

# Case Study Analysis Report

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Case Study Title: Uncovering Patterns in Hotel Booking Data for Operational Efficiency and Revenue Growth

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## Executive Summary

This report is all about analyzing hotel booking data. Imagine you're a hotel manager trying to understand who books, when they book, and how much they pay.

We looked at:

- When people book (early or late)
- Where they're from (countries)
- If they get room upgrades
- How many nights they stay
- What affects the price they pay per night (called ADR - *Average Daily Rate*)

We used some basic statistics and graphs to make sense of this. In the end, we gave suggestions to improve bookings and make more money.

## Table of Contents

1. Introduction
2. Background / Context
3. Analysis
4. Conclusion

### 1. Introduction

We took a big table (dataset) full of hotel booking details like:

- Guest nationality
- Type of room they booked
- How long they stayed
- How much they paid

We cleaned up the data and used it to find useful patterns and trends.

### 2. Background / Context

This data was from two types of hotels — a **city hotel** and a **resort hotel**. We had over 100,000 bookings. But, some parts of the data were messy:

- 1 Some columns had lots of missing values (so we removed or fixed them).
- 2 Date information was split into day, month, and year I combined it into one single date.

### 3. Analysis

We used different tools to understand the data:

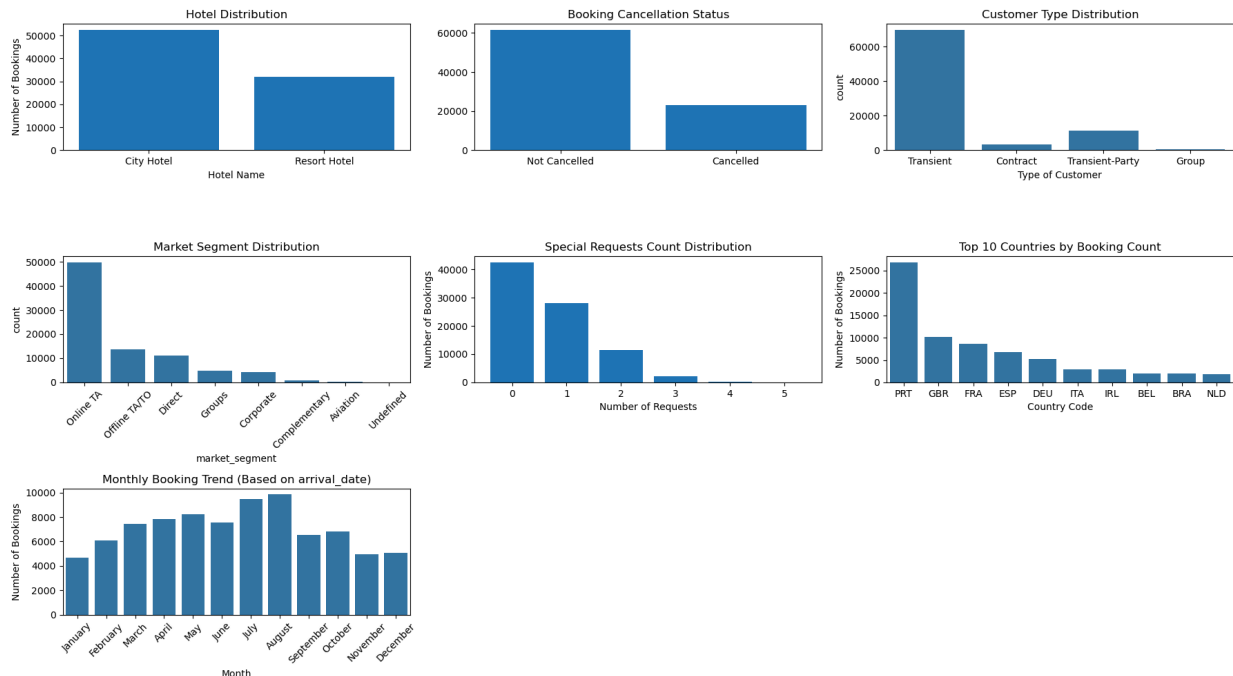
- **Univariate Analysis:**

We looked at each column separately to understand basic patterns.  
For example:

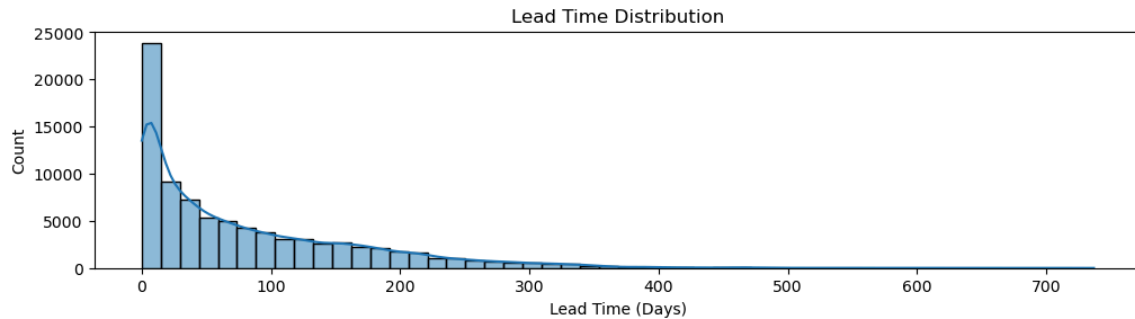
- How many bookings came from each country?
- Which room types were booked most often?
- What's the most common number of guests?

This helped us get a feel for the data before comparing anything.

Bar chart for categorical values for univariate analysis:

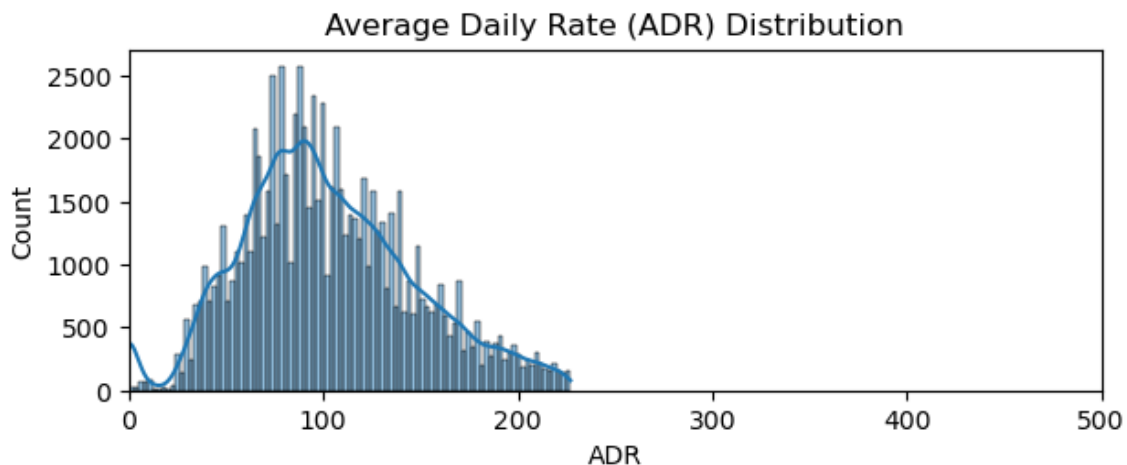


Created histogram for continuous and discrete column for univariate analysis:



This chart shows how many days in advance people book their hotel stays:

- Most people book very close to their stay date, especially within the first 0–20 days.
- As the number of days increases, the number of bookings drops sharply.
- Very few guests book more than 100 days in advance.



This chart shows how hotel room prices per night (ADR) are spread out:

- Most bookings are priced between 50 and 150 units.
- The peak is around 100, meaning that's the most common nightly rate.
- Prices above 200 are rare.

- **Bivariate/Multivariate Analysis:**

Next, we looked at how two or more things are related.  
For example:

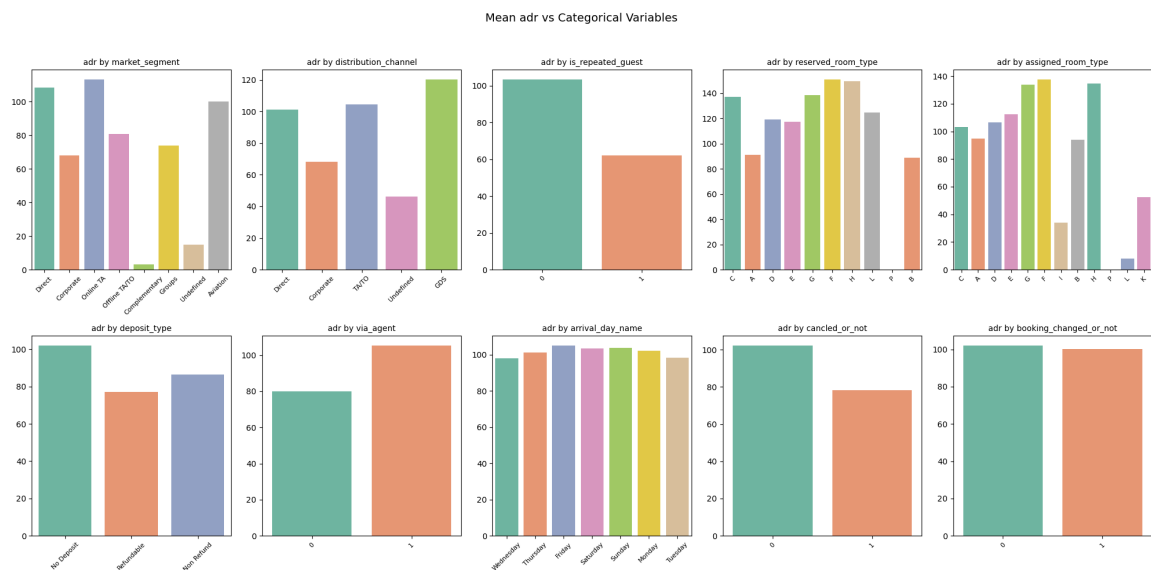
- Is there a connection between room type and price?
- Do guests from different countries pay more or less?
- Does lead time (how early someone books) affect cancellations?

This helped us find relationships between columns.

Boxplot for bivariate analysis:

This chart shows how the average price per night (ADR) varies based on guest or booking characteristics.

- Corporate and Offline TA/TO guests tend to pay more.
- Guests who are repeated usually pay higher rates.
- Assigned and reserved room types affect ADR — some types are priced much higher.
- Bookings via agents or with deposits tend to have lower ADR.
- Cancellations lead to lower ADR, while booking changes don't affect ADR much.



The figure displays eight bar charts arranged in a 2x4 grid, showing revenue by various factors. The y-axis for all charts represents revenue, with scales varying by chart.

**Top Row Charts:**

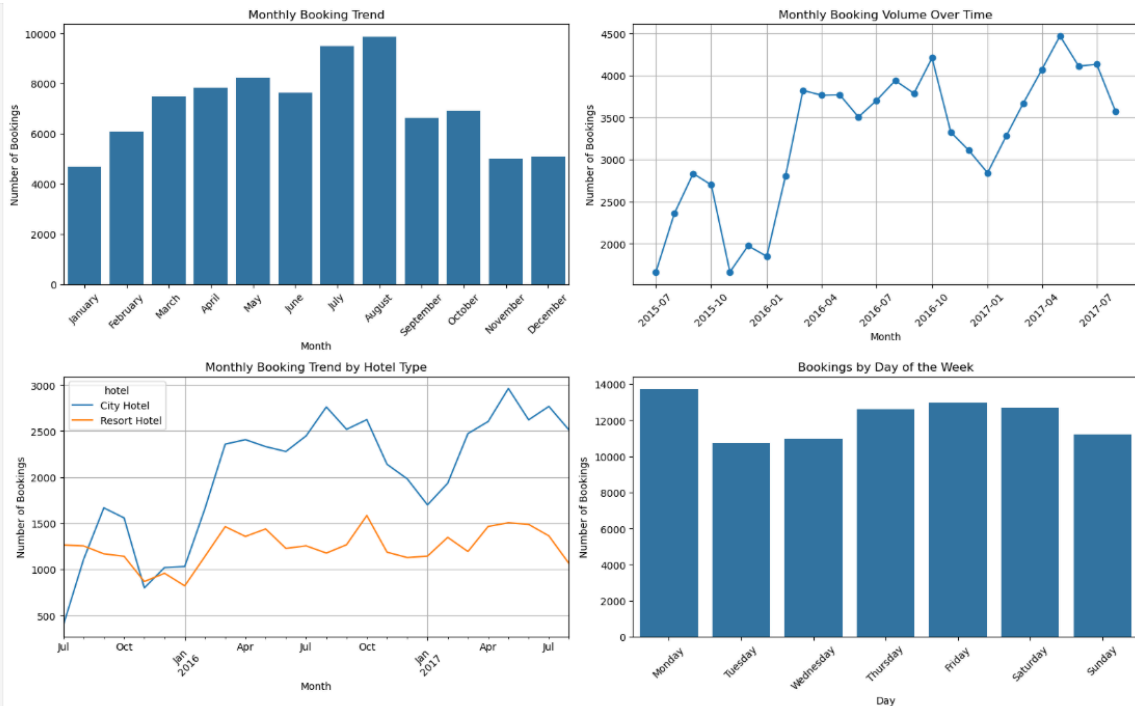
- revenue by market\_segment:** Shows revenue for different market segments. The y-axis ranges from 0 to 400. The segments and their approximate revenues are: Direct (~370), Corporate (~140), Online TA (~410), Online + TA/D (~380), Complimentary (~10), Group (~250), Unlabeled (~20), and Another (~360).
- revenue by distribution\_channel:** Shows revenue for different distribution channels. The y-axis ranges from 0 to 400. The channels and their approximate revenues are: Direct (~350), Corporate (~170), TA/D (~390), Unlabeled (~230), and GDS (~240).
- revenue by is\_repeated\_guest:** Shows revenue for repeated guests. The y-axis ranges from 0 to 400. The categories are 0 (~380) and 1 (~140).
- revenue by reserved\_room\_type:** Shows revenue for different reserved room types. The y-axis ranges from 0 to 700. The room types and their approximate revenues are: 0 (~680), 1 (~300), 2 (~480), 3 (~560), 4 (~580), 5 (~580), 6 (~150), 7 (~150), and 8 (~300).
- revenue by assigned\_room\_type:** Shows revenue for different assigned room types. The y-axis ranges from 0 to 500. The room types and their approximate revenues are: 0 (~430), 1 (~330), 2 (~410), 3 (~500), 4 (~560), 5 (~500), 6 (~120), 7 (~280), 8 (~550), 9 (~10), 10 (~10), and 11 (~150).

**Bottom Row Charts:**

- revenue by deposit\_type:** Shows revenue for different deposit types. The y-axis ranges from 0 to 350. The types and their approximate revenues are: No Deposit (~370), Refundable (~290), and Non-Refundable (~240).
- revenue by via\_agent:** Shows revenue for different agents. The y-axis ranges from 0 to 400. The agents are 0 (~210) and 1 (~400).
- revenue by arrival\_day\_name:** Shows revenue for different arrival days. The y-axis ranges from 0 to 400. The days and their approximate revenues are: Wednesday (~340), Thursday (~360), Friday (~340), Saturday (~390), Sunday (~420), Monday (~390), and Tuesday (~360).
- revenue by canceled\_or\_not:** Shows revenue for canceled or not. The y-axis ranges from 0 to 350. The categories are 0 (~370) and 1 (~270).
- revenue by booking\_changed\_or\_not:** Shows revenue for booking changed or not. The y-axis ranges from 0 to 400. The categories are 0 (~370) and 1 (~400).

We studied how bookings change across months and years.  
For example:

- This helped us understand seasonal patterns in the data.



- Bookings peak in July and August, showing summer is the busiest time.
- City hotels consistently get more bookings than resort hotels throughout the year.
- Over time, total booking volume increased, showing growing business.
- Monday has the highest bookings, suggesting many people book after weekends.

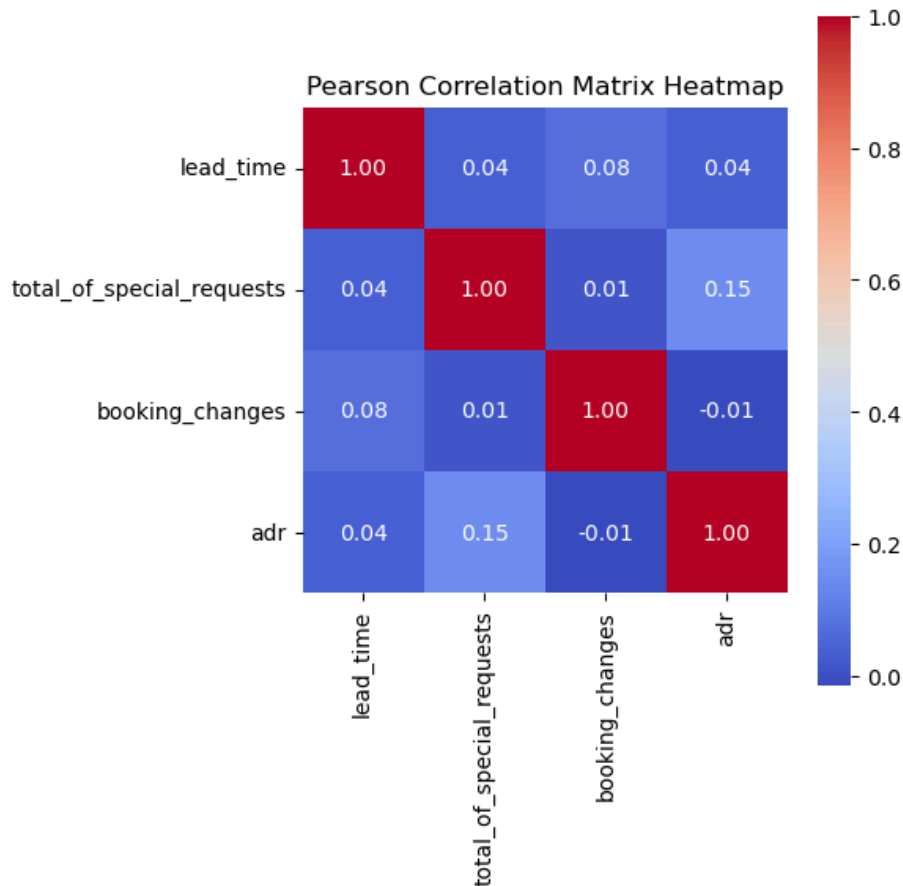
These insights help hotels plan staffing, marketing, and pricing.

## Correlation – Are Things Related?

We used correlation to check how strongly different factors move together.  
For example:

- If a guest books earlier, do they usually pay more?
- Do longer stays mean higher total prices?

Correlation helps us find what affects what, even if it's not obvious.



- total\_of\_special\_requests and adr (average price per night) have a slight positive correlation (0.15) — guests who pay more tend to make more requests.
- Other features like lead\_time, booking\_changes, and adr show very weak or no strong relationship.
- Nothing here is highly correlated, meaning no variable strongly predicts another in this small selection.

### Hypothesis Testing – Are Our Guesses Statistically True?

Sometimes we have a gut feeling (like “guests who book early cancel less”). We used hypothesis testing to check if these guesses are true using math.

It’s like A/B testing — we compare groups and check if the difference is real or just by chance.

### Cleaning the Data – Fixing the Mess

Before analyzing, we had to clean up the messy parts of the data:



Removed the "company" column

- The "company" column had too many missing values, so we deleted it.
- It didn't give us useful information, so we dropped it to avoid confusion.

### **Filled Missing Values**

For some important columns, we filled in the blanks:

- "Agent": Filled with the most common agent ID.
- "Country": Filled missing countries with the one that appeared the most.
- "Children": If the number of children was missing, we assumed it was zero or the most common number.

This way, we avoided errors or gaps in our analysis.

## 7. Conclusion

Through our detailed analysis of the hotel booking dataset, we gained valuable insights into customer behavior, booking patterns, and factors that influence revenue. Here's what we concluded:

- Pricing (ADR) is most influenced by the hotel type, customer type, and lead time. Guests who book earlier or belong to certain customer groups tend to pay more.
- Transient guests and international travelers usually book earlier and stay for shorter durations, but contribute significantly to revenue.
- There are noticeable differences in booking habits by country—for example, UK and France guests book earlier, while Portuguese guests stay for shorter durations.
- Special requests and booking modifications are more common among high-paying guests.
- Guests who have their room upgraded or reassigned are less likely to cancel, and about 1 in 4 bookings involve such changes.
- Certain market segments, like corporate or direct bookings, are more reliable—they cancel less and pay more.
- Data cleaning was crucial. We filled missing values smartly and removed irrelevant columns to keep the analysis accurate.