Case study: Cyclistic bike-share analysis for year 2023

Abount Company

Cyclistic, a bike-share program launched in 2016, has grown to include 5,824 bikes and 692 stations in Chicago. The bikes can be unlocked and returned at any station. The company offers flexible pricing plans: single-ride passes, full-day passes, and annual memberships. Single-ride and full-day pass users are casual riders, while annual membership buyers are Cyclistic members.

Financial analysis shows that annual members are more profitable than casual riders. The current goal is to convert casual riders into annual members. Moreno, a team leader, believes this conversion is crucial for growth and aims to design marketing strategies to achieve it. To do so, the team needs to understand the differences between annual members and casual riders, motivations for casual riders to buy memberships, and the role of digital media in marketing. Analyzing historical bike trip data is key to identifying trends and informing these strategies.

Questions for Analysis

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?

Prepare

For the analysis, I utilized Cyclistic's Historical Trip Data to identify trends. The data covers a period from January 1, 2023, to December 30, 2023, and is stored in CSV files, with each file representing one month's data, totaling 12 CSV files. The data is well-organized and structured.

Although the datasets have different names since Cyclistic is a fictional company, they are suitable for this case study. The data is provided by Motivate International Inc. under this license. Given that this data is from an actual bike-sharing company in Chicago, it is reliable, original, current, and properly cited (meeting the ROCCC criteria). However, it is not entirely comprehensive as it lacks certain information.

In terms of data integrity, it is accurate, consistent, and trustworthy.

Peparing data for analysis

Importing libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import glob

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
plt.style.use(['dark_background']) #style
```

In [3]:
```
%matplotlib inline
```

Importing data

In [4]:
```
df1=pd.read_csv('202301-divvy-tripdata.csv') #importing data from CSV files
df2=pd.read_csv('202302-divvy-tripdata.csv')
df3=pd.read_csv('202303-divvy-tripdata.csv')
df4=pd.read_csv('202304-divvy-tripdata.csv')
df5=pd.read_csv('202305-divvy-tripdata.csv')
df6=pd.read_csv('202306-divvy-tripdata.csv')
df7=pd.read_csv('202307-divvy-tripdata.csv')
df8=pd.read_csv('202308-divvy-tripdata.csv')
df9=pd.read_csv('202309-divvy-tripdata.csv')
df10=pd.read_csv('202310-divvy-tripdata.csv')
df11=pd.read_csv('202311-divvy-tripdata.csv')
df12=pd.read_csv('202312-divvy-tripdata.csv')
```

In [5]:
```
data = pd.concat( [df1,df2,df3,df4,df5,df6,df7,df8,df9,df10,df11,df12], ignore_index = T
```

In [6]:
```
data.shape
```

Out[6]:
```
(5719877, 13)
```

In [7]:
```
data.head(10)
```

Out[7]:

	ride_id	rideable_type	started_at	ended_at	start_station_name	start_station_id	end_station_na
0	F96D5A74A3E41399	electric_bike	2023-01-21 20:05:42	2023-01-21 20:16:33	Lincoln Ave & Fullerton Ave	TA1309000058	Hampden C Diversey A
1	13CB7EB698CEDB88	classic_bike	2023-01-10 15:37:36	2023-01-10 15:46:05	Kimbark Ave & 53rd St	TA1309000037	Greenwood Av 47th
2	BD88A2E670661CE5	electric_bike	2023-01-02 07:51:57	2023-01-02 08:05:11	Western Ave & Lunt Ave	RP-005	Valli Produ Evanston Pl
3	C90792D034FED968	classic_bike	2023-01-22 10:52:58	2023-01-22 11:01:44	Kimbark Ave & 53rd St	TA1309000037	Greenwood Av 47th
4	3397017529188E8A	classic_bike	2023-01-12 13:58:01	2023-01-12 14:13:20	Kimbark Ave & 53rd St	TA1309000037	Greenwood Av 47th
5	58E68156DAE3E311	electric_bike	2023-01-31 07:18:03	2023-01-31 07:21:16	Lakeview Ave & Fullerton Pkwy	TA1309000019	Hampden C Diversey A
6	2F7194B6012A98D4	electric_bike	2023-01-15 21:18:36	2023-01-15 21:32:36	Kimbark Ave & 53rd St	TA1309000037	Greenwood Av 47th
7	DB1CF84154D6A049	classic_bike	2023-01-25 10:49:01	2023-01-25 10:58:22	Kimbark Ave & 53rd St	TA1309000037	Greenwood Av 47th
8	34EAB943F88C4C5D	electric_bike	2023-01-25 20:49:47	2023-01-25 21:02:14	Kimbark Ave & 53rd St	TA1309000037	Greenwood Av 47th
9	BC8AB1AA51DA9115	classic_bike	2023-01-06 16:37:19	2023-01-06 16:49:52	Kimbark Ave & 53rd St	TA1309000037	Greenwood Av 47th

Data Cleaning

Removing data that is not needed for this analysis to improve performance

In [8]:
```
data = data.drop(columns=['start_station_name', 'start_station_id', 'end_station_name',
data
```

Out[8]:

	ride_id	rideable_type	started_at	ended_at	member_casual
0	F96D5A74A3E41399	electric_bike	2023-01-21 20:05:42	2023-01-21 20:16:33	member
1	13CB7EB698CEDB88	classic_bike	2023-01-10 15:37:36	2023-01-10 15:46:05	member
2	BD88A2E670661CE5	electric_bike	2023-01-02 07:51:57	2023-01-02 08:05:11	casual
3	C90792D034FED968	classic_bike	2023-01-22 10:52:58	2023-01-22 11:01:44	member
4	3397017529188E8A	classic_bike	2023-01-12 13:58:01	2023-01-12 14:13:20	member
...	...	...	...	...	...
5719872	F74DF9549B504A6B	electric_bike	2023-12-07 13:15:24	2023-12-07 13:17:37	casual
5719873	BCDA66E761CC1029	classic_bike	2023-12-08 18:42:21	2023-12-08 18:45:56	casual
5719874	D2CF330F9C266683	classic_bike	2023-12-05 14:09:11	2023-12-05 14:13:01	member
5719875	3829A0D1E00EE970	electric_bike	2023-12-02 21:36:07	2023-12-02 21:53:45	casual
5719876	A373F5B447AEA508	classic_bike	2023-12-11 13:07:46	2023-12-11 13:11:24	member

5719877 rows × 5 columns

Checking for duplicates

In [9]:
```
print(data.duplicated().sum())
```

```
0
```

In [10]:
```
data.isnull().sum()
```

Out[10]:
```
ride_id          0
rideable_type    0
started_at       0
ended_at         0
member_casual    0
dtype: int64
```

Manipulating data

Splitting date and time to separate columns and fixing datatypes

In [11]:
```
data[['st_date','st_time']]=data.started_at.str.split(expand=True)
```

In [12]:
```
data[['end_date','end_time']]=data.ended_at.str.split(expand=True)
```

In [13]:
```
data["started_at"]=pd.to_datetime(data["started_at"])
data['ended_at']=pd.to_datetime(data['ended_at'])
```

In [14]:
```
data['st_date']=pd.to_datetime(data['st_date'])
data['end_date']=pd.to_datetime(data['end_date'])
data['end_time']=pd.to_datetime(data['end_time'])
data['st_time']=pd.to_datetime(data['st_time'])
```

In [15]:
```
data['day_of_week'] = data['started_at'].dt.dayofweek
```

In [16]:
```python
data['hour']=data.st_time.dt.hour
```

In [17]:
```python
data['ord_day']=data.started_at.dt.day_of_year
```

In [18]:
```python
data['name_day']=data.st_date.dt.day_name()
```

In [19]:
```python
data['name_day']=data.st_date.dt.day_name()
```

In [20]:
```python
data['name_month']=data.started_at.dt.month_name()
```

In [21]:
```python
data['num_month']=data.started_at.dt.month
```

In [22]:
```python
data['total_ride_length']=data['ended_at']-data['started_at']
```

In [23]:
```python
data['total_ride_length']=pd.to_numeric(data['total_ride_length'])/6e+10
```

In [24]:
```python
data=data.drop(data[data['total_ride_length']<1].index) #removing negative values
```

In [25]:
```python
data[data['total_ride_length']<1].count()
```

Out[25]:
```
ride_id              0
rideable_type        0
started_at           0
ended_at             0
member_casual        0
st_date              0
st_time              0
end_date             0
end_time             0
day_of_week          0
hour                 0
ord_day              0
name_day             0
name_month           0
num_month            0
total_ride_length    0
dtype: int64
```

Analysing Data

In [26]:
```python
data #top and bottom 5 rows of the final dataset
```

Out[26]:

	ride_id	rideable_type	started_at	ended_at	member_casual	st_date	st_time	end_date
0	F96D5A74A3E41399	electric_bike	2023-01-21 20:05:42	2023-01-21 20:16:33	member	2023-01-21	2024-07-09 20:05:42	2023-01-21
1	13CB7EB698CEDB88	classic_bike	2023-01-10 15:37:36	2023-01-10 15:46:05	member	2023-01-10	2024-07-09 15:37:36	2023-01-10
2	BD88A2E670661CE5	electric_bike	2023-01-02 07:51:57	2023-01-02 08:05:11	casual	2023-01-02	2024-07-09 07:51:57	2023-01-02
3	C90792D034FED968	classic_bike	2023-01-22 10:52:58	2023-01-22 11:01:44	member	2023-01-22	2024-07-09 10:52:58	2023-01-22
4	3397017529188E8A	classic_bike	2023-01-12 13:58:01	2023-01-12 14:13:20	member	2023-01-12	2024-07-09 13:58:01	2023-01-12
...	...	...	...	...	...	...	...	...

5719872	F74DF9549B504A6B	electric_bike	2023-12-07 13:15:24	2023-12-07 13:17:37	casual	2023-12-07	2024-07-09 13:15:24	2023-12-07
5719873	BCDA66E761CC1029	classic_bike	2023-12-08 18:42:21	2023-12-08 18:45:56	casual	2023-12-08	2024-07-09 18:42:21	2023-12-08
5719874	D2CF330F9C266683	classic_bike	2023-12-05 14:09:11	2023-12-05 14:13:01	member	2023-12-05	2024-07-09 14:09:11	2023-12-05
5719875	3829A0D1E00EE970	electric_bike	2023-12-02 21:36:07	2023-12-02 21:53:45	casual	2023-12-02	2024-07-09 21:36:07	2023-12-02
5719876	A373F5B447AEA508	classic_bike	2023-12-11 13:07:46	2023-12-11 13:11:24	member	2023-12-11	2024-07-09 13:07:46	2023-12-11

5570262 rows × 16 columns

In [27]:
```
data.describe()
```

Out[27]:

	started_at	ended_at	st_date	st_time	end_date	
count	5570262	5570262	5570262	5570262	5570262	
mean	2023-07-16 19:10:09.162088448	2023-07-16 19:28:48.912187648	2023-07-16 04:34:37.007940352	2024-07-09 14:35:32.154150400	2023-07-16 04:43:53.695577344	14:4
min	2023-01-01 00:02:06	2023-01-01 00:07:23	2023-01-01 00:00:00	2024-07-09 00:00:00	2023-01-01 00:00:00	
25%	2023-05-21 17:21:34.500000	2023-05-21 17:44:51.500000	2023-05-21 00:00:00	2024-07-09 11:09:29	2023-05-21 00:00:00	
50%	2023-07-21 06:40:50.500000	2023-07-21 07:01:09	2023-07-21 00:00:00	2024-07-09 15:26:46	2023-07-21 00:00:00	
75%	2023-09-17 01:36:05.750000128	2023-09-17 02:00:38	2023-09-17 00:00:00	2024-07-09 18:10:48	2023-09-17 00:00:00	
max	2023-12-31 23:58:55	2024-01-01 23:50:51	2023-12-31 00:00:00	2024-07-09 23:59:59	2024-01-01 00:00:00	
std	NaN	NaN	NaN	NaN	NaN	

In [28]:
```
member=data[data.member_casual=='member']
```

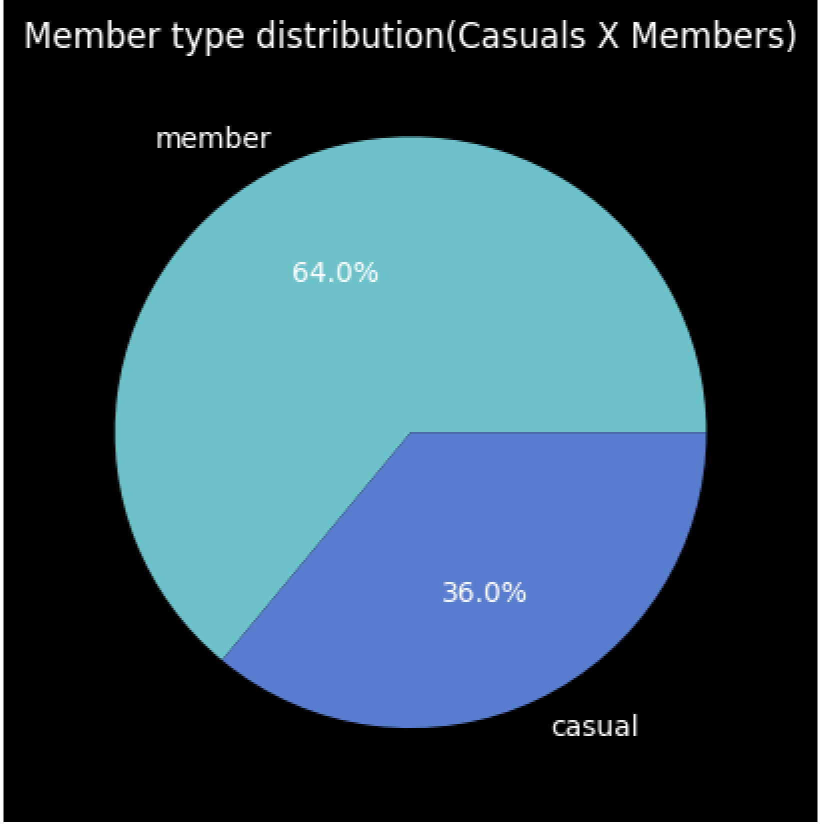
In [29]:
```
casual=data[data.member_casual=='casual']
```

In [30]:
```
d=data.member_casual.value_counts()
d=pd.DataFrame(d)
d.reset_index(drop=False, inplace=True)
d
```

Out[30]:

	member_casual	count
0	member	3564512
1	casual	2005750

In [31]:
```
plt.pie(d['count'],labels=d['member_casual'],autopct='%1.1f%%',colors=['#6dc2ca', '#597d
plt.title("Member type distribution(Casuals X Members)")
plt.show()
```



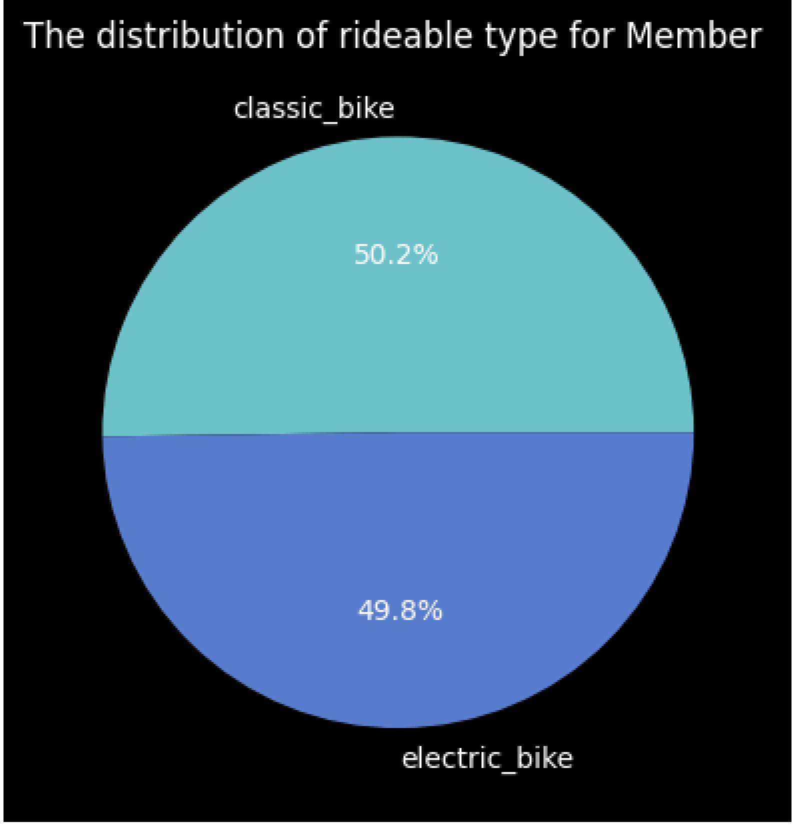
- Members: 64%
- Casual: 36% This chart indicates that the majority of users are members, accounting for 64% of the total, while casual users make up 36%.

In [32]:
```
m3=member.rideable_type.value_counts()
m3=pd.DataFrame(m3)
m3.reset_index(drop=False, inplace=True)
m3
```

Out[32]:

	rideable_type	count
0	classic_bike	1790185
1	electric_bike	1774327

In [34]:
```
plt.pie(m3['count'],labels=m3['rideable_type'],autopct='%1.1f%%',colors=['#6dc2ca', '#59
plt.title("The distribution of rideable type for Member ")
plt.show()
```



- Classic Bike: 50.2%
- Electric Bike: 49.8%

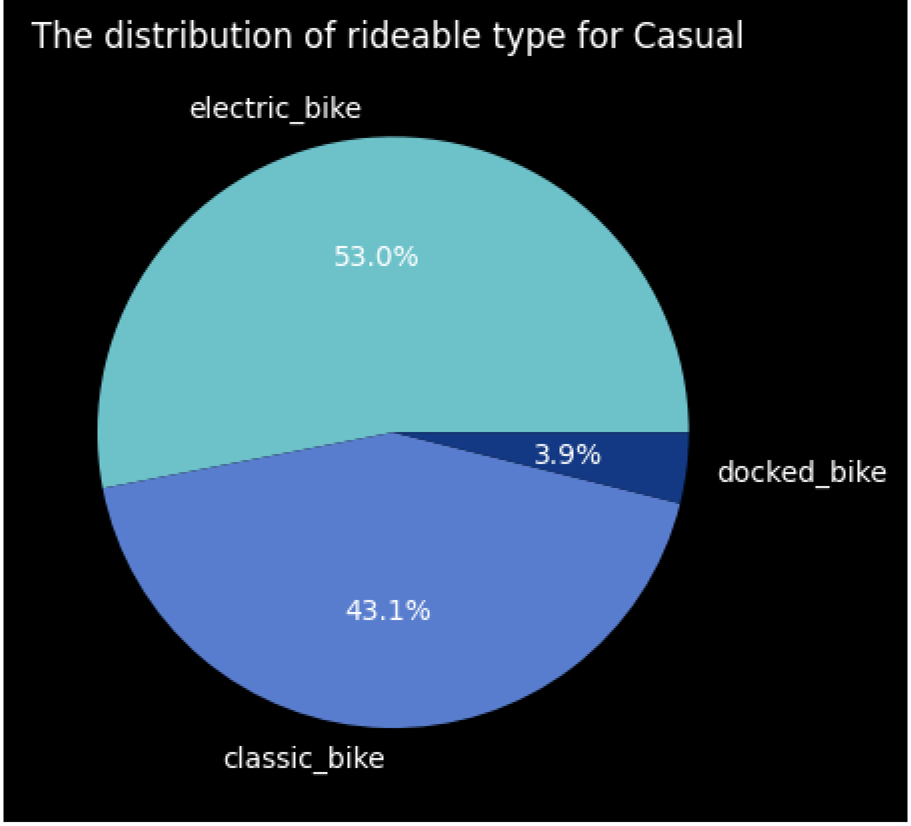
Among members, the usage of classic bikes and electric bikes is almost evenly split, with classic bikes being slightly more popular at 50.2%.

In [35]:
```
c3=casual.rideable_type.value_counts()
c3=pd.DataFrame(c3)
c3.reset_index(drop=False, inplace=True)
c3
```

Out[35]:

	rideable_type	count
0	electric_bike	1063621
1	classic_bike	864555
2	docked_bike	77574

In [37]:
```
plt.pie(c3['count'],labels=c3['rideable_type'],autopct='%1.1f%%',colors=['#6dc2ca', '#59
plt.title("The distribution of rideable type for Casual ")
plt.show()
```

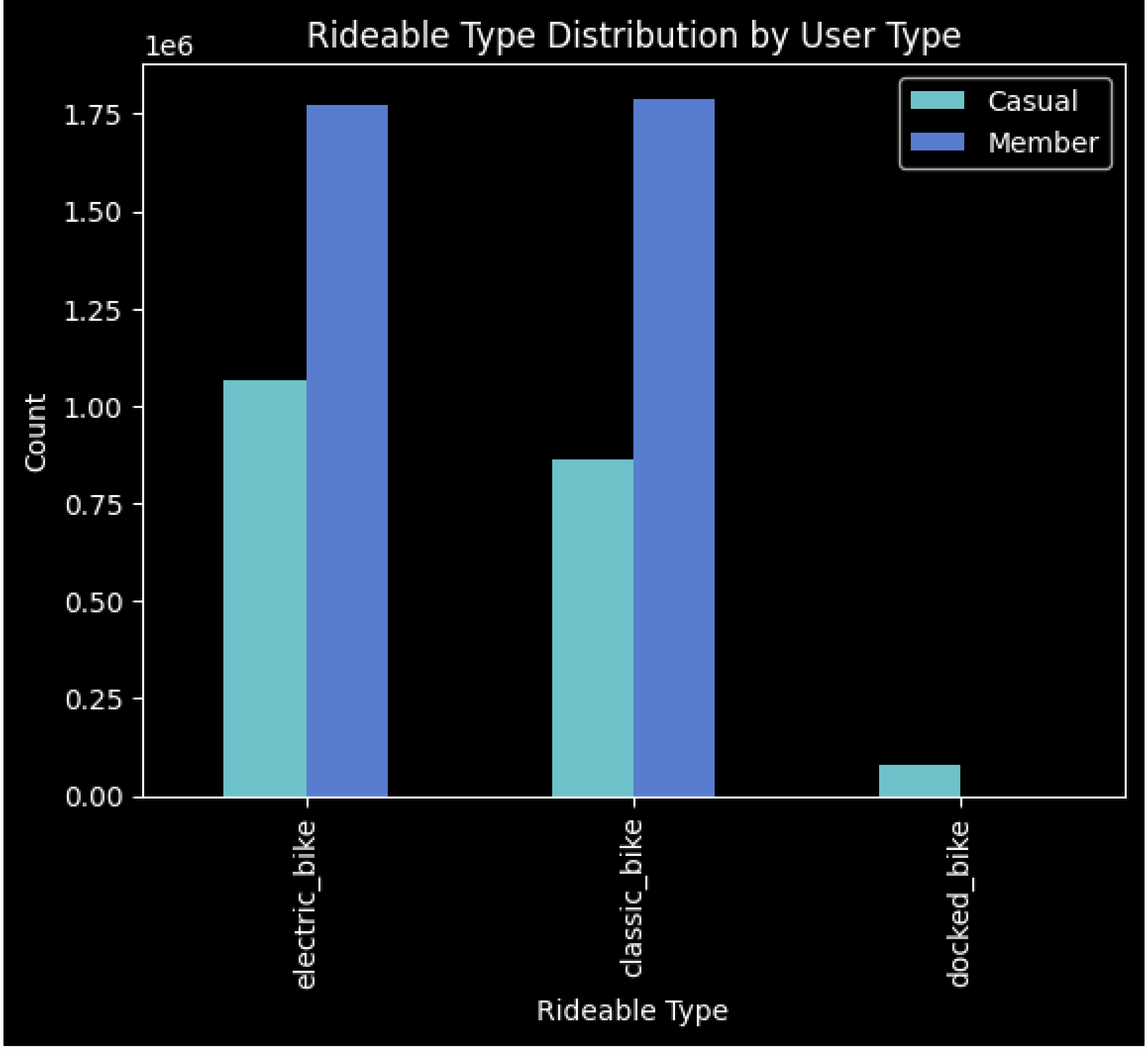


- Electric Bike: 53%
- Classic Bike: 43.1%
- Docked Bike: 3.9%

Casual users show a preference for electric bikes, which constitute 53% of their rides. Classic bikes account for 43.1%, and docked bikes are the least used at 3.9%.

In [38]:
```
m1=member.rideable_type.value_counts()
m1=pd.DataFrame(m1)
c1=casual.rideable_type.value_counts()
c1=pd.DataFrame(c1)
```

In [39]:
```
df = pd.concat([c1, m1] , axis=1)
df.columns = ['Casual', 'Member']
df.plot(kind='bar',color=['#6dc2ca', '#597dce'])
plt.xlabel('Rideable Type')
plt.ylabel('Count')
plt.title('Rideable Type Distribution by User Type')
plt.show()
```



Electric and classic bikes are preferred by both user types, while docked bikes are less popular.

In [63]:
```
d2=data.name_month.value_counts()
d2=pd.DataFrame(d2)
d2.reset_index(drop=False, inplace=True)
months_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August'
d2['month_order'] = d2['name_month'].apply(lambda x: months_order.index(x))
d2_sorted = d2.sort_values(by='month_order')
d2_sorted.drop('month_order', axis=1, inplace=True)
d2_sorted
```

Out[63]:

	name_month	count
11	January	184113
10	February	184444
8	March	249601
6	April	411607
4	May	586955
2	June	700835
1	July	747487
0	August	753322
3	September	652054
5	October	525420
7	November	355114

9	December	219310

In [65]:
```
plt.figure(figsize=(20,11))
plt.plot(d2_sorted['name_month'],d2_sorted['count'],'ro-')
plt.title("total ride count by users per month")
plt.ylabel("count")
plt.xlabel("month")
plt.show()
```

The highest number of bike trips occurred between month of June and August.

In [44]:
```
m2=member.name_month.value_counts()
m2=pd.DataFrame(m2)
m2.reset_index(drop=False, inplace=True)
m2
```

Out[44]:

	name_month	count
0	August	449587
1	July	424922
2	June	407789
3	September	396288
4	May	359580
5	October	352461
6	April	269086
7	November	258852
8	March	189322
9	December	168723
10	January	145276
11	February	142626

In [45]:
```
c2=casual.name_month.value_counts()
c2=pd.DataFrame(c2)
c2.reset_index(drop=False, inplace=True)
c2
```

Out[45]:

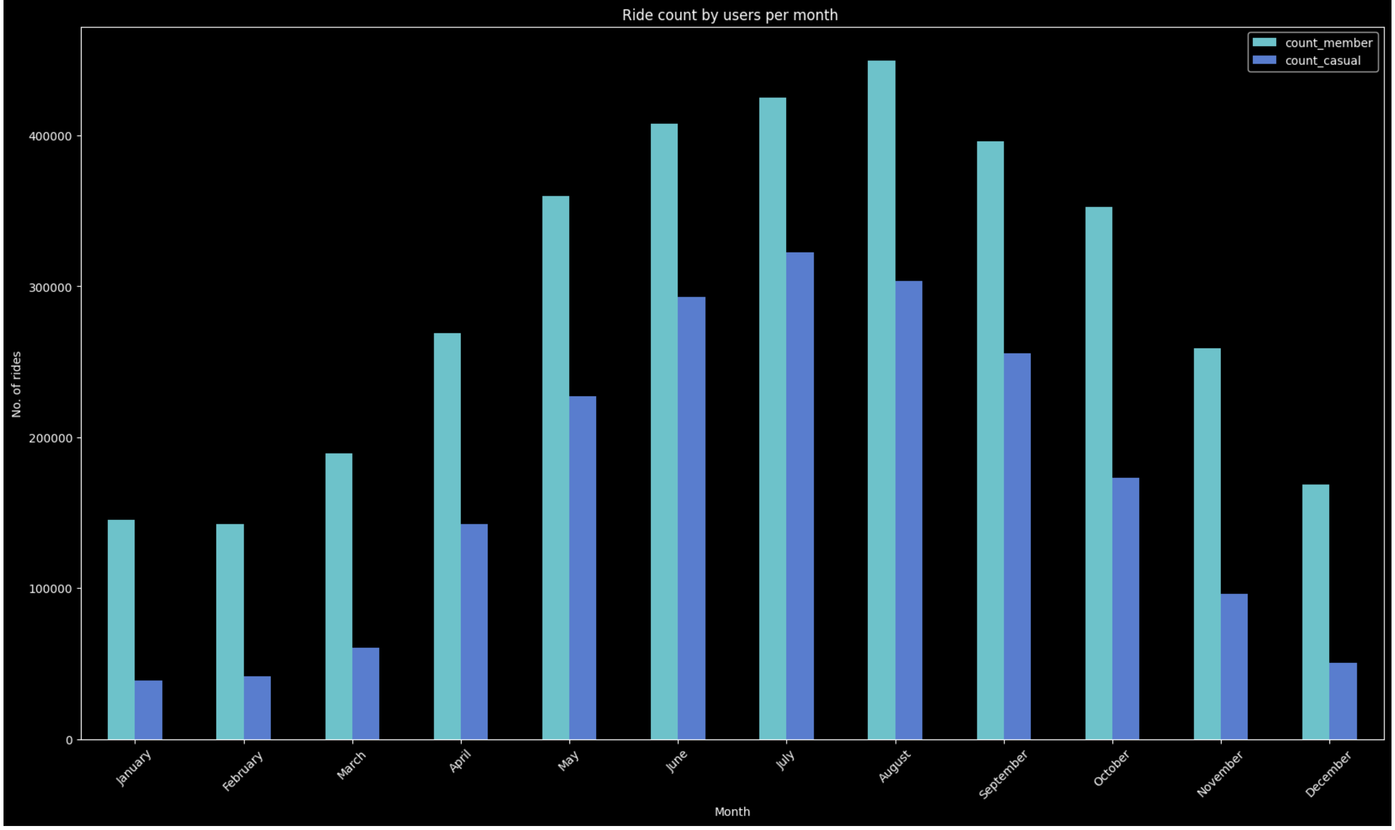
	name_month	count
0	July	322565
1	August	303735
2	June	293046
3	September	255766
4	May	227375
5	October	172959
6	April	142521
7	November	96262
8	March	60279
9	December	50587
10	February	41818
11	January	38837

In [46]:
```
mrg1=pd.merge(m2,c2, on='name_month', how='outer', suffixes=('_member', '_casual'))
months_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August'
mrg1['month_order'] = mrg1['name_month'].apply(lambda x: months_order.index(x))
mrg_sorted1 = mrg1.sort_values(by='month_order')
mrg_sorted1.drop('month_order', axis=1, inplace=True)
mrg_sorted1
```

Out[46]:

	name_month	count_member	count_casual
4	January	145276	38837
3	February	142626	41818
7	March	189322	60279
0	April	269086	142521
8	May	359580	227375
6	June	407789	293046
5	July	424922	322565
1	August	449587	303735
11	September	396288	255766
10	October	352461	172959
9	November	258852	96262
2	December	168723	50587

In [47]:
```
fig, ax = plt.subplots(figsize=(20,11))
mrg_sorted1.plot(kind='bar',color=['#6dc2ca', '#597dce'],ax=ax)
plt.title("Ride count by users per month ")
plt.ylabel("No. of rides")
plt.xlabel("Month")
plt.xticks(np.arange(12), mrg_sorted1['name_month'], rotation=45)
plt.show()
```



1. Seasonal Trends:

   - Summer Peak: Months from June to August (June, July, August) show consistently high ride counts for both members and casual riders, with June and July having the highest overall counts.
   - Winter Decrease: Months from November to February (November, December, January, February) generally have lower ride counts, especially among casual riders.

2. Member vs. Casual Rider Usage:

   - Member Dominance: Across most months, members tend to have a higher number of rides compared to casual riders, indicating that members are more consistent in their usage throughout the year.
   - Casual Rider Spikes: There are noticeable spikes in casual rider counts during peak summer months (June, July, August), suggesting increased usage by occasional or seasonal users during vacation periods.

3. Annual Trends:

   - Overall Increase: The total number of rides generally increases from the beginning of the year (January) through the summer months, peaking in July.
   - Fall Decrease: Rides tend to decrease starting from September through December, reflecting seasonal trends and potentially cooler weather affecting ridership.

4. Implications for Marketing and Strategy:

   - Targeted Campaigns: Understanding these seasonal variations can help Cyclistic design targeted marketing campaigns to attract more casual riders during peak seasons and encourage membership during slower months.
   - Service Planning: Insights into member usage patterns can inform service planning and resource allocation, such as bike maintenance and station management.

In [48]:
```
m1=member.name_day.value_counts()
```

```
m1=pd.DataFrame(m1)
m1.reset_index(drop=False, inplace=True)
m1
```

Out[48]:

	name_day	count
0	Thursday	573822
1	Wednesday	571585
2	Tuesday	561963
3	Friday	517281
4	Monday	481944
5	Saturday	459879
6	Sunday	398038

In [49]:

```
c1=casual.name_day.value_counts()
c1=pd.DataFrame(c1)
c1.reset_index(drop=False, inplace=True)
c1
```

Out[49]:

	name_day	count
0	Saturday	399905
1	Sunday	326829
2	Friday	303857
3	Thursday	263642
4	Wednesday	242761
5	Tuesday	239914
6	Monday	228842

In [50]:

```
mrg=pd.merge(m1,c1, on='name_day', how='outer', suffixes=('_member', '_casual'))

weekdays_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'S
mrg['day_order'] = mrg['name_day'].apply(lambda x: weekdays_order.index(x))
mrg_sorted = mrg.sort_values(by='day_order')
mrg_sorted.drop('day_order', axis=1, inplace=True)
mrg_sorted
```

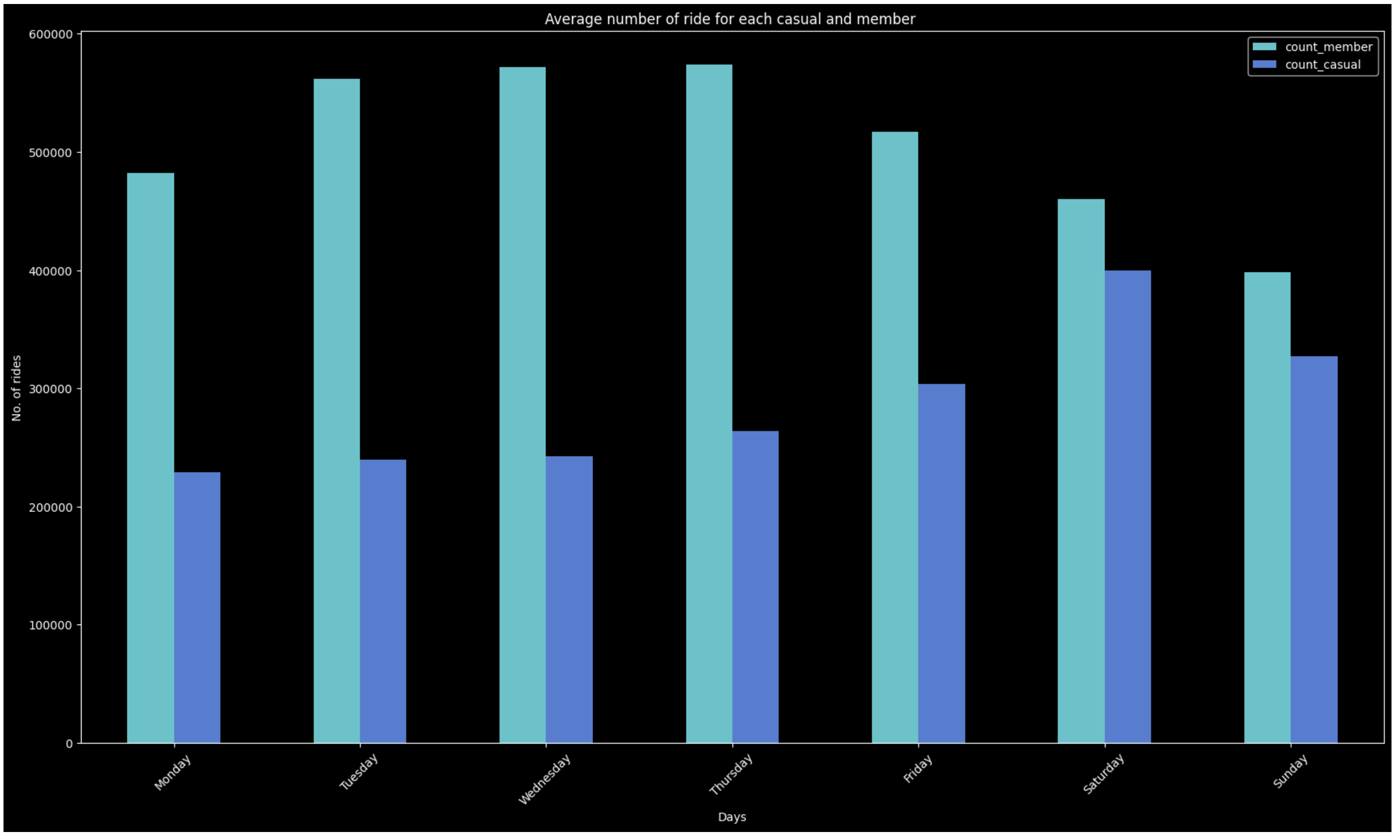
Out[50]:

	name_day	count_member	count_casual
1	Monday	481944	228842
5	Tuesday	561963	239914
6	Wednesday	571585	242761
4	Thursday	573822	263642
0	Friday	517281	303857
2	Saturday	459879	399905
3	Sunday	398038	326829

In [51]:

```
fig, ax = plt.subplots(figsize=(20,11))
mrg_sorted.plot(kind='bar',color=['#6dc2ca', '#597dce'],ax=ax)
plt.title("Average number of ride for each casual and member ")
plt.ylabel("No. of rides")
plt.xlabel("Days")
```

```
plt.xticks(np.arange(7), mrg_sorted['name_day'],rotation=45)
plt.show()
```



1. Weekday vs. Weekend Usage:

   - Weekday Peaks: Thursday and Wednesday have the highest total ride counts, with 573,822 and 571,585 rides respectively. This suggests that members and casual riders alike tend to use Cyclistic bikes more on weekdays.
   - Weekend Decrease: Saturday and Sunday show lower total ride counts compared to weekdays, which aligns with typical commuter patterns where bike-sharing usage may decrease on weekends.

2. Member vs. Casual Rider Trends:

   - Member Dominance: Members consistently outnumber casual riders in ride counts across all days of the week. This indicates that members are more frequent users of the bike-share service, relying on it for regular commuting or daily transportation needs.
   - Casual Rider Spikes: While members generally dominate, there are notable spikes in casual rider counts on weekends (Saturday and Sunday). This suggests that casual riders might be more likely to use the service for recreational or leisure purposes during weekends.

3. Daily Patterns:

   - Midweek Consistency: Ride counts for both members and casual riders are relatively consistent from Monday to Thursday, with slight variations.
   - Friday Variation: Fridays show a higher count of rides compared to weekends, particularly among casual riders, which might indicate increased usage for social or weekend starting activities.

4. Implications for Strategy:

   - Targeted Promotions: Understanding these daily patterns can help Cyclistic tailor promotions and incentives to encourage more frequent usage, especially among casual riders during weekends.

- Operational Planning: Insights into member usage can inform operational decisions such as bike deployment and station management during peak weekdays.

In [52]:
```
mh=member.hour.value_counts()
mh=pd.DataFrame(mh)
mh.reset_index(drop=False, inplace=True)
mh['hour'] = mh['hour'] + 1
mh_sorted = mh.sort_values('hour')
mh_sorted.head()
```

Out[52]:

	hour	count
18	1	34485
20	2	20522
21	3	11906
23	4	7734
22	5	8489

In [53]:
```
ch=casual.hour.value_counts()
ch=pd.DataFrame(ch)
ch.reset_index(drop=False, inplace=True)
ch['hour'] = ch['hour'] + 1
ch_sorted = ch.sort_values('hour')
ch_sorted.head()
```

Out[53]:

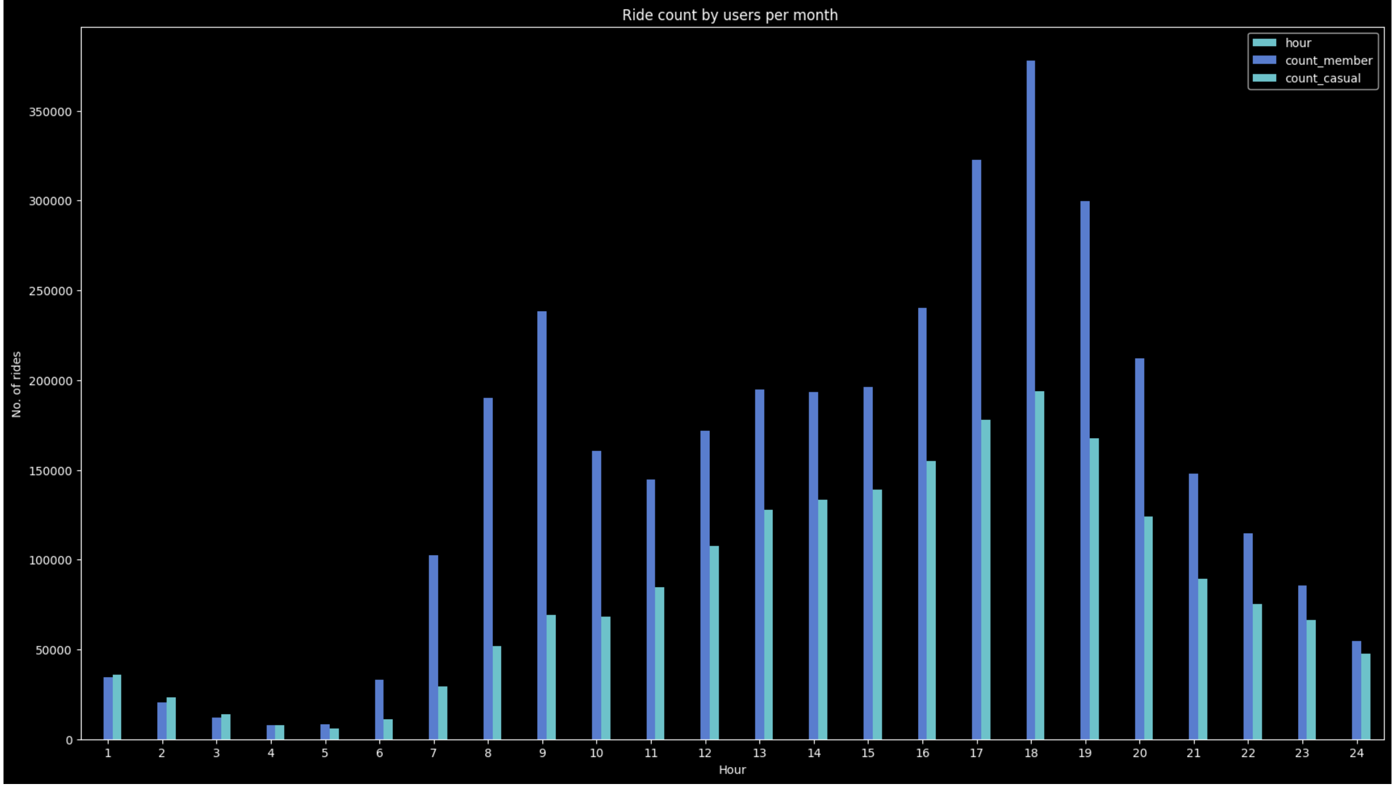
	hour	count
17	1	35781
19	2	23195
20	3	14018
22	4	7715
23	5	5811

In [71]:
```
mrg2=pd.merge(mh_sorted,ch_sorted, on='hour', how='outer', suffixes=('_member', '_casual
mrg2.head()
```

Out[71]:

	hour	count_member	count_casual
0	1	34485	35781
1	2	20522	23195
2	3	11906	14018
3	4	7734	7715
4	5	8489	5811

In [55]:
```
fig, ax = plt.subplots(figsize=(20,11))
mrg2.plot(kind='bar',color=['#6dc2ca', '#597dce'],ax=ax)
plt.title("Ride count by users per month ")
plt.ylabel("No. of rides")
plt.xlabel("Hour")
plt.xticks(np.arange(24), mrg2['hour'], rotation=0)
plt.show()
```



1. Peak Hours:

   - Evening Peak: The highest counts of rides occur during late afternoon to early evening hours, particularly between 4 PM and 6 PM (hour 16 to 18), for both members and casual riders. This suggests that many users utilize the bikes for commuting home from work or school.
   - Morning Surge: There's also a notable peak in the morning, particularly between 7 AM and 9 AM (hour 7 to 9), indicating morning commute usage primarily by members.

2. Usage Patterns Throughout the Day:

   - Member Dominance: Throughout most hours of the day, members tend to have higher ride counts compared to casual riders. This indicates that members are consistent users of the bike-sharing service for daily commuting or regular transportation needs.
   - Casual Rider Patterns: Casual riders show more fluctuation in their ride counts throughout the day, with peaks during late afternoon to evening hours, likely reflecting recreational or leisure use.

3. Late Night and Early Morning Usage:

   - Late Night Decline: Ride counts decrease significantly during late night and early morning hours (hour 0 to 5), indicating minimal usage during these times.
   - Potential for Service Adjustments: Understanding these patterns can help Cyclistic optimize bike deployment and station operations, ensuring bikes are available where and when they are most needed by riders.

4. Strategic Insights:

   - Targeted Marketing: Based on these usage patterns, Cyclistic could focus marketing efforts on promoting membership benefits for daily commuters during peak hours and offer incentives to casual riders during evening and weekend peaks.
   - Operational Efficiency: Insights into hourly usage can inform operational decisions such as scheduling maintenance, redistributing bikes, and managing station capacities more effectively.

In [56]:
```
d1=data.groupby("member_casual").agg({"total_ride_length":"mean"})
```

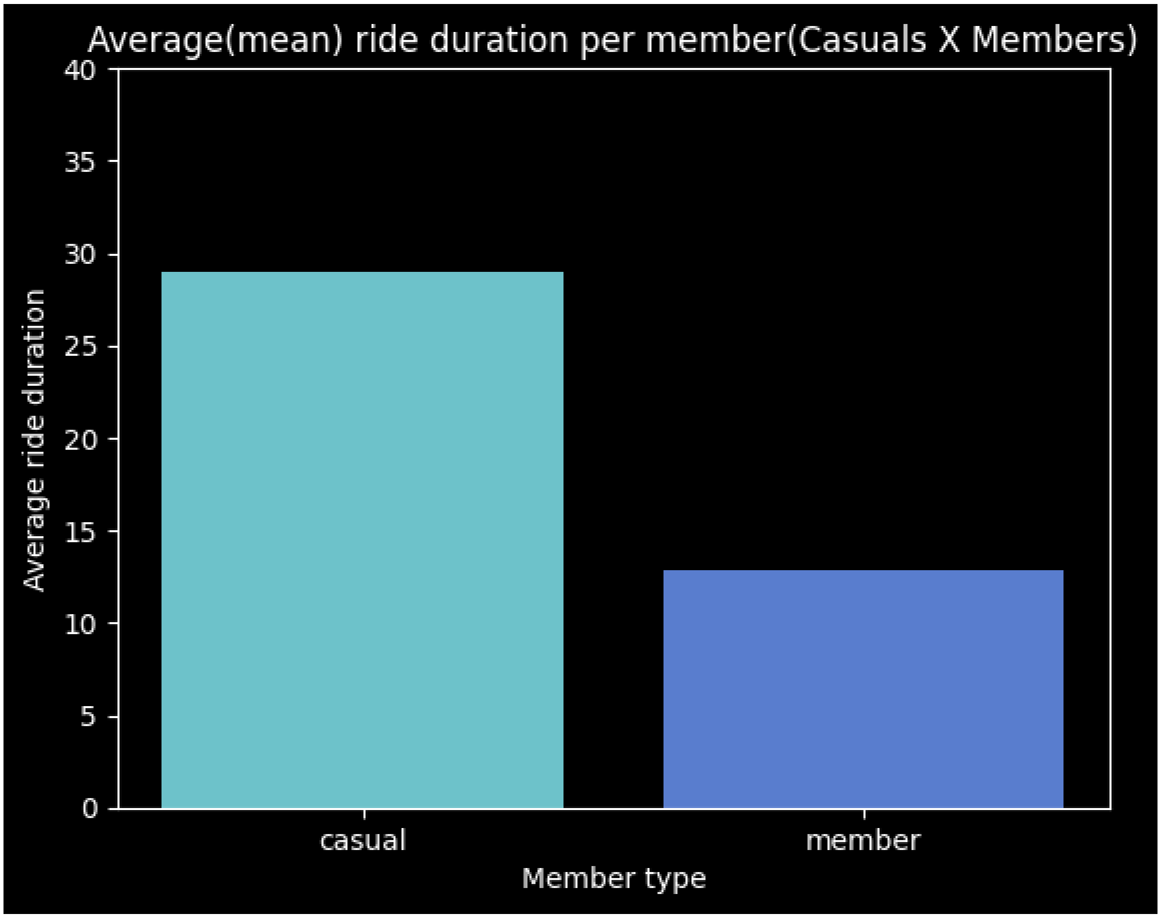
```
d1.reset_index(drop=False, inplace=True)
d1
```

Out[56]:

	member_casual	total_ride_length
0	casual	28.987448
1	member	12.852657

In [57]:

```
plt.bar(d1.member_casual,d1.total_ride_length,color=['#6dc2ca', '#597dce' ])
plt.title("Average(mean) ride duration per member(Casuals X Members)")
plt.ylabel("Average ride duration")
plt.xlabel("Member type")
plt.ylim(0,40)
plt.show()
```



1. Average Ride Length:

   - Casual Riders: On average, casual riders have longer bike rides with an average duration of approximately 28.99 minutes.
   - Members: Members, on the other hand, have shorter bike rides with an average duration of about 12.85 minutes.

2. Implications:

   - Usage Patterns: The longer average ride length for casual riders may indicate that they use the bikes for leisurely activities or longer-distance trips compared to members, who likely use the service more frequently for shorter commutes or routine travel.

In [58]:

```
m4=member.groupby("name_month").agg({"total_ride_length":"mean"})
m4.reset_index(drop=False, inplace=True)
m4
```

Out[58]:

	name_month	total_ride_length
0	April	12.123603
1	August	14.098308
2	December	11.685570
3	February	11.062655
4	January	10.706461
5	July	14.046708
6	June	13.532983
7	March	10.823058
8	May	13.429322
9	November	11.799580
10	October	12.402766
11	September	13.416386

In [59]:

```
c4=casual.groupby("name_month").agg({"total_ride_length":"mean"})
c4.reset_index(drop=False, inplace=True)
c4
```

Out[59]:

	name_month	total_ride_length
0	April	28.584172
1	August	36.090705
2	December	20.354585
3	February	23.845751
4	January	23.593841
5	July	33.202546
6	June	30.216061
7	March	22.082546
8	May	29.360879
9	November	20.324220
10	October	23.403470
11	September	25.752194

In [60]:

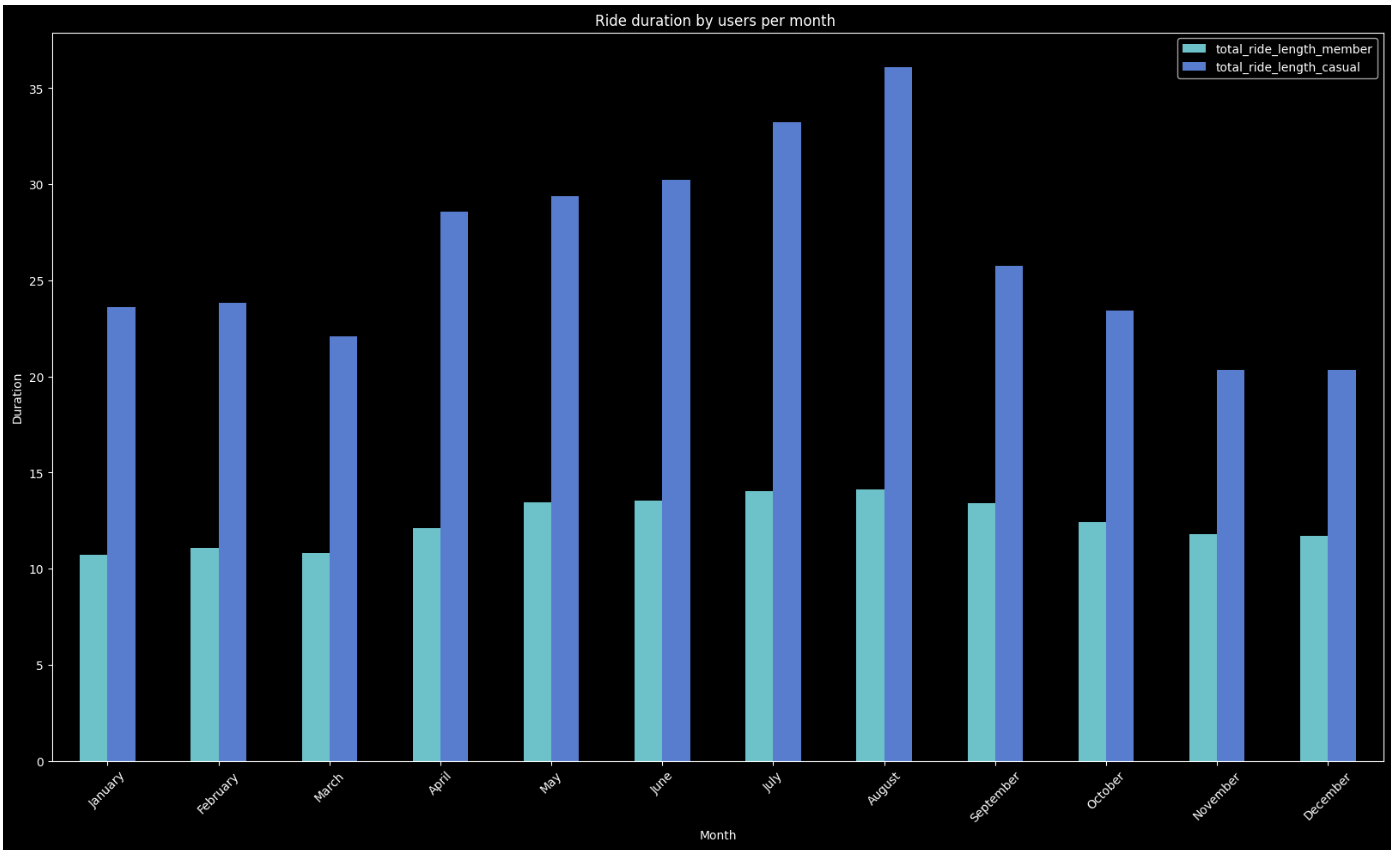
```
mrg4=pd.merge(m4,c4, on='name_month', how='outer', suffixes=('_member', '_casual'))

months_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August'
mrg4['month_order'] = mrg4['name_month'].apply(lambda x: months_order.index(x))
mrg_sorted4 = mrg4.sort_values(by='month_order')
mrg_sorted4.drop('month_order', axis=1, inplace=True)
mrg_sorted4
```

Out[60]:

	name_month	total_ride_length_member	total_ride_length_casual
4	January	10.706461	23.593841
3	February	11.062655	23.845751
7	March	10.823058	22.082546
0	April	12.123603	28.584172

8	May	13.429322	29.360879
6	June	13.532983	30.216061
5	July	14.046708	33.202546
1	August	14.098308	36.090705
11	September	13.416386	25.752194
10	October	12.402766	23.403470
9	November	11.799580	20.324220
2	December	11.685570	20.354585

In [74]:
```
fig, ax = plt.subplots(figsize=(20,11))
mrg_sorted4.plot(kind='bar',color=['#6dc2ca', '#597dce'],ax=ax)
plt.title("Ride duration by users per month ")
plt.ylabel("Duration")
plt.xlabel("Month")
plt.xticks(np.arange(12), mrg_sorted4['name_month'], rotation=45)
plt.show()
```



1. Seasonal Trends in Ride Length:
   - Summer Peaks: Months from June to August (June, July, August) consistently show the longest average ride lengths for both members and casual riders. This suggests that users tend to take longer rides during the warmer months, possibly for leisure or recreational purposes.
   - Winter Decrease: Ride lengths tend to be shorter during winter months (December to February), which may indicate reduced bike usage for commuting or outdoor activities during colder weather.
2. Member vs. Casual Rider Patterns:
   - Consistent Differences: Throughout the year, casual riders generally have longer average ride lengths compared to members. This pattern holds across most months, indicating that casual

riders may use the bikes for longer trips or more extended periods compared to members who might use the service for shorter, more frequent trips.

3. Monthly Variations:

    - August Peak: August shows the highest average ride lengths for both groups, suggesting peak summer usage patterns.

4. Strategic Insights:

    - Service Planning: Understanding these seasonal and monthly variations can help Cyclistic optimize bike deployment, station management, and maintenance schedules to meet the differing needs of riders throughout the year.
    - Marketing and Promotions: Tailoring marketing campaigns and promotions based on these insights can help attract and retain riders during peak months and encourage usage during quieter periods.

Recommendations

Based on the analyses of Cyclistic's bike-share data, here are several recommendations for improving service delivery, attracting more riders, and maximizing the conversion of casual riders into annual members:

1. Targeted Marketing Campaigns:

    - Design marketing strategies that target casual riders during peak usage periods, such as weekends and summer months. Highlight the convenience and benefits of becoming a member, including cost savings and priority access.
    - Use digital media effectively to reach potential members, emphasizing the flexibility and cost-effectiveness of annual memberships compared to single-ride or day-pass options.

2. Promotional Incentives:

    - Offer promotions and discounts specifically aimed at converting casual riders into members. For instance, provide discounted membership rates for first-time sign-ups or introduce referral programs where current members can earn rewards for referring new members.
    - Tailor promotional offers based on seasonal trends and rider preferences identified in the data, such as longer rides during summer and leisure activities.

3. Service Optimization:

    - Based on hourly and daily usage patterns, adjust bike deployment and station capacities to meet peak demand, especially during commuting hours and weekends.
    - Ensure that stations are well-maintained and strategically located in areas with high rider traffic, enhancing convenience for both members and casual riders.

4. Enhanced Customer Experience:

    - Improve the overall customer experience through user-friendly mobile apps and intuitive station interfaces. Simplify the membership sign-up process and provide real-time updates on bike availability and station statuses.
    - Gather feedback from current members and casual riders to identify pain points and areas for improvement, focusing on enhancing service reliability and user satisfaction.

5. Data-Driven Decision Making:

- Continue analyzing historical trip data to monitor trends and adjust strategies accordingly. Use predictive analytics to forecast future demand and optimize resource allocation, such as bike inventory and station capacity.
- Implement A/B testing for marketing campaigns to evaluate effectiveness and refine strategies based on performance metrics.

6. Community Engagement:

- Foster a sense of community among Cyclistic users through events, social media engagement, and partnerships with local businesses. Highlight the environmental benefits and community impact of bike-sharing to attract socially conscious riders.

By implementing these recommendations, Cyclistic can effectively capitalize on its existing user base, attract new riders, and enhance overall operational efficiency and customer satisfaction in its bike-share program.