

Data Analysis Overview

In this analysis file, we will leverage Python libraries such as `pandas`, `numpy`, `matplotlib`, and `seaborn` to derive insights from the processed data obtained in the data-cleansing file. The analysis will encompass:

1. **Basic Statistics:**
 - Compute descriptive statistics to gain an overview of the dataset's central tendencies and distributions.
2. **Time Series Analyses and Trends:**
 - Explore temporal patterns, trends, and seasonality in the data using time series analysis techniques.
3. **Operational Insights:**
 - Extract operational insights, such as peak activity periods, common routes, and other operational trends.
4. **Visualization and Reporting:**
 - Create visualizations using `matplotlib` and `seaborn` to effectively communicate findings. Generate reports summarizing key insights.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

# Suppress all warnings
warnings.filterwarnings('ignore')

from os import listdir

year = 2023

all_dfs = []
folder_path = f'../../assets/data/processed/{year}/'

# load all file from folder path
for file_name in listdir(folder_path):
    all_dfs.append(pd.read_excel(f'{folder_path}{file_name}'))

logistics_df = pd.concat(all_dfs, ignore_index=True)
logistics_df
```

	load_id	time_span_in_hours	destination_city	destination_state
0	10711141	0.04	Ft Worth	TX
1	10711143	0.06	Ft Worth	TX

2	10711145	0.29	Ft Worth	TX	
3	10711151	0.14	Ft Worth	TX	
4	10711155	0.96	ORLA	TX	
...	
11378	10724771	0.08	SARASOTA	FL	
11379	10726991	20.82	MARYLAND HE	MO	
11380	30316024	1.11	LA VALLE	WI	
11381	30320680	2.24	COLFAX	WI	
11382	30320994	0.68	PEKIN	IL	
	origin_city	origin_state	comment	miles	shipper
truck_type	...	\			
0	ABEILENE	TX	NO COMMENT	0	NO SHIPPER
F ...					
1	ABEILENE	TX	NO COMMENT	0	NO SHIPPER
F ...					
2	ABEILENE	TX	NO COMMENT	0	NO SHIPPER
F ...					
3	ABEILENE	TX	NO COMMENT	0	NO SHIPPER
F ...					
4	ABEILENE	TX	NO COMMENT	0	NO SHIPPER
F ...					
...
...					
...					
11378	ZWOLLE	LA	NO COMMENT	0	NO SHIPPER
F ...					
11379	ZWOLLE	LA	NO COMMENT	0	NO SHIPPER
F ...					
11380	ZWOLLE	LA	MUST TARP	1055	VFP
F ...					
11381	ZWOLLE	LA	MUST TARP	1151	VFP
F ...					
11382	ZWOLLE	LA	MUST TARP	798	VFP
F ...					
	added_hour	added_minute	added_second	added_week	
deleted_month	\				
0	12	7	52	48	
11					
1	11	50	31	48	
11					

2	12	10	26	48
11				
3	11	53	48	48
11				
4	10	40	12	48
11				
...
...				
11378	8	9	6	50
12				
11379	12	48	7	50
12				
11380	16	31	11	51
12				
11381	9	49	55	52
12				
11382	11	24	32	52
12				
	deleted_day	deleted_hour	deleted_minute	deleted_second
deleted_week				
0	28	12	10	27
48				
1	28	11	53	49
48				
2	28	12	27	53
48				
3	28	12	2	9
48				
4	29	11	37	34
48				
...
...				
11378	12	8	13	45
50				
11379	14	9	37	28
50				
11380	18	17	37	42
51				
11381	27	12	4	35
52				
11382	27	12	5	5
52				
[11383 rows x 25 columns]				

Basic Statistics and Time Series Trend Analysis

In this analysis, we will explore the average time a load stays in the system overall. Additionally, we will delve into time series trends, examining load duration patterns at a more granular level,

such as weekly or monthly intervals. Visualization techniques will be employed to provide a clear representation of these insights. This combined approach aims to offer both a holistic understanding of load durations and nuanced insights into temporal trends.

```
overall_load_stays_average = logistics_df.time_span_in_hours.mean()

sns.set(style="whitegrid")

plt.figure(figsize=(8, 4))
sns.barplot(x=['Average Value'], y=[overall_load_stays_average],
            color='skyblue')

plt.title('Overall Load Stays Average')
plt.ylabel('Value')
plt.show()
```

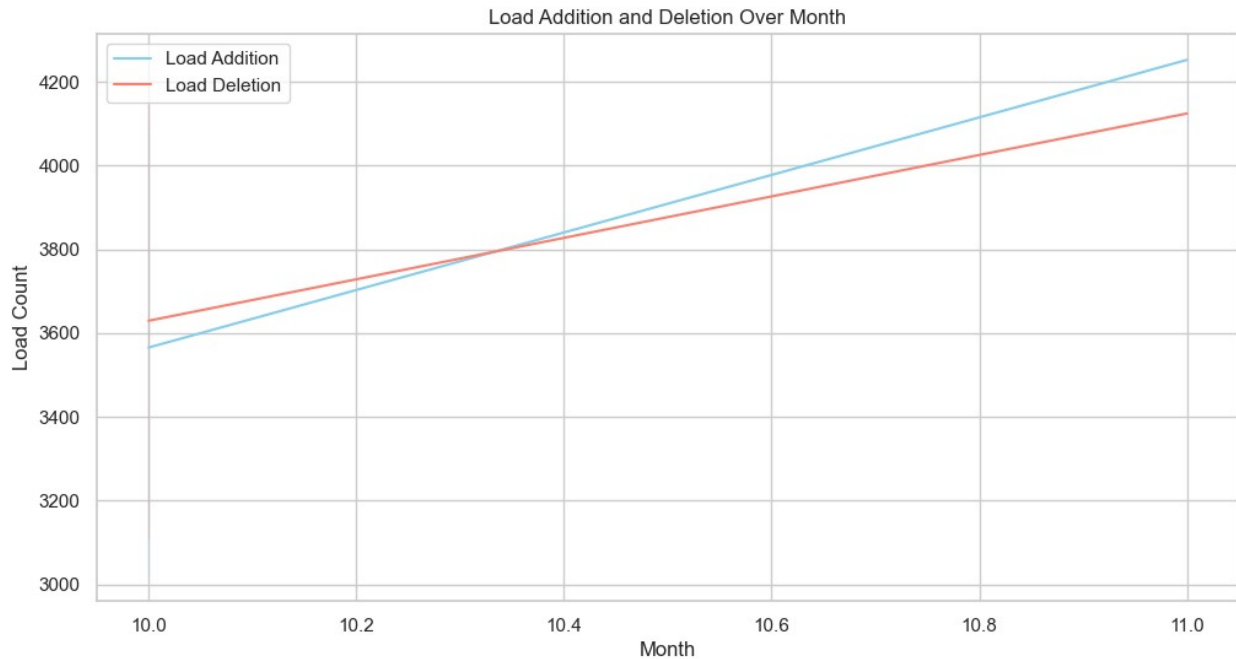


```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
sns.lineplot(x='added_month',
             y=logistics_df.groupby('added_month').size(),
             data=logistics_df, color='skyblue', label='Load Addition', legend=True)
sns.lineplot(x='deleted_month',
             y=logistics_df.groupby('deleted_month').size(),
             data=logistics_df, color='salmon', label='Load Deletion', legend=True)

plt.title('Load Addition and Deletion Over Month')
```

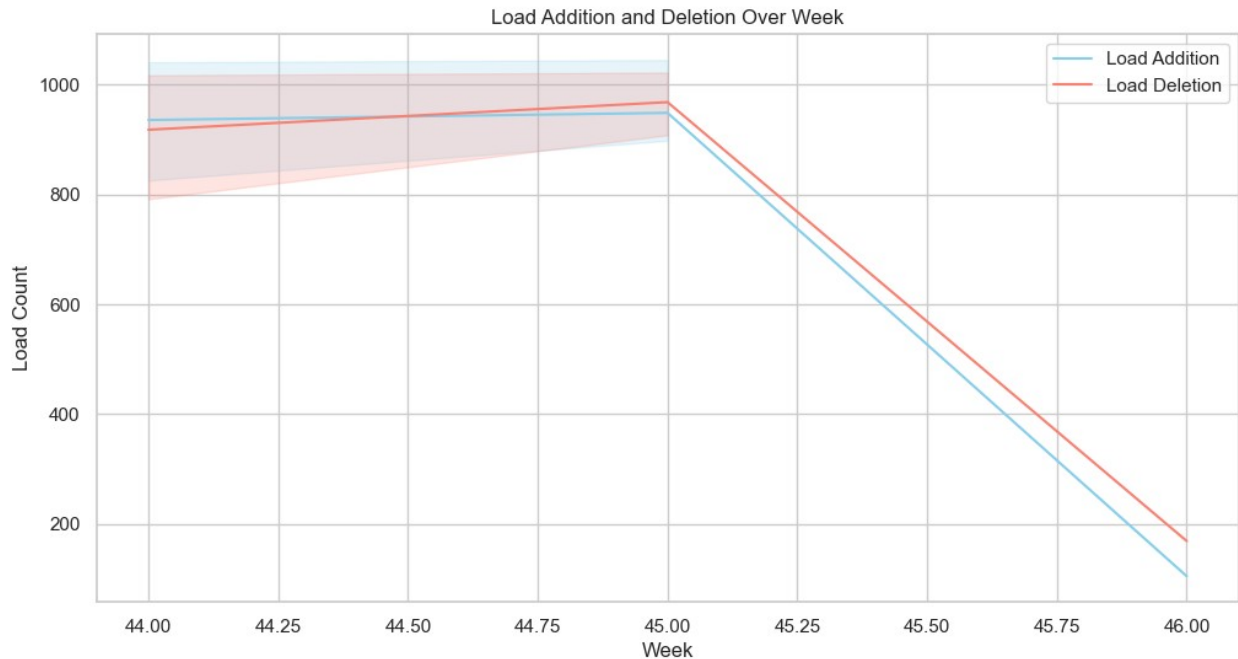
```
plt.xlabel('Month')
plt.ylabel('Load Count')
plt.legend()
plt.show()
```



```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
sns.lineplot(x='added_week',
y=logistics_df.groupby('added_week').size(
), data=logistics_df, color='skyblue', label='Load
Addition', legend=True)
sns.lineplot(x='deleted_week',
y=logistics_df.groupby('deleted_week').size(
), data=logistics_df, color='salmon', label='Load
Deletion', legend=True)

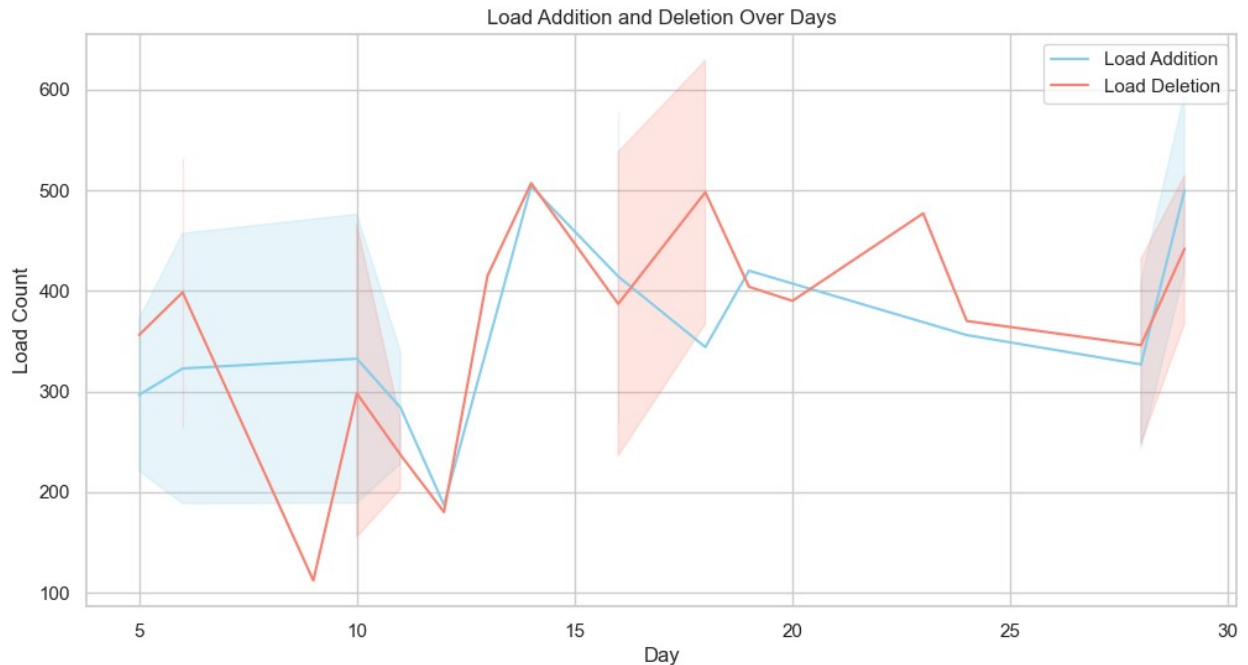
plt.title('Load Addition and Deletion Over Weeks')
plt.xlabel('Week')
plt.ylabel('Load Count')
plt.legend()
plt.show()
```



```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
sns.lineplot(x='added_day', y=logistics_df.groupby('added_day').size(), data=logistics_df, color='skyblue', label='Load Addition', legend=True)
sns.lineplot(x='deleted_day', y=logistics_df.groupby('deleted_day').size(), data=logistics_df, color='salmon', label='Load Deletion', legend=True)

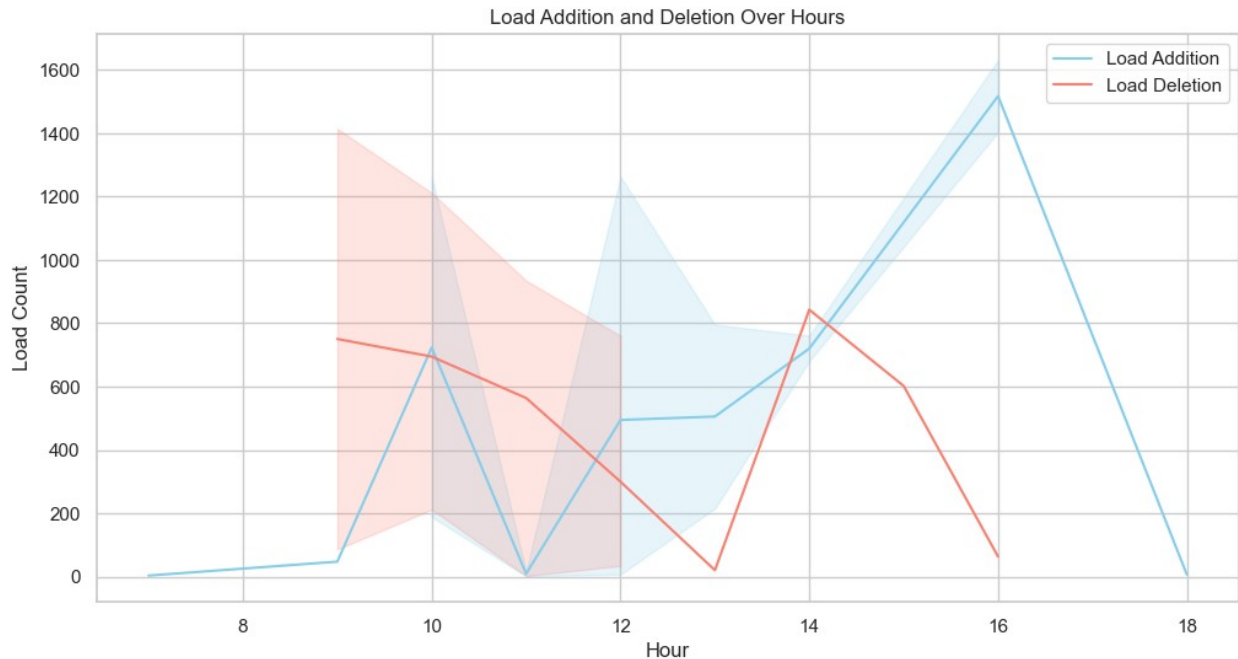
plt.title('Load Addition and Deletion Over Days')
plt.xlabel('Day')
plt.ylabel('Load Count')
plt.legend()
plt.show()
```



```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
sns.lineplot(x='added_hour',
y=logistics_df.groupby('added_hour').size(
), data=logistics_df, color='skyblue', label='Load
Addition', legend=True)
sns.lineplot(x='deleted_hour',
y=logistics_df.groupby('deleted_hour').size(
), data=logistics_df, color='salmon', label='Load
Deletion', legend=True)

plt.title('Load Addition and Deletion Over Hours')
plt.xlabel('Hour')
plt.ylabel('Load Count')
plt.legend()
plt.show()
```



Operational Insights

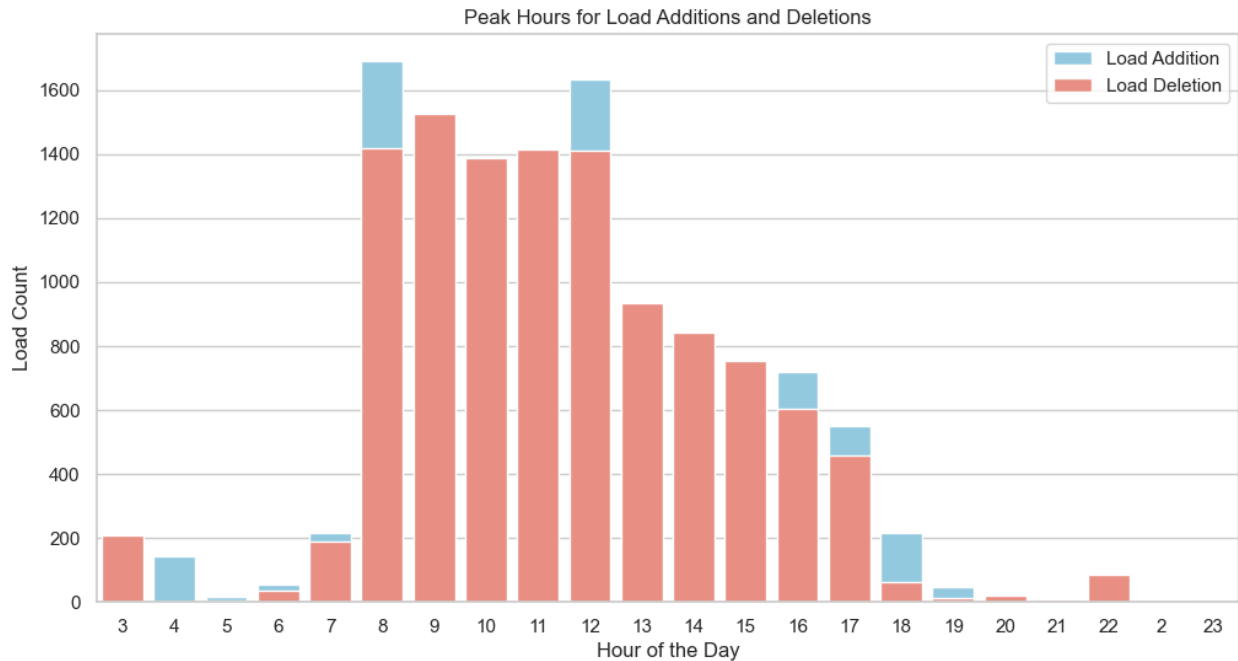
In this analysis, we focus on two key operational insights:

- Peak Periods Identification:**
 - Utilizing time-based analysis, we identify peak periods for both load additions and deletions. Visualization through bar plots highlights the hours of the day with the highest load activity.
- Average Turnaround Time Assessment:**
 - Calculating the average turnaround time for loads provides insights into the typical duration a load stays in the system. This metric aids in understanding operational efficiency and performance.

```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
sns.countplot(x='added_hour', data=logistics_df, color='skyblue',
label='Load Addition')
sns.countplot(x='deleted_hour', data=logistics_df, color='salmon',
label='Load Deletion')

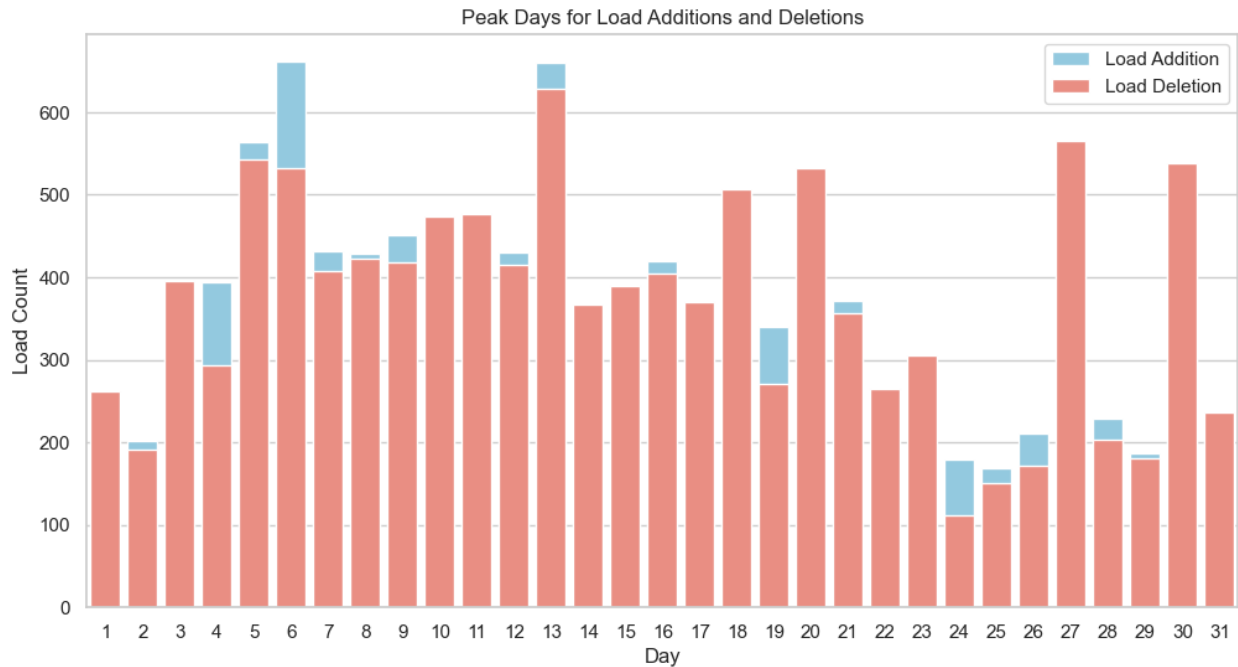
plt.title('Peak Hours for Load Additions and Deletions')
plt.xlabel('Hour of the Day')
plt.ylabel('Load Count')
plt.legend()
plt.show()
```

```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
sns.countplot(x='added_day', data=logistics_df, color='skyblue',
label='Load Addition')
sns.countplot(x='deleted_day', data=logistics_df, color='salmon',
label='Load Deletion')

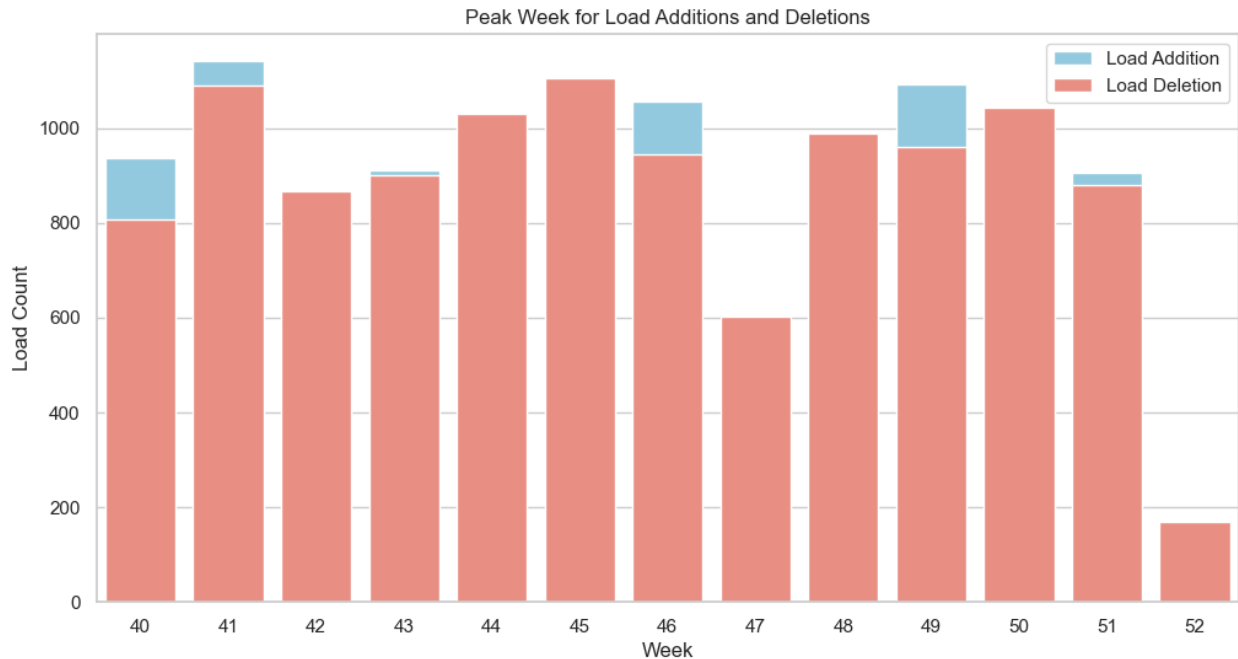
plt.title('Peak Days for Load Additions and Deletions')
plt.xlabel('Day')
plt.ylabel('Load Count')
plt.legend()
plt.show()
```



```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
sns.countplot(x='added_week', data=logistics_df, color='skyblue',
label='Load Addition')
sns.countplot(x='deleted_week', data=logistics_df, color='salmon',
label='Load Deletion')

plt.title('Peak Week for Load Additions and Deletions')
plt.xlabel('Week')
plt.ylabel('Load Count')
plt.legend()
plt.show()
```



```
average_turnaround_time = logistics_df.time_span_in_hours.mean()
```

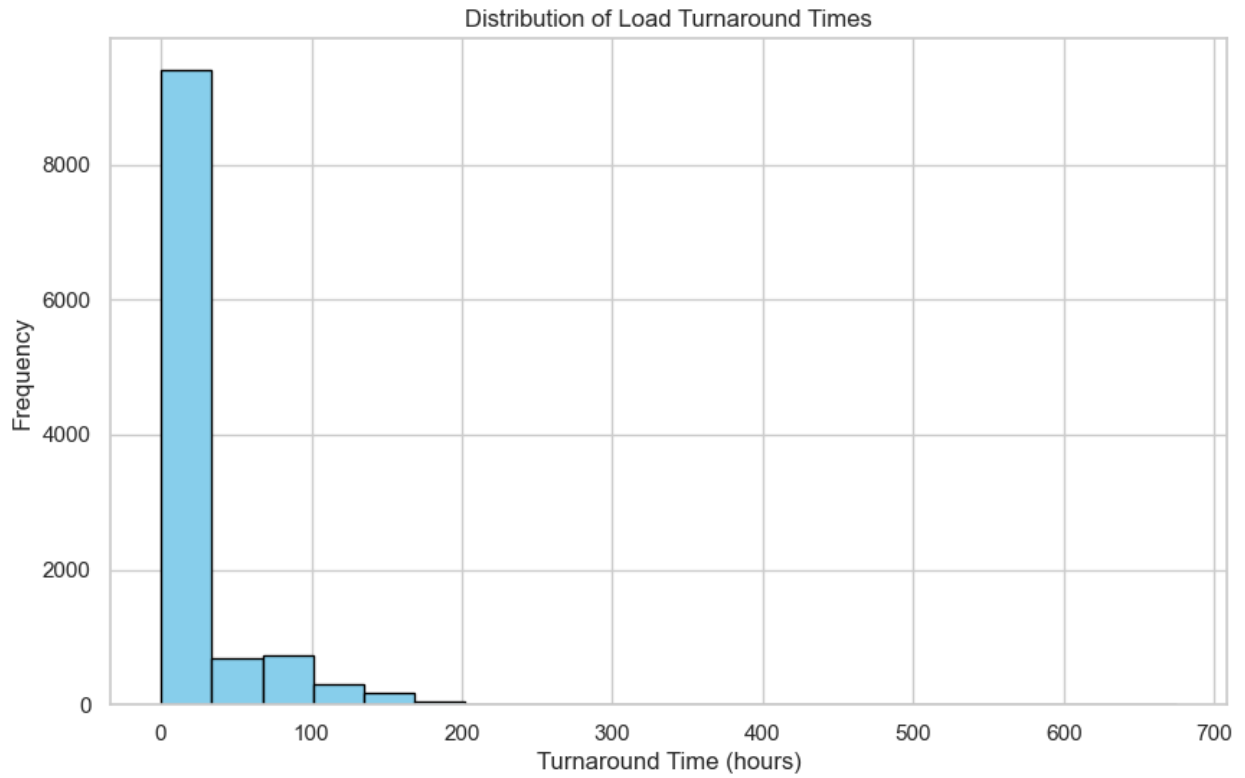
```
df = pd.DataFrame(data={'average_turnaround_time_hours':  
[round(average_turnaround_time)]})  
df
```

```
average_turnaround_time_hours  
0                             21
```

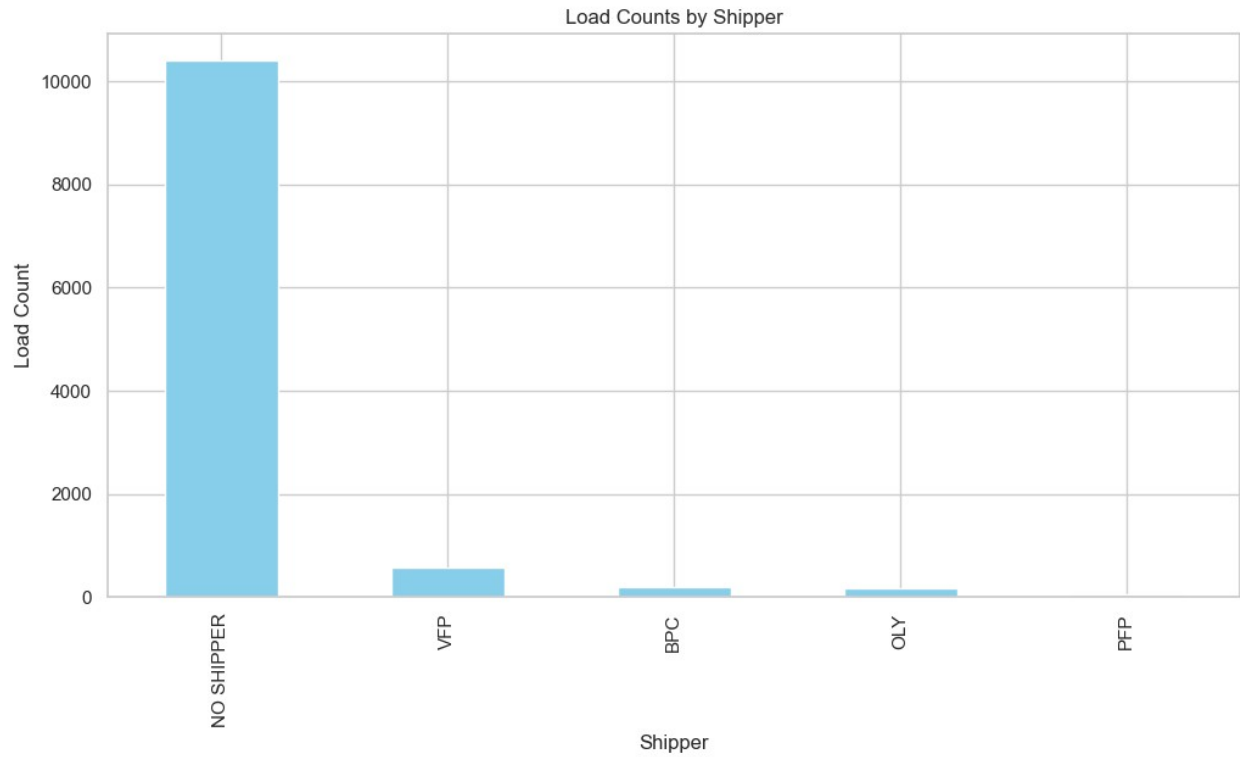
Visualization and Reporting

In this analysis, we leverage visualizations to succinctly convey key findings. Utilizing graphs and charts, we provide a clear and intuitive representation of the dataset's patterns and insights. This visual approach enhances the accessibility and interpretation of the data, facilitating effective communication of our analytical results.

```
plt.figure(figsize=(10, 6))  
plt.hist(logistics_df['time_span_in_hours'], bins=20, color='skyblue',  
edgecolor='black')  
plt.title('Distribution of Load Turnaround Times')  
plt.xlabel('Turnaround Time (hours)')  
plt.ylabel('Frequency')  
plt.show()
```



```
plt.figure(figsize=(12, 6))
logistics_df['shipper'].value_counts().plot(kind='bar',
color='skyblue')
plt.title('Load Counts by Shipper')
plt.xlabel('Shipper')
plt.ylabel('Load Count')
plt.show()
```



```
plt.figure(figsize=(10, 6))
plt.scatter(logistics_df['miles'],
logistics_df['average_rate_per_mile'], color='green')
plt.title('Scatter Plot: Miles vs Average Rate per Mile')
plt.xlabel('Miles')
plt.ylabel('Average Rate per Mile')
plt.show()
```

Scatter Plot: Miles vs Average Rate per Mile

