Profiling Customers Using Their Credit Card Spending

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Abstract

The banking industry is very competitive, and to improve their top lines, the bank wants to improve the services offered to their customers. Therefore, the bank spends a lot of time understanding the customer's profile and developing relevant propositions and offers for each customer segment. Given the richness of credit card transactional data, the authors propose how the bank can apply data analytics to profile the customers and understand their spending patterns. In this paper, the authors use RFM analysis to profile the bank customers into various segments, identify the most valuable customers segment, and understand their characteristics and purchasing patterns to promote relevant marketing strategies to increase bank revenue.

Keywords
Segmentation, customer profile, RFM analysis, and credit card transaction

1. Introduction
The financial sector is the backbone of Singapore's economy. In 2021, the finance and insurance sectors contributed 14.6% of GDP. According to government data, it is the third significant contributor and has created 190'000 employment. More than 9400 new jobs in the financial sector were made, according to a report from the Monetary Authority of Singapore (MAS). The industry grew by an annual average of 7.2 percent in 2020-21. 80% of the people in Singapore own one or more bank accounts and hold multiple credit cards. Banks also provide short-term loans like personal loans that the customer can repay in 6 months to 5 years and long-term loans like mortgages from 20-35 years. For business or corporate, banks also provide other services such as letters of guarantee, letters of credit, or investment opportunities for investors. Banks also offer remittance services or transfers between two parties in the same country or around the globe using the SWIFT network.

As technology advances, consumers today use mobile banking more than others. They also use different payment methods like Apple Pay or Android Pay, or mobile wallets as a form of payment. As a result, finTech companies have been soaring in recent years. They provide financial inclusion, especially in less developed countries where there are physical barriers or enormous investment costs to go to the remote area of the country. In those cases, mobile banking has become more critical. Due to COVID-19, the number of people using internet banking or mobile banking has increased exponentially over the past two years. As of 2020, as many as 1.9 billion individuals worldwide actively used online banking services. This number is forecast to reach 2.5 billion by 2024.

Banks today are more complex in terms of operations. Driven by the increasingly competitive landscape, banks are the early adaptors of new technologies. As a result, some banks have put data analytics to work by utilizing relational databases, call-center logs, social media data, distributed processing, and harnessing unstructured data. For instance, banks are using vast amounts of data, including social media, call-center logs, customer feedback, and emails, along with in-house transactional/traditional databases and publicly available economic statistics from various government agencies such as import-export volume, unemployment rate, and job data to gain insights into current and emerging consumer trends.

About 95% of data generated every day worldwide is unstructured and captures large volumes of information. Effective use of this information can help better explain the past, understand the present and predict the future. Language, expressions, and communication mechanisms are constantly evolving. In addition, due to technological advancement, banks can now store a vast amount of these data on the cloud at a relatively low cost. However, getting meaningful insights from unstructured text is a challenging task.

Data analytics promises to improve the fraud detection capabilities of banks by allowing them to aggregate and analyze all the available information about a customer from different divisions. For example, banks can check customers' accounts holdings, mortgages, and wealth management and fuse this with social media data to gauge the propensity to fraud. We can also use data analytics to identify the most valuable customers in the bank through various customer life cycles and how we could improve customer satisfaction with the bank.

For instance, the bank has only a vague idea of who is a good client (whom to offer additional services) and a bad client (whom to observe to minimize the bank losses). Fortunately, the bank stores data about their clients, the accounts (transactions within several months), the loans already granted, and the credit cards issued. Thus, the bank hopes to improve its understanding of customers and seek specific actions to improve services. A mere application of a discovery tool will not be convincing for them. The bank would like to understand the profiles of segments and develop relevant propositions and offers for each customer segment.

We have masked sensitive information such as customers' IDs and only reported the finding as generalized information. However, this paper describes all the steps and methods in detail. They will benefit others keen to start on an analytics journey in the financial sector to understand customers' profiles and gain a competitive advantage over its competitors. In section 2, we will do a literature review of the industry and topics related to customer profiling and k-means clusters. Section 3 will focus on data analysis, and we use RFM analysis to understand the customers and share the insights. Finally, we indicate the limitation of the model, challenges that we face, and future direction for the research.

2. Literature Review

Ko et al. (2005) used the classification method to profile the customers utilizing the electricity load demand accurately. The load demand is the most critical input to analyzing the customer information and understanding their usage pattern. Using the classification method, the characteristics of each customer group are discussed as well as their demand. Peng (2011) used the clustering method to segment the customers for a commercial bank using the customer's current value and the increment value. The customer's current value is the profit the customers generate for the bank based on their consumption power of the banking products and services. The results obtained can help the bank managers effectively use the limited marketing resources to target high-value customers.

Gu (2010) focused on implementing reward programs to current customers of commercial banks and studying the impact of these programs between two groups of customers, who redeemed the rewards and those who didn't redeem. The results show that reward programs can attract more valuable customers, and the bank should recruit more clients to these rewards programs.

In another paper, Daoud et al. (2015) used RFM (recency, frequency, and monetary) model and clustering method to evaluate the customers' values in e-commerce. K-means clustering method has been applied to segment 730 customers into eight clusters using RFM as the segment variables. The characteristics of each group are compared. The result showed that the most important clusters, that are profitable to the company are those clusters where RFM values are higher than the overall average value. RFM model is also used by Wei et al. (2016) to analyse the customers' values at a veterinary hospital in Taiwan, to maintain a good relationship with their customers. A combination of self-organizing maps and the k-means method is used for the cluster analysis and recency,

frequency, and monetary are the three inputs for the clusters. The hospital can use the result to identify customers with high recency and provide effective marketing campaigns to meet the customer needs and effectively improve customer relationship management.

Yoseph and Heikkila (2018) have explored using RFM score with the customer lifetime value model to gain insight into customers for a medium-sized clothing and fashion retailer in Kuwait. First, a modified regression algorithm is used to analyse the customers purchasing patterns based on point-of-sale data. Then, k means clustering is used to segment the customers and suggest profitable customers group for the company to focus on appropriate marketing strategies.
Similarly, Rahim et al. (2021) applied RFM model and data modeling techniques, such as multi-layer perceptron (MLP), support vector machine (SVM), and decision tree classification (DTC), to predict the customers repurchasing behavior in retail with high accuracy.

Lastly, customer analysis and the RFM model are widely used to understand the customers' characteristics better and gain insight into their purchasing behavior. Kessara & Chongwatpol (2022) integrated RFM and cluster analysis to improve the marketing decision to determine the future customers' lifetime value (CLV) and those who are likely to return. The model has been applied to the healthcare industry to demonstrate the practicality and validity of the proposed methods.

The literature review identified that RFM and clustering analysis are commonly used in the healthcare, financial sectors, and retail. The contribution of our paper is two folds. Firstly, we intend to use the credit card transaction to identify the RFM value of the customers based on their past purchasing patterns. Secondly, we use the RFM score, to identify three customer segments that are more valuable to the bank to spend their marketing resources to promote their products and services to improve the bank revenue. In the following section, we will discuss the data and the business problem and model development in detail.

3. Business Problem and Data Understanding

As consumption preferences of Singaporeans change, credit cards are playing an increasingly crucial role in consumers' routine payments. Nearly three-quarters of Singaporean hold a credit card, and in fact, most people hold multiple credit cards in Singapore; there are 1.62 credit cards per capita. These years, from a statistic report, 73% of Singaporeans own at least one credit card, and 10% have six or more credit cards. P&S Market Research identified the Singapore cards and payments market as one of the most competitive and attractive markets in Asia. It can be seen that the credit card market in Singapore has great potential. Thus, it is important for the bank to consider ways to retain and obtain new credit card users is very important for the future business development of the bank.

While the amount of credit card spending has increased, the homogenization competition between banks is becoming more and more intense. According to the Singapore credit card satisfaction study released by JD Power in 2019, Singaporeans are most likely to value rewards programs, cash back, and other discounts, and well over half (64%) of credit cardholders have used discounts or special privileges offered by issuers' strategic partners.

Therefore, in this paper, the authors are going to focus on customer profiling to identify the most valuable customers and formulate appropriate strategies for these customers to improve the customers' spending based on credit card consumption and customer loyalty. These strategies mainly include – (i) determining which types of customers with demographic characteristics the bank should target on through RFM, (ii) analyzing the valuable customer groups, and recommending actions for the bank.

Due to confidentiality issues in providing actual customer data, the bank has applied various techniques to desensitize the data provided so that it is not attributable to an identified individual customer. Due to PDPA, personally identifiable data points are removed. Transaction values have also been altered in a non-significant way as an additional data protection control. The bank has shared with us three months of credit cards from the past. The customer database includes the customer demographic information such as customer ID, age bands in the interval of 10 years, gender, postal districts code of the residential address, credit card limit to the nearest 10,000, card revolver type, and card type (core card, platinum card, co-brand card). The bank earns most of its credit card revenues from the revolvers, and those are customers who only pay the minimum sum and pay a high-interest rate to the bank. The card revolver types

are new customer, transactor, occasional revolver, middle revolver, hard revolver, and inactive customer. Transactors are credit card users who make the full balance each month and so they don't incur any interest charges. Revolvers are credit card users who occasionally or regularly pay off only part of their monthly balance or just pay the minimum amount, and they will incur interest charges. In order to earn more revenue from the high-interest charge, banks do want to identify customers who are revolvers, and the profile of these customers will help the bank to run an appropriate marketing campaign to attract them.

There is another dataset that contains millions of credit card transactions. Customer ID will be used as a key to retrieve the relevant date and time of the transaction, merchant name, merchant category (e.g., hotel, airline, service), and transaction amount. In a Credit Card business, multiple stakeholders might ask the analytics team questions to help them improve the card's business performance. We are encouraged to look beyond the data, and get any external data if required. Some of the external data are from the working partners such as retailers, telecommunications and insurance companies, and even airlines. These external data, together with the credit card transactions, can help the bank to gain insights from the data and recommend any strategy to achieve the long-term goals of business sustainability and customer loyalty. We have outlined the descriptive analytics and advanced analytics questions where the bank is interested.

Exploratory analysis
Analyze the card spending by age group
Analyze the card spending by weekdays or weekend
What is the average spending per age group?
Is there any difference between the customers spending between various age groups?

Advanced analytics
Is there any correlation between the customers' spending and other input variables?
Which are the most important predictors if we want to predict customer spending?
What are the basic customer segments based on frequency, recency, and monetary RFM model?
Identify various customer segments and understand their purchasing patter so that the bank can offer the right product to the right customer at the right time.
Produce a profile analysis of the highest spending customers – showing differences in demographics, card holdings, or spend categories from the norm of the base.
Show how spending amount and category types vary as people progress through different life stages.

Customer segment

Characteristics of each customer segment

What are the spending patterns of this segment of customers?
How do the Affinities differ from the whole customer base or with other segments?
What other merchant categories would you promote to try and stimulate further spending?
What is the recommendation if you try to stimulate further spending?
How could you up-sell or cross-sell for the customer segments?
What types of merchants would we need to work closely with for such a proposition to be attractive?

4. Models development
We explored the data and presented some statistics for the customer demographics. We use all the customer demographic information, and table 1 and figure 1 represents the overview of customers. We also combined all the transactions amount during the time period and computed the total amount spent by each customer. Table 2 shows the descriptive statistics of the total transaction amount. The average amount spent is $2231.9, and the mode is 55, while the standard deviation is 21247 indicating there is a large variation in the amount spent. The ratio of standard deviation to the mean (Coefficient of variation – CV) $CV = \frac{\sigma}{\mu} * 100\% = 952\%$ is computed, which shows very high variability and greater dispersion in the data. We also plot the histogram of the amount spent in table 3 and figure2. From the

histogram, we can also see that 70% of the customers spent less than 2000, and only 10% of the customers spent more than $5000 on the credit card within the time horizon of 3 months.

Table 1. Summary of customer information

|	
Age Band	Over 82% of the customers fall into the categories between 30 to 59 years old.
Credit limit	Over 90% of the customers have the first two categories of credit limit, which are within 10k – 20k.
Postal district	Mapped the customers into the official five regions mapping for Singapore, namely North, North-East, East, Central, and West of Singapore. Over 76% of the customers stayed in the sub-urban areas such as North, East, West, and North-East.
Gender	There is a fair distribution of customers among Male (51%) and Females (49%).
Card Type	49% is co-brand card, 47% are core card, and the remaining (4%) is a platinum card
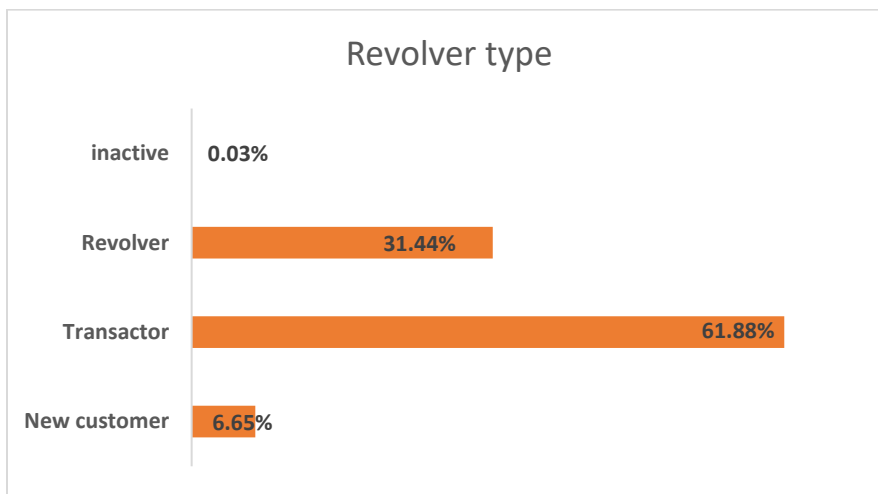
Figure 1. Summary of Revolver type

Table 2. Transaction amount statistics

transaction amount statistics	
Mean	$ 2231.9
Standard Deviation	$ 21247.7
Median	$888.0
Mode	$55.6

Table 3. Histogram of the transaction amount

bin	RF%	Cumulative RF %
100	10%	10.14%
500	25%	35.29%
1000	18%	53.12%
1500	11%	64.14%
2000	8%	71.78%

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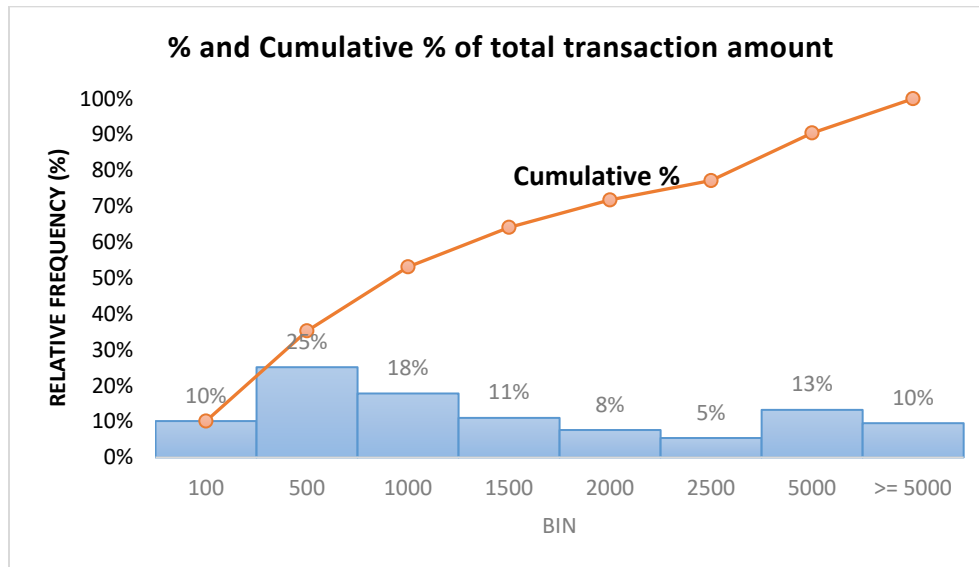|		
2500	5%	77.19%
5000	13%	90.45%
>= 5000	10%	100.00%

Figure 2. Total transaction amount histogram

Recency, Frequency, and Monetary (RFM) Analysis

RFM means segmenting the customer based on recency (how recent the customer last purchased an item or used the card), frequency (how often do they purchase or use the card within the time frame), and monetary (how much the customers purchase). We can use the credit card transaction data; three variables – Recency, Frequency, and Monetary (RFM) are derived for each customer ID. Every customer is given an RFM score. Recency is denoted as the last transaction date, and the most recent data, the higher the recency score. In this analysis, we have computed the recency score as the number of day difference from the last transaction in the data set. Recency is defined as the number of days difference from the last transaction date in the dataset. Recency = maximum date of the transaction in the data – record transaction date. Day 0 means that the customer has bought something most recently; it will be assigned a recency score of 3 in RFM analysis. Since we have three months' worth of data, the maximum day is 91. We will assign a high recency score to a small day difference. We can change the model very easily if we are using the real-time data from the day difference from today's date. For frequency, we consolidate the total number of transactions during the time horizon of three months. The higher frequency score means that the customers used the credit card multiple times. For the monetary value, it is the accumulated total transaction amount that each customer spent within the time period and the higher the total amount, the higher the monetary score. We have developed the RFM analysis model to scratch in Python and run the analysis.

Table 4. Summary statistics of Recency (R), Frequency (F), and Monetary (M) value

	Recency	Frequency	Monetary	
Mean	73.95	16.56	$	2,231.91
Median	85.00	10.00	$	887.99
Mode	91.00	1.00	$	55.55
Standard Deviation	22.81	21.94	$	21,247.70
Range	91.00	1349.00	$	2,594,884.16
Minimum	0.00	1.00	$	0.67
Maximum	91.00	1350.00	$	2,594,884.83

During the data preparation stage, we have also removed the outliers from the data as one the customer has charged $0.01, and the total number of frequency is about 132,000. After data preparation, we run some statists and found that the average number of days from the last transaction date is 74 days, with a standard deviation of 22 days. The average number of times the customers use the credit card is 16 times, with a standard deviation of 21 times. There are less than 1% of the customers who have used the credit card more than 200 times in three months time period. The expected total monetary value per customer is $2231. The maximum monetary value is $2.5 million, and the minimum value is $0.67.
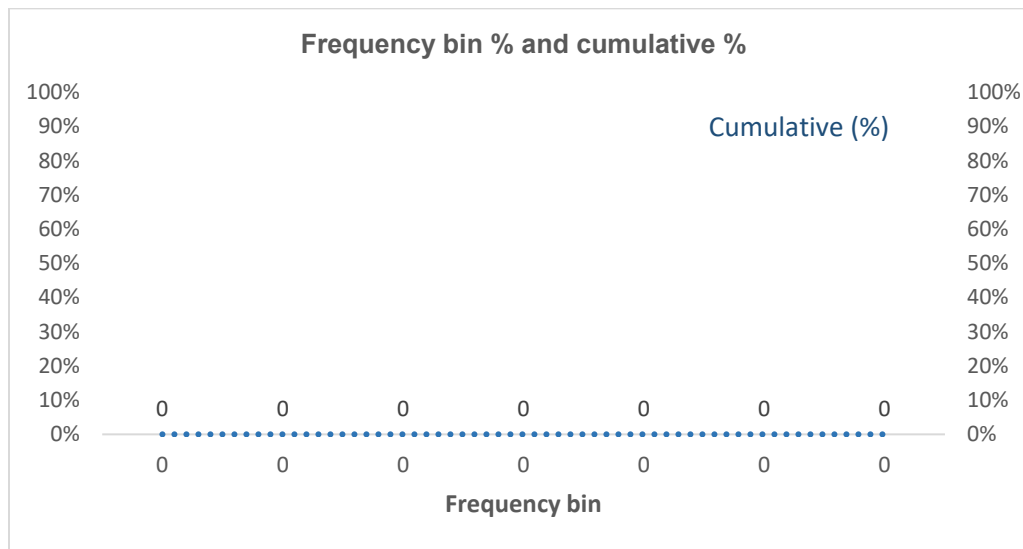

Figure 3. Total frequency histogram

We have used three bins (1, 2, 3) for each R, F, and M, and a total of 3 x 3 x 3 = 27 bins or RFM scores have been generated, namely (111, 112, …, 333). We have used the independent binning method, and it provides unambiguous results and allows the bank to understand their customers by the three aspects. Based on the raw data, the model will assign a mapping score to each customer with recency score (1, 2, 3), frequency score (1, 2, 3), and monetary score (1, 2, 3) independently. After running the RFM model, the customer is mapped into the RFM score; then, we can create the RFM table with the total number of numbers in each RFM segment.

Table 5 shows the RFM clusters, and cluster size (%), which indicates the percentage of customers who has the RFM score and their respective revenue contribution. Even though in RFM analysis, recency and frequency are more important than monetary value, bank managers are still driven by revenue targets. Thus, they want to focus on the customer group, which contributed to high revenue. A total of 27 bins will provide the bank with actionable results to create specific and targeted marketing strategies for each RFM group.

Table 5. RMF clusters, cluster size, and revenue contribution

RMF	Cluster size%	Revenue Contribution %	Average spending ($)	
311	16.1%	1.06%	$	147
133	15.7%	46.17%	$	6,577
222	8.2%	3.26%	$	893
233	6.6%	17.21%	$	5,830
132	6.3%	3.08%	$	1,098

322	5.1%	2.03%	$	885
211	5.1%	0.37%	$	164
122	5.0%	2.09%	$	925
221	4.2%	0.55%	$	287
232	3.7%	1.80%	$	1,080
223	3.6%	6.41%	$	3,977
312	3.4%	1.22%	$	798
321	2.9%	0.36%	$	277
121	2.5%	0.32%	$	290
123	2.3%	3.85%	$	3,786
323	2.0%	3.71%	$	4,117

We have selected the top 12 RFM clusters based on the cluster size, which contributed to 90% of the customers and 90% of the total revenue listed above. We can see that for RFM 311, even though the cluster size is the highest at 16.1% but the revenue contribution by this group is merely 1%. Thus the bank shouldn't spend too much marketing budget to attract this group. However, the second RFM group (133) with high frequency and monetary score contributed 46% of the total revenue of the bank. Thus, we will recommend the bank spend substantial market efforts to lure the customers into encouraging them to use the card again. They can do this by sending relevant promotional messages via the bank's mobile apps to allow customers to easily redeem and use the card. Next, we can look at RFM 233, who are more recent card users to promote reward programs such that if they reach a certain spending limit, e.g., $5000 this month, then they will get an additional 1% cash rebate on their reward program. We further analyzed the expected revenue of each customer. The different revenue amounts the customers are expected to generate will guide the bank in considering how to approach each group (e.g., Increase customer base, increase stickiness to the bank or capture high-value transactions).

From a transaction revenue perspective, we recommend the bank to focus on the 133, 233, and 223 groups – namely 'Long lost high-value customers,' 'Good Value Customers,' and 'High Rollers'. To identify ways to make our product more attractive to these groups, we examine the different demographics, merchant categories they spend on, and some of the popular merchant names. The first group with an RFM score (113) called – 'Long lost high-value customers' have average spending of $6577, which is the highest spending group with the highest frequency score. This group spent three times more than the average spending of the general population (~$2231). This is one of the most valuable customers group which the bank can't ignore. The second group will be the RFM score (233), and we named it 'Good Value Customers'. 'Good Value Customers' group has average spending of $5830, and it is about 2.6 times of the population average. They have also recently spent the card as compared to the first group, which is good for the business as the bank can earn more revenue from existing customers than for a new customer as the acquiring cost is much higher than the maintenance cost. Lastly, the third group has an RFM score of (223) - 'High Rollers' have a significantly higher average spending of (~$3977) as compared to the average spending of the general population (~$2231). We can also look at other demographics such as revolver type and credit limit for this group to better understand their profiles and make a recommendation for the actionable insights for the bank to take necessary action.

In table 6, we will outline some recommended action for the bank for the customer segments and summarizes the marketing strategy to employ for the different RFM groups of customers to enable more effective marketing to boost revenue.

Table 6. RFM Analysis and Proposed Plans

RFM group	Segment	Marketing strategy to boost revenue through adoption of new product
133	Long lost high-value customers	• Good group to test out new products

		• Increase the marketing costs to lure the customers into using the bank card • Make them feel special and love
233	Good Value Customers	• Work with merchant categories of mid to high transaction amounts such as beauty services, health care, air tickets, department stores • Create programs e.g., cashback promos for spending above $5,000 to boost customer numbers and provide 6 monthly installments plan to attract the customers to use the card for big volume purchased
223	High Rollers	• Work with merchant categories that have single large value transactions, e.g., insurance, hospital bills, travel agencies • Increase their frequency of spending
xx1	Low-value customers	• Create promotions with merchants to increase the frequency of usage/transaction • Create stickiness • Don't need to spend so much marketing budget on this group
xx2	Average spenders	• Occasionally send them promotions and maintain a good relationship with customers.

As there was no significant difference in the Gender and Age band factors across the RFM groups, the bank should not use these factors to distinguish the product offerings. The bank can also use RFM analysis to identify customers who are about to churn (where recency and frequency score is relatively low) and work with the marketing department to win the customer back if they are valued customers.

The limitation of the RFM analysis is it is backward-looking, and we need the customers to have at least one transaction with the bank so that an RFM score can be generated. For the new customers, who just joined the bank and haven't used the card yet, then we can't generate the RFM score. But we can look at some external data from our partners, such as telecommunication companies, to understand the customer's credit profile and use it as a proxy for a credit limit. The recency factor is not a differentiating factor due to the short time frame, which may not be comprehensive enough for the bank to understand the associations that result in the cardholders' behavior.

We have also combined the customer demographic for these three groups of customers and will explain their distinctive characteristics. Of the "Long lost high-value customers," 66% are transactors, 31% revolver, and only 3% are new customers. 85% of the customers have a credit limit lower than 20,000, and 56% are within the age band of 40 – 59 years old. This group of people should have higher annual income and spending power. Thus, the bank can review their credit limit and increase their spending power to encourage them to spend. Next, the "Good Value Customers" group comprises 61% transactors and 35% revolvers. The bank will earn many interest charges from this group of customers and thus need to spend resources to maintain a good customer relationship with this group. 80% of them are within 30 – 59, with only 10% between 20 - 29 and 10% above 60 years old. Finally, for the "High Roller," 40% of them are revolvers, the highest among the three groups and 10% higher than the average revolver of 31% of the population. 90% of the customers have a credit limit lower than 20,000. The bank can also focus on this group by increasing their credit limits, giving them installment plans without processing charges for huge purchase items, or high rewards points if they exceed a specific limit. By doing all these actions, the bank can encourage their customers to spend more, make them feel special, and increase their revenue.

 Overall Strategies - The pandemic has reshaped the retail sectors and accelerated the shift towards a more digital world, and triggered changes in online shopping behaviors. The analysis has been performed comprehensively with various analytics methodologies to provide a complete picture of customer profiles, spending patterns, and some hidden insights.

5. Conclusion

To boost the merchant offering and ecosystem to attract the 'Long lost high-value customer", 'Good value customer,' and 'High Roller,' the bank needs to increase the recency and the frequency of their transactions. We can also include the customer's demographics information and run cluster analysis with RFM score, which will be the direction for our future research; we can further explore using association analysis or Market Basket Analysis (MBA) to explore the merchant categories and merchants that the bank can consider working with.

We will recommend the following to the bank:

A Generic Cash Back / Rewards Card, targeted at the certain customer segments mentioned above specifically to encourage them to spend larger amounts more frequently.

Merchant Ecosystem: A seamless multi-brand, multi-category card promotion and rebate ecosystem integrated with the bank credit card. The merchant ecosystem is specifically catered to our target customer group, including partnerships with preferred merchant categories and merchants. Sign up perks to drive spending on the merchants in the merchant ecosystem and develop a stickiness towards these merchants. Promotional campaigns to encourage spending within the merchant ecosystem to drive up wallet-share, improve merchant loyalty and increase card utilization. The bank could look into acquiring more similar merchants to the currently identified merchants in the prime merchant categories, adjusting the merchant mix to keep up with changing and current spending trends, and work closely with these new and existing merchants for product and deal promotions for our target group. In light of the current COVID-19 situation, the bank can account for the geographical sensitivity, which was evident in our insight of transactions being highly location-dependent, predominantly within the residential regions where the cardholders live. There could be an introduction of a "Buy Local" Campaign where the users of the bank can benefit from better rewards and higher cashback by spending at merchants within their residential regions.

Marketing Efforts: Targeted location-specific marketing campaigns, targeted advertisements on social media platforms, and online marketing campaigns leveraging on the recent e-commerce boom. Targeted at existing and new customer profiles that fit our targeted profiles.

To further increase revenue from the larger pool of revolvers, the bank can focus on high spenders or occasional revolvers, or both. Increasing transaction volume and value from this group will have a significant impact on generating higher revenue for the bank. Through the profiling of these customers, the authors recommended that curating promotional/ marketing campaigns based on the identified profiles can help improve customer experience and, in turn, drive sales and revenue for the bank.

Acknowledgments

References

F. Yoseph and M. Heikkila, "Segmenting Retail Customers with an Enhanced RFM and a Hybrid Regression/Clustering Method," in *2018 International Conference on Machine Learning and Data Engineering (iCMLDE)*, Sydney, Australia, pp. 108-116, 2018.

J. Ko, I. Yu, J. Lee and S. Kim, "A Method for Classification of Electricity Demands Using Load Profile Data," in *Proceedings. Fourth Annual ACIS International Conference on Computer and Information Science*, Jeju Island, South Korea, pp. 164-168, 2005.

J. Wei, S. Lin, Y. Yang and H. Wu, "Applying Data Mining and RFM Model to Analyze Customers' Values of a Veterinary Hospital," in *2016 International Symposium on Computer, Consumer and Control (IS3C)*, Xi'an, China, pp. 481-484, 2016.

Kanchanapoom, Kessara, and Jongsawas Chongwatpol. 2022. "Integrated Customer Lifetime Value (CLV) and Customer Migration Model to Improve Customer Segmentation." *Journal of Marketing Analytics*, March, 1–14.

RAHIM, M. A. *et al.* RFM-based repurchase behavior for customer classification and segmentation. Journal of Retailing & Consumer Services, *[s. l.]*, v. 61, p. N.PAG, 2021.

R. Ait Daoud, A. Amine, B. Bouikhalene and R. Lbibb, "Combining RFM model and clustering techniques for customer value analysis of a company selling online," in *2015 IEEE/ACS 12th International Conference of Computer Systems and Applications (AICCSA)*, Marrakech, Morocco, 2015 pp. 1-6, 2015.

Y. Gu, "The Impact of Reward Programs on Customer Behavior of Commercial Bank," in *2010 Third International Symposium on Information Processing*, Qingdao, Shandong China, pp. 110-112, 2010.

Y. Peng, "Evaluation and Classification of Commercial Bank Customer Value," in *2012 Fifth International Conference on Business Intelligence and Financial Engineering*, Wuhan, Hubei China, pp. 682-686, 2011.

Biographies

Nang Laik is an Associate Professor in the School of Business, Singapore University of Social Sciences (SUSS). She has more than ten years of teaching undergraduate courses and master's courses throughout her academic career. She teaches undergraduate core modules and master-level courses in the areas related to business modeling using spreadsheets, data analytics, and logistics and supplies change operations. She holds a Ph.D. from Imperial College, London, where her research focused on operations research (OR) in the area of optimization of resources. Her research expertise lies in the simulation and modeling of large-scale real-world problems and the development of computationally efficient algorithms to enable sound and intelligent decision-making in the organization. Nang Laik is an expert in the financial sector as she has worked in the IT department in one of the largest banks in Singapore and understands the technology and the lack of efficiency in the system. She serves as a consultant for one of the best airports - Changi Airport Group, to use data and decision analytics to generate insights, make better decisions and improve business efficiency and productivity. She has also previously worked in one of the largest container ports to develop and implement a multi-million dollar decision support system.

Murphy is an experienced analytics specialist with extensive experience in risk analytics, marketing analytics, social media, and Big Data analytics. He has extensive experience in developing new techniques and models to achieve business objectives in real-world applications. He is also passionate about lifelong learning and is an active contributor to several international publications.