# A EUROPEAN LOYALTY PROGRAM: EXAMINING PURCHASE BEHAVIOR TO PREDICT LIKELIHOOD OF RETAINING INDIVIDUAL CUSTOMERS

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## ABSTRACT

*Several studies have established that it is more costly to acquire customers than it is to retain existing customers. These findings have led to a number of firms instituting loyalty programs as a means forincreasing customer retention. In this study we extend prior research by identifying which customers within a loyalty program are more likely to be retained, thus enabling firms to strategically allocate marketing resources according to the likelihood of individuals remaining as customers. Data from a European loyalty program were used for this investigation. The loyalty program allowed customers to make purchases from a network of partner vendors as well as out-of-network purchases.Logit models which yielded retention scores were constructed. Testing of the models showed that customers were more likely to be retained if they were heavy purchasers and/or maintained a low ratio of in-network to out-of-network purchases.*

***Keywords****: Customer retention, loyalty program, retention score*

## 1. INTRODUCTION

The objective of this study is to determine the usefulness of customer purchase histories forpredicting retention of customers in a loyalty program. This study will make a contribution to academic literature by extending the body of knowledge for loyaltyprograms by examining the contribution of several measures of customer purchases on the probability of retention. A goal of this research is to determine if these measures have predictive usefulness so that managers can take corrective actions and/or find the impact of changes in loyalty policies for retention of customers.

Retention of customers has the largest impact on the lifetime value of customers and the firm (Gupta, Lehmann and Stuart, 2004). Tying the concepts of customer purchases and retention is of value to furthering the knowledge on loyalty programs.

A unique aspect of the dataset used in this study is the loyalty program is structured so that customers are given a membership card that identifies them as belonging in the loyalty program and it also serves as a credit card. The credit card feature allows customers to use their loyalty card with any vendor, including vendors outside of the loyalty program's vendor network. This structuring of the program adds flexibility which is attractive to customers and contributes to their loyalty to the program but it can adversely affect promoting vendors within the loyalty program. These features of the loyalty program enable our study to focus on determining which customers are retained within the loyalty program regardless of where they shop. The results of a study of this nature will support evaluating customer retention and the merits of having specific named vendors as part of a loyalty program versus providing a loyalty credit card that customers can use with any vendor.

## 2. LITERATURE REVIEW

Loyalty has been a subject of research for the past two decades and such programs have reached a state of maturity (Capizzi, Ferguson, 2005). Studies on loyalty programs are often based on real-world data that has been collected (Bolton, Kannan, Bramlett, 2000), or simulation experiments (Lewis, 2004), or game theory approaches (Kim, Shi, and Srinivasan 2001). These studies typically examine narrow research questions such as "Customers'repatronage intentions have a positive effect on their subsequent repatronage decisions," (Bolton, Kannan, Bramlett, 2000), or "Consumers gradually increase their usage level after joining a loyalty program." (Liu, 2007). In contrast, our study will answer a broader question related to the utility of dimensions of customer purchases that predict customer retention.

Retention of customers has been shown to be critical in the valuation of a firm and is the most sensitive variable for determining customer lifetime value (Gupta, Lehmann and Stuart, 2004). Dawkins and Reichheld (1990) determined that a 5% increase in customer retention resulted in an increase of 25% to 85% of a customer's net present value. The empirical research of Gupta et al. (2004) indicated that a 1% increase in retention rate resulted in improving the firm's value by more than 5%, which is magnitudes in excess of improvements in other measures such as acquisition costs, margins, promotions, and discount rates. Customer lifetime value (CLV) may be a critical determinant of the overall profitability of loyalty programs and thus tying the research on retentions and customer purchases is deemed to be critical.

In our research, we conceptualize customer purchases in terms of several dimensions that can be obtained from the sponsor's loyalty data. These dimensions are described next.

*Dimensions of Customer Purchases*

1) Initial Type of Consumer: Heavy, Moderate, or Light
2) Longevity: Time in the program
3) Intensity: Local currency Per Day
4) Purchase Velocity: Change in value of transactions from one period to the next period.
5) Breadth Outlets: Number of different types of in-network outlets used.
6) Breadth Purchase: Log Ratio of In-Network outlets to Out-Network outlets

Past researches on loyalty has indicated that the changes in consumer purchases vary based on the initial type of consumer, which has been incorporated as one of the dimensions (Liu, 2007). Liu (2007) also hypothesized and confirmed that moderate users' loyalty levels increase at a faster rate than for heavy and light users, which has been incorporated by us as the velocity dimension. Since one of the outcomes for loyalty programs is to increase the switching costs, the longer a consumer has been with the loyalty program, the greater vested the consumer becomes with its offerings (Sharp and Sharp, 2007). Hence, longevity is a dimension to be considered for loyalty programs. Liu (2007) showed that consumers gradually increase their usage level after joining loyalty programs. Thus, intensity of purchase activities is a dimension important for understanding the loyalty behavior of consumers. The coalition-lite model of loyalty (Capizzi and Ferguson, 2005), which the research sponsor's loyalty model closely follows, offers consumers more choices in redeeming their vouchers and thus capturing the breadth of purchases was important for this study.

## 3. METHODOLOGY

### *3.1 Dataset*

The dataset for this study was obtained from a European loyalty program company, access to the dataset was provided by the Wharton Customer Analytics Initiative (WCAI). The dataset consisted of 8,088 accounts with various entry points into the loyalty program over a 12 year window of customer transactions from 2000 to 2012. The data fields used in our analysis included entry date into the program, account status, transaction dates, transaction amounts, and purchasing partner identifiers (with an indication of network status, i.e., in-network or out-of-network).

### *3.2 Procedure*

According to Liu (2007), the purchasing behavior of loyalty customers is significantly different for heavy, moderate, and light buyers. Thus, we created three segments to represent these buyers and developed models that were specific to each of the three segments.

A four-step procedure was applied to derive a retention probability score for each customer's account. In summary, the four steps were: (1) using account statuses to label each account as retained or not retained, (2) categorize the usage type of each customer as heavy, moderate, or light based on the number of purchase transactions completed, (3) segment the dataset into a 60% training set and a 40% test set, and (4) develop and test logit models for each usage type. Steps (1) and (2) are elaborated below, the effect of enacting steps (3) and (4) are given in the results section.

Step (1): Each account was labeled as either retained or not retained. Labels were determined by examining account statuses. All accounts with an account status indicating any of the following were classified as not retained: "inactive of own choice", "inactive unknown", "inactive purchasing behavior", or "not OK – credit rating". This definition was developed and agreed upon after discussions with management within the loyalty program company. The rationale was any account that had any type of inactive status was not considered to be retained because the customer ceased making purchases as of some specific transaction. Customers with "not OK – credit rating" scores were classified as not retained because the customers were lacking in ability to pay for purchases, i.e., the customers were bad credit risks.

Step (2): Usage classifications were determined by counting the total number of purchase transactions that each customer made. All customers were ranked according to the total number of purchases. The resulting distribution was divided into tertiles where customers in the top tertile were labeled as heavy purchasers, those customers in the middle tertile were labeled as moderate purchasers, and the remaining customers as light purchasers.

## 4. RESULTS

Prior to model building, the data were examined for observable patterns; this included tabulating summary and descriptive statistics for attributes in the dataset. Following the initial characterization of the data, in cooperation with our corporate sponsor we selected appropriate data for model building. The selected data elements from the possible several hundred data elements available were reduced to those listed above in the dataset description and given in the dimensions of customer purchases.

When the *retained* and *not retained* classification rules were applied, 64.6% of the accounts were classified as retained and the remaining as not retained. When the usage categorization process was applied there was evidence that as accounts graduated from light to moderate and from moderate to heavy purchasers there was a positive correlation with retention of accounts. Table 1 below shows a cross tabulation of customers classified by their purchase behavior versus whether the customer's account was retained.

| **Initial Type of Customer** | **Number of Purchase Transactions** | **Accounts Retained** | **Accounts Not Retained** | **Total** |
|---|---|---|---|---|
| Light | <= 18 | 885 (33%) | 1834 (67%) | 2719 |
| Moderate | 19 - 98 | 1970(73%) | 724 (27%) | 2694 |
| Heavy | > 98 | 2371 (89%) | 304 (11%) | 2675 |
| **Total** | | **5226** | **2862** | **8088** |

**Table 1**: Cross tabulation of customers based on purchase volume and whether their accounts were retained.

A breadth of purchase measure was computed. The breadth of purchase measure is defined as:

*BreadthPurchase* = Ln(((Number of In Network Transactions+0.1))/((Number of Purchase Transactions-Number of In Network Transaction+0.1) ))

To prevent division by zero in the event that a customer only makes in-network purchases an offsetting term of 0.1 is added to the numerator and denominator of the BreadthPurchase equation. Breadth of purchase measures loyalty to vendors within the loyalty program. Negative breadth of purchase values indicate that customers are using the loyalty card with more vendors that are outside of the loyalty program's list of preferred vendors, whereas positive values indicate that customers are doing more shopping with vendors participating within the loyalty program. In Table 2 below it can be noted that more accounts are retained when customers use their loyalty cards with more vendors outside of the network.

| **BreadthPurchase** | **Accounts Retained** | **Accounts Not Retained** |
|---|---|---|
| <= -4.39 | 96% | 4% |
| -4.38 to -3.01 | 98% | 2% |
| -3.00 ti -2.22 | 94% | 6% |
| -2.21 to -1.40 | 95% | 5% |
| -1.39 to -0.39 | 95% | 5% |
| -0.38 to 1.08 | 89% | 11% |
| 1.09 to 2.70 | 85% | 15% |
| 2.71 to 4.11 | 84% | 16% |
| 4.12 to 5.44 | 80% | 20% |
| >= 5.45 | 42% | 58% |

**Table 2**: Breadth of Purchases measure, larger negative numbers indicate more purchases were made out-of-network than in network, larger positive numbers indicate more purchases were made in network.

After completing a descriptive analysis of the data,logit models were created for each of the usage categories using a stepwise process to determine which of the purchase dimension variables were significant. The resulting logit model for retained customers in the light usage category is given below in Table 3. Only the variables that were significant in predicting the odds of retention are shown in the table. Purchase Velocity is defined as the change in the number of purchase transactions between the first half of a customer's time in the program compared to the second half of their time in the program. Purchase velocity exceeds 0.5 if the number of purchase transactions in the second half in the program exceeds those of the first half in the program, purchase velocity is 0.5 when the number of purchase transactions is constant between halves, and less than 0.5 otherwise. Maximum days since entry into the program is the number of days that have elapsed from entry into the program until the last purchase transaction occurred. Number of purchase transactions is the total number of purchase transactions a customer has made while in the program.

| Logit Model - Light Usage | B | S.E. | Wald | dF | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| Purchase Velocity | -1.046 | 0.442 | 5.599 | 1 | 0.018 | 2.846 |
| Breadth Purchase | -0.474 | 0.029 | 268.25 | 1 | 0.000 | 1.606 |
| Max Days Since Entry | 0.0002 | 0.000 | 7.353 | 1 | 0.007 | 1.000 |
| Number of Purchase Transactions | 0.055 | 0.019 | 8.169 | 1 | 0.004 | 0.946 |
| Constant | 0.486 | 0.401 | 1.475 | 1 | 0.225 | 0.615 |

**Table 3**: Low Usage logit model

The logit generates the log odds of customers not being retained. The equations (1 through 2) for the model are as follows:

1. Ln(Odds) = Ln((Retained)/(NotRetained))

2. Ln($Odds_{Light}$) = Constant - 1.046*PurchaseVelocity- 0.474*BreadthPurchase + 0.0002*MaxDaysSinceEntry+ 0.055*NumberPurchaseTransactions

These equations were used to score light usage customers, these customers were then ranked and evaluated as to whether they were retained. The ranked light usage customers were divided into deciles and the retention rates for each decile were computed, see Table 4 below.

| Scores Deciles | Percentage Retained |
|---|---|
| Top Decile | 91% |
| 2 | 88% |
| 3 | 85% |
| 4 | 77% |
| 5 | 61% |
| 6 | 39% |
| 7 | 23% |
| 8 | 13% |
| 9 | 18% |
| Bottom Decile | 14% |

**Table 4**: Percentage of retained accounts based on scores deciles

The trend present in Table 4 is higher decile light usage customers are more likely to be retained. This shows the usefulness of the logit model for identifying customers likely to remain with the loyalty program and provides a means of identifying customers for specific types of marketing efforts.

Tables 5 and 6 show the logit model for moderate and high usage customers respectively.The likelihood of retaining lightand moderate usage accounts is increased if the customer has a larger ratio of out-of-network purchases compared to in network purchases (BreadthPurchase is the dominant variable based on the Wald values of 268, 280, 131 for light, moderate, and heavy models respectively). For the light usage model the retention scores from the model are highly indicative of the percentage of retained customers, the Cox & Snell $R^2$ is 0.36; the top decile retention rate is 91% while the bottom decile retention rate is 14%. The Cox & Snell $R^2$ for the moderate usage model is 0.27 and 0.11 for the heavy usage model. For the moderate and heavy usage models the greater the number of days within the loyalty program, the greater is a customer's chance of staying in the program, i.e., satisfied customers are likely to continue being satisfied customers, hence they will stay in the program. For the moderate and heavy usage models, the more the total purchase amount, the more likely a customer will be retained.

The moderate usage logit model is given below in Table 5 and in equation 3.

| **Logit Model - Moderate Usage** | **B** | **S.E.** | **Wald** | **dF** | **Sig.** | **Exp(B)** |
|---|---|---|---|---|---|---|
| Total Purchase Amount | 0.0001 | 0.000 | 7.314 | 1 | 0.007 | 1.000 |
| Purchase Velocity | -2.815 | 0.620 | 20.580 | 1 | 0.000 | 16.687 |
| Breadth Purchase | -0.386 | 0.023 | 279.675 | 1 | 0.000 | 1.471 |
| Max Days Since Entry | 0.0002 | 0.000 | 40.168 | 1 | 0.000 | 1.000 |
| Number of Unique Partners | -0.068 | 0.029 | 5.725 | 1 | 0.017 | 1.071 |
| Constant | 2.202 | 0.370 | 35.411 | 1 | 0.000 | 0.111 |

**Table 5**: Moderate Usage Logit Model

3. $\text{Ln}(\text{Odds}_{\text{Moderate}}) = \text{Constant} - 2.815{*}\text{PurchaseVelocity} - 0.386{*}\text{BreadthPurchase} + 0.0002{*}\text{MaxDaysSinceEntry} - 0.068{*}\text{NumberOfUniquePartners} + 0.0001{*}\text{TotalPurchaseAmount}$

The heavy usage model is given below in Table 6 and in equation 4.

| **Logit Model - Heavy Usage** | **B** | **S.E.** | **Wald** | **dF** | **Sig.** | **Exp(B)** |
|---|---|---|---|---|---|---|
| Purchase Amount Divided ByLongevity | 0.269 | 0.136 | 3.931 | 1 | 0.047 | 0.764 |
| Purchase Velocity | -2.895 | 0.884 | 10.730 | 1 | 0.001 | 18.080 |
| Breadth Purchase | -0.323 | 0.028 | 131.163 | 1 | 0.000 | 1.381 |
| Max Days Since Entry | 0.0002 | 0.000 | 25.251 | 1 | 0.000 | 1.000 |
| Constant | 2.170 | 0.597 | 13.199 | 1 | 0.000 | 0.114 |

**Table 6**: Moderate Usage Logit Model

4. $Ln(Odds_{Heavy})$ = Constant - 2.895*PurchaseVelocity- 0.323*BreadthPurchase+ 0.269*PurchaseAmountDividedByLongevity + 0.0002*MaxDaysSinceEntry

## 5. DISCUSSION & CONCLUSIONS

The logit models according to customer usage levels of the loyalty program provided scores that when tested proved to be predictive of customer retention. It turned out that the breadth of a customer's purchases, that is, whether customers were making more out of network purchases compared to in network purchases, was predictive of customer retention. Based on the Cox & Snell $R^2$ values the light usage model yielded the strongest (most accurate) predictions of customer retention compared to the moderate and heavy usage models. Examining results of light usage model scores by deciles indicated that 91% of customer accounts receiving top decile scores were retained, whereas 14% of customer accounts with bottom decile scores were retained. This suggests that customers are more likely to remain with the loyalty program if they have access to many vendors, and, evidently their preferred vendors are not currently participating in the loyalty program.

Also it was noted that customers who made few purchases were significantly more likely to stop using the program. The breadth of usage dimension becomes less important the longer a customer remains in the loyalty program. Findings from this study can help a firm determine how to deploy resources to enhance customer retention. Two different ways that a company can approach this are: (1) direct marketing efforts to encourage likely to be retained light-usage customers to become moderate or heavy users, thus increasing the lifetime value of these customers; (2) direct marketing efforts to encourage customers not likely to be retained to stay in the program through long-term relationship incentives. For both of these approaches firms need to consider first, do they want to keep all of the customers that they do not retain (is it worth the expense and effort from a CLV perspective) and second, will incentives cause changes in actions only but not in long-term behavior.

This study demonstrated that it is possible to create logit models for predicting customer retention based on purchase histories. Furthermore, the developed logit models had increased predictive power by segmenting customers according to their level of participation (usage) within the loyalty program. Using models such as these firms can strategically deploy marketing resources so as to increase customer lifetime value which in turn will increase profits for the firm.

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