HOTEL BOOKINGS ANALYTICS

Analize hotel bookings.

The data is from Kaggle:

User: *MOJTABA*

Title: *Hotel Booking - Hotel booking demand datasets(Data in Brief:2019)*

Link: https://www.kaggle.com/datasets/mojtaba142/hotel-booking

For this project, I will analyze hotel bookings to continue practicing my analytical skills using my knowledge of ***Python and Power BI***. Machine learning techniques will be applied where possible.

I will work with the following files:

- ***hotel_booking_mojtaba.csv***

1. Import libraries

In [ ]:
```
# Libraries to manipulate the data
import pandas as pd
import numpy as np

# Library to deploy charts with the data
import seaborn as sns
import matplotlib.pyplot as plt

# Statmodels for predictions
import statsmodels.api as sm
import statsmodels.formula.api as smf

# This is to ignore warnings.
import warnings
warnings.filterwarnings('ignore')
```

2. Importing our data file

Let's import the file '***hotel_booking_mojtaba.csv***' to start the analysis. This is .csv file. First, I will clean and prepare the data for the analysis. I will look for insights to help the stakeholders make better data-driven decisions.

In [ ]:
```
df_rawdata = pd.read_csv('../hotel_bookings/csv_files/hotel_booking_mojtaba.csv')
df_rawdata.head(5)
```

Out[ ]:

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_number
0	Resort Hotel	0	342	2015	July	27
1	Resort Hotel	0	737	2015	July	27
2	Resort Hotel	0	7	2015	July	27
3	Resort Hotel	0	13	2015	July	27
4	Resort Hotel	0	14	2015	July	27

5 rows × 36 columns

2.1 Cleaning the data

Now it's time to view how the data is composed, check for missing values, and select the data I will be working with. Once the data is ready for analysis, I will change the name of the data frame, which is now called 'df_rawdata'.

In [ ]:

```
df_rawdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
Data columns (total 36 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   hotel                           119390 non-null  object 
 1   is_canceled                     119390 non-null  int64  
 2   lead_time                       119390 non-null  int64  
 3   arrival_date_year               119390 non-null  int64  
 4   arrival_date_month              119390 non-null  object 
 5   arrival_date_week_number        119390 non-null  int64  
 6   arrival_date_day_of_month       119390 non-null  int64  
 7   stays_in_weekend_nights         119390 non-null  int64  
 8   stays_in_week_nights            119390 non-null  int64  
 9   adults                          119390 non-null  int64  
 10  children                        119386 non-null  float64
 11  babies                          119390 non-null  int64  
 12  meal                            119390 non-null  object 
 13  country                         118902 non-null  object 
 14  market_segment                  119390 non-null  object 
 15  distribution_channel            119390 non-null  object 
 16  is_repeated_guest               119390 non-null  int64  
 17  previous_cancellations          119390 non-null  int64  
 18  previous_bookings_not_canceled  119390 non-null  int64  
 19  reserved_room_type              119390 non-null  object 
 20  assigned_room_type              119390 non-null  object 
 21  booking_changes                 119390 non-null  int64  
 22  deposit_type                    119390 non-null  object 
 23  agent                           103050 non-null  float64
 24  company                         6797 non-null    float64
 25  days_in_waiting_list            119390 non-null  int64  
 26  customer_type                   119390 non-null  object 
 27  adr                             119390 non-null  float64
 28  required_car_parking_spaces     119390 non-null  int64  
 29  total_of_special_requests       119390 non-null  int64  
 30  reservation_status              119390 non-null  object 
 31  reservation_status_date         119390 non-null  object 
 32  name                            119390 non-null  object 
 33  email                           119390 non-null  object 
 34  phone-number                    119390 non-null  object 
 35  credit_card                     119390 non-null  object 
dtypes: float64(4), int64(16), object(16)
memory usage: 32.8+ MB
```

3 Data Cleaning

I will delete some columns as they are not necessary for the analysis. The columns that store the data of the customers are the ones I will delete.

I will call the new dataframe as '*df_hb*'.

In [ ]:
```
# Making a copy of our dataframe
df_hb = df_rawdata.copy()
df_hb.columns
```

Out[ ]:
```
Index(['hotel', 'is_canceled', 'lead_time', 'arrival_date_year',
       'arrival_date_month', 'arrival_date_week_number',
       'arrival_date_day_of_month', 'stays_in_weekend_nights',
       'stays_in_week_nights', 'adults', 'children', 'babies', 'meal',
       'country', 'market_segment', 'distribution_channel',
       'is_repeated_guest', 'previous_cancellations',
       'previous_bookings_not_canceled', 'reserved_room_type',
       'assigned_room_type', 'booking_changes', 'deposit_type', 'agent',
       'company', 'days_in_waiting_list', 'customer_type', 'adr',
       'required_car_parking_spaces', 'total_of_special_requests',
       'reservation_status', 'reservation_status_date', 'name', 'email',
       'phone-number', 'credit_card'],
      dtype='object')
```

In [ ]:
```
# Checking for missing values
missing_values = df_hb.isnull().sum()
print('Number of missing values: ', missing_values)
```

```
Number of missing values:  hotel                                   0
is_canceled                        0
lead_time                          0
arrival_date_year                  0
arrival_date_month                 0
arrival_date_week_number           0
arrival_date_day_of_month          0
stays_in_weekend_nights            0
stays_in_week_nights               0
adults                             0
children                           4
babies                             0
meal                               0
country                          488
market_segment                     0
distribution_channel               0
is_repeated_guest                  0
previous_cancellations             0
previous_bookings_not_canceled     0
reserved_room_type                 0
assigned_room_type                 0
booking_changes                    0
deposit_type                       0
agent                          16340
company                       112593
days_in_waiting_list               0
customer_type                      0
adr                                0
required_car_parking_spaces        0
total_of_special_requests          0
reservation_status                 0
reservation_status_date            0
name                               0
email                              0
phone-number                       0
credit_card                        0
dtype: int64
```

3.1 Some observations

I discovered that the columns *'country', 'agent', and 'company'* are the ones with the most missing values. I recommend for a future, to fill the data with the agents that are bringing the most customers to the hotels. Gathering this information will help to create special discounts for each of them.

Because I want to work with the '*country*' column, I will fill in the missing values with the code **'OTR'**. I want to analyze from which country the customers are most.

I will delete those four missing values from the column '*children*'; they will not affect our analysis.

In [ ]:
```
# Filling the missing values in the 'country' column
df_hb['country'].fillna('OTR', inplace=True)

# Dropping columns that will not be used in the analysis
df_hb.drop(['previous_cancellations', 'previous_bookings_not_canceled', 'days_in_wa

df_hb.columns
```

Out[ ]:
```
Index(['hotel', 'is_canceled', 'lead_time', 'arrival_date_year',
       'arrival_date_month', 'arrival_date_week_number',
       'arrival_date_day_of_month', 'stays_in_weekend_nights',
       'stays_in_week_nights', 'adults', 'children', 'babies', 'meal',
       'country', 'market_segment', 'distribution_channel',
       'is_repeated_guest', 'reserved_room_type', 'assigned_room_type',
       'booking_changes', 'deposit_type', 'customer_type', 'adr',
       'required_car_parking_spaces', 'total_of_special_requests',
       'reservation_status', 'reservation_status_date'],
      dtype='object')
```

In [ ]:
```
# Removing those four missing values from the column 'children'
df_hb.dropna(subset=['children'], inplace=True)

missing_values2 = df_hb.isnull().sum()
print('Number of missing values: ', missing_values2)
```

```
Number of missing values:  hotel                          0
is_canceled                    0
lead_time                      0
arrival_date_year              0
arrival_date_month             0
arrival_date_week_number       0
arrival_date_day_of_month      0
stays_in_weekend_nights        0
stays_in_week_nights           0
adults                         0
children                       0
babies                         0
meal                           0
country                        0
market_segment                 0
distribution_channel           0
is_repeated_guest              0
reserved_room_type             0
assigned_room_type             0
booking_changes                0
deposit_type                   0
customer_type                  0
adr                            0
required_car_parking_spaces    0
total_of_special_requests      0
reservation_status             0
reservation_status_date        0
dtype: int64
```

In [ ]:
```
df_hb_lens = len(df_hb)
print('Number of rows in the dataframe is: ', df_hb_lens)
```

```
Number of rows in the dataframe is:  119386
```

4 Working with the data

With the data clean and ready for analysis, it is time to generate the insights that will help our **stakeholders** make *better data-driven decisions.*

4.1 Filter the data

I will separate the data into two categories: *City Hotel* and a *Resort Hotel*. Later, I will compare them together to understand their tendencies and seasons.

Let's create the two dataframes.

In [ ]:
```
# CITY HOTEL
df_hb_CH = df_hb.groupby(by=['hotel']).get_group('City Hotel')

df_hb_CH.head(5)
```

Out[ ]:

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_numb
40060	City Hotel	0	6	2015	July	
40061	City Hotel	1	88	2015	July	
40062	City Hotel	1	65	2015	July	
40063	City Hotel	1	92	2015	July	
40064	City Hotel	1	100	2015	July	

5 rows × 27 columns

In [ ]:
```
# RESORT HOTEL
df_hb_RH = df_hb.groupby(by=['hotel']).get_group('Resort Hotel')

df_hb_RH.head(5)
```

Out[ ]:

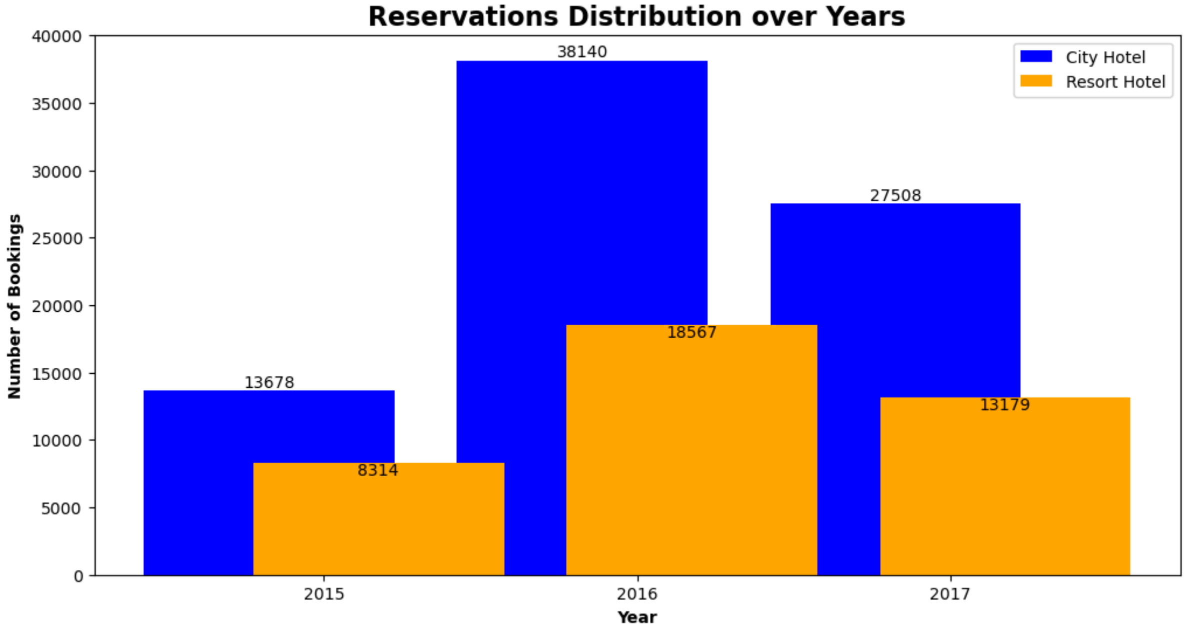
	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_number
0	Resort Hotel	0	342	2015	July	27
1	Resort Hotel	0	737	2015	July	27
2	Resort Hotel	0	7	2015	July	27
3	Resort Hotel	0	13	2015	July	27
4	Resort Hotel	0	14	2015	July	27

5 rows × 27 columns

In [ ]:

```
# First, let's figure out which hotel got more activity by year
bookings_activity = df_hb.groupby(['arrival_date_year','hotel']).size().unstack()
print(bookings_activity)

# Total and percentage variables to use on our charts
total_bk_count = bookings_activity.sum()
canceled_percentage = (bookings_activity / total_bk_count) * 100

# Extracting values to create the bar chart
years = bookings_activity.index
ch_count = bookings_activity['City Hotel']
rh_count = bookings_activity['Resort Hotel']

# Chart size
fig, ax = plt.subplots(figsize=(12, 6))

# Positions for the bars
r1 = range(len(years))
r2 = [x + 0.35 for x in r1]

# Bars
bar1 = ax.bar(r1, ch_count, color='blue', label='City Hotel')
bar2 = ax.bar(r2, rh_count, color='orange', label='Resort Hotel')

# Legends
ax.set_xlabel('Year', fontweight='bold')
ax.set_ylabel('Number of Bookings', fontweight='bold')
ax.set_title('Reservations Distribution over Years', fontsize=16, fontweight='bold'
ax.set_xticks([r + 0.35/2 for r in range(len(years))])
ax.set_xticklabels(years)
ax.legend()

# Adding the counts over the bars
for bar in bar1:
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2.0, height, f'{int(height)}', ha='center

for bar in bar2:
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2.0, height, f'{int(height)}', ha='center
plt.show()

# ax = bookings_activity.plot.bar(rot=0)
```

```
hotel              City Hotel  Resort Hotel
arrival_date_year
2015                    13678          8314
2016                    38140         18567
2017                    27508         13179
```



4.2 City Hotel Analysis

I will fix the values in the column '*is_canceled*'. I will replace the 0 and 1 for the values where 0 = canceled and 1 = not canceled. I'm aware I can do this step earlier, but for the purpose of practicing, I decided to do it twice, one time for each dataframe.

Let's go there

In [ ]:
```python
# Changing the values
cancel = {
    0: 'canceled',
    1:'not canceled'
}

df_hb_CH['is_canceled'] = df_hb_CH['is_canceled'].map(cancel)

df_hb_CH['is_canceled'].head(5)
```

Out[ ]:
```
40060        canceled
40061    not canceled
40062    not canceled
40063    not canceled
40064    not canceled
Name: is_canceled, dtype: object
```

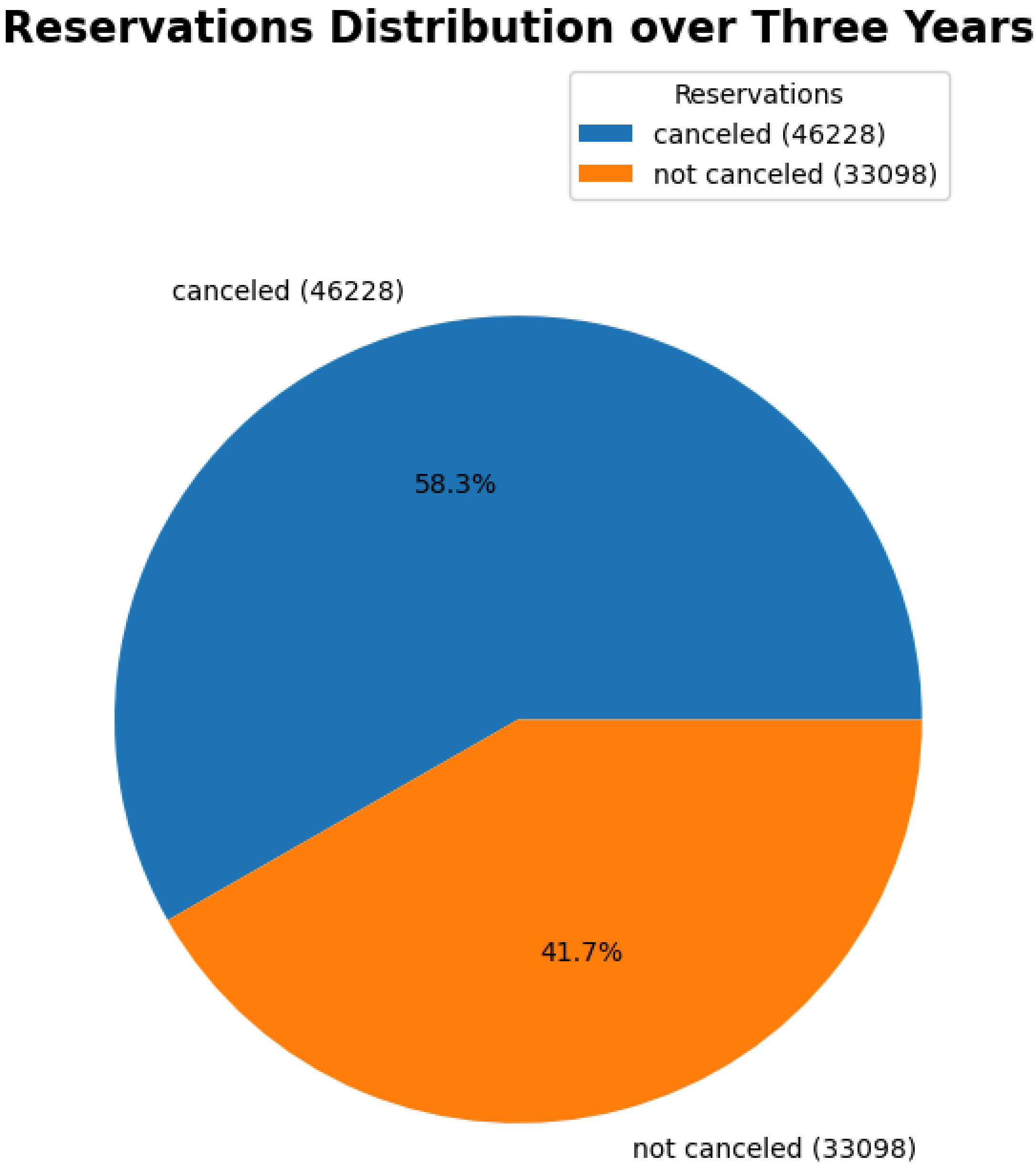
4.2.a Canceled Reservations

This database has data for reservations from the years *2015, 2016,* and *2017*. So, first, I will look at the cancellations as a total of those 3 years, and then I will **separate** the data individually by year.

It will allow stakeholders to know the *overall number of cancellations and then be able to compare by year*.

In [ ]:
```
# Counting the canceled or not canceled reservations values and storage them into c
canceled_counts = df_hb_CH['is_canceled'].value_counts()
print(canceled_counts)

# Total and percentage variables to use on our charts
total_count = canceled_counts.sum()
canceled_percentage = (canceled_counts / total_count) * 100

# labels = canceled_counts.index
# Using a function to create the labels
labels = [f'{canceled} ({count})' for canceled, count in zip(canceled_counts.index,

# Chart size
fig, ax = plt.subplots(figsize=(6, 9))

# Chart generation
plt.pie(canceled_counts, labels=labels, autopct='%1.1f%%')
plt.legend(title='Reservations')
ax.set_title('Reservations Distribution over Three Years', fontsize=16, fontweight=
plt.axis('equal')
plt.show()
```

```
canceled        46228
not canceled    33098
Name: is_canceled, dtype: int64
```



The data shows that over the past three years, there have been more canceled reservations, with a **total percentage of 58.3%**.

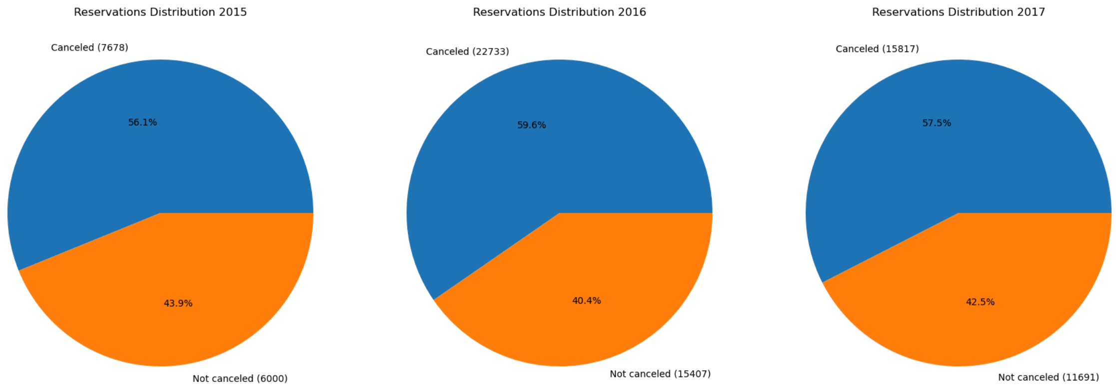
It is recommended to try to understand what is causing the cancellations. This will help you better understand your clients, create promotions to attract them, and reduce the cancellation ratio.

Let's analyze which of the three years shows the most canceled reservations.

In [ ]:
```
# Separating the cancellations by years
canceled_by_years_count = df_hb_CH.groupby('arrival_date_year', group_keys=False)[[
print(canceled_by_years_count)

# Plotting the data
fig, axs = plt.subplots(1, 3, figsize=(18, 6))
```

```
# Creating the labels
for i, year in enumerate(canceled_by_years_count.index):
    data = canceled_by_years_count.loc[year]
    labels = [f"{status.capitalize()} ({count})" for status, count in data.items()]
    axs[i].pie(data, labels=labels, autopct='%1.1f%%')
    axs[i].set_title(f'Reservations Distribution {year}')

plt.tight_layout()
plt.show()
```

```
is_canceled         canceled  not canceled
arrival_date_year
2015                    7678          6000
2016                   22733         15407
2017                   15817         11691
```



4.3 Resort Hotel Analysis

Because this is a practice project, I will perform the same analysis on the Resort Hotel. I will fix the values in the column '*is_canceled*'. I will replace the 0 and 1 for the values where 0 = canceled and 1 = not canceled. I'm aware I can do this step earlier, but for the purpose of practicing, I decided to do it twice, one time for each dataframe.

Let's start working with the data.

In [ ]:
```
# Changing the values
cancel = {
    0: 'canceled',
    1:'not canceled'
}

df_hb_RH['is_canceled'] = df_hb_RH['is_canceled'].map(cancel)

df_hb_RH['is_canceled'].head(5)
```

Out[ ]:
```
0    canceled
1    canceled
2    canceled
3    canceled
4    canceled
Name: is_canceled, dtype: object
```

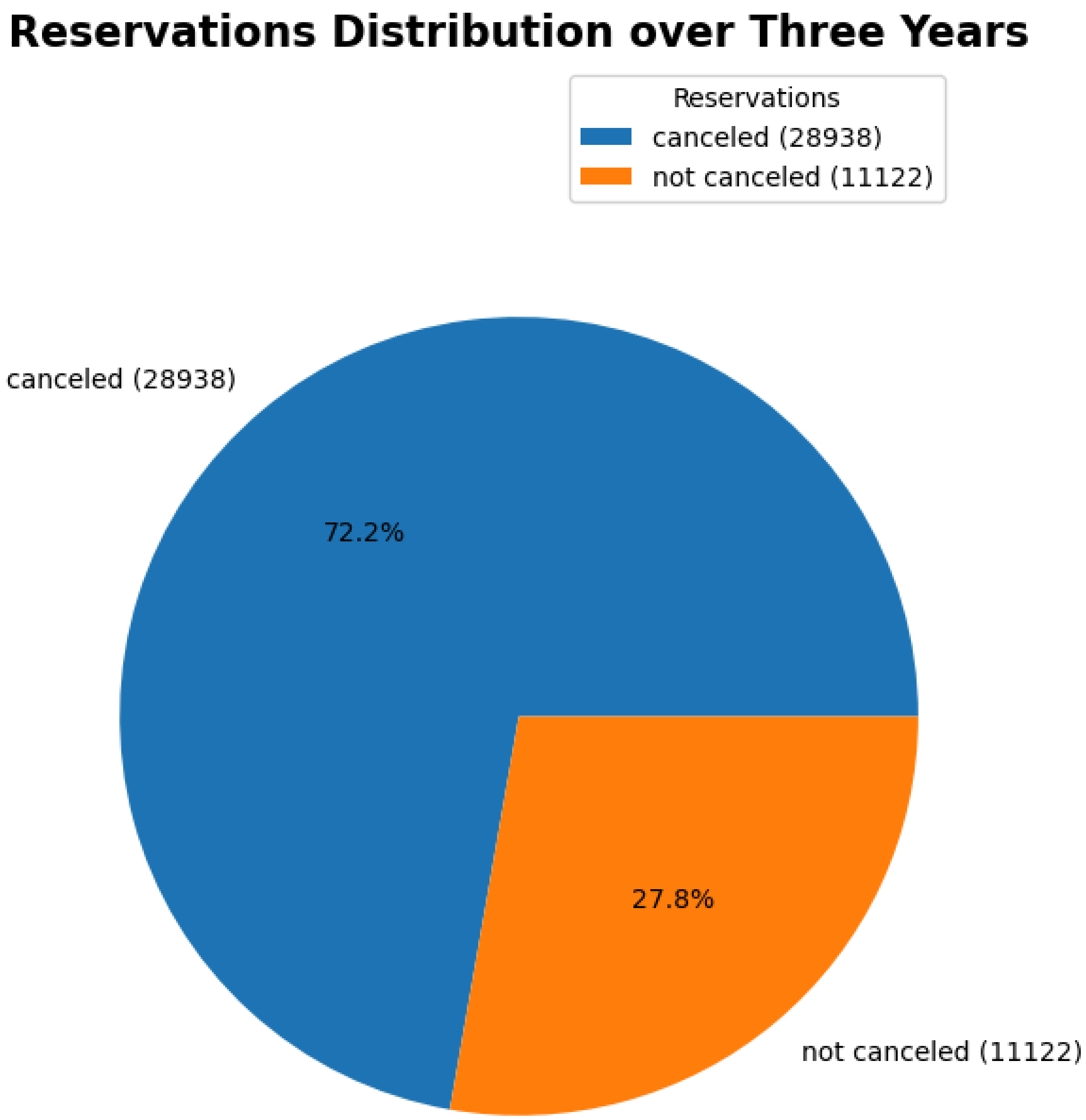
4.3.a Canceled Reservations

This database has data for reservations from the years *2015, 2016*, and *2017*. So, first, I will look at the cancellations as a total of those 3 years, and then I will **separate** the data individually by year.

It will allow stakeholders to know the *overall number of cancellations and then be able to compare by year*.

In [ ]:
```
# Counting the canceled or not canceled reservations values and storage them into a
canceled_counts = df_hb_RH['is_canceled'].value_counts()
print(canceled_counts)

# Total and percentage variables to use on our charts
total_count = canceled_counts.sum()
canceled_percentage = (canceled_counts / total_count) * 100

# labels = canceled_counts.index
# Using a function to create the labels
labels = [f'{canceled} ({count})' for canceled, count in zip(canceled_counts.index,

# Chart size
fig, ax = plt.subplots(figsize=(6, 9))

# Chart generation
plt.pie(canceled_counts, labels=labels, autopct='%1.1f%%')
plt.legend(title='Reservations')
ax.set_title('Reservations Distribution over Three Years', fontsize=16, fontweight=
plt.axis('equal')
plt.show()
```

```
canceled        28938
not canceled    11122
Name: is_canceled, dtype: int64
```



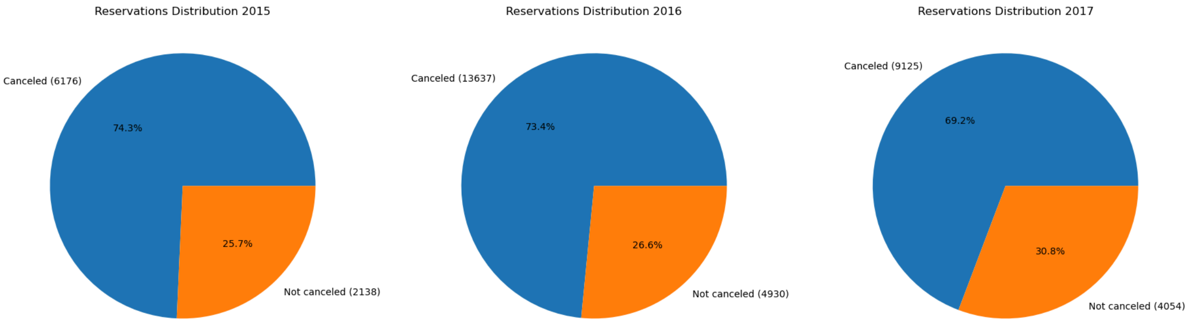
The data shows that over the past three years, there have been <u>more canceled</u> reservations, with a **total percentage of 72.2%**.

Let's analyze which of the three years shows the most canceled reservations.

In [ ]:
```
# Separating the cancellations by years
canceled_by_years_count = df_hb_RH.groupby('arrival_date_year', group_keys=False)[[
print(canceled_by_years_count)

# Plotting the data
fig, axs = plt.subplots(1, 3, figsize=(18, 6))

# Creating the labels
for i, year in enumerate(canceled_by_years_count.index):
    data = canceled_by_years_count.loc[year]
    labels = [f"{status.capitalize()} ({count})" for status, count in data.items()]
```

```
    axs[i].pie(data, labels=labels, autopct='%1.1f%%')
    axs[i].set_title(f'Reservations Distribution {year}')

plt.tight_layout()
plt.show()
```

```
is_canceled         canceled  not canceled
arrival_date_year
2015                    6176          2138
2016                   13637          4930
2017                    9125          4054
```



By analyzing both hotels, **CITY** and **RESORT**, it can be seen that the *RESORT* has a higher percentage of cancellations, with a total of **72.2%** against a **58.3%** of the *CITY* hotel. However, when I analyzed the cancellations by year, I observed a slight decrease in cancellations at the *RESORT* can be observed over the years, as opposed to the *CITY* hotel that showed an increase in the last year.

4.4 What affects Cancellations?

For this analysis, I will create a new database with the columns *hotel, is_canceled, lead_time, market_segment, and customer_type*, to examine and understand, What is causing the cancellations?

Let's create our new database to work with.

4.4.a New Database

In [ ]:
```
# Creating the new data structure
df_cancellations = df_hb[['hotel','is_canceled','lead_time','market_segment','custo

df_cancellations.head(5)
```

Out[ ]:

	hotel	is_canceled	lead_time	market_segment	customer_type	arrival_date_year
0	Resort Hotel	0	342	Direct	Transient	2015
1	Resort Hotel	0	737	Direct	Transient	2015
2	Resort Hotel	0	7	Direct	Transient	2015
3	Resort Hotel	0	13	Corporate	Transient	2015
4	Resort Hotel	0	14	Online TA	Transient	2015

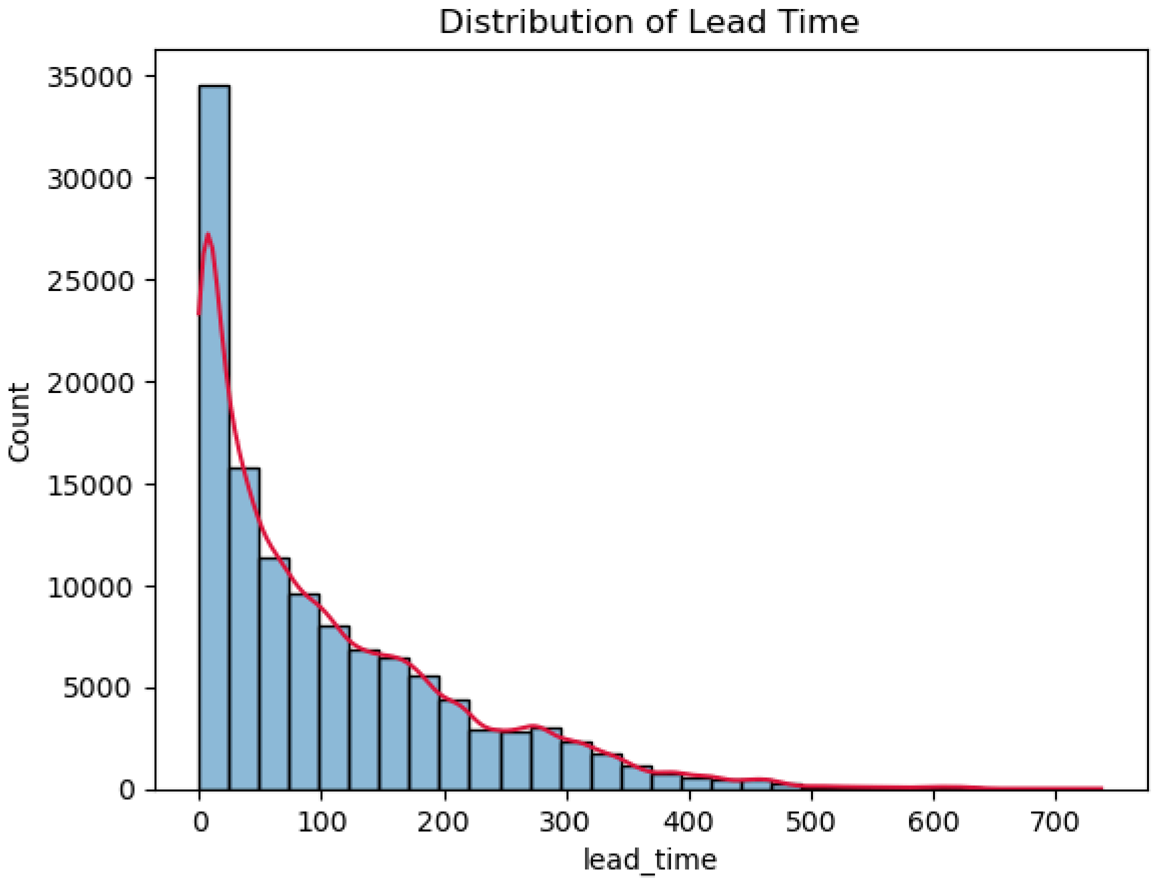
In [ ]:
```
df_cancellations.dtypes
```

Out[ ]:
```
hotel                  object
is_canceled             int64
lead_time               int64
market_segment         object
customer_type          object
arrival_date_year       int64
dtype: object
```

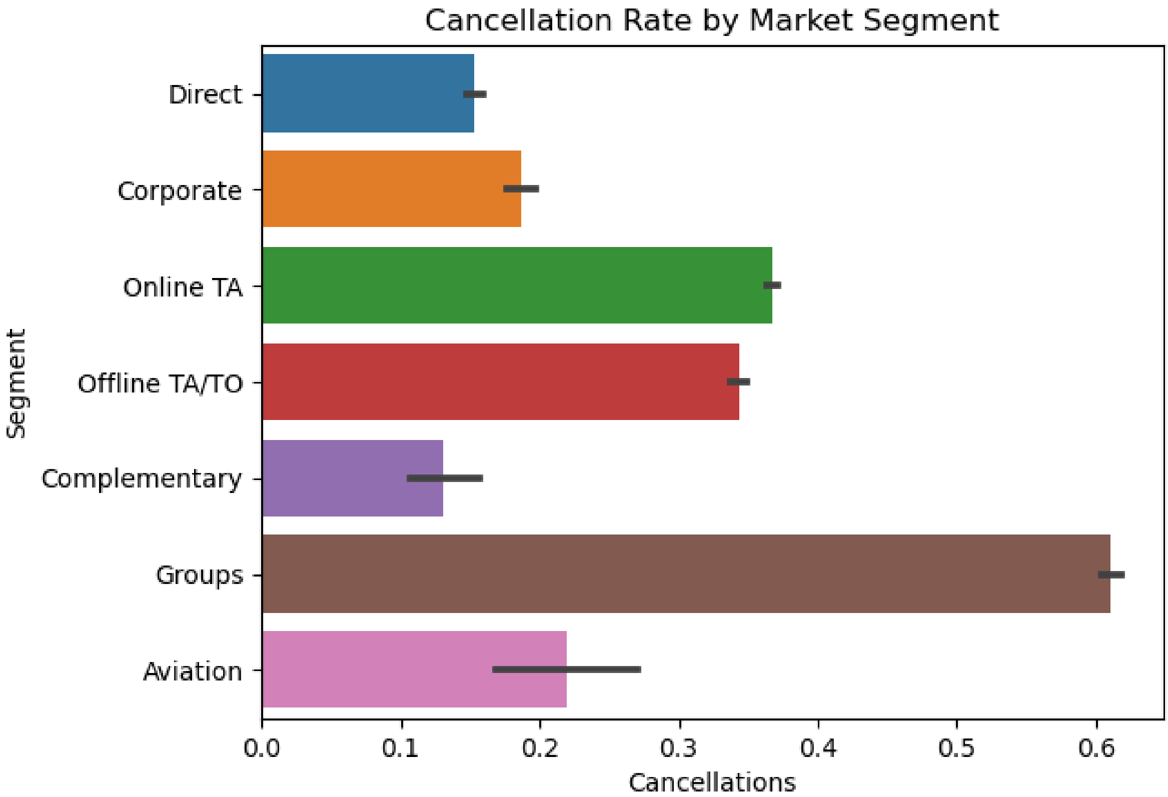
With the new database, let's visualize distributions and relationships between variables.

I will use the values from the column '*lead_time*' into a histogram to visualize the number of days that elapsed between the entering date and the arrival date. The histogram will show the distribution of a variable, counting the number of observations.

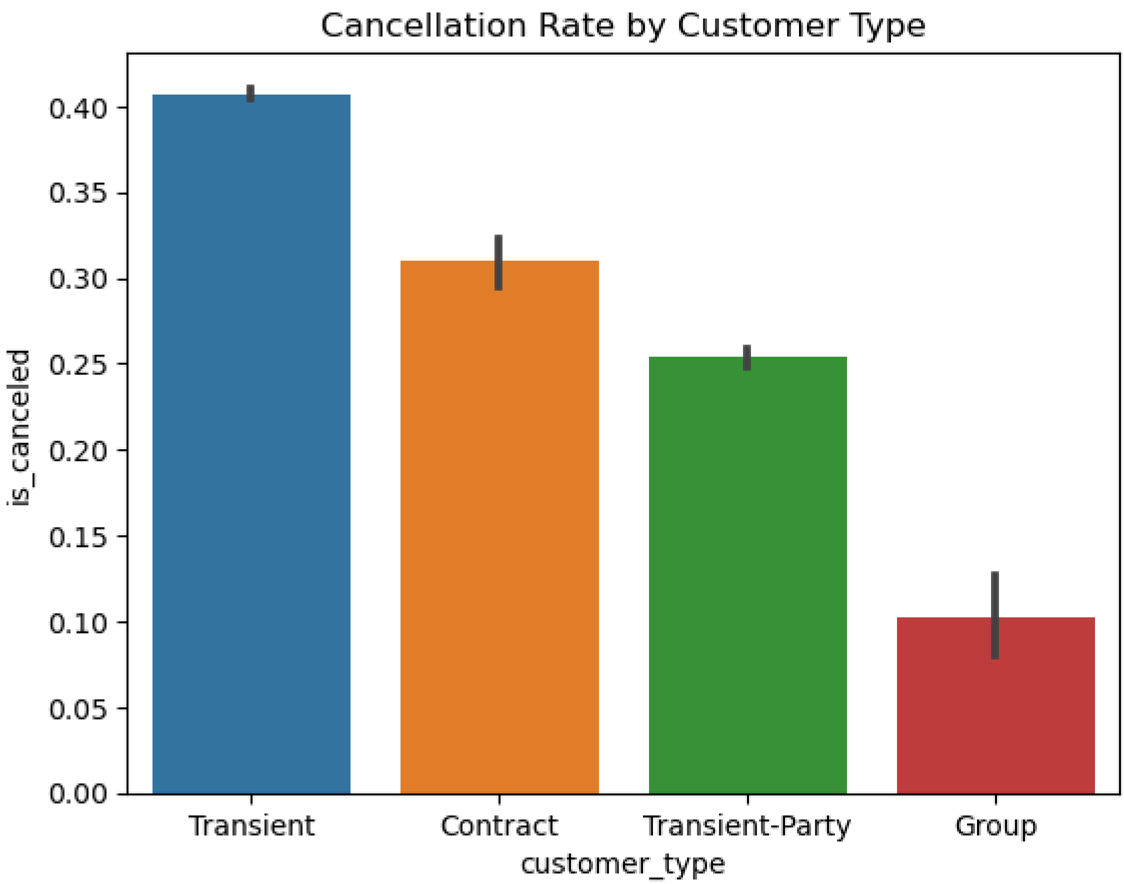
In [ ]:
```python
ax = sns.histplot(df_cancellations['lead_time'], bins=30, kde=True)
ax.lines[0].set_color('crimson')
plt.title('Distribution of Lead Time')
plt.show()
```



In [ ]:
```python
# Cancellation rate by market segment

sns.barplot(x='is_canceled', y='market_segment', data=df_cancellations)
plt.title('Cancellation Rate by Market Segment')
plt.xlabel('Cancellations')
plt.ylabel('Segment')
plt.show()
```



In [ ]:
```
# Cancellation rate by customer type
sns.barplot(x='customer_type', y='is_canceled', data=df_cancellations)
plt.title('Cancellation Rate by Customer Type')
plt.show()
```



4.4.b Analyzing the impact of the variables used

Is it time to use a machine learning model to understand which of our variables are *affecting the cancellations? I will use a logistic regression model to understand the relationship between the data in the columns 'is_canceled', 'lead_time', 'market_segment', and'customer_type'.*

In [ ]:

```
# First let's create our logistic regression model
cancellation_model = smf.logit('is_canceled ~ lead_time + C(market_segment) + C(cus

# Model Synposis
print(cancellation_model.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.563430
         Iterations 6
                           Logit Regression Results
==============================================================================
Dep. Variable:            is_canceled   No. Observations:               119386
Model:                          Logit   Df Residuals:                   119375
Method:                           MLE   Df Model:                           10
Date:                Tue, 25 Jun 2024   Pseudo R-squ.:                  0.1452
Time:                        15:02:18   Log-Likelihood:                -67266.
converged:                       True   LL-Null:                       -78695.
Covariance Type:            nonrobust   LLR p-value:                     0.000
==================================================================================
=====================
                                          coef    std err          z      P>|z|
[0.025      0.975]
----------------------------------------------------------------------------------
---------------------
Intercept                              -2.3478      0.163    -14.375      0.000
-2.668      -2.028
C(market_segment)[T.Complementary]     -0.7135      0.192     -3.711      0.000
-1.090      -0.337
C(market_segment)[T.Corporate]          0.0173      0.162      0.106      0.915
-0.301       0.335
C(market_segment)[T.Direct]            -0.7147      0.160     -4.462      0.000
-1.029      -0.401
C(market_segment)[T.Groups]             1.8303      0.160     11.443      0.000
1.517       2.144
C(market_segment)[T.Offline TA/TO]      0.3801      0.159      2.388      0.017
0.068       0.692
C(market_segment)[T.Online TA]          0.2978      0.159      1.879      0.060
-0.013       0.608
C(customer_type)[T.Group]              -0.4647      0.149     -3.126      0.002
-0.756      -0.173
C(customer_type)[T.Transient]           1.1394      0.041     27.881      0.000
1.059       1.220
C(customer_type)[T.Transient-Party]    -0.6750      0.043    -15.556      0.000
-0.760      -0.590
lead_time                               0.0055   7.26e-05     76.162      0.000
0.005       0.006
==================================================================================
=====================
```

After the model has been developed and presented, it is necessary to comprehend the significance of ***every variable****.*

In [ ]:

```
# Extracting the values and coefficients
cancellation_coef = cancellation_model.params
cancellation_values = cancellation_model.pvalues
```

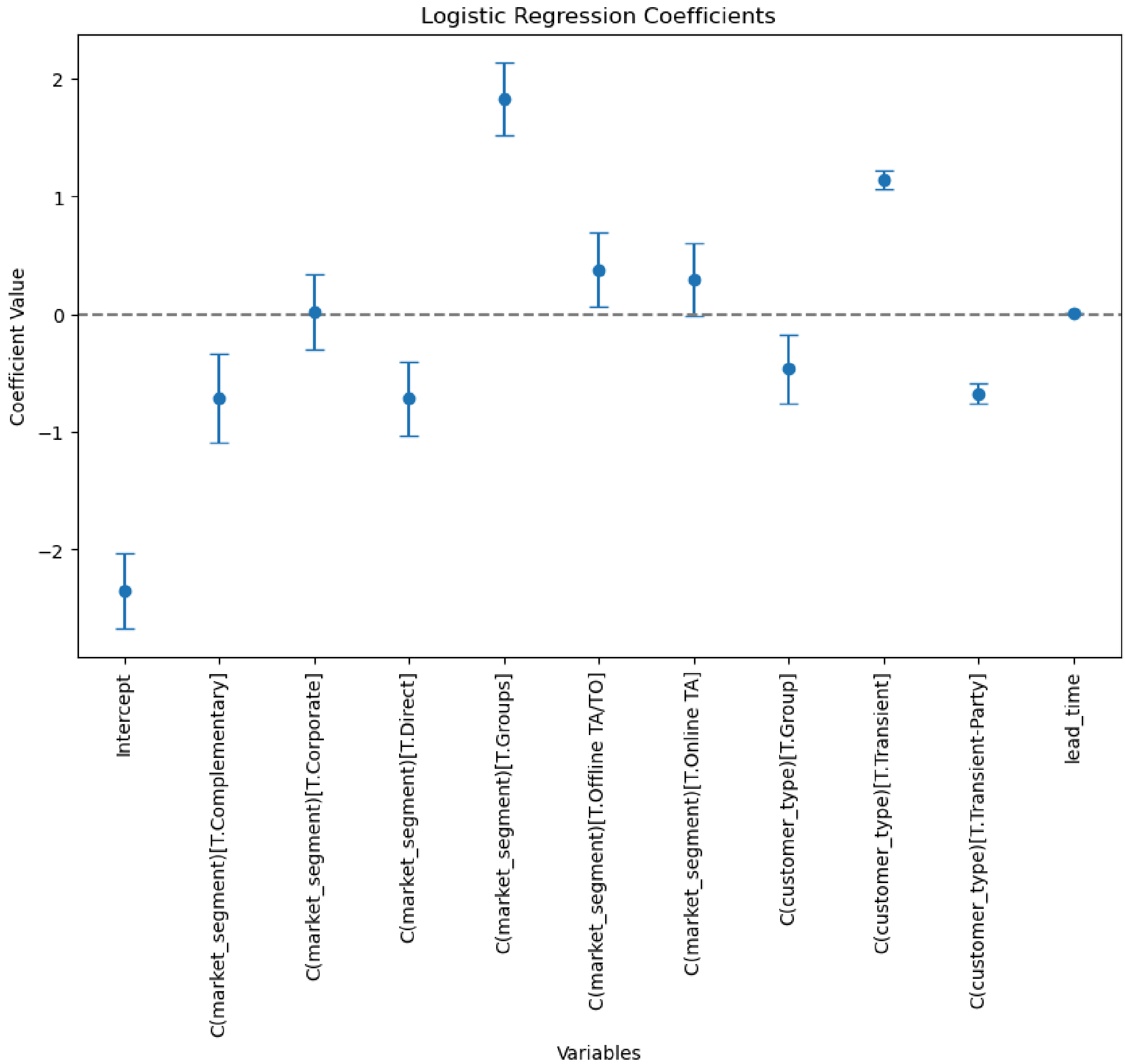
```
# Display coefficients and p-values
print(f"Coefficients:\n{cancellation_coef}\n")
print(f"P-values:\n{cancellation_values}\n")
```

```
Coefficients:
Intercept                                 -2.347786
C(market_segment)[T.Complementary]       -0.713530
C(market_segment)[T.Corporate]            0.017277
C(market_segment)[T.Direct]              -0.714733
C(market_segment)[T.Groups]               1.830286
C(market_segment)[T.Offline TA/TO]        0.380110
C(market_segment)[T.Online TA]            0.297807
C(customer_type)[T.Group]                -0.464664
C(customer_type)[T.Transient]             1.139408
C(customer_type)[T.Transient-Party]      -0.675040
lead_time                                 0.005531
dtype: float64

P-values:
Intercept                                 7.434710e-47
C(market_segment)[T.Complementary]        2.063348e-04
C(market_segment)[T.Corporate]            9.152015e-01
C(market_segment)[T.Direct]               8.137130e-06
C(market_segment)[T.Groups]               2.546703e-30
C(market_segment)[T.Offline TA/TO]        1.694970e-02
C(market_segment)[T.Online TA]            6.027475e-02
C(customer_type)[T.Group]                 1.769141e-03
C(customer_type)[T.Transient]            4.542420e-171
C(customer_type)[T.Transient-Party]       1.446957e-54
lead_time                                 0.000000e+00
dtype: float64
```

Let's create a chart to visualize our data

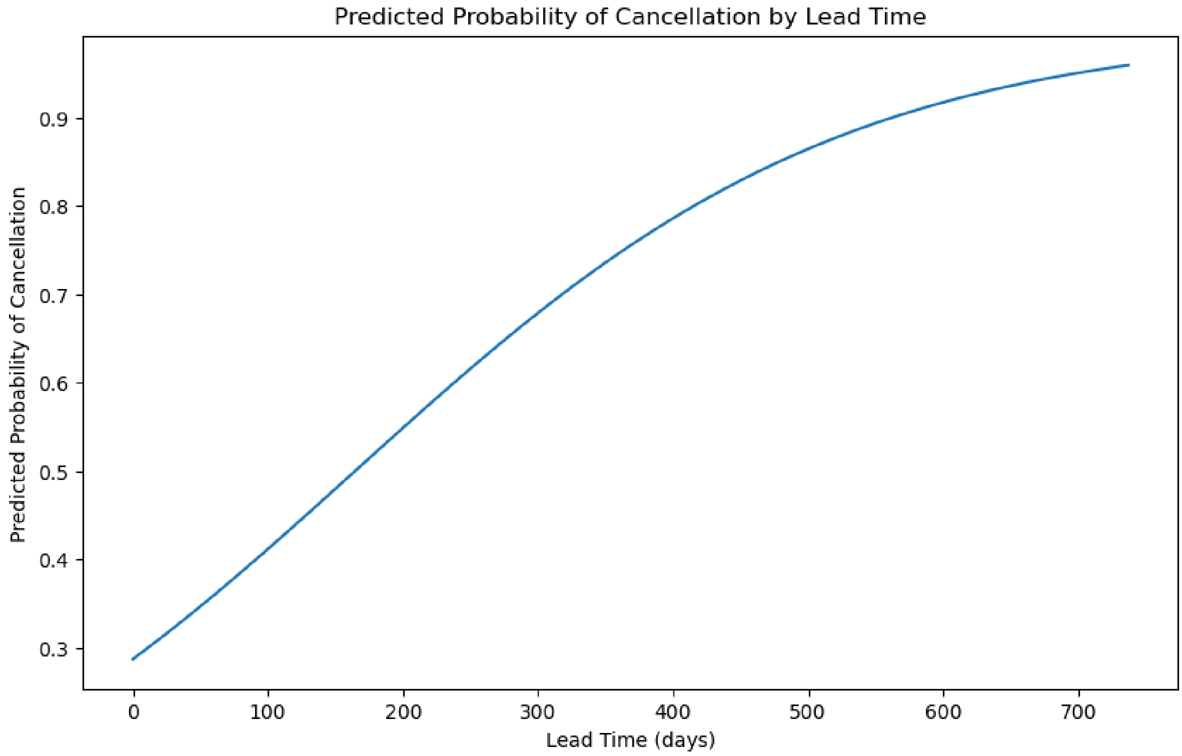
In [ ]:

```
# I will need the confidence intervals. Remember the coef I already have them
cancell_conf = cancellation_model.conf_int()

# Adding the coefficients to the confidence model
cancell_conf['coeff'] = cancellation_coef

# To understand the data let's rename the columns
cancell_conf.columns = ['2.5%','97.5%', 'coeff']

# Creating the chart
plt.figure(figsize=(10, 6))
plt.errorbar(cancell_conf.index, cancell_conf['coeff'], yerr=[cancell_conf['coeff']
plt.axhline(0, color='gray', linestyle='--')
plt.xticks(rotation=90)
plt.title('Logistic Regression Coefficients')
plt.xlabel('Variables')
plt.ylabel('Coefficient Value')
plt.show()
```



In [ ]:

```
# Generate a range of lead time values
lead_time_range = np.linspace(df_cancellations['lead_time'].min(), df_cancellations
predict_data = pd.DataFrame({
    'lead_time': lead_time_range,
    'market_segment': 'Online TA',  # Set to a reference category for simplicity
    'customer_type': 'Transient'  # Set to a reference category for simplicity
})

# Predict probabilities
predict_data['predicted_prob'] = cancellation_model.predict(predict_data)

# Plot predicted probabilities
plt.figure(figsize=(10, 6))
plt.plot(predict_data['lead_time'], predict_data['predicted_prob'])
plt.title('Predicted Probability of Cancellation by Lead Time')
plt.xlabel('Lead Time (days)')
plt.ylabel('Predicted Probability of Cancellation')
plt.show()
```



4.5 How about the lead time on bookings?

For this analysis, I will create a new database with the columns hotel, lead_time, is_canceled, adr, arrival_date_year, arrival_date_month, market_segment, customer_type to analyze if the lead time on bookings is affecting the cancellations.

Let's try to understand booking patterns so the hotel can create pricing strategies to offer their clients.

4.5.a Database for the Bookings Analysis

In [ ]:
```
# Creating bookings database
df_book_lt = df_hb[['hotel','lead_time','is_canceled','adr','arrival_date_year','ar

df_book_lt.head(5)
```

Out[ ]:

	hotel	lead_time	is_canceled	adr	arrival_date_year	arrival_date_month	market_segment	cus
0	Resort Hotel	342	0	0.0	2015	July	Direct	
1	Resort Hotel	737	0	0.0	2015	July	Direct	
2	Resort Hotel	7	0	75.0	2015	July	Direct	
3	Resort Hotel	13	0	75.0	2015	July	Corporate	
4	Resort Hotel	14	0	98.0	2015	July	Online TA	

In [ ]:
```
df_book_lt.dtypes
```

Out[ ]:
```
hotel                  object
lead_time               int64
is_canceled             int64
adr                   float64
arrival_date_year       int64
arrival_date_month     object
market_segment         object
customer_type          object
dtype: object
```

With the new database, let's visualize distributions and relationships between variables.

4.5.a.1 Bookings Analysis

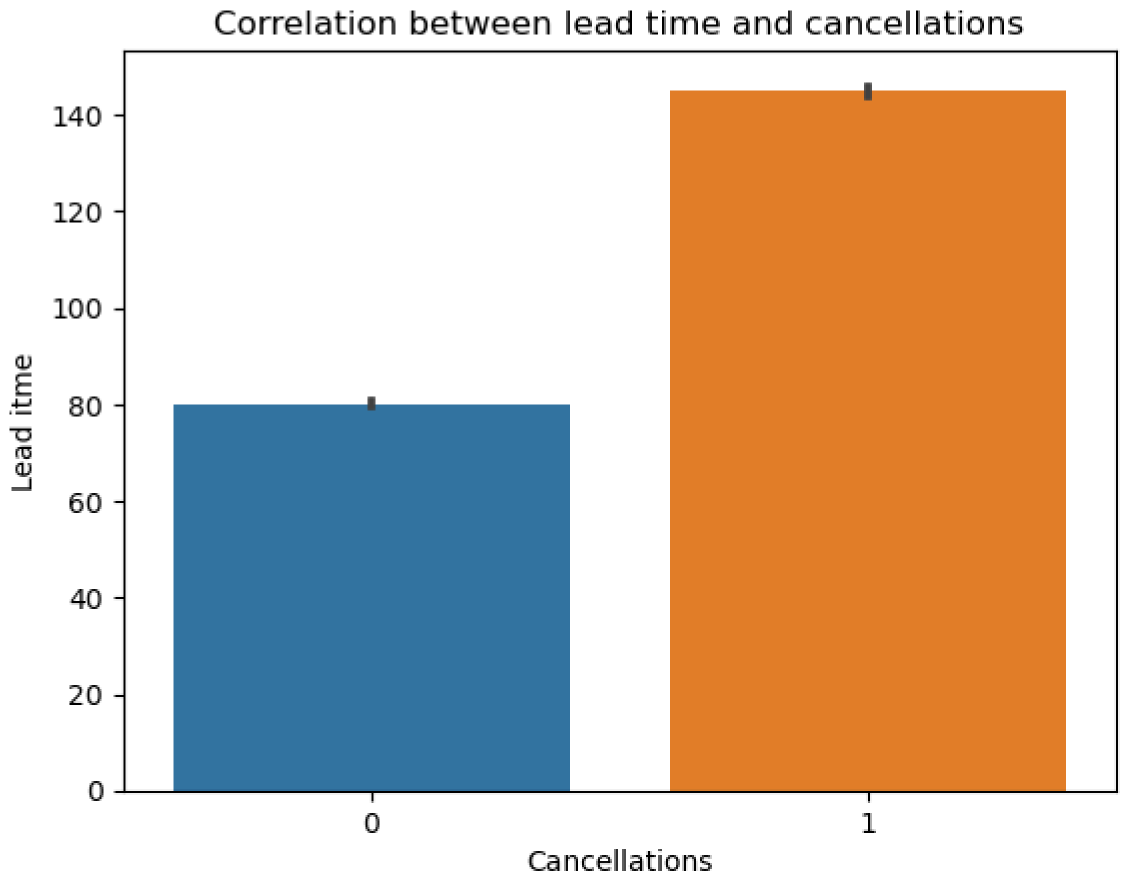
Let's start analyzing the average lead time between the city and resort hotel to understand which hotel has more anticipation with bookings.

In [ ]:
```
# Average lead time bookings
bavg_lead_time = df_book_lt.groupby('hotel')['lead_time'].mean()
print(bavg_lead_time)
```

```
hotel
City Hotel      109.741106
Resort Hotel     92.675686
Name: lead_time, dtype: float64
```

In [ ]:
```
# Let's analyze the correlation between lead time and cancellations
corr_cancellation = df_book_lt['lead_time'].corr(df_book_lt['is_canceled']).round(2
print(f"Correlation between lead time and cancellation rate: {corr_cancellation}")


# Data visualization
sns.barplot(x='is_canceled', y='lead_time', data=df_book_lt)
plt.title('Correlation between lead time and cancellations')
plt.xlabel('Cancellations')
plt.ylabel('Lead itme')
plt.show()
```

```
Correlation between lead time and cancellation rate: 0.29
```



*The results of our analysis show that there is little association between the two variables, 'Lead Time' and 'Cancellations', with a correlation coefficient of **0.29**. The cancellations are unaffected by the time.*

*Let's introduce a new variable to our analysis, the **ADR (Average Daily rate)**, and try to identify if this variable is affecting the cancellations in the hotel.*

In [ ]:
```
# Correlation between lead time and ADR
corr_adr = df_book_lt['lead_time'].corr(df_book_lt['adr']).round(2)
print(f"Correlation between lead time and ADR: {corr_adr}")
```

```
Correlation between lead time and ADR: -0.06
```

*The results of the analysis show a correlation coefficient of **-0.06**. There is no correlation between the two variables, 'Lead Time' and 'ADR'. This variable is not affecting the cancellations.*

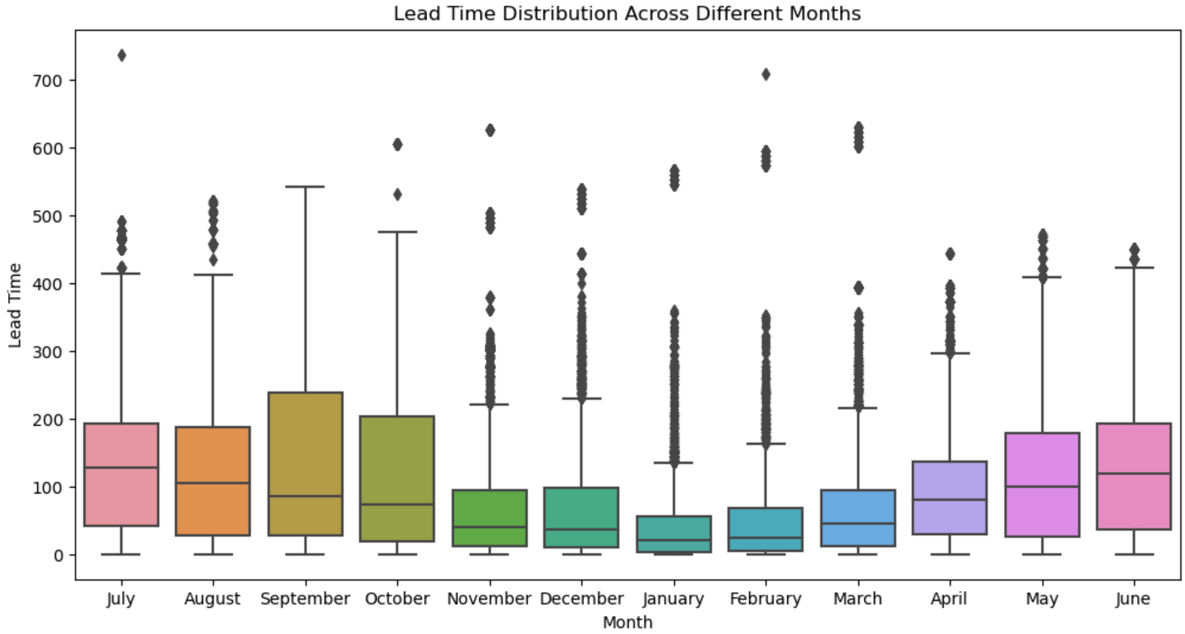
Let's add some visualization to our data and try to figure out how variables are working between them. This will help us find meaningful insights.

<u>Visualizing the Lead Time Distribution</u>

To visualize our data, I will use the values from the 'arrival_date_month' column. These values and the histogram will help us better understand our analysis.

In [ ]:
```
# Creating the visualization with the correlation between 'lead_time' and 'arrival_
# Size of the boxplot
plt.figure(figsize=(12, 6))

# Boxplot for the months
sns.boxplot(x='arrival_date_month', y='lead_time', data=df_book_lt)
```

```
plt.title('Lead Time Distribution Across Different Months')
plt.xlabel('Month')
plt.ylabel('Lead Time')
plt.show()
```



As expected, the most occupied time is when vacations occur. It starts in May and ends in October. It is important to highlight September as one of the months showing the most reservations.

Let's analyze how occupation distributes for the different hotel segments

In [ ]:
```
# I will use the customer data from the customer_type column. Let's create our char
# Giving our boxplot a size
plt.figure(figsize=(12,6))

# Boxplot with the customer segments
sns.boxplot(x='customer_type', y='lead_time', hue='arrival_date_year', data=df_book
plt.title('Lead Time distribution for the different customer segments')
plt.xlabel('Customer Type')
plt.ylabel('Lead Time Distribution')
plt.show()
```

After visualizing the data, let's discribe the conclusions by customer segments:

- *Transient customers, because there are too many outlier values. This customers shows disparate reservations, but most of the time their bookings are close to the stay date. Between the three years, their median lead time is approximately 50 days.*
- *Contract customers, the variability in lead time bookings in 2015 shows a high variability, and from 2016 it starts to decrease. Also, the median was around 50 days in 2015, but then increased in 2016 to around 180 days, and by 2017, it decreased to approximately 150 days. The booking spread is also in advance of the arrival date.*
- *A close look at Transient-Party customers data shows that the median number of bookings significantly increased from 2015 to 2017, going from 80 to 100 days approximately. There is not much variability in the lead time for bookings. They present a reduction in lead time variability in 2017. In 2016, because of some outlier values, they are starting to book far in advance of their arrival date.*
- *Group customers show the lowest median lead time among all customers; they tend to book near the stay date. It's important to notice that because of too many outlier values, they also register bookings far in advance of the stay date. They are the most consistent with their bookings across the years.*

Recommendations:

- *Create targeted marketing strategies for customers based on their booking patterns. One of them can be a booking discount with the purpose of encouraging customers to book at a more advanced time.*
- *Establish long-term pricing contracts to help advance bookings with the Contract customers. This type of strategy will help to optimize revenue.*
- *Is it possible to allocate resources and staffing to more predictable segments because of their booking pattern to give them a different management approach.*

4.6 Revenue Analysis

*It's time to analyze the **ADR** (Average Daily Rate) for each hotel. Let's understand how much revenue is made for each of the hotels, City, and Resort. I will start comparing the ADR between both of them. Later, I will analyze the variation by segment and lead time.*

For this new analysis I will create a new data frame.

In [ ]:
```
# Creating the new data frame for the revenue analysis
df_revAdr = df_hb[['hotel','adr', 'market_segment', 'customer_type', 'lead_time',

df_revAdr.head(5)
```

Out[ ]:

	hotel	adr	market_segment	customer_type	lead_time	arrival_date_year	reserved_room_type
0	Resort Hotel	0.0	Direct	Transient	342	2015	C
1	Resort Hotel	0.0	Direct	Transient	737	2015	C
2	Resort Hotel	75.0	Direct	Transient	7	2015	A
3	Resort Hotel	75.0	Corporate	Transient	13	2015	A
4	Resort Hotel	98.0	Online TA	Transient	14	2015	A

4.6.a Comparing the ADR between City and Resort Hotels.

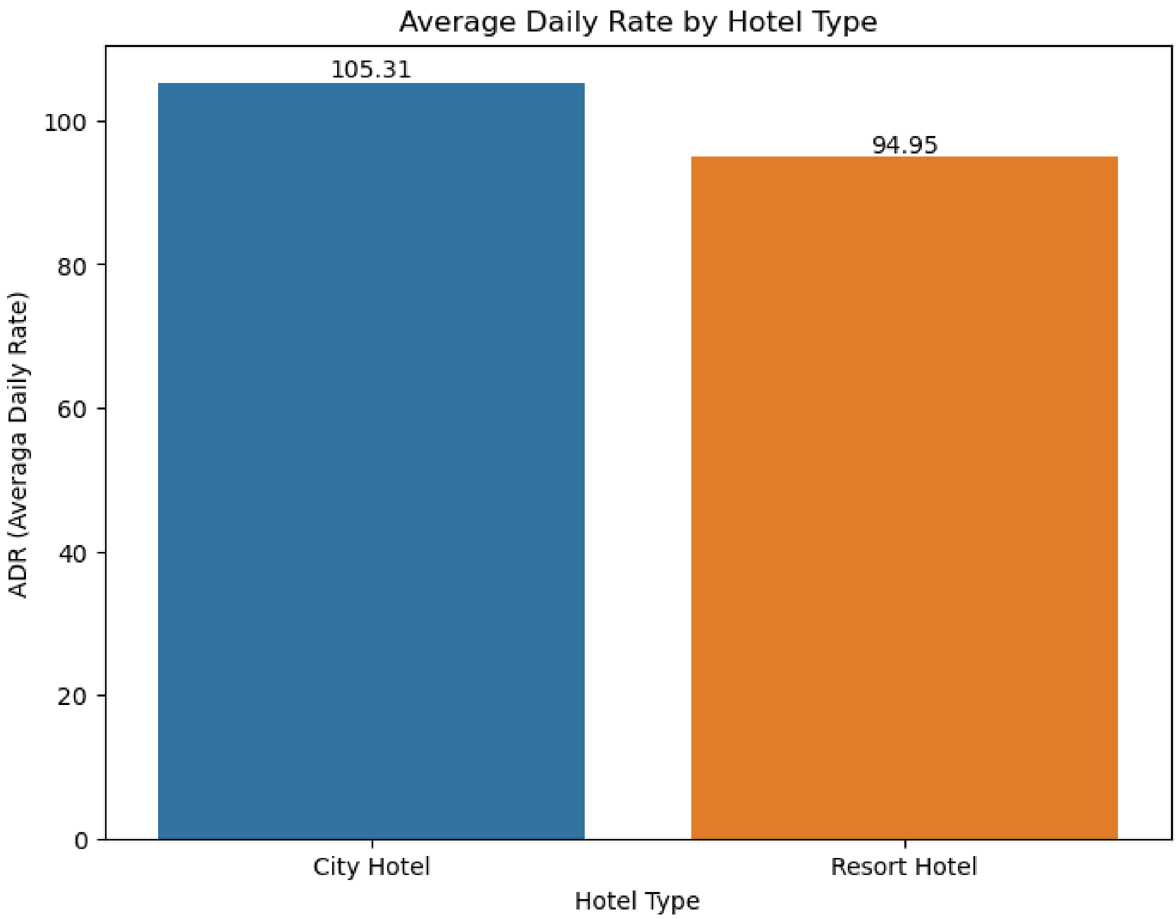
In [ ]:

```
# Grouping the data by hotel
mean_Adr = df_revAdr.groupby('hotel')['adr'].mean().round(2).reset_index()

print(mean_Adr)
```

```
          hotel     adr
0    City Hotel  105.31
1  Resort Hotel   94.95
```

In [ ]:

```
# Visualizing the data with a barplot
plt.figure(figsize=(8, 6))

# Creating the plot
ax = sns.barplot(x='hotel', y='adr', data=mean_Adr)
ax.bar_label(ax.containers[0], fontsize=10)
plt.title('Average Daily Rate by Hotel Type')
plt.xlabel('Hotel Type')
plt.ylabel('ADR (Averaga Daily Rate)')
plt.show()
```



*The data shows us that the ADR for the City Hotel is **105.31**, and for the Resort Hotel is **94.95**.*

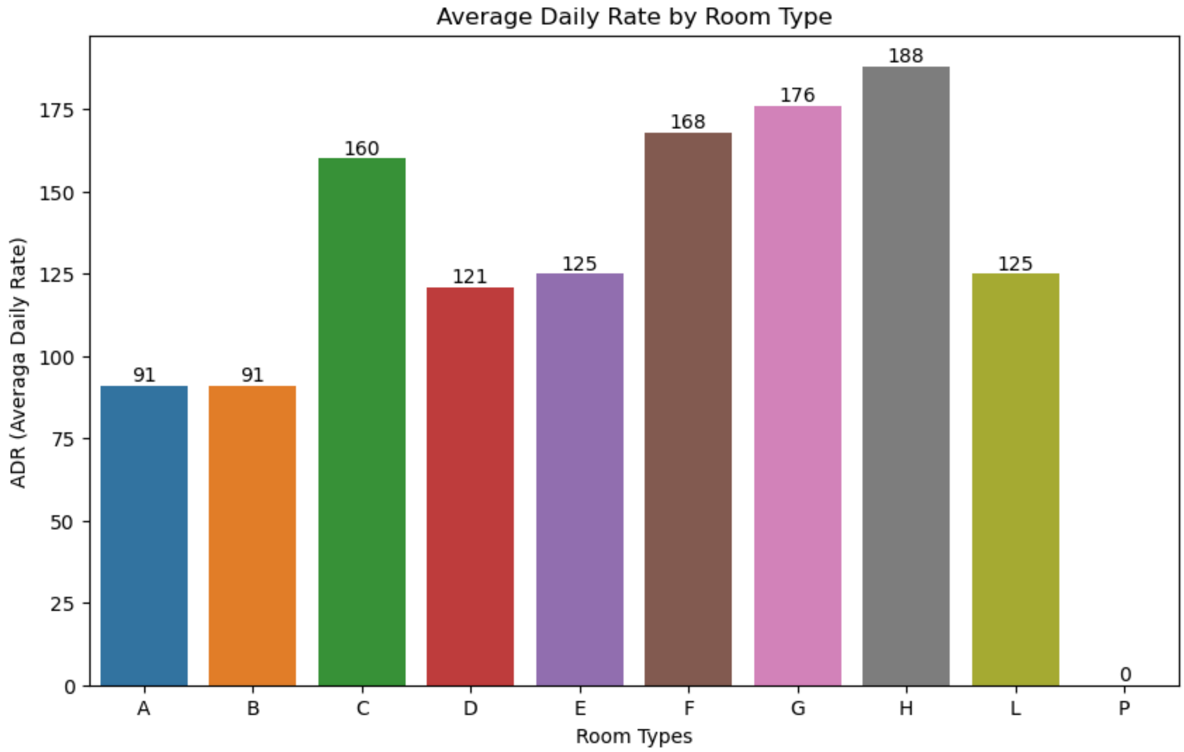
4.6.b Analyzing the ADR variation between Room Types, Market Segment and Lead Time.

4.6.b.1 ADR variation by Room Types.

In [ ]:
```
# Variation by room types
mean_adr_rt = df_revAdr.groupby('reserved_room_type')['adr'].mean().round().reset_i

print(mean_adr_rt)
```

```
  reserved_room_type    adr
0                  A   91.0
1                  B   91.0
2                  C  160.0
3                  D  121.0
4                  E  125.0
5                  F  168.0
6                  G  176.0
7                  H  188.0
8                  L  125.0
9                  P    0.0
```

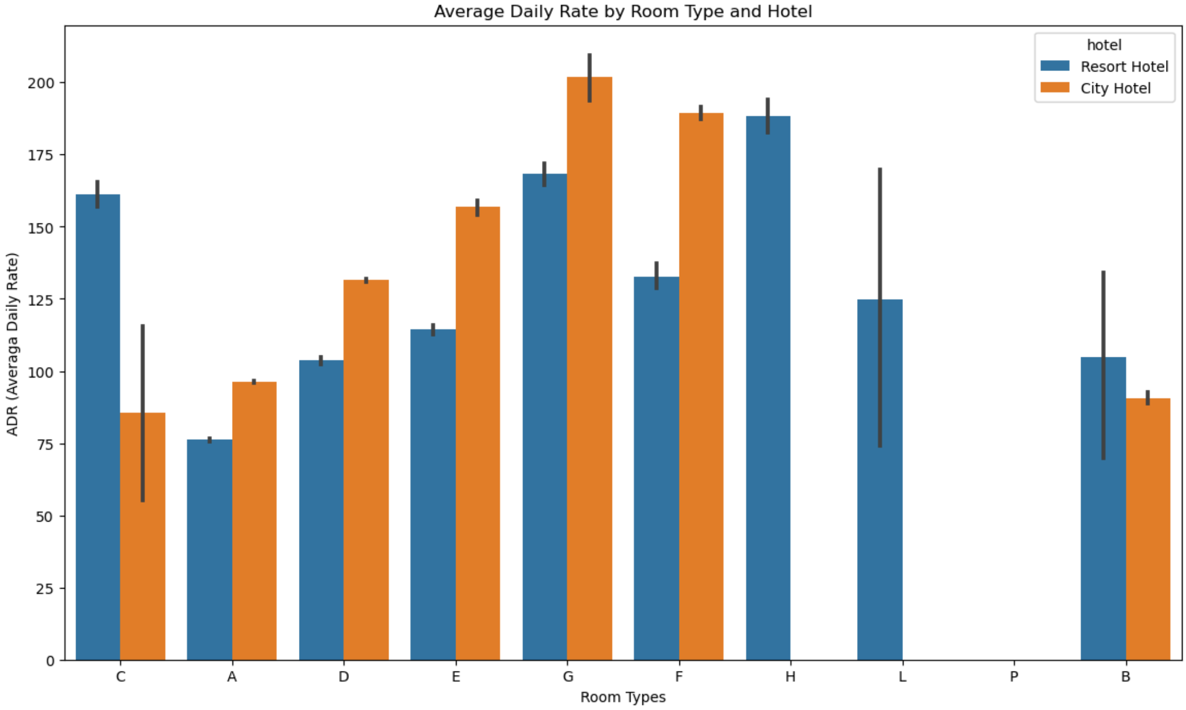
In [ ]:
```
# Creating the plot
plt.figure(figsize=(10, 6))

ax = sns.barplot(x='reserved_room_type', y='adr',  data=mean_adr_rt)
ax.bar_label(ax.containers[0], fontsize=10)
plt.title('Average Daily Rate by Room Type')
plt.xlabel('Room Types')
plt.ylabel('ADR (Averaga Daily Rate)')
plt.show()
```



*When I analyze the ADR by 'Room Type', the data shows us that room **H** has the highest average daily rate with a total of $188.-. Then, with the lower average daily rate, we have rooms **A** and **B**. For this analysis, I won't consider the parking spaces.*

Room Types variation by Hotels

In [ ]:
```
# Creating the plot
plt.figure(figsize=(14, 8))

ax = sns.barplot(x='reserved_room_type', y='adr',  hue='hotel', data=df_revAdr)

plt.title('Average Daily Rate by Room Type and Hotel')
plt.xlabel('Room Types')
plt.ylabel('ADR (Averaga Daily Rate)')
plt.show()
```



*When I split the data between the two hotels, room **H** only reports at the Resort Hotel, and with room **C** and **G**, these rooms are the ones with the highest ADR. Different is the case of the City Hotel, where rooms **G** and **F** are the ones with the highest ADR. And rooms **C**, **A**, and **B** show the lowest ADR.*

Looking at both analyses, they show different numbers for the ADR. This is important to keep in mind for the purpose of creating special offers for each Hotel.

Let's analyze if the hotels assign the rooms the customers have booked.

I will compare the values from the column 'reserved_room_type' and 'assigned_room_type'. I will store the result of the comparison into a new column called 'room_assigned_correctly', with 0 for False values, and 1 for True values.

In [ ]:

```
# Let's compare the values from the columns
df_revAdr['room_assigned_correctly'] = (df_revAdr['reserved_room_type'] == df_revAd

df_revAdr.head()
```

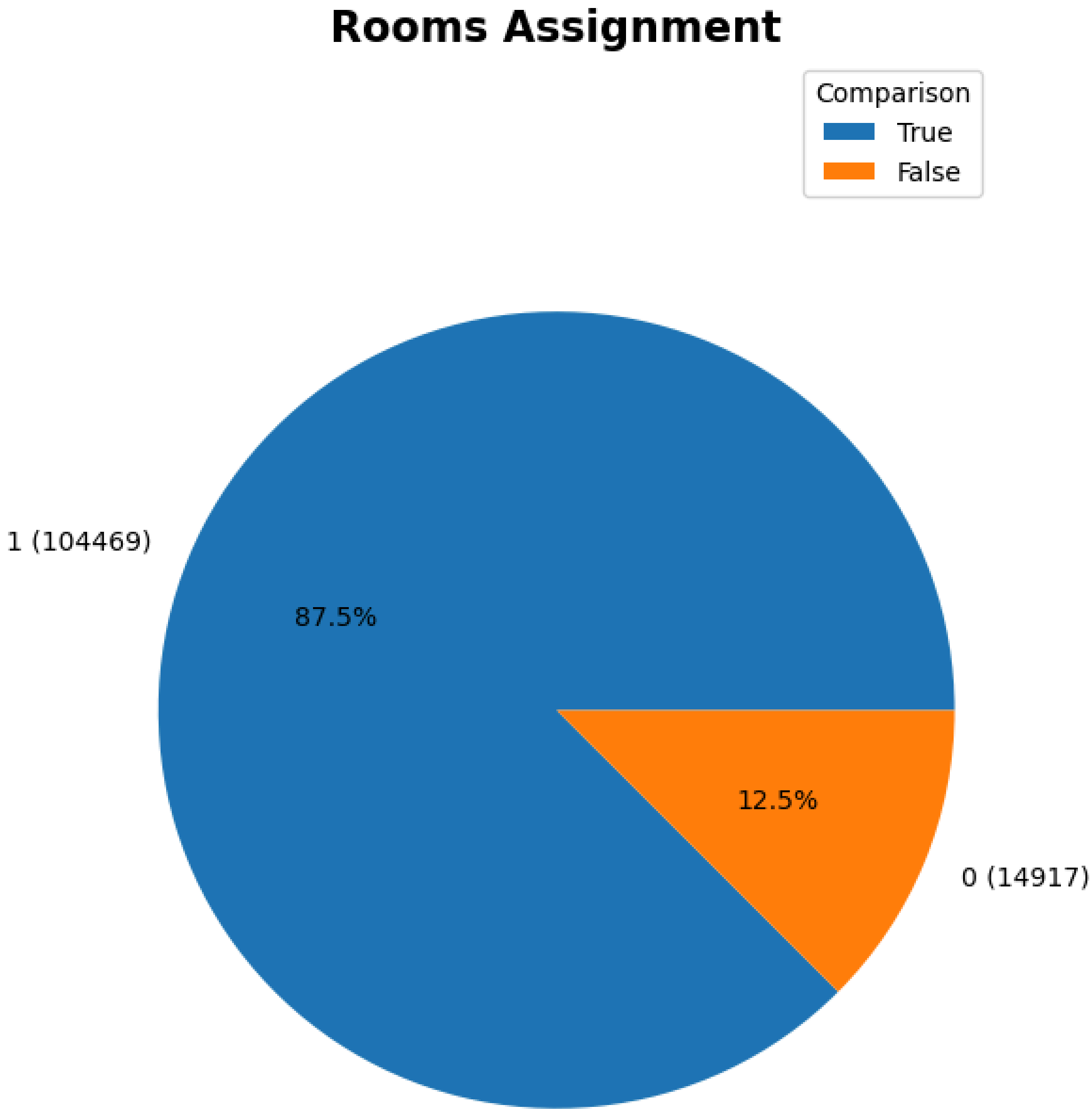
Out[ ]:

	hotel	adr	market_segment	customer_type	lead_time	arrival_date_year	reserved_room_type
0	Resort Hotel	0.0	Direct	Transient	342	2015	C
1	Resort Hotel	0.0	Direct	Transient	737	2015	C
2	Resort Hotel	75.0	Direct	Transient	7	2015	A
3	Resort Hotel	75.0	Corporate	Transient	13	2015	A
4	Resort Hotel	98.0	Online TA	Transient	14	2015	A

Now with the new column let's visualize how the room assignment is working

In [ ]:
```
# Counting the values
room_corr_assigned = df_revAdr['room_assigned_correctly'].value_counts()

print(room_corr_assigned)

# Total and percentage variables to use on our charts
total_rca_count = room_corr_assigned.sum()
rca_percentage = (room_corr_assigned / total_rca_count) * 100

# labels = room_corr_assigned.index
# Using a function to create the labels
labels = [f'{rooms} ({count})' for rooms, count in zip(room_corr_assigned.index, rc

# Chart size
fig, ax = plt.subplots(figsize=(6, 9))

# Chart generation
plt.pie(room_corr_assigned, labels=labels, autopct='%1.1f%%')
ax.legend(['True', 'False'], loc='upper right', title='Comparison')
# plt.legend(title='Correctly')
ax.set_title('Rooms Assignment', fontsize=16, fontweight='bold')
plt.axis('equal')
plt.show()
```

```
1    104469
0     14917
Name: room_assigned_correctly, dtype: int64
```



*Analyzing room assignment, shows us that **87.5%** of the rooms are assigned correctly, this means that the customers recieve the room they booked for. It's recommended for a future, try to reduce the **12.5%** of wrong assignment of the rooms. A higher percentage of wrong room assignment can produce discomfort with the customers and at some point lose them.*

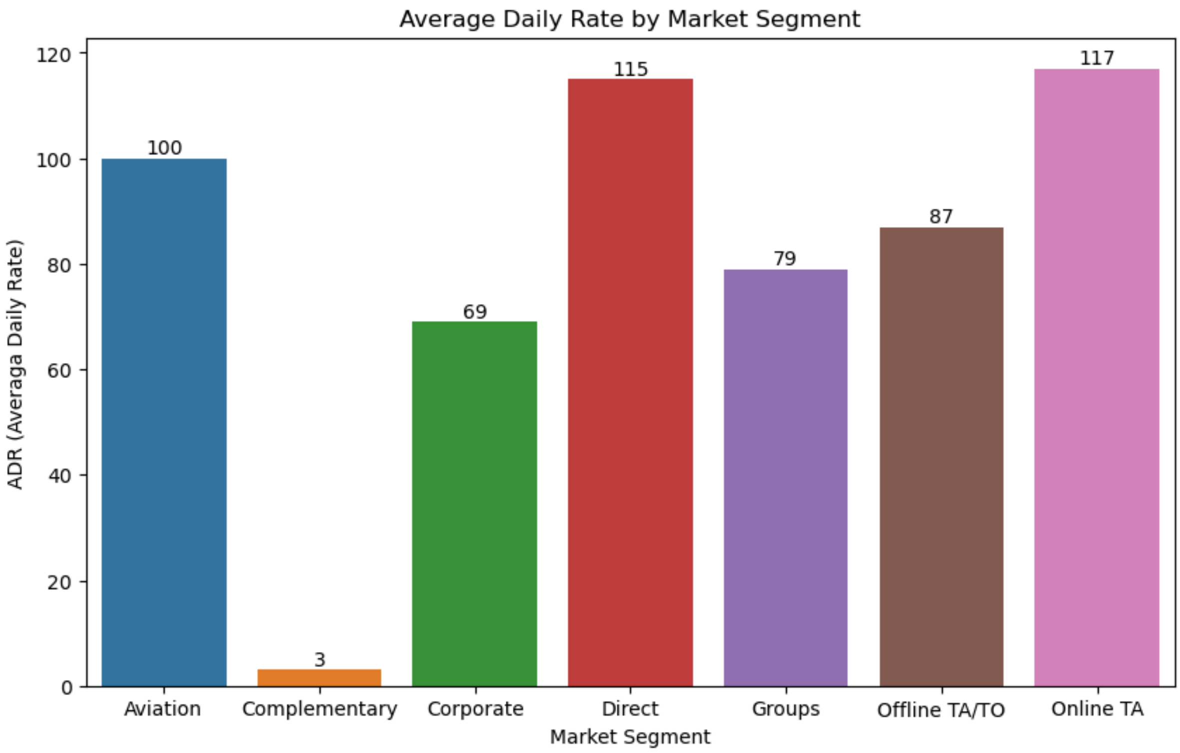
*It will be interesting to confirm later whether or not the **12.5%** translates to a room upgrade. A nicer room almost always means a happier customer.*

4.6.b.2 ADR variation by Market Segments.

In [ ]:
```
# Variation by market segment
mean_adr_mkt = df_revAdr.groupby('market_segment')['adr'].mean().round().reset_inde

print(mean_adr_mkt)
```

```
  market_segment    adr
0        Aviation  100.0
1  Complementary    3.0
2       Corporate   69.0
3          Direct  115.0
4          Groups   79.0
5   Offline TA/TO   87.0
6       Online TA  117.0
```

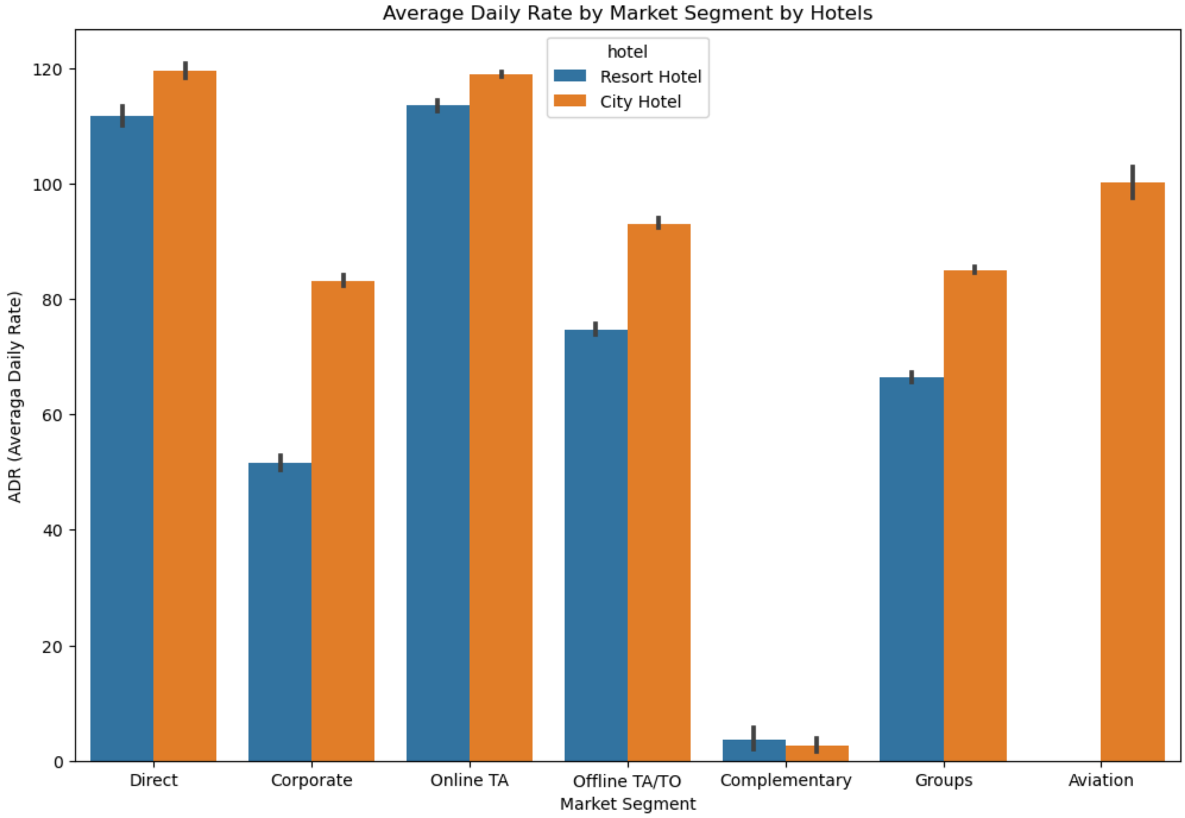
In [ ]:
```python
# Creating the plot
plt.figure(figsize=(10, 6))

ax = sns.barplot(x='market_segment', y='adr', data=mean_adr_mkt)
ax.bar_label(ax.containers[0], fontsize=10)
plt.title('Average Daily Rate by Market Segment')
plt.xlabel('Market Segment')
plt.ylabel('ADR (Averaga Daily Rate)')
plt.show()
```



Analyzing the ADR by market segment shows that Direct, Aviation, and Online are where the hotel receives the most reservations. These markets are where the Hotel can offer special benefits or direct the offers to other segments to help them grow.

Market Segment variation by Hotels

In [ ]:
```python
# Creating the plot
plt.figure(figsize=(12, 8))

ax = sns.barplot(x='market_segment', y='adr', hue='hotel', data=df_revAdr)
plt.title('Average Daily Rate by Market Segment by Hotels')
plt.xlabel('Market Segment')
plt.ylabel('ADR (Averaga Daily Rate)')
plt.show()
```



The analysis of the market segments by Hotels, doesn't show too much variation. This analysis helps us create more specific offers by hotel and market segment.

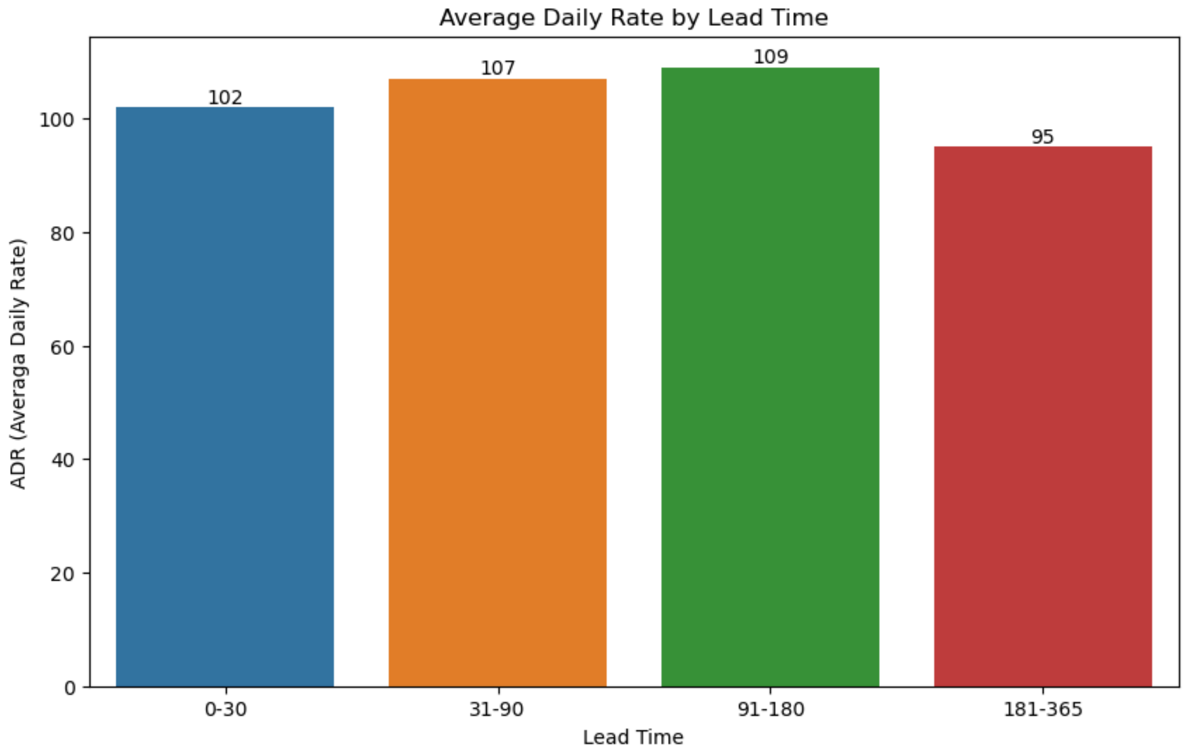
4.6.b.3 ADR variation by Lead Time.

In [ ]:
```
# Variation by Lead Time: Because the values are too big, I separate the values int
# Enclosing the data values
df_revAdr['lt_enclosed'] = pd.cut(df_revAdr['lead_time'], bins=[0, 30, 90, 180, 365
mean_adr_ltbucket = df_revAdr.groupby('lt_enclosed')['adr'].mean().round().reset_in
mean_adr_lt = df_revAdr.groupby('lead_time')['adr'].mean().round().reset_index()

print(mean_adr_lt)
print(mean_adr_ltbucket)
```

```
     lead_time   adr
0            0  83.0
1            1  90.0
2            2  94.0
3            3  93.0
4            4  95.0
..         ...   ...
474        622  62.0
475        626  63.0
476        629  62.0
477        709  68.0
478        737   0.0

[479 rows x 2 columns]
  lt_enclosed    adr
0        0-30  102.0
1       31-90  107.0
2      91-180  109.0
3     181-365   95.0
```

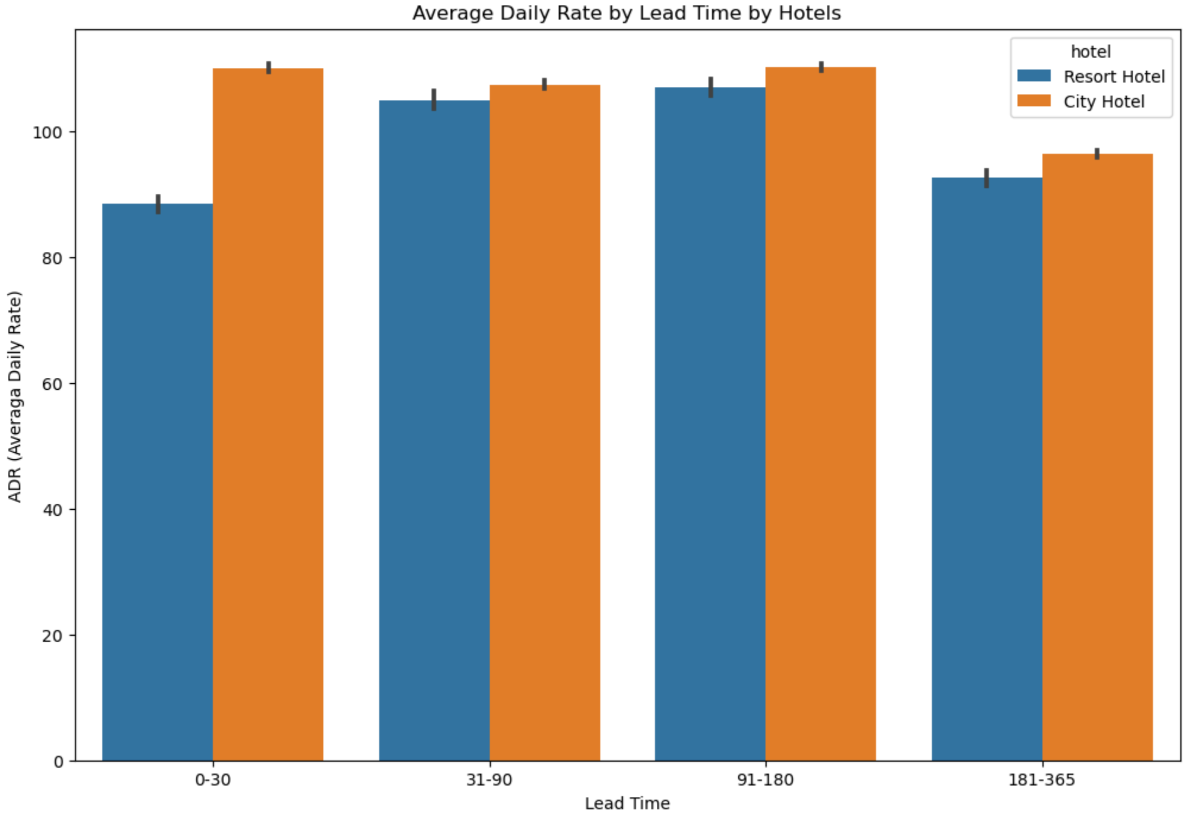
In [ ]:
```
# Creating the plot
plt.figure(figsize=(10, 6))
```

```
ax = sns.barplot(x='lt_enclosed', y='adr', data=mean_adr_ltbucket)
ax.bar_label(ax.containers[0], fontsize=10)
plt.title('Average Daily Rate by Lead Time')
plt.xlabel('Lead Time')
plt.ylabel('ADR (Averaga Daily Rate)')
plt.show()
```



Lead Time variation by Hotels

In [ ]:
```
# Creating the plot
plt.figure(figsize=(12, 8))

ax = sns.barplot(x='lt_enclosed', y='adr', hue='hotel', data=df_revAdr)
plt.title('Average Daily Rate by Lead Time by Hotels')
plt.xlabel('Lead Time')
plt.ylabel('ADR (Averaga Daily Rate)')
plt.show()
```

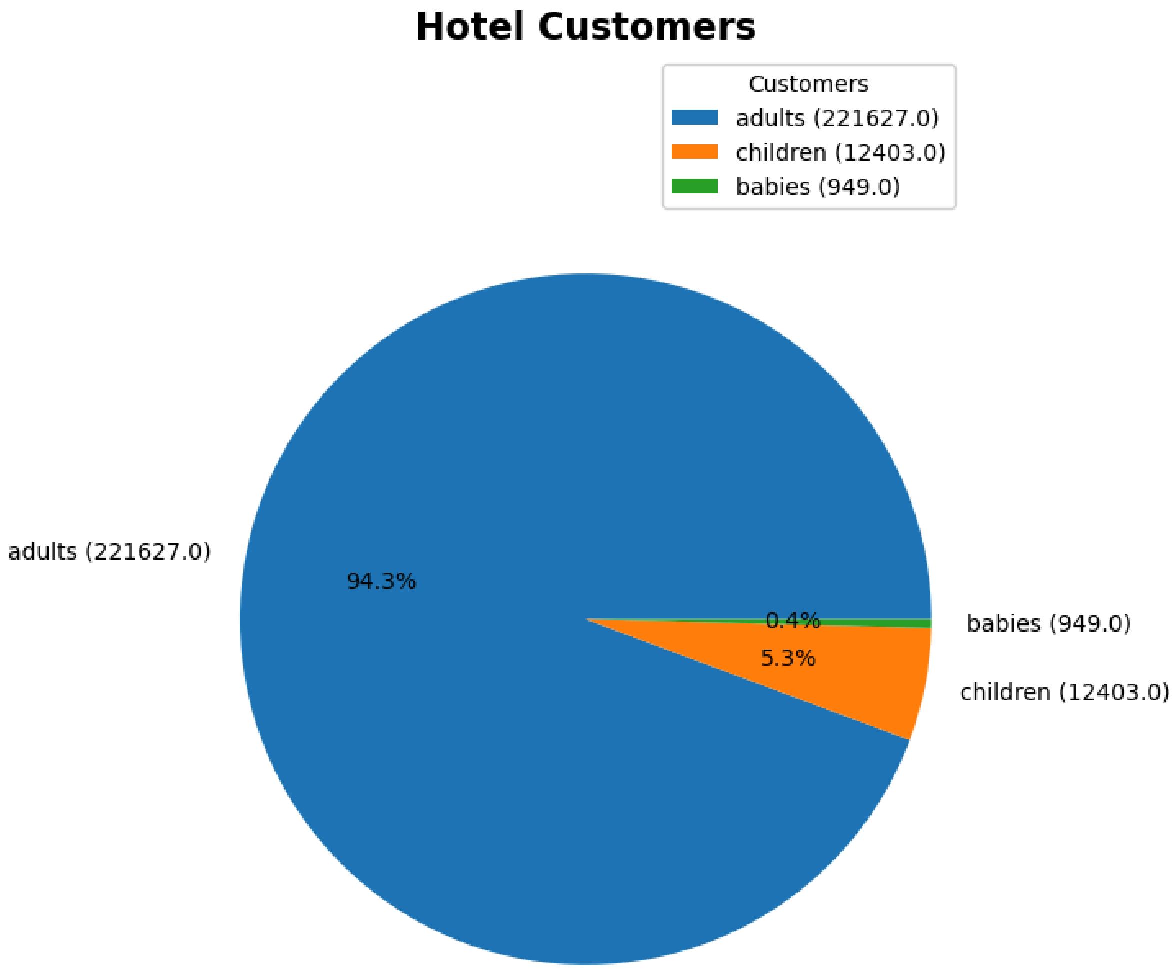


4.7 Customer Segmentation

In [ ]:

```
customer_count = df_hb[['adults', 'children', 'babies']].sum()

print(customer_count)

# Total and percentage variables to use on our charts
total_ctmr_count = customer_count.sum()
ctmr_percentage = (customer_count / total_ctmr_count) * 100

# Using a function to create the labels
labels = [f'{customer} ({count})' for customer, count in zip(customer_count.index,

# Chart size
fig, ax = plt.subplots(figsize=(6, 9))

# Chart generation
plt.pie(customer_count, labels=labels, autopct='%1.1f%%')
plt.legend(title='Customers', loc='upper right')
ax.set_title('Hotel Customers', fontsize=16, fontweight='bold')
plt.axis('equal')
plt.show()
```

```
adults      221627.0
children     12403.0
babies         949.0
dtype: float64
```



In [ ]:
```
# Count the different countries from where the customers are
country_count = df_hb['country'].value_counts()

print(country_count)

# Because there are many different countries, I will group those that have less tha
less_than_500_customers = 500
new_ctry_count = country_count[country_count < less_than_500_customers].sum()
country_count = country_count[country_count >= less_than_500_customers]
country_count['OTHERS'] = new_ctry_count

# Let's verify how the last code works
print(country_count)

# Creating the labels for our chart
labels = [f'{country} ({count})' for country, count in country_count.items()]

# Plotting using Bar Chart
fig, ax = plt.subplots(figsize=(10, 6))
ax.bar(country_count.index, country_count.values)
ax.set_xticklabels(labels, rotation=90)
ax.set_title('Hotel Customers by Country')
ax.set_xlabel('Country')
ax.set_ylabel('Number of Customers')
plt.tight_layout()
plt.show()
```

```
PRT    48586
GBR    12129
FRA    10415
ESP     8568
DEU     7287
       ...
DJI        1
BWA        1
HND        1
VGB        1
NAM        1
Name: country, Length: 178, dtype: int64
PRT       48586
GBR       12129
FRA       10415
ESP        8568
DEU        7287
ITA        3766
IRL        3375
BEL        2342
BRA        2224
NLD        2104
USA        2097
CHE        1730
CN         1279
AUT        1263
SWE        1024
CHN         999
POL         919
ISR         669
RUS         632
NOR         607
ROU         500
OTHERS     6871
Name: country, dtype: int64
```