INSIGHTS FOR INCREASING LOYALTY PROGRAM USAGE

Final Capstone Report

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Business Case

Objective:

The primary objective of this data analysis project is to optimize The Canadian Brewhouse's loyalty program, specifically doing a closer look at the current app itself. The goal is to enhance customer engagement, increase retention, and drive revenue growth through targeted and data-driven strategies.

Company Overview:

- The Canadian Brewhouse is a chain of 40 sports bar restaurants with multiple locations throughout the country.
- Created a loyalty program in 2018 using a 3rd party loyalty partner (PUNCHH).
- CBH app controls the loyalty program, emphasizing incentives to encourage regular visits.

Current State:

The Canadian Brewhouse has been mostly focusing on the "Teams and Leagues" program as an initiative aimed at recreational teams. Most of the recent campaign efforts have been dedicated to this program. We feel that they have narrowed their scoop too much by just focusing on recreational teams and don’t have a clear idea of their customer base.

Existing Challenges:

- Limited visibility into the effectiveness of current loyalty program initiatives.
- Limited knowledge of customers’ experience with application and customer base.
- Currently there are little insights into customer demographics and behavior patterns.
- Potential untapped opportunities for improvement.

Problem Statement

Leading Questions:

- How do we get more people to interact with the loyalty program?

- What can we learn from user activity to increase usage into the loyalty program?
- How can we get more information from our users?
- Are people more likely to use their program offers?
- What are factors that prevent people from using the app?

Goal of Analysis:

- By focusing on the loyalty program, we can hopefully get an idea of who our customer base is, what might make them come back and encourage customers to create accounts to help data collection.
- With increased interaction with the loyalty program, it is an opportunity to not only directly market to customers, but to also gather more information that could create more opportunities to create business insights with further analysis.

Project Scope:

- Analyze historical data related to the loyalty program.
- Identify patterns and trends in customer behavior, engagement, and spending.
- Evaluate the effectiveness of current incentives and campaigns.

Data Sources:

- Loyalty program data from the CBH app.
- Transactional data.

Key Analysis Areas:

Customer Segmentation:

- Understand different customer segments participating in the loyalty program.
- Identify high-value and at-risk segments.

Sentiment Analysis:

- Understand customer sentiment of the Canadian Brewhouse and
- Determine which incentives drive the desired customer behavior.

RFM Analysis of App Users' Redemption:

- Develop predictive models to forecast customer behavior and spending patterns.
- Use these models to tailor future campaigns and incentives.

RFM Analysis of Different Campaigns:

- Quantify the return on investment for the loyalty program.
- Assess the financial impact of the different campaigns.

Customer Segmentation Analysis:

Customer segmentation analysis is a tool that business can use to closely align their strategies, and better target their current and future customers. It divides customers into common characteristics like demographics in a way to make marketing to customers more effectively. The purpose of segmentation analysis is to better understand the diverse needs, preferences, and behaviors of different customer groups so that businesses can tailor their marketing strategies, product offerings, and customer service efforts more effectively.

The guest dataset has information about users who are part of the loyalty program and holds identifying keys that will allow us to link with other datasets like receipt items and check-in information. Any columns that held personal information were completely left blank, so we made an easy decision to drop those columns.

Overall we tried to keep the guest data as fully intact as possible as we would not like to remove too much information, as we want to know as much as possible especially when we try to merge some datasets together to get a better understanding of guests' habits.

Our analysis will be pulled from the guest information provided, and would look at their common characteristics and activities on the app.

The common features we'll be looking at for this analysis are:

- Device Type
- Age (had to remove some outliers where customers was over 100)

- Total Spend (for any zero values in total spend, we put in a median value as we assumed the customer spend money there, however for some reason it was not recorded in the database. We used median as it isn't heavily effected by outliers like mean is.)
- Marketing email subscription status
- Total Card Based Redemption
- Pust Notification Token Available
- Favorite Location ID
- Signup Channel

Some features that we did not include in the analysis and their reasons:

- Gender, since over 90% of that information is unknown, we believed it would not be worth looking into
- Checkin information, as it would have been captured in other information like spending and card redemption when it comes to activity.
- Birthday, we'll be using age for that.
- Loyalty points earned, as there was some weird information that wasn't clear without context of what happened to some of the points or what was it really showing. For easier analysis, we just didn't put it in.

Demographic Distribution:

Below are graphs that show the distribution of different categorical information along with their insights we can consider.

Age:

To get age values from the dataset, we calculated the difference between this current date (April 19) to the birthdate recorded for the users. Any nulls that were created from this calculation (*about 27% of the values*), we filled in with the median value of age, (33 years old) for our analysis. We noticed some outliers for age (some being almost 200 years old) and decided to remove those accounts that exceed 100 years old as their information did not hold too much value in them.

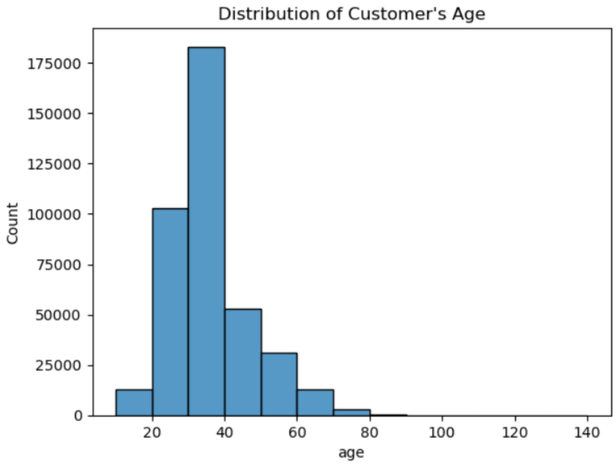


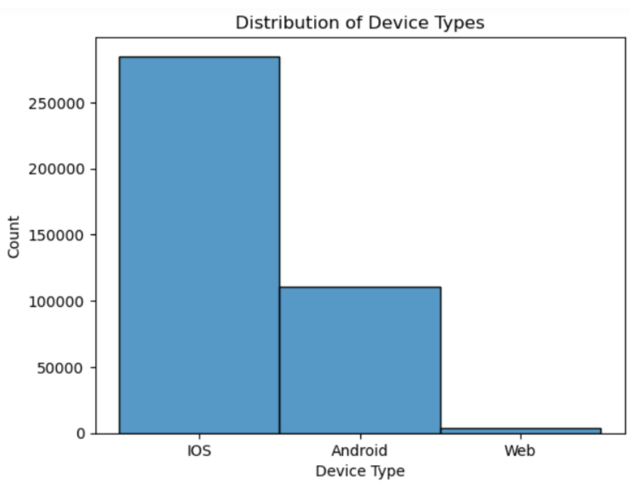
Figure 1: Distribution of Customer's Ages from Guest Information.

Insights:

- Most of our users are in the 20–40-year demographic. (71% of accounts)
- 30–40-year-olds make up about 46% of the accounts.
- 20-30-year-olds make up about 26% of the accounts.
- 40-60-year-olds make up about 21% of the accounts

Device Types:

Not much cleaning is needed for this column.



Insights:

71% of the accounts are from an IOS device.

28% of the accounts are from an Android device.

Segmentation Model:

To create the segmentation model, we will be using the k-means algorithm where the main goal is to separate the dataset into kpre-defined distinct groups. The main goal is to make sure that each data point belongs to only one specific group. They try to make these data points as similar as possible so we could have a grab ideas of demographics and spending habits.

We have used the elbow method to find the optimal number of clusters our features *(labeled about)* create. Below is our results of this method:

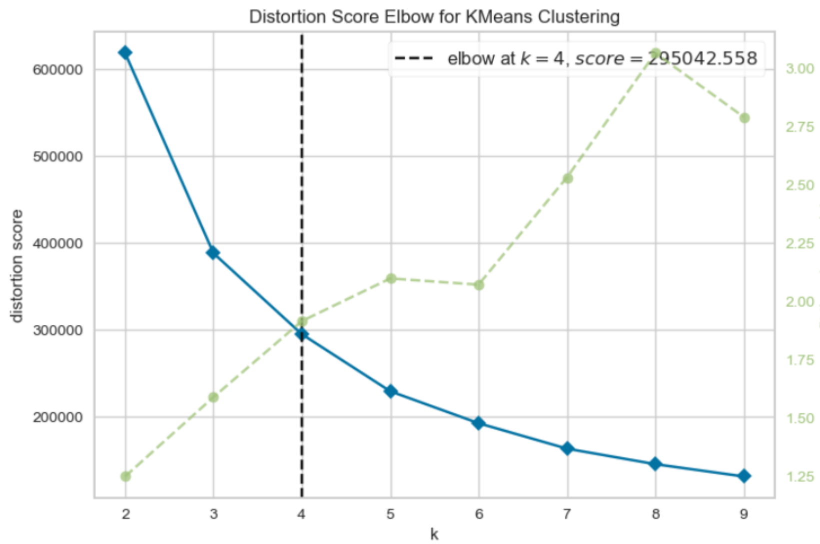


Figure 2: Elbow method for KMeans Clustering.

According to this model, our optimal number of clusters is four. From here we will start to investigate the details of the different clusters to have a better idea of what kind of customers we have.

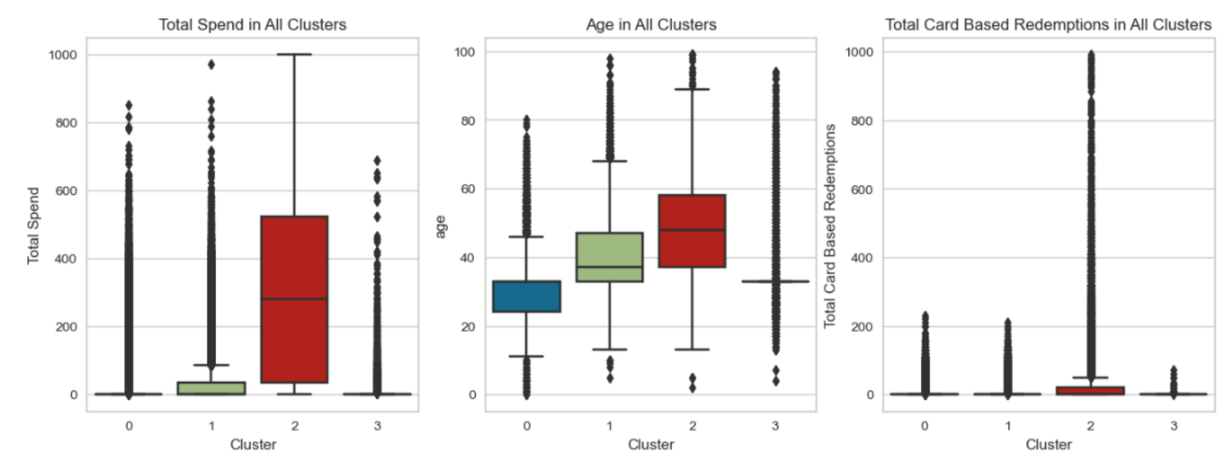


Figure 3: Distribution of different features for Customer Segmentation.

As we see in fig. 3, cluster 2 has the most total spending and card-based redemption. We can assume that this cluster is the one that interacts with the app more. Cluster 2’s age demographic is also higher than our original age demographic, showing that customers between the age of 40-60 are interacting with the app more.

Cluster 3 has the least amount of total spending and card-based redemption. We can assume that this cluster does not interact with the app as much.

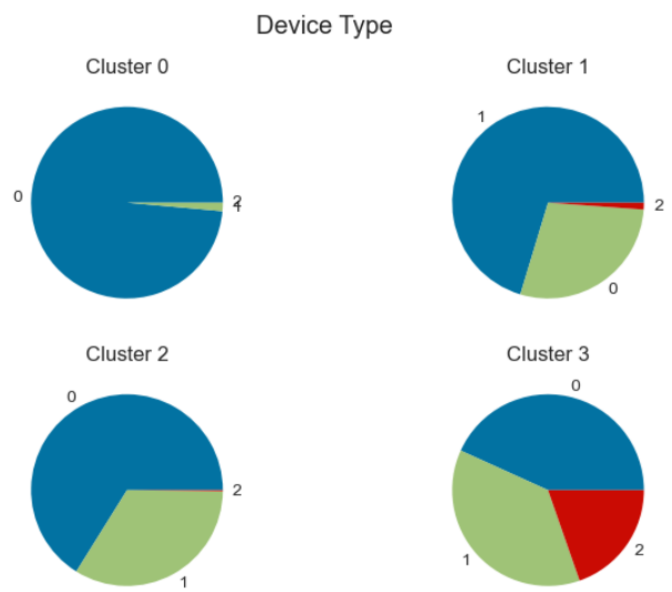


Figure 4: Cluster distribution of Device Usage. 0 = IOS, 1=Android, 2=Web

This graph shows which device the clusters prefer more.

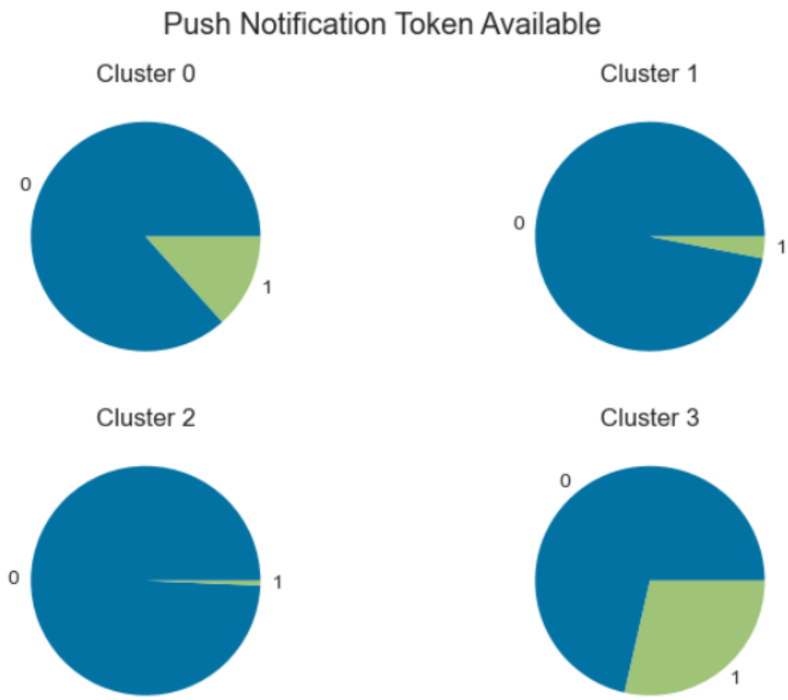


Figure 5: Cluster distribution of Push Notifications. 0 = Yes, 1 = No

Push notification being enabled allows for the app to send notification to the user about updates and promotions that the Canadian Brewhouse can directly send to the user.

<u>Cluster Details:</u>

- Cluster 0: This cluster is mostly made of people between the age of 20-30, having a vast variety of spending habits that isn't really concentrated anywhere. These are all IOS users and have low activity when it comes to redemptions. A small portion of users have notifications turned off.
- Cluster 1: This cluster is mostly people between the age of 35-55, they seem to spend slightly more than cluster 0, but still on the lower end of the spending total. Though the IOS system seems to be the majority, there are a good portion of users who use the Android system.
- Cluster 2: This cluster consists of people between the age of 40-60, being the group that has the most amount of spending by a signification amount. This cluster also has a

higher count of card-based redemptions, being the cluster that most interacts with the app. The also have the lowest proportion of users who disabled push notifications.

- Cluster 3: This cluster has a lot of evidence of the group being the lowest to interact with the app. Their total spending and card-based redemptions are the lowest of the other clusters. They also have their accounts on different types of devices, as it is the only cluster that includes web-based interactions. They are also the group that has the highest proportion of users who have push notifications disabled.

Final Insights:

Looking at the cluster demographics, we can see one thing that is clear. The demographic of people who are actively using the app is actually a very small amount. When we focus on age, the people who are mostly interact with the app are between the ages of 40-60 years old. That is only about 21% of the accounts actually being used most often; while the age demographic of 20–40-year olds (about 71% of the accounts) are in clusters that interact with the app the least amount of times and spend the least amount of money. This shows a huge number of the accounts not being used to track information.

A growing opportunity is to investigate ways to market the app to the younger demographic so that they become more active accounts. Since this demographic is mostly assumed to be more tech savvy, one can assume that this generation is more likely to adopt a mobile app; however, in this situation it seems to be the opposite. Overall, the Canadian Brewhouse should find ways to market to the younger generation.

Sentiment Analysis:

For the “User Feedback NAIT” dataset we started with dropping some of the unnecessary columns that where wither mostly null, or did not have data that would be applicable to the project. The columns that were dropped were “First Name”, “Last Name”, “Negative Feedback”, “Date of Reply”, and “Requires Response”. With those columns dropped we are left with “Location ID”, “User ID”, “Location Name”, “Feedback”, “Feedback Rating”, “Store Number”, “Date of Feedback”, and “Feedback ID”. In the “Feedback” column there are a lot of nulls, but the data within the column is still useful. We decided to make 2 versions of the dataset, one with the null “Feedback” rows, and one with the null rows taken out, this helped with one of the first modes we decided to build with this dataset.

For the first set of analysis, we decided to perform sentiment analysis on the “Feedback” column to see if customer’s ratings match the mood of what they are writing. To start we used a pre trained model that uses tokenizing to classify each comment into a rating of 1 to 5, with 5 being a very positive comment and 1 being a very negative comment. This model was called the “bert base multilingual uncased sentiment” model and was very easy to use due to the data already being pre trained and us only needing to test the review data that we had. After the model finished doing its analysis, we placed the results into the dataset that had all the null comments taken out.

Two graphs were made to compare the amount that each level of rating achieved. The two graphs at first glance look fairly similar to each other, but when overlapped, it shows that the amount of 5 and 4 star ratings goes down, while the amount of 1 and 2 star ratings goes up, 3 star ratings stay relatively the same. This proves that some customers were writing down their thought and inputting a random rating just to get the message out there. An example of this is a customer saying “Lose all my points when I haven’t used them up”, that person rate 5 stars, and the sentiment analysis model labeled it as a 1. Another example is “Philly cheesesteak was disgusting. I would not recommend it to anyone. Service could have been better. No one checked in to see how our food was. This was not our best experience.”, the customer also rated this 5 stars, where the sentiment analysis rated it a 1, it seems the customer had a bad experience overall so the rating of a 1 seems more fit.

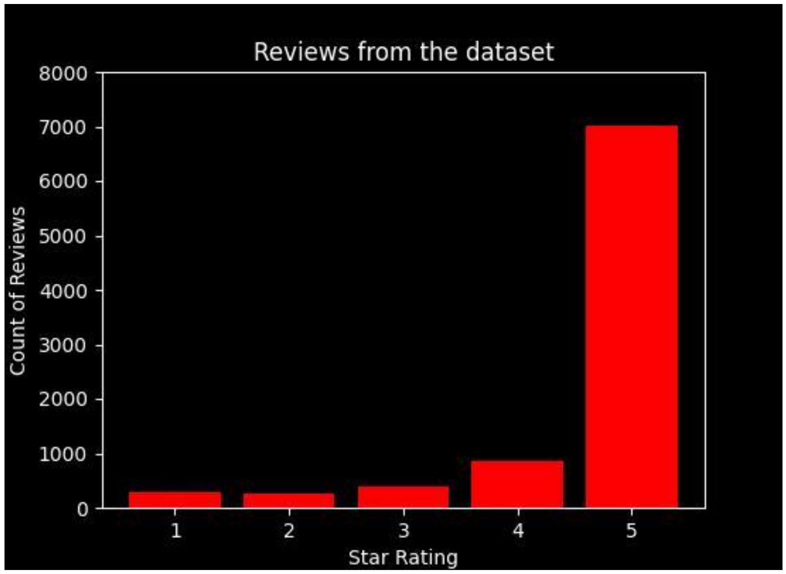


Figure 6. Reviews from User Feedback NAIT Dataset

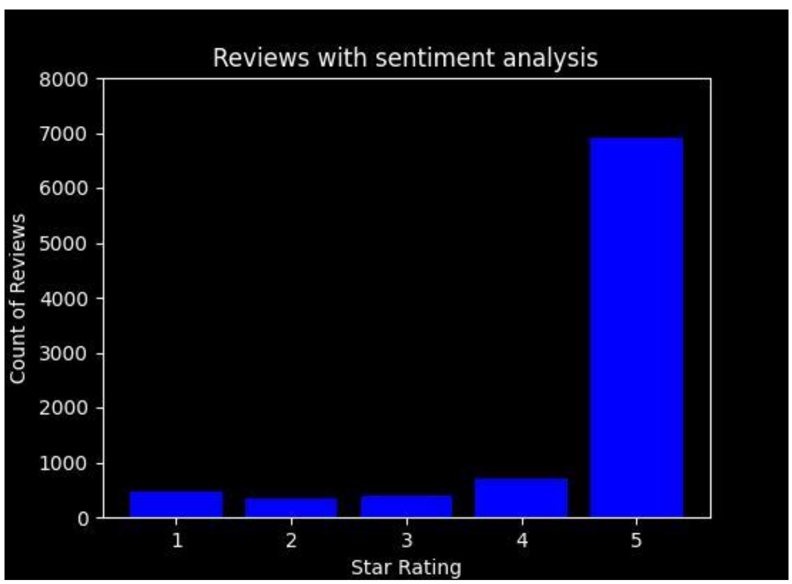


Figure 7. Reviews from Sentiment Analysis

<u>Feedback Given:</u>

Next, we decided to analyze how many people are giving feedback within the app. After counting, it seems that only 28.22% of users were leaving actual feedback , while 71.78% of all users were not leaving reviews. With such a low number of comments, there should be a further incentive to leave behind a comment, even if it is just “I enjoyed the food” or a “I disliked the food”, comments like those still get the true feelings of the customer, because as we saw earlier some customers had very negative experiences while leaving a 5 star review.

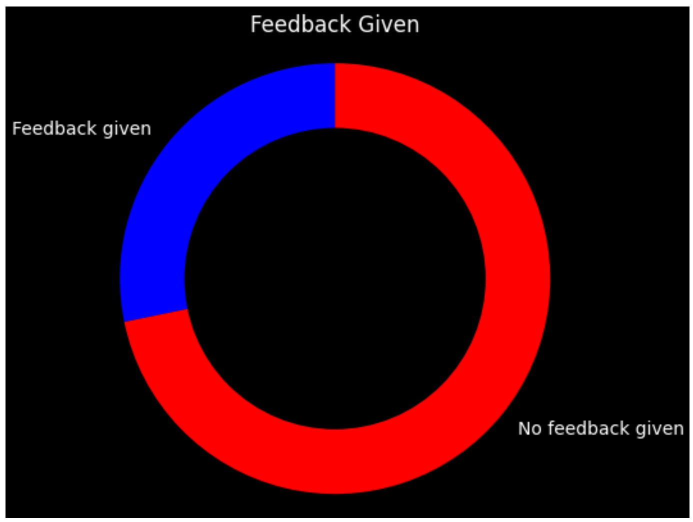


Figure 8. Donut Chart on Feedback

Location Data:

Lastly, we decided to look at the number of reviews received across the board per location. For this one used the dataset that contained all the review rows in it so that we could see all the data for these different locations. After displaying the top 10 locations, we can clearly see that the Lewis Estates location has the most reviews but 2,500, which is a huge difference from the 2nd place store. It may be worth inquiring about Lewis Estates if they try to push customers to leave a review. Asking all stores to give customers a friendly reminder to leave a review to gather more feedback for improvement of things such as foods and services.

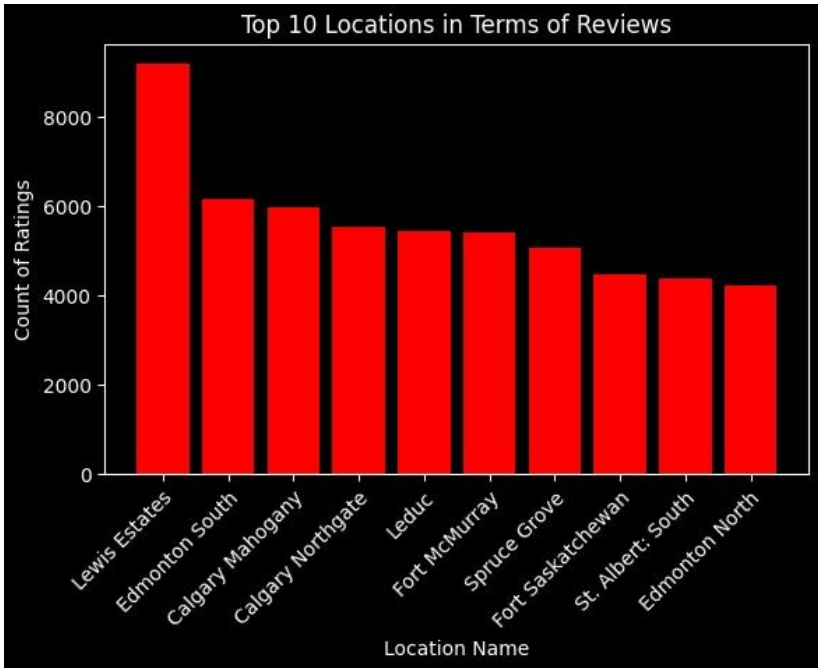


Figure 9. Top 10 Locations by Review Size

One of the difficulties we experienced when dealing with this dataset was customers leaving feedback without giving a number rating, this was remedied by removing the columns that had null “Feedback Rating” values in the dataset that only had non null values in the “Feedback” column. Another difficulty we faced was with the dataset we used to train the sentiment analysis model, at first we tried using a dataset from Kaggle called “Restaurant Reviews.CSV” and while it contained what we need to a degree, it had one major flaw, it was only 1000 rows. When trying to train the model with that dataset, we were getting results of 100% accuracy with low epoch counts, which isn’t very good, also upon manually reviewing the results, some comments that were very clearly negative, showed up as positive. After these results we decided to do some research into finding a new dataset to train the data and found a way to use a pre trained model.

RFM Analysis of App Users' Redemption:

RFM analysis categorizes customers based on their purchasing habits, using three main measures: recency, frequency, and monetary value. It assigns a score to each customer, considering how recently they made a purchase, how often they buy, and how much they spend (Canakci, G. 2022). This method provides businesses with valuable insights into their customers' buying behavior, helping them adjust their marketing strategies such as offering personalized promotions and targeted communications to better meet customer needs. Through conducting RFM analysis on CBH's redemption dataset, our goal is not only to uncover customers' purchasing behaviors but also to gain insights into their redemption patterns and preferences.

EDA and Data Cleaning:

Before starting our RFM analysis of the Redemption dataset, we followed several exploratory data analysis and data imputation steps to enhance the suitability of the dataset for analysis. Initially, unnecessary columns like 'Status', 'Employee ID', 'GPS Accuracy', and 'IP Address' were removed to focus on essential variables, reducing complexity. Missing values in the 'Channel' column, indicating the redemption method, were filled by conditional imputation using data from the 'User Agent' and 'Redemption Code Status' columns. Similarly, missing values in the 'Redeemable Name' column, critical for understanding redemption patterns, were replaced with 'Point Redemption only' through conditional imputation. Additionally, date and time columns were standardized for easier analysis. These actions collectively optimized the dataset for an insightful examination of app usage and user behavior.

Methodology:

The RFM analysis was conducted by analyzing the historical redemption and purchase data of CBH app users. Each user was assigned a score for Recency, Frequency, and Monetary Value based on their most recent loyalty app usage date, the frequency of app usage, and the total monetary value of their transactions, respectively. Subsequently, users were segmented into distinct categories based on these scores to reveal patterns and trends within the customer base.

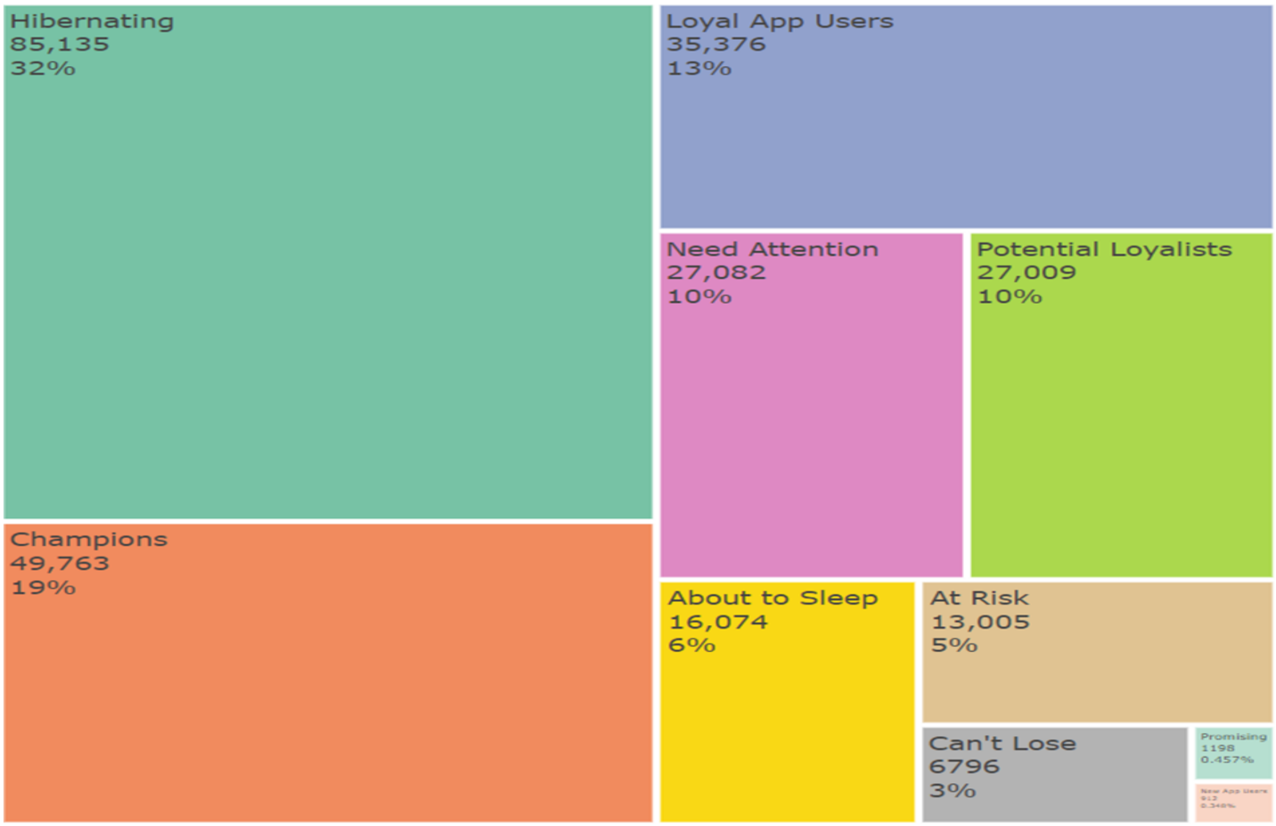


Figure 10. Tree map of RFM Analysis on Redemption data

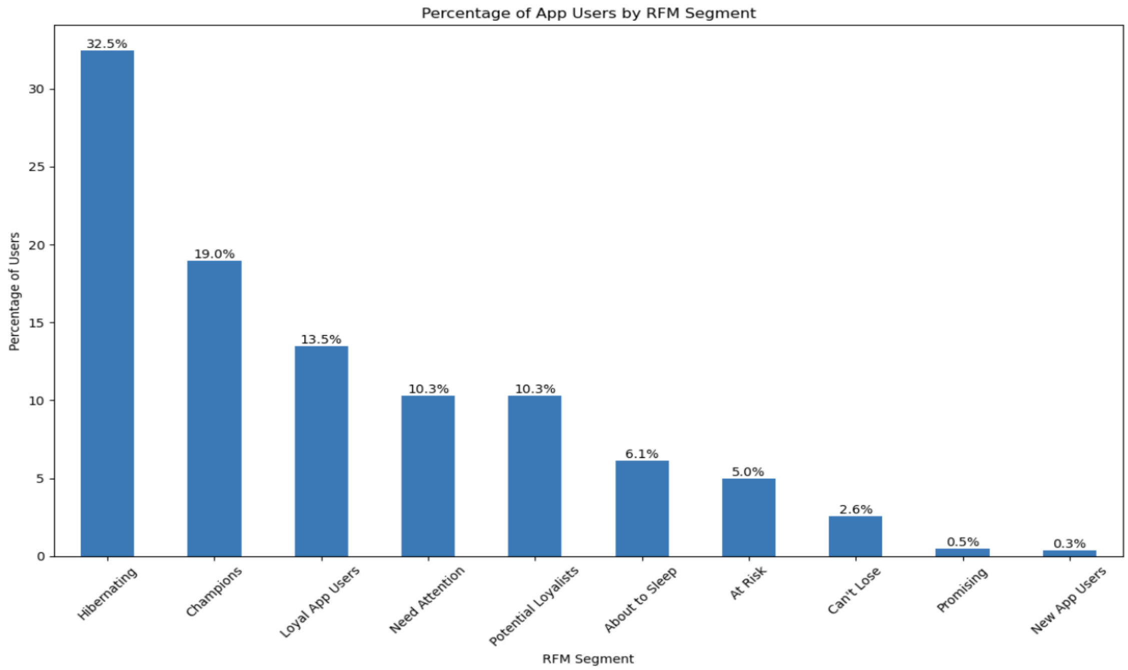


Figure 11. Bar graph displaying total percentages of each segment

Findings:

Hibernating Customers:

The largest segment, Hibernating customers, accounts for one-third of the total app user base, characterized by low RFM scores. Users in this segment have shown minimal recent engagement with the app, infrequent purchases, and low spending levels. Some may have only used the app once or twice, or simply downloaded it to claim a free item. Their lack of activity suggests a potential loss of interest or other reasons. Moreover, the redemption pattern of users in this segment mirrors their disengagement from the app (Figure 11). Our analysis reveals that approximately 85% of users in the Hibernating segment have redeemed free golden garlic fingers, a promotional item received upon app download.

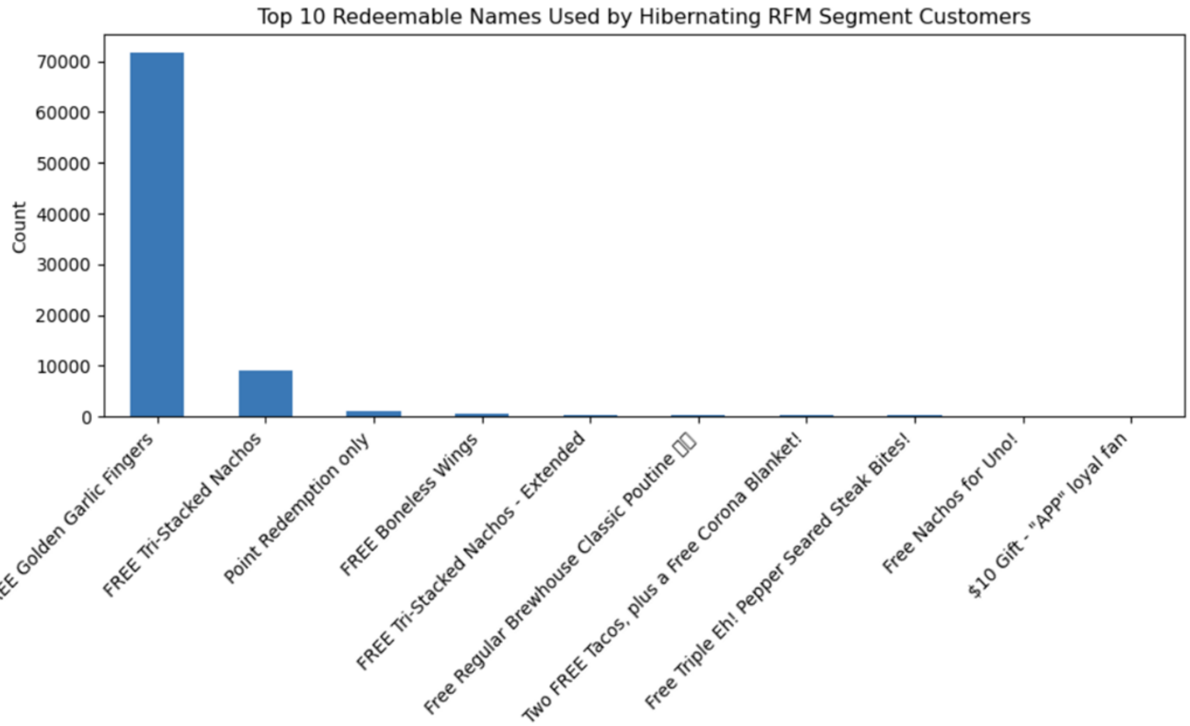


Figure 12. Top 10 Redeemable Names used by Hibernating Users Segment

Champions:

The Champions segment comprises 19% of the total app user base and represents the most valuable group. These customers are highly engaged, making frequent purchases and spending significant amounts. Their active involvement is evident in their redemption pattern, primarily focused on point redemption (Figure 12). The combination of their high app usage and spending enables them to accrue enough points for redemption. Furthermore, we observe a diverse range of offers being redeemed by this segment, indicating their enthusiasm for exploring various benefits offered by the app. The Champions includes highly engaged and loyal customers, and it's essential to incentivize them to sustain their loyalty by continuing to use the app.

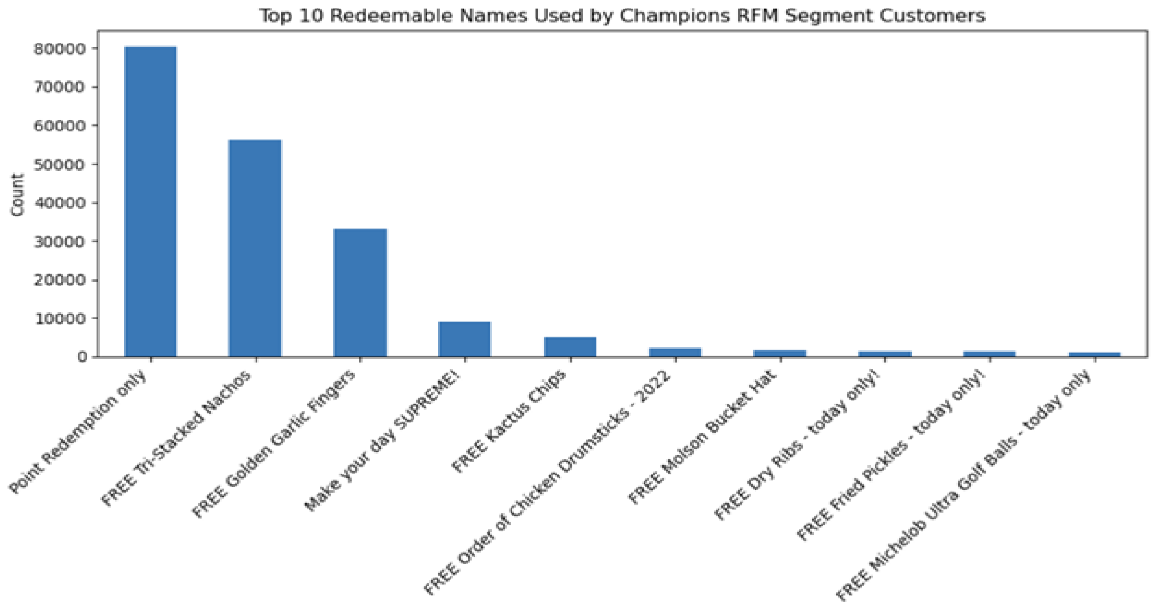


Figure 13. Top 10 Redeemable Names used by Champions Segment

<u>Loyal App Users:</u>

Loyal customers show high Recency, Frequency, and Monetary Value scores like champions. They represent a significant portion of the customer base, with a high RFM score, indicating their consistent engagement and valuable contribution to the app's success. Sustaining the continued interest and engagement of these customers is crucial, as they possess the potential to move up to the higher segment. The redemption pattern observed among Loyal App Users (Figure 13) closely resembles that of the Champions segment (Figure 12), characterized by frequent point redemption events and a diverse range of redeemed items.

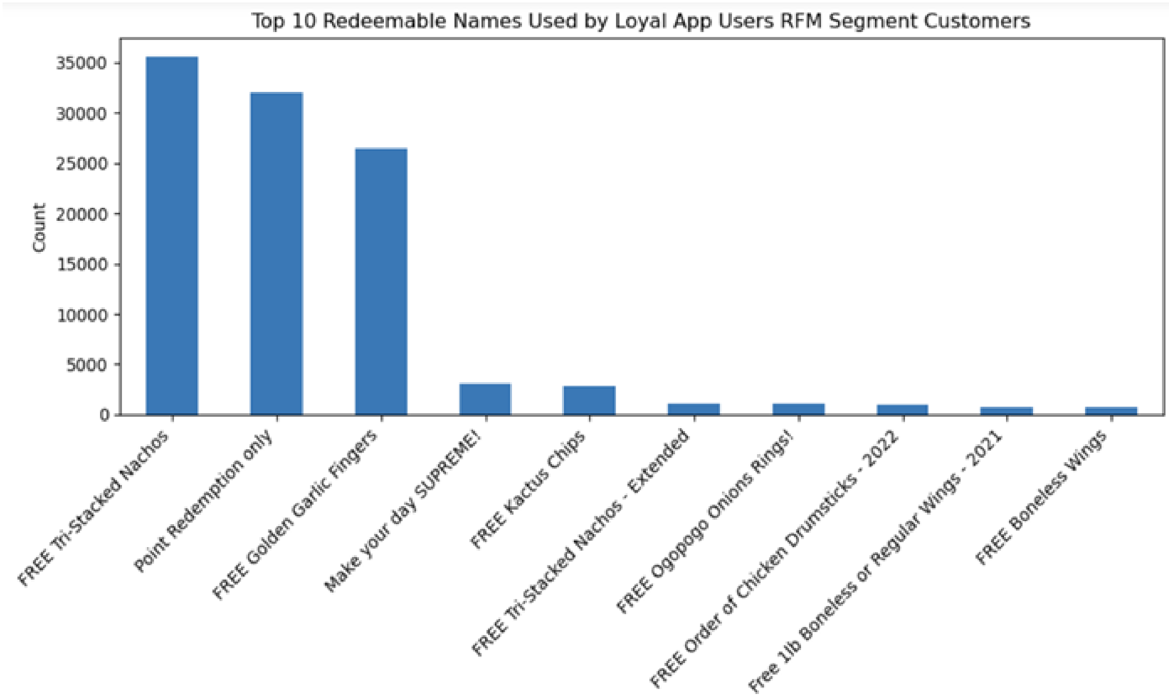


Figure 14. Top 10 Redeemable Names used by Champions Segment

<u>Can't Lose, At-Risk, About to Sleep Customers:</u>

Customers in these segments share a common trait of having demonstrated historically high levels of engagement and monetary value, indicating their past loyalty and value to the app. Despite this, there has been a recent decline in their activity, posing a potential risk to their continued engagement and loyalty. Their prior active involvement with the app is evident in the variety of offers they have redeemed (Figure 14).

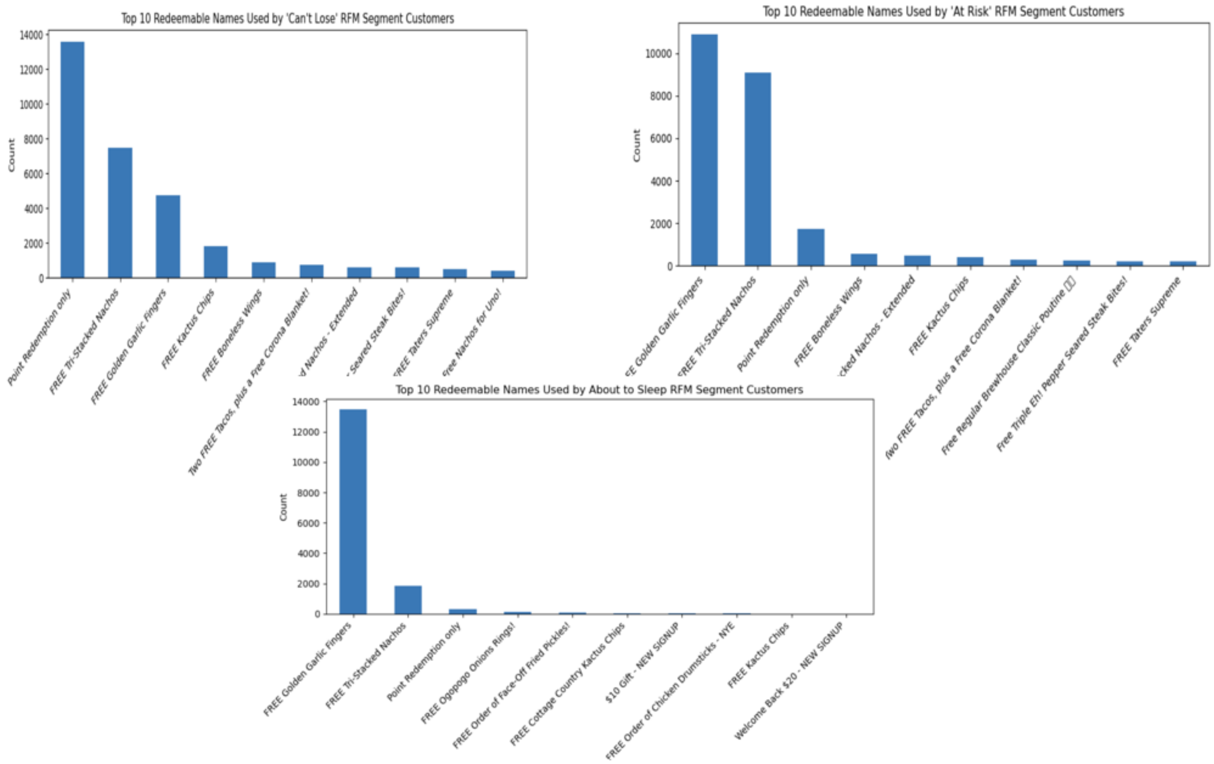


Figure 15. Top 10 Redeemable Names used by Can't Lose, At-Risk, About to Sleep Customers

Promising, Need Attention and Potential Loyalists:

Promising Users, Potential Loyalists, and Users who Need Attention are characterized by their relatively recent engagement with the app, as evidenced by their high recency scores. Despite their current low to moderate frequency and spending levels, these customers hold the potential to enhance their activity and loyalty over time. With targeted efforts and incentives, they can be encouraged to elevate their engagement levels and become valuable, loyal app users. Upon examining their redemption behaviors, it's evident that this group displays a wide variety in the types of offers they redeem, highlighting their active interest in engaging with the app.

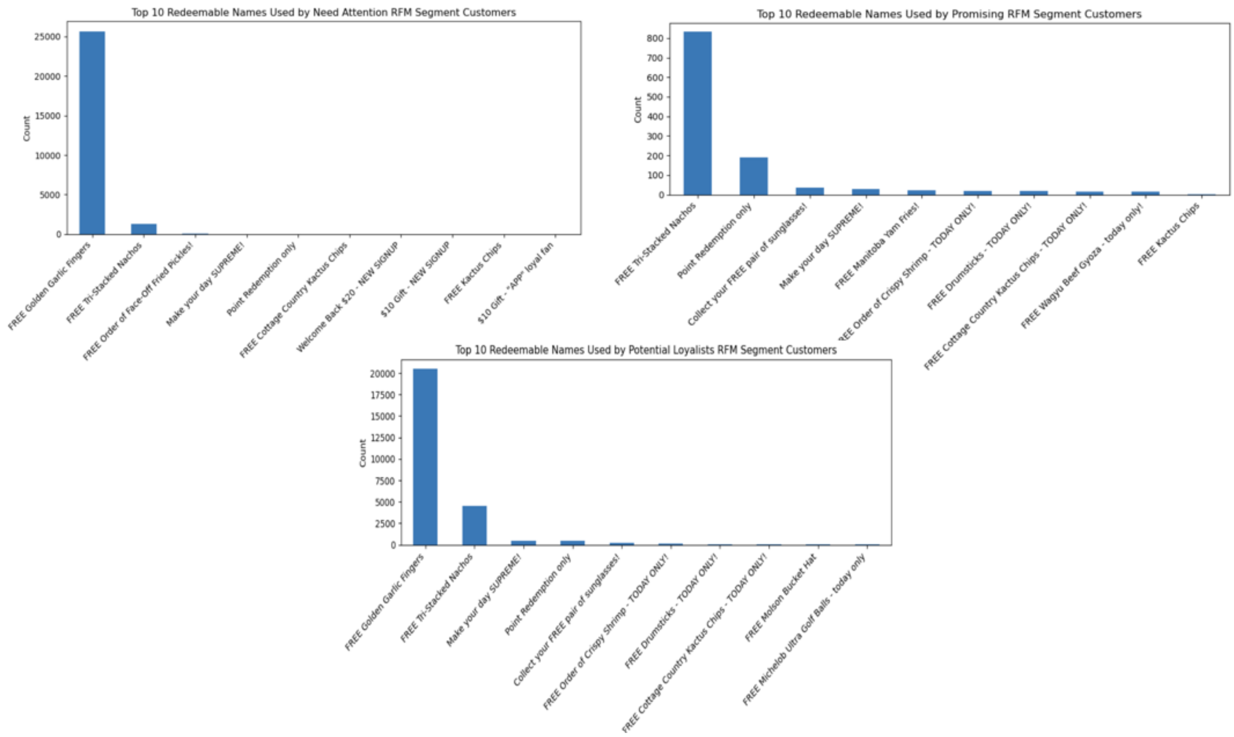


Figure 16. Top 10 Redeemable Names used by Promising, Need Attention and Potential Loyalists

<u>New Users:</u>

New users are those who recently adopted the app and made initial purchases. These customers have low Recency, Frequency, and Monetary Value scores, reflecting their early-stage status. Despite comprising only 0.3 percent of total app users, it is imperative to make a positive impression on new customers and retain their attention on the app to encourage their continued engagement.

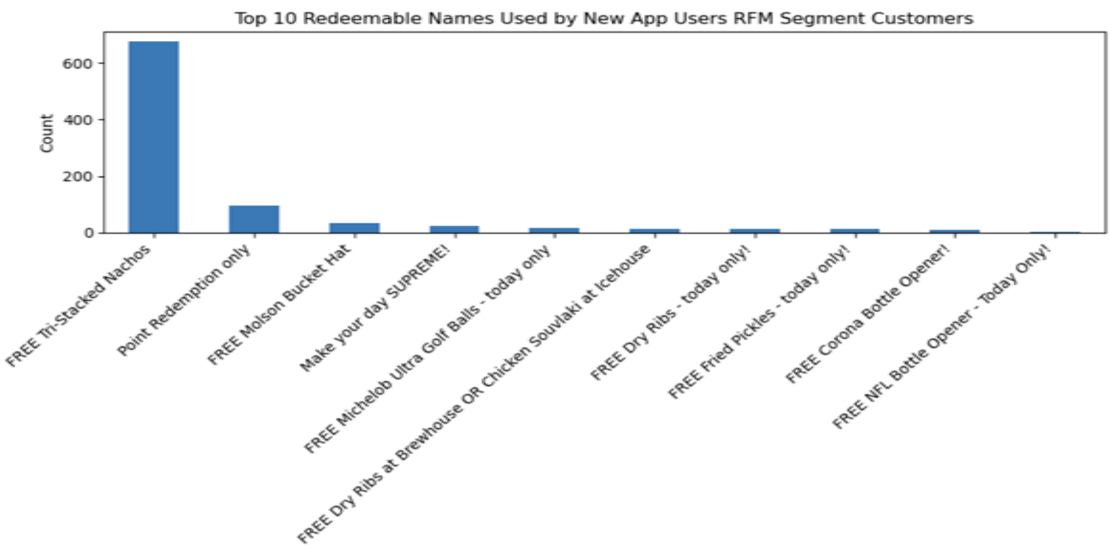


Figure 17. Top 10 Redeemable Names used by New app Users

<u>Marketing Recommendations:</u>

Implementing targeted marketing strategies that are data-driven and precisely aligned with the needs and interests of different customer segments is essential for the success of the business. By harnessing the power of insights derived from RFM analysis of CBH's app users' redemption data, we have gathered the following marketing strategies:

- Re-engagement campaigns need to be implemented to reignite interest among Hibernating Customers. Personalized incentives or discounts should be offered to encourage them to revisit the app and make purchases.
- Consistent communication should be maintained with Champions and Loyal App Users to reinforce their loyalty and encourage continued engagement. Exclusive rewards or incentives should be offered to show appreciation for their ongoing support.
- Focus should be on retaining the loyalty of Can’t Lose, At-Risk, and About to Sleep Customers by offering targeted incentives or promotions to re-engage them with the app. Highlighting the benefits of continued usage and showcasing new features or promotions can reignite their interest.

- Strategies should be implemented to nurture Promising, Need Attention, and Potential Loyalists, encouraging them to increase their activity and loyalty over time. Special incentives or rewards should be provided to encourage higher spending and more frequent app usage
- New Users should be given a positive impression to encourage continued engagement and loyalty. Free onboarding incentives like Free Garlic Fingers upon downloading the app is an effective initial incentive to catch new users' attention. However, to sustain engagement, it's crucial to maintain ongoing communication and offer supplementary incentives and point rewards.
- Regular monitoring and review of data from RFM analysis should be conducted to refine marketing strategies and tactics, ensuring they remain aligned with customer preferences and behaviors over time.
- Experimentation with different marketing channels and techniques should be encouraged to identify the most effective approaches for engaging with different customer segments.

Campaign Methodology

The initial challenge lay in devising a method to effectively measure the value of the campaigns. Within the campaign dataset, no information was available regarding usage volume or any tangible measurable variables. Consequently, it became important to locate an alternative dataset containing pertinent measurable data, either encompassing campaign details or amenable to integration through inner joins.

Subsequently, it was discovered that the coupon redemption dataset contained all requisite campaign information, documenting each instance of campaign redemption. This dataset provided comprehensive details including redemption dates and corresponding monetary values.

To discern the efficacy of various campaign types, given the impracticality of individually listing all campaigns, a cluster analysis utilizing KMeans was employed to categorize them into distinct groups. An optimal cluster count of 10 was determined through experimentation. Post-establishing these clusters, subsequent analysis ensued.

Our approach to categorizing campaign performance involved employing a Recency, Frequency, Monetary (RFM) analysis. This entailed scrutinizing campaigns based on the recency of their last usage, frequency of usage, and total monetary value associated with redemptions.

Subsequently, each campaign was filtered based on its performance in the RFM analysis, categorizing them as either high-value or low-value campaigns. This categorization facilitated the measurement of performance across different campaign clusters, enabling the identification of well-performing and underperforming campaign types.

Campaign Findings

Clusters:

We categorized the groups into 10 different clusters:

Cluster 0: NYE 2022 Promo Campaign

Cluster 1: Kids Eat Free Day

Cluster 2: Sport Teams

Cluster 3: Tattle Survey Coupons

Cluster 4: Tattle Coupons

Cluster 5: Radio Contest

Cluster 6: Sport Teams in 2023

Cluster 7: Rec League

Cluster 8: Free Kactus Chips

Cluster 9: Chase The Ace

To examine these clusters further, we analyzed the frequency of coupon redemptions within each cluster. Our results indicated varying levels of popularity among campaigns, with certain campaigns, particularly those related to sport teams (Clusters 2 and 6), comprising a significant percentage of redemptions. Other notable clusters by raw count included Cluster 1: Kids Eat Free Day, Cluster 3 & 4: Tattle Coupons, and Cluster 0: NYE 2022 Promo Campaign. However, raw count alone does not provide a comprehensive picture, as it may be influenced by the distribution of coupons. Hence, we sought to assess which types of campaigns were performing well proportionally to their size.

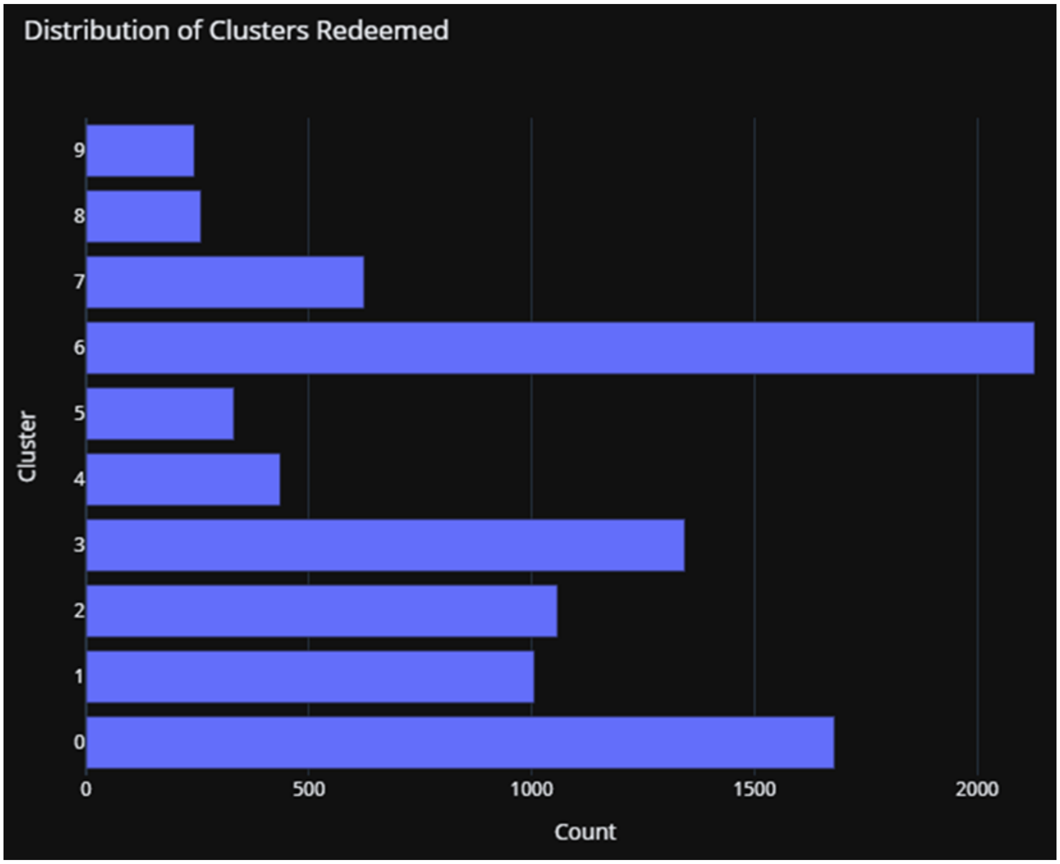


Figure 18. Distribution of Coupon Redeemed by Cluster

RFM Analysis:

By assigning a numerical value from 1 to 5 for recency, frequency, and monetary metrics to each campaign with redemptions, we categorized campaigns into different groups. We identified only 210 unique campaigns within the coupon redemption dataset, a notably small figure compared to the dataset of over 30,000 campaigns. This discrepancy may stem from certain campaigns being redeemed without entering them into the system, as suggested by insights from presentations and internal knowledge.

We then classified segments into performing and non-performing categories. Performing campaigns included 'Best Performing Campaigns,' 'Consistently Engaging Campaigns,' 'Promising Campaigns,' and 'Regularly Performing Campaigns,' while non-performing ones encompassed 'Declining Campaigns,' 'Low Interest Campaigns,' 'At Risk Campaigns,' and 'Stagnant Campaigns.' We found that 33% of campaigns had a positive outlook, 25% had a negative outlook, and 37% fell into the middling category.

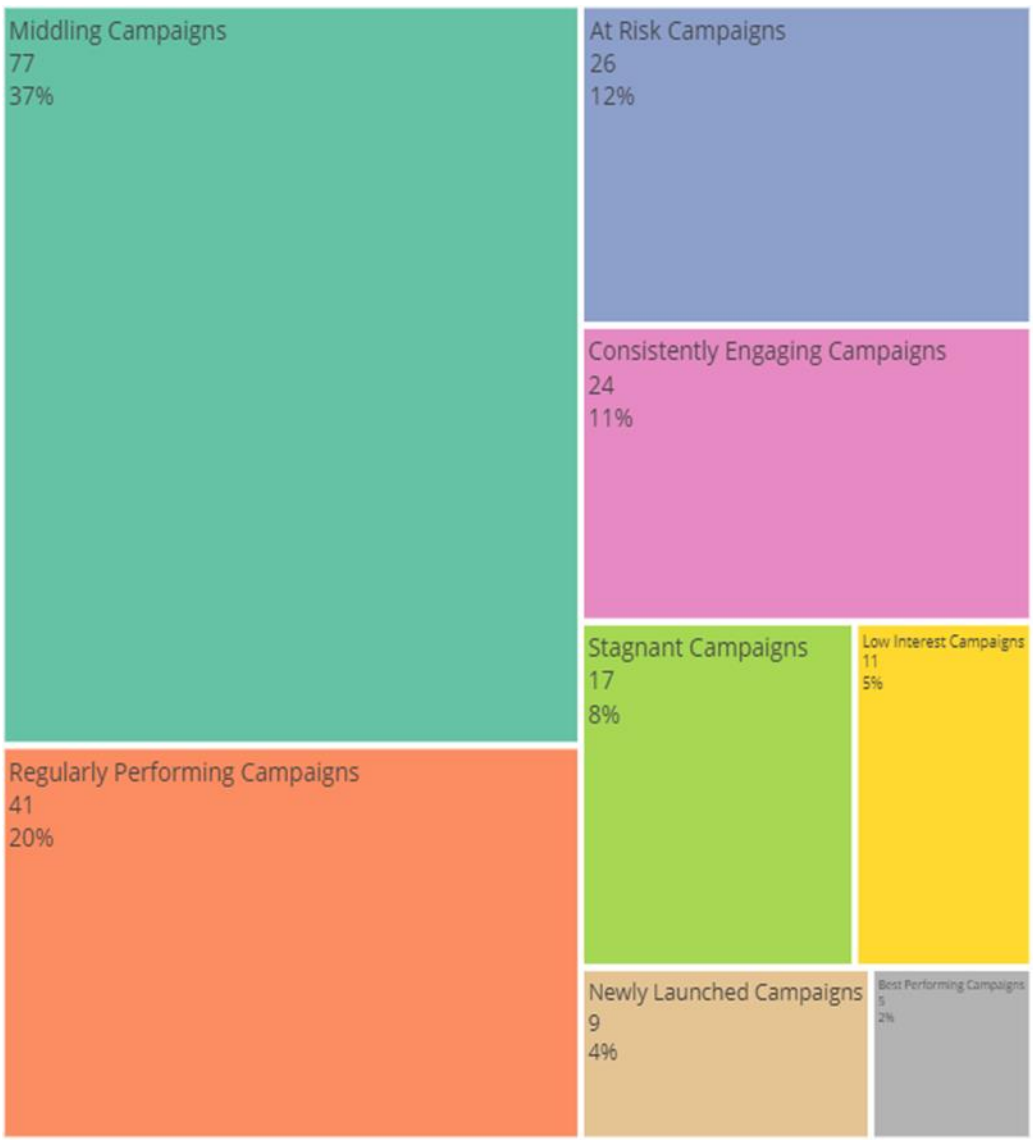


Figure 19. Treemap of RFM Analysis for Campaigns Redeemed

High-Value Campaigns:

Promising campaigns primarily centered around specific sport teams, which is understandable given their prevalence in the dataset. It is evident that users who support particular teams, such as their local home team, are more inclined to patronize the Canadiana Brewhouse to utilize the coupon.

Proportionally, 'Chase the Ace' and radio contests performed exceptionally well considering the volume of coupon redemptions they generated. Additionally, notable mentions include free Kactus chips, tattle survey coupons, and kids eat free days.

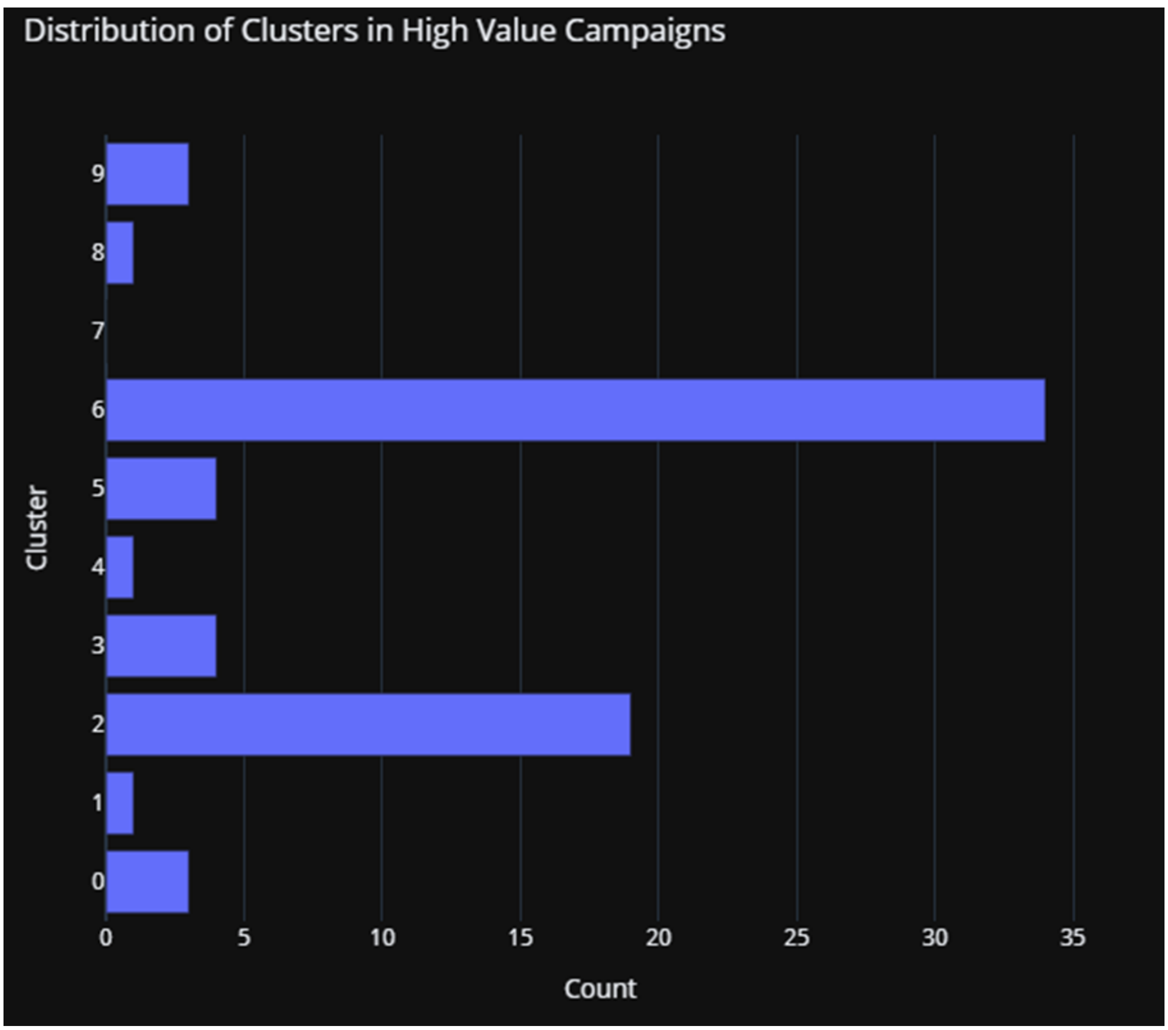


Figure 20. Distribution of Cluster in High Value Campaigns

Low-Value Campaigns:

We observe that certain sport team campaigns underperformed. This is likely attributable to the inherent variability associated with campaigns targeting sport teams. Moreover, many of the sport teams for which Canadian Brewhouse promotes are local and relatively small. If a smaller team is unaware of a specific promotion or if the team's size is too modest, the campaign turnout is likely to be disappointing.

Some other clusters that did not perform as anticipated were the NYE 2022 promos and rec league campaigns. Despite neither being classified as low-value campaigns, rec leagues failed to produce a single high-value campaign. Similarly, NYE 2022 promos, while abundant in quantity, yielded few high-value campaigns.

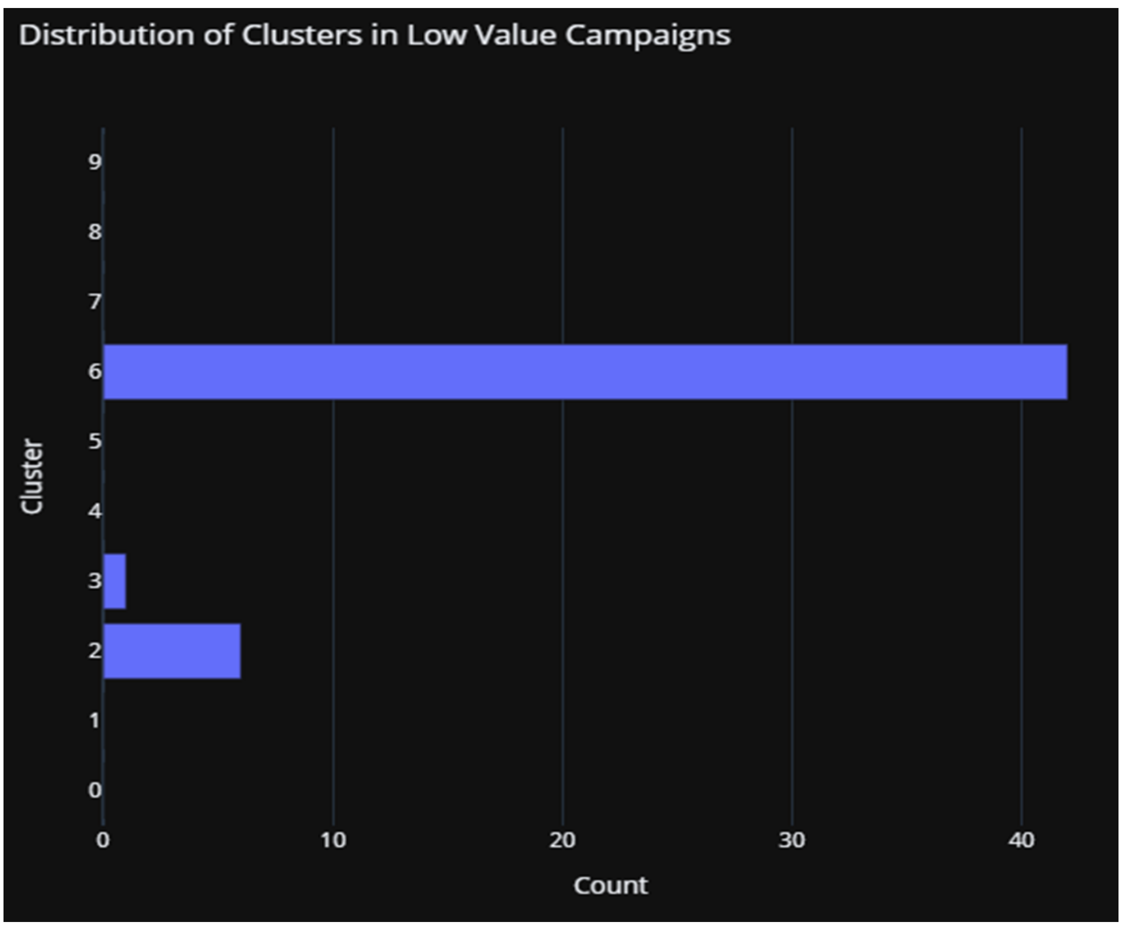


Figure 21. Distribution of Cluster in Low Value Campaigns

Campaign Recommendations:

We recommend further investment in successful campaigns, particularly those involving sport teams, radio contests, and free food promotions. Conversely, campaigns targeted at rec leagues should be scaled back, though not eliminated entirely. Adjustments to coupon distribution strategies may enhance campaign effectiveness.

Another notable concern is the discrepancy between the 9,110 entries in the coupon redemption dataset over four and a half years and the over 500,000 actual redemptions. This suggests inaccuracies in data collection, possibly due to campaigns being redeemed without system input due to the process in collecting this information. Addressing this issue is crucial to ensure accurate data collection in the future.

Final Recommendations:

- Opportunities to market towards different age demographics: As pointed out in earlier, the main demographic of users within the app is between the ages of 20 and 40, trying to find ways to expand to the older and slightly younger age groups would allow Canadian Brewhouse to be a place that is appealing for all age groups
- Create a new rating system to gain further insights to growth: the current rating system only allows for one rating for the overall experience, but expanding that system to allow for something like 3 rating would be beneficial for know areas that need to be improved. An example of these 3 categories can be food quality, service, and entertainment.
- Refocus on personalize promotions: We propose increasing efforts toward specific customer segments. By identifying groups of users likely to appreciate particular food or beverage products, the application would notify them and offer discounts or

recommendations. This strategy aims to incentivize increased coupon usage among users, thereby enhancing overall app engagement rates.

- Investigate ways to increase redemptions: finding ways to allow more customers to be aware of current promotions through things like push notifications and emails to try and get customers thinking about Canadian Brewhouse.

Citations:

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Canakci, Gurkan. (2022) *Customer segmentation with RFM analysis using Python*, *Medium*. Available at: https://medium.com/@gurkanc/customer-segmentation-with-rfm-analysis-using-python-8ba043252d33