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UNDERSTANDING HOTEL BOOKING BEHAVIOUR THROUGH RESERVATION PATTERNS AND CUSTOMER CHARACTERISTICS

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ABSTRACT

The cancellations of hotel bookings pose significant operational and revenue management problems as the bookings recorded in the systems do not necessarily translate to actual bookings. This study investigated the hotel booking behaviour in order to determine the factors affecting the cancellation of the booking. After cleaning the data, a quantitative secondary data design was used for 118,564 valid hotel reservations. The analysis of booking volume, seasonality, customer categories, lead time, duration of stay, deposit type, market segment, previous booking history, and special requests was performed in descriptive statistics, chi-square test, group comparison, correlation analysis and binary logistic regression. The general cancellation rate was 37.3%, with City Hotel reservations having a higher cancellation rate than Resort Hotel reservations. Repeat customers showed more consistent booking behaviour, while transient customers and new customers were more likely to cancel. The lead time for cancelled reservations was significantly longer than for non-cancelled reservations. The strongest categorical association was with deposit type, and previous cancellations were a significant risk factor for cancellation. On the other hand, frequent guests and extra special requests were strong factors in decreasing the chance of cancellation. Seasonal differences were also seen for the arrival month. The results presented herein illustrate how reservation timing, booking trends, customer characteristics, conditions of deposit, hotel classification, and engagement cues can be used to help forecast customer cancellations, communicate with customers, and manage hotel revenue by risk.

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1. Introduction

To manage demand, optimise room availability, minimise revenue loss, and enhance service delivery, the hotel industry has come to heavily rely on the right information about customer booking patterns. Prices and locations are no longer the only factors determining a hotel booking; other factors such as customer characteristics, booking channels, previous experience, perceived risk, online information, service expectations and the conditions of the hotel reservation are also playing a part.

The way travellers are searching and booking accommodation has been revolutionised by digital platforms. The quality of a website, the accuracy of information, the usability, the perceived usefulness, and customer satisfaction affect whether customers will proceed with booking online or drop out (Ahmad & Sharma, 2025). However, trust is also a significant factor, particularly when customers rely on information provided by the platform and the service providers' disclosures to carefully consider the credibility of an accommodation option (Akhtar & Siddiqi, 2024). Likewise, when the booking website or platform is reliable and user-friendly, confidence in the system can boost purchase intentions, as can consumer participation and electronic word-of-mouth (Kumar et al., 2020). Guest interaction with information on the hotel website is thus a key element of the booking process, and customers assess the hotel's service description, policy, availability and perceived value before confirmation (Selem et al., 2024).

One of the most important sources of information in the selection of hotels is online reviews. Customers tend to rely on ratings, user experiences and review sentiment to make decisions and to evaluate alternatives to alleviate uncertainty. The review quality and price can indirectly influence the booking intention by increasing or decreasing the trust in an online travel agency (Christin & Nugraha, 2022). The impact of the reviews on the customers' decision may be further adjusted with other elements such as hotel brand image, star category, and room price (El-Said, 2020). Apart from that, the emotional tone of online reviews is also significant as it affects the purchase intent of accommodation differently when there is a positive or negative topic of review (Sim et al., 2021). The impact of online reviews may also vary based on the broader traveller orientation, as customers from other countries may be influenced differently by destinations and properties that they do not know. The context of travellers' orientation also has the potential to influence the impact of online reviews, as customers from overseas may be more or less affected when they encounter unfamiliar destinations and properties (Tran, 2020). Therefore, the relationship among online reviews, brand reputation, and price is an important basis of hotel booking decisions (Wen et al., 2021). Incorporate ratings and reviews from several sites, which could enhance hotel comparison and selection by offering a more holistic view of the perceived quality of service (Zhao et al., 2021).

Travellers are not all the same and prefer different things. The type of hotel chosen may depend on the trip's objective, the level of service, the level of flexibility in making bookings, the size of the group, the level of price sensitivity, and the desired hotel features (Boto-García et al., 2021). Additionally, engaging with the website and its ratings, along with the advice from trusted online figures, can affect booking decisions due to their perceived credibility and influence (Kareem & Venugopal, 2023). With the hospitality sector finally beginning to recover from the pandemic, consumers are now paying attention to the quality of service as well as the value of what they are eating, along with factors of health, convenience and cost (Ray et al., 2023). The influence of perceived risk could be more pronounced among travellers who are travelling alone or going to unfamiliar places, where electronic word-of-mouth can build up self-confidence or reinforce doubts (Islam et al., 2024).

However, external conditions can also affect the behaviour of making hotel reservations. In times of uncertainty, consumers can react strongly to perceived threats, concerns for safety and their confidence in coping with risks associated with travel (Apaolaza et al., 2022). The willingness of customers to book during these times may be affected by brand loyalty or the nature of hotel promotions (Ju & Jang, 2023). In fact, the research on quarantine accommodation reveals that perceived usefulness, risk, trust, and service expectations all influence the likelihood of booking a quarantine under unusual travel circumstances (Wu et al., 2022). The results of this research show that a combination of routine consumer preference and situational pressures influences the behaviour of consumers when booking a hotel.

While previous work has focused on the topic of online reviews, booking intent, website quality, trust, and perceived risk, less research attention has been paid to the combination of actual booking patterns and customer characteristics to explain booking outcomes. There may be behavioural differences evident in variables that are not captured by intention-driven research, such as length of stay, previous hotel cancellations, return customer status, deposit status, booking source, and special requests.

Research Objectives

1.To analyze hotel reservation patterns by booking periods, hotel categories and customer groups.

2.To evaluate the association between customer features and booking cancellation behaviour.

3.To determine the most important factors in the reservations and customer which can be used to predict hotel booking cancellations.

2. Methodology

2.1 Research Design

In this study quantitative and explanatory in nature research design was used to explore the behaviour of the hotel booking because of reservation patterns and characteristics of the customers. A secondary data approach was chosen because the research was to be conducted using data from hotel reservations that had been previously recorded. The main objective of the study was to identify factors contributing to booking cancellation and to compare the behavioural patterns between the different categories of customers and reservations.

2.2 Data Source

The publicly available Hotel Booking Demand dataset was used for the study. The data set had 119,390 entries of reservations and 32 variables related to hotels in the city and resort and their reservations, made from 2015 to 2017 (Mostipak, 2019). It contained booking lead time, arrival period, length of stay, customer type, guest composition, market segment, distribution channel, room category, deposit type, previous booking history, average daily rate, special requests and booking status.

2.3 Unit of Analysis and Study Sample

The unit of analysis was at the hotel reservation level. Each row in the table was a booking and did not represent an individual customer. All the data was considered at first. Data cleaning was performed as records with missing, invalid or contradictory information were considered, but eliminated only if the analysis required it.

2.4 Study Variables

The dependent variable was booking cancelled, with 0 indicating a booking that was not cancelled and 1 indicating a booking that was cancelled. The independent variables were hotel type, lead time, arrival month and year, weekend/weekday nights, customer type, number of adults, number of children and babies, repeat guest, previous room cancellations, market segment, distribution channel, type of deposit, reserved room type, average daily rate, room change, parking space requests, and total special requests. Weekend nights were added to weekday nights to determine the total length of stay.

2.5 Data Cleaning and Preparation

All data were checked for missing data, duplicate records, and outlier data, as well as implausible observations and inconsistent categories. The data were completed for children when appropriate, and missing values for country and agent were recoded as “Unknown” and “No Agent.” Because of the high rate of missing data, the company variable was not included in the main analysis. Records that lack guests, have zero-night stays, negative average daily rates and extreme values were examined and handled by exclusion, recoding and/or sensitivity analysis.

2.6 Descriptive Analysis

Categorical variables like hotel type, customer type, cancellation status, deposit type, market segment and repeat-guest status were summarised using frequencies and percentages. Continuous variables like lead time, ADR, LoS, booking changes and special requests were calculated and processed with means, standard deviations, median and ranges. Seasonality was also explored by using monthly and annual cycles to establish seasonal variations in booking numbers and booking and cancellation patterns.

2.7 Inferential Analysis

The chi-square test was used to examine associations between booking cancellation and categorical variables. Independent-samples t-tests or Mann–Whitney U tests were used to compare continuous variables between cancelled and non-cancelled bookings. For more than two customer groups, comparisons were made using analysis of variance or the Kruskal-Wallis test. Pearson or Spearman correlation analysis was used to examine relationships between continuous variables in the reservations.

2.8 Logistic Regression Analysis

Logistic regression was performed to examine the factors influencing reservation cancellation and customer factors influencing customer cancellation. Binary logistic regression was conducted to determine the factors that influence the cancellation of reservations and the customer factors that influence the cancellation of customers. Model variables were hotel type, lead time, length of stay, customer type, repeat guest, previous cancellations, deposit type, market segment, distribution channel, average daily rate, and special requests. Odds ratios, 95%

confidence intervals, regression coefficient and p-values were reported.

2.9 Model Assessment

Variance inflation factor and tolerance statistics were used to check for multicollinearity. The Nagelkerke R2, classification accuracy, sensitivity, specificity, precision, F1 score, and area under the receiver operating characteristic curve were used to measure model performance. A two-tailed ($p<0.05$) was considered statistically significant.

2.10 Ethical Considerations

This Research was conducted with an anonymised and publicly available secondary data set, which did not contain any personally identifiable customer data. Customers and staff of the hotel were not contacted directly. Hence, informed consent of the individual participant was not necessary, but the source of the original data set should be cited in the article.

3. Results

3.1 Data Screening and Analytical Sample

The initial Hotel Booking Demand data set had 119,390 records related to booking reservations. There were 118,564 bookings after excluding 180 that had no reported guests, 715 that were zero-night reservations, and 13,008 that had invalid negative average daily rates. The final sample consisted of 78,899 City Hotel bookings and 39,665 Resort Hotel bookings. A total of 44,176 reservations were cancelled, accounting for 37.3% of the total, and another 74,388 reservations were not cancelled.

3.2 Descriptive Characteristics of Hotel Reservations

Table 1 describes the bookings analysed. The booking lead time was positively skewed, with an average booking lead time of 104.51 days, but a median of 70 days. The average number of nights stayed in the hotel was 3.44, and the average number of adults per room booking was about two people. The average daily rate was 102.52, and the average number of special requests made per booking was 0.57.

Table 1. Descriptive statistics of the hotel reservations

Variable	N	Mean	SD	Median	Minimum	Maximum
Lead time, days	118,564	104.51	106.92	70.00	0	709
Total stay, nights	118,564	3.44	2.53	3.00	1	69
Adults	118,564	1.86	0.58	2.00	0	55

Children	118,564	0.10	0.40	0.00	0	10
Average daily rate	118,564	102.52	50.00	95.00	0	5,400
Special requests	118,564	0.57	0.79	0.00	0	5

The volume of reservations fluctuated from month-to-month as seen in Figure 1. August saw the highest number of bookings, followed by July and May, while January saw the lowest number of bookings. The pattern shows a definite peak in hotel demand in the mid part of the year, suggesting a seasonal hotel demand pattern.

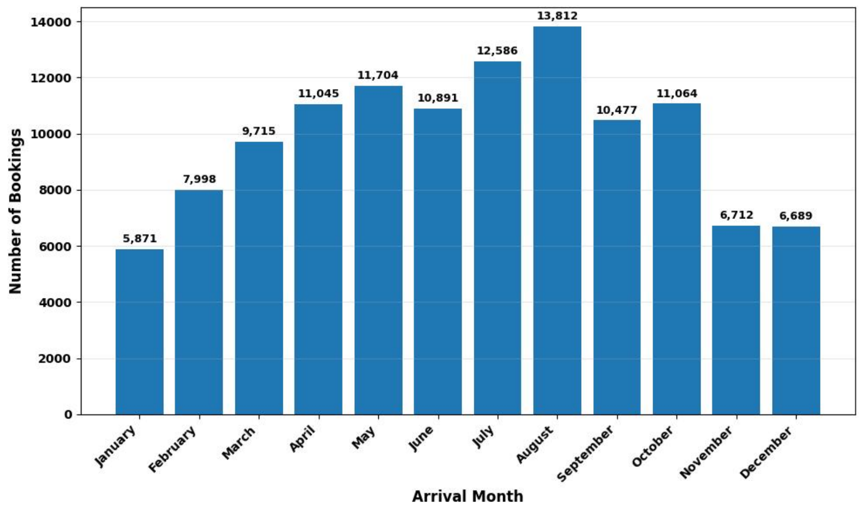

Figure 1. Monthly distribution of hotel booking volume

3.3 Cancellation Patterns Across Reservation and Customer Characteristics

As presented in Table 2, the hotel and customer category cancellation pattern was very different. The Resort Hotel cancellation rate was 28.0% while the City Hotel cancellation rate was 41.9%. The highest cancellation rate was experienced by transient customers (41.0%) and the lowest was experienced by group customers (10.2%). The cancellation rate among the first-time guests, however, was 37.9%, while that of the repeated guests was 15.7%. The non-refundable deposit reservations had an extremely high cancellation rate, indicating that the terms of the deposit strongly predicted the actual booking.

Table 2. Cancellation patterns by selected booking and customer characteristics

Characteristic	Category	Bookings	Cancellation rate (%)
Hotel type	City Hotel	78,899	41.9
	Resort Hotel	39,665	28.0
Customer type	Contract	4,056	31.1
	Group	569	10.2
	Transient	88,935	41.0

	Transient-Party	25,004	25.5
Repeated guest	No	115,066	37.9
	Yes	3,498	15.7
Deposit type	No Deposit	103,911	28.4
	Non Refund	14,535	99.4
	Refundable	118	22.9

The distinction of City Hotel v Resort Hotel bookings is shown graphically in Figure 2. Consistently, the City Hotel bookings were more likely to be cancelled. Figure 3 further demonstrates substantial variation across customer types, with transient bookings producing the highest cancellation rate and group bookings producing the lowest. This also shows significant differences between customer types, as the transient booking type had the highest cancellation rate, and the group booking type had the lowest.

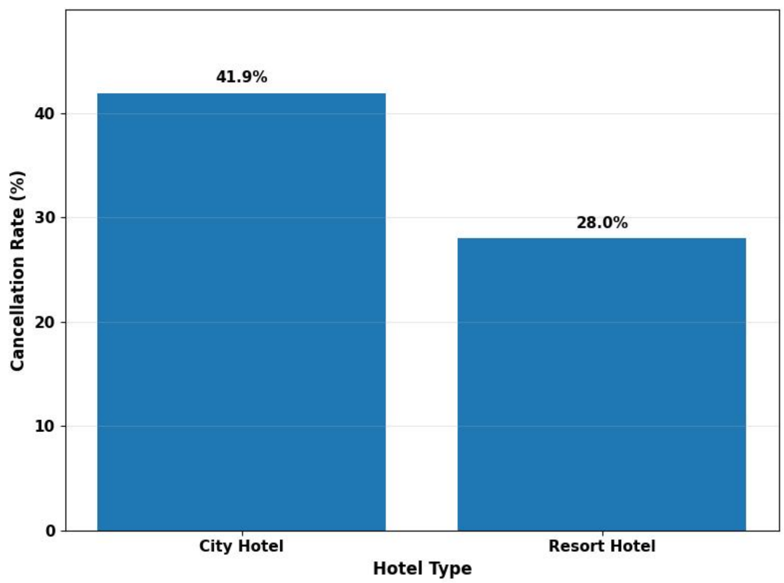

Figure 2. Cancellation rate by hotel type

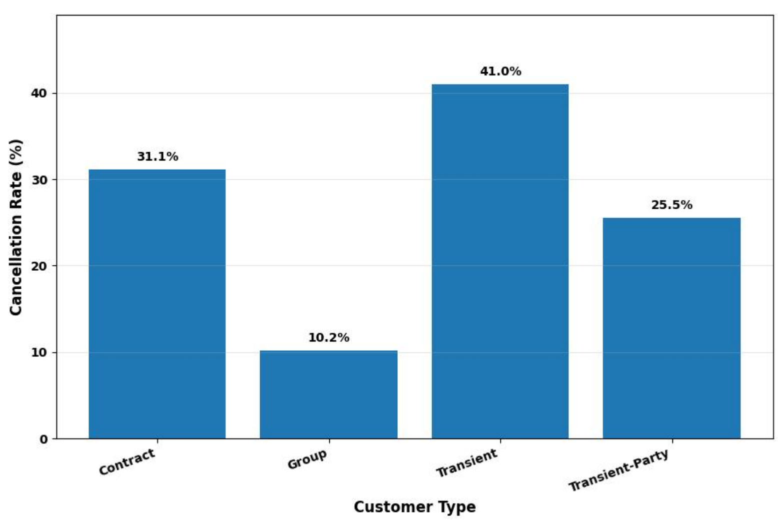

Figure 3. Cancellation rate by customer type

3.4 Seasonal Variation in Booking Cancellation

The cancellation rates per month were between 30.7% and 41.6% for each month from January to June. The comparatively high cancellation rates were in April, May and June, and the lower rates were in November, March and January. The monthly results are shown in Table 3 and in Figure 4.

Table 3. Monthly booking volume and cancellation rates

Arrival month	Number of bookings	Cancellation rate (%)
January	5,871	30.7
February	7,998	33.6
March	9,715	32.4
April	11,045	40.9
May	11,704	39.9
June	10,891	41.6
July	12,586	37.6
August	13,812	37.9
September	10,477	39.3
October	11,064	38.4
November	6,712	31.6
December	6,689	35.4

There were substantial jumps in the cancellation rate between March and April and June, as shown in Figure 4. It then dropped in July and August but then increased a little in September. These results suggest that the highest cancellation rate was not necessarily the most consistent with the highest booking volume.

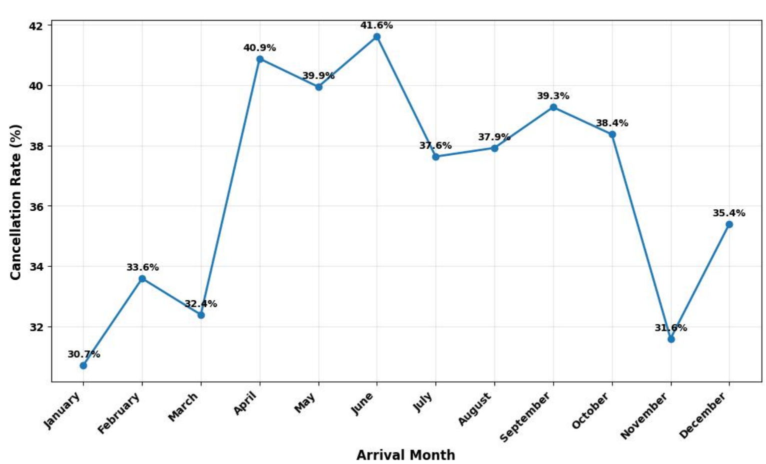

Figure 4. Monthly variation in hotel booking cancellation rates

3.5 Comparison of Cancelled and Non-Cancelled Reservations

Cancelled bookings were typically made before completed bookings. The mean lead time for cancelled reservations was 144.95 days, and for non-cancelled reservations, it was 80.49 days, as shown in Table 4. This difference was statistically significant and had a medium rank-biserial effect size. The average length of stay was slightly longer for cancelled reservations, as was the average daily rate.

Table 4. Comparison of cancelled and non-cancelled hotel reservations

Variable	Non-cancelled Mean ± SD	Cancelled Mean ± SD	Rank-biserial r	p-value
Lead time, days	80.49 ± 91.20	144.95 ± 118.61	0.376	<0.001
Total stay, nights	3.42 ± 2.54	3.49 ± 2.52	0.036	<0.001
Average daily rate	101.01 ± 48.41	105.08 ± 52.49	0.052	<0.001
Booking changes	0.29 ± 0.72	0.10 ± 0.45	−0.137	<0.001
Special requests	0.72 ± 0.83	0.33 ± 0.65	−0.273	<0.001
Previous cancellations	0.02 ± 0.27	0.21 ± 1.33	0.127	<0.001

The connection between the booking lead time and the booking cancellation is further illustrated in Figure 5. The cancellation rate rose gradually for each of the lead time categories, suggesting that the longer one booked ahead, the more likely they were to back out, compared to those who booked closer to the day of arrival.

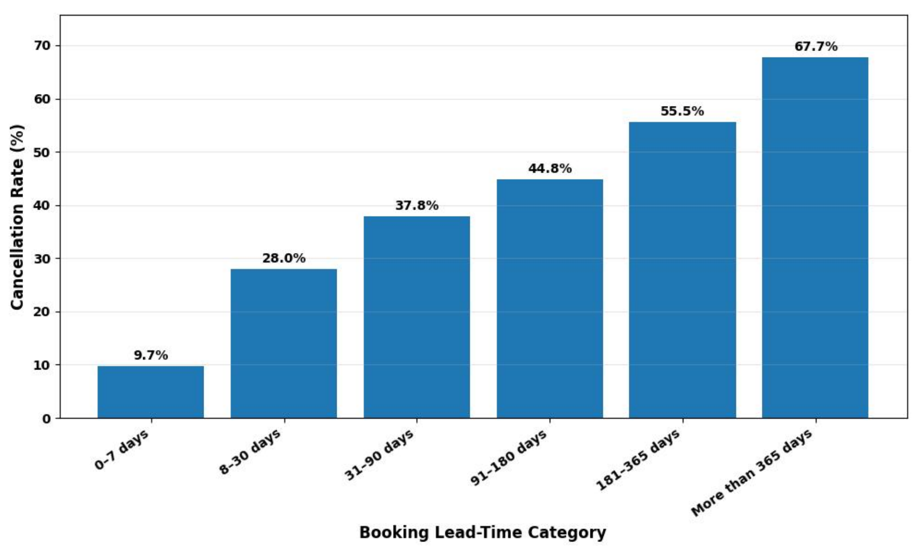

Figure 5. Cancellation rates across booking lead-time categories

3.6 Associations Between Categorical Characteristics and Cancellation

All of the major categorical characteristics examined were associated with the booking cancellation in a statistically significant way according to the chi-square tests. The strongest association was for deposit type (Cramér's V = 0.481) as shown in Table 5

Table 5. Chi-square associations between booking characteristics and cancellation

Variable	χ^2	df	Cramér's V	p-value
Hotel type	2,180.90	1	0.136	<0.001
Customer type	2,251.32	3	0.138	<0.001
Repeated-guest status	716.05	1	0.078	<0.001
Deposit type	27,445.46	2	0.481	<0.001
Market segment	8,419.76	7	0.266	<0.001
Distribution channel	3,699.18	4	0.177	<0.001

3.7 Predictors of Hotel Booking Cancellation

To determine the characteristics of the reservation and customers that are each independently associated with cancellation, binary logistic regression was performed. The other predictors were controlled for, and the probability of cancellation was found to be approximately 17.7% lower for Resort Hotel bookings than for City Hotel bookings.

The Nagelkerke R^2 of the regression model was around 45.0%. The area under the receiver operating characteristic (ROC) curve was 0.826, showing good discriminatory performance. The overall classification accuracy of the model was 79.7%, with a sensitivity of 55.3%, specificity of 94.2%, precision of 85.0% and an F1 score of 0.670.

The receiver operating characteristic curve is shown in Figure 6. The curve was still significantly above the diagonal reference line, indicating that the model was able to categorize cancelled and non-cancelled bookings significantly better than a random classification.

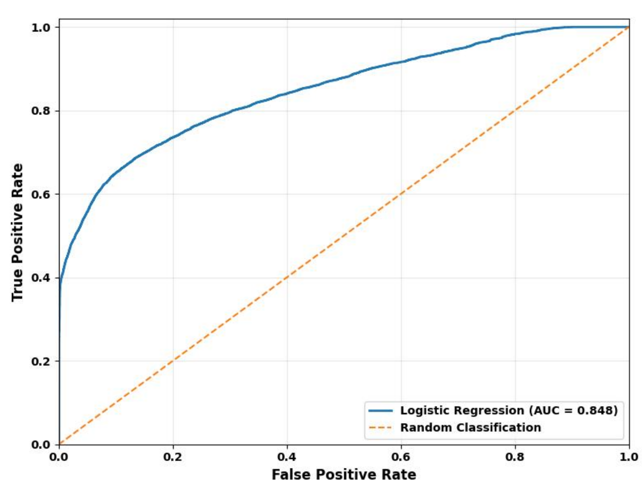

Figure 6. Receiver operating characteristic curve for the booking-cancellation model

3.8 Summary of Findings

The findings also show that the patterns in hotel bookings and the customers' attributes were each significant factors in shaping the behavior of hotel booking. The factors associated with a higher cancellation risk were City Hotel reservations, transient customers, online travel agent bookings, longer lead times, previous bookings that were cancelled, and non-refundable deposits. On the other hand, frequent guests and more special requests dramatically decreased the prospect of cancellation. Seasonality was also noted, with the most cancellations taking place in the season of April-June and the highest number of bookings in July-August.

4. Discussion

The results indicate that the different factors related to the reservations, customer history, booking conditions and hotel type influence hotel booking behaviour. Those who had booked a City Hotel were more likely to cancel their reservations than those who had booked a Resort Hotel, and transient customers, first-time guests, bookings that were made far in advance, and reservations with previous cancellation history had a greater cancellation risk. These patterns validate the need for reservation-level data to inform demand management and revenue planning at the reservation level.

One of the most powerful behavioural indicators was lead time. Increased chance of cancellation with higher lead time categories, cancelled reservations made much earlier than non-cancelled. This means that people booking rooms very early in the process might be in a more difficult situation when it comes to planning their trip, booking the room, making their own decisions, etc., as well as have more uncertainty about where they will stay if the room is not available. Other studies showed that lead time is an essential factor since the longer the interval between reservation and arrival, the higher the chance for customers to change or cancel their plans (Saputro & Nanang, 2021). Studies based on predictions have also revealed that the timing of the reservation is a significant factor in the classification of the cancellations and should be considered with hotel forecasting models (Andriawan et al., 2020; Rusakova & Radionova, 2021).

The categorical association with cancellation was more significant for deposit type. The cancellation rate for non-refundable reservations was unexpected, and the adjusted odds ratio was quite large. Non-refundable policies are normally designed to prevent cancellation, but this outcome could be based on the makeup of specific market segments, group deals or booking processes that are recorded. It can also mean that the type of deposit is dependent upon lead time, distribution channel or customer category. Predictive research revealed that the effects of cancellation factors are not independent of each other (Chen et al., 2023). Hotels should therefore not presume that tougher payment terms will lead to fewer cancellations but should take into account the type of customers and channels the policy is being enforced on.

Booking behaviour was also very significant in previous years. More previous cancellations gave the guest a higher chance of canceling, while repeat visitors had quite significantly lower chances of cancellation. This means consistency in behaviors over different reservations. Repeat guests may be more knowledgeable about the hotel, more trusting, more defined in their expectations, and may have more solid plans for travel. Customers who have cancelled in the past might have a recurring lack of confidence or booking patterns that take advantage of the process. The results suggest that historical reservation data can be used for the prediction of cancellations and customer-risk segmentation. Similar to the comparative modelling studies, previous cancellations and repeated-guest status can also enhance the accuracy of the cancellation models (Chen et al., 2022; Tekin & Gök, 2021).

There was a negative relationship between the number of special requests and cancellation. Those who made more requests might be more committed to the hotel stay since they've interacted with the hotel about their preferences or service requirements. These interactions can suggest a higher level of decision-making and commitment to making a reservation. This might consequently serve as a viable indicator of customer engagement. Special-request behaviour, together with repeat-guest history and booking changes, should help hotels identify high-commitment reservations from those that need a reminder of the booking or targeted communication.

Seasonal variations were also noted. Booking volumes were highest at the mid-point of the year and cancellation rates fluctuated from month to month, with the peak occurring over some of the busy periods. This demonstrates that the realised demand does not necessarily rise with a high volume in reservations. When forecasting room occupancy, managers should take into account the number of bookings as well as the likelihood of cancellations. (Fiori & Foroni, 2020). Incorporating several behavioural variables in the big-data approach and continuously updating cancellation probabilities, as done in Sánchez-Medina & Caballero-Sánchez (2020), could enhance forecasting further.

The logistic regression model had fair discrimination (AUC of ROC = 0.826). This indicates that the chosen factors related to customers and reservations could differentiate between cancelled and non-cancelled at a useful level. The lower sensitivity than specificity, however, means that some cancellations were tricky to identify (Chen et al., 2022; Chen et al., 2023). The performance of algorithms has been compared in the past, and it has been found that the algorithm's performance depends on the data preprocessing, class balance, feature selection, and evaluation measures (Rusakova & Radionova, 2021; Tekin & Gök, 2021).

The results of the research have important implications for demand forecasting beyond the constraint of structured reservation information (Wu et al., 2024). Future demand and booking confidence can be further gained from the topics of the online reviews and the attitude of the customers.

5. Conclusion

This research study analyzed hotel booking behaviour using the patterns of hotel bookings and characteristics of the users who cancel their hotel bookings. The results revealed that there are more than one determinant of cancellation behaviour, not a single reservation attribute. Factors that increased the likelihood of cancellations were city hotel bookings, transient customers, longer booking lead time, previous cancellation history, online travel agent reservations, and non-refundable deposits. Repeated guests and customers who placed more special requests, however, exhibited more stable levels of booking behavior and less likelihood of cancellation. There was also a seasonality factor, as booking and cancellation rates also varied by arrival months. The results show that a high demand for reservations does not necessarily mean that the reservations are filled, especially when cancellations rise at high volume. The model had a good discriminatory ability, showing the ability to use reservation and customer information to identify bookings with a high cancellation risk. The study has practical value for hotel management to help in better forecasting of demands, communication to customers, flexible pricing strategy and different cancellation policies. Hotels can gain better operational planning by tracking lead time, engagement indicators like special requests, booking history, customer type, and the condition of the deposits. Additional research can incorporate customer demographics, satisfaction data, sentiment from online reviews, and booking behaviour in real-time to create more detailed and adaptive hotel demand models.

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