OPTIMIZING REVENUE LEAKAGES IN THE HOSPITALITY SECTOR

Presentation by Team : Data Decoders

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HOSPITALITY SECTOR

Business Context

In the highly competitive and dynamic hospitality industry, many mid-sized hotels face challenges like unexplained revenue leakage, low profitability, and underutilized services. Despite access to data on bookings, customer behavior, and service usage, most hotels lack a structured analytical approach to identify and act on revenue inefficiencies.

This project used data analytics to identify revenue leakage in the hospitality sector. Through KPI tracking, cancellation analysis, and visual insights, we uncovered key opportunities to improve profitability and efficiency.

Problem Statement Breakdown

Mid-sized hotels are facing unexplained revenue leakage, underperforming services, and missed opportunities due to a lack of actionable insight from available data.

Key Problems :

- Revenue Leakage
- Underutilized Services
- Low Visibility of Booking Patterns
- Inefficient Pricing
- Lack of Targeted Strategy

Expected Outcomes

This analysis aims to build a structured understanding of what causes revenue inefficiencies in the hospitality sector. By analyzing bookings, room capacity, customer behavior, and hotel performance across time, room types, and cities, we aim to:

- Find key reasons for revenue leakage across hotels, room types, and cities
- Measure hotel performance using important KPIs like Revenue, RevPAR, ADR, and Occupancy %.
- Give data-based suggestions to improve bookings, reduce cancellations, and fix pricing issues.
- Help hotel teams make smarter business decisions using clear insights, visualizations, and dashboards.

Key Performance Indicators

Revenue

Total earned money from all services.

ADR (Average Daily Rate)

$$\text{ADR} = \frac{\text{Total Revenue Realized}}{\text{Rooms Nights Booked}}$$

Occupancy Percentage

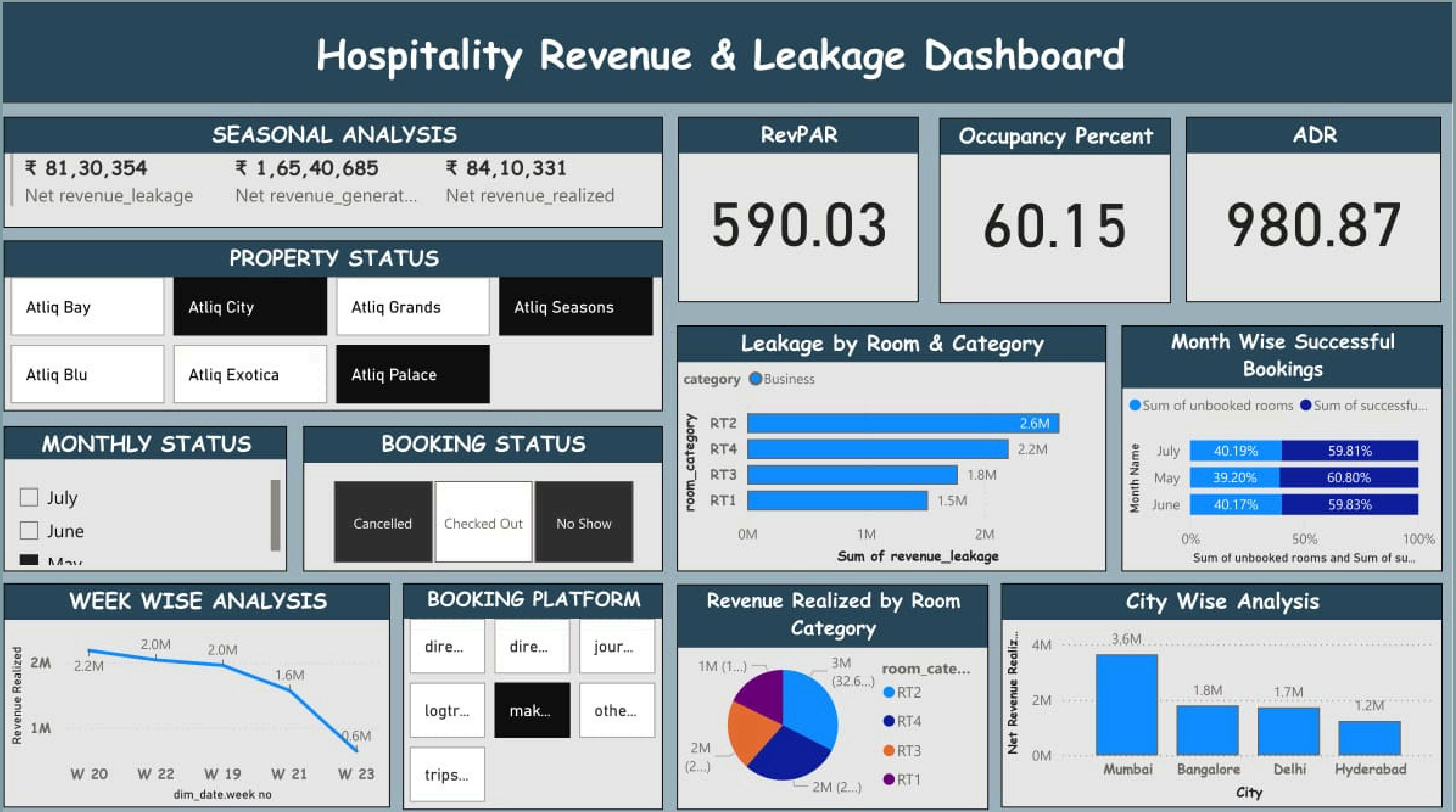
$$\text{Occupancy\%} = \frac{\text{Total occupied rooms}}{\text{Total rooms}}$$

RevPAR (Revenue per Available Room)

$$\text{RevPAR} = \frac{\text{Total Revenue Realized}}{\text{Total Room Capacity}}$$

Key Insights

- Delhi is the most underperforming city in both Occupancy % and RevPAR, despite having decent room capacity.
- Atliq Exotica is the highest revenue-generating hotel (luxury category), while Atliq Grands among the lowest, indicating underperformance.
- RT2 rooms are booked most often but also show the highest revenue leakage, mainly due to cancellations.
- RT4 rooms contribute the highest to RevPAR, despite having the lowest capacity, showing a strong pricing strategy and demand.
- RT2 also shows low RevPAR despite high capacity, highlighting inefficient pricing or poor demand alignment.
- Major revenue leakage was observed in May, which also had the highest revenue generation, indicating gaps between bookings and actual realization.

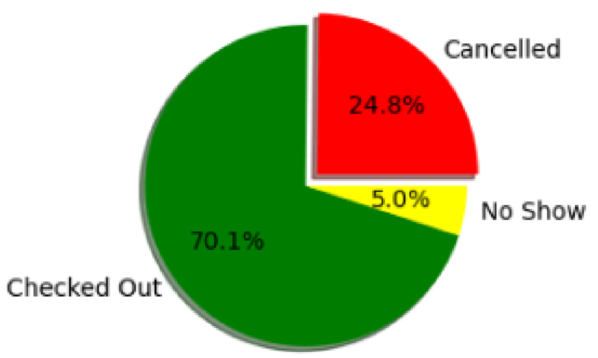


Hospitality Revenue & Leakage Dashboard
SEASONAL ANALYSIS
₹ 81,30,354
Net revenue_leakage
₹ 1,65,40,685
Net revenue_generat...
₹ 84,10,331
Net revenue_realized
RevPAR
590.03
Occupancy Percent
60.15
ADR
980.87
PROPERTY STATUS
Atliq Bay
Atliq City
Atliq Grands
Atliq Seasons
Atliq Blu
Atliq Exotica
Atliq Palace
Leakage by Room & Category
category
Business
room_category
RT2
2.6M
RT4
2.2M
RT3
1.8M
RT1
1.5M
0M
1M
2M
Sum of revenue_leakage
Month Wise Successful Bookings
Sum of unbooked rooms
Sum of successfu...
Month Name
July
40.19%
59.81%
May
39.20%
60.80%
June
40.17%
59.83%
0%
50%
100%
Sum of unbooked rooms and Sum of su...
MONTHLY STATUS
July
June
BOOKING STATUS
Cancelled
Checked Out
No Show
WEEK WISE ANALYSIS
Revenue Realized
2M
1M
2.2M
2.0M
2.0M
1.6M
0.6M
W 20
W 22
W 19
W 21
W 23
dim_date.week no
BOOKING PLATFORM
dire...
dire...
jour...
logtr...
mak...
othe...
trips...
Revenue Realized by Room Category
1M (1...)
3M (32.6...)
2M (2...)
2M (2...)
room_cate...
RT2
RT4
RT3
RT1
City Wise Analysis
Net Revenue Realiz...
4M
2M
0M
3.6M
1.8M
1.7M
1.2M
Mumbai
Bangalore
Delhi
Hyderabad
City

Statistical Visualizations

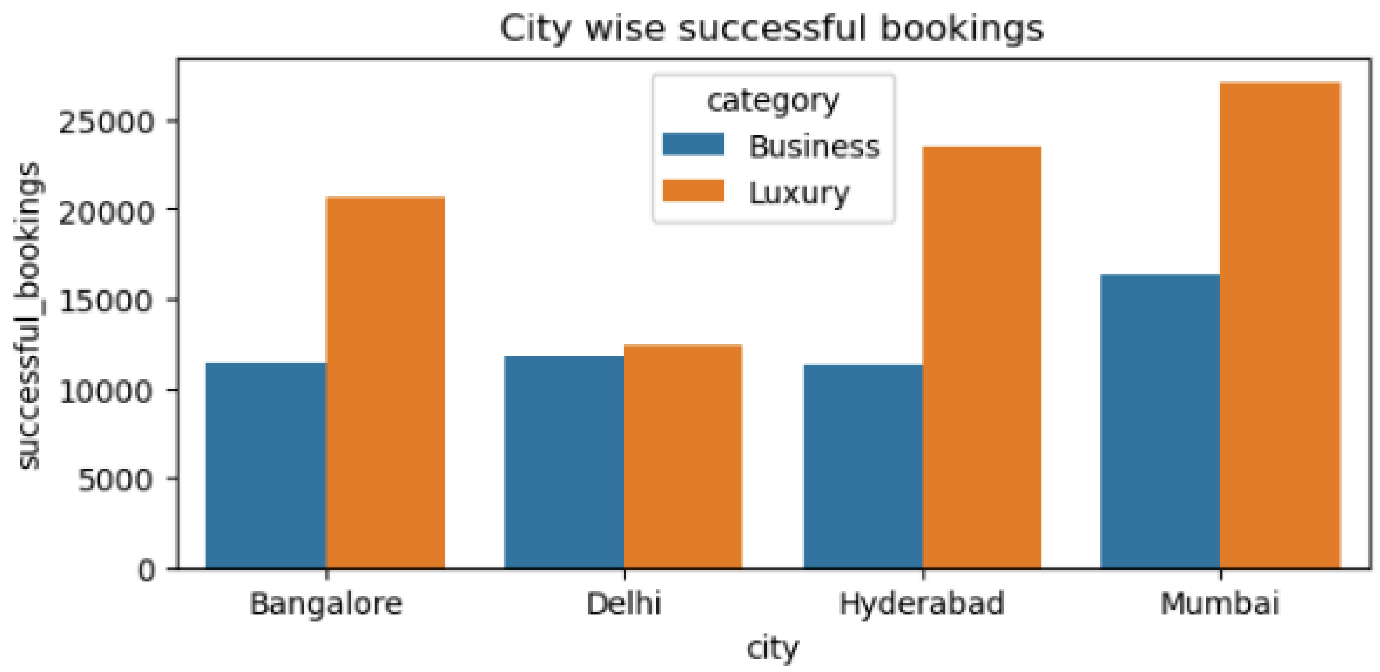
1.Booking Status wise distribution

```
plt.figure(figsize=(7,3))
plt.pie(status['booking_id'],labels=status['booking_status'],explode=[0.1,0,0],autopct='%0.1f%%',shadow=True,colors=['red','green','yellow'])
plt.show()
```



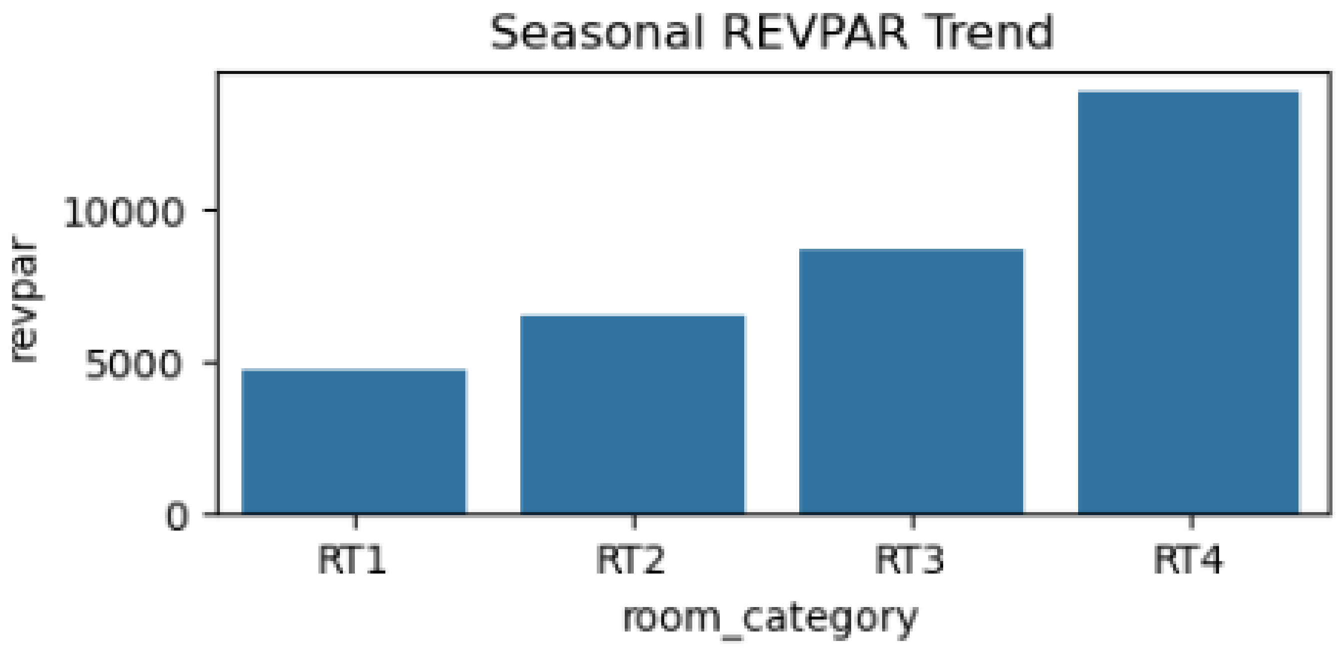
3.City wise Successful Bookings

```
plt.figure(figsize=(7,3))
sns.barplot(data=sucb,x=sucb['city'],y='successful_bookings',errorbar=None,hue='category')
plt.title('City wise successful bookings')
plt.show()
```



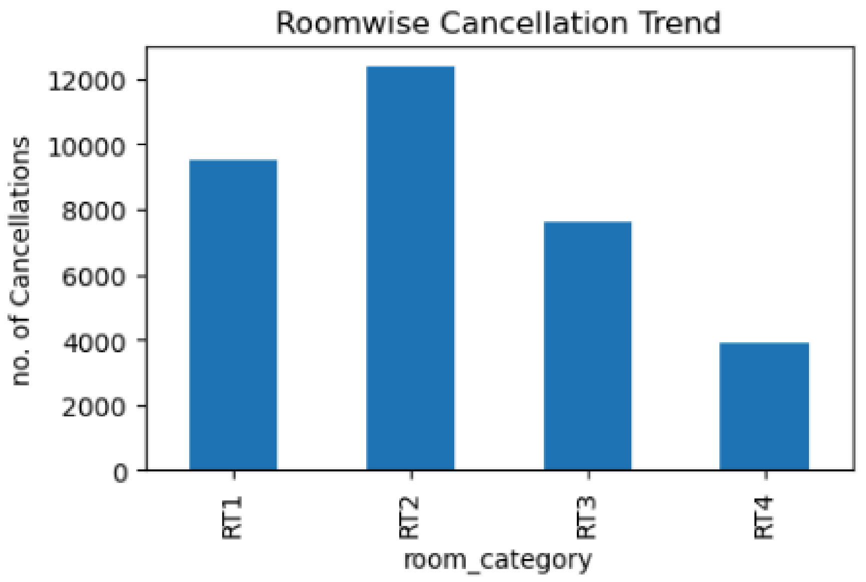
2.Seasonal REVPAR Trend

```
plt.figure(figsize=(5,2))
sns.barplot(revpar)
plt.title('Seasonal REVPAR Trend')
plt.ylabel('revpar')
plt.show()
```



4.Room Category wise Cancellation Trend

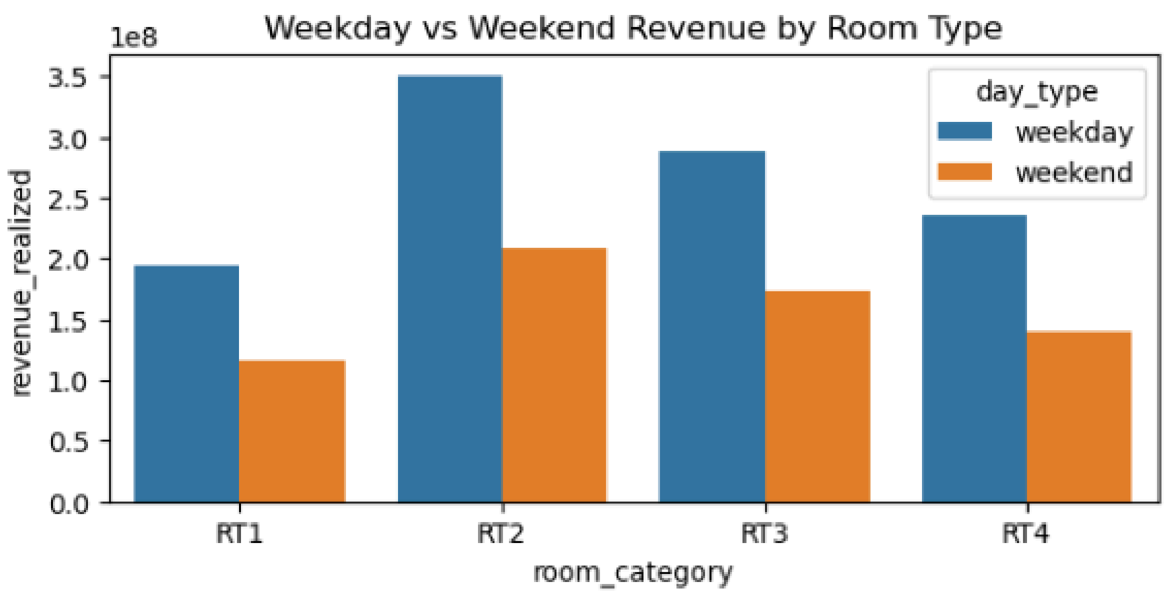
```
df_canc.groupby('room_category')['booking_id'].count().plot(kind='bar',figsize=(5,3),ylabel='no. of Cancellations',title='Roomwise Cancellation Trend')
plt.show()
```



Statistical Visualizations

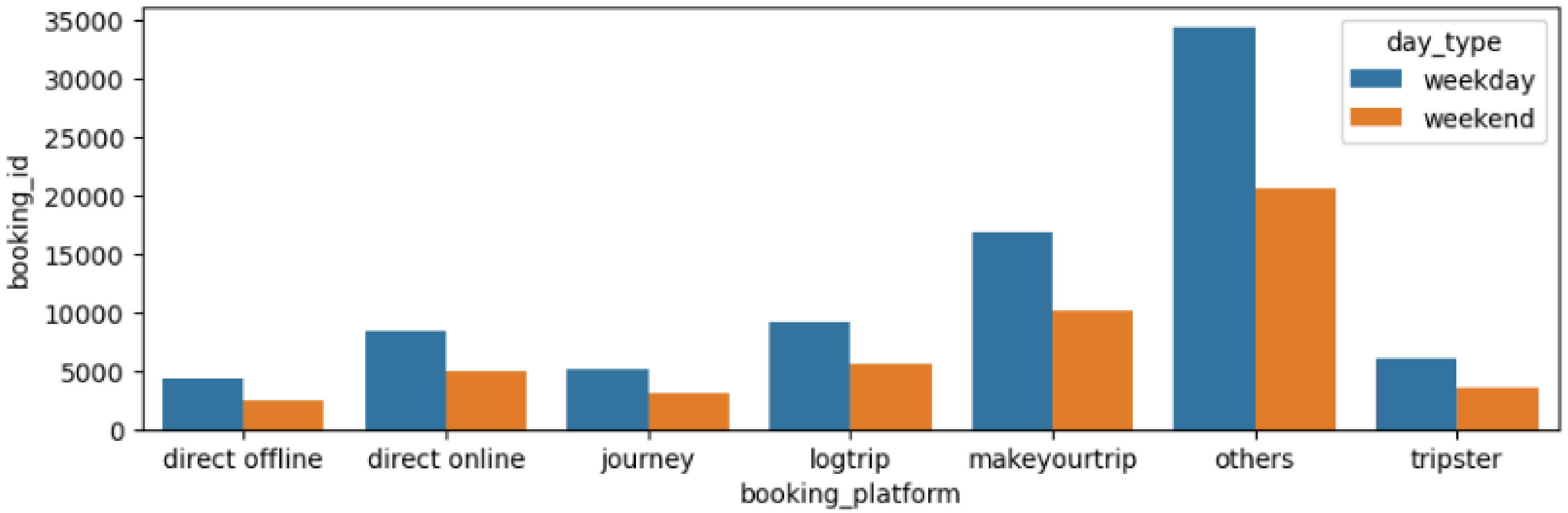
5.Weekday vs Weekend Revenue by room category

```
plt.figure(figsize=(7,3))
sns.barplot(data=wow4,x=wow4['room_category'],y='revenue_realized',errorbar=None,hue='day_type')
plt.title('Weekday vs Weekend Revenue by Room Type')
plt.show()
```



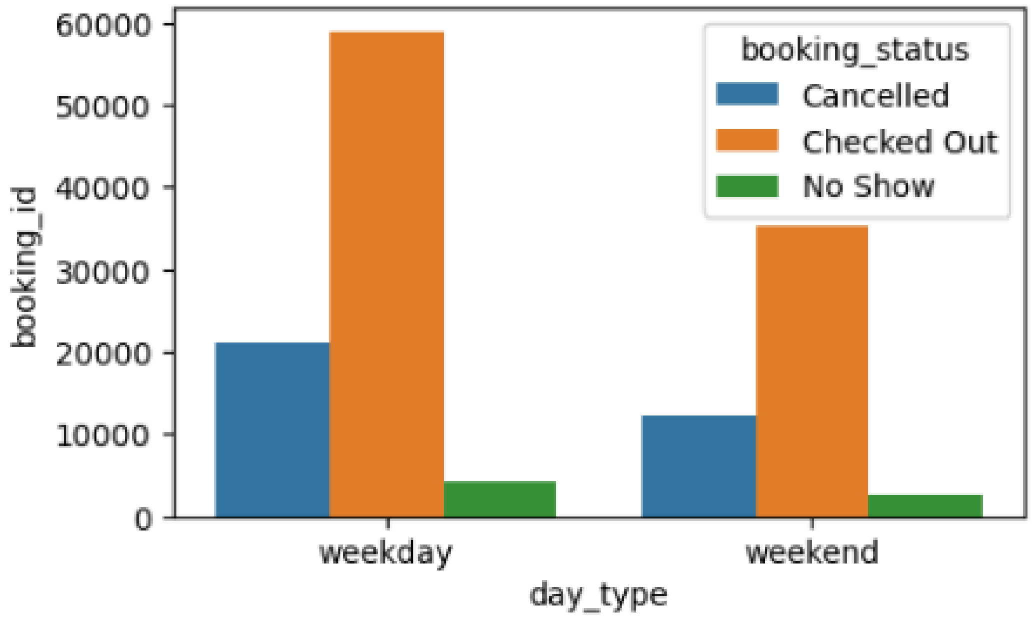
7.Booking Platforms vs Bookings

```
plt.figure(figsize=(10,3))
sns.barplot(data=wow2,x=wow2['booking_platform'],y='booking_id',errorbar=None,hue='day_type')
plt.show()
```



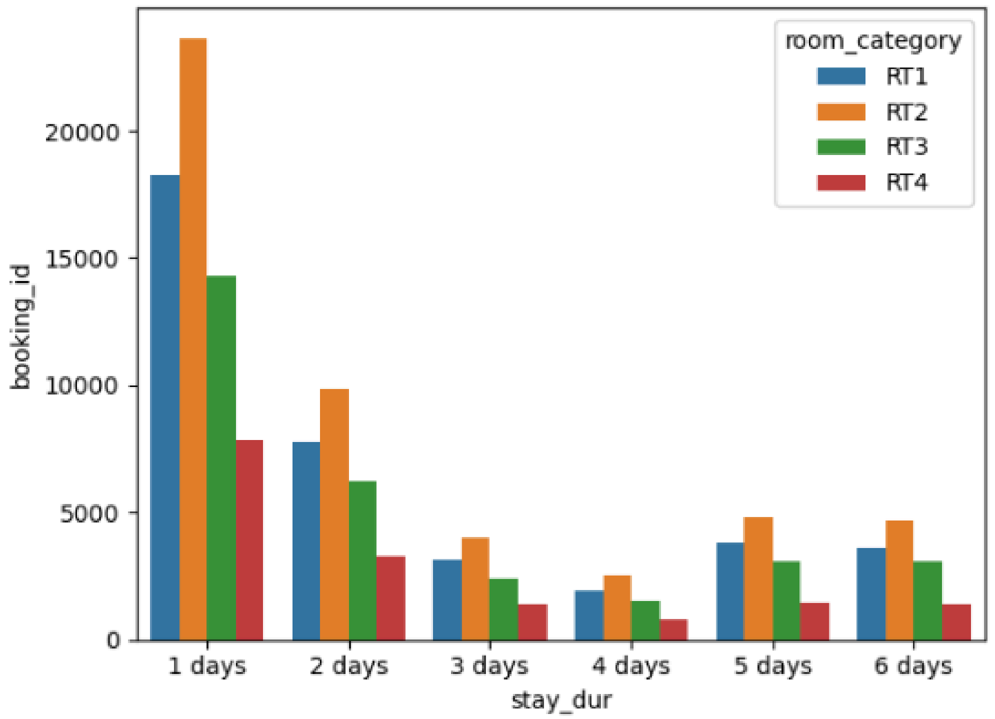
6.Weekday vs Weekend Revenue by booking status

```
plt.figure(figsize=(5,3))
sns.barplot(data=wow3,x=wow3['day_type'],y='booking_id',errorbar=None,hue='booking_status')
plt.show()
```



8.Stay Duration vs bookings

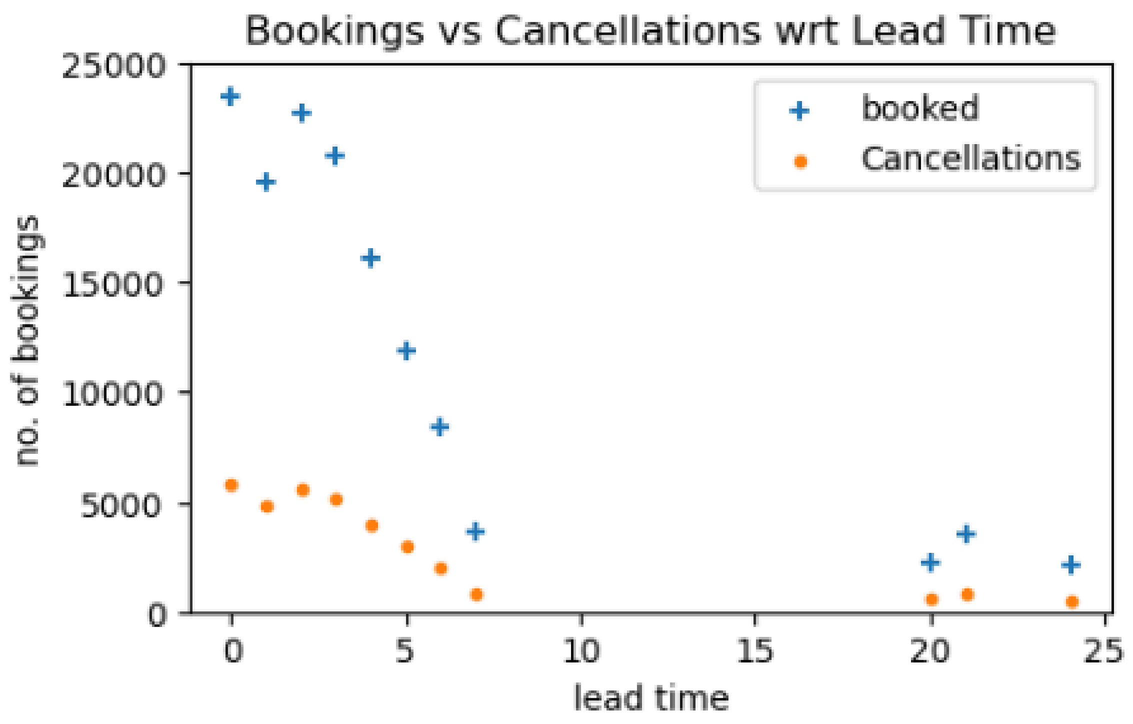
```
sns.barplot(data=booking_data.groupby(['stay_dur','room_category'])['booking_id'].count().reset_index(),x='stay_dur',y='booking_id',hue='room_category')
plt.show()
```



Statistical Visualizations

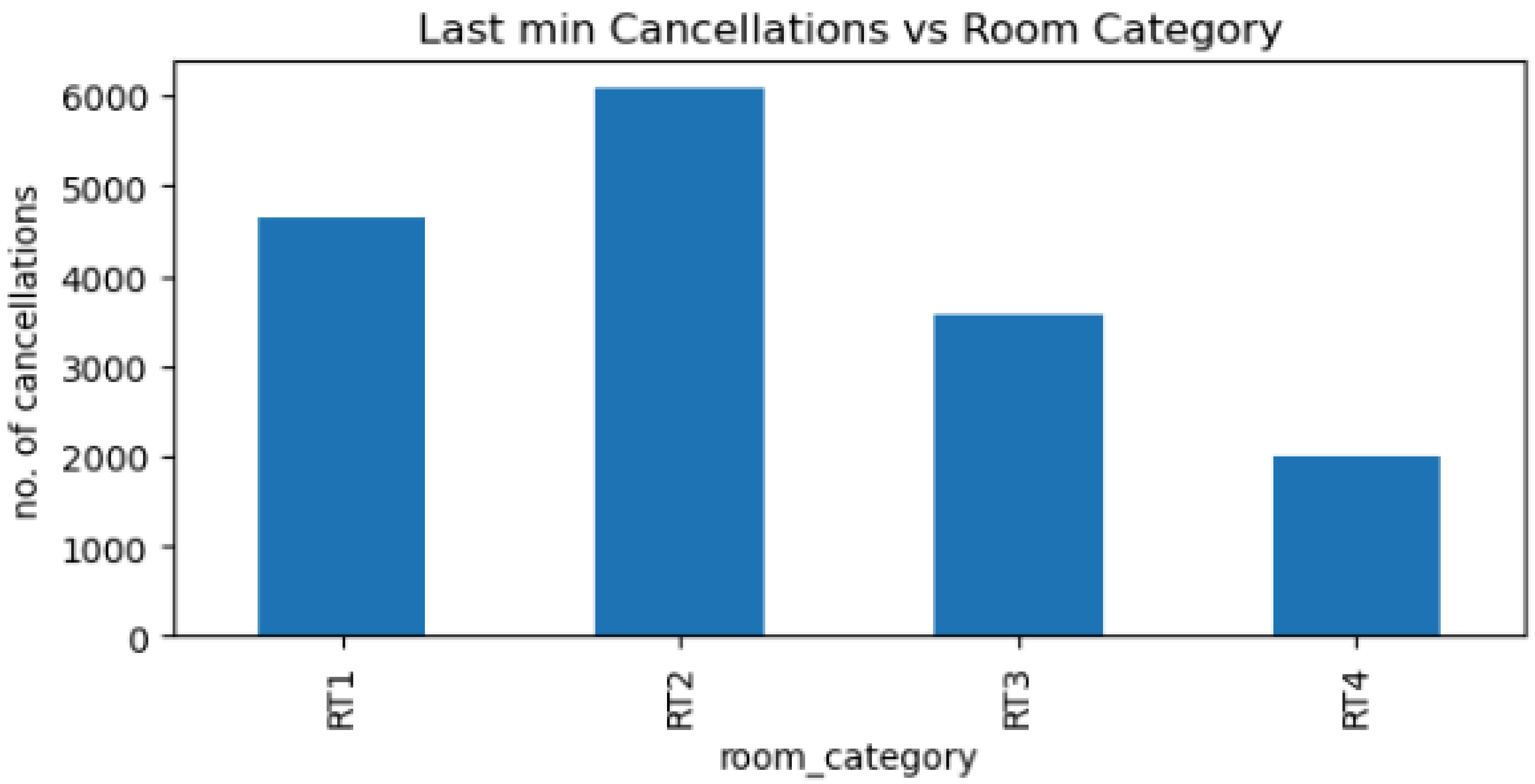
9.Booking vs Cancellations wrt Lead Time

```
booking_data['lead_time']=(booking_data['check_in_date']-booking_data['booking_date']).dt.days
lead=booking_data.groupby('lead_time')['booking_id'].count().reset_index()
lead_canc=df_canc.groupby('lead_time')['booking_id'].count().reset_index()
plt.figure(figsize=(5,3))
plt.scatter(lead['lead_time'],lead['booking_id'],marker='+',label='booked')
plt.scatter(lead_canc['lead_time'],lead_canc['booking_id'],marker='.',label='Cancellations')
plt.xlabel('lead time')
plt.ylabel('no. of bookings')
plt.title('Bookings vs Cancellations wrt Lead Time')
plt.ylim(0,25000)
plt.legend()
plt.show()
```



10.Last min Cancellations vs Room Category

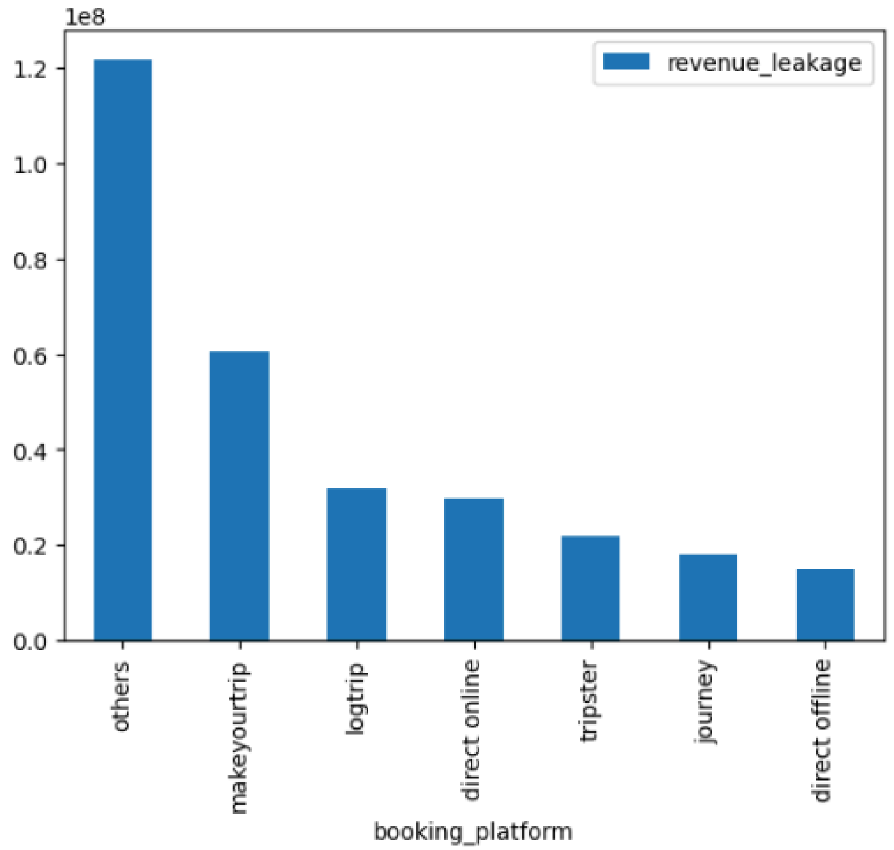
```
lstmin_canc=df_canc[df_canc['lead_time']<=2]
lstmin_canc.groupby('room_category')['booking_id'].count().plot(kind='bar',figsize=(7,3))
plt.ylabel('no. of cancellations')
plt.title('Last min Cancellations vs Room Category')
plt.show()
```



Statistical Visualizations

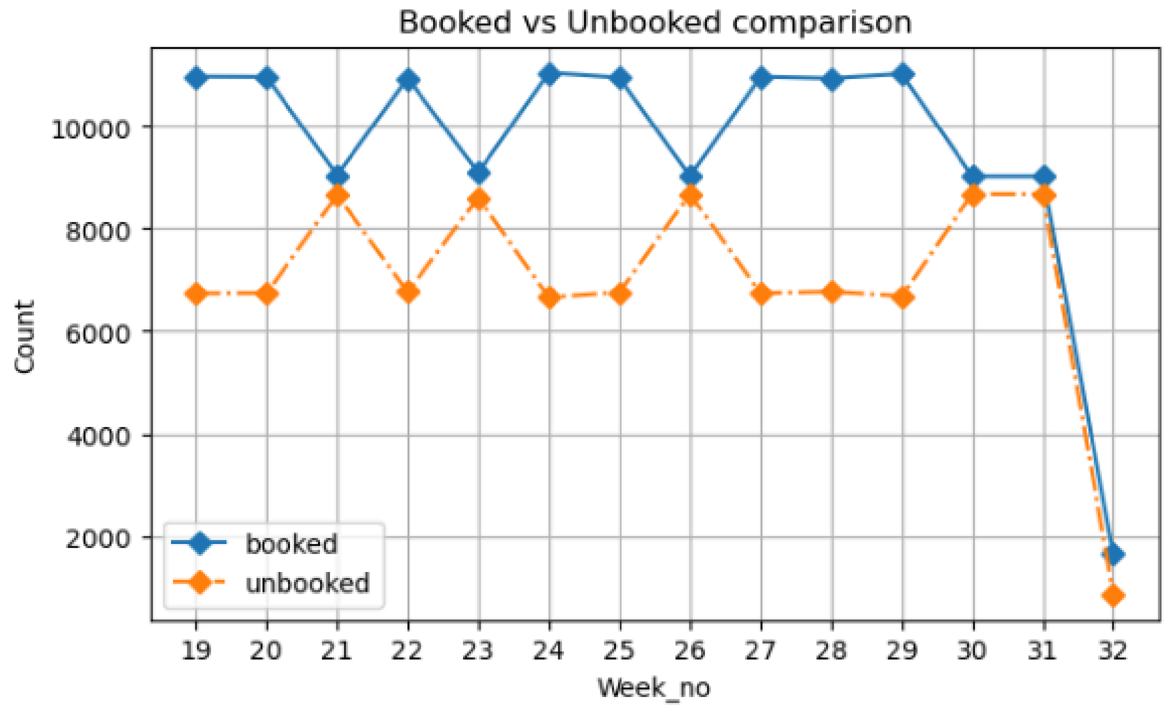
11.Revenue Leakage caused vs Booking Platform

```
booking_data.groupby('booking_platform')['revenue_leakage'].sum().sort_values(ascending=False).reset_index().set_index('booking_platform').plot(kind='bar
plt.show()
```



12.Booked vs Unbooked comparison

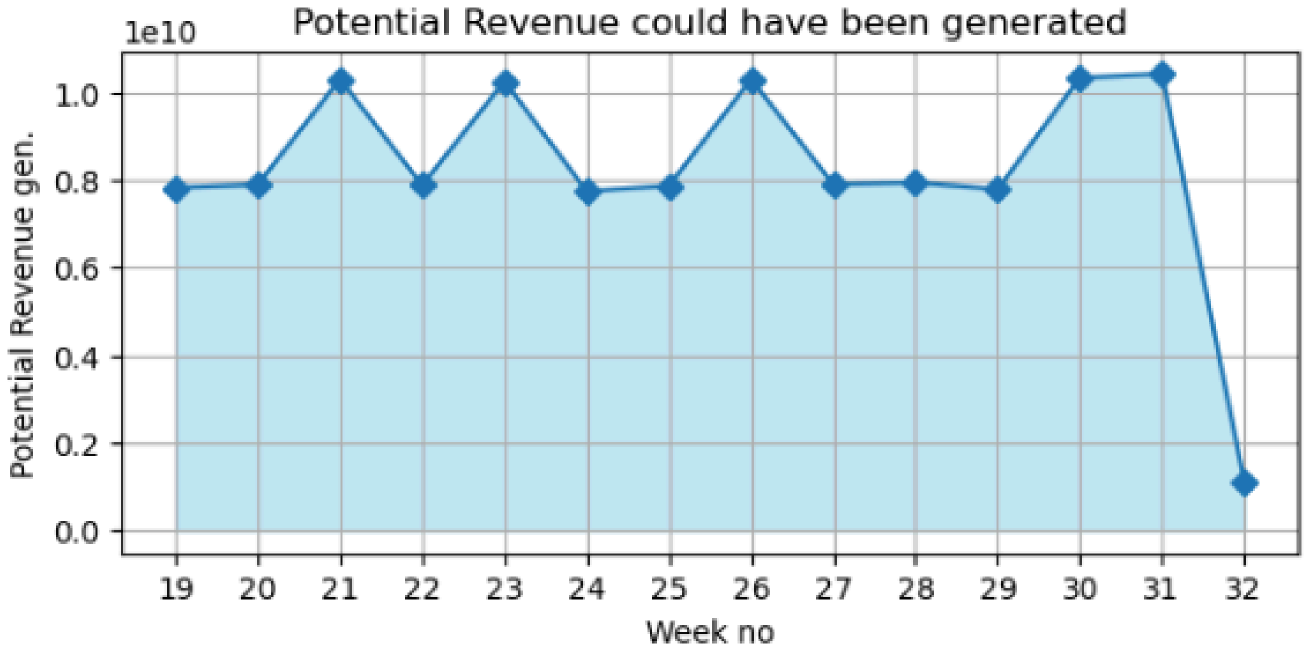
```
plt.figure(figsize=(7,4))
plt.plot(bub['week no'],bub['successful_bookings'],marker='D',label='booked')
plt.plot(bub['week no'],bub['unbooked'],marker='D',linestyle='dashdot',label='unbooked')

plt.title('Booked vs Unbooked comparison')
plt.xlabel('Week_no')
plt.ylabel('Count')
plt.legend()
plt.grid()
plt.show()
```



Statistical Visualizations

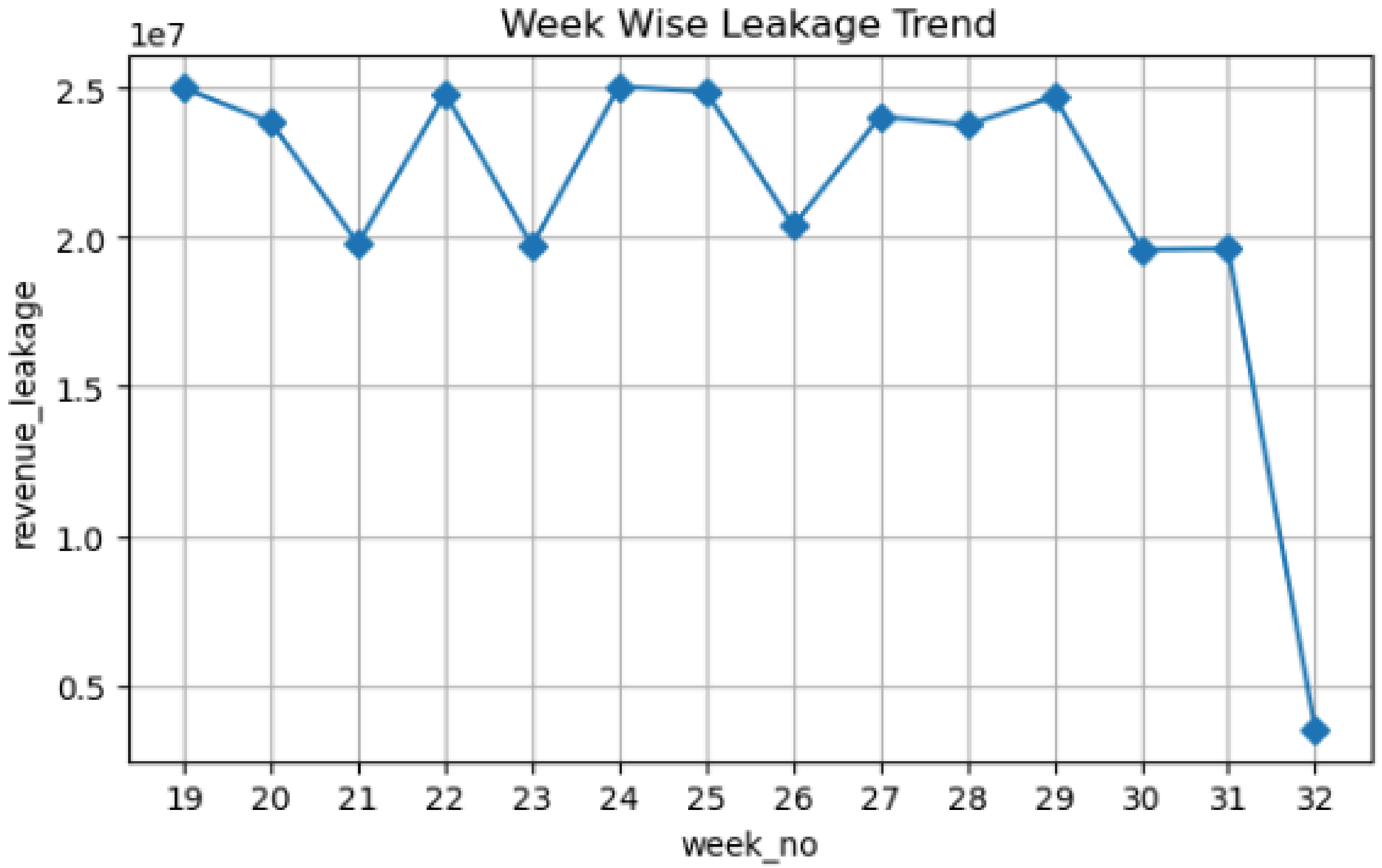
13.Potential Revenue could have been generated

```
ao['unbooked']=ao['capacity']-ao['successful_bookings']
ao['potrev']=ao['unbooked']*ao['adr']
plt.figure(figsize=(7,3))
plt.plot(ao['week no'],ao['potrev'],marker='D')
plt.fill_between(ao['week no'], ao['potrev'], color="skyblue", alpha=0.5)
plt.title('Potential Revenue could have been generated')
plt.xlabel('Week no')
plt.ylabel('Potential Revenue gen.')
plt.grid()
plt.show()
```



14.Week Wise Leakage Trend

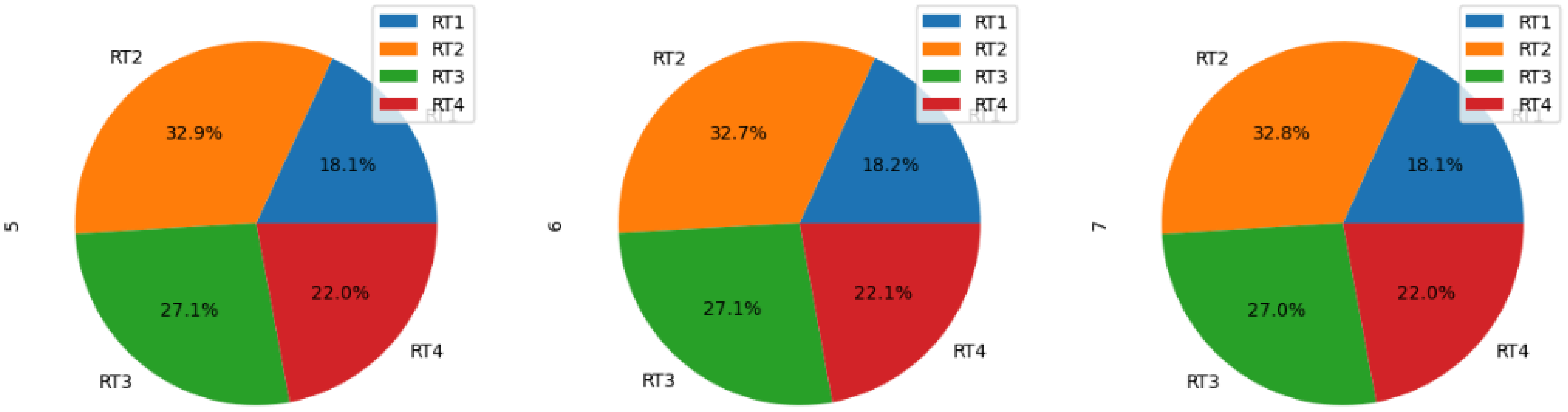
```
plt.figure(figsize=(7,4))
plt.plot(w_leak['week no'],w_leak['revenue_leakage'],marker='D')
plt.xlabel('week_no')
plt.ylabel('revenue_leakage')
plt.title('Week Wise Leakage Trend')
plt.grid()
plt.show()
```



Statistical Visualizations

15.Month wise Revenue Realized by room category ¶

```
rt.pivot_table(index=['room_category'],columns=['mmm yy'],values='revenue_realized',aggfunc='sum').plot(kind='pie',autopct='%0.1f%%',subplots=True,figsi
plt.show()
```



Statistical Visualizations

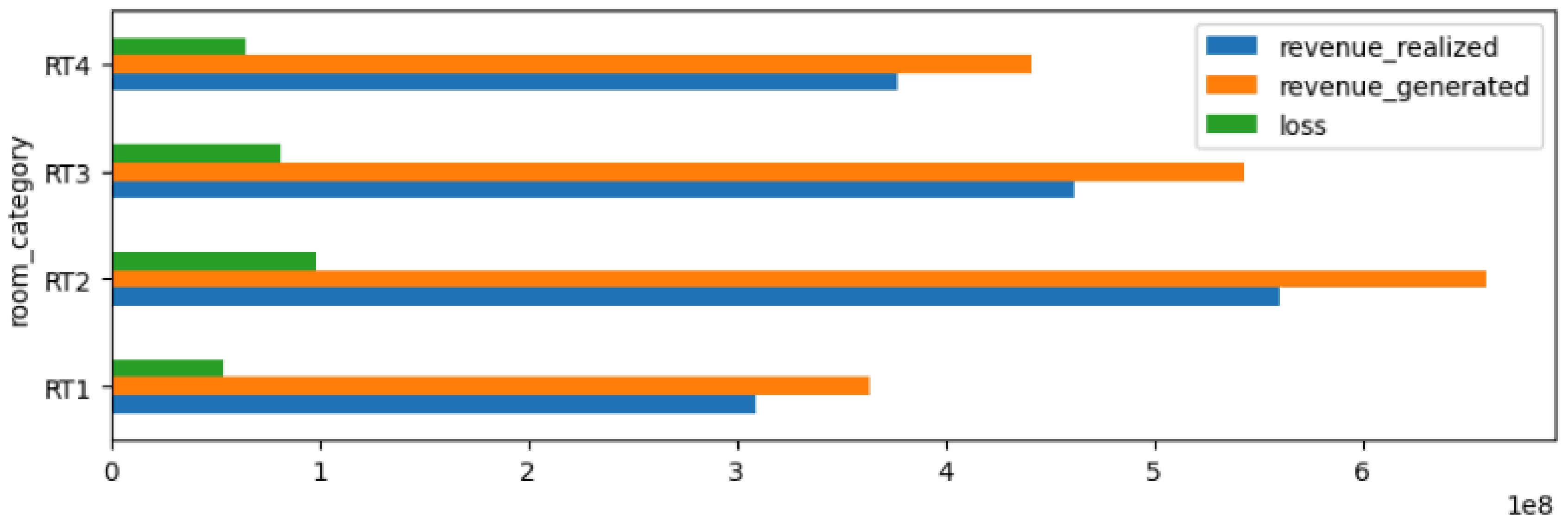
16.Room Category wise Revenue Realization

```
rt.pivot_table(index=['room_category'],columns=['mmm yy'],values='revenue_realized',aggfunc='sum').plot(kind='bar',stacked=True,figsize=(7,3),ylabel='rev
```

<Axes: title={'center': 'Room Category wise Revenue Realization'}, xlabel='room_category', ylabel='revenue_realized'>

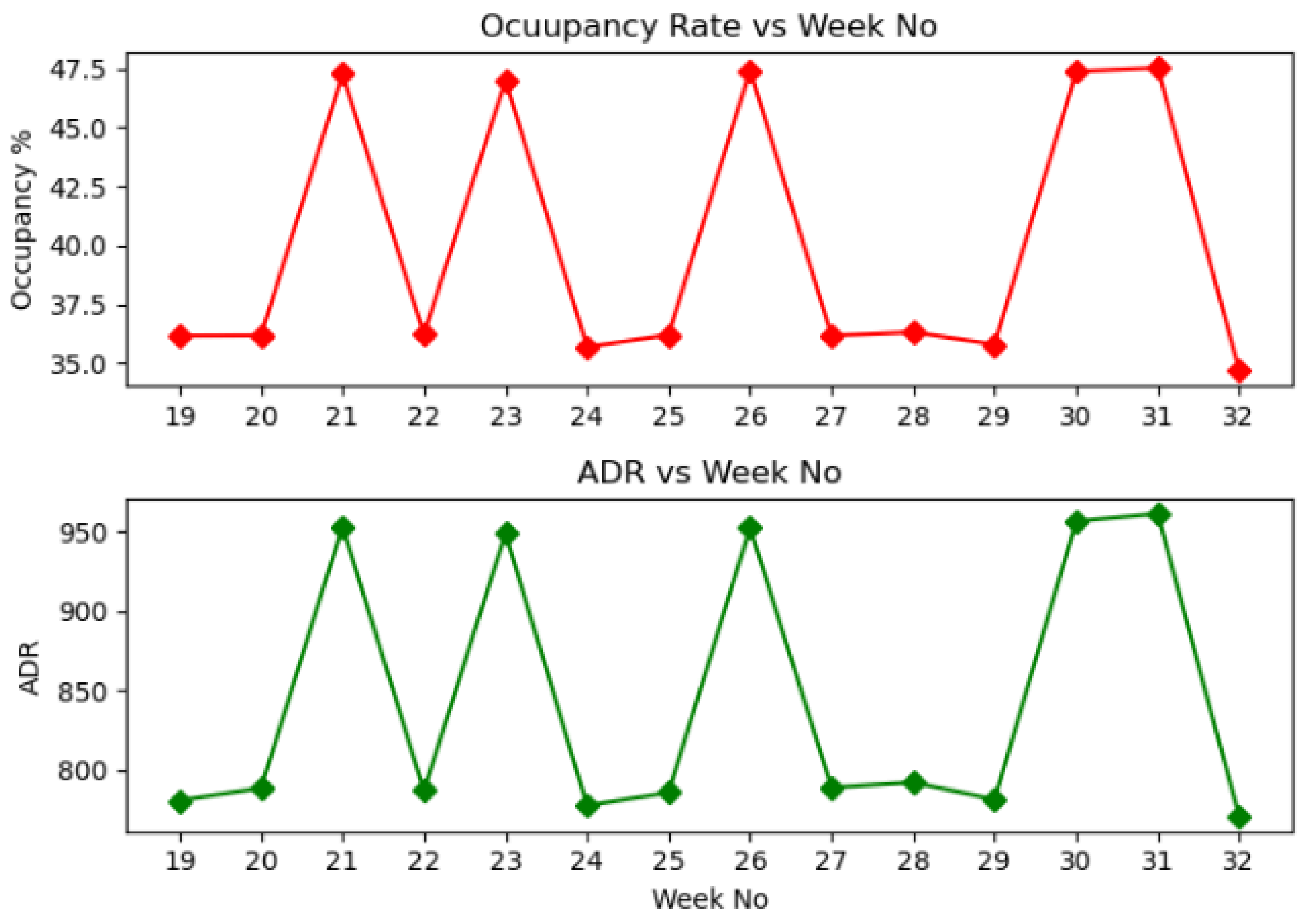
17.Revenue Realized vs Generated (Loss %) by Room Type

```
loss=booking_data.groupby('room_category')[['revenue_realized','revenue_generated']].sum()
loss['loss']=loss['revenue_generated']-loss['revenue_realized']
loss.plot(kind='barh',figsize=(10,3))
plt.show()
```



18.Occupancy Rate and ADR (Average Daily Rate) Comparison

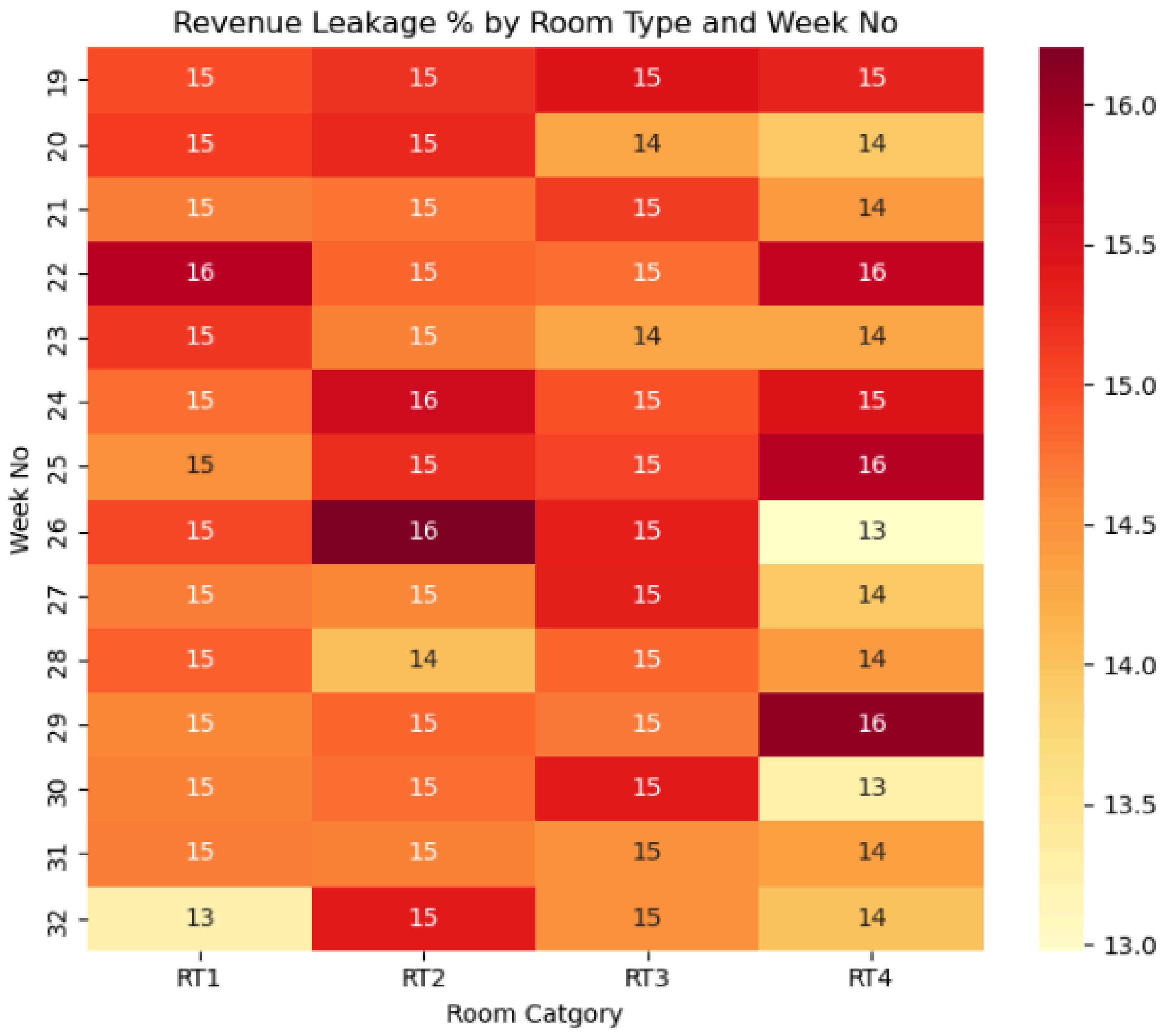
```
fig,ax=plt.subplots(2,1,figsize=(7,5))
ax[0].plot(ao['week no'],ao['occupancy rate'],marker='D',color='red')
ax[0].set_title('Ocuupancy Rate vs Week No')
ax[0].set_ylabel('Occupancy %')
ax[1].plot(ao['week no'],ao['adr'],marker='D',color='green')
ax[1].set_title('ADR vs Week No')
ax[1].set_xlabel('Week No')
ax[1].set_ylabel('ADR')
plt.tight_layout()
plt.show()
```



Statistical Visualizations

19.Revenue Leakage Heatmap (Room Type × Day of Week)

```
summ=booking_data.merge(date_data,how='left',left_on='check_in_date',right_on='date')
summ['leakage_pct']=(summ['revenue_leakage']/summ['revenue_generated'])*100
heat_data1=summ.groupby(['week no','room_category'])['leakage_pct'].mean().unstack()
plt.figure(figsize=(7, 6))
sns.heatmap(heat_data1, annot=True, cmap="YlOrRd")
plt.title("Revenue Leakage % by Room Type and Week No")
plt.xlabel("Room Catgory")
plt.ylabel("Week No")
plt.tight_layout()
plt.show()
```



Conclusion

The analysis reveals key revenue leakages from last-minute cancellations, poor pricing of high-capacity rooms like RT2, and underperforming cities like Delhi. Targeted strategies can help improve profitability and room utilization.

Recommendations

- Introduce non-refundable bookings or late cancellation charges to reduce last-minute drop-offs.
- Offer perks like discounts or reward points for guaranteed bookings to encourage reliable customers.
- Identify users with a history of repeated cancellations and apply restrictions or warnings to prevent revenue loss.
- Adjust room prices based on demand, room type, seasonality, and performance of the booking platform.
- Implement real-time KPI tracking (e.g., RevPAR by room type and weekday) to enable proactive pricing and inventory strategies.

Thank You

Explore the complete project documentation, including detailed EDA, KPIs, visual insights, business interpretations, and the Power BI dashboard via the link below - Click Here