

## Title: Hotel Booking Cancellation Analysis: Maximizing Revenue Efficiency

#### Introduction:

In this report, we will analyze the issue of high cancellation rates in City Hotel and Resort Hotel, aiming to provide valuable insights and recommendations to address this challenge. The focus is on optimizing revenue generation and improving operational efficiency by reducing cancellation rates.

## **Objective:**

The primary objective of this analysis is to understand the factors contributing to high cancellation rates in both City Hotel and Resort Hotel. By identifying these factors, we can develop targeted strategies to minimize cancellations, increase revenue, and optimize hotel room utilization.

## Methodology:

To achieve our objective, we will perform a comprehensive analysis of hotel booking cancellations, examining various factors that influence cancellation rates. We will consider factors such as pricing strategies, seasonal variations, hotel location, and quality of service. The analysis will involve studying historical data, industry trends, and customer behavior patterns.

## **Key Deliverables:**

- 1. Identification of key factors influencing cancellation rates in City Hotel and Resort Hotel.
- 2. Evaluation of the impact of pricing strategies, seasonal variations, and location on cancellation rates.
- 3. Assessment of the quality of service and its correlation with cancellations.
- 4. Recommendations for targeted strategies to reduce cancellation rates and increase revenue efficiency.

5. Suggestions for improving hotel room utilization and overall operational efficiency.

#### **Conclusion:**

By analyzing hotel booking cancellations and related factors, this report aims to provide actionable insights for City Hotel and Resort Hotel. By implementing the recommended strategies, both hotels can minimize cancellations, increase revenue, and improve overall business performance. With a focus on revenue efficiency and optimized hotel room utilization, the hotels can enhance customer satisfaction and drive long-term success in the hospitality industry.

#### **LINKEDIN LINK:**

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#### **GIT HUB LINK:**

https://github.com/Asadxio (https://github.com/Asadxio)

## **Importing Libraries**

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

## **Loading The Data Set**

```
In [2]:

df = pd.read_csv("C:/Users/Asad/Downloads/Compressed/Hotel booking/hotel_booking.csv")
```

## **Exploratory Data Analysis and Data Cleaning**

[n [3															
f.he	ead()														
ut[3	3]:														
h	hotel	is_c	anceled	lead	_time	arriv	/al_date_year	arri	val_date_m	onth	arriv	al_date	_week	_nur	
	esort Hotel		0		342		2015			July					
	esort Hotel		0		737		2015			July					
	esort Hotel		0		7		2015			July					
	esort Hotel		0		13		2015			July					
	esort Hotel		0		14		2015			July					
rows	's × 32	2 col	umns											<b>+</b>	
n [4	/s × 32 4]:		umns											<b>&gt;</b>	
n [4	rs × 32		umns											•	
n [4 f.ta	4]: ail()		umns											•	
n [4 f.ta	4]: 4]: 4]:			eled	lead_ti	me	arrival_date_	year	arrival_da	te_mo	nth	arrival_	date_v		
n [4 f.ta ut[4	4]: 4]: 4]: ho			eled 0	lead_ti	<b>me</b> 23		<b>year</b> 2017	arrival_da	<b>te_mo</b> i Aug		arrival_	date_v		
n [4 f.ta ut[4 11938	4]: 4]: 4]: ho	<b>otel</b>					:		arrival_da		ust	arrival_	date_v		
n [4 f.ta ut[4 11938	4]: 4]: 4]: 60 85 (Ho	City otel		0		23	:	2017	arrival_da	Aug	ust	arrival_	date_v		
n [4	4]: ail() 4]: ho 85 (According to the content of th	City otel City otel City		0		23 102	:	2017	arrival_da	Aug Aug	ust	arrival_	date_v		

5 rows × 32 columns

In [5]:

df.shape

Out[5]:

(119390, 32)

In [6]: ▶

df.columns

#### Out[6]:

In [7]: ▶

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119390 entries, 0 to 119389
```

Data columns (total 32 columns):

#	Column	Non-Null Count	Dtype
0	hotel	119390 non-null	
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	<pre>previous_bookings_not_canceled</pre>	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
dtype	es: float64(4), int64(16), objec	t(12)	

In [8]:

df["reservation\_status\_date"] = pd.to\_datetime(df["reservation\_status\_date"])

memory usage: 29.1+ MB

M

M In [9]:

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 119390 entries, 0 to 119389

Data columns (total 32 columns):

#	Column	Non-Null Count	Dtype
	h-4-1	110200	
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	<pre>previous_bookings_not_canceled</pre>	119390 non-null	int64
19	reserved_room_type	119390 non-null	•
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	datetime64[ns]
dtyp	es: datetime64[ns](1), float64(4	), int64(16), obj	ect(11)
	ny usago: 20 1± MR	, , , ,	• •

localhost:8888/notebooks/HOTEL\_BOOKING .ipynb

memory usage: 29.1+ MB

In [10]: ▶

df.describe(include = 'object')

#### Out[10]:

	hotel	arrival_date_month	meal	country	market_segment	distribution_channel	r
count	119390	119390	119390	118902	119390	119390	
unique	2	12	5	177	8	5	
top	City Hotel	August	ВВ	PRT	Online TA	TA/TO	
freq	79330	13877	92310	48590	56477	97870	
4							•

```
In [11]: ▶
```

```
for col in df.describe(include = "object").columns:
   print(col)
   print(df[col].unique())
   print('-'*70)
hotel
['Resort Hotel' 'City Hotel']
arrival_date_month
['July' 'August' 'September' 'October' 'November' 'December' 'January'
 'February' 'March' 'April' 'May' 'June']
______
meal
['BB' 'FB' 'HB' 'SC' 'Undefined']
country
['PRT' 'GBR' 'USA' 'ESP' 'IRL' 'FRA' nan 'ROU' 'NOR' 'OMN' 'ARG' 'POL'
 'DEU' 'BEL' 'CHE' 'CN' 'GRC' 'ITA' 'NLD' 'DNK' 'RUS' 'SWE' 'AUS' 'EST'
 'CZE' 'BRA' 'FIN' 'MOZ' 'BWA' 'LUX' 'SVN' 'ALB' 'IND' 'CHN' 'MEX' 'MAR'
 'UKR' 'SMR' 'LVA' 'PRI' 'SRB' 'CHL' 'AUT' 'BLR' 'LTU' 'TUR' 'ZAF' 'AGO'
 'ISR' 'CYM' 'ZMB' 'CPV' 'ZWE' 'DZA' 'KOR' 'CRI' 'HUN' 'ARE' 'TUN' 'JAM'
 'HRV' 'HKG' 'IRN' 'GEO' 'AND' 'GIB' 'URY' 'JEY' 'CAF' 'CYP' 'COL' 'GGY'
 'KWT' 'NGA' 'MDV' 'VEN' 'SVK' 'FJI' 'KAZ' 'PAK' 'IDN' 'LBN' 'PHL' 'SEN'
 'SYC' 'AZE' 'BHR' 'NZL' 'THA' 'DOM' 'MKD' 'MYS' 'ARM' 'JPN' 'LKA' 'CUB'
 'CMR' 'BIH' 'MUS' 'COM' 'SUR' 'UGA' 'BGR' 'CIV' 'JOR' 'SYR' 'SGP' 'BDI'
 'SAU' 'VNM' 'PLW' 'OAT' 'EGY' 'PER' 'MLT' 'MWI' 'ECU' 'MDG' 'ISL' 'UZB'
 'NPL' 'BHS' 'MAC' 'TGO' 'TWN' 'DJI' 'STP' 'KNA' 'ETH' 'IRQ' 'HND'
 'KHM' 'MCO' 'BGD' 'IMN' 'TJK' 'NIC' 'BEN' 'VGB' 'TZA' 'GAB' 'GHA' 'TMP'
 'GLP' 'KEN' 'LIE' 'GNB' 'MNE' 'UMI' 'MYT' 'FRO' 'MMR' 'PAN' 'BFA' 'LBY'
 'MLI' 'NAM' 'BOL' 'PRY' 'BRB' 'ABW' 'AIA' 'SLV' 'DMA' 'PYF' 'GUY' 'LCA'
 'ATA' 'GTM' 'ASM' 'MRT' 'NCL' 'KIR' 'SDN' 'ATF' 'SLE' 'LAO']
market_segment
['Direct' 'Corporate' 'Online TA' 'Offline TA/TO' 'Complementary' 'Groups'
 'Undefined' 'Aviation']
distribution channel
['Direct' 'Corporate' 'TA/TO' 'Undefined' 'GDS']
reserved_room_type
['C' 'A' 'D' 'E' 'G' 'F' 'H' 'L' 'P' 'B']
assigned room type
['C' 'A' 'D' 'E' 'G' 'F' 'I' 'B' 'H' 'P' 'L' 'K']
-----
deposit_type
['No Deposit' 'Refundable' 'Non Refund']
customer_type
['Transient' 'Contract' 'Transient-Party' 'Group']
reservation_status
['Check-Out' 'Canceled' 'No-Show']
```

In [12]: ▶

```
df.isnull().sum()
```

#### Out[12]:

dtype: int64

```
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
                                         0
distribution_channel
is_repeated_guest
                                         0
                                         0
previous_cancellations
previous_bookings_not_canceled
                                         0
                                         0
reserved_room_type
                                         0
assigned_room_type
booking_changes
                                         0
deposit_type
                                         0
agent
                                    16340
                                    112593
company
days_in_waiting_list
                                         0
                                         0
customer_type
                                         0
required_car_parking_spaces
                                         0
total_of_special_requests
                                         0
                                         0
reservation_status
reservation_status_date
```

In [13]:

```
df.drop(['agent','company'], axis =1, inplace = True)
df.dropna(inplace = True)
```

In [14]: ▶

df.isnull().sum()

#### Out[14]:

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
<pre>stays_in_weekend_nights</pre>	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
previous_cancellations	0
previous_bookings_not_canceled	0
reserved_room_type	0
assigned_room_type	0
booking_changes	0
deposit_type	0
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
dtype: int64	J
acype. Inco-	

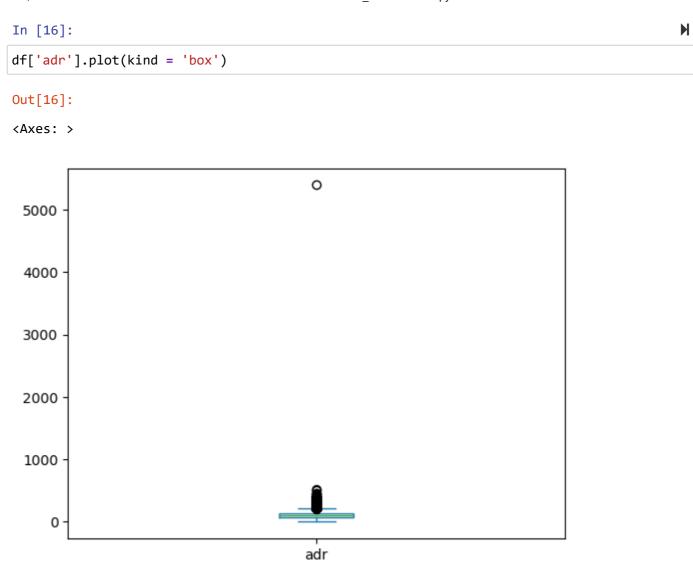
In [15]:

df.describe()

#### Out[15]:

	is_canceled	lead_time	arrival_date_year	arrival_date_week_number	arrival_date
count	118898.000000	118898.000000	118898.000000	118898.000000	
mean	0.371352	104.311435	2016.157656	27.166555	
std	0.483168	106.903309	0.707459	13.589971	
min	0.000000	0.000000	2015.000000	1.000000	
25%	0.000000	18.000000	2016.000000	16.000000	
50%	0.000000	69.000000	2016.000000	28.000000	
75%	1.000000	161.000000	2017.000000	38.000000	
max	1.000000	737.000000	2017.000000	53.000000	
4					<b>&gt;</b>

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## **Data Analysis and Visualization**

```
In [18]:

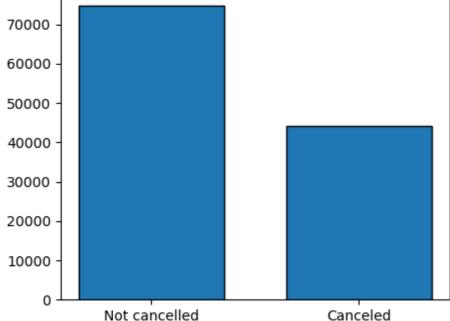
cancelled_prec = df['is_canceled'].value_counts(normalize=True)
print(cancelled_prec)

plt.figure(figsize=(5, 4))
plt.title('Reservation status count')
plt.bar(['Not cancelled', 'Canceled'], df['is_canceled'].value_counts(), edgecolor='k', wplt.show()
```

0 0.6286531 0.371347

Name: is\_canceled, dtype: float64

# Reservation status count



```
In [19]:
                                                                                           H
plt.figure(figsize=(8, 4))
```

```
ax1 = sns.countplot(x='hotel', hue='is_canceled', data=df, palette="Blues")
legend_labels, _ = ax1.get_legend_handles_labels()
ax1.legend(bbox_to_anchor=(1, 1))
plt.title('Reservation status in different hotels', size=20)
plt.xlabel('hotel')
plt.ylabel('number of reservations')
plt.show()
```

## Reservation status in different hotels



```
In [20]:
                                                                                           M
resort_hotel = df[df['hotel'] == 'Resort Hotel']
```

```
resort_hotel['is_canceled'].value_counts(normalize = True)
```

#### Out[20]:

0.72025 0.27975

Name: is\_canceled, dtype: float64

```
In [21]:
```

```
city_hotel = df[df['hotel'] == 'City Hotel']
city_canceled_prec = city_hotel['is_canceled'].value_counts(normalize=True)
print(city_canceled_prec)
```

0 0.582918 0.417082

Name: is\_canceled, dtype: float64

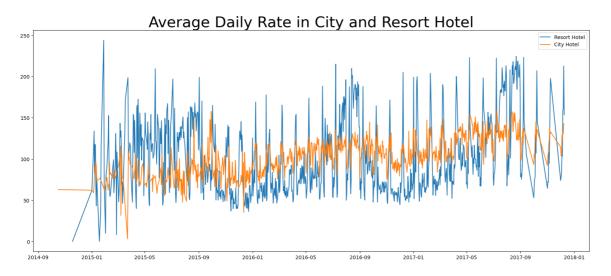
H

```
In [22]:
```

```
resort_hotel = resort_hotel.groupby('reservation_status_date')[['adr']].mean()
city_hotel = city_hotel.groupby('reservation_status_date')[['adr']].mean()
```

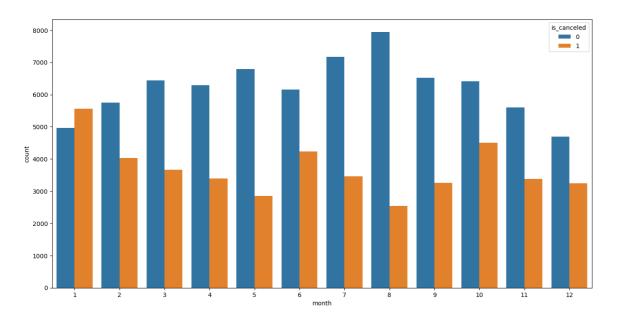
```
In [23]:
```

```
plt.figure(figsize=(20, 8))
plt.title('Average Daily Rate in City and Resort Hotel', fontsize=30)
plt.plot(resort_hotel.index, resort_hotel['adr'], label="Resort Hotel")
plt.plot(city_hotel.index, city_hotel['adr'], label="City Hotel")
plt.legend()
plt.show()
```



```
In [24]: ▶
```

```
df['month'] = df['reservation_status_date'].dt.month
plt.figure(figsize=(16, 8))
ax1 = sns.countplot(x='month', hue='is_canceled', data=df)
plt.show()
```



In [25]: ▶

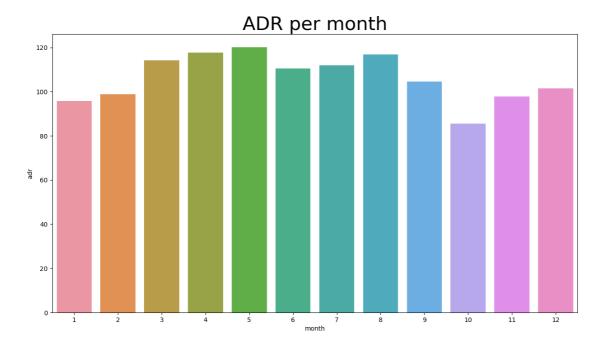
```
plt.figure(figsize=(15, 8))
plt.title('ADR per month', fontsize=30)

canceled_reservations = df[df['is_canceled'] == 1]

# Group the data by month and calculate the mean of ADR
monthly_adr = canceled_reservations.groupby('month')['adr'].mean().reset_index()

# Plot the bar chart
sns.barplot(x='month', y='adr', data=monthly_adr)

plt.show()
```

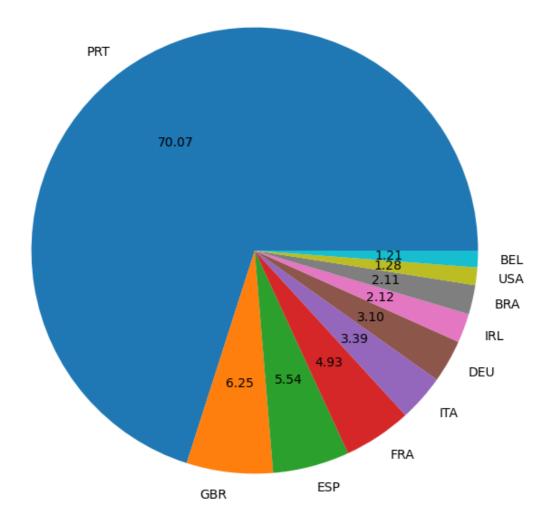


In [26]: ▶

```
cancelled_data = df[df['is_canceled'] == 1]
top_10_country = cancelled_data['country'].value_counts().head(10)

plt.figure(figsize=(8, 8))
plt.title('Top 10 Countries with Reservations Canceled')
plt.pie(top_10_country, autopct='%.2f', labels=top_10_country.index)
plt.show()
```

Top 10 Countries with Reservations Canceled



```
In [27]:
                                                                                          H
df['market_segment'].value_counts()
Out[27]:
Online TA
                 56402
Offline TA/TO
                 24159
Groups
                 19806
Direct
                 12448
Corporate
                  5111
Complementary
                   734
                   237
Aviation
Name: market_segment, dtype: int64
In [28]:
                                                                                          M
df['market_segment'].value_counts(normalize = True)
Out[28]:
Online TA
                 0.474377
Offline TA/TO
                 0.203193
Groups
                 0.166581
                 0.104696
Direct
Corporate
                 0.042987
Complementary
                 0.006173
Aviation
                 0.001993
Name: market_segment, dtype: float64
In [29]:
                                                                                          M
cancelled_data['market_segment'].value_counts(normalize = True)
Out[29]:
Online TA
                 0.469696
Groups
                 0.273985
Offline TA/TO
                 0.187466
Direct
                 0.043486
Corporate
                 0.022151
Complementary
                 0.002038
Aviation
                 0.001178
Name: market segment, dtype: float64
```

In [30]:

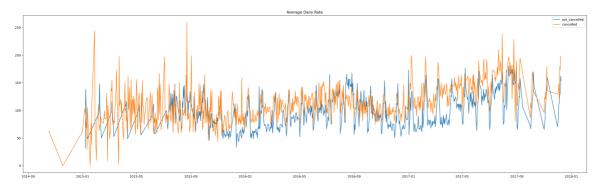
H

```
import matplotlib.pyplot as plt

cancelled_df_adr = cancelled_data.groupby("reservation_status_date")["adr"].mean().reset_cancelled_df_adr.sort_values("reservation_status_date", inplace=True)

not_cancelled_data = df[df['is_canceled'] == 0]
not_cancelled_df_adr = not_cancelled_data.groupby("reservation_status_date")["adr"].mean(not_cancelled_df_adr.sort_values("reservation_status_date", inplace=True)

plt.figure(figsize=(32, 9))
plt.title('Average Daily Rate')
plt.plot(not_cancelled_df_adr['reservation_status_date'], not_cancelled_df_adr['adr'], laplt.plot(cancelled_df_adr['reservation_status_date'], cancelled_df_adr['adr'], label='carplt.legend()
plt.show()
```



## Suggestions:

- 1 Pricing strategies: Hotels can analyze the relationship between cancellation rates and pricing. By adjusting their pricing strategies, they can offer lower rates for specific hotels based on their locations or seasons. This can attract more bookings and potentially reduce cancellations.
- 2 Weekend and holiday discounts: Since resort hotels have a higher cancellation ratio compared to city hotels, offering reasonable discounts on room prices during weekends or holidays can incentivize guests to book and reduce the likelihood of cancellations. Special promotions or packages tailored to these periods can also be effective.
- 3 January campaigns: Given that January has the highest cancellation rate, hotels can launch targeted marketing campaigns during this month. Offering attractive deals, such as

discounted rates or value-added services, can encourage guests to maintain their bookings and increase revenue during this period.

4 Quality improvements: Focusing on improving the quality of hotels and services, particularly in Portugal where cancellations are prominent, can enhance guest satisfaction and reduce cancellations. This can include upgrading facilities, enhancing customer service, and actively addressing guest feedback to create a positive experience that encourages guests to keep their reservations.

Implementing these suggestions can halp betale minimize