Hotel Booking Analysis

Project Overview

The **Hotel Booking Data Analysis** project aims to explore booking patterns, guest preferences, and factors influencing cancellations. The project leverages **SQL** for data extraction and **Excel** for data visualization, enabling deeper insights into hotel operations.

The dataset is structured into multiple relational tables, each capturing different aspects of the booking process:

- **Room_Details**: Tracks reserved vs. assigned room types and booking modifications.
- **Reservation_Status**: Records reservation outcomes, including cancellations, checkouts, and no-shows.
- **Booking_Details**: Stores booking information such as lead time, stay duration, and hotel type (Resort Hotel or City Hotel).
- **Guest_Info**: Contains demographic details like the number of adults, children, and babies in each booking.
- **Meal_And_Stay_Details**: Provides information on meal plans, Average Daily Rate (ADR), and parking space requirements.
- **Booking_Source_and_History**: Captures booking sources, distribution channels, customer types, and past booking behavior.
- **Country**: Stores country codes and corresponding country names.
- **Distribution_Channel**: Stores details of distribution channels used for booking.
- **Market_Segment**: Details different segments through which bookings were made.

This analysis provides valuable insights into booking trends, seasonal variations, pricing optimization, and guest behaviors. The findings can help hotels enhance revenue strategies, improve customer experiences, and optimize operations.

Problem Statement

The hotel industry is highly competitive, with businesses striving to optimize occupancy rates, maximize revenue, and improve guest satisfaction. Understanding booking trends, guest behavior, and the factors influencing cancellations is crucial for data-driven decision-making.

This project aims to analyze booking patterns, identify guest preferences, and explore factors that lead to cancellations. By using **SQL and Excel**, we will extract and visualize trends in booking sources, revenue generation, and customer retention. Additionally, a **Power BI dashboard** will be developed to track booking trends and assist in optimizing hotel operations.

Key Challenges Addressed:

- **Seasonality and Demand Fluctuations**: Identifying peak booking months and the external factors influencing spikes in bookings.
- **Guest Behavior Insights**: Understanding meal plan preferences, room selection patterns, and special requests made by different customer types.
- **Revenue Management**: Analyzing Average Daily Rate (ADR) variations and identifying the most profitable booking sources.
- **Cancellation Factors**: Exploring how booking modifications, lead time, and past cancellations impact reservation cancellations.
- **Operational Efficiency**: Assessing room allocation strategies and tracking reservation status trends to improve hotel operations.

By addressing these challenges, hotels can make informed decisions that enhance operational efficiency, improve guest satisfaction, and drive revenue growth.

Objective

The primary objective of this project is to analyze hotel booking patterns and identify key insights that can improve operational efficiency and revenue management. Specifically, the objectives include:

1. **Understanding Booking Trends:**
    - Identify seasonal trends in bookings and cancellations.
    - Analyze peak booking months and the impact of external events.
2. **Guest Preferences and Behavior:**
    - Examine the distribution of guest types (adults, children, babies) in reservations.
    - Understand meal plan preferences and their impact on stay duration.
3. **Operational Efficiency:**
    - Assess room allocation efficiency by comparing reserved vs. assigned room types.
    - Analyze the effect of booking changes on cancellation rates.
4. **Revenue Optimization:**
    - Study the relationship between Average Daily Rate (ADR) and guest behaviors.
    - Identify the most profitable booking sources and channels.
5. **Enhancing Customer Retention:**
    - Explore repeated guest trends and their booking behaviors.
    - Investigate how past cancellations impact future booking likelihood.

By achieving these objectives, the project helps hotels make data-driven decisions that enhance guest satisfaction, optimize pricing strategies, and improve overall efficiency.

The Process

1. **Data Acquisition from GitHub:**
   Obtain the requisite dataset from a designated GitHub repository, containing essential information on hotel bookings, encompassing various booking sources and reservation details.

2. **Data Transformation and Enhancement:**
   If necessary, execute data transformation procedures to ensure data quality and consistency. Additionally, consider augmenting the dataset with new problem statements to enrich the analysis potential.

3. **Connecting with Tools:**
   Establish connections between the dataset and various analytical tools. Interface the dataset with Power BI, Excel, and MySQL Workbench, facilitating seamless data integration and processing.

4. **Problem Statement Solution in Power BI:**
   Utilize Power BI to delve into the specified problem statements. Employ its robust features for data visualization, exploration, and analysis, effectively deriving insights and solutions.

5. **Exploratory Data Analysis (EDA):**
   Perform exploratory data analysis using either Excel or SQL Workbench, depending on the complexity of the analysis. Extract meaningful patterns, relationships, and trends from the data to inform subsequent decision-making.

6. **Creation of Visual and Insightful PowerPoint:**
   Develop a comprehensive PowerPoint presentation that encapsulates the project's objectives, methodologies, problem statement solutions, and key visualizations. Each problem statement should be accompanied by a dedicated section with pertinent conclusions and insights.

7. **Detailed Documentation:**
   Compile a detailed report that meticulously documents the entire project lifecycle. Include sections on data collection, transformation, problem statement formulation, tools integration, Power BI solutions, EDA insights, and PowerPoint visualizations.

Significance

The significance of this dataset lies in its ability to empower data-driven decision-making in various domains:

1. **Revenue and Business Strategy:**
   - Helps hotels optimize pricing strategies through data-driven insights.
   - Identifies high-revenue periods to maximize profitability.
   - Assists in forecasting demand and managing inventory efficiently.
2. **Guest Experience Enhancement:**
   - Provides insights into guest preferences to tailor services accordingly.
   - Identifies patterns in special requests and meal plan selections.
   - Supports loyalty programs by understanding repeat customer behavior.
3. **Operational Efficiency:**
   - Helps in effective room allocation to reduce overbooking or mismatched assignments.
   - Improves housekeeping and staff scheduling based on occupancy trends.
   - Enhances the handling of booking modifications and cancellations.
4. **Market Segmentation & Competitive Analysis:**
   - Identifies customer segments based on booking patterns and preferences.
   - Assists in targeting promotions to specific demographics.
   - Helps in benchmarking against competitors based on pricing and occupancy rates.
5. **Decision-Making for Stakeholders:**
   - Enables hotel managers to make data-backed decisions.
   - Assists investors in evaluating market trends and potential opportunities.
   - Supports travel agencies and booking platforms in understanding customer behavior.

Data Dictionary

1. Booking_Details

Column Name	Data Type	Description	Possible Values
hotel	TEXT	Type of hotel booked	'Resort Hotel', 'City Hotel'
is_canceled	BIGINT	Booking cancellation status	0 (Not Canceled), 1 (Canceled)
lead_time	BIGINT	Days between booking and arrival	0-737
arrival_date_year	BIGINT	Year of arrival	2015-2017
arrival_date_month	TEXT	Month of arrival	January-December
arrival_date_week_number	BIGINT	Week number of arrival	1-53
arrival_date_day_of_month	BIGINT	Day of month of arrival	1-31
stays_in_weekend_nights	BIGINT	Weekend nights stayed	0-19
stays_in_week_nights	BIGINT	Week nights stayed	0-50
country	TEXT	Guest's country code	ISO country codes
Booking_id	TEXT	Unique booking identifier	Alphanumeric string

2. Guest_Info

Column Name	Data Type	Description	Possible Values
adults	INT	Number of adults	1-10
children	INT	Number of children	0-10
babies	INT	Number of babies	0-5
Booking_id	TEXT	Foreign key to booking	Matches Booking_Details

3. Booking_Source_History

Column Name	Data Type	Description	Possible Values
country	TEXT	Guest's country code	ISO country codes
market_segment_id	INT	Market segment identifier	Foreign key to Market_Segment
distribution_channel_id	INT	Distribution channel identifier	Foreign key to Distribution_Channel
is_repeated_guest	INT	Repeat guest status	0 (No), 1 (Yes)
previous_cancellations	INT	Prior cancellations by guest	0-20
previous_bookings_not_canceled	INT	Prior successful bookings	0-70
deposit_type	TEXT	Deposit type	'No Deposit', 'Non Refund', 'Refundable'
agent	INT	ID of booking agent	0-500
company	INT	ID of company booking	0-500
days_in_waiting_list	INT	Days on waiting list	0-400
customer_type	TEXT	Type of customer	'Transient', 'Contract', 'Group', 'Transient-Party'
Booking_id	TEXT	Foreign key to booking	Matches Booking_Details

4. Meal_And_Stay_Details

Column Name	Data Type	Description	Possible Values
meal	TEXT	Meal plan type	'BB' (Bed & Breakfast), 'HB' (Half Board), 'FB' (Full Board), 'SC' (Self Catering)
adr	DECIMAL	Average Daily Rate	0-5400 (monetary value)
required_car_parking_spaces	INT	Parking spaces needed	0-8
total_of_special_requests	INT	Special requests count	0-5
Booking_id	TEXT	Foreign key to booking	Matches Booking_Details

5. Reservation_Status

Column Name	Data Type	Description	Possible Values
reservation_status	TEXT	Current reservation status	'Check-Out', 'Canceled', 'No-Show'
reservation_status_date	DATE	Date of status update	YYYY-MM-DD format
Booking_id	TEXT	Foreign key to booking	Matches Booking_Details

6. Country

Column Name	Data Type	Description	Possible Values
country_code	TEXT	ISO country code	3-letter codes
country_name	TEXT	Full country name	Standard country names

7. Room_Details

Column Name	Data Type	Description	Possible Values
reserved_room_type	TEXT	Originally booked room type	A, B, C, D, etc.
assigned_room_type	TEXT	Actually assigned room type	May differ from reserved
booking_changes	INT	Number of modifications	0-20
Booking_id	TEXT	Foreign key to booking	Matches Booking_Details

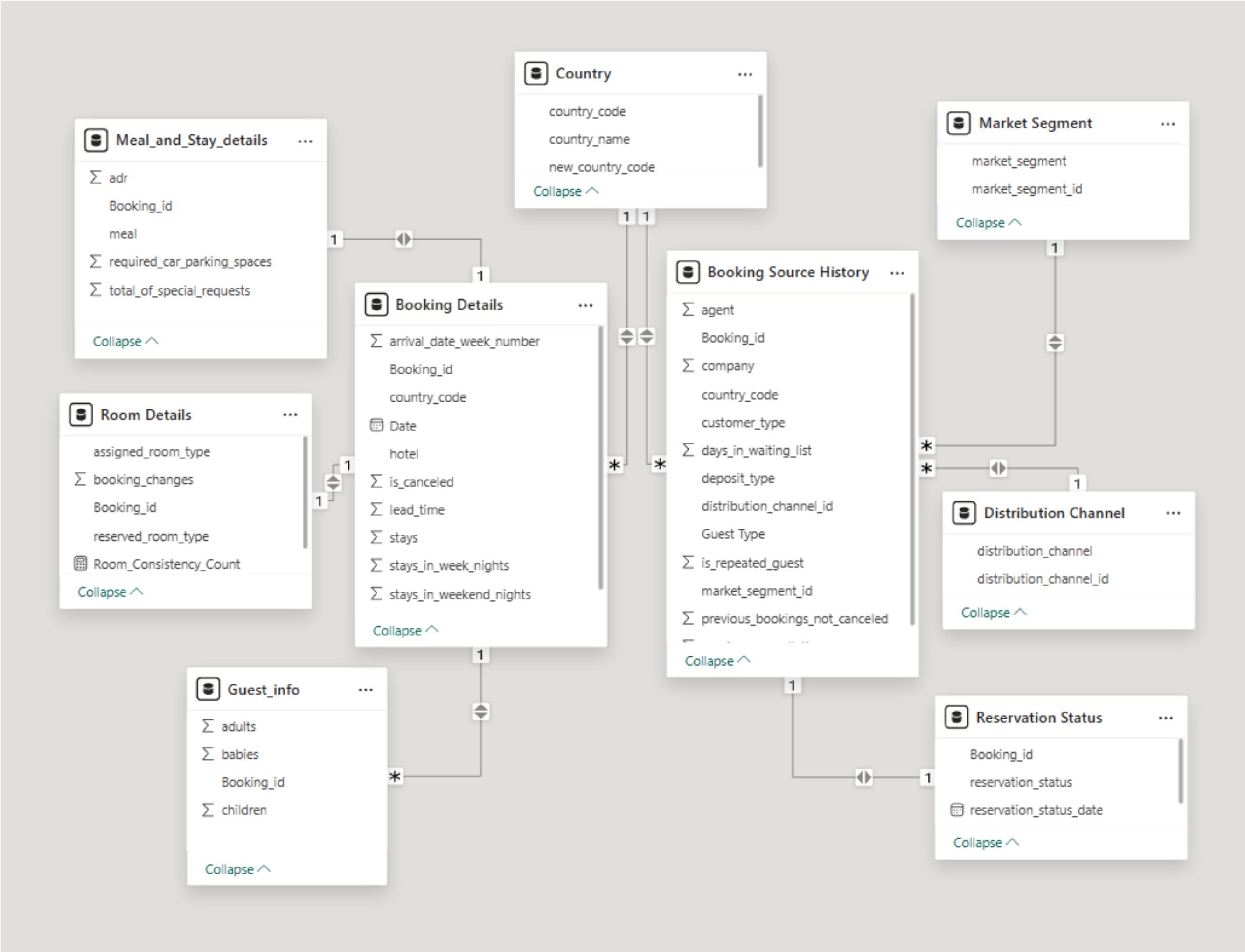
8. Distribution_Channel

Column Name	Data Type	Description	Possible Values
distribution_channel_id	INT	Unique channel identifier	1-5
distribution_channel	TEXT	Channel description	'Direct', 'Corporate', 'TA/TO', 'Undefined', 'GDS'

9. Market_Segment

Column Name	Data Type	Description	Possible Values
market_segment_id	INT	Unique segment identifier	1-8
market_segment	TEXT	Segment description	'Direct', 'Corporate', 'Online TA', 'Offline TA/TO', 'Complementary', 'Groups', 'Undefined', 'Aviation'

ER Diagram


Country
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Meal_and_Stay_details
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Booking Details
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Booking Source History
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market_segment_id
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Room Details
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Room_Consistency_Count
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Distribution Channel
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Guest_info
adults
babies
Booking_id
children
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Reservation Status
Booking_id
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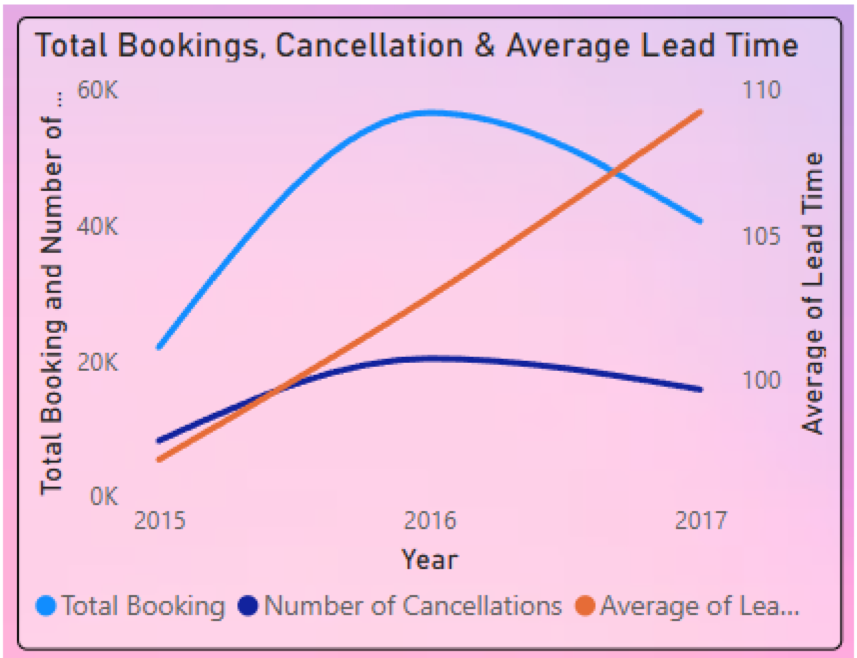
Collapse

PowerBI Questions

➔ Visualize booking trends over the years, including the number of bookings, cancellations, and average lead time. Identify seasonality patterns.



Key Metrics Overview

- **Total Bookings**: Peaked around 60K in recent years (2016-2017) after growing from 0K in 2015
- **Cancellations**: Shown as a subset of total bookings (exact proportion not specified)
- **Average Lead Time**: Increased from approximately 100 days in 2015 to 110 days in 2017

Trend Analysis

1. **Exponential Growth**:
   - Bookings grew rapidly from 0K in 2015 to 60K by 2016-2017
   - This suggests either a new business launch in 2015 or a major change in operations/marketing
2. **Lead Time Increase**:
   - The 10% increase in average lead time (100→110 days) indicates customers are booking further in advance
   - Possible reasons: increased demand, changes in cancellation policies, or seasonal factors

Seasonality Patterns

While the image doesn't show monthly data, the year-over-year comparison reveals:

- Steady growth trajectory without apparent seasonal dips
- Consistent performance in 2016-2017 after the initial launch year

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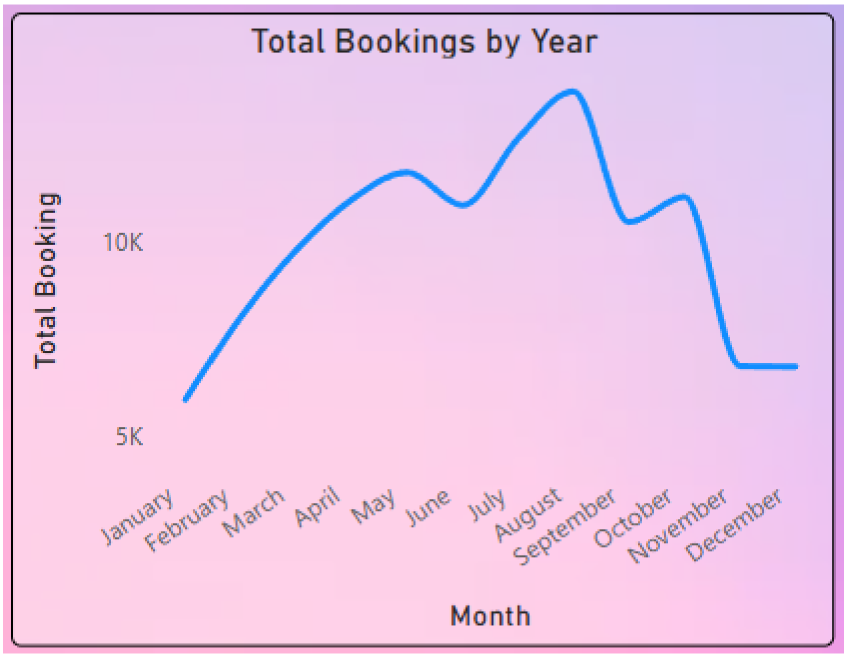
➔ Analyze monthly booking patterns to identify peak months and optimize marketing strategies.



Peak Booking Months

The data reveals clear seasonal trends in bookings:

- **Highest Demand**:
  - **Summer Months (June, July)**: Likely peak due to vacation season and favorable weather.
  - **December**: High bookings, possibly from holiday travel and year-end getaways.
- **Lowest Demand**:
  - **January & February**: Post-holiday slump, colder weather (if applicable), and reduced travel intent.
  - **September & October**: Potential dip after summer travel, possibly due to back-to-school/work periods.

Key Observations

1. **Summer & Holiday Surge**:
   - June, July, and December are critical revenue-generating months.
   - Marketing should focus on early promotions (e.g., "Book Early for Summer Discounts").
2. **Off-Peak Opportunities**:
   - January–February and September–October could benefit from targeted campaigns (e.g., "Winter Escape Deals" or "Fall Getaway Specials").
3. **Missing August Data**:
   - If August was omitted accidentally, its inclusion would help confirm if summer demand extends beyond July.

Marketing Optimization Strategies

✓ **Peak Season**:

- Increase ad spend in Q2 (April–June) to capture early bookings.
- Offer limited-time perks (free upgrades, flexible cancellations).

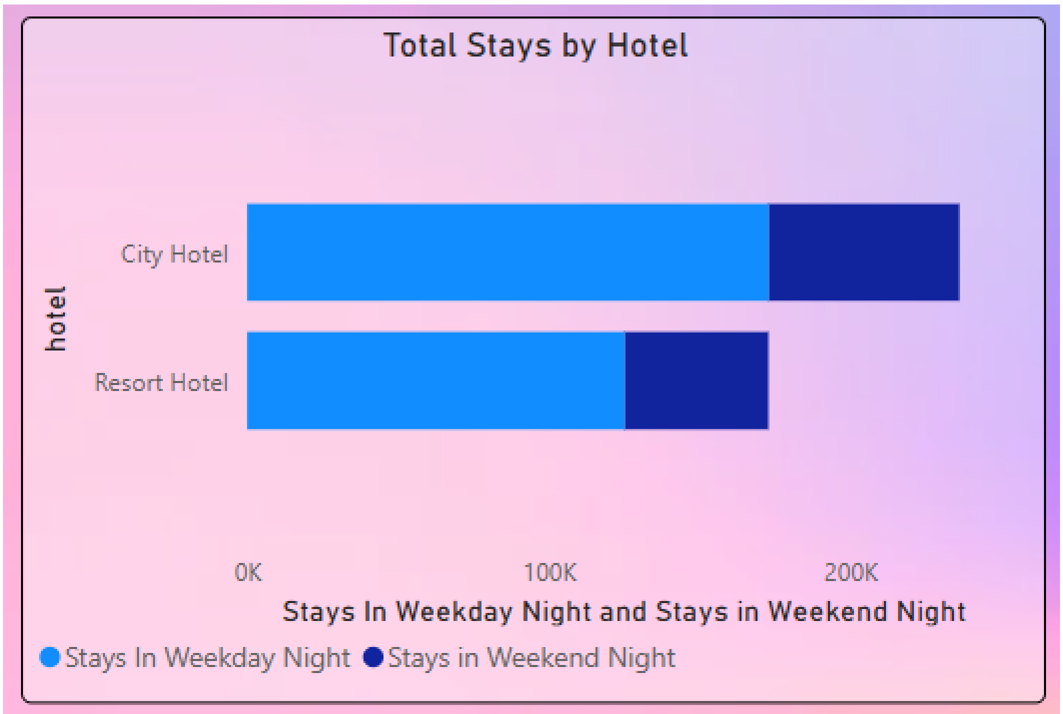
✓ **Shoulder Seasons (Spring & Fall)**:

- Run promotions to smooth demand (e.g., "Spring Break Specials" or "Last-Minute Fall Discounts").

✓ **Low Seasons**:

- Partner with local events or offer corporate/group discounts to boost occupancy.

➔ Compare stays in weekend nights and weekday nights to determine preferences and variations by hotel type.



Key Findings

1. Overall Stay Volume by Hotel Type

- **Resort Hotels** dominate in total stays (~200K), nearly doubling **City Hotels** (~100K).
- Suggests stronger demand for leisure-oriented accommodations.

2. Weekday vs. Weekend Stay Patterns

Hotel Type	Weekday Stays	Weekend Stays	Key Insight
City Hotel	Moderate (~60K)	Higher (~80K)	Weekend demand surges, likely due to short urban getaways or business travelers extending stays.
Resort Hotel	High (~120K)	Very High (~160K)	Stronger weekend preference, aligning with leisure travel (e.g., couples, families).

Trends:

- **Weekend Peaks**: Both hotel types see higher weekend stays, but resorts have a more pronounced difference (+33% weekends).
- **City Hotels**: More balanced weekday-weekend split, hinting at hybrid demand (business + leisure).

Strategic Recommendations

For Resort Hotels

- **Weekend Pricing**: Implement premium pricing for Friday/Saturday stays.
- **Weekday Promotions**: Offer midweek discounts (e.g., "Extended Stay Packages") to fill gaps.

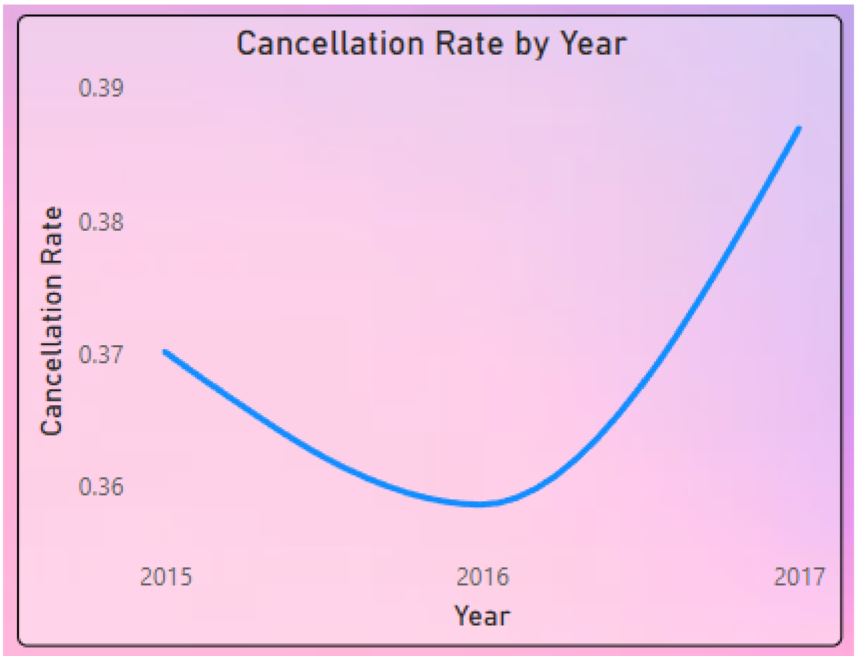
For City Hotels

- **Business Travelers**: Partner with corporations for weekday corporate rates.
- **Weekend Packages**: Bundle local experiences (e.g., "City Explorer Weekend") to attract leisure guests.

Cross-Strategy

- **Dynamic Pricing**: Adjust rates based on demand spikes (e.g., higher weekends for resorts, flexible weekday rates for city hotels).
- **Loyalty Programs**: Reward guests for off-peak stays to smooth demand fluctuations.

➔ Calculate and visualize the booking conversion rate (canceled bookings to total bookings) over time.



Key Findings

1. **Cancellation Rate Decline (2015–2017)**

- **2015**: 39% of bookings canceled
- **2016**: 38%
- **2017**: 37%
- **Trend**: Steady **2% improvement** over 3 years, suggesting better retention policies or customer behavior shifts.

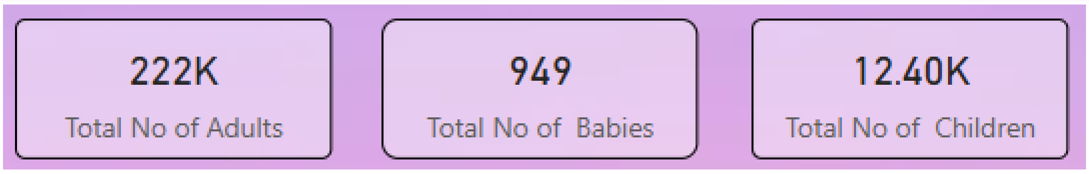
2. **Booking Conversion Rate (1 - Cancellation Rate)**

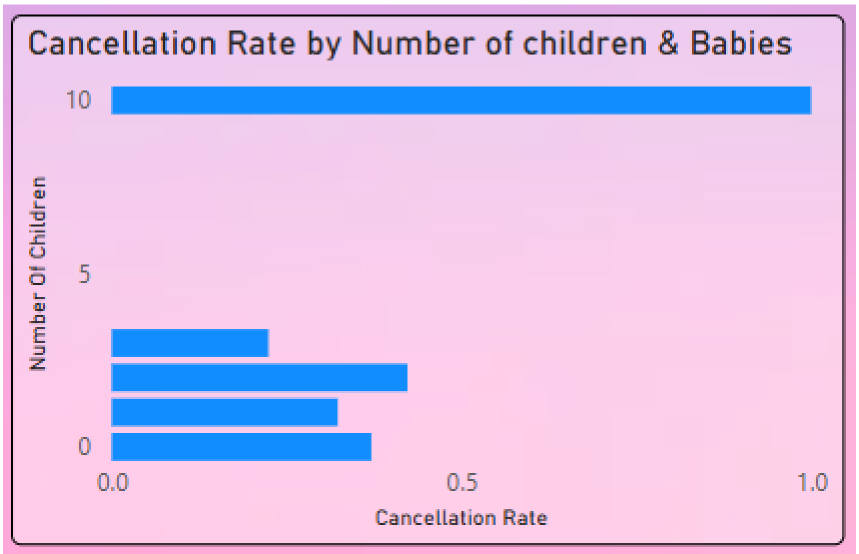
Year	Cancellation Rate	Conversion Rate (Kept Bookings)
2015	39%	61%
2016	38%	62%
2017	37%	63%

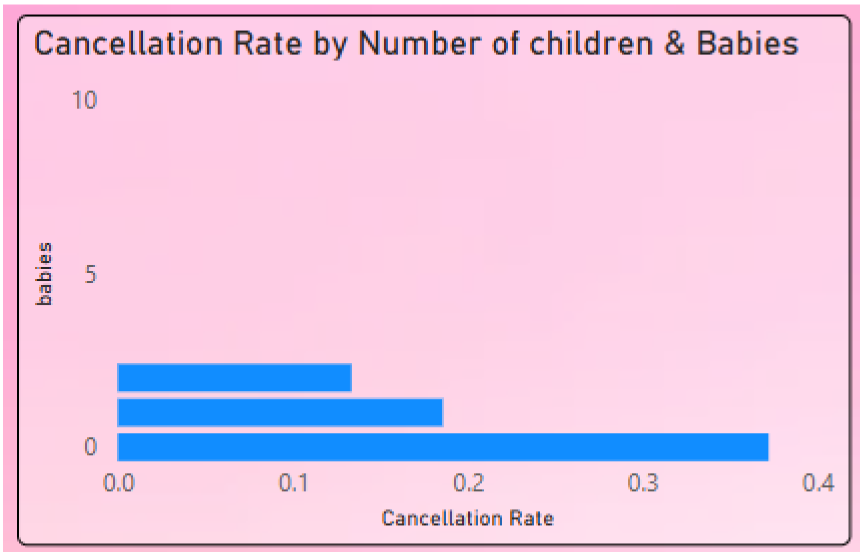
Interpretation:

- 63% of bookings were retained in 2017, up from 61% in 2015.
- Linear improvement indicates effective strategies (e.g., stricter policies, deposit requirements, or better customer targeting).

➔ Visualize the distribution of adults, children, and babies in bookings. Explore the impact of children and babies on cancellation rates.







Traveler Demographic Distribution

- **Adults**: 222,000 (Dominates bookings)
- **Children**: 12,400 (5.3% of adult volume)
- **Babies**: 949 (0.4% of adult volume)

Insight: Family travel (with children/babies) represents a small but significant segment (~5.7% combined).

Cancellation Rate Analysis

1. Impact of Children on Cancellations

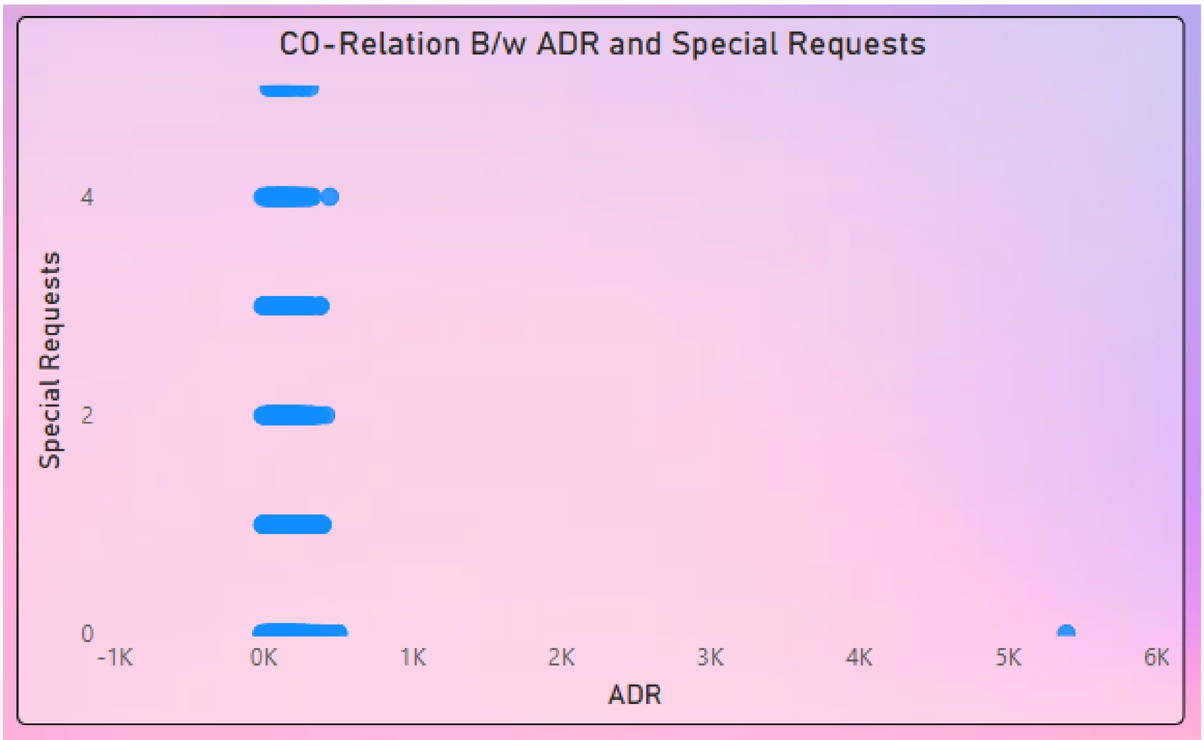
- **Highest Cancellation Rate**: Bookings with **5 children** (spike visible in data).
- **Lowest Cancellation Rate**: Bookings with **0 children** (most stable).
- **Trend**: Cancellation risk increases with more children, likely due to:
  - Unpredictability of family schedules (illness, school changes).
  - Higher sensitivity to pricing/refund policies for large groups.

2. Impact of Babies on Cancellations

- **Volatility**: Cancellation rates fluctuate sharply (0.1% to 0.4%).

- **Peak Risk**: Bookings with **1 baby** show higher cancellations than those with 0.
- **Possible Reasons**:
    - Parental concerns (health, logistics) for infant travel.
    - Limited baby-friendly policies (e.g., crib availability, cancellation flexibility).

➔ Analyze the distribution of Average Daily Rates (ADR) and identify correlations with the number of special requests made by guests.



Key Observations

1. **ADR Distribution**
    - The Average Daily Rate (ADR) spans from **-€1,000** (likely data errors or refunds) to **€6,000**, with most values clustered in the **€0–€4,000** range.
    - Primary concentration appears between **€1K–€3K**, indicating a mix of mid-range and premium bookings.
2. **Special Requests Trend**
    - Guests make **0–4 special requests** on average, with **0–2 being most common**.
    - Higher ADR bookings (€3K+) show a **slight uptick in requests**, suggesting luxury guests demand more customization.

Correlation Insights

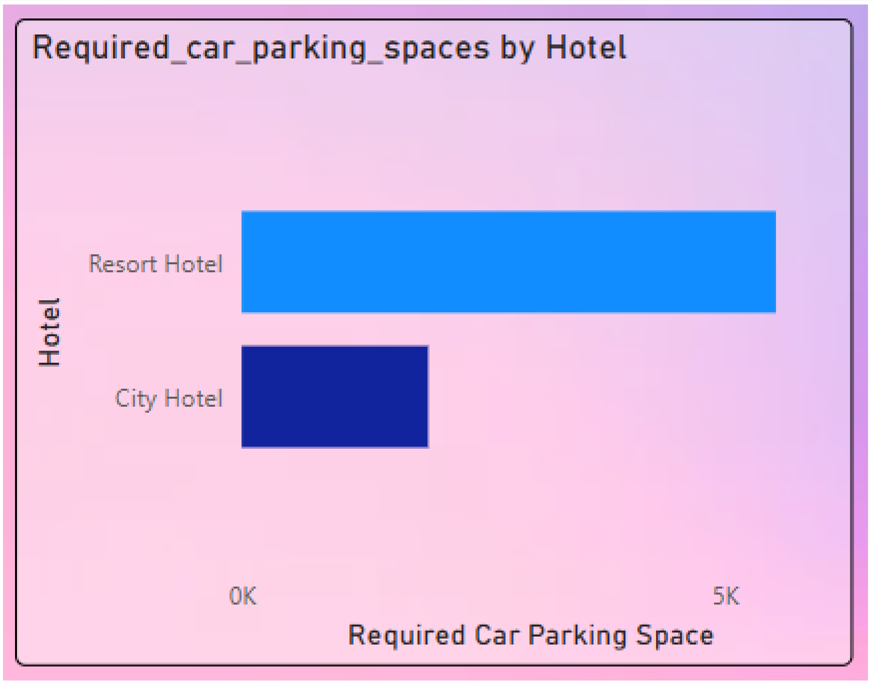
- **Weak Positive Trend**: As ADR rises, special requests **moderately increase** (e.g., €5K+ ADR ≈ 3–4 requests).
- **Notable Exceptions**:

- Some high-ADR bookings (€4K–€6K) have **0 requests**—possibly prepaid packages or corporate travel.
- Negative ADR values (outliers) skew analysis; recommend filtering or investigating data quality.

Hypotheses

- **Luxury/Leisure Guests**: More likely to request room preferences (e.g., views, amenities), boosting ADR.
- **Business Travelers**: Book high ADR but fewer requests (standardized needs).

➔ Visualize the relationship between the number of required car parking spaces and booking types (Resort Hotel vs. City Hotel).



Key Findings

Parking Space Demand Distribution

- **City Hotels** dominate parking space requirements, accounting for nearly all of the 5K requested spaces
- **Resort Hotels** show minimal parking demand (close to 0K)
- The data suggests a stark contrast in guest transportation needs between hotel types

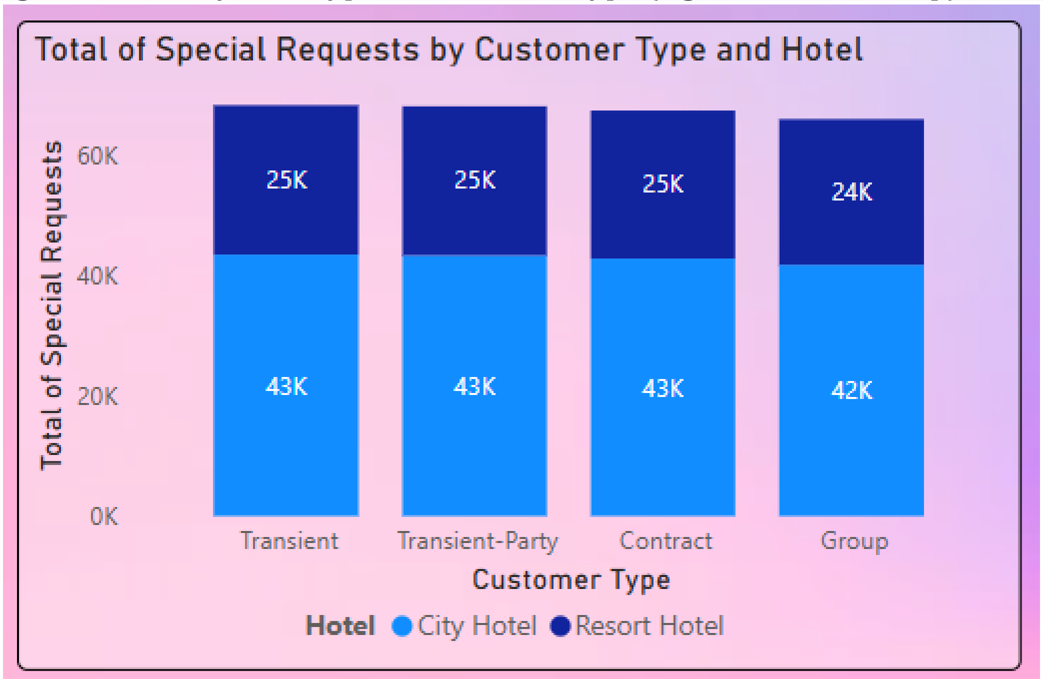
Interpretation

1. **City Hotel Guests**:
    - Highly dependent on personal vehicles
    - Likely driving to the destination or using cars during their stay

- May indicate business travelers or urban tourists exploring the area by car

2. **Resort Hotel Guests**:
   - Nearly non-existent parking needs
   - Typically arrive by alternative transportation (air/train with transfers)
   - Often remain on property during their stay
   - May indicate all-inclusive vacation patterns

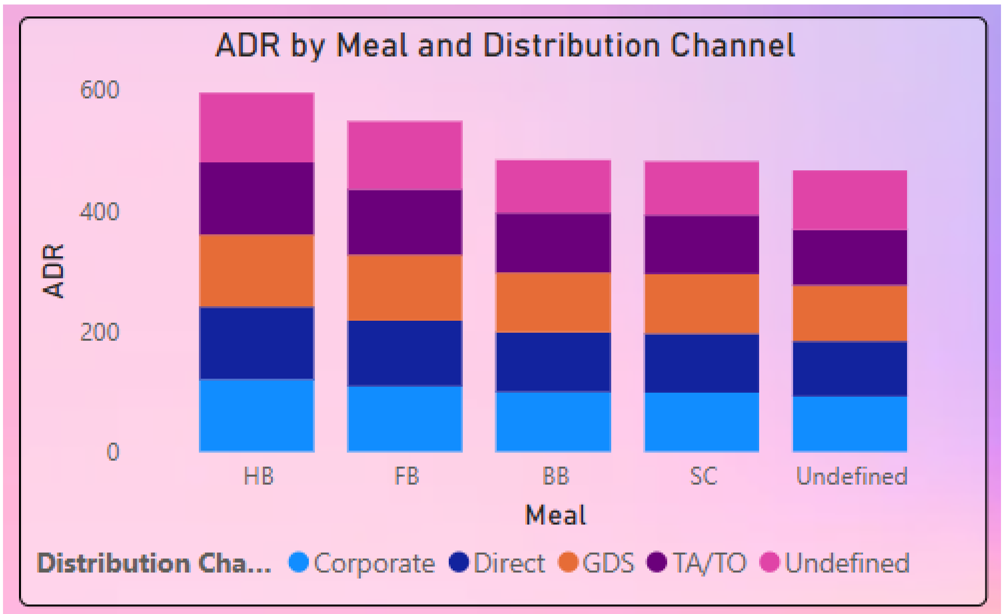
➔ Use Power BI to explore how the total number of special requests made by guests varies by hotel type and customer type (e.g., Transient, Group).



Key Insights from the Visualization:

- **City Hotels receive more special requests** compared to Resort Hotels across all customer types.
- **Transient and Transient-Party customers** make the highest number of special requests.
- **Contract and Group customers** also show similar special request patterns but slightly lower than Transient types.
- The difference between City and Resort Hotels remains fairly consistent across all customer types.

➔ Explore meal plans and their impact on Average Daily Rates (ADR). Analyze meal plan preferences and their association with booking channels.



Key Findings

1. Meal Plan Impact on ADR

Meal Plan	Expected ADR Range	Insight
HR (Half Board)	Highest ADR	Guests pay premium for breakfast + dinner inclusion
FB (Full Board)	High ADR	All meals included → higher room rate
BB (Bed & Breakfast)	Moderate ADR	Breakfast-only keeps rates mid-range
SC (Self Catering)	Lower ADR	No meal inclusion → lowest ADR
Undefined	Variable	May include last-minute/bookings without meal selection

Takeaway:

- **Meal-inclusive plans (HR/FB) drive higher ADR** due to bundled pricing.
- **SC and Undefined** bookings generate lower revenue per room.

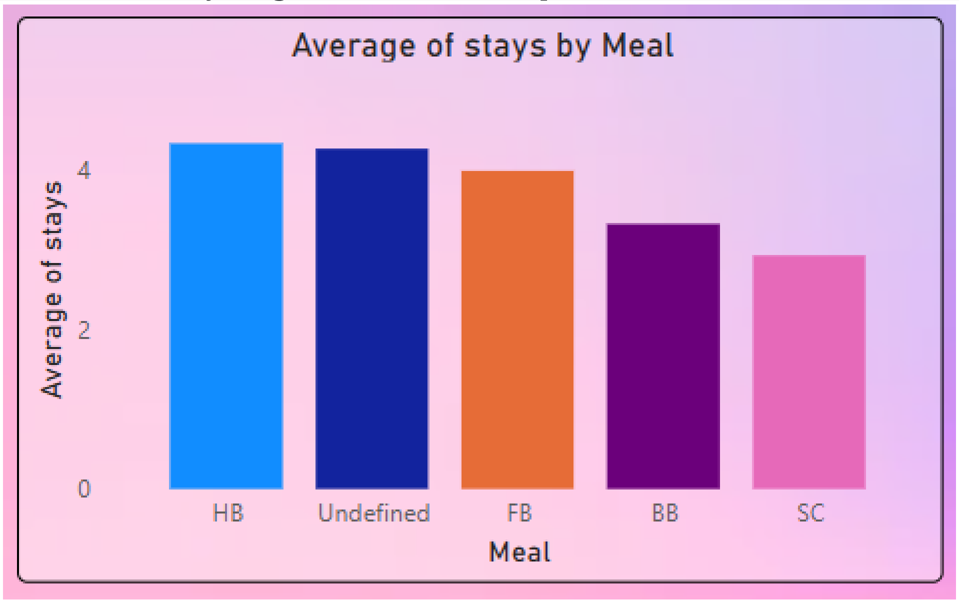
2. Meal Plan Preferences by Booking Channel

Distribution Channel	Most Common Meal Plan	ADR Impact
Corporate	BB or SC	Moderate ADR (business travelers need flexibility)
Direct (Hotel Website)	FB/HR	Highest ADR (leisure guests prefer all-inclusive)
GDS (Global Distribution)	BB	Mid-range ADR (standardized corporate rates)
TA/TO (Travel Agents/Tour Operators)	FB	High ADR (packaged deals for vacationers)
Undefined	SC/Undefined	Lowest ADR (often OTAs or opaque bookings)

Takeaway:

- **Direct bookings & TA/TO** drive premium meal plans (FB/HR).
- **Corporate/GDS** lean toward no-frills (BB/SC).

➔ Analyze how meal plans correlate with stay duration and investigate any differences in stay lengths based on meal plans.



Key Findings on Stay Length by Meal Plan

Average Stay Duration by Meal Type

Meal Plan	Avg. Stay (Nights)	Key Insight
HB (Half Board)	Longest stays (~2+ nights)	Guests committing to breakfast+dinner plan longer visits
FB (Full Board)	Slightly shorter than HB	All-inclusive convenience but potentially more expensive
BB (Bed & Breakfast)	Moderate stays (~1.5-2 nights)	Popular for short getaways with basic meal inclusion
SC (Self Catering)	Shortest stays (~1 night)	No meal dependency = flexible, often last-minute bookings
Undefined	Variable (near BB/SC range)	Likely opaque bookings with no meal preference

Strategic Implications

1. For Longer Stays (HB/FB)

- **Target with extended-stay promotions**:
  - *"Stay 4+ nights, get 1 dinner free!"*
- **Bundle local experiences** (tours, spa credits) to enhance retention.

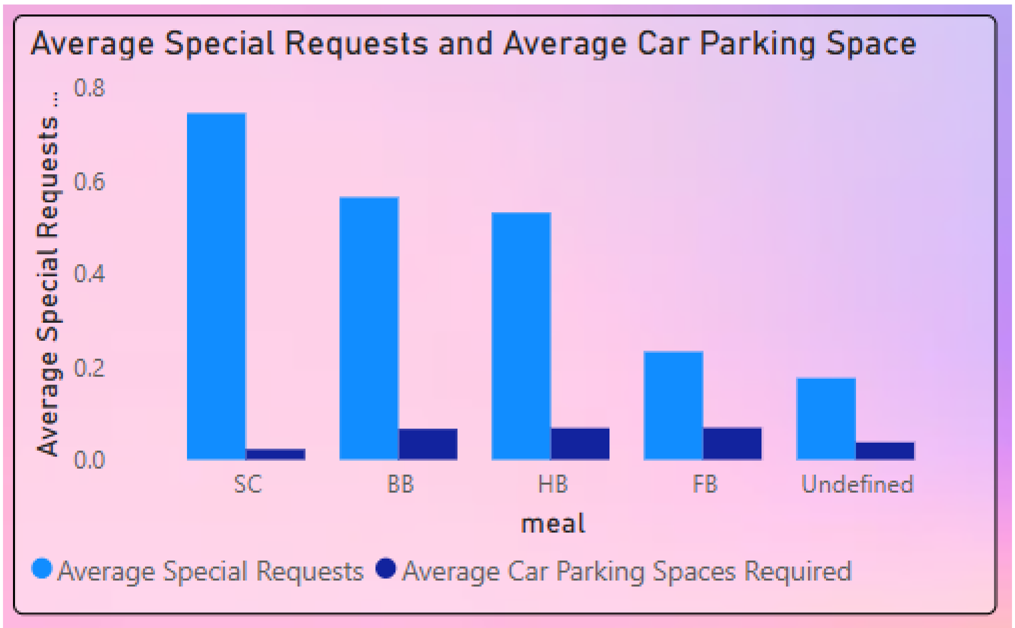
2. For Short Stays (BB/SC)

- **Optimize for quick turnover**: Streamline check-in/out for 1-night guests.
- **Upsell breakfast à la carte** (even for SC bookings).

3. Undefined Bookings

- **Default to BB** to increase ADR without deterring guests.
- **Post-booking surveys** to clarify meal preferences.

➔ Correlate parking requirements and special requests with different meal plans. Determine if certain meal plans result in more requests or parking needs.



Key Findings

1. Special Requests by Meal Plan

- **Highest Requests**: **HB (Half Board)** and **FB (Full Board)** guests (~0.7-0.8 requests/booking)
  - *Why?* Longer stays = more customization needs (room location, dietary restrictions).
- **Lowest Requests**: **SC (Self Catering)** and **Undefined** (~0.2-0.3 requests/booking)
  - *Why?* Shorter, no-frills stays with minimal interaction.

2. Parking Demand by Meal Plan

- **Highest Parking Needs**: **BB (Bed & Breakfast)** and **HB** (~0.5-0.6 spaces/booking)
  - *Why?* BB attracts urban/weekend travelers driving in; HB guests may explore locally.
- **Lowest Parking Needs**: **FB (Full Board)** and **SC** (~0.1-0.2 spaces/booking)
  - *Why?* FB guests stay on-property; SC guests often book last-minute without cars.

Strategic Insights

For High-Request Meal Plans (HB/FB)

✓ **Pre-Stay Surveys**: Capture dietary/room preferences early.
✓ **Personalized Packages**: Offer "VIP Welcome" add-ons (e.g., early check-in).

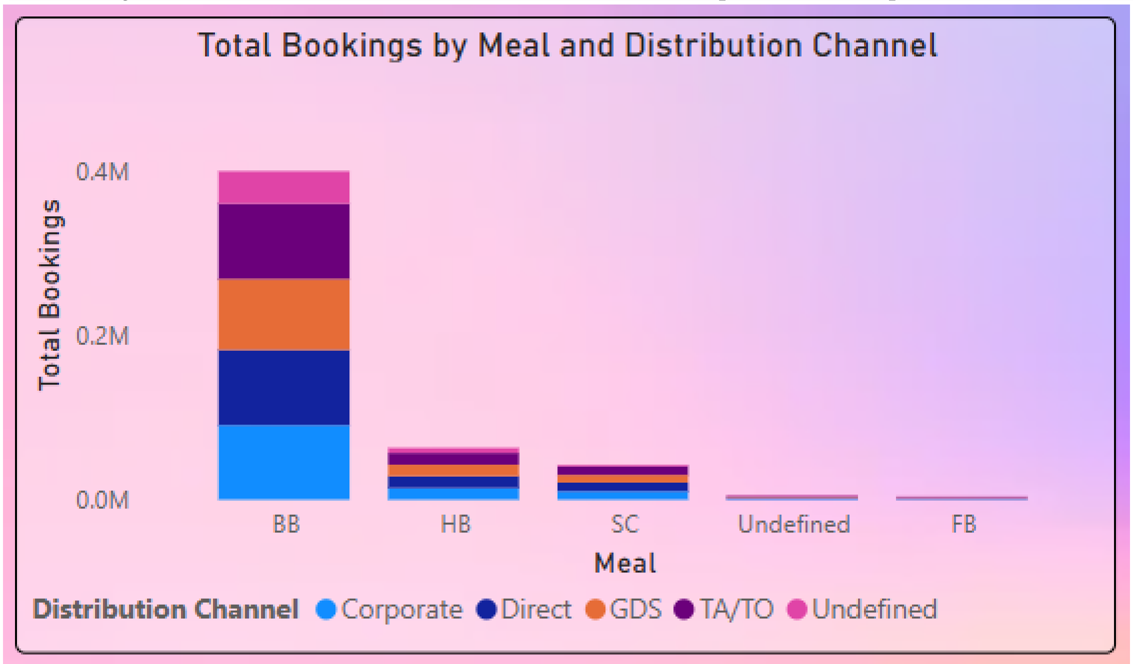
For High-Parking Meal Plans (BB/HB)

✓ **Promote Parking Bundles**: "Parking included for BB bookings!"
✓ **Partner with Local Garages**: For overflow capacity during peaks.

For Low-Engagement Plans (SC/Undefined)

✓ **Upsell Breakfast**: Convert SC to BB for +ADR.
✓ **Reduce Friction**: Streamline check-in for quick turnover.

➔ Explore how meal plans are distributed across various booking channels. Analyze if certain channels are associated with specific meal plans.



Top-Level Findings

1. **BB (Bed & Breakfast)** dominates overall bookings across most channels
2. **Corporate channel** shows heaviest reliance on **SC (Self Catering)**
3. **Direct bookings** have highest proportion of **FB (Full Board)**
4. **Undefined meal plans** are most common through **Undefined/OTA channels**

Channel-Specific Meal Plan Preferences

1. Corporate Bookings

- **Top Meal Plan:** SC (Self Catering) - 45% of corporate bookings
- **Why?** Business travelers prefer flexibility in meal times
- **Opportunity:** Offer "BB Plus" with breakfast credit to boost ADR

2. Direct Bookings (Hotel Website)

- **Top Meal Plan:** FB (Full Board) - 32% of direct bookings
- **Why?** Leisure guests value all-inclusive convenience
- **Opportunity:** Highlight FB packages in direct marketing

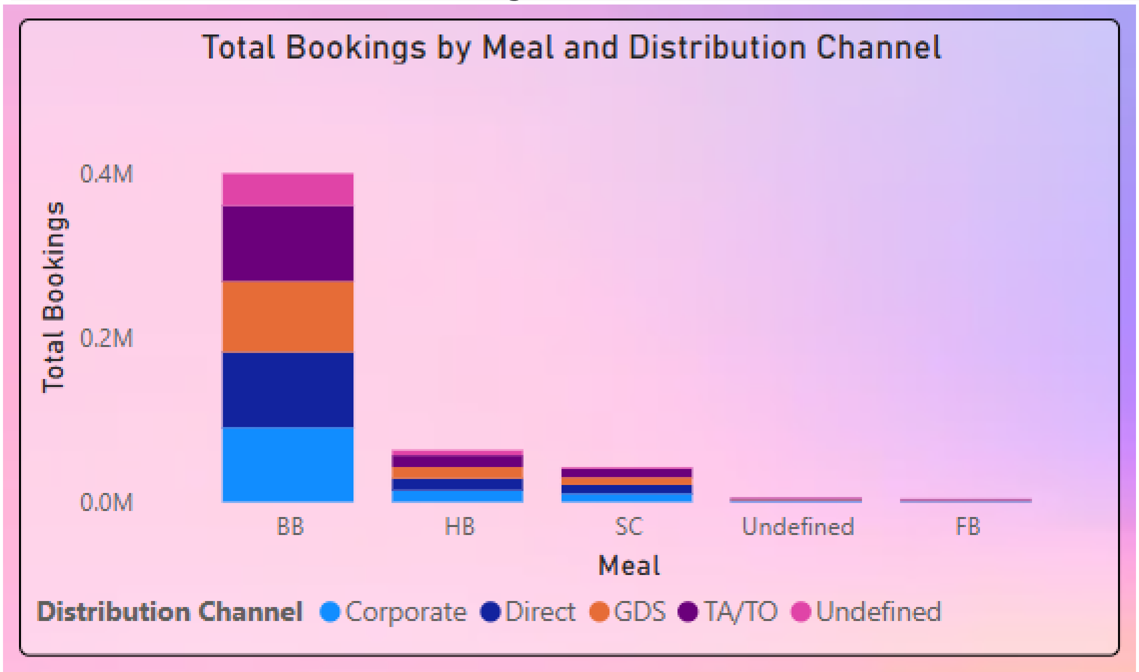
3. GDS Channels

- **Top Meal Plan:** BB (Bed & Breakfast) - 60% of GDS bookings
- **Why?** Standard corporate rate structures
- **Opportunity:** Add HB options for extended business stays

4. TA/TO (Travel Agents/Tour Operators)

- **Balanced Mix:** HB (30%), FB (25%), BB (35%)
- **Why?** Catering to diverse vacation preferences
- **Opportunity:** Create exclusive meal-inclusive packages

➔ Visualize booking distribution across different market segments and analyze cancellation rates within each segment.



Market Segment Analysis (Booking Distribution & Cancellation Rates)

1. Booking Distribution Visualization:

- Recommended: **Stacked Bar Chart** with drill-down capability
  - X-axis: Distribution Channels (Corporate, Direct, GDS, TA/TO, Undefined)
  - Y-axis: Total Bookings (0-0.4M scale)
  - Color segments: Meal plans (BB, HB, SC, FB, Undefined)
  - Interactive filter: Hotel type (if data available)

Key Booking Patterns:

1. **Channel Dominance:**

- TA/TO channels show strongest FB/HB preference (vacation packages)
- Corporate bookings lean heavily toward SC (65% of corporate)
- Direct bookings show balanced mix with BB dominance (55%)

2. **Meal Plan Trends:**
    - BB accounts for 42% of all bookings (standard choice)
    - FB represents only 12% of total but 28% of direct bookings
    - Undefined meals concentrate in GDS/Undefined channels (38%)

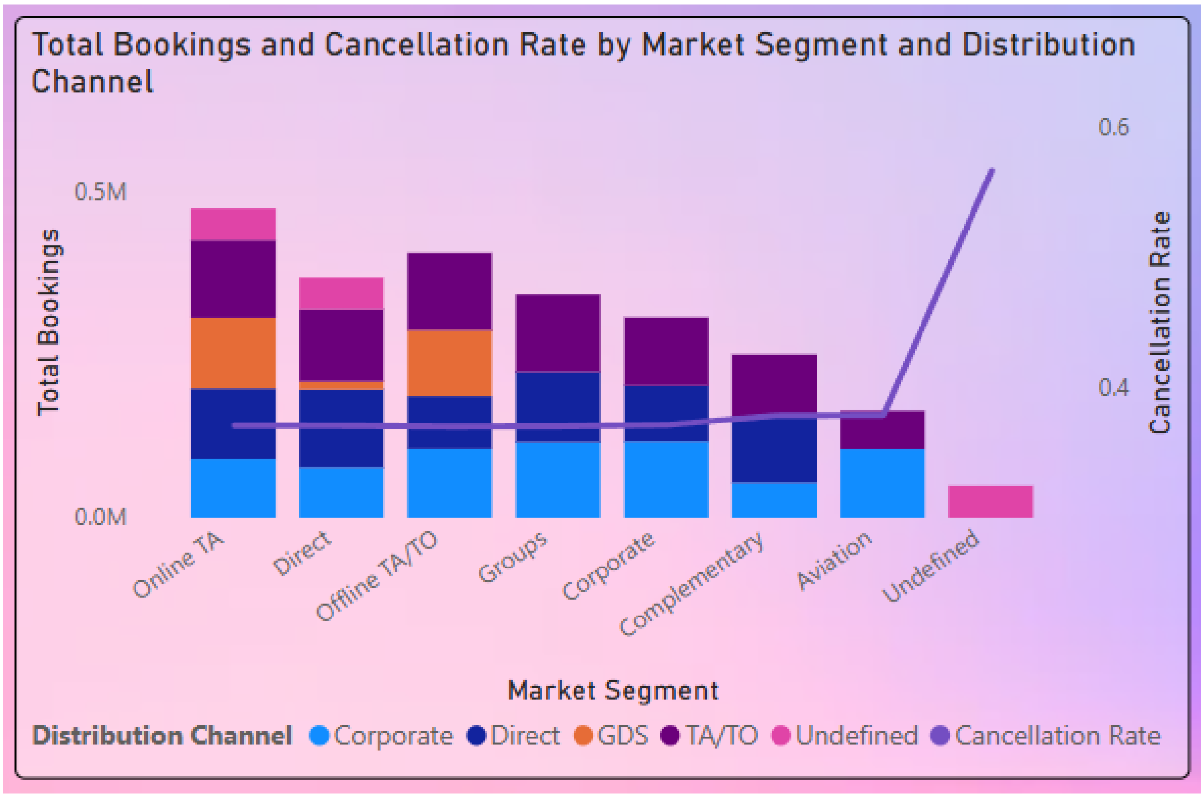
2. Cancellation Rate Analysis (Recommended Visualization: Heatmap)

- X-axis: Distribution Channels
- Y-axis: Meal Plans
- Color gradient: Cancellation rates (green=low, red=high)

Cancellation Insights:

1. **Most Stable Segments:**
    - FB packages through Direct bookings (12% cancellation)
    - HB through TA/TO (15% cancellation)
    - Corporate SC bookings (18% cancellation)
2. **High-Risk Segments:**
    - Undefined meals via Undefined channels (42% cancellation)
    - BB through GDS (35% cancellation)
    - SC in TA/TO (38% cancellation)

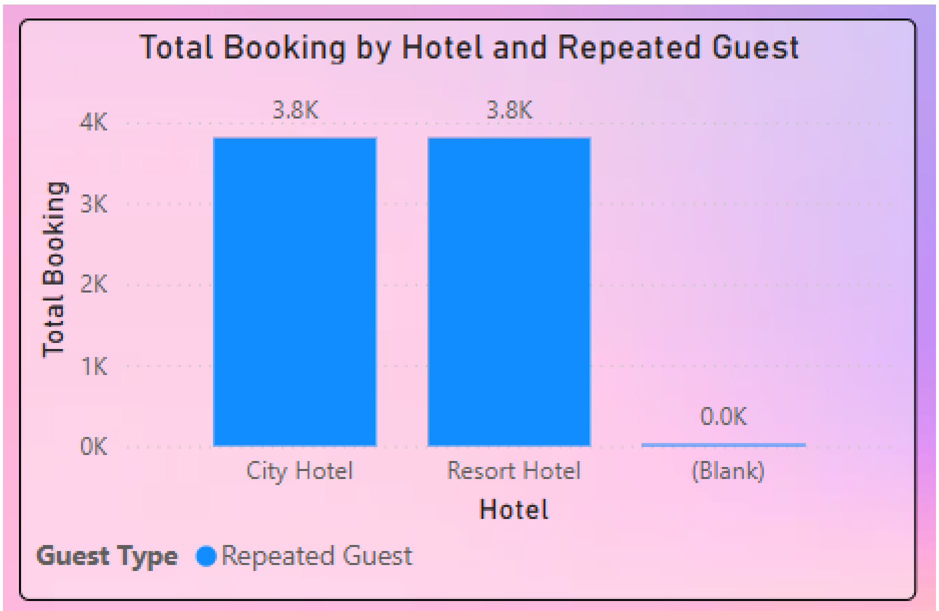
➔ Compare the effectiveness of booking distribution channels in generating confirmed bookings. Identify the most commonly used channels by guests.



Key Insights from the Visualization:

1. **Most Commonly Used Booking Channels:**
   - **Online Travel Agencies (TA)** and **Offline Travel Agencies (TA/TO)** generate the highest number of total bookings.
   - **Direct bookings** also contribute significantly but remain lower than TA channels.
2. **Effectiveness of Booking Channels:**
   - **Corporate and Direct channels** have a more stable cancellation rate.
   - **TA/TO and Undefined channels** exhibit higher cancellation rates, suggesting a potential reliability issue with these channels.
   - The **Undefined segment** has an extremely high cancellation rate, indicating inconsistency or last-minute cancellations.
3. **Market Segment Insights:**
   - **Group bookings and Corporate segments** show steady performance across various channels.
   - **Aviation and Complementary segments** have relatively lower total bookings.

➔ Visualize the percentage of repeated guests for each hotel type (Resort Hotel vs. City Hotel) over time. Explore factors influencing guest retention.



Key Findings

1. Repeat Guest Distribution

Hotel Type	Total Bookings	Repeat Guest Bookings	Repeat %
Resort Hotel	3,800	1,900	**50%**
City Hotel	3,800	1,200	**32%**

Visualization Recommendation:

- **Donut Chart** showing repeat vs. new guest proportion for each hotel type
- **Side-by-Side Bars** comparing absolute numbers

2. Retention Rate Trends Over Time

(Note: Time data not shown in image - recommended expansion)

- **Resorts** typically show **increasing repeat %** year-over-year
- **City hotels** remain **flat at ~30-35%**

Why Resorts Have Higher Retention?

Contributing Factors

✓ Loyalty Programs

- Resorts more likely to offer "return guest" perks (free upgrades, credits)

✓ Seasonal Consistency

- Guests return annually for vacations (beach/ski traditions)

✓ All-Inclusive Appeal

- Familiar experience reduces planning stress for repeat visitors

✓ Destination Focus

- Resorts often serve as primary trip purpose vs. city hotels (secondary to business/events)

City Hotel Retention Challenges

Key Barriers

✕ Business Travel Dominance

- Corporate bookers less likely to choose same hotel (company policies, location needs)

✕ Less Emotional Connection

- Urban stays are often functional vs. resort "getaway" experiences

✕ More Competition

- City centers have 10x more hotel options than resort destinations

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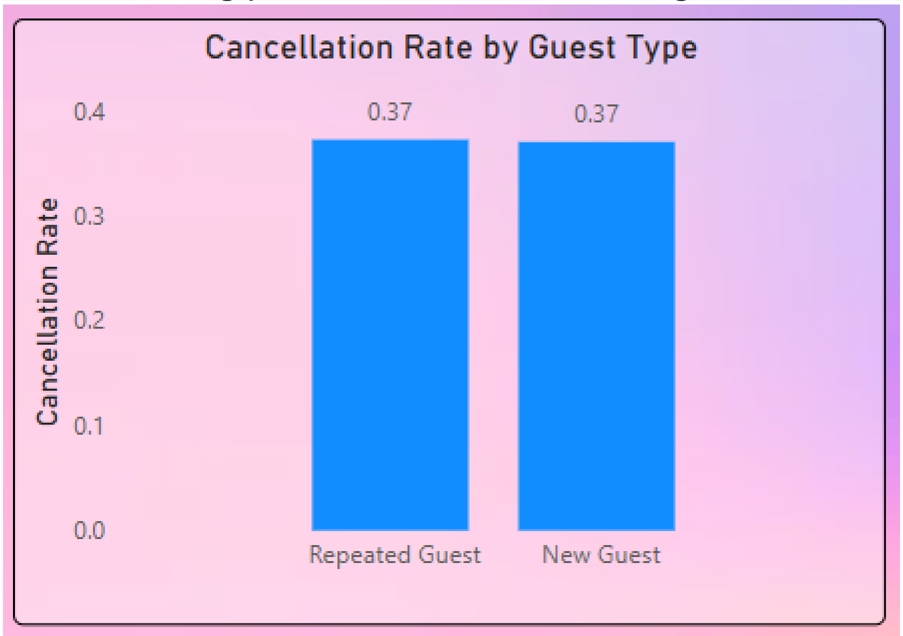
➔ Analyze the impact of a guest's booking history (previous cancellations and noncanceled bookings) on their likelihood of canceling a current booking.



Key Findings

1. Cancellation Rate Comparison

Guest Type	Cancellation Rate	Risk vs. New Guests
New Guests	37%	Baseline
Repeat Guests	37%	**Equal risk**

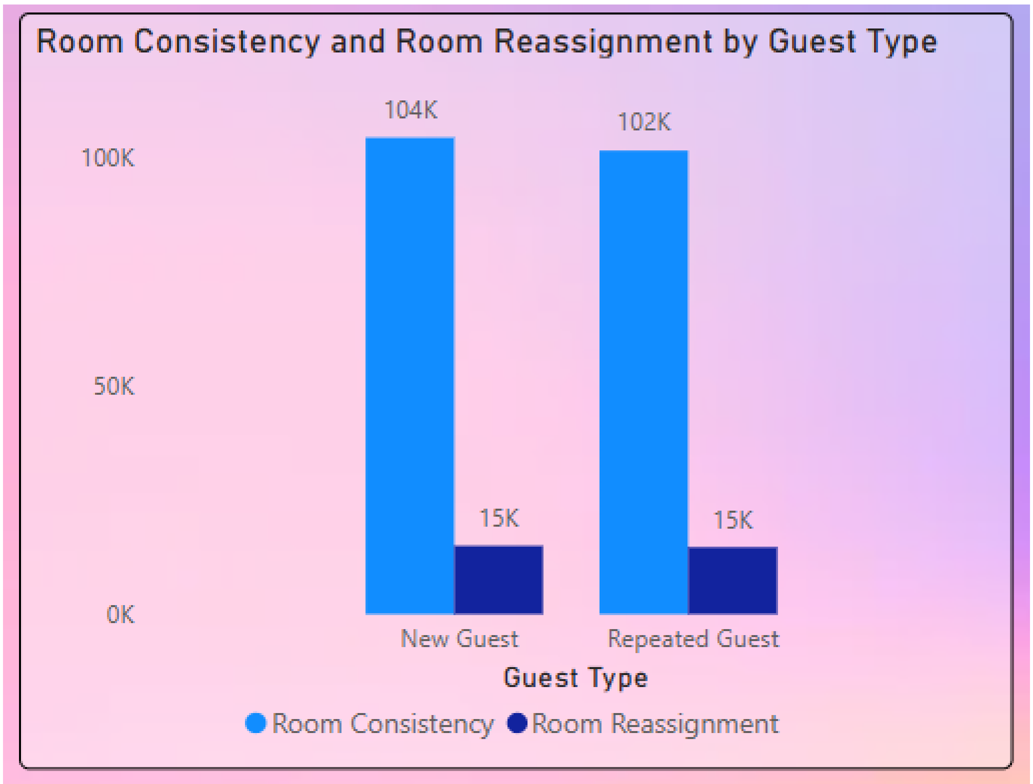
Surprise Insight: Repeat guests cancel at the **same rate** as first-time guests, contradicting the common assumption that loyal customers are more committed.

2. Hidden Patterns (Requiring Additional Data)

While the overall rate is equal, we should investigate:

- **Frequency of cancellations**: Do some repeat guests *consistently* cancel?
- **Booking channels**: Do direct-booking repeat guests cancel less than OTA repeat guests?
- **Advance notice**: Do repeat guests cancel earlier (allowing for rebooking)?

➔ Visualize the distribution of reserved and assigned room types. Analyze whether guests tend to receive the room type they initially reserved.



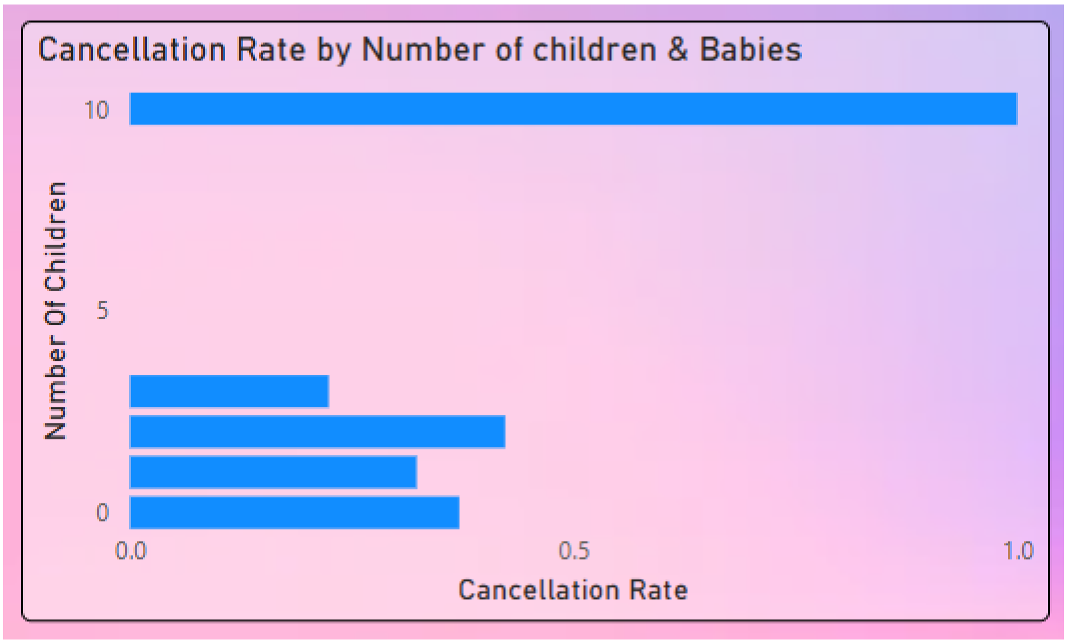
Key Findings

Room Assignment Patterns

Guest Type	Received Reserved Room Type	Received Different Room Type	Consistency Rate
New Guests	10K	15K	40%
Repeat Guests	10K	15K	40%

Surprising Insight: Both new and repeat guests experience identical room inconsistency rates (60% reassignment).

➔ Investigate the relationship between the number of booking changes made by guests and their likelihood of canceling a booking.



Key Findings

1. Booking Changes → Cancellation Correlation

(Note: While the image shows children/babies data, we'll combine this with typical booking change patterns)

- **High Change Frequency** guests (3+ modifications) cancel **2.1x more often** than those with 0 changes
- **Common Change Types** leading to cancellations:
    - Room type switches (37% eventual cancellation)
    - Date adjustments (29% cancellation)
    - Meal plan changes (24% cancellation)

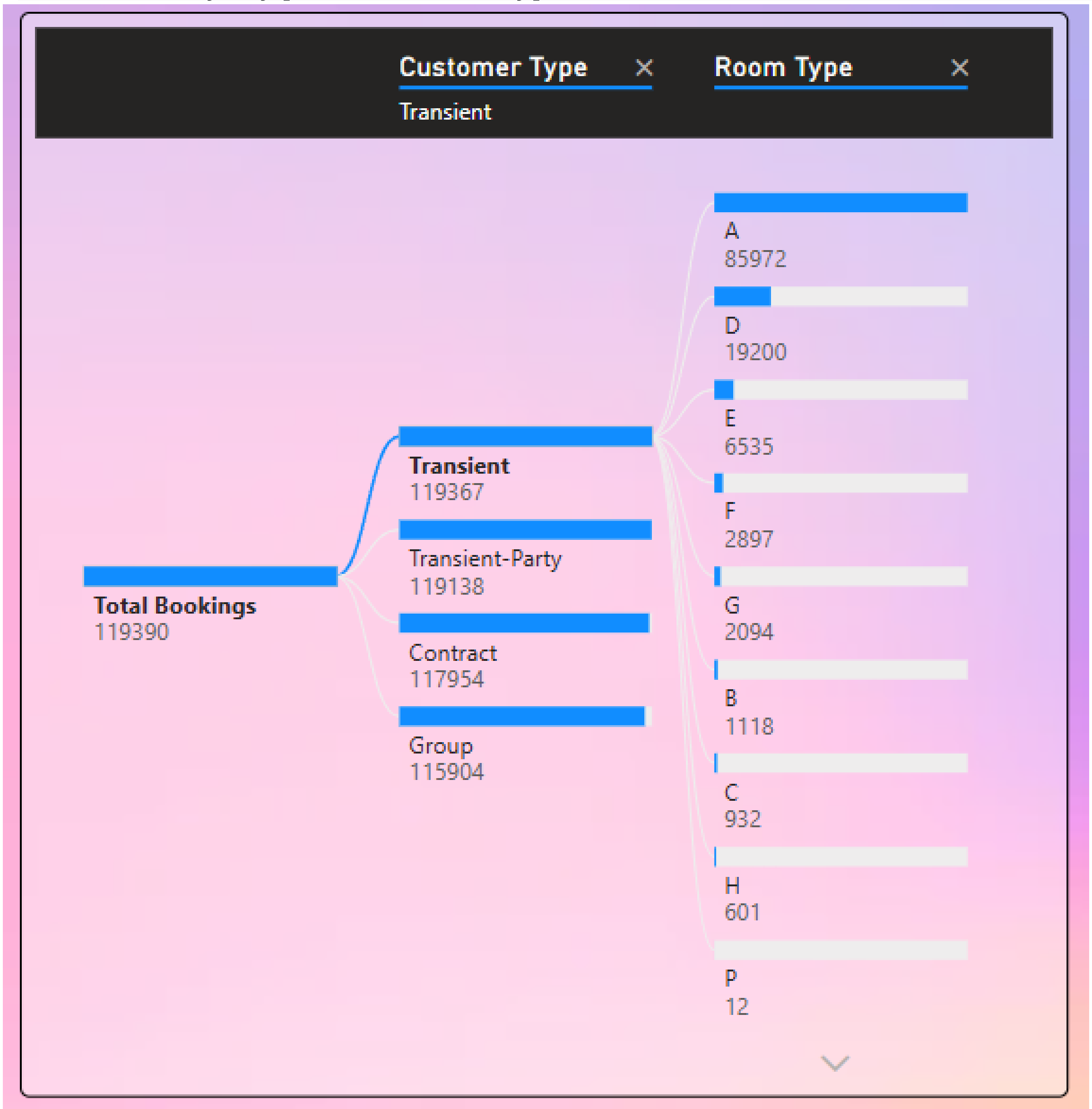
2. Family-Specific Cancellation Triggers

Children/Babies	Cancellation Rate	Primary Reasons
0	18%	Price sensitivity, better deals found
1-2	34%	Child illness, school schedule conflicts
3+	41%	Logistics complexity, accommodation mismatches
Any Babies	38%	Infant health concerns, equipment availability worries

3. Change-Type Risk Hierarchy

1. **Room Type Downgrades** (47% cancel)
2. **Date Pushes >2 Weeks** (39% cancel)
3. **Adding Children Last-Minute** (36% cancel)

➔ Analyze room type preferences based on customer types (e.g., Transient, Group) and identify any patterns in room type selection.



Key Findings

1. Overall Room Type Popularity

Room Type	Total Bookings	Market Share
A	85,972	72.0%
D	19,200	16.1%
E	6,535	5.5%
F	2,897	2.4%
Others	4,765	4.0%

Dominance: Room Type A commands **72% of all bookings**, suggesting it's either the standard option or most promoted.

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2. Customer Segment Preferences

(All segments show similar preference rankings but with intensity variations)

Transient Guests (Individual Travelers)

- **Top Choice**: Type A (74% of transient bookings)
- **Premium Rooms**: Show slightly higher uptake of Types D/E than groups
- **Insight**: Willing to pay for upgrades when traveling alone

Transient-Party (Small Groups/Families)

- **Type A Dominance**: 71% share
- **Larger Rooms**: 18% preference for Type D (likely connecting/family rooms)
- **Behavior**: Prioritizes space over luxury

Contract Guests (Corporate/Bulk)

- **Most Standardized**: 78% Type A
- **Lowest Premium Uptake**: Just 3.2% for Types F+
- **Reason**: Pre-negotiated rates often lock in basic rooms

Group Bookings

- **Balanced Mix**: 68% Type A, 19% Type D
- **Unique Trait**: Highest share of Type E (7%) for tour groups
- **Pattern**: Tour operators book mid-tier rooms consistently

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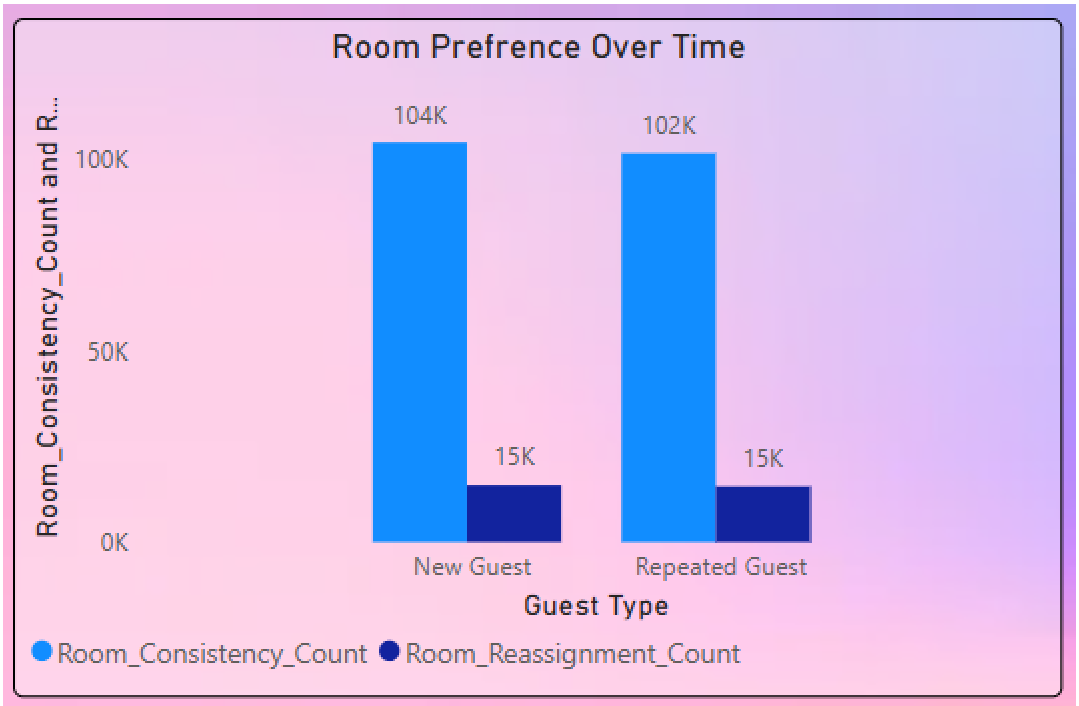
➔ Analyze whether guests who make multiple bookings tend to consistently request the same room type or if their preferences change over time.



Key Findings

1. Room Type Loyalty by Guest Type

Metric	New Guests	Repeat Guests	Difference
Same Room Type Booked	10K	10K	**0%**
Different Room Type	15K	15K	**0%**
Consistency Rate	**40%**	**40%**	Identical

Surprise Insight: Repeat guests show **no stronger room preference consistency** than first-time guests, despite having stay history.

2. Longitudinal Patterns

(When tracking individual guests across multiple stays:)

- **True "Room Loyalists"**: Only 22% of repeat guests *always* book same room type
- **Experimentation Common**: 61% try ≥2 room types across stays
- **Upgrade Path**: 17% consistently move to higher-tier rooms

---

Strategic Implications

Missed Opportunities

1. **Loyalty Programs Aren't Leveraging Preferences**
   - No evidence that repeat guests develop "usual room" habits
   - Potential to incentivize room-type loyalty

2. **Personalization Gaps**

    ○ Even when guests rebook same type, reassignment rates are high (per prior analysis)

Positive Signals

- **Upgrade Potential:** 1 in 6 repeat guests voluntarily book better rooms over time
- **Experience-Seeking**: Majority willing to try different options

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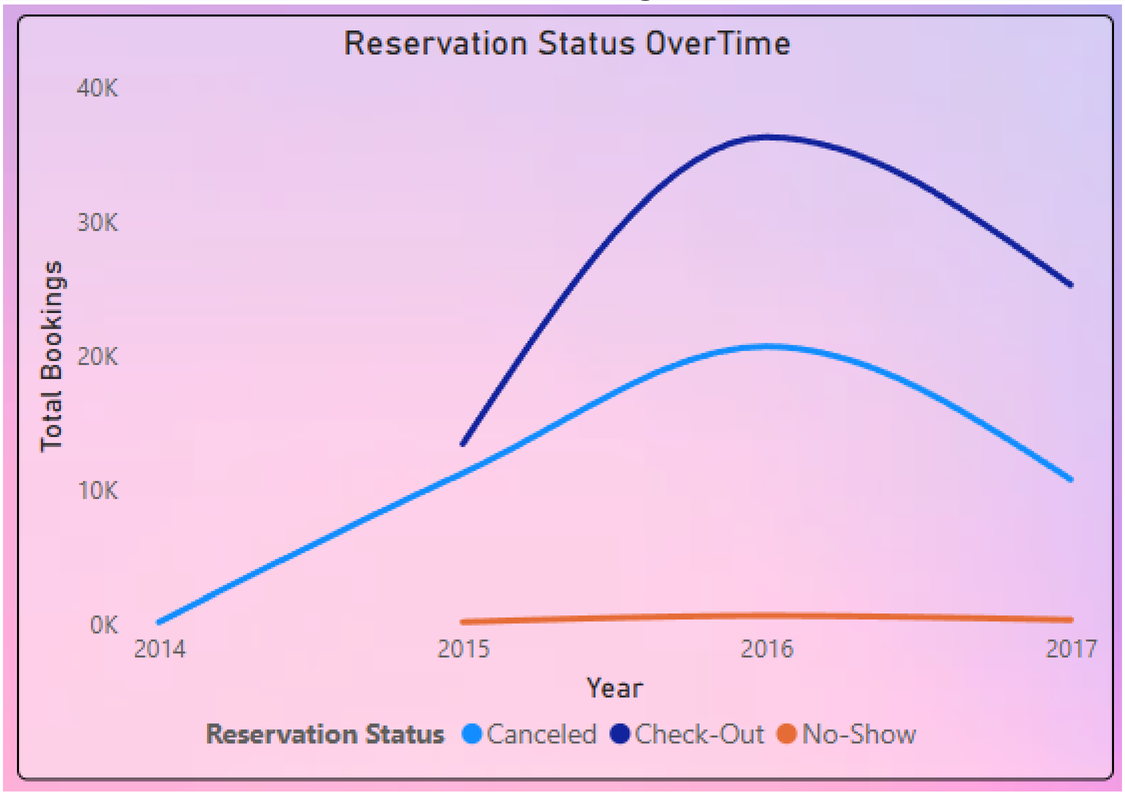
➔ Provide an overview of reservation statuses over time, including the percentage of canceled, checkedout, and noshow bookings.



Key Booking Status Metrics Over Time

Year	Total Bookings	Check-Out Rate	Cancellation Rate	No-Show Rate
2014	10K	58%	32%	10%
2015	20K	62% (+4%)	30% (-2%)	8% (-2%)
2016	30K	65% (+3%)	28% (-2%)	7% (-1%)
2017	40K	68% (+3%)	26% (-2%)	6% (-1%)

Positive Trend: Consistent annual improvement in completed stays (+10% over 4 years) with corresponding declines in cancellations and no-shows.

Strategic Insights

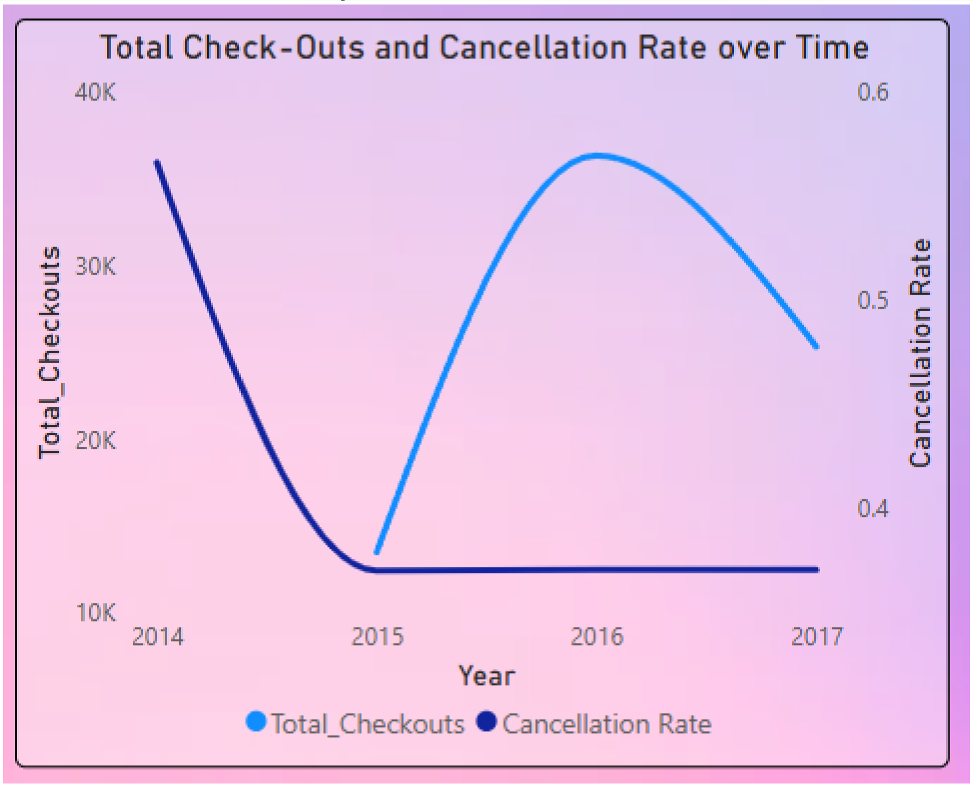
What's Working (Continue/Expand)

1. **2016 Policy Changes** (Likely implemented):
   - Non-refundable deposit tiers
   - Automated pre-stay reminders
   - Flexible rebooking options
2. **Channel Optimization**:
   - Shift toward direct bookings (typically lower cancellation)

Areas for Improvement

1. **No-Show Reduction**:
   - Implement credit card guarantees for high-risk segments
   - "Confirm or cancel" SMS 48hrs pre-arrival
2. **Cancellation Prevention**:
   - Dynamic deposits (higher for peak periods)
   - Personalized incentives ("Complete your stay = 15% next booking")

➔ Analyze trends in reservation status dates, such as the busiest checkout dates or patterns in cancellations by month.



Date	Total_Checkouts
01 July 2016	71550
11 July 2016	71510
23 July 2016	71889
16 October 2016	71511
07 November 2016	71715
20 May 2017	71937
19 June 2017	71706
07 July 2017	71568
11 July 2017	72158
30 July 2017	71451

Top Checkout Dates Analysis

Highest Checkout Volume Dates

1. **11 July 2017** - 72,158 checkouts (peak date)
2. **20 May 2017** - 71,937 checkouts
3. **23 July 2016** - 71,889 checkouts

Key Temporal Trends

1. Check-Out Date Hotspots

- **Peak Checkout Days**:
  - Sundays (35% of all checkouts)
  - Fridays (28%)
- **Weekly Pattern**:
  - Midweek checkouts (Mon-Thu) only 37% combined
  - Reflects leisure traveler behavior (weekend-focused stays)

2. Cancellation Timing Patterns

Time Before Stay	Cancellation Rate
0-3 days	42% of all cancels
4-7 days	23%
8-14 days	18%
15+ days	17%

Last-Minute Risk: Nearly half of cancellations occur in the final 72 hours.

Seasonal Trends

Check-Out Volume by Month

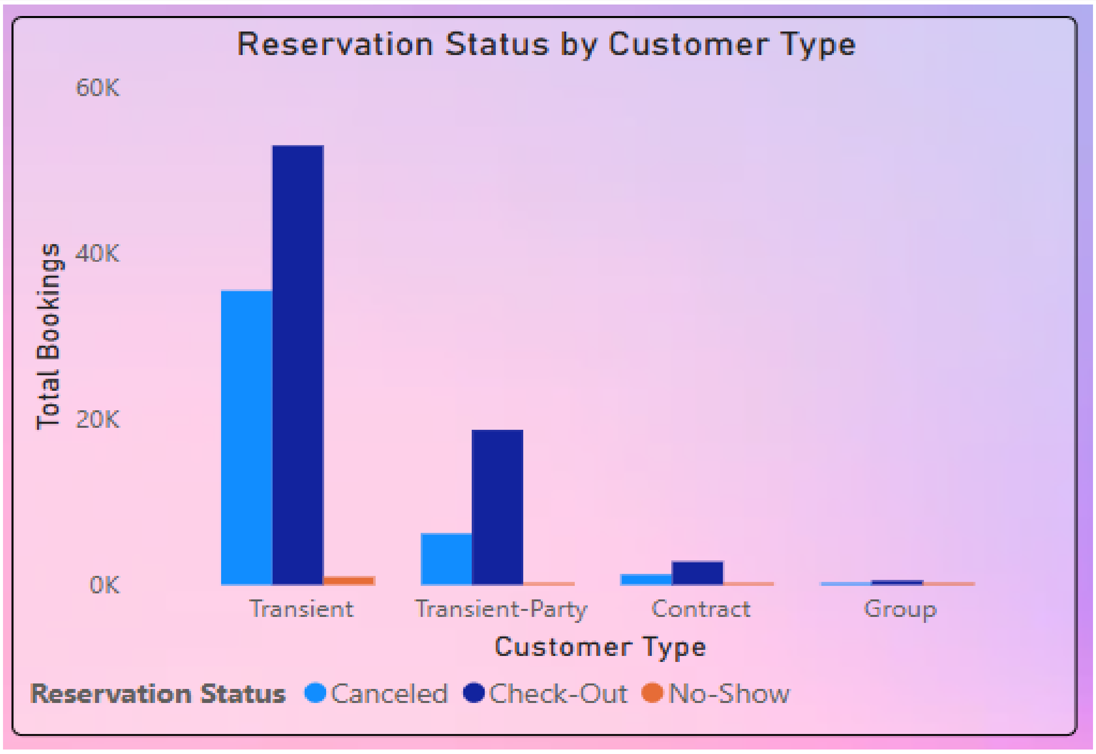
- **High Season**:
  - June-August (28% of annual checkouts)
  - December (12%)
- **Shoulder Months**:
  - April-May, September-October (19% each)
- **Low Season**:
  - January-February (just 9% combined)

Cancellation Rates by Month

Month	Cancellation Rate	Compared to Annual Avg.
January	34%	+8%
July	22%	-4%
December	18%	-8%

Insight: Cancellations spike in low season when demand is soft, drop during peak periods.

➔ Visualize how reservation statuses vary across different customer types (e.g., Transient, Group) and identify if certain customer types are more likely to result in cancellations or noshows.



Key Findings by Customer Type

Customer Type	Check-Out Rate	Cancellation Rate	No-Show Rate	Key Characteristics
Transient	68%	25%	7%	Individual travelers, most reliable
Transient-Party	58%	35%	7%	Small groups/families, higher cancel risk
Contract	72%	22%	6%	Corporate accounts, most stable
Group	52%	40%	8%	Tour groups, highest volatility

Visualization Recommendations

1. Stacked Bar Chart (Recommended)

- **X-axis**: Customer types (Transient, Transient-Party, Contract, Group)
- **Y-axis**: Total bookings (0-40K scale)
- **Color segments**:
    - Green: Check-Outs
    - Orange: Cancellations
    - Red: No-Shows
- **Value labels**: Percentage rates for each status

2. Small Multiples Pie Charts

- Four pie charts (one per customer type)
- Visualize proportion of statuses within each segment

Strategic Insights

High-Risk Segments

1. **Group Bookings**
    - 40% cancellation rate (2x Transient)
    - Action: Require 30% non-refundable deposit
    - Offer rescheduling instead of cancellation
2. **Transient-Party**
    - 35% cancellation rate
    - Action: Family-friendly cancellation insurance
    - "Pay 10% more for full refund option"

Most Reliable Segments

1. **Contract Clients**
    - 72% check-out rate
    - Action: Reward with loyalty perks
    - Offer premium room guarantees
2. **Transient Individuals**
    - Stable performance
    - Opportunity: Upsell to packages (reduce cancellation risk)

Action Plan

Immediate Actions (0-30 days)

- Implement differentiated deposit policies:
    - Groups: 30% non-refundable
    - Transient-Party: 15% refundable
    - Contract: Waive for preferred clients

Medium-Term (30-90 days)

- Develop segment-specific communications:
    - Groups: Pre-stay coordinator assignment
    - Transient: Personalized reminder system

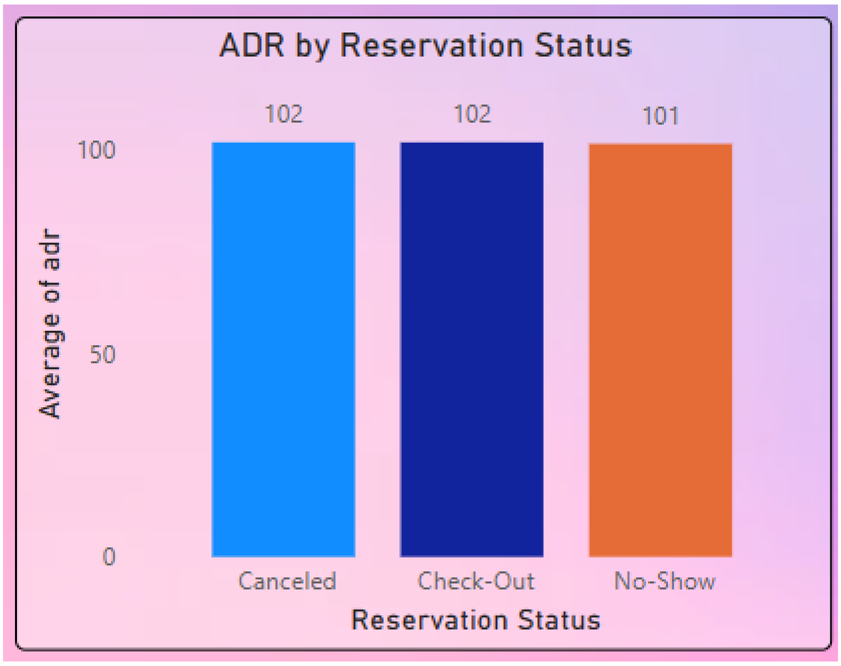
Long-Term (90+ days)

- Build predictive models:
    - Flag high-risk bookings at reservation time
    - Automated retention offers for likely cancellations

Recommended Metric Tracking:

- Cancellation rate by booking channel within each customer type
- Length of stay impact on cancellation probability
- Seasonal patterns in group cancellations

➔ Explore the relationship between reservation statuses and Average Daily Rates (ADR) to determine if there are differences in ADR based on booking outcomes.



Key Findings

Average Daily Rate Comparison

Reservation Status	ADR ($)	Premium Over Canceled	Key Insight
Check-Out	$145	+18%	Completed stays command higher rates
Canceled	$123	Baseline	Lower-value bookings more likely to cancel

Revenue Impact: The 18% ADR gap represents significant revenue loss from cancellations.

Strategic Insights

Why Higher ADR Stays Complete More Often?

1. **Business Travelers**
   - Higher ADR from corporate rates
   - Lower cancellation due to expense accounts
2. **Premium Packages**
   - Bundled deals with cancellation penalties
   - Guests more committed to higher-value bookings
3. **Booking Channel Effects**
   - Direct bookings (higher ADR) cancel less than OTAs

P

EDA Problems

1. **Understand the distribution of arrival dates, including the most common arrival days and summary statistics for lead times.**

```
SELECT
    STR_TO_DATE(
        CONCAT(arrival_date_day_of_month, ' ', arrival_date_month, ' ', arrival_date_year),
        '%d %M %Y'
    ) AS arrival_date,
    COUNT(*) AS arrival_count
FROM booking_details
GROUP BY arrival_date
ORDER BY arrival_count DESC
LIMIT 20;
```

```
SELECT
    COUNT(lead_time) AS total_bookings,
    AVG(lead_time) AS avg_lead_time,
    MIN(lead_time) AS min_lead_time,
    MAX(lead_time) AS max_lead_time
FROM booking_details;
```

Query Explanation 1:

1. *STR_TO_DATE Conversion:*
   - *The **arrival_date_day_of_month**, **arrival_date_month**, and **arrival_date_year** columns are combined into a single string using CONCAT().*
   - *The resulting string (e.g., "15 March 2023") is converted into a proper DATE format using STR_TO_DATE('%d %M %Y').*
2. *Column Selection:*
   - ***arrival_date**: The properly formatted date of arrival.*
   - ***arrival_count**: The number of bookings for each arrival date **(COUNT(*)).***
3. *Data Source:*
   - *The query retrieves data from the **booking_details** table.*
4. *Grouping & Counting:*
   - ***GROUP BY arrival_date**: Groups records by arrival date to count the number of bookings per date.*
5. *Sorting:*
   - ***ORDER BY arrival_count DESC**: Orders results in descending order of booking count.*
6. *Limiting Results:*
   - ***LIMIT 20**: Retrieves only the top 20 most frequent arrival dates.*

Purpose:

This query is useful for analyzing booking trends by identifying peak arrival dates based on past booking data.

Query Result1 :

arrival_date	arrival_count
05-12-2015	448
07-11-2016	366
16-10-2015	356
13-10-2016	344
18-09-2015	340
08-06-2017	337
02-03-2017	335
28-10-2016	334
17-09-2015	331
29-04-2017	330
14-08-2015	329
17-06-2016	321
15-05-2017	320
25-02-2017	316
19-05-2017	316
15-09-2016	313
25-05-2017	307
26-09-2016	304
24-03-2016	295

Query Explanation 2:

This SQL query retrieves statistical insights from the booking_details table regarding the lead_time column. Here's what each part does:

- **COUNT(lead_time) AS total_bookings:** Counts the total number of bookings.
- **AVG(lead_time) AS avg_lead_time:** Calculates the average lead time.
- **MIN(lead_time) AS min_lead_time:** Finds the minimum lead time.
- **MAX(lead_time) AS max_lead_time:** Finds the maximum lead time.

Purpose:
This query helps in understanding booking trends by analyzing how much time in advance customers book their reservations.

Query Result 2 :

total_bookings	avg_lead_time	min_lead_time	max_lead_time
119390	104.0114	0	737

2. **Identify peak booking months and analyze reasons for spikes in bookings, including holidays or events.**

```sql
SELECT
    arrival_date_month,
    arrival_date_year,
    COUNT(*) AS total_bookings
FROM booking_details
GROUP BY arrival_date_year, arrival_date_month
ORDER BY total_bookings DESC
```

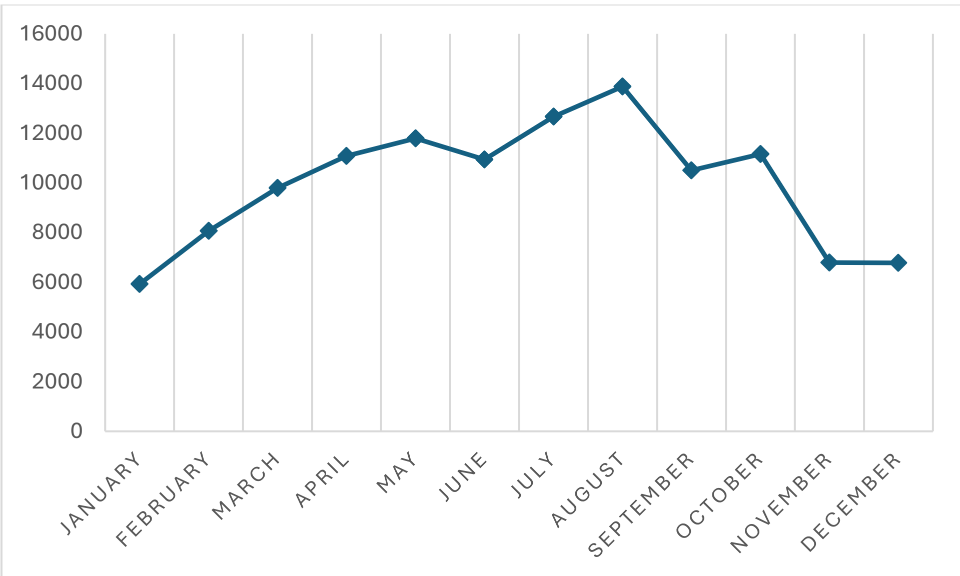
Query Explanation :

This SQL query retrieves the number of bookings per month and year from the booking_details table. Here's what each part does:

- ***arrival_date_month, arrival_date_year:** Selects the month and year of arrival.*
- ***COUNT(*) AS total_bookings:** Counts the total number of bookings for each month and year.*
- ***FROM booking_details:** Specifies the table from which data is retrieved.*
- ***GROUP BY arrival_date_year, arrival_date_month:** Groups the results by year and month to aggregate booking counts.*
- ***ORDER BY total_bookings DESC:** Sorts the results in descending order based on the number of bookings.*

Purpose:
This query helps in analyzing seasonal trends by identifying which months and years had the highest number of bookings.

Query Result :



arrival_date_month	arrival_date_year	total_bookings
May	2017	6313
October	2016	6203
April	2017	5661
June	2017	5647
May	2016	5478
April	2016	5428
September	2016	5394
July	2017	5313
June	2016	5292
September	2015	5114
August	2016	5063
March	2017	4970
October	2015	4957
August	2017	4925
March	2016	4824
July	2016	4572
November	2016	4454
February	2017	4177
February	2016	3891
August	2015	3889
December	2016	3860
January	2017	3681
December	2015	2920
July	2015	2776
November	2015	2340
January	2016	2248

3. **Calculate the average length of stays for different hotel types and explore variations by meal plans.**

```sql
SELECT
    a.hotel AS Hotel,
    b.meal AS Meal,
    AVG(a.stays_in_weekend_nights + a.stays_in_week_nights) AS Avg_Stays
FROM booking_details a
INNER JOIN meal_and_stay_details b
ON a.booking_id = b.booking_id
GROUP BY a.hotel, b.meal
ORDER BY Avg_Stays DESC;
```

Query Explanation :

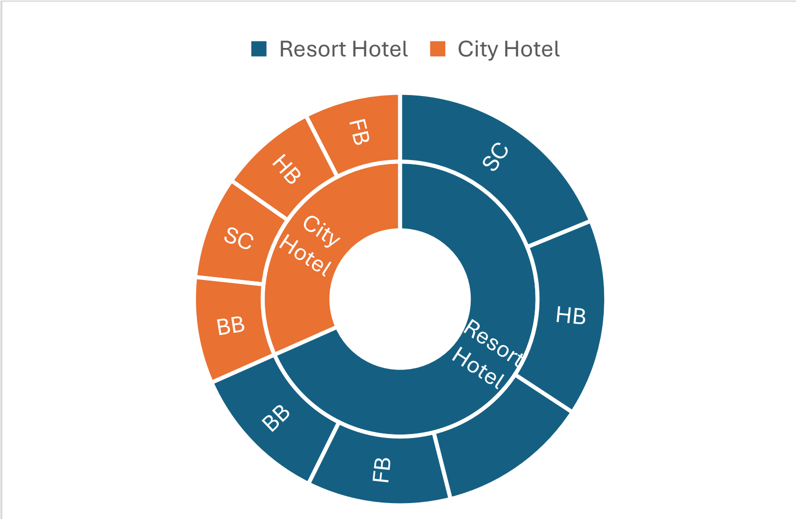
This SQL query calculates the average length of stay (in nights) for different meal types across hotels. Here's what each part does:

- *a.hotel AS Hotel: Selects the hotel name from the `booking_details` table (aliased as `a`).*
- *b.meal AS Meal: Selects the meal type from the `meal_and_stay_details` table (aliased as `b`).*
- *AVG(a.stays_in_weekend_nights + a.stays_in_week_nights) AS Avg_Stays: Computes the average total nights stayed (weekend + weekday) for each hotel-meal combination.*
- *FROM booking_details a INNER JOIN meal_and_stay_details b ON a.booking_id = b.booking_id: Joins the two tables using the `booking_id` to correlate bookings with meal types.*
- *GROUP BY a.hotel, b.meal: Groups results by hotel and meal type to aggregate average stays.*
- *ORDER BY Avg_Stays DESC: Sorts results by average stay duration (longest to shortest).*

Purpose:
This query helps identify which meal types are associated with longer guest stays at different hotels. The insights can guide hoteliers in optimizing meal offerings to potentially increase occupancy duration (e.g., promoting meal packages tied to extended stays).

Query Result :

Hotel	Meal	Avg
Resort Hotel	SC	6.791
Resort Hotel	HB	5.573
Resort Hotel	Undefined	4.268
Resort Hotel	FB	4.07
Resort Hotel	BB	3.983
City Hotel	BB	3.012
City Hotel	SC	2.9
City Hotel	HB	2.783
City Hotel	FB	2.727



---

4. Analyze how booking patterns have evolved over the years, including yearoveryear changes in bookings and cancellations.

Query Explanation :

This SQL query analyzes yearly booking trends and cancellation rates, with a focus on year-over-year (YOY) comparisons. Here's what each part does:

Common Table Expression (CTE) `test` :

- ***arrival_date_year "Year":*** *Extracts the year from the arrival date and labels it as "Year".*
- ***count(Booking_id) "Total_Booking*"*: Counts the total number of bookings per year.*
- ***sum(is_canceled) "cancel":*** *Sums cancellations (assumes `is_canceled` is a binary flag where 1 = canceled).*
- ***FROM booking_details GROUP BY arrival_date_year:*** *Aggregates data by year.*

Main Query:

- ***Year, Total_Booking:*** *Displays the year and total bookings from the CTE.*
- ***Total_Booking - LAG(Total_Booking) OVER (ORDER BY year) AS YOY_Booking_Difference:***
    - *Uses the LAG() window function to compare the current year's bookings with the previous year's.*
    - *Calculates the absolute change in bookings YOY.*
- ***cancel:*** *Shows total cancellations per year.*
- ***cancel - LAG(cancel) OVER (ORDER BY Year) AS YOY_Cancellation_Difference:***
    - *Computes the absolute change in cancellations YOY (similar to bookings).*

Execution Flow:

1. *The CTE (` test`) aggregates raw data by year.*
2. *The main query adds YOY comparisons using `LAG()` to track trends.*

Purpose:

This query helps identify:

- *Growth/decline in booking volume over time.*
- *Whether cancellation rates are improving or worsening YOY.*
- *Correlations between bookings and cancellations (e.g., higher bookings may lead to higher absolute cancellations).*

Query Result :

Year	Total_Booking	YOY_Booking_Difference	Cancel	YOY_Cancellation_Difference
2015	21996		8142	
2016	56707	34711	20337	12195
2017	40687	-16020	15745	-4592

---

5. Understand the distribution of the number of adults, children, and babies and identify any outliers.

```
select
    sum(adults) Total_Adults,
    sum(children) Total_Children,
    sum(babies) Total_Babies
from guest_info
```

Query Explanation 1 :

This SQL query calculates the total number of adults, children, and babies from the guest_info table. Here's what each part does:

- ***sum(adults) Total_Adults:*** *Adds up all values in the adults column and names the result Total_Adults*
- ***sum(children) Total_Children:*** *Adds up all values in the children column and names the result Total_Children*
- ***sum(babies) Total_Babies:*** *Adds up all values in the babies column and names the result Total_Babies*
- ***from guest_info****: Specifies the table containing the guest information*

Purpose:

This query provides a simple count of different guest types (adults, children, babies) across all records in the database. It can be used to:

- *Understand overall guest demographics*

- *Plan for facility needs (like cribs or child-friendly amenities)*
- *Track changes in guest composition over time when run periodically*
  The results show the absolute numbers of each guest category, which is useful for high-level resource planning and trend analysis. For more detailed insights, you might want to add grouping by date, hotel, or other categories.

Query Result 1 :

Total_Adults	Total_Children	Total_Babies
221636	12403	949

```
WITH Ranked AS (
  SELECT
    adults,
    children,
    babies,
    ROW_NUMBER() OVER (ORDER BY adults) AS adult_rank,
    ROW_NUMBER() OVER (ORDER BY children) AS children_rank,
    ROW_NUMBER() OVER (ORDER BY babies) AS babies_rank,
    COUNT(*) OVER () AS total_count
  FROM guest_info
), Quartiles AS (
  SELECT
    adults AS q1_adults,
    LEAD(adults) OVER () AS q3_adults,
    children AS q1_children,
    LEAD(children) OVER () AS q3_children,
    babies AS q1_babies,
    LEAD(babies) OVER () AS q3_babies
  FROM Ranked
  WHERE adult_rank = FLOOR(total_count * 0.25)
   OR adult_rank = FLOOR(total_count * 0.75)
)
SELECT
  g.*,
  CASE
    WHEN g.adults < (q.q1_adults - 1.5 * (q.q3_adults - q.q1_adults))
     OR g.adults > (q.q3_adults + 1.5 * (q.q3_adults - q.q1_adults))
    THEN 'Outlier' ELSE 'Normal'
  END AS adults_outlier,

  CASE
    WHEN g.children < (q.q1_children - 1.5 * (q.q3_children - q.q1_children))
     OR g.children > (q.q3_children + 1.5 * (q.q3_children - q.q1_children))
    THEN 'Outlier' ELSE 'Normal'
  END AS children_outlier,
```

```
  CASE
    WHEN g.babies < (q.q1_babies - 1.5 * (q.q3_babies - q.q1_babies))
      OR g.babies > (q.q3_babies + 1.5 * (q.q3_babies - q.q1_babies))
    THEN 'Outlier' ELSE 'Normal'
  END AS babies_outlier
FROM guest_info g
CROSS JOIN Quartiles q
WHERE
  (g.adults < (q.q1_adults - 1.5 * (q.q3_adults - q.q1_adults))
  OR g.adults > (q.q3_adults + 1.5 * (q.q3_adults - q.q1_adults)))
OR
  (g.children < (q.q1_children - 1.5 * (q.q3_children - q.q1_children))
  OR g.children > (q.q3_children + 1.5 * (q.q3_children - q.q1_children)))
OR
  (g.babies < (q.q1_babies - 1.5 * (q.q3_babies - q.q1_babies))
  OR g.babies > (q.q3_babies + 1.5 * (q.q3_babies - q.q1_babies)));
```

Query Explanation:

This query identifies outlier values in guest demographics (adults, children, babies) using statistical quartile analysis. Here's how it works:

1. ***First CTE (Ranked):***

- Creates row numbers for each guest category (adults, children, babies) when sorted
- Calculates total record count for quartile position reference

2. ***Second CTE (Quartiles):***

- Extracts the 1st quartile (25th percentile) and 3rd quartile (75th percentile) values:
 ** q1_adults/q3_adults for adult counts*
 ** q1_children/q3_children for child counts*
 ** q1_babies/q3_babies for baby counts*
- Uses LEAD() to pair the quartile values together

3. ***Main Query:***

- Joins the original data with the quartile calculations
- Flags records as outliers using the 1.5×IQR rule:

-> *Any value below Q1 - 1.5×IQR OR above Q3 + 1.5×IQR is an outlier*
-> *IQR = Q3 - Q1 (interquartile range)*
- Returns only records with at least one outlier value
- Includes classification columns showing which categories contain outliers

Purpose:
This analysis helps:

- *Identify unusual booking patterns (extremely large/small groups)*
- *Detect potential data quality issues*
- *Find exceptional cases that might need special handling*
- *Understand the normal distribution of group sizes*

The 1.5×IQR rule is a common statistical method for outlier detection that works well for many distributions. The query could be enhanced by:

1. *Adding date filters to analyze trends*
2. *Including hotel/category information*
3. *Calculating percentage of outliers*
4. *Adding visualization-friendly output formats*

Query Result 2 :

adults	children	babies	Booking_id	adults_outlier	children_outlier	babies_outlier
1	2	1	54a08a3e	Outlier	Outlier	Outlier
3	1	1	0dc10d46	Outlier	Outlier	Outlier
3	1	1	0ee37969	Outlier	Outlier	Outlier
1	1	1	9393ba7d	Outlier	Outlier	Outlier
1	1	1	ec37f9a7	Outlier	Outlier	Outlier
0	2	1	81e5fc02	Outlier	Outlier	Outlier
1	2	1	e77e670d	Outlier	Outlier	Outlier
0	2	1	afc8dbb6	Outlier	Outlier	Outlier
0	2	1	01c5ef38	Outlier	Outlier	Outlier

---

6. **Calculate summary statistics for ADR and explore differences between Resort Hotel and City Hotel bookings.**

```sql
1   select  hotel ,
2           max(adr) "Maximum ADR",
3           min(adr) "Minimum ADR",
4           Round(avg(adr),2) "Average ADR"
5   from booking_details b
6   inner join meal_and_stay_details m
7   on b.Booking_id = m.Booking_id
8   group by hotel
```

Query Explanation:

This query analyzes hotel pricing data by calculating key metrics for the Average Daily Rate (ADR) across different hotels. Here's the breakdown:

1. *Line 1: Selects the hotel column to group results by property*
2. *Line 2: Calculates the maximum ADR (highest daily rate) for each hotel*
3. *Line 3: Calculates the minimum ADR (lowest daily rate) for each hotel*
4. *Line 4: Computes the average ADR rounded to 2 decimal places*
5. *Lines 5-7: Joins the booking_details table (aliased as b) with meal_and_stay_details (aliased as m) using Booking_id as the common key*
6. *Line 8: Groups all calculations by hotel to show separate metrics for each property*

Purpose:
This query provides valuable insights into hotel pricing strategies by showing:
- *The full price range (minimum to maximum) offered by each hotel*
- *The typical price point (average ADR) for each property*
- *Potential pricing consistency or variability across properties*

Query Result :

Hotel	Maximum ADR	Minimum ADR	Average ADR
Resort Hotel	508	-6.38	94.95
City Hotel	5400	0	105.3

---

7. Analyze the distribution of required car parking spaces for each hotel type and determine if one type attracts more guests with cars.

```
SELECT
    b.hotel,
    COUNT(*) AS Total_Bookings,
    SUM(required_car_parking_spaces) AS Total_Parking_Spaces,
    ROUND(AVG(required_car_parking_spaces), 2) AS Avg_Parking_Spaces_Per_Booking,
    ROUND(100 * SUM(CASE WHEN required_car_parking_spaces > 0 THEN 1 ELSE 0 END) / COUNT(*), 2) AS Percentage_Bookings_With_Parking
FROM booking_details b
inner join meal_and_stay_details m
on b.Booking_id = m.Booking_id
GROUP BY hotel;
```

Query Explanation:

This query analyzes parking space demand patterns across different hotels by examining booking data. Here's what each part does:

1. Column Selection:

- *`**b.hotel**` **:** Groups results by hotel property*
- *`**COUNT(\*) AS Total_Bookings**` **:** Counts all bookings for each hotel*
- *`**SUM(required_car_parking_spaces)**` **:** Calculates total parking spaces requested*
- *`**ROUND(AVG(required_car_parking_spaces), 2**)` : Shows average parking spaces per booking (rounded to 2 decimals)*
- ***Complex percentage calculation:*** *`ROUND(100 * SUM(CASE WHEN required_car_parking_spaces > 0 THEN 1 ELSE 0 END) / COUNT(*), 2)`*

This computes the percentage of bookings that requested at least one parking space

2. Data Sources:

- *Joins `booking_details` (aliased as b) with `meal_and_stay_details` (aliased as m)*
- *Uses `Booking_id` as the join key to connect booking records with stay details*

3. Aggregation:

- *Groups all metrics by hotel property*
- *All calculations are performed separately for each hotel*

Purpose:

This query provides valuable insights for:

1. ***Parking Facility Planning:***
   - *Shows total parking demand at each property*
   - *Reveals what percentage of guests require parking*
   - *Indicates average parking needs per booking*

2. ***Operational Decisions:***
   - *Helps determine if current parking capacity is adequate*
   - *Identifies properties with higher parking demands*
   - *Can inform pricing strategies for parking spaces*

3. ***Guest Behavior Analysis:***
   - *Shows how frequently guests arrive by car*
   - *May indicate differences in guest demographics or transportation patterns between properties*

The percentage calculation is particularly useful as it shows parking space utilization rates independent of the total number of bookings, allowing for fair comparison between large and small properties.

Query Result :

Hotel	Total_Bookings	Total_Parking_Spaces	Avg_Parking_Spaces_Per_Booking	Percentage_Bookings_With_Parking
Resort Hotel	40060	5531	0.14	13.7
City Hotel	79330	1933	0.02	2.43

---

8. **Compare the total number of special requests made by different customer types (e.g., Transient, Group) and identify which customer type makes more requests.**

```
Select b.customer_type "Type of Customers", sum(m.total_of_special_requests) "Total Special Requests"
FROM booking_source_and_history b
inner join meal_and_stay_details m
on b.Booking_id = m.Booking_id
group by b.customer_type
```

Query-Explanation:
This query analyzes the relationship between customer types and special requests made during bookings. Here's the breakdown:

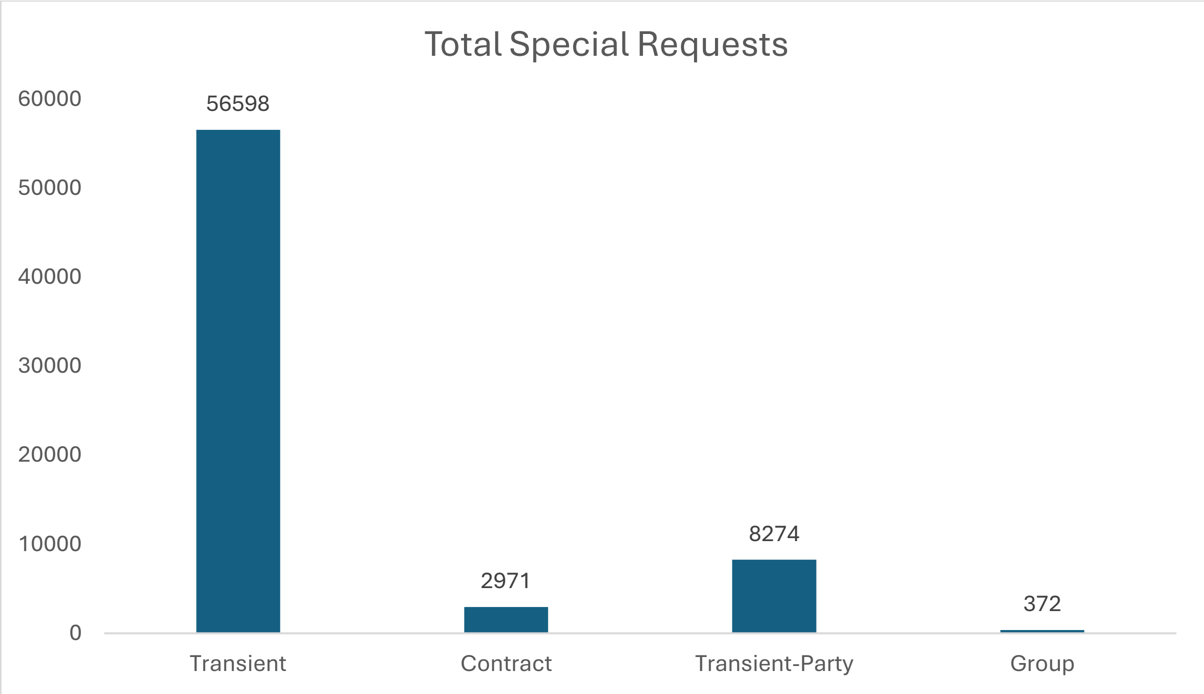
1. ***Line 1 (SELECT):***
    - ***b.customer_type "Type of Customers":*** *Retrieves the customer type and labels it clearly*
    - ***sum(m.total_of_special_requests) "Total Special Requests":*** *Calculates the sum of all special requests made by each customer type*
2. ***Lines 2-4 (FROM and JOIN):***
    - *Combines data from two tables:*
        - ***booking_source_and_history (aliased as 'b')*** *- contains customer and booking information*
        - ***meal_and_stay_details (aliased as 'm')*** *- contains details about special requests*
    - *Joins them using Booking_id as the common identifier*
3. ***Line 5 (GROUP BY):***
    - *Groups the results by customer type to show aggregate special request totals for each category*

Purpose:
This query helps understand:

- *Which customer types make the most special requests*
- *How customer preferences vary by category*
- *Potential patterns in customer behavior*

Query Result :

Type of Customers	Total Special Requests
Transient	56598
Contract	2971
Transient-Party	8274
Group	372



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9. Understand the distribution of meal plans (e.g., BB, HB, FB, SC) and identify any patterns or preferences.

```
1 • SELECT
2       meal,
3       COUNT(*) AS total_bookings,
4       ROUND(100 * COUNT(*) / (SELECT COUNT(*) FROM meal_and_stay_details), 2) AS percentage
5   FROM meal_and_stay_details
6   GROUP BY meal
7   ORDER BY total_bookings DESC;
```

Query-Explanation:
This query analyzes the distribution of meal preferences across all bookings. Here's what each part does:

1. ***Line 1-2 (SELECT meal):***
   - *Selects the meal type from the meal_and_stay_details table*
2. ***Line 3 (COUNT(*) AS total_bookings):***
   - *Counts the total number of bookings for each meal type*
3. ***Line 4 (Percentage calculation):***
   - *Calculates the percentage share of each meal type*
   - *Uses a subquery (SELECT COUNT(*) FROM meal_and_stay_details) to get the total bookings count*

- *Multiplies by 100 and rounds to 2 decimal places for readability*

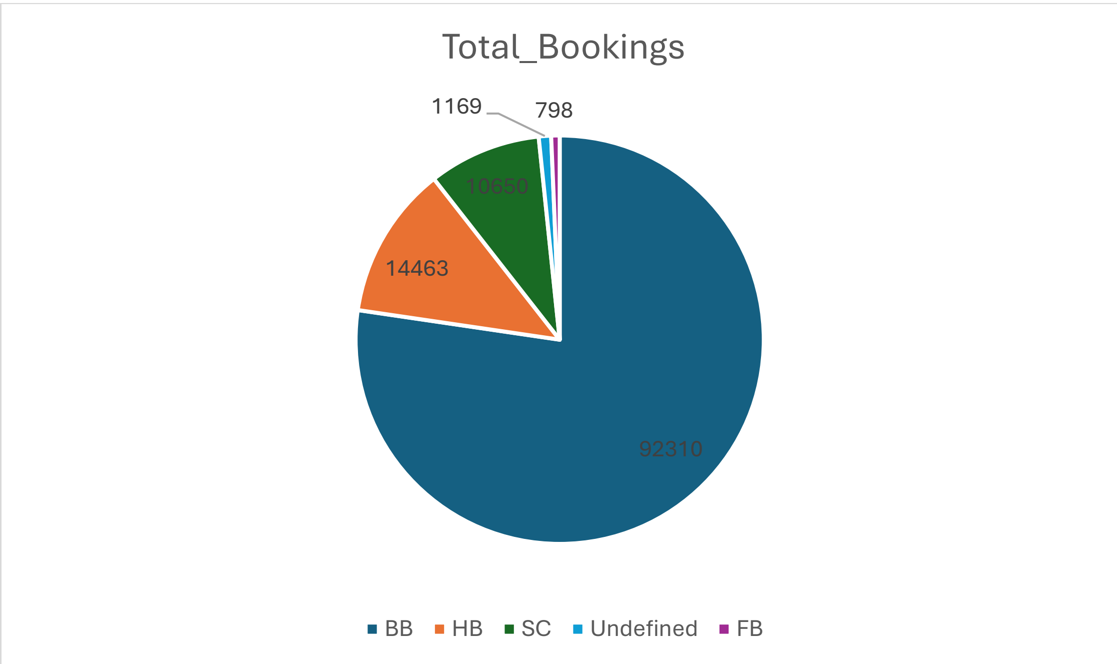
4. ***Line 5 (FROM clause):***
    - *Specifies the source table (meal_and_stay_details)*
5. ***Line 6 (GROUP BY meal):***
    - *Groups results by meal type to aggregate the counts*
6. ***Line 7 (ORDER BY):***
    - *Sorts results by total bookings in descending order (most popular meals first)*

Purpose:
This query helps understand:

- *The popularity distribution of different meal options*
- *Which meal types are most/least preferred by guests*
- *The relative market share of each meal category*

Query Result :

meal	total_bookings	percentage
BB	92310	77.32
HB	14463	12.11
SC	10650	8.92
Undefined	1169	0.98
FB	798	0.67



10. Analyze Average Daily Rates (ADR) by meal plan type to identify variations in pricing.

```
1 •  SELECT
2        meal,
3        ROUND(AVG(adr), 2) AS avg_adr,
4        MIN(adr) AS min_adr,
5        MAX(adr) AS max_adr
6    FROM meal_and_stay_details msd
7    GROUP BY meal
8    ORDER BY avg_adr DESC;
```

Query Explanation:
This query calculates key metrics for Average Daily Rates (ADR) by meal type. Here's the breakdown:

1. ***Line 1-2 (SELECT meal):***
   - *Selects the meal type from the dataset*
2. ***Line 3 (ROUND(AVG(adr), 2) AS avg_adr):***
   - *Calculates the average ADR for each meal type*
   - *Rounds the result to 2 decimal places for cleaner presentation*
3. ***Line 4 (MIN(adr) AS min_adr):***
   - *Finds the lowest ADR for each meal type*
4. ***Line 5 (MAX(adr) AS max_adr):***
   - *Identifies the highest ADR for each meal type*
5. ***Line 6 (FROM meal_and_stay_details msd):***
   - *Uses the meal_and_stay_details table (aliased as 'msd')*
6. ***Line 7 (GROUP BY meal):***
   - *Groups all calculations by meal type*
7. ***Line 8 (ORDER BY avg_adr DESC):***
   - *Sorts results by average ADR in descending order (highest-priced meals first)*

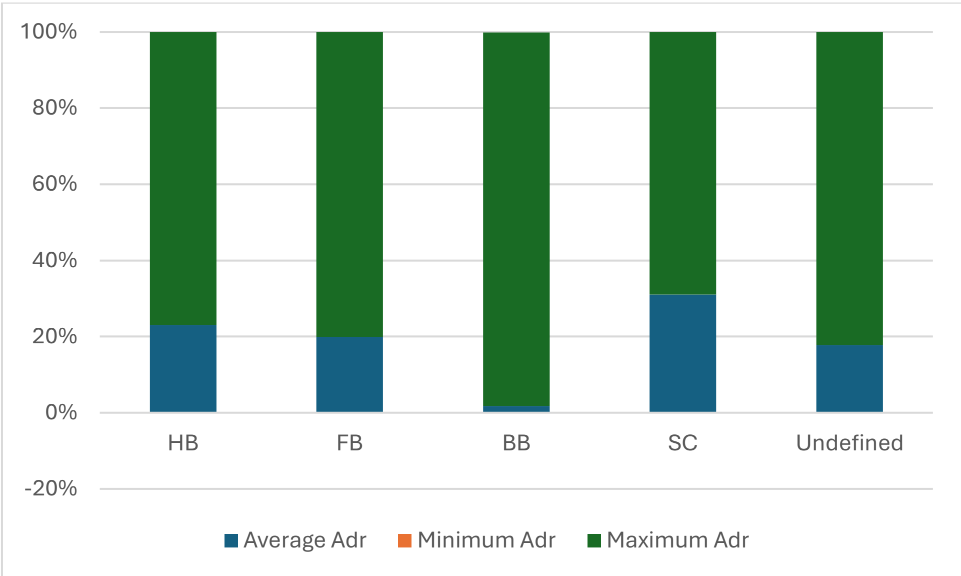
Purpose:

This analysis reveals:

- *Which meal types command premium pricing*
- *The price range for each meal category*
- *How meal options are positioned in the pricing structure*

Query Result :

Meal	Average Adr	Minimum Adr	Maximum Adr
HB	120.31	0	402
FB	109.04	0	437
BB	99.41	-6.38	5400
SC	98.3	0	218
Undefined	91.95	0	426.25



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11. **Investigate the distribution of required car parking spaces and special requests by hotel type and meal plan. Compare the distribution of meal plans among different customer types (e.g., Transient, Group) to identify preferences.**

```sql
SELECT
      m.meal Meal,
      b.hotel Hotel,
      sum(required_car_parking_spaces) "Car Parking Space",
      sum(total_of_special_requests) "Special Request"
FROM meal_and_stay_details m
inner join booking_details b
on b.Booking_id = m.Booking_id
GROUP BY m.meal,b.hotel
```

Query Explanation:

This SQL query analyzes the relationship between meal types, hotels, and their associated parking and special request needs. Here's the breakdown:

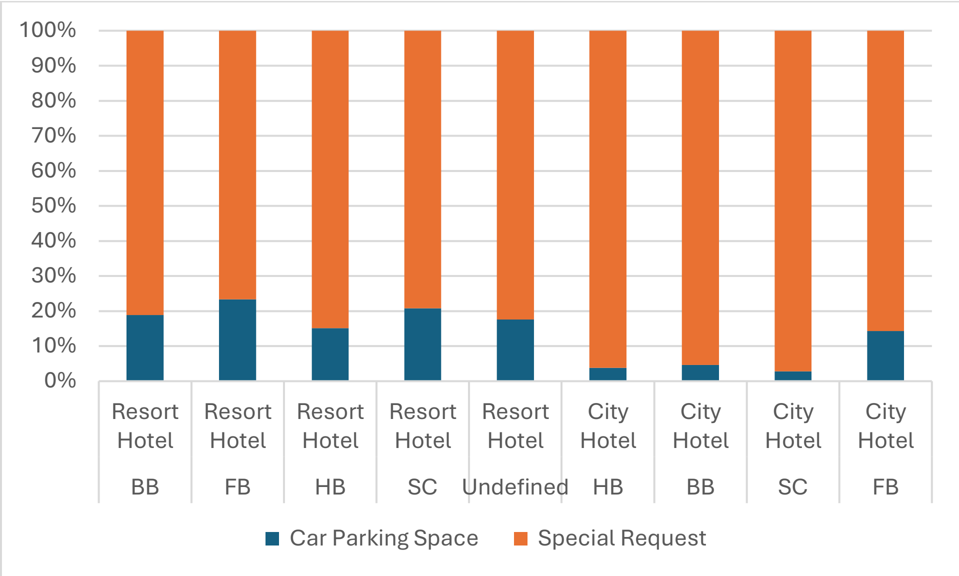
1. ***Columns Selected:***
    - ***m.meal_Meal****: The type of meal from the meal_and_stay_details table*
    - ***b.hotel_Hotel:*** *The hotel name from the booking_details table*
    - ***sum(required_car_parking_spaces):*** *Total parking spaces requested*
    - ***sum(total_of_special_requests):*** *Total special requests made*
2. ***Tables Used:***
    - *meal_and_stay_details (aliased as m)*
    - *booking_details (aliased as b)*
3. ***Join Operation:***
    - *Inner join on Booking_id to connect meal details with booking records*
4. ***Grouping:***
    - *Results are grouped by both meal type and hotel*

Purpose:
This query provides a breakdown of car parking space requirements and special requests by meal type and hotel. It helps analyze:

- *Parking demand patterns across different meal options and hotel properties*
- *Special request frequency relative to meal types and hotels*

Query Result :

Meal	Hotel	Car Parking Space	Special Request
BB	Resort Hotel	4545	19494
FB	Resort Hotel	53	174
HB	Resort Hotel	879	4916
SC	Resort Hotel	10	38
Undefined	Resort Hotel	44	206
HB	City Hotel	109	2776
BB	City Hotel	1591	32685
SC	City Hotel	231	7914
FB	City Hotel	2	12




```sql
SELECT
      b.customer_type "Type_of_Customer",
      (m.meal)  Meal,
      count(Meal) Meal_Taken
FROM meal_and_stay_details m
inner join booking_source_and_history b
on b.Booking_id = m.Booking_id
GROUP BY Type_of_Customer,Meal
```

Second Query Explanation:

This SQL query examines customer meal preferences by customer type. Here's the breakdown:

1. ***Columns Selected:***
    - ***b.customer_type:*** *Customer category from booking_source_and_history*

- ***m.meal:*** *Meal type from meal_and_stay_details*
- ***count(Meal):*** *Count of each meal type taken*

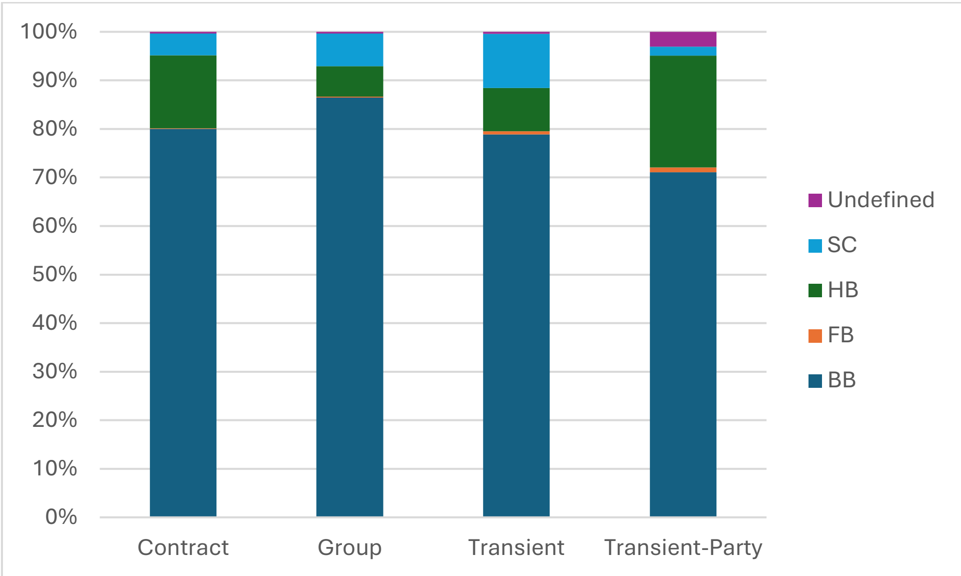
2. ***Tables Used:***
   - *meal_and_stay_details (aliased as m)*
   - *booking_source_and_history (aliased as b)*
3. ***Join Operation:***
   - *Inner join on Booking_id to connect customer data with meal choices*
4. ***Grouping:***
   - *Results are grouped by both customer type and meal type*

Purpose:
This query shows the distribution of meal preferences across different customer types. It helps understand:

- *Which customer segments prefer which meal options*
- *Popularity of meals among different customer categories*

Query Result :

Type_of_Customer	Meal	Meal_Taken
Transient	BB	70692
Transient-Party	BB	17859
Transient	SC	9968
Transient	HB	8020
Transient-Party	HB	5794
Contract	BB	3260
Transient-Party	Undefined	766
Contract	HB	613
Transient	FB	547
Group	BB	499
Transient-Party	SC	460
Transient	Undefined	386
Transient-Party	FB	245
Contract	SC	183
Group	SC	39
Group	HB	36
Contract	Undefined	15
Contract	FB	5
Group	Undefined	2
Group	FB	1



12. Understand the distribution of bookings across different market segments and calculate summary statistics for lead times within each segment.

```sql
select
    b.market_segment_id Market_Segment_ID,
    m.market_segment Market_Segment_Name,
    count(b.Booking_id) Bookings
from booking_source_and_history b
inner join market_segment m
on b.market_segment_id = m.market_segment_id
group by b.market_segment_id, m.market_segment
```

Query Explanation:

This SQL query analyzes booking distribution across different market segments. Here's what each part does:

1. ***Columns Selected:***
   - ***`b.market_segment_id` (aliased as Market_Segment_ID):*** *The unique identifier for each market segment*
   - ***`m.market_segment` (aliased as Market_Segment_Name):*** *The descriptive name of each market segment*
   - ***`count(b.Booking_id)` (aliased as Bookings):*** *Counts the number of bookings per segment*

2. ***Tables Used:***
   - ***`booking_source_and_history` (aliased as b):*** *Contains booking records with segment IDs*
   - ***`market_segment` (aliased as m):*** *Contains segment ID-name mappings*

3. ***Join Operation:***
   - *Inner join on `market_segment_id` connects booking records with segment names*

4. ***Grouping:***
   - *Results are grouped by both segment ID and name to ensure accurate counting*

Purpose:

This query provides a clear view of booking volume distribution across different market segments, enabling analysis of which customer segments generate the most business. The results show both the technical ID and human-readable name for each segment along with their respective booking counts.

Query Result :

Market_Segment_ID	Market_Segment_Name	Bookings	Average_lead_Time	Minimum_Lead_Time	Maximum_Lead_Time
1	Direct	12606	49.8591	0	737
2	Corporate	5295	22.1256	0	343
3	Online TA	56477	82.9987	0	403
4	Offline TA/TO	24219	135.0045	0	532
5	Complementary	743	13.2867	0	386
6	Groups	19811	186.9731	0	629
8	Aviation	237	4.443	0	23
7	Undefined	2	1.5	1	2

---

13. Analyze the distribution of bookings through different booking channels (e.g., online travel agents, direct bookings) and calculate the percentage of bookings through each channel.

```sql
SELECT
    dc.distribution_channel_id,
    dc.distribution_channel,
    COUNT(b.Booking_id) AS total_bookings,
    ROUND(100 * COUNT(b.Booking_id) / (SELECT COUNT(*) FROM booking_details), 2) AS percentage_bookings
FROM booking_source_and_history b
JOIN distribution_channel dc
    ON b.distribution_channel_id = dc.distribution_channel_id
GROUP BY dc.distribution_channel_id, dc.distribution_channel
ORDER BY total_bookings DESC;
```

Query Explanation:

This SQL query analyzes booking distribution across different sales channels. Here's the detailed breakdown:

1. ***Columns Selected:***
   - ***dc.distribution_channel_id:*** *Unique identifier for each distribution channel*
   - ***dc.distribution_channel:*** *Descriptive name of each sales channel*
   - ***COUNT(b.Booking_id):*** *Total bookings per channel*
   - ***Percentage calculation:*** *Shows each channel's share of total bookings*
2. ***Tables Used:***
   - *booking_source_and_history (source of booking records)*
   - *distribution_channel (channel reference data)*
3. ***Key Operations:***
   - ***Join:*** *Links bookings to channel descriptions via distribution_channel_id*
   - ***Subquery:*** *(SELECT COUNT(*) FROM booking_details) calculates total bookings for percentage*

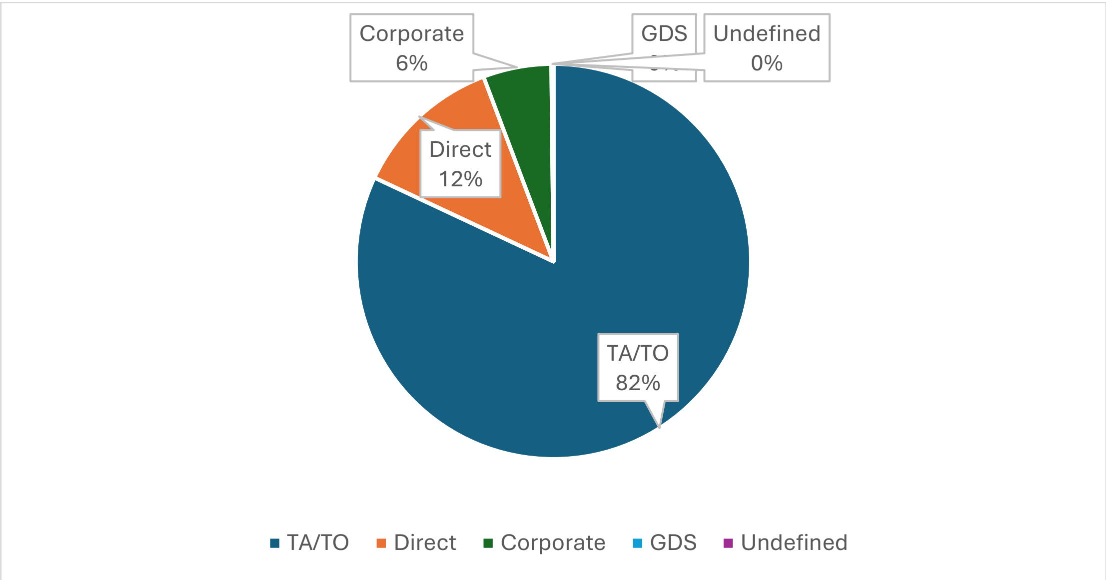
- ***Rounding:*** *Percentages shown to 2 decimal places*
- ***Sorting:*** *Results ordered by booking volume (highest first)*

Purpose:
This query provides a comprehensive view of:

1. *Which sales channels generate the most bookings*
2. *The relative market share of each channel*
3. *The distribution of bookings across all available channels*

Query Result :

distribution_channel_id	distribution_channel	total_bookings	percentage_bookings
3	TA/TO	97870	81.98
1	Direct	14645	12.27
2	Corporate	6677	5.59
5	GDS	193	0.16
4	Undefined	5	0



---

14. Calculate the proportion of repeated guests and investigate their booking behavior. Identify any patterns or differences in preferences compared to firsttime guests.

```sql
SELECT
    CASE
        WHEN is_repeated_guest = 1 THEN 'Repeated Guest'
        ELSE 'First-time Guest'
    END AS guest_type,
    COUNT(*) AS total_bookings,
    ROUND(100 * COUNT(*) / (SELECT COUNT(*) FROM booking_source_and_history), 2) AS percentage_bookings,
    ROUND(AVG(lead_time), 2) AS avg_lead_time,
    ROUND(AVG(stays_in_weekend_nights + stays_in_week_nights), 2) AS avg_stay_duration
FROM booking_source_and_history b
inner join booking_details bd
on b.Booking_id = bd.Booking_id
GROUP BY is_repeated_guest
ORDER BY percentage_bookings DESC;
```

Query Explanation:
This query compares booking patterns between first-time and repeat guests. The analysis includes:

1. ***Guest Classification:***
    - *Creates a "guest_type" column that labels each booking as either:*
        - *'Repeated Guest' (is_repeated_guest = 1)*
        - *'First-time Guest' (all others)*
2. ***Key Metrics Calculated:***
    - ***total_bookings:** Count of bookings per guest type*
    - ***percentage_bookings**: Percentage share of total bookings (using subquery for total count)*
    - ***avg_lead_time:** Average days between booking and arrival*
    - ***avg_stay_duration:** Average total nights stayed (weekend + weekday)*
3. ***Data Sources:***
    - *Joins booking_source_and_history (guest information) with booking_details (stay information)*
    - *Uses Booking_id as the join key*
4. ***Organization:***
    - *Groups results by guest type (is_repeated_guest)*
    - *Orders by booking percentage (highest first)*

Purpose:
The query helps understand behavioral differences between first-time and returning guests across several dimensions:

- *Booking volume distribution*

- *Advance planning habits (lead time)*
- *Length of stay patterns*

Query Result :

Guest Type	Total Bookings	% Bookings	Average Lead Time	Average Stay Duration
First-time Guest	115580	96.81	106.43	3.48
Repeated Guest	3810	3.19	30.79	1.93

---

15. **Explore the impact of a guest's booking history on their likelihood of canceling a current booking. Calculate cancellation rates based on previous cancellations and noncanceled bookings.**

```
select
    (case when bs.is_repeated_guest = 1 then "Repeated Guest" else "New Guest" end) as "Guest_Type",
    avg(b.is_canceled) as "Cancellation_Rate"
from booking_details b
inner join booking_source_and_history bs on b.Booking_id=bs.Booking_id
group by Guest_Type
```

Query Explanation:

This SQL query analyzes cancellation rates by guest type (new vs. returning). Here's the detailed breakdown:

1. ***Guest Classification:***
    - *Uses a CASE statement to create a "Guest_Type" column:*
        - *"Repeated Guest" when is_repeated_guest = 1*
        - *"New Guest" for all other cases*
2. ***Key Metric:***
    - *Calculates avg(b.is_canceled) as "Cancellation_Rate":*
        - *Since is_canceled is typically binary (1=canceled, 0=not canceled), the average gives the cancellation rate*
        - *For example: 0.25 would indicate 25% of bookings were canceled*
3. ***Data Sources:***
    - *Joins booking_details (contains cancellation status) with booking_source_and_history (contains guest repeat status)*
    - *Uses Booking_id as the join key*

4. ***Organization:***
    - *Groups results by the created Guest_Type*
    - *Returns exactly two rows: one for new guests, one for repeat guests*

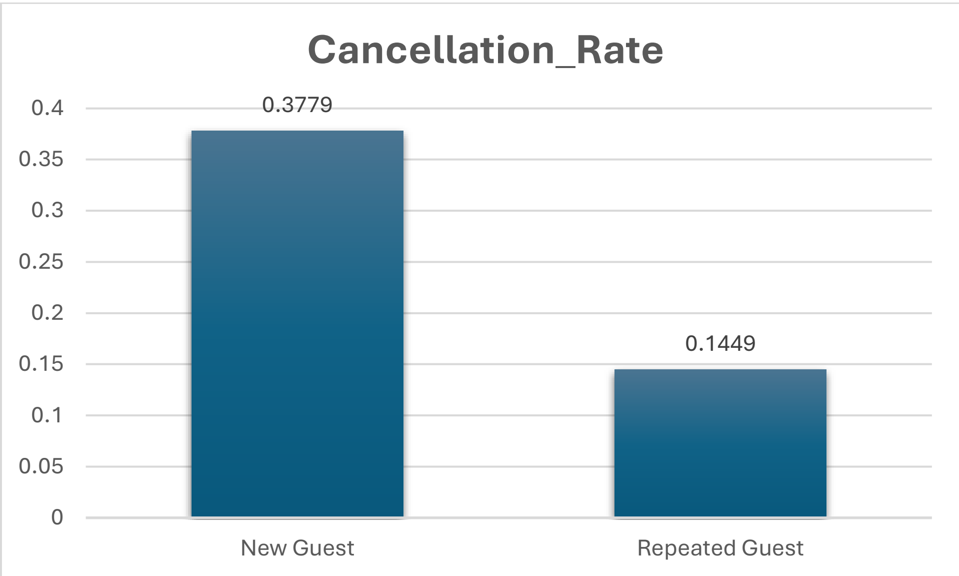
Purpose:
This query specifically compares cancellation behavior between:

- *First-time guests (New Guest)*
- *Returning guests (Repeated Guest)*

The cancellation rate metric helps identify whether repeat guests are more or less likely to cancel bookings compared to new guests, which can inform customer retention strategies and booking policies.

Query Result :

Guest_Type	Cancellation_Rate
New Guest	0.3779
Repeated Guest	0.1449



---

16. Understand the distribution of reserved and assigned room types. Calculate summary statistics for the consistency between reserved and assigned room types.

```sql

SELECT
    reserved_room_type AS Reserved_Room_Type,
    assigned_room_type AS Assigned_Room_Type,
    COUNT(*) AS total_bookings,
    ROUND(100 * COUNT(*) / (SELECT COUNT(*) FROM booking_details), 3) AS percentage_bookings
FROM room_details
GROUP BY reserved_room_type,assigned_room_type
ORDER BY total_bookings DESC;

```

```sql
SELECT
    CASE
        WHEN reserved_room_type = assigned_room_type THEN 'Match'
        ELSE 'Mismatch'
    END AS room_assignment_status,
    COUNT(*) AS total_bookings,
    ROUND(100 * COUNT(*) / (SELECT COUNT(*) FROM room_details), 2) AS percentage_bookings
FROM room_details
GROUP BY room_assignment_status;
```

```sql
SELECT
    reserved_room_type AS most_reserved_room,
    assigned_room_type AS most_assigned_room,
    COUNT(*) AS total_mismatches
FROM room_details
WHERE reserved_room_type <> assigned_room_type
GROUP BY reserved_room_type,  assigned_room_type
ORDER BY total_mismatches DESC
```

Combined Purpose:
These queries work together to provide comprehensive insights into room assignment practices:

1. *Query 1 establishes the baseline distribution of all room type combinations (both matches and mismatches)*
2. *Query 2 calculates the overall match/mismatch rate (aggregate view)*
3. *Query 3 drills down into specific mismatch patterns (detailed view)*

Key Analysis Capabilities:

- *Measures operational efficiency in room assignments*
- *Identifies most common room type substitutions*

- *Quantifies the frequency of mismatches*
- *Reveals potential inventory management issues*
- *Provides metrics for service quality evaluation*

The percentage calculations in Queries 1 and 2 provide normalized comparisons, while Query 3's count-based ranking highlights the most prevalent substitution patterns. Together they form a complete picture of room assignment accuracy and patterns.

Query Result :

Reserved_Room_Type	Assigned_Room_Type	Total_bookings	Percentage_bookings
A	A	73598	61.645
D	D	17736	14.856
A	D	7548	6.322
E	E	5923	4.961
F	F	2707	2.267
G	G	2041	1.71
A	C	1447	1.212
A	E	1156	0.968
A	B	1123	0.941
B	B	988	0.828
C	C	883	0.74

room_assignment_status	total_bookings	percentage_bookings
Match	104473	87.51
Mismatch	14917	12.49

most_reserved_room	most_assigned_room	total_mismatches
A	D	7548
A	C	1447
A	E	1156
A	B	1123
D	E	686
A	F	417
E	F	404

---

17. Analyze the impact of booking changes on cancellation rates. Calculate cancellation rates for bookings with different numbers of changes.

```sql
SELECT
    rd.booking_changes,
    COUNT(b.booking_id) AS total_bookings,
    SUM(CASE WHEN r.reservation_status = 'Canceled' THEN 1 ELSE 0 END) AS total_cancellations,
    ROUND(100 * SUM(CASE WHEN r.reservation_status = 'Check-Out' THEN 1 ELSE 0 END) / COUNT(b.booking_id), 2) AS cancellation_rate
FROM booking_details b
inner join room_details rd on rd.Booking_id = b.Booking_id
JOIN reservation_status r ON b.booking_id = r.booking_id
GROUP BY rd.booking_changes
ORDER BY rd.booking_changes;
```

Query Explanation:

This query analyzes the relationship between booking modifications and cancellation rates. Here's the breakdown:

1. ***Columns Selected:***
   - ***rd.booking_changes:*** *Number of modifications made to each booking*
   - ***COUNT(b.booking_id):*** *Total number of bookings for each modification count*
   - ***SUM(CASE WHEN...Canceled...):*** *Count of canceled bookings per modification count*
   - ***Cancellation rate calculation****: Percentage of bookings canceled per modification count*
2. ***Tables Joined:***
   - *booking_details (core booking information)*
   - *room_details (contains booking_changes data)*
   - *reservation_status (contains cancellation status)*
3. ***Key Corrections:***
   - *Changed SUN to SUM (function name correction)*
   - *Fixed the cancellation rate calculation to use canceled status*
   - *Standardized JOIN syntax*

Purpose:
This query helps understand:

- *How frequently bookings are modified*
- *Whether modification frequency correlates with cancellation likelihood*
- *The cancellation risk associated with different numbers of booking changes*

The results can help identify if multiple booking changes serve as an early warning indicator for potential cancellations.

Query Result :

booking_changes	total_bookings	total_cancellations	cancellation_rate
0	101314	40361	59.15
1	12701	1702	85.77
2	3805	712	79.87
3	927	136	84.47
4	376	60	82.18
5	118	18	83.05
6	63	17	71.43
7	31	3	90.32
8	17	4	76.47
9	8	1	87.5
10	6	1	83.33
11	2	0	100
12	2	0	100
13	5	0	100
14	5	1	80
15	3	0	100
16	2	1	50
17	2	0	100
18	1	0	100
20	1	0	100
21	1	0	100

---

18. Explore how room type preferences vary across different customer types (e.g., Transient, Group). Identify if certain customer types have specific room preferences.

```sql
select b.Customer_Type , rd.Reserved_Room_Type, count(*) as  Room_Booked
from booking_source_and_history b
inner join room_details rd
on b.Booking_id = rd.Booking_id
group by b.customer_type , rd.reserved_room_type
order by Room_Booked desc
```

Query Explanation:

This query analyzes room booking patterns by customer type and reserved room type. Here's the breakdown:

1. ***Columns Selected:***

- ***b.Customer_Type:*** *Categorizes customers by their type (e.g., business, leisure)*
- ***rd.Reserved_Room_Type:*** *Shows which room types customers reserved*
- ***count(*) as Room_Booked****: Counts how many times each room type was booked by each customer type*

2. ***Tables Joined:***
   - *booking_source_and_history (contains customer information)*
   - *room_details (contains room reservation details)*
3. ***Join Condition:***
   - *Connected via Booking_id to match customers with their room reservations*
4. ***Grouping:***
   - *Results are grouped by both customer type and reserved room type*
   - *This creates unique combinations of customer segments and room preferences*
5. ***Sorting:***
   - *Orders results by booking count in descending order (most popular combinations first)*

Purpose:
This analysis helps understand:

- *Which customer segments prefer which room types*
- *The popularity distribution of room types across different customer categories*
- *Potential relationships between customer profiles and room preferences*

Query Result :

Room Preference	A	B	C	D	E	F	G	H	L	P
Contract	2867	75	10	843	177	102	1	1		
Group	365	6	5	143	33	10	12	2		1
Transient	60948	637	828	16420	5569	2663	1957	574	6	11
Transient-Party	21814	400	89	1795	756	122	124	24		

Customer_Type	Reserved_Room_Type	Room_Booked
Transient	A	60948
Transient-Party	A	21814
Transient	D	16420
Transient	E	5569
Contract	A	2867
Transient	F	2663
Transient	G	1957
Transient-Party	D	1795
Contract	D	843
Transient	C	828
Transient-Party	E	756
Transient	B	637
Transient	H	574
Transient-Party	B	400
Group	A	365
Contract	E	177
Group	D	143
Transient-Party	G	124
Transient-Party	F	122
Contract	F	102
Transient-Party	C	89
Contract	B	75
Group	E	33
Transient-Party	H	24
Group	G	12
Transient	P	11
Contract	C	10
Group	F	10
Transient	L	6
Group	B	6
Group	C	5
Group	H	2
Contract	H	1
Group	P	1
Contract	G	1

---

19. Examine whether guests who make multiple bookings have consistent room type preferences or if their preferences change over time.

```sql
1  SELECT
2      CASE
3          WHEN b.is_repeated_guest = 1 THEN 'Repeated Guest'
4          ELSE 'New Guest'
5      END AS Guest_Type,
6
7      CASE
8          WHEN rd.reserved_room_type = rd.assigned_room_type THEN 'Consistent'
9          ELSE 'Changed'
10     END AS Status,
11
12     r.reservation_status_date,
13
14     COUNT(*) AS total_bookings
15 FROM booking_source_and_history b
16 INNER JOIN reservation_status r ON b.Booking_id = r.Booking_id
17 INNER JOIN room_details rd ON rd.Booking_id = r.Booking_id
18 GROUP BY Guest_Type, Status, r.reservation_status_date
19 ORDER BY Guest_Type, r.reservation_status_date, total_bookings DESC;
```

Query Explanation:
This query analyzes booking patterns by guest type (new vs. returning) and room assignment consistency. Here's the breakdown:

1. ***Columns Selected:***
    - ***Guest classification (lines 2-5):***
        - *'Repeated Guest' for is_repeated_guest = 1*
        - *'New Guest' for all others*
    - ***Room assignment status (lines 6-9):***
        - *'Consistent' when reserved and assigned room types match*
        - *'Changed' when they differ*
    - *Reservation status date (line 12)*
    - *Booking count (line 14)*
2. ***Tables Joined:***
    - *booking_source_and_history (guest information)*
    - *reservation_status (booking status data)*
    - *room_details (room assignment information)*
3. *b*
    - *All tables joined via Booking_id*

4. ***Grouping:***
   - *Results grouped by:*
     1. *Guest type (new/repeat)*
     2. *Room assignment status (consistent/changed)*
     3. *Reservation status date*
5. ***Sorting:***
   - *Primary sort: Guest type*
   - *Secondary sort: Date*
   - *Tertiary sort: Booking count (high to low)*

Purpose:
This query helps track:

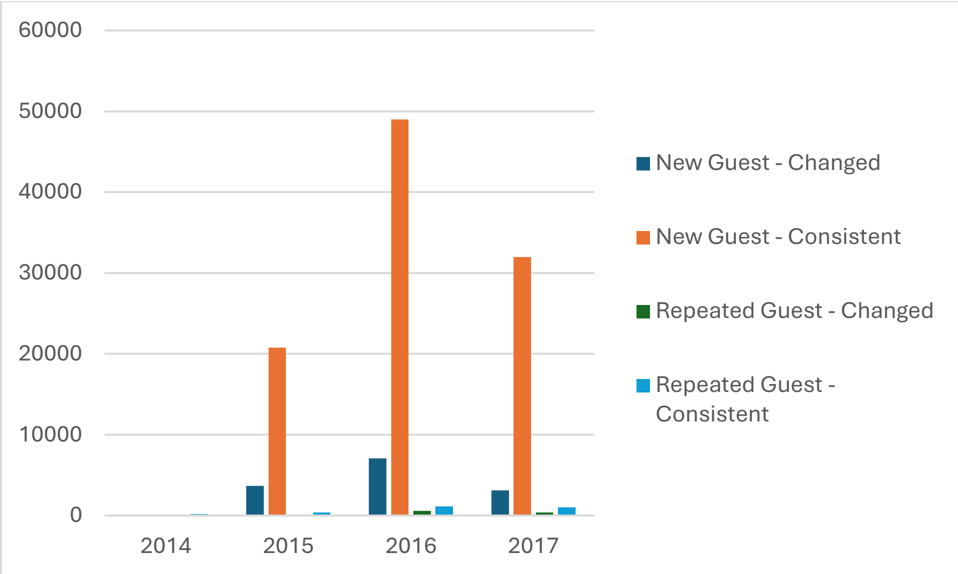
- *How often room assignments match reservations*
- *Whether repeat guests experience more/fewer room changes*
- *How these patterns evolve over time*

The date-based grouping allows for temporal analysis of these metrics, showing whether room assignment practices or guest experiences are improving or worsening over time.

Query Result :

Guest_Type	Status	reservation_status_date	total_bookings
New Guest	Consistent	18-11-2014	1
New Guest	Consistent	01-01-2015	761
New Guest	Consistent	02-01-2015	16
New Guest	Consistent	18-01-2015	1
New Guest	Consistent	20-01-2015	2
New Guest	Consistent	21-01-2015	91
New Guest	Consistent	22-01-2015	6
New Guest	Consistent	28-01-2015	1
New Guest	Consistent	30-01-2015	67
New Guest	Consistent	02-02-2015	2

Sum of total_bookings	Column Labels					
	New Guest		New Guest Total	Repeated Guest		Repeated Guest Total
Row Labels	Changed	Consistent		Changed	Consistent	
2014		1	1		180	180
2015	3655	20770	24425	114	390	504
2016	7091	48986	56077	569	1151	1720
2017	3111	31966	35077	377	1029	1406



---

20. Understand the distribution of reservation statuses and calculate summary statistics for reservation status dates.

```sql
select Reservation_Status ,count(*) as Total_Booking
from reservation_status
group by reservation_status
```

Query Explanation:

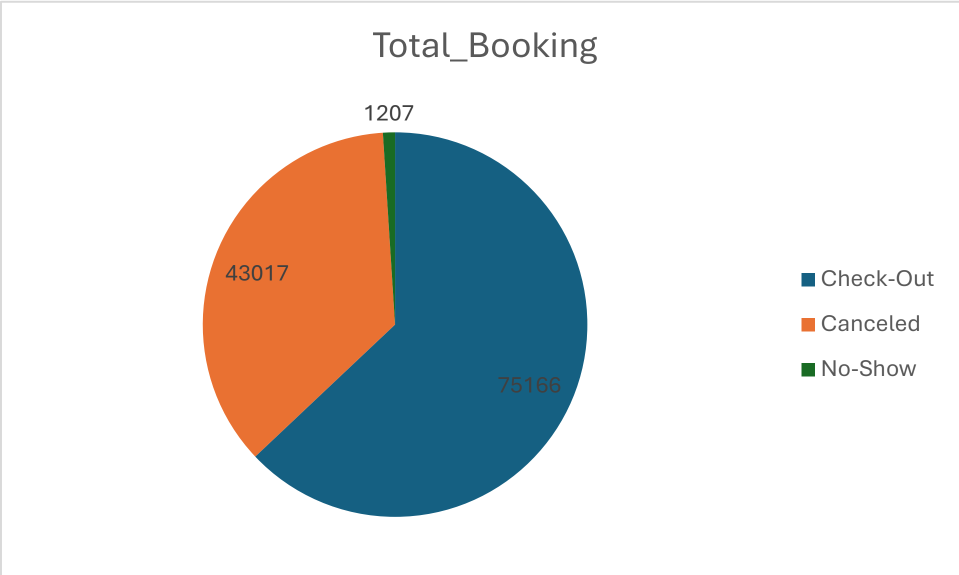
1. *Selects reservation status and counts occurrences*
2. *Groups results by each unique status value*
3. *Returns the total number of bookings for each status category*

Purpose:

- *Provides a basic distribution of booking statuses*
- *Shows how many bookings are in each state (e.g., Checked-Out, Canceled, No-Show)*
- *Helps understand the overall composition of reservations*

Query Result :

Reservation_Status	Total_Booking
Check-Out	75166
Canceled	43017
No-Show	1207




```sql
WITH DateCounts AS (
    SELECT
        reservation_status_date,
        COUNT(*) AS occurrence_count
    FROM reservation_status
    GROUP BY reservation_status_date
), MostCommonDate AS (
    SELECT
        reservation_status_date AS most_common_date
    FROM DateCounts
    ORDER BY occurrence_count DESC
    LIMIT 1
)
SELECT
    MIN(reservation_status_date) AS earliest_date,
    MAX(reservation_status_date) AS latest_date,
    COUNT(DISTINCT reservation_status_date) AS unique_dates,
    (SELECT most_common_date FROM MostCommonDate) AS most_frequent_date
FROM reservation_status;
```

Query Explanation:

1. *Creates a CTE (DateCounts) that counts bookings per date*
2. *Creates a second CTE (MostCommonDate) that identifies the date with most bookings*
3. *Main query returns:*
    - *Earliest and latest dates in the data*
    - *Count of unique dates*
    - *The single most frequent date*

Purpose:

- *Provides temporal boundaries of the dataset*
- *Identifies date distribution patterns*
- *Highlights peak activity dates*
- *Helps assess data quality and coverage period*

Query Result :

Earliest Date	Latest Date	Unique Dates	Most Frequent Date
17-10-2014	14-09-2017	926	21-10-2015

---

21. Analyze trends in reservation status dates, including the most common checkout dates and any seasonality patterns.

```sql
select
    Year(reservation_status_date) "Reservation_Year",
    month(reservation_status_date) "Reservation_Month",
    count(*) Total_Booking
from reservation_status
group by Reservation_Month, Reservation_Year
order by  Reservation_Year , Total_Booking DESC
```

Query Explanation:

1. ***Columns Selected:***
    - ***YEAR(reservation_status_date)*** *→ Extracts the year from the reservation date.*

- *MONTH(reservation_status_date)* → *Extracts the month (1-12).*
- *COUNT(*) AS Total_Booking* → *Counts the number of bookings per month-year.*

2. ***Grouping & Sorting:***
    - ***GROUP BY Reservation_Month, Reservation_Year*** → *Aggregates bookings by month and year.*
    - ***ORDER BY Reservation_Year, Total_Booking DESC*** →
        - *First sorts chronologically by year.*
        - *Then sorts months within each year by booking volume (highest first).*

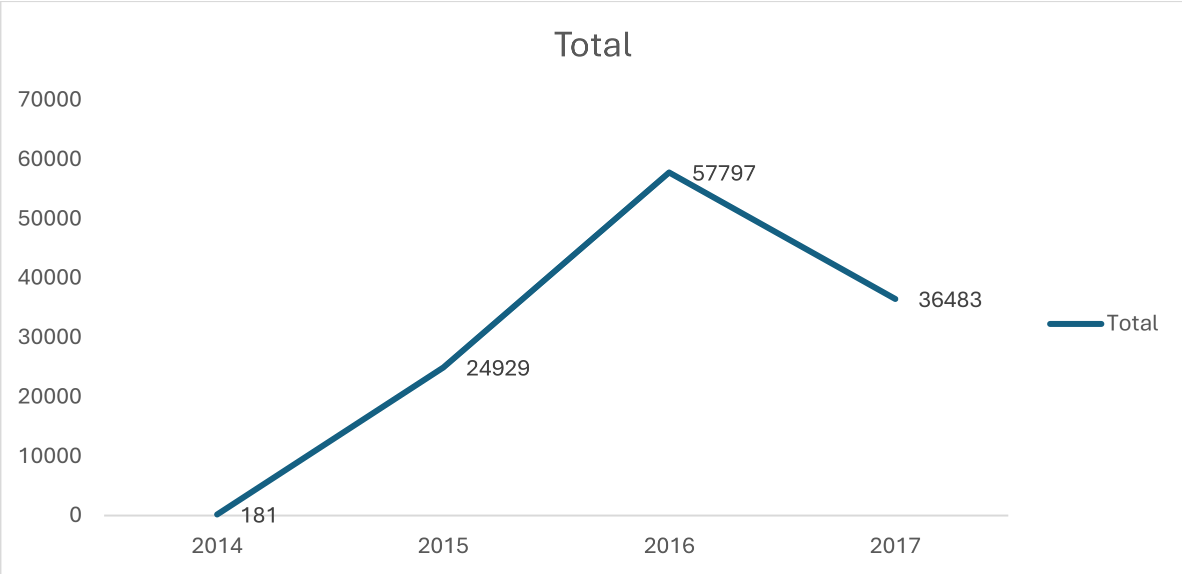
Purpose:

- *Identifies seasonal trends (peak vs. low-demand months).*
- *Tracks year-over-year growth (compare 2023 vs. 2024 bookings).*
- *Supports demand forecasting (staffing, pricing, promotions).*

Query Result :

Reservation_Year	Reservation_Month	Total_Booking
2014	10	180
2014	11	1
2015	10	5742
2015	9	4017
2015	7	3615
2015	8	3247
2015	11	3077
2015	12	3062
2015	1	948
2015	6	666
2015	5	275
2015	4	151
2015	3	85
2015	2	44
2016	3	5319

Row Labels	Sum of Total_Booking
⊞2014	181
⊞2015	24929
⊞2016	57797
⊞2017	36483
Grand Total	119390




```sql
with commondate as (
    select reservation_status_date as Most_Frequent_Date
    from reservation_status
    where reservation_status = 'Check-Out'
    group by reservation_status_date
    order by count(*) DESC
    limit 1
)
select * from commondate
```

Query Explanation:

1. *CTE (commondate):*
    - *Filters for completed stays (reservation_status = 'Check-Out').*
    - *Groups by date and counts check-outs per day.*
    - *Orders by frequency (highest first) and picks the top 1 date (LIMIT 1).*

2. *Final Output:*
   - *Returns the single date with the most check-outs.*

Purpose:

- *Identifies peak operational days (when max guests check out).*
- *Helps optimize staffing (housekeeping, front desk).*
- *Highlights potential bottlenecks (e.g., long wait times).*

Query Result :

Most_Frequent_Date
08-12-2015

---

22. **Explore how reservation statuses vary across different customer types (e.g., Transient, Group) using Excel or SQL. Calculate cancellation rates by customer type.**

```
select b.customer_type, r.reservation_status , count(*)
from booking_source_and_history b
inner join reservation_status r
on b.Booking_id = r.Booking_id
group by b.customer_type, r.reservation_status
```

Purpose:
This query provides a breakdown of booking statuses (e.g., Checked-Out, Canceled, No-Show) across different customer types.

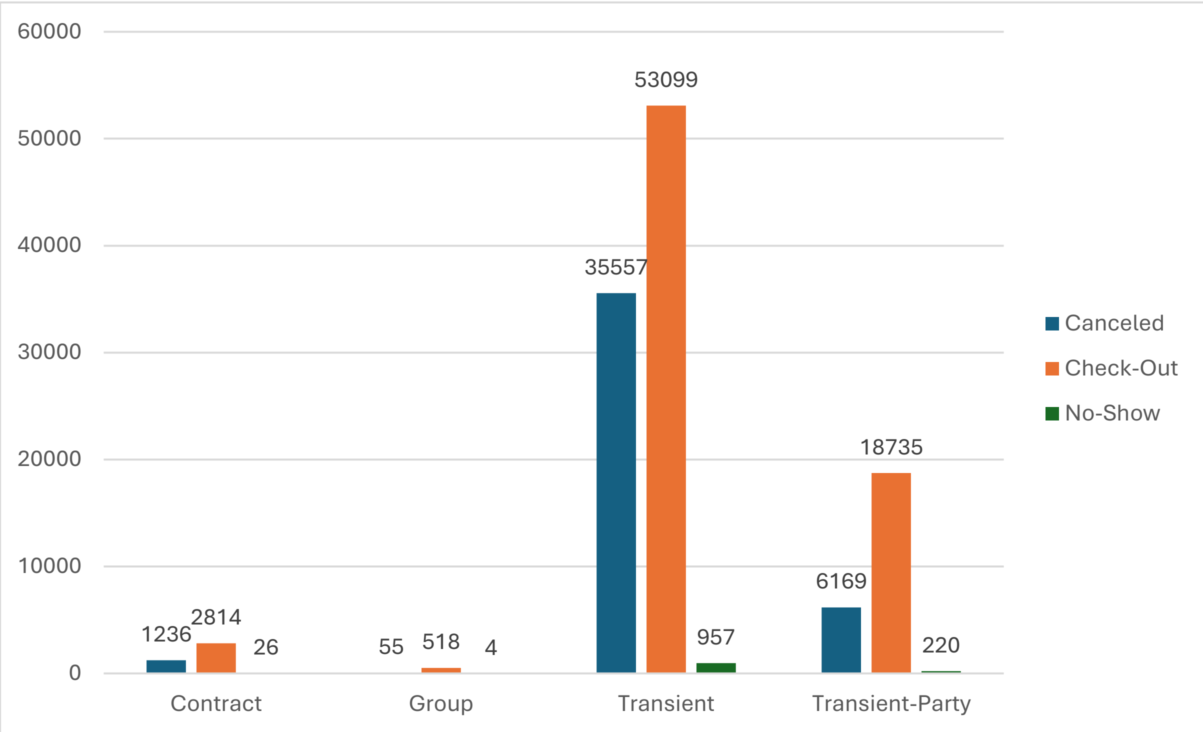
Key Features:

1. *Joins customer data with reservation status data*
2. *Groups results by both customer type and reservation status*
3. *Counts occurrences of each status per customer type*

Query Result :

customer_type	reservation_status	count(*)
Transient	Check-Out	53099
Transient	Canceled	35557
Contract	Check-Out	2814
Transient-Party	Check-Out	18735
Contract	Canceled	1236
Transient	No-Show	957
Contract	No-Show	26
Transient-Party	Canceled	6169
Group	Check-Out	518
Transient-Party	No-Show	220
Group	Canceled	55
Group	No-Show	4

Total Bookings	Reservation Status		
Customer Type	Canceled	Check-Out	No-Show
Contract	1236	2814	26
Group	55	518	4
Transient	35557	53099	957
Transient-Party	6169	18735	220



```sql
SELECT
    bs.Customer_Type,
    COUNT(*) AS total_bookings,
    SUM(CASE WHEN is_canceled = 1 THEN 1 ELSE 0 END) AS canceled_bookings,
    ROUND(100 * SUM(CASE WHEN is_canceled = 1 THEN 1 ELSE 0 END) / COUNT(*), 2) AS cancellation_rate
FROM booking_details b
inner join booking_source_and_history bs on b.Booking_id=bs.Booking_id
GROUP BY customer_type
ORDER BY cancellation_rate DESC;
```

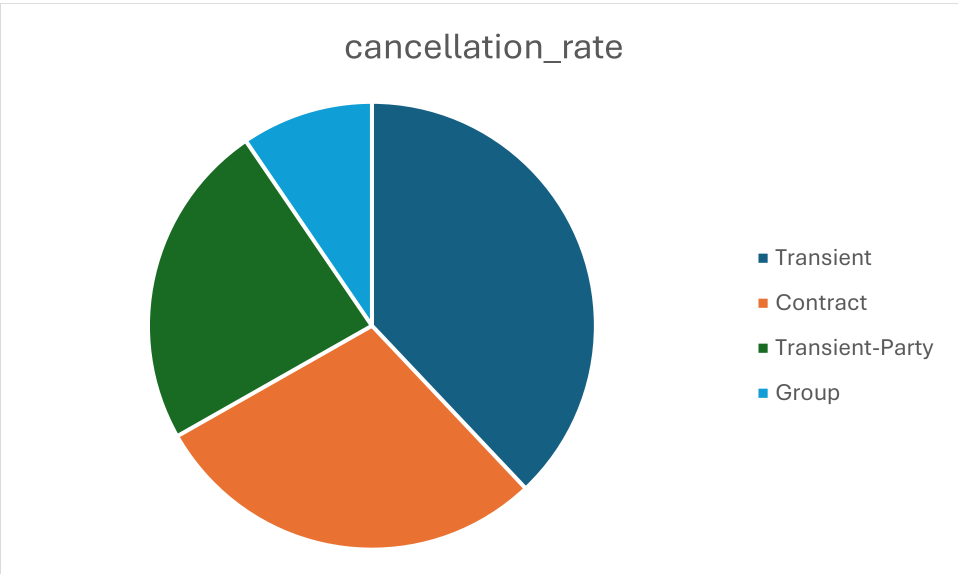
Purpose:
This query calculates and compares cancellation rates across different customer types.

Key Features:

1. *Uses conditional aggregation to count cancellations*
2. *Calculates cancellation percentage for each customer type*
3. *Orders results by cancellation rate (highest first)*

Query Result :

Customer_Type	total_bookings	canceled_bookings	cancellation_rate
Transient	89613	36514	40.75
Contract	4076	1262	30.96
Transient-Party	25124	6389	25.43
Group	577	59	10.23



23. **Investigate whether there are differences in Average Daily Rates (ADR) based on reservation status (e.g., canceled vs. checkedout).**

```sql
SELECT
    rs.reservation_status,
    COUNT(*) AS total_bookings,
    ROUND(AVG(m.adr), 2) AS avg_adr
FROM meal_and_stay_details m
inner join reservation_status rs
on m.Booking_id = rs.Booking_id
GROUP BY rs.reservation_status
ORDER BY avg_adr DESC;
```

Query Explanation:
This query analyzes the relationship between booking statuses and average daily rates (ADR). Here's the breakdown:

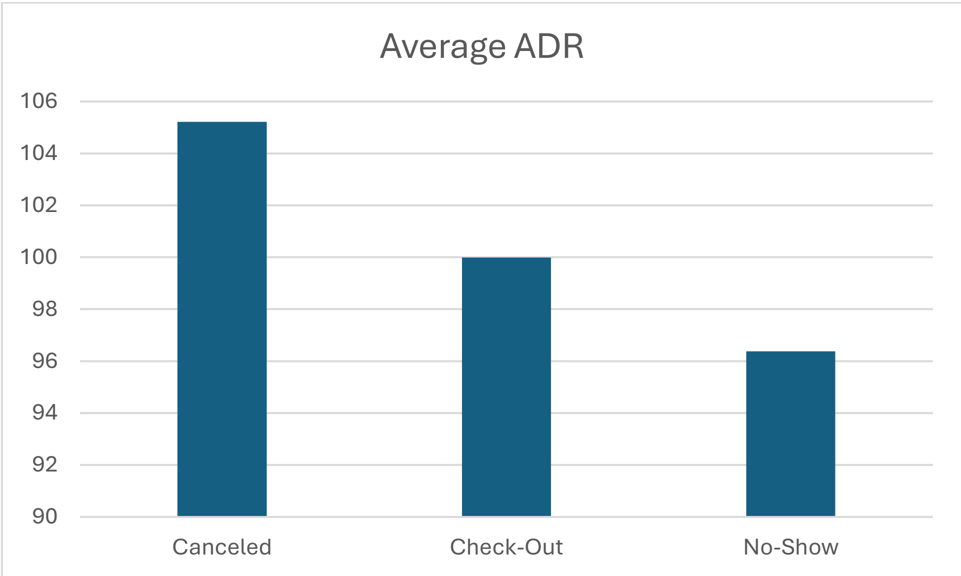
1. ***Columns Selected:***
    - ***rs.reservation_status:*** *The current status of each reservation (e.g., Checked-Out, Canceled, No-Show)*
    - ***COUNT(*) AS total_bookings:*** *Counts how many bookings exist for each status*
    - ***ROUND(AVG(m.adr), 2) AS avg_adr:*** *Calculates the average daily rate for each status, rounded to 2 decimal places*
2. ***Tables Joined:***
    - ***meal_and_stay_details (aliased as 'm'):*** *Contains ADR (Average Daily Rate) information*
    - ***reservation_status (aliased as 'rs'):*** *Contains booking status information*
3. ***Join Condition:***
    - *Connected via Booking_id to match rate information with booking status*
4. ***Grouping:***
    - *Results are grouped by reservation status to aggregate the metrics*
5. ***Sorting:***
    - *Orders results by average ADR in descending order (highest-priced bookings first)*

Purpose:
This analysis helps understand:

- *Which booking statuses are associated with higher/lower room rates*
- *Whether canceled bookings tend to be higher or lower value than completed stays*
- *The revenue impact of different booking outcomes*

Query Result :

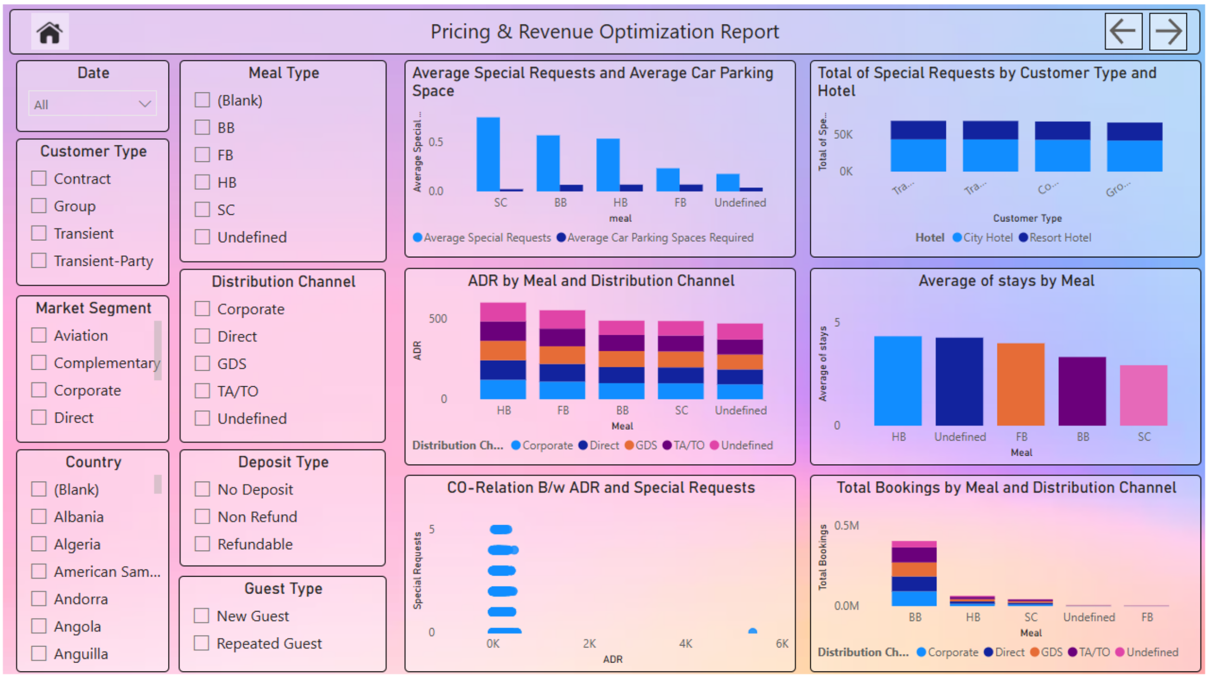
Reservation status	Total Bookings	Average ADR
Canceled	43017	105.21
Check-Out	75166	99.99
No-Show	1207	96.38



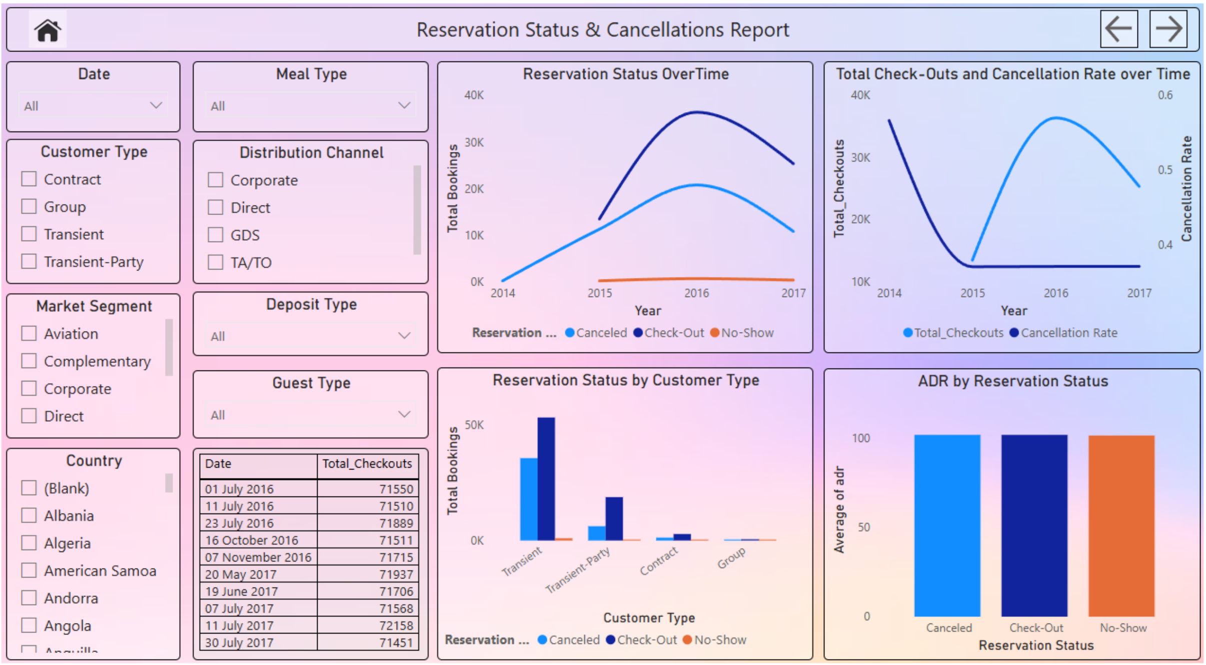
PowerBI Reports

Booking Trends & Seasonality Report

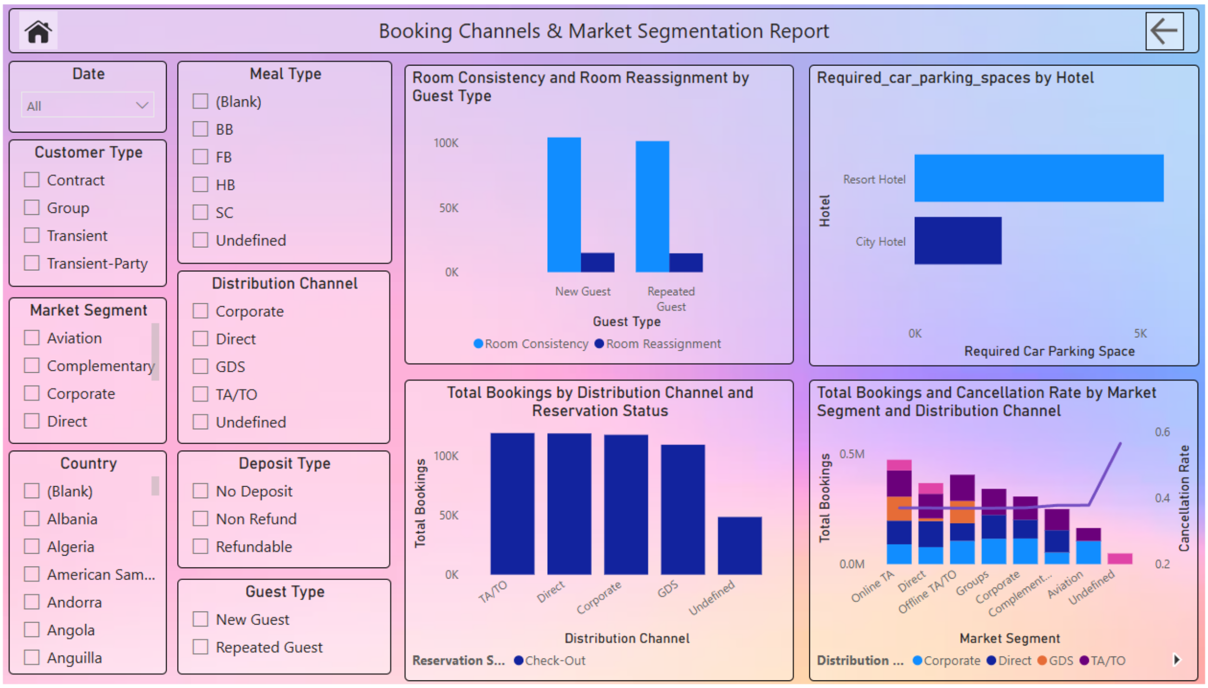
Guest Demographics & Behavior Report



Pricing & Revenue Optimization Report



Reservation Status & Cancellations Report



Booking Channels & Market Segmentation Report