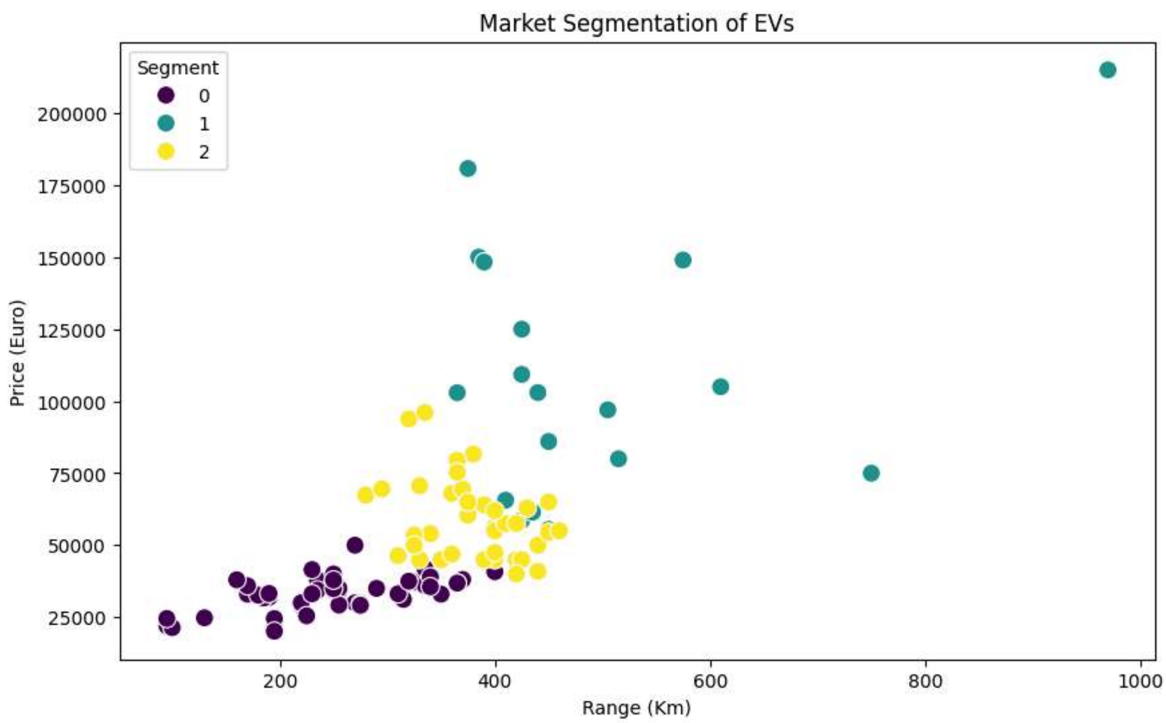




```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarning: The default value of `n_init` will change fro
  super()._check_params_vs_input(X, default_n_init=10)
```




```
             PriceEuro    Range_Km  Efficiency_WhKm  TopSpeed_KmH  \
Segment
0         33235.104167  249.166667       171.125000    148.520833
1        109304.944444  494.444444       193.111111    249.611111
2         59076.135135  379.324324       210.648649    184.729730
```

```
          FastCharge_KmH
Segment
0             282.500000
1             743.333333
2             508.648649
```

The code performs market segmentation on electric vehicles (EVs) based on features like price, range, efficiency, top speed, and fast charging speed.

Key Steps:

1. **Feature Selection:** Relevant features for segmentation are chosen (price, range, efficiency, top speed, fast charging speed).
2. **Standardization:** Features are standardized using StandardScaler to ensure they have a mean of 0 and a standard deviation of 1.
3. **Elbow Method:** The Elbow method is used to determine the optimal number of clusters (segments) by plotting the within-cluster sum of squares (inertia) against the number of clusters. The optimal number of clusters is typically where the "elbow" of the plot occurs.
4. **K-Means Clustering:** K-Means clustering is applied with the optimal number of clusters to assign each EV to a segment.
5. **Visualization:** The segments are visualized using a scatter plot, with different colors representing different segments.
6. **Segment Analysis:** The characteristics of each segment are analyzed by calculating the mean values of the features for each segment.

Summary of Market Segmentation:

The analysis aims to group EVs into distinct market segments based on their key attributes. This segmentation can help manufacturers and marketers better understand their target customers and tailor their products and strategies accordingly.

For example, one segment might consist of high-priced, long-range EVs with fast charging capabilities, targeting affluent customers who prioritize performance and convenience. Another segment might comprise more affordable, shorter-range EVs, appealing to budget-conscious buyers who primarily use their vehicles for city driving.

By understanding the characteristics of each segment, businesses can make informed decisions regarding pricing, product development, and marketing campaigns to effectively target different customer groups.

```
# Calculate the percentage of EVs in each segment
segment_counts = df['Segment'].value_counts()
segment_percentages = segment_counts / segment_counts.sum() * 100

# Print the percentages
for segment, percentage in segment_percentages.items():
  print(f"Segment {segment}: {percentage:.2f}%")
```

```
Segment 0: 46.60%
Segment 2: 35.92%
Segment 1: 17.48%
```

The percentages of EVs in each segment provide insights into the relative sizes of different market segments. For instance:

- **If Segment 0 has the highest percentage:** This suggests that a large portion of the EV market consists of vehicles with a specific combination of features (e.g., affordable, shorter-range EVs).
- **If the percentages are relatively evenly distributed:** This indicates a more diverse market with a balanced demand for different types of EVs.

Further Analysis and Business Implications:

By understanding the distribution of EVs across segments, businesses can:

- **Target Marketing Efforts:** Focus marketing campaigns on the segments with the highest potential for growth or profitability.
- **Tailor Product Development:** Develop new EV models with features that cater to the needs and preferences of specific segments.
- **Optimize Pricing Strategies:** Adjust pricing to reflect the perceived value and affordability within each segment.

```
df1 = pd.read_csv('/content/2-wheeler-EV-bikewale.csv')
```

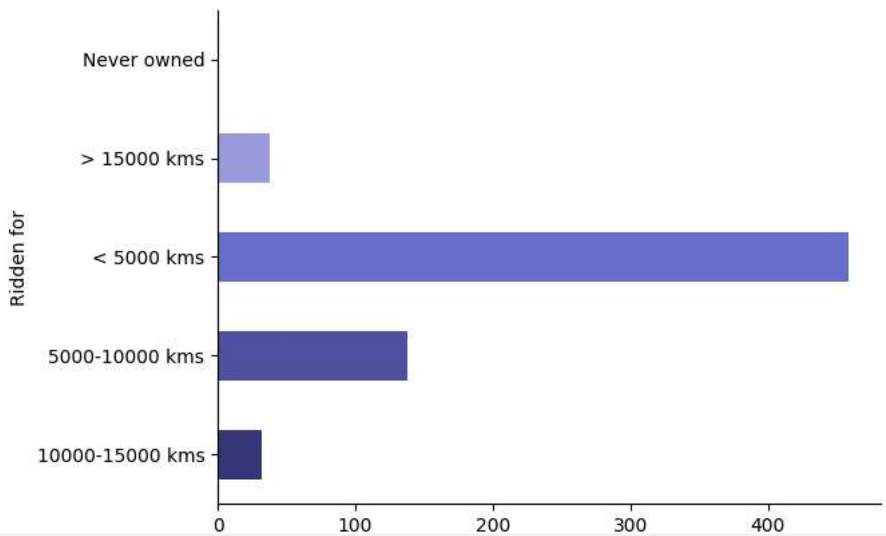
```
df1.head()
```

	review	Used it for	Owned for	Ridden for	rating	Visual Appeal	Reliability	Performance	Service Experience	Extra Features	Comfort	Maintenance cost	Value for Money	Mc N
0	We all checked the bike's capacity to be 150 k...	Daily Commute	Never owned	NaN	1	3.0	4.0	NaN	NaN	NaN	4.0	NaN	1.0	iC
1	Performance is very poor on this bike. The cha...	Everything	> 1 yr	< 5000 kms	1	3.0	1.0	NaN	1.0	NaN	3.0	NaN	3.0	iC
	I purchased													

Next steps: Generate code with df1 View recommended plots New interactive sheet

Ridden for

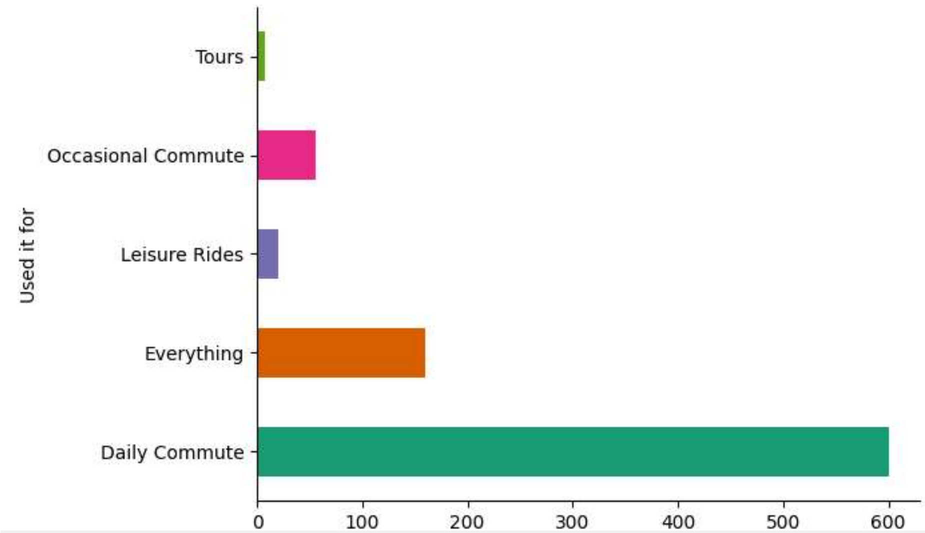
Show code



The horizontal bar chart displays the distribution of electric two-wheelers based on their intended usage. Each bar represents a specific usage category ("Ridden for"), and its length corresponds to the number of vehicles associated with that category. This visualization provides a clear overview of the primary purposes for which electric two-wheelers are being used.

Used it for

Show code

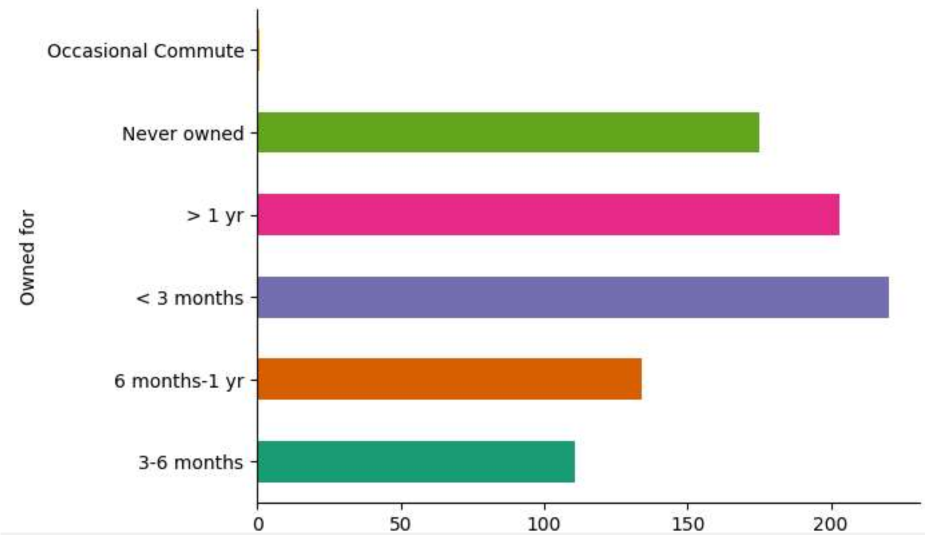


The horizontal bar chart displays the distribution of responses for the "Used it for" category in the dataset. Each bar represents a specific use case for electric two-wheelers, and the length of the bar corresponds to the number of respondents who indicated that use.

This visualization provides a clear overview of the most common and least common reasons people use electric two-wheelers, allowing for a quick understanding of the primary applications of these vehicles in the surveyed population.

Owned for

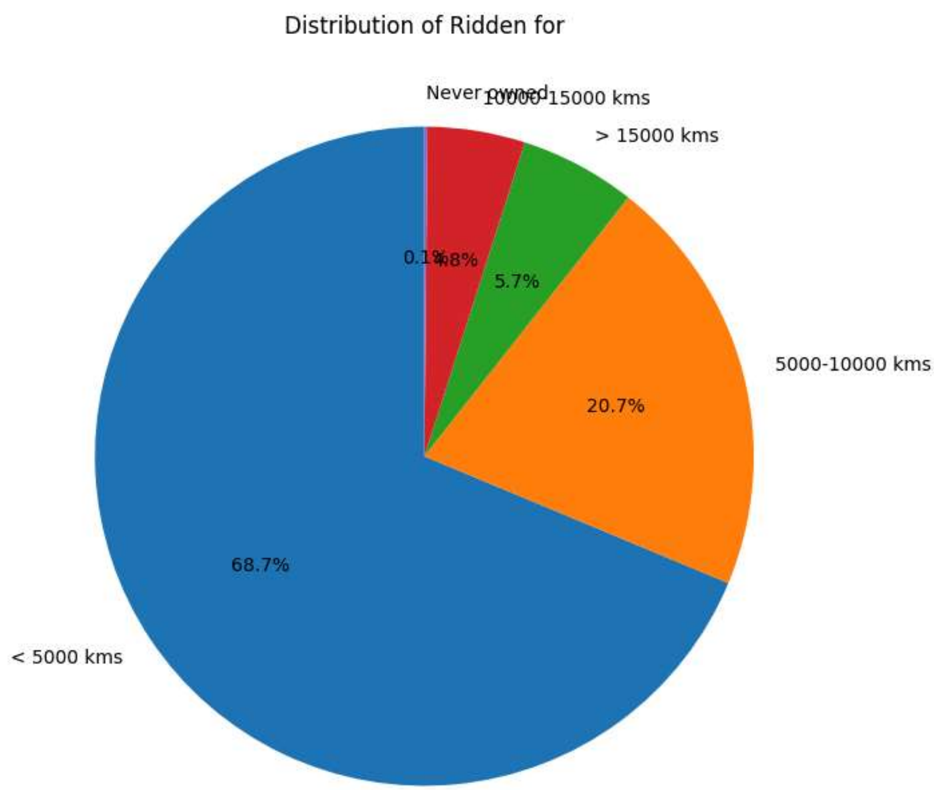
Show code



The horizontal bar chart displays the distribution of electric vehicles (EVs) based on the duration of ownership. Each bar represents a category of ownership duration (e.g., "1 yr 9 mo", "1 yr 3 mo"), and the length of the bar corresponds to the number of EVs that fall within that category.

This visualization provides insights into how long people typically own their EVs before selling or replacing them. It can be useful for understanding customer retention and predicting the frequency of EV purchases in the used market. For example, a longer average ownership duration might indicate higher customer satisfaction and a slower turnover of EVs in the market.

```
column_to_visualize = 'Ridden for'

category_counts = df1[column_to_visualize].value_counts()

plt.figure(figsize=(8, 8))
plt.pie(category_counts, labels=category_counts.index, autopct='%1.1f%%', startangle=90)
plt.title(f'Distribution of {column_to_visualize}')
plt.show()
```



The pie chart shows the distribution of 'Ridden for' in the dataset.

The category '< 5000 kms' represents 459 entries (68.7% of the total).

The category '5000-10000 kms' represents 138 entries (20.7% of the total).

The category '> 15000 kms' represents 38 entries (5.7% of the total).

The category '10000-15000 kms' represents 32 entries (4.8% of the total).

The category 'Never owned' represents 1 entries (0.1% of the total).

Generate | market segmentation on df1 plot and result | Close

1 of 1 Undo changes Use code with caution

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler


features = ['Owned for', 'Ridden for']  # Replace with actual column names
X = df1[features].dropna()  # Handle missing values if necessary

# Convert non-numeric features to numerical (if any)
# For example, if 'Ownership' is categorical:
X['Owned for'] = X['Owned for'].astype('category').cat.codes

X['Ridden for'] = X['Ridden for'].str.extract('(\d+)').astype(float)

X['Ridden for'] = X['Ridden for'].fillna(X['Ridden for'].mean())
# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Determine the optimal number of clusters using the Elbow method
inertia = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

plt.plot(range(1, 11), inertia, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.show()
```

```
df2 = pd.read_csv('/content/1_ev_charger_dataset.csv')
```

```
df2.head()
```

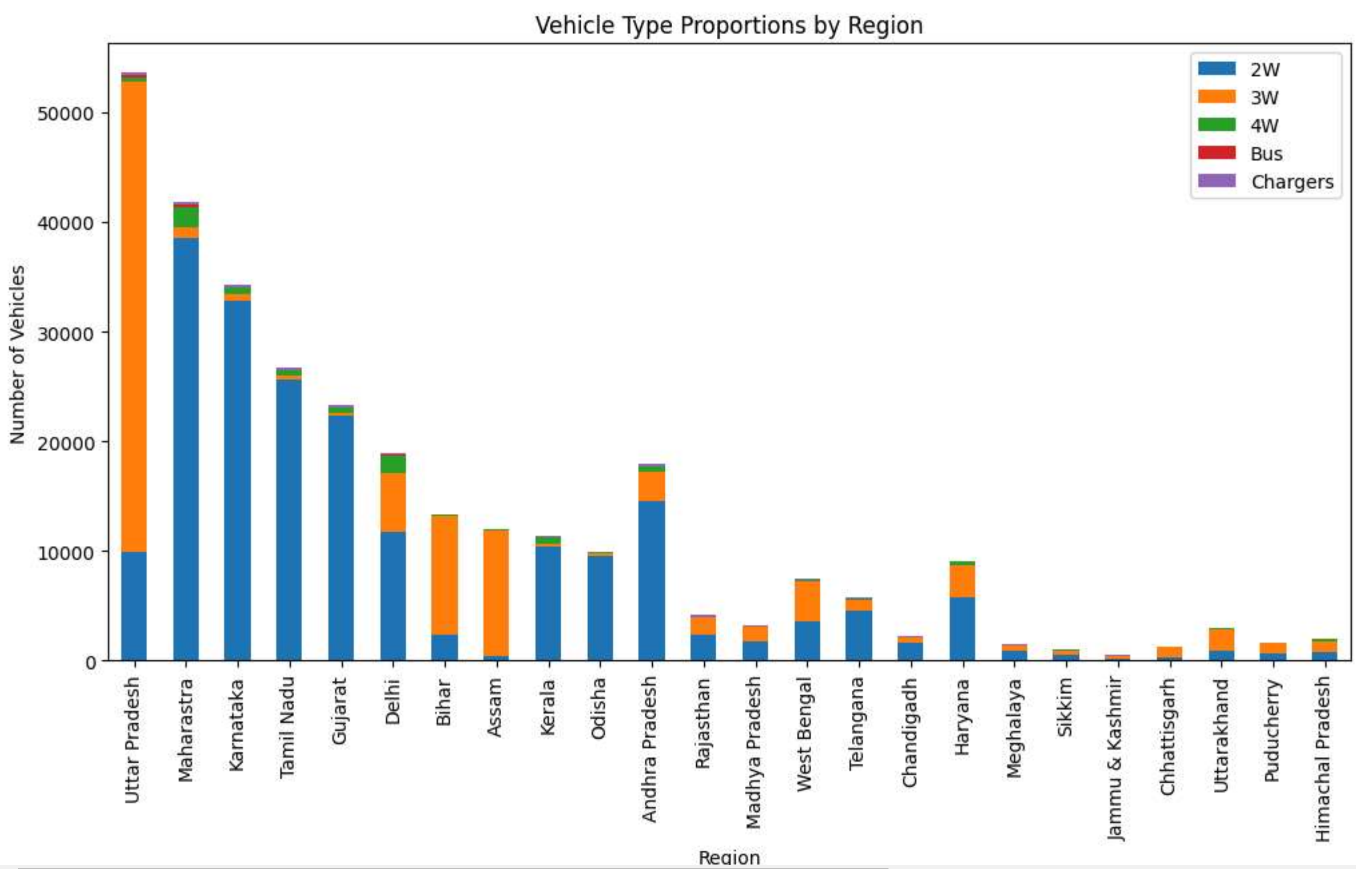
	Region	2W	3W	4W	Bus	Chargers
0	Uttar Pradesh	9852	42881	458	197	207
1	Maharastra	38558	893	1895	186	317
2	Karnataka	32844	568	589	57	172
3	Tamil Nadu	25642	396	426	0	256
4	Gujarat	22359	254	423	22	228

Next steps: Generate code with df2 View recommended plots New interactive sheet

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarning: The default value of `n_init` will change from 1
```

Vehicle Type Proportions by Region

Show code



The stacked bar chart illustrates the distribution of different vehicle types across various regions. Each bar represents a region, and its segments correspond to the number of vehicles of each type within that region.

By comparing the heights of the segments, we can observe the relative popularity of different vehicle types in each region. For instance, some regions might have a higher concentration of passenger cars, while others might show a greater adoption of buses or trucks.

The stacked bar chart allows for a quick visual assessment of the regional variations in vehicle type preferences.

Dataset 1: Electric Car Data

- Visualizations are used to explore the distribution of efficiency by brand, top speed trends, the relationship between powertrain and plug type, and the distribution of top speed by rapid charging capability.
- A bar chart shows the prevalence of rapid charging support among the cars.
- A violin plot illustrates the distribution of EV prices by body style.
- Market segmentation is performed using K-Means clustering based on features like price, range, efficiency, top speed, and fast charging speed.

- The characteristics of each segment are analyzed and the percentage of EVs in each segment is calculated.

Dataset 2: Electric Two-Wheeler Data

- Bar charts display the distribution of electric two-wheelers based on usage categories like "Ridden for," "Used it for," and "Owned for."
- A pie chart visualizes the distribution of "Ridden for" categories.
- K-Means clustering is attempted on features like "Owned for" and "Ridden for" to potentially identify segments within the electric two-wheeler market.

Overall, the code provides insights into various aspects of the EV market, including efficiency, pricing, usage patterns, and potential market segments.

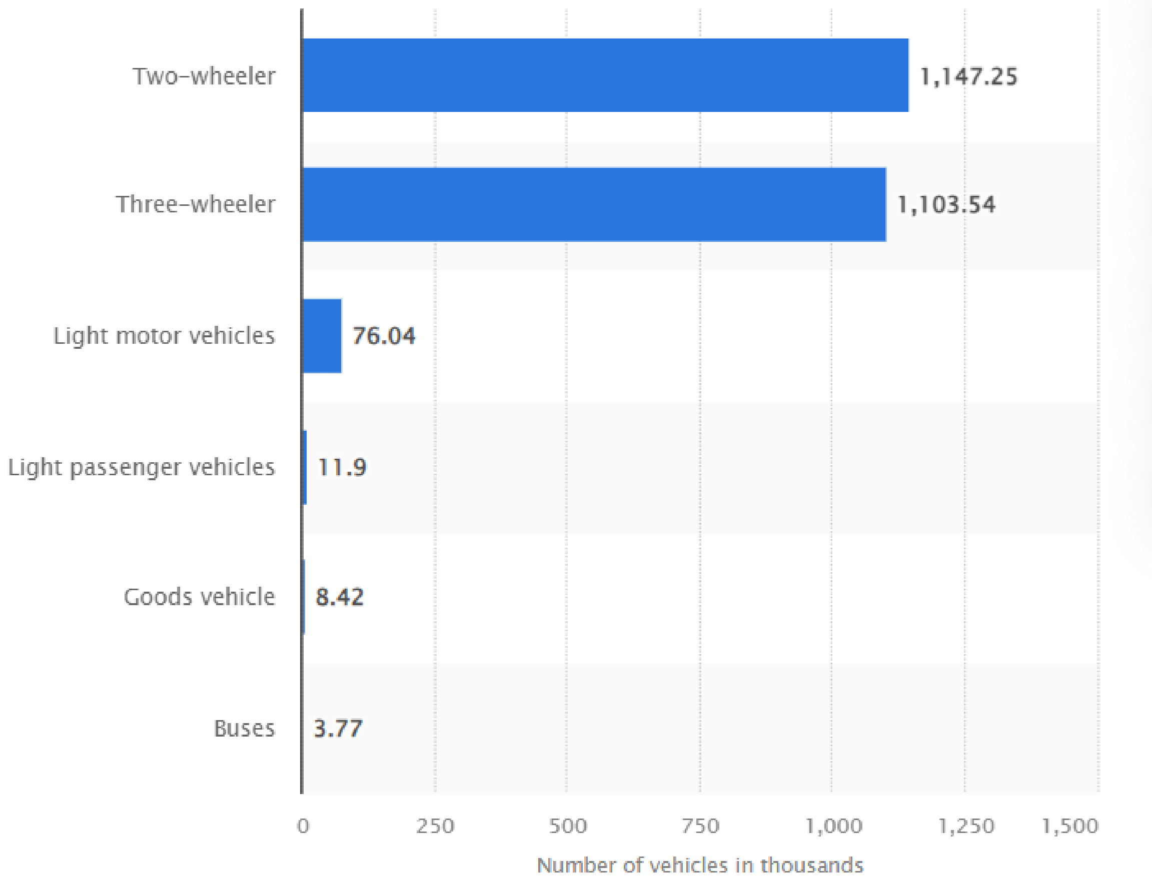
Further analysis could involve:

- Deeper investigation of outliers in efficiency and top speed.
- Exploring the relationship between rapid charging support and other factors like price and range.
- Analyzing trends in rapid charging adoption over time.
- Refining the market segmentation approach for electric two-wheelers, potentially incorporating additional features and addressing missing data.

```
Start coding or generate with AI.
```

Operational Electric Vehicles in India: Focus on Two and Three-Wheelers

In India, the adoption of electric vehicles (EVs) has seen significant growth, particularly in the two and three-wheeler segments. These vehicles are gaining popularity due to their cost-effectiveness, environmental benefits, and suitability for urban mobility.



Two-Wheelers

Market Dominance:

Electric two-wheelers account for a large share of EV sales in India. They are an attractive option for consumers due to lower operational costs, ease of maintenance, and government incentives.

Popular Models and Manufacturers:

Ather Energy: Known for its Ather 450X, which is popular for its performance and smart features.

Okinawa Autotech: Offers a range of electric scooters like the Okinawa PraisePro.

Hero Electric: A major player in the segment with models like Hero Photon and Hero Optima.

Applications:

Personal Use: Many urban commuters are switching to electric scooters for their daily travel needs due to rising fuel prices and environmental concerns.

Delivery Services: Electric two-wheelers are increasingly being used by delivery companies (e.g., food delivery, e-commerce) due to their low running costs and ease of navigation in congested city traffic.

Three-Wheelers

Market Growth:

Electric three-wheelers, including e-rickshaws and e-autos, are becoming common in Indian cities, especially in Tier 2 and Tier 3 cities. They offer an affordable and sustainable mode of transportation for short-distance travel.

Popular Models and Manufacturers:

Mahindra Electric: Known for its e-Alfa Mini, an electric rickshaw that is widely used for passenger transport.

Kinetic Green Energy: Offers models like Kinetic Safar, which are popular for both passenger and cargo transport.

Piaggio Vehicles: Entered the electric three-wheeler market with the Ape E-City.

Applications:

Public Transportation: Electric three-wheelers are increasingly used for last-mile connectivity in urban and semi-urban areas.

Cargo Transport: The cargo versions of electric three-wheelers are used by small businesses and vendors for transporting goods within cities.

Challenges and Opportunities

Battery Technology: Limited range and long charging times are still concerns, but advancements in battery technology are gradually addressing these issues.

Infrastructure: The lack of widespread charging infrastructure is a significant challenge, although it is improving with government and private sector efforts.

Policy Support: Government incentives, such as subsidies on EV purchases and tax benefits, are driving growth in the two and three-wheeler segments.

Future Outlook

The Indian EV market is poised for exponential growth in the coming years. With ongoing investments in technology, infrastructure, and government support, the country is expected to see a significant rise in EV adoption across both personal and commercial segments. Additionally, India's focus on becoming a global manufacturing hub for EVs is likely to drive further expansion and innovation in the industry.