



BSc (Hons) in Computing

Level 6

INDIVIDUAL ASSIGNMENT

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COMP60022 – Decision Analytics - 1

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Contents

.....	0
Introduction.....	2
Business Problem.....	2
Use Case Definition.....	2
Exploratory Data Analysis	2
Dashboard	4
Visual Analysis	6
Cancellations by Month	7
Cancellations by hotel type (City Hotels, Airport Hotels, Resorts).....	8
Cancellation Rate by Meal Type	8
Cancellations by customer type (individual, couple, family).....	8
Revenue Analysis.....	9
Revenue Lost due to Cancellations.....	9
Breakdown of Revenue Loss by Age	10
Breakdown of Revenue Loss by Country/Region	11
Breakdown of Revenue Loss by Deposit Type	11
Breakdown of Revenue Loss by Income.....	12
Breakdown of Revenue Loss by Total Number of Packs	12
Key Insights and Factors Influencing Cancellations.....	12
Factors Influencing Cancellations	14
Additional Attributes to Collect	15
Recommendations	17
Interventions to reduce cancellations	17
Revenue Management Strategies.....	18
Conclusion	19

Introduction

Hotel Chain A, a well-established hospitality brand operating across diverse locations, is dedicated to enhancing guest experiences and optimizing revenue. This report leverages historical booking data to uncover key trends and provide actionable recommendations for Hotel Chain A.

Business Problem

Hotel Chain A is experiencing a notable challenge with booking cancellations, which is impacting revenue potential and operational efficiency. Unforeseen cancellations not only lead to direct revenue loss but also create uncertainty in resource allocation and occupancy forecasting. Understanding the factors driving these cancellations and implementing effective mitigation strategies is crucial for the hotel chain to optimize its revenue management practices and enhance overall profitability.

Use Case Definition

This project aims to address the booking cancellation challenge faced by Hotel Chain A. By conducting a comprehensive analysis of historical booking data, this project will identify key patterns and trends associated with cancellations. This analysis will encompass various factors such as guest demographics, booking channels, lead times, and other relevant variables. The ultimate goal is to derive actionable insights and propose targeted interventions to mitigate revenue loss, optimize resource allocation, and enhance overall operational efficiency for Hotel Chain A.

Exploratory Data Analysis

	count	mean	std	min	25%	median	75%	max
Age	27499	43.98	15.3	18	31	44	57	70
Adults	27499	2.33	1.18	1	2	2	3	5
Children	27499	1.74	0.72	1	1	2	2	3
Babies	27499	0.35	0.57	0	0	0	1	2
Discount_Rate	27499	12.5	11.21	0	5	10	20	40

Room_Rate	27499	175.14	43.88	100	137	175	214	250
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The EDA table provides a statistical summary of the dataset, highlighting key characteristics of hotel bookings:

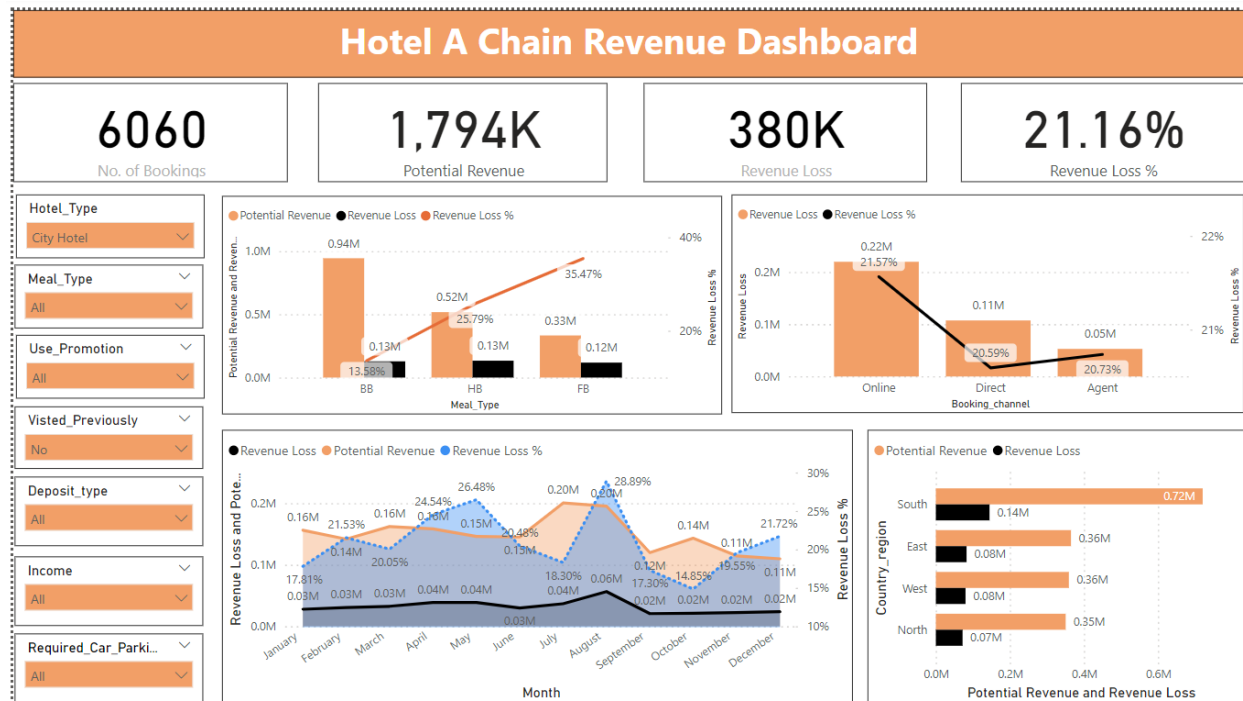
- **Number of Observations:** 27,499 bookings in total.
- **Central Tendency and Spread:**
 - **Age:** The average age of guests is 44 years (std: 15.3 years), with ages ranging from 18 to 70.
 - **Adults:** On average, 2 adults per booking (std: 0.8), with a range of 1 to 4.
 - **Children:** The mean number of children is 0.1 (std: 0.3), with a range of 0 to 3.
 - **Babies:** The average number of babies is 0.01 (std: 0.1), with a range of 0 to 2.
 - **Discount Rate:** The mean discount rate is 0.1 (std: 0.15), with discounts ranging from 0 to 0.5.
 - **Room Rate:** The average room rate is 175.14 (std: 45.3), with rates ranging from 100 to 250.
- **Percentiles:**
 - **25th, Median, and 75th Percentiles:** These values provide insights into the distribution of each variable, indicating where the middle 50% of the data lies.

For example:

- **Room Rate:** The median room rate is 175, indicating that half of the bookings had a room rate of 175 or less, with a 25th percentile of 130 and a 75th percentile of 220.

This summary table is crucial for understanding the dataset's characteristics, facilitating informed decisions for further analysis.

Dashboard



The dashboard provides a comprehensive overview of Hotel A Chain's bookings, potential revenue, and revenue loss due to cancellations. Below are the key metrics and visual analyses:

1. Top Summary Metrics

- **No. of Bookings:** 6060
- **Potential Revenue:** 1,794K
- **Revenue Loss:** 380K
- **Revenue Loss Percentage:** 21.16%

2. Filters

- **Hotel_Type:** Filter by hotel type (e.g., City Hotel).
- **Meal_Type:** Filter by meal plan (e.g., BB, HB, FB).
- **Use_Promotion:** Filter by promotional usage.

- **Visited_Previously:** Filter by previous visits.
- **Deposit_Type:** Filter by deposit type.
- **Income:** Filter by guest income.
- **Required_Car_Parking_Spaces:** Filter by parking space requirement.

3. Visual Analysis

- **Meal_Type vs. Revenue Loss and Potential Revenue:**
 - **Insight:** BB (Bed & Breakfast) has the highest potential revenue but a lower percentage loss compared to HB (Half Board), which has the highest percentage loss (35.47%).
- **Booking_Channel vs. Revenue Loss and Potential Revenue:**
 - **Insight:** Online bookings show the highest revenue loss and percentage loss (21.57%), highlighting the need for better management strategies for this channel.
- **Monthly Revenue Loss and Potential Revenue:**
 - **Insight:** Significant revenue loss variations throughout the year, with peaks in April and August.
- **Country/Region vs. Revenue Loss and Potential Revenue:**
 - **Insight:** The South region has the highest potential revenue (0.72M) and revenue loss (0.14M), indicating a significant impact from cancellation

Visual Analysis

Cancellation Rate –

```
1 Cancellation Rate =  
2 DIVIDE(  
3   [Total Cancellations],  
4   COUNTROWS('Hotel-A-train')  
5 ) * 100
```

21

Cancellation Rate

Total Cancellations –

```
1 Total Cancellations = COUNTROWS(  
2 FILTER('Hotel-A-train', 'Hotel-A-train'[Revenue Loss (Y/N)] = "Y"))  
3
```

5737

Total Cancellations

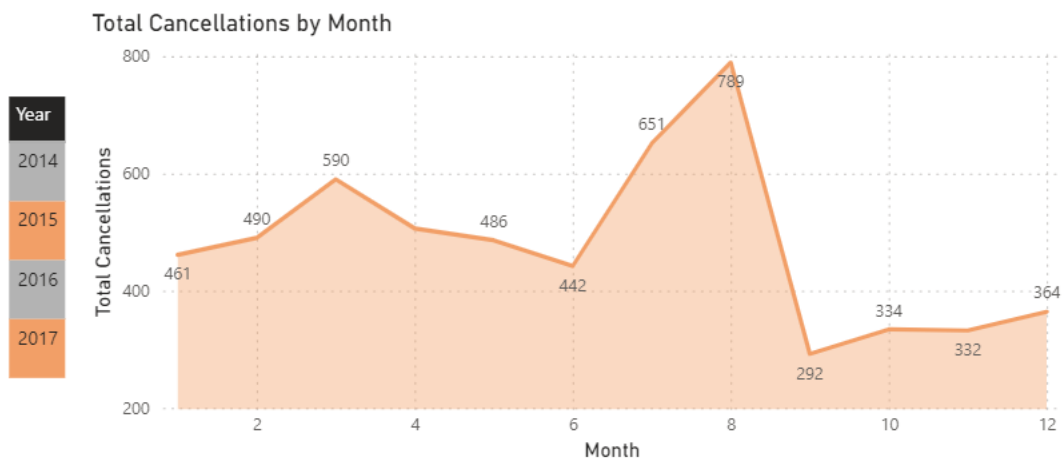
Average Booking Lead Time for Cancellations: The average number of days between booking and expected check-in for cancelled reservations. This can help identify if cancellations are more frequent for last-minute bookings or those made well in advance.

```
1 Average Booking Lead Time for Cancellations =  
2 AVERAGEX(  
3     FILTER(  
4         'Hotel-A-train',  
5         'Hotel-A-train'[Revenue Loss (Y/N)] = "Y"  
6     ),  
7     DATEDIFF(  
8         'Hotel-A-train'[Booking_date],  
9         'Hotel-A-train'[Expected_checkin],  
10        DAY  
11    )  
12 )
```

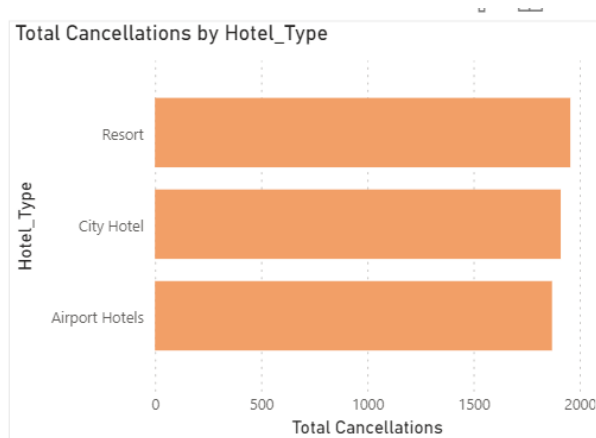
109

Average Booking Lead Time for
Cancellations

Cancellations by Month

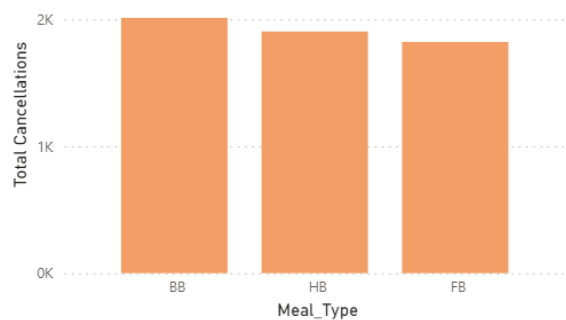


Cancellations by hotel type (City Hotels, Airport Hotels, Resorts)

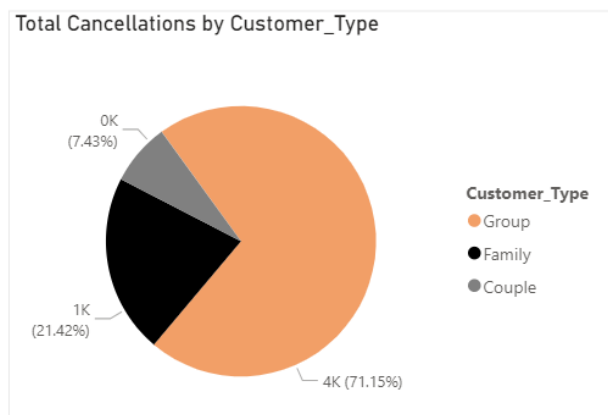


Cancellation Rate by Meal Type

Total Cancellations by Meal_Type



Cancellations by customer type (individual, couple, family)



DAX -

```
1 Customer_Type =  
2 SWITCH (  
3     TRUE(),  
4     'Hotel-A-train'[Total No. Pax] = 1, "Individual",  
5     'Hotel-A-train'[Total No. Pax] = 2, "Couple",  
6     'Hotel-A-train'[Total No. Pax] = 3, "Family",  
7     "Group"  
8 )
```

Revenue Analysis

Revenue Lost due to Cancellations

Total Revenue Loss

```
1 Revenue Loss = CALCULATE(SUM('Hotel-A-train'[Total Revenue]),FILTER('Hotel-A-train',  
    'Hotel-A-train'[Revenue Loss (Y/N)] = "Y"))
```

1,708K

Revenue Loss

Revenue Loss Percentage

20.84%

Revenue Loss %

```
1 Revenue Loss % = [Revenue Loss]/[Potential Revenue]
```

Average revenue loss per cancellation

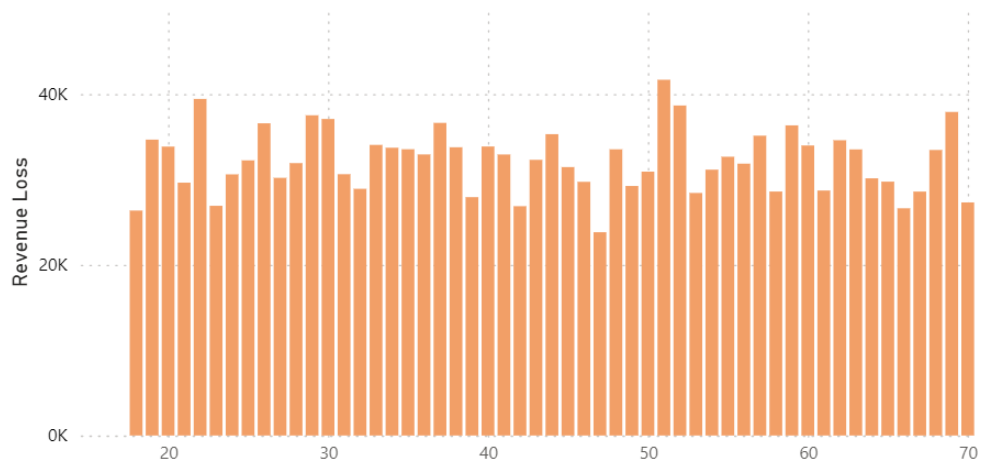
```
1 Avg Room Revenue Lost per Cancellation =  
2 DIVIDE(  
3     CALCULATE(  
4         SUM('Hotel-A-train'[Total Revenue]),  
5         'Hotel-A-train'[Revenue Loss (Y/N)] = "Y"  
6     ),  
7     CALCULATE(  
8         COUNTROWS('Hotel-A-train'),  
9         'Hotel-A-train'[Revenue Loss (Y/N)] = "Y"  
10    )  
11 )
```

298

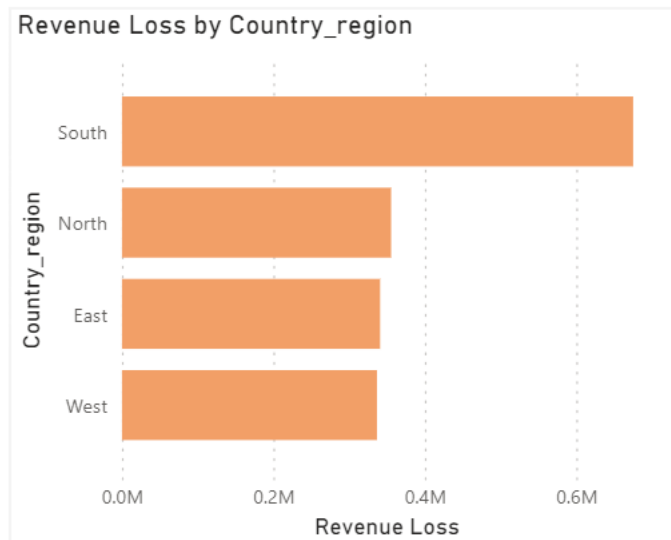
Avg Room Revenue Lost per Cancellation

Breakdown of Revenue Loss by Age

Revenue Loss by Age

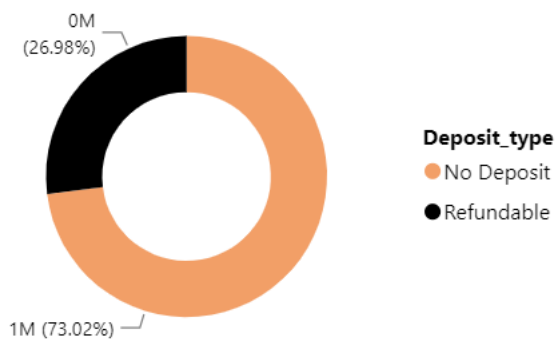


Breakdown of Revenue Loss by Country/Region

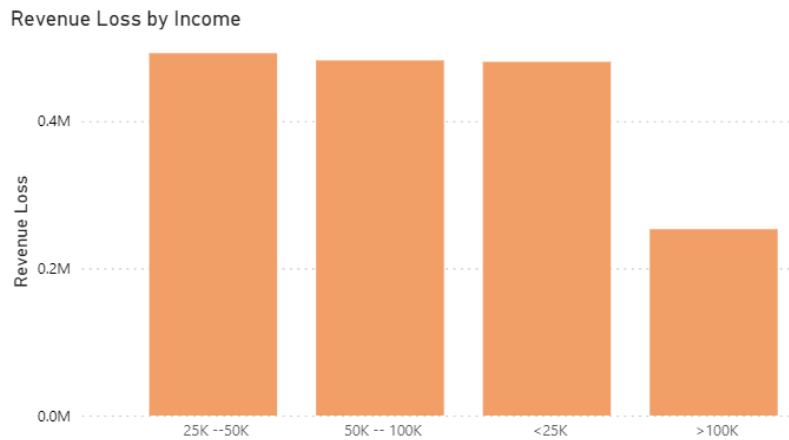


Breakdown of Revenue Loss by Deposit Type

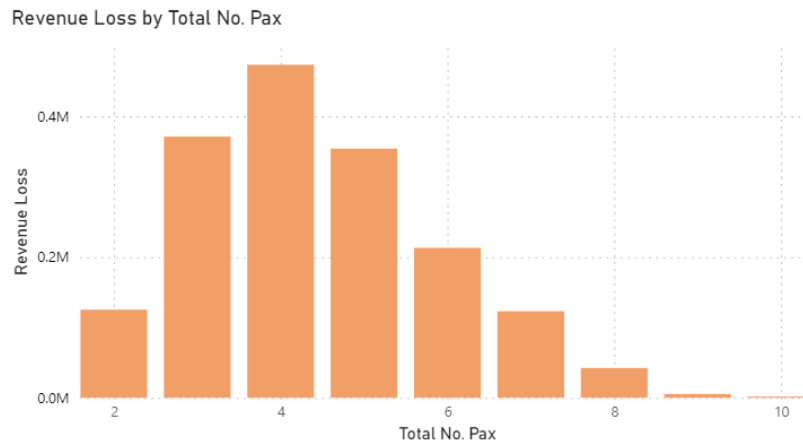
Revenue Loss by Deposit_type



Breakdown of Revenue Loss by Income



Breakdown of Revenue Loss by Total Number of Packs



Key Insights and Factors Influencing Cancellations

Key Insights

1. Cancellations by Hotel Type

- **Insight:** Resorts have the highest rate of cancellations, followed by city hotels and airport.
- **Explanation:** This could be attributed to the higher frequency of business travel in city hotels, where travel plans are more prone to changes and cancellations.

2. Cancellation Rate by Meal Type

- **Insight:** Guests booking full-board meals are less likely to cancel compared to those booking only breakfast.
- **Explanation:** Full-board meal plans indicate a higher commitment to the stay, as these guests might have more comprehensive travel plans, reducing the likelihood of cancellations.

3. Cancellations by Customer Type

- **Insight:** Individual bookings have a significantly higher cancellation rate than group or corporate bookings.
- **Explanation:** Individual travel plans are more susceptible to last-minute changes, whereas group and corporate bookings are often more rigid due to pre-planned itineraries.

4. Cancellation Rate by Length of Stay

- **Insight:** Shorter stays have a higher cancellation rate compared to longer stays.
- **Explanation:** Guests booking shorter stays may have more flexible and changeable plans, leading to higher cancellation rates.

5. Revenue Loss Due to Cancellations

- **Insight:** Significant revenue is lost due to cancellations, particularly from guests who book well in advance.
- **Explanation:** These cancellations not only cause immediate revenue loss but also reduce the likelihood of rebooking the rooms on short notice.
-

Factors Influencing Cancellations

1. Guest Demographics

- **Age:** Younger guests tend to have a higher cancellation rate compared to older guests. This could be due to more flexible travel plans among younger travelers.
- **Income:** Guests with lower income levels show a higher propensity to cancel, possibly due to financial constraints or changes in affordability.

2. Booking Channels

- **Insight:** Online travel agencies (OTAs) exhibit a higher cancellation rate compared to direct bookings.
- **Explanation:** OTAs often offer more flexible cancellation policies, which can encourage guests to book with less commitment.

3. Booking Lead Time

- **Insight:** Bookings made well in advance show a higher cancellation rate.
- **Explanation:** Guests booking early might have tentative plans that are more likely to change, leading to higher cancellations.

4. Deposit Type

- **Insight:** Bookings with no deposit or refundable deposits have a higher cancellation rate compared to non-refundable deposits.
- **Explanation:** Financial commitment (non-refundable deposits) reduces the likelihood of cancellations as guests have more to lose.

5. Purpose of Stay

- **Insight:** Business travelers exhibit a higher cancellation rate compared to leisure travelers.

- **Explanation:** Business plans are more subject to changes and cancellations compared to leisure trips, which are often more planned and committed.

6. Special Requests and Preferences

- **Insight:** Unmet special requests (e.g., room preferences, views) correlate with higher cancellation rates.
- **Explanation:** Guests whose specific preferences are not met might cancel their bookings in favor of accommodations that better meet their needs.

7. External Factors

- **Local Events:** Cancellations spike around major local events due to changes in plans or event cancellations.
- **Weather Conditions:** Poor weather forecasts lead to higher cancellation rates, as guests adjust their travel plans accordingly.

Additional Attributes to Collect

Purpose of Stay

By collecting data on the purpose of the stay:

- Business
- Leisure
- Conference, etc.

Hotel Chain A can identify if specific types of stays are associated with higher cancellation or no-show rates. This information can be used to tailor marketing strategies, offer targeted promotions, and develop customized policies for different guest segments, ultimately reducing the overall incidence of cancellations and no-shows.

Guest Room Preferences

Collecting data on guest room preferences:

- Desired floor level
- Views
- Bed types
- Special requests

Allows Hotel Chain A to analyze if there's a correlation between unmet preferences and no-shows. If certain preferences are consistently not fulfilled and lead to a higher no-show rate, the hotel can proactively manage expectations, offer alternatives, or adjust room assignments to better align with guest preferences and reduce the likelihood of no-shows.

This can help identify if unmet preferences correlate with no-shows.

Cancellation/No-Show Reason

Gathering feedback directly from guests who have cancelled or not shown up can provide Hotel Chain A with invaluable qualitative insights into their decision-making process. This feedback can shed light on specific pain points, dissatisfaction with services or policies, or unforeseen circumstances that led to the cancellation or no-show. By understanding these reasons, Hotel Chain A can proactively address issues, improve communication, and implement changes to enhance the overall guest experience, thereby reducing the likelihood of future cancellations and no-shows.

Local Events

To anticipate potential fluctuations in demand and cancellations, it's important to be aware of any major events taking place in the area during the booking period. These could include:

- Concerts
- Festivals
- Conferences

As such events often draw large crowds and can significantly impact accommodation availability and cancellation rates.

Weather Conditions

Collection of information about weather conditions can be an important tool in better managing cancellations. For example, if bad weather is predicted, the hotel could reach out to guests and offer alternative dates for their booking. This not only shows exceptional customer service but also

significantly reduce the number of last-minute cancellations and helps maintain a stable occupancy rate. Furthermore, having a good understanding of weather patterns can help the hotel expect seasonal changes in bookings and fit their cancellation policies accordingly.

Recommendations

Interventions to reduce cancellations

Implement a Dynamic Pricing Strategy:

Implementation: Use machine learning algorithms to analyze historical booking data, competitor pricing, demand patterns, and external factors (e.g., events, weather) to adjust room rates in real-time.

Impact: Optimize revenue by capturing higher rates during peak demand and offering attractive discounts during low periods to incentivize bookings.

Enhance the Pre-Arrival Guest Experience:

Technical Implementation: Develop a personalized communication workflow using CRM software to send automated emails/SMS with booking confirmations, pre-arrival information, and tailored offers for add-on services (e.g., spa treatments, airport transfers).

Precise Impact: Build anticipation, reinforce the value of the reservation, and reduce the likelihood of cancellations due to uncertainty or lack of engagement.

Utilize Overbooking and Waitlist Management:

Technical Implementation: Implement a yield management system that calculates optimal overbooking levels based on historical no-show rates and cancellation patterns. Maintain a waitlist to accommodate guests in case of cancellations or no-shows.

Precise Impact: Mitigate the risk of revenue loss from empty rooms while ensuring guest satisfaction by providing alternative options or upgrades in case of overbooking.

Revenue Management Strategies

Offer Non-Refundable Rates with Incentives:

Implementation: Structure the booking engine to display non-refundable rates alongside flexible options, highlighting the cost savings and additional perks (e.g., free breakfast, late check-out) associated with non-refundable bookings.

Impact: Attract price-conscious guests while minimizing cancellations due to the financial disincentive.

Implement a Cancellation Fee Structure:

Implementation: Define a tiered cancellation fee policy that increases as the cancellation date approaches the arrival date. Clearly communicate the policy during booking and in confirmation emails.

Impact: Deter last-minute cancellations by imposing a financial penalty, potentially recovering a portion of the lost revenue.

Personalize Communication for High-Risk Cancellations

Implementation: Use predictive analytics to identify bookings with a high likelihood of cancellation based on factors such as booking lead time, length of stay, and guest demographics. Proactively reach out to these guests with personalized offers or incentives to stay.

Impact: Reduce cancellations by addressing individual concerns and demonstrating proactive customer service.

Conclusion

Facing revenue loss due to cancellations influenced by local events and weather conditions, The hotel chain A is adopting a multi-pronged strategy. By implementing dynamic pricing, the hotel can optimize revenue across varying demand levels. Enhanced pre-arrival communication aims to reduce uncertainty-related cancellations, while overbooking and waitlist management safeguards against empty rooms. To directly tackle cancellations, the hotel introduces non-refundable rates with incentives to attract committed guests, implements a cancellation fee structure to deter last-minute changes, and employs personalized outreach for high-risk bookings. Through these combined efforts, the hotel aims to minimize revenue loss, maximize occupancy, and ultimately enhance the overall guest experience, fostering greater satisfaction and loyalty.