

Insurance coverage can terminate for several reasons such as cancellation due to the policyholder obtaining coverage elsewhere or allowing the coverage to lapse. Insurance lapses typically result from not paying the premium when due. It is no secret that customer retention is a top priority for many companies; acquiring new customers can be 5 times more expensive than retaining existing ones. How can we use data science to uncover the key indicators driving lapse and estimate the lapse risk associated with individual customers for a data-driven retention strategy? By prioritizing and targeting customers for retention campaigns based on their likelihood to lapse, businesses can reduce the cost of campaigns, reduce lapse rates, increase profitability and ultimately improve customer loyalty.

How do you gain an in-depth understanding of the customer behavior and lifetime value to meet ambitious business targets around reducing lapse, driving cross sell/upsell and improving their marketing capabilities? How do you avoid losing a significant chunk of your high value customers to competitors despite marketing initiatives and hence wanted a better way to identify and target their "high risk" base?

GOALS	APPROACH	RESULTS
<ul style="list-style-type: none"> <li>Prove power of data science</li> <li>Create lifetime value customer segments</li> <li>Improve retention rates across segments</li> </ul>	<ul style="list-style-type: none"> <li>Define "lapse" types: renewal lapse, mid-term lapse, etc.</li> <li>Segment policyholders by tenure or lifetime value segment groups</li> <li>Build lapse propensity models across segments creating a lapse risk score along with identifying top lapse triggers</li> <li>Create 5-6 key uplift scenarios and quantifying their impact</li> <li>Design a treatment campaign to prevent policyholder churn (or policy lapses) for high value segments</li> </ul>	<ul style="list-style-type: none"> <li>8 weeks from whiteboard to results</li> <li>Achieved overall model predictive accuracies above 77%</li> <li>50% lapse reduction for high value customers over a 1-year campaign period, 40% reduction in campaign costs</li> <li>Quantified potential retention savings of \$10M+ across individual life insurance business</li> <li>Key predictors – policy type, tenure, previous claim history, number of policies coming up for renewal across the portfolio, age</li> <li>12 insights (6 new and actionable for the business)</li> <li>300 features available in a CAR model allowed for additional 5 machine learning models to be built</li> <li>Availability of lapse propensity scores and lifetime value segments on CRM for easy targeting in outbound campaigns</li> </ul>

### In executives' own words:

*"We've been product-centric forever. We didn't understand our customers and what motivated them. We have been able to drive customer satisfaction through improved retention initiatives"*

– Head of Customer Analytics

## OPERATIONALIZING & COMMERCIALIZING RESULTS

### 1 Productionize the model

The lapse prediction models offered insights into lapse drivers and risk scores across segments and lapse types. In order to use the risk scores to drive actions, the model was part of a customer analytics platform that exposed scores to both inbound and outbound channels via a next best action hub

### 2 Layer-on additional models

After measuring the success of the lapse prediction model over a 6-month period via retention campaigns, addition models were built around quote conversion and loan underwriting for better customer acquisition and a more comprehensive view on next best actions

### 3 Operationalize the solution

Once a complete solution is built, tested and accepted, it is integrated with business operations by applying consistent and sustainable changes to the existing operating model

Policyholder Data	Policy Data	Total number of policies	5,373,840
Agents/Agent Data	Premium Data	Total number of target policies	1,217,923
Claims Data	Loans Data	Total premium of target policies	~US\$ 548m
Insured's Data	Expenses (including commission)	Total premium of lapsed policies	~US\$ 49m
Volatility of cash flows*	Surrenders Data	Average new policies per year	202,987
Product Data		Average policy lapses per year	48,396

No.	Variable	Least impact	Level importance	Observation
18	CURRENT_TENURE	11.51		<b>I. Observation</b> Contrary to our expectations that cross-selling is key to customer retention, the number of products a customer holds is not strongly correlated with lapse propensity.
19	RENEWAL_YEARLY_TENURE	11.50		
20	LOAN_AMOUNT	10.88		
21	CALL_CENTER_CONTACT	10.58		
22	PRODUCT_TYPE	10.54		
13	CALL_CENTER_COUNT	8.42		
14	CLAIM_HISTORY	7.92		
23	CLAIM_STATUS	3.47		<b>II. Possible causes</b> - This could be linked to the lack of strong loyalty amongst AA clients, or amongst many insurance customers in general. Further analysis will be needed. - Customers are becoming more complex and educated, and loyalty is not one of the major factors in retention.
25	AGE_GROUP	3.40		<b>III. Recommendations</b> - In the context of a full engagement following the ROC (rental) analysis products held by the most valuable clients, their cost, cross referenced with policy holder age, policy value. - No focus on up-selling as opposed to cross-selling.
27	AGE_GROUP_OA	2.98		

