

MSIN0093 Business Strategy and Analytics

Group Assignment

Pineapple Pizza

Group member:

Benedict Halim 25100553

Gianni Chen 25057622

Hanley Ho 25120620

Yen-Yu Chang 25039313

Zhengpeng Wang 25115696

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Table of Contents

1. Company Overview	2
2. Strategic problem or Opportunity-Pricing inefficiency	3
2.1. Overall Pricing Problem	3
2.2. Exploratory Data Analytics	3
2.2.1. Net Revenue in each Booking Channel.....	3
2.2.2. Average Spending by Nationalities	4
2.3. Summary Statistics & Regression Analysis	5
2.3.1. Summary Statistics	5
2.3.2. Regression Analysis	5
3. Proposed Strategy	7
3.1. Customer Segments	7
3.2. Targeted Season.....	8
3.3. Targeted Booking Channel	8
3.4. Promotion Strategies	9
4. Strategic alignment with existing business and feasibility	11
5. Validation.....	13
5.1. Evidence from internal data	13
5.2. Regression evidence on pricing drivers.....	13
5.3. Competitor and market context.....	13
6. Risk Assessment	15
6.1. Risk 1: Unable to accurately determine exact discount rate and price hike	15
6.2. Risk 2: Lack Of Competitor Data	15
6.3. Risk 3: Spillover Effect Across Nationalities and Room Type	16
7. Scenario Analysis	17
8. Generative AI Component	18
8.1. Occupancy Rate Calculation.....	18
8.2. Scenario Analysis	18
9. Conclusion	19
10. Attribution Statement.....	20
11. Reference list.....	21
12. Appendix	22

1. Company Overview

Airis Luxury Villa & Spa is a boutique resort located in Bali, Indonesia. It offers private villa accommodation aimed at international tourists looking for short-term and mid-term stays. The property consists of 16 Villas and 32 rooms with 5 main categories- One-bedroom Luxury, One-bedroom Superior, Two-bedroom Deluxe, Two-bedroom Duplex, and Three-bedroom Luxury. Guests include local and international travellers (Airisvilla, 2021).

The current method of sales is via a mix of online travel agencies (OTAs) and direct channels such as walk-in guests or offline travel agencies. Major OTAs such as Booking.com and Agoda currently account for a large share of the booking and revenue; other OTAs such as Expedia and Ticket.com contribute to smaller quantities. Revenue is denominated in Indonesian Rupiah (IDR), and the resort operates all year round experiencing a high season between the months of July –September and low season of January-March.

In the remainder of this report, we will use the resort's own booking data to examine how to maximise customer value via customer segmentation and a more structured, data-driven approach to pricing strategy.

2. Strategic problem or Opportunity-Pricing inefficiency

2.1. Overall Pricing Problem

Airis's pricing approach heavily relies on market trend provided by online agency platforms rather than implementing its own data-driven pricing system. This limits the company to understand their pricing positioning and capture optimal revenue. Given that Airis is playing a role of price taker, they may risk either under-pricing or overpricing. Therefore, this is an opportunity to examine the existing data and adjust room price strategically to optimize overall revenue.

2.2. Exploratory Data Analytics

2.2.1. Net Revenue in each Booking Channel

Based on the data we got directly from the company, we targeted the variables “Net Amount” (Net Revenue), “Booking Channel”, “Date”, and “Guest Residence Country” to generate visualisation charts and analyse the business insights.

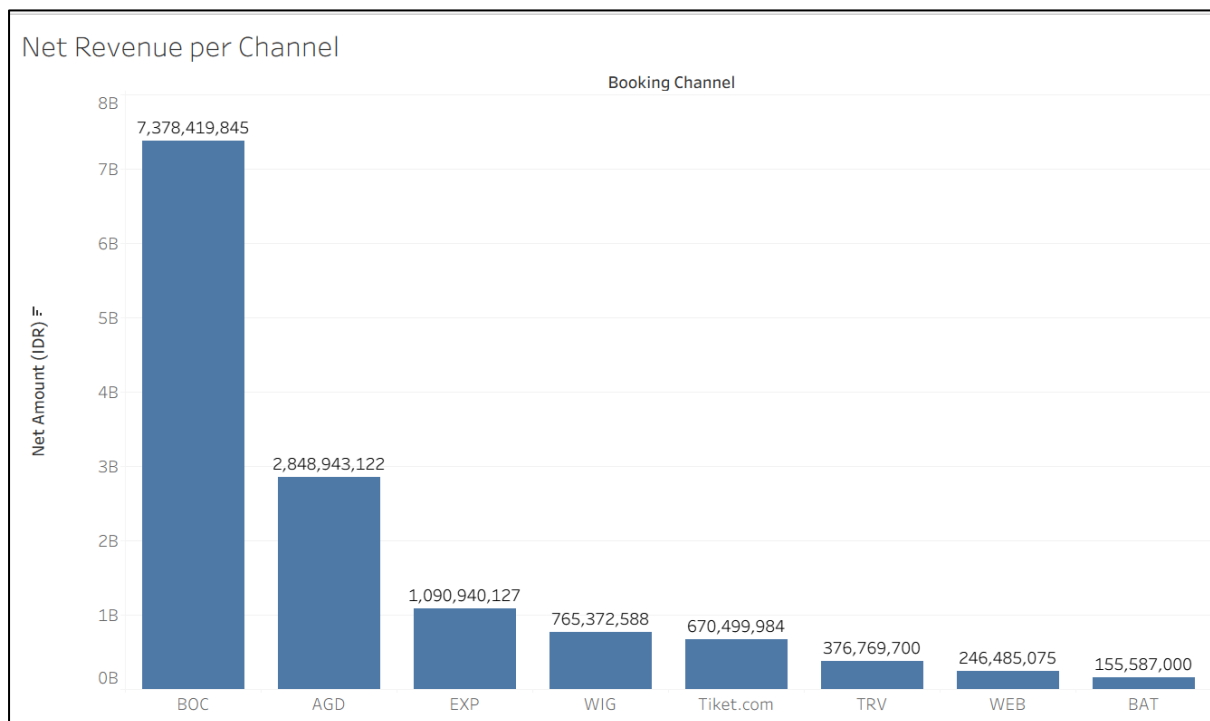


Figure 1: Net revenue across different channels

The above bar chart (Figure 1) shows the total net revenue in each booking channel from 1/1/2024 to 30/09/2025. Based on the data, Booking.com (BOC) and Agoda (AGD) were the

top two booking channels with the highest net revenue, which were IDR 7.3 billion and IDR 2.8 billion respectively. They generated most of the net revenue, exceeding the contribution from Expedia (EXP), Tiket.com and Walk-in Guest (WIG) channels. The chart also indicates that Airis sold almost its entire villa rooms through third-party booking platforms rather than reserving for direct bookings.

2.2.2. Average Spending by Nationalities

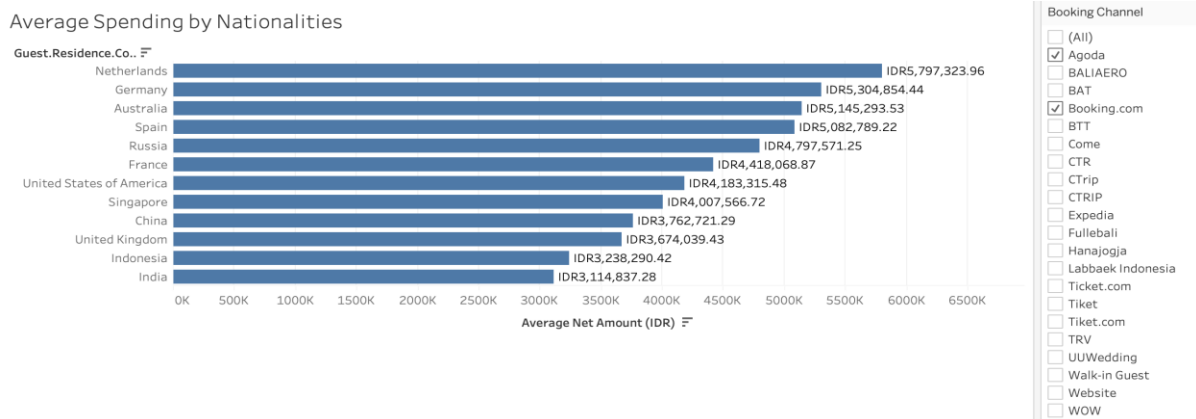


Figure 2 Non-Peak Season Average Spending by Nationalities (1£ ~ 22,042 IDR)

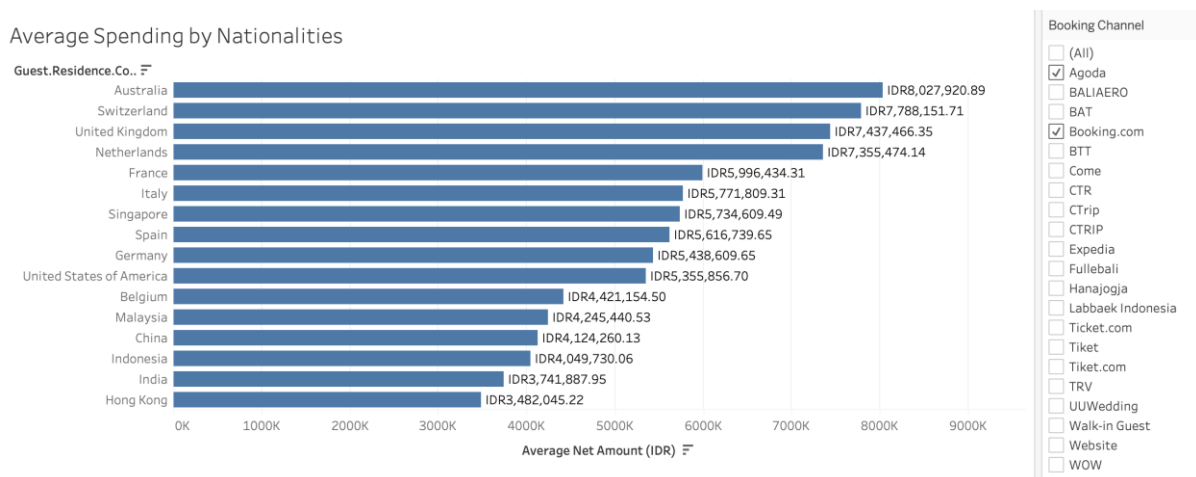


Figure 3: Peak Season Average Spending by Nationalities (1£ ~ 22,042 IDR)

Given that Booking.com and Agoda are the top two channels generating the highest net revenue, Figures 2 and 3 examine the average net amount spent on stays of up to seven days through these two channels during the low season (January to March) and peak season (July and September), respectively.

Referring to Figure 2, it shows that the Netherlands, Germany, Australia, Spain and Russia are the top 5 spending nationalities, with an average spending of approximately IDR 5.23 million per booking. This indicates that European and Oceanic travellers tend to spend more on average

and appear less price sensitive. Travellers from France, The United States, Singapore and China are considered as mid-spending group, with an average of IDR 3.05 million. The lowest-spending groups during the low peak season are travellers from the United Kingdom, India and Indonesia (locals).

Figure 3, on the other hand, shows that travellers from Australia become the top spenders during peak season, followed closely by visitors from Switzerland, the Netherlands, the United Kingdom. This suggests that European and Australian travellers consistently belong to the top-spending segment throughout the year, except for guests from Germany, the UK and Switzerland whose ranking varies between seasons. Meanwhile, for travellers from France, Italy, Singapore, Spain, Germany and the US, the average spending ranges from IDR 5.25 to 6.19 million, placing them into the mid-tier segment which generally seek value-for-money offers. Customers whose average spending is IDR 4.41 million or below are classified as budget travellers. This group is predominantly composed of guests from Asian countries and tends to be more price sensitive.

2.3. Summary Statistics & Regression Analysis

2.3.1. Summary Statistics

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
AMOUNT	2	2147	5683547.5	4715645.97	4262500	4869202.28	3287665.5	123977	37115000	36991023	2.2031576	6.99947709	101771.264
Commission	4	2147	724909.764	929168.537	422145	552508.963	625872.177	0	6680700	6680700	1.98166735	5.58113573	20052.9594
Bank.fee	5	2147	102099.63	99470.7157	72914.58	86521.229	67220.4435	0	742300	742300	2.02810692	6.09435587	2146.73887
Net.Amount	6	2147	4856538.11	3880348.61	3593353.19	4201599.6	2657440.33	121497.46	29692000	29570502.5	2.14779659	6.63065879	83744.1969
Repeat.Guest.Flag*	8	2147	1.09548207	0.2939481	1	1	0	1	2	1	2.75102657	5.5707425	0.00634388
Room.Nights	9	2147	2.54727527	1.78504082	2	2.24665503	1.4826	1	16	15	2.32009679	9.45383993	0.03852407
Room.Revenue.Total	14	2147	5924131.97	5087851.86	4373969	5033710.24	3297575.2	495868	37914608	37418740	2.39599972	8.19738445	109804.069
Grand.Total	15	2147	6428973.86	5549950.53	4772000	5476282.6	3597899.55	600000.28	67625879	67025878.7	2.71631506	13.1641857	119776.906
room_rate_night	16	2147	2270742.65	902403.553	2092500	2170100.72	806814.611	495868	8550000	8054132	1.39178093	3.52089511	19475.3277
net_room_nightly_rate	18	2147	1940600.5	834299.933	1764000	1851772.52	722322.72	121497.46	11170722	11049224.5	2.23411258	14.3337492	18005.5415
booking_month*	19	2147	6.15929204	3.04589943	6	6.13554392	2.9652	1	12	11	-0.0077296	-0.8521788	0.06573543
booking_weekday	21	2147	3.96786213	1.97335259	4	3.95986038	2.9652	1	7	6	-7.40E-05	-1.2274104	0.04258814
Room.Types_num	22	2147	3.97950629	1.96463351	3	3.84991274	1.4826	2	7	5	0.32671989	-1.6066608	0.04239997
booking_channel2_num	23	2147	2.5454122	1.75375012	2	2.22280396	1.4826	1	7	6	1.44714517	0.924941	0.03784876
booking_weekday_num	24	2147	3.96786213	1.97335259	4	3.95986038	2.9652	1	7	6	-7.40E-05	-1.2274104	0.04258814
booking_month_num	25	2147	6.15929204	3.04589943	6	6.13554392	2.9652	1	12	11	-0.0077296	-0.8521788	0.06573543

Table 1. Summary statistic of the data

From the summary statistics above we noticed that the attribute we are interested in (net_room_nightly_rate) is highly skewed. This would indicate that we would need to do a log transformation in the later regression.

2.3.2. Regression Analysis

Using regression analysis, we would want to understand the relationship between price and other attributes. Hence, we set the dependent variable as the net_nightly_room_rate and created 3 models with varying control factors. We applied log-transformation to the dependent variable as it can very skewed.

Model 1:

$$\ln(\text{netnightrate}) = \beta_0 + B_channel \cdot \text{Channel_i} + \varepsilon_i$$

Model 2:

$$\ln(\text{netnightrate}) = \beta_0 + B_channel \cdot \text{Channel_i} + \beta_1 \cdot \text{RepeatGuest_i} + B_room \cdot \text{RoomType_i} + \beta_2 \cdot \text{Weekday_i} + B_month \cdot \text{Month_i} + \varepsilon_i$$

Model 3:

$$\ln(\text{netnightrate}) = \beta_0 + B_channel \cdot \text{Channel_i} + \beta_1 \cdot \text{RepeatGuest_i} + B_room \cdot \text{RoomType_i} + \beta_2 \cdot \text{Weekday_i} + B_month \cdot \text{Month_i} + B_country \cdot \text{Country_i} + \varepsilon_i$$

Looking at the regression results from the appendix, we see that the type of booking channel used is a major driver in the price difference, even after controlling everything else. The baseline booking channel is Agoda.

$$\text{Formula: \%changeinnight_room_rate} \approx (e^{\beta_1} - 1) \times 100\%$$

Channel	Model 2 coefficient	Approx % difference vs baseline
Booking.com (BOC)	0.072***	7.46% higher
Expedia (EXP)	0.095***	9.97% higher
Ticket.com	0.070*	7.25% higher
TRV	0.151***	16.3% higher
Walk-in Guest (WIG)	0.166***	18.1% higher

Table 2: Main drivers of net room rates (Booking Channels)

Based on the regression analysis, it could be beneficial to target booking channels with the highest increase net_nightly_room_rate such as TRV and walk in guest. However, there is a need to consider the net revenue to make a sound decision on which channel to target as the regression does not reveal the quantity of bookings coming through these channels.

3. Proposed Strategy

Our strategy is to introduce a data-driven marketing and pricing strategy that accurately segments customers based on nationalities and booking channels. The objective is to maximise profits by putting out optimal prices for the right season and customer, all while protecting the brand image of the resort.

3.1. Customer Segments

We divided our customers into three segments base on nationalities:

Low Season

- (1) High-value customers: Travelers from Australia, the Netherlands, Spain, Germany and Russia
- (2) Mid-tier customers: Travelers from the United States, France, Italy, Spain, and Singapore, China
- (3) Budget customers: Travelers from The United Kingdom, India and local guests

Peak Season

- (1) High-value customers: Travelers from Australia, the Netherlands, Switzerland, and the United Kingdom
- (2) Mid-tier customers: Travelers from the United States, Germany, France, Italy, Spain, and Singapore
- (3) Budget customers: Travelers from China, Malaysia, Belgium, Hong Kong, India and local guests.

Our targeted segment focuses on mid-tier customers given that they are generally looking for value-for-money accommodation and offering promotion deals could effectively increase their motivation to visit the villa.

The rationale behind not targeting top spender is that high-value customers already demonstrate low price sensitivity and naturally consume premium products due to their higher purchasing power. A study has been conducted that the price sensitivity of shoppers reduces when their income level increases (Nassar, Gad and Kortam, 2021). Additionally, top spenders often benefit from strong currency rates relative to the Indonesian Rupiah, further enhancing their purchasing power in Bali (Figure 4). It appears that extra promotional efforts on top spender would likely generate minimal incremental value as they are willing to stay at the villa without requiring discounts.

Budget travellers, on the other hand, are considered as high price sensitivity and allocating marketing resources to attract them would require deep discounts, which may result in low return. Moreover, since the villa is offering luxurious accommodation experience, excessive discount may risk diluting brand value and potentially affect brand's perceived exclusivity. Therefore, focusing on mid-tier customers (United States, France, Italy, Spain, and Singapore, China) in low season enables a strategic balance between revenue optimization and maintaining brand's positioning.

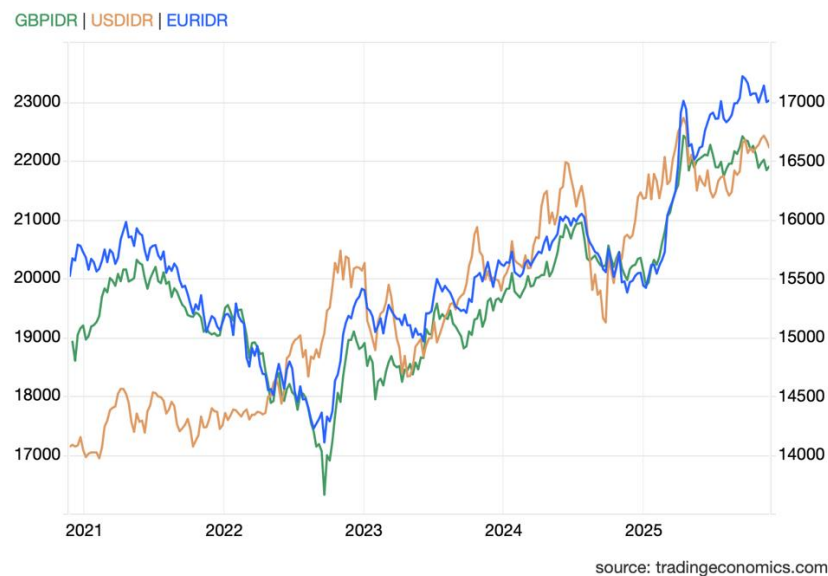


Figure 4. The currency rate of USD-IDR, GBP-IDR & EUR-IDR from 2021 to 2025 (Trading Economics, 2019)

3.2. Targeted Season

Our strategic goal is to help the brand maximise customer value by increasing the occupancy rate of rooms in low demand. Given that we observed that the occupancy rate of the hotel in low season (January – March) is relatively low, which will be discussed later, we decided to focus on implementing our strategy specifically in the low season. This approach aims to enhance the brand's overall business performance throughout the year.

3.3. Targeted Booking Channel

Using the insights from Figure 1 and Table 2, Booking.com and Agoda will be used to provide exclusive discount offers to customers in the countries mentioned in section 3.1. Booking.com has a 7.46% higher net nightly room rate than Agoda and is the highest generator of revenue. Agoda, while does not fare as well in terms of nightly room rate to other booking channels, generates the second highest revenue for the company and delivers over 150% more revenue than the next booking channel.

3.4. Promotion Strategies

Airis's pricing approach heavily relies on market trend provided by online agency platforms rather than implementing its own data-driven pricing system. Therefore, we would like to set different pricing based on our customer demand in each season in the past two years, and give more discount offers for the room types that has lower occupancy rates. The main goal is to attract more customers to book these room types and increase the demands of booking, which has the potential to increase overall revenue.

To decide which months and which room type to provide discounts offer, we analysed the occupancy rate of each room type in peak season and low season first.

(1) Occupancy Rate Analysis in each Room Type during Peak/Low Seasons

```
> peak_occ
# A tibble: 5 × 2
  Room.Type      Occupancy
  <chr>          <dbl>
1 ONE BEDROOM LUXURY VILLA 1.29
2 ONE BEDROOM SUPERIOR VILLA 0.921
3 THREE BEDROOM LUXURY VILLA 0.571
4 TWO BEDROOM DELUXE VILLA 0.705
5 TWO BEDROOM DUPLEX VILLA 0.389
> unpeak_occ
# A tibble: 5 × 2
  Room.Type      Occupancy
  <chr>          <dbl>
1 ONE BEDROOM LUXURY VILLA 0.830
2 ONE BEDROOM SUPERIOR VILLA 0.785
3 THREE BEDROOM LUXURY VILLA 0.351
4 TWO BEDROOM DELUXE VILLA 0.529
5 TWO BEDROOM DUPLEX VILLA 0.133
> |
```

Figure 5 - Occupancy Rate of Each Room Type* (calculated by ChatGPT)

- **Formula of Occupancy Rate Calculation:**

$$\text{Occupancy Rate} = \frac{\text{Total Occupied Room} - \text{Nights in Season}}{\text{Total Available Room} - \text{Nights in Season}}$$

- **Seasons based on popularity:**

1. Peak Season: July-September
2. Low Season: January-March

Occupancy Rate Analysis¹:

Figure 5 is the occupancy rate of each room type in peak and low seasons. The result shows that the average occupancy rate in peak season is already very high, especially the one-bedroom villas have approximately 100% of occupancy rate. On the contrast, the occupancy rate of low season is much lower, with many rooms unsold between January and March.

On the other hand, in low season, each room type still has different occupancy rate. As shown in Figure 5, one-bedroom villas have higher occupancy rate, which is around 0.8 (80%). The Two Bedroom Duplex Villa has the lowest occupancy rate, 0.1 (10%), indicating that nearly no customer chose this room type during low season. Therefore, we can provide different discounts offer by room type during low season.

(2) Target Low Season and Provide Discounts by Room Types

Target Season	Low Season - January, February, March		
Occupancy Rate	High (0.7)	Medium (0.5)	Low (<0.4)
Room Types	1. One Bedroom Luxury Villa 2. One Bedroom Superior Villa	Two Bedroom Deluxe Villa	1. Three Bedroom Luxury Villa 2. Two Bedroom Duplex Villa
Discount Ratio	Low	Medium	High

Table 4: Proposed low-season discount structure by room type and occupancy rate

Based on the observations from the occupancy rate analysis, we could conclude that low season has lower occupancy rate, and the three-bedroom and two-bedroom room types have lower occupancy rate compared to one-bedroom units.

Therefore, we plan to target low season (from January to March) to provide exclusive discounts on Booking.com and Agoda in United States, France, Italy, Spain, and Singapore, China (countries based on 3.1). During low season, the discount in each room type would be different. For example, the One Bedroom Luxury Villa and One Bedroom Superior Villa have higher occupancy rate (0.7), then we could provide lower discount ratios for these room types; as for the Three Bedroom Luxury Villa and Two Bedroom Duplex Villa with lower occupancy rate (<0.4), we could provide higher discount ratio. As for the exact number of discount ratio, we can predict this by using “Price Elasticity” method to calculate in the future.

¹ Occupancy exceeds the value of 1 as two-bedroom villas are dynamically converted to one-bedroom villas during the peak season to accommodate to demand for that room type.

4. Strategic alignment with existing business and feasibility

The proposed strategy utilises the current data obtained from analysing the OTA insights as well as demographic data. Airis is positioned as a boutique villa resort that targets international leisure travellers who prioritise privacy and high-quality service rather than low prices. A more structured, data-driven pricing approach supports this positioning because it allows the resort to price more accurately across guest segments and seasons, without shifting towards a discount-focused model. In addition, using selective promotions for mid-range segments and value-added packages for higher-spending markets helps maintain Airis's image as a luxury brand.

From a business perspective, the strategy builds on Airis's existing channel and market structure rather than replacing it. The resort already depends mainly on Booking.com and Agoda for visibility and booking volume, with smaller contributions from other OTAs and direct bookings. By being strategic with their advertising strategy like applying targeted discounts to specific room types with low occupancy and using channels for value-added offers are therefore incremental adjustments to how prices are managed on these platforms. Similarly, distinguishing between high-spending, mid-tier and budget markets is in line with the current guest profile. High-spending long-distance international guests are offered premium packages instead of deep discounts, while mid-tier guests become the primary focus for price-based promotions. Very low-budget segments are not actively targeted, to avoid weakening the brand's luxury positioning. As Yusuf et al. (2018) state, this approach is consistent with research showing that market segmentation is often implemented through multichannel communications (Shim et al., 2004), brand development (Bucklin & Gupta, 1992), differentiated pricing strategies (Yelkur & DaCosta, 2001), and targeted promotional tools such as family discounts (Díaz-Martín et al., 2000).

From a feasibility perspective, the strategy is practical because it uses data that Airis already collects information on booking channel, guest nationality, room type, number of room nights, repeat-guest status, booking month and weekday is available in the existing property management and booking systems and has already been used in the analysis. As a result, implementing the seasonal price grid and operational targeting does not require significant new IT investments. In the short term, performance can be monitored using accessible tools such as R for regression analysis and simple dashboards in Tableau or Excel. More advanced revenue

management software would only be needed if the resort decides to scale up the approach in future.

Organisationally, the change would be manageable. In a boutique property of this size, pricing is usually done based on intuition and limited information from similar room rates from neighbouring properties. Under the proposed strategy, pricing would be formalised and there would be a clear structure to follow to ensure the right price is published. The main task would be to maintain a seasonal grid by channel, approve market-specific offers, and mid-tier discount campaigns.

Financially, the strategy is low cost but potentially high impact. The main resources required are management time for analysis and implementation, plus some effort to update OTA rate plans and communicate new offers. In addition, the use of regression analysis and dashboards allows management to monitor the effects of price changes and promotions and to reverse or adjust them if they do not perform as expected, which helps to limit financial risk.

5. Validation

This section uses Airis’s internal booking data and basic market information to assess whether the proposed channel- and nationality-based seasonal pricing strategy is likely to be effective.

5.1. Evidence from internal data

The booking data for 2024–2025 show clear patterns in both channels and nationalities. Figure 1 indicates that net revenue is highly concentrated in Booking.com and Agoda, while other OTAs and direct channels account for much smaller shares. This confirms that a few OTAs dominate visibility and price comparison for Airis and supports the decision to make booking channel a primary segmentation dimension and to introduce minimum net rates and channel-specific rules.

Figures 2 and 3 show that average net spending per booking differs substantially by nationality in both non-peak and peak seasons. European and Australian guests consistently spend more on average, while several regional markets appear in the mid-tier or budget range. These differences in observed spending validate the segmentation into high-spending, mid-tier and budget markets, and underpin the strategy of focusing discounts on mid-tier customers and using value-added packages rather than deep discounts for high-spending markets.

5.2. Regression evidence on pricing drivers

In addition to the descriptive analysis, we estimate regression models with the (log) net room nightly rate as the dependent variable. Following prior work that combines descriptive statistics with econometric models of room prices to study dynamic pricing strategies (Abrate et al., 2012), we specify booking channel and nationality as the key explanatory variables, with controls for room type, length of stay, booking month, weekday and repeat-guest status. Several booking channels are statistically significant, indicating that effective prices differ systematically across channels and markets in our data, consistent with evidence that hotel room prices vary across distribution channels and countries.

5.3. Competitor and market context

Discussions with management suggest that current prices are largely set by matching or slightly undercutting nearby competitors on OTAs, rather than by analysing Airis’s own booking data. Given the strong OTA dominance and the clear spending differences observed across nationalities, a more structured, data-driven approach that differentiates prices by channel,

market and season has clear potential to improve revenue without undermining the resort's luxury positioning.

Taken together, the internal data and regression results indicate that there is meaningful scope to improve performance through a segmented, seasonal pricing strategy focused on channels and nationalities, supporting the potential effectiveness of the proposed approach.

6. Risk Assessment

6.1. Risk 1: Unable to accurately determine exact discount rate and price hike

While the proposal is promising, there are limitations. One limitation is the lack of sufficient data such as internal cost reports to determine financial metrics such as the break-even rate, Return on investment (ROI). Without these metrics, it becomes difficult to determine optimal price adjustments across seasons. Any price increases during high demand periods or discounts during low season would therefore be based on incomplete information, making them either overly conservative or excessively aggressive. Both scenarios carry financial risks: conservative pricing leads to missed revenue opportunities, while overly deep discounts or hikes can reduce profitability or harm demand. A way to mitigate this risk is to integrate the analysis with the cost data. With the crucial information, we would be able to suggest an estimated price range which the resort could use to ensure that they are constantly maximising profits. This would allow the resort to implement data-driven pricing strategies that maximise occupancy while ensuring sustained profit margins. Such integration would significantly enhance the precision and reliability of the recommendations.

6.2. Risk 2: Lack Of Competitor Data

Another limitation is the absence of competitor pricing and occupancy data. If the data of similar resorts are made available, we would be able to understand how we would be able to price competitively without compromising on the vision of maintaining a luxurious image. The lack of benchmarking introduces risk such as setting prices too high that it drives customers to similar villas or pricing too low that it attracts the wrong target audience. While it would be beneficial to obtain such data to position the resort optimally, it is not feasible as this data is highly confidential, and similar resorts would not be willingly to provide this information that would aid their competitors.

To mitigate this risk, the resort could implement an automated web-scraping tools to collect competitor pricing data from major OTAs. By continuously gathering this data, they would be able to track market trends in real time, identify price movements from competitors and benchmark their own prices accordingly.

6.3. Risk 3: Spillover Effect Across Nationalities and Room Type

A potential risk that might associate with the strategy is the spillover effect, which occurs when the behaviour of the treatment group affects the control group (Ha and Kitchen, 2020). In the marketing strategy, high value customers, who are not the targeted customers to receive discount, are still able to access to the promotion deals. For instance, travellers from Australia could use a VPN (Virtual Private Network) to browse other OTA websites that are for the mid-tier markets such as France and the United States, and book discounted room type. This could result in revenue loss as the top spenders may shift from high profit margin room type to discounted ones and it may also lead to perceived unfairness as customers may think that the strategy is a price discrimination across different segments. Prior research on OTAs booking shows that price discrimination directly shapes guest's fairness perceptions, and through fairness, their intention to make a reservation (Chen et al,2023).

To mitigate this adverse outcome, Airis can make use of Rate Plan with Eligibility provided by booking channels so that the promotion offers will not be determined based on IP location. For instance, Booking.com and Agoda allow hotels to set specific criteria for discount rates such as the registered country in users' accounts. In such way, even if consumers are using VPN, the booking platforms could still detect their account detail and only show the offers they are eligible for. As a result, this could ensure that the discount offers are only applied to specific countries and reduce the spillover effect. On the other hand, to improve the perceived unfairness, Airis could provide value-added services to their high-value customers such as offering complimentary breakfast or personalised welcome amenities to enhance their guest experiences.

7. Scenario Analysis

Scenario 1: External Forces Affect International Demand for Accommodations in Bali

The COVID-19 pandemic demonstrated the importance of building a business model that is resilient to sudden and severe disruptions. One plausible scenario the resort must be prepared for is substantial decline in international tourist, it could be a result of global economic downturn, geopolitical tensions, new travel restrictions, or maybe a new health concern. In such circumstances, tourist arrivals could fall sharply, pushing occupancy down and increasing traveller's sensitivity to price.

During the data collection process, we also interviewed the general manager, and he commented on the COVID-19 situation. He noted that the resort turned to aggressive price cuts to attract the domestic Indonesian market. Although this approach helped to fill the rooms in the short term, it ultimately diluted the brand's premium positioning and reduced profitability. In hindsight, the overcorrection of discounts was driven by the absence of formal pricing guidance. While our proposed strategy aims to target customer segments based on nationalities and booking channels, it could be modified to suit different situations and adjusted for different granularity. For example, referring to the recent COVID-19, similar analysis could be done for the domestic market to create customer segments. By identifying distinct segments within Indonesian travellers (such as regional origin and booking platform), the resort can develop targeted offers and pricing strategies that align with local demand behaviour. (Copilot, 2025)

Scenario 2: Coping With a Demand Boom

The best-case scenario is that there might be a strong demand from international travellers. This could be driven by external factors such as promotions by the government tourism board, favourable exchange rates for foreign travellers and many more. This would increase demand and occupancy rate rates will be closer to 1. While this is a favourable condition for the resort, the introduction of the data driven strategy will be able to guide the resort to make decisions that maximise profits and brand image. The usage of the strategy in this scenario would allow the resort to capture high-value customer segments at optimal price points and tailor offers to specific customer segments. The approach would sustain brand prestige without undermining rate integrity. (Copilot, 2025)

8. Generative AI Component

8.1. Occupancy Rate Calculation

In Section 3.4, to decide which months and which room type to provide discounts offer, we asked ChatGPT to calculate the occupancy rate of each room in different seasons, and we analysed the result ourselves. Occupancy rate is crucial to our strategy, since it helped us identify which rooms were less popular and therefore, we could target them to provide discount offers.

8.2. Scenario Analysis

In Section 7, we feed ChatGPT information about the project and ask it to generate two scenarios, one best and one worst case, to do the scenario analysis. AI do give us some useful direction about the best and worst cases, but the performance of our strategies under each case was not satisfactory due to a lack of understanding about the strategies' details.

9. Conclusion

In conclusion, the proposed strategy aligns with Airis' brand positioning and operational capabilities. With the existing data collected, we can leverage on insights from nationalities patterns, channel performance and seasonality trends. The strategy provides a data-driven roadmap for optimising profit and maintaining the resort's premium identity. Additionally, the strategy does not require major organisational changes, instead it complements existing systems in place, allowing the team to transition smoothly towards making decisions with more information.

While there are limitations to the proposal- such as the lack of cost information and incomplete competitor intelligence, they do not discount the analytical value in this proposal. It forms the foundations for a Standard Operating Procedure(SOP) for pricing and marketing and integrating more data would further enhance the pricing precision.

Moreover, the strategy is robust under different future situations. The framework can be adjusted accordingly to match the market situation at that point in time. The strength of the proposal is in its flexibility, allowing the company respond strategically rather than reactively.

10. Attribution Statement

Benedict Halim: He brainstormed ideas with the teams. He collected and communicated with the hotel to get the relevant information. He ran regression analysis on the net nightly room rate. He worked on the introduction, risk assessment and conclusion.

Gianni Chen: He brainstormed ideas with the teams and started drafting the report. Responsible for the strategic alignment with existing business and feasibility and validation sections. He helped edit and refine the other sections so that the arguments were consistent. He searched for relevant sources to support the analysis.

Hanley Ho: She brainstorms ideas with the team. She created the visualization on Tableau regarding net revenue across different nationalities. She worked on the proposed strategy regarding customer segmentation and the targeted season. She also helped write part of the risk assessment.

Yen-Yu Chang: She brainstormed ideas with the teams. She analysed the data and created the visualisation regarding booking platforms and revenue. She considered the current problem the company has faced, and came up with the proposed strategy, especially the promotion strategy part.

Zhengpeng Wang: He brainstormed ideas with the teams. He setup project management website Asana. He writes validation, Scenario analysis part of the report. He do the proofread for the report.

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12. Appendix

Appendix 1:

AMOUNT	Commisio n	Bank.fee	Net.Amou nt	Room.Nig hts	Room.Typ es_num	Room.Rev enue.Total	Grand.Tot al	net_room_ nightly_rat e	booking_ month_nu m	booking_c hannel2_n um	booking_ weekday_n um	
AMOUNT	1	0.836801	0.928696	0.991081	0.754254	0.199234	0.924204	0.905589	0.471049	0.076799	-0.07573	-0.00665
Commisio n	0.836801	1	0.816258	0.756554	0.583472	0.158825	0.783491	0.742883	0.338198	0.075087	-0.07763	-0.01921
Bank.fee	0.928696	0.816258	1	0.907519	0.704162	0.165343	0.86206	0.842732	0.402565	0.068408	-0.26645	-0.01506
Net.Amou nt	0.991081	0.756554	0.907519	1	0.758851	0.199852	0.913442	0.90104	0.481146	0.073597	-0.06661	-0.0031
Room.Nig hts	0.754254	0.583472	0.704162	0.758851	1	-0.02789	0.844785	0.831341	-0.05825	0.025954	-0.13871	0.000762
Room.Typ es_num	0.199234	0.158825	0.165343	0.199852	-0.02789	1	0.180764	0.178917	0.400814	0.027645	0.023803	-0.01531
Room.Rev enue.Total	0.924204	0.783491	0.86206	0.913442	0.844785	0.180764	1	0.978655	0.308355	0.08478	-0.09617	-0.00716
Grand.Tot al	0.905589	0.742883	0.842732	0.90104	0.831341	0.178917	0.978655	1	0.300992	0.075538	-0.08097	0.000488
net_room_ nightly_rat e	0.471049	0.338198	0.402565	0.481146	-0.05825	0.400814	0.308355	0.300992	1	0.097096	0.111195	-0.02704
booking_ month_nu m	0.076799	0.075087	0.068408	0.073597	0.025954	0.027645	0.08478	0.075538	0.097096	1	0.003269	-0.01163
booking_c hannel2_n um	-0.07573	-0.07763	-0.26645	-0.06661	-0.13871	0.023803	-0.09617	-0.08097	0.111195	0.003269	1	0.014897
booking_ weekday_n um	-0.00665	-0.01921	-0.01506	-0.0031	0.000762	-0.01531	-0.00716	0.000488	-0.02704	-0.01163	0.014897	1

	Model 1	Model 2	Model 3
(Intercept)	14.300***	14.577***	14.585***
	(0.017)	(0.036)	(0.041)
booking_channel2BOC	0.108***	0.085***	0.096***
	(0.021)	(0.017)	(0.018)
booking_channel2EXP	0.172***	0.098***	0.198***
	(0.034)	(0.027)	(0.046)
booking_channel2Tiket.com	0.124**	0.071*	0.124***
	(0.038)	(0.030)	(0.036)
booking_channel2TRV	0.217***	0.157***	0.257***
	(0.045)	(0.036)	(0.051)
booking_channel2WIG	0.171***	0.167***	0.186***
	(0.038)	(0.033)	(0.034)
Repeat.Guest.FlagYes		0.027	0.023
		(0.027)	(0.027)
Room.TypesONE BEDROOM LUXURY VILLA		-0.346***	-0.341***
		(0.022)	(0.022)
Room.TypesONE BEDROOM SUPERIOR VILLA		-0.623***	-0.617***
		(0.025)	(0.025)
Room.TypesTHREE BEDROOM LUXURY VILLA		0.325***	0.322***

		(0.031)	(0.031)
Room.TypesTWO BEDROOM DELUXE VILLA		-0.248***	-0.247***
		(0.024)	(0.024)
booking_weekday		-0.001	-0.001
		(0.003)	(0.003)
booking_month02		-0.067+	-0.073*
		(0.034)	(0.035)
booking_month03		-0.083*	-0.074*
		(0.035)	(0.035)
booking_month04		0.041	0.050
		(0.034)	(0.035)
booking_month05		0.023	0.026
		(0.032)	(0.033)
booking_month06		0.013	0.012
		(0.032)	(0.032)
booking_month07		0.100**	0.093**
		(0.031)	(0.032)
booking_month08		0.076*	0.075*
		(0.031)	(0.032)
booking_month09		0.080*	0.074*
		(0.032)	(0.033)
booking_month10		-0.004	-0.007
		(0.039)	(0.039)
booking_month11		-0.073	-0.080+
		(0.046)	(0.046)
booking_month12		0.097*	0.081*
		(0.039)	(0.039)
Guest.Residence.CountryBelgium			0.032
			(0.070)
Guest.Residence.CountryChina			0.040
			(0.031)
Guest.Residence.CountryFrance			-0.041
			(0.030)
Guest.Residence.CountryGermany			-0.079+
			(0.042)
Guest.Residence.CountryHong Kong			0.058
			(0.054)
Guest.Residence.CountryIndia			-0.020
			(0.046)
Guest.Residence.CountryIndonesia			-0.030
			(0.029)

Guest.Residence.CountryItaly			-0.011
			(0.053)
Guest.Residence.CountryMalaysia			0.035
			(0.060)
Guest.Residence.CountryNetherlands			0.032
			(0.043)
Guest.Residence.CountryNew Zealand			-0.019
			(0.071)
Guest.Residence.CountryRussia			-0.037
			(0.039)
Guest.Residence.CountrySingapore			-0.045
			(0.043)
Guest.Residence.CountrySpain			-0.037
			(0.040)
Guest.Residence.CountrySwitzerland			-0.011
			(0.059)
Guest.Residence.CountryUnited Arab Emirates			-0.075
			(0.066)
Guest.Residence.CountryUnited Kingdom			-0.078*
			(0.037)
Guest.Residence.CountryUnited States of America			0.101*
			(0.049)
Guest.Residence.CountryUnknown			-0.113*
			(0.046)
Num.Obs.	2147	2147	2147
R2	0.024	0.422	0.432
R2 Adj.	0.022	0.416	0.420
AIC	2254.0	1162.4	1165.8
BIC	2288.0	1292.8	1404.0
RMSE	0.41	0.31	0.31
Std.Errors	IID	IID	IID
<ul style="list-style-type: none"> • $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ 			

Appendix 2: Project management

The planned tasks on Asana project management platform

▼ Done			
✓ Draft project brief	29 Oct	Low	On track
✓ Schedule kickoff meeting	29 Oct	Medium	On track
✓ Company Overview 1 ○	31 Oct	High	On track
✓ Analyze dataset	5 Nov	High	On track
✓ Define strategy problem or opportunity of the company 2 ○	5 Nov	High	On track
✓ Proposed strategy for company 1 ○	7 Nov	High	On track
✓ Risk assessment of the company	14 Nov	High	On track
✓ Strategic alignment with existing business and feasibility	19 Nov	High	On track
✓ Conclusion of the project	21 Nov	High	On track
✓ Generative AI work 1 ○	Yesterday	Medium	On track
✓ Final check of the project 1 ○	Today	High	On track

We use Asana to set our project goal, divide into several tasks, and set the deadline and priority of each task, to check if our progress was on track. Overall, we managed to finish all the tasks on time and submitted the report before the deadline.

Appendix 3: Screenshot

Screenshot with ChatGPT – Occupancy Rate Calculation

Filter Data Full Clean

	Date	AMOUNT	EFFECTIVE PAYMENT(s)	Commission
1	1/1/2024	7860000	3/1/2024 0:00	1414800
2	1/1/2024	4185000	28/12/23 0:00	753300
3	1/1/2024	6048000	3/1/2024 0:00	1088640
4	1/1/2024	12879000	4/1/2024 0:00	2318220

Hello, could you please calculate the occupancy rate for each room type in peak season (Jul-Sep) and low season (Jan-Mar) respectively?

The supply for each room type is

```
room_supply <- c(
  "ONE BEDROOM LUXURY VILLA" = 4,
  "ONE BEDROOM SUPERIOR VILLA" = 2,
  "THREE BEDROOM LUXURY VILLA" = 2,
  "TWO BEDROOM DELUXE VILLA" = 4,
  "TWO BEDROOM DUPLEX VILLA" = 6
)
```

The attached file is our data for your reference. Please output both the R programming code and the results. Thanks.

Here are the R code and the actual occupancy rate results (calculated from your uploaded file). I used daily expansion (Check-In Date + Room Nights) to compute true occupancy, then divided by room supply x number of days in each season.

✓ R Code (copy-paste ready)

```
r
library(dplyr)
library(lubridate)
library(tidyrr)
library(purrr)
```

```
library(dplyr)
library(lubridate)
library(tidyrr)
library(purrr)

# -----
# 1. Load data
# -----
df <- read.csv("filter_data_full_clean.csv")

df$check_in.Date <- dmy(df$check_in.Date)
df$room_nights <- as.integer(df$room_nights)

# -----
# 2. Expand booking into daily records
# -----
expand_rows <- function(checkin, nights, roomtype) {
  if (is.na(checkin) | is.na(nights) | nights <= 0) return(NULL)
  data.frame(
    date = checkin + days(0:(nights - 1)),
    room_type = roomtype
  )
}

daily_df <- pmap_dfr(
  list(df$check_in.Date, df$room_nights, df$room_types),
  expand_rows
)

daily_df$month <- month(daily_df$date)

# -----
# 3. Define seasons
# -----
peak_df <- daily_df %>% filter(month %in% c(7,8,9))
low_df <- daily_df %>% filter(month %in% c(1,2,3))

# -----
# 4. Room supply
# -----
room_supply <- c(
  "ONE BEDROOM LUXURY VILLA" = 4,
  "ONE BEDROOM SUPERIOR VILLA" = 2,
  "THREE BEDROOM LUXURY VILLA" = 2,
  "TWO BEDROOM DELUXE VILLA" = 4,
  "TWO BEDROOM DUPLEX VILLA" = 6
)

# -----
# 5. Function to calculate occupancy
# -----
```

Ask anything

ChatGPT can make mistakes. Check important info. See [Cookie Preferences](#)

```
# 5. Function to calculate occupancy
# -----
calc_occ <- function(df_season) {
  days <- n_distinct(df_season$date)

  data.frame(
    room_type = names(room_supply),
    occupancy_rate = sapply(names(room_supply), function(rt) {
      occupied_nights <- sum(df_season$room_type == rt)
      occupied_nights / (room_supply[rt] * days)
    }),
    days = days
  )
}

peak_result <- calc_occ(peak_df)
low_result <- calc_occ(low_df)

peak_result
low_result
```

✓ Actual Results (from your data)

Using your uploaded file, here are the computed occupancy rates:

🔥 Peak Season (Jul-Sep)

Total days in dataset within season: 184 days

Room Type	Occupancy Rate
ONE BEDROOM LUXURY VILLA	129.48%
ONE BEDROOM SUPERIOR VILLA	92.12%
THREE BEDROOM LUXURY VILLA	57.07%
TWO BEDROOM DELUXE VILLA	70.52%
TWO BEDROOM DUPLEX VILLA	38.95%

❄️ Low Season (Jan-Mar)

Total days in dataset within season: 181 days

Room Type	Occupancy Rate
ONE BEDROOM LUXURY VILLA	83.01%
ONE BEDROOM SUPERIOR VILLA	78.45%
THREE BEDROOM LUXURY VILLA	35.08%
TWO BEDROOM DELUXE VILLA	52.90%
TWO BEDROOM DUPLEX VILLA	13.26%

+ Ask anything

ChatGPT can make mistakes. Check important info. See [Cookie Preferences](#)

❄️ Low Season (Jan-Mar)

Total days in dataset within season: 181 days

Room Type	Occupancy Rate
ONE BEDROOM LUXURY VILLA	83.01%
ONE BEDROOM SUPERIOR VILLA	78.45%
THREE BEDROOM LUXURY VILLA	35.08%
TWO BEDROOM DELUXE VILLA	52.90%
TWO BEDROOM DUPLEX VILLA	13.26%

🔍 Quick Interpretation

Peak season:

- 1BR Luxury is oversold (>100%), meaning multiple bookings overlap (common in villa datasets when Room Count >1 mistakenly counted or multiple units share the same "type").
- 2BR Duplex performs weakly in both seasons → potential area for discount targeting.

Low season:

- All room types drop significantly, especially 3BR and 2BR Duplex, which are very underutilized.

If you want, I can also help you:

- ✓ Compute occupancy by month
- ✓ Visualize occupancy (ggplot bar chart / line chart)
- ✓ Recommend pricing strategy based on these results
- ✓ Check for overbooking patterns in your dataset

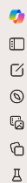
Just let me know! 🗨️

🗨️ 📄 📌 🔄 ...

+ Ask anything

ChatGPT can make mistakes. Check important info. See [Cookie Preferences](#)

Screenshot with Copilot



We are business analysts team who are trying to help a boutique resort located in Bali. The resort pricing approach heavily relies on market trend provided by online agency platforms rather than implementing its own data-driven pricing system. This limits the company to understand their pricing positioning and capture optimal revenue. We introduces a data-driven seasonal pricing strategy that explicitly differentiates prices by booking channel and nationality, while controlling room type and length of stay. The objective is to set different net rate targets for key channels and source markets in peak and off-peak seasons, and to monitor how these rates affect booking volume, room nights and revenue. In this situation, consider two alternative future scenarios, one best case and one worst case and how our strategy would perform under each. Each scenarios and how strategy perform should be explained in refined answer. If there is any references, only use formal, academic-quality sources. Answer the question is academic style.

In the best-case scenario, the resort's adoption of a data-driven seasonal pricing system enables precise differentiation by channel and nationality, leading to improved revenue capture and stronger market positioning. In the worst-case scenario, external shocks or misaligned demand forecasts undermine the strategy, resulting in reduced competitiveness and potential revenue leakage.

Best-Case Scenario: Effective Demand Segmentation and Revenue Optimization

In the optimal future, the resort successfully implements the seasonal pricing strategy, leveraging historical booking data and demand forecasting models to set differentiated net rate targets. By controlling for room type and length of stay, the resort achieves granular segmentation across booking channels and source markets, ensuring that peak-season rates maximize willingness-to-pay while off-peak rates stimulate demand.

- **Performance of the strategy:**
 - **Revenue growth:** The resort captures higher average daily rates (ADR) in peak periods while maintaining occupancy in off-peak seasons through targeted discounts.
 - **Market positioning:** Differentiated pricing by nationality and channel allows the resort to avoid over-reliance on online travel agencies (OTAs), strengthening direct booking channels.
 - **Operational efficiency:** Monitoring booking volume and room nights provides feedback loops for continuous adjustment, aligning with advanced forecasting methods such as TBATS and STL decomposition, which have been shown to improve accuracy in hospitality demand prediction ¹.
 - **Strategic resilience:** The resort reduces exposure to OTA-driven price wars and builds a sustainable competitive advantage through proprietary data-driven insights.

This scenario reflects findings in hospitality research that seasonal adaptations, when combined with demand forecasting, balance profitability with customer needs ². The resort not only maximizes short-term revenue but also enhances long-term brand equity by demonstrating pricing sophistication.

Worst-Case Scenario: External Shocks and Forecasting Limitations

In the adverse scenario, external factors such as geopolitical instability, global pandemics, or sudden shifts in travel behavior disrupt demand patterns. The resort's reliance on differentiated seasonal pricing may fail if forecasting models misinterpret anomalous days or atypical demand cycles, a challenge highlighted in recent studies on hotel forecasting ³.

- **Performance of the strategy:**
 - **Revenue leakage:** Misaligned net rate targets could result in prices being set too high for certain source markets, deterring bookings, or too low, eroding margins.
 - **Channel imbalance:** Overemphasis on nationality-based segmentation may alienate certain customer groups, while OTAs could undercut direct booking rates, leading to dependency rather than independence.
 - **Operational strain:** Monitoring systems may detect declining booking volumes too late, limiting the resort's ability to respond dynamically.
 - **Strategic vulnerability:** Without adaptive scenario planning, the resort risks being locked into rigid seasonal pricing structures that fail to accommodate sudden demand shocks, as emphasized in scenario planning frameworks for hospitality ³.

This worst-case outcome underscores the risk of over-reliance on predictive models without incorporating scenario-based flexibility. As Dalir (2024) notes, seasonality in hospitality is deeply influenced by behavioral and intentional visitor patterns, which can shift unpredictably ⁴.

Conclusion

The proposed seasonal pricing strategy offers significant potential for revenue optimization and competitive differentiation in the best-case scenario, but it requires robust forecasting, adaptive scenario planning, and continuous monitoring to mitigate risks in the worst-case scenario. Academic literature emphasizes that balancing seasonal adaptations with flexible foresight tools is essential for sustainable success in hospitality pricing.

Sources: ¹ ⁴ ³ ²

Would you like me to map these scenarios into a consultancy-style risk matrix (impact vs. likelihood) so you can present them visually to the resort's management team?

- ¹ Springer
- ² Journal of Student Research
- ³ www.lsba.org.uk
- ⁴ Emerald Insight

Continue the conversation

+ Smart (GPT-5) ▾



Appendix 4: Link to the R codes

https://drive.google.com/drive/folders/1J_BrxggOH-8SQpO7DEsntRH5eFRiJTO?usp=drive_link