Amazon Delivery Data Analysis

Team 1

Team Members

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1-Introduction

This project aims to analyze and understand the operational efficiency and customer satisfaction in Amazon's delivery service using a real-world dataset. The dataset contains over **43,000 delivery records**, each capturing various aspects of the delivery process, including:

- Order, pickup, and delivery timestamps
- Customer order ratings
- Weather and traffic conditions during delivery
- Type of delivery vehicle used
- Geographic coordinates of pickup and drop-off locations
- Customer and delivery agent demographics (e.g., age)
- The data spans from **January to April 2022**, allowing for time-based pattern analysis and identification of peak delivery periods.

Through cleaning, processing, and analyzing this dataset, the goal is to extract meaningful insights and key performance indicators (KPIs) that reflect:

- **Delivery efficiency**
- **Customer satisfaction**
- **Operational performance**
- These insights can help in optimizing logistics, improving customer experience, and supporting data-driven decision-making for last-mile delivery operations.

2. Dataset Overview

The dataset used in this project is titled **"Amazon Delivery Dataset"**, originally sourced from Kaggle. It contains **43,551 records** representing individual delivery transactions made by Amazon across different regions and times.

Each record includes a wide range of features grouped into the following categories:

Column	Description
Order_ID	Unique identifier for each order , Data Type : Object , Prefix: 4 letters ,ID: 9 digits
Agent_Age	Age of the delivery agent (in years) , Data Type : Integer
Order Rate	Rating of the order , Data Type : Float
Store Latitude	Store's geographic latitude
Store Longitude	Store's geographic longitude
Drop Latitude	Drop-off location latitude
Drop Longitude	Drop-off location longitude
Distance_km	The difference between store location and drop off location in Kilometer , Data Type : Float
Order Date	Date the order was placed , Data Type : Object
Order Time	Time the order was placed ,Data Type : Object
Pickup Time	Time the agent picked up the order ,Data Type : Object
Weather	Weather condition at time of delivery (Sunny, Stormy, Sandstorms, Cloudy, Fog, Windy) , Data Type : Object
Traffic	Traffic condition during delivery (High, Jam, Low, Medium) ,Data Type : Object
Vehicle	Type of vehicle used for delivery (motorcycle, scooter, van, bicycle) , Data Type : Object
Area	Type of area where delivery occurred (Urban, Metropolitian, Semi-Urban, Other) , Data Type : Object
Delivery Time	Time taken for delivery (in minutes) , Data Type : Object
Category	Product category being delivered (Clothing, Electronics, Sports, Cosmetics, Toys,books ,Outdoors ,Snacks ,Jewelry) , Data Type : Object

1-Categories of Weather

Value	Description
Sunny	Clear skies with plenty of sunshine. Ideal delivery conditions.
Stormy	Severe weather with thunderstorms, heavy rain, or lightning.
Sandstorms	Dust-filled winds common in desert areas, causing low visibility.
Cloudy	Overcast sky with clouds but no precipitation.
Fog	Thick mist causing very low visibility, potentially delaying delivery.
Windy	Strong winds without precipitation, which may affect travel stability.

2. Traffic

Value	Description
High	Heavy traffic with slow vehicle movement.
Jam	Traffic jam; roads are congested or completely stopped.
Medium	Moderate traffic flow; occasional slowdowns but mostly moving.
Low	Light traffic; smooth vehicle movement.

3. Area

Urban	Densely populated city area with well-developed infrastructure.
Metropolitian	Large central city area including urban core and suburbs.
Semi-Urban	Transitional zone between rural and urban with developing infrastructure.
Other	An area that does not fit the predefined categories (rural or unclassified).

3-Business Questions & Problem Definition

This project aims to explore key delivery patterns and challenges to help improve operational efficiency and customer satisfaction. Below are the core business questions driving the analysis:

Main Business Goal:

How can we improve customer satisfaction?

Sub-Questions for Analysis:

1. What is the average delivery distance?
2. Which orders had the longest delays?
3. How much time passed between order time and pickup time?
4. What are the average agent ratings overall?
5. Which geographic areas receive the most orders from?
6. Which days of the week have the highest delivery volume?
7. What is the average delivery time for each area?
8. Which vehicle types are used most?

Diagnostic Questions:

1. Why are some orders getting lower ratings?
2. Why do some orders have longer pickup delays?
3. Why are ratings lower during certain times?
4. Why do agents have different performance metrics?

4-Data Cleaning & Processing Summary

This project involved cleaning and preparing an Amazon delivery dataset for analysis. The following steps were applied:

1. Initial Cleaning and Column Renaming

- Removed irrelevant columns and rows with missing or duplicate values.
- Renamed some columns for clarity, such as changing `Agent_Rating` to `Order_Rating`.

2. Handling Missing Values

- Missing values in key categorical and numerical features were filled based on the nature of the data:
  - `Weather_Conditions` and `Traffic_Conditions` were filled using the **mode** (most frequent category).
  - `Order_Rating` was filled using the **median** to avoid skew from outliers.

3. Date and Time Format Correction

- Columns containing time and date values such as `Order_Date`, `Order_Time`, and `Pickup_Time` were converted to appropriate **datetime formats**.
- This enabled accurate analysis of order patterns over time and calculation of delivery durations.

4. Order Rating Correction

- Ratings in the `Order_Rating` column above 5 were considered invalid (e.g., rating of 6).
- All such values were replaced with **5**, assuming a 1–5 rating scale.

5. Distance Calculation using Haversine Formula

- A custom `haversine()` function was implemented to calculate the geographical distance between the store and drop-off location.
- The function used **latitude and longitude** to calculate the straight-line distance in kilometers.
- The result was stored in a new column called `Distance_km`.

6. Outlier Detection and Handling

- Basic outlier detection was performed by checking **value distributions**, **descriptive statistics**, and **box plots**.
- Inconsistent or unrealistic values were manually corrected where necessary.
- In particular, **outliers in the `Distance_km` column** were handled by examining extreme values and adjusting or excluding them from analysis when clearly invalid.

5. *Data Segmentation*

Before diving into the analysis and business questions, the dataset was segmented to improve clarity and enable deeper insights:

- **Weather Segmentation**
  The `Weather` column was grouped into:
  - *Good Weather*: Sunny, Cloudy
  - *Normal Weather*: Windy
  - *Bad Weather*: Sandstorms, Stormy, Fog

This helped us understand how weather conditions affect delivery time and agent ratings.

- **Speed Segmentation**
  Delivery speed was calculated and categorized into:
  - *Extremely Fast*, *Very Fast*, *Fast*, *Medium*, *Slow*, and *Very Slow*
    This allowed for performance comparisons and identifying delays.
- **Pickup Delay Calculation**
  A new column `pickup_delay_minutes` was created by calculating the time difference between `Order Time` and `Pickup Time`.
  Negative delays (e.g., midnight orders) were corrected by adding 24 hours (1440 minutes).
- **Age Segmentation**

Agent ages were grouped into two main segments for clearer analysis:

- **20–30 years**
- **30–40 years**

This segmentation allowed for a more focused comparison of delivery performance metrics, such as **average delivery speed**, **customer rating**, and **pickup delays**.

Total Delivery Time Segmentation

To better understand agent performance in relation to delivery efficiency, **total delivery time** (calculated as:
`Total Time = Pickup Delay + Delivery Time`) was grouped into the following segments:

- **0–60 minutes**
- **60–120 minutes**
- **120–200 minutes**
- **200–285 minutes**

These groups were used alongside the **age segments (20–30 and 30–40)** to explore how different age groups perform across varying delivery time ranges.

This combined segmentation allowed for detailed cross-analysis between **agent age** and **total time taken**, highlighting patterns in performance and identifying areas for operational improvement.

Time-of-Day Segmentation

In addition to demographic and operational segmentations, we also categorized orders based on the **time of day** they were placed. The `Hours` variable was grouped into four segments:

- **Morning**: 00:00 – 12:00
- **Afternoon**: 12:00 – 17:00
- **Evening**: 17:00 – 21:00
- **Night**: 21:00 – 24:00

This segmentation allowed for further exploration of performance and customer behavior trends throughout different parts of the day. These time-based categories were later used in the analysis of delivery time, agent performance, and customer satisfaction.

6-Data Analysis

This section presents a detailed analysis of the cleaned Amazon delivery dataset. The aim is to uncover insights related to delivery performance, agent behavior, and customer satisfaction.

1. Average Delivery Distance

- The average delivery distance across all orders was **9.73 kilometers**.
- This value gives insight into the typical range covered by delivery agents. It helps in understanding logistics planning, fuel usage, and potential time requirements for standard deliveries.

2. Longest Delivery Delays

- To determine how much time passes between when an order is placed and when it is picked up by the delivery agent, a new column named *pickup_delay_minutes* was added to the dataset. This value represents the waiting time before the order is actually picked up.
- We then calculated the **total time** from order placement to delivery by adding the pickup delay to the delivery time. The formula used was:
- **Total Time = Pickup Delay Minutes + Delivery Time**
- Using this, we identified the order with the longest total delay, which was approximately **250 minutes**.

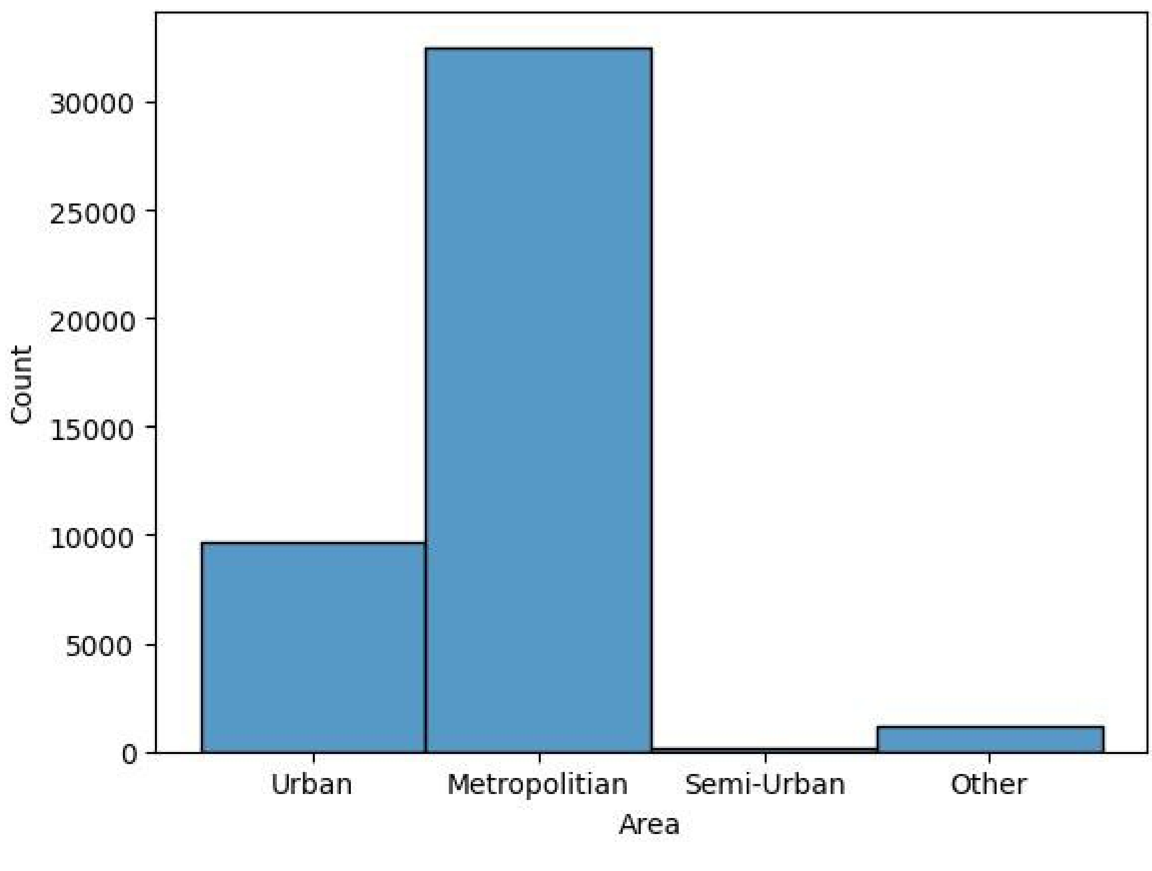
3. Average Agent Ratings

- The overall average rating received by delivery agents was **4.64 out of 5**.

- This indicates that, on average, customers were generally satisfied with the service provided by the delivery agents. A rating close to 5 reflects a high level of performance and customer satisfaction.

4. Delivery Volume by Area

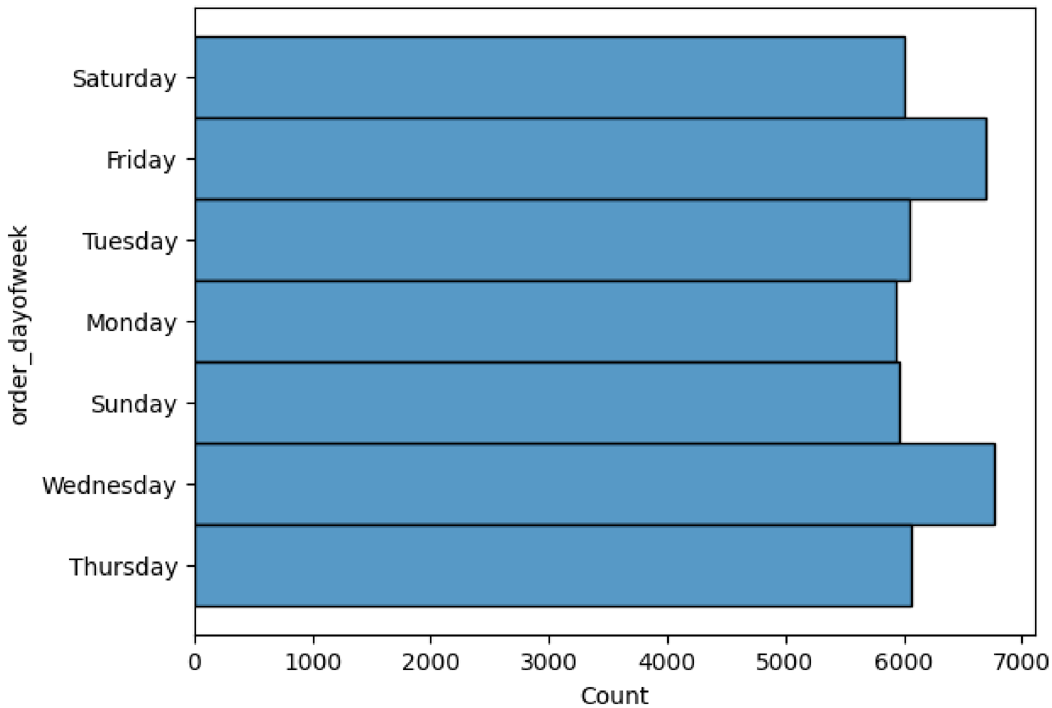
- To explore regional demand, we grouped the dataset by geographic area and counted the number of orders placed in each location.
- The results showed:
- **Metropolitan** areas received the highest number of orders: **32,522 orders**
- **Urban** areas followed with **9,685 orders**
- **Other** areas recorded **1,133 orders**
- **Semi-Urban** areas had the lowest number of orders with just **152**
- This indicates that Metropolitan regions are the busiest delivery zones, highlighting a higher customer density and demand in these areas. Companies may consider allocating more delivery resources and staff to these locations for greater efficiency.



5. Delivery Volume by Day of Week

- To understand delivery trends throughout the week, we grouped the orders by the day of the week and counted the number of orders placed each day. The results showed:

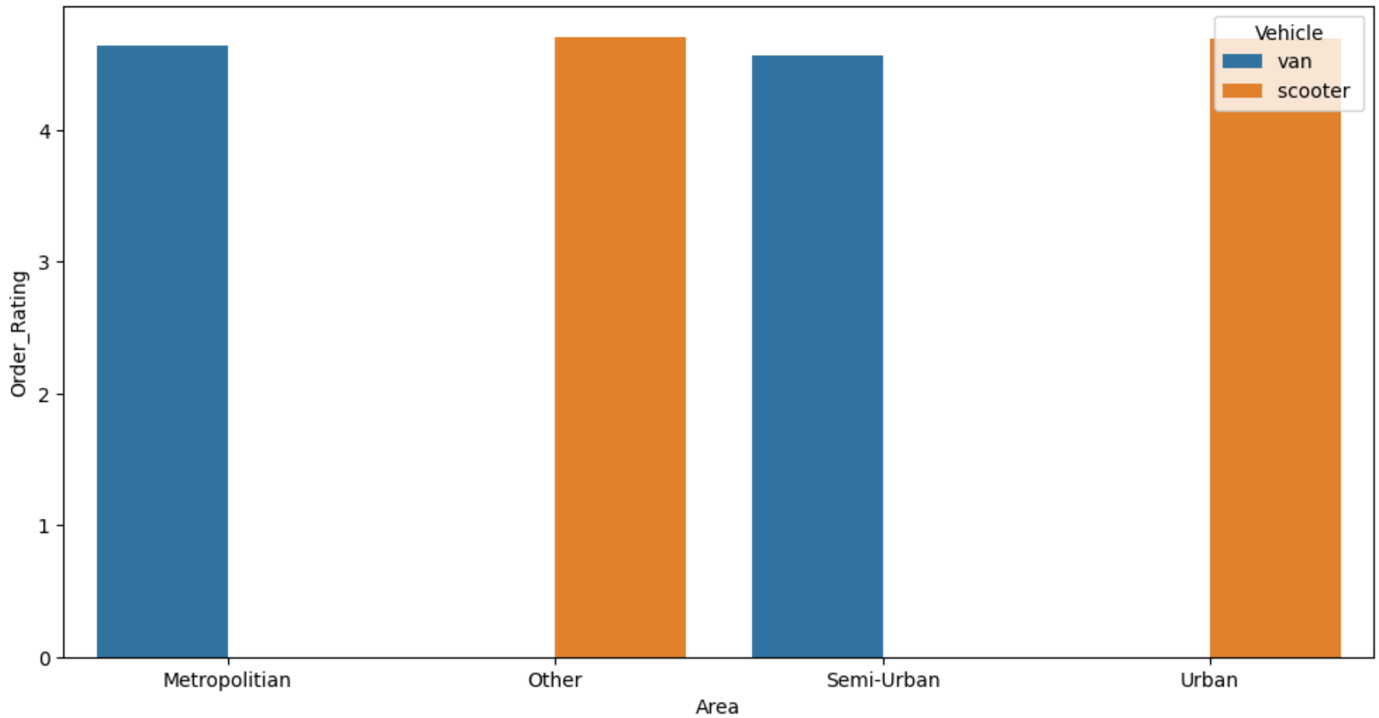
- **Wednesday** had the highest number of orders: **6,771**
- **Friday** came next with **6,701** orders
- **Monday** had the lowest volume: **5,930** orders
- This analysis helps in identifying peak days for deliveries, which can support better resource allocation and delivery agent scheduling.

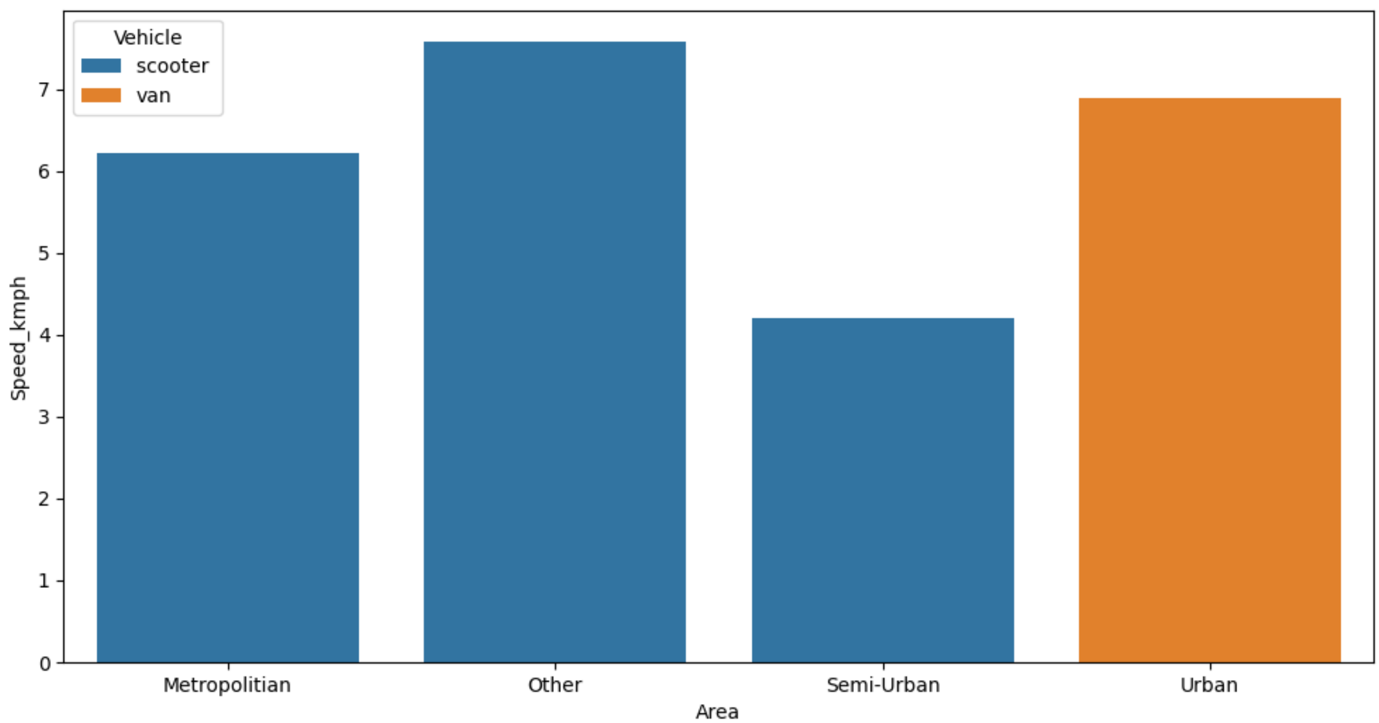


6. Vehicle Type Usage and Delivery Time by Area

- We analyzed vehicle performance in each area based on **average delivery speed** to better understand efficiency across regions.
- **Metropolitan:**
  Scooters were the fastest (6.22 km/h), slightly outperforming vans (6.19 km/h) and motorcycles (5.45 km/h).
- **Urban:**
  Vans performed best with the highest average speed (6.89 km/h), followed by scooters (6.66 km/h) and motorcycles (6.16 km/h).
- **Other Areas:**
  Scooters led with the highest speed (7.58 km/h), followed by vans (6.31 km/h) and motorcycles (6.46 km/h).
- **Semi-Urban:**
  All vehicle types were slower overall. Scooters remained the fastest (4.20 km/h), while vans were the slowest (2.90 km/h).
- **Conclusion:**
  Scooters consistently show strong performance across most areas, especially in **Other** and **Metropolitan** regions. Vans, on the other hand, perform better in **Urban** areas.

Insight: Vehicle performance varies by area. Scooters are generally the fastest, especially in Metropolitan and Other areas, while vans perform best in Urban regions.

- 



- **7. Effect of Weather on Delivery Speed**

  The dataset was segmented into three main weather groups: **Good**, **Normal**, and **Bad**. We analyzed the **average delivery speed (km/h)** for each group across all vehicle types:

- **Good Weather** resulted in the highest overall delivery speed:
  - Scooter: **6.50 km/h**
  - Van: **6.50 km/h**

- Motorcycle: **5.71 km/h**

- **Normal Weather** showed slightly slower performance:
  - Scooter: **6.65 km/h** *(the highest overall scooter speed)*
  - Van: **6.35 km/h**
  - Motorcycle: **5.79 km/h**
- **Bad Weather** led to reduced delivery speeds:
  - Scooter: **6.19 km/h**
  - Van: **6.26 km/h**
  - Motorcycle: **5.50 km/h**
- **Conclusion:**
  Bad weather conditions tend to lower delivery speed, particularly for motorcycles. Scooters maintain relatively high performance across all weather types, suggesting they may be more adaptable in varied conditions.
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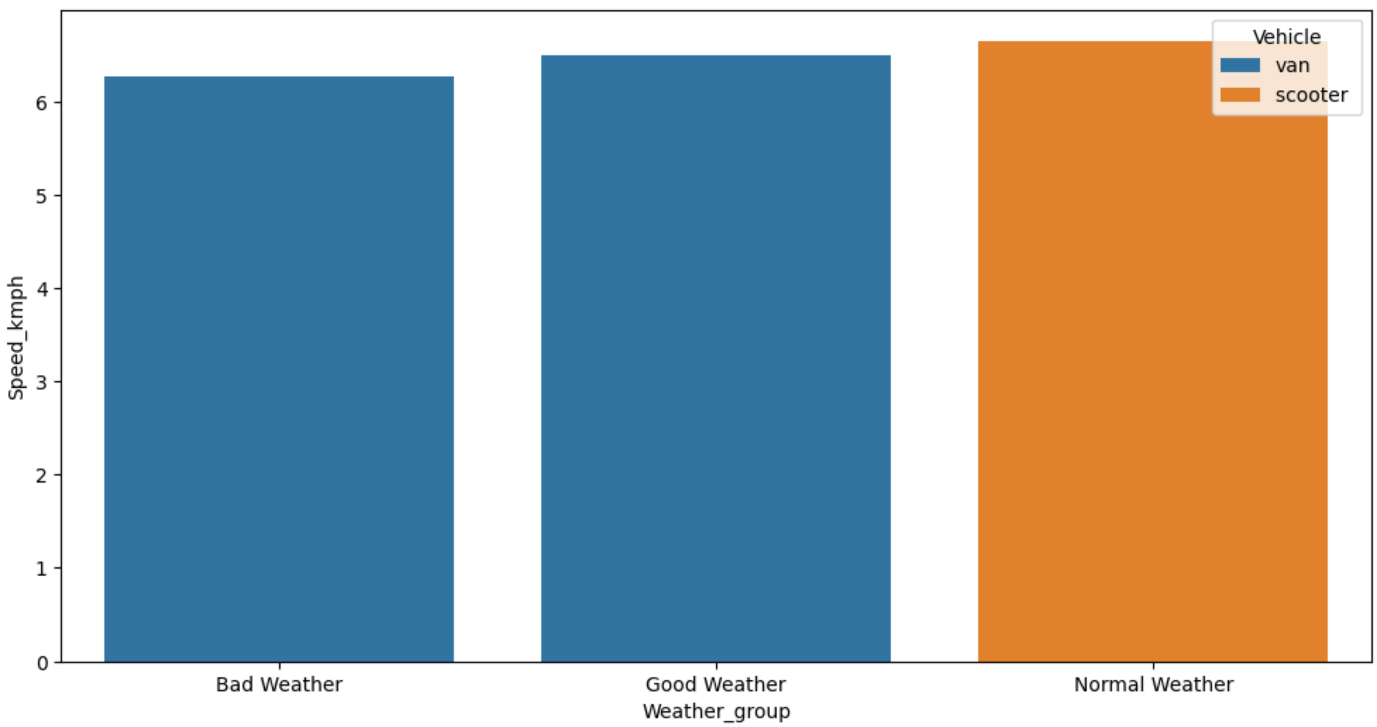
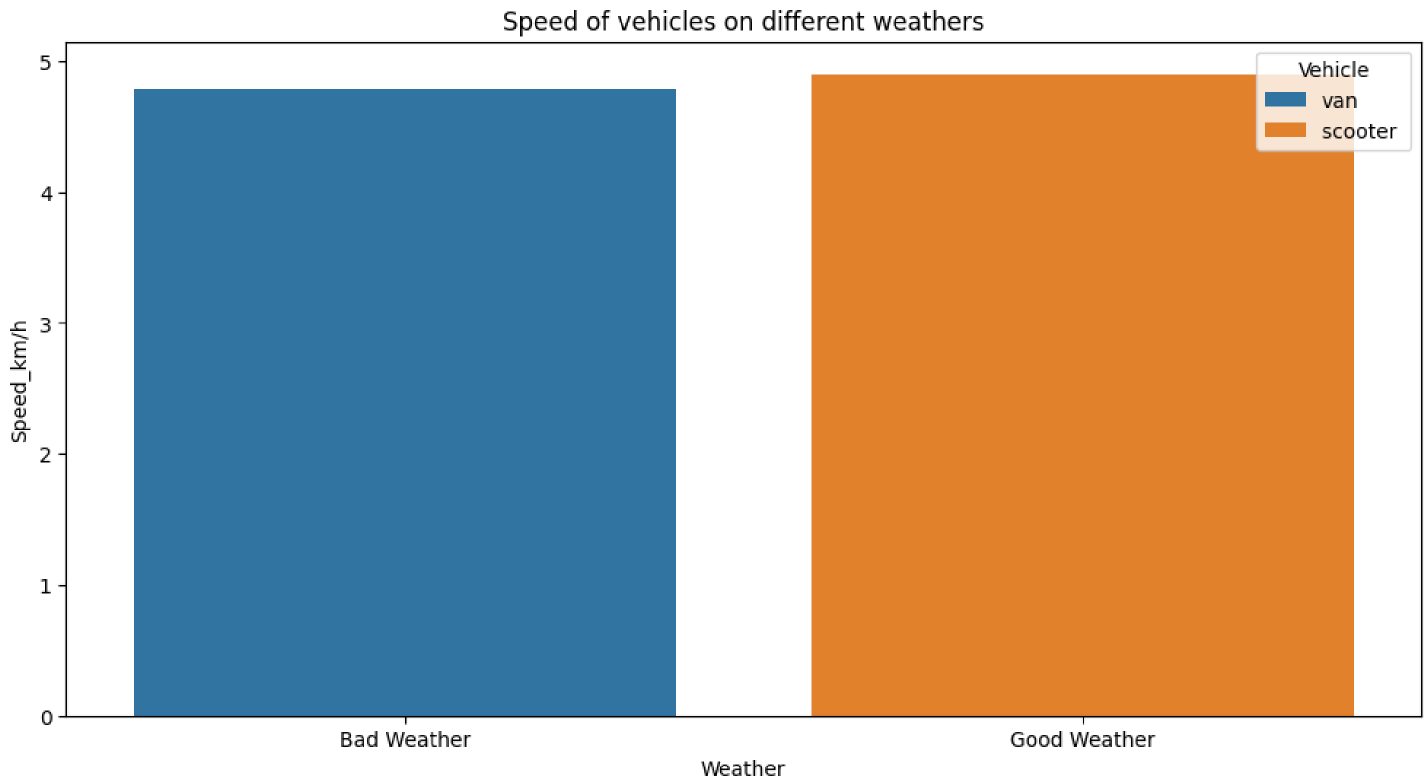
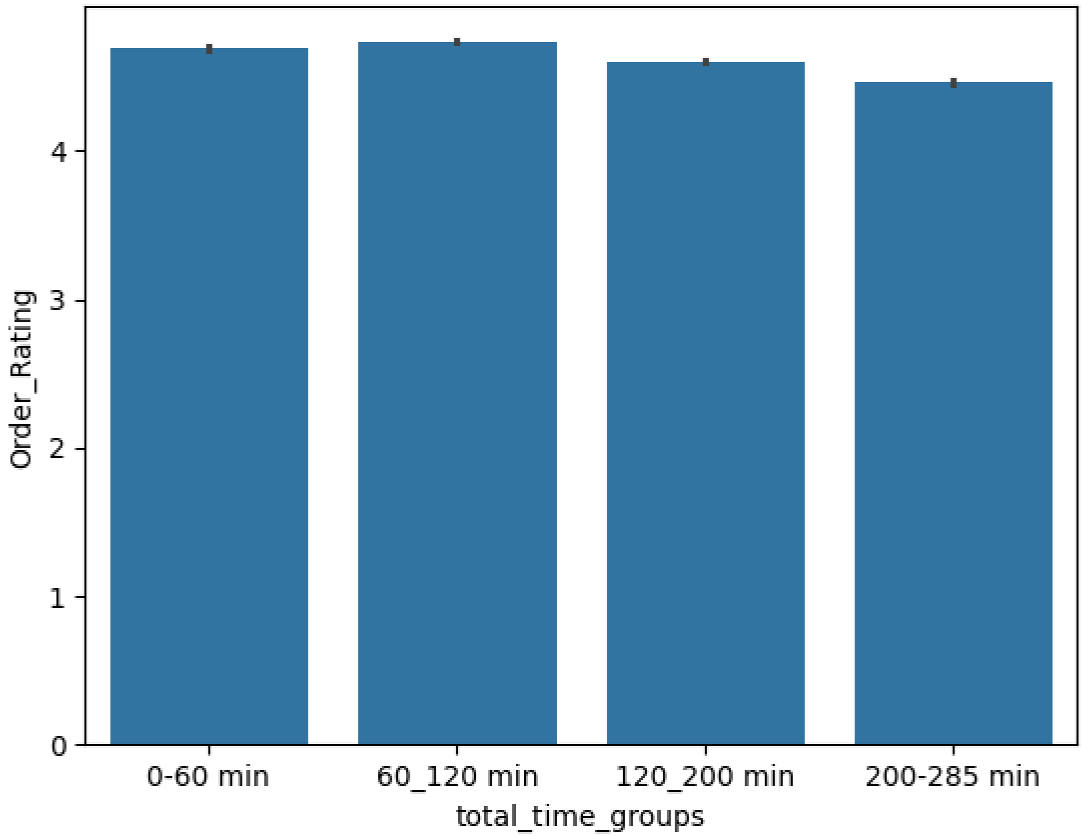




8. Relationship Between Delivery Time and Order Rating

- To assess how delivery duration impacts customer satisfaction, we grouped orders based on **total delivery time** into four categories:
- **0–60 minutes**
- **60–120 minutes**
- **120–200 minutes**
- **200–285 minutes**
- We then calculated the **average order rating** within each time segment.
- The results revealed:
- Orders delivered within **60–120 minutes** received the **highest average ratings**.
- Very fast deliveries (**0–60 minutes**) also had high ratings, though slightly lower than the 60–120 min group.
- Ratings started to **decline gradually** for deliveries in the **120–200 min** and **200–285 min** segments.
- The **lowest ratings** were observed in the **longest time group (200–285 minutes)**, suggesting a **negative correlation** between longer delivery times and customer satisfaction.
- This pattern indicates that **moderately quick deliveries (within 1–2 hours)** yield the best customer experience, while delays beyond 2 hours may lead to lower satisfaction levels.



"A regression analysis was performed to understand the impact of delivery speed on customer satisfaction. The scatter plot shows a slight positive correlation between speed and order rating, suggesting that faster deliveries may slightly improve customer satisfaction :

📌 Discussion – Relationship Between Delivery Time and Customer Rating by Area

To explore the connection between delivery performance and customer satisfaction, we compared the **average delivery time** and **average order rating** across different areas:

- **Metropolitan** areas had the **longest average delivery time** (135.7 minutes) and a slightly **lower order rating** (4.62).
- **Urban** and **Other** areas showed **faster delivery** times (115.3 and 110.9 minutes respectively) and achieved **higher ratings** (4.67 and 4.66).
- **Semi-Urban** areas had both the **slowest deliveries** (249.2 minutes) and the **lowest ratings** (4.47).

These patterns indicate a **negative relationship** between delivery time and customer satisfaction. In other words, **faster deliveries are generally associated with better customer ratings**, highlighting the importance of improving delivery efficiency to enhance the overall customer experience.

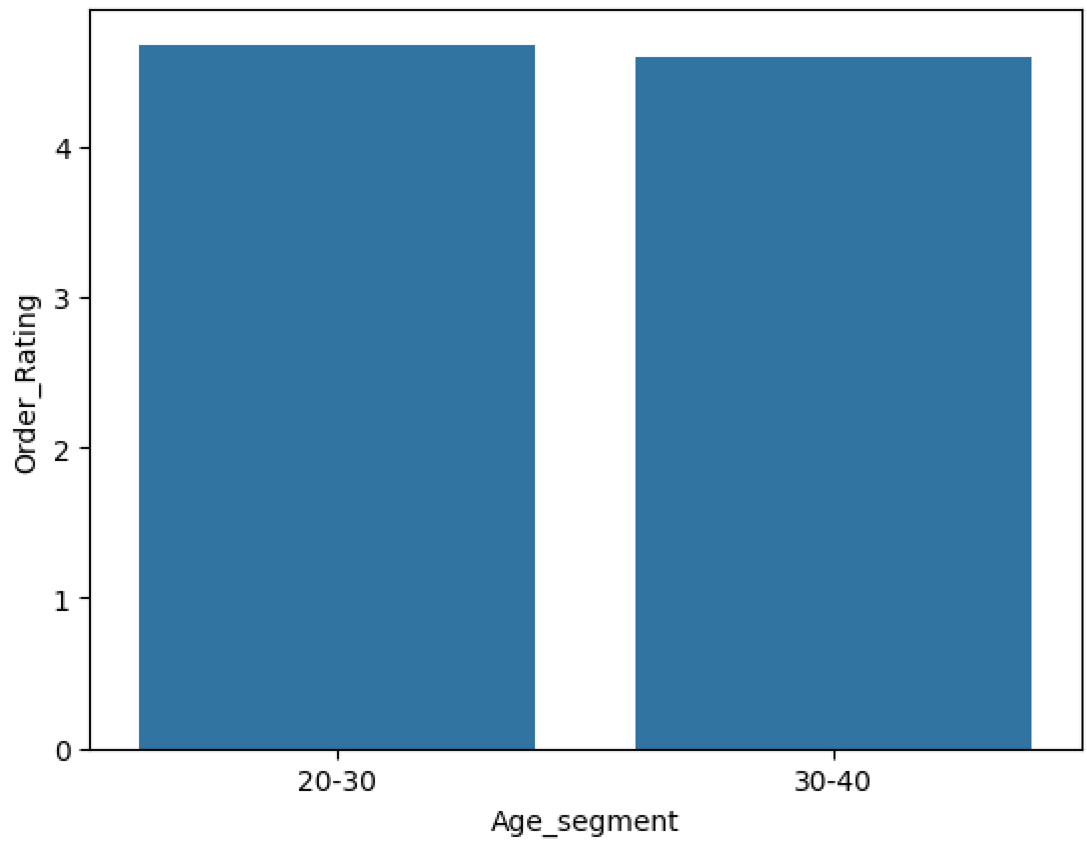
10-Age Effect on Delivery Speed

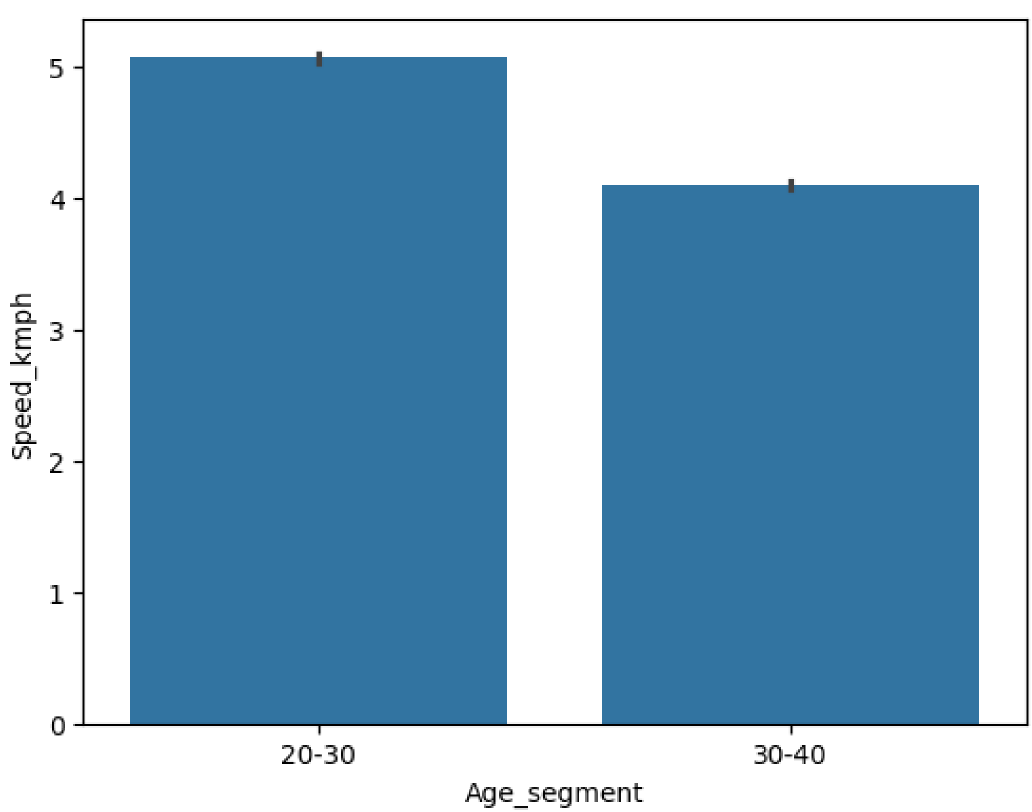
Delivery agents were grouped into two age segments: **20–30** and **30–40**. We analyzed their **average delivery speed (km/h)** and found the following:

- Agents aged **20–30** achieved the highest average speed at **5.1 km/h**.
- Agents in the **30–40** segment had a lower average speed of approximately **4.1 km/h**.

When it comes to **customer rating**, both age groups scored very closely, with slightly higher ratings for the younger segment.

Conclusion:
Younger delivery agents (especially those in their 20s) tend to deliver faster than older agents, while maintaining a similar level of customer satisfaction. This could be attributed to higher physical activity or quicker navigation.


Order_Rating
0
1
2
3
4
20-30
30-40
Age_segment


Speed_kmph
0
1
2
3
4
5
20-30
30-40
Age_segment

11. Order Time vs Pickup Time

To calculate how much time passes between the order being placed and the pickup by the delivery agent, a new column `pickup_delay_minutes` was created.

Some records showed negative values (e.g., -1430 minutes), likely due to orders made just before midnight and pickups happening after. These were corrected by adding 1440 minutes (24 hours) to align them within the same day context.

After correction, the pickup delay values were standardized to:

- **5 minutes**
- **10 minutes**
- **15 minutes**

This indicates that, on average, agents pick up orders within **5 to 15 minutes** of being placed.

12-Delivery Time Distribution by Area

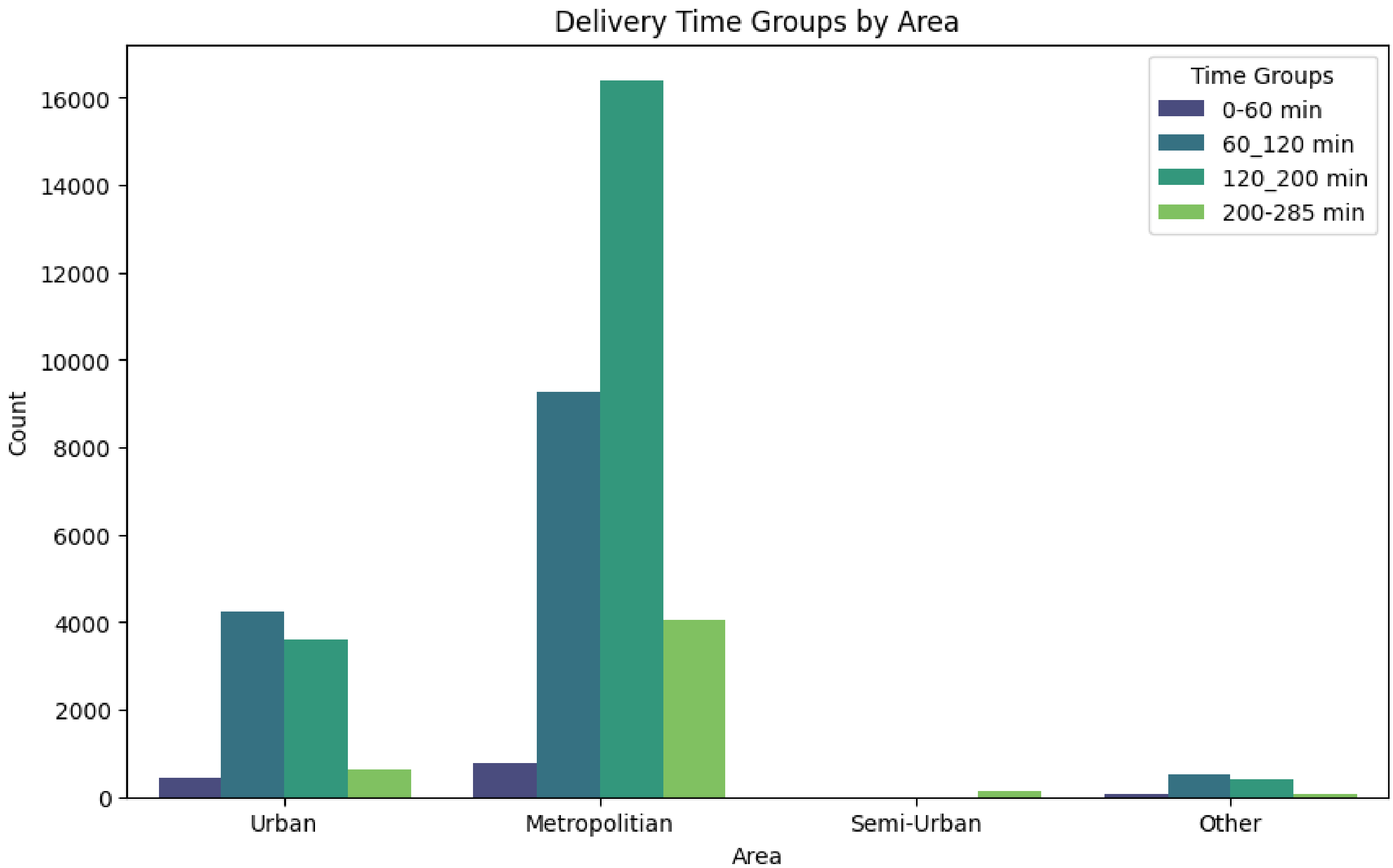
To examine how total delivery time varies across different geographical areas, we segmented the total delivery time into four categories:

- **0–60 minutes**
- **60–120 minutes**
- **120–200 minutes**
- **200–285 minutes**

We then analyzed the number of deliveries within each time segment per area. The findings were as follows:

- **Metropolitan areas** had the highest number of deliveries across all time segments, especially in the **120–200 minutes** range (16,398 deliveries), indicating a high workload or dense delivery network.
- **Urban areas** also showed a large concentration in the **60–120 minutes** range (4,237 deliveries) and a balanced spread across other time groups.
- **Other areas** had relatively fewer deliveries overall, with the highest count in the **60–120 minutes** segment (523 deliveries).
- **Semi-Urban areas** had no deliveries in the first three time segments, and all recorded deliveries (144) fell within the **200–285 minutes** segment, suggesting longer delivery cycles, possibly due to distance or infrastructure limitations.

This distribution highlights how geography impacts delivery efficiency, with **urban and metropolitan zones** showing faster and more frequent deliveries, while **semi-urban areas** lean toward significantly longer delivery times.

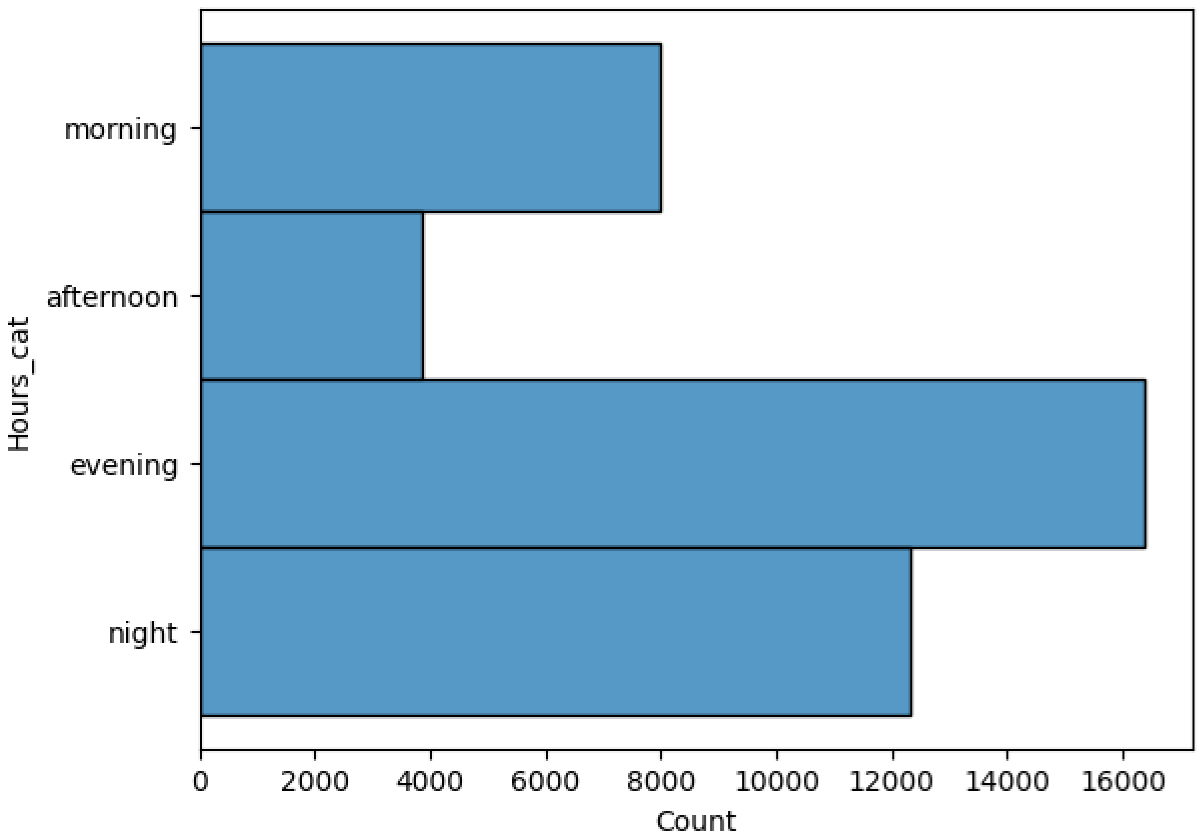


13-Time-of-Day Insights

From the segmentation based on order hours, we observed the following distribution:

- **Evening (17:00–21:00)** witnessed the **highest number of orders**, indicating a peak in customer activity during this time.
- **Night (21:00–00:00)** also showed a significant volume, possibly due to late-night ordering behavior or operational strategies.
- **Morning (00:00–12:00)** had moderate order activity.
- **Afternoon (12:00–17:00)** recorded the **lowest number of orders**, suggesting either a reduced demand or limited availability of delivery services in this period.

These insights can help optimize delivery agent allocation and resource planning during peak and off-peak hours.



14-Traffic Conditions vs Vehicle Speed

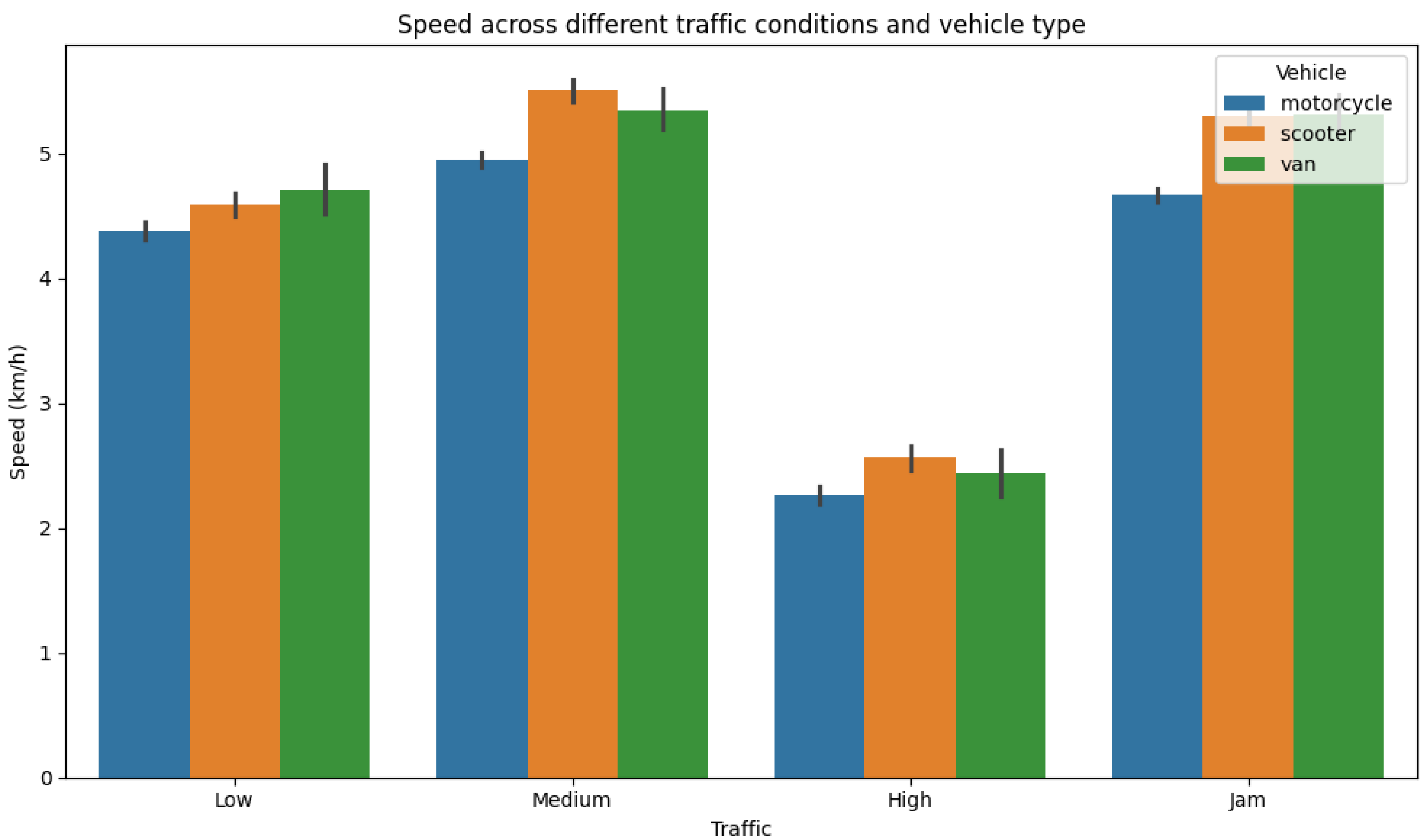
Traffic Condition	Fastest Vehicle	Average Speed (km/h)	Observations
Low	Van	≈ 4.7 (van) → 4.6 (scooter) → 4.4 (motorcycle)	Speed differences are minor; all vehicles perform similarly.
Medium	Scooter	≈ 5.5 (scooter) → 5.35 (van) → 4.95 (motorcycle)	Moderate congestion favours agile vehicles (scooters).
High	Scooter	≈ 2.6 (scooter) → 2.45 (van) → 2.3 (motorcycle)	All vehicles slow sharply; scooters retain a slight edge.
Jam	Scooter	≈ 5.3 (scooter) → 5.2 (van) → 4.7 (motorcycle)	Despite “jam” conditions, speeds remain moderate—likely brief or lightly congested episodes.

Key Findings

- **Scooters deliver the most consistent performance** across all traffic levels and remain the fastest in medium, high, and jam scenarios.
- **Vans match scooter speed in low traffic and jam situations**, suggesting route flexibility or power advantage, but fall slightly behind in medium traffic.
- **Motorcycles are the most traffic-sensitive**, losing more speed than scooters or vans as congestion increases.
- Variability (error bars) is lowest in low traffic and jam conditions, but rises in medium and high traffic, indicating inconsistent congestion patterns.

Implications

- Deploy **more scooters** in areas prone to medium or heavy congestion.
- Support van routes with dynamic rerouting tools to maintain speed advantages outside peak times.
- Investigate motorcycle routing and training to mitigate performance drops in dense traffic.



15 – Time-of-Day Traffic Insights

Based on the segmentation of order hours and corresponding traffic conditions, the following patterns were identified:

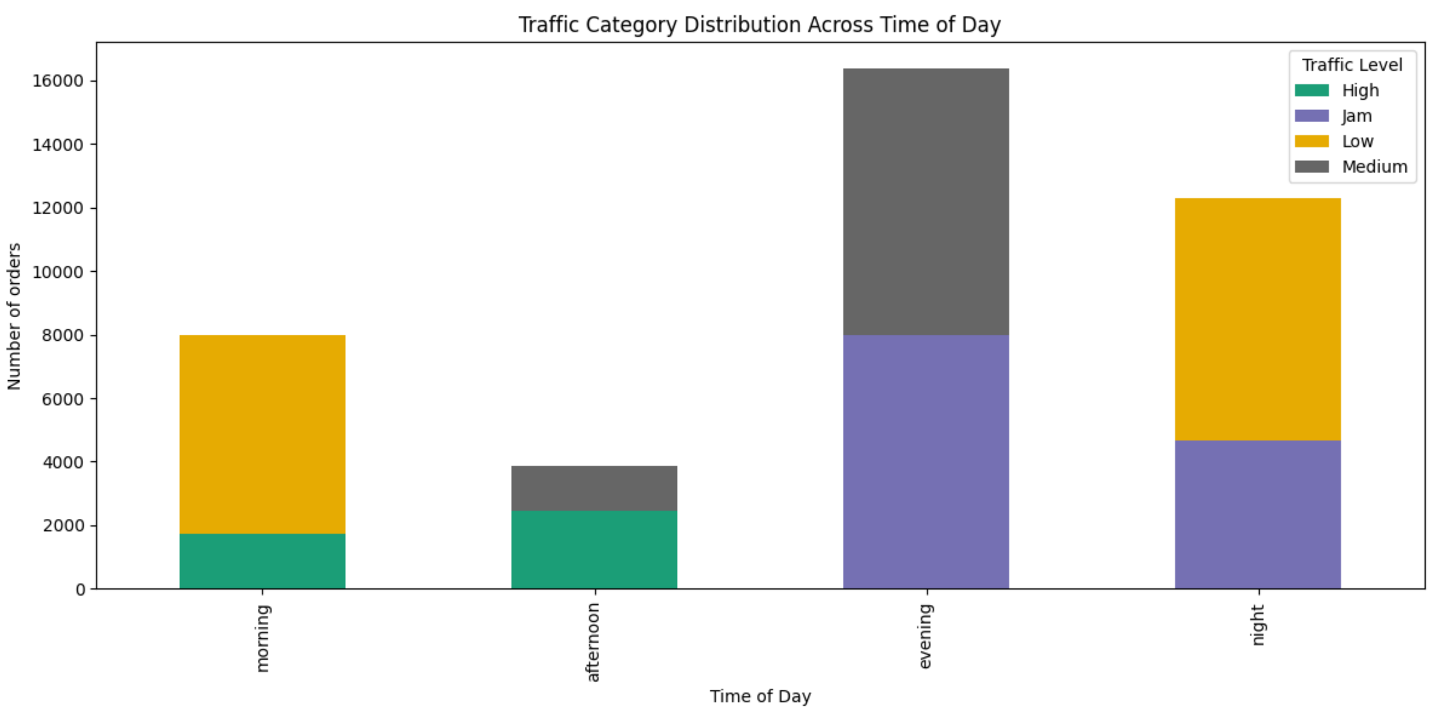
Morning (00:00–12:00) experienced relatively smooth conditions, with the majority of orders placed during low traffic. High traffic was present to a smaller extent, while medium and jam conditions were nearly absent.

Afternoon (12:00–17:00) saw a drop in total order volume, with high traffic being the most common condition. Medium traffic was also observed, while low and jam conditions were not recorded during this period.

Evening (17:00–21:00) had the highest number of orders overall, dominated by jam and medium traffic levels. This suggests a clear congestion peak, likely tied to post-work or rush-hour activity.

Night (21:00–00:00) showed a mixed traffic profile, with a majority of orders placed during low traffic, but a significant portion also under jam conditions. Medium and high traffic were not present.

These findings indicate that traffic conditions vary significantly across the day, with congestion peaking in the evening and smoother conditions occurring in the morning and night. This can inform delivery route planning and help improve service efficiency during different time windows.



16 – Age and Vehicle Usage Analysis

Analyzing delivery trends across age groups reveals clear preferences and operational behaviors in terms of vehicle choice:

Agents Aged 20–30

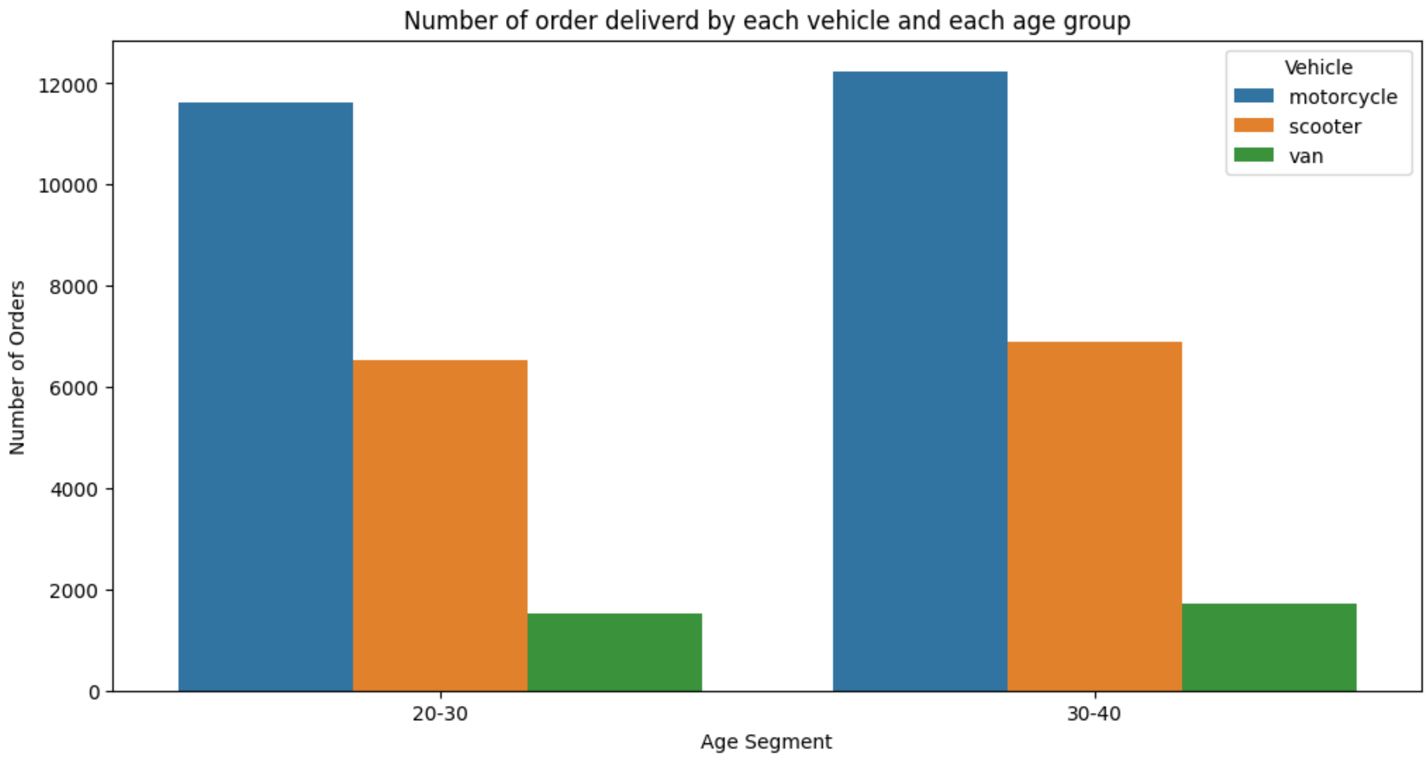
- The majority of deliveries were completed using **motorcycles** (~11,600 orders), making it the most favored option.
- **Scooters** came in second (~6,600 orders), reflecting their popularity among younger couriers for short-distance or dense urban routes.
- **Vans** were used the least (~1,500 orders), likely due to higher costs, licensing requirements, or lack of access at a younger age.

Agents Aged 30–40

- **Motorcycle usage** increased slightly (~12,300 orders), remaining the top choice even among older agents.
- **Scooter usage** also saw a minor rise (~6,900 orders), indicating consistent usage across age groups.
- **Van usage** showed the highest relative growth (~1,700 orders), suggesting greater access to commercial vehicles with age and experience.

Key Insights

- **Motorcycles dominate** across both age segments due to their speed, maneuverability, and affordability.
- **Scooter usage** is stable, showing a small increase with age, possibly due to comfort or familiarity.
- **Van usage**, although still low overall, **grows the most proportionally** in the 30–40 group, likely reflecting increased professional responsibilities or investment capacity.



7-Performance Diagnostics and Root Cause Analysis

1. Why are some orders receiving lower ratings?

Lower ratings are often associated with **longer delivery times**. Our analysis revealed a **negative correlation** between delivery time and customer ratings — as delivery time increases, customer satisfaction tends to decrease.

Additionally, **weather conditions** such as **sandstorms** or **fog** contributed to delivery delays, which may have negatively impacted the customer experience and led to lower ratings.

Vehicle type and **operating area** also played a role:

- In **semi-urban areas**, average ratings were slightly lower — possibly due to infrastructure limitations or a lower availability of agents and suitable vehicles.

2. Why do some orders have longer pickup delays?

Most pickup delays were within a reasonable **5–15 minute** window. However, some initial data points showed **negative pickup times**, primarily around midnight. These were identified as **system time-logging issues** and have since been corrected.

Remaining pickup delays may be attributed to:

- Limited **agent availability** in certain time slots or locations
- **Traffic congestion**, especially during peak hours
- **Weather disruptions** affecting agent response time
- **Operational inefficiencies**, such as assigning agents who are far from pickup points

3. Why are ratings lower at certain times of the day?

Ratings tended to **dip during late-day and evening hours**, which also coincided with:

- **Higher traffic levels** slowing down delivery times
- **Batch deliveries**, leading to accumulation of delays
- **Agent fatigue**, possibly affecting delivery quality or communication
- **Increased order volumes** during lunch and dinner rush

Plotting ratings against the time of day revealed that **slight declines** align with **delivery slowdowns**, not necessarily with agent behavior, emphasizing the need for **dynamic agent allocation during peak hours**.

4. Why do agents have different performance metrics?

Performance variations among delivery agents can be explained by several intersecting factors:

Age Group

- Agents in their **30s** tend to handle **more orders** and utilize a broader range of vehicles, particularly vans. Their higher volume may reflect **greater experience** and **route familiarity**.
- However, agents in their **20s** achieve **slightly higher customer ratings**, which could indicate **better engagement, energy, or adaptability**, despite lower order volumes.

Vehicle Type

- **Motorcycles** dominate among all age groups due to speed and cost-effectiveness.
- Agents in their 30s make **greater use of vans**, enabling bulk delivery but potentially facing delays in dense urban environments.
- **Scooter use** remains steady, especially among younger drivers.

Time of Day & Traffic Conditions

- Agents operating during **morning or late-night hours** typically benefit from **lower traffic**, leading to more consistent performance.
- **Evening shifts**, being the busiest, are heavily impacted by congestion, affecting all performance metrics.

Experience & Route Familiarity

- **More experienced agents** show higher consistency and efficiency.
- **Younger agents** may compensate with **speed, agility**, and **better customer interaction**, contributing to their higher ratings.

8-Recommendations to Improve Customer Satisfaction

Based on the detailed analysis, several actionable strategies are recommended to enhance the customer experience and boost satisfaction levels:

1. Reduce Delivery Time During Peak Hours and Bad Weather

A clear inverse relationship exists between delivery time and customer ratings. Efforts should focus on minimizing delivery time, especially during **peak hours** and **adverse weather conditions**.
Possible actions include smarter order allocation, increasing agent availability during high-demand periods, and dynamically adjusting delivery time estimates.

2. Optimize Pickup Time

Although most pickup delays ranged between **5–15 minutes**, reducing even small delays can positively impact the overall delivery experience.
Improved agent dispatching and ensuring proximity to pickup points can help shorten these delays.

3. Tailor Agent Allocation Based on Age Group Strengths

Agents in their **30s** tend to handle more orders and show higher delivery productivity, making them suitable for high-volume periods or challenging areas.
Meanwhile, agents in their **20s** received slightly higher ratings, possibly due to stronger engagement or responsiveness. Assigning them to customer-sensitive or time-critical orders can leverage their strengths.

4. Match Vehicle Type to Area Conditions

Vans demonstrated better performance in **urban** and **metropolitan** areas, especially for bulk or multi-order deliveries.
In contrast, **motorcycles and scooters** offered better maneuverability and speed in traffic-heavy or narrow-street areas.
Vehicle allocation should be aligned with area characteristics and order type.

5. Reinforce Coverage on High-Demand Days

Order volumes were significantly higher on **Wednesdays and Fridays**. Planning ahead by boosting agent availability and optimizing shift schedules during these peak days can ensure consistent performance.

6. Adjust Operations Based on Time-of-Day Trends

Ratings tended to dip slightly during **evening hours**, likely due to agent fatigue or accumulated delays.
Introducing staggered shifts or rebalancing workload throughout the day can help maintain service quality.

7. Proactively Manage Weather Impact

Bad weather (e.g., fog, rain, or sandstorms) contributed to delivery slowdowns.
Integrating real-time weather data into operations can help with proactive planning, such as setting realistic delivery expectations and deploying more agents in affected areas.

8. Leverage Qualitative Customer Feedback

While data analysis provided clear patterns, open-ended customer feedback may reveal hidden issues like packaging concerns, agent behavior, or communication gaps.
Encouraging feedback collection post-delivery and analyzing it periodically can lead to further service improvements.