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B2B and Its Market Segmentation Based On RFM with Clustering Method

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ABSTRACT:- With 925 active clients extracted from data warehouse, the market segments are clarified with the support of several clustering algorithms for selection and preprocessing data. Some of these algorithms are RFM and Customer Value Matrix. Findings are quite important contribution to effective marketing and sales strategies, not only to avoid occurred spams but also to limit churn risk and maintain customer retention. Also it brings a tangible effect on operation results by allowing higher percentage opportunities for company sales revenue. Company spends less time on less profitable opportunities and more on the most successful sections to ultimately increase revenues.

Keywords: *B2B, RFM, Customer value matrix*

I. INTRODUCTION

Many scholars concern quantitative methods toward market segmentation, their findings are significant contributions not only to competitive strategy development, but also academic through predictive algorithms. To segment a market, (Safari, Safari, & Montazer, 2016) and (Doğan, Ayçin, & Bulut, 2018) used three measures of recency, frequency and monetary, so called RFM to segment the market, with a support of clustering method. To compete with competitors, firms currently pay attention much how to classify their customers into groups to manage. In fact, RFM is popular to support for market segmentation, it is also used to identify customer lifetime value (CLV), which CVL defined not different from customer loyalty, and it is a way to know how much profit that an individual customer contributes to the company. With an application of RFM, (Golmah & Mirhashemi, 2012) and (Safari et al., 2016) identified CLV.

In fact, there are many scholars to employ RFM toward market segmentations in terms of B2C, but not popular for B2B, may be a difficulty of data gathered. Unlikely, this paper is a different approach of RFM for the case of B2B, which is basic to calculate CLV. In terms of B2B, the current study concerns on a company located in Vietnam, who offers sustainable cleaning and sanitation solutions to maintain international standards of hygiene and cleanliness in food safety, and infection prevention. Its products and services have been developed with several hygiene sensitive sectors in mind: Food and Beverage Processors, Lodging and Hospitality, and Healthcare. Market of the company focuses on high-class hotels, villas and resorts, fast-service restaurant chains, gourmet restaurants and hypermarkets.

Professional cleaning products are substances into liquid, gel, powder or spray forms which used to safely and effectively remove dust, stains, germs and other contaminants on surfaces. They play an essential role in daily lives at accommodation, factories or in public areas.

The report of Asia-Pacific Industrial and Institutional Cleaning Chemicals Market Research in 2018 shown that the market value of industrial and institutional cleaning chemicals is at 13,127 million USD in 2017 and expects to reach 20,897 million USD by the end of 2024. Asia-Pacific will occupy for more market share in following years, especially in China, also fast growing India and Southeast Asia regions.

According to the report published by Institute for brand and competitiveness strategy in collaboration with Vietnam Business Monitor, the chemical industry in Vietnam consists of eight product categories: Fertilizer and Nitrogen, Detergent, Pants and Printing Ink, Synthetic Rubber and Polymer, Plant Protection Chemical, Basic Chemical, Synthetic Fibers and Other. In particular, professional cleaning products account for the bulk of detergent segment. Together with the strong growth of manufacturing chemical sector in Vietnam, professional cleaning products were not only imported from China, Thailand, Korea or Japan, but also manufactured by various local companies.

With a review on previous studies and actual situation of a company doing business of B2B in Vietnam, this study aims to investigate customer behavior toward a market segmentation and address CLV.
To do this, the paper employs RFM to be a basic tool to segment and measure how much benefit customers contribute to the company.

1. Related work

As known, segmentation is a concept to divide overall customers into a subset with similar characteristics based on demographic factors or actions. It also allows fleshing out data which put company in a stronger position to easily identify patterns as well as trends, gain a competitive edge and, demonstrate a deeper knowledge of your customers' demands.

With a deep understanding of how a company's best existing customers are portioned, a business focuses on market to allocate and spend efficiently its valuable human and capital resources. Customer segmentation provides other advantages which include staying ahead of rivals in particular market sections and identifying fresh items that current and targeted customer might be keen on or improve products to fulfill many expectations of customer.

In addition to the fact that companies strive to detect similarities and differences among customers into quantifiable segments as indicated by their demands, behaviors or demographics yet they also aim to determine the expected profit of each segment by analyzing its revenue they generate and cost of relationship maintenance. It also supports a company firmly propose better options and opportunities to customers who became the significant part of customer-company engagement and decide which segments are the most and least profitable to adjust their marketing budgets accordingly.

As known, RFM is a good tool to measure customer behavior, it seems as an incredible and perceived technique to evaluate the customers' commitment to business units and differentiates important customers from large data by three attributes of recency, frequency and monetary. Based on customers' purchasing history, RFM is quite supported to address customers' classification and ranking.

According to (Cheng & Chen, 2009), the detail definitions of Recency, Frequency and Monetary method are described as the following: *(i) Recency (R)* is defined as an interval between the time when the latest purchasing order presents and happens such as one week, one month or one quarter. A lower recency value means that customers frequently visit to company. Likewise, the higher value implies that in the near future, customer sometimes or rarely visits the company; *(ii) Frequency (F)* is shown as the number of purchasing transactions made in a given period of time by customer, for example, one time per year, two times per quarter or three times per month. The higher frequency value, the more loyal customers regarding company; *(iii) Monetary (M)* is identified as total money amount that customers spent during one specified time. So, the much more money amount of consumption, the more earnings customers bring to the company.
Accordingly, (Wu & Lin, 2005) demonstrated that the higher the value of R and F is, the more comparable customers make a new transaction with companies. In addition, the higher M value is, the more comparable customers purchase products or services of companies in several times.

All customers are analyzed by recency, frequency, and monetary scores which take place in the scale from 1 to 5 as a quintile based on its original records, in which1 being unlikely and 5 being likely. Scores of combination of RFM are assumed to get remarkable attributes as shown in table 1. Once all R, F and M are the most recent, the most frequent, and the highest spend, respectively, the score of customers belong to this group is called "champions" with the highest score of 5. Conversely, once indicators of R, F, M are the least recent, only one transaction, and the lowest spent, respectively, customers belong to this group is called "lost", due to its score is the smallest score of 1.

Table 1: Recency, Frequency and Monetary Score Description

Score	Classification	Recency	Frequency	Monetary
5	Champions	Most recent	Most frequent	Highest spend
4	Promising	Much recent	Much frequent	Much spend
3	Can't-lose them	Recent	Frequent	Average spend
2	At risk	Less recent	Less frequent	Less spend
1	Lost	Least recent	Only one transaction	Lowest spend

Source: Wu & Lin, 2005

Customer Value Matrix Model

The model of Customer Value Matrix introduced by (Marcus, 1998) completely evolved from recency, frequency and monetary method, which is presented in table 2. This is a convenient table for a firm know well an interaction between two of three elements, such as between F and M; L and R. Value Matrix model is absolutely convenient for companies to easily analyze customer values in two formulas. Each of them is four quadrants combined by both the average frequency and monetary values (F and M) and both the length and recency (L and R) value for details as shown in table 2.

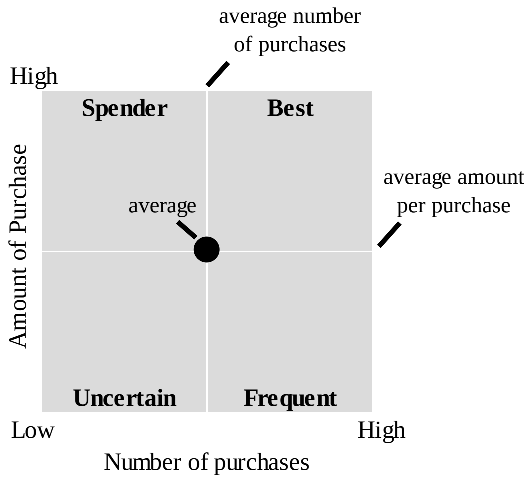
Table 2: Presentation of customer value matrix

Formula	Matrix 2 x 2 description	
Frequency (F) and Monetary (M)	F↓ M↑ (spender)	F↑ M↑ (best)
	F↓ M↓ (uncertain)	F↑ M↓ (frequent)
Length (L) and Recency (R)	L↑ R↓ (potential relationship)	L↑ R↑ (close relationship)
	L↓ R↓ (lost relationship)	L↓ R↑ (establishing relationship)

Source: (Marcus, 1998)

The second step is segmentation process after calculation of the average values of the purchase amount and amount spent on average. Each customer is allocated into one of four resulting quadrants as illustrated in figure 1, which we can see information about two parameters that need calculating for the customer value matrix.

Figure 1: Customer value matrix and its description



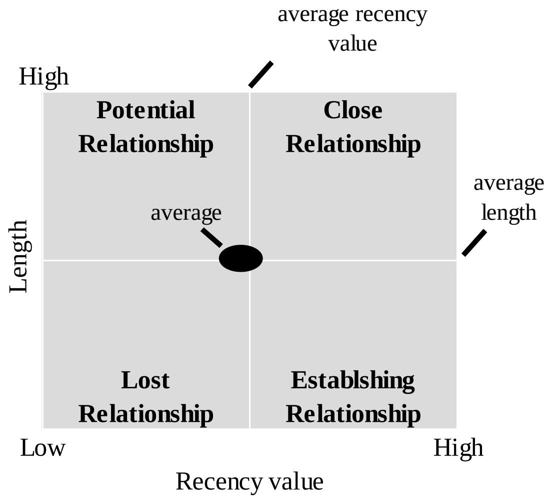
- Total amount of purchases
- Total quantity of customer
- Total sales revenue
- Average number of purchase = Total amount of purchases/ Total quantity of customers
- Average purchase amount = Total sales/ Total quantity of customers

The next step of Customer Value Matrix process is comparison of Average Number of Purchases and Average Purchase Amount with total average values in each customer. Finally, each of them is allocated into one of four quadrants with position name, such as best, spender, frequent and uncertain, which are depended on whether its parameters are higher or lower the axis averages.

Length and Recency values

In current competitive market, customers are viewed as one of the biggest priorities of company. To create loyalty and customer retention, companies needs to identify their customer relationship based on some techniques. One of them is customer relationship matrix that provides the management classification pursuant to many characteristics of four different groups between companies and their customers through two factors length and recency as depicted in figure 2. In conclusion, customer value is evaluated by customer value matrix or/and customer relationship matrix.

Figure 2: Customer value matrix and its description



Where,
- Length (length of stay) = the number of days from the first visit date to the last visit date
- Recency = the number of days since the last visit

According to (Sunder, Kumar, & Zhao, 2016), CLV is calculated in various ways by scholars. Customer lifetime value described as a fraction of cash flows using a weighted average of capital costs over the lifetime of a customer relationship with the company. To recognize and invest in potential customers, the calculation of customer lifetime value has become increasingly essential. Estimating CLV supports company in some important decisions.

Generally, there are various methodologies to calculate CLV for different organizations. Based on arguments of (Safari et al., 2016), CLV estimated is based on the algorithm of RFM. The selected characteristics pursuant on this method include latest purchase date as Recency, the number of buying frequency during period time as Frequency, and total money spent by customers over period time as Monetary.

Min-max method of normalization is used for the normalization phase. This method performs on the initial data a linear transformation. Suppose that max_A and min_A are the maximum and minimum values of an attribute, A. Then Min-max normalization maps a value, v, of A in the range of [$newmin_A$, $newmax_A$] by computing in the followings equation:

$$v' = \frac{v - min_A}{max_A - min_A}(newmax_A - newmin_A) + newmin_A$$

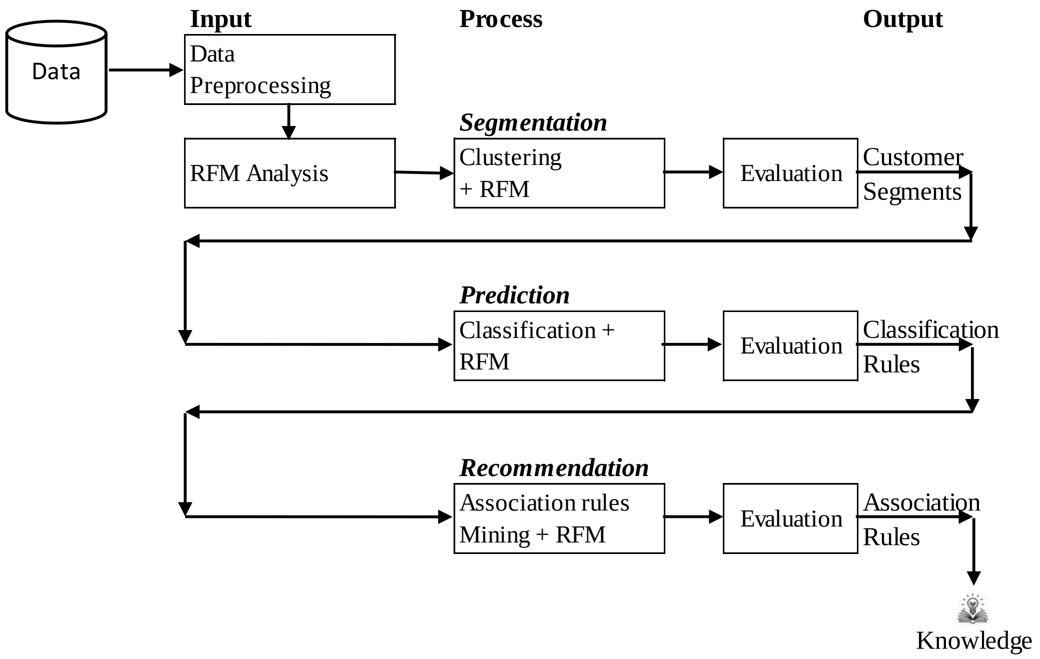
In order to calculate CLV for each cluster, and weighed RFM method is used. The average CLV value of each cluster is calculated with the followings equation:

$$CLV_{ci} = NR_{ci} \times WR_{ci} + NF_{ci} \times WF_{ci} + NM_{ci} \times WM_{ci}$$

Where,
NR_{ci} refers to normal Recency of cluster ci,
WR_{ci} is Weighted Recency,
NF_{ci} is normal Frequency,
WF_{ci} is weighted Frequency,
NM_{ci} is normal Monetary, and
WM_{cii} is weighted Monetary.

Calulating RFM is a step to address the method of cluster analysis. To do this, each element of RFM is asked to categorize in five categories, which 1 being very low, 2 being low, 3 being medium, 4 being high, and 5 being very high.

Figure 3: The diagram of proposed model



As stated previous, how the paper takes an approach to address objectives of study is presented in figure 3. Besides RFM employed, generation rule is also considered to investigate more detailed customer behavior by each segment, which the method of association analysis is taken in to account.

Long-term customer value is considered to be one of the quantitatively basic metrics belonging to the financial consequences of customer relationships with company. This value can be a suitable benchmark for evaluating the company's efficiency and its financial markets. Rather than products, it totally focuses on customers. As the accessibility of information increases at the client stage, the value of client life can play a crucial part in future marketing and corporate policy (Gupta et al., 2006).

II. DATA COLLECTION

Database of this study is gathered from data warehouse of the firm of business B2B from January 2015 to December 2018, all customers selected in the sample are active and organizational customers. Prepared data provide information that there are 7,498 rows, it means 7,498 transaction, equivalent to 845 active customers. This tells that one customer has more business transaction with the company. Based on the result of data preparation, there are 12 fields extracted from data warehouse of the company.

Table 3: Variables in sample

No.	Name of factors	Definition	Measurement
1.	Cust ID	Identification of customer in system	String
2.	Search Name	Customer's property name	String
3.	Item ID	Identification of products in system	String
4.	Item Name	Product name	string
5.	Line of business	Types of industrial sectors including (VND): 1: Lodging, 2: Quick Service Restaurant, 3: Commercial Laundry, 4: Business cleaning service, 5: Hypermarket, 6: Catering, 7: School, 8: Hospital, 9: Cinema, 10: Retailer.	Continuous
6.	Location	Location in Vietnam including:	Nominal

		HN-CM: North area DN-CM: Central area NT-CM: Southeast area HCM-CM: Southwest area PQ-CM: Phu Quoc town in Kien Giang province	
7.	Start date	Date of the first purchasing order	Date/string
8.	End date	Date of the last purchasing order	Date/string
9.	INVENTQTY	Quantity of each product delivering to each customer	Continuous
10.	USD Exw	Total Ex-work of each product delivering to each customer	Continuous
11.	USD Amt	Revenue of each product delivering to each customer	Continuous
12.	Numbers of transaction	Number of orders and direct transaction of each customers during the period of study	Continuous

III. Empirical analysis

According to the descriptive statistics, ten lines of business are domain in the sample of 925 clients, as depicted in figure 3. Accordingly, lodging product is the most popular one, accounting 43.9% of sales contribution. The second one as commercial laundry is popular for restaurant for quick service, accounting for 19.74%, while the retailer, hypermarket and business cleaning service for 14.55%, 8.51% and 7.83% respectively. The rest are commercial laundry, catering, cinema, school, and hospital are small quantity, accounting for only 3.49%, 0.68%, 0.17%, 0.85%, and 0.26%. Consequently, the shares of customers' position differ greatly from each other, especially lodging.

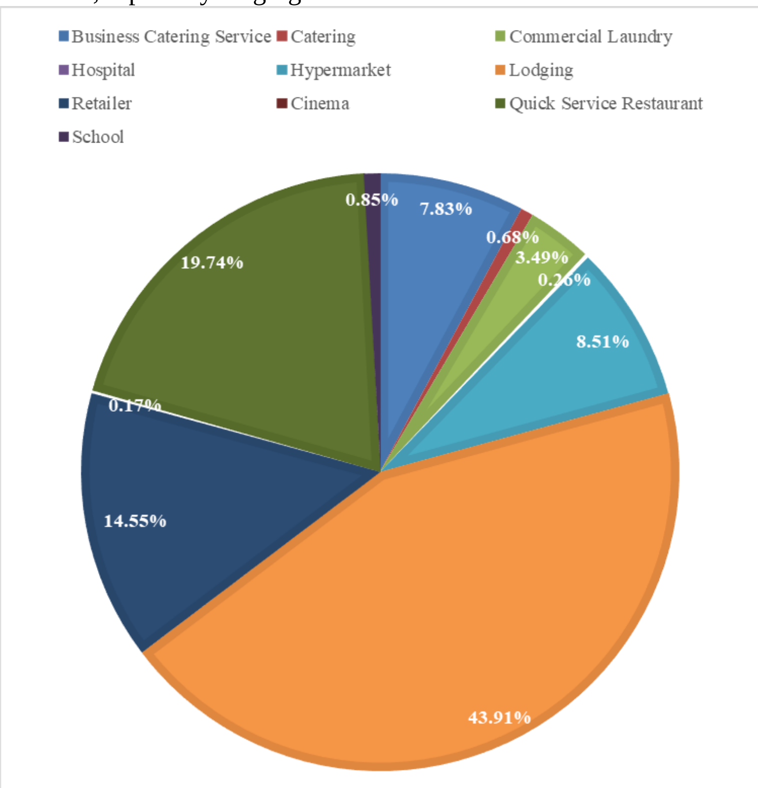


Figure 3: Sales share of product line

Source: Internal dataset

Customers of the company is mostly local customers located in five areas of Vietnam, such as North, Central, Southeast, Southwest, and Phu Quoc town. As depicted in figure 4, Southwest and North are two leading market accounting for 43% and 31%, respectively.

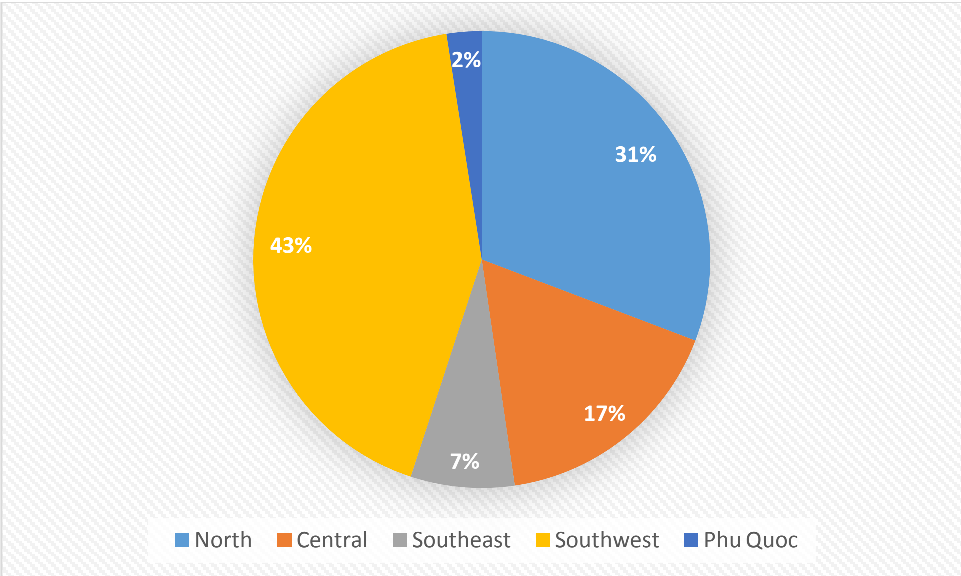


Figure 4: Share of sales by area in Vietnam
Source: Internal dataset

Based on statistic result of dataset, customers with the LOS under 12 months occupy the highest proportion with 43% (table 4), next as the LOS range from 37 to 48 months accounting for 31%, while LOS range from 13 to 24 months is 13%, the rest is of the range from 25 to 36 months. As a result, except for customer who visit only one time, the lowest and highest LOS are greater than 2 months and 48 months (equal to four years) respectively. Conclusively, it is an acceptable sample to evaluate the lifetime of customer.

Table 4: Length of stay of customer in B2B

Length of stay	Count	Percentage
From 1 to 12 months	410	43%
From 13 to 24 months	126	13%
From 25 to 36 months	128	13%
From 25 to 36 months	299	31%
Total	**963**	**100%**

In terms of combination between F and M

Based on Customer Value matrix method mentioned previously, two different clustering methods are considered for customer segmentation including combination between Frequency and Monetary values, and combination between Length and Recency values, respectively. Accordingly, with the dataset concerned, the overall Frequency and Monetary values of all customers after calculation have results as shown in Table 4.

Table 4: Results of overall variables for customer value matrix

No.	Variables	Result
1	Average number of purchase	37
2	Total Number of purchases	31,451
3	Total number of customers	845
4	Average purchase amount	14,003
5	Total sales	11,832,656
6	Total number of customers	845

After calculation for overall values, each customers in the total sample is addressed in the separated results of variables in average number of purchase and average purchase amount during their lifetime. Accordingly, customers are classified in four segments separately: best, frequency, spender or uncertain. The number and percentage of these customers who distribute into these four segments are depicted in table 5.

As resulted in table 5, the uncertain segment received the highest percentage with three fourth of the total number of customers. The best segment comes as the second highest percentage with 15%. Spender segment is followed by best segment, which is exercised by 7%. Otherwise, the smallest percentage with only 3% belongs to spender segment.

Table 5: Percentages of customers who are arranged in each segment

Segment	Customer number	Percentage
Best	128	15%
Frequency	58	7%
Spender	22	3%
Uncertain	637	75%

Best segment consists of the most valuable and profitable customers for company. The company can focus on providing additional value to customers by up-selling and cross-selling actions instead of limiting them to already-encountered products. For up-selling actions, the company may introduce customers about higher-class product ranges, such as eco-friendly range in compliance with current sustainable trend, or natural components in manufacture. Frequency segment includes the customers who frequently buy a few products and spend less money because of their low hygiene standard. They may be three-star hotels or small restaurants instead of high-class ones. The company should introduce them new products that they need but buy from another supplier to grow up their average purchase amount.

Spender segment represents valuable customers for company because they sometimes send the purchasing orders but in a high total amount or expensive products. Therefore, the company pays more attention on the direction to increase their frequency. The company's technicians visit to customer's site and check their standard using procedure and dispensers to truly understand their efficiency of products usage and consider whether the company sells more products or not. Finally, they will become the most beneficial customers of the company.

On the other side, uncertain segment contains walking customers who rarely buy products with a little amount. It is impossible for the company to treat them as normal because they easily absorb with other suppliers. The company realizes that a part of them are big customers who buy only one or two high quality products. Thus the company should builds the relationship with them by free trial products or free consultants at their site for their experiment with the company's products.

In terms of combination between L and R

Application on customer relationship matrix, the overall length and recency values of the whole customers. The result of this case is depicted in table 6.

Table 6: Results of variables for customer relationship matrix

No.	Variables	Result
1	Average length (months)	19.43
2	Total length (months)	16,426
3	Total number of customers	845
4	Average months since the last visit	11.61
5	Total number of months since the last visit	9,814
6	Total number of customers	845

With the same process with customer value matrix model, after calculation for overall values, each customers in the total sample will get the separated results of variables in average length in month and average months since the last visit. Then, using these results, the customers in the study are classified into four segments separately, such as close, establishing, potential and lost relationship. The number and percentage of these customers who distribute into four segments are shown in table 7.

Table 7: Percentage of customers by each segment in terms of L an R combination

Segment	Customer number	Percentage
Close relationship	62	7%
Establishing relationship	308	36%
Potential relationship	228	27%
Lost relationship	247	29%

The result tell that establishing relationship toward segment received the highest percentage of 36%. The segment of lost relationship exercised by 29% seems equal to potential relationship segment accounting for 27%. Otherwise, the smallest percentage with only 7% belongs to close relationship segment.

Customer relationship segments seem more easily understand for company than customer value matrix because the variables only bases on time period. The company should maintains the long-term relationship with close and potential relationship segments because of their long lifetimes. In addition, customers in establishing relationship segments may be new customers in 2017 or 2018, so the company tries to keep the fine relationship with them and tends to move them into close relationship segments. For lost relationship segment, the company can serve them well when they come and visit the company.

In terms of combination toward RFM

As stated above, RFM values are calculated for each client, the value of each component in RFM is ranked by a scale of five points, of which one is exceptionally poor and five is exceptionally high. However, R is the opposite, which one represents the time of the last purchase is far from the current study time, and five represents the time of the last purchase is the closest to the current study time. As a result, the values of each RFM element are mean values, the higher value, and the higher probability as shown in figure 5.

Label	Description	Size	Inputs		
R= LOW; F= LOW; M= LOW	Churn group	26.5%	Recency (1.35)	Frequency (1.43)	Monetary (1.54)
R= HIGH; F= HIGH; M= HIGH	Best group	34.5%	Recency (3.73)	Frequency (4.54)	Monetary (4.48)
R= HIGHT; F= LOW ;M= LOW	New group	19.5%	Recency (3.39)	Frequency (1.96)	Monetary (2.05)
R= LOW; F= HIGH; M= HIGH	Frequent group	19.8%	Recency (2.20	Frequency (3.22)	Monetary (3.34)

Figure 5: Customers segments based on RFM

Source: Analytics result on internal data

To cluster 1: it is defined as a churn group, which customers include the low recency (R=LOW), the low frequency (F=LOW), and the low monetary (M=LOW). As a result, the customers of this cluster spent not much on buying, together with a few frequencies of buying and the last buying is so farm from the present of study. This group accounts for 26.5% as figure 5, equivalent to 224 customers.

To cluster 2: it is identified as a best group, with all high recency, frequency, and monetary of customers (R=HIGH, F=HIGH, and M=HIGH). These customers gain currently the high transactions, buying more frequency with the large value amount. As a result, this best group contributes extremely valuable, thus the company should develop premium plans to keep them stay in a long-term and approach their loyalty in the future. Best group represents for the highest part of 34.5%, equivalent to 289 customers.

To cluster 3: it is shown as a new group, which customers consist of low recency (R=HIGH), low frequency (F=LOW) and low monetary (M=LOW). These customers just have a closer transaction with the company for their buying. As a result, the company should note them to attract them return and present to them some promotions, because this group accounts for 19.5% of total customers, equivalent to 165 customers.

To cluster 4, it is defined as a frequent group, which customers include low recency (R=LOW), high monetary (M=HIGH), and high frequency (F=HIGH). These customers of this group often take transactions with the company for their buying; every transaction is a large enough value amount. As a result, a company should be responsible for attracting these customers by fresh services because of their quite potential and not risk. As shown, the frequent group makes up 19.8%, equivalent to 167 customers.

Customer Lifetime Value

According to (Gupta et al., 2006), it is progressively evident that a company's value depends on its intangible resources into off-balance sheet. There are many definitions of marketing measurements recently, including marketing productivity and ideal marketing measurement. Every customer in the company has a separated value cycle. A company's purpose is to calculate and estimate a customer's lifespan by which the company can set targets on its marketing plans based on each customer.

Based on arguments of (Khajvand, et al., 2011), customer lifetime value (CLV) is calculated through the RFM approach. Accordingly, the weights of R, F, M are derived by AHP as follows: the weight of recency (WR) is 0.100, the weight of frequency (WF) is 0.390, and the weight of monetary (WM) is 0.600. Based on the equation below, the CLV of each cluster is calculated.

$$CLV_{ci} = NR_{ci} \times WR_{ci} + NF_{ci} \times WF_{ci} + NM_{ci} \times WM_{ci}$$

RFM approach in the first strategy is only included in the clustering. Clustering of K-means is used for customer segmentation. The amount of clusters is determined by the decision maker in K-means clustering method. After determination, there are four clusters of customers which have the similar behavior in RFM attributes.

As the result of RFM method for each cluster, the highest lifetime value is 6.628 months in best segment (or cluster 2). The remaining clusters including frequent segment (cluster 4), churn segment (cluster 1) and new segment (cluster 3) get a quite low lifetime value, accounting for 1.022, 0.685 and 0.197 months, respectively.

IV. CONCLUSION

An approach of RFM analysis to B2B isn't popularly done, which 925 active clients extracted from data warehouse is employed in the study. Market segments are clarified with the support of K-means algorithms. This finding is quite important contribution to effective marketing and sales strategies, not only to avoid to occurred spams but also to limit churn risk and maintain customer retention.

In fact, the customer segmentation is a practice of separating a customer base into specifically comparable groups. Without a profound knowledge of how the best current customers of company are segmented, a company often lacks of concentration on the market, effectively allocate and invest its valuable human and capital resources. In addition, absences of best segment focus of current customers may result in diffused product development strategies that impede the ability of company to fully participate with its targeted segments. All of these variables together can eventually hamper the development of a company.

The better customer segmentation analysis brings a tangible effect on operation results by allowing higher percentage opportunities for company sales revenue. Company spends less time on less profitable opportunities and more on the most successful sections to ultimately increase revenues. Besides that, it is not equal for all earnings per customer. Sales into the incorrect segments may be cost more to sell and retain, and get a higher churn rate or reduced upselling potential after the first purchase has been made. Staying away from these customer segments and concentrating on better ones will boost the margins and enhance the stability of customer base.

According to the paper's aim, the first objective is a performance of behavior-based customer segmentation without human direct intervention. The second one is a concentration on customer profiling and discovering a profile-segment relationship. The construction of customer segmentation was applied several clustering algorithms for selection and preprocessing data. Some of these algorithms are RFM, Customer Value Matrix and Customer Lifetime Value. Significant or less significant prospective customers can also be recognized and classified by a company to create a proper marketing plan for those specific customers.

Frequent group also is the second significant customer group although they may not have bought recently but they frequently make a purchase with high total spending amount, while customers in new group purchased recently with low total spending less amount because of their lower standard quality than best group and frequent group. The company can focuses on the most efficient strategies including a free trial provision and additional offer. Giving them a limited period of free trial with product's premium characteristics and providing on boarding support is to let them consider between the company and other suppliers they are using.

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