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AN APPROACH ON RFM TOWARD CLV: THE CASE OF B2B GARMENT SUPPLIERS

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ABSTRACT

Based on the database of 36,199 rows, equivalent to 263 active customers extracted from big data of a textile company, the model of RFM is applied toward the market segment. Parallel, the customer lifetime value (CLV) is approached. The finding is a significant contribution to the textile industry toward the four market segments. Particularly, the CLV is found, it is a very important contribution not only to discouraging spam, but also to reducing churn risk and retaining customer satisfaction through sales and marketing strategies.

KEYWORDS: Customer lifetime value, RFM, Vietnam.

1. INTRODUCTION

A satisfactory relationship between firms and clients is of worth importance for commercial company. Obtaining new customers is an important task, but maintaining existing customers is even more important, since losing a customer means losing the entire stream of purchase value that the clients will make for whole lifetime. When the industry becomes more competitive, it is vital for a firm to identify and retain high value and important potential customers. In addition, in order to meet customer satisfaction and to gain profitability, the business needs to customize marketing strategies and effectively fulfill.

The study of a company's large-scale transaction data involves separating all customers into a suitable number of internally homogeneous and mutually heterogeneous clusters based on certain similarities between these customers from the point of view of market segmentation. Here, segmentation is done using behavioral data called RFM (Recency-Frequency- Monetary) model. It is the technique used for ranking customers based on their purchasing behavior. Recency represents the length of a time period since last purchase, while Frequency depicts number of purchases within a specified time period, and Monetary means the amount of money that the customer spent in the specified time period.

Firms have used many techniques and methods to make strategic decisions. Among of that, customer lifetime value (CLV) is the common tools that have been adopted by many firms for such critical decisions. Therefore, CLV represents the total amount of money a customer is expected to spend in a firm's business or products during their lifetime. This is an important statistic to consider because it helps to determine how much money to spend in recruiting new clients and maintaining existing ones. Correct calculation of CLV can help a firm to classify and evaluate its customers based on their lifetime value so that various marketing strategy can be adopted for each segment. By measuring CLV for homogeneous customer groups instead of individual customers, companies may rate the customer groups based on their contribution to the benefit of the companies (Kumar, et al. 2008).

In fact, RFM and CLV have been widely concerned on retailing industry or B2C (also known as business-to-consumer). B2C marketing focuses much of the time on emotion-based buying decisions, while B2B (also known as business-to-business) marketing focuses on rational buying decisions driven by processes. On this paper, the aim of study is going to utilize relevant concepts onto a B2B firm operating in textile and garment industry to evaluate its customers. Because of competition, the name of company is asked to keep secretly. This company's age is more than 20 years of existing in Vietnam. This is much supported to extract sales dataset for analyzing customer purchasing behaviors. The company had to grow with increasing number of competitors recently; it is the consequence of the general development of textile and garment industry in this South East Asian country.

Many scholars have been study about B2C customer relationship satisfaction, but very less articles have discussed about B2B customers. The new point of this study is to employ big data to predict customer behavior; this is one of the new fields in the field of B2B marketing. The processing of data has been made more feasible and cost-effective by recent developments, and information can be collected from both internal and external data sources. There is a great opportunity for B2B companies in big data analytics, but B2B practitioners seem to lack the resources and guidance to understand the potential. Based on problems above, the current paper concerns to investigate changes in customers' behavior toward buying product and to measure customer lifetime value (CLV) based on RFM (Recency-Frequency-Monetary).

2. LITERATURE REVIEW

There were some scholars have used RFM model to determine CLV in former works, but they are more relevant to B2C or online business than B2B. These could be utilized as a basic theory to spread this study in a specific industry, e.g. the garment industry, which usually is thought as a traditional industry with inherent relationship base business. This is a new point of this paper, because we rarely see firms utilizing their data analysis for sales activities planning.

The comparison of RFM model to other modern methods will be also indicated to provide pros and cons, as well as applications of this method to determine CLV. In order to improve marketing efficiency, Jiang and Tuzhilin (2009) established that both consumer segmentation and buyer targeting are important. These two activities are combined into a step-by-step approach, but unified optimization is the problem faced. A three-dimensional approach to enhancing customer lifetime (CLV), customer loyalty and customer behavior was proposed by Sunder and Zhao (2016). They concluded that customers are different from each other and their desires are often different. Segmentation helps to find their market and desires and to show a successful service. A personalized recommendation method using weighted frequent pattern mining was proposed by Cho and Moon (2013). In order to find prospective clients using the RFM model, consumer profiling is carried out. For each transaction, the author has specified varied weights to generate weighted association rules through mining. Using the RFM model would provide the client with a more reliable recommendation, which in turn increases the company's profit.

A new integrated approach to segmentation with the RFM and CLV methods was designed by Sheshasaayee and Logeshwari (2017). With the first stage being the statistical approach, they used a two-phase approach and perform clustering is the second phase. After the two-phase model, they plan to conduct K-means clustering and then use a neural network to boost their segmentation. The consumer churn forecast was analyzed by Lu et al, 2014. To construct a new distinct prediction model, the authors used logistic regression and separated the transactional data. With its experimental execution, it is noted that it is possible to classify consumers with the highest churn value and can maintain them using individual marketing strategies. Zhang claims that it is important for the long life of the company to deduce the cause of a customer's churn actions and to meet individual needs. A direct clustering approach is proposed by Jiang and Tuzhilin (2009), which clusters clients not on the basis of computed statistics, but by integrating transactional data from several clients. The authors also demonstrated that finding an optimal segmentation solution is NP-hard.

RFM

The RFM model consists of three measurements (Recency, Frequency and Monetary) that are combined into a 3-digit RFM cell code, covering five equal quintiles (20 percent group). The recruitment is also considered to be the most critical of the three RFM steps. However, the RFM values are vulnerable to being firm-specific and are dependent on the product design (Lumsden et al., 2008). Fader et al (2005) found that higher frequencies appeared to have less opportunity for future sales than those with lower pre-purchase rates. Similar results have been found by Lumsden et al. (2008) that there are major variations between recurring and frequent classes.

This model of RFM was proposed by Hughes (1994), whom used transaction history to define behavior-based customer segmentation. RFM is also advantageous in real business environments because of its user-friendly and interpretable data. It allows firms to target specific clusters of customers with communications that are much more relevant for their behavior, and thus generate much higher rates of response, plus increased loyalty and customer lifetime value.

The quantification process for customer behavior through RFM is as follows. Sort the database by each RFM dimension and split the customer list into five point scales. It is understood that the method is exactly the same size. Different RFM quintiles are responding at different rates. Customers are sorted by purchase dates for recruitment. Recency is generally defined by the number of times from the last purchase which takes into account the interval between the latest transaction period and the time of examination (days or months), that means that the fewer days the higher the recency score. A consumer with a high recency score means that he or she would make a recurring purchase more likely. The top 20% is encoded as 5, while the next 20% is encoded as 4 and so on. In conclusion, the number 5 to 1 for each customer is indicated in the database (Tsai and Chiu, 2004).

For frequency, the database is sorted in a certain time period by purchase frequency (number of purchases). Two states, like single and repetitive transactions, also simplify the concept of frequencies. A value of 5 is given to the top quintile and the other values of 4, 3, 2 and 1. Higher frequency score however suggests higher customer loyalty. A consumer with a high frequency results in a high demand for the commodity and is more likely to buy the goods over and over.

For money, the total sum spent over a given period of time is coded for customers. The currency term is determined by the dollar value spent by the consumer in this period or the average dollar amount per transaction or purchase to date. Marcus (1998) proposed that the average buying sum rather than the total buying quantity should be used to reduce the co-linearity between frequency and money. Finally, 555, 554, 553... 111 are submitted to all customers and 125 (5 to 5 to 5) RFM cells have been created. In addition, the highest segment of customers is 555, while the worst segment of customers is 111. Customers can be divided into groups based on the assigned RFM behavioral principles and their income can be analyzed further (Cheng and Cheng, 2009).

The customer quintile approach is to sort customers down (from the best to the worst) in order. The benefit is that each section has the same number of customers. This form, however, has a significant drawback. It faces many score challenges in frequency calculation and is relatively sensitive, resulting in customers with similar conduct at the lower quintiles but with group customers with substantial variations in purchasing behavior (Alam and Khalifa, etc. 2009).

Miglautsch (2000) suggested incorporating the behavioral quintile scoring system with the mean method of score developed by Ted Miglautsch. The frequency score is determined by the fact that the single buyers have a score of 1. The sum of the other frequency values is then used to calculate the mean. When the overall frequency value of a customer is lower than the average, a score of 2 will be given to that customer. The method can be replicated again. Five quintiles are still produced for monetary purposes and each has equivalent revenue amounts.

In addition to assessing cells' value, some studies indicate that the possible combinations of RFM are obtained by assigning or on the basis of the average value of R (F, M) for a cluster that is less than or above the total average value of R (F, M). Eight segments are formed in this scenario.

Composite RFM values are obtained by multiplying uniform RFM values of individual customers and RFM variables by weight (Liu and Shih, 2005).

There are two ways of generating a single RFM value when talking about the weighting method of the RFM model. One approach Libey suggests is to add values of recurrence, frequency and currency together by adding an average order and frequency each year, while the other method is used more often in practice by adding RFM scores together (Miglautsch, 2000). According to Doğan and Bulut (2018), when computing a composite score, every calculation of RFM has the same weight. For example, the composite score for cell (5,2, 4) is 11 (5 + 2 + 4). However, Miglautsch (2000) suggested that it is also possible for each calculation of RFM to be assigned a different weight. In addition, the summative formula of the RFM score is given as the composite total score = (R bis 3) + (F bis 2) + (M hasta1) (Miglautsch, 2000). In addition, Miglautsch (2000) claimed that a composite score is another formula, which is a total composite score = (R hasta9.9) + (F hasta6.6) + (M pas 3.3). Tsai and Chiu (2004), in comparison to the formulas shown in Miglautsch (2000), pointed out that the sum of the weight of each RFM measure should be equal to 1. On the other hand, Stone (1995) has allocated different weights to RFM measures to quantify a single RFM value, if the product and industry characteristics are taken into account. The new acquisition is precisely given a weight of 24 if it has a time span of 3 months, 12 if it is three to six months, 6 if the period of purchase is six to nine months, 3 if the time is nine to 12 months and 0 if the time of measurement is longer than 12 months. The weighted frequency value is calculated by multiplying the buying frequency by 4 points; while the currency value is calculated by multiplying the buying sum by 10 percent (highest value is 9 percent).

Liu and Shih (2005) used the analytic hierarchy method to evaluate the relative weights of the RFM variables rather than randomly assigning a specific weight to every variable of RFM. On the other hand, McCarty and Hastak (2007) assigned a weight to each RFM measure based on previous experience and then created an appraisal feature for database marketers using a database, which was called an RFM based on judgment. Contrary to judgmental RFM, Doğan and Bulut (2018) suggested a two-step empirical RFM method. First, the customer quintile approach is identical, while the second stage consists of a test mail to a randomly sampled subset of each cell (10%). When the answers from the test mail are collected, the proportion of respondents can be reached in each cell. First, the cells can be ordered as an answer percentage feature. The marketer may then either e-mail a specific part of the remaining file (that is, the top 20% of the cells) or e-mail cells that surpass the per cent split, dividing the mailing costs by revenue earned per order. This leads to the value of the test mailing for the unique offer for each RFM measure.

Tsai and Chiu (2004) summarized that an RFM value can be converted into a z-score through the actual values obtained from the original transaction database, not coding the value of every RFM calculation into a certain score. After the transformation of the RFM ratings, the multiplication of each RFM value and the weight will produce a new RFM value.

The description of the above mentioned RFM model contains some minor changes based on the study focus. Hsieh (2004), for example, analyzed the actions of bank clients by taking recurrent steps in terms of the average time period between the date the charge is applied and the day the bill is charged. Frequency measures the total number of credit card transactions and the amount of consumption expended throughout the year. Cost is classified as monetary by network transportation unit and is measured as monthly / monthly network traffic.

Customer Lifetime Value

In order to attract and retain customers by increasing their loyalty and satisfying their needs, CRM is considered a collection of methodologies and organizational processes. CRM is regarded as a theory of business operations aimed at attracting and retaining clients, maximizing their value and loyalty, as well as incorporating customer-centered approaches (Gupta, 2006). Enterprises planning to create an outstanding customer relationship will minimize their sales cycle and improve customer satisfaction and overall business profits.

In marketing literature, companies have to follow customer-centric methods such as customer value evaluation in order to have a successful CRM. Customer value is the value that the consumer brings from the present era to the business over its lifespan. Firms need to determine the metric is sufficient to define the importance of customers in the assessment of consumer value (Nyman, 2014). In the CRM domain, CLV is a term that is considered to be an acceptable marketing metric for assessing the importance of customers (Kumar, 2008).

Forty years ago, CLV was described as the present value of the future profit stream expected over a given time horizon of transacting with the" over a given time horizon. CLV and its applications have received growing attention in recent years (Reinartz and Kumar, 2000). Some of these studies have proposed models that use past customer data to calculate CLV, while some others take into account their future behavior. Due to the lack of historical data about customers, the literature is dominated by studies in the latter category. Correct calculation of CLV can assist a company to classify and rank its clients on the basis of their lifetime value in order to develop different marketing strategies for each segment (Doğan and Bulut, 2018). By calculating CLV for homogeneous customer groups rather than individual customers, companies can rank the customer groups based on their contribution to the profit of the firms (Kumar, 2008). Instead of treating all customers in the same way, calculating CLV for client groups of customers can help the company to treat each group differently based on their value. The CLV estimate helps the company to understand how much it can invest in maintaining customers in order to obtain a positive return on investment (Kumar, 2008).

According to Sunder, Kumar and Zhao (2016), the CLV is computed by scholars in different ways. The value of consumer life defined as a fraction of cash flow using a weighted average capital cost over a customer-to-company lifetime.

In general, different methodologies for calculating CLV are available for various organizations. Based on Safari et al (2016), the approximate CLV is based on the RFM algorithm. The selected features of this strategy included the latest buying date as Recency, the amount of purchasing frequencies across times as Frequency and total money spent by customers over time as Monetary.

For the normalization process, Min-max standardization method is used. This method performs a linear transformation on the initial data. Assume the maximum and minimum values of an attribute, A, are maxA and minA. Then Min-max normalization maps, through a calculation, a value, v, of A in the range of [newminA, newmaxA]:

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

To calculate the CLV and the weighed RFM method for each cluster. Each cluster has an average CLV value with the following equation:

$$CLV_{ci} = NR_{ci} \times WR_{ci} + NF_{ci} \times WF_{ci} + NM_{ci} \times WM_{ci} \qquad (1)$$

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_{ci} is weighted Monetary.

RFM calculation is a step to address the cluster analysis method. Each element of RFM is to be classified into five categories: 1 very small, 2 low, 3 medium, 4 high, and 5 very high.

How to calculate the weights of WRci, WFci, and WMci are based on the AHP (Analytics Hierarchy Process). For arranging and analysing complex decisions, AHP is a systematic methodology based on mathematics and psychology. It was created by Thomas L. Saaty in the 1970s, who collaborated to establish Expert Preference with Ernest Forman in 1983 and has since been extensively studied and refined. It is a comprehensive approach for quantifying the requirements for decision weights. Via pair-wise comparisons, the experiences of individual experts are used to estimate the relative magnitudes of variables. Each of the respondents must compare the relative value between the two items under the special designed questionnaire (note that while most of the surveys followed the Likert five-point scale, the AHP questionnaire is 9 to 1 to 9 (Liu and Shih, 2005).

Customer Segmentation

Customer segmentation is an efficient way to manage different customers with different preferences. It divides heterogeneous customer groups into uniform groups on the basis of common attributes. Customer segmentation not only increases satisfaction but also the expected company profit. Different marketing strategies in the segmentation of customers could increase the value of customers. By fulfilling customer needs, the company maintains long-term customer relationships. Companies can also increase revenues through low cost acquisitions and retention.

The main goals of customer segmentation include the use of new customer potentials, customer acquisition, and the development of current customer potentials and better targeting of marketing measures. Clustering is one of the most useful methods for recognizing the homogeneous customer base and developing tailor-made marketing strategies for each group (Liu and Shih 2005).

The segmentation remains an important field of business research and practice for companies and the underlying assumption is that the main objective of this process is to identify aspects of group homogeneity while maintaining an appropriate degree of heterogeneity between groups and our segmentation definition follows this logic.

3. RESEACRCH METHODOLOGY

Data collection

The data based used in the study is internal data extracted from the data warehouse of the company. In total, there are 36,199 rows, equivalent to 263 active customers employed in the study, that means one customer have more transactions with the company. The period time of data consideration is monthly data from 2017 to July 2020, which 21 fields are employed (table 1). However, during cleaning data, 124 rows are removed due to their missing value of invoice as well as transaction value. The software used to data analytics as IMB Modeler.

Because of requiring the confidential to be against the competition, the database and findings are asked not to be shared and re-used.

Table 1: Information of fields enclosed in the study

Field name	Definition of field	Measures/value
1. Code_ID	Customers ID/customer code	String
2. Year	Year of customer's purchase	Continuous
3. Month	Month of customer's purchase	date
4. Group	Sales group	Nominal
5. Customer Name	Customer name	

6. Inv. Date	Invoice date	Date
7. Inv. No.	Invoice number	Nominal
8. Customer #PO	PO number	Nominal
9. Currency	Currency US$	Continuous
10. Inv. Amount	Invoice amount	Continuous
11. Width	Width of product	Continuous
12. Inv. Unit Px	Unit price	Continuous
13. Product Line	Product type	Nominal
14. Item	Product name	Nominal
15. Color	Color	Nominal
16. Qty	Quantity	Continuous
17. SQM	Square meter	Continuous
18. Buyer	End buyer brand	Nominal
19. Area	Sales Area	Continuous
20. Salesman	Salesman	Nominal
21. Segment	Product Segment	Nominal

Source: Internal data extracted from data warehouse

Concepts approached

In addition, the organization needs to customize marketing strategies and effectively meet various efficiencies in order to achieve improved customer satisfaction and. Sohrabi and Khanlari (2007) concluded that, as not all customers are equally financially attractive to the business, it is necessary to first assess their viability and then deploy resources to clients in accordance with their values.

The study of the large-scale transaction data of an organization involves dividing all customers into a suitable number of clusters from the point of view of market segmentation, which are internally homogeneous and mutually heterogeneous on the basis of certain similarities between these customers. Segmentation is conducted here using behavioral information called the RFM (recency, frequency, and monetary) model. It is the method used on the basis of their buying actions for rating clients. Recency is the duration of a period after the last purchase, whereas frequency indicates the number of sales within a defined period of time and monetary time implies the amount of money invested in that specified period of time.

4. DATA ANALYSIS

Big data alone however is not a cornerstone but can be treated as a raw material that needs to be further converted into business insights. In general, analytics refers to the extraction of secret data insights in order to produce market intelligence, referring to improved knowledge and understanding of business processes and business environments. Customer big data analytics used in this study therefore apply to the collection, storage, processing and analysis of a huge amount, variety and speed of customer-related data to generate useful knowledge for the decision-making process of the organization and to discover market value and insights in a timely fashion.

The tool used in this paper is SPSS Modeler, which support to calculate 3 indicators of RFM that will be explained by following content.

As mentioned previously, there are 36,199 transactions of 263 active customers employed in the study. The main business of the company researched is to sell industrial products, which there are seven group of product lines as presented in figure 2, such as CAVAS, INTERLINING, NON-WOVEN, OTHERS, SHIRT, SL-TAPE, and WOVEN.

As resulted in figure 1, except to the monthly sales of seven months in 2020 (January to July), the three years (2017-2019) present monthly sales amount of 12 months. The figure brings an important message that the sales amount of the first quarter years are a stable increase, but from April to July 2020 the sales growth declined severely. This reduction is due to the impact of the Covid19 pandemic.

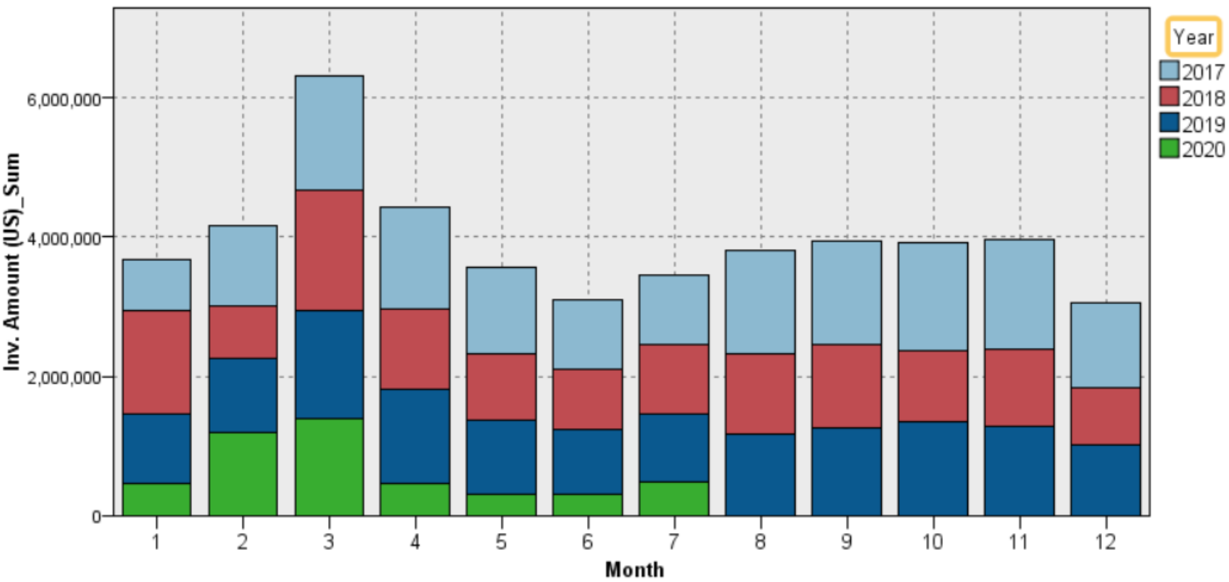

Figure 1: Selling amount from 2017-2020 by month

Source: Internal database extracted from data warehouse

As resulted in figure 2, the product line of WOVEN always accounts for the highest share of months. The second share is the product line of SHIRT, except to March, because NON-WOVEN has the second highest share in March. As mentioned, the pandemic of Covid19 has caused a serious damage for the textile and garment industry, this make a significant decrease of product lines after the first quarter of 2020.

The impact of the Covid-19 epidemic, the situation of production and export of the T&G industry still faces many difficulties due to the shortage of export orders, making the export turnover of T&G from the beginning of the year down to 12% compared to the same period in 2019. This makes Vietnam National Textile and Garment Group (Vinatex) giving a negative forecast for the industry's exports in the last months of 2020, as export turnover continues to decline from 14% -18 % compared to the same period last year. Thus, total textile export turnover in 2020 is only about 32.75 billion USD, down about 16% compared to 2019 and is the largest decrease in the past 10 years.

As a unit of T&G supply chain, author’s company is also facing the same difficulty in 2020 and even decrease more significantly because of the products of company is served for high value segment such as suit and shirt which have got the strongest impact. The decreases of each product lines are different and depend on the business status of buyers in EU, US and Japan market. For instance, as the social distance requirement, demand for formal segments like shirt, men-suit has dropped significantly, that caused the output for canvas, shirt products from author’s company were dropped appropriately. While informal segment like t-shirt, pants, home-wear which require non-woven or woven products, could maintain certain sales volume despite of Covid pandemic.

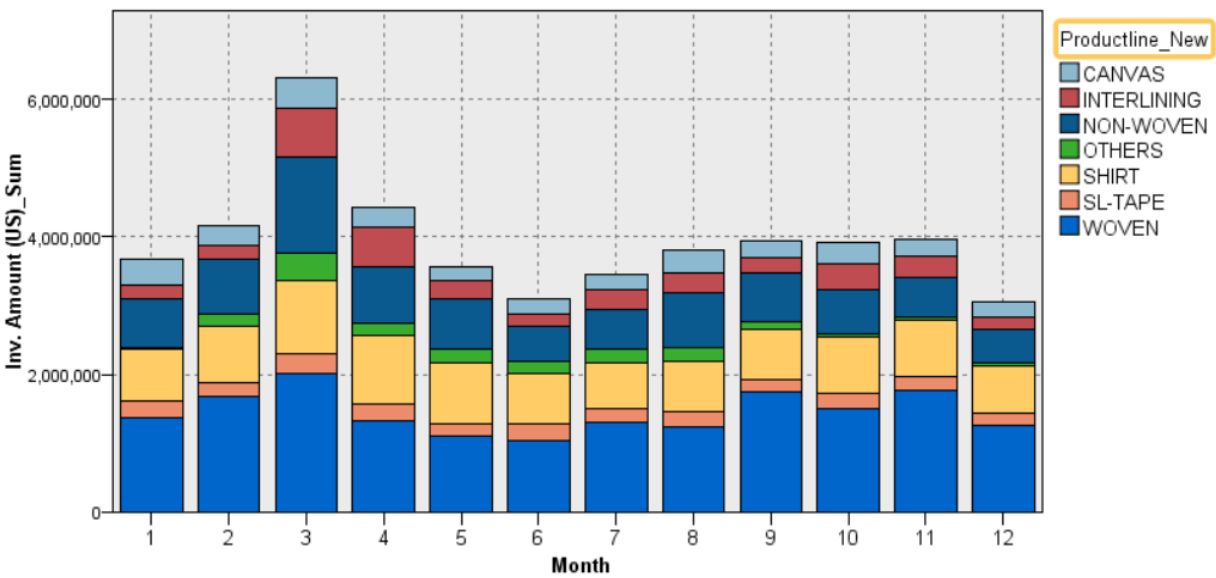

Figure 2: Sales amount of product line by month

Source: Internal database extracted from data warehouse

Although the product line of WOVEN and SHIRT have a leading contribution to the total sales, but the value per invoice of the business transaction of CANVAS and INTERLINING is the highest between 3000-4000 USD/invoice. As a result, WOVEN, SHIRT, and NON-WOVEN are popular and often used, however their invoice values are low, due to the price of them are low. While the CANVAS and INTERLINING are typical and often concerned in months of April, August and November (figure 3).

The figure result is true because CANVAS is only used for men-suit and sometimes jacket, which usually has the highest value in a garment sector. INTERLINING here actually is some special product range that the company sells to specific customers, thus the value is also high. Other product lines like WOVEN, NON-WOVEN can be found in any basic garments and has no technology advantage in the market, therefore price unit of those lines are relatively low and make total contribution to company turnover less than CANVAS or INTERLINING group.

However, due to orders frequency of each product line has its own characteristic, this can be explained by seasonal orders, repeated order or new develop orders. These all will be explained by CLV of each product lines that contribute to company.

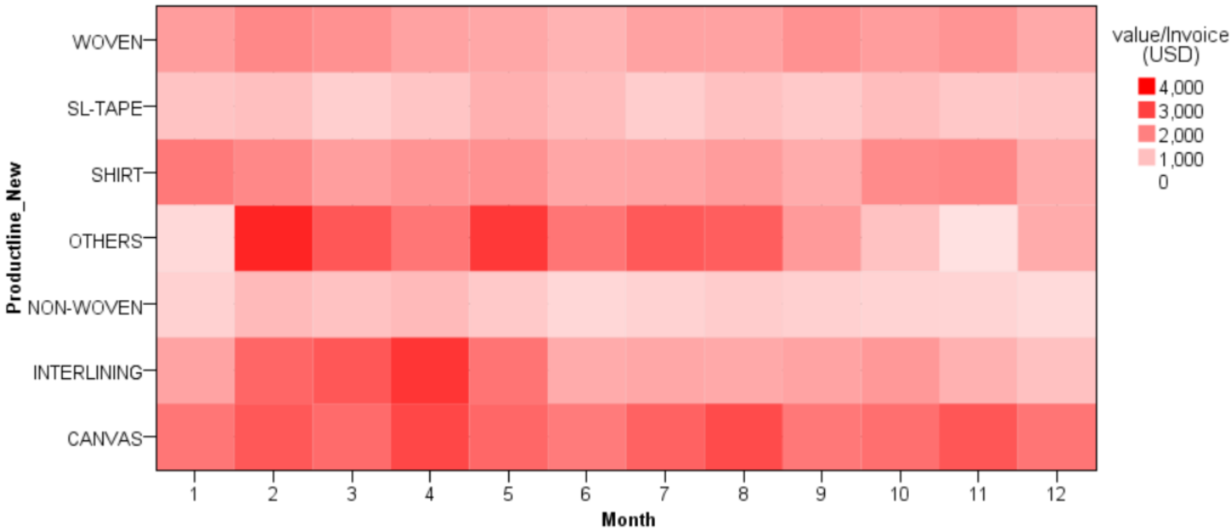

Figure 3: Value per invoice by product line

Source: Internal database extracted from data warehouse

Market segment

In order to investigate how the relationship between the customers' LOS (length of service) and the recency time of customer's buying, Wu and Lin (2005) developed a combination matrix based on LOS and Recency. As resulted in figure 4, there are quarters of cell, each cell provides information of customers and kind of product lines.

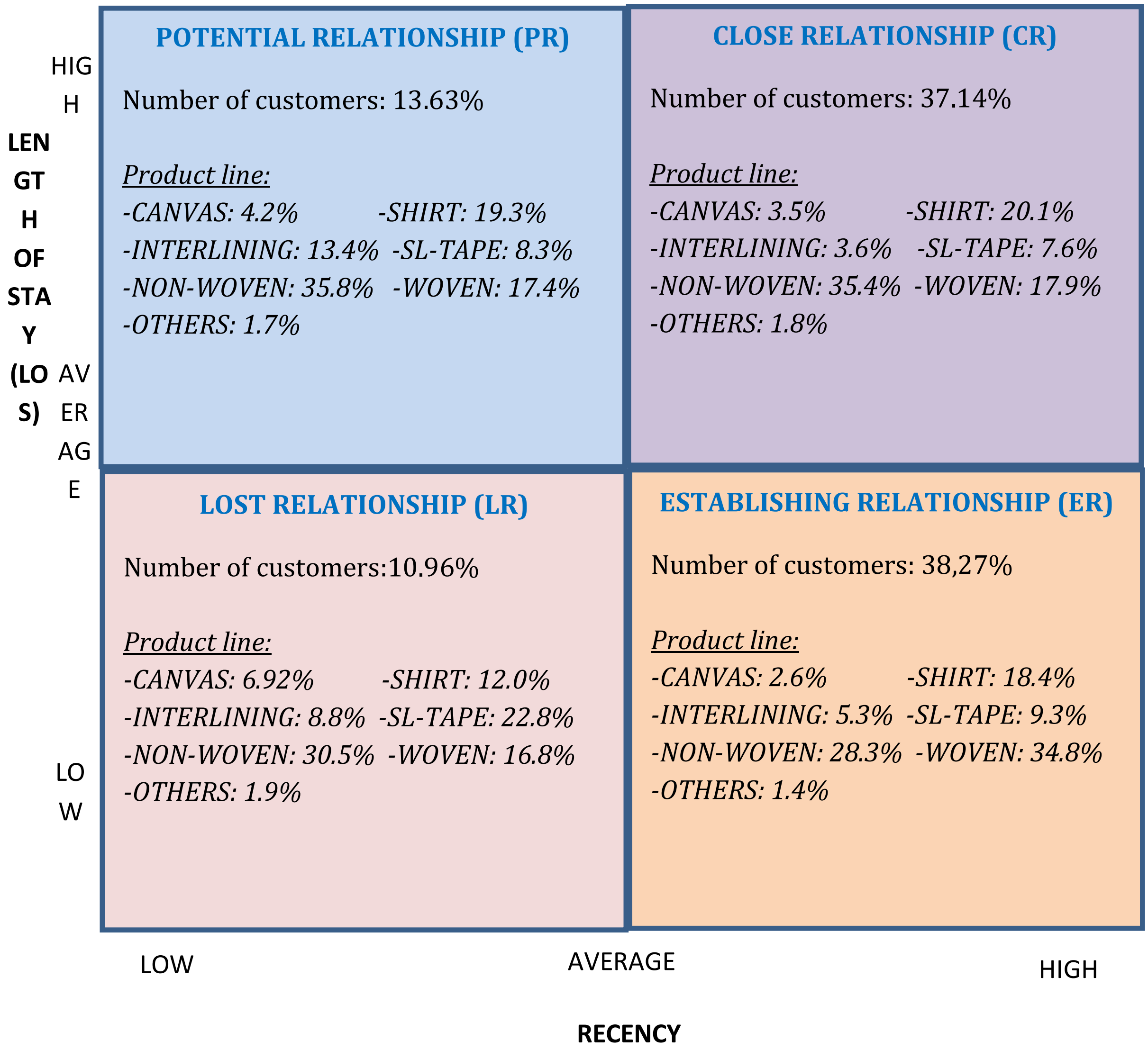

Figure4: Combination matrix between LOS and Recency of customer

Source: Internal database extracted from data warehouse

1) Potential Relationship (PR): It is an integration between High of LOS and LOW of Recency, so called "potential relationship", accounting for 4,915 transactions, and equivalent to 13.63% percent of total customers. Non-woven is the best consideration of this group with 35.8%, next as Shirt with 19.3%, woven with 17.4%.
2) Lost Relationship (LR): It is integration between LOW of LOS and LOW of Recency, so called "lost relationship", accounting for 10.96% of total transactions. The Non-woven is best consideration of customers with the share 30.5%, next SL-tapes with 22.8% and woven with 16.8%.
3) Close Relationship (CR): It is an integration between HIGH of Recency and HIGH of LOS, accounting for 13,398transactions, and equivalent to 37.14% of total transactions. The group is highest contributor to company.
4) Establishing Relationship (ER): It is an integration between HIGH of Recency and LOW of LOS. There are only 13,807 customers in this cell, equivalent 38.27%.

As resulted in figure 5, the method of RFM is quite supported to develop four segments, such as the uncertain group; the best group, the new group, and the spender group.

Cluster	Label	Size	Inputs		
cluster-1	Uncertain group: Low M – Low F – Low R	35.6% (94)	Monetary Score 1.61	Frequency Score 1.57	Recency Score 1.62
cluster-2	Best group: High M – High F – High R	34.0% (89)	Monetary Score 4.47	Frequency Score 4.44	Recency Score 4.27
cluster-3	New group: Low M – Low F – High R	17.5% (46)	Monetary Score 2.38	Frequency Score 2.38	Recency Score 3.79
cluster-4	Spender group: High M – High F – Low R	12.9% (34)	Monetary Score 3.72	Frequency Score 3.80	Recency Score 2.12

Figure 5: Customer segments based on RFM

Source: Internal database extracted from data warehouse

Based on the method of Safari, et al. (2016), the function (1) is applied to calculate CLV. Accordingly, CFVG is found in figure 8 and it presents its contribution to the company, which the highly ranked CLV of SHIRT is 0.673, next as NON-Woven 0.642, WOVEN with 0.638,CANVAS which has big amount of value but CVL value is relatively low compared to other product line (figure 6).

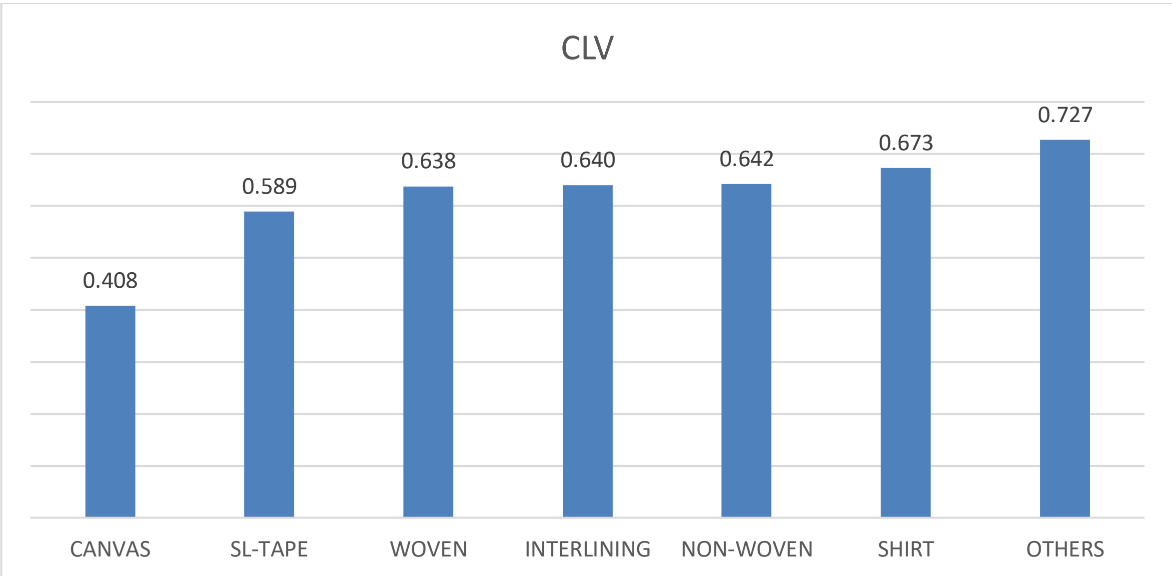

Figure 6: CLV by product line

Source: Internal database extracted from data warehouse

By analyzing CLV calculation by product line based on market segment, the figure 7 depicted that NON-WOVEN has the highest rank in term of CLV contribution, next as WOVEN and SHIRT. This can be explained easily because author's company is market leader for NON-WOVEN products and have wide ranges commodity could meet customers' requirement. While with WOVEN and SHIRT item, they all are

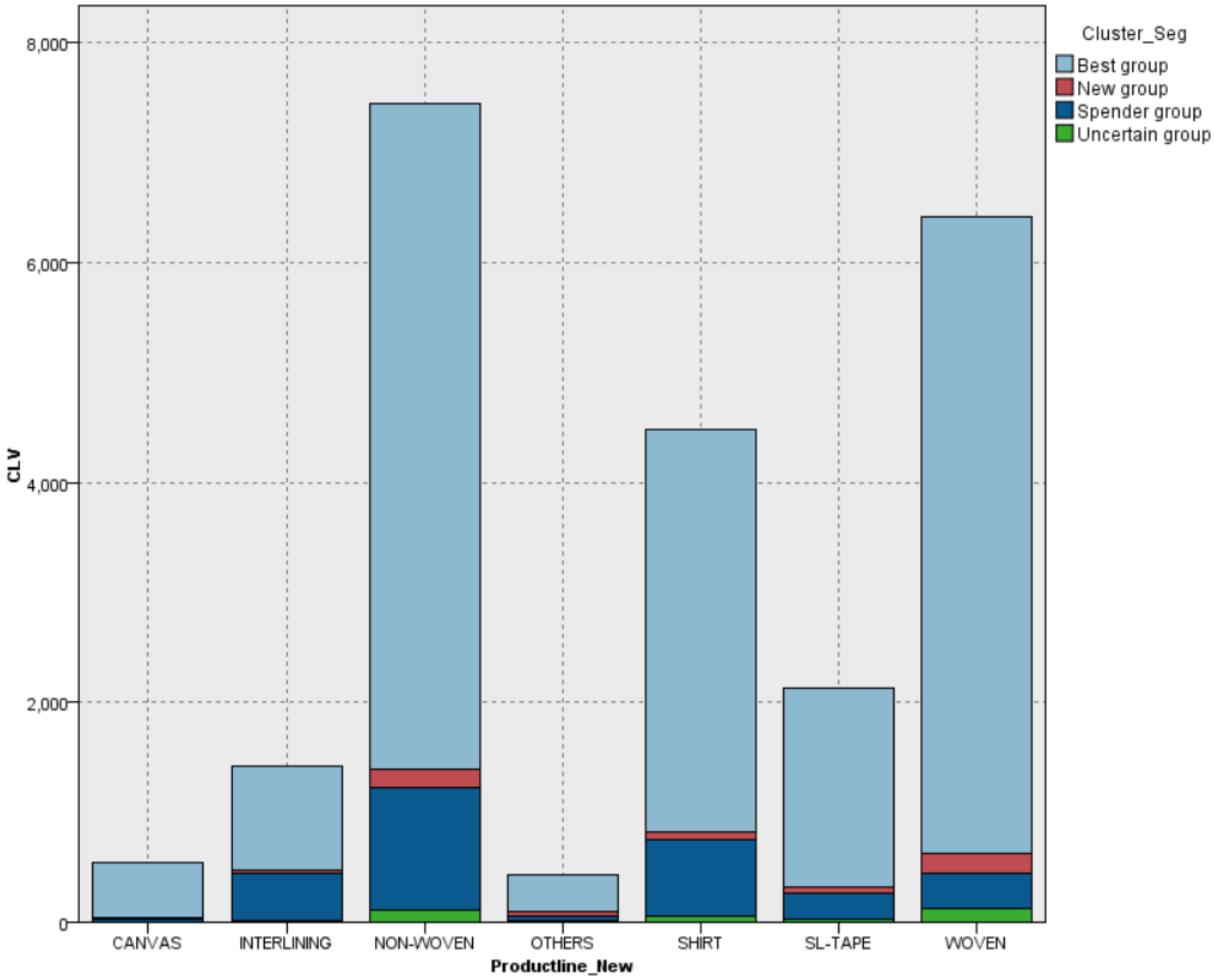

Figure 7: CLV contribution by product line based on market segment

Source: Internal database extracted from data warehouse

According to the data analysis above, each product line carries different CLV values for the company. While each customer group through analysis indicators also shows the specific characteristics that the management of the company needs to pay attention to building development strategies. Retaining, maintaining and developing existing customers is an art in business management that, if done well, will bring sustainable growth to the company rather than hunting and wasting of time to new customers if company resource is really limited.

5. DISCUSSION

In reality, customer segmentation is a technique of dividing a customer base into specifically comparable categories. Without a clear understanding of how the best current clients of the organization are segmented, a company also lacks business focus, allocates and effectively invests its important human and financial resources. Furthermore, the absence of the best segment focus of current customers will result in diffuse product development strategies that impede the ability of the business to fully engage with its targeted segments. Together all these factors will ultimately hamper the growth of a company.

The better customer segmentation analysis brings a tangible effect on operating efficiency by allowing higher percentage opportunities for company sales revenue. The business spends less time on less profitable opportunities and more on the most promising segments in order to ultimately maximize profits. Furthermore, all income per buyer are not equal. Sales in the incorrect segments may cost more to sell and sustain and earn a higher churn rate or decreased up selling potential after the first purchase has been made. Staying away from these segments of customers and concentrating on better ones will increase margins and boost the reliability of the customer base.

Since segmentation is centered on the values of Recency, Frequency, and Monetary values, the company can adapt its marketing strategy to the consumers based on their buying behavior. Future study includes evaluating the performance of customers in each category, such as the products typically purchased by each segment's representatives. This would make it better for unique goods and better promotional deals to be included.

Companies should devise and execute customer-centric strategies to optimize the lifetime benefit of each group and thereby customer loyalty, based on the proposed methodology of this report. Companies that have limited resources should concentrate on those customers who offer maximum value and loyalty to the business rather than treating all customers in the same way by measuring CLV for each customer group. By measuring the entire lifetime value of the customers, managers will consider the proposed CLV measurement technique for offering the next best services or products to the community of customers who are more important. In order to handle different categories of clients differently and improve brand satisfaction, businesses should formulate customer-specific contact strategies.

There are some drawbacks to our study that can guide future research. First, given that the trim supplier company model of this study was applied and the weights of RFM were derived based on the characteristics of the industry. In order to address this restriction, businesses need to extract their own preferences in order to incorporate the proposed technique in other industries and sectors, as different industries may have different concerns about the value of R, F and M.

Analysis of the RFM model is important and can provide fruitful insight for researchers and decision-makers. Currently, the RFM model has been shown to be very successful in a variety of practical areas. Not only for profit-making businesses (including the marketing, banking and insurance, telecommunications, travel and internet sectors), but also for non-profit organizations and government agencies, RFM may help identify important consumers and create an effective marketing strategy.

For researchers, they can get a complete understanding of the RFM model description, so that they can have more ideas about the refined implementation of RFM. On the other hand, decision-makers may consider valuable customers and set up significant plans by implementing RFM. Indeed, RFM helps decision-makers to analyze consumer behavior, segment customers, estimate the probability of reaction for each type of offer, assess customer satisfaction and customer lifetime value and evaluate online reviewers. Direct marketing has a long history of using the model of RFM. Through the analysis of the implementation of the RFM model, decision-makers will then gain insights into RFM and be able to apply RFM more effectively to resolve the issues faced in daily operations and devices.

6. CONCLUSION

In the study, which employs 263 active clients derived from the data warehouse, the RFM study approach to B2B is commonly used. Market segments are explained with the aid of the RFM model. This result is a very important contribution not only to discouraging spam, but also to reducing churn risk and retaining customer satisfaction, to successful marketing and sales strategies. In the contemporary business environment, since consumer loyalty is of great importance, the key focus of companies is on finding the most valuable customers from whom customer satisfaction and market share can be improved.

The paper presents a general picture of garment industry in Vietnam, in which negative impacts of the COVID19 crisis is clearly. It causes a sharp decline in retail sales in key export markets; this has affected workers and businesses across supply chains. An application of RFM produced 4 market segments: Best group (34.0%); new group (17.5%); Spender group (12.9%); Uncertain group (35.6%). Continuously, with application of RFM, CLV is calculated, which the product of SHIRT is the highest CLV (0.727), next as NON-WOVEN (0.642), INTERLINING (0.640), WOVEN (0.638), SL-TAPE (0.589), CANVAS (0.408). Notablely, customers who are the highest CLV is belong to the product of NON-WOVEN and WOVEN.

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