



Original Article

Modeling Framework for Customer Retention in Auto Service

Vaibhav Tummalapalli
Independent Researcher, Atlanta, GA, USA.

Received On: 12/10/2025

Revised On: 16/11/2025

Accepted On: 24/11/2025

Published on: 12/12/2025

Abstract - The automotive industry faces a critical challenge in maintaining long-term relationships with customers post-sale. Retaining customers in the after-sales service market is vital, given its competitive nature and potential for recurring revenue. This paper proposes a machine learning-based framework for customer retention by predicting attrition probability and future spending potential. By leveraging data segmentation, personalized engagement strategies, and predictive modeling, this framework aims to optimize marketing efforts and enhance customer loyalty. We also explore additional insights based on current trends in customer analytics and service personalization.

Keywords - Marketing Analytics, Customer retention, Cohort Analysis, Machine Learning, Segmentation, Value, Attrition, Potential, Regression.

1. Introduction

As emphasized by Reichheld and Sasser [1], reducing defections in service-based industries can significantly improve profitability, highlighting the need for strong retention models [1]. The automotive after-sales market is a critical revenue stream for dealerships, yet it is plagued by high attrition rates as customers defect to competitors. Engaging customers through personalized communications and offers is pivotal in mitigating this attrition. A robust analytical framework, grounded in machine learning, enables dealerships to identify valuable customer segments and craft strategies to reduce defection. This paper outlines a data-driven approach to customer retention using predictive modeling and segmentation, emphasizing its alignment with business objectives and customer needs.

2. Challenges in Customer Retention

2.1. Competitive Aftersales Market

The automotive service industry is flooded with independent service providers and third-party repair shops that often offer lower prices, making it challenging for dealerships to retain customers. These alternatives provide convenience and competitive pricing, drawing customers away from authorized service centers. Additionally, customers may perceive dealership services as more expensive, further increasing defection rates. Rust and Zahorik [3] demonstrate the link between customer satisfaction and retention, reinforcing the importance of understanding service experience in loyalty modeling.

2.2. Irregular Service Patterns

Unlike other industries with predictable customer interactions, the automotive service sector faces wide variability

in service intervals. Customers' vehicle usage, geographic location, and maintenance habits contribute to inconsistent patterns. This irregularity makes it difficult to forecast service needs and develop proactive engagement strategies, resulting in missed opportunities to retain customers.

2.3. Lack of Personalization

Generic marketing campaigns and one-size-fits-all offers fail to resonate with a diverse customer base. Customers expect personalized communications and value-driven promotions tailored to their vehicle's condition, service history, and personal preferences. Without data-driven personalization, dealerships struggle to build meaningful connections, leading to disengagement and attrition.

3. Strategic Approach

3.1. Personalization

Personalization lies at the heart of modern customer engagement. Strategic marketing should be grounded in data-driven insights, transforming customer analytics into competitive advantage [7]. By leveraging advanced data analytics and customer profiling, dealerships can identify both profitable and non-profitable customers. The aim is to craft communications and offers that resonate with individual preferences, service histories, and spending patterns. Personalized experiences not only enhance customer satisfaction but also build trust and loyalty over time.

3.2. Segmentation

Segmentation is essential to understanding the diversity within the customer base. By categorizing customers based on their attrition probability and future spending potential,

dealerships can uncover distinct groups with unique needs and behaviors. For instance, affluent but vulnerable customers who are at risk of defection require tailored retention strategies, whereas brand loyalists with consistent engagement need exclusive perks to maintain their loyalty. Effective segmentation enables a targeted approach to engagement and resource allocation.

3.3. Optimal Resource Allocation

With finite marketing budgets and operational resources, optimizing their allocation is critical. This involves prioritizing high-value segments and focusing efforts where they yield the most significant returns. By aligning investment with customer lifetime value and propensity scores, dealerships can maximize ROI and improve overall retention rates.

4. Modeling/Analytical Framework

Effective CRM strategies such as those outlined by Kumar and Reinartz [2] are fundamental to segmenting and personalizing customer interactions for higher retention. To better capture the temporal characteristics of customer behavior, the analysis uses multiple cohort dates. Cohorts allow us to observe customer behavior at regular intervals and assess whether they avail themselves of services during the defined time windows. This approach ensures the model captures temporal dynamics and trends in customer engagement.

4.1. Attrition Prediction

Detecting churn early improves marketing precision and ROI, as supported by defection detection frameworks proposed by Neslin et al. [4]. Comprehensible churn prediction models, like those introduced by Verbeke et al. [5], are particularly valuable in operational settings such as automotive service marketing

- Definition: Here attrition/churn is defined as a customer who has not availed of service within 12 months of their last service date.
- Model Setup:
 - Eligible Population: Customers with at least one service in the 12 months leading up to the cohort date. The cohort date acts as a reference point for capturing customer activity.
 - Dependent Variable: Flag as 1 for no service in 12 months from the last service date, 0 otherwise.
 - Time Windows:
 - Observation Window: Historical data up to the cohort date (e.g., demographics, service history, transaction patterns).
 - Performance Window: This period starts from the last service date and extends for 12 months, varying in length for each customer depending

on when they last avail themselves of service before the cohort date.

- Machine Learning Model: Supervised classification model using customer demographics, psychographics, and service/sales transactions.

4.2. Future Spending Potential

The goal of this model is to predict the customer pay (i.e., the total amount spent by a customer on auto services during the performance window). Targeting retention investments based on profitability potential, as recommended by Lemmens and Gupta [6], enables businesses to maximize returns from churn interventions. Since the outcome variable is continuous, the model relies on regression-based approaches to estimate spending behavior. This ensures a tailored and accurate prediction of potential revenue contribution for each customer.

- Target Variable: Amount spent on auto service during the performance window.
- Predictors: Aggregated sales and service data (recency, frequency, monetary value, and vehicle-related features).
- Model Objective: Given the continuous nature of the target variable, we develop a regression-based model or use machine learning techniques (e.g., Gradient Boosting, Random Forest) designed for continuous outcomes to predict customer pay.

4.3. Segmentation Framework

Rank attrition scores and future spending potential into deciles. Create a 10x10 frequency matrix to classify customers into segments.

		Potential Rank									
		1	2	3	4	5	6	7	8	9	10
Attrition Rank	1	Affluent & Vulnerable 26%					Value Seekers 14%				
	2										
	3										
	4										
	5	Steady Eddies 12%					Measured Services 16%				
	6										
	7	Brand Loyalists 13%					Newbies 20%				
	8										
	9										
	10										

Fig 1: Segmentation Framework

4.4. Segment Examples:

- Affluent & Vulnerable: Customers with high attrition risk and high spending potential. The focus for this group should be retention through personalized offers and proactive engagement.
- Value Seekers: Customers with medium/low spending potential and medium/high attrition risk. The goal is

- to retain and engage them with cost-effective services and promotional offers.
- **Steady Eddies:** Customers with medium spending potential and medium attrition risk. Efforts should focus on maintaining their engagement through consistent service quality and communication.
- **Brand Loyalists:** Customers with high spending potential and low attrition risk. For this group, the strategy should be to surprise and delight them with exclusive rewards and VIP services.

- **Measured Servicers:** Customers with low spending potential and medium/low attrition risk. The goal is to improve potential services by introducing relevant add-ons and package deals.
- **Newbies:** Customers with low spending potential and low attrition risk. Efforts should focus on maintaining their relationship through introductory offers and educational outreach.



Fig 2: Segment Descriptions

5. Reactivation Strategy for Inactive customers

The objective is to re-engage customers who have lapsed, we employ a targeted framework focused on reactivation.

5.1. Definition

Inactive Customers: Customers who have not availed of any service in the last 12 months from the cohort date. This lapse in activity suggests a potential defection to competitors or a lack of engagement.

5.2. Reactivation Framework

- **Propensity Model:**
 - Objective: Predict the likelihood of a customer returning for service within a short time frame.
 - Performance Window: A 60-day period from the cohort date during which customer behavior is observed to determine reactivation likelihood.
 - Target Variable:

- Assign a value of 1 if a customer avails a service within 60 days of the cohort date.
- Assign a value of 0 if no service occurs in this period.

- **Implementation:**
 - Build a supervised machine learning model (e.g., logistic regression, decision trees) to predict reactivation propensity [9].
 - Identify key predictors such as time since last service, historical service spends, vehicle age, and prior engagement history [10].
 - Decile the population based on model scores and prioritize the top deciles for reactivation campaigns.

5.3. Reactivation Strategy

- **Targeted Campaigns:** Design customized offers or incentives to appeal to high-propensity customers (e.g., discounted services, complimentary checks).

- Omnichannel Outreach: Leverage multiple communication channels (email, SMS, app notifications) to ensure campaign reach.
- Continuous Monitoring: Track campaign performance and refine models periodically to adapt to customer behavior changes

6. Model Evaluation Metrics

Before finalizing any machine learning model, it is essential to evaluate its performance thoroughly to ensure its reliability and applicability [9]. Performance evaluation must reflect strategic objectives, as articulated in 'you are what you measure' by Hauser and Katz [8]. The following metrics and techniques can be used:

6.1. Classification Models (Attrition and Propensity Models):

- Lift: Measures the improvement in targeting efficiency achieved by the model compared to random selection [9].
- Capture Rate: Represents the proportion of positive cases (e.g., reactivated customers) captured within the top-ranked segments [9].
- KS Statistic: Evaluates the maximum separation between cumulative distributions of positive and negative cases, helping assess the model's discriminatory power [9].
- ROC-AUC Score: Assesses the model's ability to differentiate between classes (attrition vs. non-attrition).

6.2. Regression Models (Spending Potential):

- Mean Absolute Error (MAE): Calculates the average magnitude of prediction errors.
- Mean Squared Error (MSE): Penalizes larger errors more heavily, useful for outlier detection.

6.3. Segmentation Metric:

Predicted spend is grouped into 10 deciles. We compare the mean values of predicted and actual spend within each decile. The goal is to closely align the mean values of predicted and actual spend within each decile, ensuring the model's predictions accurately represent customer spending behavior

7. Conclusion

The proposed framework combines machine learning models for attrition prediction and spending potential with

segmentation strategies to address customer retention challenges in the automotive service industry. By focusing on personalization and targeted engagement, dealerships can foster loyalty and reduce attrition, ultimately driving revenue growth. Future work could integrate real-time data analytics and explore the impact of external factors such as economic conditions and industry disruptions.

References

- [1] F. F. Reichheld and W. E. Sasser, "Zero defections: Quality comes to services," *Harvard Business Review*, vol. 68, no. 5, pp. 105–111, 1990.
- [2] V. Kumar and W. Reinartz, *Customer Relationship Management: Concept, Strategy, and Tools*, 3rd ed. Springer, 2018.
- [3] R. T. Rust and A. J. Zahorik, "Customer satisfaction, customer retention, and market share," *J. Retailing*, vol. 69, no. 2, pp. 193–215, 1993.
- [4] S. A. Neslin, S. Gupta, W. Kamakura, J. Lu, and C. H. Mason, "Defection detection: Measuring and understanding the predictive accuracy of customer churn models," *J. Marketing Res.*, vol. 43, no. 2, pp. 204–211, 2006.
- [5] W. Verbeke, D. Martens, C. Mues, and B. Baesens, "Building comprehensible customer churn prediction models with advanced rule induction techniques," *Expert Syst. Appl.*, vol. 38, no. 3, pp. 2354–2364, 2011.
- [6] A. Lemmens and S. Gupta, "Managing churn to maximize profits," *J. Marketing Res.*, vol. 57, no. 1, pp. 52–69, 2020.
- [7] N. Dawar, "When marketing is strategy," *Harvard Business Review*, vol. 91, no. 12, pp. 100–108, 2013.
- [8] J. R. Hauser and G. Katz, "Metrics: You are what you measure!," *Eur. Manag. J.*, vol. 16, no. 6, pp. 517–528, 1998.
- [9] V. Tummalapalli, "Machine learning pipeline for automotive propensity models," *International Journal of Core Engineering & Management*, vol. 8, no. 3, 2025, ISSN 2348-9510
- [10] V. Tummalapalli, "Feature Engineering for Building Machine Learning Models in Automotive Industry," *International Scientific Journal of Engineering and Management*, vol. 4, no. 8, pp. 1–9, 2025. doi: 10.55041/ISJEM04985.