Report: Optimising NYC Taxi Operations

Include your visualisations, analysis, results, insights, and outcomes. Explain your methodology and approach to the tasks. Add your conclusions to the sections.

1. Data Preparation

1.1. Loading the dataset

1.1.1. Sample the data and combine the files

As suggested, we can begin the analysis using 250K to 300K records. However, applying a 5% sampling approach—by extracting 5% of data from each month—provides a more accurate and representative dataset. Using this method, the final sample consists of approximately 1.9 million records, which will support more precise prediction and analysis.

2. Data Cleaning

2.1. Fixing Columns

2.1.1. Fix the index

The index was reset to align the Vendor ID column. Unwanted columns were removed here.

2.1.2. Combine the two airport_fee columns

In the final sample dataset, two ambiguous columns were identified: **airport_fee** and **Airport_fee**. To resolve this, I applied a maximum-value approach—calculating the maximum value from both columns for each record. A new column, **airport_fee_combined**, was then created to store the consolidated values.

2.2. Handling Missing Values

2.2.1. Find the proportion of missing values in each column

Highlighted columns in the below table contain blank values.

Column Name	**Missing %**
VendorID	0
tpep_pickup_datetime	0
tpep_dropoff_datetime	0
passenger_count	**0.034255**
trip_distance	0
RatecodeID	**0.034255**
store_and_fwd_flag	**0.034255**
PULocationID	0
DOLocationID	0
payment_type	0
fare_amount	0
extra	0
mta_tax	0
tip_amount	0
tolls_amount	0
improvement_surcharge	0
total_amount	0
congestion_surcharge	**0.034255**
airport_fee_combined	**0.034255**

2.2.2. Handling missing values in passenger_count

The **passenger_count** column contained a notable number of null values, which could directly influence key metrics such as average fare and other trip-based analyses. To address this, all null values were replaced with **1**, based on the reasonable assumption that any recorded trip would involve at least one passenger. This approach preserves the overall distribution of the data without introducing skewness.

2.2.3. Handle missing values in RatecodeID

To address the null or blank values in the **RatecodeID** column, all missing entries were replaced with **1**. The decision is based on the assumption that *Rate Code 1* represents the standard rate typically applied to most trips. By applying this default value, the analysis can proceed under the assumption that at least the standard rate was used, without altering the overall data profile or introducing bias.

2.2.4. Impute NaN in congestion_surcharge

Missing values in the **congestion_surcharge** column were addressed by replacing them with the **median** of the non-null values. Using the median helps avoid the influence of extreme outliers, ensuring the imputed values align with the central tendency of the data and maintaining the integrity of the column's distribution.

2.3. Handling Outliers and Standardising Values

2.3.1. Check outliers in payment type, trip distance and tip amount columns

Payment Type:

Outliers were identified where **payment_type** had a value of *0*, which is not a valid category. These invalid records were removed from the dataset.

Trip Distance:

Several types of outliers were detected in the **trip_distance** column:

- Trips with distances **< 0.1 miles** but fares **greater than $300** were considered inconsistent and removed.
- Trips with distances **> 250 miles** were treated as extreme outliers and excluded.
- Records showing **0 distance and 0 fare**, yet having different pickup and drop-off locations, were deemed invalid and removed from the dataset.

Tip Amount:

No filtering was applied for **tip_amount = 0**, as tipping is optional. However, extremely high tip values (outliers) were naturally minimized through **min–max standardization**, which scales all values between 0 and 1, reducing the influence of extreme tips on the analysis.

3. Exploratory Data Analysis

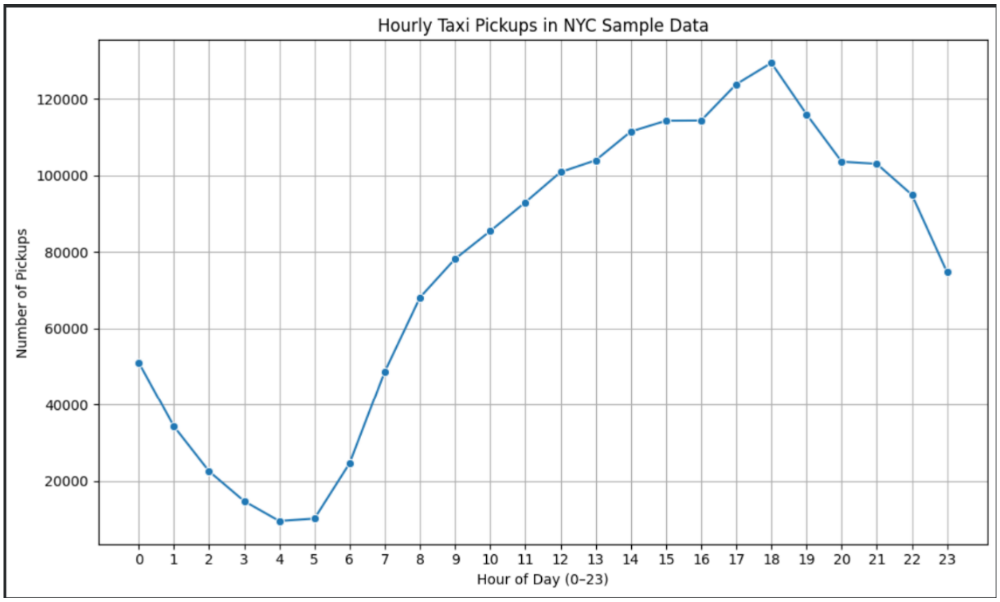
3.1. General EDA: Finding Patterns and Trends

3.1.1. Classify variables into categorical and numerical

Variable Name	Type	Notes
VendorID	Categorical	Coded identifier for vendor
tpep_pickup_datetime	Datetime	Timestamp of trip start
tpep_dropoff_datetime	Datetime	Timestamp of trip end
passenger_count	Numerical	Discrete count of passengers
trip_distance	Numerical	Continuous measurement (miles)
RatecodeID	Categorical	Coded rate type
PULocationID	Categorical	Pickup location code
DOLocationID	Categorical	Drop-off location code
payment_type	Categorical	Coded payment method
pickup_hour	Numerical	Derived from pickup timestamp
trip_duration	Numerical	Duration in minutes/seconds
fare_amount	Numerical	Monetary value
extra	Numerical	Monetary value
mta_tax	Numerical	Monetary value
tip_amount	Numerical	Monetary value
tolls_amount	Numerical	Monetary value
improvement_surcharge	Numerical	Monetary value
total_amount	Numerical	Monetary value
congestion_surcharge	Numerical	Monetary value
airport_fee	Numerical	Monetary value

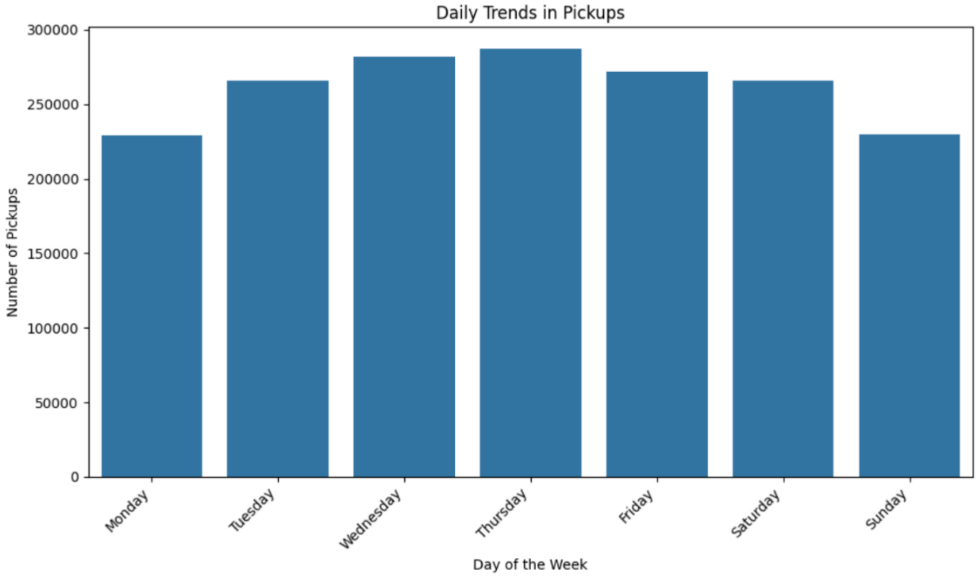
3.1.2. Analyse the distribution of taxi pickups by hours, days of the week, and months

Tax-Pickups by Hour



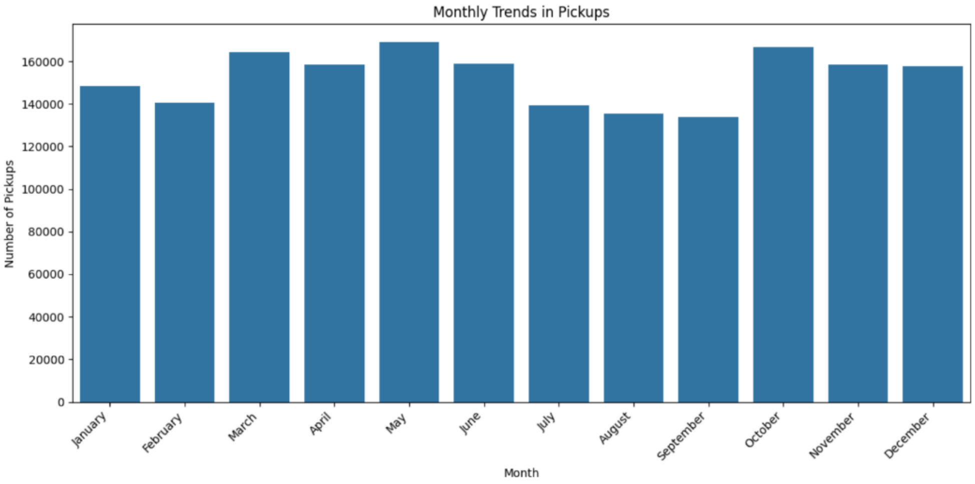
The data shows a clear daily pattern, with minimal taxi demand before dawn, a sharp increase during the morning commute, and the highest activity occurring in the early evening. Demand then tapers off steadily into the night.

Tax-Pickups by Day



Taxi pickups steadily increase from Monday and peak mid-week (Wednesday–Thursday), reflecting higher weekday commuting activity. Demand slightly tapers on Friday and Saturday, followed by a noticeable drop on Sunday. Overall, weekdays show consistently higher pickup volumes compared to weekends.

Tax-Pickups by Month



Taxi pickups fluctuate moderately throughout the year, with higher activity observed in spring and early summer (March–June). There is a dip during late summer and early fall, followed by another rise in October. Overall, seasonal variations are present but not extreme.

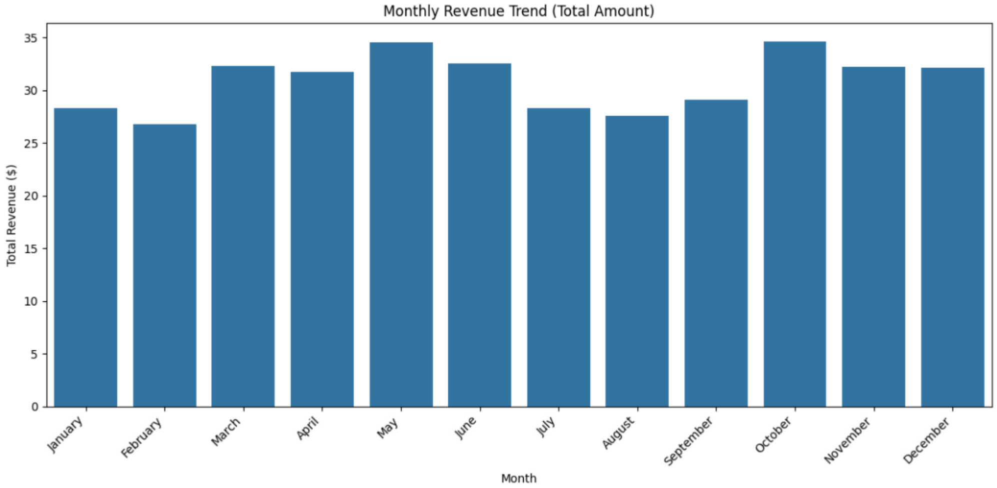
3.1.3. Filter out the zero/negative values in fares, distance and tips

To ensure data quality, the dataset was filtered using the following criteria:

- Records with **fare_amount** or **total_amount** equal to zero were removed, as these typically indicate canceled or invalid trips.
- Trips with zero **trip_distance** despite having different pickup and drop-off locations were flagged as inconsistent and excluded.
- Zero **tip_amount** values were retained because tipping is optional, and many valid trips legitimately report no tip while still showing a correct total fare.

This approach cleans the dataset effectively while preserving real-world behaviors—such as passengers choosing not to tip.

3.1.4. Analyse the monthly revenue trends



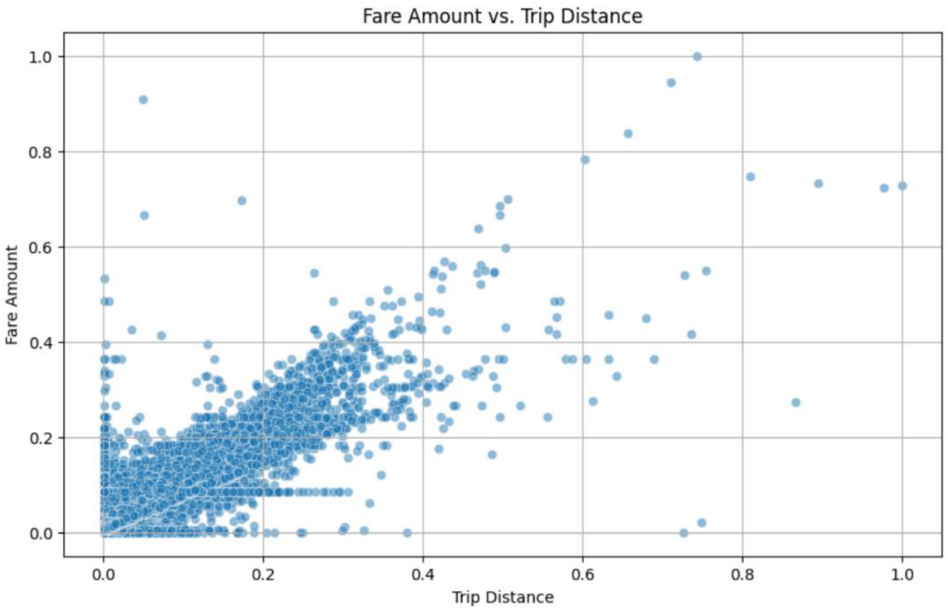
Revenue shows a steady increase from February through May, peaking during late spring and early summer. A dip occurs in July and August, followed by a strong rebound in October, the highest revenue month. Overall, revenue patterns align closely with seasonal travel and activity levels.

3.1.5. Find the proportion of each quarter's revenue in the yearly revenue

Quarterly revenue shows noticeable fluctuations, with 2023 Q2 and Q4 recording the highest average total amounts. Revenue dips in 2023 Q3, indicating a seasonal slowdown before rising again at year-end. Overall, 2023 maintains consistently stronger performance compared to late 2022.

Quarter	Average Total Amount ($)
2022 Q4	0
2023 Q1	23.69
2023 Q2	26.75
2023 Q3	22.76
2023 Q4	26.81

3.1.6. Analyse and visualise the relationship between distance and fare amount



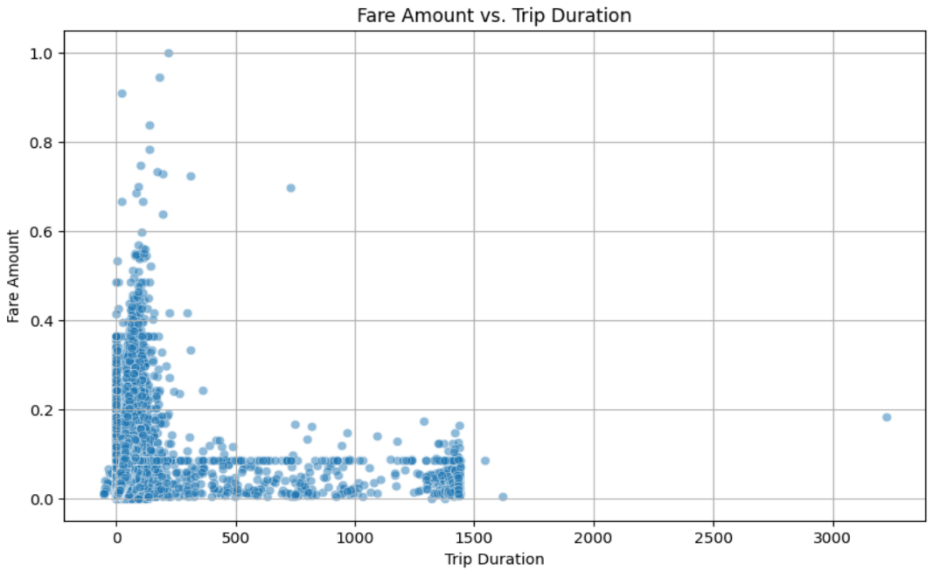
The scatter plot shows a clear upward trend, indicating that higher trip distances generally correspond to higher fare amounts. Most data points are concentrated at shorter distances, but even there, the positive relationship holds.

This visual pattern supports the **strong correlation (0.94)** between distance and fare.

3.1.7. Analyse the relationship between fare/tips and trips/passengers

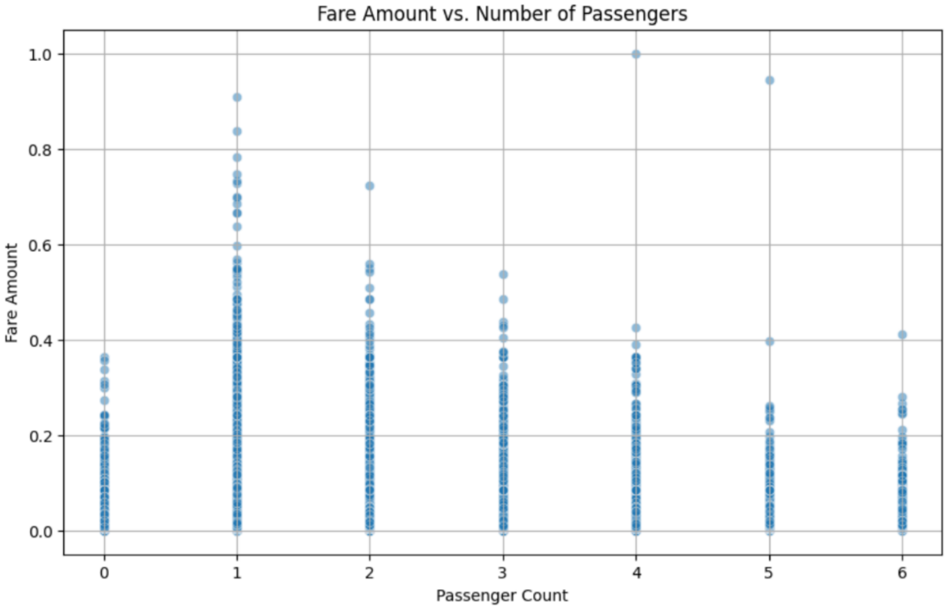
Fare Amount Vs. Trip Duration

The scatter plot shows a weak relationship between trip duration and fare amount, with most points scattered widely and no strong upward trend. The correlation value of **0.27** confirms only a mild positive association. This suggests that fare pricing is driven more by **distance** than by **duration**.



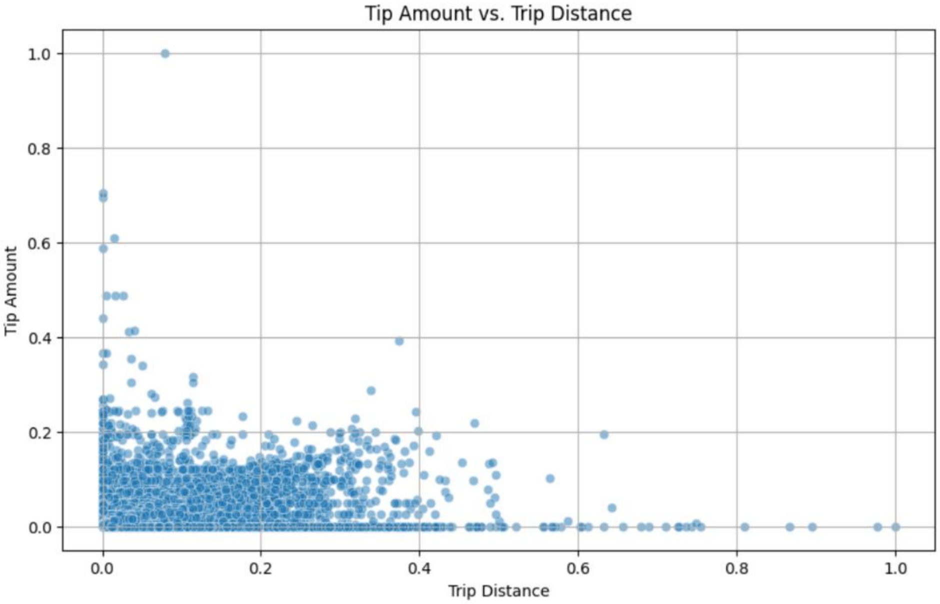
Fare Amount vs. Number of Passengers

The scatter plot shows no meaningful relationship between passenger count and fare amount, with fare values spread similarly across all passenger counts. The very low **correlation of 0.05** confirms that the number of passengers has almost no impact on fare calculations. This indicates fares are primarily distance-based rather than influenced by how many people share the ride.

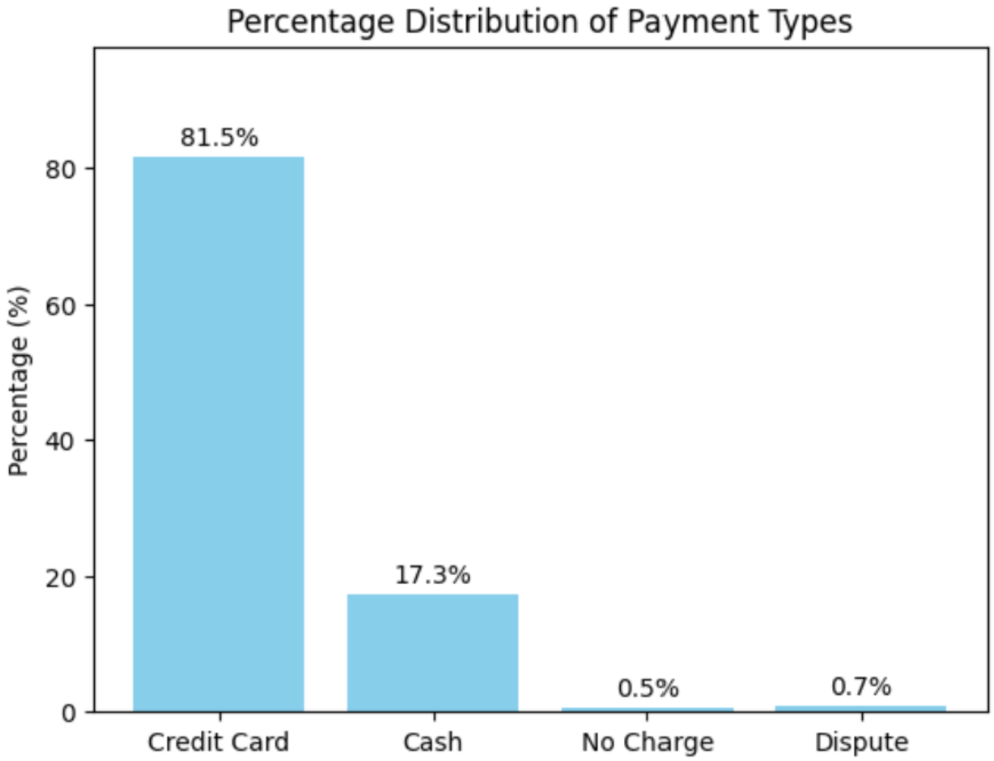


Tip Amount vs. Trip Distance

The scatter plot shows a moderate upward trend, indicating that tip amounts tend to increase with trip distance, although the relationship is not very strong. The correlation of **0.57** confirms a moderate positive association. Overall, longer trips generally lead to slightly higher tips, but tip behavior still varies widely among riders.

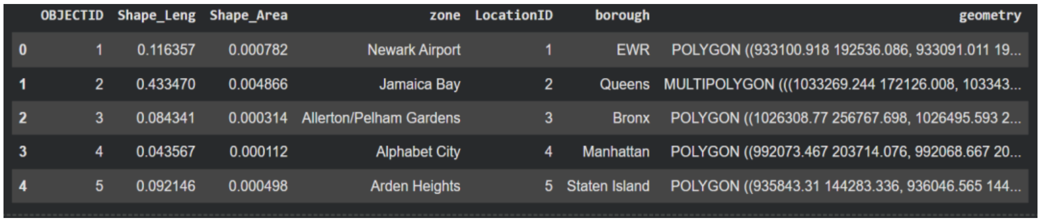


3.1.8. Analyse the distribution of different payment types

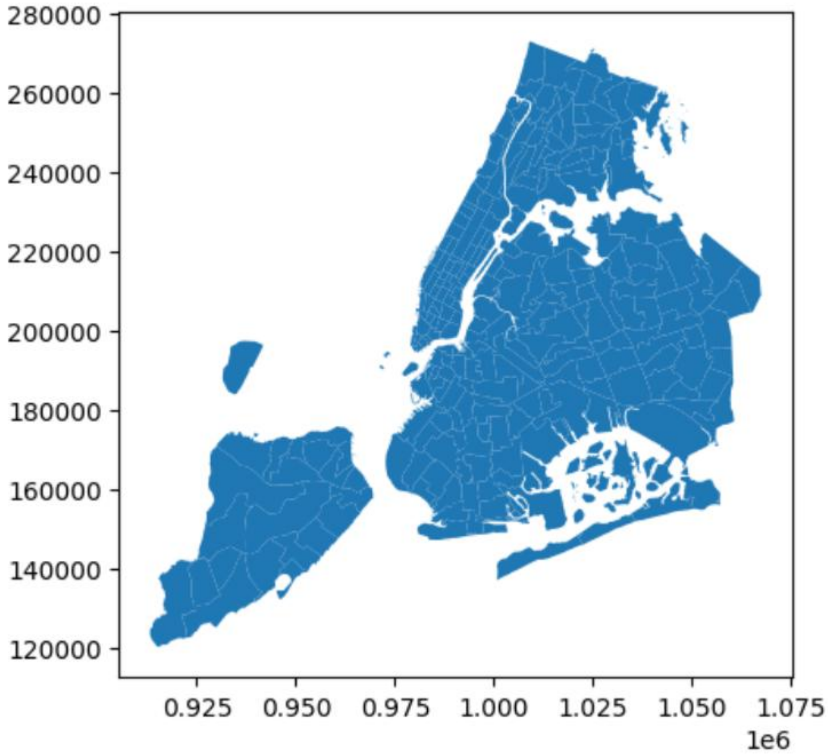


Credit cards account for **81.5%** of all payments, showing a strong preference for digital transactions. Cash makes up **17.3%**, while **No Charge** and **Dispute** categories together contribute less than **1.5%**. Overall, the data highlights a predominantly cashless taxi ecosystem.

3.1.9. Load the taxi zones shapefile and display it



	OBJECTID	Shape_Leng	Shape_Area	zone	LocationID	borough	geometry
0	1	0.116357	0.000782	Newark Airport	1	EWR	POLYGON ((933100.918 192536.086, 933091.011 19...
1	2	0.433470	0.004866	Jamaica Bay	2	Queens	MULTIPOLYGON (((1033269.244 172126.008, 103343...
2	3	0.084341	0.000314	Allerton/Pelham Gardens	3	Bronx	POLYGON ((1026308.77 256767.698, 1026495.593 2...
3	4	0.043567	0.000112	Alphabet City	4	Manhattan	POLYGON ((992073.467 203714.076, 992068.667 20...
4	5	0.092146	0.000498	Arden Heights	5	Staten Island	POLYGON ((935843.31 144283.336, 936046.565 144...



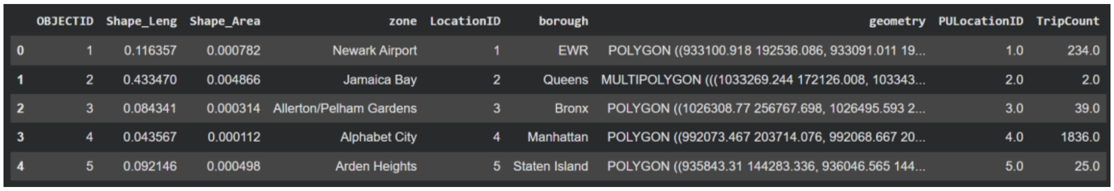
3.1.10. Merge the zone data with trips data

A merge operation was performed to combine the zones dataset with the trip dataset by matching the **LocationID** field from the zones data with the **PULocationID** field in the trip data.

3.1.11. Find the number of trips for each zone/location ID

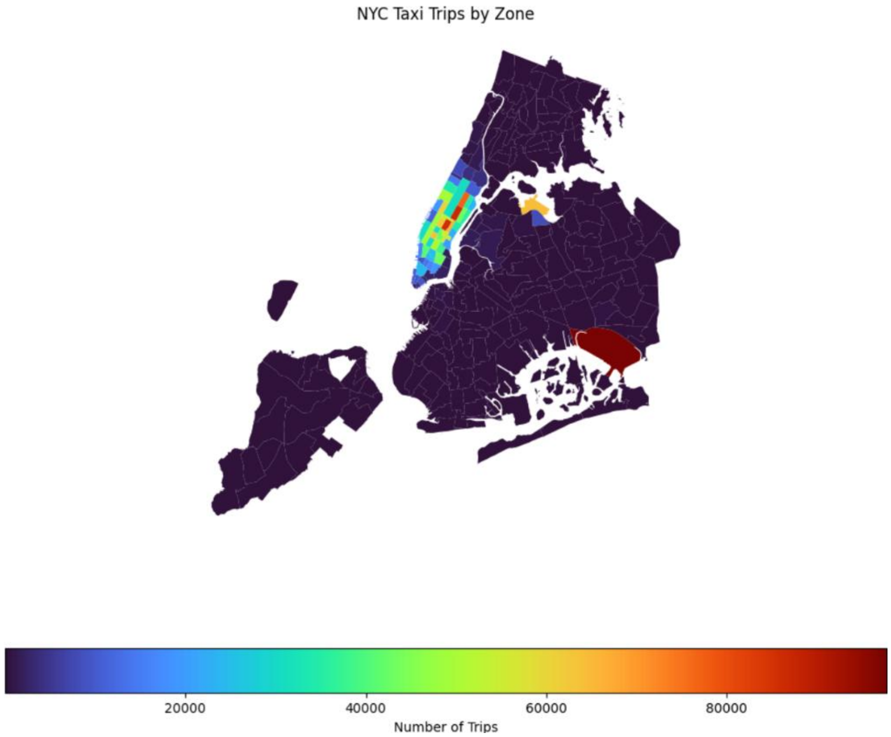
	PULocationID	TripCount
0	1	234
1	2	2
2	3	39
3	4	1836
4	5	25

3.1.12. Add the number of trips for each zone to the zones dataframe



	OBJECTID	Shape_Leng	Shape_Area	zone	LocationID	borough	geometry	PULocationID	TripCount
0	1	0.116357	0.000782	Newark Airport	1	EWR	POLYGON ((933100.918 192536.086, 933091.011 19...	1.0	234.0
1	2	0.433470	0.004866	Jamaica Bay	2	Queens	MULTIPOLYGON (((1033269.244 172126.008, 103343...	2.0	2.0
2	3	0.084341	0.000314	Allerton/Pelham Gardens	3	Bronx	POLYGON ((1026308.77 256767.698, 1026495.593 2...	3.0	39.0
3	4	0.043567	0.000112	Alphabet City	4	Manhattan	POLYGON ((992073.467 203714.076, 992068.667 20...	4.0	1836.0
4	5	0.092146	0.000498	Arden Heights	5	Staten Island	POLYGON ((935843.31 144283.336, 936046.565 144...	5.0	25.0

3.1.13. Plot a map of the zones showing number of trips



JFK Airport emerges as the most prominent hotspot, highlighted in deep red, while central Manhattan shows moderate activity in green and yellow tones. The majority of outer-borough zones appear in darker shades, reflecting comparatively low taxi demand.

3.1.14. Conclude with results

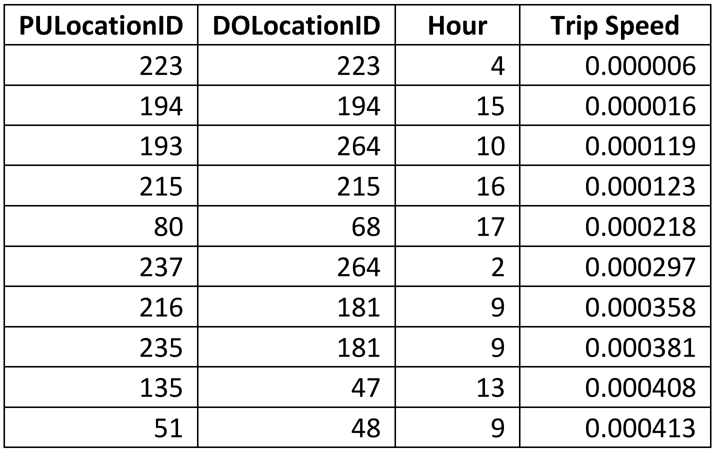
- Rigorous data cleaning and standardization ensured a reliable foundation for analysis by removing inconsistencies, correcting numeric fields, and resolving missing values.
- Travel patterns reveal that **airport zones and Midtown Manhattan consistently attract the highest trip volumes**, highlighting their role as major transportation hubs.

- **Weekday commuting peaks** dominate the morning and evening hours, while **weekends shift activity toward late-night travel**, reflecting different rider behavior.
- The data shows that **most rides involve just one or two passengers**, and **credit card transactions overwhelmingly lead payment choices**, underscoring the system's shift toward cashless mobility.
- A clear **seasonal pattern** emerges, with **Q3 registering the highest trip activity**, likely influenced by tourism and summer travel.
- A strong positive relationship between **distance and fare amounts** confirms that trip length remains the primary driver of pricing.

3.2. Detailed EDA: Insights and Strategies

3.2.1. Identify slow routes by comparing average speeds on different routes

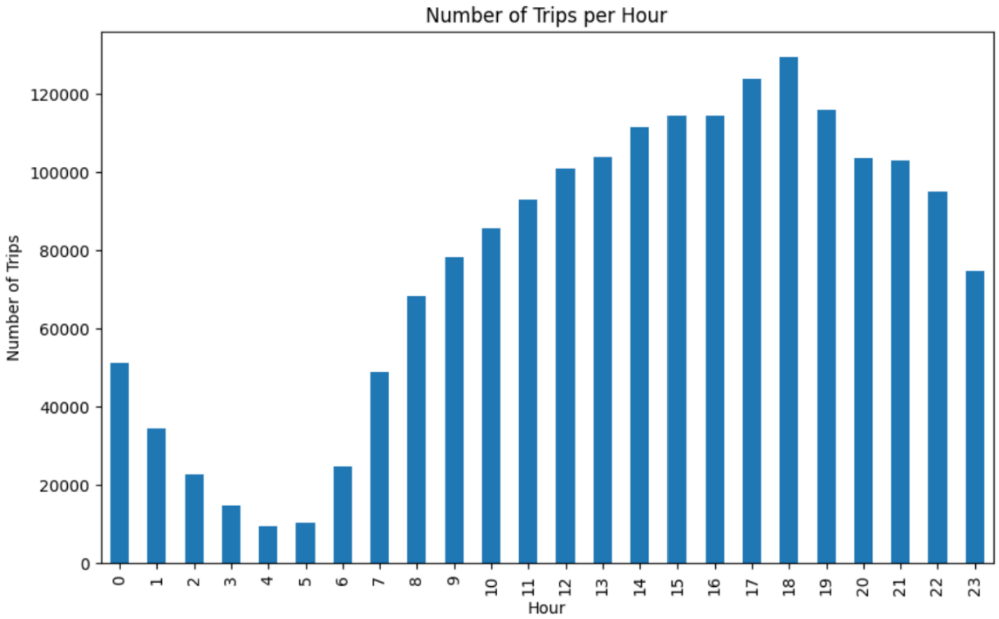
These records show trips with extremely low speeds, often caused by very short distances or heavy congestion. Many occur within the same pickup and drop-off zones, indicating minimal vehicle movement during the trip.



PULocationID	DOLocationID	Hour	Trip Speed
223	223	4	0.000006
194	194	15	0.000016
193	264	10	0.000119
215	215	16	0.000123
80	68	17	0.000218
237	264	2	0.000297
216	181	9	0.000358
235	181	9	0.000381
135	47	13	0.000408
51	48	9	0.000413

3.2.2. Calculate the hourly number of trips and identify the busy hours

The busiest hour for taxi trips is **6 PM,** with **approximately 129,425 rides**, reflecting peak evening commute demand. Trip volumes steadily build throughout the day and reach their highest point during this rush-hour window.



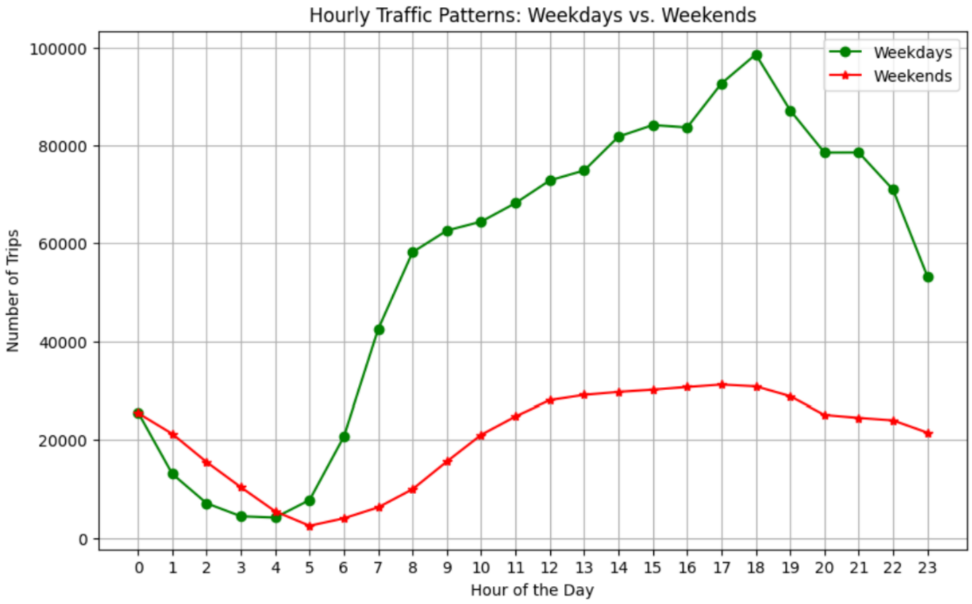
3.2.3. Scale up the number of trips from above to find the actual number of trips

Top 5 Busiest Hour

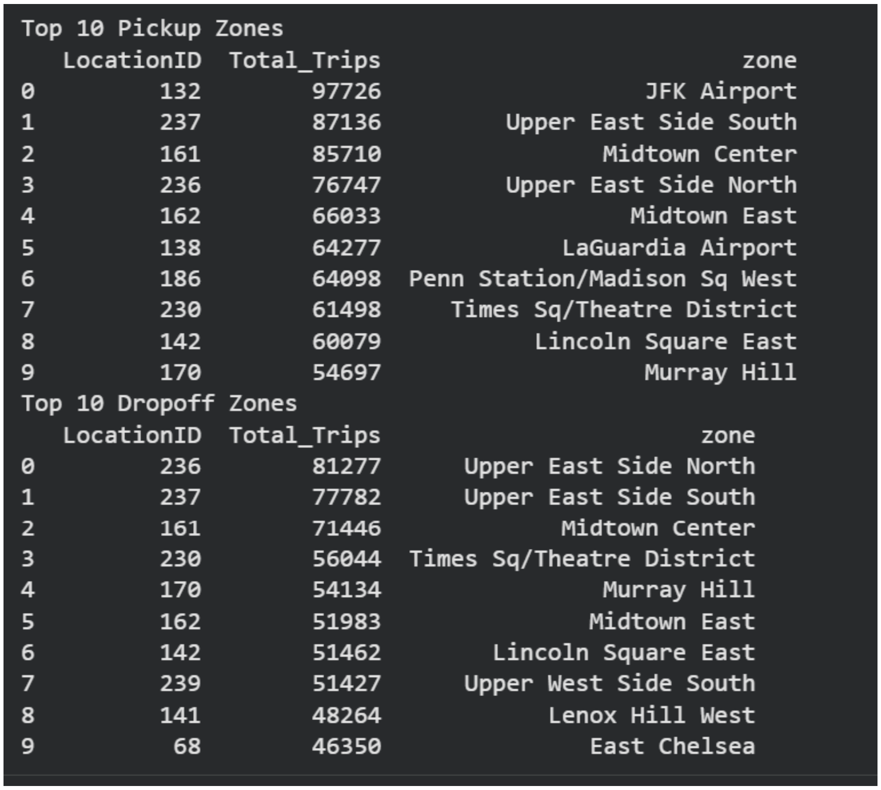
Hour	Trip Count
18	2,588,500
17	2,476,800
19	2,320,340
16	2,287,060
15	2,286,020

3.2.4. Compare hourly traffic on weekdays and weekends

Weekday traffic shows clear morning and evening peaks, driven by commuter activity, with the highest demand occurring around 5–6 PM. In contrast, weekend traffic remains much steadier throughout the day, with no sharp spikes and overall lower trip volumes. This reflects a shift from work-driven travel on weekdays to more flexible, leisure-oriented movement on weekends.

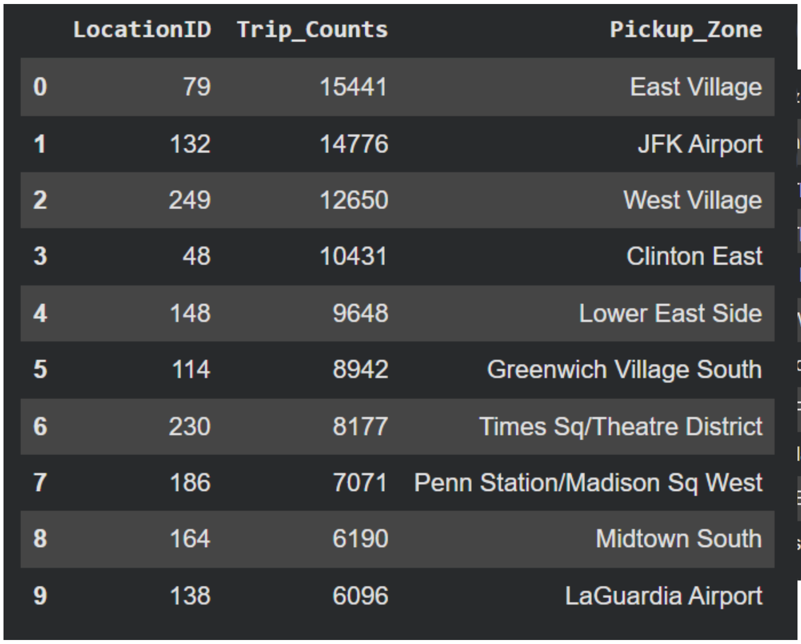


3.2.5. Identify the top 10 zones with high hourly pickups and drops



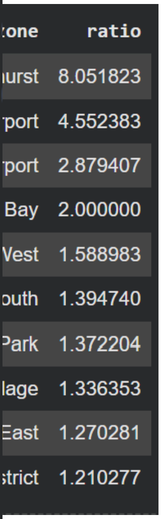
```
Top 10 Pickup Zones
   LocationID  Total_Trips                          zone
0         132        97726                   JFK Airport
1         237        87136         Upper East Side South
2         161        85710                Midtown Center
3         236        76747         Upper East Side North
4         162        66033                  Midtown East
5         138        64277             LaGuardia Airport
6         186        64098  Penn Station/Madison Sq West
7         230        61498     Times Sq/Theatre District
8         142        60079           Lincoln Square East
9         170        54697                   Murray Hill
Top 10 Dropoff Zones
   LocationID  Total_Trips                       zone
0         236        81277      Upper East Side North
1         237        77782      Upper East Side South
2         161        71446             Midtown Center
3         230        56044  Times Sq/Theatre District
4         170        54134                Murray Hill
5         162        51983               Midtown East
6         142        51462        Lincoln Square East
7         239        51427      Upper West Side South
8         141        48264            Lenox Hill West
9          68        46350               East Chelsea
```

3.2.6. Find the ratio of pickups and dropoffs in each zone



	LocationID	Trip_Counts	Pickup_Zone
0	79	15441	East Village
1	132	14776	JFK Airport
2	249	12650	West Village
3	48	10431	Clinton East
4	148	9648	Lower East Side
5	114	8942	Greenwich Village South
6	230	8177	Times Sq/Theatre District
7	186	7071	Penn Station/Madison Sq West
8	164	6190	Midtown South
9	138	6096	LaGuardia Airport

Top 10



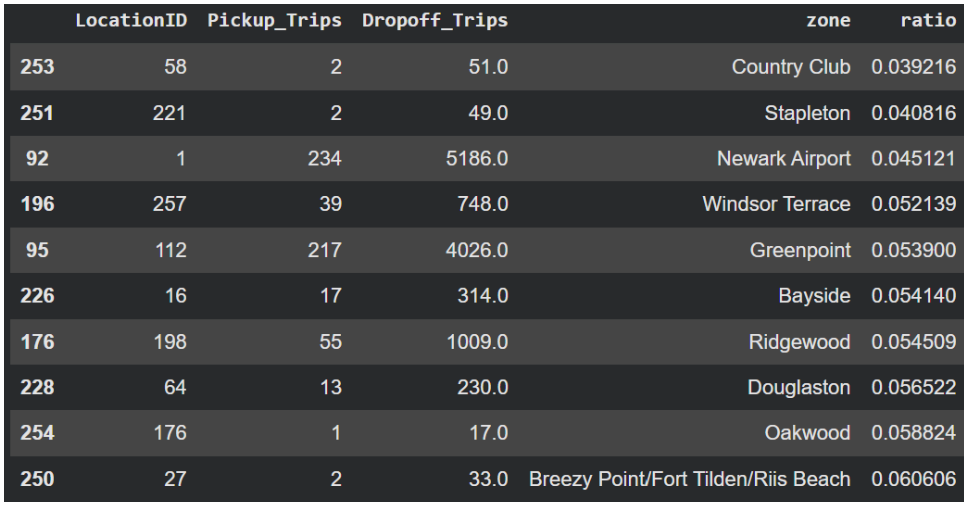
one	ratio
urst	8.051823
port	4.552383
port	2.879407
Bay	2.000000
Vest	1.588983
outh	1.394740
Park	1.372204
lage	1.336353
East	1.270281
strict	1.210277

Pickup Zones

Top 10 Drop off Zones

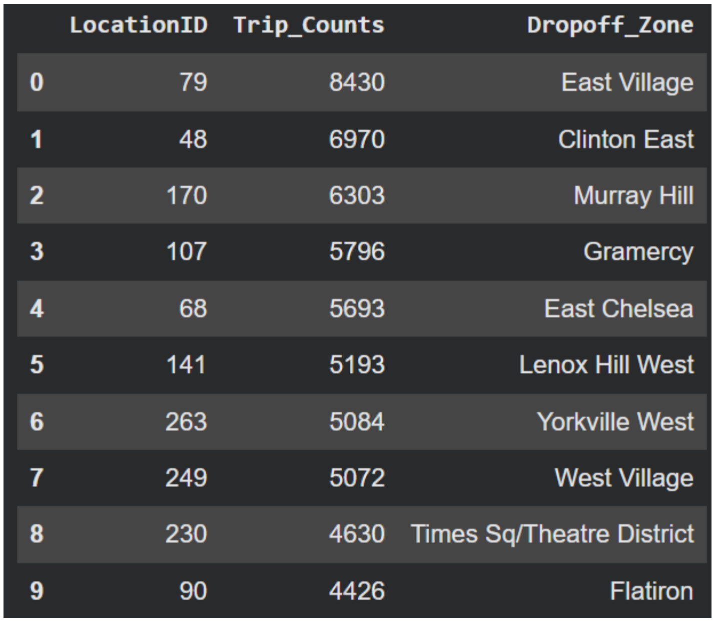
3.2.7. Identify the top zones with high traffic during night hours

Top 10 Pickup Zones at Night



	LocationID	Pickup_Trips	Dropoff_Trips	zone	ratio
253	58	2	51.0	Country Club	0.039216
251	221	2	49.0	Stapleton	0.040816
92	1	234	5186.0	Newark Airport	0.045121
196	257	39	748.0	Windsor Terrace	0.052139
95	112	217	4026.0	Greenpoint	0.053900
226	16	17	314.0	Bayside	0.054140
176	198	55	1009.0	Ridgewood	0.054509
228	64	13	230.0	Douglaston	0.056522
254	176	1	17.0	Oakwood	0.058824
250	27	2	33.0	Breezy Point/Fort Tilden/Riis Beach	0.060606

Top 10 Dropoff Zones at Night

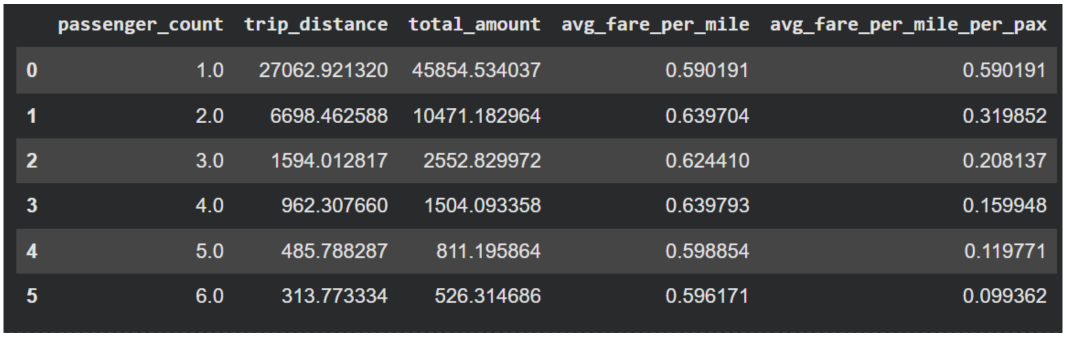


	LocationID	Trip_Counts	Dropoff_Zone
0	79	8430	East Village
1	48	6970	Clinton East
2	170	6303	Murray Hill
3	107	5796	Gramercy
4	68	5693	East Chelsea
5	141	5193	Lenox Hill West
6	263	5084	Yorkville West
7	249	5072	West Village
8	230	4630	Times Sq/Theatre District
9	90	4426	Flatiron

3.2.8. Find the revenue share for nighttime and daytime hours

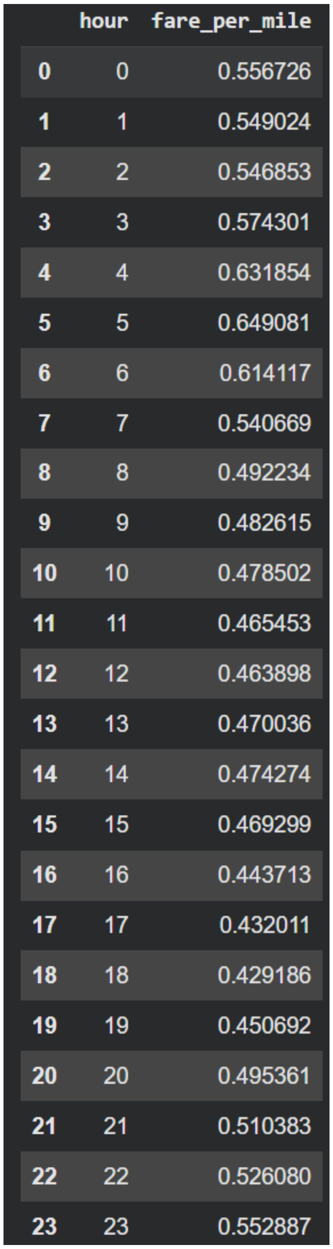
Night-time revenue Share	12.12%
Daytime revenue Share	87.88%

3.2.9. For the different passenger counts, find the average fare per mile per passenger

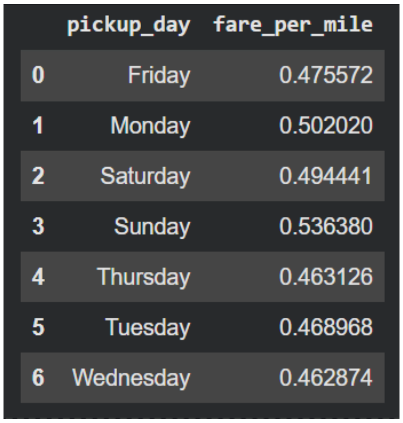


	passenger_count	trip_distance	total_amount	avg_fare_per_mile	avg_fare_per_mile_per_pax
0	1.0	27062.921320	45854.534037	0.590191	0.590191
1	2.0	6698.462588	10471.182964	0.639704	0.319852
2	3.0	1594.012817	2552.829972	0.624410	0.208137
3	4.0	962.307660	1504.093358	0.639793	0.159948
4	5.0	485.788287	811.195864	0.598854	0.119771
5	6.0	313.773334	526.314686	0.596171	0.099362

3.2.10. Find the average fare per mile by hours of the day and by days of the week



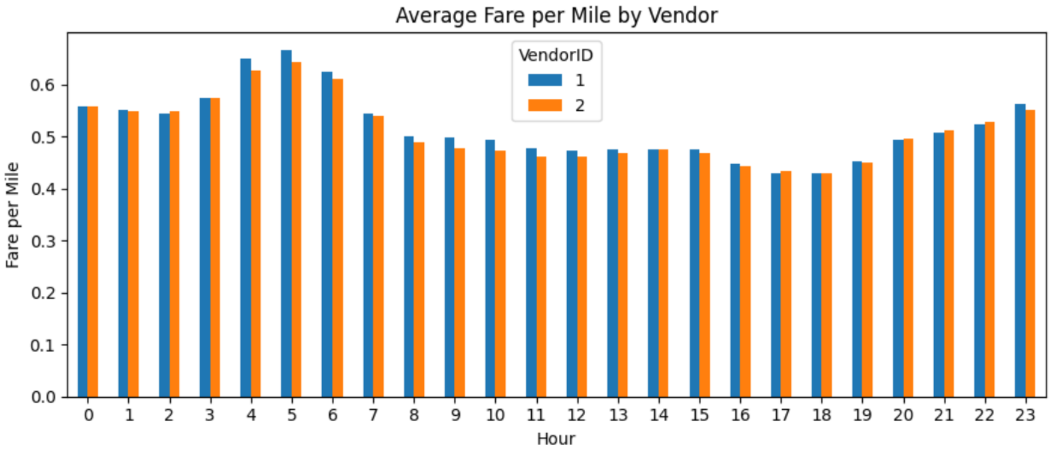
	hour	fare_per_mile
0	0	0.556726
1	1	0.549024
2	2	0.546853
3	3	0.574301
4	4	0.631854
5	5	0.649081
6	6	0.614117
7	7	0.540669
8	8	0.492234
9	9	0.482615
10	10	0.478502
11	11	0.465453
12	12	0.463898
13	13	0.470036
14	14	0.474274
15	15	0.469299
16	16	0.443713
17	17	0.432011
18	18	0.429186
19	19	0.450692
20	20	0.495361
21	21	0.510383
22	22	0.526080
23	23	0.552887



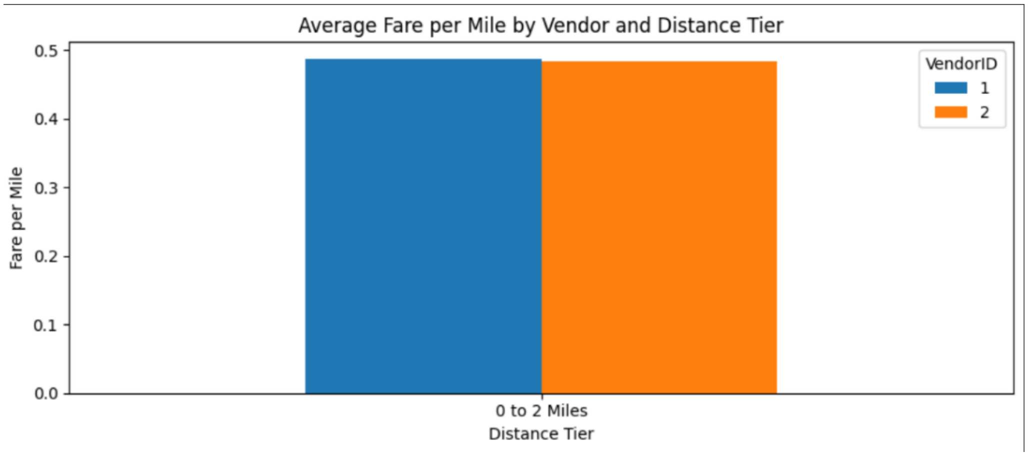
	pickup_day	fare_per_mile
0	Friday	0.475572
1	Monday	0.502020
2	Saturday	0.494441
3	Sunday	0.536380
4	Thursday	0.463126
5	Tuesday	0.468968
6	Wednesday	0.462874

3.2.11. Analyse the average fare per mile for the different vendors

Average fare per mile stays fairly consistent across vendors, though Vendor 1 generally charges slightly higher rates during most hours. Both vendors show early-morning peaks around 4–6 AM, followed by lower, more stable fares throughout the day. Late evenings see a gradual rise again, likely due to reduced traffic and longer-distance trips.

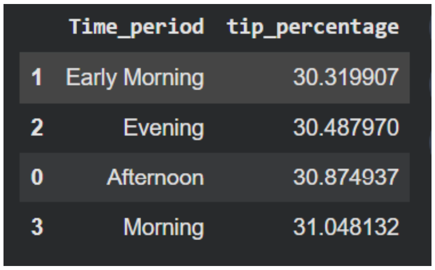


3.2.12. Compare the fare rates of different vendors in a distance-tiered fashion



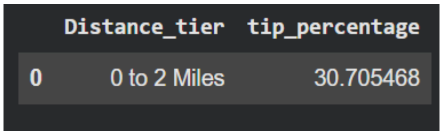
3.2.13. Analyse the tip percentages

Time period with lowest tip %



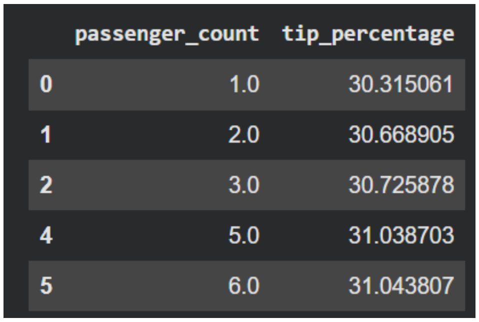
	Time_period	tip_percentage
1	Early Morning	30.319907
2	Evening	30.487970
0	Afternoon	30.874937
3	Morning	31.048132

Distance Tier with lowest tip %



	Distance_tier	tip_percentage
0	0 to 2 Miles	30.705468

Pax segment with lowest tip %

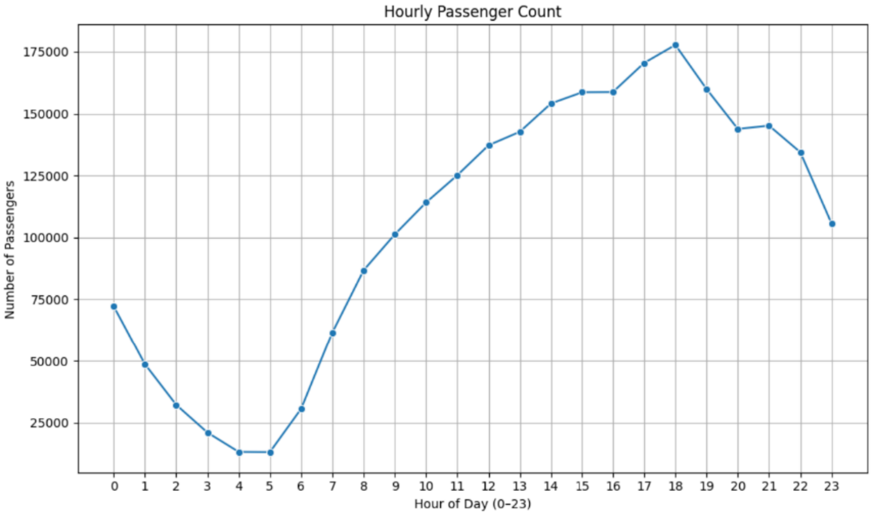


	passenger_count	tip_percentage
0	1.0	30.315061
1	2.0	30.668905
2	3.0	30.725878
4	5.0	31.038703
5	6.0	31.043807

3.2.14. Analyse the trends in passenger count

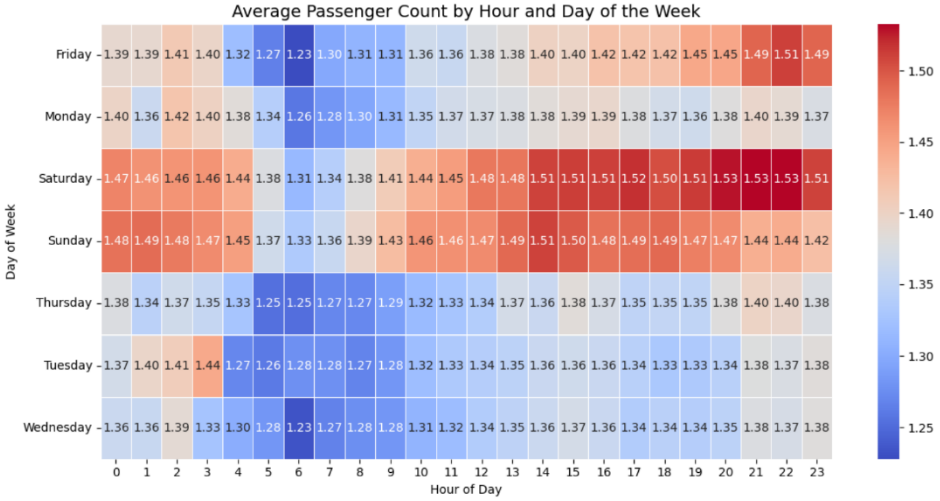
Hourly Trend

Passenger volumes are lowest during the early morning hours but rise sharply after 6 AM, peaking in the late afternoon and early evening. The highest passenger activity occurs around 6–7 PM, aligning with the evening commute. After this peak, counts gradually decline through the night.



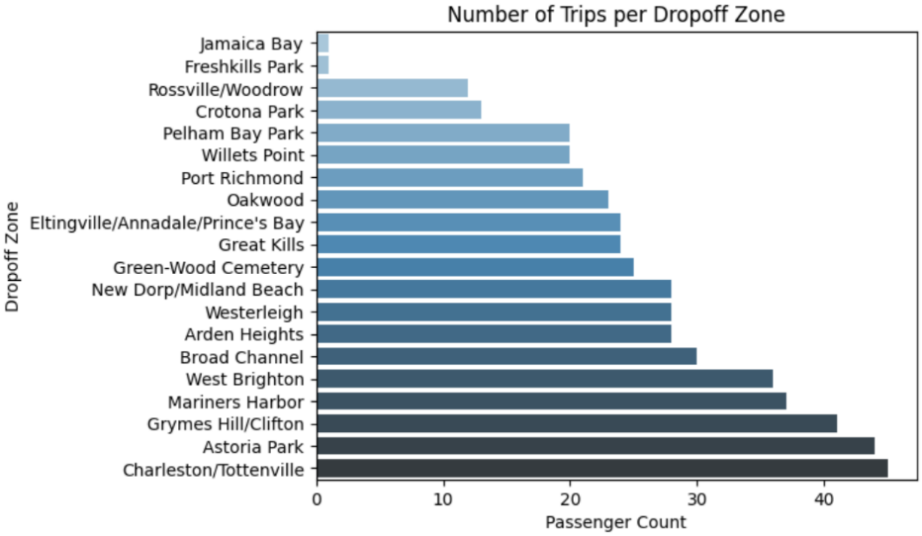
Day wise Trend

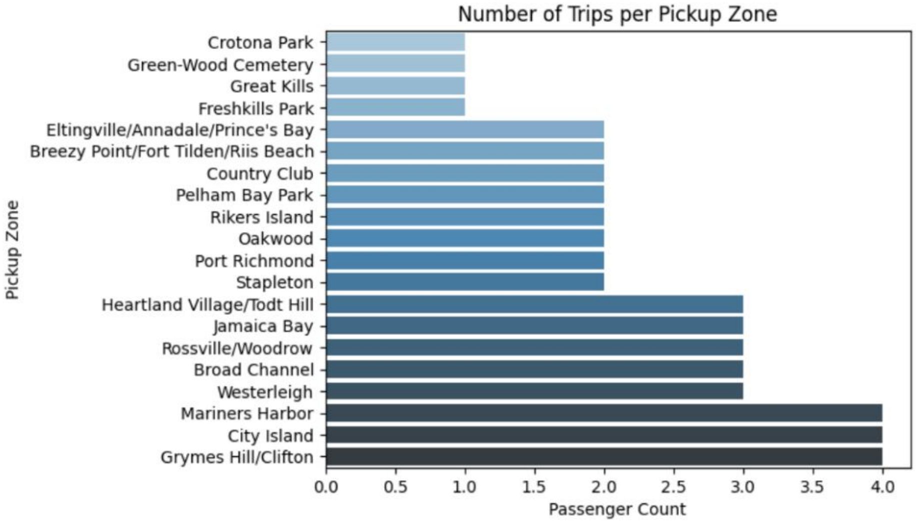
Average passengers per trip remain fairly stable across days, but weekends—especially Saturday and Sunday—consistently show higher passenger counts. Early mornings across all days have the lowest averages, while afternoon and evening hours see the highest. Overall, weekends tend to carry slightly more shared or group rides compared to weekdays



3.2.15. Analyse the variation of passenger counts across zones

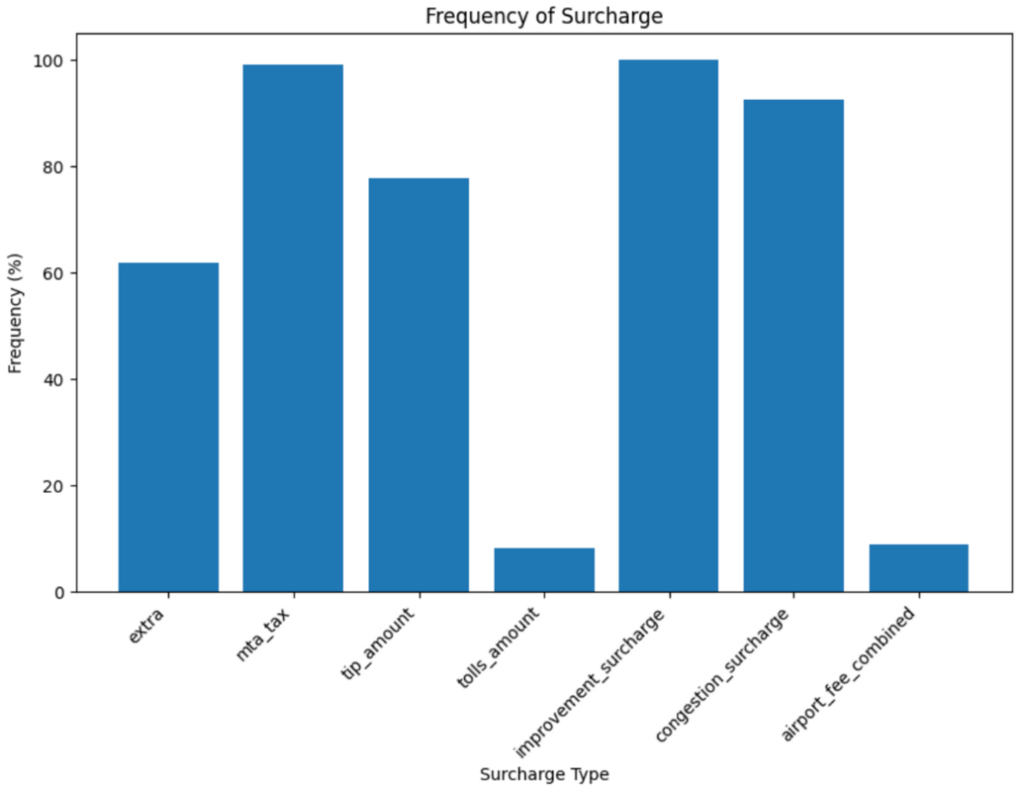
The pickup and dropoff charts both highlight low-activity zones, but notable differences appear in their rankings. Pickup activity is more evenly distributed across zones, with places like Grymes Hill/Clifton, City Island, and Mariners Harbor showing relatively higher counts. In contrast, dropoff patterns are more concentrated, with zones such as Charleston/Tottenville, Astoria Park, and Grymes Hill/Clifton receiving significantly more dropoffs compared to others.





3.2.16. Analyse the pickup/dropoff zones or times when extra charges are applied more frequently.

The chart shows that **mta_tax** and **improvement_surcharge** appear in nearly all trips, indicating they are mandatory fees. **Congestion surcharge** is also highly frequent, reflecting heavy use of high-traffic zones. In contrast, **tolls** and **airport fees** occur far less often, suggesting they apply only to specific routes or locations.



4. Conclusions

4.1. Final Insights and Recommendations

4.1.1. Recommendations to optimize routing and dispatching based on demand patterns and operational inefficiencies.

Key Takeaways

- **When people travel:** Demand shoots up during office rush hours, weekends, and a few busy months of the year. Areas with nightlife stay active late into the night.
- **How money flows:** Fares mostly depend on how far and how long the trip is. Shared rides often come with discounts. Tip amounts change based on the type of trip and customer experience.
- **Where people go**: Airports, major hubs, and tourist spots attract the most rides. Some areas get more pickups than drop-offs and vice-versa. Nightlife areas turn into hotspots after dark.
- **Vendors and extra charges**: Different vendors follow different pricing patterns. Some surcharges appear often, and long-distance trips may follow tiered prices.

Optimization Recommendations

- **Demand Strategy**
  - Prioritize coverage in high-demand areas and peak timings.
  - Strengthen late-night operations in nightlife corridors.
  - Develop tailored offerings for groups and shared-ride customers.
- **Supply Strategy**
  - Increase fleet presence in high-demand zones during peak hours.
  - Implement dynamic pricing aligned with demand and trip attributes.
  - Guide drivers to reposition strategically to balance supply.
  - Offer incentives for servicing low-demand periods or underserved locations.
- **Customer Experience**
  - Elevate service quality through training, monitoring, and standards.
  - Provide multiple payment options for convenience.
  - Promote ride-sharing as a cost-effective and eco-friendly choice.
- **Continuous Improvement**
  - Continuously track performance and refine strategies using analytics and customer feedback.
  - Work with city authorities to address operational and regulatory challenges.

Conclusion

By leveraging data-driven insights into demand, supply, and customer behavior, NYC taxi operators can enhance efficiency, meet rider expectations, and deliver a consistently positive travel experience. Through smarter planning and continuous improvement, the city’s taxi ecosystem can thrive and adapt to changing transportation needs.

4.1.2. Suggestions on strategically positioning cabs across different zones to make best use of insights uncovered by analysing trip trends across time, days and months.

Strategic Cab Positioning

- **Time-Based Deployment**: Adjust cab availability according to daily patterns—morning and evening rush hours, late-night surges, quieter midday periods, and monthly demand shifts.

- **Day-Specific Approach**: Target business hubs on weekdays and shift focus to entertainment and residential areas on weekends. Stay flexible for festivals, events, and city gatherings.
- **Zone-Focused Positioning**: Prioritize zones with consistently high demand, correct pickup–dropoff imbalances, and maintain strong coverage in nightlife hotspots after dark.
- **Data-Led Decisions**: Utilize real-time data, predictive algorithms, and ride-hailing platforms to guide dynamic cab placement.
- **Collaborative Operations**: Maintain continuous driver communication and coordinate with city authorities to streamline traffic flow and enhance service reliability.
- **Tech-Powered Optimization**: Use GPS tracking, heatmaps, and analytics dashboards to gain actionable insights and refine positioning strategies.

By integrating these smart positioning methods, taxi operators can better match supply with demand, reduce passenger wait times, and improve overall service efficiency across NYC.

4.1.3. Propose data-driven adjustments to the pricing strategy to maximize revenue while maintaining competitive rates with other vendors.

Data-Driven Pricing Adjustments

- **Dynamic Fare Management**: Modify fares in real time based on demand, driver availability, and traffic patterns. Increase prices during peak periods and introduce incentives or discounts during slower hours.
- **Tiered & Zoned Pricing:** Keep short-trip rates competitive while using tiered pricing for longer journeys. Introduce zone-based variations to better reflect regional demand and trip complexity.
- **Shared Ride Incentives:** Promote group travel and shared-ride options to boost occupancy, reduce costs for passengers, and improve overall fleet efficiency.
- **Smarter Surcharge Strategies**: Review surcharge patterns and apply peak surcharges only when justified. Ensure passengers receive clear, upfront communication to maintain trust.
- **Competitor Benchmarking:** Stay aware of market pricing trends, adjust rates strategically, and emphasize unique service benefits to justify premium pricing when appropriate.
- **Continuous Optimization:** Use ongoing data collection, A/B price testing, and performance tracking to refine pricing models and balance revenue growth with customer satisfaction.