OneHealth Data Analysis

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```
# Importing dependencies

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import zipfile # for dealing with zip files
from datetime import timedelta # for dealing with time series calculations
from statsmodels.tsa.seasonal import seasonal_decompose # import statsmodel time series decomposer
```

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

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```
# import the cleaned data

df = pd.read_excel("Assessment_Data_Output.xlsx")
```

```
# Check the column names

df.columns
```

```
Index(['hmo_id', 'prescription_code', 'name', 'date_created', 'status',
       'delivery_status', 'delivery_time', 'lead_time'],
      dtype='object')
```

```
# check data information

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5337 entries, 0 to 5336
Data columns (total 8 columns):
```

```
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   hmo_id             5337 non-null   object
 1   prescription_code  5337 non-null   object
 2   name               5337 non-null   object
 3   date_created       5337 non-null   datetime64[ns]
 4   status             5337 non-null   object
 5   delivery_status    5337 non-null   object
 6   delivery_time      5337 non-null   datetime64[ns]
 7   lead_time          5337 non-null   float64
dtypes: datetime64[ns](2), float64(1), object(5)
memory usage: 333.7+ KB
```

```
# check the first 5 row for a preview
```

```
df.head()
```

	hmo_id	prescription_code	name	date_created	status	delivery_status	delivery_time	lead_time
0	10136AVLC	294E6A17	Ijete	2024-05-01 06:29:03	Dispensed	Delivered	2024-05-01 13:23:00	6.899167
1	10054PVLA	850258F2	Abdullahi	2024-05-01 06:56:48	Dispensed	Delivered	2024-05-01 12:00:00	5.053333
2	10506OPAA	175FBA94	FAGBAMIGBE	2024-05-01 06:57:10	Dispensed	Delivered	2024-05-01 14:23:00	7.430556
[illegible]	[illegible]	[illegible]	[illegible]	2024-05-01	[illegible]	[illegible]	2024-05-01	[illegible]

```
# print the rows and colums

print(f"The total number of columns is: {df.shape[1]}")
print(f"The total number of rows is: {df.shape[0]}")
```

```
The total number of columns is: 8
The total number of rows is: 5337
```

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```
# Sumarry statistics

df.describe(include='all')
```

	hmo_id	prescription_code	name	date_created	status	delivery_status	delivery_time	lea
count	5337	5337	5337	5337	5337	5337	5337	5337.
unique	4699	5328	3502	NaN	1	1	NaN	
top	10684MEXA	79CFEB1D	Emmanuel	NaN	Dispensed	Delivered	NaN	
freq	6	2	24	NaN	5337	5337	NaN	
mean	NaN	NaN	NaN	2024-05-17 04:26:23.273187328	NaN	NaN	2024-05-17 13:28:20.224845568	4.
min	NaN	NaN	NaN	2024-05-01 06:29:03	NaN	NaN	2024-05-01 11:00:00	0.
25%	NaN	NaN	NaN	2024-05-09 13:42:22	NaN	NaN	2024-05-09 17:40:00	3
50%	NaN	NaN	NaN	2024-05-16 22:15:18	NaN	NaN	2024-05-17 11:35:00	4.
75%	NaN	NaN	NaN	2024-05-24 14:02:22	NaN	NaN	2024-05-24 17:34:00	5.

Observation

- Data appears to be clean

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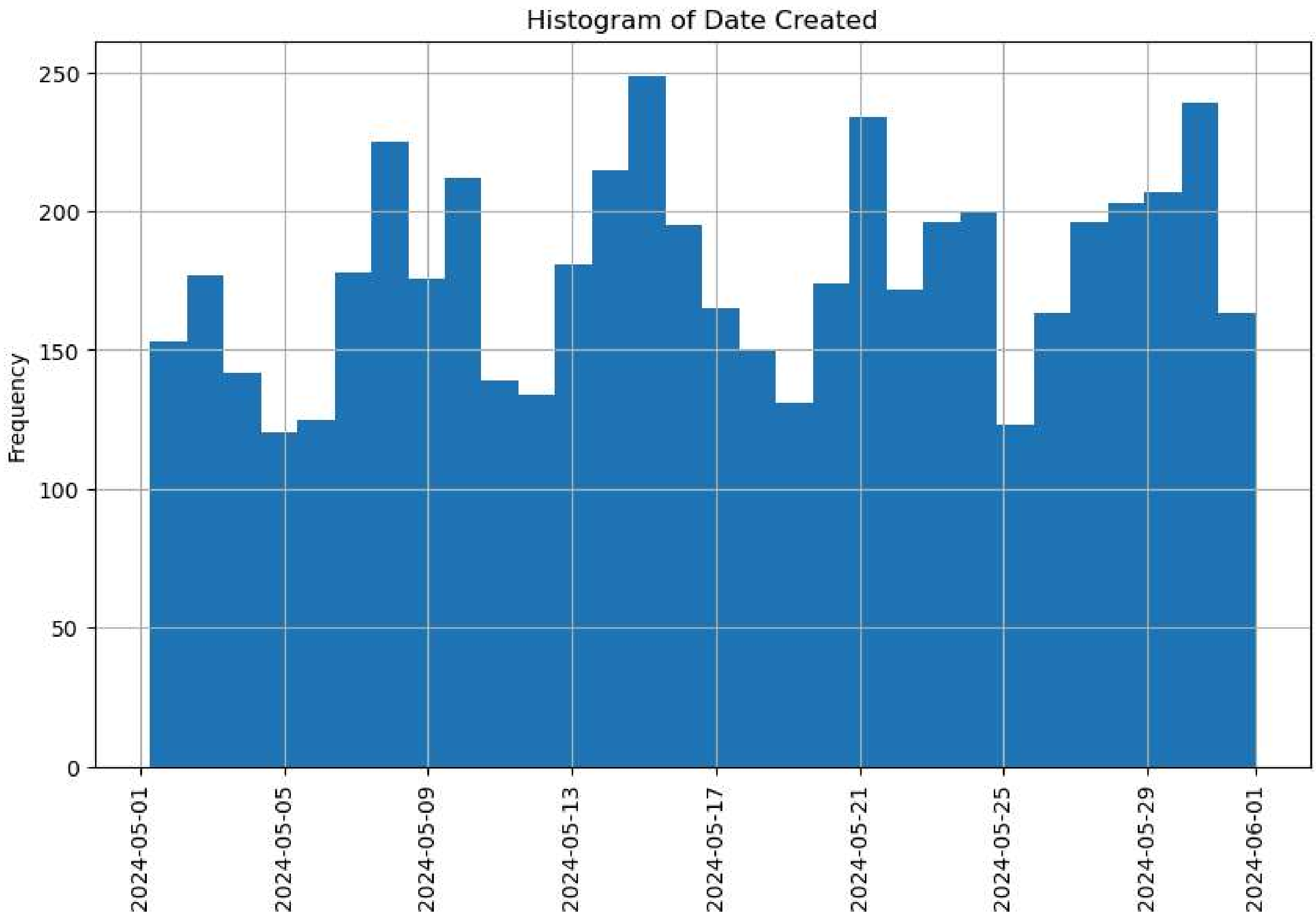
Distribution plots

```
# Plot histogram for date_created
plt.figure(figsize=(10, 6))
df['date_created'].hist(bins=30)
plt.ylabel('Frequency')
plt.title('Histogram of Date Created')
plt.xticks(rotation = 90)
plt.show()
```



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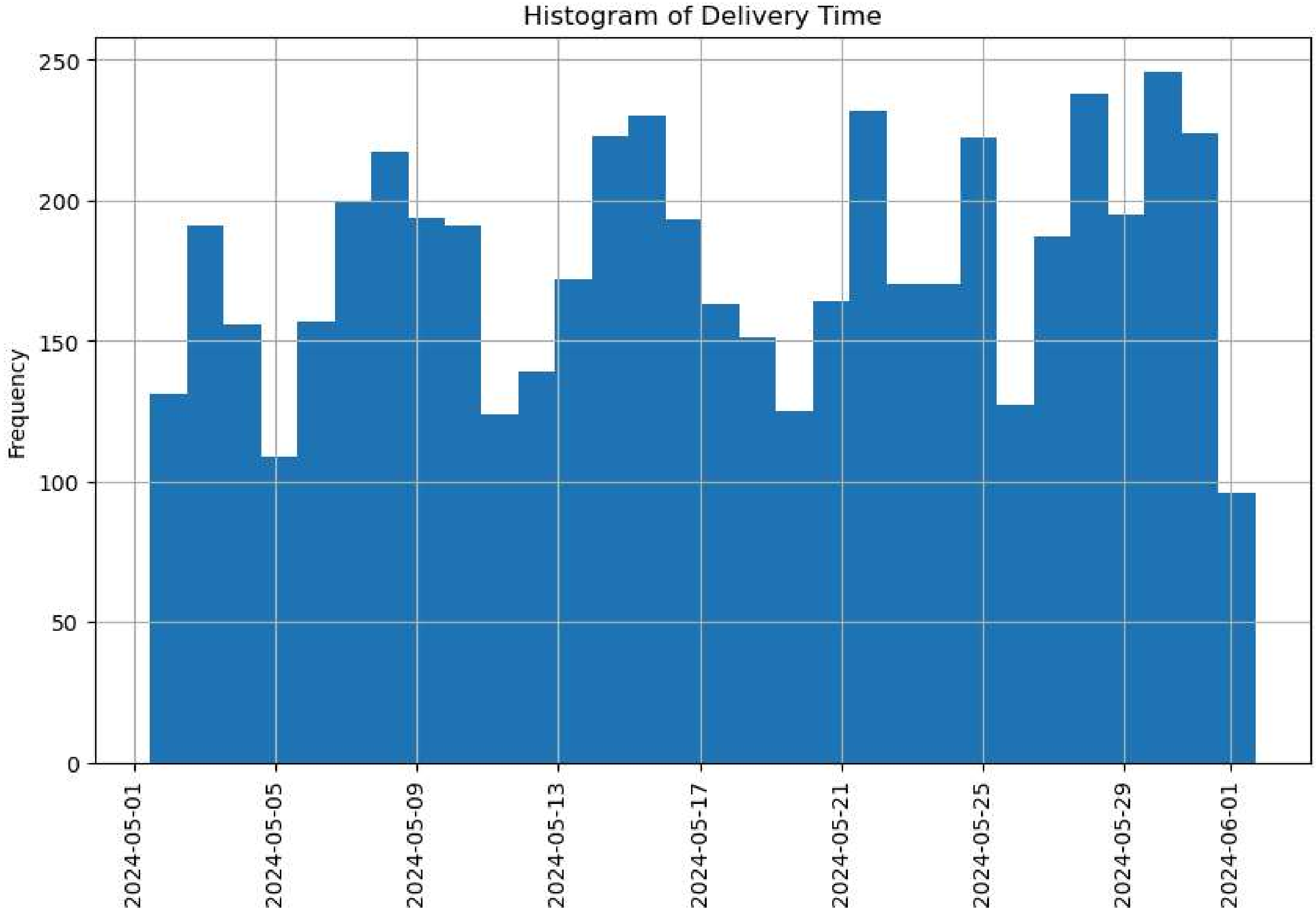
```
# Plot histogram for delivery_time
plt.figure(figsize=(10, 6))
df['delivery_time'].hist(bins=30)
plt.ylabel('Frequency')
plt.title('Histogram of Delivery Time')
plt.xticks(rotation = 90)
plt.show()
```



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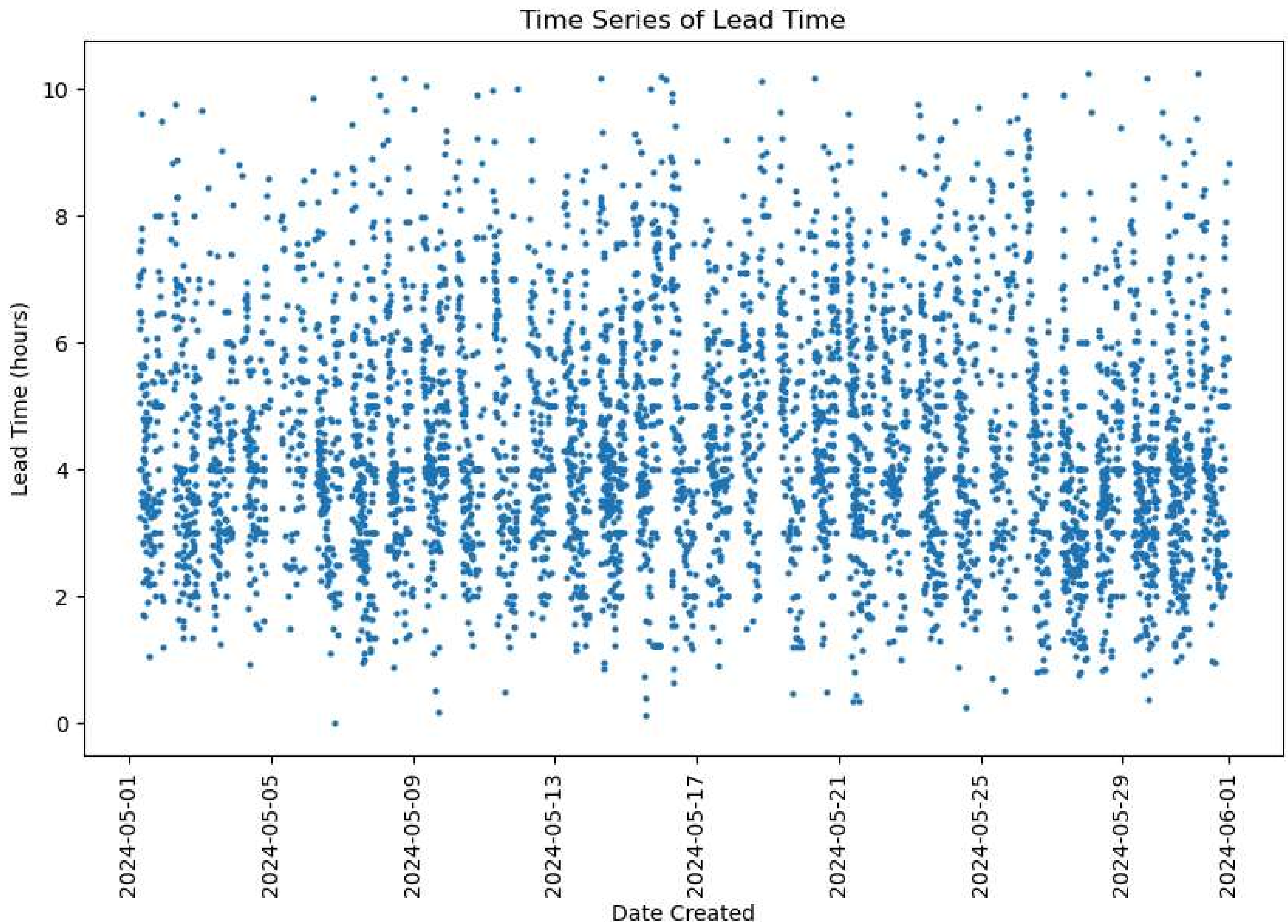
```
# Time series plot of lead_time
plt.figure(figsize=(10, 6))
plt.plot(df['date_created'], df['lead_time'], 'o', markersize=2)
plt.xlabel('Date Created')
plt.ylabel('Lead Time (hours)')
plt.title('Time Series of Lead Time')
plt.xticks(rotation = 90)
plt.show()
```



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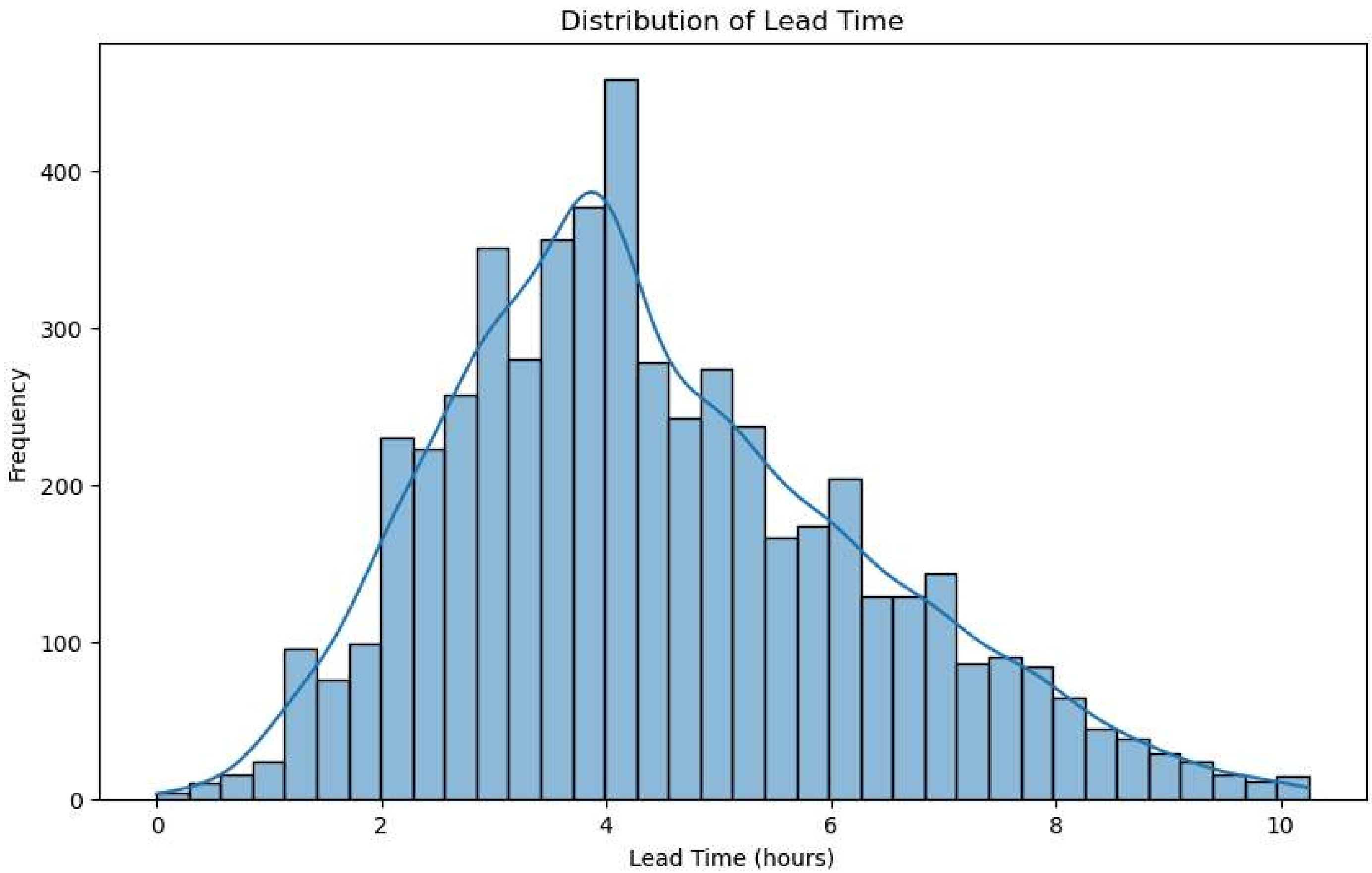
```
# Plot histogram with KDE for lead_time
plt.figure(figsize=(10, 6))
sns.histplot(df['lead_time'], kde=True)
plt.xlabel('Lead Time (hours)')
plt.ylabel('Frequency')
plt.title('Distribution of Lead Time')
plt.show()
```



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Observations:

The time histograms and the series plot of lead_time against date_created shows how the lead time (in hours) varies over the period during which the records were created. Here's a detailed analysis of the plot:

- Overall Trend: There seems to be a relatively stable range for lead times, mostly between 0 and around 10 hours, across the entire time span.
- Clusters: The data points are fairly evenly distributed over the date range, indicating a consistent recording of lead times.
- Outliers: There are no obvious extreme outliers in the plot. The values stay within a reasonable range, confirming the data's integrity after removing negative lead times and other anomalies.

- Density: Some dates might have higher densities of points (more records created), indicating busy days, but this is not extremely pronounced.

Interpretation:

- Consistency: The lead times are consistent over the dates, showing no significant trends or changes over time. This suggests that the process or system producing these records is stable.
- No Sudden Changes: There are no abrupt changes or patterns in lead time, which could indicate issues or improvements in the delivery process.

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```
# Drop the status and delivery_status colums for our trend analysis

df_trend = df.drop(['status', 'delivery_status'], axis=1)
```

Trend Analysis

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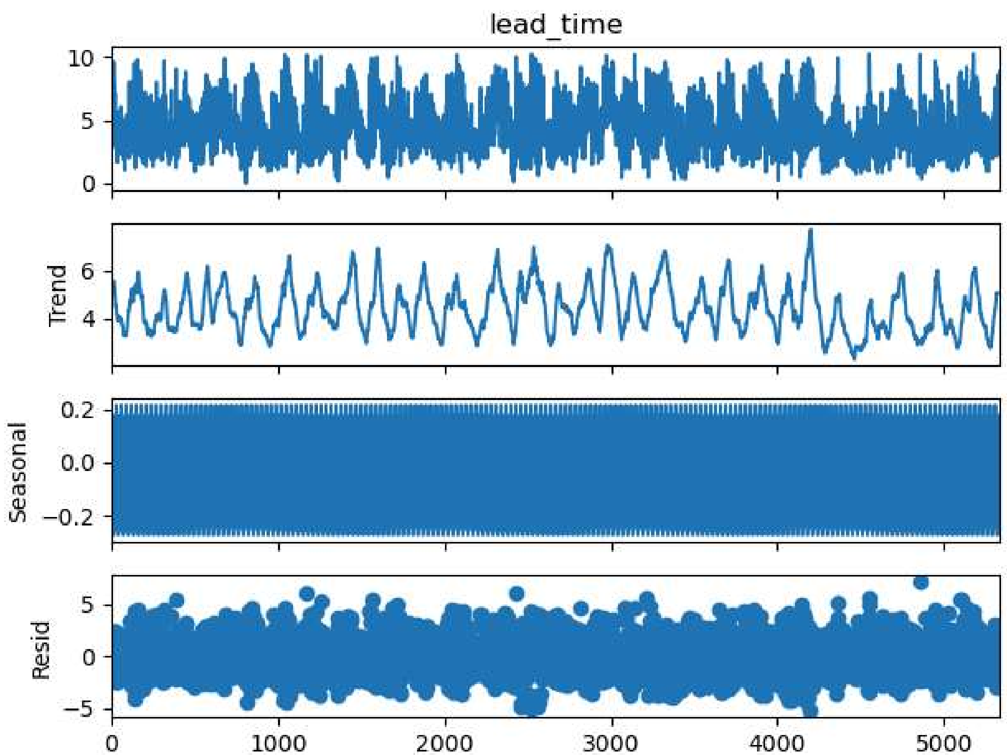
Delivery Time and Lead Time Trends

```
# Repeat the analysis for delivery_time
# copy the data frame for deliverytime trend analysis
df_trend_delivery = df_trend.copy()
df_trend_delivery = df_trend_delivery.set_index('delivery_time')
```

```
df_trend_delivery.head()
```

delivery_time	hmo_id	prescription_code	name	date_created	lead_time
2024-05-01 13:23:00	10136AVLC	294E6A17	Ijete	2024-05-01 06:29:03	6.899167
2024-05-01 12:00:00	10054PVLA	850258F2	Abdullahi	2024-05-01 06:56:48	5.053333
2024-05-01 14:23:00	10506OPAA	175FBA94	FAGBAMIGBE	2024-05-01 06:57:10	7.430556
2024-05-01 13:27:00	10023EVGA	B8D45EBC	Ovie	2024-05-01 06:57:55	6.484722
2024-05-01 14:34:00	10059OPBA	392A2E5B	Ogundare	2024-05-01 07:06:16	7.462222

```
# Time Series Decomposition for delivery_time
df_delivery_time = df_trend['lead_time'].dropna()
decomposition = seasonal_decompose(df_delivery_time, model='additive', period=30)
decomposition.plot()
plt.show()
```



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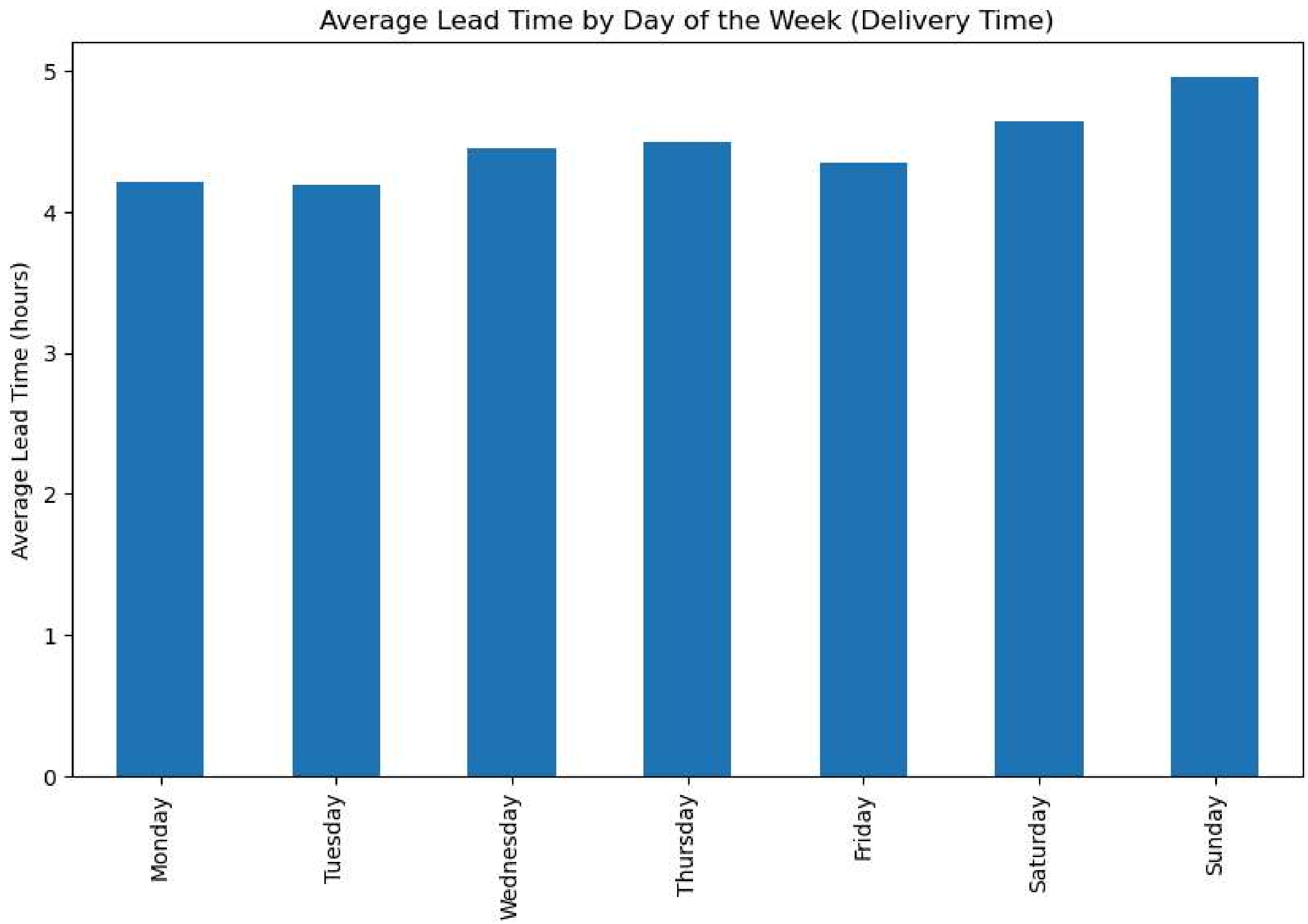
```
# Extract the day of the week
df_trend_delivery['day_of_week'] = df_trend_delivery.index.day_name()

# Calculate the mean delivery time by day of the week
mean_delivery_time_by_day = df_trend_delivery.groupby('day_of_week')['lead_time'].mean().reindex([
    'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'])

# Plot the results
plt.figure(figsize=(10, 6))
mean_delivery_time_by_day.plot(kind='bar')
plt.title('Average Lead Time by Day of the Week (Delivery Time)')
plt.xlabel('')  # Remove the xlabel as the days of the week are already on the x-axis
plt.ylabel('Average Lead Time (hours)')
plt.show()
```



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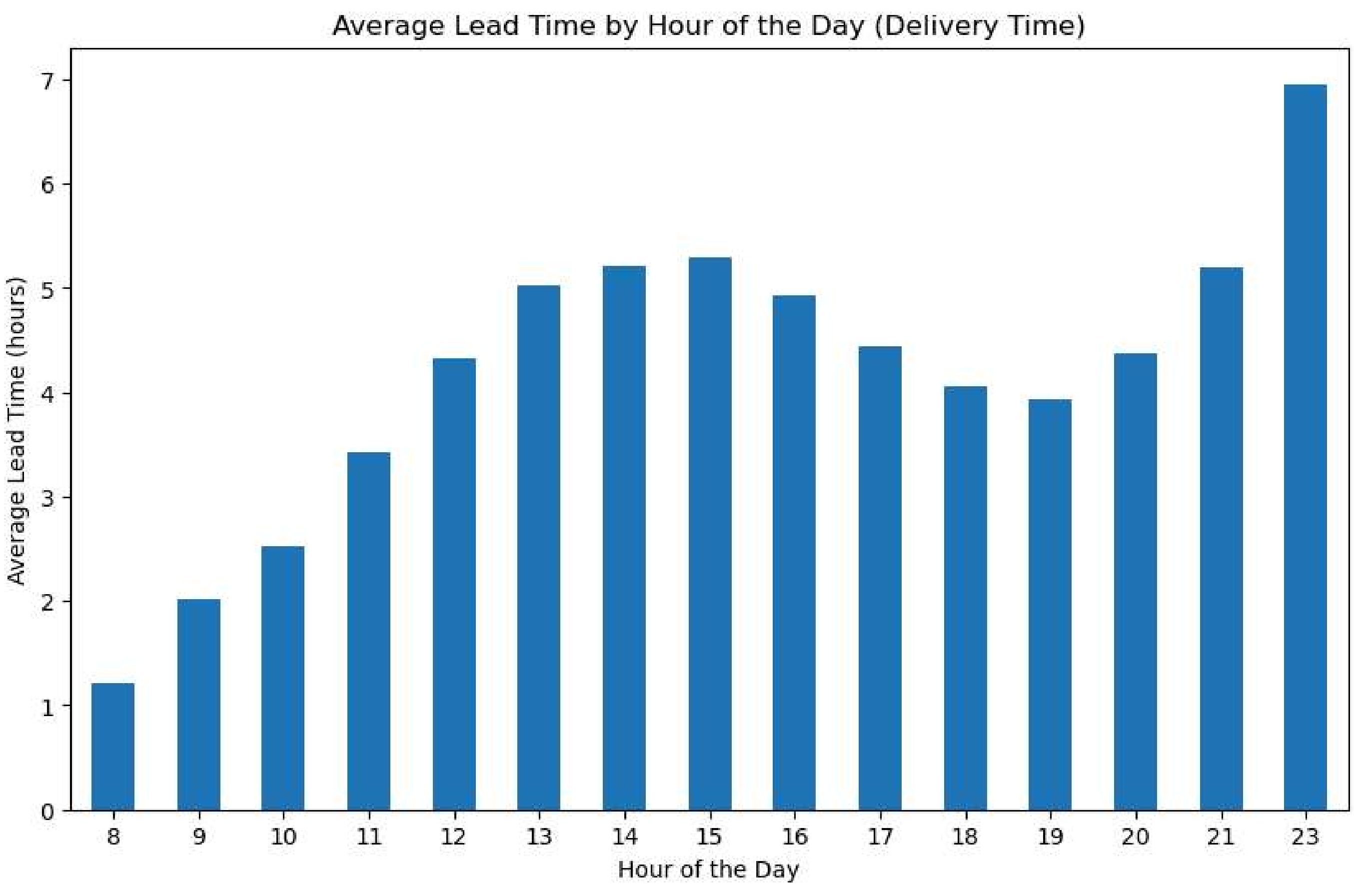
```
# Analyze by Hour of the Day for delivery_time
# Extract the hour of the day
df_trend_delivery['hour_of_day'] = df_trend_delivery.index.hour

# Calculate the mean delivery time by hour of the day
mean_delivery_time_by_hour = df_trend_delivery.groupby('hour_of_day')['lead_time'].mean()

# Plot the results
plt.figure(figsize=(10, 6))
mean_delivery_time_by_hour.plot(kind='bar')
plt.title('Average Lead Time by Hour of the Day (Delivery Time)')
plt.xlabel('Hour of the Day')
plt.xticks(rotation = 0)  # Ensure all hours are shown
plt.ylabel('Average Lead Time (hours)')
plt.show()
```



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Observations

1. **Average Lead Time by Hour of the Day (Delivery Time):**
    - Lead times are shortest in the early morning hours (8 AM) and gradually increase, peaking around the afternoon (14-16 hours).
    - There's a noticeable drop after the peak, followed by another rise in the late evening (23 hours).
    - This indicates a potential bottleneck during the middle of the day.
2. **Average Lead Time by Day of the Week (Delivery Time):**
    - Lead times are relatively consistent across weekdays, with a slight increase on weekends.
    - Sunday has the highest average lead time, suggesting that weekend deliveries are slower.
3. **Lead Time Decomposition:**
    - The trend component shows periodic fluctuations, indicating a cyclical pattern in lead times.
    - The seasonal component appears to be constant, suggesting minimal impact from seasonal variations.
    - The residual component shows random noise, implying that other factors might be influencing lead times unpredictably.

Recommendations

1. **Optimize Mid-Day Operations:**
    - Since lead times peak during the afternoon, consider investigating the processes and workloads during these hours.
    - Introduce additional resources or shift schedules to handle the increased load during peak hours.
    - Implement more efficient batching or prioritization methods to manage orders effectively.
2. **Improve Weekend Delivery Performance:**
    - Since lead times are higher on weekends, especially Sundays, analyze the factors contributing to this delay.
    - Ensure adequate staffing and resources are available during weekends.
    - Consider partnering with third-party logistics providers to handle overflow during weekends.
3. **Enhance Early Morning and Late Evening Operations:**
    - The early morning and late evening hours show shorter lead times, which can be leveraged.
    - Promote early or late delivery options to customers, potentially offering discounts or incentives for choosing these time slots.
    - Utilize the shorter lead times during these periods to offset peak times.
4. **Continuous Monitoring and Adjustment:**
    - Regularly monitor lead time trends to identify any emerging patterns or issues.

- Use real-time data analytics to dynamically adjust operations based on current workloads and lead times.
- Implement a feedback loop for continuous improvement, involving frontline staff to suggest and test operational changes.

5. **Address Random Variations:**
   - Investigate the factors contributing to the residual noise in the lead time decomposition.
   - Identify and mitigate any irregular or unpredictable elements impacting lead times, such as equipment failures, traffic delays, or unexpected surges in order volume.

By addressing these observations and implementing the recommendations, you can improve the overall efficiency and reliability of your delivery operations, leading to better SLA compliance and customer satisfaction.

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Performance Metrics:

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```
# Calculate average delivery time (in hours)
average_delivery_time = (df['delivery_time'] - df['date_created']).dt.total_seconds().mean() / 3600
print(f"Average Delivery Time: {average_delivery_time:.2f} hours")

# Calculate average lead time ('lead_time' column is already in hours)
average_lead_time = df['lead_time'].mean()
print(f"Average Lead Time: {average_lead_time:.2f} hours")
```

```
Average Delivery Time: 9.03 hours
Average Lead Time: 4.43 hours
```

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Determining On-time vs Late Deliveries

To determine whether a delivery is on time or late, we need a threshold. Let's assume a delivery is considered "on time" if it is completed within a certain number of hours after the date_created. You should define what constitutes "on time" based on your business rules.

Let's assume "on time" means delivery within 4 hours

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```
# Define the threshold for on-time delivery in hours
on_time_threshold = 4

# Calculate the delivery times in hours
df['delivery_duration'] = (df['delivery_time'] - df['date_created']).dt.total_seconds() / 3600

# Determine if each delivery is on time
df['on_time'] = df['delivery_duration'] <= on_time_threshold

# Calculate the proportion of on-time deliveries
on_time_proportion = df['on_time'].mean()
late_proportion = 1 - on_time_proportion

print(f"Proportion of On-time Deliveries: {on_time_proportion:.2%}")
print(f"Proportion of Late Deliveries: {late_proportion:.2%}")
```

```
Proportion of On-time Deliveries: 30.19%
Proportion of Late Deliveries: 69.81%
```

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SLA Compliance Analysis:

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Firstly: Calculate SLA Compliance

First, we need to calculate whether each prescription meets the SLA criteria.

Create a column to determine if the prescription was created before or after 3 PM. Determine if the prescription was delivered the same day or by 12 PM the next day. Combine these conditions to create an sla_compliant column. Here is the code for these calculations:

```
df_sla = df.copy()


# Ensure the date_created and delivery_time columns are datetime objects
df_sla['date_created'] = pd.to_datetime(df_sla['date_created'])
df_sla['delivery_time'] = pd.to_datetime(df_sla['delivery_time'])
```

```
# Calculate SLA Compliance
time_3pm = pd.Timestamp('15:00:00').time()
time_12pm_next_day = pd.Timestamp('12:00:00').time()

# Check if created before or after 3 PM
df_sla['created_before_3pm'] = df_sla['date_created'].dt.time <= time_3pm

# Check if same day delivery
df_sla['same_day_delivery'] = (df_sla['date_created'].dt.date == df_sla['delivery_time'].dt.date)

# Check if next day delivery by 12 PM
df_sla['next_day_delivery'] = (
    (df_sla['date_created'].dt.time > time_3pm) &
    ((df_sla['delivery_time'].dt.date == df_sla['date_created'].dt.date + pd.Timedelta(days=1)) &
     (df_sla['delivery_time'].dt.time <= time_12pm_next_day))
)

# Combine the conditions to define SLA compliance
df_sla['sla_compliant'] = df_sla['created_before_3pm'] & df_sla['same_day_delivery'] | (~df_sla['created_before_3pm'] & df_sla['next_day_delivery'])

# Display to ensure the column was created correctly
df_sla[['date_created', 'delivery_time', 'created_before_3pm', 'same_day_delivery', 'next_day_delivery', 'sla_compliant']].head()
```

	date_created	delivery_time	created_before_3pm	same_day_delivery	next_day_delivery	sla_compliant
0	2024-05-01 06:29:03	2024-05-01 13:23:00	True	True	False	True
1	2024-05-01 06:56:48	2024-05-01 12:00:00	True	True	False	True
2	2024-05-01 06:57:10	2024-05-01 14:23:00	True	True	False	True
3	2024-05-01 06:57:55	2024-05-01 13:27:00	True	True	False	True
4	2024-05-01 07:06:16	2024-05-01 14:34:00	True	True	False	True

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1. Analyze and Trend the Average Turnaround Time per Order

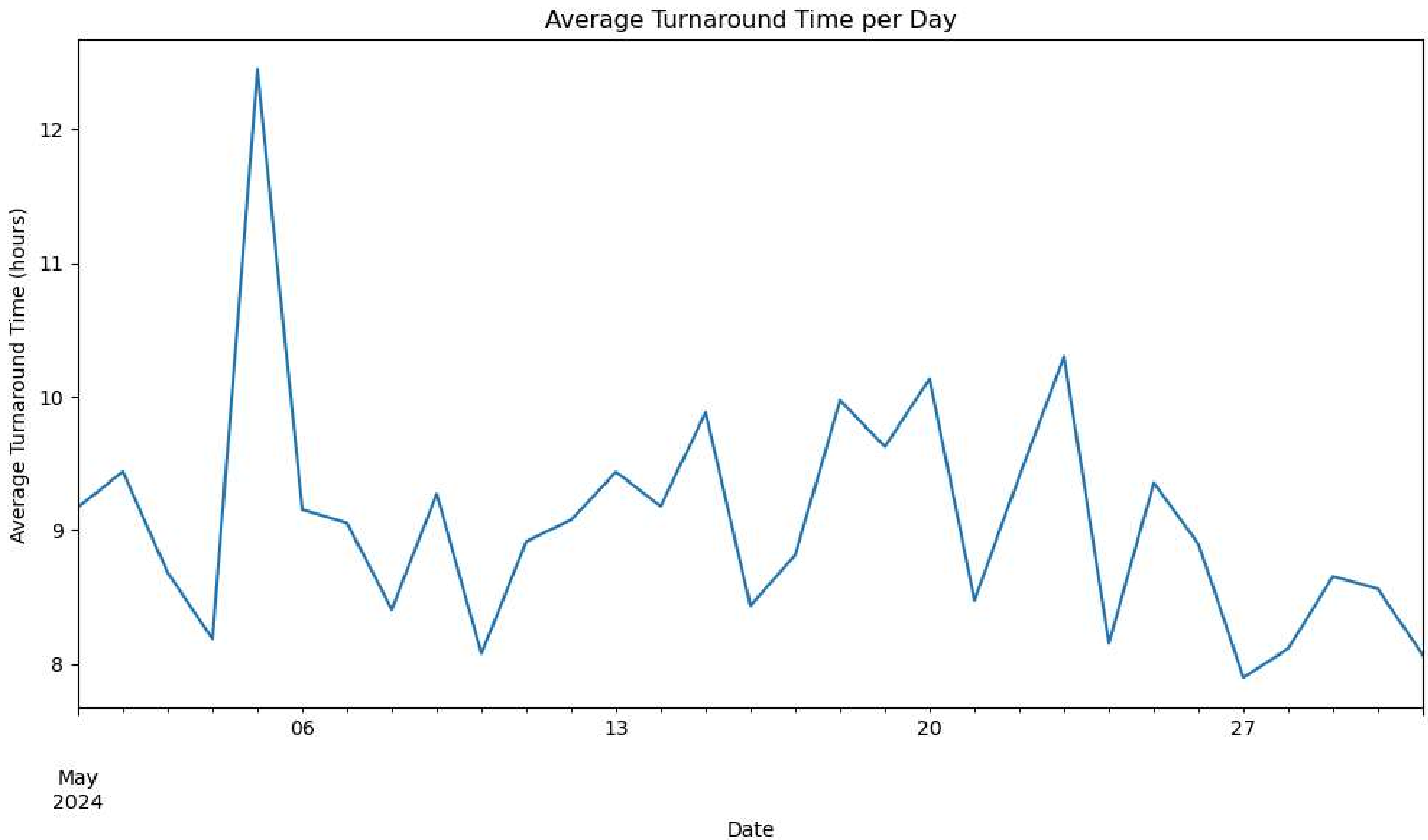
Turnaround Time Calculation:

Turnaround time is the total time taken from order creation to delivery.

```
# Calculate Turnaround Time
df_sla['turnaround_time'] = (df_sla['delivery_time'] - df_sla['date_created']).dt.total_seconds() / 3600  # Convert to hours

# Trend Average Turnaround Time per Day
turnaround_time_trend = df_sla.resample('D', on='date_created')['turnaround_time'].mean()

plt.figure(figsize=(12, 6))
turnaround_time_trend.plot()
plt.title('Average Turnaround Time per Day')
plt.xlabel('Date')
plt.ylabel('Average Turnaround Time (hours)')
plt.show()
```



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2. Analyze SLA Achievement Trends per Day

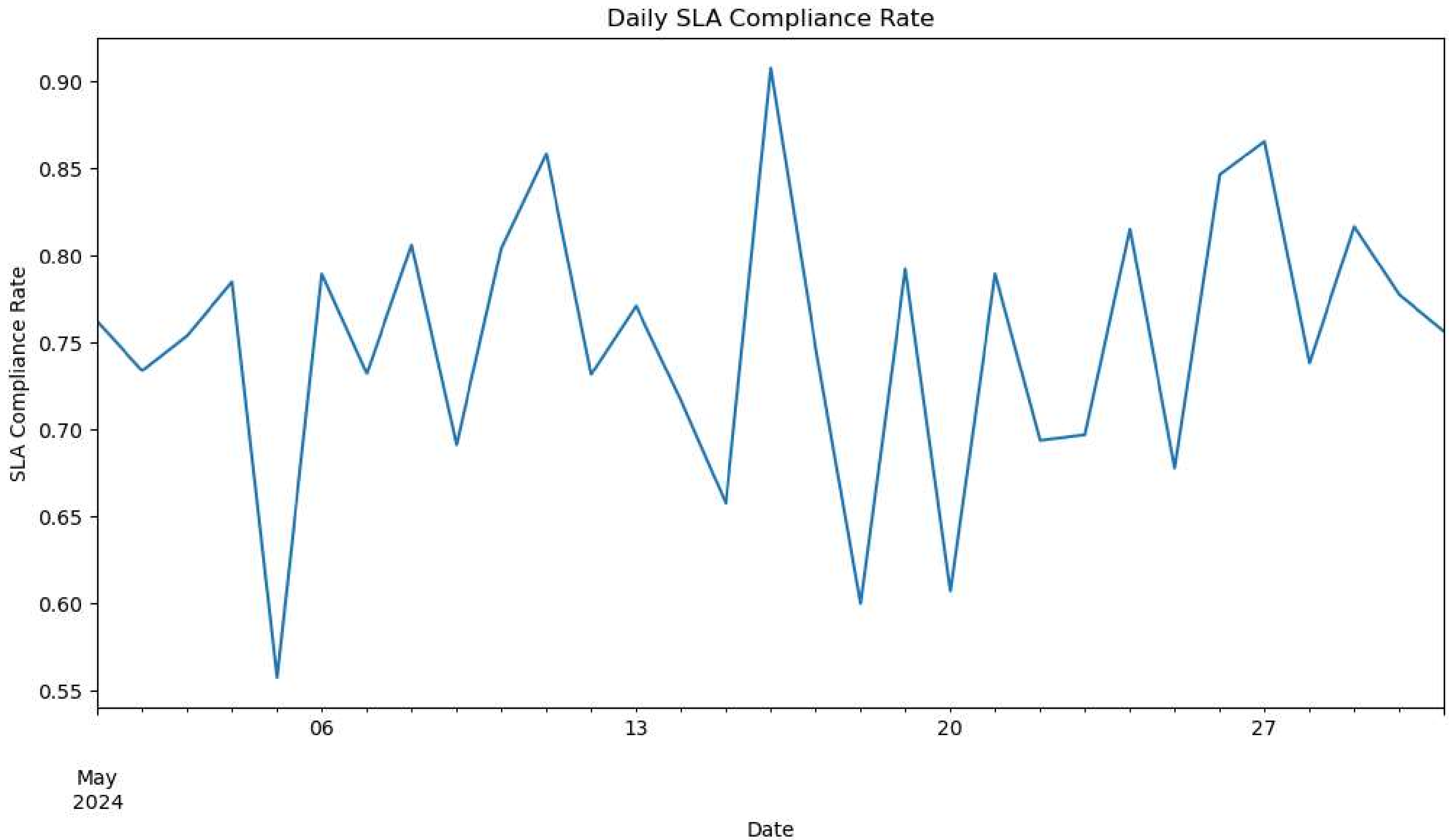
Daily SLA Compliance Calculation:

Calculate the daily SLA compliance rate.

```
# Set the date_created as the index for resampling
df_sla_reindexed = df_sla.set_index('date_created')

# Analyze SLA Achievement Trends per Day
daily_sla_compliance = df_sla_reindexed.resample('D')['sla_compliant'].mean()

plt.figure(figsize=(12, 6))
daily_sla_compliance.plot()
plt.title('Daily SLA Compliance Rate')
plt.xlabel('Date')
plt.ylabel('SLA Compliance Rate')
plt.show()
```



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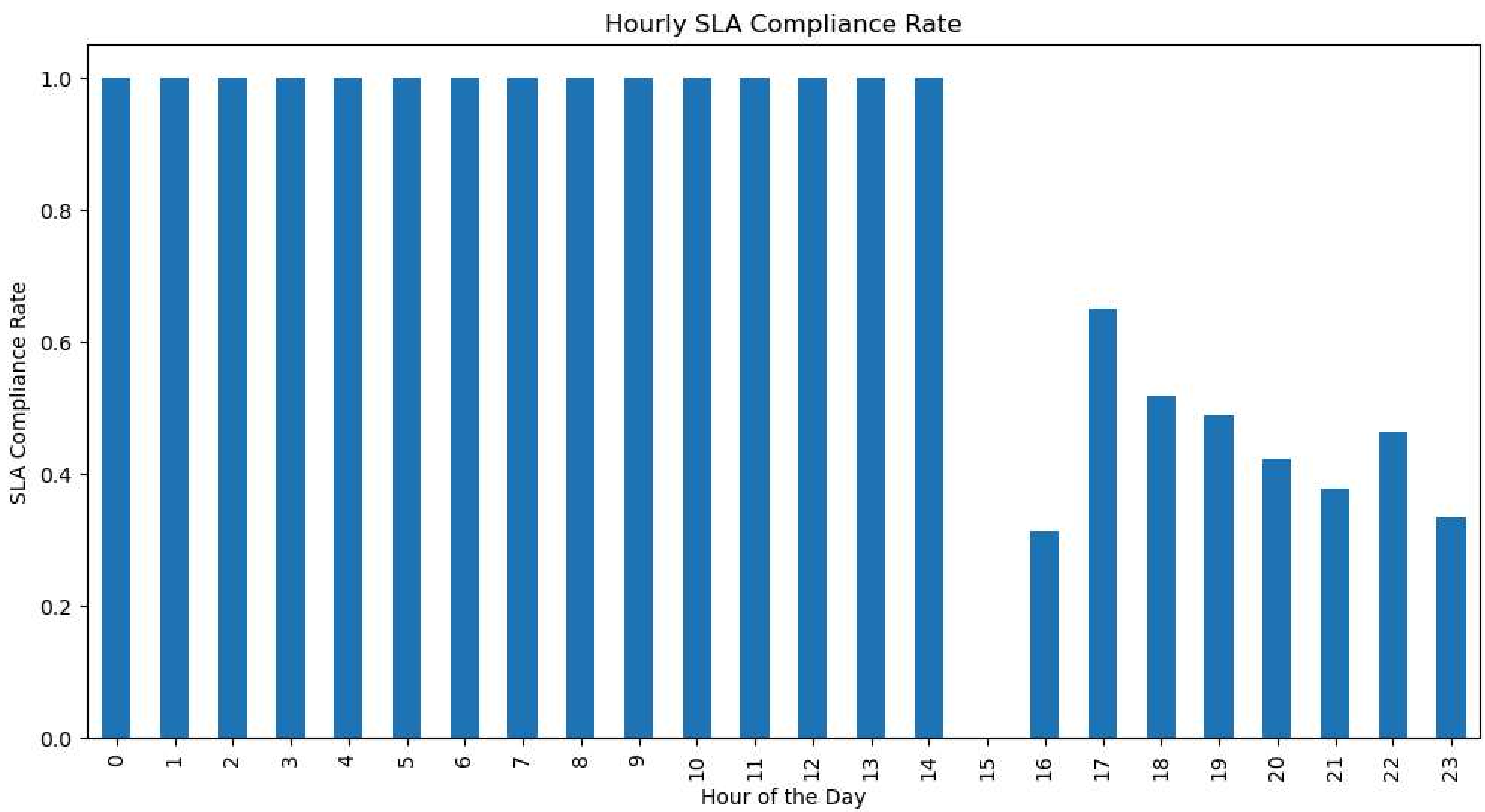
3. Analyze/Trend the Average SLA Achievement of Orders Sent per Hour per Day

Hourly SLA Compliance Calculation:

Calculate the SLA compliance rate for each hour of the day.

```
# Analyze/Trend the Average SLA Achievement of Orders Sent per Hour per Day
df_sla_reindexed['hour'] = df_sla_reindexed.index.hour
hourly_sla_compliance = df_sla_reindexed.groupby('hour')['sla_compliant'].mean()

plt.figure(figsize=(12, 6))
hourly_sla_compliance.plot(kind='bar')
plt.title('Hourly SLA Compliance Rate')
plt.xlabel('Hour of the Day')
plt.ylabel('SLA Compliance Rate')
plt.show()
```



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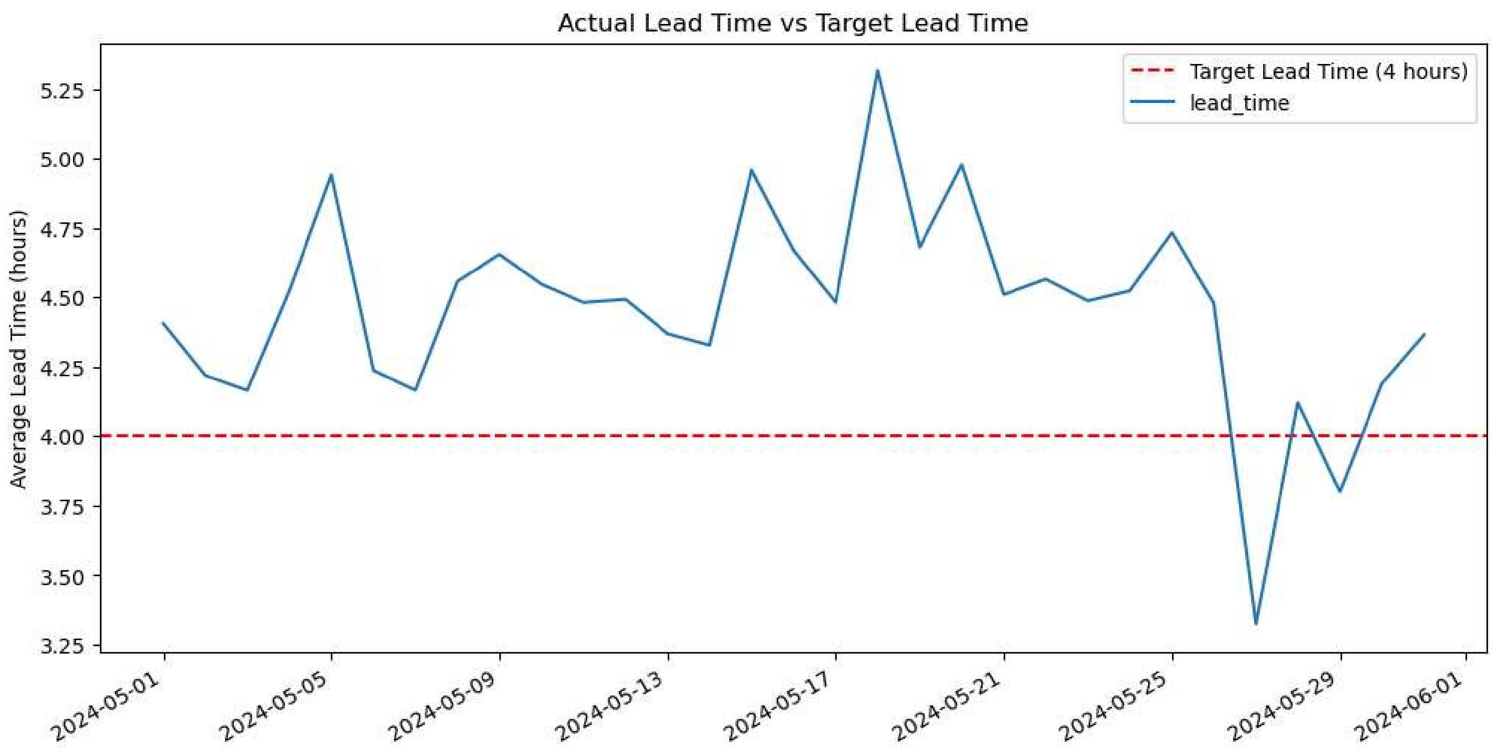
4. Compare and Trend Actual Lead Times Against the Target Lead Time of Four Hours

Lead Time Comparison:

Plot actual lead times and highlight the target lead time of four hours.

```
# Compare and Trend Actual Lead Times Against the Target Lead Time of Four Hours
plt.figure(figsize=(12, 6))
plt.axhline(y=4, color='r', linestyle='--', label='Target Lead Time (4 hours)')
df_sla_reindexed.resample('D')['lead_time'].mean().plot()
plt.title('Actual Lead Time vs Target Lead Time')
plt.xlabel('')
plt.ylabel('Average Lead Time (hours)')
plt.legend()
plt.show()
```




```
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```

5. Assess and Trend Compliance with the SLA

SLA Compliance Trends:

```
# Assess and Trend Compliance with the SLA

# Resample to daily compliance rate
daily_sla_compliance = df_sla.resample('D', on='date_created')['sla_compliant'].mean()
daily_sla_compliance.head()
```

```
date_created
2024-05-01    0.761905
2024-05-02    0.733728
2024-05-03    0.753846
2024-05-04    0.784615
2024-05-05    0.557692
Freq: D, Name: sla_compliant, dtype: float64
```

```
plt.figure(figsize=(12, 6))
daily_sla_compliance.plot()
plt.title('Daily SLA Compliance Rate')
plt.xlabel('Date')
plt.ylabel('SLA Compliance Rate')
plt.show()
```