Methodology Report:
Visualisation & Analysis on Namma Yatri Data

Include your visualisations, analysis, results, insights, and outcomes.

Explain your methodology and approach to the tasks. Add your conclusions to the sections.

Table 1: Data Description

Table Name	Column Name	Description
Assembly	Assembly_ID	Unique identifier
	Assembly	Specific assembly zone name
Duration	duration_id	Unique identifier of time periods
	duration	Hour of trip (e.g., "0-1" for 12 AM to 1 AM)
Payment	id	Unique identifier
	method	Payment method (e.g., Cash, UPI, Credit Card)
Trip Details	tripid	Unique identifier of trips
	loc_from	Source Location code
	searches	Trip request count
	searches_got_estimate	Got an estimated price (1 = user gets an estimate, 0 = does not get an estimate)
	searches_for_quotes	Searched for drivers after estimate (1 - searched, 0 - not searched)
	searches_got_quotes	Got quotes (1 = Driver allotted, 0 = not allotted)
	customer_not_cancelled	Whether customer cancelled or not (1 = Not cancelled)
	driver_not_cancelled	Whether driver cancelled or not (1 = Not cancelled)
	otp_entered	(1 = OTP entered, 0 = not entered)
	end_ride	Whether ride was completed (1 = Completed)
Trips	tripid	Links to Trip Details
	faremethod	Payment method ID, links to Payment table
	fare	Fare amount
	loc_from	Location ID of source
	loc_to	Location ID of destination, links to Assembly table
	driverid	Driver ID
	custid	Customer ID
	distance	Distance in KM from source to destination
	duration	Unique identifier of time periods like duration_id

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Points to Note:

1. **Without this methodology document, the other parts of your case study will not be evaluated.**
2. This assignment is different from the ones you have solved before. Make sure that you treat this case study as a storytelling exercise and not an analysis/visualisation one. This will help you be better prepared for the presentations.
3. Once you are done with the analysis and visualisations, there will be many insights at your hand.
Make sure that you map the right visuals and takeaways with the right audience since some of these insights might be relevant to one group but not to the other group.
4. **DO NOT** change the text or numbering of any task, as it may cause problems with grading. Write your solutions to a task in the space provided below the respective task.

Tasks to be performed

- Present the overall approach of the analysis.
- Mention the problem statement and the analysis approach briefly.
- To solve a task, you have to create relevant visualisations and derive appropriate insights from the visualisations.
- Add all the plots, insights, calculated field commands, results and outcomes for a task with proper numbering and sequence in the report.
- The scores for all tasks (except conclusions) comprise both analysis work in the visualisation tool and its outcome in the report.
- You will be awarded a score for a task only if the Tableau/PowerBI analysis is correct and is included in the report along with the subsequent insights.
- Finally, draw conclusions based on the analysis.

Scoring:

Report Total Marks: 70

Sections: 3 sections (10 marks + 40 marks + 20 marks)

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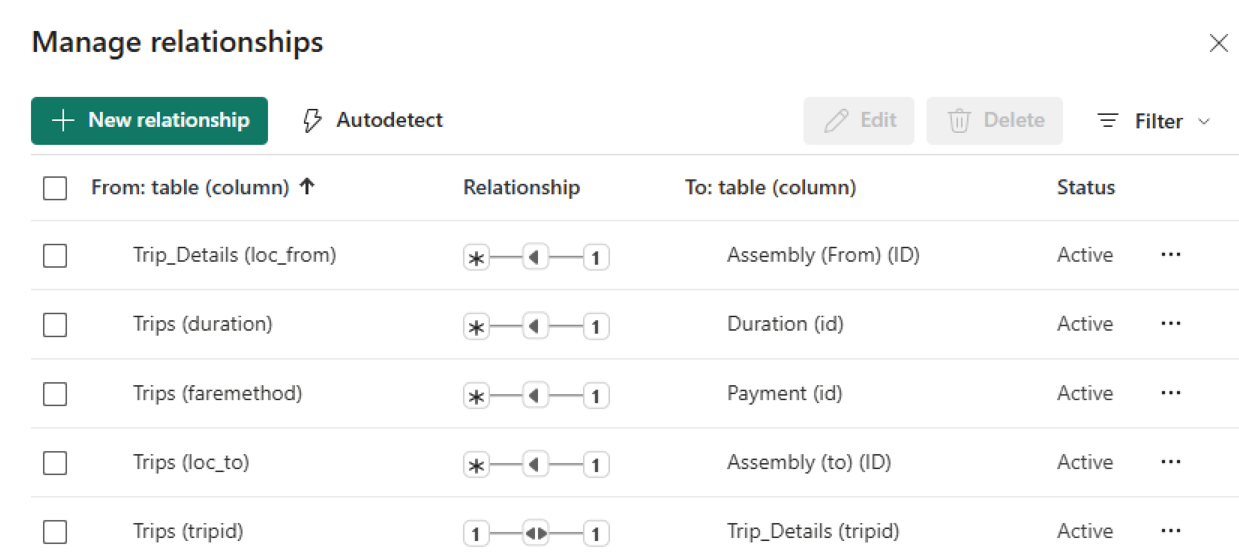
Analysis and Visualisation

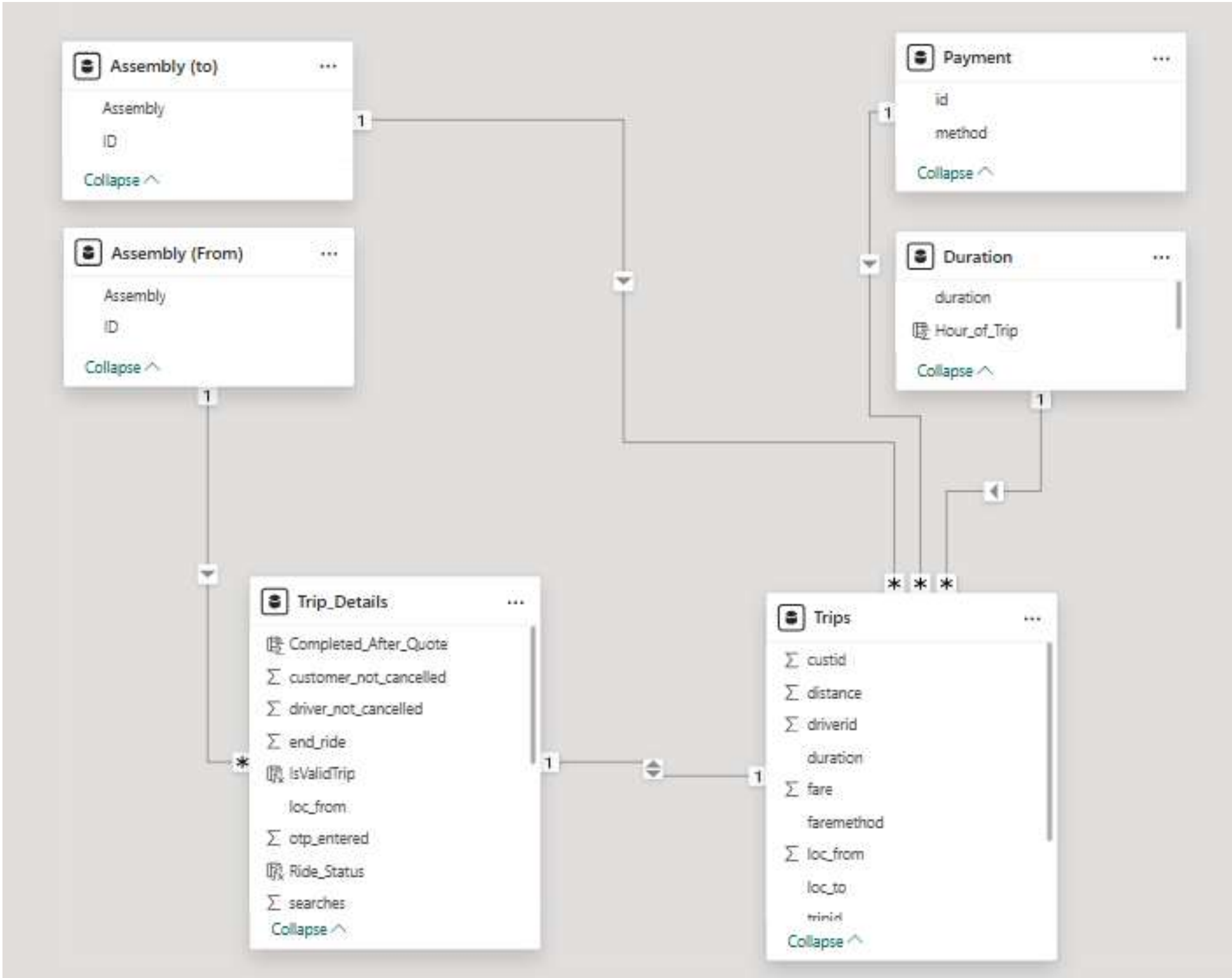
1. Data Preparation [10 Marks]

1.1. Import and Join Tables Correctly [5 Mark]

- Import the Namma Yatri dataset into Tableau/Power BI.
- Ensure that you correctly join all tables to create a unified dataset for analysis.
- Verify the relationships between different tables and confirm that data from various sources is properly aligned for accurate insights.

Solution:





1.2. Find and Resolve Inconsistencies [5 Marks]

- Identify and resolve any inconsistencies or issues in the dataset that might affect the analysis.
- Clean the data to ensure it is structured properly for analysis, removing any irrelevant, duplicate, or erroneous entries.
- While performing the analysis, create calculated fields as needed to ensure the accuracy and relevance of the insights.

Solution:

Upon importing the dataset into Power BI, we verified all relevant tables (Trips, Trip_Details, Payment, Assembly, and Duration) for structural inconsistencies. The following observations and actions were taken:

- No null or missing values were found in key columns such as tripid, fare, distance, end_ride, or any of the categorical flags, indicating clean data.
- No duplicate values were present in primary key columns such as tripid, duration_id, id, or Assembly_ID, confirming referential integrity across joins.
- To support more robust analysis, following calculated columns were created using DAX
    - **IsValidTrip** was created in the Trip_Details table:

```
IsValidTrip =
IF(
    RELATED(Trips[fare]) > 0
    && RELATED(Trips[distance]) > 0
    && Trip_Details[end_ride] = 1,
    "Valid",
    "Invalid"
)
```

    - **successfull_ride** was created in the Trip_Details table :

```
successfull_ride = if([driver_not_cancelled]=1 && [customer_not_cancelled]=1 && [end_ride]=1,1,0)
```

    - **Ride_Status** was created in the Trip_Details table:

```
Ride_Status =
SWITCH(
    TRUE(),
    Trip_Details[end_ride] = 1, "Completed",
    Trip_Details[driver_not_cancelled] = 0, "Driver Cancelled",
    Trip_Details[customer_not_cancelled] = 0, "Customer Cancelled",
    "Unknown"
)
```

    - **Completed_After_Quote** was created in the Trip_Details table:

```
Completed_After_Quote =
IF(Trip_Details[searches_got_quotes] = 1 && Trip_Details[end_ride] = 1, 1, 0)

```

    - **Hour_of_Trip** was created in the Duration table:

```
Hour_of_Trip =
SWITCH(
    TRUE(),
    'Duration'[duration] = "0-1", 1,
    'Duration'[duration] = "1-2", 2,
    'Duration'[duration] = "2-3", 3,
    'Duration'[duration] = "3-4", 4,
    'Duration'[duration] = "4-5", 5,
    'Duration'[duration] = "5-6", 6,
    'Duration'[duration] = "6-7", 7,
    'Duration'[duration] = "7-8", 8,
    'Duration'[duration] = "8-9", 9,
    'Duration'[duration] = "9-10", 10,
    'Duration'[duration] = "10-11", 11,
    'Duration'[duration] = "11-12", 12,
    'Duration'[duration] = "12-13", 13,
    'Duration'[duration] = "13-14", 14,
    'Duration'[duration] = "14-15", 15,
    'Duration'[duration] = "15-16", 16,
    'Duration'[duration] = "16-17", 17,
    'Duration'[duration] = "17-18", 18,
    'Duration'[duration] = "18-19", 19,
    'Duration'[duration] = "19-20", 20,
    'Duration'[duration] = "20-21", 21,
    'Duration'[duration] = "21-22", 22,
    'Duration'[duration] = "22-23", 23,
    'Duration'[duration] = "23-24", 24,
    0
)
```

- And following measures were created using DAX
    - **Cancelled Trip %**

```
Cancelled Trips % =
DIVIDE(
    CALCULATE(COUNT(Trip_Details[tripid]), Trip_Details[end_ride] = 0),
    COUNT(Trip_Details[tripid]),
    0
)

```

    - **Completed Trips**

```
Completed Trips =
CALCULATE(
    COUNT(Trip_Details[tripid]),
    Trip_Details[end_ride] = 1
)
```

- ### Quote to Completion Ratio

```
Quote to Completion Ratio =
DIVIDE(
    SUM(Trip_Details[Completed_After_Quote]),
    SUM(Trip_Details[searches_got_quotes]),
    0
)
```

- ### Total Trips

```
Total Trips = COUNT(Trips[tripid])
```

- ### Revenue

```
revenue = sum(Trips[fare])
```

2. Exploratory Data Analysis [40 Marks]

2.1. Classify Variables into Categorical and Numerical [2 Marks]

- Classify all the variables in the dataset into numerical and categorical types.

Solution:

Categorical Variables:

1. Trip Details
    a. Trip Details[tripid]: Trip Identifier
    b. Trip Details[loc_from]: Source Location Code
    c. Trip Details[searches_got_estimate]: Got Estimate Flag (Binary)
    d. Trip Details[searches_for_quotes]: Searched for Quotes Flag (Binary)
    e. Trip Details[searches_got_quotes]: Got Quotes Flag (Binary)
    f. Trip Details[customer_not_cancelled]: Customer Cancellation Flag (Binary)
    g. Trip Details[driver_not_cancelled]: Driver Cancellation Flag (Binary)
    h. Trip Details[otp_entered]: OTP Entered Flag (Binary)
    i. Trip Details[end_ride]: Ride Completion Flag (Binary)
2. Trips
    a. Trips[tripid]: Trip Identifier (for join)
    b. Trips[faremethod]: Payment Method ID (Foreign Key)
    c. Trips[loc_from]: Source Location ID
    d. Trips[loc_to]: Destination Zone ID (Foreign Key)
    e. Trips[driverid]: Driver Identifier
    f. Trips[custid]: Customer Identifier
3. Duration
    a. Duration[duration_id]: Time Bucket ID
    b. Duration[Hour of trip]: Time Slot Description (e.g., “0-1”)
4. Payment
    a. Payment[id]: Payment Method ID
    b. Payment[method]: Payment Method Name
5. Assembly
    a. Assembly[Assembly_ID]: Zone ID
    b. Assembly[Specific Assembly Zone Name]: Zone Name

Numerical Variables:

1. Trip Details[searches]: Number of Trip Requests
2. Trips[fare]: Fare Amount (₹)

3. Trips[distance]: Trip Distance (km)

2.2. Analyse Ride Demand Over Time [3 Marks]

- Explore the distribution of ride demand over time, including trends across different periods.
- Identify the peak demand periods. Choose an appropriate parameter for demand based on your own understanding.

Solution:

To understand the ride demand trends, we chose Trip Details[searches] as the primary parameter to represent ride demand, since it captures how many times users initiated a ride search — the earliest point in the booking funnel.

We joined **Trip Details** to **Trips** using **tripid**, and further joined **Trips** to **Duration** using **Trips[duration] → Duration[id].** This allowed us to analyze demand by hour buckets (Hour of trip).

Visualisation:

We created a line chart with:

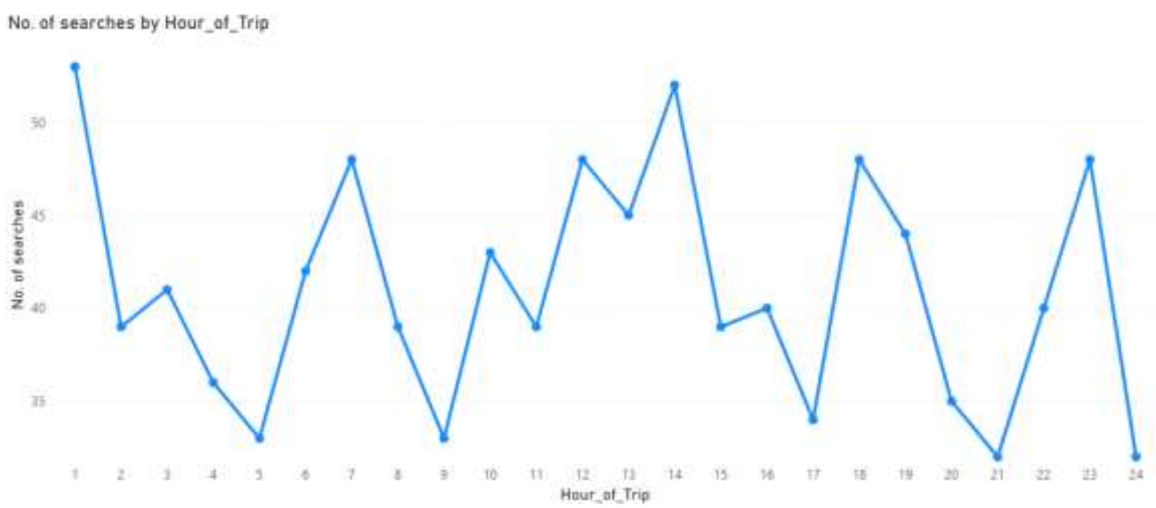
X-axis: Duration[Hour of trip] (sorted chronologically)

Y-axis: SUM(Trip Details[searches])

Only isValidTrips are considered for this visual

Total Demand

983



Key Insights:

- 1 AM sees the highest search activity, indicating strong early-morning demand, possibly from airport or intercity travelers.

- After a dip between 2 AM to 5 AM, demand steadily increases and spikes again at 7 AM, 10 AM, and 2 PM (14th hour).

- A mid-day plateau is observed from 11 AM to 4 PM, followed by a smaller rise during evening hours (6–8 PM).

- Late night hours (10 PM onward) show a sharp decline, confirming that most trips occur during early to mid-day.

Interpretation:

- The platform should prioritize driver availability around 1 AM, 7 AM, 10 AM, and 2 PM where spikes in search activity occur.
- Low demand hours (3 AM – 5 AM and post 10 PM) could be used to schedule driver breaks or vehicle maintenance.
- Targeted incentives could be introduced in rising-demand time slots (early morning, mid-morning, and mid-afternoon).

2.3. Proportion of Total Revenue from Different Time Periods [3 Marks]

- Calculate the proportion of revenue generated during different time periods and visualise how it contributes to total revenue.

Solution:

We analyzed total revenue across each hourly time slot using SUM(Trips[fare]), grouped by Hour_of_Trip from the Duration table. Only valid trips were included (fare > 0, distance > 0, and ride completed).

Visualisation:

Visual Type: Bar chart

X-axis: Hour_of_Trip (1 to 24)

Y-axis: Revenue = SUM(Trips[fare])

Total Revenue: ₹751,000

Key Insights:

The highest revenue is generated at 1 AM, contributing more than ₹45K.

Additional revenue spikes appear at: 7 AM, 13–14 hours (1–2 PM), and 11 PM (23rd hour)

The lowest revenue hours are: 9 AM, 4–5 AM, and 10 PM (22nd hour)

Revenue is relatively evenly distributed between 6 AM and 8 PM, indicating a steady stream of earnings throughout the working day.

Interpretation:

The 1 AM peak suggests high late-night demand, possibly airport drop-offs or long-haul rides.

The afternoon peak (1–2 PM) aligns with post-lunch errands or shift-based workers.

Late evening (10 PM – 12 AM) shows another rise, possibly driven by return trips or nightlife-related travel.

Strategic fleet planning and pricing optimization during these revenue-heavy hours can maximize earnings.

Low-revenue windows (early morning and mid-evening) can be ideal for driver rest, vehicle maintenance, or battery charging (if EV-based).

2.4. Explore the Relationship Between Trip Hour and Revenue [3 Marks]

- Investigate the correlation between trip hour and total fare.
- Explain any trends or patterns that emerge.

Solution:

We analyzed the average fare per trip by hour to identify time slots where individual rides generate the most value. This metric helps distinguish high-volume from high-margin periods.

Visualisation:

Chart Type: Column chart

X-axis: Hour_of_Trip (1–24)

Y-axis: Average of Trips[fare]

Total Average Revenue per Trip: ₹764.34

Key Insights:

Peak fare hours include: 1 AM, 7 AM, 1 PM (13), 5 PM (17), and 8 PM (20) — all exceeding ₹800/trip

Lowest average fares appear during: 9 AM, 6 PM, and 10–11 PM, falling closer to ₹650–700/trip

Revenue per trip is relatively stable across most hours, with slight spikes during late night and afternoon periods.

Interpretation:

Late-night (1 AM) and afternoon-to-evening slots (13–20 hours) are likely driven by longer or more premium rides, possibly due to airport transfers, intercity bookings, or fewer shared trips.

Early commute hours (6–9 AM) show average or below-average fares, suggesting short-distance, high-frequency trips with lower ticket sizes.

These insights support dynamic pricing and driver engagement strategies — e.g., offer incentives or surge pricing during high-value hours to maximize margin.

This layer of analysis goes beyond ride volume and gives a profitability view per trip, which is critical for margin-based decision making.

2.5. Examine the Popularity of Different Payment Methods [3 Marks]

- Analyse the distribution of various payment methods used by customers.
- Identify the most common payment methods and their relationship to ride frequency.

Solution:

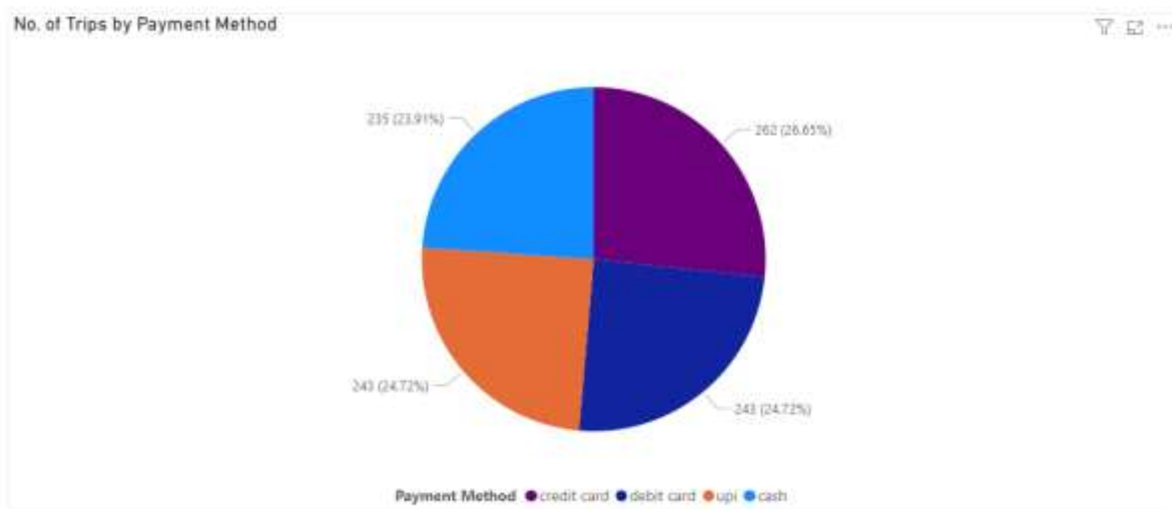
We analyzed how users paid for rides by joining the Trips table with the Payment table on faremethod = id. The final metric used was the count of completed trips per payment method.

Visualisation:

Chart Type: Pie Chart

Categories: Payment[method]

Values: COUNT(Trips[tripid])



Key Insights:

The most frequently used method is credit card, accounting for 26.65% of total trips.

UPI and debit card are tied at 24.72% each, showing strong digital adoption.

Cash is close behind at 23.91%, indicating a segment of users still prefers physical payments.

Interpretation:

The usage distribution across payment methods is fairly balanced, with no single method dominating.

The high share of cashless payments (~76%) reflects a digitally mature customer base, suitable for automated settlement processes and fast onboarding.

A mild preference for credit cards could point to urban professionals or users leveraging loyalty points or EMI options.

Namma Yatri can:

Offer UPI-based incentives to reduce reliance on cash.

Optimize the backend to handle digital volume efficiently (e.g., surge pricing + instant wallet refunds).

Encourage customers to save preferred payment methods for faster checkouts.

2.6. Identify High-Performing Zones [6 Marks]

Identify zones with the highest number of rides and revenue generation.
Analyse factors contributing to their performance:

- **2.6.1. Rides:** Identify pickup zones with the highest number of trip requests.
[3 marks]

Solution:

We analyzed ride demand by pickup zone using the searches field from the Trip Details table and joined it with Assembly to get zone names. We also introduced a derived flag IsValidTrip based on conditions (fare > 0, distance > 0, ride completed) to distinguish between successful and failed ride attempts.

Visualisation:

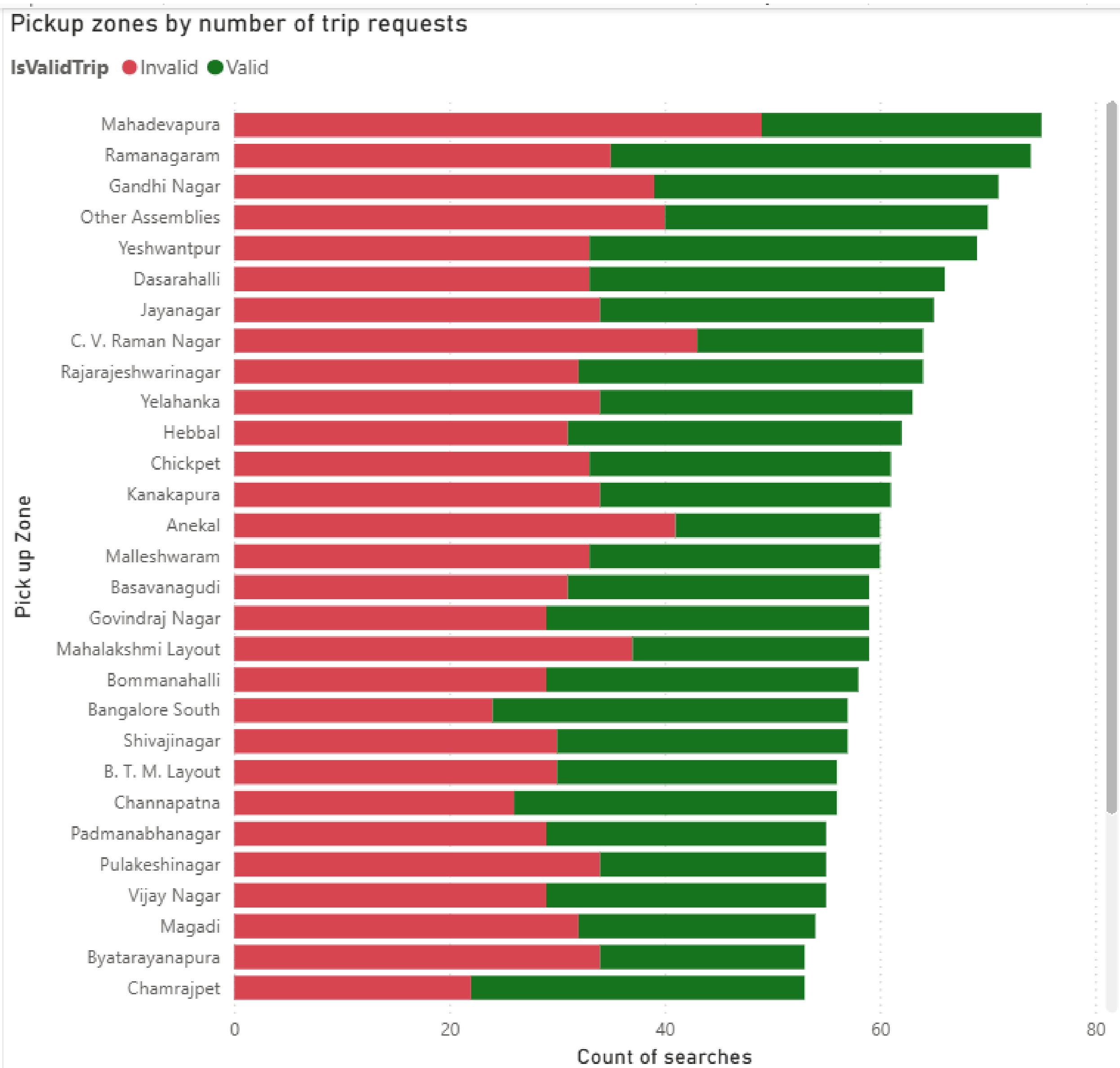
Chart Type: Stacked horizontal bar chart

X-axis: Count of searches

Y-axis: Assembly[Specific Assembly Zone Name]

Legend: IsValidTrip (Green = Valid, Red = Invalid)

Sort: Descending by total searches



Key Insights:

The top 5 zones by total demand are:

1. Mahadevapura
2. Ramanagaram
3. Gandhi Nagar
4. Other Assemblies
5. Yeshwantpur

However, a significant portion of requests from top zones like Mahadevapura and Yeshwantpur are invalid, indicating high cancellation or failure rates.

Zones like Malleswaram, Basavanagudi, and Rajarajeshwarinagar show a higher proportion of valid trips, making them more reliable pickup areas.

Interpretation:

While Mahadevapura has the most searches, its high invalid trip ratio could signal issues like driver unavailability, price mismatch, or app drop-offs.

Namma Yatri should: Investigate reasons for failure in high-demand but low-conversion zones.

Consider targeted driver allocation, retry prompts, or price flexibility in zones like Mahadevapura and Dasarahalli.

Focus growth and promotion strategies in zones like Malleswaram and Hebbal that already convert well.

This nuanced view of demand and fulfillment helps balance opportunity vs. service reliability.

- **2.6.2. Revenue**: Identify pickup zones generating the highest revenue. **[3 marks]**

Solution:

We evaluated the total revenue generated from trips originating in each zone, using SUM(Trips[fare]) grouped by Trips[loc_from], which was linked to zone names via the Assembly table.

Only valid trips were considered (fare > 0, distance > 0, and ride completed), to ensure the revenue reflects completed services.

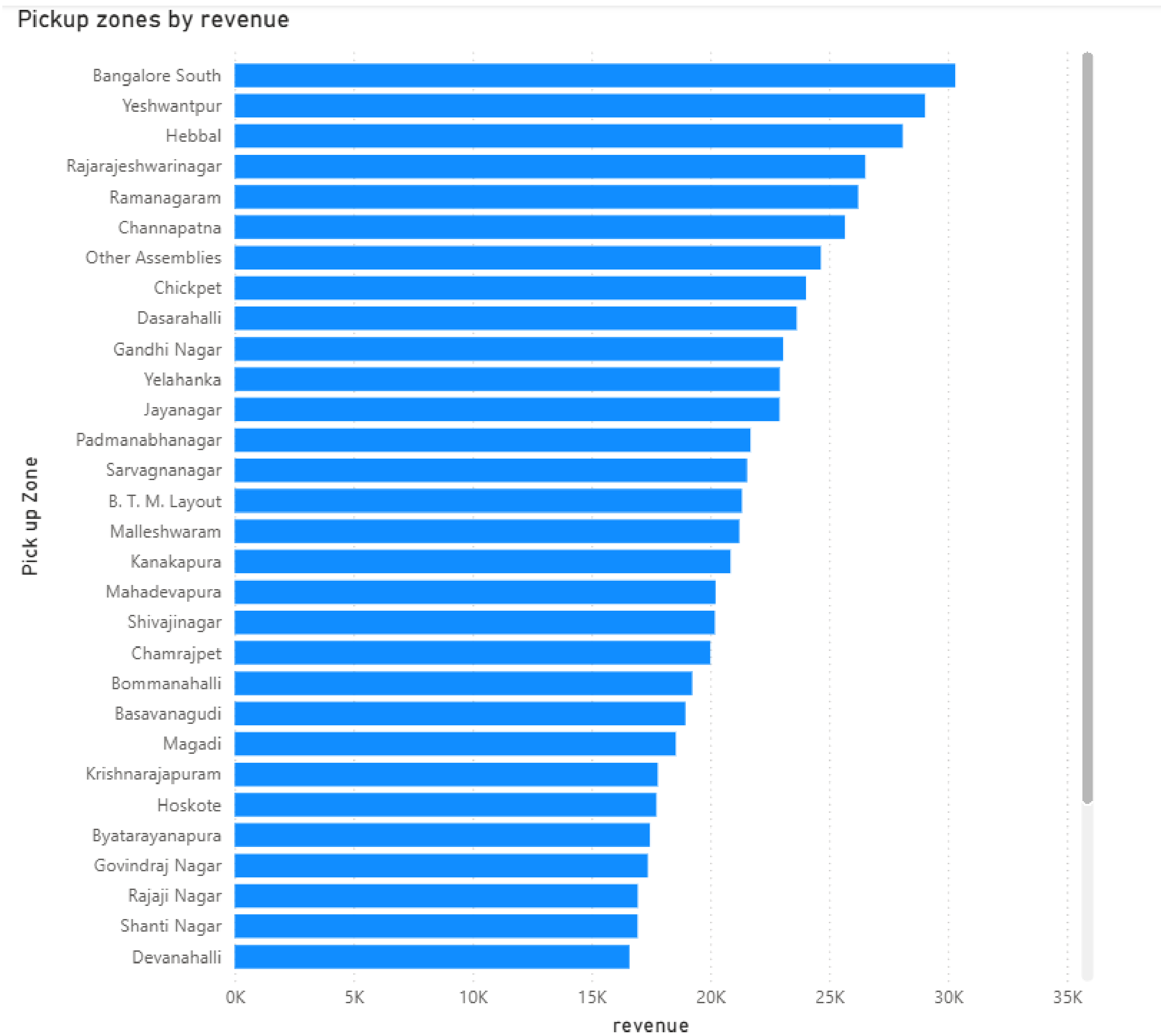
Visualisation:

Chart Type: Horizontal bar chart

X-axis: SUM(Trips[fare])

Y-axis: Assembly[Specific Assembly Zone Name]

Sort: Descending by revenue



Key Insights:

The top 5 revenue-generating pickup zones are:

1. Bangalore South
2. Yeshwantpur
3. Hebbal
4. Rajarajeshwarinagar
5. Ramanagaram

Bangalore South clearly leads with over ₹33,000 in revenue, followed closely by Yeshwantpur and Hebbal.

Interestingly, Mahadevapura, which had the highest number of searches, ranks much lower in revenue — indicating a high invalid trip ratio or short low-fare trips.

Interpretation:

Zones like Bangalore South, Hebbal, and Rajarajeshwarinagar offer a strong balance between demand and trip value, making them ideal for:

Surge pricing strategies

Driver prioritization

Premium service offerings (e.g., larger vehicles, EVs)

Zones with high demand but low revenue (e.g., Mahadevapura) may require investigation — are trips cancelled? too short? poorly monetized?

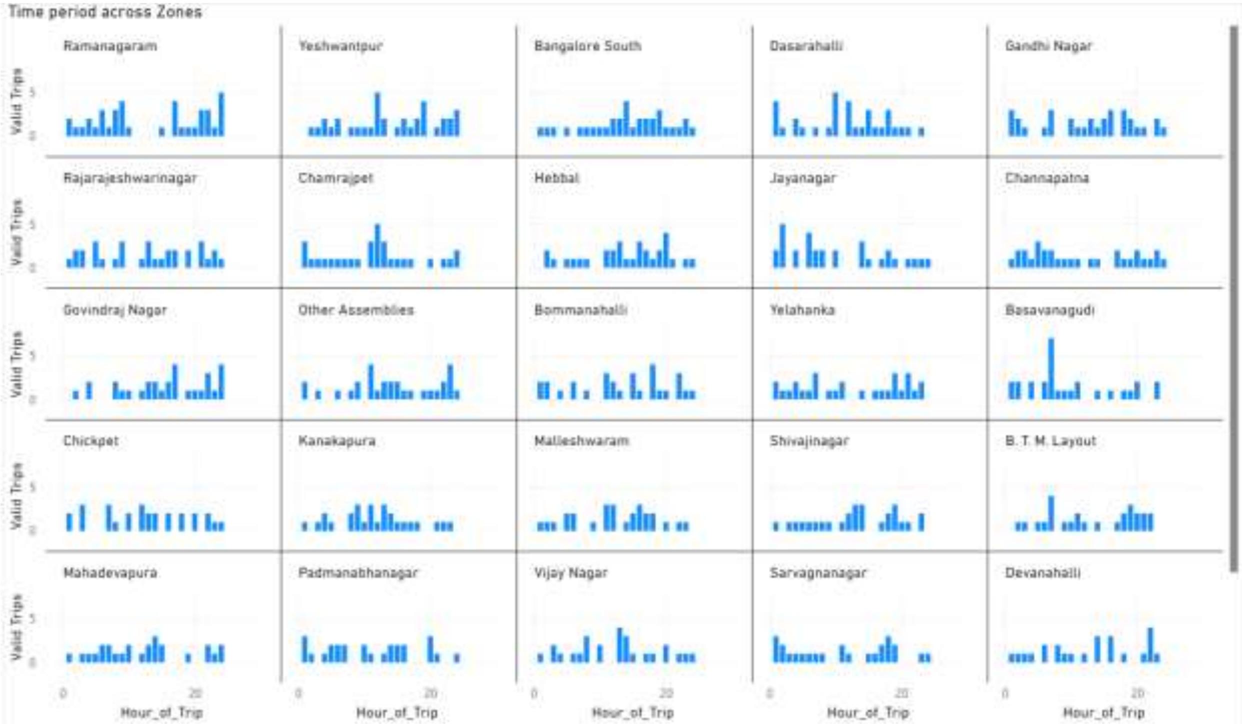
This view enables Namma Yatri to optimize revenue per driver-hour and zone-level profitability, not just volume.

2.7. Analyse Ride Time Periods Across Zones [4 Marks]

- Compare the trip trends for different time periods across pickup zones.

Solution:

We used a small multiples chart to analyze how ride activity varies across time in different pickup zones. Each subplot represents a zone and shows the count of trips across the 24-hour day (Hour_of_Trip).



Only valid trips were considered to reflect actual completed rides.

Key Insights:

Ramanagaram, Dasarahalli, and Gandhi Nagar show relatively consistent demand from early morning (6 AM) to late evening (10 PM).

Hebbal, Jayanagar, and Yeshwantpur exhibit pronounced morning and evening peaks, aligned with typical commuter behavior.

Zones like Devanahalli, Sarvagnanagar, and Magadi show sporadic usage, often concentrated in off-peak or edge-hour slots — possibly indicating long-distance or airport-bound travel.

Basavanagudi has a sharp, isolated spike around 8–10 AM, suggesting concentrated local demand.

Interpretation:

These time-sensitive patterns help Namma Yatri:

Optimize driver shift scheduling per zone (e.g., late starts in Devanahalli, early starts in Yeshwantpur).

Predict rider availability and waiting time risks per zone-hour.

Plan in-app incentives (e.g., early bird discounts or surge boosts) in specific time-zone blocks.

2.8. Top Zones with Highest Trip Volume [3 Marks]

- Identify the top 5 pickup zones with the highest total number of completed trips.
- Analyse factors contributing to the higher number of trips.

Solution:

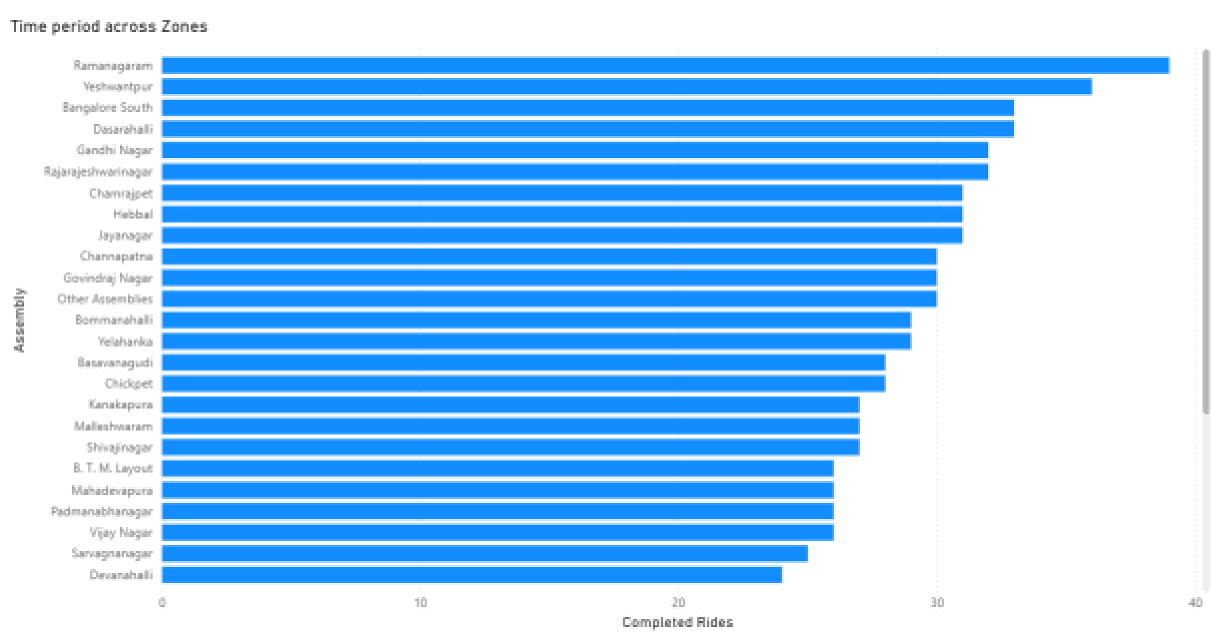
We analyzed which pickup zones generated the highest number of completed rides, using Ride Status = Completed to count only successful trips. The pickup location (loc_from) was linked to Assembly for readable zone names.

Visualisation:

Chart Type: Horizontal bar chart

X-axis: Count of completed trips

Y-axis: Pickup Zone (Assembly Name)



Key Insights:

The top 5 zones by completed ride volume are:

1. Ramanagaram
2. Yeshwantpur
3. Bangalore South
4. Dasarahalli
5. Gandhi Nagar

These zones show strong end-to-end ride fulfillment, indicating a healthy balance of demand and driver availability.

Ramanagaram, despite being slightly peripheral, tops the chart, possibly due to intercity or airport runs that get completed more often.

Interpretation:

These high-volume zones are ideal for:

Reinforcing operational support — e.g., preferred pickup locations, driver hubs

Service-level monitoring — since they likely influence CSAT and ETA metrics

Testing new features or pricing pilots, as consistent traffic helps in early feedback

This view helps Namma Yatri prioritize volume-driven growth zones and ensure service continuity in high-use areas.

2.9. Basic Analytical Tasks [8 Marks]

- **2.9.1**
  What are the percentages of cancellations and successful rides by both driver and customer? **[3 marks]**

Solution:

Solution:

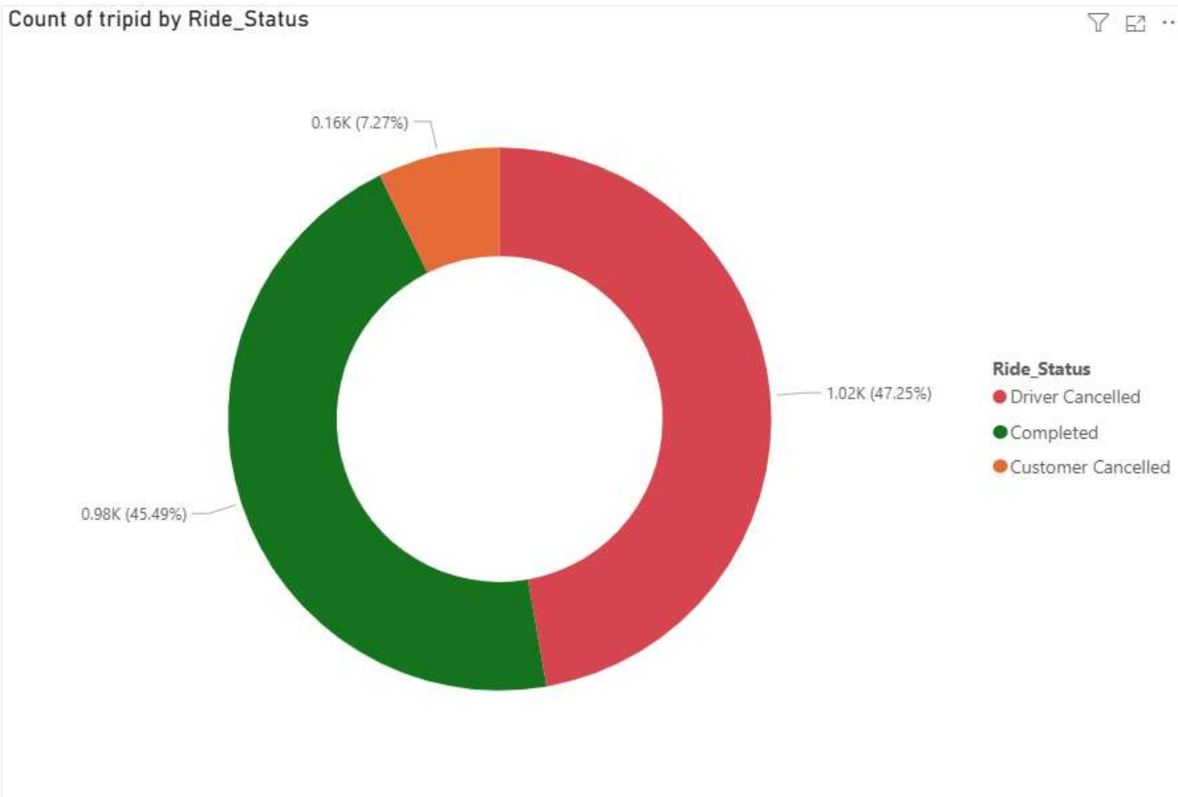
We classified all trips based on their final status using Trip Details[end_ride], driver_not_cancelled, and customer_not_cancelled. The breakdown was visualized using a donut chart.

Visualisation:

Chart Type: Donut chart

Measure: Count of TripID

Grouped by: Derived field Ride_Status using logic:



Ride Status Distribution:

Ride Status	Count	Percentage
Driver Cancelled	1.02K	47.25%
Completed	0.98K	45.49%
Customer Cancelled	0.16K	7.27%

Interpretation:

A high 47.25% of rides are cancelled by drivers, indicating major supply-side frictions (availability, distance mismatch, low incentives).

Only 45.49% of trips are successfully completed, which is significantly below an acceptable fulfillment benchmark for ride platforms (>70%).

Customer cancellations are relatively low (7.27%), possibly due to high friction in driver allocation or quote delays.

To improve completion:

Namma Yatri should optimize driver-rider matching logic,

Provide real-time ride tracking or fallback options, and

Explore incentive plans or penalties to reduce driver drop-offs.

- **2.9.2**
  Analyse the percentage of people who completed trips after searching for quotes. Visualise the variation of this ratio by time periods. **[5 marks]**

Solution:

We analyzed the conversion from quote received (searches_got_quotes = 1) to ride completion (end_ride = 1) and segmented outcomes by time (Hour_of_Trip) and Ride_Status. This helped identify how quote-to-completion behavior varies across the day — and revealed structural drop-offs.

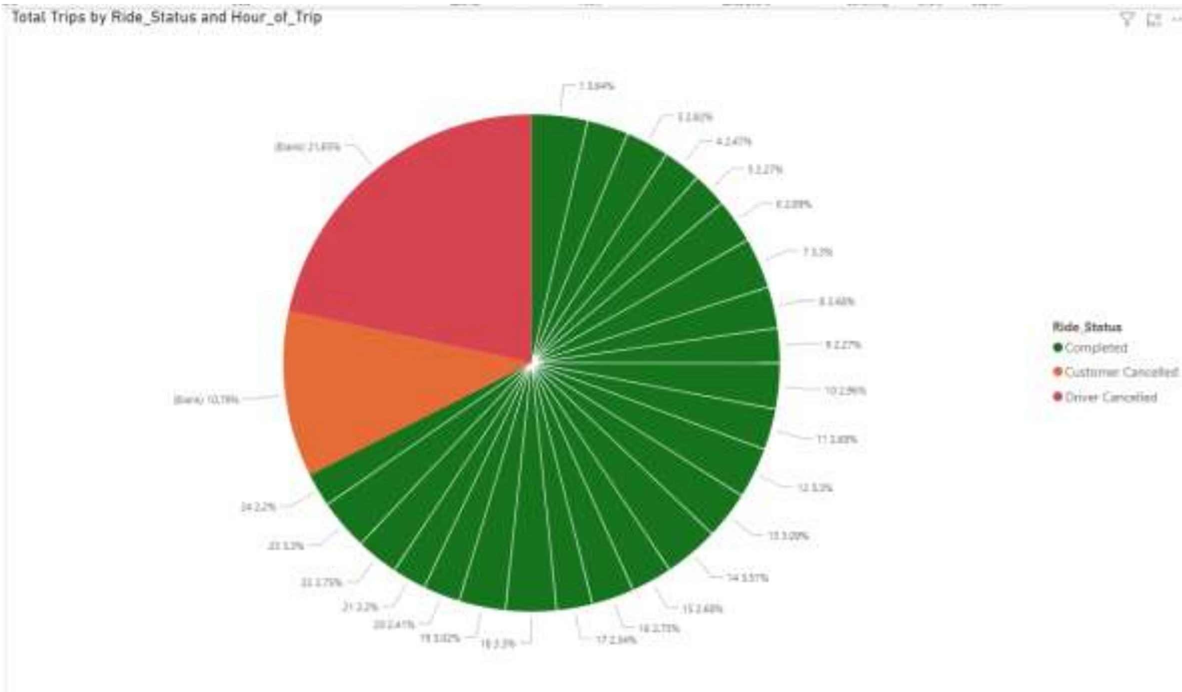
Visualisation:

Chart Type: Pie chart

Legend: Ride status (Completed, Customer Cancelled, Driver Cancelled)

Sliced By: Hour_of_Trip

The (Blank) slices reflect trips where time information was unavailable — i.e., they were cancelled before completion and thus not captured in the Trips table.



Key Observations:

Completed rides (green) are distributed across all 24 hours, with steady volumes from 6 AM to 10 PM.

Cancelled trips — both Driver (21.65%) and Customer (10.79%) — are concentrated entirely in the (Blank) category.

This clearly shows that quote drop-offs occur before a trip is officially created (i.e., before time is captured).

Interpretation:

Over 32% of users who received a quote cancelled before the trip started, and this cancellation cannot be analyzed by hour because the system doesn't track when they happened.

Only completed rides have a Hour_of_Trip, which limits your ability to:

Analyze conversion patterns over time

Identify cancellation-prone hours

Predict low-performing windows for driver allocation or pricing optimization

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2.10. Create a Parameter and Use Filters [5 Marks]

- Create a parameter and use it as a filter on an appropriate subset of the data to interactively analyse and visualise different subsets of the data.

- Explain your choice of filter and insights drawn from this step.

Solution:

We implemented a What-if parameter named MinFare to allow users to interactively filter trips based on fare thresholds. This enabled on-the-fly analysis of high-value trips without hardcoding filters into each visual.

📌 Parameter Details:

Name: MinFare

Range: ₹0 to ₹1500

Increment: ₹50

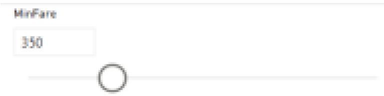
Type: Decimal number

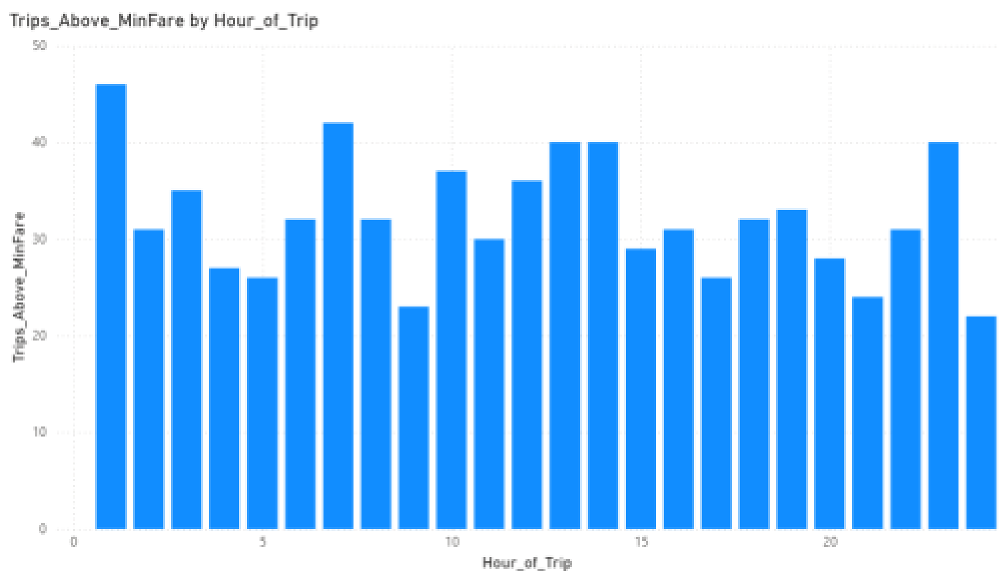
Slicer: Included for user selection

Visualisation:

A bar chart displaying number of trips with fare ≥ selected value, grouped by Hour_of_Trip.

The chart dynamically updates as the slider is adjusted.





DAX Used:

```
Trips_Above_MinFare =
CALCULATE(
    COUNT(Trips[tripid]),
    FILTER(
        Trips,
        Trips[fare] >= MinFare[MinFare Value]
    )
)

```

Interpretation:

Users can instantly see which hours of the day tend to have higher-value rides.

For example, setting the fare to ₹1500 reveals that early morning (1–2 AM) and evening hours (7–9 PM) show relatively more premium rides.

This enables Namma Yatri to:

Identify surge-worthy windows

Target driver incentives for long-distance or high-value trip windows

Understand when luxury or intercity demand peaks

3. Conclusion [20 Marks]

3.1. Recommendations for Operational Efficiency [10 Marks]

- Based on your findings from the analysis, provide recommendations on how Namma Yatri can optimise its operations.
- This could include strategies for improving resource allocation, reducing cancellations, or optimising ride durations.
- Add supporting dashboards.

Solution:

Based on the analysis of ride data, revenue trends, and user behavior across zones and time periods, the following recommendations are made to improve Namma Yatri's operational efficiency:

1. Driver Allocation Based on Demand Peaks

Allocate drivers dynamically based on time-specific demand:

Morning peaks: 6 AM – 9 AM (zones like Yeshwantpur, Hebbal, Jayanagar)

Evening peaks: 6 PM – 9 PM (zones like Bangalore South, Rajarajeshwarinagar)

Use zone-hour heatmaps to anticipate and pre-position drivers.

2. Reduce Driver Cancellations

Driver cancellations account for 47.25% of all incomplete rides.

Introduce:

Penalty mechanisms

Incentive bonuses for high acceptance and completion rates

Better quote previews for drivers (fare + distance)

3. Optimize for High-Value Trips

Use fare parameters to identify premium hours/zones (e.g., 1 AM, 8 PM).

Prioritize:

Driver availability during these hours

Deployment of larger/EV fleet

Faster matching for long-distance riders

4. Target High-Fulfillment Zones

Focus on zones with high trip completion ratios: Bangalore South, Hebbal, Ramanagaram.

These zones show consistent user reliability and revenue performance — ideal for pilot programs, auto-accept models, or preferred driver features.

5. Improve Quote-to-Completion Funnel

To reduce drop-offs between quote and ride start:

- Capture timestamps at the quote/search stage — not just at trip creation — so all user actions can be time-segmented.
- Implement visual countdown timers or “Confirm Now” nudges once quotes are shown, to reduce rider hesitation.
- Introduce fallback options (e.g., auto-requote, alternate driver) if the quote is ignored or rejected.
- Add "Quick Confirm" buttons or incentives in low conversion hours (e.g., midday, late night) based on observed patterns.

This will help Namma Yatri prevent drop-offs, improve funnel visibility, and increase overall ride conversion — especially in time slots where current cancellations go untracked.

Data revealed that less than half of users who received quotes went on to complete the ride (45.49%), and a significant portion of quote recipients — especially those who cancelled — had no timestamp (i.e., dropped off before ride confirmation and logging).

3.2. Marketing and Operational Strategy Improvements [10 Marks]

- Suggest improvements to Namma Yatri's marketing or operational strategies based on your analysis.
- Recommendations could involve promotional efforts, driver incentives, or regional targeting to increase customer satisfaction and service efficiency.
- Add supporting dashboards.

Solution:

The marketing strategy should focus on improving ride conversion, user trust, and service visibility across Bengaluru. Based on data-driven insights, the following recommendations are proposed:

1. Zone-Based Campaigns

Promote targeted offers in high-demand, low-conversion zones (e.g., Mahadevapura, Dasarahalli).

Offer cashback or ride credits for users in zones with high cancellations.

2. Incentivize Off-Peak Hours

Afternoon and late night hours show lower trip volume.

Run time-sensitive coupons or fare discounts (e.g., 15% off for 2–4 PM rides).

3. Highlight Reliable Zones

Promote top zones with successful rides in the app (e.g., "Fast pickups in Hebbal!").

Encourage users to book in these zones with higher confidence.

4. Digital Payment Promotions

With UPI, debit cards, and credit cards dominating usage (~76%), offer:

Referral bonuses

Discounts for digital payers

Loyalty points for repeat UPI use

5. Campaigns Around High-Value Time Blocks

Early morning and evening (based on MinFare parameter chart) have more high-fare rides.

Launch premium/EV rides, intercity push, or airport-specific promotions during these windows.