WILL THEY COME OR NOT? THE INVESTIGATION OF THE NON-ATTENDANCE BEHAVIOR OF THE HOTEL GUESTS

Stepan CHALUPA
(Corresponding Author)
Czech Technical University in Prague, Masaryk Institute of Advanced Studies, Institute of Management Studies, Czech Republic
E-mail: stepan.chalupa@cvut.cz

Martin PETRICEK
Czech Technical University in Prague, Masaryk Institute of Advanced Studies, Institute of Economic Studies, Czech Republic
E-mail: martin.petricek@cvut.cz

Barbora KOKLAROVA
University College Prague,
Department of Management, Czech Republic
E-mail: koklarova@ucp.cz

Abstract

Purpose – This paper investigates cancellations and no-shows in hotel reservations using granular transaction data from a property management system. The aim is to identify typical behavioural patterns of guests who cancel their stays or fail to attend.
Methodology/Design/Approach – A dataset of 33,263 reservations was analysed using the CHAID decision tree model. Classification included various nominal and continuous variables: reservation status, number of guests, length of stay, distribution channel, gross rate, rate type, lead time, and number of rooms.
Findings – The analysis revealed that cancellations are more likely for reservations with long lead times and flexible cancellation policies. No-shows are more frequently associated with bookings at lower gross rates. Reservations made via intermediaries such as OTAs and wholesalers show higher cancellation and no-show rates compared to other channels.
Originality of the research – The study's originality stems from the use of detailed user transaction data, offering empirical evidence of customer behaviour in the hotel booking process. By analysing real operational data, the study contributes to a deeper understanding of cancellation and no-show behaviour, supporting more accurate forecasting and revenue management strategies in the hospitality industry
Keywords Customer behaviour, cancellation policy, bookings cancellations, hotel guest no-shows

Original scientific paper
Received 19 November 2024
Revised 07 July 2025
Accepted 10 September 2025
https://doi.org/10.20867/thm.32.3.1

INTRODUCTION

In current hotel revenue management research, much of the focus is on pricing methods, strategies, and customer behaviour regarding the acceptance or refusal of visibly offered rates with predefined booking characteristics. Revenue managers need to use empirical data to build solid and stable predictions of customers' behaviour, as booking cancellations and no-shows can significantly affect the quality of the prediction and lead to a loss due to overbookings. (Antonio et al., 2019)

Unrealised demand, in the form of reservation cancellations and no-shows, plays a significant role in current revenue management. Cancellations significantly impact hotel revenue and reputation, whereas proper cancellation forecasting might improve hotel performance (Sekhon & Ahuja, 2023). Both reputation and revenue might be harmed by implementing rigid cancellation policies and overbooking strategies (Antonio et. al, 2017). Furthermore, implementing cancellations and no-shows in the development of the overbooking strategy is essential to reach an optimal level of hotel occupancy and gross operational profit (Bertsimas & Popescu, 2003). The issue of no-shows and late cancellations was previously discussed by Toh (1985), who focused on overbooking strategies that were commonly established through a trial-and-error approach. The empirical data were not taken into account.

Romero Morales and Wang (2010) focused on forecasting cancellation rates, which should be considered when building comprehensive revenue forecasts and revenue management strategies. The authors concluded that it is more important to forecast and predict the cancellation rate in upcoming periods and seasons. In contrast, classifying reservations and focusing on predicting individual cancellations can be complicated when applied to hotel operations.

Cancellations and no-shows are particularly relevant to the hospitality industry and gastronomy (Chiang, 2023). The study by Chiang (2023) highlights the importance of understanding not only the cancellation behaviour of customers but also their no-shows and walk-ins, to effectively plan marketing and revenue management strategies and overcome issues such as overbooking or profit loss due to unrealised demand. Cancellation patterns based on historical data might significantly improve the quality of the forecasts (Phumchusri & Maneesophon, 2014).

As cancellation behaviour is primarily perceived as the rate taken into account when building overbooking strategies as part of a complex total revenue management strategy, a proper understanding of cancellation behaviour is lacking to predict possible cancellations more accurately and propose actions to minimise them. On the other hand, cancellations are only part of the non-attendance behaviour of the customers who skip their stay and do not show up (Hua et al., 2024). A nuanced understanding of non-attendance behaviour might strengthen the accuracy of revenue management forecasts, reduce financial losses, and enhance overall guest satisfaction. (Viverit et al., 2023)

This study aims to investigate the cancellations and no-shows of the selected accommodation using highly granular transaction data mined from the hotel's property management system, along with a classification CHIAD decision tree model.

1. LITERATURE REVIEW

Several studies in hospitality have focused solely on cancellation behaviour. Falk & Vieru (2018) analysed the data of a hotel chain in Finland, comprising 230,000 bookings with an 8% cancellation rate, to provide new insights into the factors driving hotel booking cancellations. The study employs a probit model to estimate the probability of booking cancellations. The study results show a higher cancellation rate for online bookings than offline bookings (a difference of 7 percentage points between online and offline and 13 percentage points for travel agencies). The model used showed a higher probability of cancellations for early bookings, large group bookings, and reservations made during high season, as well as for adults-only reservations and those made by guests from the selected countries. The most crucial factors in estimating the probability of booking cancellation were lead time and country of origin.

Antonio et al. (2019) adopted the CRISP-DM model for big data analysis through data mining. They focused on the empirical data of eight Portuguese hotels (four resorts and four city hotels) combined with the weather data, data about local events and holidays in guest source countries, social reputation mined from TripAdvisor.com and Booking.com (which was used as well as a source of pricing and availability data for the market). In the preliminary data analysis stage, the correlation between OTA share on bookings and cancellation rate for individual hotels was calculated, and a moderated correlation was found, which led to the previously mentioned estimate that online sources cause more cancellations (Falk & Vieru, 2018). The classification analysis provided additional results showcasing the effect of lead time, country of origin (similar to Falk & Vieru (2017)), agent type, and deposit type. It is crucial to note that the importance of the factors varies among individual accommodation facilities in the selection.

There may be identified studies that attempt to address the issues or cancellations in predictive models. For example, artificial intelligence may identify reservations with a higher likelihood of cancellation (another approach for classifying cases), particularly for those with shorter lead times (Sánchez et al., 2020). The artificial network was also used in another study, yielding similar results when focusing on reservations with shorter lead times (Sánchez-Medina & C-Sánchez, 2020).

Romero Morales and Wang (2010) focused on forecasting hotel cancellations, where the probability of reservation cancellation was estimated based on categorical and nominal variables. The authors concluded that cancellation behaviour varies over time, a finding later confirmed by the previously mentioned studies (Sánchez et al., 2020; Sánchez-Medina & C-Sánchez, 2020). The variability of the cancellation rate and cancellation behaviour over time was mentioned by Fouad et al. (2014), who focused on the development of an overbooking strategy based on simulations. These simulations utilised transaction data, emphasising the timing of reservations (date of arrival, length of stay), cancellations, or seasonality of demand. The consequences of an incorrectly developed overbooking strategy were discussed by Noone and Lee (2011), who focused on the compensation of hotel guests when accommodation was denied due to a lack of available rooms.

Other studies are focusing on the forecasting of hotel cancellations using different methodologies, for example, profit-driven extreme gradient boosting (XGBoost) (Liu et al., 2022), K-Nearest Neighbour classification model (Nababan et al., 2022), neural network method (Sekhon & Ahuja, 2023), classification models based on the Boosted Decision Tree, Decision Jungle, Locally Deep Support Vector Machine and Neural Network or machine learning (Antonio et al., 2017).

Antonio et al. (2017) used the CRIP-DM process to analyse the transactional data of selected accommodation facilities using historical data about individual reservations. The study is an extensive set of variables that comprehensively describe the hotel guests' behaviour regarding the realisation of their stays. The previously mentioned effect of time variables is proven, as well as the other behaviour, where more understanding of this domain is provided. The authors mention different cancellation behaviours by the distribution channel used by the hotel guest (mainly due to different cancellation policies applied) and the different rate types (flexible, semi-flexible or non-refundable). In addition, the authors point out that the customers' previous behaviour should be considered. The more stays were realised before the upcoming stays, the higher the probability of not being cancelled.

Smith et al. (2015) focused on the impact of the strictness of the cancellation policy on the quality of revenue forecasts and revenue generation. Revenue managers must balance the uncertainty (high revenue forecast errors) caused by flexible rates, demand fluctuations, and rate decreases while applying non-refundable rates and improving forecast quality. The study also has essential implications for hotel revenue managers, as there is no difference between free cancellations available the day before arrival and those with a 48-hour limit.

Cancellation behaviour is strongly connected to the cancellation policy applied by the accommodation facility (Smith, 2012). Currently, a very soft cancellation policy is applied for online best available rates (BAR), where clients can only choose between flexible reservations with a cancellation possibility up to a day before arrival or non-refundable rates with no refunds and full pre-payments. On the other hand, it is crucial to perceive the effect of the strictness level of the cancellation policy on revenue generation in terms of the number of realised demand and offered rates. A liberal cancellation policy leads to revenue forecasting errors and potential profit loss (Smith et al., 2015). Similar findings are also provided by other authors and studies (Chen et al., 2011; Xie & Gerstner, 2007).

The cancellation policy and levels of cancellation fees are strongly connected with the accepted rates, where the strict cancellation policy (and non-refundable offers) are commonly connected with the lower selling rates, and the flexibility should be perceived and additional service, which is charged by the service provider (Ancarani et al., 2009).

A free cancellation policy (or flexible or semi-flexible rates) allows customers to rebook their stay when prices drop prior to arrival (Masiero et al., 2020). At the same time, customers tend to book more options and postpone their decisions, leading revenue managers to prefer non-refundable offers. This behaviour significantly increases the cancellation rates and makes forecasting even more complicated.

Another demonstration of non-attendance behaviour is the phenomenon of no-shows. The client is not attending the stay, despite the reservation being created. To avoid no-shows, direct interaction with the client can be initiated after the reservations are processed, providing the guest with precise details about their stay and reducing the level of uncertainty. Similarly, no-shows might be eliminated by applying stricter cancellation policies and offering non-refundable options. (Hua et al., 2024)

Although strategies for eliminating cancellations and no-shows have been previously described, hoteliers should still expect certain instances of no-shows in their operations (Toh, 1986). The novel study, which utilises machine learning techniques, aims to enhance the overbooking strategy by predicting the no-show behaviour of individual clients (i.e., their probability of not attending) and reflecting their data. (Zhai et al., 2023)

Non-attending behaviour is not crucial only to the service industries. The problem of non-attending clients plays a significant role in education, healthcare, sports, and many other industries, where several studies have been created to highlight strategies for handling such behaviour or mitigating its effect on business operations (Amberger & Schreyer, 2024). A similar approach based on the machine learning technique was selected to reduce the number of non-attending patients in the hospital, resulting in decreased efficiency of the provided services, higher stress levels, and lower satisfaction among both service providers and patients (Batool et al., 2021).

To mention at least a few of the strategies, the most effective ones require minimum payments as a guarantee or deposits to initiate communication, which will increase the value of the business for the customer. (Song et al., 2021)

Connecting with clients may significantly affect their cancellation behaviour (Shuqair et al., 2022). The authors focused on the type of interpersonal connection with clients, where communal relationships might increase the likelihood of cancellation behaviour. In other words, customers who have created a strong communal relationship with the hotel employees, based on a closed social context, tend to reduce their obligation to attend to their booking. The exchange relationships that focus primarily on developing connections around transactions (bookings) and mutual benefits, which decrease future cancellation behaviour, lead to better performance.

2. METHOD

The study investigates the behaviour of customers who cancelled their reservations or decided not to show up for their stay (no-shows). The detailed behaviour is commonly captured in the hotel's PMS, where highly granular individual reservation data is stored. The data were collected from a centrally located hotel in Prague with a multi-segment focus. The study utilises empirical transaction data, as many previous studies have done (Antonio et al., 2019; Falk & Vieru, 2018), which were processed to reflect the behavioural characteristics better.

This study adopts the data crawling method as part of the CRISP-DM methodology used by previous studies (Antonio et al., 2019; Sánchez et al., 2020), where the following variables were used (some of them as synthetic variables derived from the variables mined from the PMS).

This variable set was adopted from the studies of Sánchez et al. (2020) and Sánchez-Medina & C-Sánchez (2020) with minor changes that reflect the findings of previous studies.

More than 55,000 transactions were collected during the data mining process. Due to the occurrence of missing cases and the inability to reliably source additional data, nearly 3% of the cases were excluded. In the second step, transactions labelled as "Z-shared" were excluded because they contained only information about the client already connected to the reservation listed within the mined database. This inactive person shared the room only with the person responsible for creating the reservation. After clearing the data set, 33,263 reservations of accommodation services were used for further processing, which included 7,436 cancelled reservations and no-shows. As mentioned in the literature review, the CHIAD Decision Tree was selected as the classification model to understand customer behaviour better.

For data processing and analysis, the Opera PMS was used as the source of data. The overall transaction reports were then exported and processed in IBM SPSS Statistics (version 25). For the data analysis, the decision tree method was selected, using the CHIAD growing method.

Table 1: **Selected variables for the classification model**

Label	Description	Type of variable
Reservation status	The reservation status reflects the type of reservation inquiry in the PMS.	Nominal
Number of quests	The number of hotel guests who share the individual reservations (or rooms if only one room is occupied), including the extra beds and baby cribs.	Continuous
Length of stay	The number of nights spent in the accommodation facility. Difference between the date of arrival and departure.	Continuous
Distribution channel	The distribution channel type was used to process the reservation inquiry. The individual reservation channels are grouped into agent types.	Nominal
Average gross rate	The average room rate for the night is calculated by dividing the overall gross rate by the number of nights.	Continuous
Rate type	The type of rate accepted by the client reflects the payment conditions and services included (Best Available Rate, Non-Refundable Rate, Bed Only, Bed and Breakfast).	Nominal
Lead time	The difference between the reservation creation date and the estimated date of arrival, in days.	Continuous
Number of rooms	For several reservations, more rooms were booked to accommodate larger groups. The number reflects only the rooms booked, without differentiating between room categories.	Continuous

Source: Own elaboration

The CHAID (Chi-squared Automatic Interaction Detection) decision tree algorithm was selected for this study due to several theoretical and practical considerations that align with the research objectives and the structure of the available data. In the context of this research, the aim was to classify reservation outcomes (i.e., attended, cancelled, no-show) based on a combination of demographic, behavioural, and transactional variables. Given the multilevel structure of the input data (e.g., rate types, lead time, distribution channels), CHAID enables effective segmentation by recursively splitting the data based on statistically significant differences in group distributions, using chi-squared tests as the basis for node splitting.

Additionally, CHAID is particularly suitable for analysing categorical variables with multiple levels, which are prevalent in this study. Variables such as distribution channel, rate type, and reservation status naturally align with the CHAID algorithm's ability to handle multi-category predictors without requiring dichotomisation or transformation. Unlike binary tree models such as CART (Classification and Regression Trees), CHAID allows for multi-way splits, which helps preserve the richness of the data and reduces the number of tree levels required to achieve meaningful classification. By adopting CHAID, this study builds upon an established methodological foundation, allowing for comparability with previous findings while providing an updated, data-driven perspective using real transactional data.

Overall, the selection of the CHAID decision tree model aligns with the study's goals of producing a robust, interpretable, and empirically grounded classification of customer non-attendance behaviour, while remaining accessible to practitioners and consistent with best practices in hospitality research.

For the validation of the results, the split-sample validation procedure was used. To set up the decision procedure, the maximum tree depth was selected as three for the CHIAD method, and size limits were set to 100 cases for parent nodes and 50 for child nodes. For analysis of the linkage between endogenous and independent variables, the Pearson's Chi-Square criterion was selected. (Breiman et al., 2017)

To validate and test the results, the previously mentioned half-split sample method was used, and the risk estimates were calculated. For the resubstitution, the estimate was 0,184 with a standard deviation of 0,002. The same values were then estimated for the crossvalidation as well. Within the classification matrix, the observed and predicted statuses of the reservations matched in 89,9 % of cases. To further analyse the mined data, a semi-structured interview was conducted with the hotel revenue manager to capture internal processes and property-specific use of PMS.

3. RESULTS

The literature review highlighted significant differences in the behaviour of clients visiting the hotel through various distribution channels and with varying lead times.

Table 2 presents the cancellation and no-show rates for identified market segments, categorised by agent type (distribution channel). With an emphasis on overall revenue management strategy and forecasting, it is crucial to note significantly higher cancellation rates in the Direct market segment, as well as in the wholesaler (Wholesalers), online travel agency (OTA), and destination management organisation (DMO) segments.

Table 2: **Cancellation and no-show rates of selected distribution channels**

Agent Type	Total	Cancellation Rate (%)	No-Show Rate (%)
CONSORTIA	1520	11,25%	1,25%
CORP	7890	6,60%	1,62%
CRS	713	11,08%	7,29%
Direct	7905	46,41%	1,86%
DMO	187	20,32%	1,60%
MP	291	0,34%	2,06%
OTA	10980	18,87%	2,51%
PTA	240	1,67%	1,25%
TO	3181	5,50%	0,53%
WHOLE	212	21,70%	0,94%
Other	144	4,17%	0,69%
Total	**33263**	**20,39%**	**1,97%**

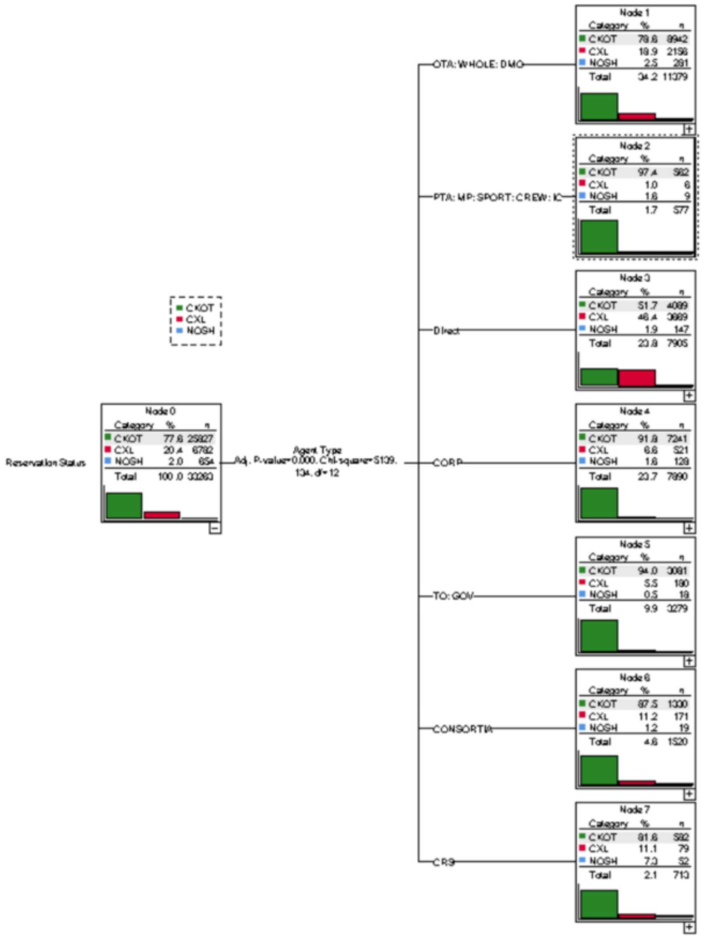
Source: Own elaboration

The high cancellation rate for the Direct market segment is being investigated, and the high value needs to be justified. The volume of cancellations was mainly caused by standard operating procedures for direct offline reservation handling, where all inquiries from clients are loaded into the PMS as reservations with an optional status (the clients have the right to confirm the reservation until the optional date). After filtering the reservations with the previous optional status and automating the status change to "cancelled", the clients cancelled only 4.92% of reservations, which aligns with the rates of corporates and TOs (Tour Operators). On the other hand, these inquiries should be considered for forecasting purposes, and more actions should be taken to increase conversion rates.

For the other distribution channels (Travel Consortia, Central Reservation Systems, Destination Management Organisations, Online Travel Agencies, and Wholesalers), the cancellation rates are similar to those found in previous research, as these channels employ more liberal cancellation policies and attract more speculative shoppers. The opposite position in terms of cancellation rates is occupied by the MP (meeting planners), PTA (personal travel agencies) and others (Government, Sports clubs, Crews). The lower cancellation rate reflects the existence of the Agreement and the fixation of the events in time.

Based on the previously mentioned description of cancellation and no-show rates, the selected variables were taken as input to the CHIAD classification model. As the independent variable, the reservation status was selected. The final decision tree had four levels of nodes (the overall node level, where all the cases are selected, was included). The classification was performed at two additional levels, where nodes were created for the nodes presented in Figure 1.

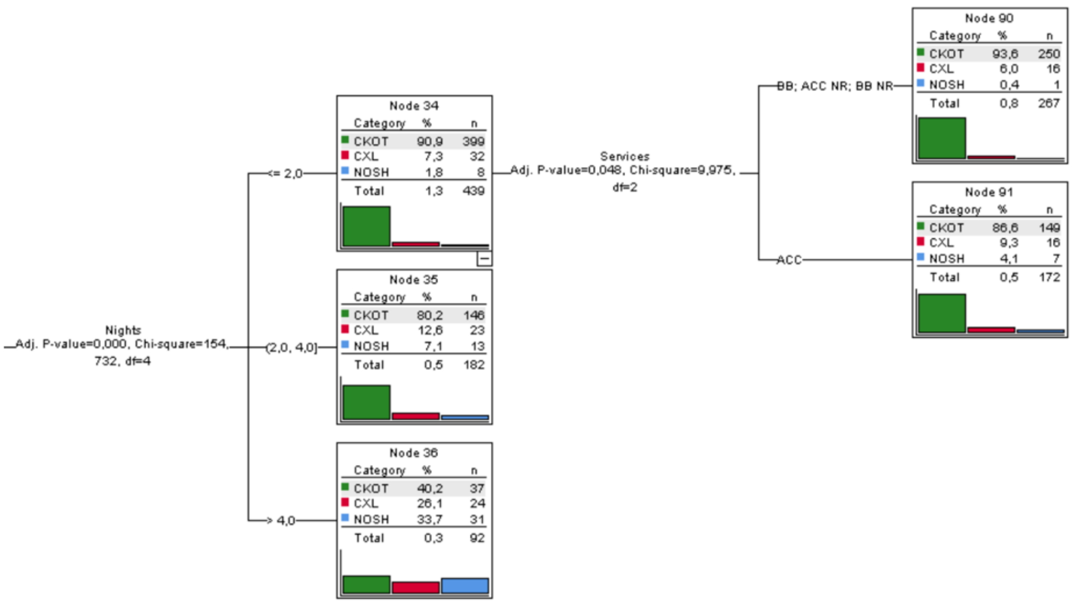
Figure 1: **CHIAD results – levels 1 and 2**



Source: Own elaboration

The first step of classification was significantly influenced by the agent type (distribution channel type), as evident in the connection to the overall description of cancellation and no-show rates presented in Table 2. Further description is proposed for the six distribution channels, emphasising cancellation and no-show rates. Figure 2 presents the sublevels of the selected tree section for the Central Reservation System.

Figure 2: **CHIAD Results – sublevels with nodes for CRS**



Source: Own elaboration

As proposed in Figure 2, one standalone branch of the decision tree was identified for the CRS (2,1 % of reservations in total). The LOS, as does the type of services ordered, plays a vital role. The results show that longer reservations, with more than two nights, are associated with a higher relative count of cancellations and no-shows. The rate types play a significant role in realising shorter reservations with two or fewer nights. The standalone accommodation without breakfast and flexible cancellation policy drives low no-shows, whereas non-refundable and bed and breakfast offers tend to eliminate the no-shows and cancellations.

Consortia represent 4.6% of the reservations (1.2% with status no-shows and 11.2% of reservations cancelled). The significant factors are the lead time and rate type. The lowest cancellation rate is observed for reservations with a lead time of 18 days or less (7, 9%), and the highest for reservations booked 35 to 54 days before arrival. The lowest no-show rate is within the reservations group, specifically for those with a lead time of 55 days or more. When focusing on the no-shows, their highest relative count is within the group with the lowest lead time and the majority of them are allocated to the accommodation-only rate type, which tends to attract more reservations than the other rate types.

The tour operators and government organisations provide nearly 10 % of the reservations. For these market segments, the lead time and gross rate are the factors that influence the most. Only eight no-shows were identified for reservations with a rate of less than 2,471 CZK. When focusing on cancellations, most are allocated to a rate span of 1554–2300 CZK, and the rates are higher than 3249 CZK. For the first interval of rates, the cancellations are driven by the lead time of the reservations. Reservations with a lead time of 25 days or less have a 4% cancellation rate and a 0.2% no-show rate, whereas reservations created 26 to 88 days before arrival do not result in any no-shows, but rather a majority of cancellations (from 13.6% to 26.4%). Compared to consortia, the highest no-show rate is observed in the group with the longest lead time, at 88 days (a 2.6% no-show rate), and the cancellation rate for this interval is 10.3%. The second interval with the high gross rate (a rate higher than 3249 CZK) is primarily associated with cancellations by Tour Operators (21% of the reservations within this segment).

Corporate reservations account for 23.7% of the hotel's overall business, with a 6.6% cancellation rate and a 1.6% no-show rate. The gross rate, number of guests and lead time are the most influential factors for this market segment. Regarding the number of guests, this factor is highly influential for reservations with an average gross rate between 3249 and 3738 CZK, where solo travellers attract cancellation and no-show rates of approximately 4%. A higher number of guests within the reservation nearly eliminates the cancellation and no-show rates. Regarding the lead time, general conclusions can be drawn that indicate higher cancellation rates for reservations with longer lead times. In the case of no-shows, there is a direct connection to the gross rate of the reservation, where no-shows are often found in the most affordable reservations within this segment.

The unique position is connected to the Information Centres, Crews, Sports Teams and Events, Meeting Planners, and Personal Travel Agencies, where the relative numbers of cancellations and no-shows are 1%, 1%, and 6%, respectively, with no significantly influential factors.

As Table 2 mentions, the market segment with the highest cancellation rate is Direct (mainly caused by the high number of optional reservations and automatic cancellations). Lead time plays a significant role in the first part of tree division, where the longer the lead time, the higher the cancellation rate. The no-show rate is below 1% for reservations created 35 days or more in advance of arrival, whereas the highest no-show rate (5%) is associated with reservations created 8 to 18 days prior to arrival. For other lead times, the no-show rate fluctuates around 1,2 %. For reservations created at least 18 days prior to arrival, the rate type is another significant factor, as the flexibility in the form of BAR rates and the absence of additional services (accommodation without breakfast) drive most cancellations. The strict cancellation policy is connected to a significant decrease in the cancellation rate. The no-show rate is nearly the same for all the rate types. The length of stay has a significant influence on reservations created less than 18 days before arrival. For these reservations, the longer the stay, the higher the likelihood of cancellation. The no-show rate is increasing with the growing lengths of stays in the short lead time.

The last market segment, comprising 34.2% of the reservations, is created by Online Travel Agencies, Wholesalers, and Destination Management Organisations. Generally, this market segment has the second-highest no-show rate of 2.5% and cancellation rate of 18.9%. There was a significant effect on the rate types (cancellation policies), the lead time for accommodation-only reservations, and the gross rate for bed-and-breakfast accommodations. The non-refundable offers eliminate the possibility of the reservation being booked, and cancellations do not harm the hotel business. For the accommodation-only reservations, the higher the lead time, the higher the cancellation rate. The situation of the no-show rate is the opposite, where the rate is growing with decreasing lead time—the bed and breakfast reservations are strongly connected to the gross rate. The reservations with higher-than-average gross rates tend to attract more cancellations. The liberal cancellation policy and limited options to recoup cancellation fees from non-guaranteed reservations result in the highest no-show rate in the reservations group, with a gross rate exceeding 2300 CZK.

4. DISCUSSION

The study results provide updated insights into customers' behaviours, derived from various variables of customer behaviour captured by transactional data mined from the hotel property management system. The CHIAD decision tree was used as a classification method, complementing previous research in the field (Falk & Vieru, 2018; Romero Morales & Wang, 2010; Sánchez-Medina & C-Sánchez, 2020).

The study's results confirm previous findings that the cancellation rate is strongly linked to the strictness of the cancellation policy (Smith et al., 2015) and the preferred rate type (Antonio et al., 2017). In this context, it is crucial to mention that the current trend in cancellation policy setting is highly influenced by the OTAs and the possibility of cancelling the stay a day before arrival. OTAs and other indirect online distribution channels share users' characteristics and behaviour (Falk & Vieru, 2018). The liberal cancellation policy may allow clients to book cheap stays in advance and reconsider their selection as the arrival date approaches. As the revenue strategies are not always appropriately prosecuted and the industry is not always up to date with the current understanding of the field and knowledge generated by the academia (Ivanov et al., 2021), the client might benefit from the malfunction of these strategies and reach better last-minute deals (Masiero et al., 2020).

The paper's results highlight the significant impact of the distribution channel type on overall non-attendance behaviour, consistent with Falk & Vieru (2018). The lowest level of cancellation rates was identified for the channel used by the market segments, with events fixed when the cancellation of the stays is connected with missed attendance at the event or meeting. It might be perceived that the corporate clients would not cancel advanced reservations, but the effect of the lead time is more robust, and the meeting might be postponed or shifted online. A particular group of corporate customers with very low cancellation and no-show rates is created by the booking with more than one client assigned to the reservation.

The study's results also showed that the cancellation rate of reservations with higher booking windows is growing. Reservations with longer booking windows tend to attract customers who are willing to pay extra for the flexibility (the cancellation option) (Arenoe & van der Rest, 2020) and behave strategically as they expect hotel managers to set low rates (Masiero et al., 2020). The lead time is crucial for most market segments. However, the most substantial connection is with the online distribution channels, cheaper tour operator reservations or direct reservations (the unique position of the direct reservation is described in the results section in more detail, where the internal processes settings mainly cause the high cancellation rate).

When focusing on the time variables, it is crucial to mention the effect of the length of stay on non-attendance behaviour, where short reservations of one night and longer reservations of four or more nights have a higher cancellation rate compared to the higher no-show rate of 2-3 night stays.

A standalone understanding of cancellation behaviour should be viewed as the first step in building a revenue management strategy, where online reservations are considered, not just online bookings. Even though there are several research papers focusing on cancellations forecasting through the combination of machine learning and probability models (Chen et al., 2023), standalone machine learning methods (Sánchez-Medina & C-Sánchez, 2020; Sekhon & Ahuja, 2023) or artificial intelligence (Sánchez et al., 2020), these mainly focus on the aggregated data not reflecting the individual characteristics of the customers and their behavior while omitting other aspects of the non-attendance behavior which might be even more devastating the hotel revenue management forecasting. Refunding non-show reservations is nearly unfeasible for hoteliers, as it brings many administrative issues that may incur additional costs.

The study's uniqueness lies in its focus on general non-attendance behaviour, rather than standalone cancellations. As Hua et al. (2024) proposed, the strong connection between cancellation policies, non-attendance behaviour, and revenue management strategies must be revisited. The paper's results highlight the variability of non-attendance behaviour, which can be improved in the future by incorporating more empirical data to provide more valid and generalisable knowledge.

4.1 Limits of the study

The main limitation of the study might be identified at the data-entry level. The study relies solely on single property data to provide evidence of customer behaviours, resulting in low external validity. In this term, further research should focus on the broader scope of the data, which would consist of multi-property data entry. A high level of sensitivity of the hoteliers to the data can lead to a low willingness to provide researchers with complex data, as seen in several research studies that use partial data (Saito et al., 2019). The results of the study may not be reliably applied to all properties, and other variables, such as destination characteristics, the marketing focus of the hotel management, the size of the accommodation facility, used technologies, and many other factors, may lead to different results. On the other hand, the study presents a methodological approach to identifying and predicting non-attended behaviour based on standard variables used in revenue management.

Contrary to the previously mentioned threat to external validity, the empirical data mined directly from the hotel PMS must be perceived as a valid and reliable source of customer behaviour, which (thanks to the internal processes) is not biased or manipulated by the customers and provides complex understanding, no matter what distribution channel was used. The data derived from the property management system (PMS) is empirical, objective, and operationally relevant; it is also inherently quantitative and behavioural, and therefore lacks qualitative depth. The PMS captures what customers did, but not why they behaved in that manner. This limits the explanatory power of the findings and restricts insight into the underlying motives, intentions, or external situational factors that may have influenced customer decisions. For example, cancellations could stem from external disruptions (such as illness, weather, or flight delays) or strategic behaviour (e.g., price comparison or speculative booking).

Many previous studies have used questioning to understand customer behaviour, where the standalone method of online anonymous questioning is mainly linked to sampling issues and does not discuss the bias of the results.

Although this highly granular dataset offers valuable insights and ensures a detailed reflection of actual customer behaviours, the findings are context-specific. The hotel's unique market positioning, customer segmentation, distribution channel mix, internal operational protocols, and location-specific dynamics may have influenced the observed behavioural patterns. Concerning total revenue management and strategically behaving customers, there may be additional hidden variables that could impact the non-attendance behaviour of customers.

The classification model can be used to understand cancellation and booking behaviour. The research's single-method focus does not test the suitability of different approaches and their potential impact on hotel operations. The study's results should be linked to empirical forecasting and simulations to verify the applicability of the outputs in hotel operations and revenue management. More advanced methods addressing the cluster class imbalance issue might be applied. (Adil et al., 2021)

The single-method bias is a significant factor in the study results. The selected methodology was employed in the previous studies cited in the literature review. To validate the results, they should be applied to the complex revenue management strategy of the specific accommodation facility used for the data collection, as well as the implications listed below.

Finally, while the study presents a descriptive and predictive view of customer behaviour, it does not extend into prescriptive analysis. That is, it does not test or simulate the operational or financial outcomes of implementing various intervention strategies, such as stricter cancellation policies, deposit requirements, or communication strategies aimed at reducing uncertainty. Nor does it quantify the economic impact of cancellation and no-show rates under different conditions.

4.2 Implications

In terms of implications, it is crucial to mention the complex scope of the research, which brought a more detailed understanding of the non-attendance behaviour. The complexity of the data used yields unique results that may complement those of other methods applicable in revenue management. Compared to previous research, the non-attendance behaviour consists of cancellations and no-shows, which are commonly separated or omitted. The researchers are focusing only partially on the very complex revenue management issues.

In the context of further research on non-attendance behaviour, it is essential to understand the motives of non-attending customers and implement them as a standalone market segment, which drives demand for services but, in many cases, generates no revenue. The understanding might be connected to further developing the mutual connection with the clients (Shuqair et al., 2022) and mitigating cancellations.

For hoteliers, the most important implications may be properly executing revenue management strategies that are up to date with current knowledge, and revising the cancellation policy (including selling restrictions and rate plans) for the accommodation facility. Proper processing of the revenue management strategy may eliminate speculation over price changes in the long and short term, as pursued by strategically behaving customers. Cancellation policies, rate types and plans may encourage clients to prefer prepaid, cheaper reservations or accept semi-flexible rates with a liberal cancellation policy. Hoteliers must also adopt advanced data mining techniques, or at least utilise their results, to reduce the research-practice gap in revenue management (Ivanov et al., 2021). Similarly, hoteliers must delve deeper into their internal data and understand their customers' behaviour, while maintaining accurate databases that reflect actual operations with all relevant details. In practice, hoteliers and employees do not care that much about the validity of the data entered into PMS, which might cause problems with forecasting and the overall quality of revenue management (Zhang et al., 2017). To enhance the understanding of customer behaviour complexity and improve the ability to forecast future behaviours accurately, hoteliers should consider combining internal data with high-quality, publicly or privately available internet data (Li et al., 2021).

CONCLUSION

The study aims to investigate the non-attendance behaviour (cancellations and no-shows) of selected hotel customers. Using the CHIAD decision tree model and highly granular transaction data mined from the hotel PMS, the study brought several insights into customer behavior that partially reflect the previous knowledge brought by a limited number of research papers focused on this issue of revenue management and widens the understandings of such behavior while reflecting not only the cancellations but as well the no-shows.

The study's uniqueness lies in its use of empirical data, which consists of confirmed reservations, allowing for a better understanding of the behaviour of hotel customers. The standalone non-attendance behaviour is then presented in the context of the entire operation, and the results highlight the significant differences in the behaviour of hotel clients. Another aspect of the study's uniqueness is its detailed understanding of the customer, where cancellations and no-shows are not considered a homogeneous group of customers, and where rates may differ for various customer groups.

The discussion complements the current state of knowledge in this field, reflects the study's limitations, and highlights the theoretical and practical implications, with a focus on the use of high-quality internal data stored in hotel PMS systems and the complementation of this data with other information available from external sources. Hoteliers should strive to understand not only their customers' behaviour but also the clients who were interested in their products at a specific time and mitigate their non-attending tendencies.

Another significant finding is the variability of factors affecting the non-attending behaviour of different market segments, where the type of distribution channel plays a crucial role, as well as the level of cooperation with the market segment. For a specific market segment, the lead time, gross room rate, or the type of selected rate may highly affect customers' behaviour. For corporate clients, the number of people staying in the hotel room has a significant impact. This behaviour must be individually investigated and later implemented in the revenue management strategies of the accommodation facilities.
Further studies and applications should incorporate these results into companies' marketing, revenue management strategies, and demand forecasting. The research should focus on gaining a complex understanding of customers, their needs, wants, motives, and actions.

REFERENCES

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.. https://doi.org/10.3390/pr9101713

Amberger, C., & Schreyer, D. (2024). What do we know about no-show behavior? A systematic, interdisciplinary literature review. *Journal of Economic Surveys*, *38*(1), 57-96. https://doi.org/10.1111/joes.12534

Ancarani, F., Gerstner, E., Posselt, T., & Radic, D. (2009). Could higher fees lead to lower prices? *Journal of Product & Brand Management*, *18*(4), 297–305. https://doi.org/10.1108/10610420910972828

Antonio, N., Almeida, A. de, & Nunes, L. (2017). Predicting hotel booking cancellations to decrease uncertainty and increase revenue. *Tourism & Management Studies*, *13*(2), 25-39. https://doi.org/10.18089/tms.2017.13203

Antonio, N., de Almeida, A., & Nunes, L. (2019). Big data in hotel revenue management: exploring cancellation drivers to gain insights into booking cancellation behavior. *Cornell Hospitality Quarterly*, *60*(4), 298–319. https://doi.org/10.1177/1938965519851466

Arenoe, B., & van der Rest, J.-P. I. (2020). Does willingness to pay for rate conditions depend on the booking window? a novel time-dependent conjoint analysis approach. *Cornell Hospitality Quarterly*, *61*(2), 213–222. https://doi.org/10.1177/1938965519864863

Batool, T., Abuelnoor, M., El Boutari, O., Aloul, F., & Sagahyroon, A. (2021). Predicting hospital no-shows using machine learning. In *2020 ieee international conference on internet of things and intelligence system (IoTaIS)* (pp. 142–148). https://doi.org/10.1109/IoTaIS50849.2021.9359692

Bertsimas, D., & Popescu, I. (2003). Revenue management in a dynamic network environment. *Transportation Science*, *37*(3), 257–277. https://doi.org/10.1287/trsc.37.3.257.16047

Breiman, L., Friedman, J., Olshen, R. A., & Stone, C. J. (2017). Classification and regression trees. New York: Chapman and Hall/CRC. https://doi.org/10.1201/9781315139470

Chen, C.-C., Schwartz, Z., & Vargas, P. (2011). The search for the best deal: How hotel cancellation policies affect the search and booking decisions of deal-seeking customers. *International Journal of Hospitality Management*, *30*(1), 129–135. https://doi.org/10.1016/j.ijhm.2010.03.010

Chen, S., Ngai, E. W. T., 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. https://doi.org/10.1016/j.dss.2023.113959

Chiang, C. I. (2023). Overbooking as a means to manage restaurant no-shows and cancellations: A novel model extension. *Journal of Hospitality & Tourism Research*, 47(8), 1530–1545. https://doi.org/10.1177/10963480211064356

Falk, M., & Vieru, M. (2018). Modelling the cancellation behaviour of hotel guests. *International Journal of Contemporary Hospitality Management*, *30*(10), 3100–3116. https://doi.org/10.1108/IJCHM-08-2017-0509

Fouad, A. M., Atiya, A. F., Saleh, M., & Bayoumi, A. E.-M. M. (2014). A simulation-based overbooking approach for hotel revenue management. In *2014 10th International Computer Engineering Conference (ICENCO),* (pp. 61–69). https://doi.org/10.1109/ICENCO.2014.7050433

Hua, Y., Che, T., Yang, C., & Hu, M. (2022). Customer no-show reduction in web-based appointment service: Investigations of non-attendance behaviors. *The Service Industries Journal*, 44(7-8), 538-562. https://doi.org/10.1080/02642069.2022.2045963

Ivanov, S., Del Chiappa, G., & Heyes, A. (2021). The research-practice gap in hotel revenue management: Insights from Italy. *International Journal of Hospitality Management*, 95, 102924. https://doi.org/10.1016/j.ijhm.2021.102924

Li, X., Law, R., Xie, G., & Wang, S. (2021). Review of tourism forecasting research with internet data. *Tourism Management*, *83*, 104245. https://doi.org/10.1016/j.tourman.2020.104245

Liu, Z., Jiang, P., Wang, J., Du, Z., Niu, X., & Zhang, L. (2022). Hospitality order cancellation prediction from a profit-driven perspective. *International Journal of Contemporary Hospitality Management, 35*(6), 2084–2112. https://doi.org/10.1108/IJCHM-06-2022-0737

Masiero, L., Viglia, G., & Nieto-Garcia, M. (2020). Strategic consumer behavior in online hotel booking. *Annals of Tourism Research*, *83*, 102947. https://doi.org/10.1016/j.annals.2020.102947

Nababan, A. A., Jannah, M., & Nababan, A. H. (2022). Prediction of hotel booking cancellation using k-nearest neighbors (K-NN) algorithm and synthetic minority over-sampling technique (SMOTE). *INFOKUM*, 10(03).

Noone, B. M., & Lee, C. H. (2011). Hotel overbooking: The effect of overcompensation on customers' reactions to denied service. *Journal of Hospitality & Tourism Research*, *35*(3), 334–357. https://doi.org/10.1177/1096348010382238

Phumchusri, N., & Maneesophon, P. (2014). Optimal overbooking decision for hotel rooms revenue management. *Journal of Hospitality and Tourism Technology, 5*(3), 261–277. https://doi.org/10.1108/JHTT-03-2014-0006

Romero Morales, D., & Wang, J. (2010). Forecasting cancellation rates for services booking revenue management using data mining. *European Journal of Operational Research*, *202*(2), 554–562. https://doi.org/10.1016/j.ejor.2009.06.006

Saito, T., Takahashi, A., Koide, N., & Ichifuji, Y. (2019). Application of online booking data to hotel revenue management. *International Journal of Information Management*, *46*, 37–53. https://doi.org/10.1016/j.ijinfomgt.2018.11.003

Sánchez, E. C., Sánchez-Medina, A. J., & Pellejero, M. (2020). Identifying critical hotel cancellations using artificial intelligence. *Tourism Management Perspectives, 35*, 100718. https://doi.org/10.1016/j.tmp.2020.100718

Sánchez-Medina, A. J., & C-Sánchez, E. (2020). Using machine learning and big data for efficient forecasting of hotel booking cancellations. *International Journal of Hospitality Management*, *89*, 102546. https://doi.org/10.1016/j.ijhm.2020.102546

Sekhon, G., & Ahuja, S. (2023). Review machine learning models for managing hotel cancellations in the tourism industry. In *2023 3rd International Conference on Intelligent Technologies (CONIT),* (pp. 1–6.) https://doi.org/10.1109/CONIT59222.2023.10205827

Shuqair, S., Costa Pinto, D., Cruz-Jesus, F., Mattila, A. S., da Fonseca Guerreiro, P., & Kam Fung So, K. (2022). Can customer relationships backfire? How relationship norms shape moral obligation in cancelation behavior. *Journal of Business Research*, *151*, 463–472. https://doi.org/10.1016/j.jbusres.2022.07.008

Smith, S. J. (2012). The relationship between perceived personal fairness, social fairness, hotel cancellation policies and consumer patronage (Unpublished doctoral dissertation). University of Central Florida. https://stars.library.ucf.edu/etd/2155/

Smith, S. J., Parsa, H. G., Bujisic, M., & van der Rest, J.-P. (2015). Hotel cancelation policies, distributive and procedural fairness, and consumer patronage: A study of the lodging industry. *Journal of Travel & Tourism Marketing, 32*(7), 886–906. https://doi.org/10.1080/10548408.2015.1063864

Song, M. K., Jung, H. S., & Yoon, H. H. (2021). An exploratory study on reservations, no-shows, and time perception. *Culinary Science & Hospitality Research*, *27*(2), 1–12.

Toh, R. S. (1985). An inventory depletion overbooking model for the hotel industry. *Journal of Travel Research, 23*(4), 24–30. https://doi.org/10.1177/004728758502300404

Toh, R. S. (1986). Coping with no-shows, late cancellations and oversales: American hotels out-do the airlines. *International Journal of Hospitality Management, 5*(3), 121–125. https://doi.org/10.1016/0278-4319(86)90004-6

Viverit, L., Heo, C. Y., Pereira, L. N., & Tiana, G. (2023). Application of machine learning to cluster hotel booking curves for hotel demand forecasting. *International Journal of Hospitality Management*, *111*, 103455. https://doi.org/10.1016/j.ijhm.2023.103455

Xie, J., & Gerstner, E. (2007). Service escape: Profiting from customer cancellations. *Marketing Science*, *26*(1), 18–30. https://doi.org/10.1287/mksc.1060.0220

Zhai, Q., Tian, Y., Luo, J., & Zhou, J. (2023). Hotel overbooking based on no-show probability forecasts. *Computers & Industrial Engineering*, *180*, 109226. https://doi.org/10.1016/j.cie.2023.109226

Zhang, G., Wu, J., Pan, B., Li, J., Ma, M., Zhang, M., & Wang, J. (2017). Improving daily occupancy forecasting accuracy for hotels based on EEMD-ARIMA model. *Tourism Economics, 23*(7), 1496–1514. https://doi.org/10.1177/1354816617706852

Please cite this article as:
Chalupa, S., Petricek, M. & Koklarova, B. (2026). Will They Come or Not? The Investigation of the Non-Attendance Behavior of the Hotel Guests. *Tourism and Hospitality Management, 32(3)*, pp, https://doi.org/10.20867/thm.32.3.1