Yulu Case Study

Yulu, India's pioneering micro-mobility service provider, has embarked on a mission to revolutionize daily commutes by offering unique, sustainable transportation solutions. However, recent revenue setbacks have prompted Yulu to seek the expertise of a consulting company to delve into the factors influencing the demand for their shared electric cycles, specifically in the Indian market.

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from scipy.stats import shapiro
from scipy.stats import levene
from scipy.stats import kruskal
from statsmodels.graphics.gofplots import qqplot
```

In [3]:
```
df = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?16
```

In [4]:
```
df.head()
```

Out[4]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

In [5]:
```
df1 = df.copy(deep = True)
```

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

Out[6]:
```
(10886, 12)
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   datetime    10886 non-null  object 
 1   season      10886 non-null  int64  
 2   holiday     10886 non-null  int64  
 3   workingday  10886 non-null  int64  
 4   weather     10886 non-null  int64  
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64  
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64  
 10  registered  10886 non-null  int64  
 11  count       10886 non-null  int64  
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
```

In [8]:
```
df.dtypes
```

Out[8]:

	0
datetime	object
season	int64
holiday	int64
workingday	int64
weather	int64
temp	float64
atemp	float64
humidity	int64
windspeed	float64
casual	int64
registered	int64
count	int64

dtype: object

In [9]:
```
df.describe()
```

Out[9]:

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	c
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.000000	10886.000000	10886.0
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	12.799395	36.0
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.245033	8.164537	49.9
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	0.000000	0.0
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	7.001500	4.0
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	12.998000	17.0
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	16.997900	49.0
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	56.996900	367.0

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

Out[10]:

	0
datetime	0
season	0
holiday	0
workingday	0
weather	0
temp	0
atemp	0
humidity	0
windspeed	0
casual	0
registered	0
count	0

dtype: int64

In [11]:
```
df['datetime'] = pd.to_datetime(df['datetime'])
```

In [12]:
```
cols = ['season','holiday','workingday','weather']

df[cols] = df[cols].astype('object')
```

In [13]:
```
df['season'].unique()
```

Out[13]:
```
array([1, 2, 3, 4], dtype=object)
```

In [14]:
```
df['weather'].unique()
```

Out[14]:
```
array([1, 2, 3, 4], dtype=object)
```

In [15]:
```
df['holiday'].unique()
```

Out[15]: array([0, 1], dtype=object)

In [16]:
```
df['workingday'].unique()
```

Out[16]: array([0, 1], dtype=object)

In [17]:
```
df['casual'].nunique()
```

Out[17]: 309

In [18]:
```
df['registered'].nunique()
```

Out[18]: 731

In [19]:
```
df['count'].nunique()
```

Out[19]: 822

In [20]:
```
df['datetime'].unique()
#= pd.to_datetime(df_yulu['datetime'])
df['datetime'] = pd.to_datetime(df['datetime'], errors='coerce')
# df['datetime'] = pd.to_datetime(df['datetime'])
```

In [21]:
```
df.dtypes
```

Out[21]:

	0
datetime	datetime64[ns]
season	object
holiday	object
workingday	object
weather	object
temp	float64
atemp	float64
humidity	int64
windspeed	float64
casual	int64
registered	int64
count	int64

dtype: object

In [22]:

```
df.season.value_counts()
```

Out[22]:

season	count
4	2734
2	2733
3	2733
1	2686

dtype: int64

In [23]:
```
df.weather.value_counts()
```

Out[23]:

weather	count
1	7192
2	2834
3	859
4	1

dtype: int64

In [24]:
```
df.workingday.value_counts()
```

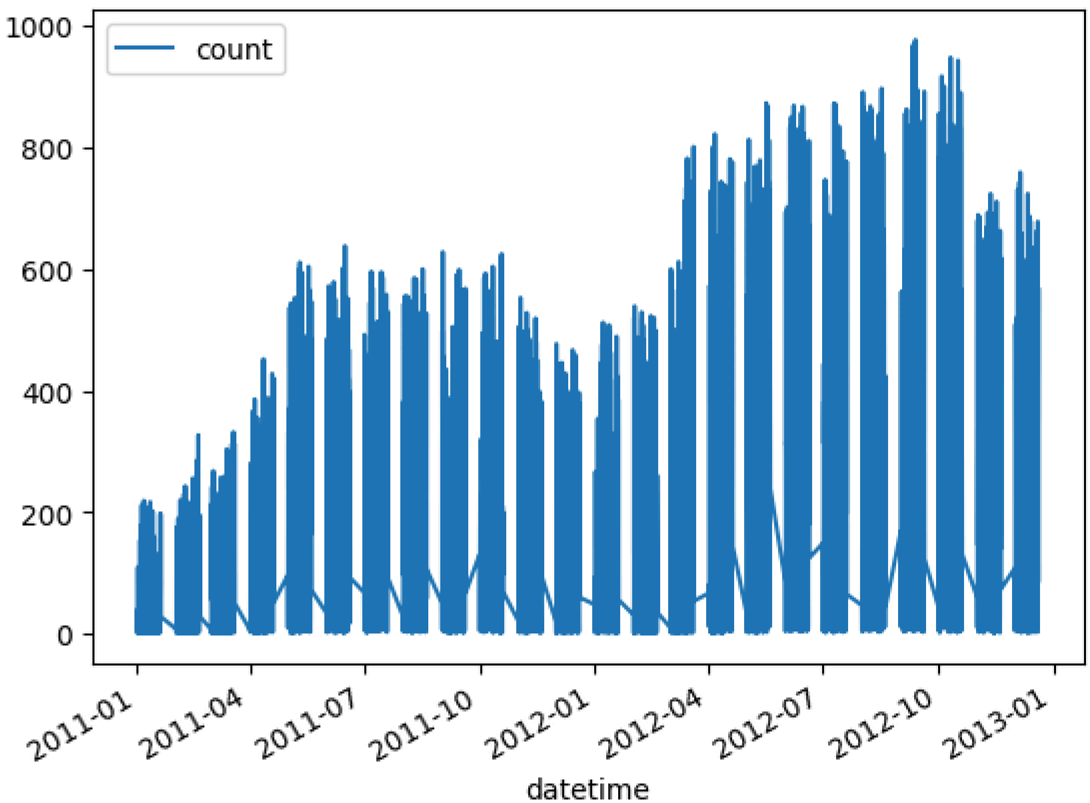
Out[24]:

workingday	count
1	7412
0	3474

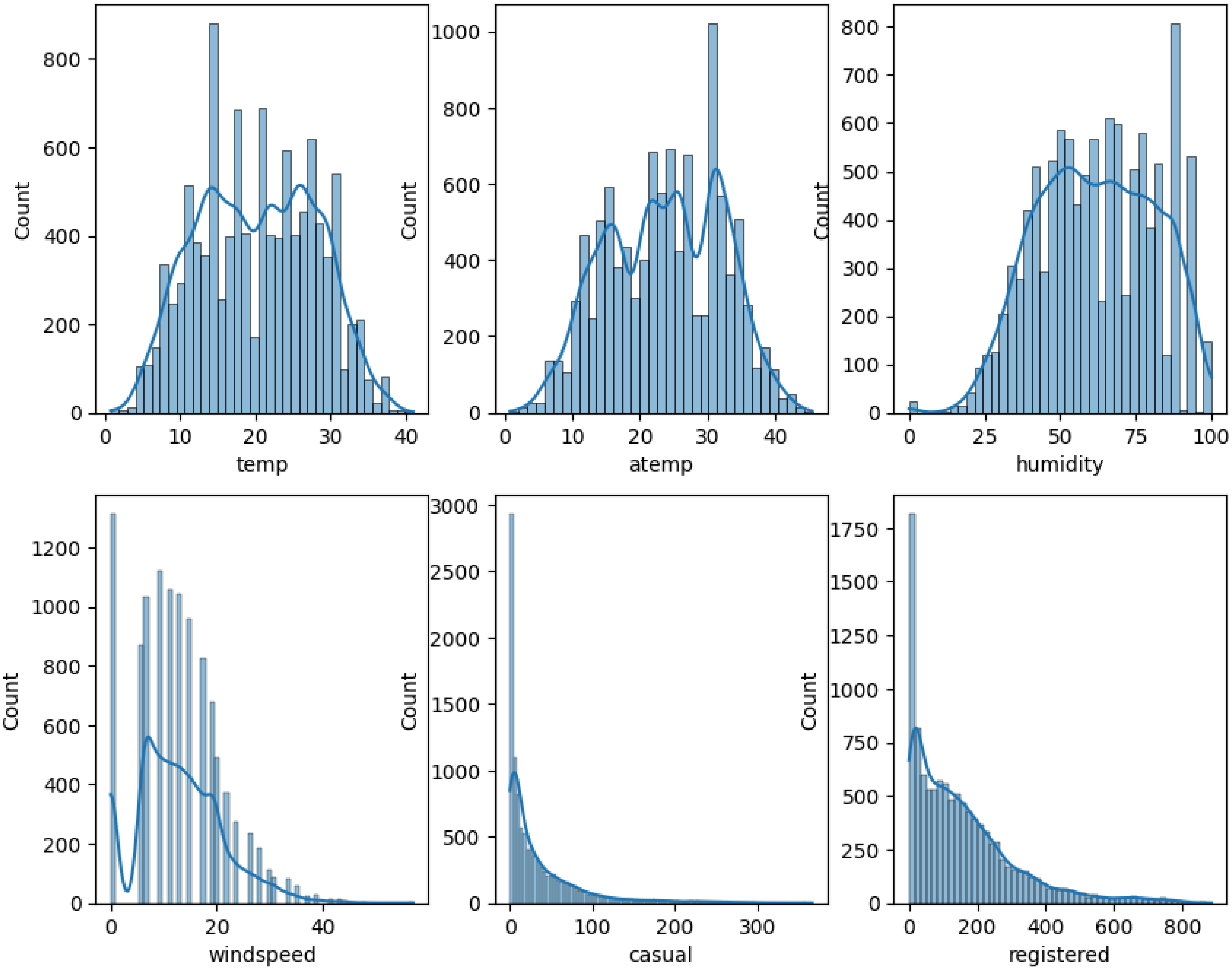
dtype: int64

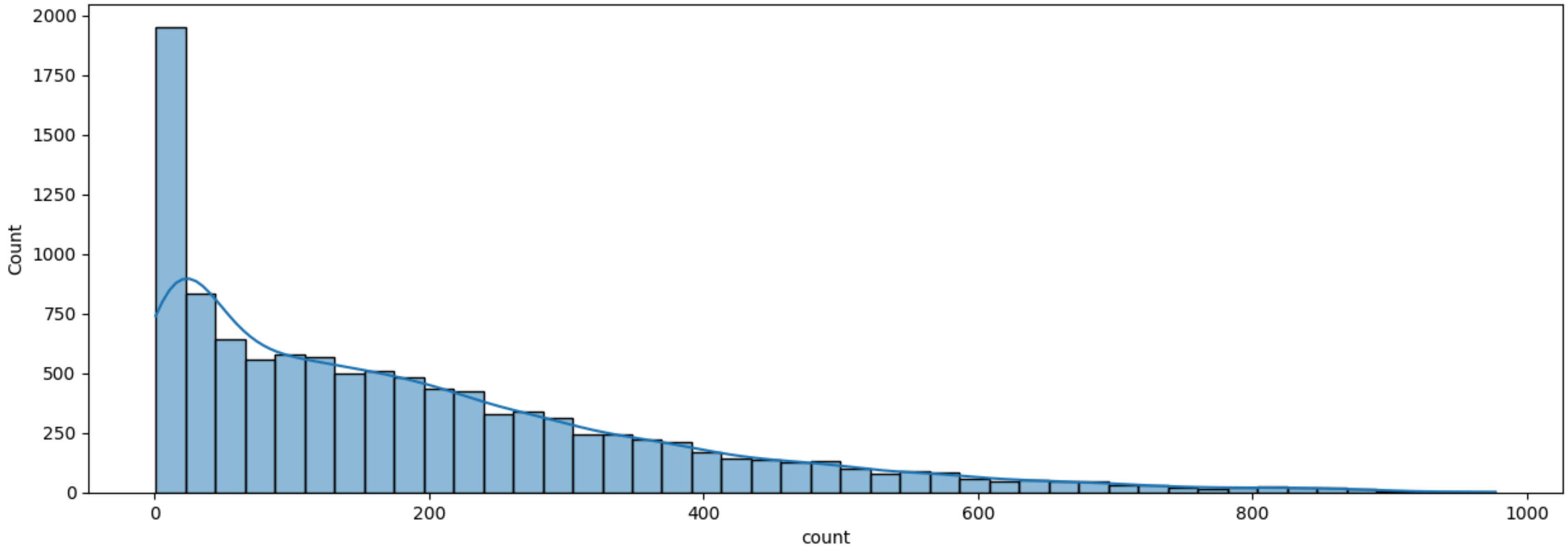
In [25]:
```
df.plot.line(x='datetime',y='count')
```

Out[25]: <Axes: xlabel='datetime'>



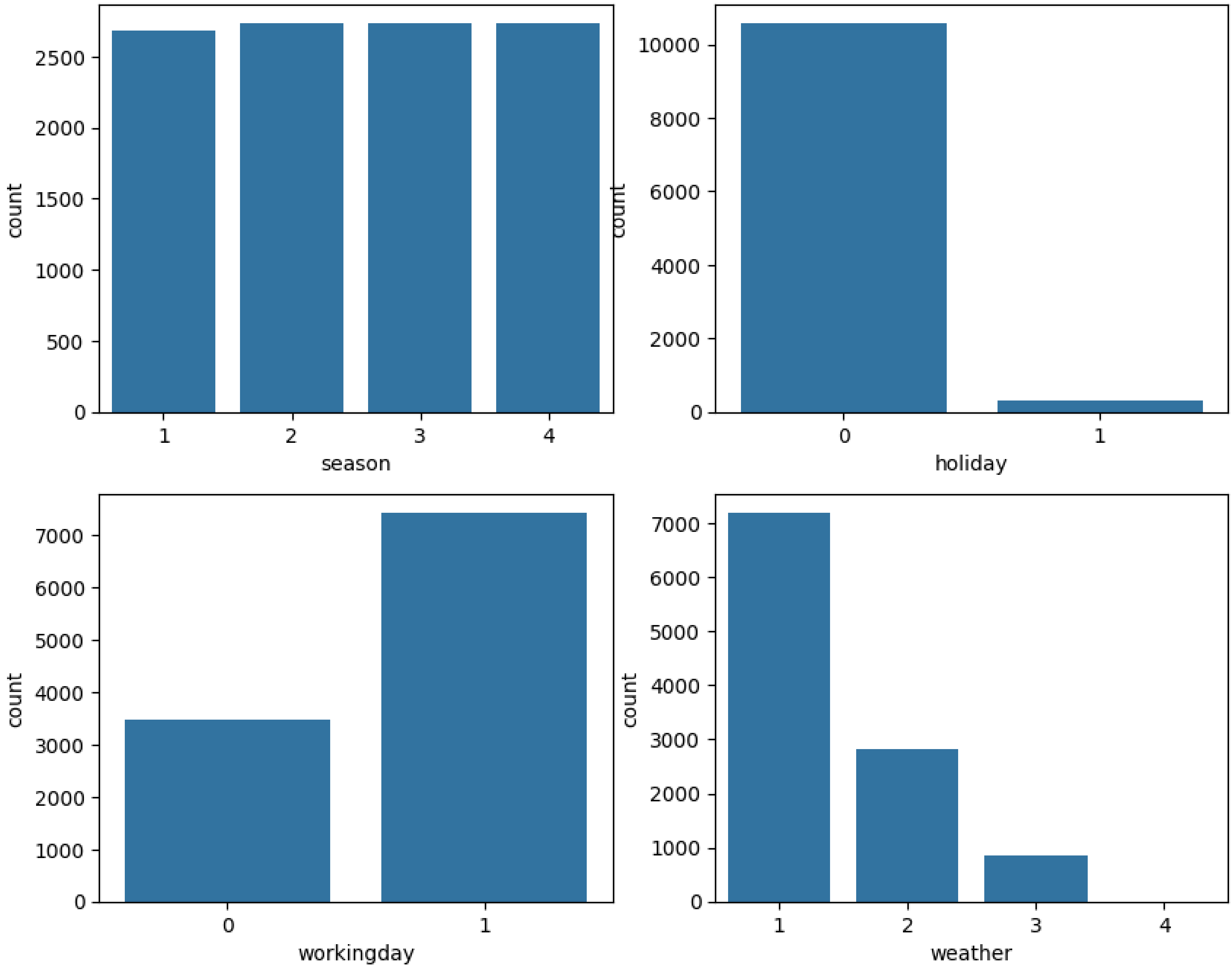
In [26]:
```
columns_cat=['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered','count']

fig,axis=plt.subplots(nrows=2,ncols=3,figsize=(10,8))

index=0
for row in range(2):
  for col in range(3):
    sns.histplot(df[columns_cat[index]],ax=axis[row,col],kde=True)
    index += 1
plt.show()

fig,axis=plt.subplots(nrows=1,ncols=1,figsize=(15,5))
sns.histplot(df[columns_cat[-1]], kde=True)
plt.show()
```


Count
temp
atemp
humidity
windspeed
casual
registered

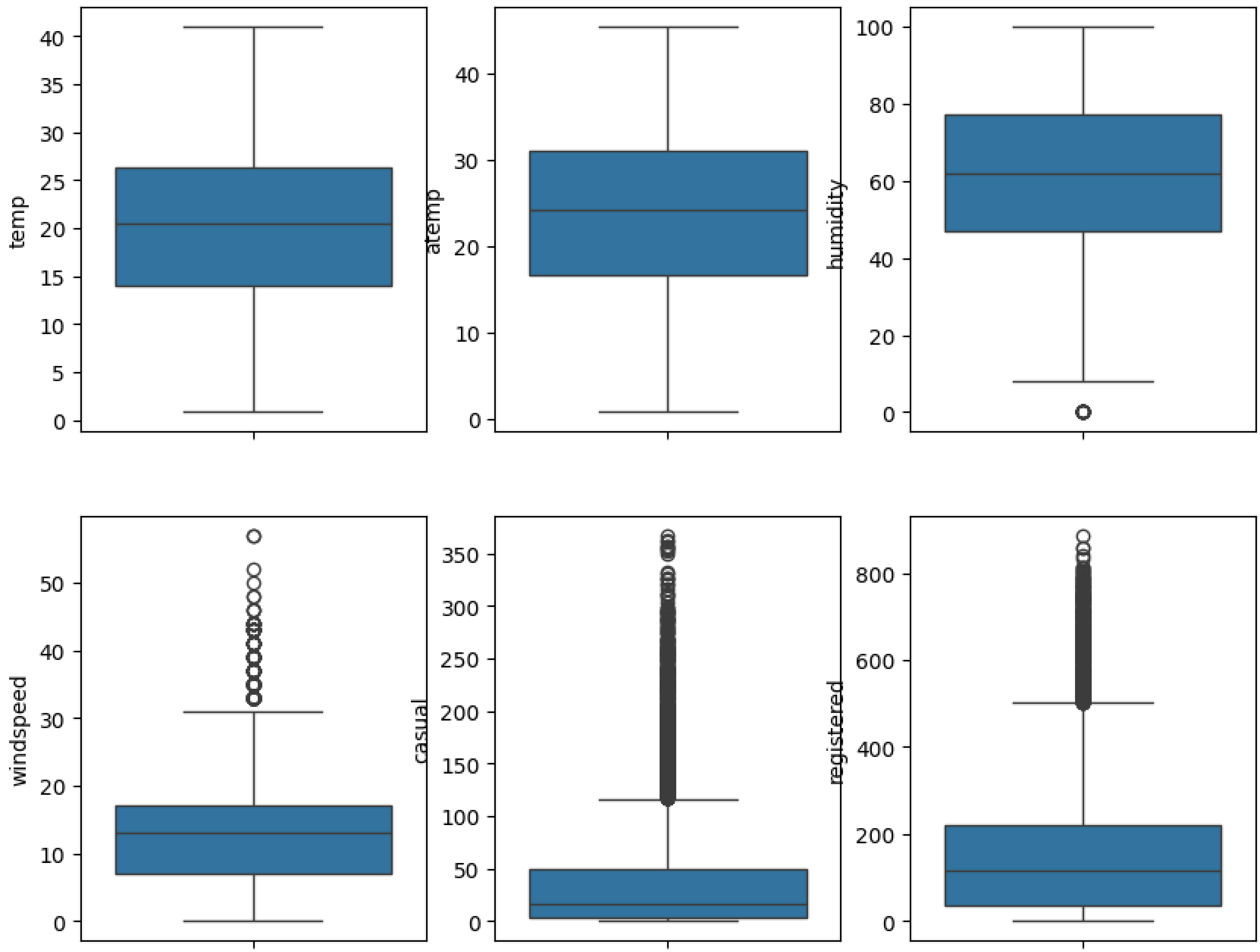


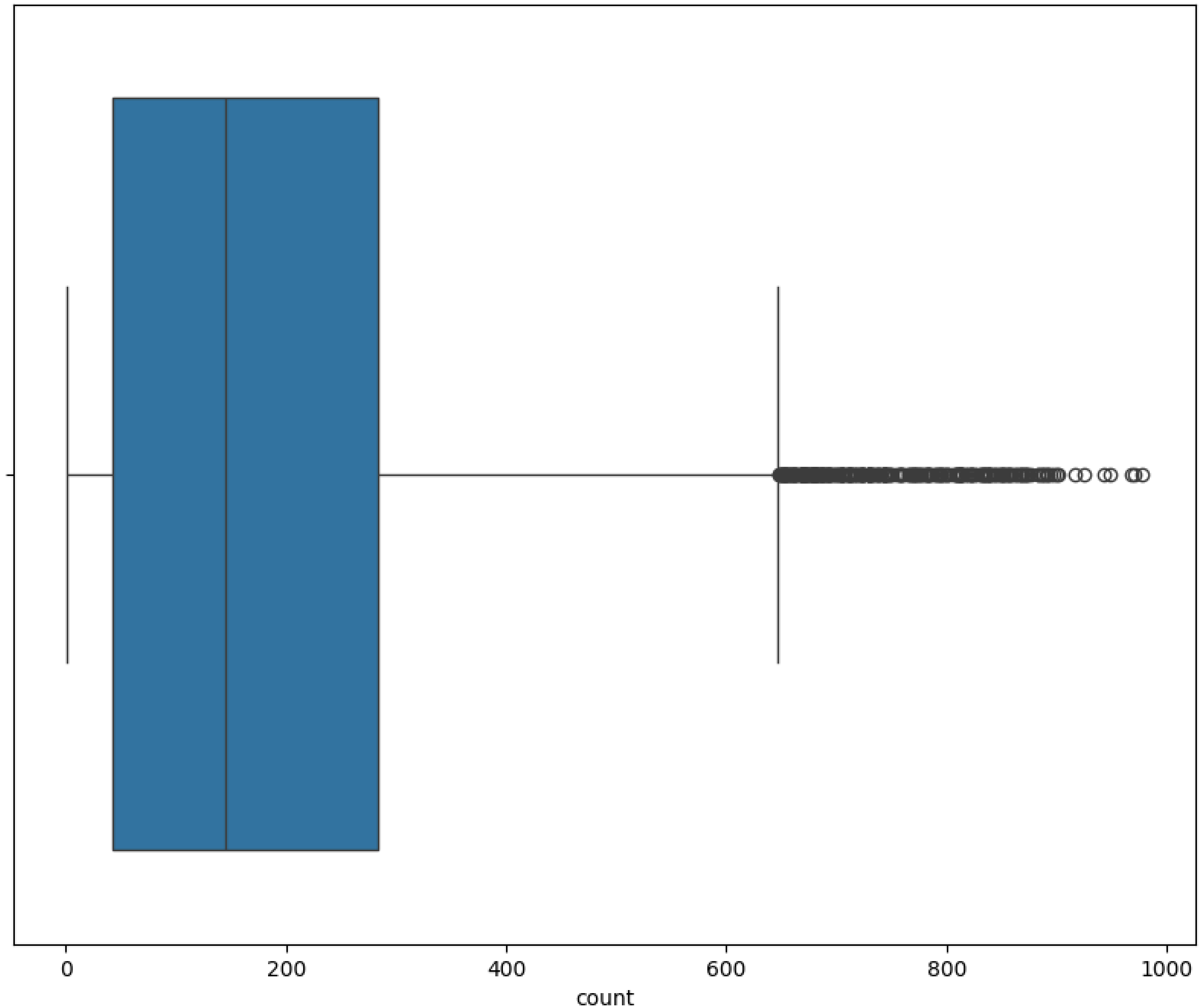
Each histogram shows the distribution of values for the respective column, providing insights into the frequency of different ranges within the data.

In [61]:
```
cat=["season","holiday","workingday","weather"]
fig,axis=plt.subplots(nrows=2,ncols=2,figsize=(10,8))

index=0
for row in range(2):
  for col in range(2):
    sns.countplot(x=df[cat[index]],ax=axis[row,col])
    index +=1
plt.show()
```

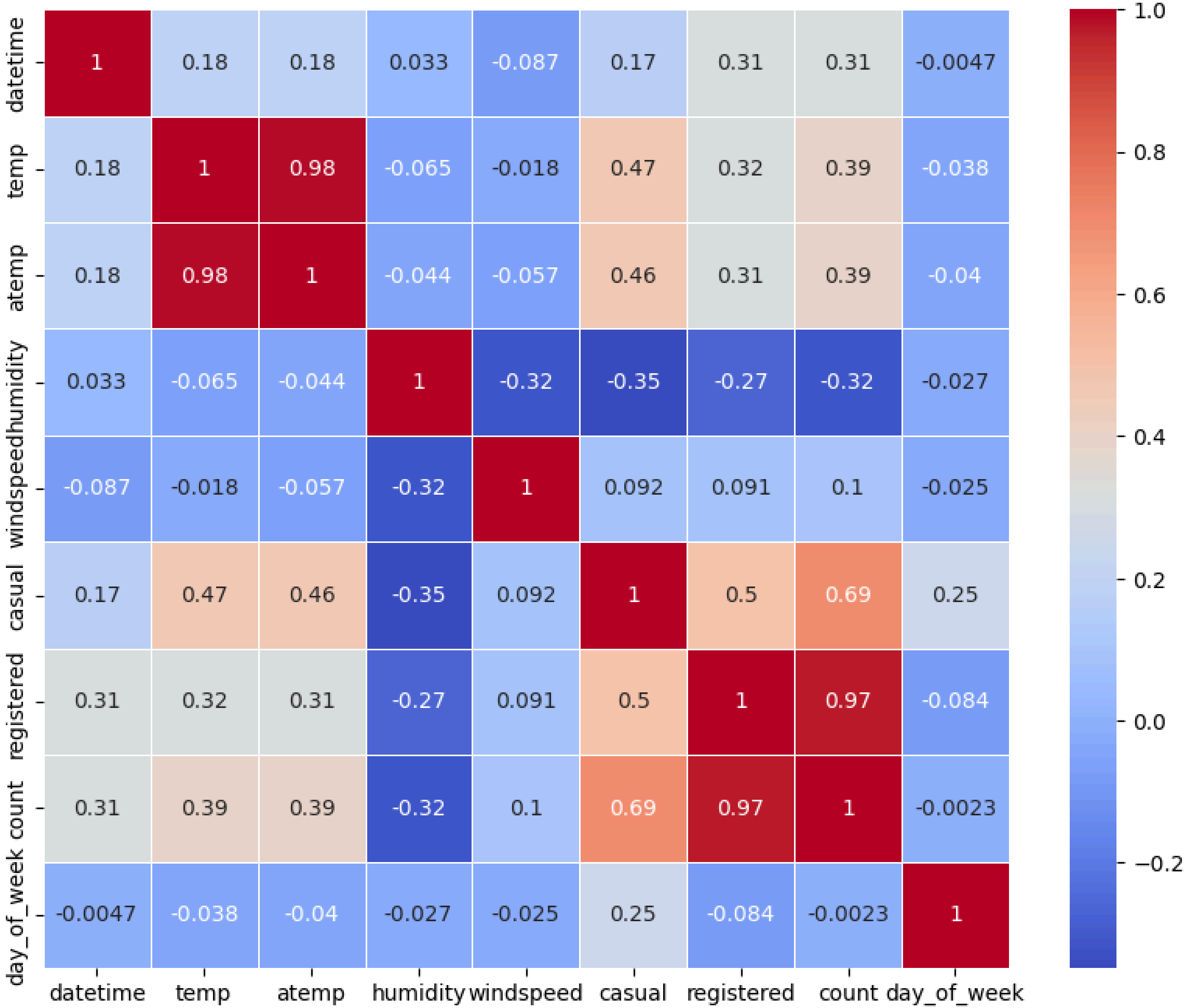

0
500
1000
1500
2000
2500
count
1
2
3
4
season
0
2000
4000
6000
8000
10000
count
0
1
holiday
0
1000
2000
3000
4000
5000
6000
7000
count
0
1
workingday
0
1000
2000
3000
4000
5000
6000
7000
count
1
2
3
4
weather

In [63]:
```
columns_cat=['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered','count']

fig,axis=plt.subplots(nrows=2,ncols=3,figsize=(10,8))

index=0
for row in range(2):
  for col in range(3):
    sns.boxplot(y=df[columns_cat[index]],ax=axis[row,col])
    index += 1
plt.show()

fig,axis=plt.subplots(nrows=1,ncols=1,figsize=(10,8))
sns.boxplot(x=df[columns_cat[-1]])
plt.show()
```


temp
atemp
humidity
windspeed
casual
registered


0
200
400
600
800
1000
count

In [64]:
```
plt.figure(figsize=(10,8))
cols = ['season', 'holiday', 'workingday', 'weather']
#df[cols] = df[cols].astype('category')

# Drop the categorical columns or encode them appropriately if needed
corr_matrix = df.drop(columns=cols).corr()
sns.heatmap(corr_matrix, annot=True,cmap='coolwarm',linewidths=0.5)
plt.show()
```



	datetime	temp	atemp	humidity	windspeed	casual	registered	count	day_of_week
datetime	1	0.18	0.18	0.033	-0.087	0.17	0.31	0.31	-0.0047
temp	0.18	1	0.98	-0.065	-0.018	0.47	0.32	0.39	-0.038
atemp	0.18	0.98	1	-0.044	-0.057	0.46	0.31	0.39	-0.04
humidity	0.033	-0.065	-0.044	1	-0.32	-0.35	-0.27	-0.32	-0.027
windspeed	-0.087	-0.018	-0.057	-0.32	1	0.092	0.091	0.1	-0.025
casual	0.17	0.47	0.46	-0.35	0.092	1	0.5	0.69	0.25
registered	0.31	0.32	0.31	-0.27	0.091	0.5	1	0.97	-0.084
count	0.31	0.39	0.39	-0.32	0.1	0.69	0.97	1	-0.0023
day_of_week	-0.0047	-0.038	-0.04	-0.027	-0.025	0.25	-0.084	-0.0023	1

In [29]:

In [30]:
```
season_group = df.groupby('season')['count'].mean()
season_group
```

Out[30]:

season	count
1	116.343261
2	215.251372
3	234.417124
4	198.988296

dtype: float64

In [31]:
```
weather_group = df.groupby('weather')['count'].mean()
weather_group
```

Out[31]:

weather	count
1	205.236791
2	178.955540
3	118.846333
4	164.000000

dtype: float64

In [32]:
```
workingday_group = df.groupby('workingday')['count'].mean() #1 is weekday or when it is no holiday 0 is weekend or ho
workingday_group
```

Out[32]:

	count
workingday	
0	188.506621
1	193.011873

dtype: float64

In [33]:
```
df.groupby(["season"])[["casual","registered","count"]].sum()
```

Out[33]:

	casual	registered	count
season			
1	41605	270893	312498
2	129672	458610	588282
3	142718	497944	640662
4	78140	465894	544034

In [34]:
```
df.groupby(["weather"])[["casual","registered","count"]].sum()
```

Out[34]:

	casual	registered	count
weather			
1	289900	1186163	1476063
2	87246	419914	507160
3	14983	87106	102089
4	6	158	164

In [35]:
```
df.groupby(["workingday"])[["casual","registered","count"]].sum()
```

Out[35]:

	casual	registered	count
workingday			
0	206037	448835	654872
1	186098	1244506	1430604

In [36]:
```
df.groupby(["holiday"])[["casual","registered","count"]].sum()
```

Out[36]:

	casual	registered	count
holiday			
0	376964	1650704	2027668
1	15171	42637	57808

In [37]:
```
df.groupby(["temp"])[["casual","registered","count"]].sum()
```

Out[37]:

temp	casual	registered	count
0.82	6	538	544
1.64	7	176	183
2.46	11	204	215
3.28	9	203	212
4.10	52	2160	2212
4.92	106	3399	3505
5.74	205	5491	5696
6.56	432	9512	9944
7.38	392	6790	7182
8.20	956	17821	18777
9.02	1105	17152	18257
9.84	1692	23722	25414
10.66	2417	28313	30730
11.48	1623	18480	20103
12.30	3834	42367	46201
13.12	4952	47931	52883
13.94	6270	53637	59907
14.76	9083	62348	71431
15.58	5891	39928	45819
16.40	10768	57319	68087
17.22	9817	55192	65009

temp	casual	registered	count
18.04	8673	44095	52768
18.86	11416	53419	64835
19.68	5934	25526	31460
20.50	13225	53703	66928
21.32	13196	57930	71126
22.14	14165	60276	74441
22.96	15069	68826	83895
23.78	9143	38694	47837
24.60	17969	74532	92501
25.42	19589	69902	89491
26.24	23562	81717	105279
27.06	19056	64088	83144
27.88	11030	34539	45569
28.70	23034	86995	110029
29.52	23158	74867	98025
30.34	22208	68447	90655
31.16	20211	65167	85378
31.98	7180	24051	31231
32.80	17886	53950	71836
33.62	12588	32694	45282
34.44	7352	19866	27218

temp	casual	registered	count
35.26	6613	19450	26063
36.08	2467	5879	8346
36.90	3796	10865	14661
37.72	2749	8545	11294
38.54	498	1174	1672
39.36	638	1269	1907
41.00	102	192	294

In [38]:
```
df.groupby(["atemp"])[["casual","registered","count"]].sum()
```

Out[38]:

atemp	casual	registered	count
0.760	0	2	2
1.515	0	3	3
2.275	1	265	266
3.030	13	563	576
3.790	19	606	625
4.545	26	701	727
5.305	57	1523	1580
6.060	176	4560	4736
6.820	189	3363	3552
7.575	172	4023	4195
8.335	227	3455	3682
9.090	404	8156	8560
9.850	551	9794	10345
10.605	1026	14902	15928
11.365	1482	23028	24510
12.120	2475	17543	20018
12.880	1463	20648	22111
13.635	2084	20267	22351
14.395	2519	28815	31334
15.150	4358	40923	45281
15.910	3212	30798	34010

	casual	registered	count
atemp			
16.665	6410	50172	56582
17.425	4738	41671	46409
18.180	1970	14461	16431
18.940	1063	5667	6730
19.695	5891	39928	45819
20.455	10768	57319	68087
21.210	9817	55192	65009
21.970	8673	44095	52768
22.725	11416	53419	64835
23.485	5934	25526	31460
24.240	13225	53703	66928
25.000	13219	57996	71215
25.760	14240	61742	75982
26.515	15069	68826	83895
27.275	9930	46612	56542
28.030	1077	9588	10665
28.790	3068	21917	24985
29.545	6870	31949	38819
30.305	16149	63403	79552
31.060	52524	154361	206885
31.820	18624	58714	77338

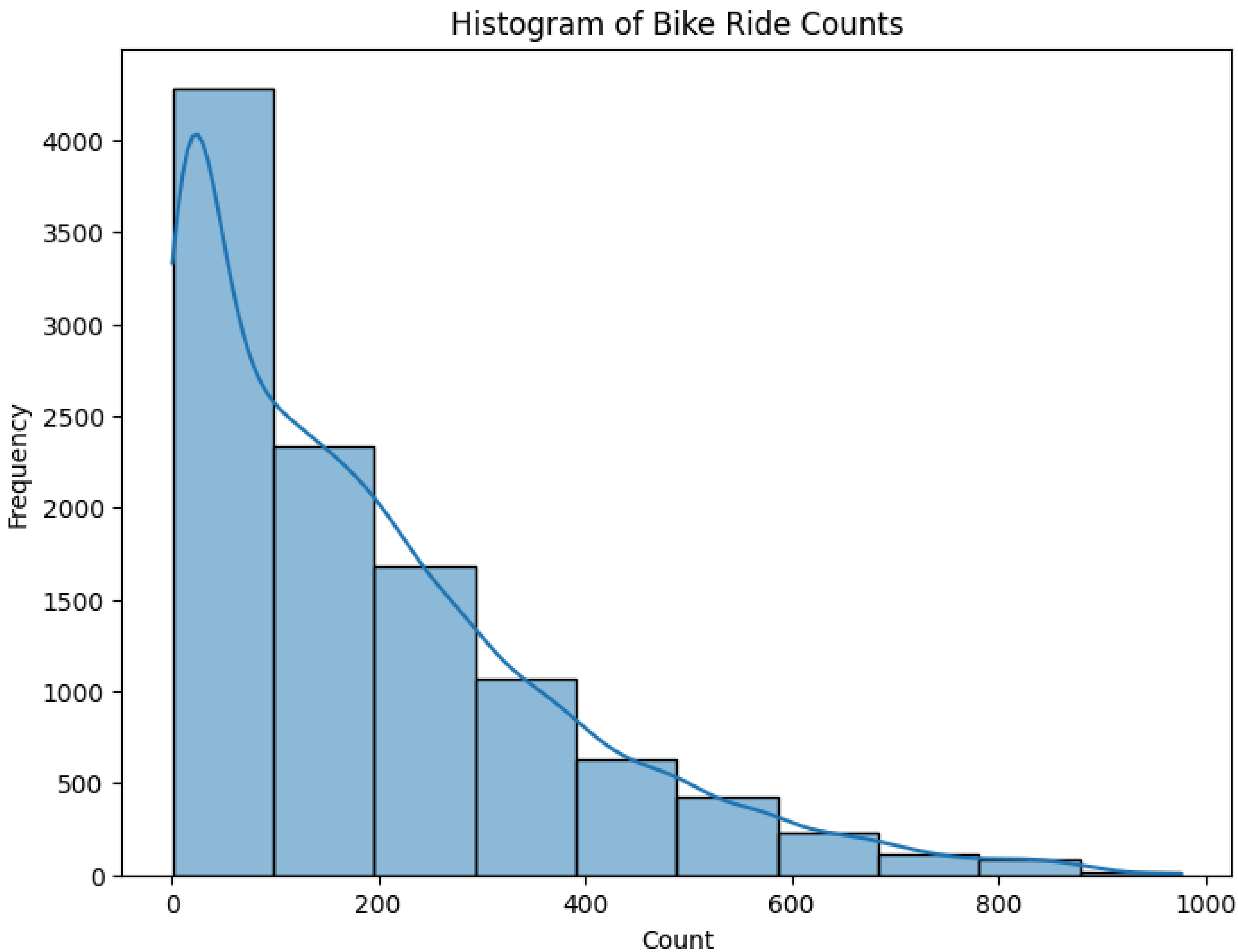
	casual	registered	count
atemp			
32.575	21910	68325	90235
33.335	18395	70460	88855
34.090	16071	50050	66121
34.850	18870	59648	78518
35.605	11726	37905	49631
36.365	11004	31953	42957
37.120	9955	29474	39429
37.880	8243	25885	34128
38.635	6673	18175	24848
39.395	5526	15860	21386
40.150	4139	12492	16631
40.910	3397	9259	12656
41.665	1576	4897	6473
42.425	2046	5201	7247
43.180	668	1482	2150
43.940	425	1083	1508
44.695	305	758	1063
45.455	77	235	312

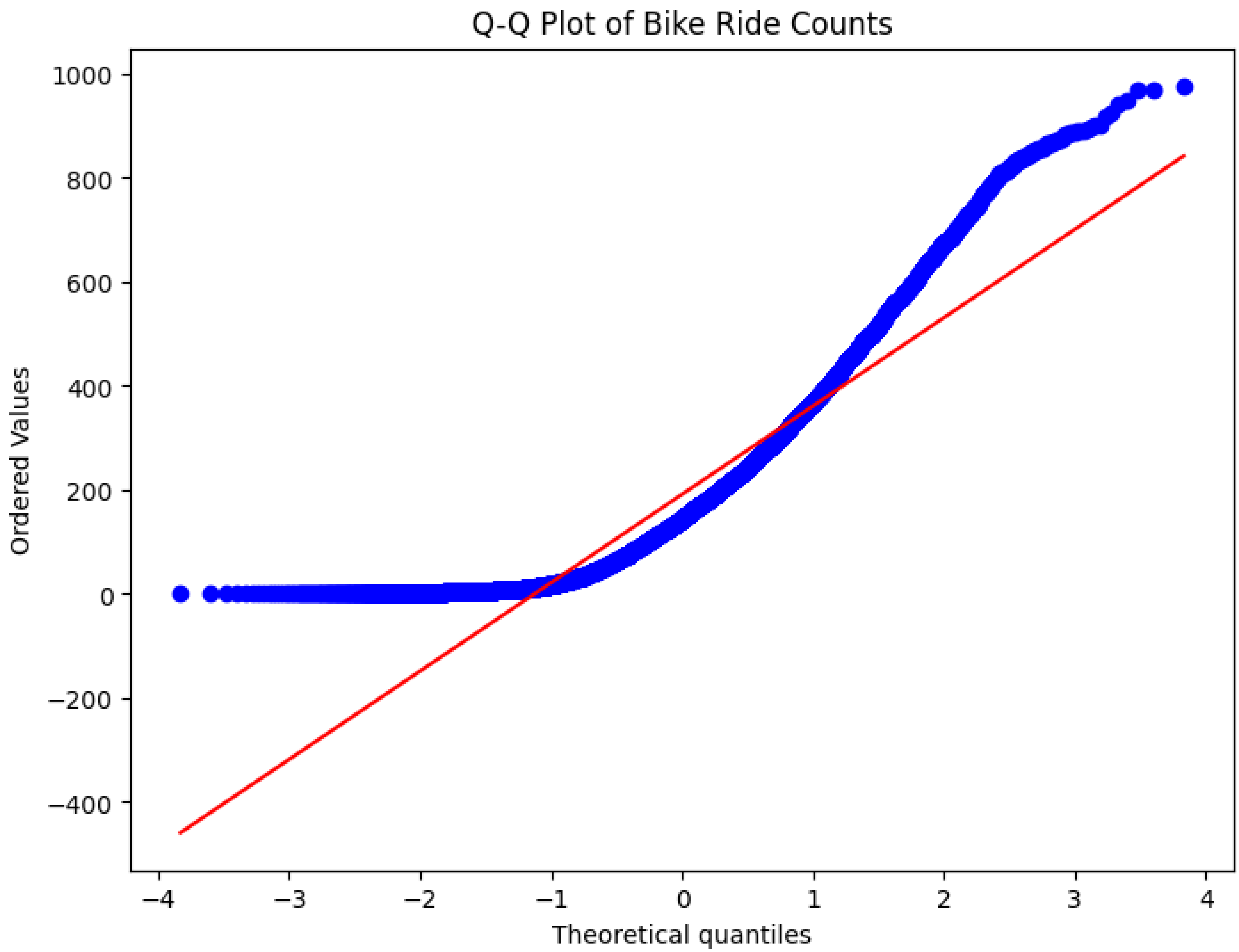
Check if there any significant difference between the no. of bike rides on Weekdays and Weekends?

In [39]:

```
#Null Hypothesis (H₀): There is no significant difference in the number of bike rides between weekdays and weekends.
#---------------------------------------------------------------------------
```

```
#Alternate Hypothesis (Ha): There is significant difference in the number of bike rides between weekdays and weekends

count_data = df['count']

# 1. Histogram
plt.figure(figsize=(8, 6))
sns.histplot(count_data, kde=True, bins=10)
plt.title('Histogram of Bike Ride Counts')
plt.xlabel('Count')
plt.ylabel('Frequency')
plt.show()

# 2. Q-Q Plot
plt.figure(figsize=(8, 6))
stats.probplot(count_data, dist="norm", plot=plt)
plt.title('Q-Q Plot of Bike Ride Counts')
plt.show()

# 3. Shapiro-Wilk Test
shapiro_test = stats.shapiro(count_data)

shapiro_test
```


Histogram of Bike Ride Counts
Frequency
Count
0
500
1000
1500
2000
2500
3000
3500
4000
0
200
400
600
800
1000




```
/usr/local/lib/python3.10/dist-packages/scipy/stats/_axis_nan_policy.py:531: UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be accurate. Current N is 10886.
  res = hypotest_fun_out(*samples, **kwds)
```

Out[39]: ShapiroResult(statistic=0.8783658962690556, pvalue=5.369837893115507e-68)

Here the data is not normal it is skewed data

In [40]:
```
df['day_of_week'] = df['datetime'].dt.dayofweek

# Define Weekends (Saturday = 5, Sunday = 6) and Weekdays (Monday to Friday)
weekends = df[(df['day_of_week'] == 5) | (df['day_of_week'] == 6)]['count']
weekdays = df[(df['day_of_week'] >= 0) & (df['day_of_week'] <= 4)]['count']

# Perform 2-Sample Independent T-test
t_stat, p_value = stats.ttest_ind(weekdays, weekends, equal_var=False)  # Assuming unequal variance

t_stat, p_value
```

Out[40]:
```
(1.0589713677293344, 0.2896542265218858)
```

In [41]:
```
if p_value <= 0.05:
    print("Reject the null hypothesis. There is a significant difference in the number of bike rides between weekdays
else:
    print("Fail to reject the null hypothesis. There is no significant difference in the number of bike rides between
```

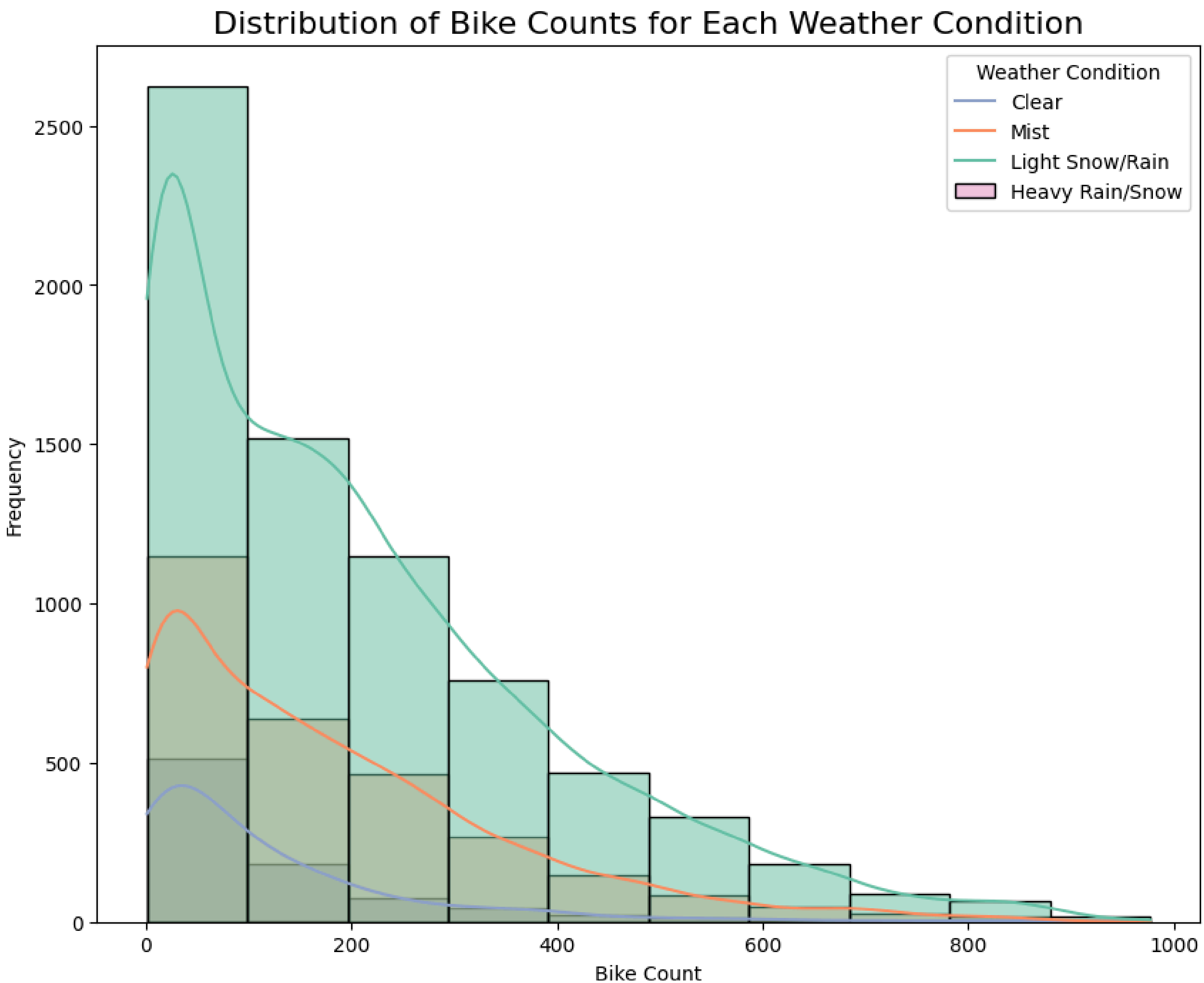
```
Fail to reject the null hypothesis. There is no significant difference in the number of bike rides between weekdays an
d weekends.
```

In [41]:
```
```

Check if the demand of bicycles on rent is the same for different Weather conditions?

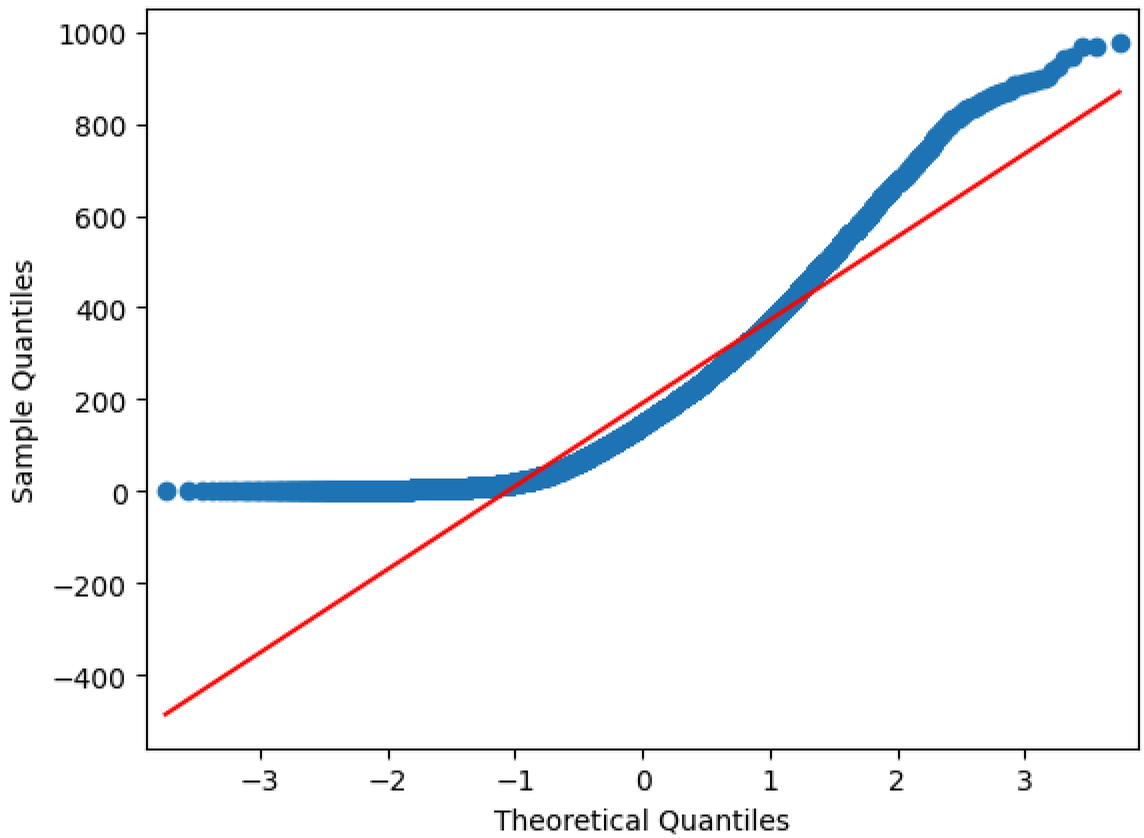
In [65]:
```
# Visualizing the distribution of bike counts for each weather condition
#Null Hypothesis (H₀): The average demand for bicycles (rental count) is the same across all weather conditions.
#-----------------------------------------------------------------------
#Alternative Hypothesis (H₁): The average demand for bicycles (rental count) is not the same for at least one pair of

# Set the data for visualization
plt.figure(figsize=(10, 8))

# Creating histograms for each weather condition
sns.histplot(data=df, x='count', hue='weather', kde=True, bins=10, palette='Set2')

# Adding titles and labels
plt.title('Distribution of Bike Counts for Each Weather Condition', fontsize=16)
plt.xlabel('Bike Count')
```

```
plt.ylabel('Frequency')
plt.legend(title='Weather Condition', labels=['Clear', 'Mist', 'Light Snow/Rain', 'Heavy Rain/Snow'])
plt.show()
```


Distribution of Bike Counts for Each Weather Condition
Weather Condition
Clear
Mist
Light Snow/Rain
Heavy Rain/Snow
Frequency
2500
2000
1500
1000
500
0
0
200
400
600
800
1000
Bike Count

As we can our data is not normal distribution

In [43]:
```
from statsmodels.graphics.gofplots import qqplot


qqplot(df['count'],line='s')
plt.show()
```



In [44]:
```
from scipy.stats import shapiro
np.random.sample(42)

count_data = df['count'].sample(1000)
```

```
test_statics, p_value = shapiro(count_data)
p_value
```

Out[44]: 2.9283215627227718e-27

In [67]:
```
if p_value < 0.05:
  print('Reject the null hypothesis')
  print('Data is not Gusian')
else:
  print('Fail to reject null hypothesis')
  print('Data is Gausian')
```

```
Reject the null hypothesis
Data is not Gusian
```

In [46]:
```
from scipy.stats import levene # Test variance
weather_groups = [df['count'][df['weather'] == i] for i in df['weather'].unique()]

# Perform Levene's Test
levene_stat, p_value = stats.levene(*weather_groups)

if p_value < 0.05:
    print("Variances are not equal")
```

```
Variances are not equal
```

In [47]:
```
#hence throught the above result we can say assumptions of anova are not satisfied and we will be using Kruskal_walli
from scipy .stats import kruskal
t_statics,p_value = kruskal(*weather_groups)
p_value
```

Out[47]: 3.501611300708679e-44

In [48]:
```
if p_value <= 0.05:
    print("Reject the null hypothesis. There is a significant difference in the average demand for bicycles across we
else:
    print("Fail to reject the null hypothesis. There is no significant difference in the average demand for bicycles 
```

```
Reject the null hypothesis. There is a significant difference in the average demand for bicycles across weather condit
ions.
```

Inference and Conclusions

- Weather conditions significantly affects bicycles demands and this proves certain weather conditions are more favourable while others are not much
- Specific Weather conditions such as Clear and partly cloudy would have more demands on renting of bicycles compared to snowfall or heavy rainfall.

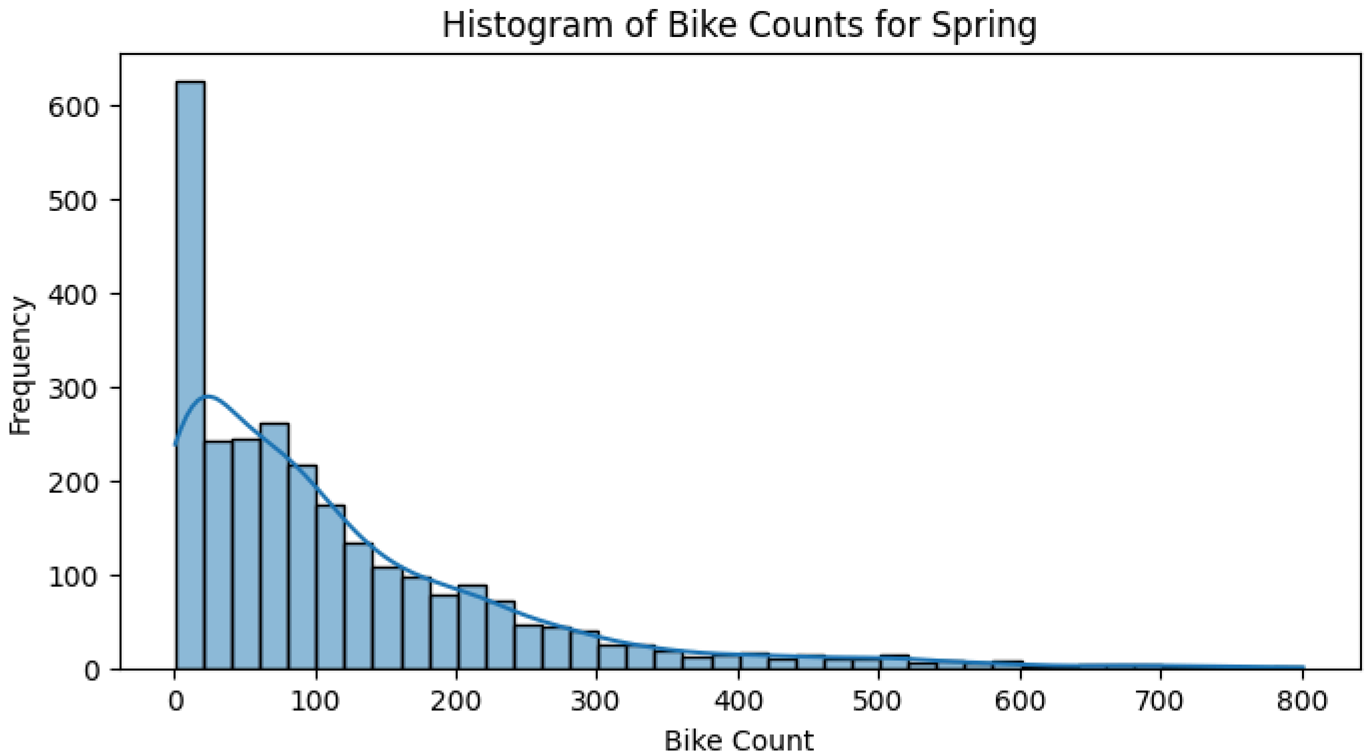
Weather-Sensitive Pricing and Availability Recommendations

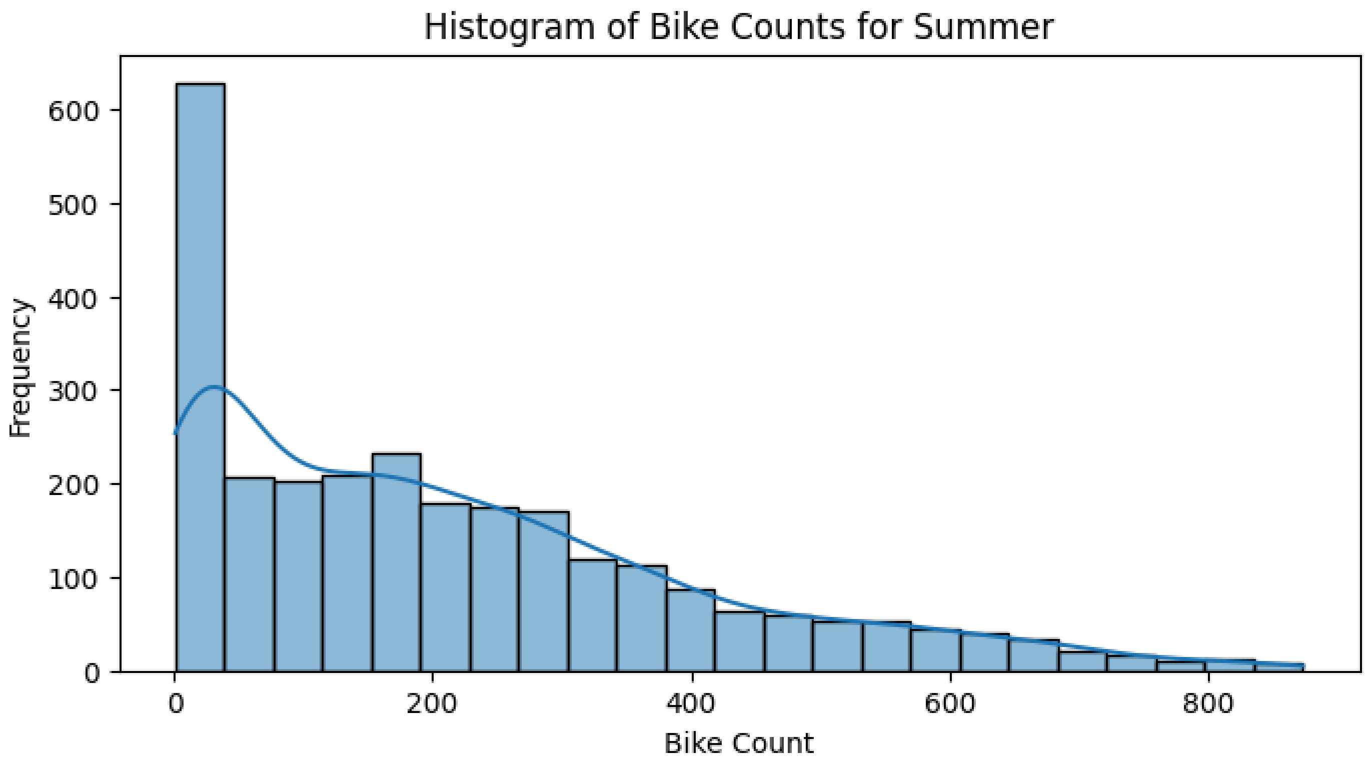
If certain weather conditions significantly decrease bike rentals, consider dynamic pricing to encourage rentals during these times or reduce the fleet to save costs. Conversely, during favorable weather conditions, ensuring a higher availability of bicycles could meet increased demand. Operational Adjustments:

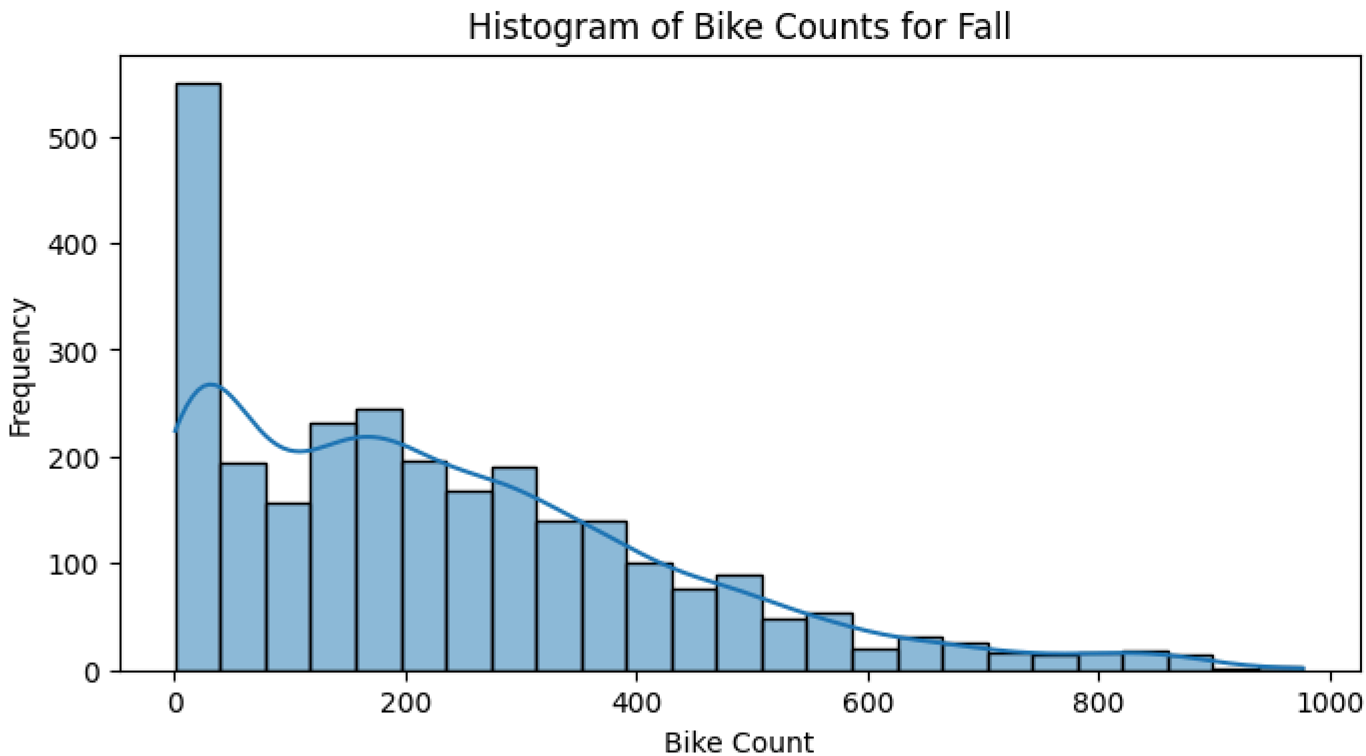
Use weather forecasts to adjust the number of bikes available at different locations. For example, if bad weather is expected, fewer bikes might be needed. Consider offering promotions or discounts on days with less favorable weather to maintain rental levels.

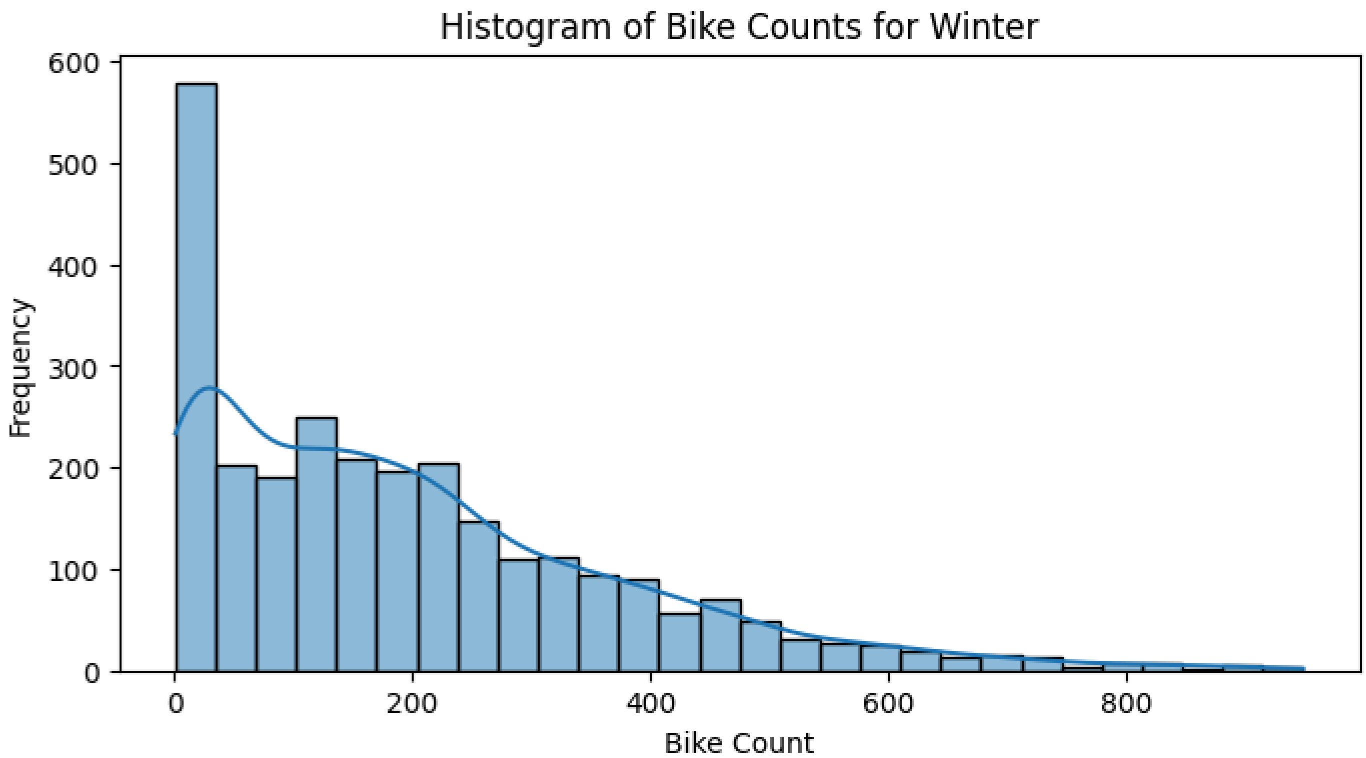
Check if the demand of bicycles on rent is the same for different Seasons?

In [49]:
```
#Null Hypothesis (H₀): The average demand for bicycles (rental count) is the same across all seasons.
#----------------------------------------------------------------
#Alternative Hypothesis (H₁): The average demand for bicycles (rental count) is not the same for at least one pair of

#Lets check for data normalization

season_labels = {1: 'Spring', 2: 'Summer', 3: 'Fall', 4: 'Winter'}

# Plot histograms for each season
for season in df['season'].unique():
    plt.figure(figsize=(8,4 ))
    sns.histplot(df[df['season'] == season]['count'], kde=True)
    plt.title(f'Histogram of Bike Counts for {season_labels.get(season, season)}')
    plt.xlabel('Bike Count')
    plt.ylabel('Frequency')
    plt.show()
```


Histogram of Bike Counts for Spring
Frequency
Bike Count
0
100
200
300
400
500
600
700
800

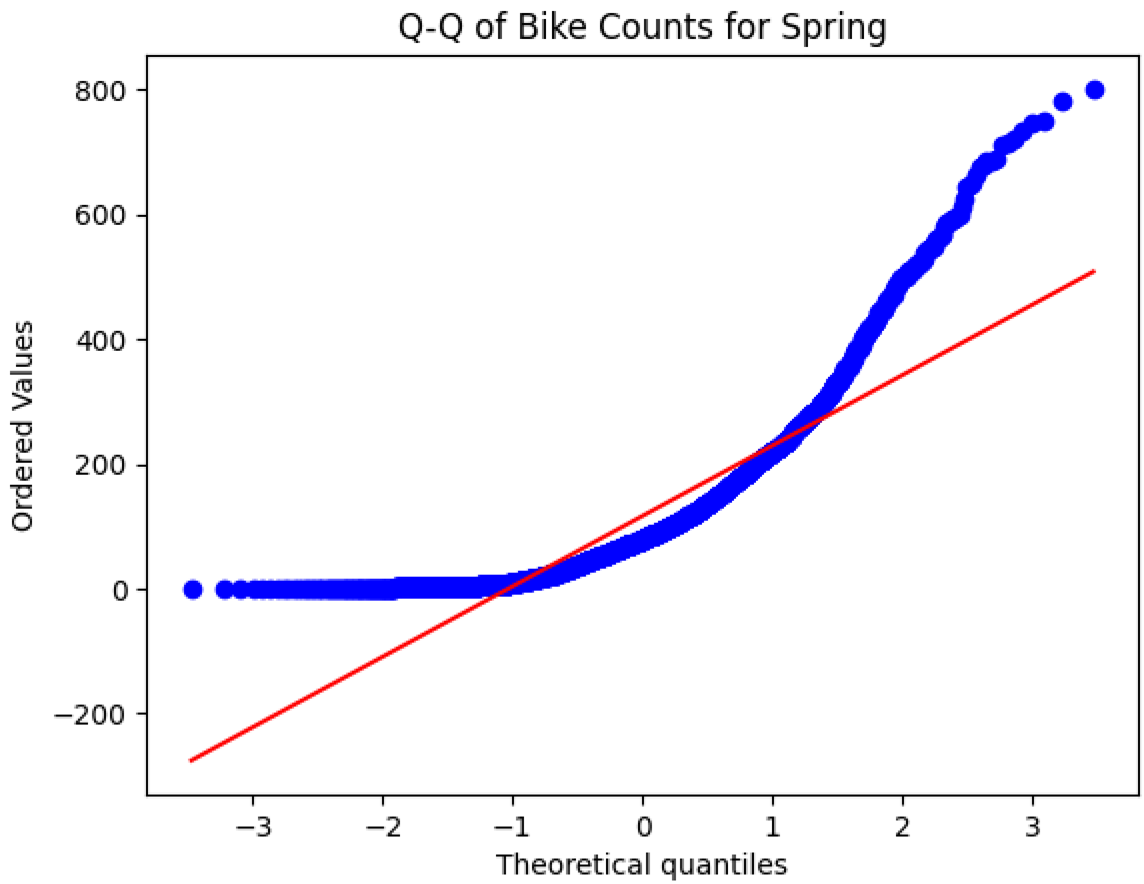

Histogram of Bike Counts for Summer
Frequency
Bike Count
0
100
200
300
400
500
600
0
200
400
600
800

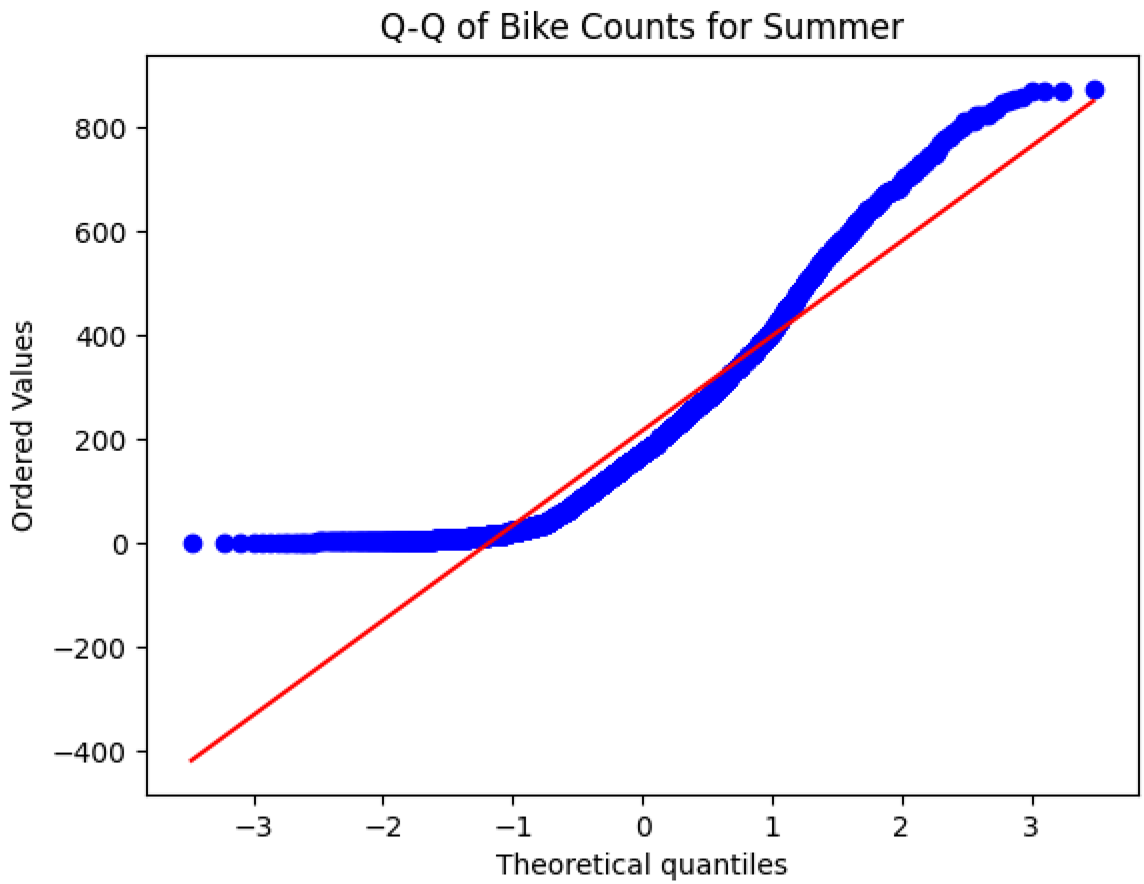

Histogram of Bike Counts for Fall
Frequency
0
100
200
300
400
500
0
200
400
600
800
1000
Bike Count

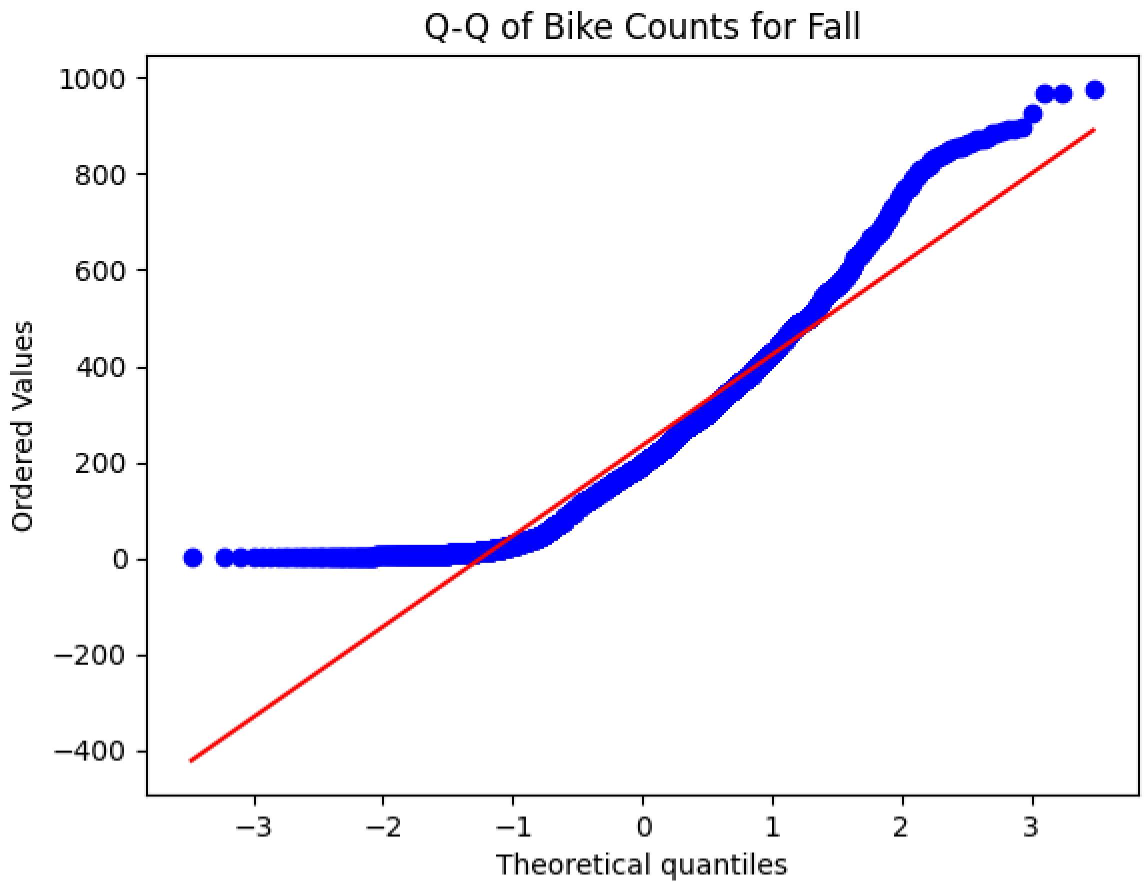


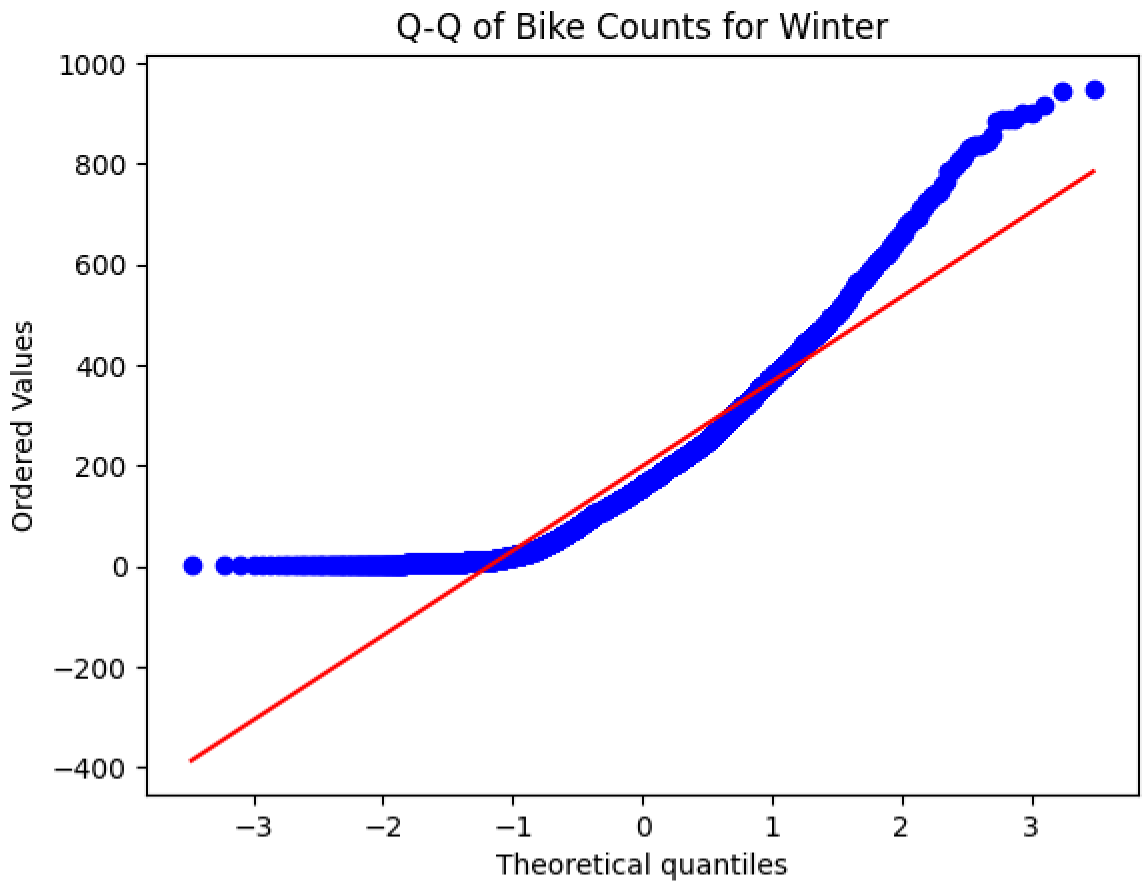
We can easily see that data is not normal it is right skewed

In [50]:
```
season_labels = {1: 'Spring', 2: 'Summer', 3: 'Fall', 4: 'Winter'}

# Plot Q-Q for each season
for season in df['season'].unique():

    stats.probplot(df[df['season'] == season]['count'], dist="norm",plot=plt)
    plt.title(f'Q-Q of Bike Counts for {season_labels.get(season, season)}')

    plt.show()
```


Q-Q of Bike Counts for Spring
Ordered Values
Theoretical quantiles
800
600
400
200
0
−200
−3
−2
−1
0
1
2
3


Q-Q of Bike Counts for Summer
Ordered Values
800
600
400
200
0
−200
−400
−3
−2
−1
0
1
2
3
Theoretical quantiles


Q-Q of Bike Counts for Fall
1000
800
600
400
200
0
−200
−400
Ordered Values
−3
−2
−1
0
1
2
3
Theoretical quantiles



In [51]:
```
season_groups = [df['count'][df['season'] == i] for i in df['season'].unique()]
for i, season in enumerate(df['season'].unique()):
    stat, p = stats.shapiro(season_groups[i])
    print(f'Shapiro-Wilk Test for Season {season}: W={stat}, p-value={p}')
    if p > 0.05:
        print('Data is normal')
    else:
        print('Data is not normal')
```

```
Shapiro-Wilk Test for Season 1: W=0.8087378401253588, p-value=8.749584618867662e-49
Data is not normal
Shapiro-Wilk Test for Season 2: W=0.9004818080893252, p-value=6.039374406270491e-39
Data is not normal
Shapiro-Wilk Test for Season 3: W=0.9148166372899196, p-value=1.043680518918597e-36
Data is not normal
Shapiro-Wilk Test for Season 4: W=0.8954637482095505, p-value=1.1299244409282836e-39
Data is not normal
```

In [52]:
```
levene_stat, p_value = stats.levene(*season_groups)
print(f'Levene’s Test: W={levene_stat}, p_value={p_value}')
```

```
Levene’s Test: W=187.7706624026276, p_value=1.0147116860043298e-118
```

In [53]:
```
if p_value < 0.05:
    print("Variances are not equal")
```

```
Variances are not equal
```

In [54]:
```
#Krsukal test
t_statics,p_value = kruskal(*season_groups)
p_value
```

Out[54]:
```
2.479008372608633e-151
```

In [55]:
```
if p_value <= 0.05:
  print("Reject the null hypothesis. There is a significant difference in the average demand for bicycles across seas
else:
  print("Fail to reject the null hypothesis. There is no significant difference in the average demand for bicycles ac
```

```
Reject the null hypothesis. There is a significant difference in the average demand for bicycles across seasons.
```

Inference and Conclusions Distribution Patterns Across Seasons:

Spring: If the histogram for spring shows a higher concentration of bike rentals around certain count values, it suggests that spring may have a relatively consistent demand for bike rentals. Summer: A wider distribution in the summer histogram might indicate more variability in bike rentals, potentially due to varying weather conditions or increased tourist activity. Fall: If the fall histogram shows a distribution similar to spring or summer, it suggests that bike rental patterns may not drastically change during fall. Winter: A histogram with lower counts or a left-skewed distribution for winter could suggest that bike rentals decrease significantly during colder months, possibly due to unfavorable weather conditions. Peak Seasons: If one season (like summer) shows a higher peak in the histogram, it indicates that this season has the highest demand for bike rentals. Off-Peak Seasons: Conversely, a lower peak or more dispersed distribution in winter suggests a lower and more unpredictable demand. Skewness: If the distribution for any season is skewed (e.g., right-skewed in summer), it might suggest occasional spikes in rentals due to specific events or days with favorable weather. Bimodal Distribution: A bimodal distribution might indicate two distinct types of rental days (e.g., weekdays vs. weekends, or normal days vs. special events).

The histograms reveal that bike rental demand varies by season, with some seasons (e.g., summer) showing higher and more variable demand, while others (e.g., winter) show lower and more stable demand.

Recommendations

Summer: Given the higher and variable demand, it would be wise to increase the number of bikes available during the summer months and potentially increase prices during peak times. Winter: Lower demand in winter suggests a potential for reducing fleet size or offering promotions to boost rentals during off-peak times. Planning and Resource Allocation:

Dynamic Inventory Management: Adjusting the number of available bikes based on the season can help optimize resource allocation and meet customer demand more effectively. Targeted Marketing: Marketing efforts can be tailored to promote bike rentals more heavily during seasons with lower demand (e.g., offering discounts or special packages in winter). Recommendations Increase Bike Availability in Peak Seasons:

Ensure more bikes are available during summer and potentially spring, as these seasons likely see higher demand. Introduce Seasonal Pricing:

Implement dynamic pricing strategies, with higher prices during peak seasons like summer and lower prices during off-peak seasons like winter. Promotions in Off-Peak Seasons:

Offer discounts or special promotions during winter to encourage more bike rentals despite the lower natural demand. Monitor Weather Patterns:

As weather can vary even within seasons, consider tracking weather forecasts to adjust bike availability and pricing in real-time.

In [56]:
```
#Null Hypothesis (H₀): Weather conditions are independent of the season. In other words, the distribution of weather
```

```
#------------------------------------------------------------------------------------------
#Alternative Hypothesis (H₁): Weather conditions are not independent of the season. In other words, the distribution
```

In [57]:
```
df_encoded = pd.get_dummies(df, columns=['weather', 'season'], drop_first=True)
df_encoded.head()
```

Out[57]:

	datetime	holiday	workingday	temp	atemp	humidity	windspeed	casual	registered	count	day_of_week	weather_2	we
0	2011-01-01 00:00:00	0	0	9.84	14.395	81	0.0	3	13	16	5	False	
1	2011-01-01 01:00:00	0	0	9.02	13.635	80	0.0	8	32	40	5	False	
2	2011-01-01 02:00:00	0	0	9.02	13.635	80	0.0	5	27	32	5	False	
3	2011-01-01 03:00:00	0	0	9.84	14.395	75	0.0	3	10	13	5	False	
4	2011-01-01 04:00:00	0	0	9.84	14.395	75	0.0	0	1	1	5	False	

In [58]:
```
contingency_vals = pd.crosstab(df['season'], df['weather'])
contingency_vals
```

Out[58]:

weather	1	2	3	4
season				
1	1759	715	211	1
2	1801	708	224	0
3	1930	604	199	0
4	1702	807	225	0

In [59]:

```
chi2_stat, p_value, dof, expected = stats.chi2_contingency(contingency_vals)

print(f"Chi-square Statistic: {chi2_stat}")
print(f"p-value: {p_value}")
```

```
Chi-square Statistic: 49.158655596893624
p-value: 1.549925073686492e-07
```

In [60]:

```
if p_value <= 0.05:
    print("Reject the null hypothesis. Weather conditions are not independent of the season.Weather conditions are si
else:
    print("Fail to reject the null hypothesis. Weather conditions are independent of the season.Weather conditions ar
```

```
Reject the null hypothesis. Weather conditions are not independent of the season.Weather conditions are significantly
different accross seasons
```

Inferences and Conclusions

Here we can see that although weather is not uniform accross the year but there is even variation in association with the season .

Recommendations Yulu should consider season specific strategies For example increasing number of bikes in clear weather and providing discounts during rainy weather

Providing Offer discounted rides during the monsoon to encourage usage. Ensure that Yulu bikes and scooters are equipped with waterproof seat covers and rain protection gear to improve user comfort during rainy days.

Introduce features like built-in sunshades or provide cooling towels and water bottles as part of a summer promotion. Also, consider offering ride discounts during early mornings and late evenings when the heat is less intense.

Launch a "Beat the Heat" campaign offering rides at discounted rates during non-peak heat hours.

Other Recommendations

Continue to focus on expanding operations in metro cities with high traffic congestion, such as Mumbai, Delhi, Bangalore, and Pune. Use localized marketing campaigns that address specific city traffic issues and highlight Yulu as an efficient alternative.

Partner with local governments for designated parking and charging stations, making Yulu an integrated part of the urban transportation infrastructure.

Customized pricing strategies to be more affordable in regions where school and colleges are more even where people go for public parks and temples

Collaborate with educational institutions and business parks to offer campus or workplace-specific Yulu zones.

yulu can design dynamic allocation and reposition the fleet based on real time demand forecast they get and can arrange it accordingly

ontinuously enhance the Yulu app with features like real-time traffic updates, route optimization, and integration with public transport schedules to provide seamless end-to-end mobility solutions