Cyclistic Case Study

Rohil Maisuria

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Contents

1 Introduction

In this case study, we explore the usage patterns of **Cyclistic bikes**, a bike-sharing service in Chicago. Our goal is to understand how bike usage varies between different customer types (e.g., casual riders and members) and to provide insights that can inform marketing strategies and business decisions.

The analysis leverages data provided by Cyclistic, focusing on trip durations, usage patterns, and customer behavior over the past year.

2 Background

Cyclistic is a bike-share program that features more than 5,800 bicycles and 600 docking stations. Cyclistic sets itself apart by also offering reclining bikes, hand tricycles, and cargo bikes, making bike-share more inclusive to people with disabilities and riders who can't use a standard two-wheeled bike. The majority of riders opt for traditional bikes; about 8% of riders use the assistive options. Cyclistic users are more likely to ride for leisure, but about 30% use the bikes to commute to work each day.

Cyclistic's marketing strategy relied on building general awareness and appealing to broad consumer segments. One approach that helped make these things possible was the flexibility of its pricing plans: single-ride passes, full-day passes, and annual memberships. Customers who purchase single-ride or full-day passes are referred to as casual riders. Customers who purchase annual memberships are Cyclistic members.

Cyclistic's finance analysts have concluded that annual members are much more profitable than casual riders. Although the pricing flexibility helps Cyclistic attract more customers, Moreno (Director of Marketing) believes that maximizing the number of annual members will be key to future growth. Rather than creating a marketing campaign that targets all-new customers, Moreno believes there is a solid opportunity to convert casual riders into members. She notes that casual riders are already aware of the Cyclistic program and have chosen Cyclistic for their mobility needs.

Moreno has set a clear goal: Design marketing strategies aimed at converting casual riders into annual members. In order to do that, however, the team needs to better understand how annual members and casual riders differ, why casual riders would buy a membership, and how digital media could affect their marketing tactics. Moreno and her team are interested in analysing the Cyclistic historical bike trip data to identify trends.

3 Scenario

I am a junior data analyst working on the marketing analyst team at Cyclistic. The director of marketing believes the company's future success depends on maximizing the number of annual memberships. Therefore, my team wants to understand how casual riders and annual members use Cyclistic bikes differently. From these insights, my team will design a new marketing strategy to convert casual riders into annual members.

4 Ask

4.1 Business Task

Design marketing strategies aimed at converting casual riders into annual members.

Three questions will guide the future marketing program:

1. How do annual members and casual riders use Cyclistic bikes differently?
2. Why would casual riders buy Cyclistic annual memberships?
3. How can Cyclistic use digital media to influence casual riders to become members?

Moreno has assigned me the first question to answer: **How do annual members and casual riders use Cyclistic bikes differently?**

5 Prepare

5.1 Data source

I will use the Cyclistics historical data from April 2025 to March 2025 which was downloaded from (divvy_tripdata).

The data has been made available by Motivate International Inc. under this (license).

Note that data-privacy issues prohibit you from using riders' personally identifiable information. This means that we won't be able to connect pass purchases to credit card numbers to determine if casual riders live in the Cyclistic service area or if they have purchased multiple single passes.

5.2 Data organisation

The dataset for this analysis includes trip-level data, which contains information about each ride, such as: - Ride duration - Customer type (casual or member) - Start and end times - Locations of trips

The column names being: ride_id, rideable_type, started_at, ended_at, start_station_name, start_station_id, end_station_name, end_station_id, start_lat, start_lng, end_lat, end_lng, member_casual.

6 Process

6.1 Tools Used

For this project, I chose the following tools:

-RStudio for data cleaning, manipulation, and analysis.

-Packages: tidyverse, dplyr, lubridate, janitor, and ggplot2.

-Tableau for creating visualisations.

-GitHub to document and share my work and maintain version control.

R was selected due to its efficiency in handling large datasets and its flexibility for customized data cleaning. Tableau was used to build clear, impactful visulisations for the analysis.

6.2 Data Integrity

I ensured the data's integrity by:

-Importing the official Cyclistic datasets directly without manual alterations.

-Verifying consistent column names across all 12 monthly files before merging.

-Removing duplicate ride_id entries to maintain unique ride records.

-Eliminating empty rows and columns to avoid bias from incomplete data.

6.3 Data Cleaning Steps

The following steps were taken to prepare the data:

-Merging the 12 monthly datasets into a single comprehensive data frame (all_trips).

-Removing all empty rows and columns using the janitor package.

-Checking for and removing 121 duplicated ride IDs.

-Creating new date-related columns (year, month, day, day_of_week) from the ride start times.

-Calculating ride length in seconds and filtering out rides less than 1 minute and greater than 24 hours.

-Dropping irrelevant columns (start_lat, start_lng, end_lat, end_lng) to focus the analysis on trip behavior.

-Removing missing values to ensure complete and reliable observations.

6.4 Verification of Data Readiness

To confirm that the dataset was clean and ready for analysis, I:

-Verified there were no missing values in the key columns after cleaning.

-Ensured all ride_ids were unique after duplicate removal.

-Confirmed that ride_length values were within the expected range (60 to 86,400 seconds).

-Aggregated mean, median, minimum, and maximum ride lengths across member types to identify any inconsistencies.

6.5 Documentation

The entire cleaning and preparation process is fully documented in my R script. This ensures that the workflow is:

-Transparent for stakeholders.

-Reproducible for future updates.

-Ready for further analysis and visualization.

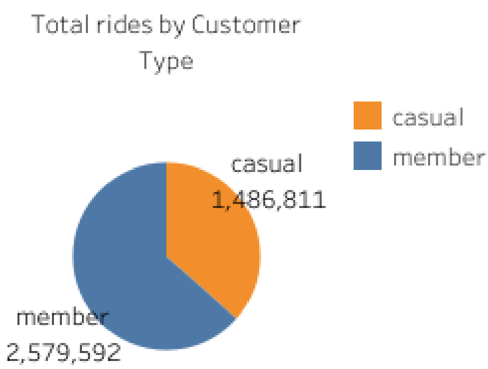
7 Analyse and Share

Reminder of analysis question:

How do annual members and casual riders use Cyclistic bikes differently?

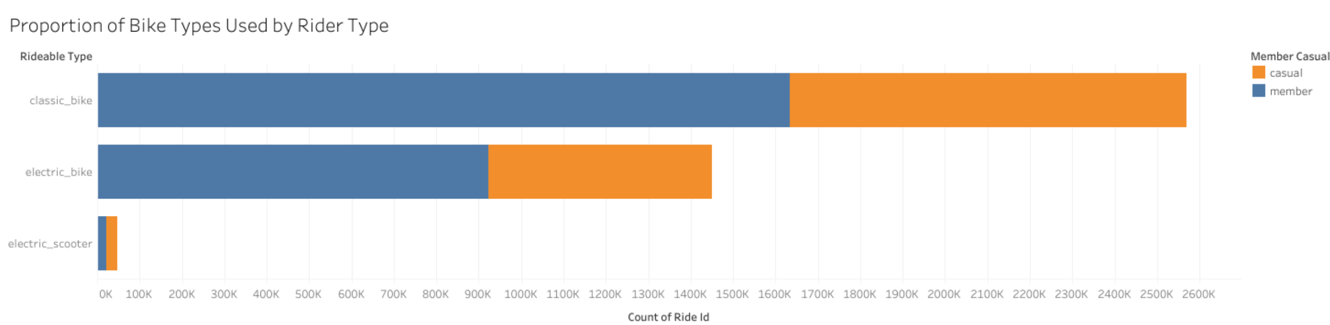
My cleaned data (all_tips_v2) was imported into tableau for analysis and to create visualisations

7.1 Total trips



The pie chart above shows the total number of rides taken by Cyclistic customers, categorized by rider type. It is observed that members make up a larger share of rides (63.4%) compared to casual riders(36.6%). This suggests that members are more engaged and consistent users of the Cyclistic bike-sharing service, highlighting the importance of targeting casual riders for membership conversion to increase overall ride volume.

7.2 Bike Type

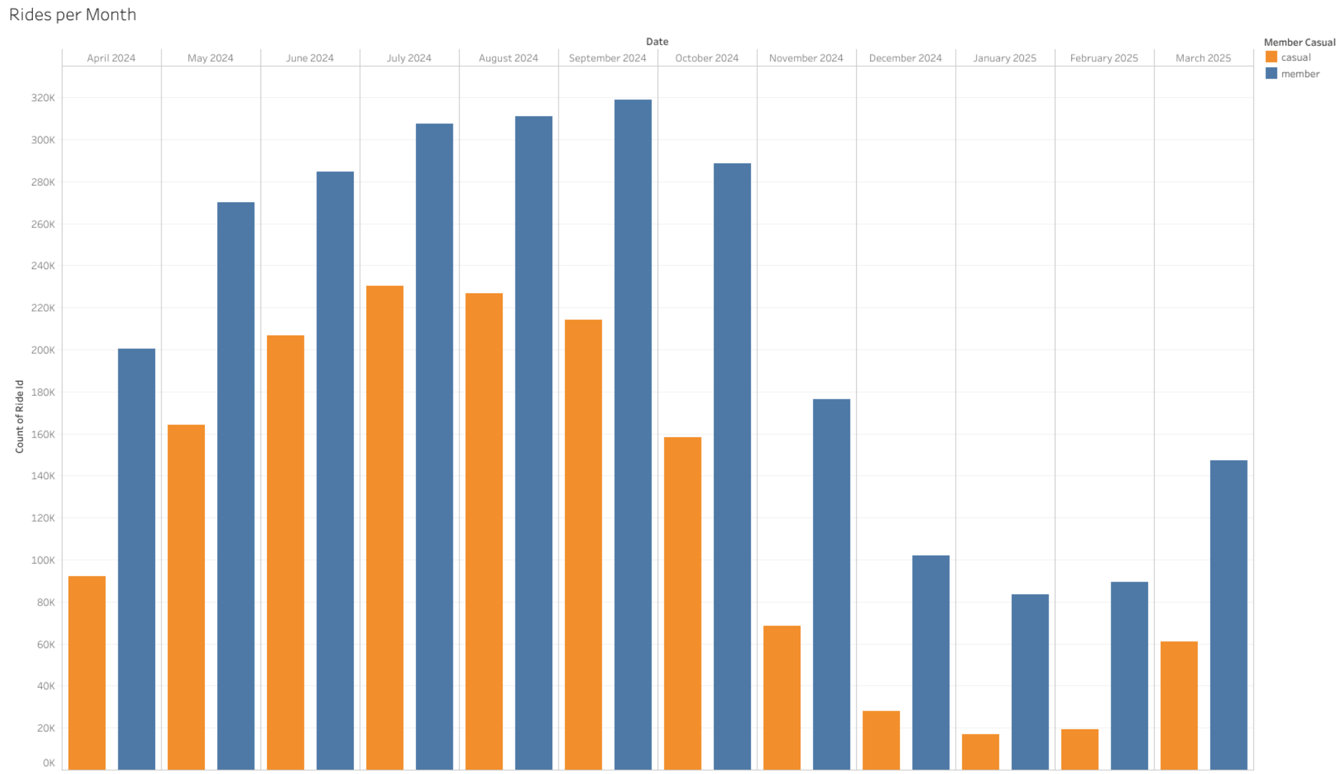


This stacked bar chart displays the distribution of bike types (classic bike, electric bike and electric scooter) used by each rider type.

Both members and casual riders primarily use classic bikes, followed by electric bikes with a very small proportion of riders using electric scooters as a whole.

This indicates that member and casual riders may prioritize convenience and shorter effort rides

7.3 Monthly bike usage



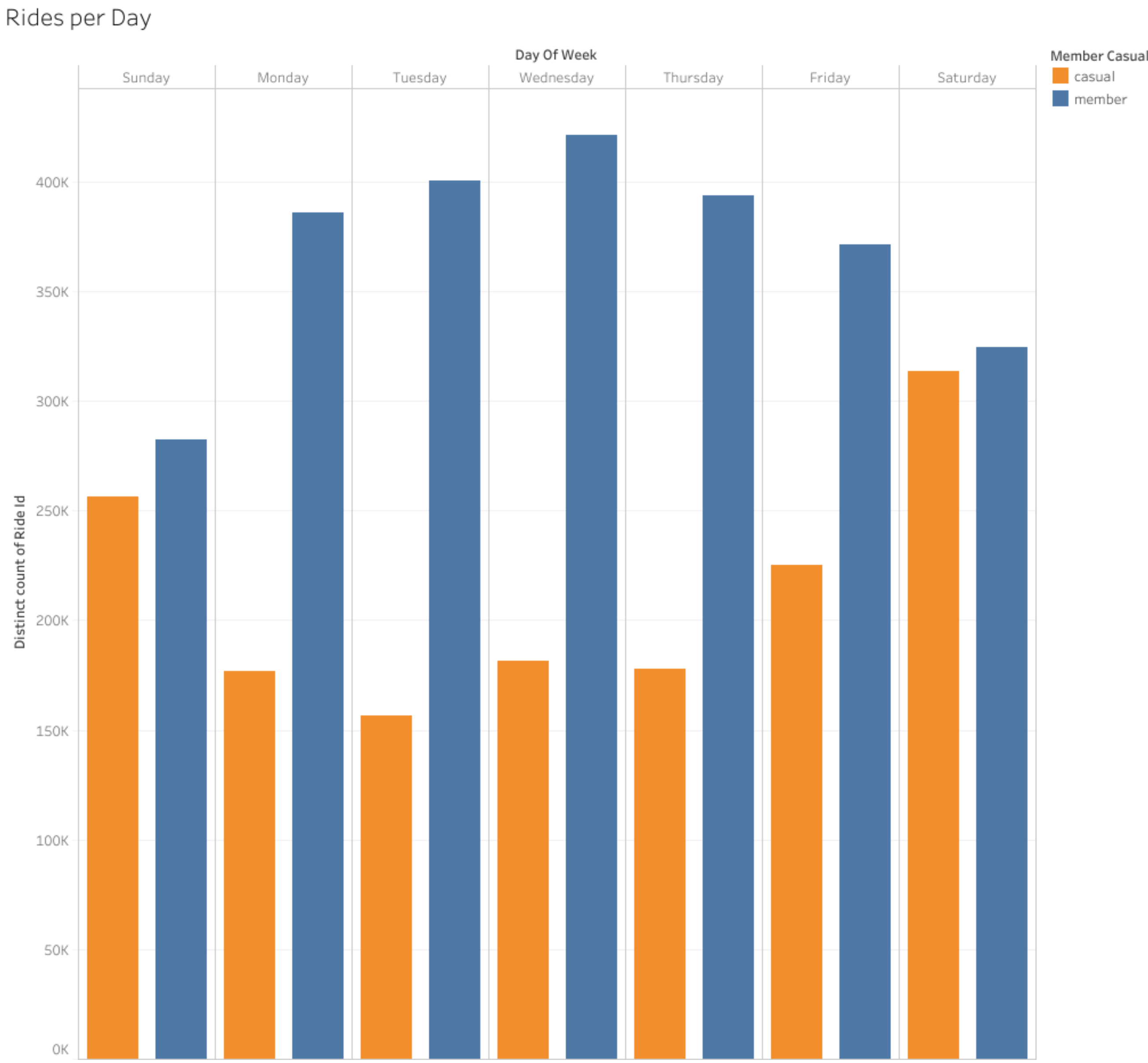
The column chart illustrates the monthly distribution of rides taken by members and casual riders throughout the year.

There is a clear seasonal trend, with both rider types showing peak usage during the summer months (June to September) and significantly fewer rides during winter.

Notably, casual riders' usage spikes more dramatically in the warmer months compared to members, suggesting that casual riders may be motivated by leisure or weather-dependent activities.

Understanding these seasonal behaviours could help us launch targeted promotions during summer to encourage annual membership purchases.

7.4 Daily ride patterns

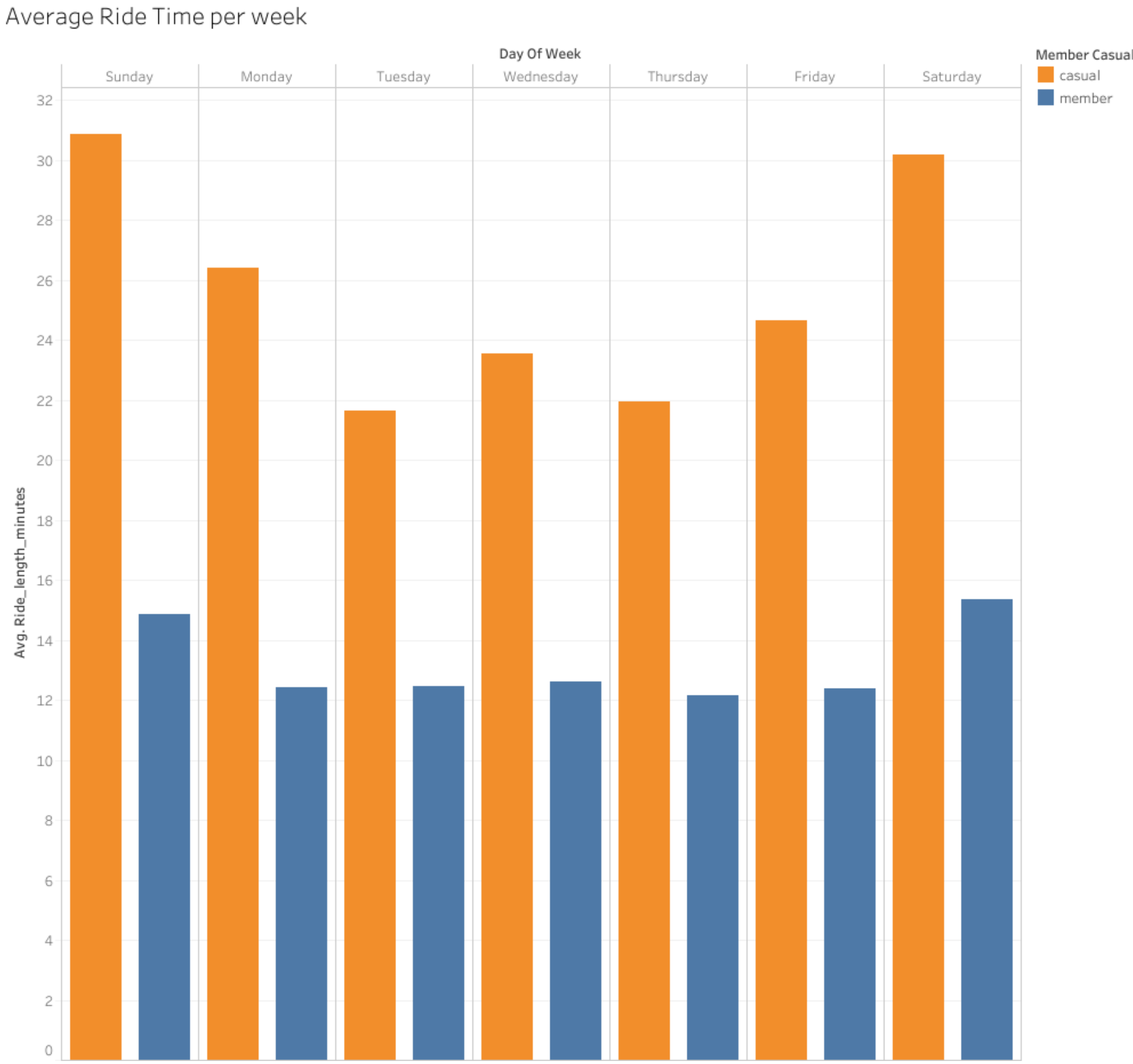


The column chart shows the total number of rides taken each day of the week by rider type.

Both members and casual riders have relatively steady ride patterns across weekdays, with members showing consistent usage from Monday to Friday, suggesting a commuting pattern. In contrast, casual riders have a noticeable increase in rides on weekends, indicating more leisure-based usage.

Marketing efforts can target casual riders with weekend special offers or events tied to annual memberships.

7.5 Daily ride average



The bar chart presents the average ride time for each day of the week, separated by rider type.

Casual riders consistently have longer average ride durations compared to members, suggesting that casual users may engage in recreational or sightseeing rides.

Members, on the other hand, maintain shorter ride durations, consistent with commuting behaviour.

This insight can help Cyclistic position memberships as offering flexibility for both short and long rides, appealing to different casual rider motivations.

7.6 Overall Findings

Across all analyses, the data shows that members are more consistent and practical users, while casual riders are more seasonal and leisure-oriented. Marketing strategies should therefore focus on highlighting membership benefits such as cost savings, flexibility and longer ride times, particularly targeted around peak leisure seasons and weekends.

8 ACT

Based on the analysis of Cyclistic's ride data, the following recommendations are proposed to increase the number of annual memberships:

1. Seasonal Campaigns Targeting Casual Riders

Launch marketing campaigns during the summer months, when casual rider usage peaks, highlighting the benefits of becoming an annual member (e.g., cost savings, unlimited rides).

2. Weekend and Event-Based Incentives

Offer weekend-exclusive deals or loyalty programs (e.g., discounted membership upgrades after a certain number of casual rides) to capture casual riders who primarily ride on Saturdays and Sundays.

3. Highlight Convenience for Recreational Use

Given casual riders' longer average ride durations, marketing materials should focus on stress-free, long rides with no additional time charges for members, enhancing the appeal for leisure users.

4. Digital Targeting and Personalisation

Use digital media platforms to target casual riders with personalized advertisements, leveraging ride history (e.g., offering membership discounts to riders who have taken multiple single rides within a month). Implementing these strategies can help Cyclistic convert more casual riders into loyal annual members, driving both customer retention and profitability.

9 Conclusion

By leveraging insights into usage patterns, Cyclistic can effectively target casual riders and convert them into annual members. Highlighting cost savings, flexibility, and exclusive member benefits, particularly during peak seasons and weekends, will resonate with casual riders and drive long-term membership growth.