Bonda Naveen Kumar

UBER REQUEST DATA ANALYSIS

Let's start with the Excel part, where I focused on initial data cleaning and dashboard creation.

- Data Cleaning in Excel

After loading the raw dataset into Excel, I began by:

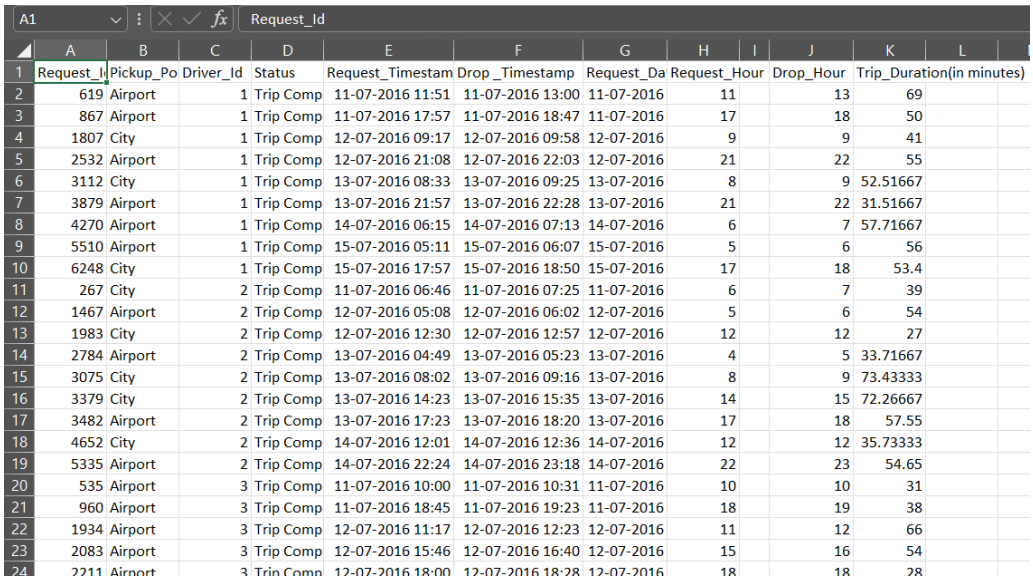
-Converting timestamps in the Request timestamp and Drop timestamp columns to proper datetime formats using Excel's "Format Cells" and "Text to Columns" features.

-I ensured that missing values in Drop timestamp and Driver id were flagged and interpreted correctly — marking these as incomplete trips.

-I extracted new columns such as "Request Hour" and "Request Date" using Excel's built-in formulas like =HOUR() and =TEXT() for temporal analysis.

-I created a new column called Trip Completed using an IF formula to differentiate completed vs. uncompleted trips.

These transformations helped structure the raw data into a more analyzable format.



A1 | Request_Id

	A	B	C	D	E	F	G	H	I	J	K	L
1	Request_I	Pickup_Po	Driver_Id	Status	Request_Timestam	Drop _Timestamp	Request_Da	Request_Hour		Drop_Hour	Trip_Duration(in minutes)	
2	619	Airport	1	Trip Comp	11-07-2016 11:51	11-07-2016 13:00	11-07-2016	11		13	69	
3	867	Airport	1	Trip Comp	11-07-2016 17:57	11-07-2016 18:47	11-07-2016	17		18	50	
4	1807	City	1	Trip Comp	12-07-2016 09:17	12-07-2016 09:58	12-07-2016	9		9	41	
5	2532	Airport	1	Trip Comp	12-07-2016 21:08	12-07-2016 22:03	12-07-2016	21		22	55	
6	3112	City	1	Trip Comp	13-07-2016 08:33	13-07-2016 09:25	13-07-2016	8		9	52.51667	
7	3879	Airport	1	Trip Comp	13-07-2016 21:57	13-07-2016 22:28	13-07-2016	21		22	31.51667	
8	4270	Airport	1	Trip Comp	14-07-2016 06:15	14-07-2016 07:13	14-07-2016	6		7	57.71667	
9	5510	Airport	1	Trip Comp	15-07-2016 05:11	15-07-2016 06:07	15-07-2016	5		6	56	
10	6248	City	1	Trip Comp	15-07-2016 17:57	15-07-2016 18:50	15-07-2016	17		18	53.4	
11	267	City	2	Trip Comp	11-07-2016 06:46	11-07-2016 07:25	11-07-2016	6		7	39	
12	1467	Airport	2	Trip Comp	12-07-2016 05:08	12-07-2016 06:02	12-07-2016	5		6	54	
13	1983	City	2	Trip Comp	12-07-2016 12:30	12-07-2016 12:57	12-07-2016	12		12	27	
14	2784	Airport	2	Trip Comp	13-07-2016 04:49	13-07-2016 05:23	13-07-2016	4		5	33.71667	
15	3075	City	2	Trip Comp	13-07-2016 08:02	13-07-2016 09:16	13-07-2016	8		9	73.43333	
16	3379	City	2	Trip Comp	13-07-2016 14:23	13-07-2016 15:35	13-07-2016	14		15	72.26667	
17	3482	Airport	2	Trip Comp	13-07-2016 17:23	13-07-2016 18:20	13-07-2016	17		18	57.55	
18	4652	City	2	Trip Comp	14-07-2016 12:01	14-07-2016 12:36	14-07-2016	12		12	35.73333	
19	5335	Airport	2	Trip Comp	14-07-2016 22:24	14-07-2016 23:18	14-07-2016	22		23	54.65	
20	535	Airport	3	Trip Comp	11-07-2016 10:00	11-07-2016 10:31	11-07-2016	10		10	31	
21	960	Airport	3	Trip Comp	11-07-2016 18:45	11-07-2016 19:23	11-07-2016	18		19	38	
22	1934	Airport	3	Trip Comp	12-07-2016 11:17	12-07-2016 12:23	12-07-2016	11		12	66	
23	2083	Airport	3	Trip Comp	12-07-2016 15:46	12-07-2016 16:40	12-07-2016	15		16	54	
24	2211	Airport	3	Trip Comp	12-07-2016 18:00	12-07-2016 18:28	12-07-2016	18		18	28	

- Dashboard in Excel

I then built an interactive Excel dashboard using:

-Pivot Tables to summarize data like the number of requests by status, by hour, and by pickup location.

-I added Pivot Charts such as stacked bar charts, line plots, and donut charts to visualize:

- Trip status over time
- Cancellations by hour
- Pickup point distribution

Pivot Tables:

Row Labels	Sum of Request_Id
Cancelled	3949069
No Cars Available	9501514
Trip Completed	9378847
Grand Total	**22829430**

Sum of Request_Id	Column Labels			
Row Labels	**Cancelled**	**No Cars Available**	**Trip Completed**	**Grand Total**
Airport	651439	6219812	4317499	11188750
City	3297630	3281702	5061348	11640680
Grand Total	**3949069**	**9501514**	**9378847**	**22829430**

Sum of Request_Id	Column Labels			
Row Labels	**Cancelled**	**No Cars Available**	**Trip Completed**	**Grand Total**
11-07-2016	123431	399927	411670	935028
12-07-2016	440062	1085497	1123108	2648667
13-07-2016	857662	1698258	1931431	4487351
14-07-2016	1129011	2746118	2492299	6367428
15-07-2016	1398903	3571714	3420339	8390956
Grand Total	**3949069**	**9501514**	**9378847**	**22829430**

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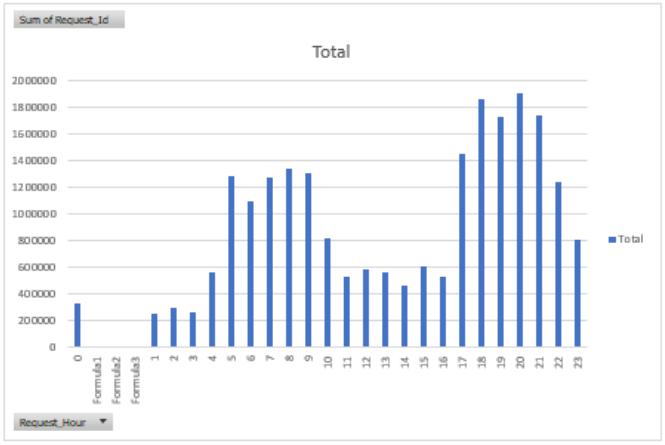
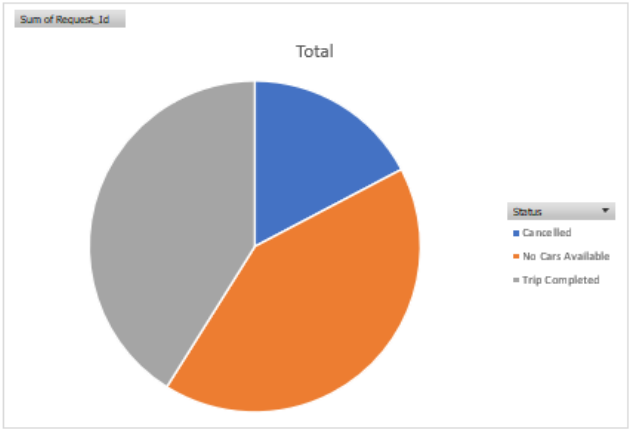
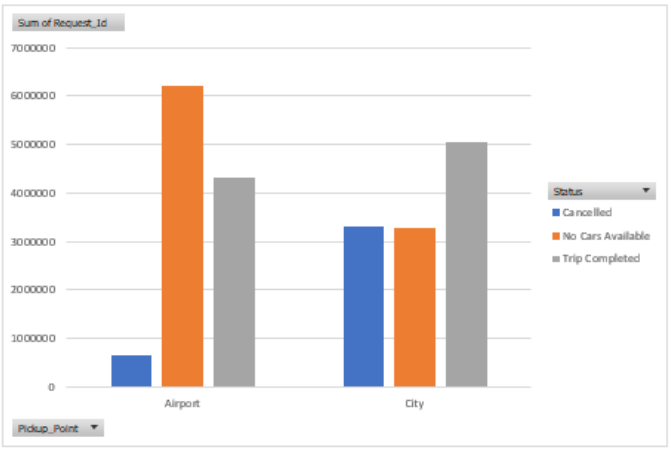
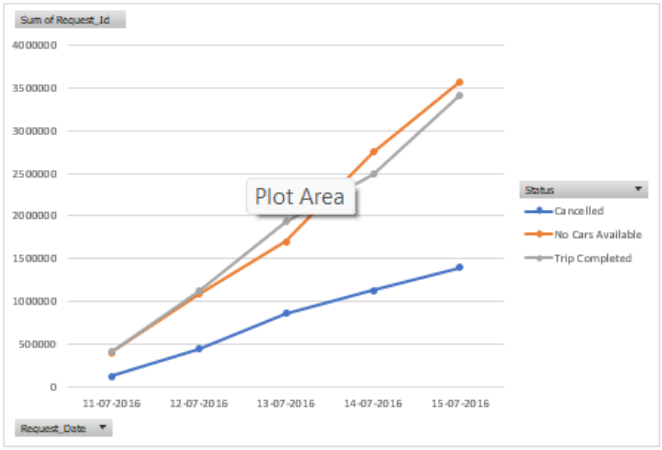
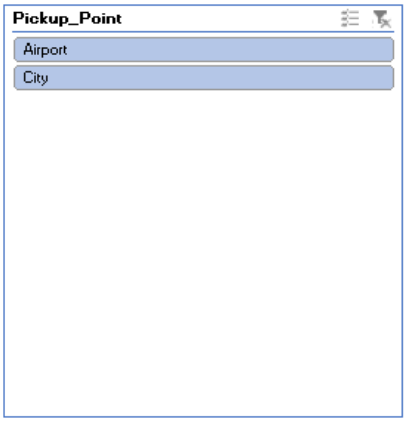


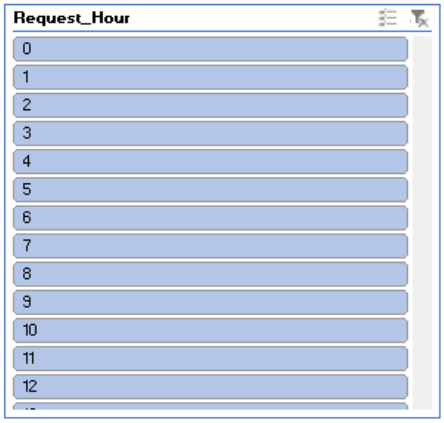






To make it dynamic, I used slicers and filters that allow the user to change the view by pickup point or hour of day.





This dashboard gives a quick, visual overview of when and where service issues occur, helping decision-makers act faster.

SQL Analysis in DB Browser :

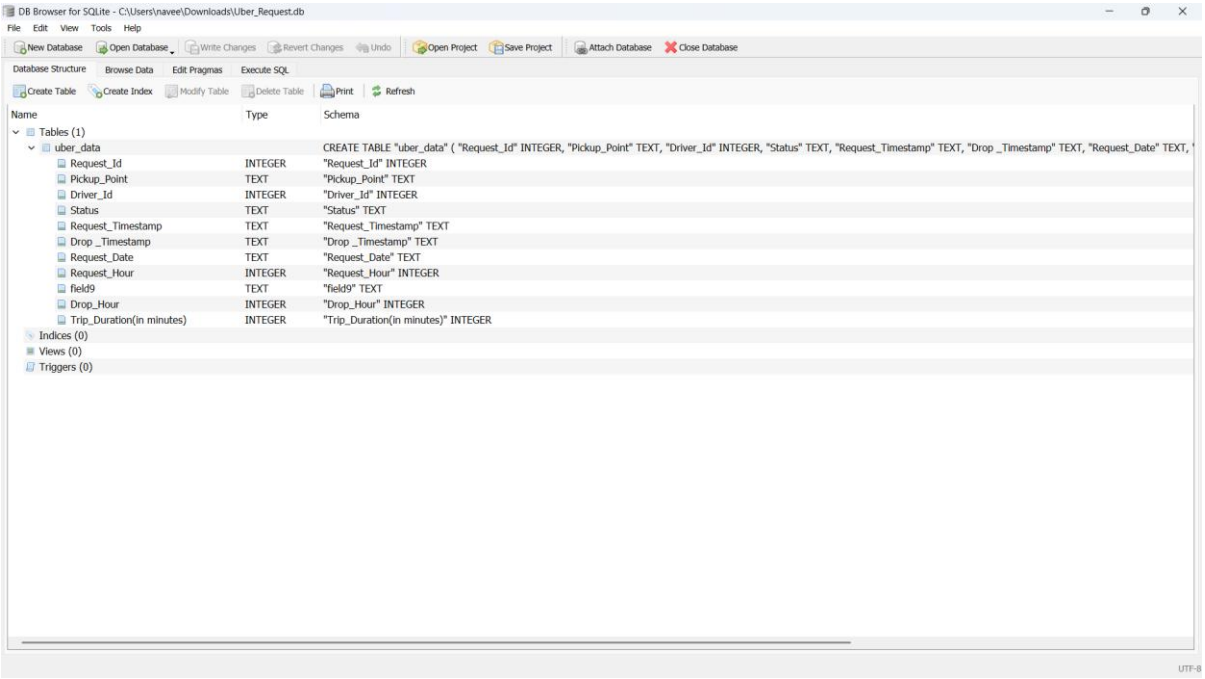
Moving on to the SQL part, I imported the cleaned data into SQLite using DB Browser and wrote queries to extract business insights.

- Data Preparation

I loaded the dataset into two tables:

-uber_requests: Containing core trip data

-driver_info: For linking driver details



- Key SQL Queries and Insights

Here are some examples of the queries and what I found:

```
SELECT
  COUNT(CASE WHEN Status = 'Trip Completed' THEN 1 END) * 1.0 / COUNT(*) * 100 AS completion_rate_percent
FROM uber_data;
```

completion_rate_percent
41.9718309859155

```sql
SELECT "Request_Hour", COUNT(*) AS total_requests
FROM uber_data
GROUP BY "Request_Hour"
ORDER BY "Request_Hour";
```

	Request_Hour	total_requests
18	17	418
19	18	510
20	19	473
21	20	492
22	21	449
23	22	304
24	23	194

```sql
SELECT
  "Pickup_Point",
  COUNT(*) AS total_requests,
  SUM(CASE WHEN Status = 'Cancelled' THEN 1 ELSE 0 END) AS cancelled_requests,
  ROUND(SUM(CASE WHEN Status = 'Cancelled' THEN 1.0 ELSE 0 END) * 100.0 / COUNT(*), 2) AS cancellation_rate_percent
FROM uber_data
GROUP BY "Pickup_Point";
```

	Pickup_Point	total_requests	cancelled_requests	cancellation_rate_percent
1	Airport	3238	198	6.11
2	City	3507	1066	30.4

```sql
SELECT
  "Request_Hour",
  SUM(CASE WHEN Status = 'Trip Completed' THEN 1 ELSE 0 END) AS completed,
  SUM(CASE WHEN Status = 'Cancelled' THEN 1 ELSE 0 END) AS cancelled,
  SUM(CASE WHEN Status = 'No Cars Available' THEN 1 ELSE 0 END) AS no_car,
  COUNT(*) AS total_requests
FROM uber_data
GROUP BY "Request_Hour"
ORDER BY "Request_Hour";
```

	Request_Hour	completed	cancelled	no_car	total_requests
6	5	185	176	84	445
7	6	167	145	86	398
8	7	174	169	63	406
9	8	155	178	90	423
10	9	173	175	83	431
11	10	116	62	65	243
12	11	115	15	41	171

```sql
SELECT
  "Pickup_Point",
  "Request_Hour",
  COUNT(*) AS cancelled_requests
FROM uber_data
WHERE Status = 'Cancelled'
GROUP BY "Pickup_Point", "Request_Hour"
ORDER BY cancelled_requests DESC
LIMIT 10;
```

	Pickup_Point	Request_Hour	cancelled_requests
1	City	8	176
2	City	5	172
3	City	9	167
4	City	7	164
5	City	6	141
6	City	10	53
7	City	4	49

```sql
SELECT
  "Pickup_Point",
  SUM(CASE WHEN Status = 'Trip Completed' THEN 1 ELSE 0 END) AS completed,
  SUM(CASE WHEN Status = 'Cancelled' THEN 1 ELSE 0 END) AS cancelled,
  SUM(CASE WHEN Status = 'No Cars Available' THEN 1 ELSE 0 END) AS no_car
FROM uber_data
GROUP BY "Pickup_Point";
```

	Pickup_Point	completed	cancelled	no_car
1	Airport	1327	198	1713
2	City	1504	1066	937

```sql
SELECT
  CASE
    WHEN "Trip_Duration(in minutes)" <= 10 THEN '0-10 min'
    WHEN "Trip_Duration(in minutes)" <= 20 THEN '11-20 min'
    WHEN "Trip_Duration(in minutes)" <= 30 THEN '21-30 min'
    ELSE '30+ min'
  END AS duration_bucket,
  COUNT(*) AS trip_count
FROM uber_data
WHERE Status = 'Trip Completed'
GROUP BY duration_bucket
ORDER BY trip_count DESC;
```

	duration_bucket	trip_count
1	30+ min	2713
2	21-30 min	118

The SQL queries helped validate the patterns I would later visualize in Python.

Exploratory Data Analysis in Python :

Finally, I conducted a full Exploratory Data Analysis (EDA) in Python using Pandas, Seaborn, and Matplotlib. This is where I followed the UBM rule: Univariate, Bivariate, and Multivariate analysis.

- Data Wrangling

Before analysis, I:

-Converted timestamps

-Created features like Request Hour, Trip Completed, and Trip Duration

-Handled null values and standardized column formats

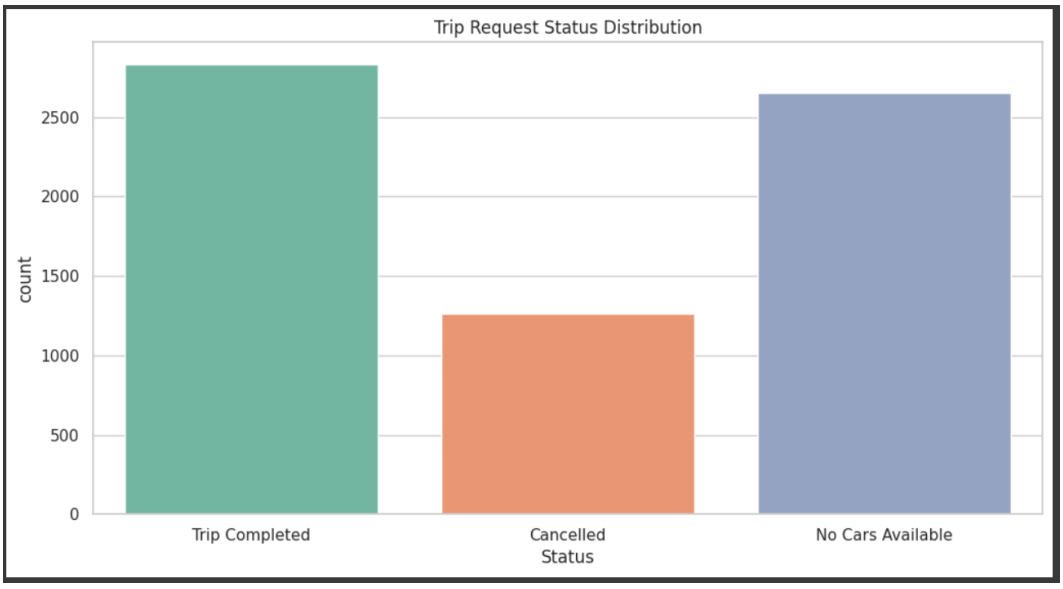
- Univariate Analysis

Here I analyzed individual variables.

-A bar chart of statuses showed that nearly half of all requests were either cancelled or unfulfilled, not completed.

-A histogram of request hours revealed two peak times — morning (5–10 AM) and evening (5–10 PM).

-Trip durations mostly lasted under 60 minutes.



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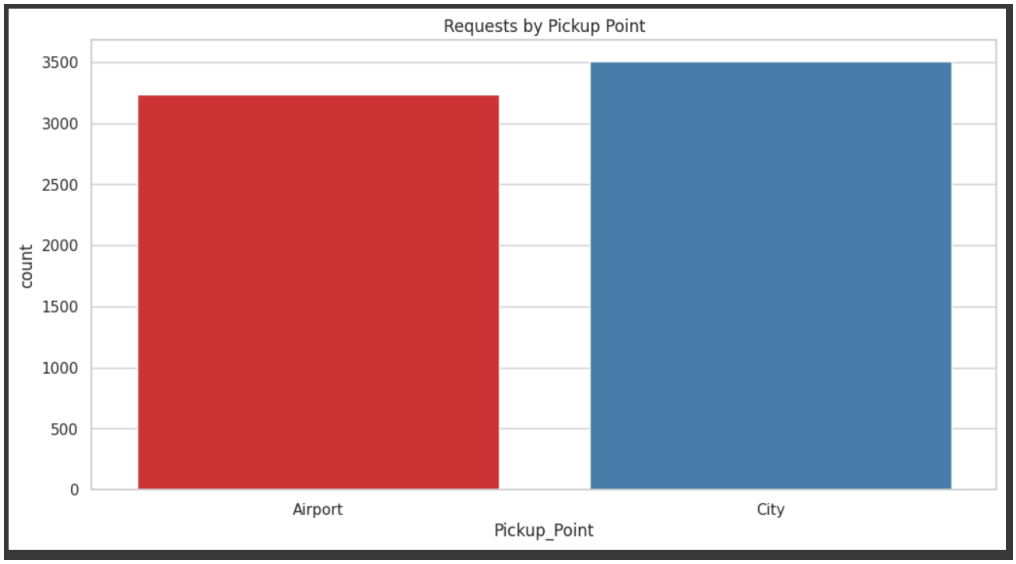
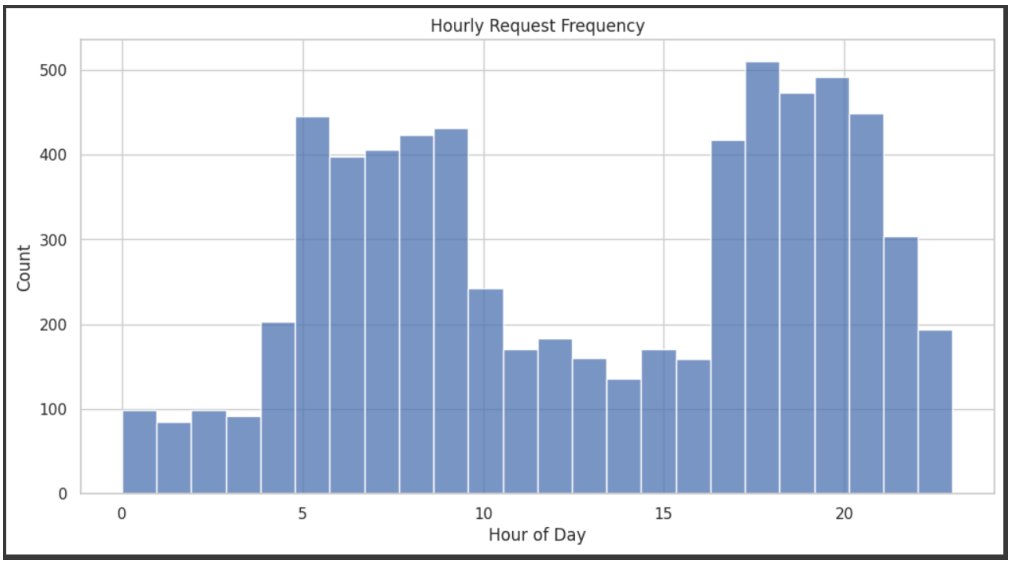
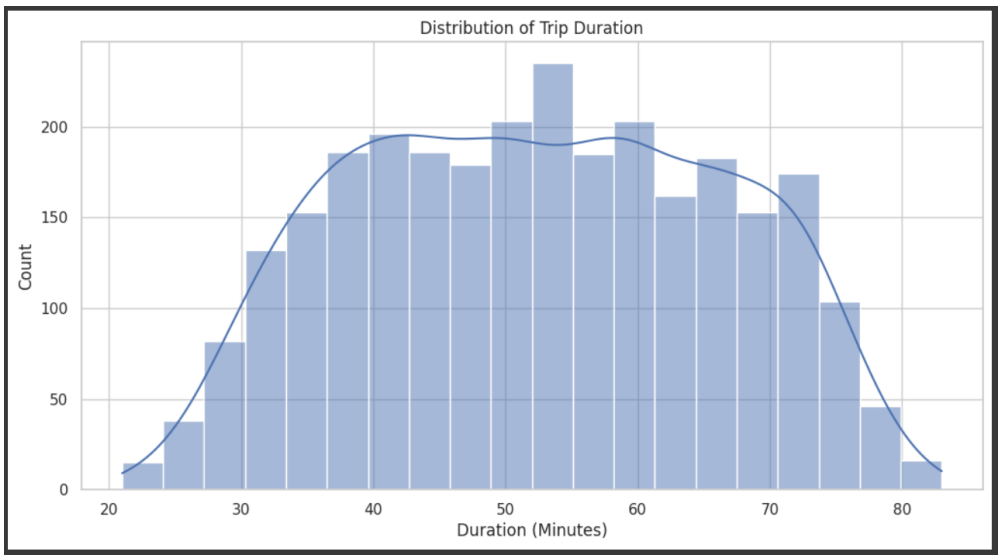
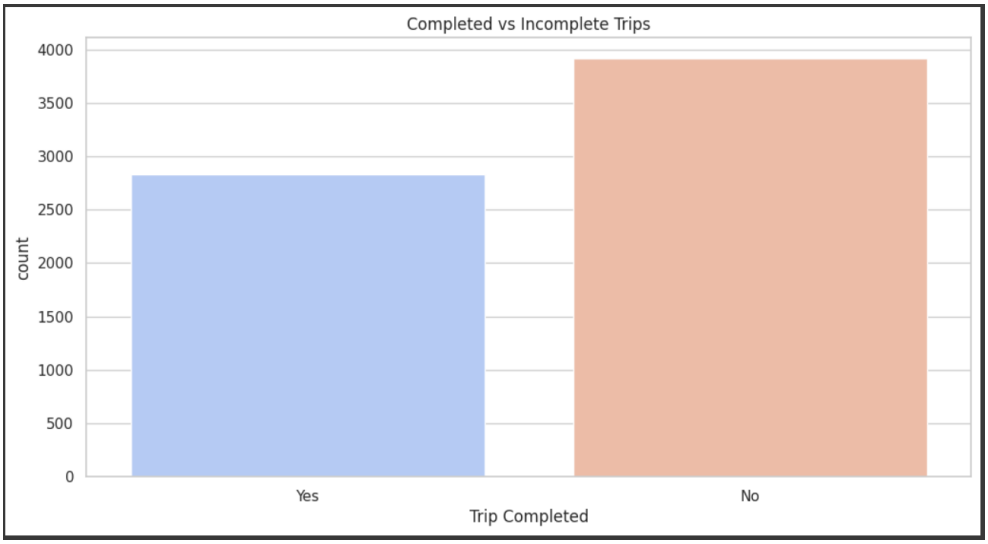








- Bivariate Analysis

This explored relationships between two variables:

-Pickup Point vs. Status showed that:

-City requests are cancelled more

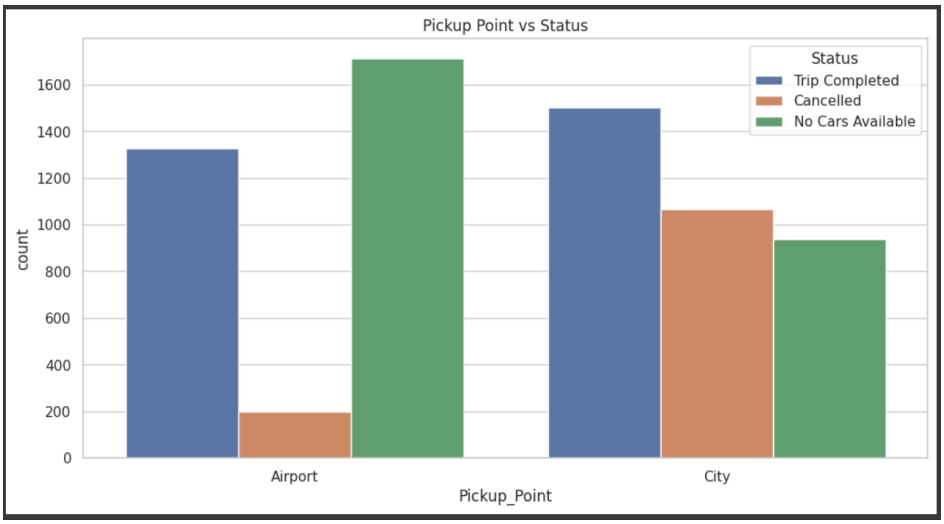
-Airport requests fail due to car unavailability

- A boxplot of Trip Duration by Pickup Point showed Airport trips tend to be longer — possibly discouraging drivers.

A stacked bar chart of status by hour revealed that:

-Cancellations peak in the morning

-No cars are available at night



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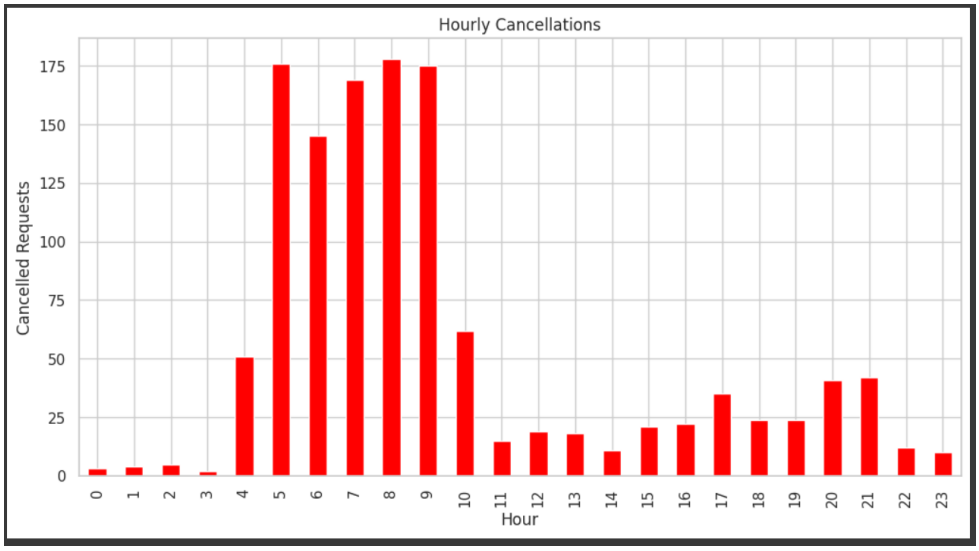
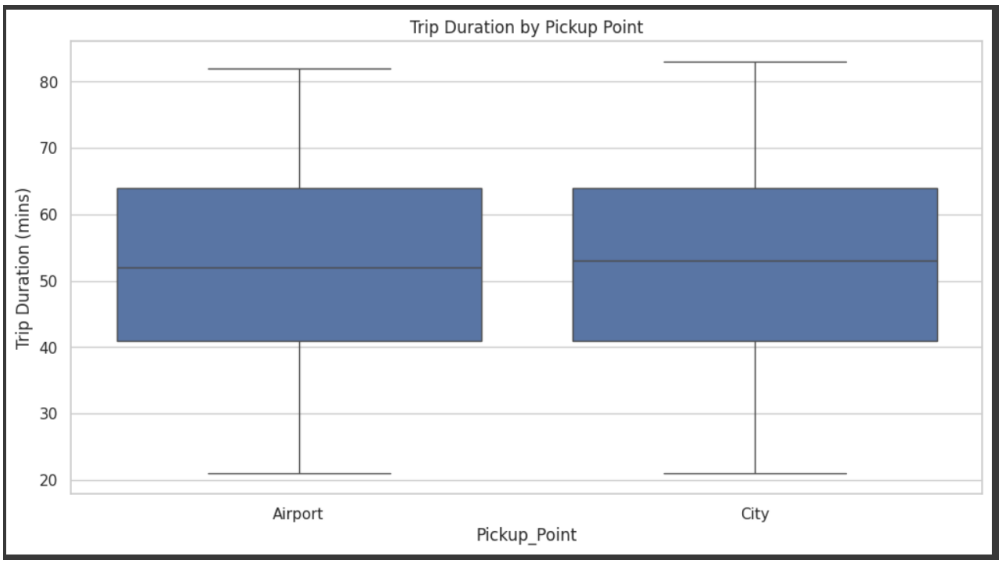
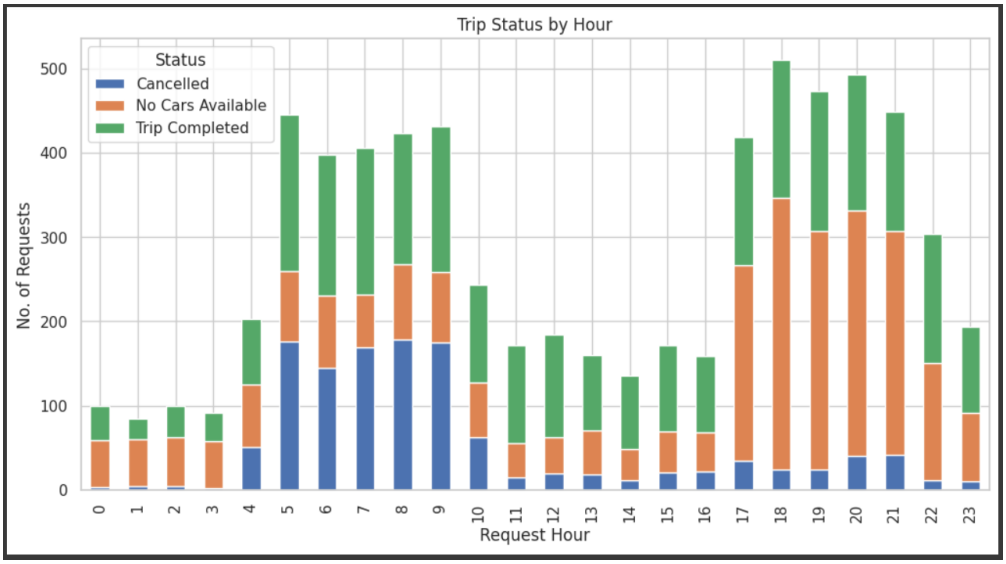
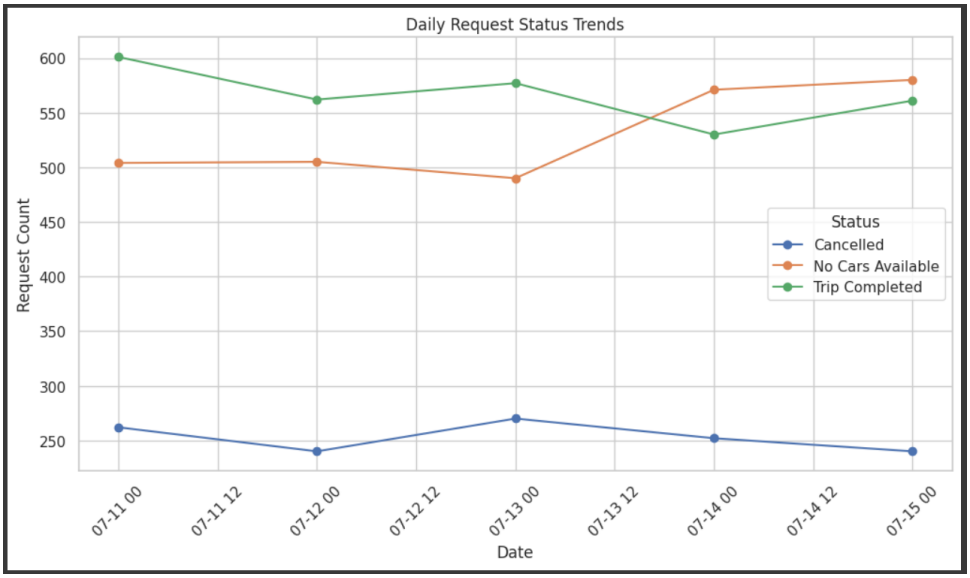








- Multivariate Analysis

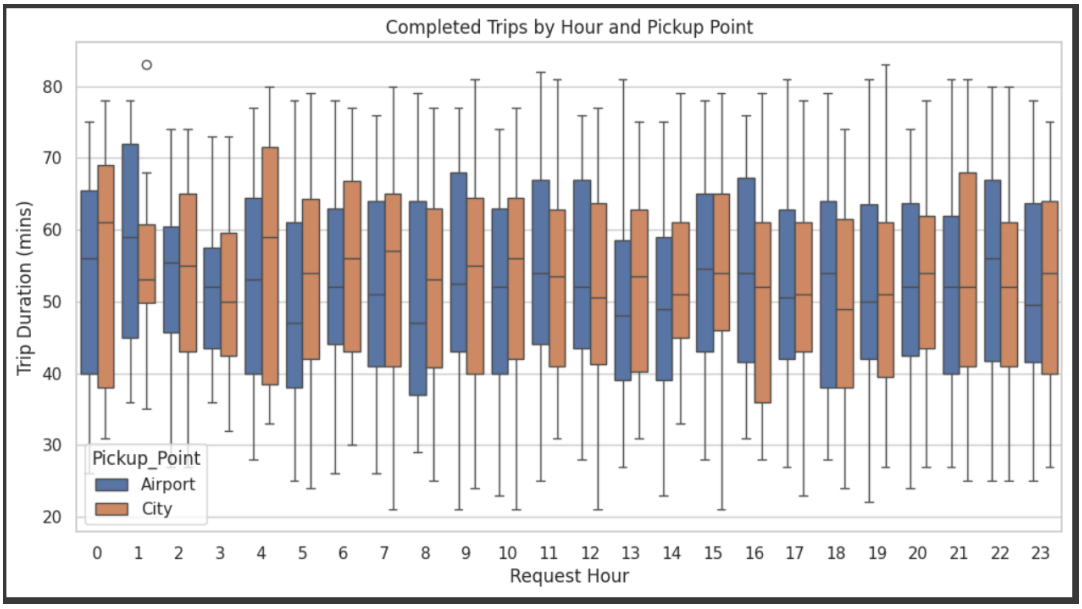
I then analyzed interactions among three or more variables:

A heatmap of cancellations showed:

-Early morning City cancellations and night-time Airport unavailability as hot spots.

-Violin and swarm plots confirmed that longer trips are less preferred.

-A facet grid of statuses by pickup and hour provided a visual drill-down of when and where failures occur.



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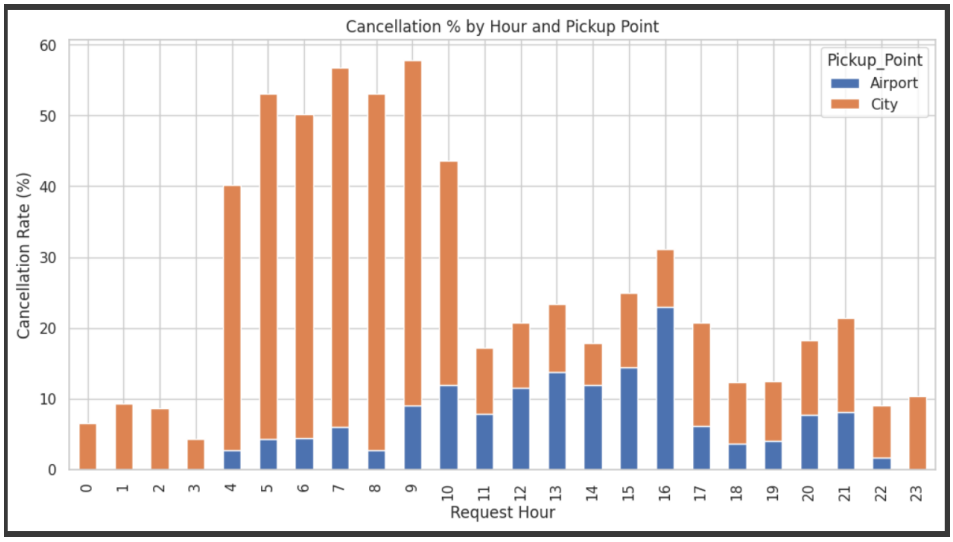

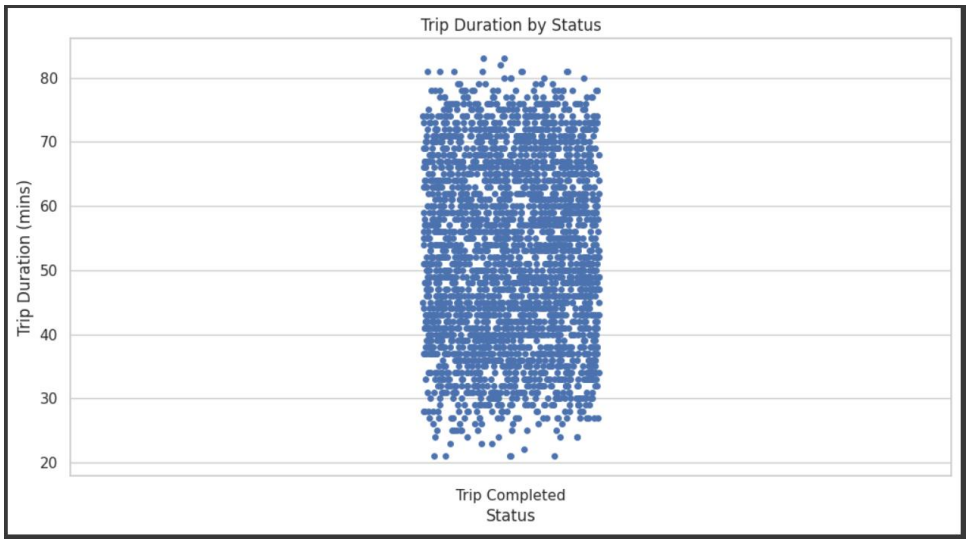

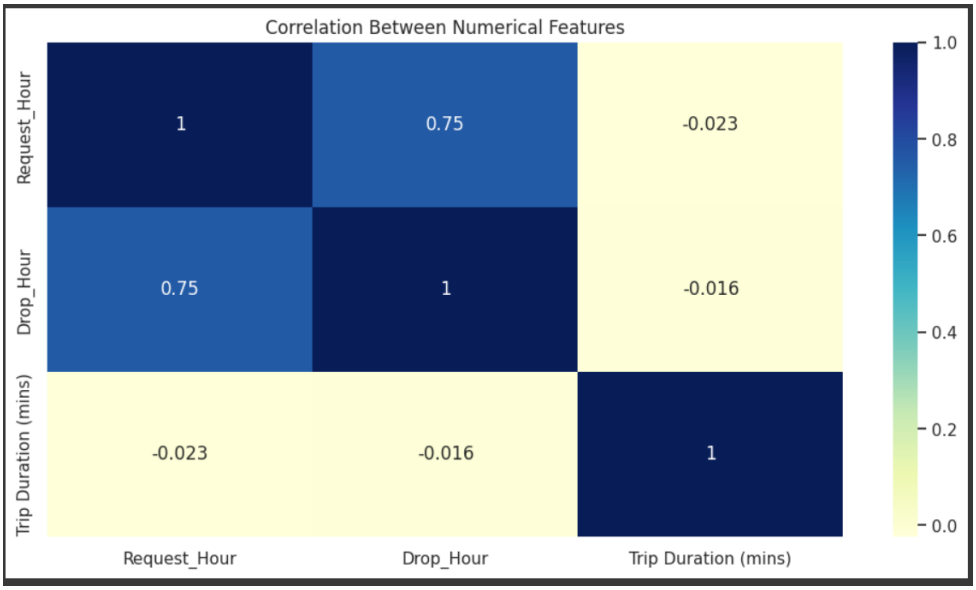

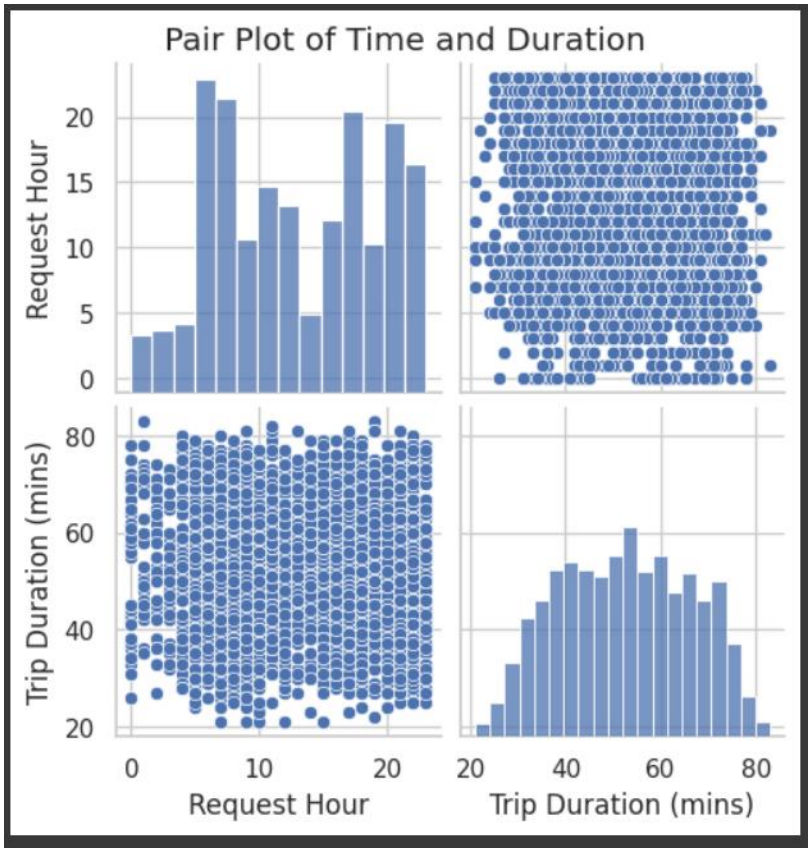

Final Insights & Recommendations :

-City cancellations during morning hours suggest a need for driver incentives in those hours.

-No cars available at Airport at night calls for better night-shift driver scheduling.

-Duration-based driver reluctance could be tackled through trip-based bonus structures.

These insights can help Uber reduce failed requests and improve operational efficiency.

Solution to Business Objective :

- **Optimize Driver Deployment Based on Time and Location Trends**
- **Implement Driver Incentive Programs to Reduce Cancellations**

- **Introduce Predictive Supply Reallocation Algorithms**
- **Enhance User Communication and Transparency**
- **Deploy Operational Heatmaps to Inform Strategy**

Conclusion :

In conclusion, I approached this project in three layers — Excel for quick overviews and dashboards, SQL for deep querying and verification, and Python EDA for in-depth pattern discovery and visualization. Each layer supported the next and helped me derive strong, actionable business recommendations for Uber.