Data-Driven Insights on Car Resale Market

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Introduction

The Car resale market is a dynamic sector influenced by various factors such as vehicle specifications, usage history, and customer preferences. To better understand these patterns, I collected and analysed a comprehensive dataset containing multiple attributes of cars, including mileage, engine capacity, fuel type, ownership history, Max power, and resale price. This dataset provides a valuable foundation for generating data-driven insights into how different variables impact the resale value of vehicles.

As with many real-world datasets, the raw data presented several inconsistencies, missing values, and mixed units across key columns. For example, mileage values varied based on the fuel type (kmpl for petrol/diesel, km/kg for CNG/LPG, and km/kWh for electric), while engine power was expressed in multiple units such as BHP, PS, and KW. To ensure reliability and accuracy, I applied systematic data cleaning techniques, including unit standardization, handling of missing or erroneous entries, and imputation strategies for categorical attributes.

Following the cleaning process, the dataset was refined into a structured format suitable for analysis and visualization. This step not only improved data consistency but also enhanced the interpretability of the results. By organizing the attributes into uniform scales and clearly defined categories, the dataset became more aligned with practical analysis needs in the automobile resale domain.

To derive actionable insights, I used Power BI to develop a range of visualizations that highlight trends and correlations across key factors. Examples include comparative mileage across fuel types, distribution of resale prices, and ownership patterns. These visual representations provide stakeholders with an accessible yet detailed view of the dataset, enabling informed decision-making within the car resale market.

Data Cleaning & Data Transformation

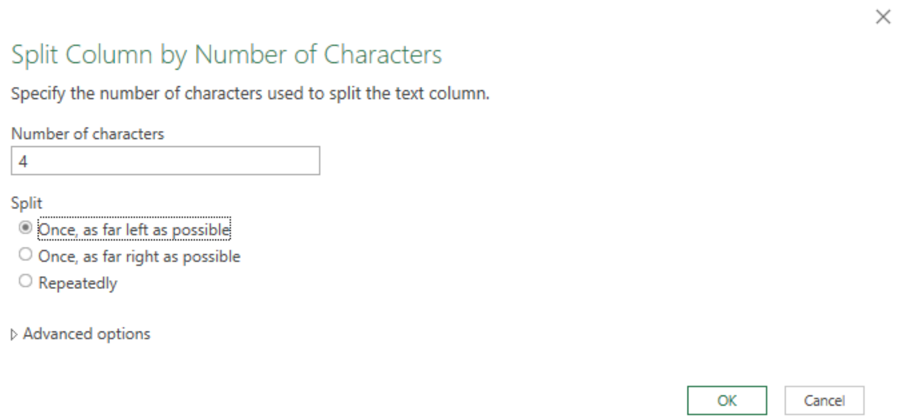
1.Split Column in Power query

Data Quality Observation

During the data validation process, inconsistencies were detected in the **registered_year** column, where several entries did not conform to the expected year format.

Resolution Approach

To standardize the data, I implemented a transformation in Power Query. Using the **full_name** column as a reference, I applied the **Split Column** function to isolate the year component from the rest of the string. This extracted value was then assigned to a new column through a **Conditional Column** step.



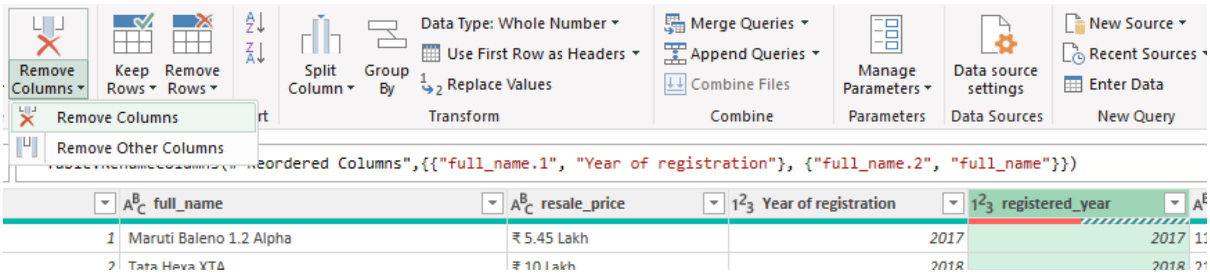
The newly created column was renamed to **"Year of Registration"**, ensuring clarity, consistency, and improved usability for subsequent analysis. This step also mitigated the risk of inaccurate year-based filtering or aggregation in future reporting.

	full_name.2	resale_price	Year of registration	registered_year
202	Mahindra Scorpio VLX SE BSIV	₹ 3 Lakh	2011	2011
203	Maruti Wagon R VXI BS IV	₹ 2.50 Lakh	2015	2015
204	Maruti Swift Dzire VDI	₹ 4 Lakh	2015	2015
205	Hyundai Verna 1.6 SX	₹ 3.70 Lakh	2012	2012
206	Audi e-tron 55 Sportback	₹ 96.80 Lakh	2021	Error
207	Audi Q3 30 TFSI Premium FWD	₹ 24.80 Lakh	2018	Error
208	BMW 6 Series GT 630i Luxury Line 2018-2021	₹ 46.90 Lakh	2018	Error
209	Audi A6 35 TFSI Matrix	₹ 21.90 Lakh	2015	Error
210	Audi A4 35 TDI Premium Plus	₹ 22.90 Lakh	2017	Error
211	Audi Q3 35 TDI Quattro Premium Plus	₹ 13.90 Lakh	2014	Error
212	Audi A4 30 TFSI Technology	₹ 27.90 Lakh	2016	Error
213	Mercedes-Benz E-Class E250 CDI	₹ 11.90 Lakh	2014	Error

Remove column

After creating the "**Year of Registration**" column, which contains more accurate and standardized values derived from the “**full_name**” column, the original **registered_year** column was deemed redundant. The original column contained uncleaned and error-prone entries that could compromise the integrity of the analysis.

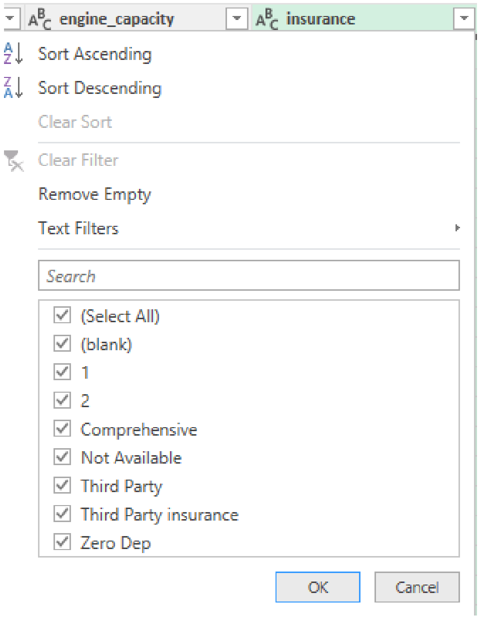
To maintain dataset quality and avoid confusion during future processing, the outdated **registered_year** column was removed entirely. This ensures that all year-related references in subsequent reporting and analysis are based solely on the verified "**Year of Registration**" field.



2. Finding Mode to fill the Blank and Unknown (1,2) values (Power Query)

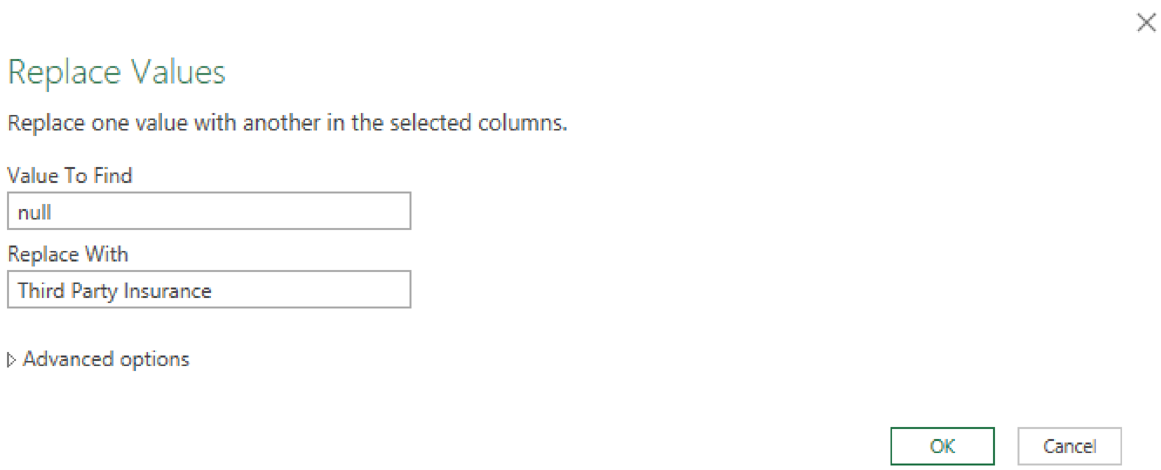
The next step I applied to clean the blank and irrelevant entries in the **Insurance** column was to impute the mode. This approach was chosen because the column contains only categorical (text) values.

I then used the **Group By** function in Power Query, along with the **Row Count** operation, to identify the most frequently selected insurance type by customers. This method was subsequently used to replace the blank and incorrectly entered entries in the column.



insurance	Count
Third Party insurance	7559
Comprehensive	6414
Zero Dep	834
Third Party	1973
Not Available	651
	7
2	3
1	5

The analysis revealed that **Third Party Insurance** was the most frequently chosen option by customers. Consequently, this value can be used to replace both the missing and incorrectly entered entries in the column.

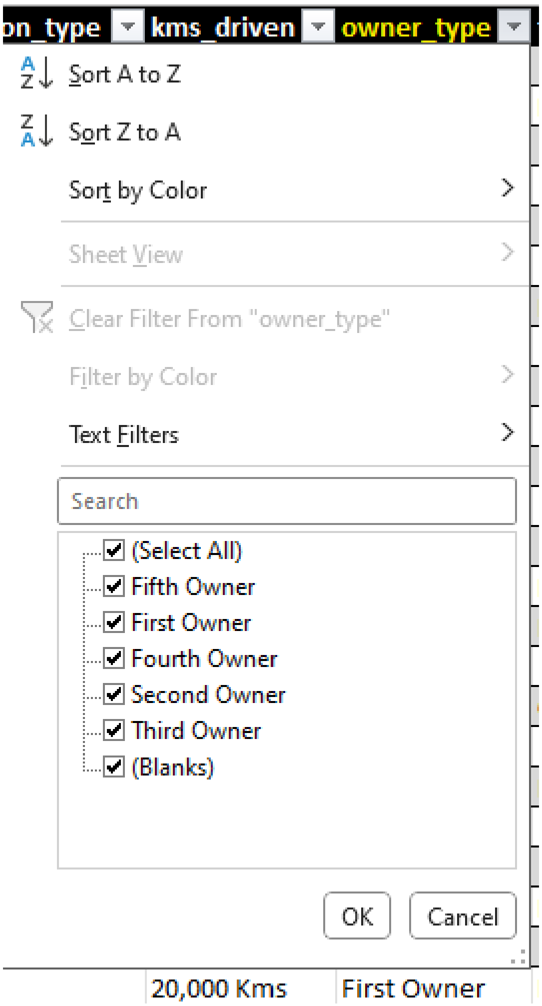


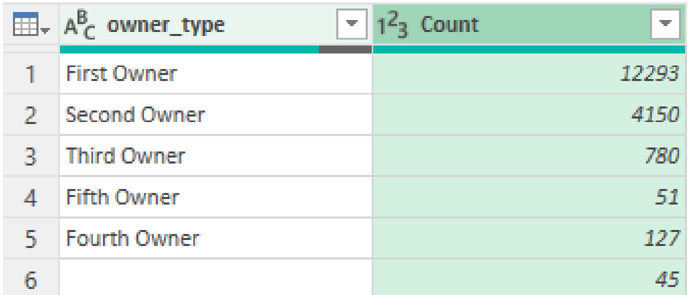
3.Finding Mode and replaced with most frequent value count for Owner type

The dataset included a column named **owner_type**, which records the number of previous owners for each vehicle. Since the column contains only categorical (text-based) values, handling missing or invalid data required a method suited for qualitative information. To address this, mode imputation was selected as the most appropriate approach.

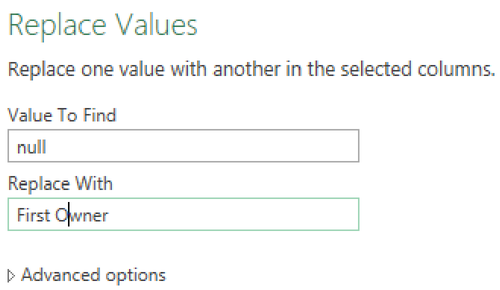
To determine the mode, I utilized Power Query's **Filter** function in combination with the **Row Count** operation. This allowed me to identify the category with the highest frequency in the column. Through this process, **First Owner** emerged as the most common category across the dataset.

Once the mode was identified, it was used to replace all missing and incorrectly entered entries in the **owner_type** column. This ensured the data was consistent, accurate, and ready for further analysis, ultimately improving the reliability of any insights derived from the dataset.





	owner_type	Count
1	First Owner	12293
2	Second Owner	4150
3	Third Owner	780
4	Fifth Owner	51
5	Fourth Owner	127
6		45



4. Cleaning the Most complex data in max_power column

In my **Car Resale** dataset, I identified a column named **max_power**, which specifies the engine power of each vehicle. Upon inspection, I found that the values in this column were highly inconsistent. Some entries were expressed in different measurement units such as BHP, PS,HP and kW, while others contained irrelevant text (e.g., “at 6600 rpm”) or missing values. Since the dataset contained a total of 17,447 rows, it was essential to apply a systematic cleaning approach to ensure data quality and consistency.

The cleaning process involved the following steps:

Defining every Unit into Separate column

To determine the different units, present in the ***max_power*** column, I extracted and transformed them into a separate column named ***Power_Unit*.**

```
=IF(ISNUMBER(SEARCH("bhp",M2)),"bhp",
IF(ISBLANK(M2),"Empty",
IF(ISNUMBER(SEARCH("PS",M2)),"PS",
IF(ISNUMBER(SEARCH("KW",M2)),"KW",
IF(ISNUMBER(SEARCH("HP",M2)),"HP",
IF(SUM(COUNTIF(M2,"*(*"),COUNTIF(M2,"*/ *"),COUNTIF(M2,"*[
*"),COUNTIF(M2,"* *"))>0,"SP",
IF(ISNUMBER(VALUE(M2)),
IF(VALUE(M2)-INT(VALUE(M2))<>0,"Decimal","False"),
"False")))))))
```

IF(ISNUMBER(SEARCH("bhp",M2)),"bhp", ...)

- Checks if the text "bhp" exists in cell **M2**.
- If yes → return "bhp".

IF(ISBLANK(M2),"Empty", ...)

- If the cell **M2** is empty → return "Empty".

IF(ISNUMBER(SEARCH("PS",M2)),"PS", ...)

- Checks if "PS" exists in M2.
- If yes → return "PS".

IF(ISNUMBER(SEARCH("KW",M2)),"KW", ...)

- Checks if "KW" exists in M2.
- If yes → return "KW".

IF(ISNUMBER(SEARCH("HP",M2)),"HP", ...)

- Checks if "HP" exists in M2.
- If yes → return "HP".

IF(SUM(COUNTIF(...))>0,"SP", ...)

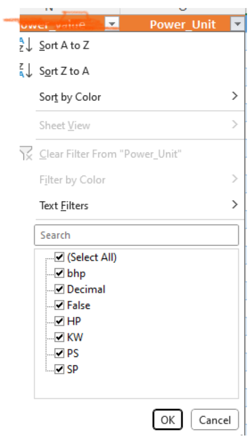
Looks for **special characters or spaces** in M2 using multiple conditions:

- "*(*" → contains an opening bracket
- "*/ *" → contains a slash
- "*[*" → contains bracket and space
- "* *" → contains space

If any of these patterns exist → return "SP".

IF(ISNUMBER(VALUE(M2)), ...)

- If the value in M2 is a **number**:
  - **IF(VALUE(M2)-INT(VALUE(M2))<>0,"Decimal","False")**
    - If it has decimal places → return "Decimal".
    - If it's a whole number → return "False".
- If it's not a number → return "False".



Extracting Numeric Values (Using TRIM and TEXTJOIN Function)

- Used text functions and regular expressions to isolate the numeric part of the power values (e.g., converting *"118PS at 6600 rpm"* into *116 BHP*).
- Removed unnecessary characters such as "at rpm" or ranges like *"4000–6000 rpm"*.

- This extracts the first block of text before a space (like 120bhp, 118PS, 100.5bhp, 132/4000-6000).
  =TRIM(LEFT(A2,SEARCH(" ",A2&" ")-1))
- This gives numeric values such as 120, 118, 100.5, 132, etc.
  =--TEXTJOIN("",TRUE,IF(ISNUMBER(MID(B2,ROW($1:$50),1)*1),MID(B2,ROW($1:$50),1),""))

Power_value
83.1
153.86
83.14
83.14
68.05
81.86
69
68.05
73
62
86.7
81.86
103.25
98.6
89
67.1
58.16
88.7
87.2
118.36
103.25
89.84
167.67
74
67.1
167.67
81.8
81.86
83.14

Handling Missing and Invalid Data

- For blank or invalid entries, applied mean/median imputation based on car segment or engine size.
- In cases where imputation wasn't suitable, flagged the rows for further review.
- Here in my Case I flagged them as SP value wich contains Special Character Like "(" , "[" and extract the value before it using **TRIM,LEN**

  =TRIM(LEFT(M2,MIN(IFERROR(FIND("(",M2),LEN(M2)+1),IFERROR(FIND("[",M2),LEN(M2)+1))-1))

max_power	Power_value	Power_Unit
90(66)	90	SP
90(66)	90	SP
90(66)	90	SP
90(66)	90	SP
90(66)	90	SP
90(66)	90	SP
90(66)	90	SP
165 [224] at 3800	165	SP
165 [224] at 3800	165	SP
66(90) / 4000	66	SP
66(90) / 4000	66	SP
165 [224] at 3800	165	SP
110(150)/5700	110	SP
165 [224] at 3800	165	SP
90(66)	90	SP
90(66)	90	SP
165 [224] at 3800	165	SP
90(66)	90	SP
165 [224] at 3800	165	SP
165 [224] at 3800	165	SP

Creating a Cleaned Column

- Generated a new standardized column containing only numeric BHP values.
- "I created a new column labelled *BHP* and used the **CONCATENATE** function to merge two text columns into a single column named "***Brake Horse Power***."

Break horse power
83.1 BHP
153.86 BHP
83.14 BHP
83.14 BHP
68.05 BHP
81.86 BHP
69 BHP
68.05 BHP
73 BHP
62 BHP
86.7 BHP
81.86 BHP
103.25 BHP
98.6 BHP
89 BHP
67.1 BHP
58.16 BHP
88.7 BHP
87.2 BHP
118.36 BHP
103.25 BHP
89.84 BHP
167.67 BHP
74 BHP
67.1 BHP
167.67 BHP
81.8 BHP
81.86 BHP
83.14 BHP
47.3 BHP
67.04 BHP
82 BHP
74 BHP
140 BHP
140 BHP
138.1 BHP

5.Transforming Milage Column

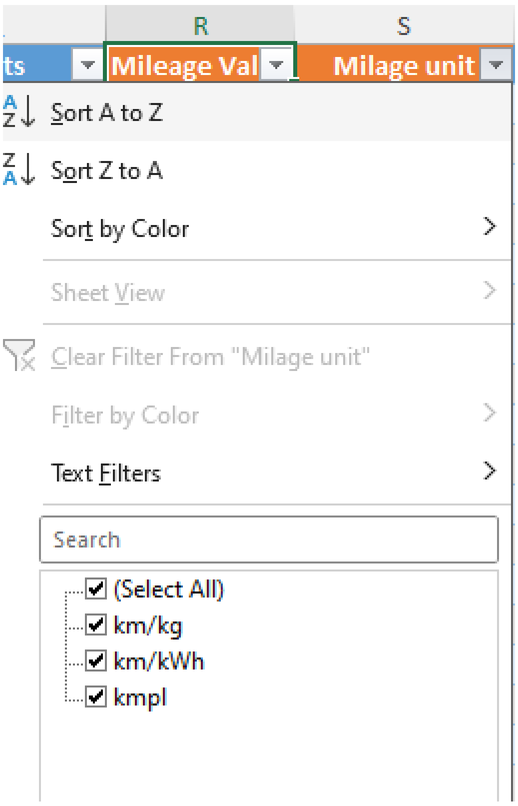
In the context of the Indian automobile market, mileage is one of the most critical factors considered by families when purchasing a vehicle, whether it is a two-wheeler or a four-wheeler. During the resale process, customers often evaluate mileage based on multiple influencing factors, including the vehicle's prior usage patterns, the type of fuel it operates on, and the number of previous owners. These attributes collectively provide valuable insights into the vehicle's efficiency and long-term performance, making mileage a key parameter for analysis in the dataset.

In the Car Resale Dataset, the *mileage* column records the fuel efficiency of each vehicle. However, the values were found to be inconsistent because the measurement units varied depending on the type of fuel used. Specifically:

- Petrol and Diesel vehicles report mileage in *kilometers per liter (kmpl)*.
- CNG and LPG vehicles report mileage in *kilometers per kilogram (km/kg)*.

Unit Identification

- Parsed each entry in the *mileage* column to detect whether it contained "kmpl","Km/Kwh" or "km/kg".
- Created a helper column (*Mileage_Unit*) to store the identified unit type.



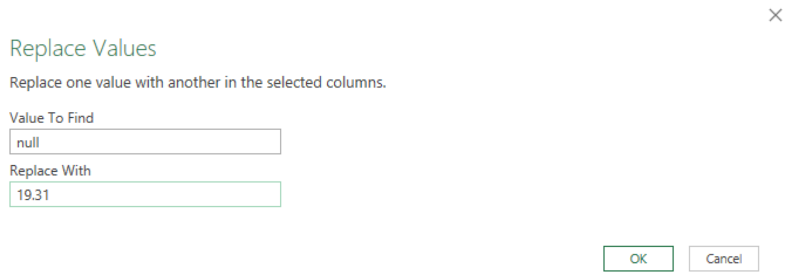
Numeric Value Extraction

- Extracted the numerical portion of each record (e.g., from “22.5 kmpl” → 22.5, from “30.2 km/kg” → 30.2).
- Converted the extracted values into a clean numeric format for further processing.
- Created a separate column for Extracted Numaric value named **Mileage_Value**

R
Mileage Value
21.4
17.6
20.85
20.85
19.81
17.19
27.28
19.81

Standardization

- Retained the numeric mileage values in one column (*Mileage_Value*).
- Handled Blank values with average of total Milage value



- Stored the corresponding unit (kmpl or km/kg) in a separate column (*Mileage_Unit*) to ensure clarity and consistency.

- To address missing unit values, I aligned them with the **Fuel Type** column. For this, I applied a mapping logic:

  Petrol/Diesel → kmpl

  CNG/LPG → km/kg

  Electric → km/kWh

  This ensured that any blank or inconsistent unit values were accurately filled based on the corresponding fuel type.

fuel_type	mileage	b
CNG	31.59 km/kg	H
CNG	31.59 km/kg	H
CNG	31.59 km/kg	H
Petrol	11.1 kmpl	S
CNG	31.59 km/kg	H
CNG	31.59 km/kg	H
CNG	31.59 km/kg	H
CNG	31.59 km/kg	H
Petrol	11.1 kmpl	S
CNG	31.59 km/kg	H

```
=IF(C2<>"",C2,
IF(OR(A2="Petrol",A2="Diesel"),"kmpl",
IF(OR(A2="CNG",A2="LPG"),"km/kg",
IF(A2="Electric","km/kWh",""))))
```

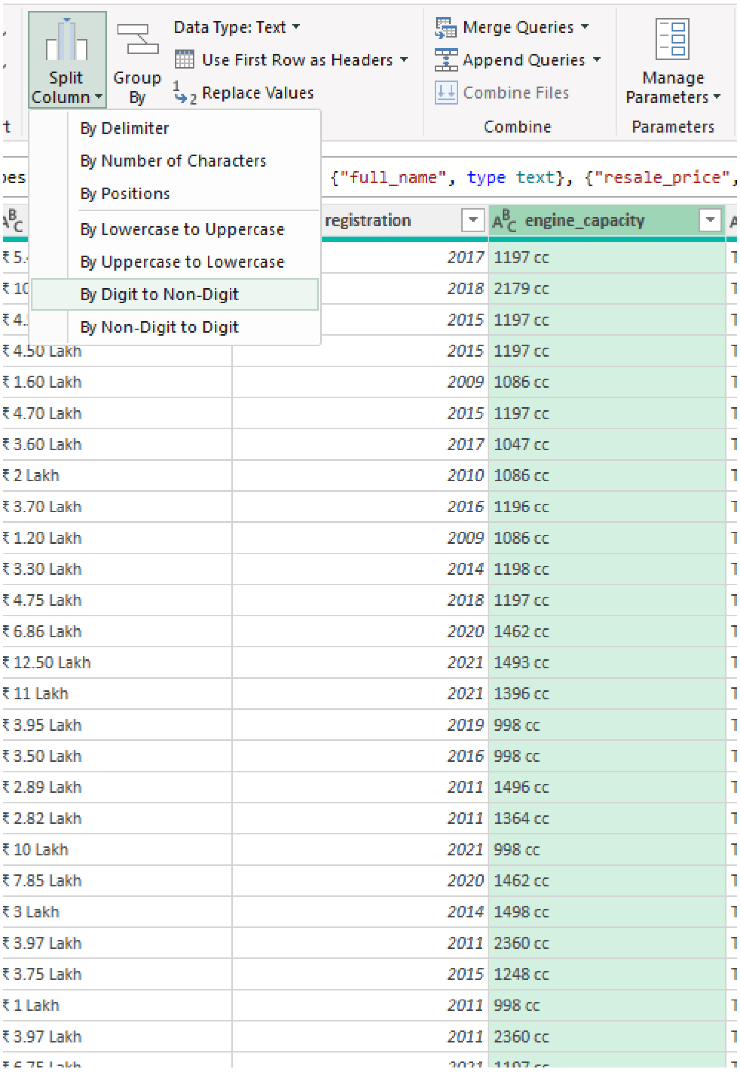
6.Cleaning engine_Capacity column using power query

a. Identifying the Issue

- The Engine_capacity column contained values in the format "1000 cc", "1500 cc", etc., representing the engine's cubic capacity.
- Some entries had incorrect values such as "0 cc" or were completely blank, which could distort analysis.

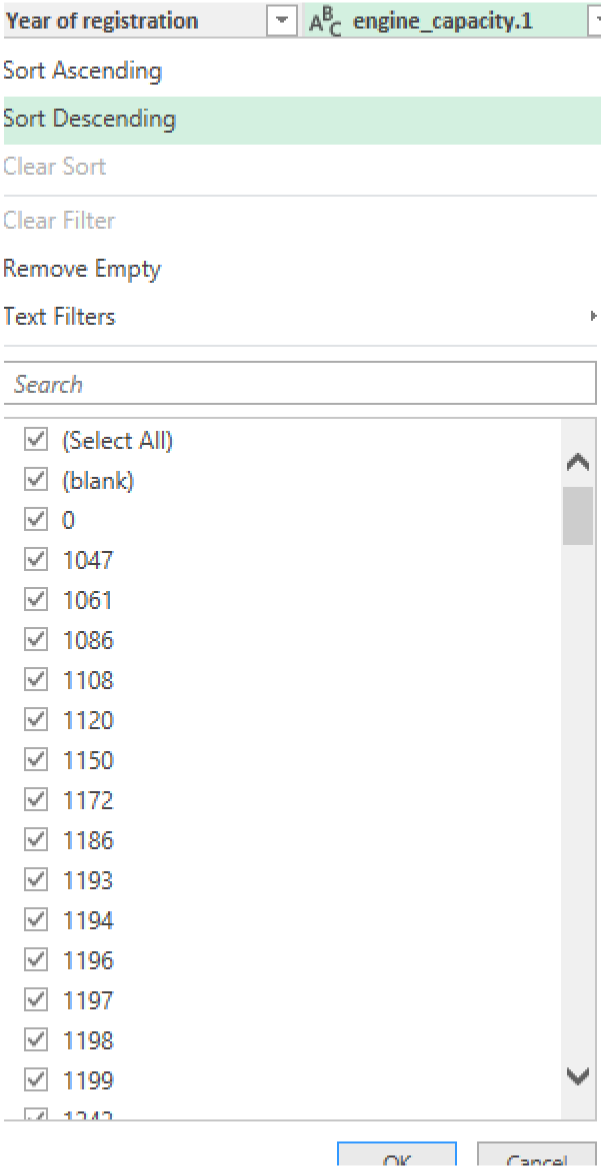
b. Data Transformation

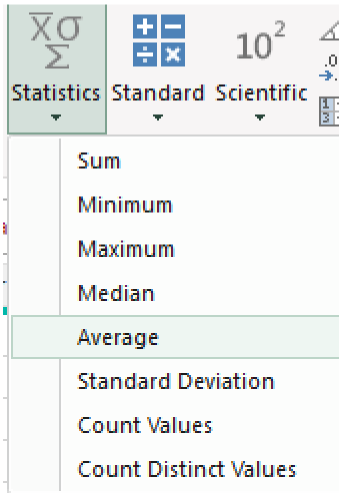
- Used **Power Query** to split the column into two parts:
  - **Numeric part** → engine capacity value.
  - **Text part** → unit (cc).
- This separation made it easier to work with the numeric values.



c. Handling Invalid Values

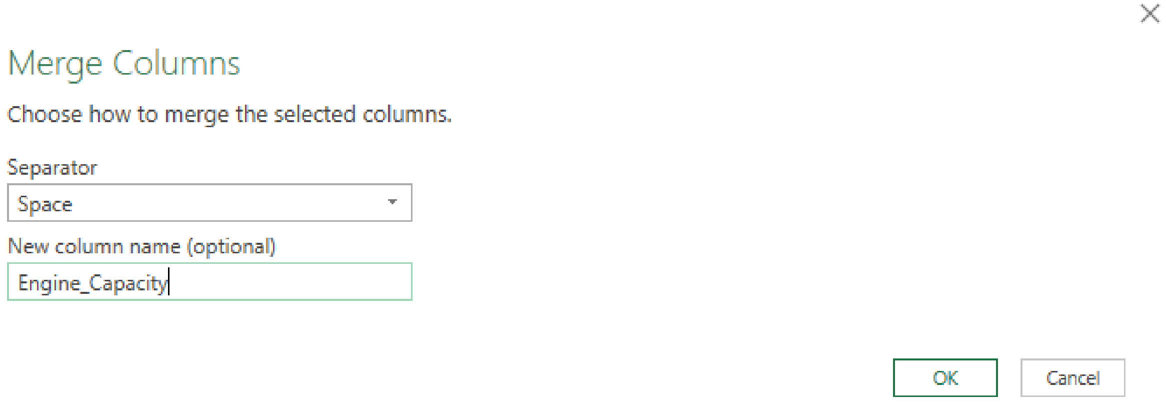
- Identified rows with "0 cc" and blank values.
- Replaced these invalid entries using appropriate imputation:
    - **Option 1**: Filled with the **average engine capacity** based on similar car models.
    - **Option 2**: Used **conditional logic** (e.g., by car segment or fuel type) for more accurate replacements.





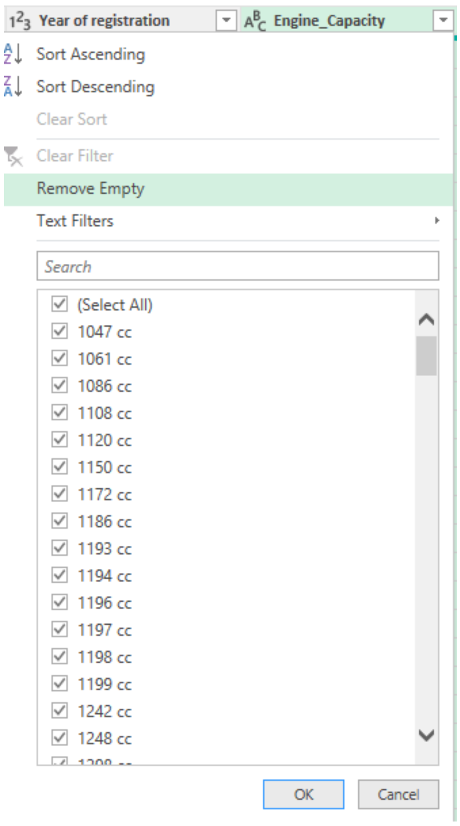
d. Data Integration

- Merged the numeric values back with the "cc" unit to maintain a clean and standardized format.
- Finalized the column as Engine_capacity (cc) with corrected and consistent entries.



e. Outcome

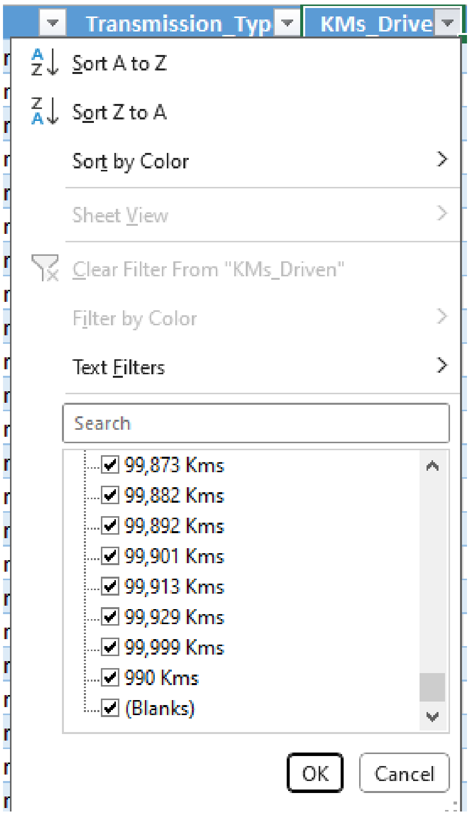
- The column was cleaned, standardized, and made analysis-ready for further steps like vehicle performance comparison and segmentation.



7.Transforming kms_driven column

In the Car_Resale dataset, there is a column named kms_driven, which represents the total distance a vehicle has traveled, i.e., how many kilometers it has been driven by its previous owners.

During the cleaning process, I noticed that the values in this column were stored in a combined text format such as "40,000 kms". Since this format contained both numeric and text components, it was not suitable for numerical analysis and required transformation.



1. **To standardize the data, I applied the following steps:**
   Extracting the Text Component
   - I created a temporary column and used the formula:
   - =RIGHT(H2,3)
   - This allowed me to isolate and extract the unit **"kms"** from each record, ensuring that the unit portion was separated from the numeric portion of the data.
2. **Extracting the Numeric Component**
   - Next, I created another column named **KM**, designed to hold only the numeric values.
   - To achieve this, I applied the formula:
   - =VALUE(SUBSTITUTE(LEFT(H2,FIND(" ",H2)-1),",",""))
   - This formula cleaned the data by removing commas, isolating the numeric portion before the text "kms", and converting it into a proper numeric value.

Through this process, I successfully transformed the **kms_driven** column into two meaningful and analysis-ready fields:

- **KM** → representing the distance travelled as a clean numeric value.
- **kms** → representing the unit of measurement, stored separately for clarity.

This approach ensures that the mileage data can now be used directly for **statistical analysis, filtering, aggregations, and modelling** without inconsistencies caused by text formatting.

Finally, I cleaned up the blank value in the "KM" column using the **AVERAGE** and **ISBLANK** function.

=IF(ISBLANK(I735), AVERAGE($I2:$I7447), I2)

H
KMs_Driver
40,000 Kms
70,000 Kms
70,000 Kms
70,000 Kms
80,000 Kms
70,000 Kms
1,20,000 Kms
60,000 Kms
20,000 Kms
30,000 Kms
70,000 Kms
60,000 Kms
50,000 Kms
60,000 Kms
60,000 Kms
20,000 Kms
40,000 Kms
50,000 Kms
1,50,000 Kms

Data cleaning Before and After

Before Data Cleaning

s.no	full_name	resale_pri	registered	engine_ca	insurance	transmiss	kms_drive	owner_typ	fuel_type	max_powe	seats	mileage	body_type	city
1	2017 Maru	â,¹5.45 La	2017	1197 cc	Third Part	Manual	40,000 Km	First Own	Petrol	83.1bhp	5	21.4 kmpl	Hatchbacl	Agra
2	2018 Tata	â,¹10 Lakl	2018	2179 cc	Third Part	Automatic	70,000 Km	First Own	Diesel	153.86bhp	7	17.6 kmpl	MUV	Agra
3	2015 Maru	â,¹4.50 La	2015	1197 cc	Third Part	Manual	70,000 Km	Second O	Petrol	83.14bhp	5	20.85 kmp	Sedan	Agra
4	2015 Maru	â,¹4.50 La	2015	1197 cc	Third Part	Manual	70,000 Km	Second O	Petrol	83.14bhp	5	20.85 kmp	Sedan	Agra
5	2009 Hyun	â,¹1.60 La	2009	1086 cc	Third Part	Manual	80,000 Km	First Own	Petrol	68.05bhp	5	19.81 kmp	Hatchbacl	Agra
6	2015 Hyun	â,¹4.70 La	2015	1197 cc	Third Part	Manual	70,000 Km	First Own	Petrol	81.86bhp	5	17.19 kmp	Hatchbacl	Agra
7	2017 Tata	â,¹3.60 La	2017	1047 cc	Third Part	Manual	1,20,000 K	First Own	Diesel	69bhp	5	27.28 kmp	Hatchbacl	Agra
8	2010 Hyun	â,¹2 Lakh	2010	1086 cc	Third Part	Manual	60,000 Km	Second O	Petrol	68.05bhp	5	19.81 kmp	Hatchbacl	Agra
9	2016 Maru	â,¹3.70 La	2016	1196 cc	Third Part	Manual	20,000 Km	First Own	Petrol	73bhp	7	15.37 kmp	Minivans	Agra
10	2009 Hyun	â,¹1.20 La	2009	1086 cc	Third Part	Manual	30,000 Km	First Own	Petrol	62bhp	5		Hatchbacl	Agra
11	2014 Honc	â,¹3.30 La	2014	1198 cc	Third Part	Manual	70,000 Km	First Own	Petrol	86.7bhp	5	18 kmpl	Sedan	Agra
12	2018 Hyun	â,¹4.75 La	2018	1197 cc	Third Part	Manual	60,000 Km	Second O	Petrol	81.86bhp	5	20.14 kmp	Sedan	Agra
13	2020 Maru	â,¹6.86 La	2020	1462 cc	Third Part	Manual	50,000 Km	Third Owr	Petrol	103.25bhp	5	21.56 kmp	Sedan	Agra
14	2021 Hyun	â,¹12.50 L	2021	1493 cc	Third Part	Manual	60,000 Km	First Own	Diesel	98.6bhp	5	23.7 kmpl	SUV	Agra
15	2021 Hyun	â,¹11 Lakl	2021	1396 cc	Third Part	Manual	60,000 Km	First Own	Diesel	89bhp	5	23.7 kmpl	SUV	Agra
16	2019 Maru	â,¹3.95 La	2019	998 cc	Third Part	Automatic	20,000 Km	First Own	Petrol	67.1bhp	5	23.95 kmp	Hatchbacl	Agra
17	2016 Maru	â,¹3.50 La	2016	998 cc	Third Part	Manual	40,000 Km	First Own	CNG	58.16bhp	5	26.6 kmpl	Hatchbacl	Agra
18	2011 Toyo	â,¹2.89 La	2011	1496 cc	Third Part	Manual	50,000 Km	Second O	Petrol	88.7bhp	5	17.6 kmpl	Sedan	Agra
19	2011 Toyo	â,¹2.82 La	2011	1364 cc	Third Part	Manual	1,50,000 K	First Own	Diesel	87.2bhp	5	21.43 kmp	Sedan	Agra
20	2021 Kia S	â,¹10 Lakl	2021	998 cc	Third Part	Manual	10,000 Km	First Own	Petrol	118.36bhp	5	18.2 kmpl	SUV	Agra
21	2020 Maru	â,¹7.85 La	2020	1462 cc	Third Part	Manual	30,000 Km	Second O	Petrol	103.25bhp	5	20.65 kmp	Sedan	Agra
22	2014 Ford	â,¹3 Lakh	2014	1498 cc	Third Part	Manual	1,50,000 K	Third Owr	Diesel	89.84bhp	5	22.7 kmpl	SUV	Agra
23	2011 Mitsu	â,¹3.97 La	2011	2360 cc	Third Part	Automatic	80,000 Km	Second O	Petrol	170PS	5	11.3 kmpl	SUV	Agra
24	2015 Maru	â,¹3.75 La	2015	1248 cc	Third Part	Manual	20,000 Km	First Own	Diesel	74bhp	5	26.59 kmp	Sedan	Agra
25	2011 Maru	â,¹1 Lakh	2011	998 cc	Third Part	Manual	1,20,000 K	Third Owr	Petrol	67.1bhp	5	20.92 kmp	Hatchbacl	Agra
26	2011 Mitsu	â,¹3.97 La	2011	2360 cc	Third Part	Automatic	80,000 Km	Second O	Petrol	170PS	5	11.3 kmpl	SUV	Agra
27	2021 Maru	â,¹6.75 La	2021	1197 cc	Third Part	Manual	40,000 Km	First Own	Petrol	81.80bhp	5	21.01 kmp	Hatchbacl	Agra
28	2018 Hyun	â,¹4.65 La	2018	1197 cc	Third Part	Manual	60,000 Km	Second O	Petrol	81.86bhp	5	20.14 kmp	Sedan	Agra
29	2015 Maru	â,¹4.80 La	2015	1197 cc	Third Part	Manual	80,000 Km	Second O	Petrol	83.14bhp	5	20.85 kmp	Sedan	Agra
30	2014 Maru	â,¹2.25 La	2014	796 cc	Third Part	Manual	1,00,000 K	First Own	Petrol	47.3bhp	5	22.74 kmp	Hatchbacl	Agra
31	2016 Maru	â,¹3.20 La	2016	998 cc	Third Part	Manual	70,000 Km	Second O	Petrol	67.04bhp	5	20.51 kmp	Hatchbacl	Agra
32	2015 Hyun	â,¹4.15 La	2015	1197 cc	Third Part	Manual	30,000 Km	First Own	Petrol	82bhp	5	18.9 kmpl	Hatchbacl	Agra
33	2012 Maru	â,¹2.40 La	2012	1248 cc	Third Part	Manual	1,20,000 K	Third Owr	Diesel	74bhp	5	22.9 kmpl	Hatchbacl	Agra
34	2013 Mahi	â,¹3.50 La	2013	2179 cc	Third Part	Manual	1,00,000 K	Third Owr	Diesel	140bhp	7	15.1 kmpl	SUV	Agra
35	2013 Mahi	â,¹3.50 La	2013	2179 cc	Third Part	Manual	1,00,000 K	Third Owr	Diesel	140bhp	7	15.1 kmpl	SUV	Agra
36	2013 Tata	â,¹2.96 La	2013	2179 cc	Third Part	Manual	90,000 Km	Second O	Diesel	138.1bhp	7	11.57 kmp	SUV	Agra

After Data Cleaning

S.N	Full_Name	Resale_Pric	Price in Numbe	Year of registratio	Engine_Capacit	Insurance	Transmission_Typ	KMs_Drive	KM	Km	Owner_Typ	Fuel_Typ	max_power	Power_valu	Power_Un	Break horse powe	Seats	Mileage Valu
1	Maruti Baleno 1.2 Alpha	₹5.45 Lakh	₹5,45,000	2017	1197 cc	Third Party insurance	Manual	40,000 Kms	40000	Kms	First Owner	Petrol	83.1bhp	83.1	bhp	83.1 BHP	5	21.4
2	Tata Hexa XTA	₹10 Lakh	₹10,00,000	2018	2179 cc	Third Party insurance	Automatic	70,000 Kms	70000	Kms	First Owner	Diesel	153.86bhp	153.86	bhp	153.86 BHP	7	17.6
3	Maruti Swift Dzire VXI	₹4.50 Lakh	₹4,50,000	2015	1197 cc	Third Party insurance	Manual	70,000 Kms	70000	Kms	Second Owner	Petrol	83.14bhp	83.14	bhp	83.14 BHP	5	20.85
4	Maruti Swift Dzire VXI	₹4.50 Lakh	₹4,50,000	2015	1197 cc	Third Party insurance	Manual	70,000 Kms	70000	Kms	Second Owner	Petrol	83.14bhp	83.14	bhp	83.14 BHP	5	20.85
5	Hyundai i10 Magna 1.1	₹1.60 Lakh	₹1,60,000	2009	1086 cc	Third Party insurance	Manual	80,000 Kms	80000	Kms	First Owner	Petrol	68.05bhp	68.05	bhp	68.05 BHP	5	19.81
6	Hyundai i20 Active 1.2	₹4.70 Lakh	₹4,70,000	2015	1197 cc	Third Party insurance	Manual	70,000 Kms	70000	Kms	First Owner	Petrol	81.86bhp	81.86	bhp	81.86 BHP	5	17.19
7	Tata Tiago 1.05 Revotorq XZ	₹3.60 Lakh	₹3,60,000	2017	1047 cc	Third Party insurance	Manual	1,20,000 Kms	120000	Kms	First Owner	Diesel	69bhp	69	bhp	69 BHP	5	27.28
8	Hyundai i10 Magna 1.1	₹2 Lakh	₹2,00,000	2010	1086 cc	Third Party insurance	Manual	60,000 Kms	60000	Kms	Second Owner	Petrol	68.05bhp	68.05	bhp	68.05 BHP	5	19.81
9	Maruti Eeco 7 Seater Standard BSIV	₹3.70 Lakh	₹3,70,000	2016	1196 cc	Third Party insurance	Manual	20,000 Kms	20000	Kms	First Owner	Petrol	73bhp	73	bhp	73 BHP	7	15.37
10	Hyundai Santro Xing GL	₹1.20 Lakh	₹1,20,000	2009	1086 cc	Third Party insurance	Manual	30,000 Kms	30000	Kms	First Owner	Petrol	62bhp	62	bhp	62 BHP	5	19.31
11	Honda Amaze E i-Vtech	₹3.30 Lakh	₹3,30,000	2014	1198 cc	Third Party insurance	Manual	70,000 Kms	70000	Kms	First Owner	Petrol	86.7bhp	86.7	bhp	86.7 BHP	5	18
12	Hyundai Xcent 1.2 VTVT SX	₹4.75 Lakh	₹4,75,000	2018	1197 cc	Third Party insurance	Manual	60,000 Kms	60000	Kms	Second Owner	Petrol	81.86bhp	81.86	bhp	81.86 BHP	5	20.14
13	Maruti Ciaz Sigma BSIV	₹6.86 Lakh	₹6,86,000	2020	1462 cc	Third Party insurance	Manual	50,000 Kms	50000	Kms	Third Owner	Petrol	103.25bhp	103.25	bhp	103.25 BHP	5	21.56
14	Hyundai Venue SX Opt Executive Diesel	₹12.50 Lakh	₹12,50,000	2021	1493 cc	Third Party insurance	Manual	60,000 Kms	60000	Kms	First Owner	Diesel	98.6bhp	98.6	bhp	98.6 BHP	5	23.7
15	Hyundai Venue SX Dual Tone Diesel BSIV	₹11 Lakh	₹11,00,000	2021	1396 cc	Third Party insurance	Manual	60,000 Kms	60000	Kms	First Owner	Diesel	89bhp	89	bhp	89 BHP	5	23.7
16	Maruti Alto K10 VXI AGS Optional	₹3.95 Lakh	₹3,95,000	2019	998 cc	Third Party insurance	Automatic	20,000 Kms	20000	Kms	First Owner	Petrol	67.1bhp	67.1	bhp	67.1 BHP	5	23.95
17	Maruti Wagon R LXI CNG	₹3.50 Lakh	₹3,50,000	2016	998 cc	Third Party insurance	Manual	40,000 Kms	40000	Kms	First Owner	CNG	58.16bhp	58.16	bhp	58.16 BHP	5	26.6
18	Toyota Etios VX	₹2.89 Lakh	₹2,89,000	2011	1496 cc	Third Party insurance	Manual	50,000 Kms	50000	Kms	Second Owner	Petrol	88.7bhp	88.7	bhp	88.7 BHP	5	17.6
19	Toyota Corolla Altis Diesel D4DGL	₹2.82 Lakh	₹2,82,000	2011	1364 cc	Third Party insurance	Manual	1,50,000 Kms	150000	Kms	First Owner	Diesel	87.2bhp	87.2	bhp	87.2 BHP	5	21.43
20	Kia Sonet HTX Plus Turbo iMT BSVI	₹10 Lakh	₹10,00,000	2021	998 cc	Third Party insurance	Manual	10,000 Kms	10000	Kms	First Owner	Petrol	118.36bhp	118.36	bhp	118.36 BHP	5	18.2
21	Maruti Ciaz Alpha BSVI	₹7.85 Lakh	₹7,85,000	2020	1462 cc	Third Party insurance	Manual	30,000 Kms	30000	Kms	Second Owner	Petrol	103.25bhp	103.25	bhp	103.25 BHP	5	20.65
22	Ford Ecosport 1.5 DV5 MT Ambiente	₹3 Lakh	₹3,00,000	2014	1498 cc	Third Party insurance	Manual	1,50,000 Kms	150000	Kms	Third Owner	Diesel	89.84bhp	89.84	bhp	89.84 BHP	5	22.7
23	Mitsubishi Outlander 2.4	₹3.97 Lakh	₹3,97,000	2011	2360 cc	Third Party insurance	Automatic	80,000 Kms	80000	Kms	Second Owner	Petrol	170PS	167.67	PS	167.67 BHP	5	11.3
24	Maruti Swift Dzire VDI	₹3.75 Lakh	₹3,75,000	2015	1248 cc	Third Party insurance	Manual	20,000 Kms	20000	Kms	First Owner	Diesel	74bhp	74	bhp	74 BHP	5	26.59
25	Maruti Alto K10 LXI	₹1 Lakh	₹1,00,000	2011	998 cc	Third Party insurance	Manual	1,20,000 Kms	120000	Kms	Third Owner	Petrol	67.1bhp	67.1	bhp	67.1 BHP	5	20.92
26	Mitsubishi Outlander 2.4	₹3.97 Lakh	₹3,97,000	2011	2360 cc	Third Party insurance	Automatic	80,000 Kms	80000	Kms	Second Owner	Petrol	170PS	167.67	PS	167.67 BHP	5	11.3
27	Maruti Baleno Zeta	₹6.75 Lakh	₹6,75,000	2021	1197 cc	Third Party insurance	Manual	40,000 Kms	40000	Kms	First Owner	Petrol	81.80bhp	81.8	bhp	81.8 BHP	5	21.01
28	Hyundai Xcent 1.2 VTVT SX	₹4.65 Lakh	₹4,65,000	2018	1197 cc	Third Party insurance	Manual	60,000 Kms	60000	Kms	Second Owner	Petrol	81.86bhp	81.86	bhp	81.86 BHP	5	20.14
29	Maruti Swift Dzire VXI	₹4.80 Lakh	₹4,80,000	2015	1197 cc	Third Party insurance	Manual	80,000 Kms	80000	Kms	Second Owner	Petrol	83.14bhp	83.14	bhp	83.14 BHP	5	20.85
30	Maruti Alto 800 LXI	₹2.25 Lakh	₹2,25,000	2014	796 cc	Third Party insurance	Manual	1,00,000 Kms	100000	Kms	First Owner	Petrol	47.3bhp	47.3	bhp	47.3 BHP	5	22.74
31	Maruti Wagon R VXI Optional	₹3.20 Lakh	₹3,20,000	2016	998 cc	Third Party insurance	Manual	70,000 Kms	70000	Kms	Second Owner	Petrol	67.04bhp	67.04	bhp	67.04 BHP	5	20.51
32	Hyundai Grand i10 Sportz	₹4.15 Lakh	₹4,15,000	2015	1197 cc	Third Party insurance	Manual	30,000 Kms	30000	Kms	First Owner	Petrol	82bhp	82	bhp	82 BHP	5	18.9
33	Maruti Swift VDI	₹2.40 Lakh	₹2,40,000	2012	1248 cc	Third Party insurance	Manual	1,20,000 Kms	120000	Kms	Third Owner	Diesel	74bhp	74	bhp	74 BHP	5	22.9
34	Mahindra XUV500 W6 2WD	₹3.50 Lakh	₹3,50,000	2013	2179 cc	Third Party insurance	Manual	1,00,000 Kms	100000	Kms	Third Owner	Diesel	140bhp	140	bhp	140 BHP	7	15.1
35	Mahindra XUV500 W6 2WD	₹3.50 Lakh	₹3,50,000	2013	2179 cc	Third Party insurance	Manual	1,00,000 Kms	100000	Kms	Third Owner	Diesel	140bhp	140	bhp	140 BHP	7	15.1
36	Tata New Safari DICOR 2.2 EX 4x2	₹2.96 Lakh	₹2,96,000	2013	2179 cc	Third Party insurance	Manual	90,000 Kms	90000	Kms	Second Owner	Diesel	138.1bhp	138.1	bhp	138.1 BHP	7	11.57
37	Tata New Safari DICOR 2.2 EX 4x2	₹2.96 Lakh	₹2,96,000	2013	2179 cc	Third Party insurance	Manual	90,000 Kms	90000	Kms	Second Owner	Diesel	138.1bhp	138.1	bhp	138.1 BHP	7	11.57
38	Tata Tiago 1.2 Revotron XE	₹3.16 Lakh	₹3,16,000	2018	1199 cc	Third Party insurance	Manual	1,00,000 Kms	100000	Kms	First Owner	Petrol	84bhp	84	bhp	84 BHP	5	23.84
39	Maruti Vitara Brezza ZDi Plus Dual Tone	₹7.50 Lakh	₹7,50,000	2017	1248 cc	Third Party insurance	Manual	1,00,000 Kms	100000	Kms	Second Owner	Diesel	88.5bhp	88.5	bhp	88.5 BHP	5	24.3
40	Maruti Ertiga VDI	₹9 Lakh	₹9,00,000	2019	1248 cc	Third Party insurance	Manual	1,20,000 Kms	120000	Kms	First Owner	Diesel	88.50bhp	88.5	bhp	88.5 BHP	7	25.47
41	Maruti Celerio VXI BSVI	₹5.60 Lakh	₹5,60,000	2022	998 cc	Third Party insurance	Manual	10,000 Kms	10000	Kms	First Owner	Petrol	65.71bhp	65.71	bhp	65.71 BHP	5	25.24
42	Maruti Vitara Brezza ZDi Plus	₹8 Lakh	₹8,00,000	2017	1248 cc	Third Party insurance	Manual	1,50,000 Kms	150000	Kms	First Owner	Diesel	88.5bhp	88.5	bhp	88.5 BHP	5	24.3
43	Hyundai Creta 1.4 E Plus	₹9 Lakh	₹9,00,000	2017	1396 cc	Third Party insurance	Manual	1,20,000 Kms	120000	Kms	Second Owner	Diesel	88.7bhp	88.7	bhp	88.7 BHP	5	22.1
44	Maruti Alto 800 LXI	₹2.80 Lakh	₹2,80,000	2019	796 cc	Third Party insurance	Manual	80,000 Kms	80000	Kms	First Owner	Petrol	47.33bhp	47.33	bhp	47.33 BHP	5	22.05
45	Toyota Innova 2.5 E Diesel MS 7-seater	₹5.50 Lakh	₹5,50,000	2013	2494 cc	Third Party insurance	Manual	90,000 Kms	90000	Kms	Second Owner	Diesel	100.6bhp	100.6	bhp	100.6 BHP	7	11.4
46	Toyota Innova 2.5 G (Diesel) 7 Seater BS III	₹2.50 Lakh	₹2,50,000	2009	2494 cc	Third Party insurance	Manual	1,50,000 Kms	150000	Kms	First Owner	Diesel	102	102	False	102 BHP	8	12.8

Data Visualization in Power Bi

1. Price Analysis

- **Bar Chart** - Average resale price by *brand* or *model*.
- **Card** – Average Resale Price
- **Line Chart** - Average Car Resale based on Insurance

2.Mileage Insights

- **Column Chart** - Average mileage grouped by fuel type (Petrol, Diesel, CNG, Electric).
- **Gauge –** Displaying Average Mileage value in Gauge visual

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3. Engine & Power Performance

- **Multi Row Card** - Average BHP
- **KPI Card** - Display average horsepower Based on Body Type

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4. Kms Driven & Registration

- **Gauge** - Displaying Average Kilometres driven in Gauge visual
- **Map** – Created Map visual to display Registration place of cars
- **Multi Row Card** – To check Average Registration Year.

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5. Ownership & Insurance

- **Pie Chart** - Car distribution based on Owner Type
- **Line chart -** Sale Based on insurance type

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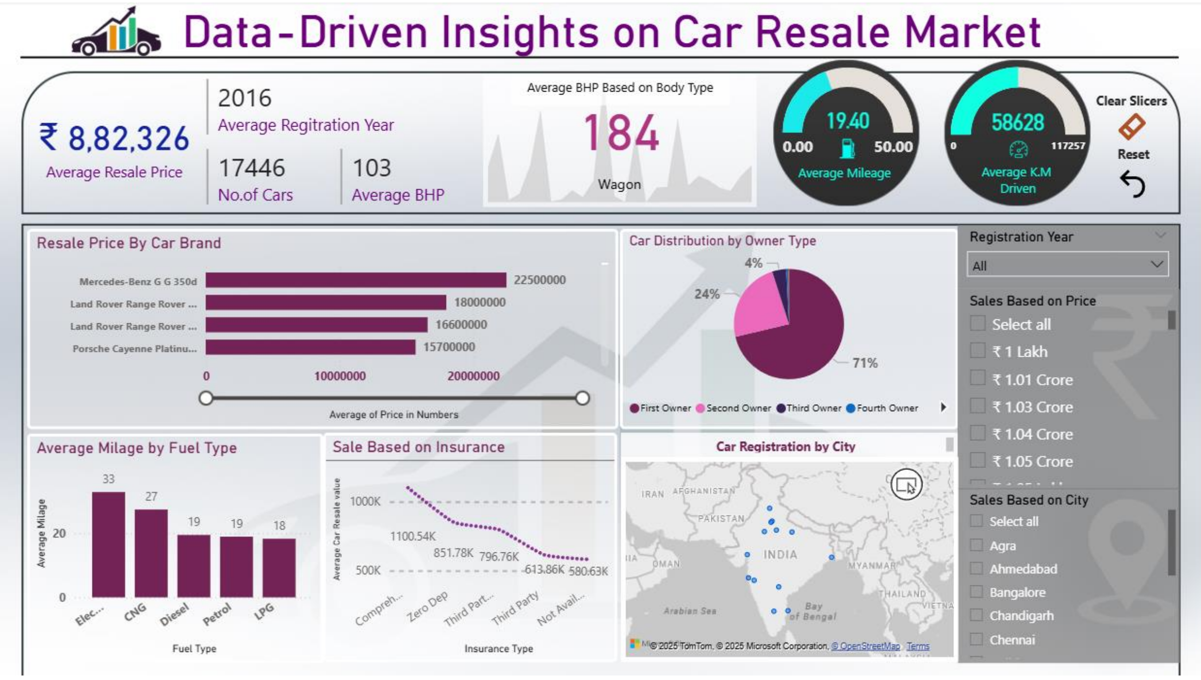
6. Dashboard Ideas

- **Slicer/Filter Panels** - Selling price, City and Registration year
- **Cards/KPIs** - No. of Cars available to resale, and Average BHP, Average resale price
- **Geographical Map** – Added based on city
- **Clear & Reset** – Clear and reset button for better user access

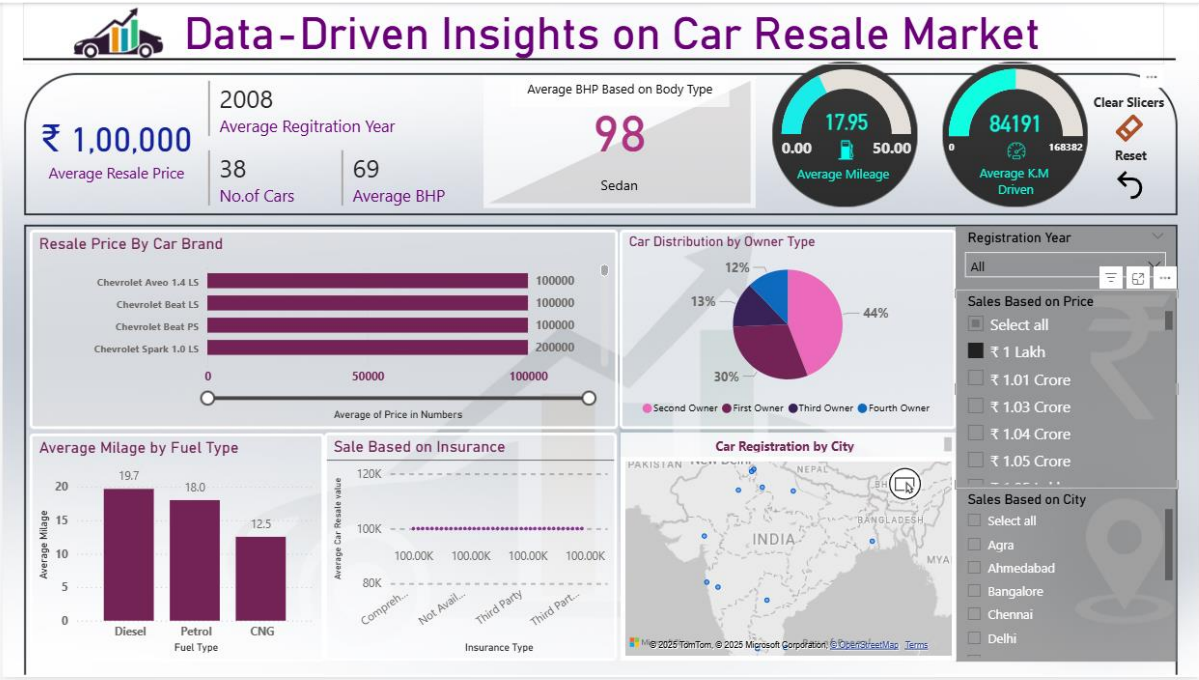
Dashboard Desktop View

(Click here to view)

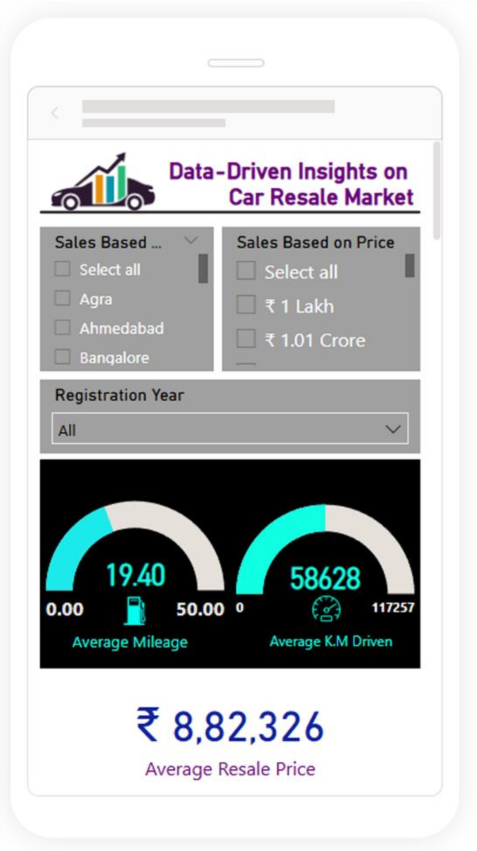
1.Normal overview



2.Filter based on 1 lakh using slicer



Dashboard Mobile View



Conclusion

In summary, the systematic data cleaning and visualization of the car resale dataset transformed raw, inconsistent information into a reliable analytical resource. By addressing missing values, standardizing measurement units, and applying structured visualization techniques in Power BI, the dataset now provides clear, actionable insights into the factors that influence resale value. This documentation not only ensures transparency in the cleaning and analysis process but also establishes a solid foundation for further research, predictive modelling, and data-driven decision-making in the Car resale market.