In [28]:
```
# Importing necessary libraries

import pandas as pd
import plotly.express as px
import plotly.graph_objects as go
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [29]:
```
# Read CSV input file

df = pd.read_csv(".//Dataset//ctr.csv")
```

In [30]:
```
df
```

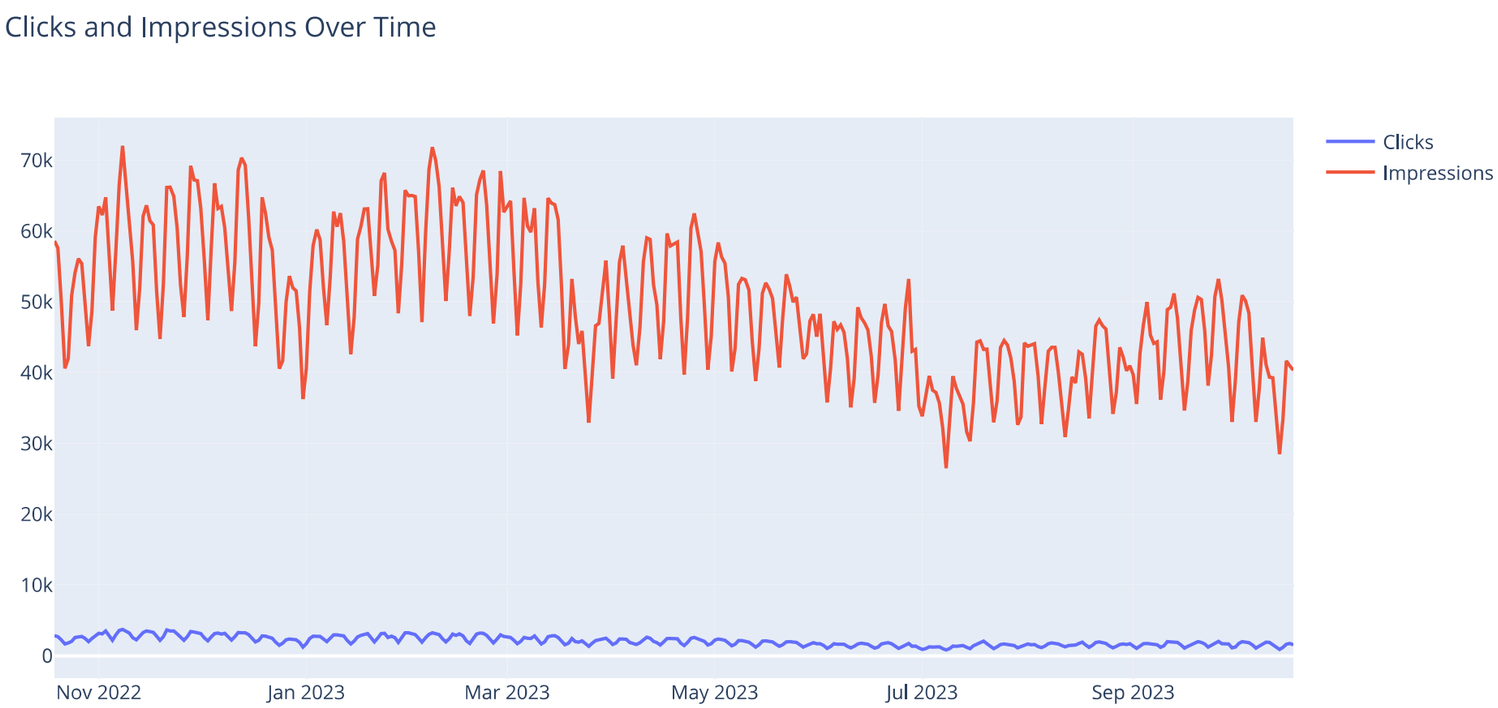
Out[30]:

	Date	Clicks	Impressions
0	2022-10-19	2851	58598
1	2022-10-20	2707	57628
2	2022-10-21	2246	50135
3	2022-10-22	1686	40608
4	2022-10-23	1808	41999
...	...	...	...
360	2023-10-14	885	28487
361	2023-10-15	1180	33440
362	2023-10-16	1624	41688
363	2023-10-17	1751	40957
364	2023-10-18	1573	40351

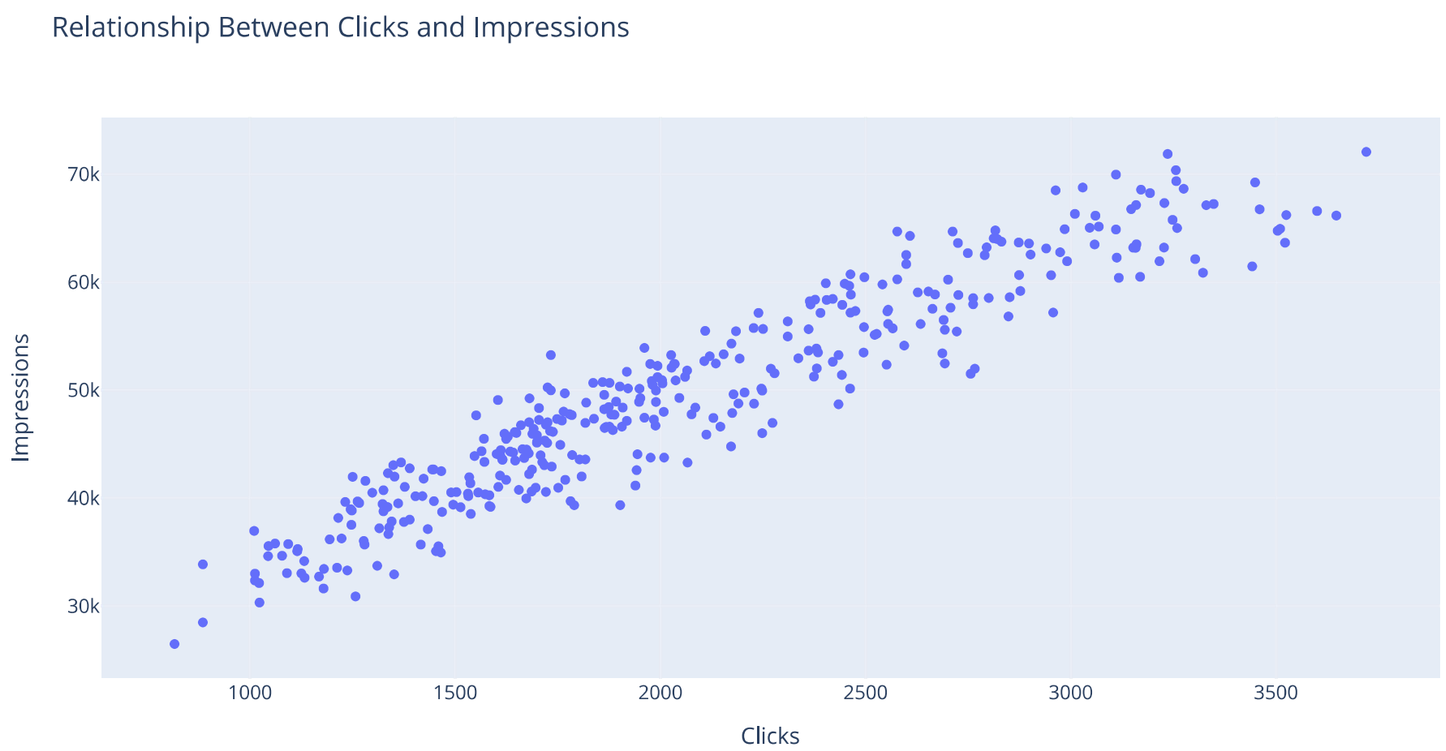
365 rows × 3 columns

In [31]:
```
# DateTime conversion
df['Date']= pd.to_datetime(df['Date'],format= "%Y-%m-%d")

df.set_index('Date', inplace=True)
```

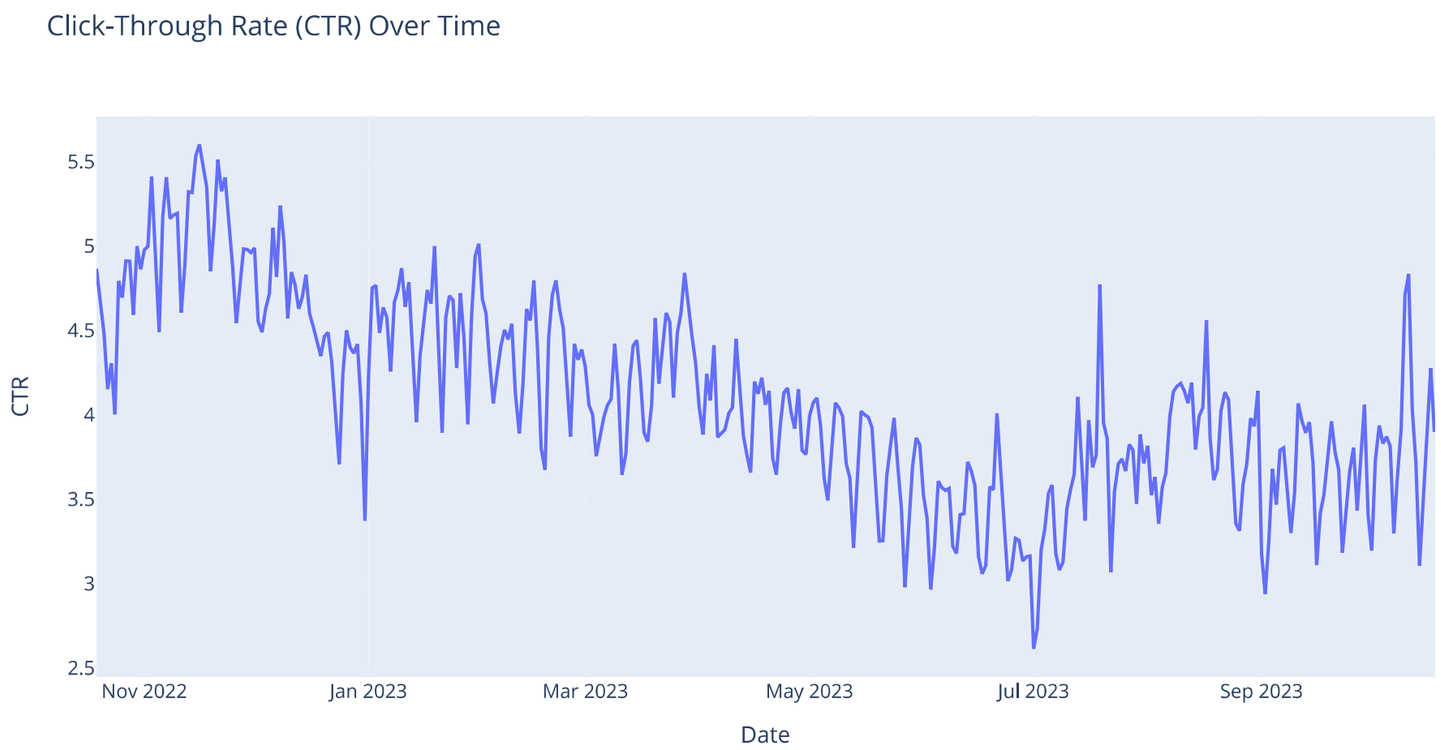
In [32]:
```
# Visualize the clicks and impressions over time

fig = go.Figure()
fig.add_trace(go.Scatter(x=df.index, y=df["Clicks"], mode="lines", name="Clicks"))
fig.add_trace(go.Scatter(x=df.index, y=df["Impressions"], mode="lines", name="Impressions"))
fig.update_layout(title='Clicks and Impressions Over Time')
```



In [33]:
```
# Relationship between clicks and impressions

# Create a scatter plot to visualize the relationship between Clicks and Impressions
fig = px.scatter(df, x='Clicks', y='Impressions', title='Relationship Between Clicks and Impressions',
                 labels={'Clicks': 'Clicks', 'Impressions': 'Impressions'})

# Customize the layout
fig.update_layout(xaxis_title='Clicks', yaxis_title='Impressions')

# Show the plot
fig.show()
```

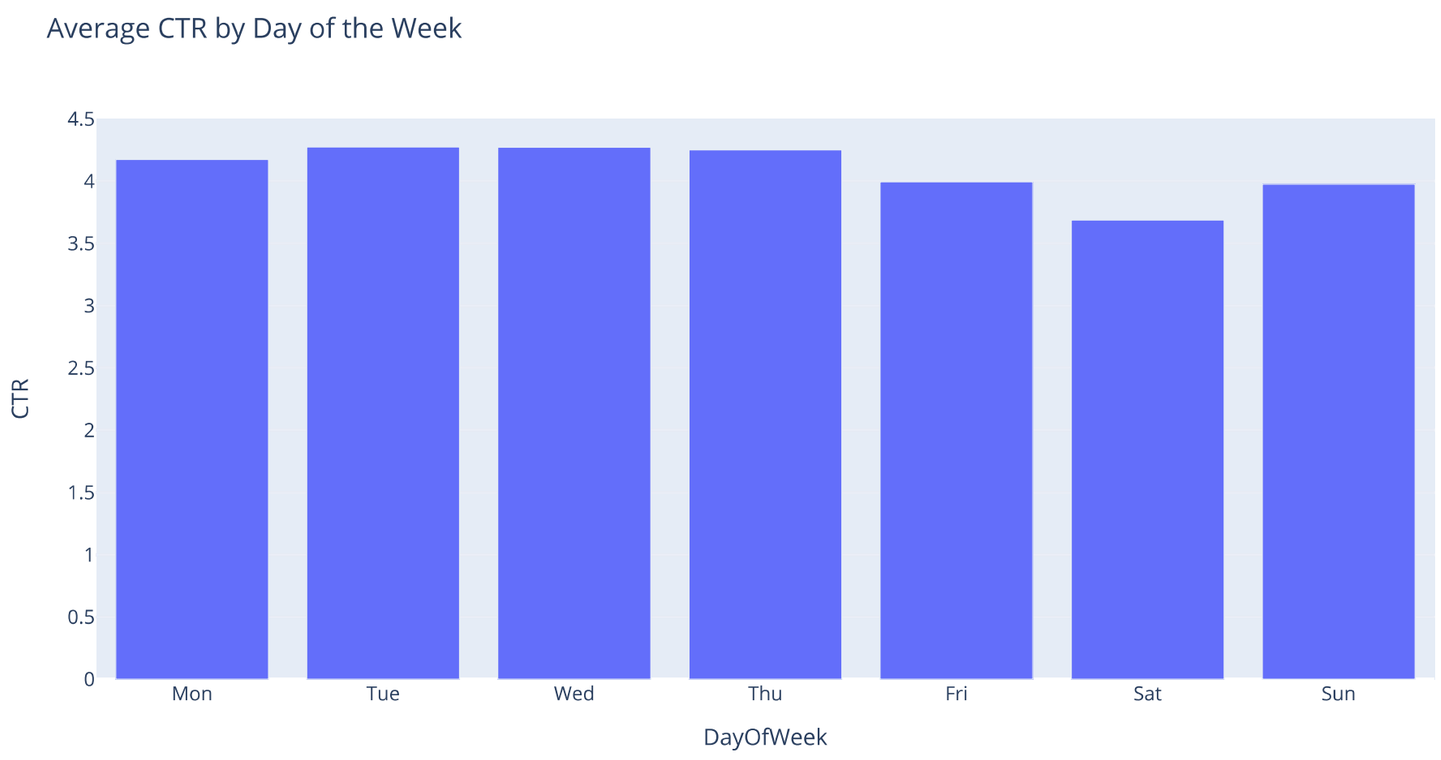


In [34]:
```
# Calculate and visualize CTR
df['CTR'] = (df['Clicks'] / df['Impressions']) * 100
fig = px.line(df, x=df.index, y='CTR', title='Click-Through Rate (CTR) Over Time')
fig.show()
```

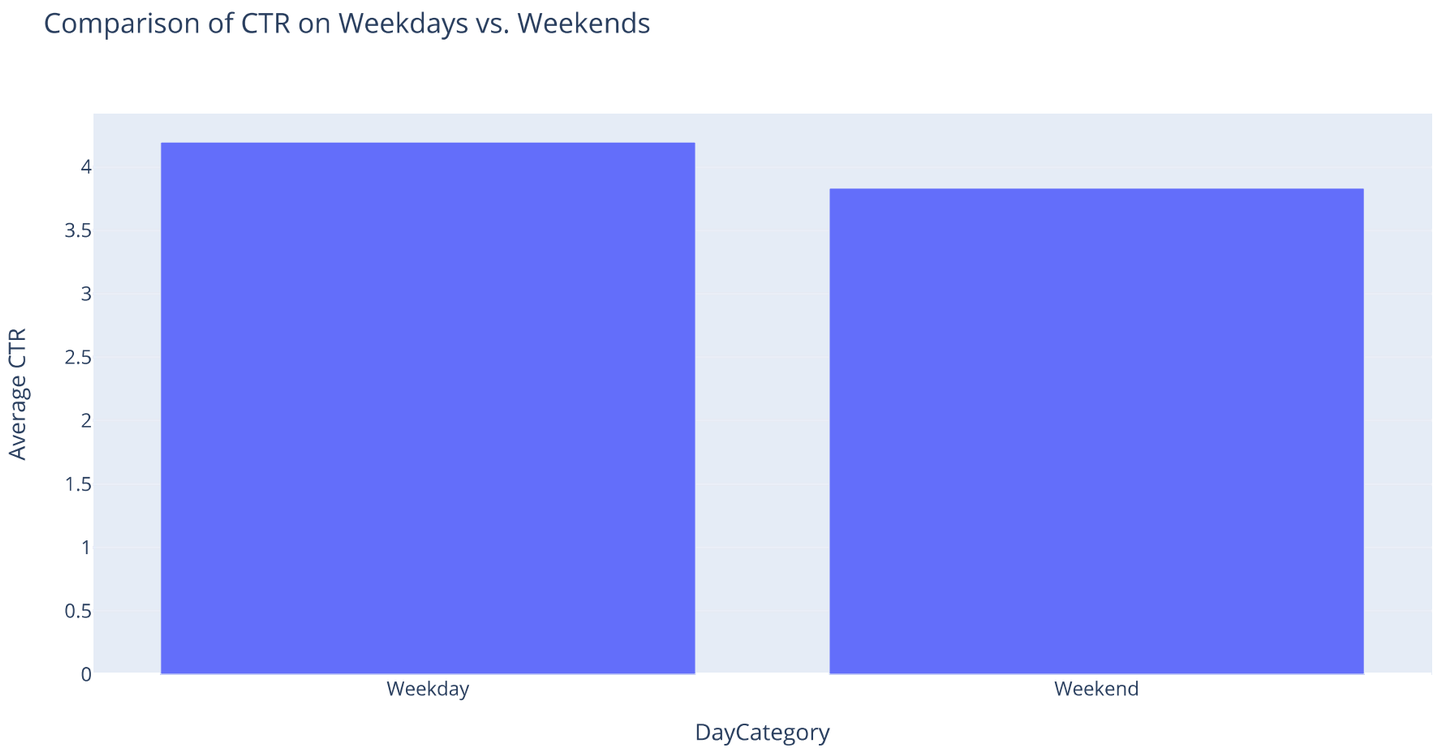


In [35]:
```
# Average CTR by day of the week:

df['DayOfWeek'] = df.index.dayofweek
df['WeekOfMonth'] = df.index.week // 4

# EDA based on DayOfWeek
day_of_week_ctr = df.groupby('DayOfWeek')['CTR'].mean().reset_index()
day_of_week_ctr['DayOfWeek'] = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']

fig = px.bar(day_of_week_ctr, x='DayOfWeek', y='CTR', title='Average CTR by Day of the Week')
fig.show()
```

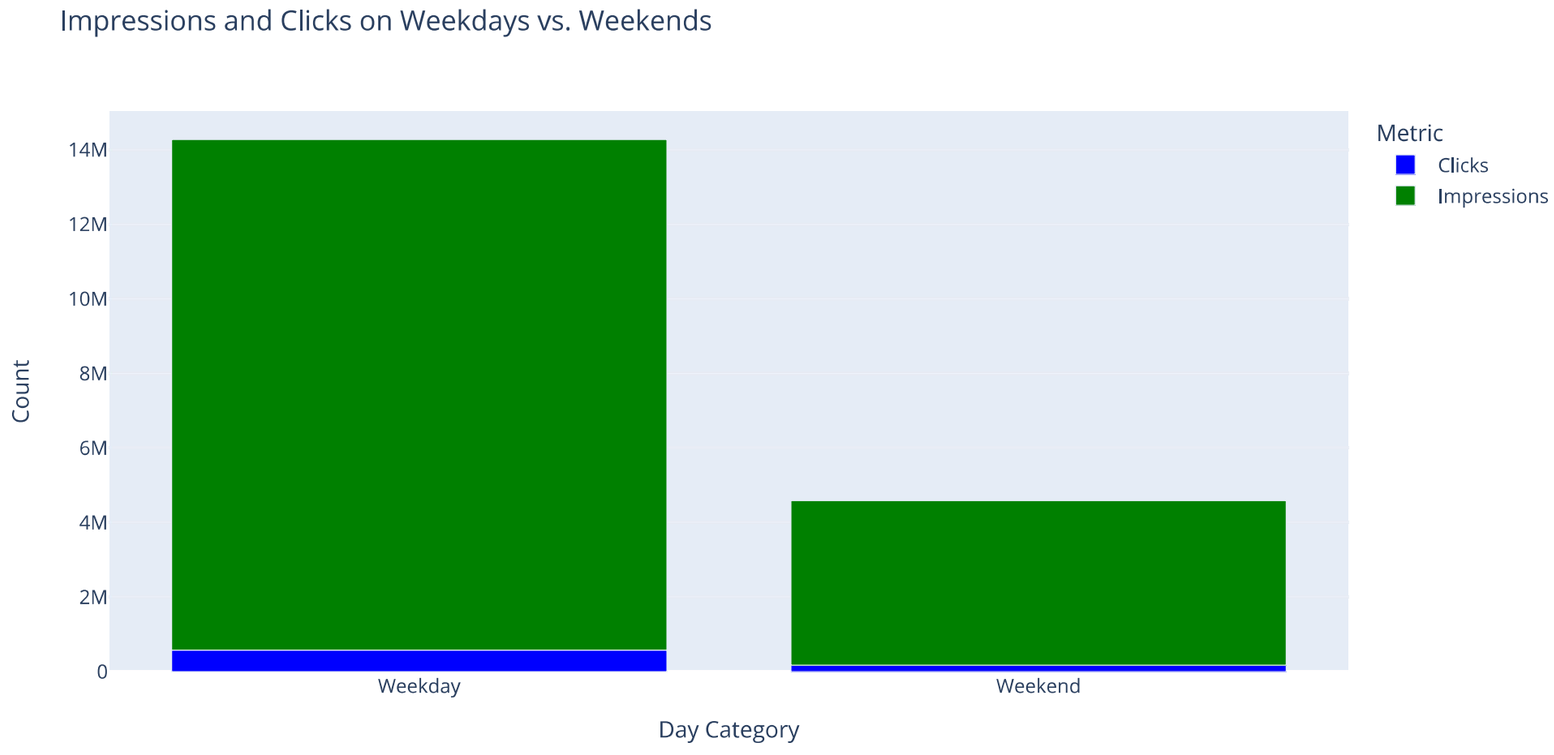
```
<ipython-input-35-69a23a82feb3>:4: FutureWarning:

weekofyear and week have been deprecated, please use DatetimeIndex.isocalendar().week instead, which returns a Series.  To exactly reproduce the behavior of week and weekofyear
and return an Index, you may call pd.Int64Index(idx.isocalendar().week)
```



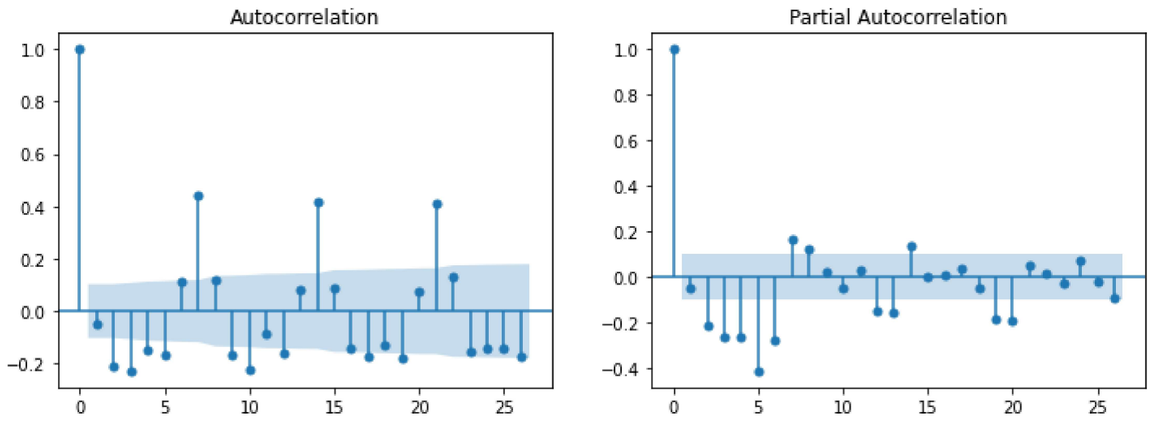
In [36]:
```
# CTR on weekdays and weekends

# Create a new column 'DayCategory' to categorize weekdays and weekends
df['DayCategory'] = df['DayOfWeek'].apply(lambda x: 'Weekend' if x >= 5 else 'Weekday')

# Calculate average CTR for weekdays and weekends
ctr_by_day_category = df.groupby('DayCategory')['CTR'].mean().reset_index()

# Create a bar plot to compare CTR on weekdays vs. weekends
fig = px.bar(ctr_by_day_category, x='DayCategory', y='CTR', title='Comparison of CTR on Weekdays vs. Weekends',
             labels={'CTR': 'Average CTR'})

# Customize the layout
fig.update_layout(yaxis_title='Average CTR')

# Show the plot
fig.show()
```



In [37]:
```
# Impressions and clicks on weekdays and weekends comparision

# Group the data by 'DayCategory' and calculate the sum of Clicks and Impressions for each category
grouped_df = df.groupby('DayCategory')[['Clicks', 'Impressions']].sum().reset_index()

# Create a grouped bar chart to visualize Clicks and Impressions on weekdays vs. weekends
fig = px.bar(grouped_df, x='DayCategory', y=['Clicks', 'Impressions'],
             title='Impressions and Clicks on Weekdays vs. Weekends',
             labels={'value': 'Count', 'variable': 'Metric'},
             color_discrete_sequence=['blue', 'green'])

# Customize the layout
fig.update_layout(yaxis_title='Count')
fig.update_xaxes(title_text='Day Category')

# Show the plot
fig.show()
```



In [38]:
```
df.reset_index(inplace=True)

# resetting index
time_series = df.set_index('Date')['CTR']

# Differencing
differenced_series = time_series.diff().dropna()

# Plot ACF and PACF of differenced time series
fig, axes = plt.subplots(1, 2, figsize=(12, 4))
plot_acf(differenced_series, ax=axes[0])
plot_pacf(differenced_series, ax=axes[1])
plt.show()
```



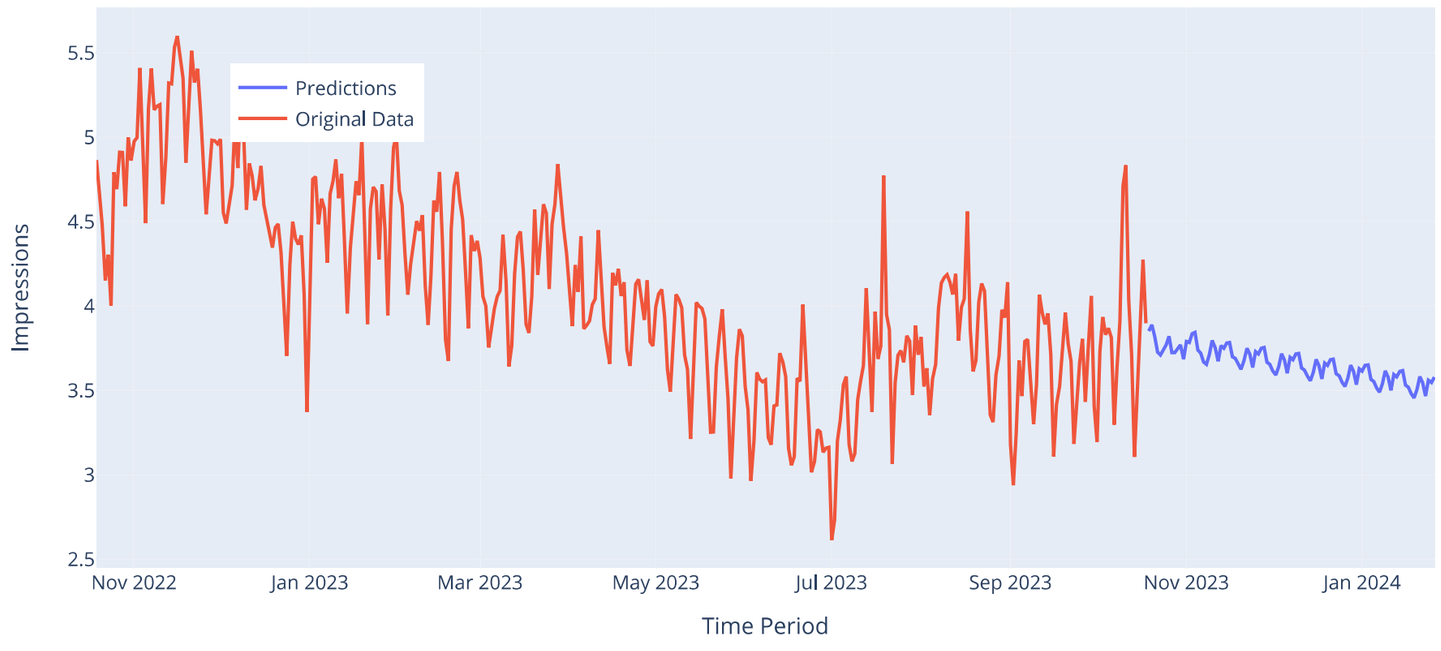
In [39]:
```
# train the forecasting model using SARIMA

p, d, q, s = 1, 1, 1, 12

model = SARIMAX(time_series, order=(p, d, q), seasonal_order=(p, d, q, s))
results = model.fit()
print(results.summary())
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWarning:

No frequency information was provided, so inferred frequency D will be used.

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWarning:

No frequency information was provided, so inferred frequency D will be used.

                                     SARIMAX Results
==========================================================================================
Dep. Variable:                               CTR   No. Observations:                  365
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood                -71.364
Date:                            Wed, 10 Apr 2024   AIC                            152.729
Time:                                    15:45:34   BIC                            172.047
Sample:                                10-19-2022   HQIC                           160.416
                                     - 10-18-2023
Covariance Type:                             opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.5266      0.070      7.508      0.000       0.389       0.664
ma.L1         -0.9048      0.036    -25.327      0.000      -0.975      -0.835
ar.S.L12      -0.1573      0.071     -2.224      0.026      -0.296      -0.019
ma.S.L12      -0.9984      1.779     -0.561      0.575      -4.486       2.489
sigma2         0.0772      0.137      0.565      0.572      -0.191       0.345
===================================================================================
Ljung-Box (L1) (Q):                   5.63   Jarque-Bera (JB):                 1.20
Prob(Q):                              0.02   Prob(JB):                         0.55
Heteroskedasticity (H):               1.14   Skew:                            -0.01
Prob(H) (two-sided):                  0.48   Kurtosis:                         3.28
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [40]:
```
# Predicting the future CTR values

future_steps = 100
predictions = results.predict(len(time_series), len(time_series) + future_steps - 1)
print(predictions)
```

```
2023-10-19    3.852386
2023-10-20    3.889481
2023-10-21    3.820334
2023-10-22    3.727538
2023-10-23    3.710386
                ...
2024-01-22    3.545527
2024-01-23    3.466600
2024-01-24    3.561147
2024-01-25    3.546659
2024-01-26    3.580067
Freq: D, Name: predicted_mean, Length: 100, dtype: float64
```

In [42]:
```
# Visualize the forecasted trend of CTR

# Create a DataFrame with the original data and predictions
forecast = pd.DataFrame({'Original': time_series, 'Predictions': predictions})

# Plot the original data and predictions
fig = go.Figure()

fig.add_trace(go.Scatter(x=forecast.index, y=forecast['Predictions'],
                         mode='lines', name='Predictions'))

fig.add_trace(go.Scatter(x=forecast.index, y=forecast['Original'],
                         mode='lines', name='Original Data'))

fig.update_layout(title='CTR Forecasting',
                  xaxis_title='Time Period',
                  yaxis_title='Impressions',
                  legend=dict(x=0.1, y=0.9),
                  showlegend=True)

fig.show()
```



In [ ]:
```

```