





Customer Churn Analysis with Logistic and Tree-Based Models October 2025



Chiawei Wang
Data & Product Analyst
chiawei.w@outlook.com



Executive Summary

Challenge

The persistent failure of customers to rebook within six months is driving **significant customer attrition** and directly **eroding long-term key value**. This analysis was commissioned to definitively **diagnose the root drivers of churn** and deploy a **predictive, proactive intervention strategy**.

Objective

- **Diagnose and quantify** the key behavioural factors driving customer attrition.
- **Develop a robust, high-precision predictive engine** to flag **high-risk customers** in real-time.
- Design and deploy **targeted, automated interventions** to **reduce churn rate and lift customer lifetime value**.

Solution

We evaluated multiple techniques, confirming the **XGBoost model** as the optimal predictive engine (**ROC AUC = 0.874**). This analysis identified **loyalty, recency, channel, and platform** as primary churn drivers. The predictive engine is now **ready for deployment into the CRM system** to enable **real-time risk scoring** and launch automated, targeted retention campaigns.

Key Insights

- **Recency threshold:** Churn risk triples after 90 days without engagement, defining the critical intervention window.
- **Loyalty status risk:** Non-members and new customers are the primary source of churn volatility.
- **Marketing channel risk:** Direct traffic is highly brand-loyal (low churn), but acquisition channels introduce a measurable risk profile (volatility).
- **Platform value:** App users are 15% more secure (lower churn rate) than web users.

Strategic Recommendations

- **Recency:** Deploy an automated, risk-scored 90 day intervention campaign to pre-empt the churn acceleration.
- **Loyalty:** Implement mandatory lottery enrollment immediately post-booking to stabilize the high-risk new customer transition..
- **Channel:** Score and strategically divert high-risk acquisition traffic into high-priority loyalty enrollment funnel to protect ROI.
- **Platform:** Use targeted incentives to migrate high-risk web users to the app platform.

Next Steps

We must establish the **predictive engine** to accurately **flag high-risk customers** (failing to rebook within 6 months), and the next step is securing **approval for the execution roadmap and engine deployment**.

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Key sections for this predictive churn analytics report

1. Overview of Data (defining customer dataset)
2. Model Foundation & Feature Importance (validation and predictive drivers)
3. Key Insights & Strategic Recommendations (from findings to actionable strategy)
4. Next Steps (implementation roadmap and approval)



1. Overview of Data

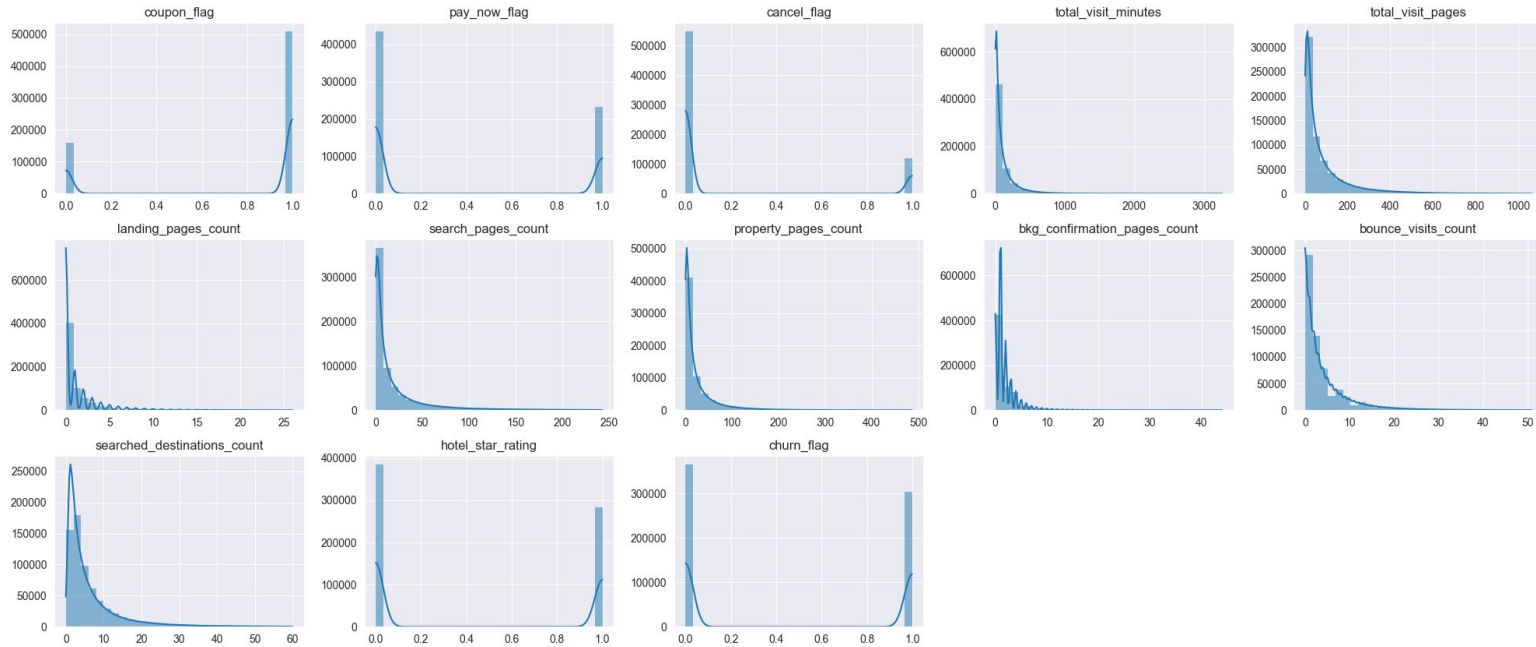
The dataset contains 689,742 entries and 21 columns. The target variable is 'churn_flag', which indicates whether a customer has churned (1) or not (0). The dataset includes various features related to customer behavior, booking details, and website interaction metrics.



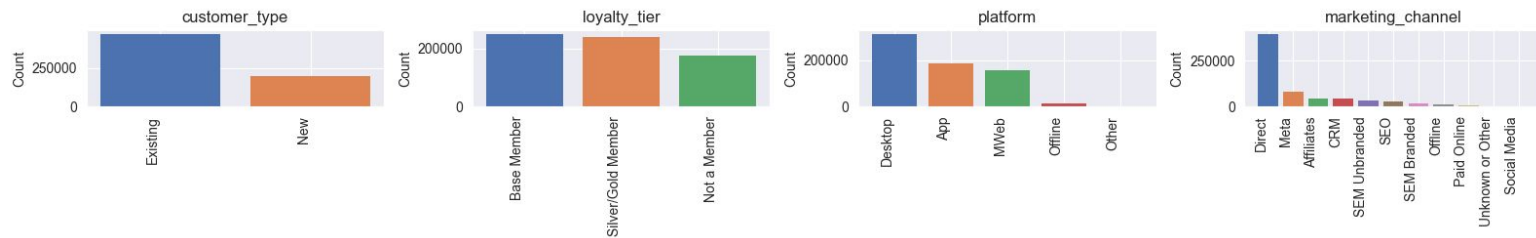
Description of Variables

| Variable | Type | Description |
|------------------------------|------------|--|
| email_address | object | Unique id for each customer |
| booking_id | object | Unique id for each booking |
| bk_date | datetime64 | Booking date, format YYYY-MM-DD |
| coupon_flag | int64 | 1 = used coupon when booking |
| pay_now_flag | int64 | 1 = payment choice 'pay now', 0 = 'pay later' |
| cancel_flag | int64 | 1 = canceled, 0 = not canceled, may contain missing values |
| cancel_date | datetime64 | Cancel date, format YYYY-MM-DD, only present if booking was canceled |
| customer_type | object | Indicates customer type (e.g., new or returning customer) |
| loyalty_tier | object | Customer's loyalty level: 0 = not a member, 1 = base member, 2 = silver/gold member |
| platform | object | Platform used for booking (e.g., desktop, mobile website) |
| marketing_channel | object | How the visit came to the website (e.g., Google, TripAdvisor), may contain missing values |
| total_visit_minutes | int64 | Total minutes of visits to the website, may contain missing values |
| total_visit_pages | int64 | Total number of pages visited on the website |
| landing_pages_count | int64 | Number of landing pages visited on the website |
| search_pages_count | int64 | Number of search pages visited on the website |
| property_pages_count | int64 | Number of property pages visited on the website |
| bkg_confirmation_pages_count | int64 | Number of booking confirmation pages visited on the website |
| bounce_visits_count | int64 | Total number of single page visits to the website |
| searched_destinations_count | int64 | Total number of different destinations searched on the website |
| hotel_star_rating | int64 | Star rating score of the booked hotel |
| churn_flag | int64 | 1 = No repeat booking 6 months after check out (churned), 0 = repeat booking (not churned) |

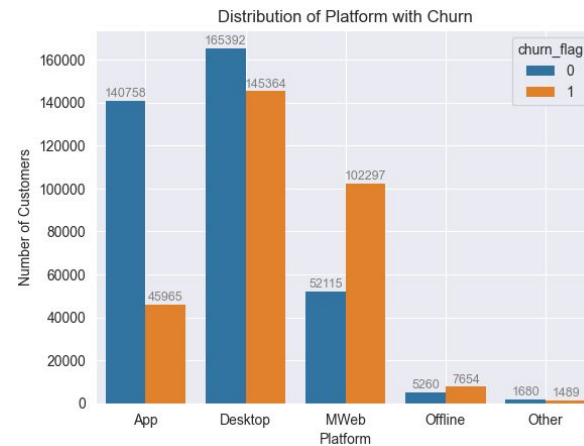
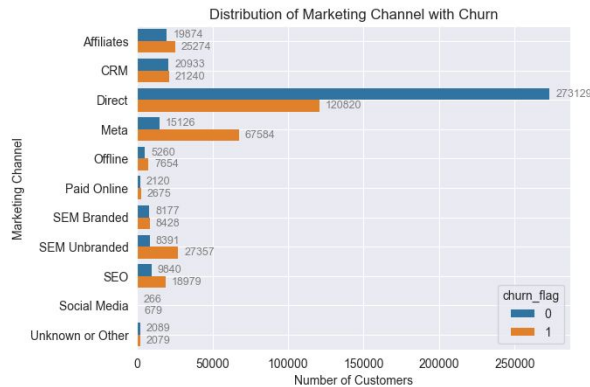
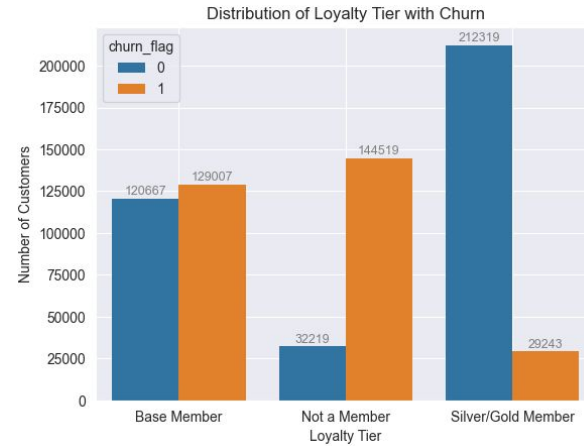
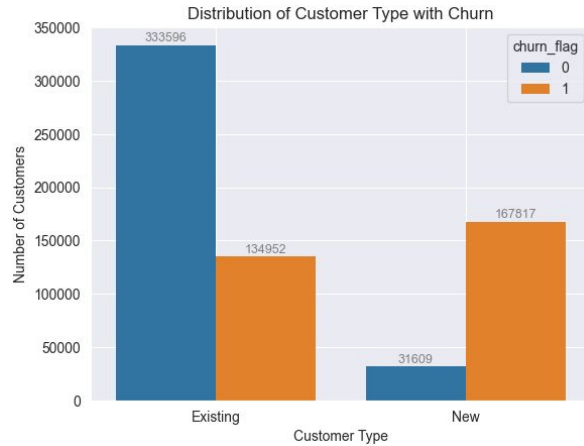
Distribution of 13 Numeric Features including the Target Variable



Distribution of 4 Categorical Features










2. Model Foundation & Feature Importance

Given the binary nature of the target variable (churned versus not churned), 4 classification algorithms were considered for modeling customer churn. The models evaluated include Logistic Regression, Decision Tree, Random Forest, and XGBoost. Each model was assessed based on its performance metrics, interpretability, and computational efficiency to determine the most suitable approach for predicting customer churn.



Model Performance

Following the evaluation of four different models, the **XGBoost model emerged as the most effective predictive engine**, achieving a strong cross-validated **ROC AUC of 0.874**.

This score confirms **excellent discrimination** power. The model correctly ranks a churner above a non-churner 87.4% of the time. Crucially for targeted action, we can **correctly identify 8 out of every 10 customers who are actually going to churn**, ensuring a low false-negative rate for retention campaigns.

The model is statistically reliable, validated for its predictive accuracy, and is **ready for immediate deployment** to score the customer base daily.

* Note that terminology is explained in the notes throughout the document.

Logistic Regression

- ROC AUC: 0.858
- Accuracy: 0.78
- Precision: 0.76
- Recall: 0.78
- F1: 0.77

Decision Tree

- ROC AUC: 0.867
- Accuracy: 0.79
- Precision: 0.8
- Recall: 0.74
- F1: 0.77

Random Forest

- ROC AUC: 0.872
- Accuracy: 0.79
- Precision: 0.8
- Recall: 0.75
- F1: 0.77

XGBoost

- **ROC AUC: 0.874**
- Accuracy: 0.79
- Precision: 0.8
- Recall: 0.75
- F1: 0.77

Influential Factors by Coefficient & Gini Importance

Top 10 most influential factors by coefficient magnitude for Logistic Regression and by Gini importance for Decision Tree, Random Forest, and XGBoost models

Logistic Regression

| | Coefficient |
|-------------------------------------|-------------|
| loyalty_tier_Not a Member_sum | 1.015602 |
| loyalty_tier_Silver/Gold Member_sum | -0.920002 |
| customer_type_New_sum | 0.817832 |
| marketing_channel_Direct_sum | -0.680318 |
| search_intensity | -0.598496 |
| customer_type_Existing_sum | -0.516183 |
| marketing_channel_Affiliates_sum | 0.438632 |
| marketing_channel_Meta_sum | 0.381890 |
| num_bookings | 0.301649 |
| platform_MWeb_sum | 0.228698 |

Decision Tree

| | gini_importance |
|-------------------------------------|-----------------|
| customer_type_Existing_sum | 0.593722 |
| loyalty_tier_Silver/Gold Member_sum | 0.190320 |
| marketing_channel_Direct_sum | 0.085609 |
| loyalty_tier_Base Member_sum | 0.026154 |
| loyalty_tier_Not a Member_sum | 0.020642 |
| bkg_confirmation_pages_count_sum | 0.018339 |
| total_visit_pages_sum | 0.011637 |
| searched_destinations_count_max | 0.009422 |
| avg_page_time | 0.007863 |
| total_visit_pages_mean | 0.005643 |

Random Forest

| | gini_importance |
|-------------------------------------|-----------------|
| customer_type_Existing_sum | 0.282381 |
| loyalty_tier_Silver/Gold Member_sum | 0.200166 |
| customer_type_New_sum | 0.121633 |
| loyalty_tier_Not a Member_sum | 0.086373 |
| marketing_channel_Direct_sum | 0.083085 |
| total_visit_pages_sum | 0.028937 |
| loyalty_tier_Base Member_sum | 0.024421 |
| avg_page_time | 0.017842 |
| total_visit_pages_mean | 0.017625 |
| searched_destinations_count_max | 0.015363 |

XGBoost

| | gini_importance |
|-------------------------------------|-----------------|
| customer_type_Existing_sum | 0.374207 |
| loyalty_tier_Silver/Gold Member_sum | 0.263442 |
| customer_type_New_sum | 0.186008 |
| loyalty_tier_Not a Member_sum | 0.049755 |
| marketing_channel_Direct_sum | 0.044610 |
| loyalty_tier_Base Member_sum | 0.029842 |
| platform_App_sum | 0.006548 |
| marketing_channel_Meta_sum | 0.005500 |
| marketing_channel_Affiliates_sum | 0.004874 |
| bkg_confirmation_pages_count_sum | 0.003226 |

Top 10 Drivers of Customer Churn


The XGBoost model's heavy reliance on the top features confirms **loyalty status and customer lifecycle are the primary drivers for intervention**, mandating an immediate focus on **loyalty enrollment** and stabilizing the **high-risk new customer transition**.

| Rank | Factors | Gini Importance | Strategic Insight |
|------|-------------------------------------|-----------------|---|
| 1 | customer_type_Existing_sum | 0.374207 | Retention anchor: The existing customer base is the core foundation of low churn. Protecting this segment is paramount. |
| 2 | loyalty_tier_Silver/Gold Member_sum | 0.263442 | Maximum loyalty lift: High-tier status provides the greatest reduction in churn probability. Loyalty works. |
| 3 | customer_type_New_sum | 0.186008 | High-risk transition: The period between the first and second booking is the most volatile and high-risk. |
| 4 | loyalty_tier_Not a Member_sum | 0.049755 | Critical enrollment failure: Not enrolled in the loyalty program is a churn indicator. Enrollment is a necessary retention step. |
| 5 | marketing_channel_Direct_sum | 0.044610 | Brand affinity: Customers who arrive directly (typing the URL) are inherently more secure and brand-loyal. |
| 6 | loyalty_tier_Base Member_sum | 0.029842 | Mid-tier stability: Base members are a secure segment, but engagement campaigns are needed to drive tier upgrades. |
| 7 | platform_App_sum | 0.006548 | Platform stickiness: Usage of the App platform contributes positively to long-term retention. |
| 8 | marketing_channel_Meta_sum | 0.005500 | Acquisition risk: Traffic acquired via Meta channels introduces measurable volatility that requires proactive management. |
| 9 | marketing_channel_Affiliates_sum | 0.004874 | Acquisition risk: Affiliate traffic also carries a measurable risk profile requiring strategic funneling. |
| 10 | bkg_confirmation_pages_count_sum | 0.003226 | Conversion signal: The total count of successful bookings is a clear signal of customer engagement and value. |



3. Key Insights & Strategic Recommendations

Based on the predictive model and factor importance, we should implement a four-pronged strategy focusing on recency, loyalty, channel and platform.



Key Insights

Timing, loyalty, channel, and platform are the dominant drivers of churn

Rency Threshold

Insight

Churn risk **triples after 90 days** without engagement or booking activity after their last stay.

Implication

Timing is critical. Intervention must be highly automated and occur proactively **before the 90-day acceleration point** to stabilize the customer.

Loyalty Status

Insight

The stability of **Existing** and **Silver/Gold** members anchors retention. The **New Customer** and **Non-Member** segments create the highest churn volatility.

Implication

Enrollment is pivotal. We must convert new customers into loyal members immediately post-booking to stabilize the critical booking transition.

Marketing Channel

Insight

Direct traffic establishes security and brand loyalty. **Acquisition channels** (Meta/Affiliates) introduce a measurable risk profile.

Implication

Mitigate risk. Immediately score all acquisition traffic and prioritize its funnelling into the **loyalty enrollment** funnel to protect ROI.

Platform Value

Insight

App users are 15% more secure than customers using desktop or mobile web.

Implication

App stickiness is a retention lever. Driving platform migration for high-risk web users is a direct retention action.

Strategic Recommendations

Shift to proactive, risk-scored intervention across four key levers

Rency

Deploy Automated 90-Day Intervention

- Intercept customers before the **90-day risk acceleration point**.
- Use the predictive score (e.g. churn risk score >0.5) to ensure **personalized offers** only hit customers truly at risk.

Loyalty

Launch Mandatory Loyalty Conversion Funnel

- Secure commitment by establishing **enrollment immediately after the first transaction**.
- **Target Not a Member and New Customer** segment to eliminate risk.
- Offer a tangible 'First Member Perk' (e.g. £20 credit) only accessible by completing **free loyalty sign-up** post-booking.

Channel

Manage and Funnel Acquisition Risk

- Immediately score and divert high-risk Meta/Affiliates traffic into the **loyalty enrollment funnel** to protect acquisition ROI.
- Recognize direct traffic loyalty with **exclusive member perks** (e.g. early access) to reinforce brand affinity.

Platform


Real-Time App Migration

- Flag **high-risk, non-app users** using the churn score.
- Integrate **real-time scoring** to drive platform migration incentives.
- Target them with a direct and **exclusive app-only incentive** (e.g. Get an extra 10% off your next stay when you download and book via the app).



4. Next Steps

We have successfully quantified the risk and identified the core levers for retention. The time for proactive intervention is now.



Implementation Plan & Approval

Technical Deployment

Embed the XGBoost Risk Score API into the CRM systems immediately. This is the foundational step required to generate the real-time, high-precision scores that will power all targeted campaigns.

Loyalty Foundation Launch

Launch the mandatory loyalty enrollment funnel immediately post-booking for all new customers. This is essential to eliminate the single highest risk factor: non-member status.

Pilot Campaign Initiation

Initiate the first-wave pilot campaigns: the automated 90-day intervention campaign (recency), the app migration campaign (platform), and channel risk funneling (channel), to validate ROI on the targeted strategy.

Call to action

- Protecting customer lifetime value is a near-term ROI opportunity.
- Approving these immediate steps allows us to reduce measurable customer attrition starting next quarter.



Any questions,
please reach out!