

Case study: How does a bike-share navigate speedy success?

(Compiled by Gladys Pangga)

I. Business task:

Cyclistic's marketing team aims to drive more annual memberships, which are more lucrative than occasional ride passes. To aid this, the business challenge is to compare and contrast ride behavior between casual riders and annual members—ride duration, timing, bike type, and usage patterns—to identify actionable insights that can inform targeted marketing campaigns.

II. A description of all data sources used

For this case study, I used Cyclistic's historical trip history data to compare and analyze bike usage patterns between annual members and casual riders. Although Cyclistic is a fictional company, the datasets are derived from real data provided by Divvy, a bike-sharing system in Chicago, and released by Motivate International Inc. under the Public Data License. Specifically, I used Divvy 2024 datasets (12 months from January – December 2024) and includes the following information: Trip start, and end time Trip duration Start and end station names Bike ID and type User type (annual member or casual rider).

The data contain no personally identifiable information (PII) by data privacy legislation. Therefore, individual users cannot be tracked across time, and one cannot determine if casual riders live in the Cyclistic service area or have bought multiple times. This data provides a firm basis for analyzing usage behavior patterns among casual riders and members and offers insights to guide marketing tactics that seek to drive membership conversion.

III. Documentation of any cleaning or manipulation of data

In advance of analysis, I downloaded the Divvy 2024 datasets for this project. When I unzipped them, I placed them in a main project directory with subdirectories, having taken good file-naming practices.

For the Cyclistic Bike-Share project, I performed a methodical data cleaning and transformation process using R. I began by setting the working directory to the proper folder and importing all the.csv files using `list.files()` and `lapply()`, which was performed for format consistency. These were then merged into a single data frame for analysis. I then converted the `started_at` and `ended_at` columns to appropriate datetime type (POSIXlt) to enable time calculations from them. I computed the `ride_length` of each trip based on them and then converted it to HMS (hour-minute-second) type for better comprehension.

To make temporal analysis easier, I created a new `day_of_week` variable based on the ride start time. Finally, I cleaned the dataset by retaining only observations with valid (non-missing) ride length values, leaving me with a cleaned and analyzable dataset saved as `df2`.

IV. A summary of your analysis

This analysis explored the behavioural patterns of Cyclistic bike-share users by comparing annual members and casual riders across months, rideable types, and days of the week.

Using grouped summary statistics, we evaluated total ride counts, average ride durations, variation in ride lengths, and most common days of usage.

Across all months and rideable types, casual riders generally took longer rides than members. For example, the mean ride length for casual users riding electric bikes during the summer months (June–August) was consistently higher than that of members, suggesting a preference for longer, likely recreational trips. In contrast, annual members favoured classic bikes and displayed shorter, more consistent ride durations across the year—indicative of regular, utilitarian use such as commuting. The most common day of the week for each user group was also calculated, with casual riders most active on weekends (especially Saturdays), while members more frequently rode on weekdays like Tuesday or Wednesday, further supporting the weekday–weekend usage split.

When analysed by day of the week, the same patterns held true: ride counts peaked for casual users on Saturdays, and they tended to have longer rides compared to members regardless of rideable type. Conversely, members showed higher usage volumes during weekdays, particularly for classic bikes. These findings suggest that casual riders are more influenced by leisure opportunities and seasonal conditions, while members maintain steady usage throughout the week and year.

V. Supporting visualizations and key findings

Figure 1. Number of users and average ride length across membership and rideable types in 2024.

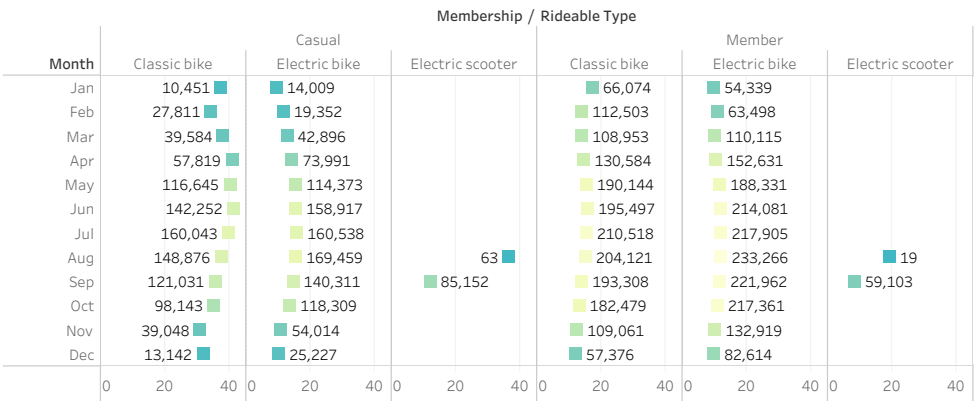
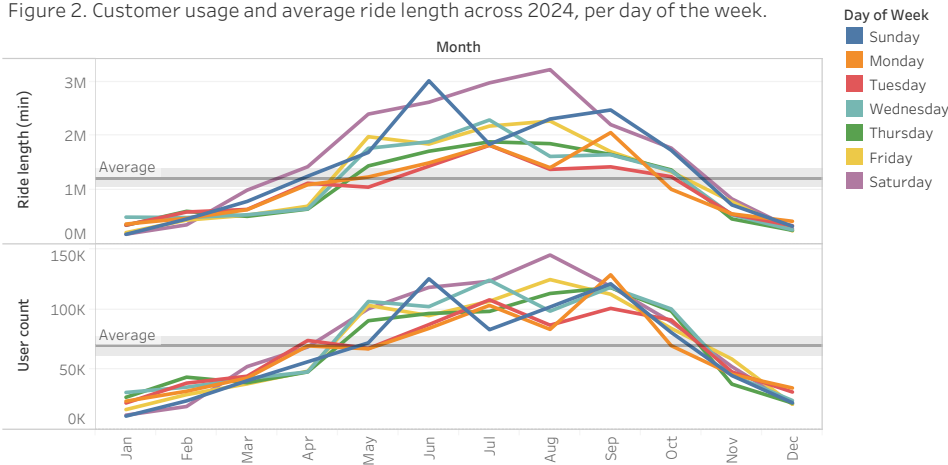
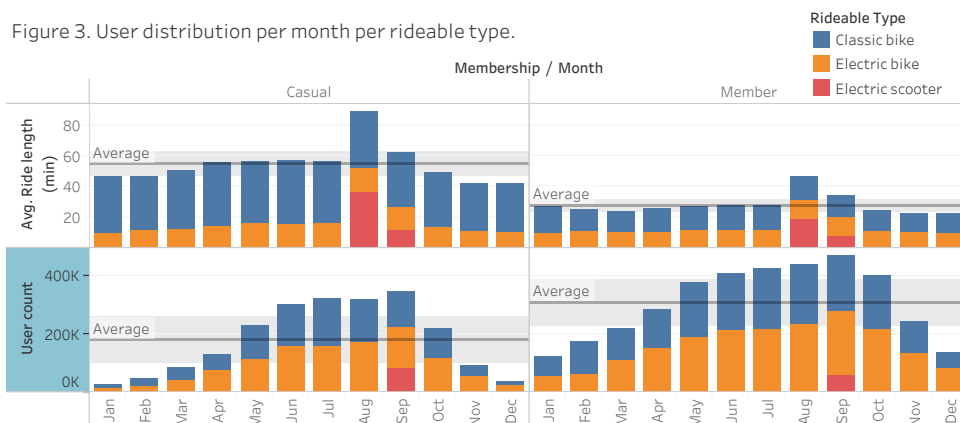


Figure 2. Customer usage and average ride length across 2024, per day of the week.



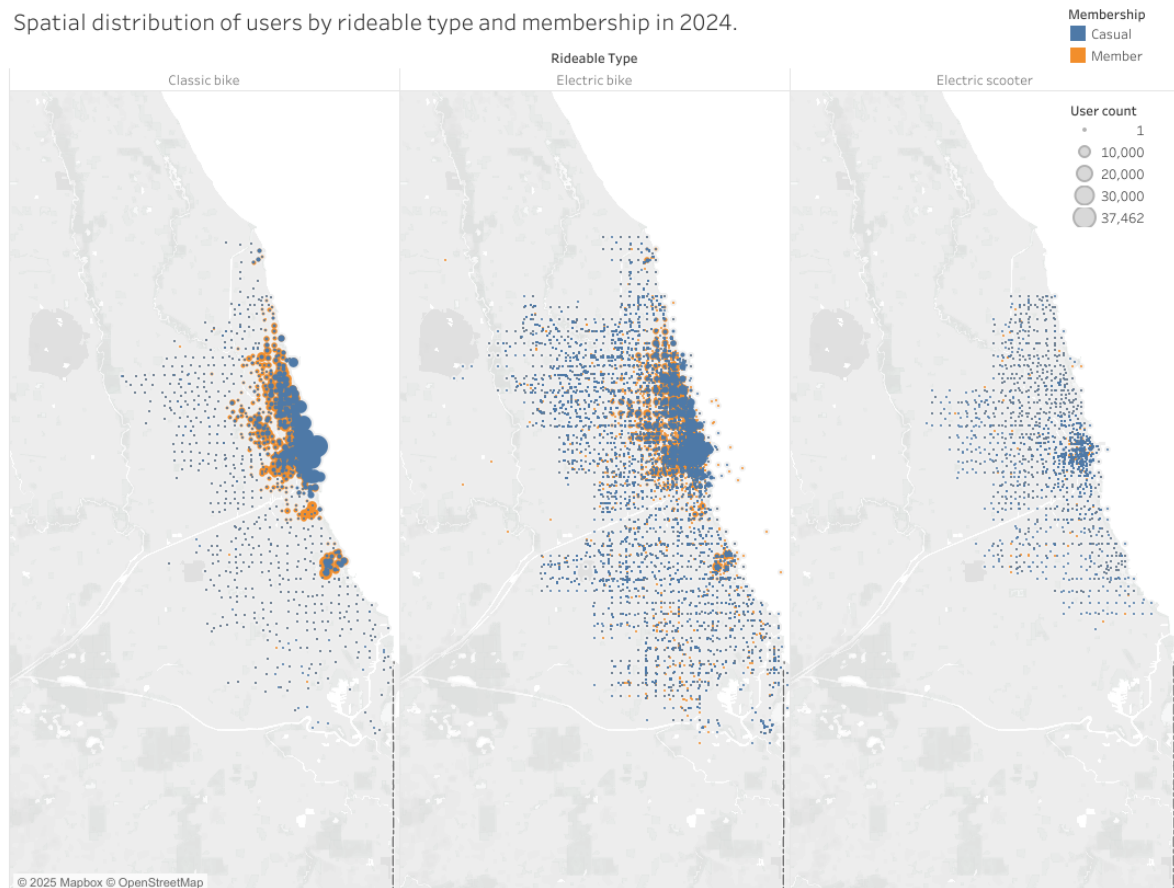
Based on the 2024 trip data, casual riders and annual members exhibit distinct usage behaviours in both ride frequency and duration. Casual riders had a mean ride length of 40.9 minutes (± 25.7 min), significantly longer than members, who averaged only 17.6 minutes (± 11.4 min) per ride. This large gap suggests that casual users likely ride for leisure or sightseeing, while members use Cyclistic bikes more for short, practical trips—potentially commuting. Furthermore, the most common day for casual riders was Saturday, while members showed highest usage on Tuesday, reinforcing this contrast in purpose: weekend recreation vs. weekday commuting.

Rideable type preferences also differed strongly. According to the Tableau dashboard, casual riders were far more likely to use electric bikes and scooters, with usage of electric scooters peaking around June–August, reaching over 73,000 rides in July. In contrast, members favoured classic bikes, with consistently high usage exceeding 190,000 rides monthly during peak summer months. The stability of classic bike usage among members, even during colder months like November (182,479 rides) and December (109,061 rides), indicates a loyal user base who depend on Cyclistic year-round.



Additionally, monthly trends revealed that casual user counts fluctuated dramatically—from just over 98,000 in January to a peak of over 233,000 in August, whereas member usage showed a more stable upward trend, suggesting growing retention or engagement. These statistics suggest a strong opportunity to convert casual riders into members by targeting recreational users during summer months, promoting the cost-efficiency of membership for frequent riders, and highlighting benefits like extended ride time for electric bikes or exclusive access during high-demand weekends.

Spatial distribution of users by rideable type and membership in 2024.



The spatial distribution map shows that annual members predominantly used classic and electric bikes in central, densely populated areas, indicating commuting or routine travel within city limits. In contrast, casual users displayed broader geographic spread, especially with electric scooters, aligning with the earlier finding that casual riders often take longer, leisure-oriented trips. This spatial trend supports the behavioural patterns identified in the summary statistics, where members ride more frequently on weekdays and casual users on weekends.

VI. Your top three recommendations based on your analysis

- **Make More Bikes Available on Weekends for Leisure Users**
Usage peaks by recreational riders were weekends, especially Saturday. To meet demand and enhance user satisfaction, redistribute more original and docked bikes to hot weekend spots (e.g., near parks, tourist zones, waterfronts) during these weekends.
- **Offer Casual Rider Seasonal Promotions**
Ride volumes are most in spring and summer months, especially among occasional users. Look into offering time-restricted passes or April-to-August discounts, focusing on tourists and leisure riders on social media and tourist sites.
- **Improve Bike Type Targeting by User Type**
There is evidence of differentiated habits and preferences between members and occasional riders. Members, who ride more on weekdays, could be served with higher availability of electric bikes in business areas and transit points, while conventional bikes can be concentrated in recreational areas for occasional riders.