In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

1. Ingest and Access Data

Reading csv file into pandas dataframe

Note: Due to technical issues in AWS, we had to abort the database instance and hence backed up the data in csv files. To see the code we accessed using PostgreSQL database, refer Data_Analysis_before_backup Notebook.

In [2]:
```
df = pd.read_csv(r'./Data/darwin_backup2.csv')
```

Data Overview

In [3]:
```
df.head()
```

Out[3]:

	route_id	unique_id	service_start_date	update_origin	train_platform	working_time_pass	working_time_arrival	working
0	202407038081744	P81744	2024-07-03	TD	CCRT	NaN	23:17:00	
1	202407038097422	P97422	2024-07-03	TD	ALBNYPK	NaN	23:14:00	
2	202407038097422	P97422	2024-07-03	TD	BEXLEY	NaN	23:16:30	
3	202407037143658	G43658	2024-07-03	TD	SHAL341	NaN	23:29:00	
4	202407037143658	G43658	2024-07-03	TD	SHALFD	NaN	23:34:00	

5 rows × 22 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 415067 entries, 0 to 415066
Data columns (total 22 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   route_id               415067 non-null  int64  
 1   unique_id              415067 non-null  object 
 2   service_start_date     415067 non-null  object 
 3   update_origin          404173 non-null  object 
 4   train_platform         415067 non-null  object 
 5   working_time_pass      0 non-null       float64
 6   working_time_arrival   415067 non-null  object 
 7   working_time_departure 415067 non-null  object 
 8   planned_time_arrival   375170 non-null  object 
 9   planned_time_departure 373563 non-null  object 
 10  actual_arrival_time    346352 non-null  object 
 11  actual_departure_time  384274 non-null  object 
 12  platform               388485 non-null  object 
 13  train_length           147550 non-null  float64
 14  estimated_time         0 non-null       float64
 15  source                 0 non-null       float64
 16  actual_time            0 non-null       float64
 17  actual_time_class      0 non-null       float64
 18  is_delayed_arrival     415067 non-null  object 
 19  is_delayed_departure   415067 non-null  object 
 20  source_instance        0 non-null       float64
 21  estimated_time_minutes 0 non-null       float64
dtypes: float64(8), int64(1), object(13)
memory usage: 69.7+ MB
```

2. Data Cleaning and Pre-processing

Dropping unnecessary columns

In [5]:
```
df = df.drop(['working_time_pass','estimated_time','source','actual_time','actual_time_class',
              'source_instance','estimated_time_minutes','working_time_arrival','working_time_departure'], axis=
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 415067 entries, 0 to 415066
Data columns (total 13 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   route_id               415067 non-null  int64
 1   unique_id              415067 non-null  object
 2   service_start_date     415067 non-null  object
 3   update_origin          404173 non-null  object
 4   train_platform         415067 non-null  object
 5   planned_time_arrival   375170 non-null  object
 6   planned_time_departure 373563 non-null  object
 7   actual_arrival_time    346352 non-null  object
 8   actual_departure_time  384274 non-null  object
 9   platform               388485 non-null  object
 10  train_length           147550 non-null  float64
 11  is_delayed_arrival     415067 non-null  object
 12  is_delayed_departure   415067 non-null  object
dtypes: float64(1), int64(1), object(11)
memory usage: 41.2+ MB
```

Checking for duplicates and dropping them as necessary

In [6]:
```
df.duplicated().sum()
```

Out[6]: 16889

In [7]:
```
df = df.drop_duplicates()
df.duplicated().sum()
```

Out[7]: 0

Reading in a rail reference file to extract the station names for every route

In [8]:
```
df2 = pd.read_csv("./Data/RailReferences.csv")
df2.head()
```

Out[8]:

	AtcoCode	TiplocCode	CrsCode	StationName	StationNameLang	GridType	Easting	Northing	CreationDateTime	Modificat
0	9100PENZNCE	PENZNCE	PNZ	Penzance Rail Station	NaN	U	147588	30599	2003-11-04T00:00:00	2011-09
1	9100STIVES	STIVES	SIV	St Ives (Cornwall) Rail Station	NaN	U	151947	40127	2005-04-04T00:00:00	2011-09
2	9100CARBISB	CARBISB	CBB	Carbis Bay Rail Station	NaN	U	152930	38745	2003-11-04T00:00:00	2011-09
3	9100STERTH	STERTH	SER	St Erth Rail Station	NaN	U	154150	35730	2003-11-04T00:00:00	2007-02
4	9100LELANTS	LELANTS	LTS	Lelant Saltings Rail Station	NaN	U	154430	36640	2003-11-04T00:00:00	2011-09

Dropping Unnecessary columns

In [9]:
```
df2 = df2.drop(["StationNameLang","GridType","AtcoCode","Modification","CreationDateTime","ModificationDateTime
df2
```

Out[9]:

	TiplocCode	StationName	Easting	Northing
0	PENZNCE	Penzance Rail Station	147588	30599
1	STIVES	St Ives (Cornwall) Rail Station	151947	40127
2	CARBISB	Carbis Bay Rail Station	152930	38745
3	STERTH	St Erth Rail Station	154150	35730
4	LELANTS	Lelant Saltings Rail Station	154430	36640
...	...	...	...	...
2623	SMRLYTN	Somerleyton Rail Station	647930	296530
2624	OULTNBS	Oulton Broad South Rail Station	651920	292205
2625	YARMTH	Great Yarmouth Rail Station	652000	308100
2626	OULTNBN	Oulton Broad North Rail Station	652420	293140
2627	LOWSTFT	Lowestoft Rail Station	654747	292890

2628 rows × 4 columns

Merging the rail reference dataframe and main dataframes

In [10]:
```
merged_df = pd.merge(df, df2, left_on='train_platform', right_on='TiplocCode', how='left')
```

Dropping the tiplocCode column

In [11]:
```
df = merged_df.drop(["TiplocCode"],axis = 1)
```

In [12]:
```
df.head()
```

Out[12]:

	route_id	unique_id	service_start_date	update_origin	train_platform	planned_time_arrival	planned_time_departure	act
0	202407038081744	P81744	2024-07-03	TD	CCRT	23:17:00	23:17:00	
1	202407038097422	P97422	2024-07-03	TD	ALBNYPK	23:14:00	23:14:00	
2	202407038097422	P97422	2024-07-03	TD	BEXLEY	23:17:00	23:17:00	
3	202407037143658	G43658	2024-07-03	TD	SHAL341	NaN	NaN	
4	202407037143658	G43658	2024-07-03	TD	SHALFD	NaN	NaN	

Checking for nulls

In [13]:
```
df.isna().sum()
```

Out[13]:
```
route_id                   0
unique_id                  0
service_start_date         0
update_origin           9397
train_platform             0
planned_time_arrival       39538
planned_time_departure     40855
actual_arrival_time        67315
actual_departure_time      29395
platform                   25850
train_length               255400
is_delayed_arrival         0
is_delayed_departure       0
StationName                30672
Easting                    30672
Northing                   30672
dtype: int64
```

Dropping the nulls in Easting and Northing before converting them to Latitude and Longitude

In [14]:
```
df = df.dropna(subset=['Easting', 'Northing'])
```

Installing bng_latlon package to convert northing and easting to latitude and longitude

In [15]:
```
#!pip install bng_latlon
```

Creating a user defined function to convert easting and northing values to longitude and latitude and writing to new columns

In [16]:
```
from bng_latlon import OSGB36toWGS84
def latlong(df):
    lat_long = []
    for i in range(len(df)):
        lat_long.append( OSGB36toWGS84(df[i][0],df[i][1]) )
    return lat_long
df['Easting'] = df['Easting'].astype('int64')
df['Northing'] = df['Northing'].astype('int64')
df1 = df [['Easting','Northing']]
values = (df1.values)
lat_long = latlong(values)
#Writing to dataframe
lat = []
long = []
for i in range(len(lat_long)):
    lat.append(lat_long[i][0])
    long.append(lat_long[i][1])

df['Latitude'] = lat
df['Longitude'] = long
```

Creating a new dataframe that drops all null values

In [17]:
```
na_df = df.dropna()
```

In [18]:
```
df = na_df
```

In [19]:
```
#getting an overview of the amount of rows dropped and if we should continue with the null dropped dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 103887 entries, 2 to 395480
Data columns (total 18 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   route_id               103887 non-null  int64
 1   unique_id              103887 non-null  object
 2   service_start_date     103887 non-null  object
 3   update_origin          103887 non-null  object
 4   train_platform         103887 non-null  object
 5   planned_time_arrival   103887 non-null  object
 6   planned_time_departure 103887 non-null  object
 7   actual_arrival_time    103887 non-null  object
 8   actual_departure_time  103887 non-null  object
 9   platform               103887 non-null  object
 10  train_length           103887 non-null  float64
 11  is_delayed_arrival     103887 non-null  object
 12  is_delayed_departure   103887 non-null  object
 13  StationName            103887 non-null  object
 14  Easting                103887 non-null  int64
 15  Northing               103887 non-null  int64
 16  Latitude               103887 non-null  float64
 17  Longitude              103887 non-null  float64
dtypes: float64(3), int64(3), object(12)
memory usage: 15.1+ MB
```

After dropping data we are left with ~100,000 datapoints which is ~25% of our total data we started. Observing the volume of the data, we believe this is significant for our analysis.

Correcting column data types

Changing the column type of the route_id appropriately for further analysis

In [20]:
```
df['route_id'] = df['route_id'].astype(str)
```

Changing the column type of the is_delayed_arrival and is_delayed_departure to boolean

In [21]:
```
df['is_delayed_arrival'] = np.where(df['is_delayed_arrival'] == "f", False, True)
```

In [22]:
```
df['is_delayed_arrival'].value_counts()
```

Out[22]:
```
is_delayed_arrival
False    94854
True      9033
Name: count, dtype: int64
```

In [23]:
```
df['is_delayed_arrival'].dtype
```

Out[23]:
```
dtype('bool')
```

In [24]:
```
df['is_delayed_departure'] = np.where(df['is_delayed_departure'] == "f", False, True)
```

In [25]:
```
df['is_delayed_departure'].value_counts()
```

Out[25]:
```
is_delayed_departure
False    94850
True      9037
Name: count, dtype: int64
```

In [26]:
```
df['is_delayed_departure'].dtype
```

Out[26]:
```
dtype('bool')
```

Changing all dates or time columns to the correct data type.

In [27]:
```
from datetime import time
#changing the columns with dates to datetime objects
df['service_start_date'] = pd.to_datetime(df['service_start_date'])
df['planned_time_arrival'] = pd.to_datetime(df['planned_time_arrival'], format='%H:%M:%S').dt.time
df['planned_time_departure'] = pd.to_datetime(df['planned_time_departure'], format='%H:%M:%S').dt.time
df['actual_arrival_time'] = pd.to_datetime(df['actual_arrival_time'], format='%H:%M:%S').dt.time
df['actual_departure_time'] = pd.to_datetime(df['actual_departure_time'], format='%H:%M:%S').dt.time
```

Converting all time columns to datetime objects with the service_start_date as the date combined with the timestamp

In [28]:
```
from datetime import datetime
from datetime import timedelta
df['actual_departure_time'] = df.apply(lambda row: datetime.combine(row['service_start_date'].date(), row['actua
df['planned_time_departure'] = df.apply(lambda row: datetime.combine(row['service_start_date'].date(), row['plan
df['planned_time_arrival'] = df.apply(lambda row: datetime.combine(row['service_start_date'].date(), row['planne
df['actual_arrival_time'] = df.apply(lambda row: datetime.combine(row['service_start_date'].date(), row['actual_
```

In [29]:
```
df.dtypes
```

Out[29]:
```
route_id                        object
unique_id                       object
service_start_date      datetime64[ns]
update_origin                   object
train_platform                  object
planned_time_arrival    datetime64[ns]
planned_time_departure  datetime64[ns]
actual_arrival_time     datetime64[ns]
actual_departure_time   datetime64[ns]
platform                        object
train_length                   float64
is_delayed_arrival                bool
is_delayed_departure              bool
StationName                     object
Easting                          int64
Northing                         int64
Latitude                       float64
Longitude                      float64
dtype: object
```

Creating user defined functions to check for cases of dates arrival times or actual departure times taking place the day after the service start day, and add a day to the column values

In [30]:
```
from datetime import datetime
from datetime import timedelta

#Adding service_start_date to time objects to get a datetime for every time column
def change_actual_departure(row):
    #Check if times occur after the initial service start day and correcting their date to the next day
    if row['actual_departure_time'] < row['planned_time_departure']:
        return row['actual_departure_time'] + timedelta(days=1)
    return row['actual_departure_time']

def change_arrival(row):
    #Check if times occur after the initial service start day and correcting their date to the next day
    if row['actual_arrival_time'] < row['planned_time_arrival']:
        return row['actual_arrival_time'] + timedelta(days=1)
    return row['actual_arrival_time']

df['actual_departure_time'] = df.apply(change_actual_departure, axis=1)
df['actual_arrival_time'] = df.apply(change_arrival, axis=1)
```

Creating a calculated time difference column for calculating delayed departure and arrival minutes

In [31]:
```
df['actual_vs_planned_arrival'] = df['actual_arrival_time'] - df['planned_time_arrival']
df['actual_vs_planned_departure'] = df['actual_departure_time'] - df['planned_time_departure']
```

Creating delayed arrival and delayed departure minutes column

In [32]:
```
df['delayed_arrival_min'] = (df['actual_vs_planned_arrival'].dt.total_seconds() / 60)
df['delayed_departure_min'] = (df['actual_vs_planned_departure'].dt.total_seconds() / 60)
```

Function to calculate origin and destination for each trip

In [33]:
```
def calculate_origin_destination(group):
    origin = group.iloc[0]['StationName']
    destination = group.iloc[-1]['StationName']
    return pd.Series({
        'Origin': origin,
        'Destination': destination
    })

# Group by route_id, unique_id, and service_start_date, then apply the function to calculate origin and destina
origin_destination = df.groupby(['route_id', 'unique_id', 'service_start_date']).apply(calculate_origin_destina

#Joining into original dataframe
df = df.merge(origin_destination, on=['route_id', 'unique_id', 'service_start_date'], how='left')
```

In [34]:
```
df2 = pd.read_excel(r'./Data/2.Passenger_population_station_TOC_2023.xlsx')
df2['StationName'] = df2['StationName'] + ' Rail Station'
```

In [35]:
```
merge = df2[['StationName','Operator']]
df = pd.merge(df,merge,left_on='StationName',right_on='StationName',how='left')
df.head()
```

Out[35]:

	route_id	unique_id	service_start_date	update_origin	train_platform	planned_time_arrival	planned_time_departure	act
0	202407038097422	P97422	2024-07-03	TD	BEXLEY	2024-07-03 23:17:00	2024-07-03 23:17:00	
1	202407037139898	G39898	2024-07-03	CIS	BOXHAWH	2024-07-03 23:18:00	2024-07-03 23:18:00	
2	202407037154196	G54196	2024-07-03	CIS	HYWRDSH	2024-07-03 23:16:00	2024-07-03 23:17:00	
3	202407037154196	G54196	2024-07-03	CIS	THBDGS	2024-07-03 23:28:00	2024-07-03 23:29:00	
4	202407037150851	G50851	2024-07-03	TD	HRPNDN	2024-07-03 23:22:00	2024-07-03 23:22:00	

5 rows × 25 columns

In [36]:
```
df = df.dropna()
```

Getting an overview of the data before exporting to csv file.

In [37]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 93416 entries, 0 to 103886
Data columns (total 25 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   route_id                     93416 non-null  object
 1   unique_id                    93416 non-null  object
 2   service_start_date           93416 non-null  datetime64[ns]
 3   update_origin                93416 non-null  object
 4   train_platform               93416 non-null  object
 5   planned_time_arrival         93416 non-null  datetime64[ns]
 6   planned_time_departure       93416 non-null  datetime64[ns]
 7   actual_arrival_time          93416 non-null  datetime64[ns]
 8   actual_departure_time        93416 non-null  datetime64[ns]
 9   platform                     93416 non-null  object
 10  train_length                 93416 non-null  float64
 11  is_delayed_arrival           93416 non-null  bool
 12  is_delayed_departure         93416 non-null  bool
 13  StationName                  93416 non-null  object
 14  Easting                      93416 non-null  int64
 15  Northing                     93416 non-null  int64
 16  Latitude                     93416 non-null  float64
 17  Longitude                    93416 non-null  float64
 18  actual_vs_planned_arrival    93416 non-null  timedelta64[ns]
 19  actual_vs_planned_departure  93416 non-null  timedelta64[ns]
 20  delayed_arrival_min          93416 non-null  float64
 21  delayed_departure_min        93416 non-null  float64
 22  Origin                       93416 non-null  object
 23  Destination                  93416 non-null  object
 24  Operator                     93416 non-null  object
dtypes: bool(2), datetime64[ns](5), float64(5), int64(2), object(9), timedelta64[ns](2)
memory usage: 17.3+ MB
```

In [38]:
```
df.head()
```

Out[38]:

	route_id	unique_id	service_start_date	update_origin	train_platform	planned_time_arrival	planned_time_departure	act
0	202407038097422	P97422	2024-07-03	TD	BEXLEY	2024-07-03 23:17:00	2024-07-03 23:17:00	
2	202407037154196	G54196	2024-07-03	CIS	HYWRDSH	2024-07-03 23:16:00	2024-07-03 23:17:00	
3	202407037154196	G54196	2024-07-03	CIS	THBDGS	2024-07-03 23:28:00	2024-07-03 23:29:00	
4	202407037150851	G50851	2024-07-03	TD	HRPNDN	2024-07-03 23:22:00	2024-07-03 23:22:00	
5	202407037150851	G50851	2024-07-03	TD	LUTOAPY	2024-07-03 23:27:00	2024-07-03 23:28:00	

5 rows × 25 columns

In [39]:
```
df.describe()
```

Out[39]:

	service_start_date	planned_time_arrival	planned_time_departure	actual_arrival_time	actual_departure_time	train_length
count	93416	93416	93416	93416	93416	93416.000000
mean	2024-07-07 04:01:46.054637056	2024-07-07 18:36:28.970411776	2024-07-07 18:36:57.866960640	2024-07-07 18:40:21.670163712	2024-07-07 18:40:58.209942528	7.155359
min	2024-07-03 00:00:00	2024-07-03 00:01:00	2024-07-03 00:01:00	2024-07-03 00:01:00	2024-07-03 00:01:00	2.000000
25%	2024-07-06 00:00:00	2024-07-06 06:31:00	2024-07-06 06:32:00	2024-07-06 06:33:00	2024-07-06 06:34:00	4.000000
50%	2024-07-07 00:00:00	2024-07-07 18:12:00	2024-07-07 18:12:00	2024-07-07 18:13:00	2024-07-07 18:14:00	8.000000
75%	2024-07-09 00:00:00	2024-07-09 10:48:00	2024-07-09 10:48:15	2024-07-09 10:54:00	2024-07-09 10:55:00	8.000000
max	2024-07-11 00:00:00	2024-07-11 06:58:00	2024-07-11 06:59:00	2024-07-11 06:58:00	2024-07-11 06:59:00	12.000000
std	NaN	NaN	NaN	NaN	NaN	2.809688

Exporting the dataframe into a csv file for use in PowerBI or other requirements

In [40]:
```
df.to_csv('./Data/cleanRailData.csv', index=False)
```

3. Delay Prediction Model

Calculating Journey time for each trip

In [41]:
```
# Group by 'route_id', 'unique_id', 'service_start_date', 'origin', and 'destination'
grouped = df.groupby(['route_id', 'unique_id', 'service_start_date', 'Origin', 'Destination'])
# Calculate earliest and latest arrival times within each group
journey_times = grouped['actual_arrival_time'].agg(EarliestArrival='min', LatestArrival='max')
# Calculate the journey time in minutes
journey_times['Journey_Time'] = (journey_times['LatestArrival'] - journey_times['EarliestArrival']).dt.total_se
# Reset index to make it easier to work with
journey_times = journey_times.reset_index()
journey_times.head()
```

Out[41]:

	route_id	unique_id	service_start_date	Origin	Destination	EarliestArrival	LatestArrival	Journey_Time
0	202407036700008	C00008	2024-07-03	Irlam Rail Station	Irlam Rail Station	2024-07-03 23:24:00	2024-07-03 23:24:00	0.0
1	202407036706303	C06303	2024-07-03	Bicester North Rail Station	Bicester North Rail Station	2024-07-03 23:29:00	2024-07-03 23:29:00	0.0
2	202407036706305	C06305	2024-07-03	Wembley Stadium Rail Station	Wembley Stadium Rail Station	2024-07-03 23:17:00	2024-07-03 23:17:00	0.0
3	202407036716226	C16226	2024-07-03	Princes Risborough Rail Station	Princes Risborough Rail Station	2024-07-03 23:22:00	2024-07-03 23:22:00	0.0
4	202407036732817	C32817	2024-07-03	Limehouse Rail Station	Limehouse Rail Station	2024-07-03 23:19:00	2024-07-03 23:19:00	0.0

Creating model dataframe and merging on Journey time values

In [42]:
```
model_df = df[['unique_id','train_length','Operator', 'is_delayed_arrival' ]]

model_df = pd.merge(model_df, journey_times, left_on='unique_id', right_on='unique_id', how='left')
model_df.head()
```

Out[42]:

	unique_id	train_length	Operator	is_delayed_arrival	route_id	service_start_date	Origin	Destination	EarliestArri
0	P97422	8.0	Southeastern	False	202407038097422	2024-07-03	Bexley Rail Station	Bexley Rail Station	2024-07 23:18
1	P97422	8.0	Southeastern	False	202407048097422	2024-07-04	Hither Green Rail Station	Hither Green Rail Station	2024-07 22:59
2	P97422	8.0	Southeastern	False	202407098097422	2024-07-09	London Waterloo East Rail Station	London Waterloo East Rail Station	2024-07 22:39
3	P97422	8.0	Southeastern	False	202407108097422	2024-07-10	Lewisham Rail Station	Crayford Rail Station	2024-07 22:58
4	G54196	12.0	Govia Thameslink Railway (Southern)	False	202407037154196	2024-07-03	Haywards Heath Rail Station	Three Bridges Rail Station	2024-07 23:17

Dropping columns in model_df that are no longer needed for the model

In [43]:
```
model_df = model_df.drop(columns=['route_id','unique_id','service_start_date','Origin',"Destination",'EarliestA
model_df
```

Out[43]:

	train_length	Operator	is_delayed_arrival	Journey_Time
0	8.0	Southeastern	False	0.0
1	8.0	Southeastern	False	0.0
2	8.0	Southeastern	False	0.0
3	8.0	Southeastern	False	25.0
4	12.0	Govia Thameslink Railway (Southern)	False	12.0
...	...	...	...	...
228186	12.0	Govia Thameslink Railway (Thameslink)	False	78.0
228187	12.0	Govia Thameslink Railway (Thameslink)	False	131.0
228188	12.0	Govia Thameslink Railway (Thameslink)	False	157.0
228189	12.0	Govia Thameslink Railway (Thameslink)	False	78.0
228190	12.0	Govia Thameslink Railway (Thameslink)	False	131.0

228191 rows × 4 columns

Creating Dummy Columns for Operator Values

In [44]:
```
model_df = pd.get_dummies(model_df, columns= ['Operator'],dtype=int)
model_df.head()
```

Out[44]:

	train_length	is_delayed_arrival	Journey_Time	Operator_Avanti West Coast	Operator_Chiltern Railways	Operator_East Midlands Railway	Operator_Elizabeth line	Operator_ Tham Ra (Ga Exp
0	8.0	False	0.0	0	0	0	0	
1	8.0	False	0.0	0	0	0	0	
2	8.0	False	0.0	0	0	0	0	
3	8.0	False	25.0	0	0	0	0	
4	12.0	False	12.0	0	0	0	0	

5 rows × 29 columns

Splitting the data into the training and test sets

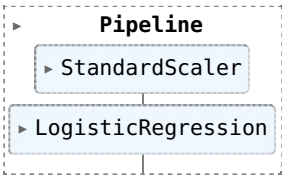
In [45]:
```
from sklearn.model_selection import train_test_split
# separate features and target
X = model_df.drop("is_delayed_arrival", axis=1)
y = model_df["is_delayed_arrival"]
```

```
# split data into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=12)
```

Creating the model

In [46]:
```
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler

pipe = make_pipeline(StandardScaler(), LogisticRegression(solver='liblinear'))
pipe.fit(X_train, y_train)  # apply scaling on training data
```

Out[46]:



Checking the accuracy of the model

In [47]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

y_pred = pipe.predict(X_test)
accuracy_score(y_pred, y_test)
```

Out[47]:
```
0.9124614894295123
```

The model predicted an accuracy of 91.25%

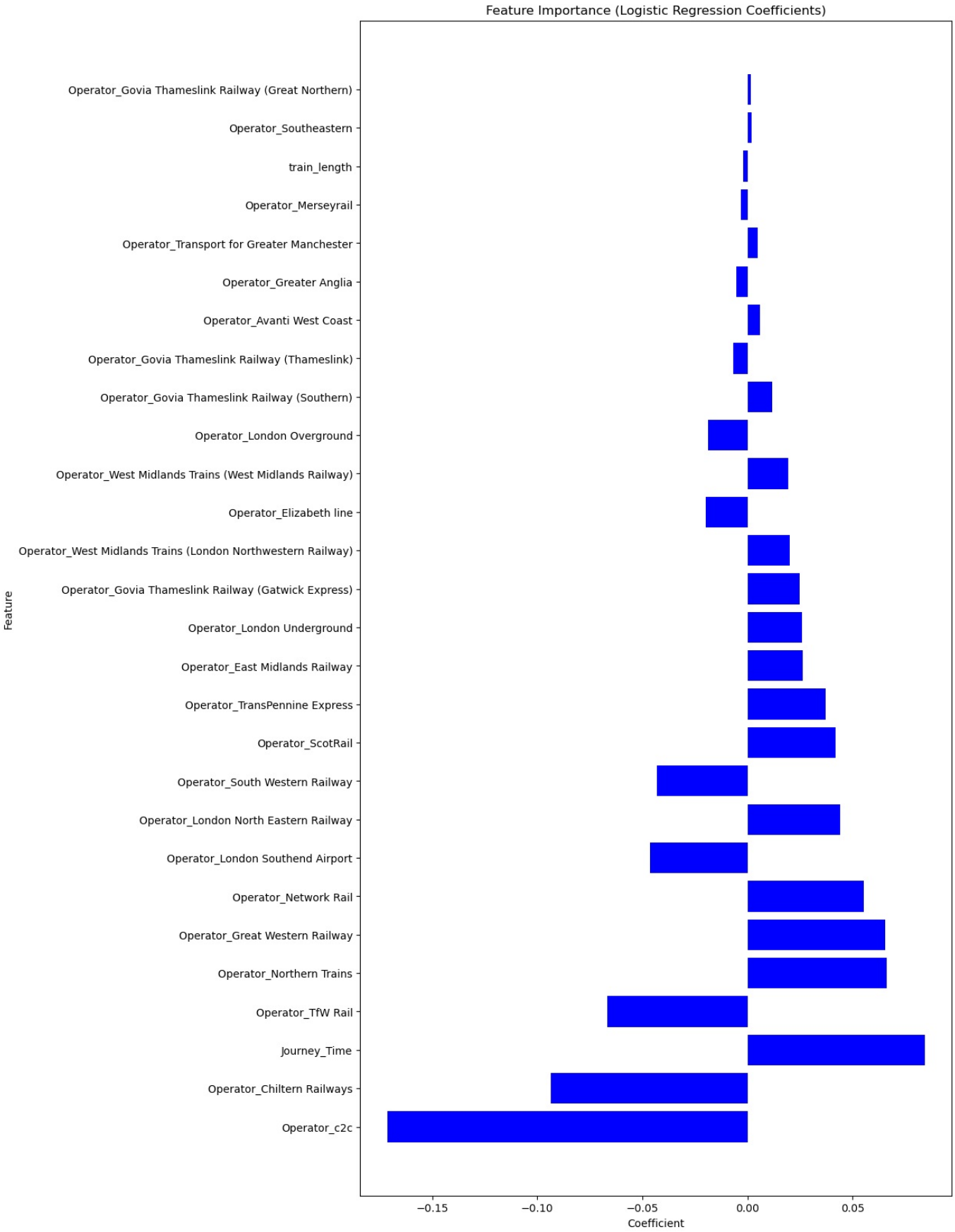
Accuracy Report

In [48]:
```
predictions = pipe.predict(X_test)

print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

       False       0.91      1.00      0.95     68712
        True       0.00      0.00      0.00      6592

    accuracy                           0.91     75304
   macro avg       0.46      0.50      0.48     75304
weighted avg       0.83      0.91      0.87     75304
```

Visualizing Feature Importance on predicting the delay of arrival

In [49]:
```
# Get the model from the pipeline
model = pipe.named_steps['logisticregression']

# Get feature names from the DataFrame
feature_names = X.columns

# Get the coefficients of the logistic regression model
coefficients = model.coef_[0]

# Create a DataFrame for easy handling
coef_df = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': coefficients,
})

# Sort by the absolute values of the coefficients
coef_df = coef_df.reindex(coef_df.Coefficient.abs().sort_values(ascending=False).index)

# Plot
plt.figure(figsize=(10, 20))
plt.barh(coef_df['Feature'], coef_df['Coefficient'], color='b')
plt.xlabel('Coefficient')
plt.ylabel('Feature')
plt.title('Feature Importance (Logistic Regression Coefficients)')
plt.show()
```



As seen in the graph, Journey_Time seems to have the highest coefficent to delayed arrival, while Operator_c2c has the lowest coefficent meaning that Journey_Time has a high impact on delay chances.

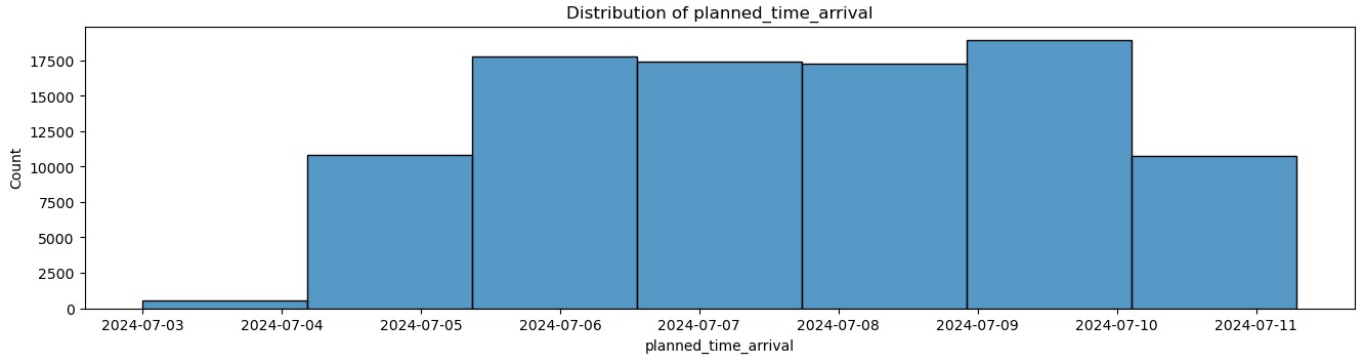
4. Data Visualization

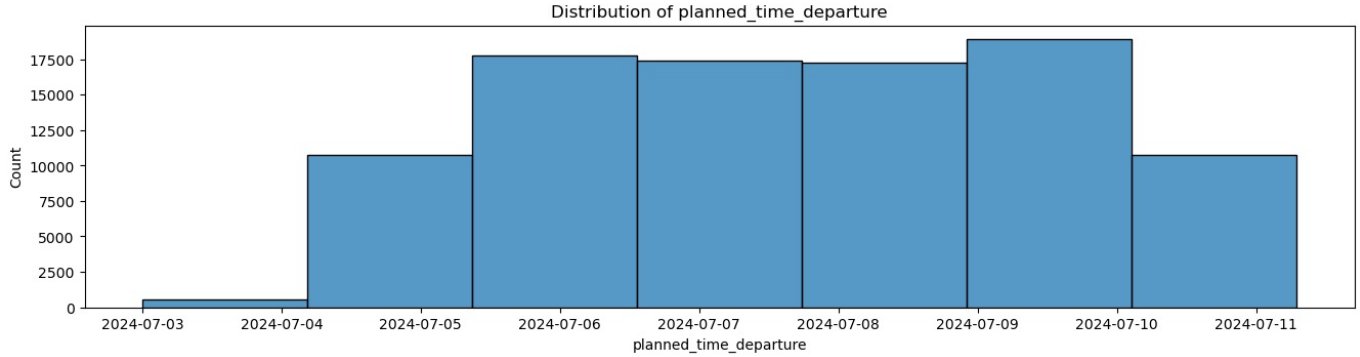
In [50]:
```
#importing libraries
import matplotlib.pyplot as plt
import seaborn as sns
```

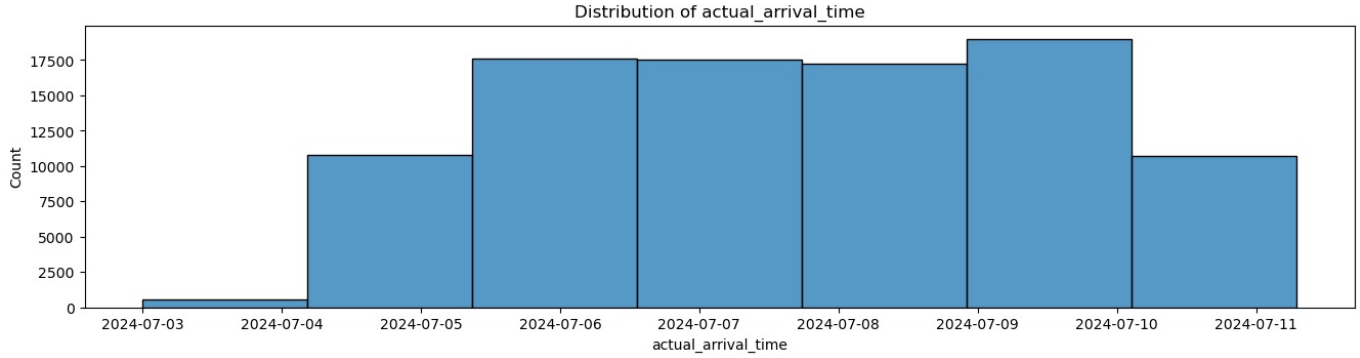
Distribution of Categorical and Numerical Data

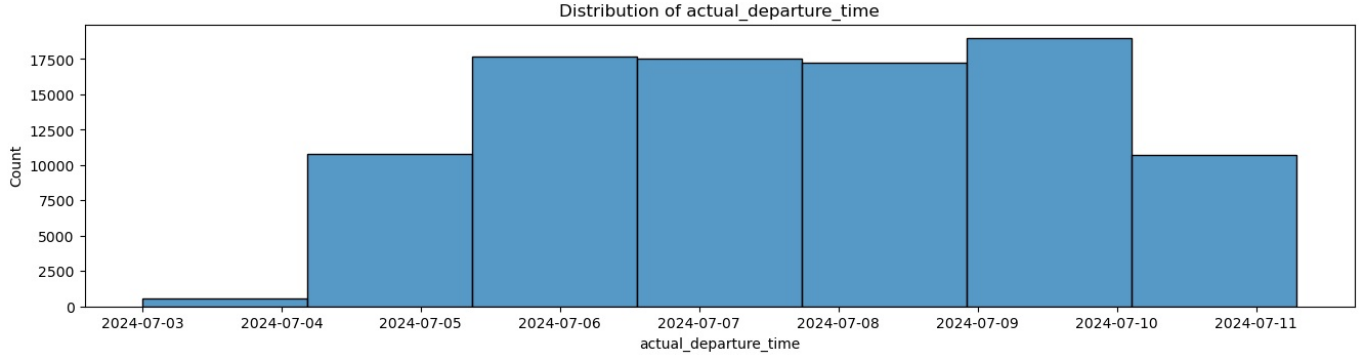
Numerical Data

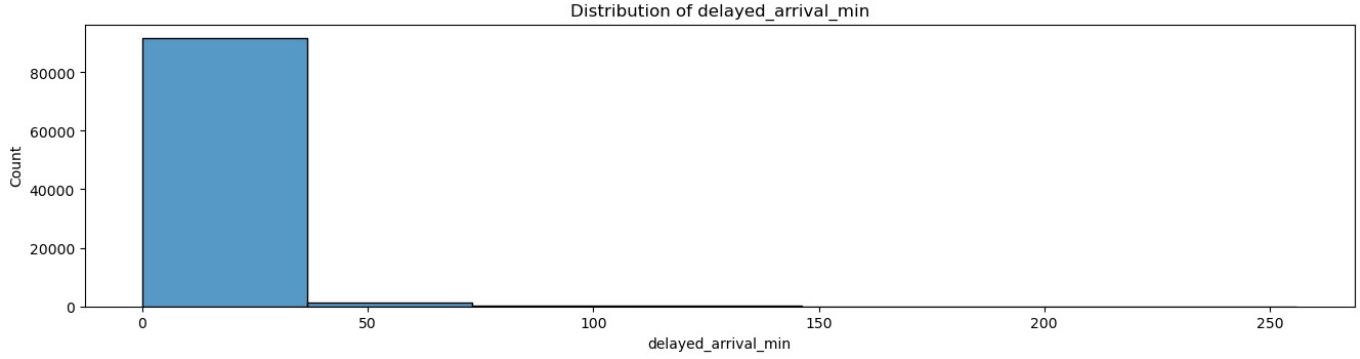
In [51]:
```
numerical_cols = ['planned_time_arrival', 'planned_time_departure', 'actual_arrival_time', 'actual_departure_ti
                  'delayed_arrival_min', 'delayed_departure_min']
subplot_index = 1
for col in numerical_cols:
    plt.figure(figsize=(16, 25))
    plt.subplot(len(numerical_cols),1,subplot_index)
    sns.histplot(df[col], bins=7)
    plt.title(f'Distribution of {col}')
    plt.show()
```

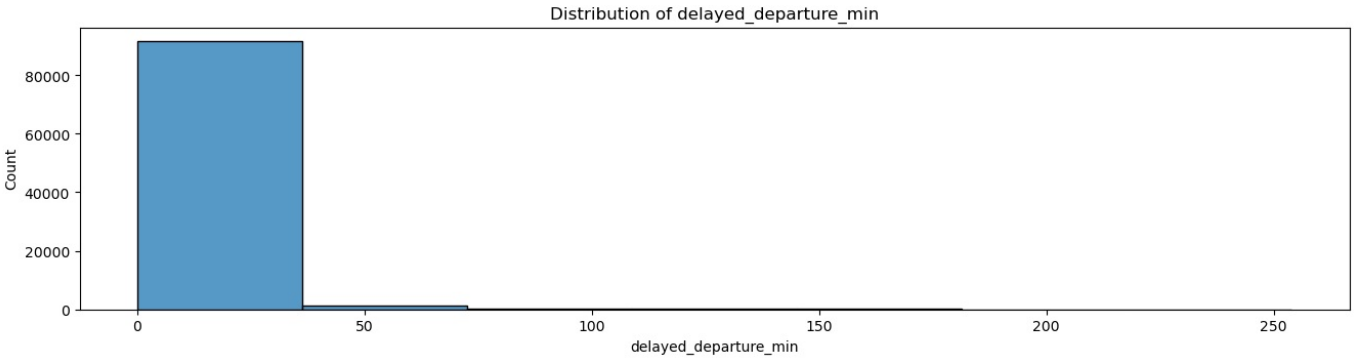






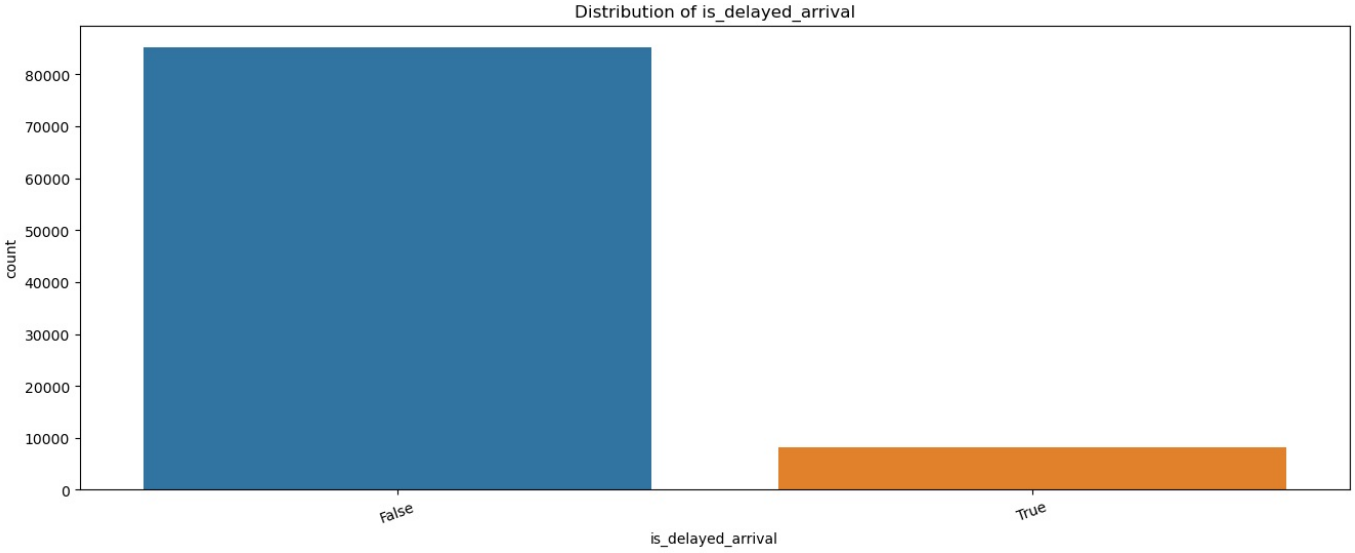


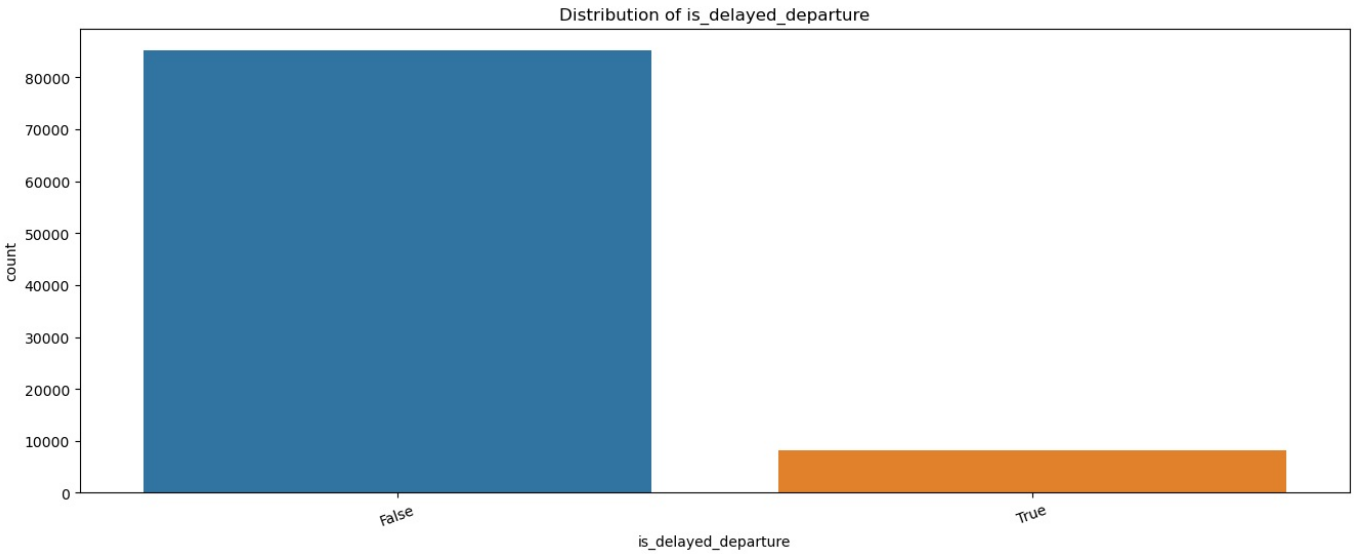


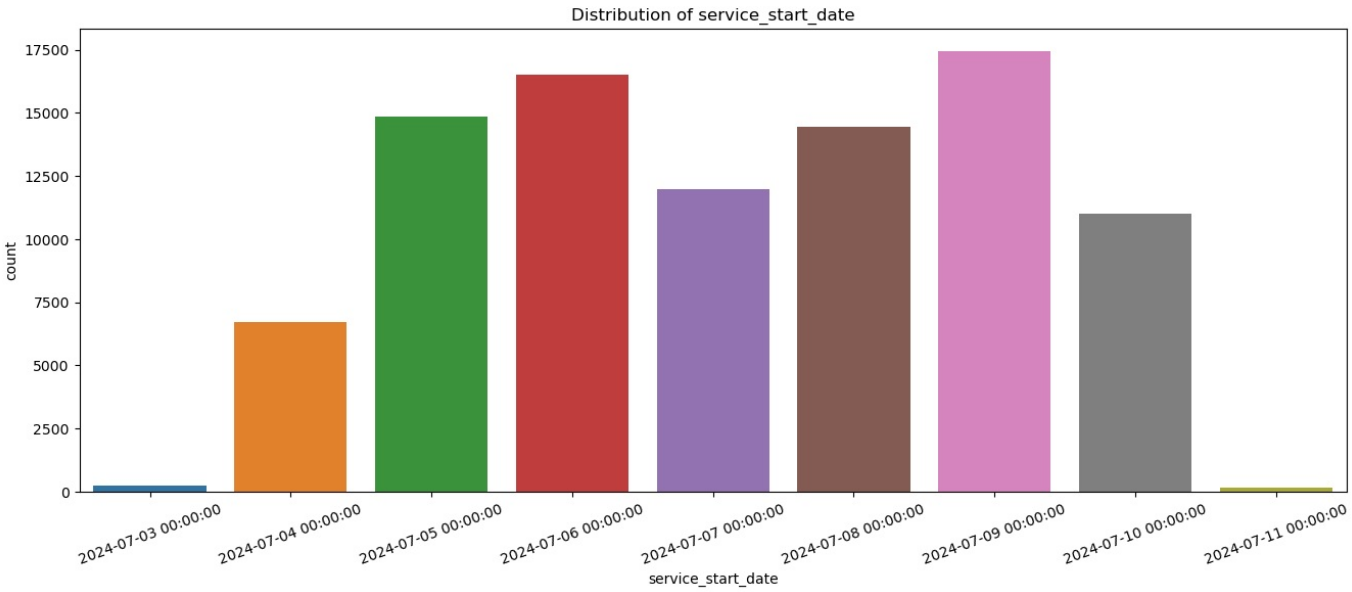


Categorical data

In [52]:
```
categorical_cols = ['is_delayed_arrival', 'is_delayed_departure','service_start_date']
#histograms for categorical variables
subplot_index = 1
for col in categorical_cols:
    plt.figure(figsize=(16, 20))
    plt.subplot(len(categorical_cols),1,subplot_index)
    sns.countplot(x=col, data=df)
    plt.title(f'Distribution of {col}')
    plt.xticks(rotation = 20)
    plt.show()
```

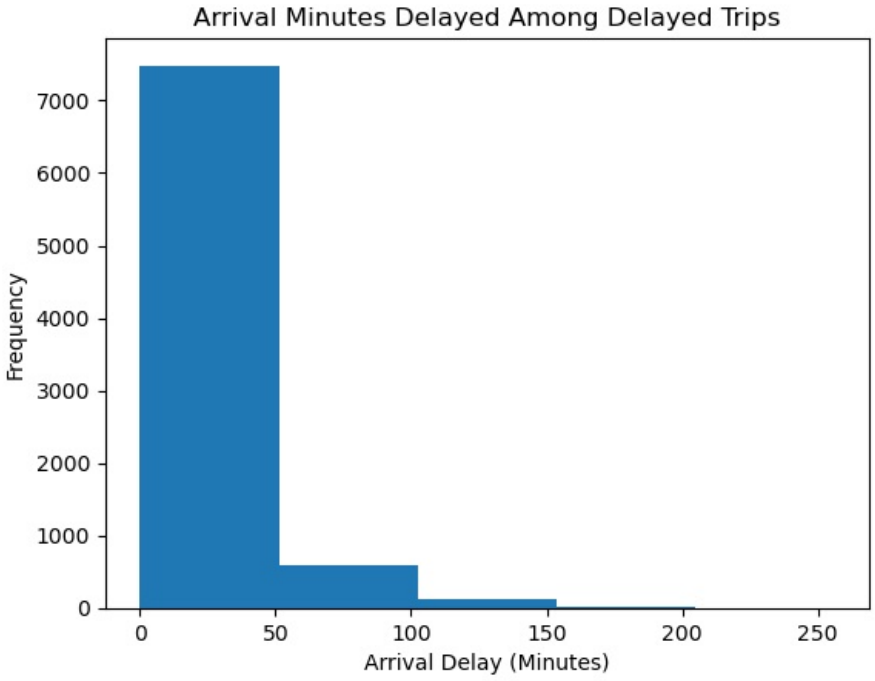






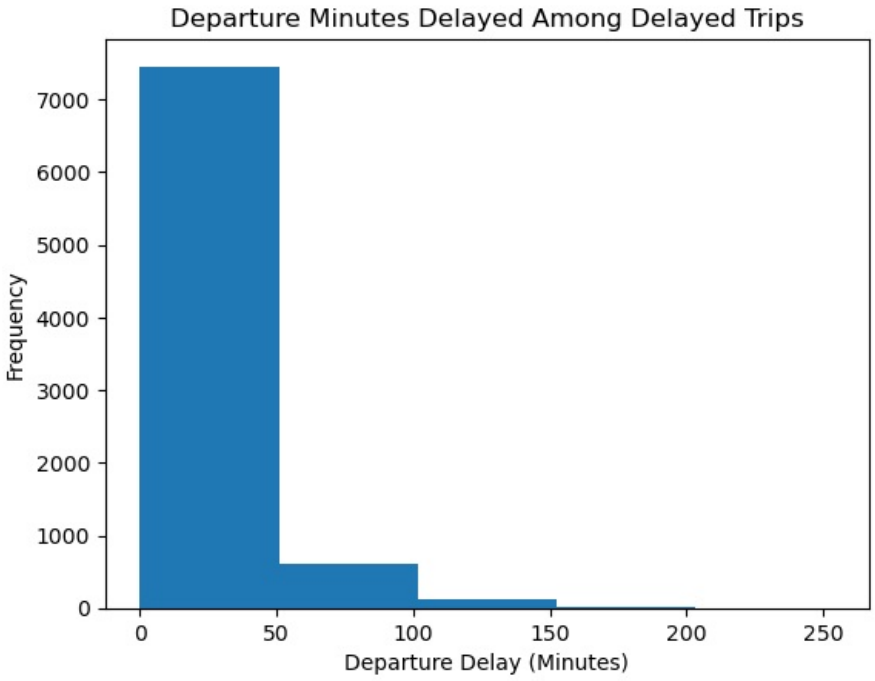
What is the distribution of if there is an actual delay in arrival and departure?

In [53]:
```
#creating a df with only delayed arrival trains
delayed_arrivals = df[df['is_delayed_arrival'] == True]
# Plotting the histogram using matplotlib
plt.hist(delayed_arrivals['delayed_arrival_min'], bins=5)

# Adding titles and labels
plt.title('Arrival Minutes Delayed Among Delayed Trips')
plt.xlabel('Arrival Delay (Minutes)')
plt.ylabel('Frequency')
plt.show()
```



In [54]:
```
#creating a df with only delayed departure trains
delayed_departures = df[df['is_delayed_departure'] == True]
# Plotting the histogram using matplotlib
plt.hist(delayed_arrivals['delayed_departure_min'], bins=5)

# Adding titles and labels
plt.title('Departure Minutes Delayed Among Delayed Trips')
```

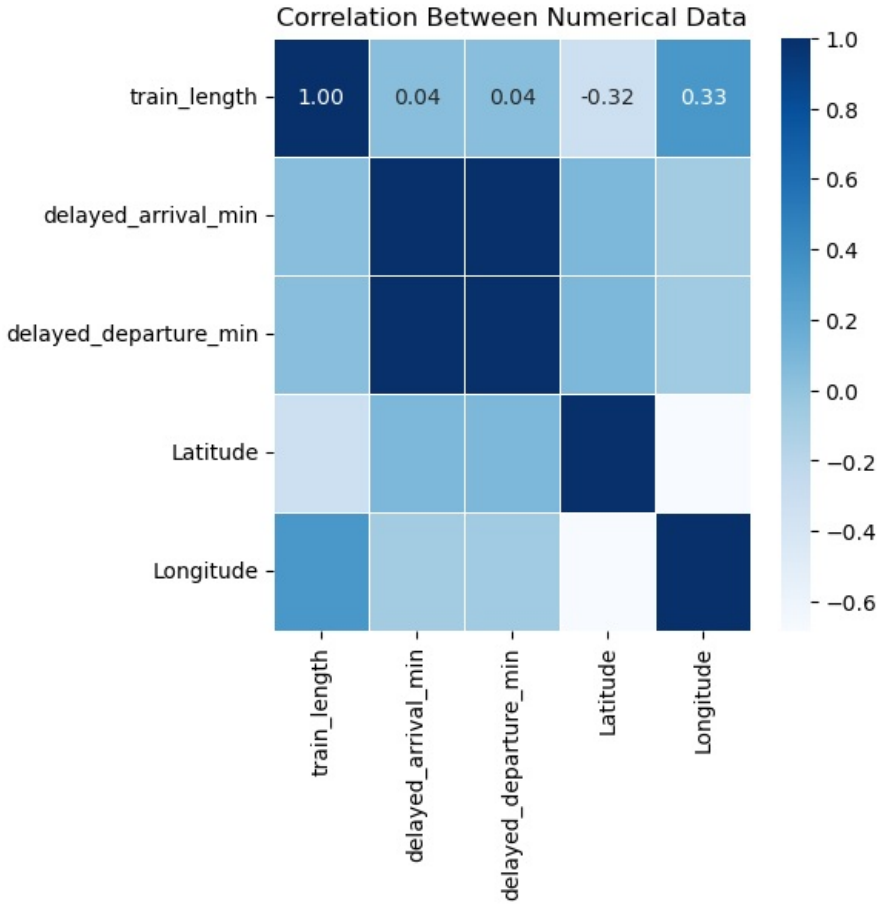
```
plt.xlabel('Departure Delay (Minutes)')
plt.ylabel('Frequency')
plt.show()
```



5. Analysis

1. Correlation Analysis among numerical data

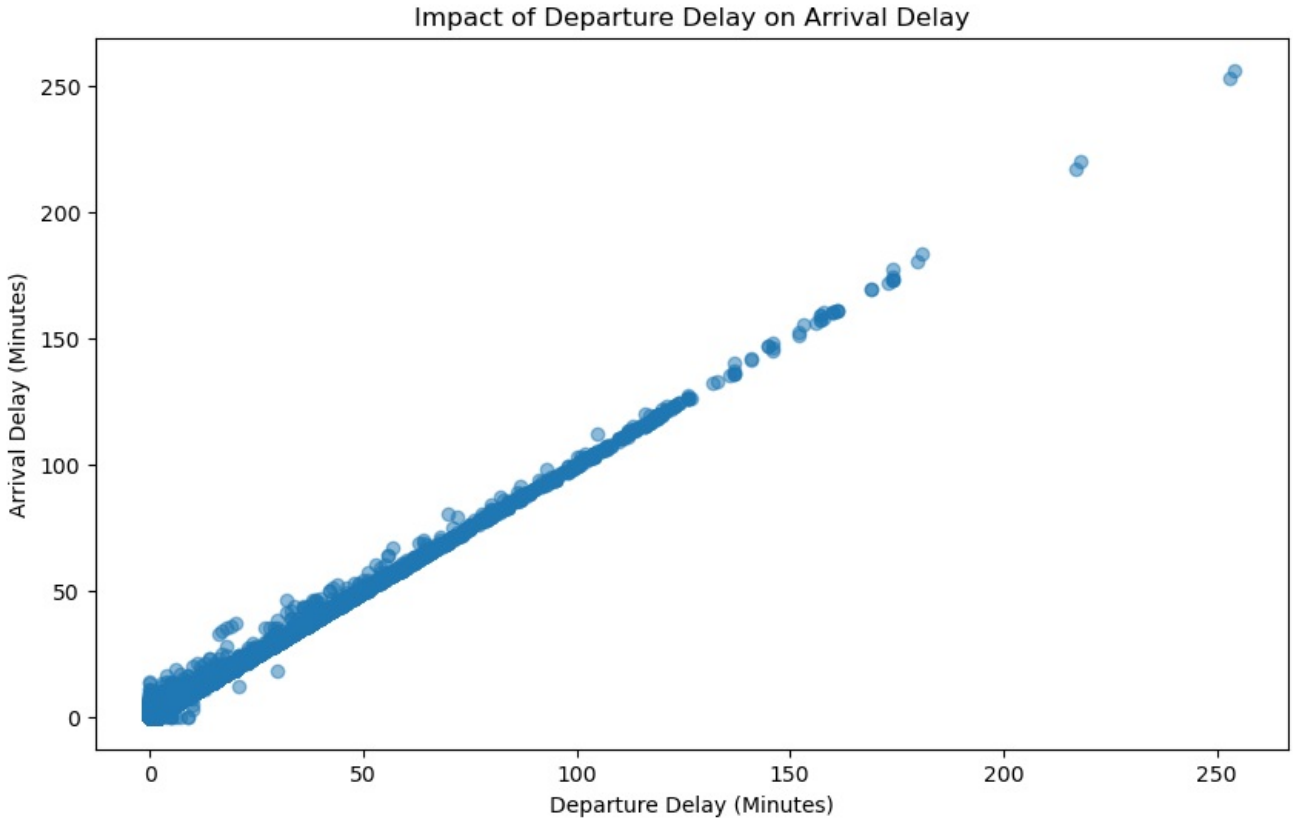
In [55]:
```
df1 = df[['train_length', 'delayed_arrival_min', 'delayed_departure_min', 'Latitude', 'Longitude']]
corr_matrix = df1.corr()

# Create a correlation heatmap
plt.figure(figsize=(5, 5))
sns.heatmap(corr_matrix, annot=True, cmap='Blues', fmt='.2f', linewidths=0.5)
plt.title('Correlation Between Numerical Data')
plt.show()
```



We found an absolute correlation between arrival delay and departure delay and decided to make a scatter plot to visualize the impact of

Departure Delay on Arrival time.

In [56]:
```
plt.figure(figsize=(10,6))
plt.scatter(df['delayed_departure_min'], df['delayed_arrival_min'], alpha=0.5)
plt.xlabel('Departure Delay (Minutes)')
plt.ylabel('Arrival Delay (Minutes)')
plt.title('Impact of Departure Delay on Arrival Delay')
plt.show()
```



This strong correlation of 1.00 shows that departure delay is significantly impacting the arrival time.

Gathered external data to find insights for our questions.

Source: https://dataportal.orr.gov.uk/

2. Which stations are the most Busiest accessed by public?

In [57]:
```
df2 = pd.read_excel(r'./Data/2.Passenger_population_station_TOC_2023.xlsx')
```

In [58]:
```
df2.head()
```

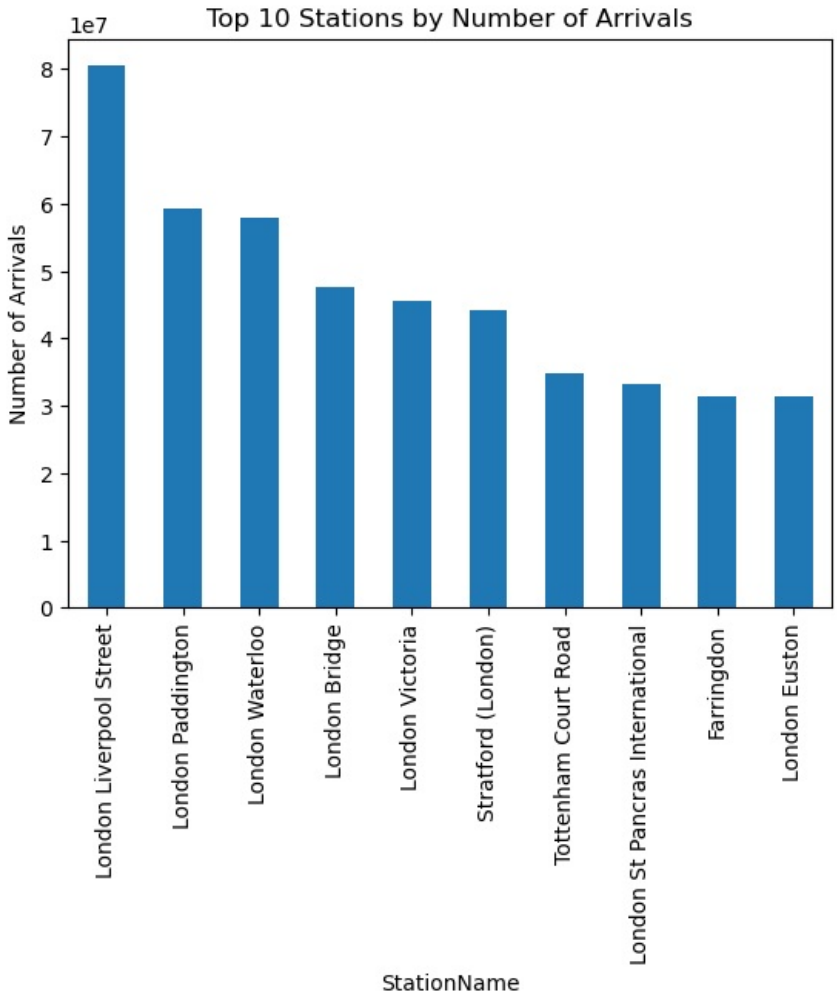
Out[58]:

	StationName	Entry_exit_population	origin_or_destination	Region	Operator
0	Abbey Wood	7118664	Tottenham Court Road	London	Elizabeth line
1	Aber	103976	Cardiff Central	Wales	TfW Rail
2	Abercynon	134880	Cardiff Central	Wales	TfW Rail
3	Aberdare	226714	Cardiff Central	Wales	TfW Rail
4	Aberdeen	1961414	Edinburgh	Scotland	ScotRail

In [59]:
```
df2['StationName'] = df2['StationName'] + ' Rail Station'
df2['StationName']
```

Out[59]:
```
0           Abbey Wood Rail Station
1                Aber Rail Station
2           Abercynon Rail Station
3            Aberdare Rail Station
4            Aberdeen Rail Station
                   ...
2570           Yoker Rail Station
2571            York Rail Station
2572          Yorton Rail Station
2573    Ystrad Mynach Rail Station
2574   Ystrad Rhondda Rail Station
Name: StationName, Length: 2575, dtype: object
```

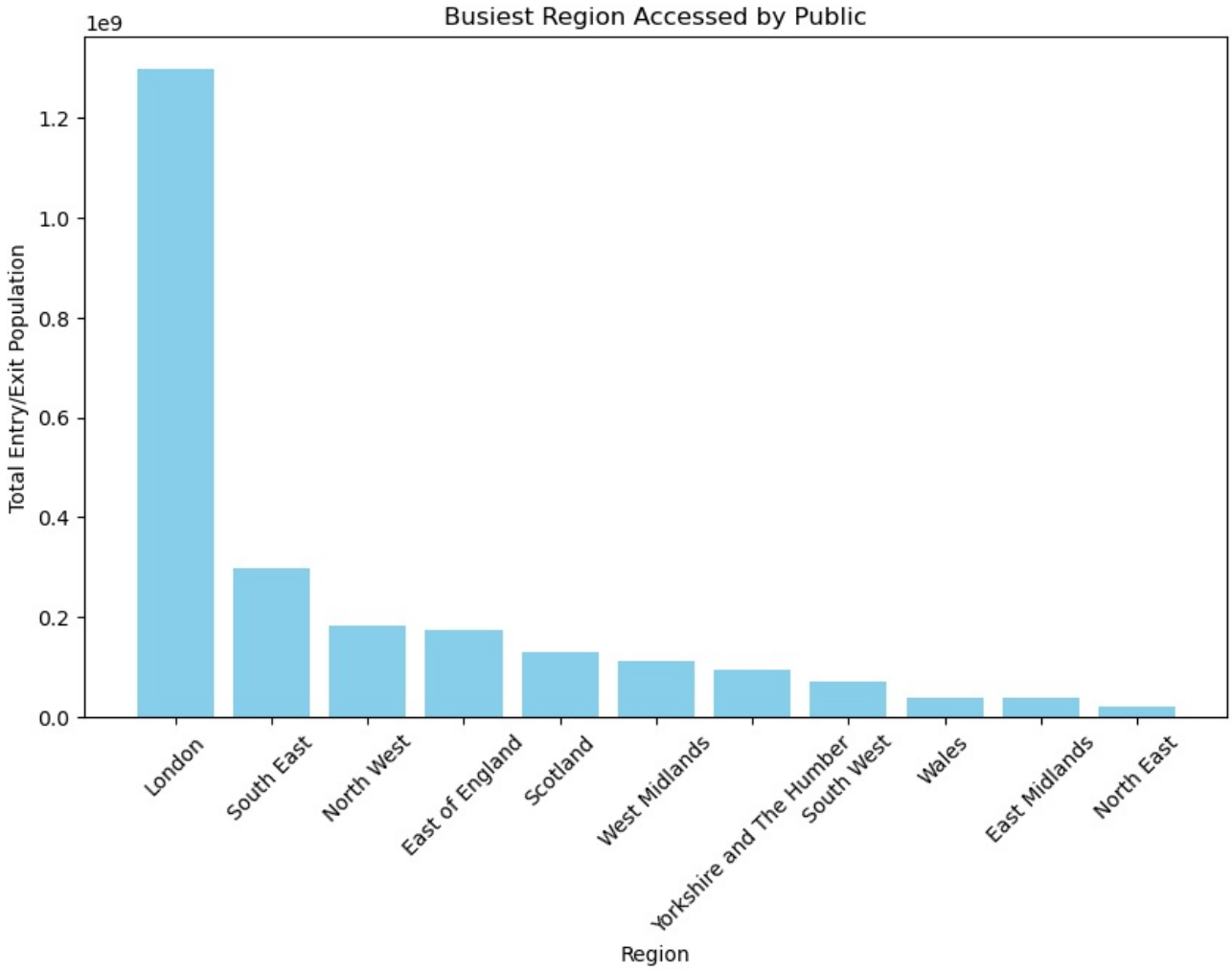
In [60]:
```
# Load the data
df2 = pd.read_excel('./Data/2.Passenger_population_station_TOC_2023.xlsx')

# Aggregate data by 'StationName' and sum the values
agg_data = df2.groupby('StationName').sum()

# Sort data by the 'Entry_exit_population' column in descending order
sorted_data = agg_data.sort_values(by='Entry_exit_population', ascending=False)

# Select the top 10 stations
top_10_stations = sorted_data.head(10)

# Plot the data
top_10_stations.plot(kind='bar', y='Entry_exit_population', legend=False)
plt.xlabel('StationName')
plt.ylabel('Number of Arrivals')
plt.title('Top 10 Stations by Number of Arrivals')
plt.show()
```



3. Which is the Busiest Region Accessed By the Public?

In [61]:
```
#Use the same dataframe as above
df = pd.read_excel('./Data/2.Passenger_population_station_TOC_2023.xlsx')

print(df.columns)

df.columns = df.columns.str.strip()

# Aggregate data by region
region_summary = df.groupby('Region')['Entry_exit_population'].sum().reset_index()

# Sort by Entry_exit_population in descending order
region_summary = region_summary.sort_values(by='Entry_exit_population', ascending=False)

# Plotting
plt.figure(figsize=(10, 6))
plt.bar(region_summary['Region'], region_summary['Entry_exit_population'], color='skyblue')
plt.xlabel('Region')
plt.ylabel('Total Entry/Exit Population')
plt.title('Busiest Region Accessed by Public')
plt.xticks(rotation=45)
plt.show()
```

```
Index(['StationName', 'Entry_exit_population', 'origin_or_destination',
       'Region', 'Operator'],
      dtype='object')
```



London is the most busiest region accessed by Public in UK.

4. Which Railway Operators are controlling more stations?

In [62]:
```
df3 = pd.read_excel(r'./Data/1.Train_Operating_Company_Stations_list_2023.xlsx')
```

In [63]:
```
df3.head()
```

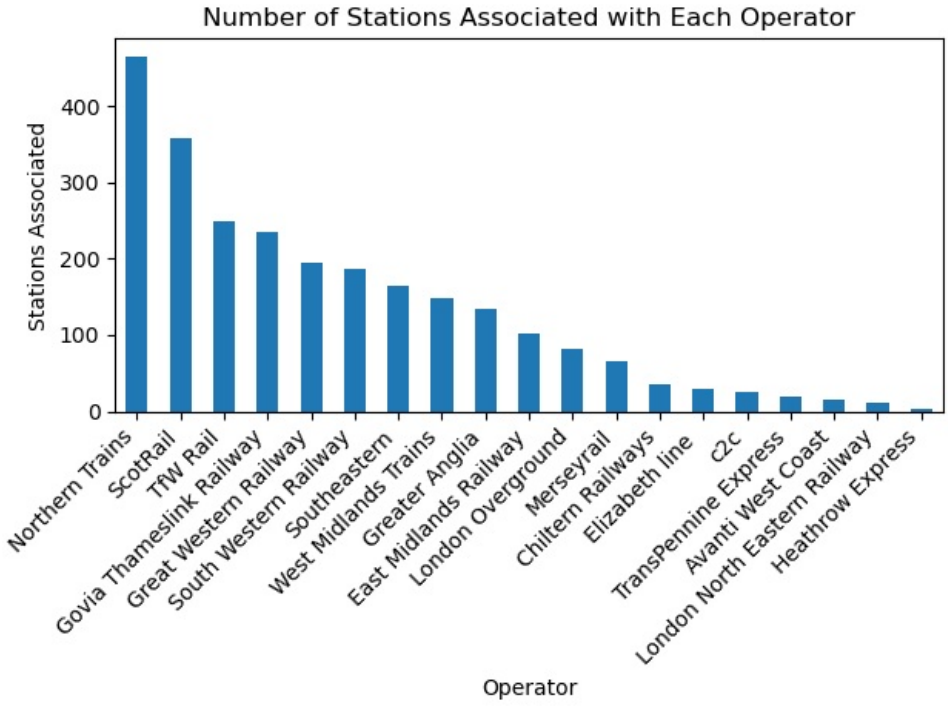
Out[63]:

	Operator	Stations_associated(As of 31 March 2023)
0	Avanti West Coast	16
1	c2c	25
2	Caledonian Sleeper \n	0
3	Chiltern Railways	35
4	CrossCountry	0

In [64]:
```
df3 = pd.read_excel('./Data/1.Train_Operating_Company_Stations_list_2023.xlsx')

print(df3.columns)

filtered_df3 = df3[(df3 != 0).all(axis=1)]

sorted_df3 = filtered_df3.sort_values(by=['Stations_associated(As of 31 March 2023)', 'Operator'], ascending=[Fa

# Plot the data
plt.figure(figsize=(15, 8))
sorted_df3.plot(kind='bar', x='Operator', y='Stations_associated(As of 31 March 2023)', legend=False)
plt.xlabel('Operator')
plt.ylabel('Stations Associated')
plt.title('Number of Stations Associated with Each Operator')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

```
Index(['Operator', 'Stations_associated(As of 31 March 2023)'], dtype='object')
```

```
<Figure size 1500x800 with 0 Axes>
```



Northern Trains TOC is operating around 400+ stations among the others.

5. Railways usage by Public over the years

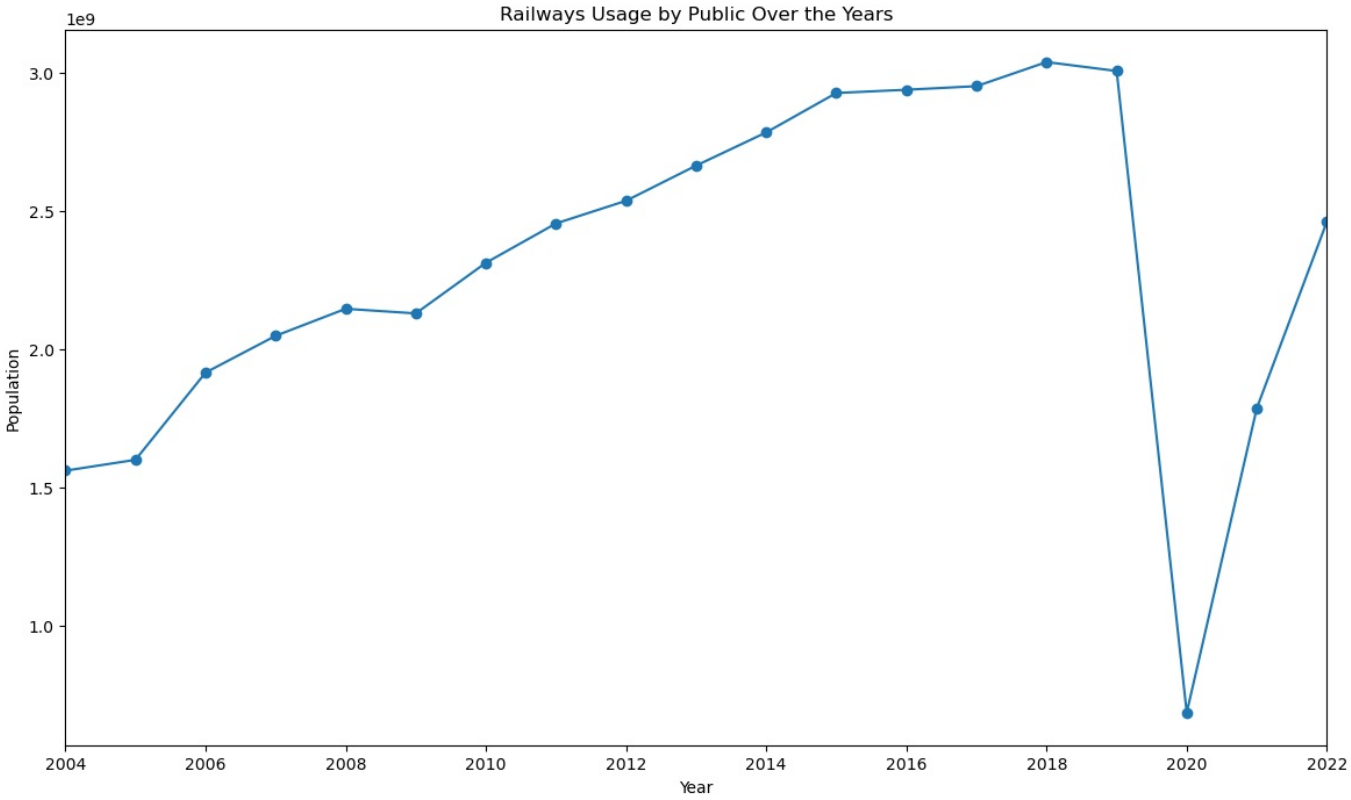
In [65]:
```
df4 = pd.read_excel(r'./Data/Passenger_population_1997_2022.xlsx')
```

In [66]:
```
df4.head()
```

Out[66]:

	Year	Population
0	1997	1.233688e+09
1	1998	1.400309e+09
2	1999	1.447963e+09
3	2000	1.459770e+09
4	2001	1.468899e+09

In [67]:
```
# Plotting the data
plt.figure(figsize=(14, 8))
plt.plot(df4['Year'], df4['Population'], marker='o')
plt.title('Railways Usage by Public Over the Years')
plt.xlabel('Year')
plt.ylabel('Population')
plt.xlim(2004, 2022)
plt.show()
```



Railway usage peaked around 2019 (pre-pandemic) before COVID-19, and it is slowly recovering but has not reached the same level as before the Pandemic.