Weather’s Impact on Bike-Share Usage in Central Chicago

Introduction

Bike-sharing systems have quickly taken up popularity as a staple for sustainable and efficient transportation within many cities around the world, addressing common urban challenges like congestion and rising carbon emissions. Despite these potential benefits, the effectiveness of these programs depends on numerous external influences, with weather conditions playing a particularly significant role. This report investigates how weather influences bike-share usage patterns in Central Chicago, analyzing ride volume, user behaviour, temporal trends, and station activity between members and casual users. By leveraging historical data derived from Kaggle’s Divvy BikeShare dataset spanning 2020–2023 and weather metrics from OpenWeatherMap API, this study provides actionable insights for stakeholders to conduct operational planning and resource allocation.

Supporting Question 1: How Does Weather Impact Ride Volume?

Weather conditions play a pivotal role in determining ridership levels. The bar chart **“Probability of Riders by Weather Type”** (Appendix 1) and side-by-side horizontal bar charts **“Top 10 Stations in Clear and Adverse Weather”** (Appendix 3) showcase that clear and cloudy weather consistently drive the highest ridership, with clear conditions averaging 204 rides per instance and cloudy weather slightly higher at 326 rides. Adverse conditions like rain and snow drastically reduce ridership, with rain averaging 202 rides and snow as low as 73 rides. These patterns suggest that favorable weather encourages both leisure and commuting trips, while harsh conditions deter ridership.

Temperature is another key determinant, as shown in the **“Scatter Plot of Temperature vs Rider Count”** (Appendix 4). Mild temperatures (10°C–20°C) correlate with the highest increasing trend in ride volumes with trends peaking at warm temperature (20°C - 30°C), while extreme temperatures—either below freezing or exceeding 30°C—result in significant declines. The Pearson correlation coefficient for temperature and ridership was calculated at approximately 0.65, indicating a moderately strong positive relationship. Conditional color formatting in the scatter plot illustrates that “below freezing” conditions align with the lowest ridership clusters.

Supporting Question 2: What Temporal Trends Emerge Across Weather Conditions?

Temporal trends in ridership reveal the nuanced ways in which weather impacts bike-share usage, with clear patterns emerging across both hourly and seasonal time frames. The line chart **“Monthly Ride Volume by Year”** (Appendix 2) demonstrates clear peaks during the summer months (June–August), when weather is typically favorable, with consistent declines in winter (December–February) due to freezing temperatures and snowfall. This seasonal pattern underscores the importance of weather in shaping both leisure and commuting behaviors.

Hourly trends, visualized in the **“Hourly Rides Normalized by Weather Probabilities”** chart (Appendix 5), and supported by **“Monthly Ride Volume by Year”** (Appendix 2), reveal distinct ridership peaks during weekday commuting hours: 7–9 AM and 5–7 PM. These peaks are most prominent under clear weather conditions, indicating that commuters are more likely to bike in favorable conditions. Adverse weather dampens these peaks, particularly among casual users, as discussed in the following section.

Weekend trends differ, with midday ridership (11 AM–3 PM) dominating, reflecting leisure trips. However, adverse weather disproportionately reduces weekend activity compared to weekdays, further underscoring the sensitivity of casual users to weather conditions.

Supporting Question 3: How Do Different User Types Respond to Weather?

The behavior of members and casual users diverges significantly in response to weather. The line chart **“Rider Type Breakdown by Weather Condition (Normalized)”** (Appendix 6), paired with the **“Rideable Type Distribution by Year/Member or Casual”** pie charts (Appendix 7) shows that members maintain relatively stable ridership levels across weather conditions, reflecting their reliance on bike-sharing for commuting purposes. In contrast, casual users display a steep decline in ridership during adverse weather, such as rain or snow.

Casual users also tend to favor shorter trips during unfavorable weather, as evidenced by additional duration-related metrics from the dataset. This indicates that casual trips are primarily leisure-driven and are easily deterred by discomfort or challenging conditions.

Further insights into user preferences are provided in the pie charts **“Rideable Type Distribution by Year/Member or Casual”** (Appendix 7), which indicate that casual users are more likely to choose electric bikes, particularly during adverse weather, likely due to the ease of use and reduced physical exertion required. Correlation analysis highlights that members are less affected by weather variations compared to casual users, with a relative drop of only 15% in adverse weather, compared to 40% for casual riders.

Supporting Question 4: How Do Weather Variables Correlate with Overall Ridership?

Station activity fluctuates with weather conditions, as depicted in the scatter plots **“Relationships Between Weather Metrics (Temperature, Pressure, Humidity, Windspeed) and Bike Usage”** (Appendices 8–11). Temperature shows the strongest correlation with ridership, peaking between 15°C and 25°C, while extreme heat and cold deter ridership significantly. The correlation coefficient for temperature was approximately 0.65, while wind speed and pressure exhibited weaker correlations of -0.34 and -0.16 respectively, indicating modest inverse relationships. Humidity’s correlation with ridership stood at -0.36, reflecting a moderate negative relationship.

The ANOVA test results for humidity further revealed a statistically significant variation in bike usage across different humidity levels, with an F-statistic of 89.99 and a p-value of 2.18e-37. Wind speed also showed significant differences in usage patterns (F-statistic = 65.01, p-value = 1.14e-27).

The importance of understanding station-level patterns is further highlighted by the **“Most Used Rideable Types by Year”** stacked bar chart (Appendix 12), which suggests that certain stations consistently see higher usage of specific bike types. For example, stations in recreational areas tend to see greater electric bike usage during clear weather.

Predictive Modeling and Forecasting

The histogram **"Predicted Ride Count by Hour with Day & Night Coloring"** (Appendix 11) highlights predicted ridership patterns across hours of the day. Daytime (6 AM to 6 PM) peaks exhibit significantly higher predicted ride counts compared to nighttime, with warmer colors representing daytime activity. This visualization supports operational planning for dynamic bike allocation.

Regression analysis was employed to predict ridership based on weather metrics, with results summarized in the scatter plots **“Relationships Between Weather Metrics (Temperature, Pressure, Humidity, Windspeed) and Bike Usage”** (Appendices 8–11). The analysis revealed low R^2 values, with temperature showing the strongest correlation at 0.1506, followed by humidity (0.0637) and pressure (0.0013). These values indicate that while weather conditions influence ridership, they explain only a small fraction of its variability.

The **"Predicted Ride Count by Hour with Day & Night Coloring"** (Appendix 11) estimated ride counts for future conditions, suggesting ~103–109 rides per hour for a clear day at 15°C. However, the model’s limited explanatory power and wide confidence intervals highlight its limitations for operational planning.

Limitations of the Analysis

While the findings provide valuable insights, several limitations must be acknowledged:

1. **Data Completeness**: Missing or incomplete weather data for specific time periods introduces potential bias.
2. **Anomalous Events**: Unusual weather conditions, such as wildfire-induced "Smoke," skew the results and may not represent typical patterns.
3. **Model Constraints**: The linear regression model assumes a linear relationship between variables, potentially oversimplifying complex interactions.
4. **Behavioral Factors**: The analysis does not account for external factors like special events, promotions, or socioeconomic conditions that may influence ridership.

Conclusion

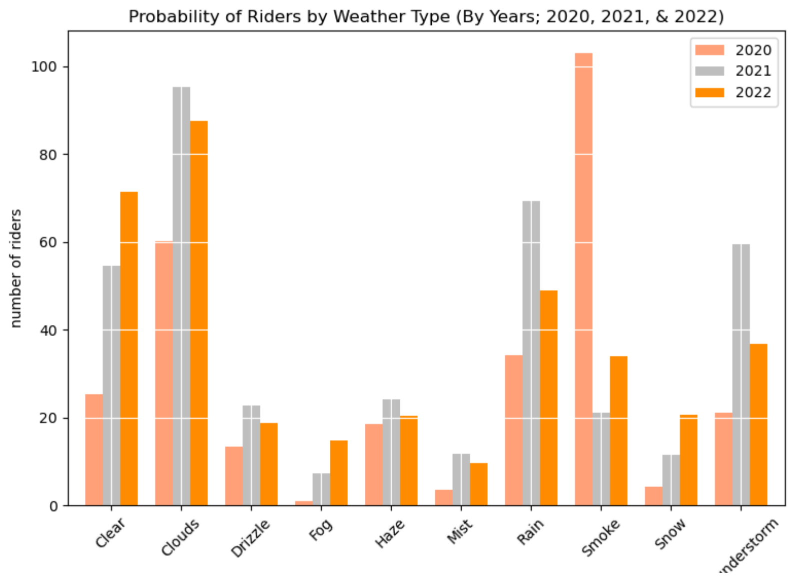
This analysis confirms that weather is a significant factor in shaping bike-share usage in Central Chicago. Key findings include:

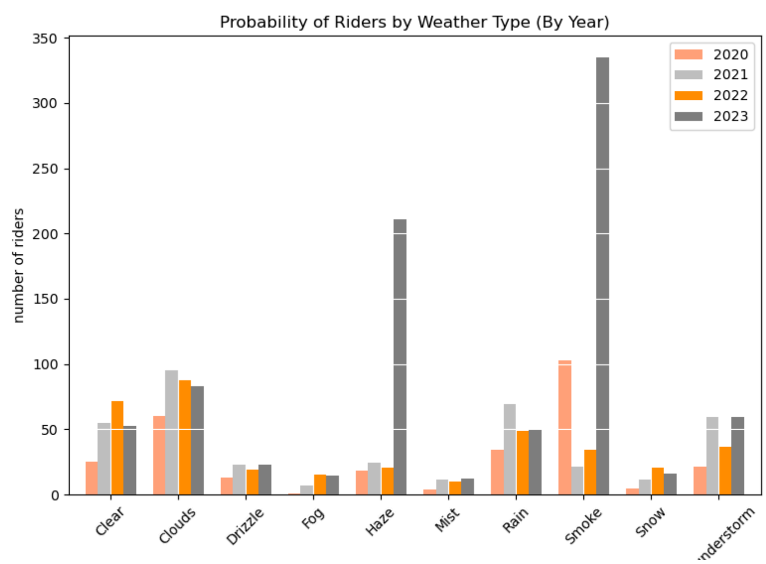
- **Ride Volume**: Clear and mild weather conditions drive the highest ridership, while adverse weather, such as rain and snow, reduces activity.
- **Temporal Trends**: Seasonal and hourly patterns reflect the dual influence of weather and commuter behavior.
- **User Behavior**: Members exhibit stable usage across weather types, while casual users are more sensitive to adverse conditions.
- **Station Activity**: Weather impacts station-specific demand, with clear weather driving activity at recreational hotspots and adverse weather concentrating demand at commuter hubs.

While predictive modeling provides a foundation for forecasting ridership, its limited accuracy suggests that additional factors, such as time of day and trip purpose, should be incorporated into future models. This analysis provides actionable insights for bike-share operators to optimize resources, improve user satisfaction, and enhance operational efficiency.

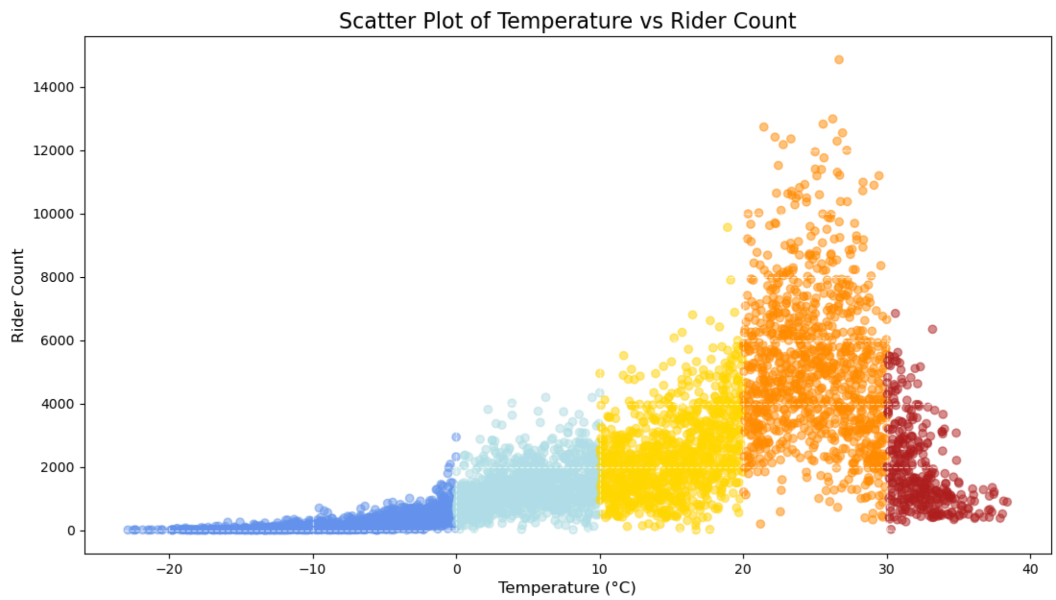
Appendix

Appendix 1 - Probability of Riders by Weather Type *(Bar Chart)*

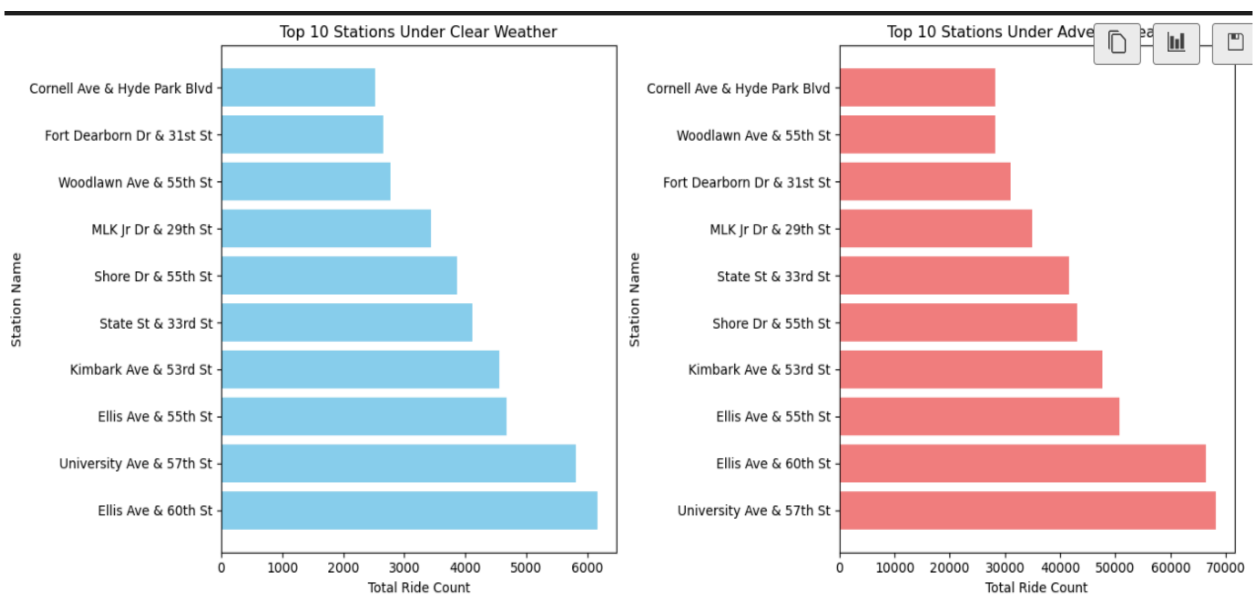




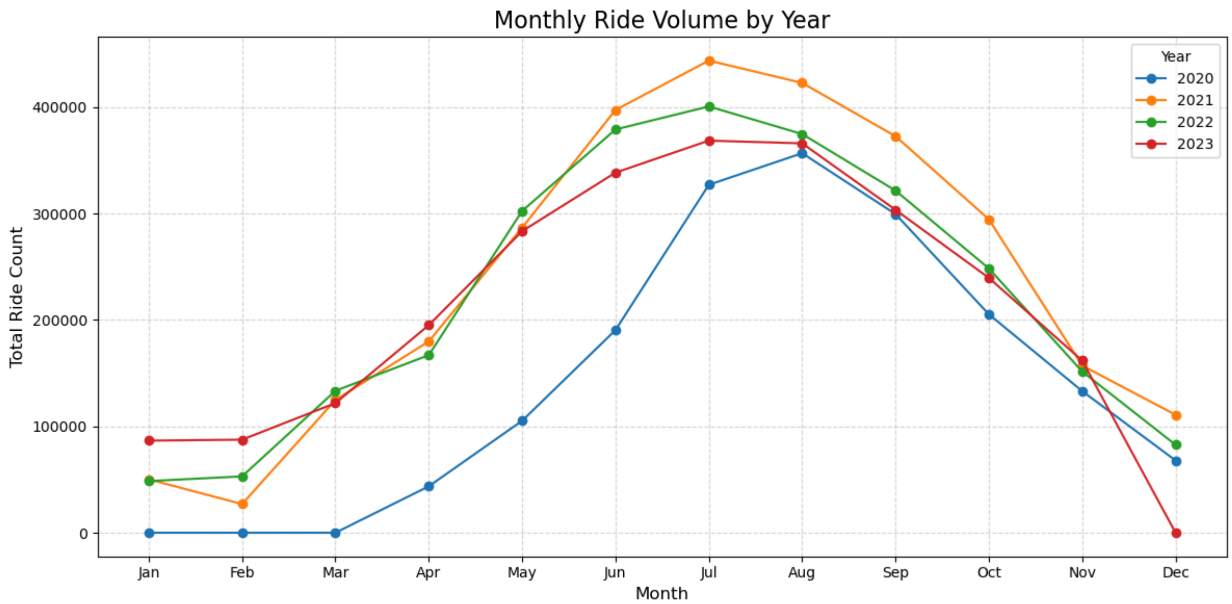
Appendix 2 - Scatter Plot of Temperature vs Rider Count *(Scatter Plot)*



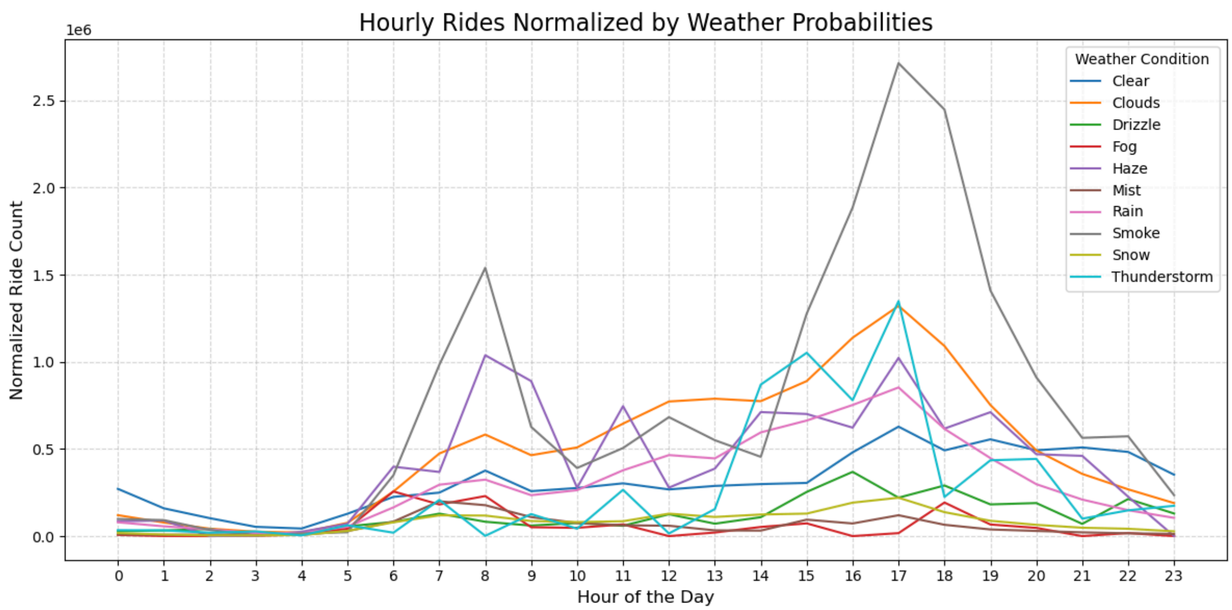
Appendix 3 - Top 10 Stations in Clear and Adverse Weather *(Side-by-Side Horizontal Bar



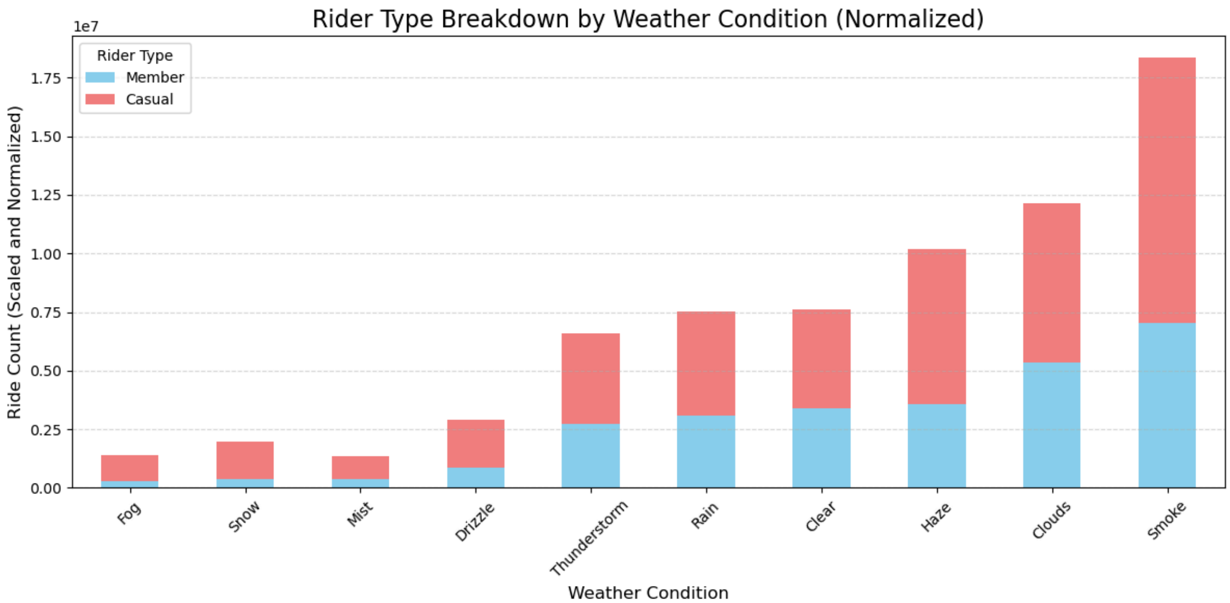
Appendix 4 - Monthly Ride Volume by Year (Line Chart)



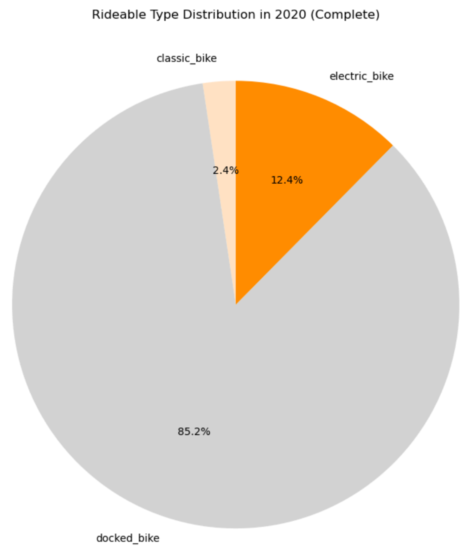
Appendix 5 - Hourly Rides Normalized by Weather Probabilities (Line Chart)

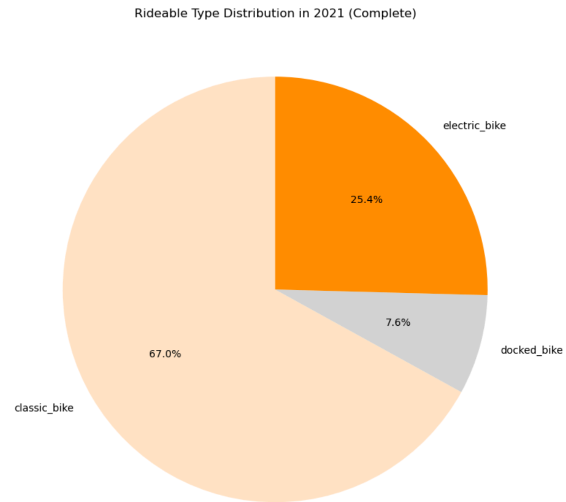


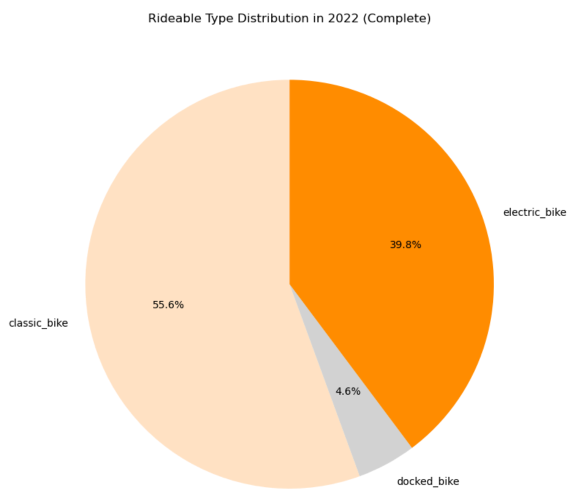
Appendix 6 - Rider Type Breakdown by Weather Condition (Normalized) (Line Chart)

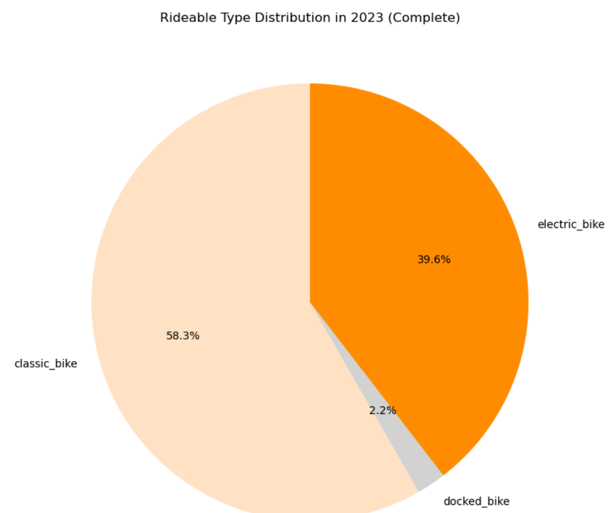


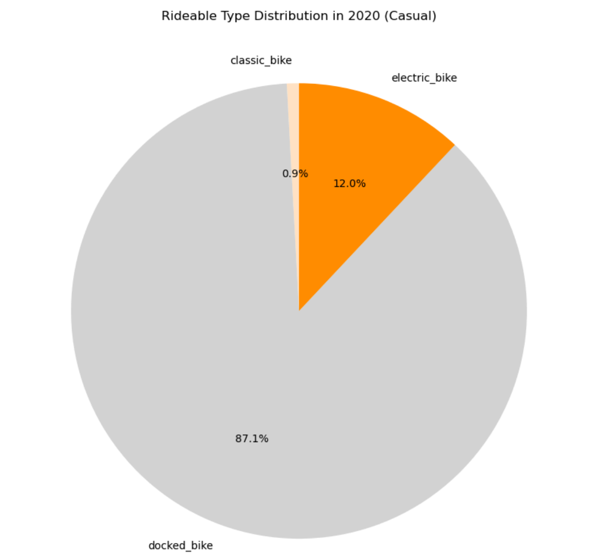
Appendix 7 - Rideable Type Distribution by Year/Member or Casual (Pie Charts)

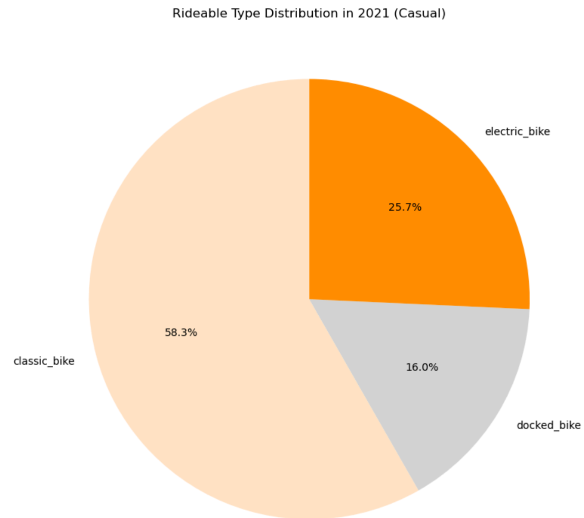


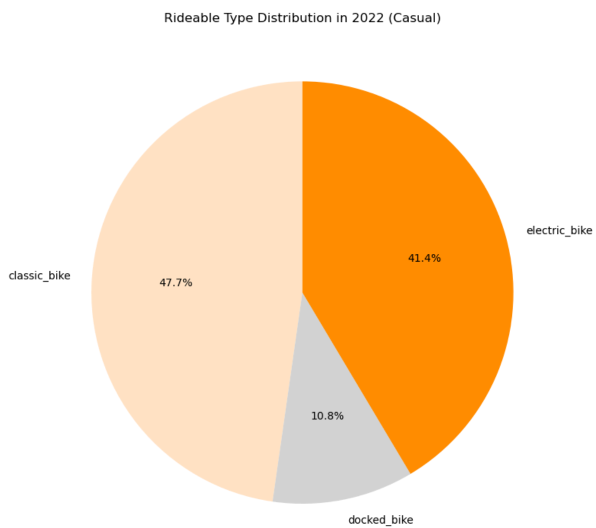


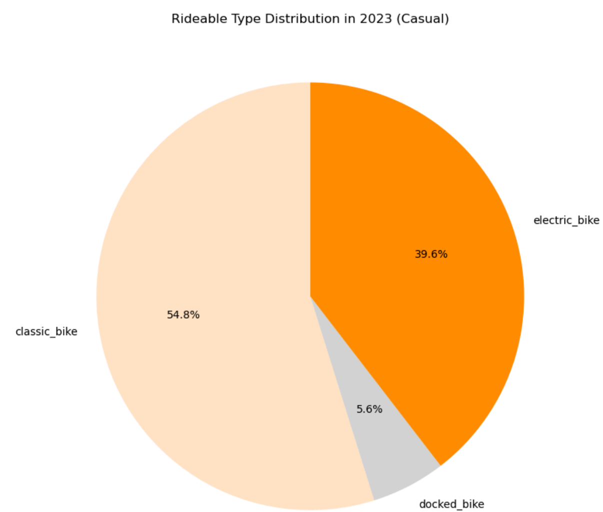


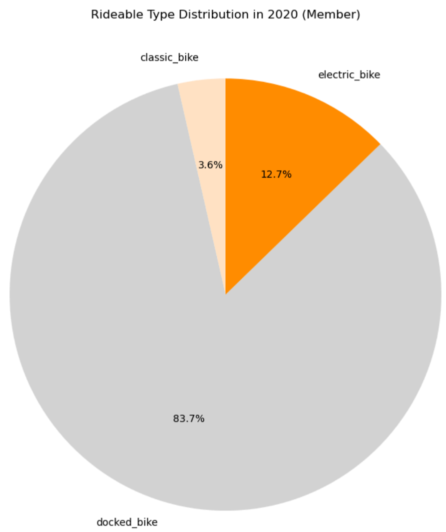


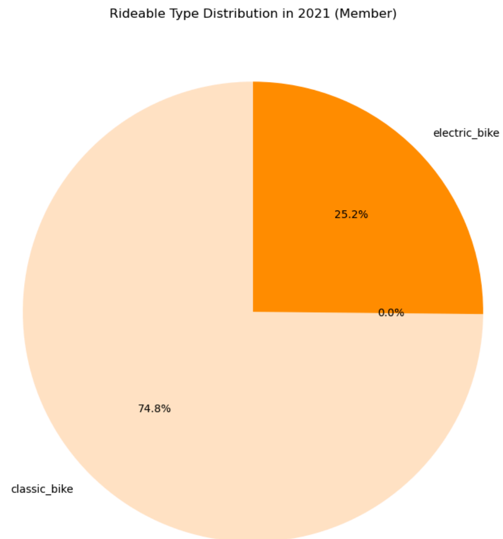

Rideable Type Distribution in 2020 (Casual)
classic_bike
electric_bike
0.9%
12.0%
87.1%
docked_bike

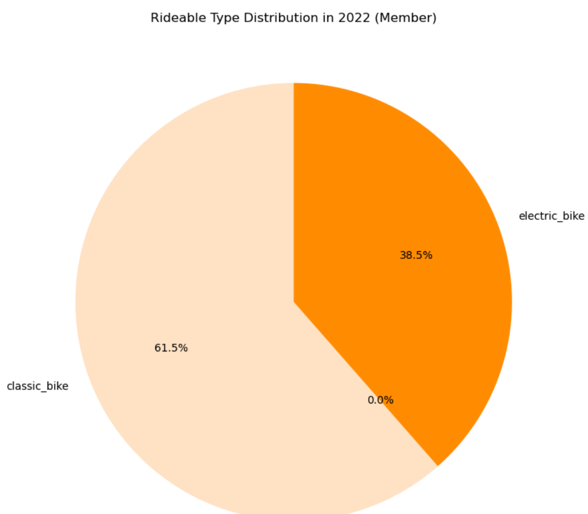

Rideable Type Distribution in 2021 (Casual)
electric_bike
25.7%
58.3%
classic_bike
16.0%
docked_bike

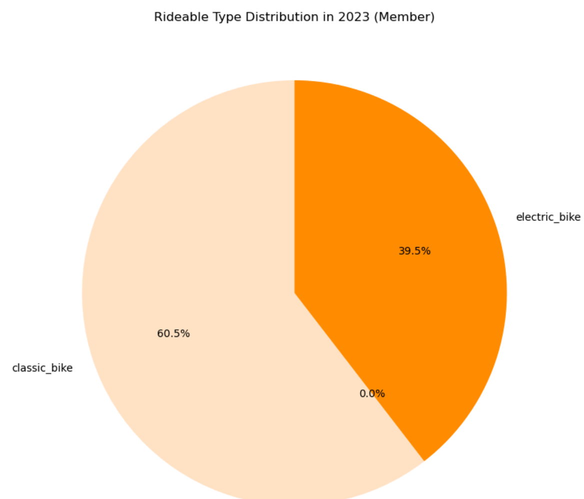

Rideable Type Distribution in 2022 (Casual)
electric_bike
41.4%
classic_bike
47.7%
10.8%
docked_bike


Rideable Type Distribution in 2023 (Casual)
electric_bike
39.6%
54.8%
classic_bike
5.6%
docked_bike

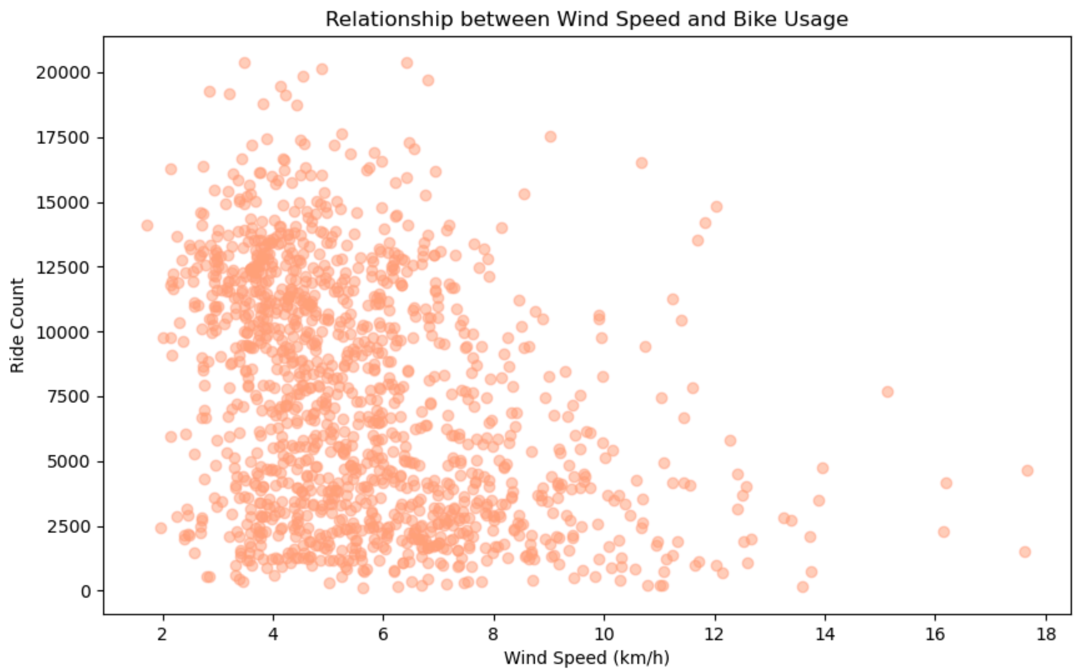

Rideable Type Distribution in 2020 (Member)
classic_bike
electric_bike
3.6%
12.7%
83.7%
docked_bike


Rideable Type Distribution in 2021 (Member)
electric_bike
25.2%
0.0%
74.8%
classic_bike

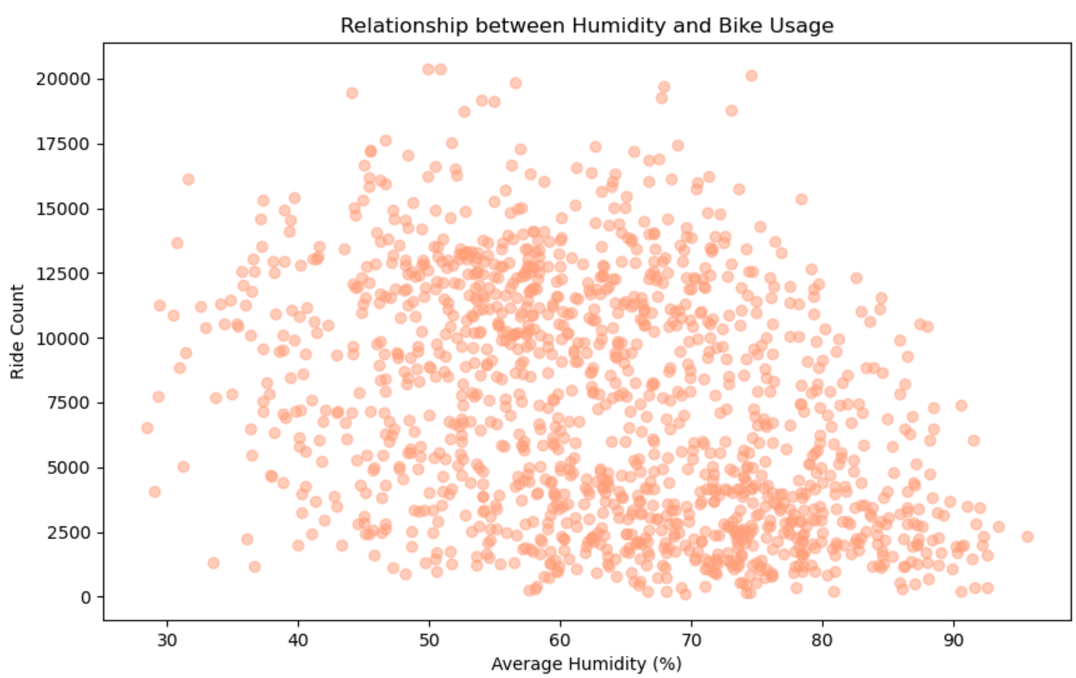

Rideable Type Distribution in 2022 (Member)
electric_bike
38.5%
61.5%
classic_bike
0.0%


Rideable Type Distribution in 2023 (Member)
electric_bike
39.5%
60.5%
classic_bike
0.0%

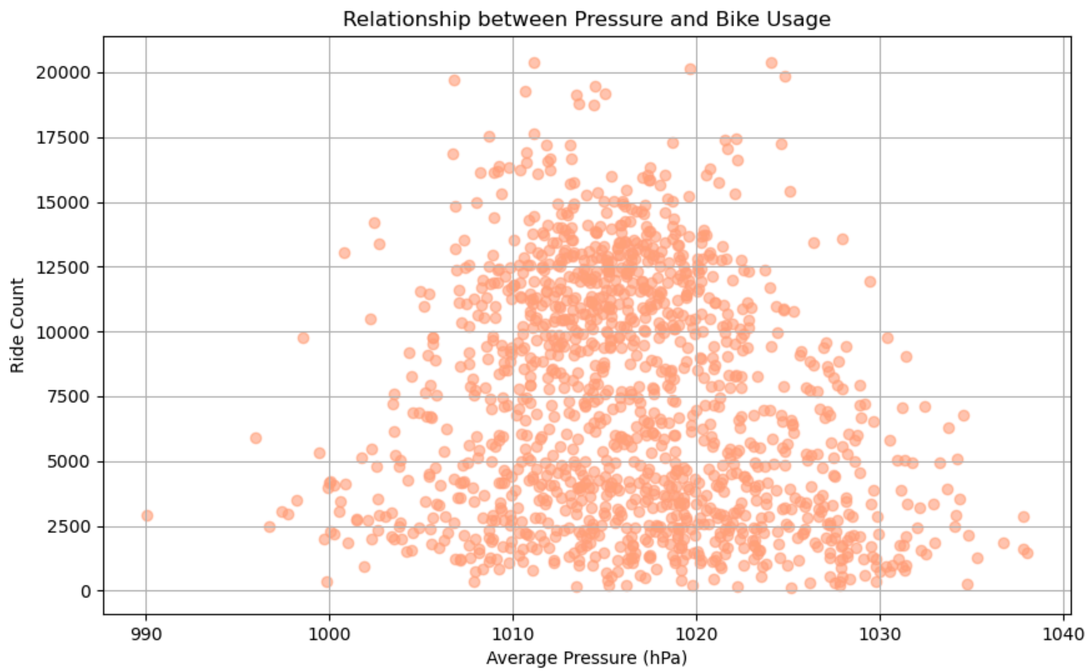
Appendix 8 - Scatter Plot: Wind Speed vs. Ride Volume (Scatter Plot)



Appendix 9 - Scatter Plot: Humidity vs. Ride Volume (Scatter Plot)



Appendix 10 - Scatter Plot: Pressure vs. Ride Volume (Scatter Plot)



Appendix 11 - Predicted Ride Count by Hour with Day & Night Coloring *(Histogram Bar Chart)*