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Cancel, rebook, save: Revenue leakage from price cuts in hotels

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ABSTRACT

Rebooking—canceling a reservation and booking the same stay at a lower rate—creates revenue leakage for hotels, whether the savings go to guests or intermediaries. We analyze 2,223,024 reservations from 628 Portuguese properties (2022–2024) and match cancellations to near-immediate, lower-priced replacement bookings. Rebookings account for 0.94 % of reservations and generate €1,241,281.58 in gross revenue displacement (i.e., the difference between the original and replacement booking values). Rebooking is more frequent in urban markets but typically involves smaller per-stay losses. Losses vary by region, season, and accommodation type. We propose a measurement framework and recommend policies: guardrails on late price cuts, fenced discounts, parity audits, and rebooking risk flags in reservation systems. To our knowledge, this is the first large-scale multi-property estimate of within-property rebooking-related revenue displacement in hotels. Results extend empirical evidence on strategic consumer behavior under dynamic pricing and inform more robust monitoring and pricing safeguards in revenue management practice.

1. Introduction

The hotel industry is undergoing a profound transformation driven by technological advancements and the increasing reliance on digital reservation channels (Abrate et al., 2012; Pérez-Ricardo et al., 2023). Online booking platforms and new technologies in the hospitality industry have transformed consumer behavior, creating new opportunities for travelers while posing considerable challenges for hotels (Falk and Vieru, 2018; Toh et al., 2011). This phenomenon has changed how consumers search for and book accommodations. They now have access to extensive information and options, which, while empowering, can complicate decision-making (Hikmawati et al., 2024; Petricek et al., 2021; Zhang and Xie, 2024).

These challenges necessitate adaptations to revenue management strategies in the hospitality industry, which focus on balancing demand, inventory, and pricing to maximize financial returns (Ivanov and Zhechev, 2011; Lim et al., 2024). Within this context, precise cancellation forecasting is essential, enabling hoteliers to anticipate booking trends, respond effectively to changing conditions, and mitigate revenue losses, while providing support for other crucial areas, including overbooking, pricing, and capacity control (Herrera et al., 2024; Hikmawati et al., 2024; Matsuoka, 2022).

Dynamic pricing is particularly significant in the revenue management process, enabling real-time rate adjustments based on demand and competition (Zhu et al., 2024), drawing on price discrimination principles common to both hospitality and aviation (Guizzardi et al., 2022). Dynamic pricing that aligns offerings with consumer expectations and market demand illustrates how hotels can maintain competitiveness while optimizing revenue (Masiero et al., 2020). There are, however, difficulties for hoteliers. As observed by Abrate et al. (2019), a significant challenge arises when strategic consumers exploit these pricing fluctuations by rebooking to secure lower rates.

We define rebooking as canceling an existing reservation and rebooking the same stay at a lower price. For example, a guest may book a room for €140 per night and later see the same room for €125; if cancellation is free, the guest can cancel and rebook to save €15 per night. This behavior has grown with online price transparency and flexible cancellation policies, which encourage customers to keep searching for better deals even after booking (Falk and Vieru, 2018; Masiero et al., 2020).

Initially developed for the airline industry, software such as Coupa, FairFly, and Trappit monitors pricing fluctuations and alerts consumers when a more economical option becomes available (Vinod, 2024). Some services, such as Pruvo, HotelSlash, Rebookey, and Thishotel, extend this capability to offer consumers the option to automatically rebook their hotel room at a lower price if the price drops (Abrate et al., 2019). Other providers, such as TripBam, Oversee, and Ramp, offer this service to travel intermediaries. This use by intermediaries can be even more

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perverse: in many situations, a travel agent cancels a booking with one provider to create a new, cheaper one, but does not pass the margin to the consumer. As a consequence of these developments, consumers and intermediaries can now obtain more favorable prices, posing a challenge for hotels in managing their revenue and underscoring the need for more adaptable strategies (Abrate et al., 2019; Masiero et al., 2020).

Every rebooked reservation results in lost revenue and increased administrative work associated with cancellations that occur before the rebooking (Almotiri et al., 2021). Hoteliers can leverage precise, reliable demand forecasting to anticipate booking trends and mitigate financial losses. The complexity of online consumer behavior further magnifies these challenges, and in the absence of such predictive insights, hotels risk misallocating resources (Talón-Ballestero et al., 2022; Herrera et al., 2024). That could result in inefficiencies that jeopardize operational performance and profitability (Lim et al., 2024; Liu et al., 2024), regardless of whether the consumer subsequently makes a new reservation. It is therefore essential that those engaged in Revenue Management can understand and predict these booking patterns, as this provides the foundation for proactive adjustments to pricing and inventory strategies (Antonio et al., 2017).

Furthermore, rebooking behavior introduces an additional layer of complexity. Rebooking can also present opportunities for revenue gains when managed effectively. By identifying the factors that lead to rebooking - such as customer demographics, booking lead times, or price sensitivity - hotels can implement dynamic pricing adjustments or targeted incentives to retain high-value customers while minimizing the adverse effects of cancellations (Gorin et al., 2012). Despite its significance, rebooking remains an underexplored area in academic research, underscoring the need for further investigation.

This study extends research on intertemporal pricing and strategic consumer behavior in hospitality by quantifying cancel-and-rebook leakage under flexible cancellation and dynamic pricing. We identify boundary conditions, such as lead time, market density, and accommodation type, under which price reductions translate into measurable revenue displacement rather than incremental demand. This study provides an exploratory, large-sample measurement of cancel-and-rebook behavior observed within a single Property Management System (PMS) environment. Our goal is not to estimate structural demand parameters or to test a specific causal mechanism; instead, we quantify the magnitude and heterogeneity of within-property revenue displacement associated with rebooking and propose portable indicators that hotels can implement with operational data.

2. Literature review

2.1. Strengths and weaknesses of existing research on rebooking

A significant body of academic research has examined hotel reservations and revenue management, including cancellations, dynamic pricing, and customer behavior. Despite the growing significance of rebooking, a comprehensive understanding of this phenomenon remains elusive. To identify the gaps that this study aims to address, this section critically analyzes the strengths and limitations of previous research in this field.

The existing literature offers fundamental insights into behaviors that affect cancellations (Masiero et al., 2020; Schwartz, 2006; Zhang and Xie, 2024), which, in turn, may affect rebooking. While rebooking itself remains underexplored, an increasing body of research has begun to provide preliminary insights into the motivations underlying consumer behavior in this context. Masiero et al. (2020) and Schwartz (2006) discuss "book and search" behavior, in which consumers cancel and rebook reservations to obtain more favorable pricing, demonstrating how customers respond to pricing tactics.

The impact of dynamic pricing on consumer behavior has also been the subject of considerable research, which underscores the intricate relationship between pricing strategies and cancellations. Although Revenue Management theory holds that prices for future dates should rise over time, cancellations or low occupancy may sometimes reduce rates through campaigns or discounts (Abrate et al., 2012; Bayoumi et al., 2013; Guizzardi et al., 2022; Talón-Ballestero et al., 2022). These findings are particularly relevant to rebooking, as a considerable proportion of cancellations are prompted by customers actively seeking more favorable terms after making their initial reservations (Antonio et al., 2019).

Research in industries such as airlines (Gorin et al., 2012) or cruises (Showker and Sehlinger, 2007) has examined rebooking more extensively, demonstrating its potential for substantial revenue growth and offering insights that can inform similar practices in hotels. However, research in those areas tends to be outdated.

Despite its growing popularity, rebooking in the hospitality industry is still under-researched (Gorin et al., 2012; Masiero et al., 2020; Schwartz, 2006). Most research treats cancellations as one-off events, without examining consumers' subsequent actions and the trends associated with rebooking. Moreover, the financial impact of rebooking has not been studied. Although revenue losses are often associated with cancellations, little is known about the operational and financial costs of rebooking (Guizzardi et al., 2022; Lacetera et al., 2024).

The results of previous research are often limited by the size and scope of their data sets (Choi and Kim, 2024; Contessi et al., 2024), making generalization difficult. Although these studies focused primarily on cancellations, the limitations could also apply to research on rebookings, given the interrelated nature of these phenomena. Studies often focus on specific types of hotels (Choi and Kim, 2024; Contessi et al., 2024; Falk and Vieru, 2018; Guizzardi et al., 2022; Hikmawati et al., 2024) or locations (Herrera et al., 2024; Jenčková and Abrhám, 2016), which limits the applicability of their findings to broader market scenarios.

2.2. Exploring patterns, drivers, and techniques in rebooking

Rebooking behaviors challenge traditional revenue models, as consumers' decisions depend on the trade-off between free cancellation flexibility and potential savings (Masiero et al., 2020). Operational uncertainty is created by strategic actions such as monitoring pricing trends and rebooking to secure better deals (Abrate et al., 2019; Schwartz, 2008), and this uncertainty is amplified by automated rebooking services, particularly for risk-takers (Masiero et al., 2020). Dynamic pricing tactics are further exploited by practices such as "Book and search" (Masiero et al., 2020; Schwartz, 2006), in which customers make reservations but continue to search for better deals, potentially affecting revenue maximization.

Cancellations and rebooking are closely related, as the first step in rebooking is cancelling a reservation. They are often driven by similar motivations, such as securing better deals, taking advantage of flexible policies, or responding to dynamic pricing strategies. While cancellations directly disrupt hotel revenue and operational planning, rebookings introduce an additional layer of complexity. As a result, much of the current research on cancellations (Herrera et al., 2024; Masiero et al., 2020) provides a valuable foundation for understanding rebooking behavior, allowing lessons learned to be applied to both situations.

Tailored policies and dynamic pricing techniques can enhance client retention and mitigate losses, with flexible policies for low-risk guests proving more effective than strict regulations (Antonio et al., 2019). Strict cancellation policies, which erode loyalty and confidence, are less effective than preventive measures, such as tailored regulations (Antonio et al., 2017). By using predictive tools to segment their customer base, hotels can implement customized strategies that reduce revenue leakage while preserving the guest experience.

2.3. Filling research gaps

Despite the growing importance of rebooking in the hotel sector, there remains a notable dearth of scholarly research on the topic (Masiero et al., 2020). A deeper understanding of rebooking is often overlooked, leading to significant knowledge gaps, even though cancellations have received considerable attention. Table 1 summarizes the most relevant strands of prior work and situates this study's contribution.

Research on strategic consumer behavior (Abrate et al., 2019; Masiero et al., 2020; Schwartz, 2008) and dynamic pricing (Abrate et al., 2012; Bayoumi et al., 2013; Guizzardi et al., 2022; Saitta et al., 2024) frequently treats rebooking as an extension of cancellations rather than as a distinct phenomenon (Antonio et al., 2017; Masiero et al., 2020). This oversight persists despite the increasing prevalence of platforms such as Rebookey and Pruvo, which have popularized rebooking (Masiero et al., 2020; Vinod, 2024). The phenomenon of rebooking has been more extensively explored regarding the airline industry, as evidenced by the work of Gorin et al. (2012). However, while these studies offer valuable insights, they fail to fully elucidate the underlying drivers, consequences, and effective strategies for managing rebooking, thereby leaving significant gaps in understanding this complex phenomenon.

Furthermore, hoteliers are unable to assess the economic consequences of rebooking or implement effective mitigation strategies due to a lack of research defining the financial impact of rebooking on key metrics such as ADR and Revenue Per Available Room (RevPAR).

Moreover, hotels' capacity to manage rebookings effectively is

Table 1
Key literature on rebooking (cancel-and-rebook) and how this study contributes to filling the research gap.

Literature stream	Representative references already cited	What this stream establishes	Explicitly studies hotel rebooking?	Quantifies the financial impact of rebooking (Average Daily Rate (ADR) / RevPAR displacement)?	Gap highlighted
Cancellations and strategic "book-and-search" behavior	Masiero et al. (2020); Schwartz (2006); Zhang and Xie (2024)	Consumers may cancel and rebook to obtain more favorable pricing; rebooking is linked to cancellation behavior but remains underexplored in hotels.	Partially	No	Rebooking is often treated as a side note; limited evidence on how often it occurs and what it costs financially / operationally.
Dynamic pricing, rate decreases, and cancellation responses	Abrate et al. (2012); Bayoumi et al. (2013); Guizzardi et al. (2022); Talón-Ballestero et al. (2022); Saitta et al. (2024); Antonio et al. (2019)	Prices can decrease due to campaigns / discounts and demand updates; some cancellations are triggered by customers seeking better terms after booking.	Mostly no	No (for rebooking)	Missing link between price drops and observed rebooking episodes and their revenue consequences in hotels.
Automated rebooking services and amplification of strategic behavior	Masiero et al. (2020); Vinod (2024)	Automation can intensify monitoring / rebooking behavior (especially among risk-takers); platforms popularize rebooking.	Indirectly/ partially	No	Limited academic evidence on scale and outcomes of rebooking in hotel operational data.
Rebooking evidence in adjacent industries (transferable but not hotel-specific)	Gorin et al. (2012) (airlines); Showker and Sehlinger (2007) (cruises)	Rebooking has been examined more in airlines/cruises, suggesting potential revenue implications and offering transferable ideas.	No (not hotels)	Yes (not hotel-focused; described as outdated)	Findings are dated and not tailored to hotels; hotel drivers, consequences, and effective strategies remain insufficiently evidenced.
Cancellation policy design and mitigation strategies	Antonio et al. (2017), (2019)	Tailored/flexible policies for low-risk guests can outperform strict rules; strict policies may erode loyalty; segmentation / predictive tools can reduce leakage while preserving experience.	Mostly no	No (for rebooking)	Guidance centers on cancellations broadly, not on measuring/managing rebooking-driven substitution specifically.
Empirical work limits: narrow hotel types / locations / small scope	Choi and Kim (2024); Contessi et al. (2024); Falk and Vieru (2018); Guizzardi et al. (2022); Hikmawati et al. (2024); Herrera et al. (2024); Jenčková and Abrhám (2016)	Use of limited-scope datasets (e.g., specific hotel types/locations), which constrain generalizability—this concern applies to rebooking too.	Mostly no	No	Need broader, multi-property evidence that generalizes across markets/property types.
Multichannel distribution, parity gaps, and rate dispersion	O'Connor and Murphy (2008); Guizzardi et al. (2022)	Multichannel distribution can generate rate dispersion (direct vs intermediaries), which can facilitate rebooking within/across channels.	Indirectly	No	Need to measure substitution/ rebooking using operational data; separate conservative within-property effects from broader channel effects.
Behavioral foundations: reference prices & loss aversion	Xia, Monroe, and Cox (2004); Kahneman and Tversky (1979)	Seeing a lower price after booking can feel like an avoidable loss; with low transaction costs (free cancellation), propensity to cancel-and-rebook increases.	Conceptu-al only	No	Need to operationalize these mechanisms with observed booking / cancellation / rebooking traces rather than theory alone.
RM theory: booking curves, tactical price revisions, and substitution	Talluri and Van Ryzin (2004); Ferguson and Smith (2014)	Tactical price decreases can be rational but may lead to substitution (not incremental demand) when made visible to already-booked customers.	Conceptu-al/ indirect	No	Hotel magnitude of substitution via rebooking is rarely quantified.
This study	This manuscript	Measures a conservative subset of substitution: within-property cancellations followed by a cheaper booking for the same stay; documents heterogeneity across time/ geography/property types and translates results into monitoring / managerial implications.	Yes	Yes	Addresses the stated gap by quantifying incidence and revenue displacement of rebooking using operational reservation data; proposes actionable monitoring indicators/guardrails.

constrained by the scarcity of data on the specific factors that influence rebooking behavior, despite a substantial body of research on the drivers of cancellation (Falk and Vieru, 2018; Antonio et al., 2019). The lack of a comprehensive understanding of consumer motivations hinders the development of effective regulatory frameworks for rebooking. Filling that research gap would provide hotel managers with the necessary tools to identify and respond to rebooking patterns more strategically. Moreover, it would improve the industry's ability to navigate rebooking complexities.

2.4. Conceptual framing

Rebooking is a form of strategic consumer behavior enabled by (i) intertemporal price variation and reference-price comparisons (Xia, Monroe, and Cox, 2004), (ii) low transaction costs under flexible cancellation, and (iii) multichannel distribution where rate dispersion can emerge across direct and intermediary channels (O'Connor and Murphy, 2008; Guizzardi et al., 2022). In classical revenue management, the booking-curve logic implies that large downward price revisions after bookings are created can induce substitution rather than incremental demand (Talluri and Van Ryzin, 2004). Our empirical design, therefore, focuses on measuring a conservative subset of substitution—within-property cancellations followed by a cheaper booking for the same stay—and on documenting heterogeneity across time, geography, and property types.

Rebooking can be interpreted through three complementary lenses. First, reference-price comparisons and loss aversion imply that once a consumer observes a lower price for the same stay, the original booking is perceived as an avoidable loss, increasing the propensity to cancel and rebook when transaction costs are low (Kahneman and Tversky, 1979; Xia et al., 2004). Second, in Revenue Management practice, tactical price decreases may be rational responses to updated demand information. However, they can create substitution when they become visible to customers who have already booked (Talluri and Van Ryzin, 2004; Ferguson and Smith, 2014). Third, in multichannel distribution, parity gaps and channel-specific promotions can create rate dispersion, facilitating rebooking within or across channels (O'Connor and Murphy, 2008; Guizzardi et al., 2022). These perspectives motivate our focus on measuring within-property substitution and on examining heterogeneity across time, geography, and property types.

3. Methodology

3.1. Research framework

We follow a standard analytics workflow based on CRISP-DM (Chapman et al., 2000), focusing on business understanding, data understanding, data preparation, and evaluation. We define two core outcomes: (1) the incidence of rebooking and (2) the revenue difference between the original and replacement booking. We use exploratory analysis to describe the data and check quality, then clean records, remove duplicates, and create derived variables (Appendix B). Because our goal is measurement and description—not prediction—we do not include a modeling step. Finally, we compare rebooked, canceled-for-rebooking, and other reservations and quantify revenue displacement across segments. Fig. 1 summarizes the workflow.

We use exploratory data analysis (EDA), summary statistics, and visualizations to describe patterns in bookings, cancellations, and rebookings. We run all analyses in Python and use statistical comparisons where needed to support the descriptive findings.

3.2. Data understanding and preparation

We analyze reservation records from 628 Portuguese properties drawn from a hotel property management system (PMS). The dataset contains 16 variables and 2,223,024 records from 2022 to 2024

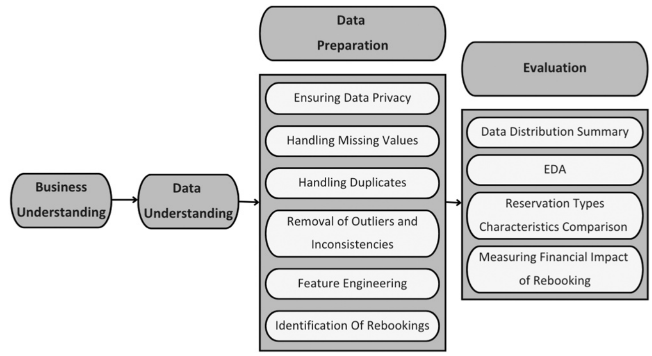

Fig. 1. Research design diagram.

(Appendix A). Because the sample comes from a single country, the numerical estimates are Portugal-specific. However, the identification logic and monitoring metrics we propose (rebooking rate, leakage per reservation/night, and ADR erosion) can be replicated in other PMS/ Central Reservation Systems (CRS) environments.

We use anonymized data and comply with applicable privacy and data protection requirements throughout the study.

We clean the data using domain-based rules rather than relying solely on statistical cutoffs (Antonio et al., 2019). We remove stays longer than 30 nights, party sizes that are implausible in this context (e.g., more than five children/infants or more than ten adults), and reservations with ADR ≤ 0. These values can arise operationally but fall outside the scope of this analysis.

We standardize categorical labels (e.g., naming conventions) and correct inconsistencies to improve interpretability (Herrera et al., 2024). We then create additional features (Appendix B) and correct clear data-entry errors (e.g., extreme ADR values and an implausible lead time resulting from an arrival date in 2055) to avoid distorting the descriptive results.

EDA revealed a considerable number of duplicates based on the reservation ID. Despite sharing the same reservation ID, certain reservations differed in ADR, timestamps, or number of visitors. The data provider company attributed the presence of these duplicates to a variety of system-related and user-driven circumstances. These include guests making multiple attempts to book, system processing delays resulting in duplicate entries, or hotel employees manually editing registration details (Alam et al., 2024).

We remove near-duplicate reservation records following Zheng et al. (2010). When multiple versions of the same reservation ID exist, we keep the most recent record because it reflects the final state of the booking (updates, cancellations, or price changes).

3.3. Identifying rebooked reservations

A critical component of the study was the identification of rebooked reservations, defined as cancellations followed by new, similar reservations at a lower price within a short interval, or new reservations followed by a cancellation of a similar reservation at a higher price. We compare reservations to identify instances in which a canceled reservation is replaced by a new, lower-priced reservation with the exact arrival date and number of guests at the same hotel, thereby detecting potential rebooking (Masiero et al., 2020), as shown in Fig. 2. To account for variation in booking behavior, we included rebooked reservations made 1 min before or after the cancellation, as customers may rebook in both scenarios depending on their preferences and availability. For clarity, the "±1 min" criterion refers to the time difference between the cancellation timestamp and the new booking creation timestamp recorded in the PMS log, or the inverse, as sometimes, a new booking is sent to the PMS before the cancellation of the original booking. This 1-minute threshold was defined as a high-precision

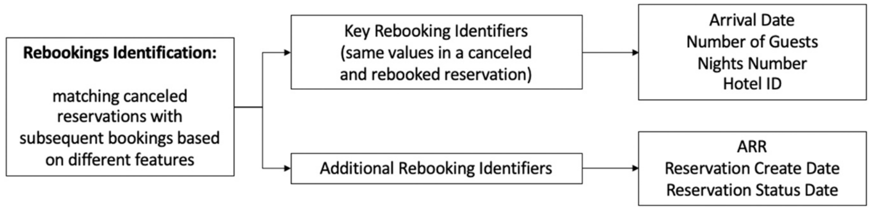

Fig. 2. Identification of rebookings.

operational rule that strongly reduces false matches in anonymized data. This window is most consistent with automated cancel/rebook workflows executed via channel managers and APIs, where cancellation and re-creation events are logged within seconds. We therefore interpret the resulting incidence as a conservative lower bound on rebooking. If this threshold is extended, we could probably identify more rebookings, but we would also see more false positives.

To make the rule concrete, consider the following illustrative example. A reservation (A) at Hotel H is created on 2024–05–01 for arrival on 2024–06–15 (2 adults, 1 night, breakfast included), with an ADR of €140. It is canceled on 2024–05–10 12:00:30, and a new reservation (B) is created on 2024–05–10 12:01:05 for the same stay details, with an ADR of €125. Because the events fall within ±1 min and ADR is lower, we label A as "canceled-for-rebooking" and B as its "rebooked reservation."

We also applied a consistent approach when multiple reservations corresponded to the same canceled booking. Only the reservation with the shortest time interval between cancellation and rebooking was retained. This approach relied on the premise that guests are more likely to make a subsequent reservation immediately before or after a cancellation to secure a more economical rate.

Finally, we created new datasets to analyze rebooking by extracting relevant columns from the preprocessed dataset and matching rebooking with cancellations. Specifically, two groups of reservations were distinguished: those canceled for rebooking and those successfully rebooked. This grouping facilitated a comparative analysis between cancellations and new rebookings. A detailed analysis revealed that 9667 rebookings (52.2 %) involved a new reservation made before the cancellation, while 8852 rebookings (47.8 %) involved cancellations made before the new reservation. Table 2 summarizes the dataset's key characteristics across reservation types.

After preprocessing, approximately 12.43 % of reservations were canceled. Percentages in Table 2 are shares of total reservations after preprocessing. For clarity, canceled-for-rebooking reservations represent 7.55 % of all canceled reservations (18,519/245,331) and 0.94 % of total reservations.

To address the research objectives of identifying patterns in rebooking behavior and understanding the financial impact of rebooking, we conducted an EDA to visualize the distribution and characteristics of canceled and rebooked reservations, identifying key trends and patterns. Afterward, to distinguish between cancellations and rebookings and to identify factors influencing rebooking behavior, we compared several characteristics, including booking lead time, ADR, customer demographics, and seasonal effects.

Table 2
Distribution of reservation types.

Type of Reservation	Count	% of Total Reservations
Reservations After Preprocessing	1,973,137	100.000 %
All Canceled Reservations	245,331	12.430 %
Canceled Reservations for Rebooking	18,519	0.939 %
Rebooked Reservations	18,519	0.939 %
Reservations Rebooked More Than Once	695	0.035 %

4. Results and discussion

4.1. Rebooking behavior compared to general booking patterns

Rebooked reservations represent only 0.94 % of nearly two million total reservations. Nonetheless, they are of considerable operational and financial significance. Table 3 presents a comprehensive analysis of the disparities between rebooked, canceled-for-rebooking, and total reservations.

From a hotel management perspective, identifying incoming reservations likely to be canceled and subsequently rebooked is crucial (Almotiri et al., 2021; Liu et al., 2024). However, the analysis revealed that such reservations differed only slightly from standard reservations, making early identification challenging. They had slightly shorter stays (2.92 vs. 2.95 nights), smaller group sizes (1.94 vs. 2.00), and were more expensive (ADR: €132.18 vs. €117.45). Interestingly, they had a longer lead time (73.0 vs. 61.8 days), suggesting that travelers who cancel and rebook tend to plan ahead. The share of family bookings was even lower than average (6 % vs. 9 %), suggesting that solo travelers or couples may be more likely to rebook strategically. Furthermore, the absence of certain variables identified in prior studies as significant predictors of cancellation (Almotiri et al., 2021; Antonio et al., 2019; Falk and Vieru, 2018) constrained the assessment of their relevance in the rebooking context.

When we compare each rebooked reservation to the canceled booking it replaces, the rebooked reservation is typically cheaper and has a shorter lead time, consistent with cost-saving behavior. Table 4 reports the mean differences and statistical tests; the largest and most consistent differences are observed for ADR and lead time (Lee, 2022).

ADR shows the clearest difference. We find that rebooked reservations have a lower ADR (€109.55) than both the overall average (€117.45) and the canceled-for-rebooking group (€132.18), consistent with price sensitivity (Abrate et al., 2019; Masiero et al., 2020). Furthermore, rebooked reservations demonstrated a 28.3 % shorter lead time, typically created 1.5 months before arrival, compared to 2 months for canceled-for-rebooking reservations.

Timing analysis revealed that approximately 80 % of rebookings occurred within 1 month of the initial booking, with nearly half occurring within 1 week. Moreover, a detailed examination of seasonal trends revealed a steady increase in rebookings since 2022, peaking in early 2024 at over 1500 per month. Simultaneously, the overall number of reservations also rose significantly during this period, surpassing 200,000 per month in early 2024. However, to determine whether rebooking became more popular or followed the broader booking surge, it is necessary to examine the rebooking rate. As shown in Fig. 3, the rate remained low but exhibited a slight, consistent upward trend, increasing from 0.67 % in 2022–0.79 % in 2023 and 1.09 % in 2024.

While the increase may seem marginal, it suggests a gradual normalization of rebooking behavior, likely driven by travelers' increasing use of online platforms (Masiero et al., 2020; Vinod, 2024). Despite the modest rise, the trend supports the idea that rebooking is becoming a more common strategy among travelers (Vinod, 2024). Notably, rebooking occurred primarily during non-tourist months, as shown in Fig. 4. However, this may reflect broader hotel pricing strategies, as room rates tend to be steady or elevated during peak seasons

Table 3
Comparison of reservation types characteristics.

		€ Revenue Per Reservation	€ ADR	Nights	Group size	Lead time	Is family?	Is expensive?
Total Reservations	min	0.00	0.00	1.00	1.00	0.00	0.00	0.00
(n = 1973,137)	**mean**	**367.93**	**117.45**	**2.95**	**2.00**	**61.81**	**0.09**	**0.25**
	max	80,283.02	7290.57	30.00	14.00	1860.00	1.00	1.00
Total Reservations (Excluding Rebooked)	min	0.00	0.00	1.00	1.00	0.00	0.00	0.00
(n = 1954,618)	**mean**	**368.13**	**117.53**	**2.95**	**2.00**	**61.90**	**0.09**	**0.25**
	max	80,283.02	7290.57	30.00	14.00	1860.00	1.00	1.00
Canceled-for-Rebooking Reservations	min	1.89	1.89	1.00	1.00	0.00	0.00	0.00
(n = 18,519)	**mean**	**413.76**	**132.18**	**2.92**	**1.94**	**72.97**	**0.06**	**0.33**
	max	22,978.85	2141.51	30.00	8.00	486.00	1.00	1.00
Rebooked Reservations	min	1.51	1.51	1.00	1.00	0.00	0.00	0.00
(n = 18,519)	**mean**	**346.74**	**109.55**	**2.92**	**1.94**	**52.30**	**0.06**	**0.16**
	max	14,339.62	1554.34	30.00	8.00	465.00	1.00	1.00

Table 4
Independent *t*-tests results.

	ADR	Lead Time
T-test statistic	25.78	27.21
P - value	<0.0000000001	<0.0000000001

and hotels are less inclined to offer discounts or reduce prices when demand is already high (Alrawabdeh, 2022), thereby limiting opportunities for deal-seeking clients to rebook.

Rebooking behavior exhibited notable variations across regions in Portugal. The country's three primary tourism regions (based on NUTS3 nomenclature) are the Lisbon Metropolitan Area, the Porto Metropolitan Area, and the Algarve (Moreira, 2018), which accounted for most bookings and rebookings. Contrary to previous studies, which frequently relied on limited or localized hotel samples (Choi and Kim, 2024; Contessi et al., 2024), this research used a diverse dataset encompassing various types of accommodations across all Portuguese regions. Consequently, while the findings may not be generalizable internationally, they are highly representative of the national hotel market. Lisbon was identified as the most popular tourist destination in Portugal, recording the highest number of bookings and rebookings (9970). At the same time, Porto exhibited a higher rebooking rate than Algarve despite fewer overall reservations (Table 5).

Porto's higher rebooking rate may be due to pricing sensitivity or distinct cancellation procedures. This phenomenon could also reflect variations in the average visitor profile. For instance, Porto may attract a higher proportion of short-term or business visitors (Gusman et al., 2019; Pinho and Marques, 2021), who are better able to monitor and respond to pricing changes (Masiero et al., 2020). Based on the findings, rebooking occurred most frequently among small groups, particularly pairs (70 % of rebookings). While larger groups, especially families, rebooked less frequently (1108 bookings out of 18,519 rebooked by families), solo travelers also accounted for a significant share (20.92 %).

Among property types, hotels were most affected by rebooking, accounting for the majority of rebooked reservations and the highest rebooking rate (Fig. 5).

Other property types experienced fewer rebookings, highlighting

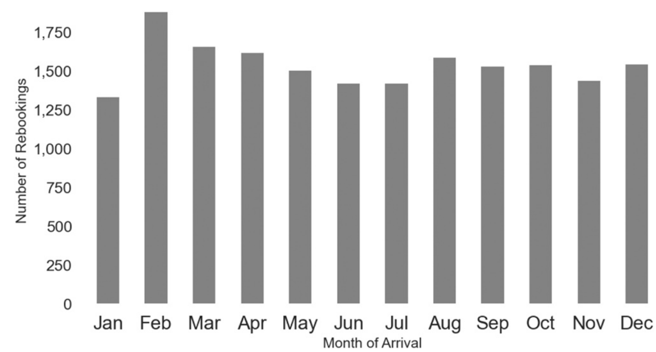

Fig. 4. Number of rebookings per month of arrival (cumulative).

Table 5
Bookings per different regions.

Region	Overall Bookings	Rebooked Reservations	Rebooking Rate
Lisbon Metropolitan Area	880,226.0	9970.0	1.13 %
Porto Metropolitan Area	137,862.0	1926.0	1.14 %
Algarve	338,769.0	2117.0	0.62 %

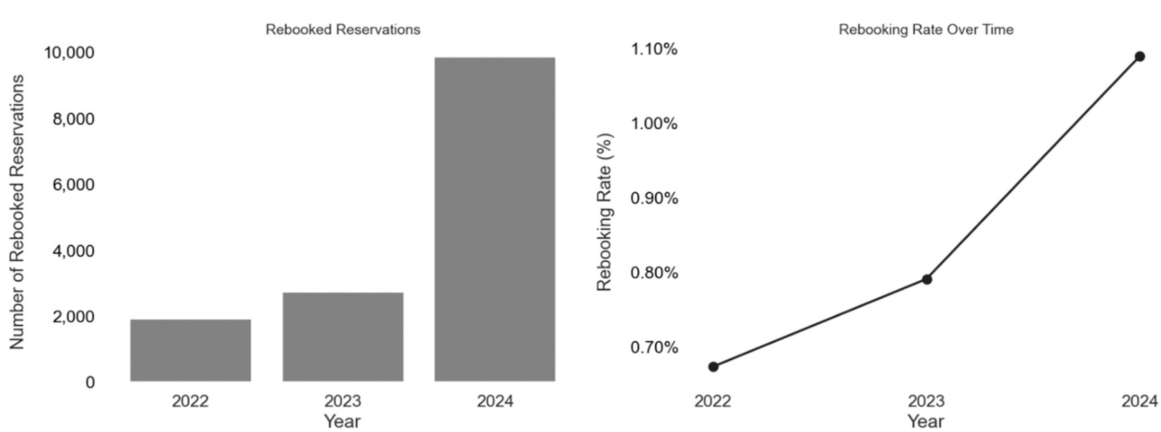

Fig. 3. Rebooking rate throughout the years.

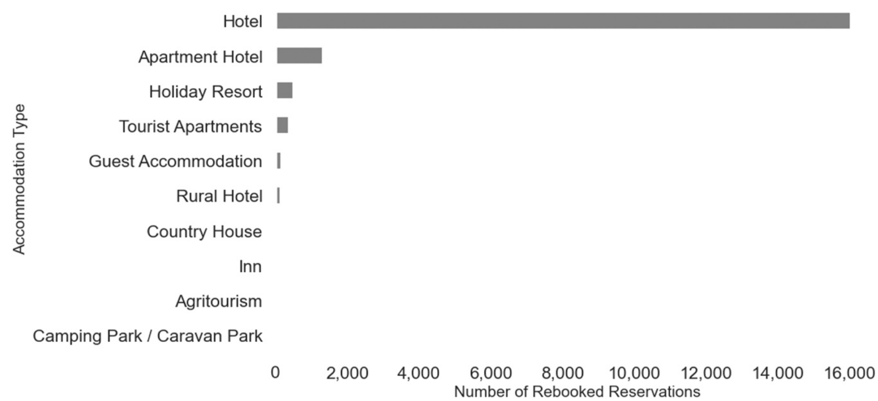

Fig. 5. Accommodation Types by Number of Rebooked Reservations (Top 10). Country House, Inn, Agritourism, and Other correspond to very small counts and may not be visible at the displayed scale.

that conventional hotels, with their larger scale, more transparent pricing structures, and accommodating cancellation and booking regulations, predominantly influence rebooking behavior (Falk and Vieru, 2018; Masiero et al., 2020). Furthermore, the distribution of rebookings across individual hotels showed some disparities. The leading hotel (Unit ID 279, Azores) recorded the highest rebooking rate of 4.17 %, but even this was relatively low in absolute terms, suggesting that rebooking remains a niche behavior. Other hotels had rebooking rates below 3 %, reinforcing the notion that rebooking is not widespread across all properties. For example, Hotel 287, which had the highest absolute number of rebookings (873), had a rebooking rate of only 2.38 %. This finding suggests that while certain hotels may be more susceptible to rebooking behavior - possibly due to their flexible cancellation policies, competitive pricing, or location - the overall adoption of rebooking remains limited in the broader hotel dataset.

4.2. *Financial impact of rebooking*

Rebooking reduces the price ultimately paid for the same stay, thereby eroding revenue. We estimate gross revenue displacement as the difference between the original booking value (canceled-for-rebooking) and the value of the cheaper replacement booking for the same stay. Across the matched rebooking cases, this amounts to €1,241,281.58 (original: €7,662,479.59; replacement: €6,421,198.01). This calculation does not include cancellation penalties, payment timing, or administrative costs because the dataset lacks policy metadata. On average, each of the 426 hotels that experienced rebooking recorded gross displacement of € 2913.81. These findings also address the current lack of financial analysis in rebooking research (Guizzardi et al., 2022; Lacetera et al., 2024), providing a quantified estimate of revenue leakage associated with rebooking.

Four hotels incurred losses exceeding €30,000, with the largest

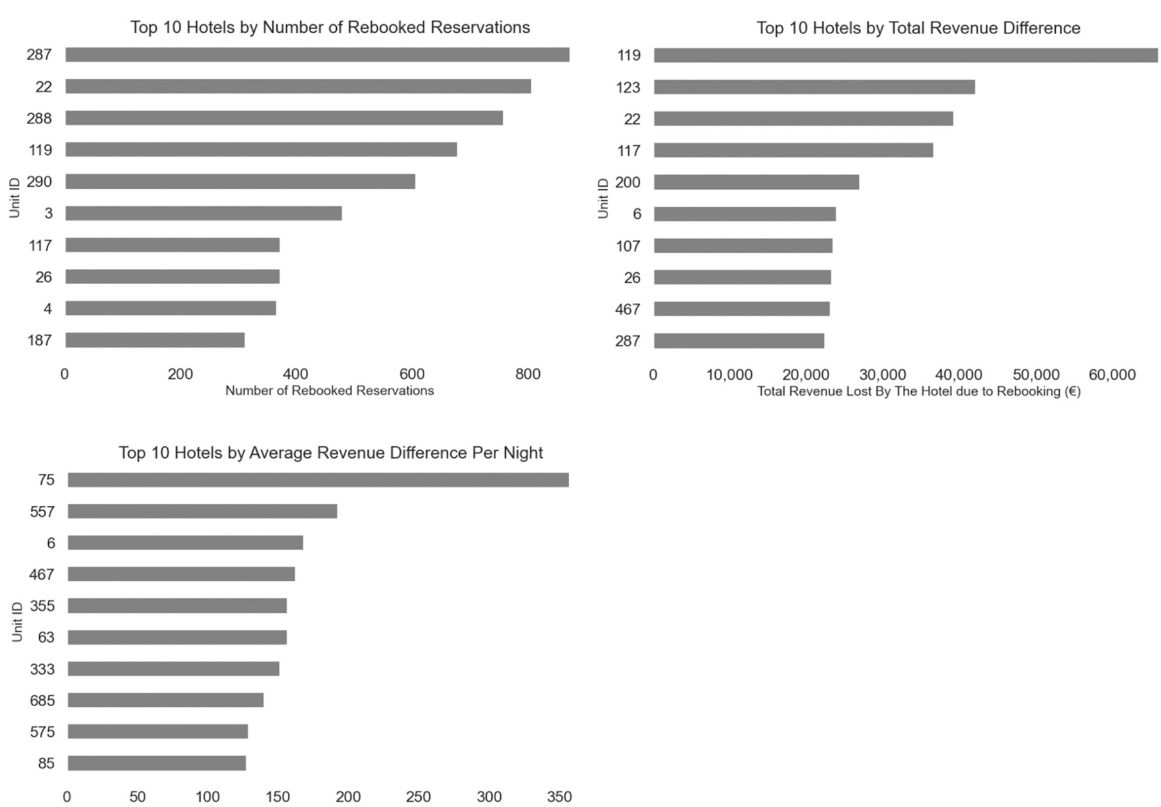

Fig. 6. Analysis of The Top 10 Hotels Across Various Performance Categories.

exceeding €60,000. High-volume properties, such as hotels 287, 22, and 288, were notably affected, but interestingly, the hotel with the most rebookings (in Lisbon) did not suffer the highest revenue loss. Instead, the hotel in the Azores experienced the largest revenue loss, driven by longer stays and higher nightly rates for rebooked reservations. Further analysis revealed that hotels with higher average losses per reservation might not coincide with those with the highest number of rebookings, nor with those with the highest total revenue loss (Fig. 6a, 6b, 6c).

The mean revenue for rebooked reservations was 16.2 % lower than for canceled-for-rebooking reservations, per reservation (see Table 6). Standardized by length of stay, hotels lost an average of €22.63 per reservation night, about 17.1 % of the initial nightly rate.

The distribution of revenue losses per night indicated that while most rebookings resulted in minor losses, a smaller number led to significant price reductions, severely affecting overall revenue, as presented in Fig. 7.

Geographically, areas such as Baixo Alentejo and Douro recorded the highest average nightly revenue losses. These regions had fewer rebookings, which can be explained by the previously mentioned distribution of revenue loss per night. Most rebookings resulted in modest losses, but a smaller number of cases involved significant price reductions, leading to higher overall revenue leakage despite fewer rebookings.

Revenue losses also varied across accommodation types. Those with lower rebooking rates incurred the highest average nightly losses (see Table 7).

Hotels that incurred the highest total revenue loss from rebooking, given their dominant share in the dataset, experienced lower average losses per reservation and per night. Specifically, the mean revenue loss per night for hotels was €22.04, compared to €26.39 for other property types. Consequently, the mean revenue loss per reservation for hotels was €60.15, whereas for all other types it reached €75.02, as presented in Table 8.

This pattern indicates that, although rebookings are more prevalent in hotels, their per-booking financial impact is smaller than in other, less frequently rebooked accommodations. This disparity likely results from differences in pricing strategies and demand trends. This pattern is also evident at the regional level: in areas with fewer rebookings, revenue losses per reservation night are greater, suggesting less proactive price adjustments by accommodations, leading to steeper discounts. Conversely, regions with a higher rebooking frequency experienced smaller revenue losses per reservation night. This phenomenon may be attributed to heightened awareness of rebooking patterns among accommodations in these areas, driven by the larger number of tourists (Moreira, 2018), enabling them to adapt their pricing strategies accordingly.

Chronologically, no clear linear relationship emerged between lead time and guest savings. Similarly, no such relationship was apparent between savings and the time between the creation of the initial reservation and its subsequent cancellation for rebooking, as illustrated in Fig. 8.

Price volatility persisted throughout the booking period, with higher savings concentrated in shorter lead times, although savings remained notable for longer lead times (Guizzardi et al., 2017; Yang and Leung, 2018). Although rebooked reservations have shorter lead times than their canceled counterparts, the average rebooking still occurs well before arrival. Thus, the observed behavior should not be interpreted solely as “last-minute discounting”; it is more consistent with post-booking price dispersion that arises during the booking window, potentially including multichannel parity gaps.

Table 6
Financial results for reservation categories.

	Canceled-for-Rebooking Reservations	Rebooked Reservations	Difference
Average Revenue Per Reservation	€413.76	€346.74	- €67.03 (-16.2 %)
Average Revenue per Reservation Night	€132.18	€109.55	- €22.63 (-17.1 %)

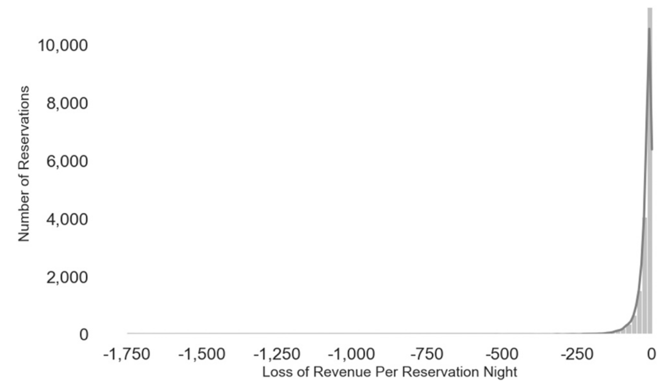

Fig. 7. Distribution of revenue per night lost from rebooked reservations.

Table 7
Average revenue loss per reservation night and rebooking rate for accommodation types.

Accommodation Type	Average Revenue Loss Per Reservation Night	Rebooking Rate
Rural Hotel	€43.15	0.57 %
Inn	€39.00	0.09 %
Holiday Resort	€32.08	1.14 %
Guest Accommodation	€25.09	0.78 %
Apartment Hotel	€24.21	0.26 %
Agritourism	€23.74	0.21 %
Hotel	€22.04	1.02 %
Tourist Apartments	€20.99	0.44 %
Country House	€15.57	0.51 %
Camping Park / Caravan Park	€14.91	0.23 %

Table 8
Hotels versus other accommodation types – financial results.

	Hotels	Other Accommodation Types
Average Revenue Loss Per Reservation Night	€22.04	€26.39
Average Revenue per Reservation	€60.15	€75.02
Total Revenue Loss	€964,436.94	€276,844.64

An examination of monthly revenue data revealed consistent revenue leakage from rebooking, with total revenue from canceled reservations exceeding that from rebooked reservations across all months (Fig. 9).

A notable finding was the uniformity in mean average savings per night across weekend and weekday stays (€22.84 to €22.32), confirming that rebooking at reduced rates is a universal practice for both business and leisure travel, not tied to specific times of stay, but rather is a more general aspect of the travel experience.

Geographically, European guests rebooked most frequently, as they were the most common travelers in the dataset from Portuguese hotels. However, North American and Asian reservations showed higher average nightly revenue losses, suggesting that guests from these regions may be better able to capitalize on price fluctuations. Similarly, family bookings, though fewer, had a significantly greater financial impact than non-family bookings (an average revenue difference of € 6.22 per night).

It is worth mentioning that the estimated financial impact was likely

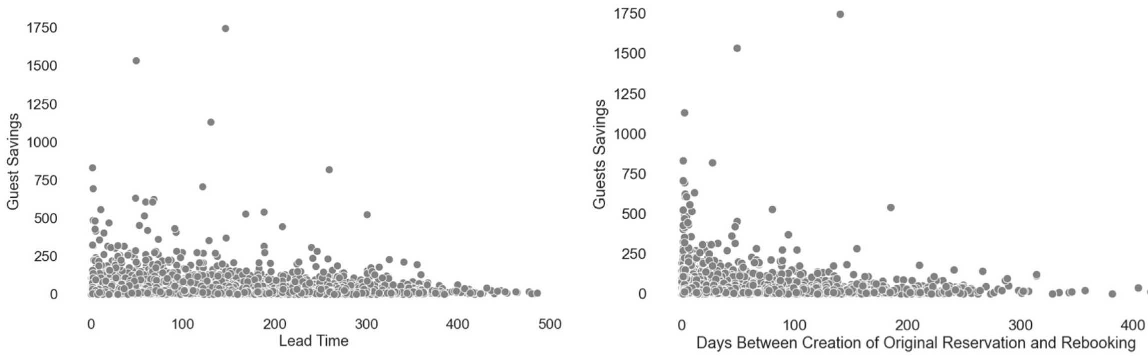

Fig. 8. Guests' savings versus lead time and days between creation of original reservation and rebooking.

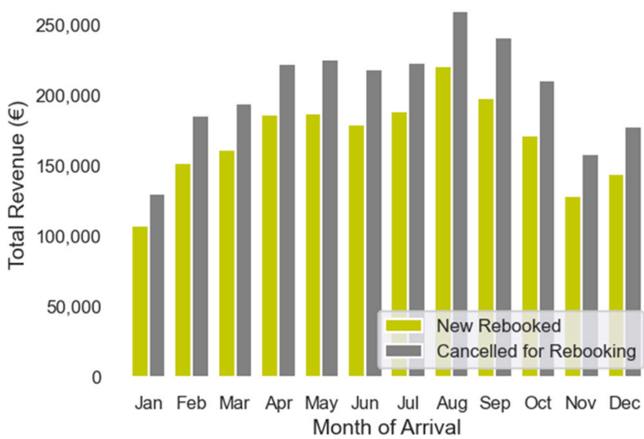

Fig. 9. Monthly revenue comparison: rebooked reservations vs cancellations for rebooking.

underestimated, as it did not account for indirect costs associated with processing cancellations and new bookings, nor the opportunity costs of potential inventory mismanagement during high demand (Almotiri et al., 2021; Ivanov and Zhechev, 2011; Lim et al., 2024). Many hotels may deliberately lower their prices, accepting the risk of rebookings, assuming the losses from it will be offset by a greater number of new bookings triggered by the lower rate (Gorin et al., 2012). It is essential to acknowledge that, while individual rebookings may appear negligible, their cumulative impact can lead to substantial revenue leakage over time.

While price reductions may intuitively influence both rebooking behavior and the volume of new reservations, the dataset used in this study does not allow a clear distinction between these outcomes. Specifically, based on the available data, it was not possible to determine whether a price drop at a hotel primarily led to rebookings or to an increase in new customer bookings. Consequently, a definitive assessment of the counterproductivity or the potential for revenue reductions remains unattainable in full.

Furthermore, the dataset lacked information on cancellation policies and associated fees, which are important for evaluating the true financial impact of rebookings (Almotiri et al., 2021; Ivanov and Zhechev, 2011; Lim et al., 2024). This limitation hinders accurate quantification of the extent to which rebookings result in revenue loss, or whether cancellation penalties partially offset such losses, thereby complicating the assessment of the risks of price adjustments in hotel revenue management. Nevertheless, this study provides the most comprehensive financial estimate of rebooking-related revenue losses to date, contributing empirical evidence to an area previously dominated by theoretical assumptions (Schwartz, 2006; Almotiri et al., 2021).

Rebookings account for less than 1 % of reservations in our sample, so aggregate displacement should be interpreted relative to the overall revenue scale. Nonetheless, the distribution is heterogeneous, and certain properties and regions experience economically meaningful leakage per case. Moreover, our measure captures only within-property substitution (cancellations and rebookings at the same property) and therefore does not quantify competitive displacement, in which a guest cancels and books elsewhere. Finally, price decreases may reflect tactical repricing in response to updated demand/competitive information. Our analysis quantifies the substitution associated with such decreases but does not infer a counterfactual "optimal" price path.

5. Conclusions

The hotel industry faces significant challenges arising from digital booking channels and increasingly transparent price discovery. Our results show that rebooking, although affecting a relatively small fraction of stays, produces economically meaningful revenue leakage that varies by season, region, and accommodation type. We use "revenue leakage" to refer to the observed price gap that arises when a booking is canceled and replaced with a lower-priced booking for the same stay. This gap can be guest-captured (the guest rebooks and pays less) or intermediary-captured (an agent/corporate platform rebooks and retains part of the savings). To our knowledge, this is the first large-scale, multi-hotel empirical demonstration of the financial impact of rebooking in the hospitality industry. Our findings are consistent with core revenue management principles and highlight an operational risk: when visible prices decrease after bookings are created—whether due to tactical repricing or channel rate dispersion—some demand may substitute through cancel-and-rebook behavior rather than arriving as incremental bookings.

The study advances knowledge by providing a replicable method for measuring rebooking and its consequences. We implement an operational identification procedure that links cancellations to subsequent bookings at the same property and for the exact stay dates, enabling consistent estimation across hotels and periods and allowing it to be reused by other researchers. We also provide a measurement framework that distinguishes between rebooking rate, revenue leakage per reservation and per night, and average daily rate erosion, enabling comparisons across contexts and monitoring change over time. Patterns in the data align with research on intertemporal pricing and strategic consumer behavior, since guests appear to exploit downward price movements, and they also reveal meaningful heterogeneity, for example, a tendency for urban locations to show higher frequency but smaller losses per case. In addition, the descriptive comparison between reservations that are rebooked and those that are not helps clarify where incentives to rebook are stronger, such as combinations of lead time, season, and observed price declines, which future work can study in more granular detail.

The practical consequences are immediate. Hotels should adopt a small set of indicators for routine revenue meetings, including rebooking-linked cancellations, rebooking rate, and revenue leakage per night, disaggregated by arrival month, region, and channel. Price changes should adhere to guardrails that limit large downward movements within defined booking windows. For example, limit downward rate changes to $\leq$ 10–15 % within a defined window (e.g., within 14 days of arrival) unless occupancy falls below a trigger threshold; require manager approval for larger cuts. When reductions are necessary, it is preferable to use targeted offers such as member-only pricing, mobile-only, closed-user-group, or non-refundable rates to reduce "public" reference-price drops, minimum stay requirements, or non-refundable conditions rather than broad public cuts. For guests who detect lower prices after booking, credits or value-added benefits can reduce the incentive to cancel and rebook while preserving the headline rate. Cancellation policies can be tuned to local conditions. Where per-case leakage is high, stricter free-cancellation windows and clearer penalties are warranted. In contrast, in areas with frequent but less costly rebookings, lighter penalties combined with fenced incentives may better balance competitiveness and revenue protection. Parity should be audited across channels, and tactical discounts should be moved to opaque or loyalty contexts when possible to limit visible price drops that trigger rebookings. To enforce this parity, daily monitoring should be enforced across direct and top OTAs. Property management and central reservation systems can incorporate a rebooking risk flag that combines lead time, recent price trajectory, and guest history, enabling frontline teams to deploy retention scripts or targeted offers, such as credits for other consumption, breakfast, upgrade priority, and more. These interventions should be evaluated through experiments and tracked using the proposed indicators to enable hotels to quantify reductions in leakage.

Because our dataset comprises 628 properties in Portugal, our study provides strong within-country representativeness. Still, it limits direct extrapolation to markets with different channel mixes, cancellation norms, consumer protection rules, or competitive structures. We therefore interpret the reported leakage levels as Portugal-specific estimates and emphasize that our main contribution is a replicable measurement approach (identification logic and monitoring metrics) that can be applied in other contexts to produce locally valid estimates. Nevertheless, the high representativeness of our study also makes it a benchmark for future studies on the topic.

The analysis also clarifies constraints that shape what can be inferred. The data exhibit substantial class imbalance, and not all systems or processes consistently validate whether a cancellation is followed by a substitution booking, which affects the completeness of the labels used to identify rebooking events. While some PMSs already perform internal validation, others do not. This heterogeneity may attenuate the performance of any predictive screening undertaken by practitioners. Also, because the dataset is anonymized and does not include customer identifiers, we cannot directly verify that the same individual (or intermediary) executed both the cancellation and the rebooking. Our deterministic matching (same property, same arrival date, exact guest count, lower ADR, near-immediate timing) is designed to maximize precision. However, it may still produce false negatives (missed rebookings outside the window) and, less likely, false positives (coincidental near-identical bookings). We therefore interpret the main estimates as conservative and encourage future work to validate matches using customer IDs or probabilistic record linkage where permissible. These limitations do not alter the core empirical findings about the scale and distribution of revenue leakage. Still, they point to specific improvements in data capture and system integration that can support better monitoring and policy design.

Because cancellation rules and fees are not observed, our financial estimates should be interpreted as an upper bound on net realized loss in cases where penalties apply, and a lower bound on total economic impact because it excludes administrative processing costs and potential inventory/forecasting distortions created by cancellations and rebookings.

Building on these insights, several lines of research appear promising. Future work should incorporate policy metadata such as cancellation windows, loyalty status, and channel rules to isolate mechanisms, test alternative matching windows and price definitions as robustness checks, and examine channel-specific dynamics and parity enforcement. It will also be helpful to study how guardrails, fences, and price protection policies affect leakage using field experiments, to document when and where they are most effective, and to develop screening tools that flag at-risk reservations using operational data that hotels already collect. Future research could enrich the model of rebooking opportunity by incorporating cancellation-policy metadata, geographic distance to points of interest and transport hubs, and measures of local market concentration/competitive density by region. Additionally, future research could also distinguish rebooking pathways (e.g., direct-to-direct, direct-to-Online Travel Agencies (OTAs), OTA-to-direct, cross-OTA) because each reflects different mechanisms and implies different managerial interventions (O'Connor and Murphy, 2008; Guizzardi et al., 2022).

An additional avenue for future research is to expand the operational definition of rebooking beyond the high-precision $\pm$1-minute matching window used here. The strict window was chosen to ensure robust identification in a large anonymized dataset without customer identifiers and to avoid overcounting coincidental near-identical reservations. However, broader matching windows could capture slower, manually executed rebooking behaviors and potentially reveal different substitution patterns across channels. Future studies should therefore conduct sensitivity analyses across alternative thresholds and incorporate probabilistic matching or validation subsamples to quantify possible false positives/negatives and refine the estimated magnitude of revenue displacement.

Together, these steps would refine estimates of financial impact, deepen understanding of guest behavior in response to price trajectories, and provide a stronger foundation for revising pricing and revenue management playbooks in contexts where rebooking is a meaningful source of leakage.

CRediT authorship contribution statement

Nuno Antonio: Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization. **Martyna Kmiecik:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. . Original Variables Description

Variable Name	Description
unit_id	Unique identifier for each hotel
nuts3	Geographic location of the hotel, based on NUTS3 regions in Portugal
unit_type	Type of property
unit_rating	The rating of the hotel (0–5)
folio_number	Reservation number
reservation_create_date	Date of the creation of the reservation
arrival_date	Check-in date of the guests
nights	Number of nights booked
adults	Number of adult individuals in the reservation
children	Number of children in the reservation
babies	Number of babies in the reservation
ADR	Average Daily Rate (price per room per night)
nationality	Nationality of the guests
distribution_channel	Booking source
reservation_status	Status of the reservation
reservation_status_date	Date when the reservation status was last updated

Appendix B. . New Features Description

Feature Name	Description
reservation_id	A reservation's unique identifier is the concatenation of the hotel identifier and the reservation number, which may be repeated across hotels. With those variables combined into the new reservation_id, distinct tracking of reservations is ensured
is_family	A binary characteristic helping to identify whether the booking includes babies or children
group_size	A variable representing the total number of guests per reservation
is_weekend_stay	A binary feature indicating whether Friday or Saturday was included in the reservation, as this may have an impact on booking trends
days_between_can_and_arr	A feature calculating the number of days between cancellation and the scheduled arrival date, showing how far in advance cancellations typically occur
reservation_create_day	A feature calculating the number of days between cancellation and the scheduled arrival date, showing how far in advance cancellations typically occur
is_expensive	A variable indicating whether ADR is above the third quartile of room rates for the same hotel
nuts2	A variable representing the NUTS2 regions in Portugal, based on the NUTS3 region of the hotel
is_Portuguese	A binary feature indicating whether the nationality of the guest is Portuguese
nationality_unknown	A binary variable identifying whether the nationality of the guest is unknown
continent	A categorical variable indicating the continent of the guest's nationality, derived from the nationality field

Data availability

The authors do not have permission to share data.

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