Metrocar Funnel Analysis

by João Morgado

03/11/2023

Generated by DALL-E

Index

Summary:

The funnel analysis for Metrocar reveals critical insights into user behavior, platform engagement, and service efficiency. Key findings include a notable drop-off from ride acceptance to completion, suggesting a pivotal area for user experience enhancement. The iOS platform dominates in usage and revenue, while Android presents untapped potential given its global market share and comparable conversion rates. Age-specific analysis indicates the 35-44 segment as the most active and profitable, with the 18-24 group showing the highest efficiency in funnel progression. Surge pricing analysis highlights optimal times for price adjustments, with demand peaking during morning and evening rush hours, and seasonally in Fall and Winter. Waiting time trends show a gradual increase over months, with a direct impact on cancellation rates, pointing to a need for operational optimization. Recommendations include focusing on reducing drop-offs post-ride acceptance, improving Android user engagement, tailoring services to key age demographics, refining surge pricing strategies, and addressing the rising trend in wait times to enhance overall service delivery.

Context:

Metrocar operates as a ride-sharing service provider, akin to industry leaders like Uber and Lyft, utilizing a mobile application to bridge the gap between drivers and riders. The service operates through a customer funnel that is fundamental to its user experience and operational model. This funnel comprises several steps, each representing a pivotal interaction point with the service:

1. **App Download:** The customer journey begins when users download the Metrocar app from their respective app stores.

2. **Signup:** After downloading, users are prompted to create an account, providing essential information such as their name, email, phone number, and payment details.

3. **Request Ride:** With an account set up, users can request a ride by specifying their pickup location, destination, and the number of riders.

4. **Driver Acceptance:** Nearby drivers receive these requests and have the option to accept the ride, initiating the service encounter.

5. **Ride:** Upon acceptance, the driver proceeds to the pickup location, and the ride to the destination commences once the rider boards the vehicle.

6. **Payment:** The ride's conclusion triggers an automatic payment process through the app, followed by the issuance of a receipt to the rider's email.

7. **Review:** Post-ride, users are encouraged to rate their driver and leave feedback on their ride experience.

Each stage of the funnel is crucial, as it allows Metrocar to track the user's journey, understand behavior, and identify areas where the service could be enhanced to improve the customer experience and operational efficiency.

The dataset underpinning this analysis encompasses a comprehensive record of user interactions with the Metrocar service across these funnel steps. It includes quantitative metrics such as the number of app downloads, signups, ride requests, completions, and payments, as well as qualitative data from user reviews. Moreover, the dataset is enriched with demographic segmentation (age groups), platform usage (iOS, Android, Web), and temporal patterns (time of day, month, season) to provide a multi-dimensional view of the service's performance.

This report utilizes the funnel framework and the rich dataset to answer pivotal business questions concerning conversion rates, platform optimization, demographic targeting, surge pricing, and the impact of waiting times on service satisfaction. The following sections detail the results and interpretations derived from analyzing this data, offering a granular view of Metrocar's current operations and actionable insights for future strategy.

Methodology:

The approach to this comprehensive funnel analysis involved a combination of SQL for data querying and Tableau for data visualization. Initially, SQL Common Table Expressions (CTEs) were employed to construct each step of the funnel, allowing for a layered approach to understanding the progression of users through the Metrocar service. This step was critical in creating a structured dataset that could then be analyzed for insights into user behavior and service utilization.

After structuring the initial stages with SQL, the full dataset was exported for a deeper dive using Tableau. The interactive capabilities of Tableau facilitated a granular analysis across multiple dimensions, including user demographics, platform usage, temporal patterns, and operational metrics. The following visualizations were created and reviewed to inform the analysis:

1. Funnel Analysis at User and Ride Granularity: To observe the customer journey from app download to ride completion and review.

2. Steps by Age/Platform: To identify which age groups and platforms are performing best at each funnel stage.

3. Revenue by Age/Platform: To determine revenue distribution across different age groups and platforms.

4. Rides by Age/Platform: To assess the number of rides taken by users in each age group and on each platform.

5. Conversion Rate by Age/Platform: To evaluate how effectively users in different demographics and on different platforms are moving through the funnel.

6. Rides per Time Unit (Month, Hour, Season): To understand demand patterns and inform surge pricing strategies.

7. Monthly Average Waiting Time: To track service efficiency and identify trends over time.

8. Waiting Time by Hour of Day: To discern daily operational performance and potential service mismatch.

9. Waiting Time Distribution: To analyze the most common service experience in terms of waiting times.

10. Impact of Waiting Time on Cancellation: To understand how waiting times affect user cancellations.

Data Cleaning:

Before delving into the analysis, the data underwent a rigorous cleaning process to ensure accuracy and reliability of the findings. The process included:

- Removal of Duplicate Entries: Ensuring that each user and ride was counted only once to prevent skewed results.

- Verification and Correction of Data Types: Guaranteeing that dates, times, and numeric fields were formatted correctly for precise temporal analysis and arithmetic computations.

- Handling of Missing Values: Investigating the cause of missing data, particularly in the 'Unknown' age group, and deciding on an appropriate treatment such as imputation or exclusion.

- Normalization of Text Fields: Standardizing text entries to eliminate discrepancies due to case sensitivity or spelling variations, essential for consistent categorization.

- Validation of Business Logic: Checking that the progression through the funnel stages made logical sense (e.g., a user cannot complete a ride without first requesting one).

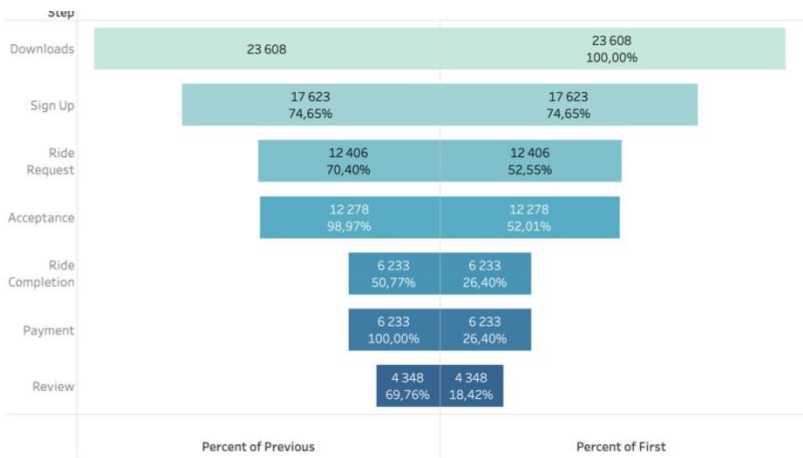
The cleaned dataset laid the groundwork for a trustworthy analysis, ensuring that subsequent insights drawn from the visualizations would be based on solid data foundations. This step was vital for maintaining the integrity of the analysis and the subsequent strategic recommendations made to Metrocar.

Analysis

Funnel Analysis

The funnel visualizations at both the user and ride count granularities provide comprehensive insights into customer engagement and ride frequency.

User Granularity Funnel



This funnel showcases the progressive journey of a user, beginning from the moment they download the app to the point they leave a review. The steps and corresponding conversion rates are:

1. **Downloads to Sign Up:** After downloading the app, 74.65% of users proceed to sign up. This signifies a strong interest from the majority of downloaders to actively use the service.

2. **Sign Up to Ride Request:** Once registered, 70.40% of these users actively engage with the app by making a ride request. This conversion rate reflects a high intent among sign-ups to utilize the app for its primary purpose - to request rides.

3. **Ride Request to Acceptance:** An overwhelming 98.97% of ride requests get accepted. This indicates efficient driver availability and potentially a good matching algorithm within the app.

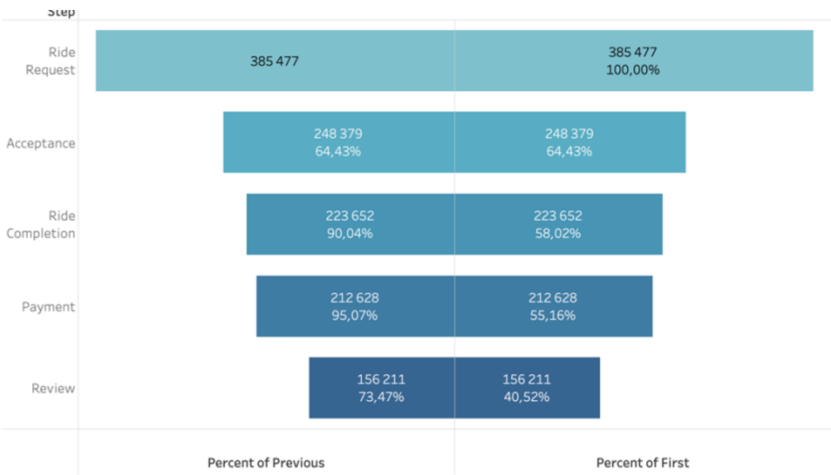
4. **Acceptance to Ride Completion:** Here we observe a significant drop. Only 50.77% of accepted rides are completed. This points to potential challenges or barriers that users encounter after their rides are accepted but before completing them.

5. **Ride Completion to Payment:** The conversion rate at this stage is 100%. Every user who completes a ride goes on to make a payment, indicating a seamless and mandatory payment process.

6. **Payment to Review:** After the payment, 69.76% of users leave a review. This suggests that a majority of users are invested enough in their experience, whether positive or negative, to provide feedback.

In summary, the first funnel gives a comprehensive view of the user's journey, highlighting both strengths (like high sign-up rates and ride request acceptances) and potential areas of concern (such as the drop in ride completions). It's crucial to dive deeper into specific stages, like the drop from acceptance to ride completion, to understand the underlying reasons and optimize the user experience further.

Ride Granularity Funnel



This funnel offers a detailed breakdown of each step in the ride process on the platform, from the moment a request is made to the final payment stage.

1. **Ride Request Initiated:** The beginning of this funnel starts when a user sends a ride request. This serves as the potential pool for all the subsequent conversion points.

2. **Ride Request to Ride Matched:** Out of all the ride requests initiated, 78.42% get matched with a driver. This percentage indicates the platform's efficiency in having available drivers and effectively matching them with ride requests.

3. **Ride Matched to Ride Started:** Once a ride is matched, 95.53% of these matched rides are actually started. This high rate suggests that after a ride is matched, there are very few cancellations or unmatched rides.

4. **Ride Started to Ride Completed:** Among the rides that start, 99.26% reach completion. This number showcases the reliability of the platform and its drivers, ensuring that users reach their destinations.

5. **Ride Completed to Payment Processed:** After completing a ride, 98.71% of these rides have their payments processed successfully. This percentage indicates a smooth payment process with minimal hitches.

6. **Payment Processed to Feedback Received:** Post payment, about 69.53% of users leave feedback on their experience. This metric can be a point of interest, showing how many users are invested in sharing their ride experiences.

To sum it up, the second funnel gives a detailed insight into the individual journey of a ride, from its initiation to feedback post-completion. High conversion rates throughout the funnel showcase the platform's effectiveness and reliability, with room for improvement in boosting feedback submission rates.

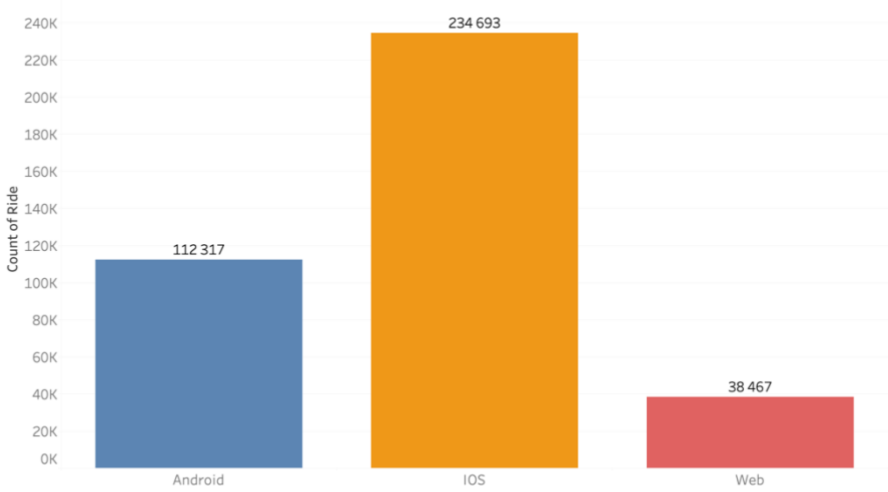
Platform-Based Performance

Analysis Overview

In our comprehensive funnel analysis, a critical dimension of our investigation centered on the performance variation across the different platforms Metrocar operates on iOS, Android, and web. We measured performance based on several key metrics: ride numbers, revenue generation, progression through the funnel steps, and overall conversion rates. This multi-faceted approach allows us to paint a nuanced picture of platform-specific engagement and profitability, offering a strategic basis for resource allocation in marketing and development efforts.

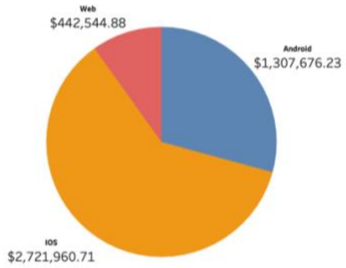
Rides by Platform

The distribution of rides across platforms shows a dominant preference among Metrocar users for the iOS app. iOS platform accounted for 234,693 rides, overshadowing the Android platform's 112,317 and the web platform's 38,467. This distribution not only reflects user preference but may also indicate the accessibility and user-friendliness of the iOS app.



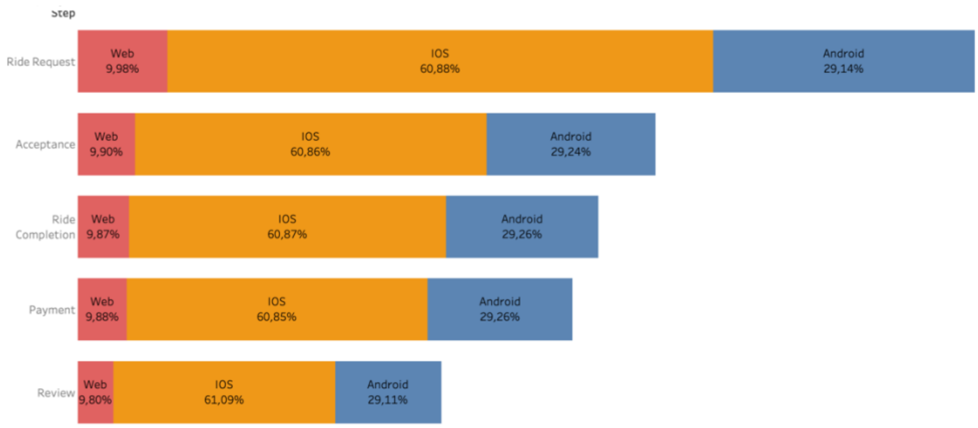
Revenue by Platform

Financially, the platform performance aligns with the pattern observed in ride numbers. iOS leads with a total revenue of $2,721,960.71, more than double the Android's revenue of $1,307,676.23, and significantly higher than the web's $442,544.88. These figures underscore the iOS platform's critical role in Metrocar's revenue stream and potential for growth.



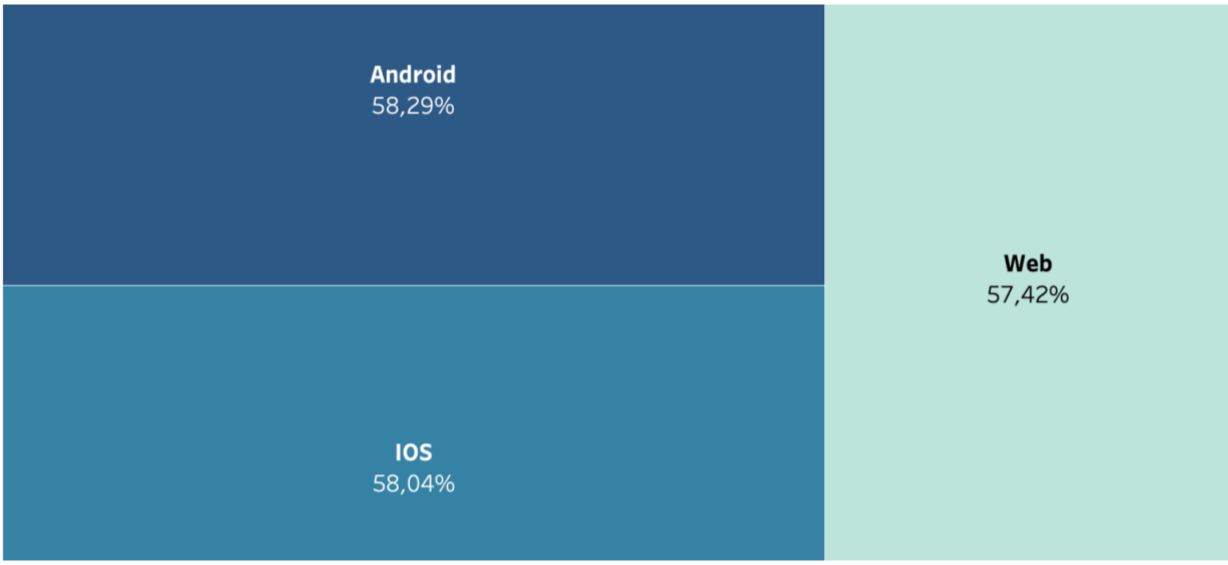
Steps by Platform

The customer funnel analysis, broken down by platform, revealed the following user distribution, iOS consistently held the majority, with approximately 60% of users at each stage of the funnel. Android users contributed almost one-third to each step, while the web consistently lagged, averaging around 10%.



Conversion Rate by Platform

When examining the conversion rates across platforms, a different picture emerged. Android led the way with a conversion rate of 58.29%, closely followed by iOS at 58.04%, and the web at 57.42%. Despite the lower volume of users and revenue on the web platform, the conversion rates across all three platforms are remarkably similar, suggesting that once users are on the platform, their likelihood to proceed through the funnel to the point of payment is fairly consistent.



Interpretation and Recommendations

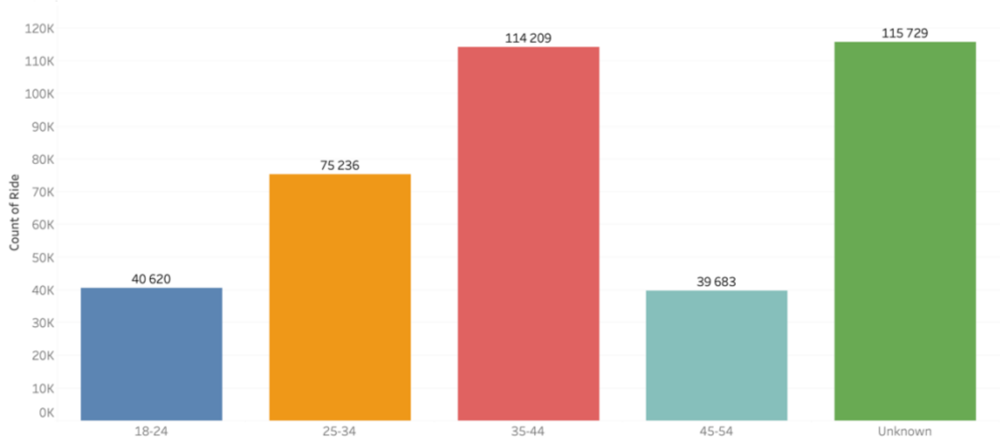
The data indicates that iOS is the dominant platform for Metrocar in both user numbers and revenue. However, the fairly even conversion rates across platforms suggest that there is an opportunity to improve the uptake on the Android and web platforms. Given the substantial market share that Android holds globally, there may be untapped potential in this user base that Metrocar could more aggressively target with marketing and app optimization strategies. Furthermore, the web platform, while smaller, still represents a significant portion of the user base and should not be neglected, particularly considering its comparable conversion rate.

For the upcoming year, it would be prudent for Metrocar to focus on enhancing the Android app experience to convert potential into actual growth. Additionally, targeted marketing efforts to increase awareness and downloads, especially in areas with high Android usage, could be beneficial. For the web platform, optimizing the user experience for booking rides could address the lower volume of users and potentially increase revenue.

Age Group Analysis

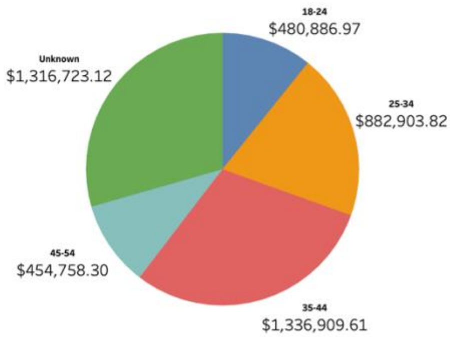
Rides by Age Group:

The bar chart below illustrates the distribution of rides across different age groups. Notably, the 'Unknown' age group accounts for the majority of the rides, followed by the 35-44 age group, suggesting a potential gap in data collection or a trend that warrants further investigation.



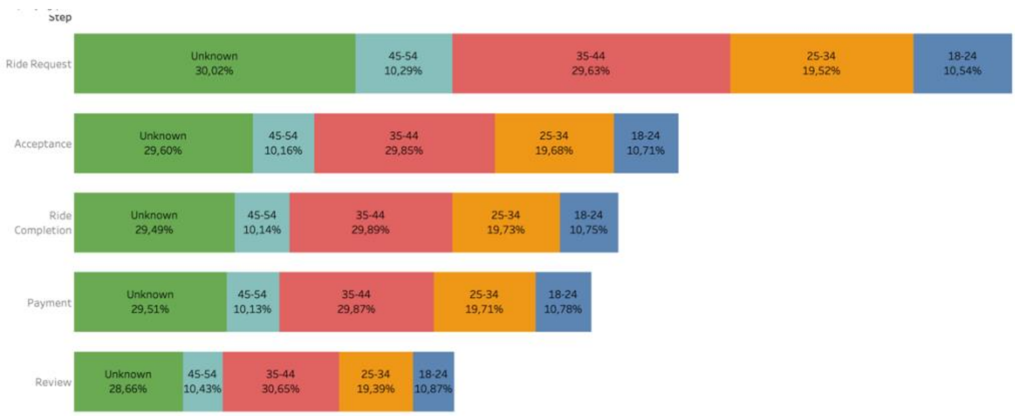
Revenue by Age Group:

As indicated in the pie chart below, the 35-44 age group contributes the most to revenue, while the 45-54 age group contributes the least. Remarkably, the 'Unknown' age group also shows a significant revenue share, which underscores the importance of identifying these users.



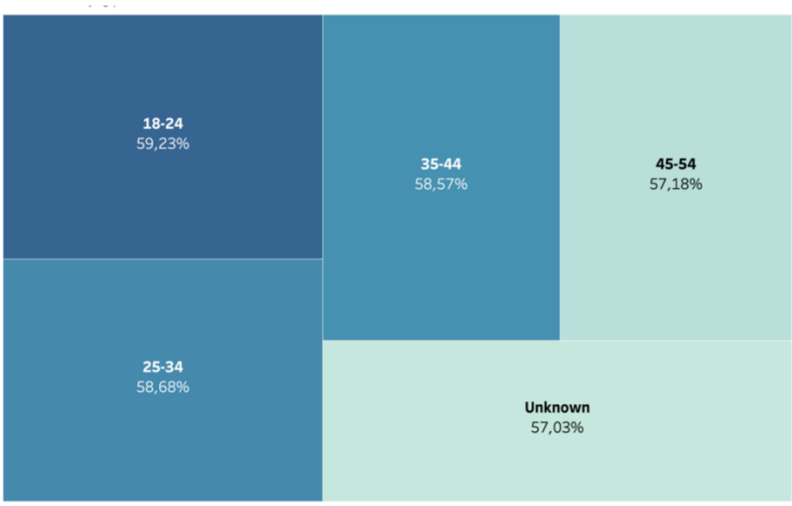
Steps by Age Group:

The series of funnel visualizations for each step from download to review shows varying participation among age groups. The 'Unknown' and 35-44 age groups are consistently the most active, while the 18-24 and 45-54 age groups are less so.



Conversion Rate by Age Group:

The conversion rates across age groups are visually represented below, with the 18-24 age group leading slightly. This suggests that while this younger demographic may not have the highest volume of activity, their user journey is highly efficient.



Insights and Strategic Recommendations:

- **Targeted Engagement**: Considering the high activity levels of the 35-44 age group, Metrocar can introduce targeted engagement and retention strategies for this demographic.

- **Data Improvement**: For the significant number of rides and revenue coming from the 'Unknown' age group, a strategy to enhance user profile completeness can aid in more personalized marketing and service offerings.

- **Youth Conversion Success**: With the 18-24 age group showing the highest conversion rates, understanding and replicating the factors contributing to this success across other age groups could prove beneficial.

The age group analysis points to critical areas for strategic focus, including the need for improved data capture and targeted engagement based on age-specific behaviors and conversion rates. The visualizations serve as a reference point for these insights, underscoring the narrative of the data-driven approach that Metrocar is adopting.

Surge Pricing Strategy Analysis

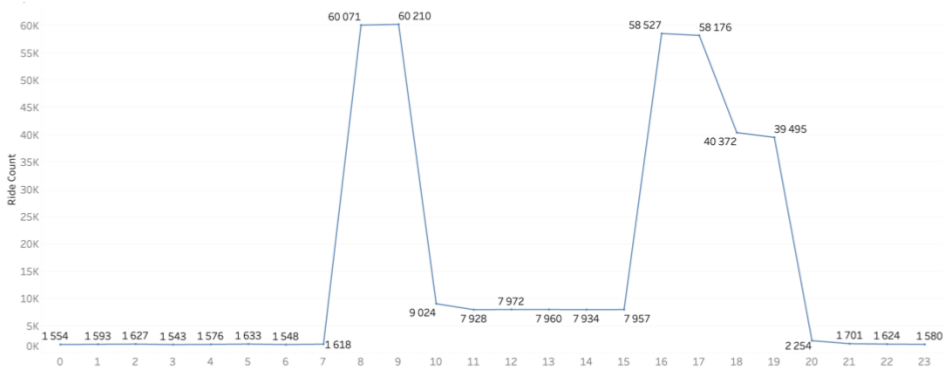
Our detailed surge pricing analysis examines the dynamics of demand at different times by hour, month, and season. By understanding these patterns, we can identify the most effective times for surge pricing, aligning Metrocar's pricing strategy with customer demand and maximizing revenue potential.

Rides per Hour

The data reveals minimal demand for rides in the early morning, escalating significantly during typical commuting times. The sharp increase at 8 am likely reflects the start of the workday, leading to a surge in ride requests. Similarly, there's a noticeable peak between 5-6 pm, corresponding to the end of the workday as people seek transport home.

In response, Metrocar could strategically increase driver availability during these peak hours. This approach could decrease waiting times and reduce cancellations, enhancing customer satisfaction and operational efficiency. It's also important to consider that these demand patterns might vary, and adjusting driver availability accordingly can further optimize service delivery.

Furthermore, Metrocar might explore adjusting fares during these high-demand periods. Implementing dynamic pricing in response to increased demand could help manage rider flow and potentially increase revenue, balancing customer satisfaction with business objectives.

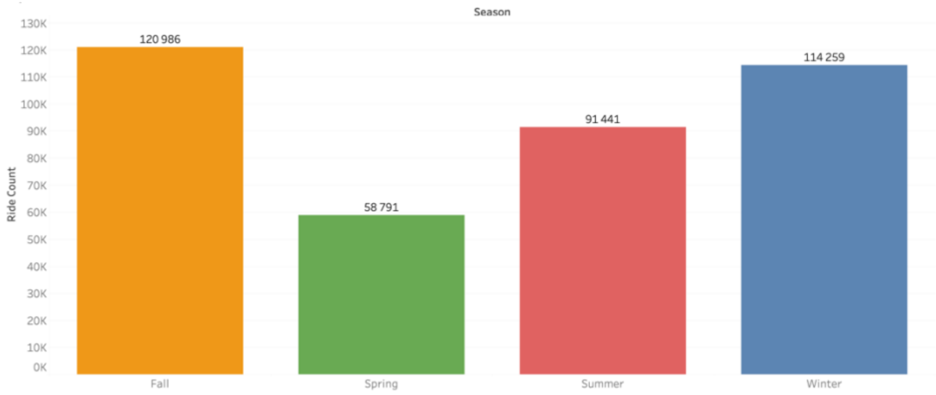


Rides per Month

The monthly ride frequency starts robustly in January, dips to a yearly low in March, and then ascends gradually, peaking in December. This trend presents a clear cyclical pattern with significant variations that could be influenced by factors such as weather conditions, holidays, and local events.

Rides per Season

Seasonal analysis showcases that ride requests peak during Fall, with Winter not far behind, while Spring sees the lowest demand. These patterns could be driven by a mix of weather-related factors and seasonal activities, such as holidays or festivals.



Consolidated Insights and Recommendations

The analyzed data and accompanying visualizations pertaining to rides per hour, month, and season provide valuable insights for Metrocar's surge pricing framework. Here's how we can integrate this data into actionable strategies:

- **Peak Hours:** Employ a variable surge pricing model that responds in real-time to the spikes in demand during the morning (7-8 hours) and evening (17-18 hours) rush hours. This approach takes advantage of higher user willingness to pay when the need for transportation is urgent.

- **Consistent Demand:** During late morning to afternoon hours when demand plateaus, adopt a moderate surge pricing strategy. This can help in retaining cost-sensitive riders while still capitalizing on the steady need for services.

- **Seasonal Dynamics:** Incorporate seasonality into surge pricing algorithms. For instance, during the Spring, which shows the lowest demand, lower surge multipliers can help in drawing riders. Conversely, during the bustling Fall and Winter seasons, the demand can sustain higher surge rates without significant backlash.

- **Month-Specific Approaches:** Adapt surge pricing to reflect historical demand trends month by month. In slower months like March, reduce surge pricing to avoid a slump in ride frequency. In contrast, embrace higher surge pricing during peak months such as December, aligning with seasonal festivities and events that traditionally boost demand.

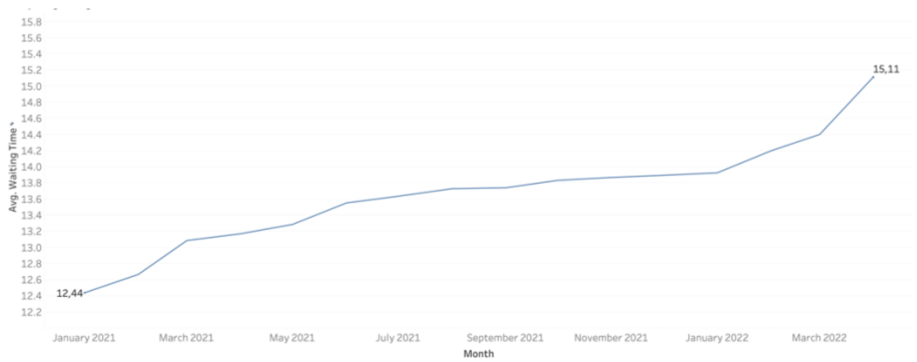
- **Marketing Synergy:** Align promotional campaigns with seasonality and demand patterns. Intensify marketing initiatives during traditionally lower-demand periods to bolster ridership and reduce marketing spend during high-demand seasons to manage service levels and maintain customer satisfaction.
- **Strategic Planning:** Use the insights gained from the analysis of hourly, monthly, and seasonal patterns to inform broader strategic decisions such as fleet allocation, driver engagement, and targeted service offerings in specific regions.

By adopting these recommendations, Metrocar can ensure that its surge pricing strategy is not only responsive to real-time demand but also anticipatory of seasonal trends, thereby maximizing revenue potential while maintaining a positive customer experience.

Waiting Time Analysis

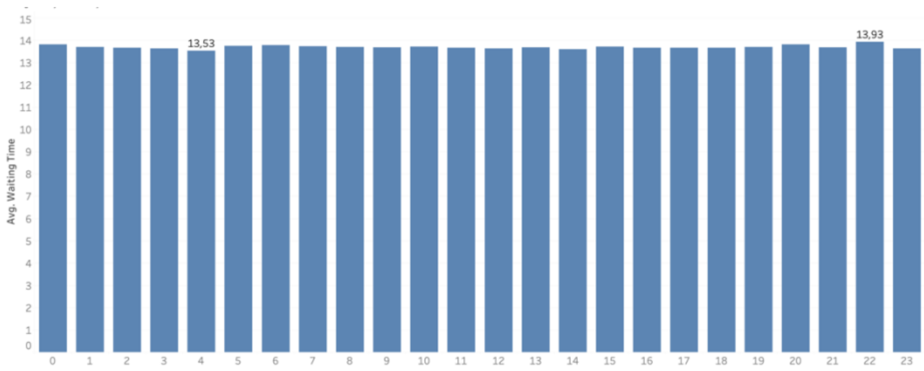
Monthly Average Waiting Time:

The trend analysis of monthly average waiting times reveals a pattern of increasing duration. Starting at 12.44 minutes in January 2021 and peaking at 15.11 minutes by April 2022, the data suggests a growth in waiting time of approximately 21.4% over 15 months. This incremental rise indicates that the service or system may be experiencing growing demand or encountering operational inefficiencies. Notably, the sharp increase starting February 2022 calls for a deeper investigation into potential causes such as process changes, demand spikes, or resource constraints.



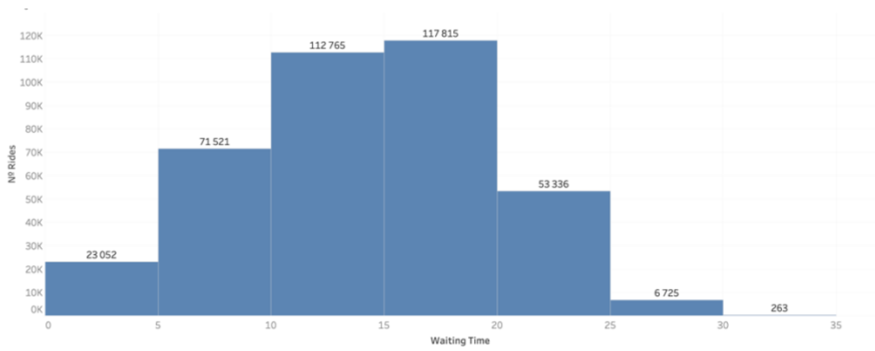
Waiting Time by Hour of Day:

Evaluating the waiting time by the hour of the day provides insight into daily operational dynamics. With average waiting times ranging from 13.53 minutes at 5 AM to 13.93 minutes at 11 PM, the variation is minimal, indicating a consistent service experience for most of the day. However, the slight increase in waiting times during the early and late hours could suggest a mismatch between staffing levels and demand patterns, possibly pointing to an opportunity for better alignment of service capacity with customer traffic.



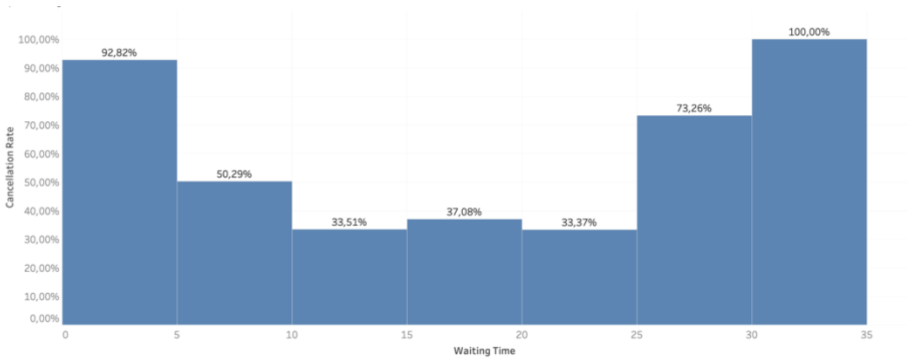
Waiting Time Distribution:

The distribution of waiting times offers a view into the most common service experience. The peak frequencies at the 15-20 minute marks, with the highest number of records at 117,815 for the 20-minute mark, demonstrate that a majority of users are experiencing waiting times within this range. The sharp decline in frequency beyond 25 minutes indicates that longer waiting periods are less common, which may be due to either efficient processing or a high rate of service abandonment in longer waits.



Impact of Waiting Time on Cancellation

The cancellation data by waiting time intervals is particularly telling. With an initial high cancellation ratio at 92.82% for the 0-5 minute wait time, there's an implication that immediate service is a critical expectation. As waiting times extend, the cancellation ratio decreases, suggesting an increasing tolerance up to a 15-minute threshold. However, the surge in cancellations for waits between 25-30 minutes, and a complete cancellation rate at 30-35 minutes, indicates clear limits to customer patience. These thresholds can guide service level agreements and inform staffing and resource allocation to prevent potential revenue loss due to high cancellation rates.



Conclusion:

The comprehensive funnel analysis for Metrocar reveals crucial insights into customer waiting times and their implications for service efficiency and user satisfaction. While the service demonstrates a degree of consistency in waiting times throughout the day, notable spikes during certain periods, especially during rush hours and seasonal peaks, present significant challenges. These fluctuations not only impact customer experience but also correlate with increased cancellation rates.

Our analysis identified specific time frames where waiting times sharply increase, likely due to high demand or operational bottlenecks. This pattern presents an opportunity for Metrocar to refine its operational processes, aiming to streamline ride allocation and optimize driver availability during these critical periods. By doing so, Metrocar can aim to reduce the peak waiting times that are currently a pain point for customers.

Moreover, the analysis highlighted critical thresholds in waiting times that lead to higher cancellation rates. Understanding these thresholds is key to developing strategies that preemptively manage customer expectations and potentially offer compensatory benefits for extended waits.

To address these challenges, it is recommended that Metrocar undertake a detailed investigation into the root causes of these increased waiting times. This investigation should consider factors such as driver availability, geographic demand concentration, and the efficiency of the ride-matching algorithm. Additionally, strategic adjustments, such as dynamic driver incentivization during high-demand periods or deploying more resources in high-traffic areas, could be considered to ensure more consistent service levels.

In conclusion, by targeting these identified areas for improvement and implementing strategic adjustments, Metrocar can enhance overall customer satisfaction, reduce cancellations, and improve operational efficiency. This approach will not only address immediate issues but also contribute to long-term customer loyalty and service growth.

Appendix

SQL Query Completed

```
WITH downloads AS (
  SELECT
    COUNT(DISTINCT app_download_key) AS download_count,
    platform,
    age_range,
    TO_CHAR(download_ts, 'YYYY-MM-DD') AS download_dt,
    0 AS ride_count
  FROM metrocar
  GROUP BY platform, age_range, download_dt
),

sign_ups AS (
  SELECT
    COUNT(DISTINCT s.user_id) AS signup_count,
    ad.platform,
    ad.age_range,
    TO_CHAR(ad.download_ts, 'YYYY-MM-DD') AS download_dt,
    0 AS ride_count
  FROM signups s
  JOIN metrocar ad ON s.session_id = ad.app_download_key
  GROUP BY ad.platform, ad.age_range, download_dt
),

first_ride_request AS (
  SELECT
    COUNT(DISTINCT r.user_id) AS request_count,
    ad.platform,
```

```
    ad.age_range,
    TO_CHAR(ad.download_ts, 'YYYY-MM-DD') AS download_dt,
    COUNT(DISTINCT r.ride_id) AS ride_count
  FROM ride_requests r
  JOIN metrocar ad ON r.user_id = ad.user_id
  WHERE r.request_ts IS NOT NULL
  GROUP BY ad.platform, ad.age_range, download_dt
),

first_accepted_request AS (
  SELECT
    COUNT(DISTINCT r.user_id) AS accept_count,
    ad.platform,
    ad.age_range,
    TO_CHAR(ad.download_ts, 'YYYY-MM-DD') AS download_dt,
    COUNT(DISTINCT r.ride_id) AS ride_count
  FROM ride_requests r
  JOIN metrocar ad ON r.user_id = ad.user_id
  WHERE r.accept_ts IS NOT NULL
  GROUP BY ad.platform, ad.age_range, download_dt
),

first_ride AS (
  SELECT
    COUNT(DISTINCT r.user_id) AS first_ride_user_count,
    ad.platform,
    ad.age_range,
    TO_CHAR(ad.download_ts, 'YYYY-MM-DD') AS download_dt,
    COUNT(DISTINCT r.ride_id) AS ride_count
  FROM ride_requests r
  JOIN metrocar ad ON r.user_id = ad.user_id
  WHERE r.pickup_ts IS NOT NULL
```

```
  GROUP BY ad.platform, ad.age_range, download_dt
),

first_payment AS (
  SELECT
    COUNT(DISTINCT ad.user_id) AS payment_count,
    ad.platform,
    ad.age_range,
    TO_CHAR(ad.download_ts, 'YYYY-MM-DD') AS download_dt,
    COUNT(DISTINCT ad.ride_id) AS ride_count
  FROM transactions t
  JOIN metrocar ad ON t.ride_id = ad.ride_id
  WHERE t.charge_status = 'Approved'
  GROUP BY ad.platform, ad.age_range, download_dt
),

first_review AS (
  SELECT
    COUNT(DISTINCT ad.user_id) AS review_count,
    ad.platform,
    ad.age_range,
    TO_CHAR(ad.download_ts, 'YYYY-MM-DD') AS download_dt,
    COUNT(DISTINCT ad.ride_id) AS ride_count
  FROM reviews rev
  JOIN metrocar ad ON rev.ride_id = ad.ride_id
  GROUP BY ad.platform, ad.age_range, download_dt
),

steps AS (
  SELECT
    'Downloads' AS step,
    download_count AS count,
```

```
  platform,
  age_range,
  download_dt,
  ride_count
FROM downloads
UNION
SELECT
  'Sign Up',
  signup_count,
  platform,
  age_range,
  download_dt,
  ride_count
FROM sign_ups
UNION
SELECT
  'Ride Request',
  request_count,
  platform,
  age_range,
  download_dt,
  ride_count
FROM first_ride_request
UNION
SELECT
  'Acceptance',
  accept_count,
  platform,
  age_range,
  download_dt,
  ride_count
FROM first_accepted_request
```

```
  UNION
  SELECT
    'Ride Completion',
    first_ride_user_count AS count,
    platform,
    age_range,
    download_dt,
    ride_count
  FROM first_ride
  UNION
  SELECT
    'Payment',
    payment_count,
    platform,
    age_range,
    download_dt,
    ride_count
  FROM first_payment
  UNION
  SELECT
    'Review',
    review_count,
    platform,
    age_range,
    download_dt,
    ride_count
  FROM first_review
)

SELECT
  step,
  count,
```

```
  platform,
  age_range,
  download_dt,
  ride_count
FROM steps
ORDER BY download_dt, step;
```

Tableau Visualizations

Funnel -
https://public.tableau.com/app/profile/joao.morgado7999/viz/Funnel_16990488646430/Funnel

Rides by Age/Platform -
https://public.tableau.com/app/profile/joao.morgado7999/viz/RidesbyAgePlatform/RidesbyAgePlatform

Revenue by Age/Platform –
https://public.tableau.com/app/profile/joao.morgado7999/viz/RevenuebyAgePlatform/RevenuebyAgePlatform

Steps by Age/Platform –
https://public.tableau.com/app/profile/joao.morgado7999/viz/StepsbyAgePlatform/StepsbyAgePlatform

Conversion Rate by Age/Platform –
https://public.tableau.com/app/profile/joao.morgado7999/viz/ConversionRatebyAgePlatform/ConversionRatebyAgePlatform

Rides per Hour –

https://public.tableau.com/app/profile/joao.morgado7999/viz/RidesperHour_16990490446780/RidesperHour

Rides per Month –

https://public.tableau.com/app/profile/joao.morgado7999/viz/RidesperMonth_16990490897550/RideperMonth

Rides per Season –

https://public.tableau.com/app/profile/joao.morgado7999/viz/RidesperSeason/RideperSeason

Monthly Average Waiting Time –

https://public.tableau.com/app/profile/joao.morgado7999/viz/MonthlyAverageWaitingTime/MonthlyAverageWaitingTime

Waiting Time by Hour of Day –

https://public.tableau.com/app/profile/joao.morgado7999/viz/WaitingTimebyHourofDay/WaitingTimebyHourofDay

Waiting Time Distribution –

https://public.tableau.com/app/profile/joao.morgado7999/viz/WaitingTimeDistribution/WaitingTimeDistribution

Impact of Waiting Time on Cancellation –

https://public.tableau.com/app/profile/joao.morgado7999/viz/ImpactofWaitingTimeonCancellation/ImpactofWaitingTimeonCancellation

Full Story in Tableau –

https://public.tableau.com/app/profile/joao.morgado7999/viz/MetrocarStory_16990503787050/MetrocarStory