IJRDO- Journal of Tourism and Hospitality

Published by: **IJRDO JOURNAL**
ISSN (Online): **XXXX XXXX**
Doi: XXXXXXX
Volume 01 | Issue 01 | March 2026

PREDICTINGHOTEL BOOKING CANCELLATIONS USINGMACHINE LEARNING: ADATA-DRIVEN STUDY OFCITY AND RESORT HOTELS

Sanagavarapu Sunitha
School of Science and Computer Studies, CMR University,
Bangalore, India. Email: sanagavarapu.sunitha@cmr.edu.in ; ORCID: 0000-0003-1167-2112

Corresponding Author: Sanagavarapu Sunitha

ABSTRACT

In the face of hotel booking cancellations, there is significant uncertainty regarding the hotel properties' occupancy planning, revenue management, staffing, and inventory control. To analyse the cancellation patterns at City Hotels and Resort Hotels, and to assess several machine learning models to forecast the risk of booking cancellations. This analysis will consider characteristics related to the behaviour of the customer, transactional characteristics, and reservation characteristics such as lead time, deposit type, customer type, market segment, changes to reservations, special requests, previous cancellations, repeated-guest status and changes to room assignments. The analysis revealed that the cancellation rate was higher when booking a City Hotel compared to booking a Resort Hotel, and that cancelled bookings had on average, a higher lead time and more positive prior cancellation indicators. Large differences were also found between the categories of deposits, groups of customers, market segments and room change. In the context of recall, Random Forest achieved the best result, suggesting its use in cases where the primary goal is to capture as many potentially cancellable items as possible. Room changes, booking channels, parking needs, past cancellations, and special requests were among the other variables that emerged as secondary predictors, with deposit-related variables being the strongest.

Key words : hotel booking cancellation; machine learning; Random Forest; revenue management; predictive analytics; City Hotels

Article History:
Article Type: **Review**
Received Date: **07/10/2025** | Revised Date: **23/12/2025** | Accepted Date: **26/02/2026** | Published Date: **24/03/2026**

1. Introduction

The cancellation of hotel bookings is a long-standing problem that is part of the set of issues in the hotel sector. A cancelled reservation can impact room revenue, occupancy planning, administration costs, staffing, pricing and inventory decisions. The number of people booking online has been rising alongside its popularity, resulting in a more streamlined booking process, but also more flexible bookings and missed appointments. Users can look at multiple properties, make reservations well ahead of time and cancel with minimal financial penalty.

The hospitality industry has undergone a digital revolution that has transformed how it gathers, manages and leverages customer and booking data. Today, artificial intelligence and big data analytics comes into play in the tourism and hospitality industry in demand prediction, customer segmentation, pricing, automation of services, recommendation systems and operational decisions (Samara et al., 2020). In addition, artificial intelligence has enabled the processing of extensive amounts of transaction data to generate actionable insights, thereby enhancing the capabilities of hotels for more effective and evidence-based management decisions (Doborjeh et al., 2022).

The traditional basis for hotel demand forecasting is historical occupancy, booking pace, seasonal patterns, market conditions and managerial experience. But these approaches might not be sufficient to capture the complex and nonlinear relationships of booking behavior. Recent studies have thus focused on the use of artificial intelligence and machine learning as more flexible prediction methods for hotel demand and outcomes (Huang & Zheng, 2023). Recent reviews have shown that the advantage of machine learning models is that they can incorporate additional behavioural, transactional, and contextual information for improved forecasting, which is not possible with traditional statistical methods (Henriques & Pereira, 2024). The factors impacting booking cancellations vary and are interdependent: lead time, deposit requirements, booking channel, market segments, type of customer, cancellation history, room assignment, average daily rate, and special requests. Online shoppers can also exhibit strategic behaviour by keeping multiple options in their shopping list and keeping only the best one in the final list near the time of arrival (Masiero et al., 2020). This problem is especially appropriate for machine learning, as it enables the classification of the reservations based on learning patterns from the historical booking characteristics. Algorithms like logistic regression, decision tree, random forest, gradient boosting, support vector machine and XGBoost can detect linear and nonlinear associations between the cancellation status and the factors likely to cause it. In recent years, segmented machine learning methods have been proposed for enhancing the predictability of occupancy and demand in hospitals related to different groups of customers and markets (Ampountolas & Legg, 2021). The value of clustering and predictive modelling has also been shown to recognise the diverse flow of demand and enhance the performance of hotel forecasting (Kaya et al., 2022).

Artificial Intelligence in tourism has gone from being experimental to offering actual assistance with pricing, capacity management, marketing and even customer relationship decisions. However, the body of literature is scattered in terms of technologies, hospitality settings and analytical goals (Knani et al., 2022). An analysis of empirical application reviews reveals that there are several studies addressing general demand forecasting or service automation problems, but few studies directly compare the cancellation pattern and predictive models for different types of hotels (Saydam et al., 2022).

Customers staying in City Hotels and Resort Hotels are likely to have different booking and cancellation habits, due to different travel objectives, time spent at the hotel, purchasing habits, and level of flexibility. Leisure travel, seasonality and longer planning horizons are some factors that can affect resort demand, and these influences present a case for using specialised forecasting techniques (Dowlut & Gobin-Rahimbux, 2023). In contrast, City Hotels might find that a higher fraction of these three types of reservations – short, business, or intermediary – cancel. This classification of hotels can therefore be more informative in terms of managerial lessons drawn from the comparisons made than a single homogeneous group of bookings.

The COVID-19 pandemic was a further reminder of hotel demand being sensitive to uncertainty, travel restrictions, evolving risk perceptions, and flexible booking cancellations. In response to the crisis, the hotels re-evaluated their

marketing strategies, booking conditions and methods of communicating with the customer (Jiang & Wen, 2020). It also fostered the growing demand for technology-enabled, resilient and flexible management systems that can adjust to the rapid evolution of tourism behaviour (Sigala, 2020).

The developments in generative and predictive AI further fuel the potential for automated customer contact, forecasting, and decision-making within the hospitality industry (Rather, 2025). But to achieve effective adoption, it is essential to have a clear understanding of the predictive performance of the model, and the variables that help make the model decisions. For this reason, in the present work, several machine learning models are applied and compared to predict hotel booking cancellations and identify the most important characteristics related to the cancellation of hotel bookings.

Research Objectives

1. To investigate and compare the booking cancellation pattern of city hotels and resort hotels.
2. To develop and test several machine learning models to forecast hotel booking cancellations.
3. To determine the highest value booking and customer-specific predictors of canceller risk.

2. Methodology

2.1 Research Design

The study adopted quantitative and secondary data analysis and predictive design to analyze the hotel booking cancellations. Supervised machine learning classification was used as the outcome variable was being classified as cancelled or not cancelled.

2.2 Dataset Description

This dataset, Hotel Booking Reservation, was sourced from Kaggle and used in the study (Bedmutha, 2024). This dataset has 119,390 reservations and 33 variables, of which 79,330 are City Hotel reservations, and 40,060 are Resort Hotel reservations. The target variable is_canceled has been encoded as 1 = cancelled booking, 0 otherwise.

2.3 Variables

Predictors were hotel type, lead time, arrival month, length of stay, number of guests, meal type, market segment, distribution channel, repeated guest, previous cancellations, room type, booking changes, deposit type, customer type, average daily rate, parking requirement, and special requests.

2.4 Data Cleaning and Preprocessing

The proportion of missing values, invalid records and extreme observations was analysed. Due to high rates of missing data, the company variable was dropped. Records that had no guests, no stay nights or negative average daily rates were reviewed and excluded as appropriate. Categorical variables were one-hot encoded, and numerical variables were standardised for models that are scale sensitive. The total stay time and total number of guests were also computed.

2.5 Prevention of Data Leakage

These variables are not included because they directly indicate the final booking status: reservation_status and reservation_status_date. Their removal ensured that the models predicted the cancellations based on only the information they had before they knew whether the reservation had been cancelled or not.

2.6 Exploratory Analysis

The data on booking characteristics and cancellation patterns were summarized using descriptive statistics. City Hotel and Resort Hotel, type of deposit, market segment, Customer type, and Month of arrival, and previous cancellation history were evaluated.

2.7 Machine Learning Models

Stratified sampling was used to split the data into 70% training and 30% testing data. The following models were developed: Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost and Support Vector Machine models. To optimize the model, five-fold cross-validation and hyperparameter tuning were performed.

2.8 Model Evaluation

Evaluation metrics used for the models were: accuracy, precision, recall, specificity, F1-score, confusion matrix and ROC-AUC. The most important predictors of the hotel booking cancellations have been identified using the features and SHAP values. Comparisons were also made separately for City Hotels and Resort Hotels.

2.9 Ethical Issues

For this research, secondary data was collected, which is publicly available and de-identified. Hence, the process did not require any human involvement, and hence there was no need for informed consent and ethics approval. The data analysis was conducted for research purposes only and presented objectively.

3. Results

3.1 Dataset Characteristics

The Hotel Booking Reservation dataset had 119,390 records of reservations, with 79,330 of those made by City Hotels and 40,060 by Resort Hotels. A total of 44,224 reservations were cancelled, with a 37.04% cancellation rate overall. The remaining 75,166 reservations, which number to 62.96% of the total, were not cancelled. Table 1 gives a summary of the general characteristics of the data set.

Table 1. General characteristics of the Hotel Booking Reservation dataset

Characteristic	Frequency	Percentage
Total reservations	119,390	100.00
City Hotel reservations	79,330	66.45
Resort Hotel reservations	40,060	33.55
Cancelled reservations	44,224	37.04
Non-cancelled reservations	75,166	62.96

3.2 Cancellation Patterns by Hotel Type

The cancelled booking rate for City Hotels was 41.73% (33,102/79,330). Table 2 shows that Resort Hotels have 11,122 of their 40,060 bookings cancelled, representing a lower level of cancellation (27.76%). There was a significant difference between the type of hotel and whether they cancelled their trip or not. As shown in Figure 1: Cancellation rate comparison between City Hotel and Resort Hotel, there was a higher cancellation rate for City Hotel as compared to Resort Hotel, the rate was around 14 percentage points higher for City Hotel.

Table 2. Booking cancellation status according to hotel type

Hotel type	Non-cancelled	Cancelled	Total	Cancellation rate (%)
City Hotel	46,228	33,102	79,330	41.73
Resort Hotel	28,938	11,122	40,060	27.76

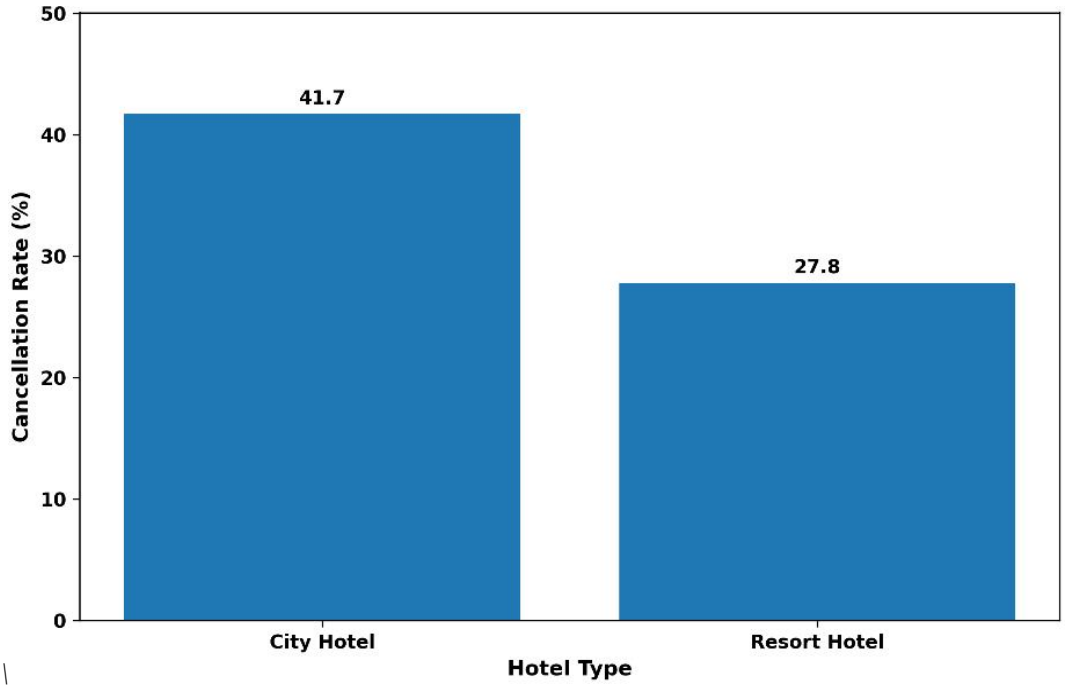

Figure 1. Comparison of booking cancellation rates between City Hotels and Resort Hotels

3.3 Numerical Characteristics of Cancelled and Non-Cancelled Bookings

Various numerical reservation characteristics were significantly different between the cancelled and non-cancelled reservations. For the cancelled reservations, the average lead time was significantly longer than the non-cancelled reservations, 144.85 days vs. 79.98 days, as shown in Table 3. The average daily rate of cancelled bookings was also slightly higher and the cancellations of previous bookings were greater. The number of booking changes and special requests was higher for non-cancelled bookings. On non-cancelled bookings, the average special request was 0.71, but it was only 0.33 for cancelled bookings. All differences reported were significant at ($p<0.001$). The monthly cancellation rates are not too bad, between 36.53% in March and 37.95% in November. The distribution of the booking cancellation rate by month has been stable and without any month showing a disproportionately high or low booking cancellation rate (36.53%–37.95%), indicating that the influence of booking level attributes is more important than the month of arrivals, as shown in Figure 2.

Table 3. Comparison of numerical variables by booking status

Variable	**Non-cancelled Mean ± SD**	**Cancelled Mean ± SD**	**p-value**
Lead time	79.98 ± 91.11	144.85 ± 118.62	<0.001
Average daily rate	99.99 ± 49.21	104.96 ± 52.57	<0.001
Total stay duration	3.39 ± 2.58	3.49 ± 2.52	<0.001
Total guests	1.94 ± 0.67	2.01 ± 0.80	<0.001
Previous cancellations	0.02 ± 0.27	0.21 ± 1.33	<0.001

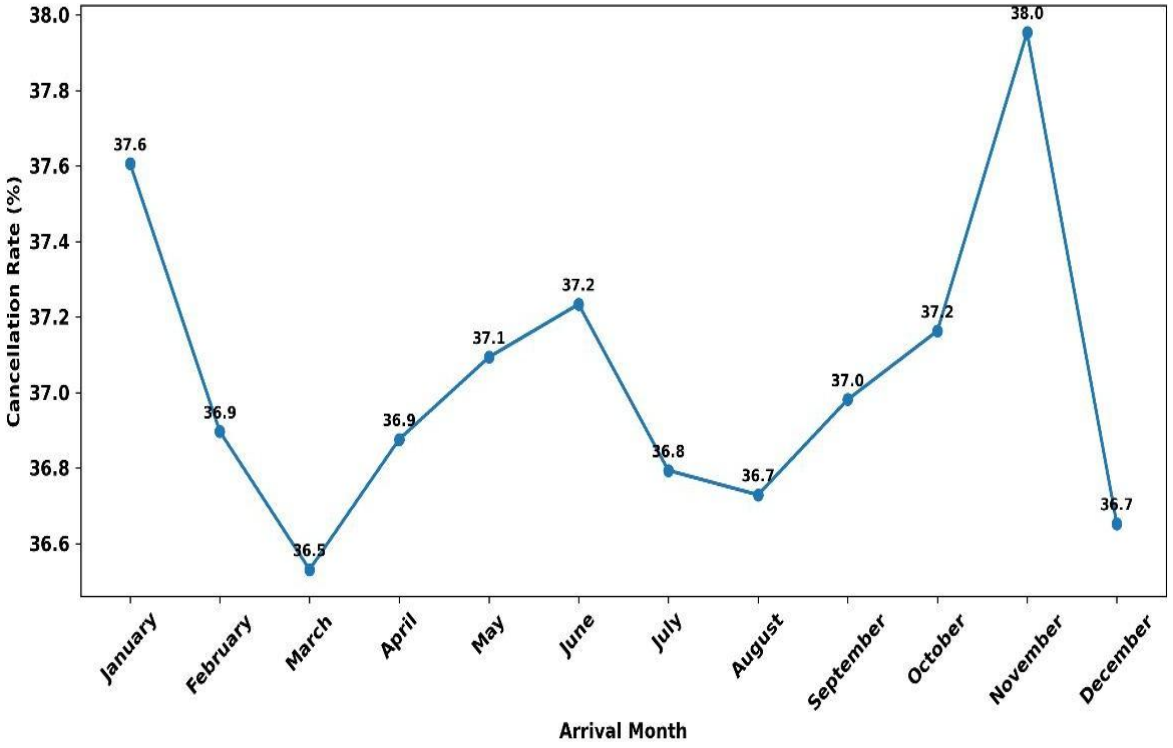

Figure 2. Monthly variation in hotel booking cancellation rates across the study period

3.4 Cancellation Rates Across Reservation Categories

Significant differences were found among deposit types, customer types, market segments, repeat guests, and room-assignment conditions. The non-refundable bookings had the highest cancellation rate of 99.36% as reported in Table 4. No-deposit and refundable bookings were at 28.38% and 22.22% cancellation rates, respectively. The cancellation rate for transient customers was 40.75% and that of group customers was the lowest at 10.23%. The highest cancellation rate was for the group market segment at 61.06%. First-time and non-repeated guests were less likely to cancel than were repeated guests.

Table 4. Cancellation rates across selected categorical variables

Variable	Category	Bookings	Cancelled	Cancellation rate (%)
Deposit type	No Deposit	104,641	29,694	28.38
Deposit type	Non Refund	14,587	14,494	99.36
Deposit type	Refundable	162	36	22.22
Customer type	Contract	4,076	1,262	30.96
Customer type	Group	577	59	10.23
Customer type	Transient	89,613	36,514	40.75
Customer type	Transient-Party	25,124	6,389	25.43

Market segment	Direct	12,606	1,934	15.34
Market segment	Groups	19,811	12,097	61.06
Market segment	Offline TA/TO	24,219	8,311	34.32
Market segment	Online TA	56,477	20,739	36.72
Repeated guest	No	115,580	43,672	37.79
Repeated guest	Yes	3,810	552	14.49
Room changed	No	104,473	43,422	41.56
Room changed	Yes	14,917	802	5.38

3.5 Machine Learning Model Performance

An independent test sample of 30% was used to test 5 machine learning models. The results of their performances are shown in Table 5. Overall accuracy was the maximum at 86.78% for XGBoost, and precision was the highest at 84.97%, specificity was the highest at 91.76%, F1 Score was the highest at 81.54%, and the ROC-AUC value was the highest at 0.943 for XGBoost. Random Forest had the highest recall score at 84.12%, which meant that it was able to correctly identify a higher percentage of actual cancellations. But it was less accurate of an algorithm compared to XGBoost, suggesting that it made more false positive predictions of cancellation. Figure 3 shows the ROC curve comparison of Logistic Regression, Decision Tree, Random Forest, Linear SVM, and XGBoost, with the highest AUC (0.943) being from the XGBoost model, revealing that all five models outperform the random classification. The best performance (the largest area under the ROC curve) was observed by the XGBoost model, followed by the Random Forest and the Decision Tree models.

Table 5. Comparative performance of machine learning models

Model	**Accuracy**	**Precision**	**Recall**	**Specificity**	**F1-score**	**ROC-AUC**
Logistic Regression	0.827	0.743	0.821	0.831	0.780	0.912
Decision Tree	0.850	0.798	0.799	0.880	0.798	0.930
Random Forest	0.850	0.776	0.841	0.856	0.807	0.934
Linear SVM	0.828	0.749	0.810	0.838	0.778	0.908

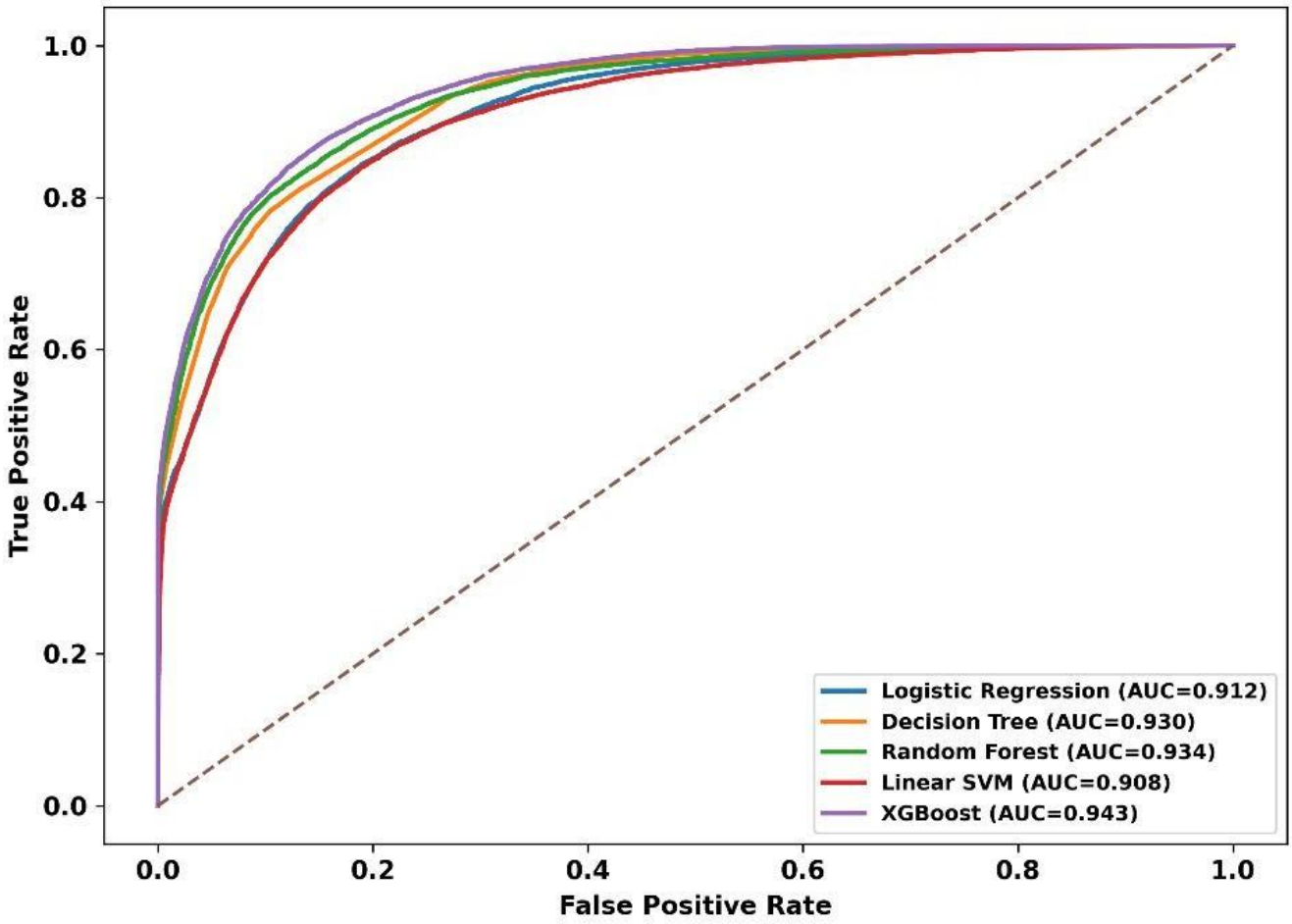

Figure 3. Receiver operating characteristic (ROC) curves comparing the predictive performance of the machine learning models

3.6 Confusion Matrix of the Best-Performing Model

In the test set, the XGBoost model was able to correctly classify 20,479 bookings that were not cancelled and 10,388 cancelled bookings. Table 6 and Figure 4 show that 1,838 bookings that were not cancelled were incorrectly classified as cancelled and there were 2,865 bookings that were cancelled but were not correctly classified as cancelled.Table 6 and Figure 4: Confusion matrix of XGBoost model showing correct and incorrect classification counts for cancelled and non-cancelled bookings give an incorrect classification of 1,838 bookings as cancelled, and an incorrect non-cancelled classification of 2,865 bookings. The confusion matrix shows that XGBoost was the best model for predicting no bookings to be cancelled. Model performance was satisfactory with 78.38% Recall rate, meaning that it missed around 20% of the actual cancellations.

Table 6. Confusion matrix results for the XGBoost model

Actual booking status	**Predicted non-cancelled**	**Predicted cancelled**
Actual non-cancelled	20,479	1,838
Actual cancelled	2,865	10,388

Figure 4. Confusion matrix of the best-performing XGBoost model for hotel booking cancellation prediction

3.7 Important Predictors of Booking Cancellation

The feature importance analysis revealed that the most significant factor for booking cancelation is the type of the deposit. Noddep and non-refund category together made up a significant part of the XGBoost model's predictive importance. Some additional predictive factors were room changes, online travel-agent bookings, needed parking spaces, booking agents, country, past cancelations and special requests. Table 7 and Figure 5 show the top 10 predictors and their importance to the booking cancellation prediction, respectively: Feature importance ranking of top 10 predictors for booking cancellation with deposit type variables dominating. Deposit-related variables were the most significant variables in the model, and the previous cancellation and special request variables also contributed to prediction, as seen in Figure 5.

Table 7. Leading predictors identified by the XGBoost model

Rank	Predictor	Importance
1	No-deposit booking	0.242
2	Non-refundable deposit	0.239
3	Room changed	0.047
4	Online travel-agent market segment	0.039

5	Required parking spaces	0.032
6	Agent 9	0.028
7	Agent 240	0.027
8	Portugal customer origin	0.017
9	Previous cancellations	0.015
10	Total special requests	0.014

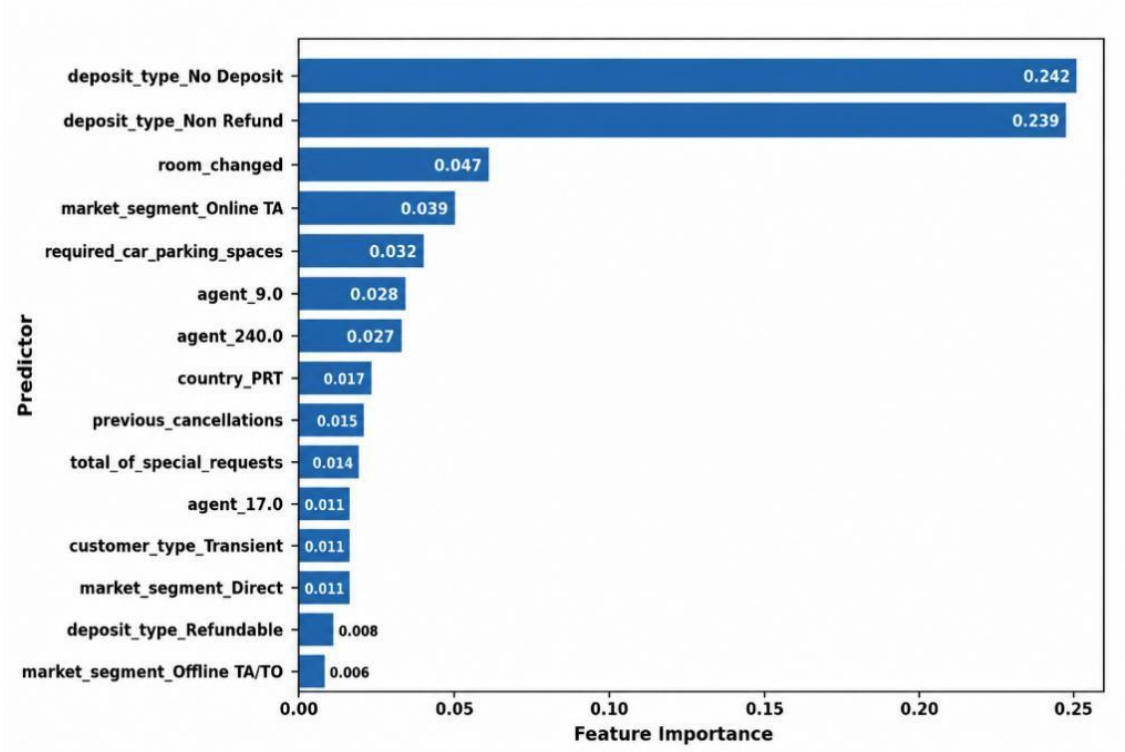

Figure 5. Feature-importance ranking of the major predictors of hotel booking cancellation identified by the XGBoost model

3.8 Summary of Findings

The outcomes revealed that there was a significant difference between the Resorts and the Cities Hotels with respect to cancellation risk. Cancelled bookings had a longer lead time, had more cancellations in the past, had fewer booking changes and had fewer special requests. The evaluation results showed that XGBoost was the most predictive algorithm among the evaluated algorithms, and the highest cancellation recall was obtained by the Random Forest algorithm. Deposit type was the top predictor of cancellation ahead of room-assignment changes, online travel-agent reservations, parking requirements, past cancellation rate, and special requests.

4. Discussion

This study's results show that machine learning can be used to accurately predict hotel booking cancellations when

the characteristics of hotel reservations, customer behavior and booking conditions are considered. The total cancellation rate was high, indicating that cancellation is still a significant issue for hotel managers.

There was an interesting difference in terms of cancellation rate: City Hotels had a significantly higher rate of cancellations than Resort Hotels. This variation might be due to differences in the purpose of travel, booking flexibility, distribution channels, and commitment (Caballero Sánchez et al., 2020).

It became apparent that there is an important behavioural factor known as lead time. The average lead time was much longer for cancelled reservations than for non-cancelled bookings, showing that bookings made further ahead were more likely to be cancelled due to changes in customer plans. Longer lead times allow for more time to reconsider destinations, prices or travel plans before arriving at a final decision. The same trend was found in previous cancellation history, with cancelled bookings having more history of cancellations, which means that past behaviour is a good indicator of future cancellation risk (Sánchez-Medina & Caballero Sánchez, 2020).

Deposit type was the strongest predictor in the XGBoost model. There were very few non-refundable bookings and those that were made had an extremely high cancellation rate, while there were no real differences in no-deposit and refundable bookings. Non-refundable policies are designed to discourage cancellations and to look after revenue, but the correlation with customer behavior can be more involved. These can be tied to specific market segments, tour operators, pricing models or reservation requirements. Moderate cancellation policies can, therefore, strike the right balance between customer flexibility and the hotel's financial performance compared to overly rigid or overly flexible policies (Altin et al., 2023). Post-pandemic travellers are also more conscientious about cancellation policies and perceived risk, which can be directly affected by policy design to influence booking confidence and cancellation decisions (Kim et al., 2023).

The results also indicated that market segment, customer type, repeat customers, room changes, booking changes and special requests had an impact. Group reservations had a higher cancellation rate, while those who booked the same property on multiple occasions had a lower cancellation rate. This implies that if a customer has been exposed to the property in the past or heard about it, their commitment to the property may be increased as a result of this. Likewise, when there are room changes and special requests, this could mean that the customer is more engaged with the product, further decreasing the chances of customer cancellation. The patterns indicate that there may be multiple interacting variables that influence cancellation behaviour, rather than a single isolated factor (Chen et al., 2023).

The overall best performing model among the ones evaluated was XGBoost, having the highest accuracy, specificity, F1 and ROC-AUC. Random Forest had the best recall, which is important if the management goal is to identify as many possible cancellations as possible. The better results of ensemble models are coherent with the results of previous hotel cancellation studies, where it was observed that the nonlinear models can better capture the complex relationship between the multiple features defined for the hotel compared to simpler classifiers (Herrera et al., 2024).

Managerial implications of the difference between recall and specificity. A model with a high recall value will have fewer high-risk reservations that are misclassified as stable, but a higher specificity will mean more low-risk customers who are not unnecessarily intervened upon. The XGBoost confusion matrix indicated that there were relatively few false positives and false negatives when compared with the total test set, meaning that both of these objectives are well balanced. However, the accuracy is not the only criterion for evaluation as class imbalance can cause a misleading impression of model performance. In cases where the distribution of classes may not be balanced in terms of cancelled and non-cancelled, the hybrid method and resampling techniques have been suggested to improve the cancellation prediction (Adil et al., 2021). However, to measure the performance of a binary classification beyond accuracy, it is possible to use metrics like the F1 score and Matthew’s correlation coefficient (Chicco & Jurman, 2020).

The explainability of models is also critical as hotel managers need to know why a reservation is deemed high risk. Deposit conditions, room changes, booking channels, parking requirements, country, previous cancellations and special requests were key features identified using feature importance. Explainable model analysis allows for the analysis of the overall model behaviour as well as individual predictions, which helps to boost managerial trust (Biecek & Burzykowski, 2021). Additionally, complex ensemble predictions can be explained in a comprehensible way for both global and local effects using the help of tree-based approaches (Lundberg et al., 2020).

While it has a high level of predictive power, it is important to recognize that the feature importance does not necessarily mean that the feature causes the model to make the prediction. A variable may be included in the prediction without directly causing the cancellation to occur. Interpretable machine learning, however, demands that models be carefully inspected, judged in the context, and communicated as having limitations (Molnar, 2022). Other literature also emphasizes simplicity, fairness, robustness, and human interpretation alongside predictive accuracy when using models in organizational decision-making (Rudin et al., 2022).

5. Conclusion

In this study, it is shown that machine learning is a reliable and practical method to predict hotel bookings' cancellations and to aid in the effective decision-making of the revenue managers. The results showed that there was a significant difference in the cancellation rate between the City Hotels and the Resort Hotels, with City Hotels having a much higher cancellation rate. Other factors that were found to relate to cancellation behaviour were previous cancellations, longer lead times, market segment, customer type, booking changes, special requests, repeated-guest status, and room-assignment changes. When it comes to predictive performance, XGBoost had the best overall prediction accuracy, specificity, F1 and ROC-AUC among the evaluated models. The highest recall values were obtained for the performance of the Random Forest algorithm, which might be useful if the main purpose is to find the largest possible number of likely cancellations. The most significant factors were deposit type, room changes, booking channels, parking requirements, previous cancellations, and special requests. As a manager, predictive models can be useful to know which bookings are likely to be cancelled, how to optimize overbooking policies to reduce cancellation rates, how to better communicate with customers, and how to fine-tune cancellation and deposit policies. Model outputs, however, should be treated with great wisdom since predictive importance does not imply causation. Continuous model updating, transparent model interpretation, and continuous performance monitoring are therefore required.

References

1. Adil, M., Ansari, M. F., Alahmadi, A., Wu, J. Z., & Chakrabortty, R. K. (2021). Solving the problem of class imbalance in the prediction of hotel cancelations: A hybridized machine learning approach. Processes, 9(10), 1713.
2. Altin, M., Chen, C. C., Riasi, A., & Schwartz, Z. (2023). Go moderate! How hotels' cancellation policies affect their financial performance. Tourism Economics, 29(8), 2165-2182.
3. Ampountolas, A., & Legg, M. P. (2021). A segmented machine learning modeling approach of social media for predicting occupancy. International Journal of Contemporary Hospitality Management, 33(6), 2001-2021.
4. Bedmutha, K. S. (2024). Hotel booking reservation: An updated 2024 dataset for hotel booking demand and cancellation analysis [Data set]. Kaggle. https://www.kaggle.com/datasets/kundanbedmutha/hotel-booking-reservation
5. Biecek, P., & Burzykowski, T. (2021). Explanatory model analysis: explore, explain, and examine predictive models. Chapman and Hall/CRC.
6. Caballero Sánchez, E., Sánchez Medina, A. J., & Pellejero Silva, M. A. (2020). Identifying critical hotel cancellations using artificial intelligence. Tourism Management Perspectives.

7. Chen, S., Ngai, E. W., Ku, Y., Xu, Z., Gou, X., & Zhang, C. (2023). Prediction of hotel booking cancellations: Integration of machine learning and probability model based on interpretable feature interaction. Decision Support Systems, 170, 113959.
8. Chicco, D., & Jurman, G. (2020). The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. BMC genomics, 21(1), 6.
9. Doborjeh, Z., Hemmington, N., Doborjeh, M., & Kasabov, N. (2022). Artificial intelligence: a systematic review of methods and applications in hospitality and tourism. International journal of contemporary hospitality management, 34(3), 1154-1176.
10. Dowlut, N., & Gobin-Rahimbux, B. (2023). Forecasting resort hotel tourism demand using deep learning techniques–A systematic literature review. Heliyon, 9(7).
11. Henriques, H., & Pereira, L. N. (2024). Hotel demand forecasting models and methods using artificial intelligence: A systematic literature review. Tourism & Management Studies, 20(3), 39-51.
12. Herrera, A., Arroyo, A., Jiménez, A., & Herrero, Á. (2024). Forecasting hotel cancellations through machine learning. Expert Systems, 41(9), e13608.
13. Huang, L., & Zheng, W. (2023). Hotel demand forecasting: a comprehensive literature review. Tourism Review, 78(1), 218-244.
14. Jiang, Y., & Wen, J. (2020). Effects of COVID-19 on hotel marketing and management: a perspective article. International journal of contemporary hospitality management, 32(8), 2563-2573.
15. Kaya, K., Yılmaz, Y., Yaslan, Y., Öğüdücü, Ş. G., & Çıngı, F. (2022). Demand forecasting model using hotel clustering findings for hospitality industry. Information Processing & Management, 59(1), 102816.
16. Kim, E. J., Kim, E. L., Kim, M., & Tanford, S. (2023). Post-Pandemic hotel cancellation policy: Situational cues as perceived risk triggers. Journal of Hospitality and Tourism Management, 55, 153-160.
17. Knani, M., Echchakoui, S., & Ladhari, R. (2022). Artificial intelligence in tourism and hospitality: Bibliometric analysis and research agenda. International Journal of Hospitality Management, 107, 103317.
18. Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., ... & Lee, S. I. (2020). From local explanations to global understanding with explainable AI for trees. Nature machine intelligence, 2(1), 56-67.
19. Masiero, L., Viglia, G., & Nieto-Garcia, M. (2020). Strategic consumer behavior in online hotel booking. Annals of Tourism Research, 83, 102947.
20. Molnar, C. (2022). Interpretable machine learning: a guide for making black box models explainable, 2nd edn. Leanpub.
21. Rather, R. A. (2025). AI-powered ChatGPT in the hospitality and tourism industry: benefits, challenges, theoretical framework, propositions and future research directions. Tourism Recreation Research, 50(3), 652-662.
22. Rudin, C., Chen, C., Chen, Z., Huang, H., Semenova, L., & Zhong, C. (2022). Interpretable machine learning: Fundamental principles and 10 grand challenges. Statistic Surveys, 16, 1-85.
23. Samara, D., Magnisalis, I., & Peristeras, V. (2020). Artificial intelligence and big data in tourism: a systematic literature review. Journal of Hospitality and Tourism Technology, 11(2), 343-367.
24. Sánchez-Medina, A. J., & Caballero Sánchez, E. (2020). Using machine learning and big data for efficient forecasting of hotel booking cancellations. International Journal of Hospitality Management.
25. Saydam, M. B., Arici, H. E., & Koseoglu, M. A. (2022). How does the tourism and hospitality industry use artificial intelligence? A review of empirical studies and future research agenda. Journal of Hospitality Marketing & Management, 31(8), 908-936.
26. Sigala, M. (2020). Tourism and COVID-19: Impacts and implications for advancing and resetting industry and research. Journal of business research, 117, 312-321.

This article is licensed under a **Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY NC ND4.0)** License; copyright remains with the author(s).