

# **Cyclistic Rider Behavior Analysis**

Understanding Casual Versus Member Ride Patterns to Increase  
Membership Conversion

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# 1.0 Executive Summary

This analysis examines the behavioral differences between casual riders and annual members of Cyclistic's bike-share service. This report highlights key insights drawn from exploratory data analysis (EDA) of ride data from January 2024 to January 2025. The goal is to inform marketing strategies aimed at increasing membership conversions.

## 1.1 Key findings:

- Casual riders have longer ride durations compared to members.
- Casual riders use the service heavily on weekends, while members have a more consistent weekday usage pattern.
- A noticeable number of casual riders use the service during weekday commute hours, which suggests that a number of casual riders are likely local residents who can be targeted for membership conversion.
- Electric bikes (eBikes) are the preferred ride type for both casual and member riders.
- Most rides occur between May and October, reaching the highest point at the end of August.

## 1.2 Recommendations:

- Market cost savings of membership pricing over casual per-ride cost.
- Market cost savings of membership rates for frequent eBike usage.
- Plan marketing campaigns and promotions around seasonal trends.

## 2.0 Introduction

The purpose of this analysis is to gain **data-driven insights** into the **behavioral differences and similarities** between casual riders and annual members. These insights will guide the development of a **targeted marketing campaign** to encourage casual riders to **sign up for a membership**.

### 2.1 Objectives:

1. **Analyze user distribution** between casual riders and annual members to identify opportunities for converting casual riders into members.
2. **Examine ride patterns** (duration, time of day, day of week, and season) to uncover behavioral differences between casual riders and members.
3. **Identify ride type preferences** to gain insight into potential membership incentives and marketing strategies related to pricing and cost savings.

### 2.2 Data Overview

The dataset analyzed consists of Cyclistic's bike-sharing ride data from January 2024 to January 2025, including 5,999,257 ride records. Key attributes include:

- Ride timestamps (started\_at, ended\_at, and day\_of\_week)
- Ride duration (in minutes)
- Ride type (classic\_bike, electric\_bike, and electric\_scooter)
- User classification (casual versus members).

### 2.3 Preprocessing Steps Summary:

- Handled missing values and standardized character entries.
- Filtered out invalid durations (negative values and extreme outliers).
- Converted timestamps into date-time format.

- Added derived time-based features (hour of day, day of week) for analysis.
- Segmented ride duration into meaningful categories (short, medium, long, extended)

*Note: A detailed breakdown of the data cleaning process is available in the Cleaning Log and Data Cleaning Spreadsheet.*

## 3.0 Exploratory Data Analysis (EDA)

This section documents the analysis process and insights that were gained. The analysis process proceeds as follows:

1. User Distribution Analysis - examining the proportion of casual riders versus annual members.
2. Time-Based Usage Patterns - analyzing ride behaviors across different times of day, days of the week, and seasons.
3. Ride Type Preference Analysis - understanding user preferences for ride types and their impact on ride duration and demand.

### 3.1 User Distribution Analysis

Table 1 shows the breakdown of casual riders versus annual members. Member rides make up 63.64% of overall ridership. Key insights from this are that the distribution shows a substantial opportunity to convert casual rides into member rides, and that the raw count of rides may not be the best option to use in our analysis moving forward.

About a third of the rides are from casual riders, which confirms a significant enough number of casual riders who may be targeted for membership conversion. The number of member rides is almost twice as many as casual rides; therefore, using the raw count of rides may produce skewed results because of the imbalance. Using percentages will facilitate better comparison of the two groups when considering ride counts.

**Table 1:** Rider Type Distribution Table

Rider_Type	Count	Percentage
Casual Riders	2144349	36.16
Member Riders	3785713	63.84
Total Riders	5930062	100.00

## 3.2 Time-Based Usage Pattern

Understanding when users ride is crucial for identifying trends and optimizing membership conversion strategies. This section explores three key aspects of time-based behaviors:

1. **Ride Duration Analysis** - examines the average ride duration for casual riders and members.
2. **Hourly and Weekly Ride Patterns** - analyzes ride demand trends throughout the week using heatmaps.
3. **Seasonal and Monthly Trends** - investigates how ridership fluctuates throughout the year to identify peak demand periods.

Insights gained from this section will help pinpoint key time-based behaviors that can inform marketing campaigns and membership promotions.

### 3.2.1 Ride Duration Number Summary Analysis

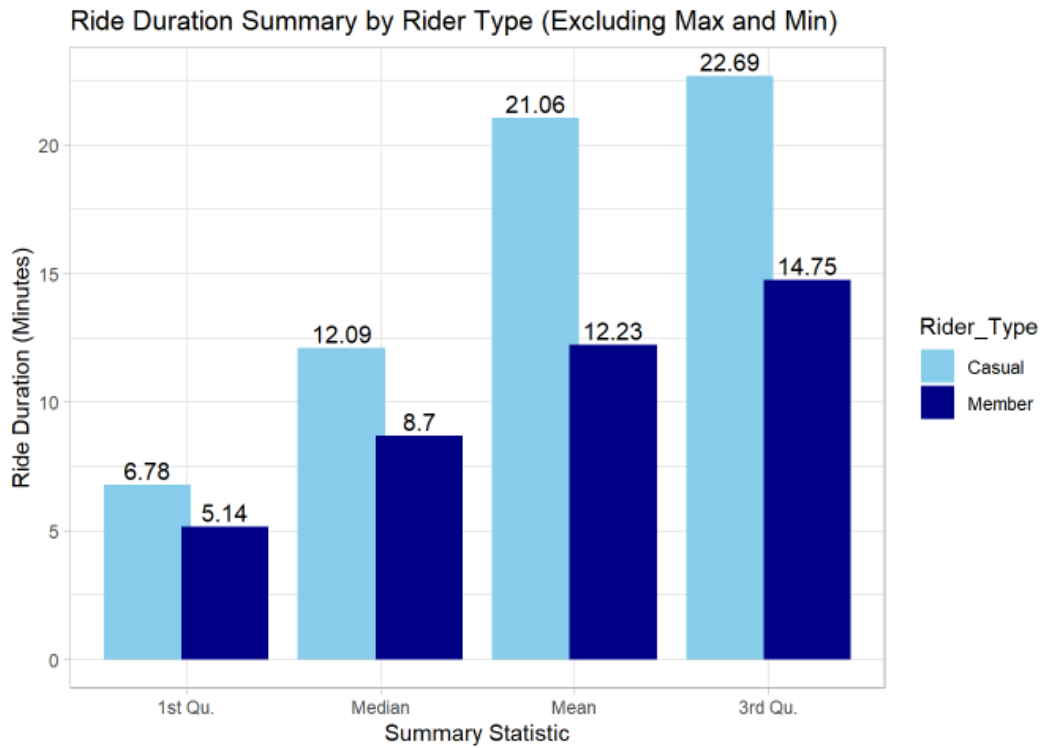
Table 2 presents a statistical summary comparing the ride durations of casual and member riders, while Figure 1 provides a visual representation of these differences. Across all key ride duration metrics (Q1, median, mean, and Q3), casual riders consistently have longer ride durations than members, with differences ranging from 31.95% to 72.12% longer rides. Figure 2 shows that 55.7% of rides are medium rides (7 to 30 minute rides) while the short and medium rides account for 90.2% of all rides.

This insight highlights a potential opportunity: Casual riders could benefit from cost savings through membership, especially given their longer ride durations. A strategic approach could involve targeted messaging that quantifies how much casual riders would have saved had they been members, particularly for frequent long-duration users and even medium ride users.

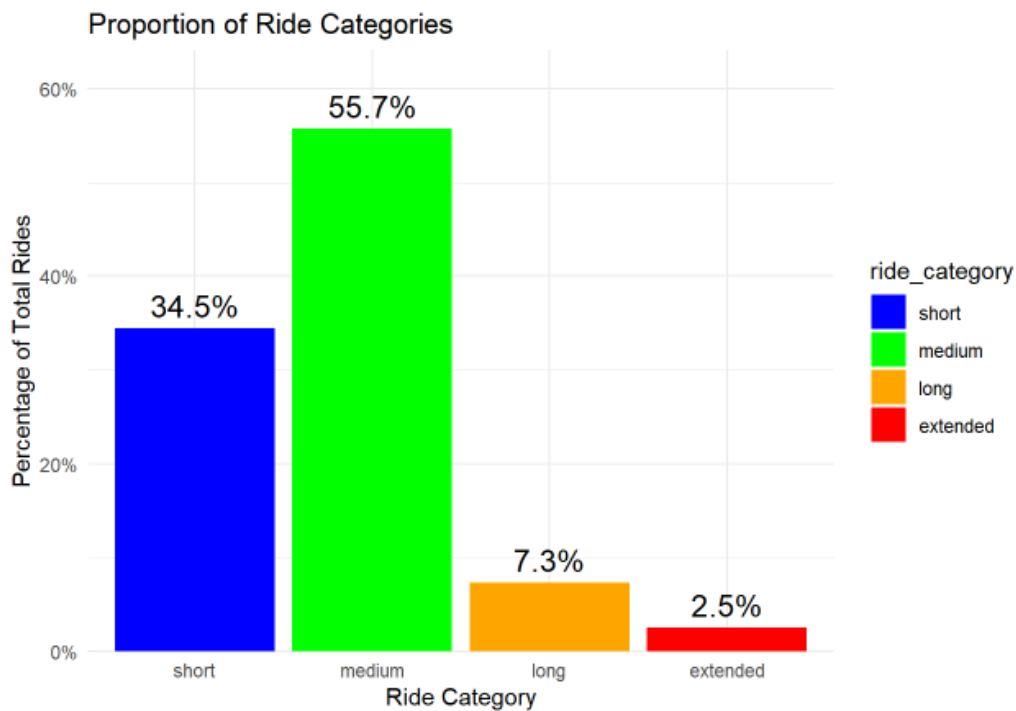
**Table 2:** Ride Duration Summary by Rider Type

Statistic	Casual	Member	Percent_Difference
Min.	0.00	0.00	NA
1st Qu.	6.78	5.14	31.95
Median	12.09	8.70	38.98
Mean	21.06	12.23	72.12
3rd Qu.	22.69	14.75	53.78
Max.	1439.83	1437.77	NA

**Figure 1: Ride Duration Summary by Rider Type**



**Figure 2: Proportion of Ride Categories**



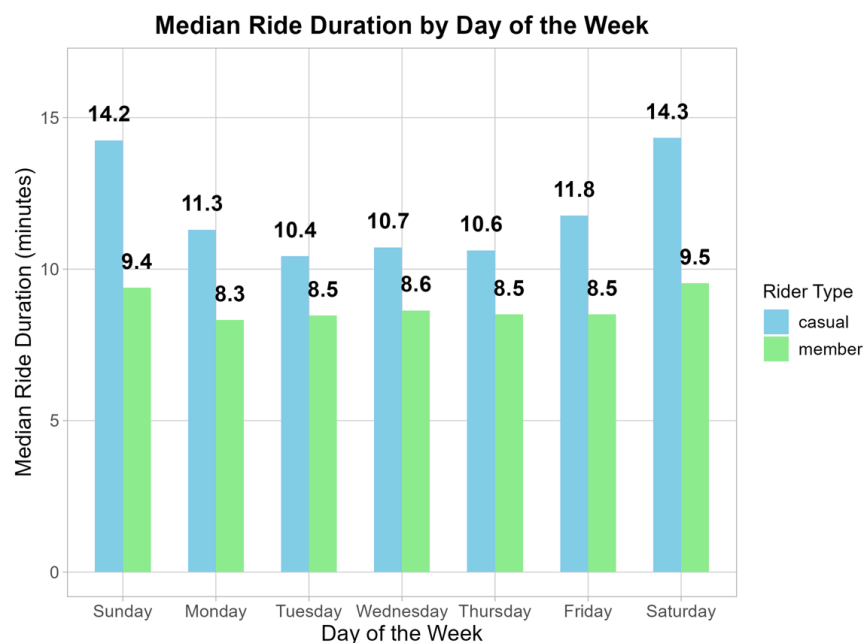


### 3.2.2 Ride Distribution Based on Day of the Week

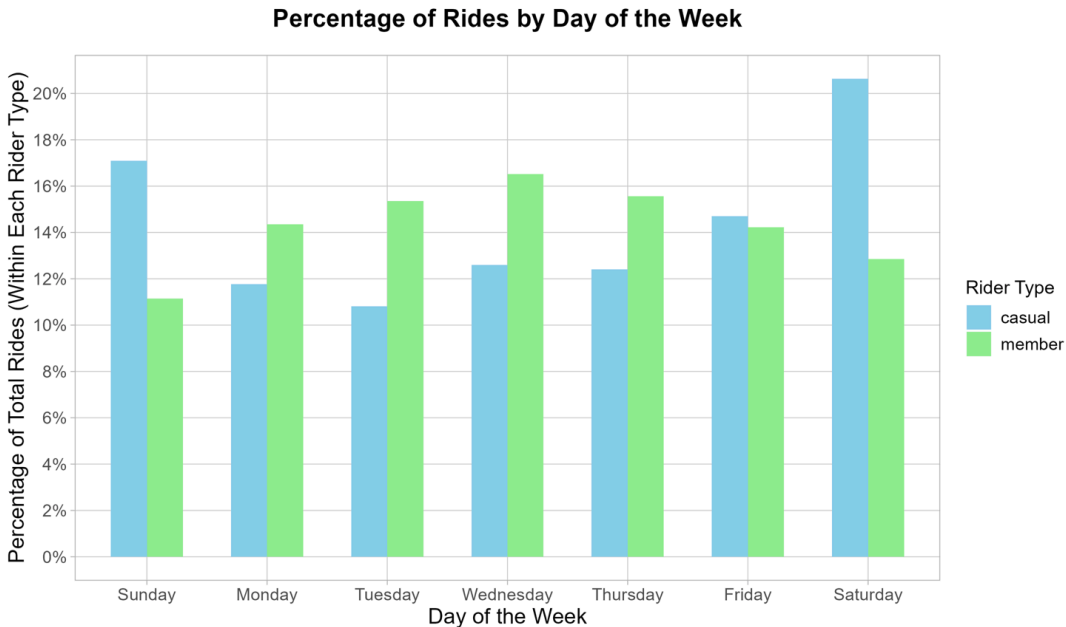
Figure 3 shows the median ride duration of casual and member riders for each day of the week. This confirms that the average ride duration for casual riders is longer than that of members every single day of the week. Figure 4 shows the percentage, with respect to rider type, for casual and member riders during the week. Figure 4 shows that not only do casual riders tend to use the service heavily during the weekend, but the percentage of casual rides that occur on weekdays is not negligible, since they are at least 10% of the total casual rides each day.

This insight further confirms that casual riders tend to use the service for a longer average duration, and the duration and percentage of usage during weekdays are significant. This supports the business goal of converting casual riders into member riders, as this indicates that a significant number of casual rides are likely from local riders who have yet to sign up for a membership.

**Figure 3:** Median Ride Duration by Day of the Week



**Figure 4: Percentage of Rides by Day of Week**

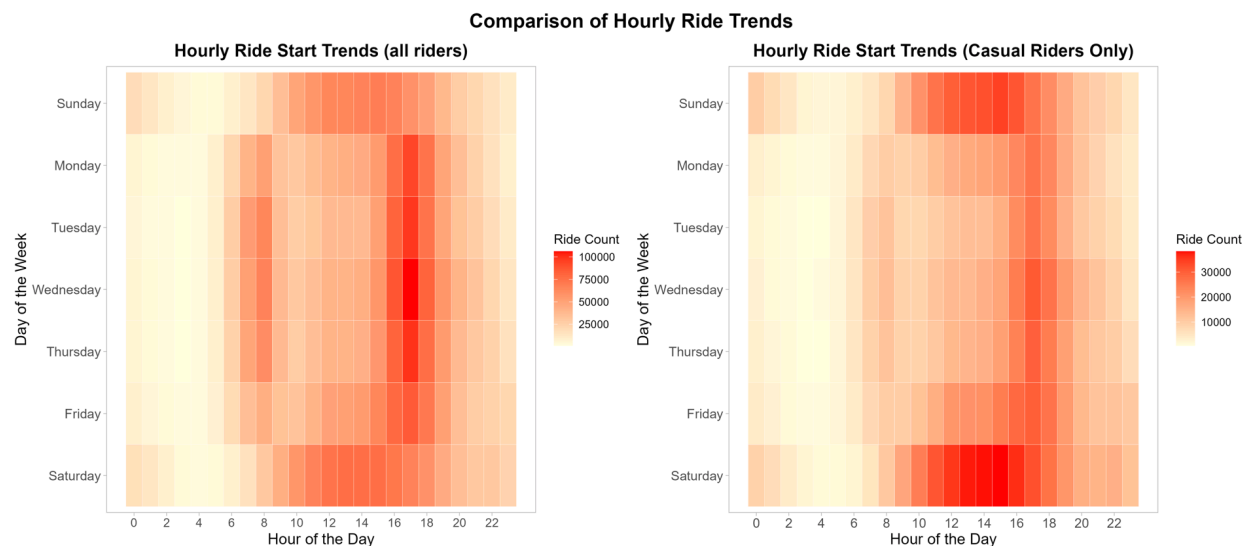


### 3.2.3 Hourly Ride Duration Analysis

Figure 5 shows a side-by-side heatmap visualization of the rides that started at every hour of each day of the week for all riders and casual riders. The all-rider heatmap shows heavy usage during weekends, during the weekday morning commute, and during the weekday afternoon commute. The casual rider heatmap shows a similar pattern, with the difference being that the heaviest usage is on weekends as opposed to the afternoon weekday commute.

An important insight from this comparison is that there is an indication that casual riders show significant use of the service during the morning and afternoon weekday commute. This further supports the business goal of identifying and marketing to local residents who use the service and have not signed up for membership.

**Figure 5: Side-By-Side Hourly Ride Start Heatmap (All Riders and Casual Riders)**



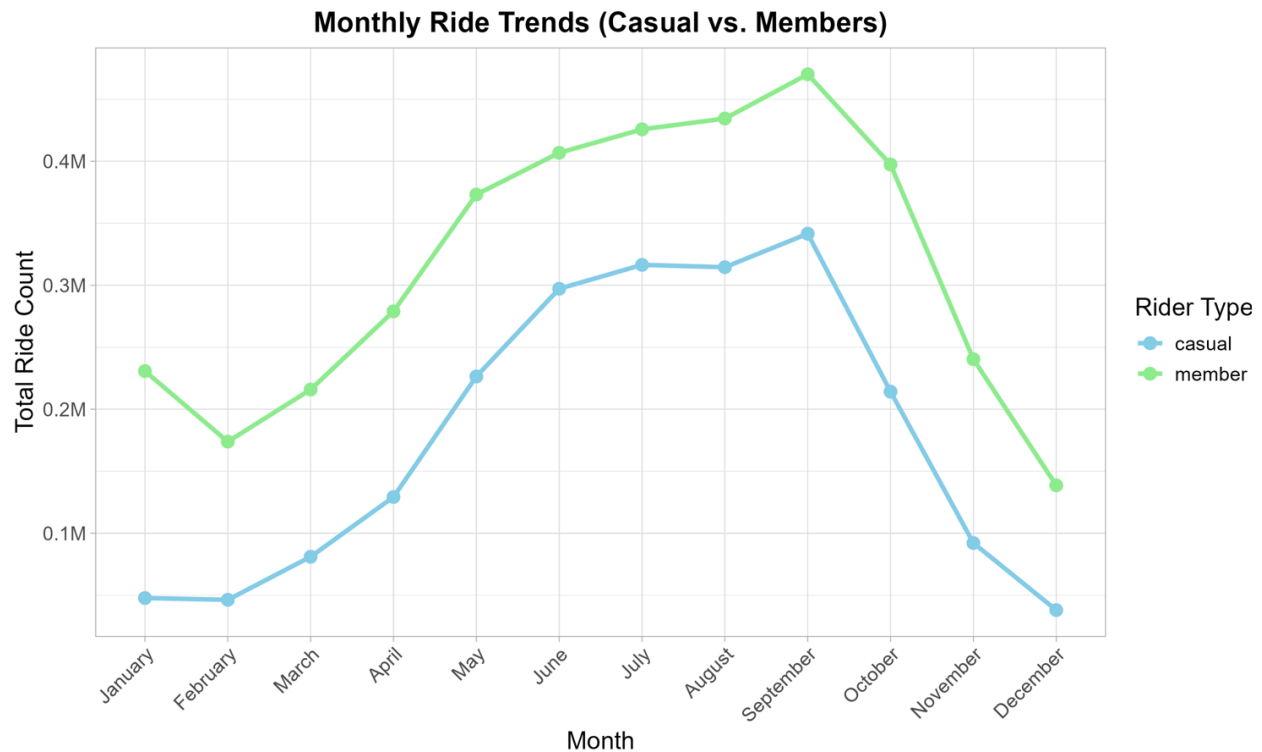
### 3.2.4 Seasonal Ride Usage Analysis

Figure 6 shows the monthly changes in ride counts for both member and casual riders. The increase and decrease phases are nearly identical when considering demand but the rate of change is more drastic for casual rides. Service demand increases from February and peaks at the end of August. The demand decreases from early September until the end of January. However, the number of rides during these months is still at least fifty thousand for casual rides and more than one hundred fifty thousand for members.

This seasonal analysis provides evidence of service usage being highly seasonal and important time-based information for strategic marketing timing. Increasing advertising and user contact just before the start of the demand increase is a good strategy to entice casual riders to sign up for trial memberships or full memberships. Using the knowledge of when demands are decreasing or low to focus resources on creating marketing projects, maintenance, and seasonal

promotions will optimize resource usage and allocations, and membership conversion.

**Figure 6:** Seasonal Riding Trend (Casual versus Members)



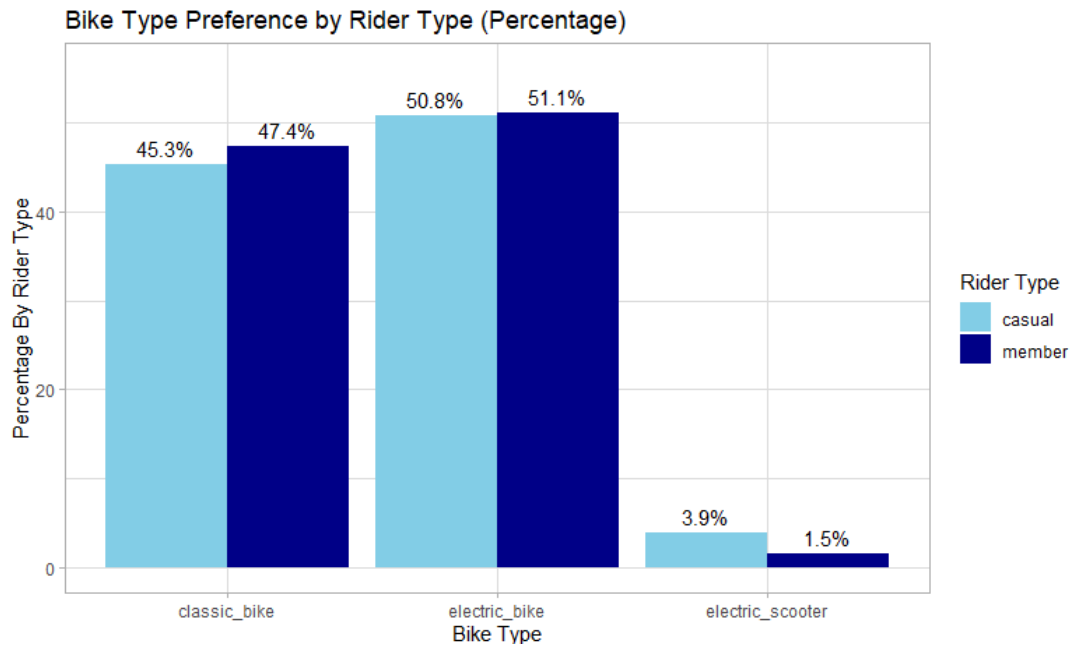
### 3.3 Ride Type Analysis

The service offers classic bike rental, electric bike rental, and electric scooter rental. Figure 7 shows that casual and member riders prefer classic and electric bicycles (97% +), with a slightly higher preference for electric bikes. Figure 8 shows the ride preference for medium rides, which account for 55.7% of all rides, further supporting the finding that both casual and member riders have a slight preference to use eBikes.

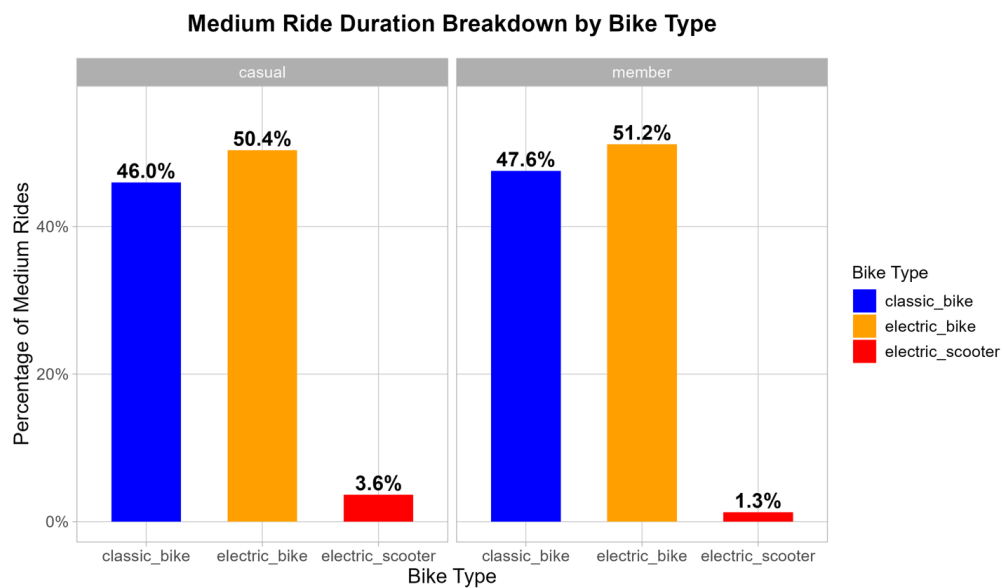
This insight provides evidence that creating a marketing plan that highlights cost savings for eBike usage is a viable option. An individualized summary of cost and

fee savings from member use of eBikes would be a strong marketing strategy to entice casual riders to consider a membership.

**Figure 7: Ride Type Preference**



**Figure 8: Ride Type Preference for Medium Rides**



## 4.0 Recommendations

Based on the EDA, these are the three recommendations based on rider behavior and preferences:

1. **Highlight cost savings of membership over casual per-ride / per-day pricing** - since casual riders tend to take longer rides than members, targeting this group with messaging around potential savings based on ride duration can support membership conversion efforts.
2. **Promote membership benefits for frequent eBike usage** - Both casual and member riders show strong preferences for eBikes, especially for medium-length rides. Marketing the cost advantages of eBike usage under a membership plan could persuade casual riders to become members.
3. **Plan campaigns around seasonal trends** - ridership patterns show a strong seasonality, with usage increasing between February and September. Launching campaigns early in the year (January - February) to promote trial memberships or seasonal deals can increase conversion rates ahead of high-demand months.

## 5.0 Conclusion

This analysis was conducted to understand how casual and member riders differ in behavior, with the goal of identifying strategies that will encourage casual users to become members.

By analyzing ride duration, time-based usage patterns, and bike type preferences, the analysis revealed important distinctions between casual and member riders. An analysis of casual rider behavior revealed that a significant number of casual riders are likely local residents who use the service and are strong candidates for membership conversion. Casual riders take longer rides,

favor eBikes, and use the service more during weekends and warm months. All insights combined, there are substantial opportunities to create timely marketing campaigns that will encourage casual riders to sign up for membership.

These findings can guide Cyclistic's marketing team in developing effective, data-driven campaigns to grow the company's member base.

## 6.0 References

Divvy. (2025). Divvy Bike Sharing Data. Retrieved from <https://divvy-tripdata.s3.amazonaws.com/index.html>



## 7.0 Links to Logs

The following logs provide detailed documentation of this project's code, data decisions, and analysis. They are written in R Markdown and exported as HTML for transparency and reproducibility.

1. Cleaning Log -

[https://jmedinacs.github.io/cyclistic\\_user\\_behavior\\_analysis/cleaning\\_log\\_cyclistic\\_user\\_behavior\\_analysis.html](https://jmedinacs.github.io/cyclistic_user_behavior_analysis/cleaning_log_cyclistic_user_behavior_analysis.html)

2. EDA -

[https://jmedinacs.github.io/cyclistic\\_user\\_behavior\\_analysis/eda\\_log\\_cyclistic\\_user\\_behavior\\_analysis.html](https://jmedinacs.github.io/cyclistic_user_behavior_analysis/eda_log_cyclistic_user_behavior_analysis.html)

3. Detailed Spreadsheet Logs -

[https://docs.google.com/spreadsheets/d/e/2PACX-1vRsdTcZUKUd6BXzZpSvwYAP8hJBCRDVilBmd9sOeeCMLLRvnmaT5X8Olv\\_txawY\\_CcYy0frfpHOpTK/pubhtml](https://docs.google.com/spreadsheets/d/e/2PACX-1vRsdTcZUKUd6BXzZpSvwYAP8hJBCRDVilBmd9sOeeCMLLRvnmaT5X8Olv_txawY_CcYy0frfpHOpTK/pubhtml)